Evaluation of Agricultural Land Transitions on Urban Fringes

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DECLARATION

I certify that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any other university; and that to the best of my knowledge and belief, it does not contain any material previously published or written by another person except where due reference is made in the text.

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20 June 2018

CO-AUTHORSHIP

This thesis focuses on four research publications in international scientific journals. Chapters 3 to 7 are written in a journal paper format. Of these, Chapter 3 ‘Agricultural Land Fragmentation at Urban Fringes’ (Wadduwage et al., 2017) was published at the time of the completion of the thesis.

Chapter 4 ‘Agricultural Land Vulnerability at Urban Fringes’; a combination of Chapters 5 and 6: ‘Peri-urban Farmers Land-change Decision Behaviours’; and Chapter 7:’ABM Simulations of the Peri-urban Agricultural Land Transitions’ are expected to be published in due course.

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ACRONYMS AND ABBREVIATIONS

ABM	agent-based model/modelling
ABS	Australian Bureau of Statistics
ACLUMP	Land Use South Australia (land cadastral map)
ALVI	Agricultural Land Vulnerability Index
ANOVA	analysis of variance
BAU	business-as-usual (scenario)
CA	cellular automata (modelling)
CBD	central business district
CI	confidence interval
CLUE	conversion of land-use change and its effects (model)
DEM	digital elevation model
df	degrees of freedom
Die	disappear from the land system (i.e., land sold to a land developer)
DL	dryland (agriculture)
DPTI	Department of Planning, Transport and Infrastructure
ECA	exploratory cluster analysis
EDS	(accelerated) economic development scenario
EFA	exploratory factor analysis
EIA	environmental impact assessment
EPS	(a high) environmental protection scenario
EU	European Union
GIS	geographic information system
GUI	graphical user interface
ha	hectare
HCA	hierarchical cluster analysis
HL	horticultural land
IFS	influence on farm success
IISD	International Institute for Sustainable Development
ILUC	influence on land-use change
IQR	inter-quartile range
LCC	land-cover change
LF	latent factor
LFA	latent factor analysis
LGAs	local government authorities

LL	livestock land
LSS	land system science
LULCC	land-use and land-cover change
LUTO	land-use trade-offs (model)
MAS	multi-agent system
Memory (R)	resilience to vulnerability
ML	maximum likelihood (method)
MPS	mean parcel size (a metric)
MS	Microsoft
MSDI	Modified Simpson's Diversity Index (a metric)
ODD + D	overview, design concepts and details (of the model) + decision
PCA	principal component analysis
PD	parcel density (a metric)
PGD	postgraduate diploma
PLAND	percentage of land (a metric)
PLUREL	Peri-Urban Land Use Relationships (research project)
PM	parameter
ROI	return on investment
RT	resilience threshold
SA	South Australia/South Australian
SEM	structural equation modelling
SPSS	IBM SPSS Statistics (formerly Statistical Package for the Social Sciences)
U–R	urban-to-rural
US/USA	United States/United States of America
USSR	Union of Soviet Socialist Republics
WLSMV	weighted least squares means and variance adjusted

ABSTRACT

In a human-dominant land system, the investigation of peri-urban agricultural land transition phenomena is challenging as they occur under the effects of urban sprawl, in which complex land change drives insights into the transitional processes of land use. Considering urban-to-rural (U–R) landscapes as a single land system that consists of socio-economic, environmental and institutional land-governing influences, this study focuses on the complexities associated with agricultural land transition processes: the spatial, behavioural and temporal dynamics. The study explores the agricultural land-use presence and its vulnerability to urban sprawl while using peri-urban farmers' land-use decision behaviours to develop an agent-centric model to understand the complex land transitions on the fringes of the city of Adelaide in South Australia.

The first part of this research investigates the peri-urban land parcel spatial structure and land-use compositional arrangement focusing on agricultural land fragmentation. For this purpose, the author developed urban-to-rural land-use gradients, in parallel with landscape metrics, to analyse the landscape's spatio-structural changes and their effects on agricultural land parcel arrangements. The author shows the prospects of using a relationship between two landscape metrics—mean parcel size (MPS) and parcel density (PD)—to identify land fragmented areas along the gradients while quantifying the agricultural land presence in the fragmented zones for informed planning decisions.

The second part of this study analyses the vulnerability of peri-urban agricultural land to urban sprawl at a local level under opposing policy directions—economic development and environmental protection. For this purpose, land administrative scenarios were developed using spatially-explicit, multi-criteria models that considered the geographic and socio-economic aspects and the land-use plans of the study area. In this analysis, the author used grid-based spatial overlay techniques to develop the Landscape Vulnerability Index to spatially visualize and quantify the effects of sprawl, with respect to geographic locations. The results show that agricultural land vulnerability is inevitable in both scenarios, and that the spatial quantifications of agricultural land in a local government area are useful as they assist in transferring scientific knowledge into practice in local land-use planning.

The third part of this research explores the characteristics of peri-urban farmers—their demography, production and farming motivations—while exploring the drivers behind their land-

use decisions, decision-making profiles and their land-use decision behaviours. For this purpose, the author used a questionnaire survey to collect information from a sample of 168 farmers to represent a population of over 5,000 peri-urban farmers on the Adelaide city fringes. The study then developed descriptive statistics that were used to identify farming characteristics while using factor dimension reduction techniques to identify the key drivers behind decisions. Cluster analysis was used to identify decision-making profiles and their decision rules were employed to make assumptions for the development of the agent-centric model. The results show the advantage of using the motivations of farmers towards land management to identify decision-making profiles and decision behaviours and when making assumptions for agent-centric modelling.

The final part of this research explores the characteristics of the agricultural land transition process (land-change patterns and system feedback) and their responses under varying model environments. Spatially-explicit agent-based model simulations (using NetLogo) were used to analyse the agricultural land transitional processes while creating hypothetical parameter set-ups for the opposing policy directions (economic development and environmental protection). The results demonstrate that agricultural land transitional processes on the Adelaide city fringes are highly path-dependent, but less self-organized, and are largely dependent on land administration and economic effects.

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CHAPTER 1 – GENERAL INTRODUCTION

This chapter presents the research outline which aims to cover the most recent land system science (LSS) studies in the field of peri-urban land transitions. It specifically identifies the problem behind the research topic, with the problem statement addressed throughout the thesis. Comprising the intended study objectives and planned research methodologies, the chapter concludes by highlighting the significance of the research and the overall structure of the thesis.

1.1 BACKGROUND

Urbanization impacts on land use on the peripheries of cities in many ways, and these impacts will become more widespread as the increasing global population concentrates in urban centres (UN [United Nations], 2015). For millennia, the world had existed in which rural dwellers exceeded those in cities, until 2008 when the United Nations (UN) calculated that the world's urban population had exceeded 50% of the global population (UN, 2012). This global transition is accelerating, and by the middle of this century, two-thirds of the global population will be living in urban areas. In addition to the 37 megacities (i.e. those with a population greater than 10 million) at the present time, new economic geographies have emerged with over 2,400 secondary cities worldwide (Roberts, 2014). These contemporary patterns of urbanization will create immense demands on land and ecosystem services to fulfil the needs of growing urban populations (Ramankutty et al., 2002, Václavík et al., 2013, Tscharntke et al., 2012, Seto et al., 2011). Due to the twin phenomena of population increase and economic growth in urban areas, many green spaces have already been converted to residential, industrial and commercial land (Seto et al., 2012a). The anticipated competition for finite land, natural resources and ecosystem services will be felt acutely on the edges of cities, and this will extend outwards as urbanization encroaches onto rural agricultural land (Fragkias et al., 2012, Bringezu et al., 2014, Tian et al., 2017, Deng et al., 2015).

Land acquisition for urban development in peri-urban areas has been identified as a widespread and frequently occurring problem that creates socio-economic and environmental issues on the fringes of cities worldwide (Rauws and De Roo, 2011, Ravetz et al., 2013, Steel et al., 2017, Irwin and Bockstael, 2007, Pozoukidou and Ntriankos, 2017). Since the mid-1990s, the research conducted globally on land-use and land-cover change (LULCC) under the LUCC and Global Land Programme/Project initiatives (Global Land Project [GLP], 2005) using remotely sensed spatial information, has identified a myriad of landscape-level changes in peri-urban areas due to urban sprawl. Farmland, non-urban residential home gardens, and ecological and conservation reserves are the land uses that are most vulnerable to urban sprawl in peri-urban landscapes. The conversion of these land-use types to various forms of urban infrastructure can significantly impact upon the lives of people, particularly those living in peri-urban areas. These impacts include rising concerns over food security, loss through restrictions of open and green spaces, deterioration in their quality of life, and the delivery of ecosystem services (Zhu et al., 2017).

As urban sprawl is spatially and temporally dynamic, peri-urban landscapes are frequently subjected to land-use compositional changes, with these indicated by land fragmentations and land ownership changes (Yu et al., 2018). Recent land-use studies in peri-urban areas have demonstrated the advantage of analysing the broad sweep of landscapes from urban to rural as continuums to examine these compositional changes (Zhang et al., 2016, Vizzari and Sigura, 2015, Kroll et al., 2012). Although the land-change literature defines the term "peri-urban" in many ways, for this research, the author identifies it as landscapes that significantly differ (physically and functionally) from the urban built-up landscape or the rural agricultural landscape referring to the context of Australian urban to rural continuums.

Land-use planning is used to allocate and zone land in peri-urban areas, while local and state/territory government administrations simultaneously manage it, guided by land development policy directions. In land-use planning, land-use maps represent the proposed or existing land-use zoning in the spatial context. At the local level, local government authorities (LGAs) plan and manage land use according to land-use plans within their administrative boundaries. These scale-up across different local government areas and are sometimes guided by regional plans. Land-use zoning maps are used as a legitimate spatial representation of land use for policy implementation. Therefore, the spatial location and composition of land use have significant connections with local and regional land administrations. Multi-criteria spatially-explicit analytical techniques are increasingly used by researchers for predicting land uses under different policy arrangements (Koschke et al., 2012, Yu et al., 2011, Bhatti et al., 2015).

The loss of agricultural land is the major land transformation on the fringes of expanding urban areas (van Vliet et al., 2017). As the main group of land managers at the rural–urban interface and immediately beyond it, that is, the soon-to-be peri-urban areas, peri-urban farmers have a well-developed understanding of the socio-economic and environmental influences on, and implications of, managing agricultural land in these zones (Duvernoy et al., 2018). These influences comprise a series of social factors, for example, the disappearance of farming communities, conflicts with non-agricultural land uses, future uncertainty about remaining in farming, and institutional regulations around land management (Wu, 2008). Economic factors are also influential, such as increasing property (land) values, changes in returns on investment (ROIs), increasing demand for labour, and demand fluctuating for production, added to which are environmental considerations such as accessibility of water, climate change and waste management. In addition to these externalities, the farmers have internal consideration when making land-use decisions such as their family and farming lifestyle, and the social and economic aspects that are entangled with farming businesses. The decisions made by peri-urban farmers about land use, as well as by other minor groups of land managers in the peri-urban zone, have significant impacts on land-use transitions on the fringes of cities that are predominantly surrounded by farmland (Duvernoy et al., 2018).

Conventional land-use models often focus on bio-physical changes in landscapes, based on mathematical equations grounded on parameter assumptions with inputs from remote-sensing investigations and defined standards, or model behaviours that are specified in terms of local interactions (i.e. cellular automata [CA] modelling). These conventional land-use models have limited potential when incorporating complex human-coupled land-system processes consisting of agile land change in functional changes in land systems—such as peri-urban land system dynamics. Although conventional land-use models provide a reasonable understanding of land-change analysis, such as urban-sprawl monitoring and land-use policy evaluations on a macro-scale, investigations aiming to develop knowledge of land systems that are experiencing complex land-system processes at a local level (micro-scale) are of little benefit. Compared to conventional land-use models, process-based land-use models (agent-centric methods) provide rich information on path-dependent processes that depend on model environments and land-system feedback which are difficult to capture via conventional land-change modelling methods. Agent-centric models require a large amount of empirical information costing time and resources. However, there is potential to incorporate statistical methods to represent agents through samples or to integrate these methods with other socio-economic modelling methods when capturing land-system drivers and behaviours to provide justifiable evidence on land-use changes in human-coupled land systems.

Land-use modellers rely on physical and socio-economic parameters for modelling land-use changes (Subasinghe et al., 2016, Shkaruba et al., 2016, Sali et al., 2016, Tayyebi et al., 2014), but generally do not develop models based on farmers' decisions when simulating the complex land-transition phenomenon (Nguyen et al., 2017b, Solano et al., 2003) on the edge of cities. The agent (farmer)-centric bottom-up models are superior to the conventional land-use models as they are capable of capturing the characteristics of complex system dynamics in land-use transitions (Parker et al., 2008b). These agent (person)-centric models are useful in constructing bottom-to-top models to represent the specific land-use transition processes associated with these complex human-coupled land systems. A farmer-centric model conceptualisation uses land-use decision-making behaviour amongst groups of farmers as the basis for defining simulation rules that represent land system dynamics in a model, while using the physical phenomena and socio-economic factors as input parameters that govern externalities in the model environments.

Land-use modellers are often challenged by the facts that make connections between causality and effects in land-use changes in dynamic model environments (Wentz et al., 2014, Lambin et al., 2001). Dynamic land-use model simulations create virtual environments for testing the cause and effect—in time and space– representing the landscape as a comprehensive land system that is continuously subject to change.

Contemporary agent-based model (ABM) simulation techniques have high value among researchers in exploring land-use changes under dynamic parameter inputs (Crooks et al., 2008, Magliocca et al., 2013). The bottom-to-top entity arrangements and the land-use change-pattern detection facilities in ABM models provide tools for evaluating the complex peri-urban land transition processes that are continuously subject to changes under urban sprawl pressures. Compared to conventional land-use models, ABM models have substantial capabilities for testing transition processes and changes in land-use composition under different land development policy directions. As a consequence, they are useful in developing knowledge about land-use transition phenomena in peri-urban areas, and also in selecting strategies for LGAs to achieve their land administration objectives (Verburg et al., 2013, Hedblom et al., 2017).

In terms of understanding and evaluating agricultural land-use transitions due to the spread of urbanization, the arguments above demonstrate a clear need for more detailed knowledge of land-use compositional changes in peri-urban areas through further carefully selected case studies. The case study approach is important in the testing and developing of general theory in this area due to the level of detail required in each study. This study aims to further develop inductive reasoning on the peri-urban agricultural land-system dynamics which contribute to the knowledge of land-transition phenomena on city fringes. The use of the agent-based modelling (ABM) approach to explore the peri-urban agricultural land-system dynamics under the analysis of different land-management scenarios enables the understanding of the patterns of system behavioural characteristics that support the general theory of land-system dynamics on city fringes. This applies particularly to the influence of land-development strategies of regional and local administrations, the wide range of land-use change drivers that might affect any one study, and variations in landowner land-use decisions.

1.2 PROBLEM STATEMENT

Contemporary urbanization expands cities at the cost of valuable farmland, mainly at the urban fringes. Loss of agricultural land due to urban sprawl has a significant negative impact on the surrounding peri-urban landscapes raising concerns about food security and ecosystem services and about the risk to the peri-urban community lifestyle. Emergent economies and social structural changes in these areas adjust the configuration of land qualities and functions differently (Duvernoy et al., 2018). On the other hand, climate change and frequently changing land administrative policies affect landowners' land-use change decisions, mainly at the city fringes.

Conventional static measurement of spatial arrangements or physical characteristics are inadequate in understanding the contemporary agricultural land-use transitions on these diverse city fringe landscapes. Exploring the scale, rate and place of these changes is also important in understanding the dynamics associated with these non-linear complex land-use transition processes, under different land-governing policy arrangements (Zhang et al., 2017).

This study investigates complex peri-urban agricultural land-use transformations using farmers' land-use decision behaviours integrated with agent-centric modelling approaches to explain complex peri-urban land-system dynamics. The knowledge gained from this study would be useful for land-use planners and policy makers when selecting land-management strategies by comparing options for land-management motivation scenarios in virtual environments.

1.3 RESEARCH OBJECTIVES AND APPROACH

This study attempts to deepen our understanding of the agricultural land-use change phenomena on city fringes using agent-based model (ABM) simulations. Firstly, this study analyses the peri-urban landscape spatial-structural changes (land fragmentation) and agricultural land vulnerability under different land-management policy directions, building knowledge on agricultural land-use changes on peri-urban landscapes in the study area. Secondly, it explores the drivers behind the land-use decisions of peri-urban farmers and land managers, while identifying land-use decision-making profiles and their decision behaviours to develop agent-centric (bottom-up) models by making assumptions on agents' (farmers') properties and decision rules to reconstruct complex land transitions in the virtual environment. Finally, this study examines the complex agricultural land-transition process characteristics in the land system, while evaluating the land-use transitions under different policy directions using the integrative ABM method with scenario analysis. The findings of the ABM simulations assist in developing inductive reasoning to improve the knowledge of land-system dynamics on the city fringes under the influence of urban sprawl.

The four main research objectives and the approaches adopted are listed as follows***:***

Objective 1: To analyse the peri-urban land parcel structure and land-use compositional arrangement focusing on agricultural land fragmentation.

Approach 1: Developed urban-to-rural land-use gradients in parallel with landscape metrics to analyse the landscape spatio-structural changes and its effects on agricultural land-parcel arrangements.

Objective 2: To analyse peri-urban agricultural land vulnerability at a local level, under opposite policy directions—economic development (ED) and environmental protection (EP).

Approach 2: Developed land administrative scenarios using spatially-explicit, multi-criteria models that considered the geographic aspects and land-use plans of the study area.

Objective 3: To explore peri-urban farmer characteristics—demography, production and farming motivations—as well as the drivers behind land-use decisions, decision-making profiles and farmers’ land-use decision behaviours.

Approach 3: Used a questionnaire survey to investigate peri-urban farmers’ characteristics and land-use decision preferences. Developed descriptive statistics for farming characteristics and used factor dimension reduction techniques to explore key drivers, while using cluster analysis to identify decision-making profiles and their decision rules.

Objective 4: To explore the agricultural land-transition process characteristics and the land-transitional responses under varying model environments.

Approach 4: Used spatially-explicit ABM simulations to capture the land-transitional process characteristics of the land system (path dependency, self-organization and system dynamics) while creating hypothetical parameter set-ups for opposite policy directions to evaluate agricultural land extinction.

1.4 RESEARCH SIGNIFICANCE

Peri-urban land-use research often focuses on physical and functional changes in landscapes due to urban sprawl, and LULCC monitoring in time and space. The current research focuses on peri-urban agricultural land transitions occurring due to urban sprawl, which has received less attention among land-use researchers and land administrative practitioners. The complex nature of these land-use transitions has created many knowledge gaps in the understanding of researchers, land-management practitioners and policy makers on farmland conversion phenomena on city fringes.

This study makes several contributions to knowledge in the fields of land system science (LSS) and peri-urban land-system research. Firstly, it provides insights into agricultural land fragmentation on these peri-urban heterogeneous landscapes, demonstrating the advantage of quantifying land use in fragmenting zones when planning land use. Secondly, it addresses the information gap among academia and administrators of peri-urban land management by spatially visualizing the land vulnerability risk in local government areas under different land-management policy directions. Thirdly, it demonstrates the advantage of using peri-urban farmers’ land-use decision trade-offs—internal and external considerations—to identify the drivers behind land-use change decisions. It provides insights for the peri-urban research community in deconstructing complex land-use transitions by understanding the causes and effects through employing land-use modelling. Furthermore, this research addresses the methodological challenge of identifying the agents—land-use decision-making profiles—and the decision rules for re-constructing the land-use transitional processes in agent-centric land-use models. The final phase of this research focuses on exploring the agricultural land transformation system dynamics using ABM simulations to build the knowledge on peri-urban agricultural land-transition phenomena using the study area as a testing site

1.5 THESIS STRUCTURE

This thesis consists of the following eight chapters.

Chapter 1: The general *Introduction* presents the background of the study by illustrating the effect of urbanization on agricultural land transitions on city peripheries. This chapter consists of the problem statement, research objectives and proposed methodologies for addressing the research objectives with a brief statement on the research significance and the thesis structure.

Chapter 2: The *Literature Review* chapter provides a conceptual framework for this research, identifying the knowledge gaps based on the insights of the land-use science research community. This chapter discusses the land system science (LSS) theories in regard to peri-urban land-use changes: spatial analysis of landscapes; land-use change drivers and decision behaviours; complexity in land-use transitional processes; and developing and using ABM simulations to understand land-system change phenomena on city peripheries.

Chapter 3: The *Land-Use Analysis on Urban Fringes* chapter focuses on Objective 1 of this study. It presents the novel approach of integrating urban-to-rural (U–R) gradient analysis with landscape metrics to explore agricultural land fragmentation areas in peri-urban landscapes. Furthermore, this chapter discusses the landscape structure analysis along urban-to-rural (U–R) gradients and the advantage of the spatial quantification of agricultural land in the land fragmentation zones for informed land-management practices.

Chapter 4: The *Agricultural Land Vulnerability at Urban Fringes* chapter addresses Objective 2 of this study. This chapter presents an application of multi-criteria, spatially-explicit modelling approaches for calculating the Agricultural Land Vulnerability Index (ALVI) values under different parameter inputs. It discusses the agricultural land vulnerability contrasts in opposite policy directions (economic development [ED] and environmental protection [EP]), while demonstrating the advantage of quantifying land vulnerabilities in local government administrative areas to address unique challenges.

Objective 3 was addressed in the following two chapters (Chapters 5 and 6) due to the higher concentration of information related to the adopted methods, detailed results and empirical justifications.

Chapter 5: The *Drivers of Peri-Urban Farmers' Land-Use Decisions* chapter addresses the methodological challenge in the first half of Objective 3—identifying the key drivers behind farmers' land-use decisions—by considering a series of primary factors that affect land-use decisions. This chapter presents a detailed description of the postal questionnaire survey used for data collection, and of the descriptive statistics of the sample representation of peri-urban farmers in the study area. Furthermore, it demonstrates the use of exploratory factor analysis (EFA) to identify key drivers, while empirically validating the results in a local context.

Chapter 6: The *Peri-Urban Farmers' Land-Use Decision-Making Profiles* chapter focuses on the second half of Objective 3. It provides an investigative pathway for exploring the land-use decision-making profiles by using the options of cluster selections in statistical data analysis (exploratory cluster analysis), while adapting the internal and external statistical validations for justification. It discusses the decision behaviours of the profiles, while contrasting distinguishable differences to make the assumptions—of agents and their decision rules—for ABM simulations with empirical validations.

Chapter 7: The *ABM Simulations of Peri-Urban Agricultural Land-Use Transitions* chapter focuses on Objective 4 of this research. This chapter provides a detailed description outlining the development of ABM simulations of peri-urban agricultural land transitions, and demonstrating the assumptions made on agents' properties, decision rules and model environment parameters, including open access for the ABM model source code (NetLogo). It discusses the land-use transition characteristics derived for the study area while testing process changes in opposite policy directions (economic development [ED] or environmental protection [EP])

Chapter 8: The *Concluding Discussion* chapter presents an overall discussion on how the main research problem was addressed through the study's methods and findings in parallel with the four specific study objectives, as documented in this thesis. The chapter uses the knowledge gaps identified in Chapter 2 *Literature Review* to assess the findings, while discussing the strengths of these techniques for addressing land system science (LSS) challenges in peri-urban landscapes. This chapter concludes with probable future research recommendations as a continuation of this research pathway to improve the knowledge on peri-urban agricultural land transitions, due to urban sprawl.

The thesis documents the current study which has focused on an evaluation of agricultural land-use transitions on the urban fringes of Adelaide in South Australia. The information about this study area—its geographic and socio-economic aspects, and land-use planning in the Greater Adelaide area—is presented in Chapters 3, 4 and 5 under the topic "study area" descriptions, while considering Adelaide as a common case study area for the entire research.

The knowledge gained in each chapter (in Chapters 3 to 7) has been used as the information source for the following chapter. The following figure (Figure 1.1) illustrates the information flow of the study which is ultimately used as a data source for developing ABM simulations in Chapter 7.

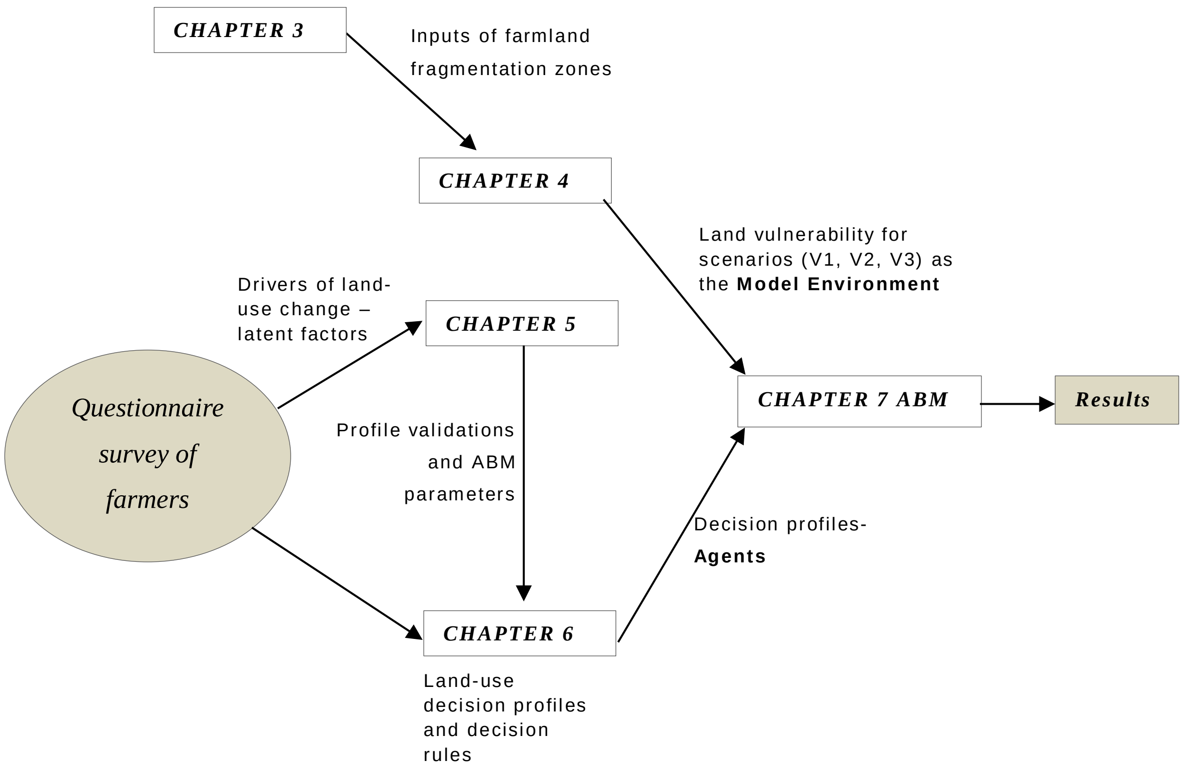


Figure 1.1: Information flow diagram for ABM development

In different stages of the current study, the following data sets and software have been used for data analysis, modelling and information visualizations.

The primary data used in this study are as follows:

- Land cadastral spatial data with land-use information: South Australian Government (Department of Planning, Transport and Infrastructure [DPTI], 2016).
- Spatial boundaries of the *30-Year Plan for Greater Adelaide* (Planning SA, 2010).
- Digital elevation model (DEM) (with 30 m resolution).
- Direct farmers' questionnaire survey data set (collected by the author).

The software used for this study is as follows:

- ArcGIS Desktop-ESRI for spatial data analysis.
- NetLogo for ABM simulations.
- IBM SPSS Statistics (SPSS) and Mplus for statistical data analysis.
- Microsoft (MS) Excel for creating charts and tables.

CHAPTER 2 – LITERATURE REVIEW

This chapter reviews the literature on land system science (LSS) in relation to agricultural land transitions in peri-urban landscapes that comprise human–environment interactions. The key areas on which the study focuses in the context of urban sprawl are: the physical land-parcel arrangement of peri-urban landscapes; the multi-disciplinary aspects of land administration; farmers' land-use decision behaviours; and the modelling of complex land-transition processes. Furthermore, this chapter provides insights on the methodologies selected to address the identified gaps, while evaluating the effectiveness of the techniques utilized in the remainder of the chapters.

2.1 HUMAN–ENVIRONMENT LAND SYSTEMS

Humans have used land and changed land use to satisfy various expectations throughout millennia (Millington, 2012a). During the last few decades, land-use and land-cover change (LULCC) research, ranging from local case studies to global scale analyses (Verburg et al., 2015), has demonstrated the effects of human contact on natural environments. The global LULCC monitoring studies show the significant effect of human intervention as it alters terrestrial ecosystems to satisfy rising demands for food, water, energy and other resources and services (Ramankutty and Foley, 1998, Seto et al., 2012a, Ramankutty et al., 2006, Foley et al., 2005, Gutman, 2004, Seto and Satterthwaite, 2010, Alexander et al., 2016). On the other hand, cities in Germany and Japan have experienced shrinking urban areas due to demographic and socio-economic changes (Lauf et al., 2016, Matanle and Rausch, 2011).

The definition of "urban" is ambiguous and controversial in the land-change science literature (Elmqvist et al., 2013b, Batty, 2015). In their recent epistemological study, Brenner and Schmid (2015) argue against the conventional definition of the term "urbanization" by demonstrating the effect of human intervention beyond the city fringes around the world. Furthermore, their study demonstrates that urbanization offers insights into the socio-economic and ecological systems entangled with LULCC (Acuto, 2015). The above facts demonstrate human involvement with LULCC in world regions, but still leave knowledge gaps on LULCC occurrence, for example, its scale, rate and space, due to its complexity. The land-use research community faces the challenge of finding the human causes and situations that create a substantial impact on natural environments (Turner et al., 1994, Elmqvist et al., 2013b) in order to improve the knowledge on land-use transitional phenomena.

Land system science (LSS) is emerging as an inter-disciplinary research area that focuses on LULCC dynamics in human–environment land systems (Turner et al., 2007). Described as a holistic approach with insights on bio-physical and socio-economic aspects, LSS is used to analyse complex LULCC in various land systems (Verburg et al., 2015, Rindfuss et al., 2008). The LSS approach has been widely accepted and utilized by land-use researchers for the exploration of LULCC drivers and their impacts on surrounding natural environments, while proposing strategic policy directions for effective land management in rural and urban land systems.

Turner (2016) explained the use of LSS in land-change research on different land systems:

> Land system science (LSS) has expanded its research focus from the drivers of land use and cover change primarily in rural wildlands to include the social-environmental consequences of this change, urban areas, and sustainability practice (p.689).

The use of LSS has significant advantages over traditional land-use change studies, as it is able to offer comprehensive solutions including adaptations and mitigations for global land-change problems, thus leading to sustainable land management practices (Verburg et al., 2013, Turner et al., 2007, Lambin and Geist, 2006). The multi-disciplinary approach of land system science (LSS) can be used when researching complex land-transition processes that occur in human-dominant land systems, such as cities and city peripheries.

2.1.1 Urbanization and land-use change

The economic aspects of societies demonstrate a significant contribution to LULCC occurrences in different geographies worldwide. The comparison of global case studies by Lambin et al. (2001) showed that markets and economic policies are major contributors to creating opportunities and constraints for LULCC, thus rejecting the conventional understanding that population and poverty are the key drivers of LULCC occurrences worldwide. Contemporary globalization trends have created new economic geographies: direct foreign investments; financial agreements between cities in different countries; and cross-border commodity supply chains, while increasing international trade, logistics and services worldwide (Lambin and Meyfroidt, 2011, Roberts, 2014, Millington, 2012a, Robinson and Carson, 2015). The new global economic trends have accelerated LULCC in developing countries, such as, China, India, Indonesia and Vietnam, demonstrating significant urbanization trends due to rising economic opportunities. Most of these countries, including China, use urbanization as a policy instrument to achieve their country’s economic goals. Several megacities (over 10 million people) have been created in China during the last decade due to accelerated urbanization. However, as the country experiencing the highest level of LULCC due to urbanization, China faces the challenge of maintaining economic development without sacrificing productive land for food security (Bai et al., 2011). These facts reveal the future global challenges of maintaining the balance between human needs and limited natural resources.

Foley et al. (2005) anticipated the key challenges in human–environment land systems as “… the challenge of managing trade-offs between immediate human needs and maintaining the capacity of the biosphere to provide goods and services in the long term" (p.570).

Globalization has accelerated the distance drivers of land change in many parts of the world. Meyfroidt et al. (2013) demonstrated the effect of the following distance drivers of land change: unexpected land-use policy changes, environmental impacts and rapid socio-economic changes as the prominent characteristics experienced in these geographies. The interconnections created between countries or regions have become the new research agenda for land-use researchers when exploring distance drivers and their effects under the theme of "teleconnections" in a global context. A multi-region input–output analysis by Yu et al. (2013) illustrates the off-country land use of developed nations and regions in percentages as follows: the United States (US) 33%, European Union (EU) 50% and Japan 95%, while Latin American countries use a large portion of their crop land—Brazil 47%, Argentina 88%—for EU export markets. Moreover, the analysis shows the effects of increasing resource demand in China and India due to rapid economic growth, with these effects being on land use in Africa, Russia and Latin American countries. On the other hand, excessive local agricultural production in peri-urban regions provides services elsewhere to support the increasing demand for food (changing dietary patterns and contemporary markets with growing populations) within countries/cities that have limited land and natural resources to fulfil rising needs, as well as issues with climatic conditions. Agricultural production provides products to export markets valued at over $4.5 billion (e.g. live cattle and sheep exports from Australia to Arabic nations and developing countries such as China, Pakistan and Indonesia; and Australian wheat exports providing products to markets in Indonesia, the Philippines and South Korea where dietary patterns are rapidly changing from rice to wheat) (Mewett, 2013, ABARES (Australian Bureau of Agricultural and Resource Economics and Sciences), 2018). These facts show the importance of integrating the distinct land connection with local land-use research to identify external drivers and the effects of land-use consequences in a local context. The concept of "tele-coupling" emerged as a commonly agreed framework that land-use researchers can use to improve knowledge of complex human-coupled land systems.

Liu et al. (2013) defined the tele-coupling concept as "... a logical extension of research on coupled human and natural systems, in which interactions occur within particular geographic locations" (p.1). The investigative study by Liu (2014), using a tele-coupling framework for China forest-cover recovery and its effects on forest sustainability in China and forest product-importing countries, highlighted the importance in regional land-use research of using distant socio-economic and environmental changes when exploring land-use changes which are unable to be explained with strictly local considerations. The urban teleconnection concept has advantages in bridging the causes of urbanization and the impact of land-use changes by considering the land from the city centre to the rural hinterland as a single land system (Güneralp et al., 2013). The economic connections between urban and non-urban areas also offer insights ranging from local to regional through to global economic processes (Hayter et al., 2003). Seto et al. (2012b) proposed a process-based conceptual framework for capturing teleconnections in land-use change studies, particularly in areas subject to urbanization. This demonstrates the potential of the teleconnection application for exploring new urban area formation, such as peri-urbanizing, with a focus on surrounding areas and regional city connections

2.1.2 Urban sprawl and peri-urbanization

The term "urban sprawl" is extensively used by researchers and land administrators to describe major land-transformation processes and their consequences on peri-urban landscapes. Urban sprawl theory has a long history since its origins in the 1920s in economically advanced countries in that era (the US and European countries). It is also identified as "semi-suburbia" and "ribbon developments", representing landscape changes into urban form that occurred mainly along transport corridors (Bruegmann, 2001). After the Second World War, the term "urban sprawl" was widely used in European countries—mainly the German-speaking countries—to describe urban expansion due to industrialisation in and around the cities (Jaeger et al., 2010). Mills (1981) identified urban sprawl as the lack of continuity in urban expansion. This was further confirmed by Peiser (1989) who demonstrated that low-density discontinuous expansions can significantly accelerate under the influence of larger utility, infrastructure and municipal land development projects occurring on city fringes.

Urban sprawl has often been described as an extension of the fringes or as urban settlement scattering over rural landscapes (Harvey and Clark, 1965). In a study on urban expansion, Gottmann (1957) identified the form of sprawl as fast-growing suburban areas closer to mega town centres, demonstrating the leap-frogging effect of sprawl due to increasing demand for land. Gottmann (1966) stated that most geographers in this era were focused on their areas of interest and on projects that created a lack of understanding of the sociological aspects associated with urban sprawl. The definitions of urban sprawl are often blurry and highly contingent on the area of research, viewpoints and associated geographies (Harvey and Clark, 1965). The existing definitions used for "urban sprawl" differ to a great extent based on the area of research interest, thus conveying contradictory interpretations. Consequently, it is difficult to agree on a consistent interpretation to compare case studies from different regions (Jaeger et al., 2010). This is further confirmed by Schneider and Woodcock (2008) who provided spatial evidence of urban growth in 25 cities around the world and indicated that "sprawl" is a relative concept that could vary in different geographies.

In a systematic review of urban sprawl definitions, Jaeger et al. (2010) separated the causes and consequences which were entangled in many definitions, resulting in a lack of clarity. The study identified the *causes*: unsystematic development; aimless and disorganized growth; demand for green landscapes; additional residences; and low-priced land parcels, while identifying the *consequences*: degradation of landscape quality; loss of agricultural land and ecosystem services; loss of open green space and recreational areas; increase in number of commuters; and increase in spatial and functional separation in landscapes (Jaeger et al., 2010). Based on 50 years (1950–2000) of land-change data in the US, Brown et al. (2005a) reported that low-density outer-city residential developments drive the sprawl to city fringes and rural landscapes. Furthermore, Hasse and Lathrop (2003) proposed that the key land resource impact indicators of urban sprawl are: increasing urban density; loss of farmland, wetland and forest habitat; and increase in impervious cover. However, Chinese case studies demonstrate that the existing urban sprawl theories are not adequate to explain the contemporary urban sprawl patterns in China that are occurring due to larger land reforms—micro-level urban centres in "development zones" and temporary migrant settlements in "semi-urbanized villages" (Deng and Huang, 2004, Yu and Ng, 2007). In addition, Tian et al. (2017) show that the urban sprawl trends in China are occurring due to "State-led" development processes, international direct investments for manufacturing industries and the oversupply of land for commercial industries by local municipalities, with these factors driving the sprawl to peri-urban and rural areas.

"Urban sprawl" is identified as a major land-use change practice that is associated with significant social and environmental costs, while presenting challenges for land-use planning on city fringes (Hasse and Lathrop, 2003, Wu, 2008). Bruegmann (2001) identified the major concerns of urban sprawl on city fringes as being environmental, social, aesthetic and equity issues. Wei and Ewing (2018) identified urban sprawl as a significant characteristic of contemporary urbanization or urban development processes. Many researchers (Ligtenberg et al., 2001, Rusk, 1993, Gimblett et al., 2001, Mancebo, 2008) have identified urban sprawl as a complex process involving the interplay of driving forces, namely, socio-economic, physical and political influences and their interactions. Land-use research has identified the fundamental forces which drive urban sprawl into nearby landscapes. Brueckner and Fansler (1983) indicated that urban sprawl is mainly driven by existing market forces rather than by economic symptoms. Furthermore, it was confirmed by Cuadrado-Ciuraneta et al. (2017) that, in the last three decades, the diffused urban sprawl that occurred in European cities was due to speculation in the market, over net population growth. Batty (2009) described that, in addition to natural and physical factors, urban sprawl is driven by the historical reasoning of "historical accidents" associated with city geography. Brueckner and Helsley (2011) demonstrated that economic factors (i.e. urban land market failures) are the key force for urban sprawl with this intensified by inefficient spatial planning in urban areas leading to excessive peri-urban development. In a US-based study, Brueckner (2000) reported that the key drivers underlying urban sprawl are rising economies, population growth and the declining commuting cost on city fringes. However, the urban economy is central to these drivers on city fringes. The above points demonstrate the significant contribution of urban economies (through market forces) to driving urban sprawl into nearby landscapes, while influencing land-transition processes by the intensity and dynamics of socio-physical and land administration.

The term “peri-urban” has been defined broadly by multi-disciplinary researchers worldwide, in accordance with the understanding and knowledge developed in different geographic areas—by case studies—(Wandl and Magoni, 2017). The term “peri-urban” is commonly understood to mean the interface between urban and rural landscapes that is regarded as the land transitional zone due to human land-use change activities (Buxton and Choy, 2007, Douglas, 2006, Brook and Dávila, 2000). Hedblom et al. (2017) have suggested the importance of specifying a specific population density or spatial distance to built-up areas to identify the peri-urban landscape by its functionalities. However, the explorative reviews by Willis (2007) on peri-urban definitions demonstrate that it is impossible to have a singular or spatial definition for the term “peri-urban” in different geographic areas worldwide. This point was further confirmed by Amirinejad et al. (2018) who demonstrated the ambiguity of the peri-urban interface due to the presence of diverse land-change drivers and the collective form of its expression in different cities worldwide. Simon (2008) provided substantial evidence that presented structurally and functionally different peri-urban areas in the world’s regional cities, namely, in North and Latin America, Europe, Asia and Oceania. In an Australian study, Burnley and Murphy (1995) identified peri-urban areas as areas on the edge of cities that structurally and functionally consolidate urban expansion. However, the current study’s author identified the term “peri-urban” as meaning landscapes that significantly differ (physically and functionally) to the urban built-up landscape or the rural agricultural landscape, in this study, referring to the context of Australian urban to rural continuums.

In many attempts and from different viewpoints, researchers have articulated peri-urban land-use characteristics and land-transitional progressions on city fringes. The key point is that peri-urban areas are the fastest-growing areas in the world’s regions (Nelson et al., 1990; Davis et al., 1994; Low Choy et al., 2007; Brown et al., 2005). In Australian case studies, Buxton and Choy (2007) and Buxton et al. (2011a) demonstrated the effects of urbanizing processes occurring in peri-urban zones (peri-urbanization), such as closer land subdivisions, land fragmentation, frequent land-use changes and the mix of urban–rural land-use practices and functions. McGranahan et al. (2004) further demonstrated that spatial features associated with these land transitions are characterized by high land-use intensities, settlement pattern variations and land fragmentation. This leads to peri-urban landscapes with their highly spatially heterogeneous land uses (Irwin and Bockstael, 2007, Jat et al., 2017). Willis (2007) listed the following land transition characteristics: fast-growing built form, land-use change, land administrative overlaps and growing population, as being significant in peri-urban areas. Low Choy et al. (2008) demonstrated that peri-urbanization is mainly occurring in the proximity of rural town centres through the sprawling of urbanizing processes into surrounding rural areas.

In regions throughout the world, cities may be surrounded by prime agricultural land, protected plantations, hilly forest areas, conservation areas and valuable wetlands, as well as by ecosystem services supporting urban inhabitants. Allen (2003) highlighted that peri-urban landscapes do not represent the attributes of either urban or rural areas. McGranahan et al. (2004) confirmed this statement by characterising peri-urban zones as areas that are significantly environmentally unstable compared to urban or rural landscapes. In a global assessment of urban and peri-urban agricultural land, Thebo et al. (2014) reported that, of all agricultural land in the world's regions, 60% of irrigated land and 35% of rain-fed agricultural land are located within the 20 km buffer to urban areas, thus providing evidence of the demand for water in peri-urban agricultural practices worldwide.

2.1.3 Impacts on the ecosystem

Contemporary urbanization has accelerated the human influence on the ecology in the biosphere (Folke et al., 2011, Ellis, 2011, Bian et al., 2018). Güneralp and Seto (2013) forecast that, by 2030, global urbanization would make significant impacts on protected areas, particularly in the regions of China and South America. Ecological research on urbanizing areas has confirmed that human influence on changes to natural environments includes the adverse impact of ecosystem services and functions (Ramalho and Hobbs, 2012, Wu, 2014, Elmqvist et al., 2013a). The land-use research community has identified the advantage of using LSS for ecosystem service quantification, valuation and management, exploring the connection between land-use change and ecosystem service alterations in the context of supply and usage (Crossman et al., 2013, Deng et al., 2016, Robinson et al., 2009, Serna-Chavez et al., 2014). Recent urban ecological studies have focused on the supply and demand of ecosystem services in the analysis of urban sustainability (Larondelle and Lauf, 2016, Kain et al., 2016, Baró et al., 2015, Lauf et al., 2014). Moreover, researchers have explored the socio-economic dimensions of the human influence on the ecosystem services of human-dominant land systems. However, as Mononen et al. (2016) demonstrated in existing land management policies, ecosystem service information gaps still exist due to the lack of concrete definitions and classifications.

The infiltration of urban sprawl onto nearby rural landscapes—peri-urban landscapes—has created the dynamic interface of human–environment interactions. Rolf et al. (2017) demonstrated the peri-urban farmland's contribution to developing the urban green infrastructure in three German cities through the maintenance of the essential habitat and functional connectivity in ecological systems. Recent urban ecological studies have focused on deteriorating ecosystem services in urban and peri-urban landscapes (Larondelle and Lauf, 2016, Zhu et al., 2017), which are often surrounded by agro-ecosystems.

Wu (2013) described the landscape as "… places where people live and work, and where ecosystems reside and provide services to people" (p.1019). Ecosystem services in agro-ecosystems often receive less attention among land management practitioners (Sandhu et al., 2012). These services in urban fringe farmland have substantial benefits for both urban and peri-urban inhabitants, fulfilling their rising demands for food and other natural resources while achieving the goals of human well-being. In peri-urban areas—which are dynamic landscapes—ecosystem services make a significant contribution when maintaining peri-urban landscape sustainability (Wu, 2013) while protecting and restoring urban ecology (Verburg et al., 2015). A comprehensive analysis of ecosystem properties by Matson et al. (1997) shows the extensive environmental consequences that could be experienced under agricultural land intensification. As well as socio-cultural changes, agricultural land-use intensification on urban fringes is often the cause for weakened ecosystem services through its contribution to changes in the quality of water, air and soil. The land-use research literature has not adequately addressed peri-urban agricultural land-use intensification and its impacts on land-use sustainability in these land transitional zones (Sonter et al., 2015).

2.1.4 Sustainability on city fringes

Many land-use studies have used the term "sustainability" when expressing the idea of achieving a balance between human expectations and the environmental system by offering thresholds (Turner, 2016, Deng et al., 2016, Verburg et al., 2015). For the UN-affiliated International Institute for Sustainable Development (IISD), Brundtland (1987) defined sustainable development as: "… development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (p.41).

A report written by Kaphengst (2014) titled "Towards a Definition of Global Sustainable Land Use" identified the unclear definitions of "sustainable land use" in the literature. Furthermore, the report identified the theoretical and conceptual implications associated with the IISD definition of "land governance", while suggesting a new definition for sustainable land use as follows.

> A global sustainable land use serves the needs (for food, energy, housing, recreation etc.) of all human beings living on earth today and in the future, respecting the boundaries and the resilience of ecological systems (Kaphengst, 2014, p.12).

Zheng et al. (2014) showed the complexity associated with sustainable development in the urban development literature, demonstrating the frequently changing definitions. Moreover, Berke and Conroy (2000) defined sustainable development as a dynamic process.

> Sustainable development is a dynamic process in which communities anticipate and accommodate the needs of current and future generations in ways that reproduce and balance local social, economic, and ecological systems, and link local actions to global concerns (p.23).

These points demonstrate the lack of clarity of the term "sustainable development" in the land-change literature as it fluctuates between different geographies amid the existence of varying socio-cultural and environmental conditions. The author recognizes the term "sustainable land use" as meaning the adaptation of the use of land to achieve an optimum balance between human needs and natural environmental services within a certain time, while changing the land use to fulfil society's rising demands.

The land-use literature demonstrates that peri-urban land transitions are becoming a popular theme among land-change researchers. This is evident in the case studies produced during the last few years (since 2014) on various cities around the world: France (Duvernoy et al., 2018); the USA (Brown and McCarty, 2018); Canada (Akimowicz et al., 2016); China (Shih, 2017); Vietnam (Nguyen et al., 2017a); Sweden (Hedblom et al., 2017); Indonesia (Winarso et al., 2015); Peru (Haller, 2014); Ghana (Appiah et al., 2014); and Australia (Liu and Robinson, 2016). Peri-urban land-transition studies have focused on the various aspects of land change and its impacts: land-use planning and urban development; urban ecology; urban sustainability; socio-economic changes; agricultural landscapes; and population dynamics, while representing cities from different geographies. These studies show the necessity of improving knowledge regarding peri-urban land transitions, following recent contemporary urbanization trends.

Peri-urban regions are characterized by socio-economic dynamics and ecosystem service depletion, while being constantly subject to land acquisitions and tenure changes (Seto et al., 2012b). Furthermore, peri-urban typology features a mixture of urban and rural land-use features with continuous land changes, conflicts of targets and higher levels of land-use heterogeneity (Low Choy et al., 2008). Peri-urbanization has a constant connection with urban sprawl as it always occurs under urban drivers (Hersperger and Bürgi, 2009). Galli et al. (2010) showed the different aspects of peri-urbanization phenomena demonstrating the opposite views in the literature: one view identifies peri-urbanization as an unsustainable process breaking the connection between city and rural areas, while the other identifies it as a new form of sustainable development that creates new opportunities with positive land transformations.

Peri-urban land-change research has identified the complexity associated with peri-urban land systems that are continuously subject to changes with insights from socio-economic policies, ecosystem services and institutional policies on land governance (Simon, 2008, Douglas, 2006, Ravetz et al., 2013, Seto et al., 2012b). Rauws and De Roo (2011) described the non-linear characteristics of complex peri-urban land transitions and their dynamics with these often not being part of the radar of land-use planners. The LSS literature has identified the importance of considering urban, peri-urban and rural areas as a common land system consisting of mutual connections, to explore land transitional processes for sustainable solutions (Seto and Reenberg, 2014). The above points demonstrate the advances made by LSS in peri-urban land transitions. However, opportunities still exist for improvements in knowledge in the areas of scale dependency, autonomous processes and the robustness of land systems.

2.1.5 Urban economic effects on peri-urban agricultural land functions

As a result of the economic shift from agriculture to industry, many cities worldwide have lost farmland in peri-urban areas (del Mar López et al., 2001), with these land-use transition processes rapidly continuing with economic development in urbanizing cities. International trade, national border opening and cross-border influences have triggered the demand for land transformation (Gardiner and Le Goulven, 2001), particularly transformation that brings about agricultural land-use functional changes or loss on city fringes. Wu (2008) demonstrated that urban sprawl affects agricultural economies on the fringes by reducing the land area—or critical mass—below the minimum required for agricultural economic survival, which ultimately leads to the collapse of farming practices and services supporting agriculture in these urban fringe areas.

The functional arrangements of the peri-urban agricultural land use of cities vary between developed and developing nations. Nugent (2000) showed the significant difference between peri-urban agricultural practices in developing countries that engaged with poor urban dwellers with less intensified (using less fertiliser/energy) agricultural practices and those of peri-urban areas of wealthy cities in developed nations that consisted of large-scale commercial/multi-functional farming practices. The countries of the Global North have identified the importance of preserving the peri-urban agricultural practices that contribute to the local economy and carry non-market benefits for urban inhabitants' quality of life. Developing Asian nations, such as China and India, are experiencing significant structural changes in peri-urban agricultural land functions to fulfil the demand for developing megacities and medium-sized cities to satisfy the increasing population and expanding economies (Hussain and Hanisch, 2013, Tian et al., 2017, Shih, 2017). Moreover, direct industrial investments in the densely populated cities in Asia (i.e. Manila, Dhaka, Chennai and Jakarta) demonstrate significant agricultural land functional changes due to the rapid change of socio-economic conditions. However, urban development and economic research in the literature have paid less attention to peri-urban agricultural functions (Bezemer and Headey, 2008).

Urban/rural research in the current literature provides limited knowledge on the economic impact on peri-urban agricultural practices that depend on the following economic variables: income, annual output and employment (Nugent, 2000) that combine as an economic force, changing agricultural land functions in peri-urban landscapes. Researchers have found, in the cities experiencing urban sprawl, that this is due to economic expansion, and significant land demand generated for housing, infrastructure and transport in and around the peri-urban and nearby rural landscapes (Livanis et al., 2006, Greene and Stager, 2001). The increasing demand for land on city fringes creates adverse effects for peri-urban agricultural land-use functions by increasing the competition for limited farmland. In a study exploring peri-urban agricultural land values, Shi et al. (1997) identified the key economic factors of nearby urban economic demand and farm income as the determinants of agricultural land value that had a significant impact on agricultural land functions in these landscapes. Furthermore, in a study on market impacts on land-use change, Sun et al. (2014) demonstrated that peri-urban farmland can prevent urban sprawl as long as the opportunity cost of converting farmland to housing is higher than urban dwellers' buying power. The increasing land demand for infrastructure and transportation projects leads to the acquisition of peri-urban farmland to facilitate the creation or expansion of services to maintain economic demand while challenging urban land-use planning in the growing cities (Mougeot, 2000, Elhadary et al., 2013, Heimlich and Anderson, 2001). These points demonstrate the effects of urban economic expansion on functional changes in peri-urban agricultural land use that are carried through on different channels.

Agricultural land intensification has become a global trend in the contemporary world (van Vliet et al., 2015, Wandl and Magoni, 2017) and is prominent in peri-urban areas. Farmers in peri-urban areas often receive higher crop prices due to urban centres' rising demand for crops for local consumption and export markets. Due to contemporary technological advancements, farmland has become competitive (Arsenault et al., 2012). To satisfy the increasing economic demand for agricultural commodities, farmland intensification is a common agricultural functional change that occurs in peri-urban landscapes by increasing the competition for farmland. Intensified agricultural practices require low-cost labour, new technology and irrigated water to maximize economic returns from the limited land of peri-urban farms. In developed nations, low-cost labour is commonly provided by poorer residents on city fringes. Farmers must, however, compete with non-agricultural sectors for labour on the fringes. Part-time elderly retirees also provide a significant labour supply for farming practices on city fringes which is not accounted for in peri-urban agricultural economics (Nugent, 1999). This situation differs in developing nations, due to non-agricultural economic opportunities in cities and the lack of labour, both of which increase the level of farmland abandonment and its conversion to housing or infrastructure development to satisfy the rising land demands of growing populations.

Land-use research has identified endogenous economic factors of concern for farmers regarding their land-use decisions on city fringes, including increasing land value, return on investment (ROI) and uncertainty about the farming business, that affect farmland functional changes (Adelaja et al., 2011), such as land leasing, abandonment and selling of land for non-agricultural practices. Furthermore, Nugent (1999) showed that knowledge is lacking on non-market impacts, such as informal labour and unseen markets on peri-urban agricultural functions; therefore, land administrators and policy networks currently have limited information on peri-urban areas. A combination of these endogenous factors with the key exogenous economic variables—income, annual output and employment—and social factors creates complex farmland functional changes on city fringes that cannot be explained solely by conventional economic theories.

Land-use planning, in parallel with economic behaviours, plays a significant role in peri-urban areas by identifying the development and preservation zones needed to satisfy the demand for land. This land-use zoning often has a significant effect on peri-urban agricultural land functional changes, with agricultural land in development zones often characterized by land-use changes—land subdivisions, fragmentation and intensification—while farmland in preservation zones is characterized by long-term stable agricultural practices on larger land parcels on city fringes. Land-use planners are also often concerned with the adverse effects of agricultural land functional changes on urban inhabitants due to land intensification, fragmentation and the extinction of green landscapes (Huang et al., 2009). Therefore, land-use regulations often focus on land subdivisions and the increase in waste water emissions associated with land intensification practices. On the other hand, peri-urban agricultural businesses provide employment opportunities for rural communities (Allen, 2003) with this rarely considered by planners with urban priorities. However, James and O'Neill (2016) argued that urban planners either neglect or underestimate the peri-urban agricultural contribution for the local economy and sustainability of cities, both in Australia and overseas.

Researchers pay special attention to peri-urban agriculture as it often operates under the influence of the urban sprawl of cities surrounded by farmlands. In land-use research, the limited literature on peri-urban agricultural practices has focused on food security (Tsuchiya et al., 2015, Thebo et al., 2014); agricultural land loss due to urban expansion (Pribadi and Pauleit, 2016, Pribadi and Pauleit, 2015, Pham et al., 2014, Elhadary et al., 2013); drivers of farmland change (Serra et al., 2017); ecosystem services in agricultural landscapes (Lee et al., 2015, Thapa and Murayama, 2008); land-use multi-functionality (Ives and Kendal, 2013, Zasada, 2011); and farmers' socio-economic aspects (Hussain and Hanisch, 2013, Wu, 2008). These multi-directional themes represent the complexity associated with the occurrence of agricultural land transition processes. Land-use research also identifies the conversion of agricultural land into an urban form as a key component of the peri-urbanization process (Fragkias et al., 2012), including the common status of agricultural land intensification, fragmentation and, ultimately, transformation into an urban form (Seto et al., 2012b). However, this sequence is not followed all the time on city fringes owing to the complexity arising from socio-economic and environmental system dynamics. Land system science (LSS) has developed, but has limited knowledge on, peri-urban agricultural land transition processes, such as: what situations lead to the occurrence of these transitions; where they are more likely to occur; the influences on peri-urban farmers' land-use decisions; and the scale, rate and space of transitions occurring in peri-urban land systems.

The author identified the lack of understanding of peri-urban agricultural land transitional phenomena as the key knowledge gap that this study intends to address. For this purpose, the next four topics of the literature review focus on the following aspects in relation to peri-urban agricultural land transitions:

- Land fragmentation in peri-urban landscapes.
- Agricultural land vulnerability in peri-urban land transitional zones.
- Peri-urban farmers' land-use decision behaviours.
- Agent-centric modelling for agricultural land transition simulations.

2.2 AGRICULTURAL LAND IN PERI-URBAN LANDSCAPES

Peri-urban landscapes show the highest land-transition dynamics, in comparison to neighbouring urban or rural landscapes (Weng, 2007, Seto et al., 2012b) and are continually subject to land fragmentation (Salvati et al., 2017b, Irwin and Bockstael, 2007, Cuadrado-Ciuraneta et al., 2017). Agricultural land-use transitions in these heterogeneous landscapes are frequently subject to land fragmentation (Serra et al., 2014, Guastella and Pareglio, 2016). The physical land-parcel spatial arrangement of these landscapes indicates that the occurrence of the underlying spatio-structural changes—land fragmentation—is due to the complex land system dynamics (Pili et al., 2017, Grimm et al., 2008). Murayama and Thapa (2011) demonstrated the advantage of using spatial analysis in land-change studies as it assists in understanding present and future changes: "if we can trace the movements of spatial phenomena in the past, we can acquire clues that will help us to unravel today's structures and formation mechanisms" (p.9).

Landscape ecology has developed as a science that investigates the spatial patterns of land patches (parcels), patch types, interaction between patches (land areas with boundaries) and the spatio-temporal changes in landscapes (McGarigal and Marks, 1995). In terms of landscape quantifications, land-change science has highly benefited from landscape measuring techniques developed within the field of landscape ecology. Landscape ecology and land-use research often use land cadastral data, which represent spatial boundaries in land-use information, to analyse spatial structures and land-use configurations in landscapes (Wrbka et al., 2004).

2.2.1 Spatial quantifications

Land-use configurations in peri-urban landscapes are multi-faceted, as they represent highly diverse land uses that constitute a wider spectrum of land parcels in terms of sizes. A systematic representation of the land-use presence is an important step in analysing complex land transitions in these heterogeneous landscapes. In terms of land-use composition and configuration analysis, geo-referenced location-based land-use quantifications have significant advantages over non-spatial land-use quantifications. However, researchers experience a series of methodological challenges in quantifying and visualizing land-use presence and configurations for landscape analysis.

Land-use change research often uses remote sensing for LULCC, particularly in land-use mapping and land-change monitoring and for spatial quantifications. Existing spatial information on land cover is mostly generated through remotely sensed data (scanned data of Earth's surface and subsurface via satellites and airborne sensors, including drones). Lambin and Geist (2006), in identifying the advantages of land-use information over land-cover data for LSS, distinguished the differences between the terms "land use" and "land cover" as follows: land use is defined as "the purposes for which humans exploit land cover" while land cover comprises the "attributes of the Earth's land surface and immediate subsurface, including built-up structures" (p.4). Although remote-sensing data are considered a consistent source with higher temporal resolutions, spatial data provide limited information for exploring land systems that have aspects of human interactions with landscapes. However, LSS research has identified the advantage of integrating socio-economic data with remotely sensed imagery featuring higher spatial resolution to produce rich spatial information on land-use and land-cover change (LULCC) (Verburg et al., 2011, Turner et al., 2007). This is evident in the ideas presented by Thompson et al. (2002), that is, "linking people to pixels" and the National Research Council (1998), namely, "socializing the pixel" that highlight the use of added value to remote-sensing data for land-use research.

The study by Robinson (2012) on land-cover versus land-parcel analysis in peri-urban (ex-urban) landscapes showed a significant difference between land-cover measurements, particularly in areas with smaller land parcels represented by land-use heterogeneity. This demonstrates the invalidity of using remote-sensing (land-cover) measurements to analyse physical land parcel spatial arrangements in these landscapes consisting of smaller land parcels with diverse land uses. On the other hand, Olofsson et al. (2013) highlighted the misinterpretation of land change in LULCC maps due to unrepresentative samples leading to misclassifications. Today, the regularly updated land cadastral spatial data sets (acquired through highly accurate land survey maps, field assessments, aerial imagery and drone technologies) provide rich information on land use and land functions on city fringes, compared to the conventional remote-sensing application that is suitable for macro-scale LULCC monitoring and evaluation.

Agricultural land uses are one of the major land-use groups that form complex land-use configurations on peri-urban landscapes. As land fragmentation areas represent a higher tendency for land-use or land-parcel changes (ownership change, subdivisions or leasing), agricultural land that is present within these zones is more vulnerable to changes compared to land in non-fragmented areas. However, land-use research in the literature does not adequately address these distinguishable differences. The author identifies that the lack of information on agricultural land presence in fragmented areas creates a knowledge gap, restricting the accuracy of land-use quantifications and validations in peri-urban landscape analysis.

2.2.2 Landscape measurements

Landscape metrics are advanced spatial measuring techniques first developed in landscape ecology and later utilized in conservation biology and urban ecology to measure landscape changes due to human intervention (Wu, 2014). McGarigal (2002) explained the advantage of using landscape metrics: "landscape metrics represent the spatial pattern of the entire landscape mosaic, considering all patch types simultaneously" (p.93).

Many land-use studies have confirmed promising results when using landscape metrics to investigate the structural dynamics of landscapes (DiBari, 2007, Robinson, 2012, Herold et al., 2005, Szabó et al., 2016, Aguilera et al., 2011). Furthermore, these metrics are extensively used as a landscape measuring tool in urban growth studies in many cities worldwide (Schneider and Woodcock, 2008). However, the scale dependency of these landscape metrics determines the validity of using them on different scales for effective landscape analysis (McGarigal, 2002). A landscape metrics scale-dependency analysis by Feng and Liu (2015) showed that the application of landscape metrics in “landscape” levels (smaller areas) is scale-independent. Moreover, another scale-dependency analysis by Uuemaa et al. (2005) showed that landscape metrics correlate to land-use information on different scales only if the information was derived from spatial data with accurate land-use classifications. These points reveal the importance of deriving landscape metrics from reliable spatial data sources that could represent the characteristics of the intended study landscape on a suitable scale.

In landscape ecology, gradient analysis originated as a conceptual method for analysing the structural measurements of landscapes in continuums. McGarigal and Cushman (2005) described the advantage of using these pattern gradients for landscape structure analysis, as they consist of categorical or continuous measurements in spatial continuums, representing parameter variations along gradients including distance influences. Land-use research benefits from gradient analysis, particularly in areas representing extensive human interactions with landscapes. McDonnell and Hahs (2008) described the advantage of using gradients in urbanizing landscapes (urban, urban-to-rural, urban-rural-urban) as they provide opportunities to systematically compare landscape structures within and beyond (distinct) urbanized areas. In the same study (a meta-analysis), gradient analysis was used in 5% of 300 articles to investigate the urbanizing geographies.

The application of urban-to-rural (U–R) gradients has an advantage in peri-urban landscape analysis, as landscape structure can be analysed on gradients, illustrating landscape variations along these gradients (Vizzari and Sigura, 2015, Haase and Nuissl, 2010, Luck and Wu, 2002). The integration of these two methods, landscape metrics and U–R gradients, provides investigative pathways for exploring land fragmentation zones by analysing probable spatio-structural changes. The corresponding, spatially referenced land-use gradients can be used to identify and quantify agricultural land presence in these land fragmentation zones. In addition, the land-use and landscape structural information along U-R gradients can be used to empirically validate landscape characteristics corresponding to these geo-locations.

2.3 PERI-URBAN LAND-USE PLANNING

Urban sprawl has become a common challenge in many cities around the world, except for the few cities that are experiencing urban shrinkage due to specific socio-economic factors in those areas. Other than that, each city or urban area exhibits unique expanding trends, both spatially and temporally. The trends in urban sprawl vary significantly between different geographies, from developing to developed nations, flat land to mountainous areas, coastal to inland areas and megacities to secondary cities. Contemporarily, economic development has become the key driving force for urban sprawl into nearby rural landscapes (Shkaruba et al., 2016). Economic development and urbanization have mutual benefits. Higher investments attract an increased number of people into urbanized areas, helping to improve economic development with low-cost labour, energy and amenities. Urban sprawl intensifies when land administrative policies set rapid economic development targets for their priorities. Extensive urban sprawl occurrences in Chinese cities provide examples where urban expansion has become a land-governing tool for maintaining higher economic growth (Tian et al., 2017) even though it brings significant costs to peri-urban communities (Shih, 2017). In contrast, land-governing policies focusing on environmental protection are resistant to urban sprawl on city peripheries. Land-use change comparisons by Shkaruba et al. (2016) between two cities in eastern Europe (formerly part of the Union of Soviet Socialist Republics [USSR]) showed that land-use planning policies—which restrict housing development on less productive agricultural land and encourage intensified agricultural land where it achieves higher economic returns—have more power to contain urban sprawl to city fringes. Current land-use policy studies have recognized strategic initiatives to face the sprawl, such as: promoting the conversion of traditional farmland into multi-functional hubs (cellar doors, recreational and tourist attractions) and land-use zoning for intensified agricultural practices while regulating environmental concerns, to increase economic returns (Zasada, 2011). These points reveal that land administrative policy makers face the fundamental challenge of directing these policies on economic development (ED) or environmental protection (EP), mainly on city fringes.

Urban sprawl has significant connections with land administration (land-use planning and land management), particularly in local government areas on city fringes. Land-use planners have identified urban sprawl as the interplay between two factors: "push and pull". The urban pushing factors or "push factors" are identified as: land demand for housing, infrastructure and industrial expansion, as well as situations that help to accommodate urban sprawl on peri-urban areas, such as property values equal to those in urban areas, transport and infrastructure development on the fringes (Sieverts, 2003, Bryant and Charvet, 2003, Ichikawa et al., 2006). The "pull factors" are identified as actions towards a new stable state of land uses to contain urban sprawl to the fringes, such as promoting multi-functional farming, hobby farming and recreational areas (Rauws and De Roo, 2011). The interplay between "push and pull" factors has been extensively discussed under the planning practices of many European cities in the PLUREL (Peri-Urban Land Use Relationships) research project on land-use planning (Piorr et al., 2011).

Moreover, urban planners describe the effects of urban sprawl as a dynamic system transformation—land system transformation from one stable situation (non-urban) to another stable situation (urban)—due to the variation in trade-offs between push and pull factors occurring on the fringes (Rauws and De Roo, 2011). Land administrators use land-use planning as a strategic tool to control urban sprawl on peri-urban landscapes, both spatially and temporally. However, these spatially heterogeneous complex landscapes—

consisting of diverse socio-economic, environmental and political interests—are challenging due to the existence of multi-stakeholder policy overlaps and disintegrated land-management practices (Sharma-Wallace, 2016, Wu et al., 2016, Douglas, 2006, Scott et al., 2013).

Urban planning strategies vary in the world's regions by landscape arrangements and geography. In contrast to Asian and European cities, distinctly located cities surrounded by large areas of farmland, with increased land availability for expansion, such as in Australia and North America, show substantially different urban planning trends (Brinkley, 2018). In Australia, urban planners have identified the effects of urban sprawl on peri-urban landscapes under metropolitan development plans (Forster, 2006). Since colonization, Australian land-use planners have been engaged with land administration in many regions that today have developed into major cities—Sydney, Melbourne, Brisbane, Adelaide, Perth and Canberra—using land survey data, maps and aerial imagery. During the last few decades, urban sprawl has occurred mainly around the larger Australian cities (Baxter et al., 2010).

Williams (1966) presented historical evidence of planners' concerns about the spread of settlements in South Australia and about maintaining a fringe with limited population and cultivation around townships. Currently, most major and secondary cities in Australia are located in coastal areas with higher population densities—over 89% of Australian settlements are urban—and are experiencing complex urban settlement trends (McGuirk and Argent, 2011). Nevertheless, in the last few decades, Australian city planners have been facing the challenge of limiting urban sprawl into peri-urban landscapes, with this occurring as the result of urban expansion which is increasing the population growth rate, while reducing the population density of major cities (Roberts, 2007, Fincher, 2011). Australian land-use studies have acknowledged the common peri-urban land management challenges as: the loss of eco-system services; bushfire resistance; and the land-management practices of new peri-urban settlers. In addition, various socio-economic factors have created disparities, while the need for integrated and well-informed land-use planning that reflects the anticipated land management targets on the fringes has been identified (Low Choy et al., 2008, Buxton et al., 2011b).

McFarland (2015) identified the peri-urban land transformation in the context of urban sprawl as follows: "[t]he peri-urban is where the non-urban is consumed for urban purposes and such consumption results in loss of land that previously provided non-urban support and services" (p.176). McFarland (2015) further stated that conventional land-use planning identifies peri-urban landscapes as an infinite stock of land available for urban consumption while highlighting the need for integrated planning in Australian peri-urban areas to address contemporary challenges. McFarland went on to explain the importance of applying an integrated land-use planning approach on Australian urban fringes instead of the customary land-use planning methods that employ the systems of science, law and economics, with all operating as separate fields. In addition, state-level land administration policies are mismatched with local land management concerns, particularly those of local government authorities (LGAs). Shaw (2013) confirmed these points by demonstrating the common land-use deregulations and the development property interests that occur in local land administration which deviate from the common social goals for socio-economic and environmental management, as agreed in State government policies. The above literature demonstrates the land-use planning complexities and challenges associated with the city fringes in Australia, ranging from population growth to land consumption patterns and their impacts on peri-urban communities and natural landscapes. The key point emerging from this literature is the need for integrated and evidence-based land-use planning approaches on urban fringes under commonly agreed land-management policies at the State government level, while addressing the area-specific land-use concerns of local government authorities (LGAs).

2.3.1 Agricultural land vulnerability on Australian city fringes

Although agricultural land use holds a significant portion of peri-urban landscapes in Australia, less attention has been given to this land use in land-use planning processes (Bunker and Houston, 2003, Houston, 2005, Buxton et al., 2011a). The literature highlights that Australian policy makers have a view that urban areas and hinterlands are assigned for urban development while agricultural land only exists in rural areas, neglecting the peri-urban farming heritage and its contribution to urban consumption (Kennedy, 1993). In the last few decades—after the Second World War and the Vietnam War—immigrants concentrated on the city fringes, providing a significant contribution towards peri-urban agricultural prospects in Australia, due to nearby consumer demands and easy access to water, labour and technology, combined with their inherited farming practices (Burnley, 2001, Mason and Knowd, 2010). Due to the combined effect of increasing property values (land market prices) and higher economic returns, peri-urban agriculture shows that the land intensification trends featured direct investments for small to medium-scale businesses—hydroponic, greenhouse and poultry shed farming—(Johnson et al., 1998) with limited water and soil dependencies (Docking and Sreekumar, 2008) but higher discharge of waste water—chemicals in weedicides and pesticides—to the natural systems (Mason and Knowd, 2010, Humphreys et al., 2001). The agricultural land intensification and multi-functionality are not unique to Australian peri-urban landscapes as many expanding cities, surrounded by farmland are experiencing similar situations—for example, in China and Europe (Jiang et al., 2013, Stürck and Verburg, 2017)—and have recognized peri-urban agricultural practices as an important functional component in complex land-change analysis. Australian land-use research has identified the importance of recognizing peri-urban agriculture in land-use planning and policy making, as it assists in finding integrated solutions for rapid landscape changes brought about by the influence of urban sprawl (Houston, 2005, Jain, 2008).

As seen in various cities worldwide in countries such as Canada and the USA, and in Europe, Australian peri-urban agricultural practices operate under the pressure of urban sprawl (Mewett, 2013, Henderson, 2003, James, 2016), due to the rising demand for land for housing, infrastructure and commercial facilities to satisfy the urban or distinct urban consumption needs (Bunker and Houston, 2003). Although farmers in these areas have benefited from the neighbouring wealthy consumer markets, farming practices are highly regulated in relation to for stock movements, applying fertiliser and noise (Mewett, 2013). The agricultural land vulnerability to urban sprawl occurs due to frequent land re-zoning for dwellings, land-use competition and conflict, and increasing market values for farmland in Australian peri-urban landscapes (Humphreys et al., 2001, Parker and Jarecki, 2004). The increasing trends of these agricultural land vulnerabilities are steadily gaining the Australian public’s attention, as they have a substantial impact on urban food security and eco-system services on Australian city fringes (Sinclair et al., 2004, Elton Consulting, 2009, 2011). These points demonstrate the series of planning challenges that exists when managing agricultural land vulnerability on urban fringes.

A study by James and O'Neill (2016) on planning peri-urban agriculture in the Sydney basin presented the following unanswered questions for planners:

Is peri-urban agriculture as important as advocates suggest?

If peri-urban farmland is important, what should be done to preserve it? (p.179)

These questions are equally valid for other major Australian cities, as they focus on the fundamental planning challenge of developing planning policies for maintaining a balance between economic development (ED) and environmental protection (EP) on the fringes.

Many case studies from different world regions have confirmed the requirement for reliable data for effective land-use planning on city fringes (Subasinghe and Murayama, 2017, Berberoğlu et al., 2016, Pearson et al., 2010, Zhu et al., 2012). As claimed by Peter Houston (2005), the national Australian Census data (2018) on agriculture undercounted the actual peri-urban agriculture production as small-scale peri-urban details were not captured in the Census. This point was further confirmed by James and O'Neill (2016) when exploring the mismatched statistics between ABS and non-ABS reported data sources. These situations have further weakened strategic land-use planning at the level of local government land administrative areas, due to insufficient statistical quantifications of agricultural land vulnerabilities. The land cadastral data, consisting of land-use information and maintained by the local government land administrative authorities in Australia, are superior to the national Census estimates or remotely sensed data sets when making strategic land-management decisions on city fringes. These cadastral data, in particular, provide rich information on land-use functions and precise spatial estimates for informed land-management decisions, in comparison to the data captured through conventional remote-sensing techniques for LULCC monitoring or to national Census data. Australian land-use research has recognized the advantage of applying evidence-based spatially-explicit analytical approaches for planning peri-urban farmland over the unclear assumptions currently practised in land-use planning and land administration.

The author identifies that the limited information on peri-urban agricultural land vulnerability—particularly, reliable and precise spatial quantifications—creates knowledge gaps in peri-urban land-use planning and in making informed policy decisions, particularly in local government administrative areas. The land-use research also suggests the strong need for knowledge transfer from academia to land management practitioners—from LULCC monitoring to evidence-based scientific spatial quantifications—to find sustainable land-management solutions in areas of complex land systems, such as those that are peri-urban (Verburg et al., 2015). To address this gap, the current study has focused on an integrative methodological approach combining multi-criteria spatially-explicit analytics and scenario-based land-use policy analytical methods.

2.3.2 Agricultural Land Vulnerability Index

When targeting integrated planning approaches on the fringes, data are required from multi-disciplinary sectors to develop an Agricultural Land Vulnerability Index (ALVI) for planning and policy decisions. Land-use research confirms the advantage of using geographic information system (GIS)-based multi-criteria analytics for developing geographically weighted spatial quantifications in systems that represent the multi-dimensional aspects of land change (Koschke et al., 2012, Pili et al., 2017, Sánchez-Lozano et al., 2013, Taleai et al., 2014, Yu et al., 2011). Feng et al. (2015) demonstrated the advantage of using multi-dimensional indicators—spatial form, density, growth and impact on landscapes—to measure land change due to urban sprawl for land-use planning, as they provide quantified evidence of landscape changes to reflect the effects of land-use planning decisions on the fringes. An agricultural land-use model prediction by Lambin et al. (2000) emphasised the importance of spatially quantifying the anticipated environmental impact of effective land-use policy decisions. However, land-use research has exposed some of the methodological challenges associated with the application of multi-criteria spatially-explicit analytics in land-use planning. A co-system multi-functionality regional scale study in the EU by Stürck and Verburg (2017) demonstrated the importance of the following challenges, that is, the selection of suitable indicators and the scale of the analysis, as they greatly affect the validity of results in land-change analysis. They also stated that the selection of suitable indicators depends solely on the research objectives and that the interpretations of these indicators vary on different scales. Many land-change studies have provided insights into the scale dependency of multi-disciplinary aspects for land-use planners by identifying and visualizing the cross-scale effects in land-use change due to urban sprawl (Hayek et al., 2015, Su et al., 2012, Bhatti et al., 2015). The integration of key dimensions of these complex landscapes and their bio-physical, economic and social aspects has an advantage in developing spatially-explicit land-change analysis to explore landscape changes due to urban sprawl (Salvati et al., 2017c).

As the literature on the above topics has demonstrated, peri-urban agricultural land vulnerability can occur due to various situations created by a combination of key drivers (land development policies—land-use zoning, demand for land, cost of land-use change, land fragmentation and farmers' economic returns) that influence land-use changes. The effects of these indicative parameters on land vulnerability clearly depends on the spatial location and the accumulated influence through trade-offs between negative and positive influences. Spatial layer overlay techniques have been widely used in GIS-based land-change analysis for urban planning (Yeh and Li, 1998, Liu and Li, 2016, Batty et al., 1999, Holloway and Bunker, 2003). These applications have proven the potential of GIS using location-based parameter calculations and spatial quantifications. In terms of scale dependency, the occurrence of errors is minimized as the current study focuses on local-scale land-change analysis with single-scale grid-based parameter inputs and outputs.

Scenario development originated as a financial analysis tool in future studies and was gradually adapted to suit other disciplines including, but not limited to, land-use change, ecology and environmental impact assessments as a modelling tool based on numerical simulations (Priess and Hauck, 2014, Van Notten et al., 2003). Bishop et al. (2007) demonstrated the advantage of using scenario analysis in future studies, as they investigated the concerns of unexpected risks and uncertainties associated with anticipated situations. Börjeson et al. (2006) suggested three main scenario typologies: predictive (forecast/'what-if' scenarios), explorative (external/strategic) and normative (preservation/ transformation) that could satisfy the knowledge required in scenario development. As this section of the study sought to identify future peri-urban agricultural land vulnerability variations under different policy directions, the author aligned the study with the explorative approach to answer the question "What can happen if we act in a certain way?", as described by Börjeson et al. (2006).

Scientific research has identified the advantage of using scenario analysis in future studies, as it has the potential to develop an understanding of system uncertainties, complexities and dynamics in alternative set-ups, while exploring interactions between the drivers and their impacts on the systems (Priess and Hauck, 2014, Maier et al., 2016). Biggs et al. (2007) showed that in socio-ecological systems, multi-scale scenario analysis generates uncertainty when linking scenarios across scales. Scenario analysis has been widely used in scientific research for projecting current knowledge to address future challenges (Acreman, 2005, Kok, 2009, Liu et al., 2008, Gounaridis et al., 2018, Titeux et al., 2016, Trubka and Glackin, 2016). Likewise, it enables inter-disciplinary knowledge exchange through interconnected problem analysis, comparison and finding justifiable solutions for future challenges (Henrichs et al., 2010, Mitchell et al., 2016, Liu et al., 2017, Rounsevell et al., 2006).

Bishop et al. (2007) highlighted scenario characteristics as follows: "[s]cenarios contain the stories of these multiple futures, from the expected to the wildcard, in forms that are analytically coherent and imaginatively engaging" (p.5). The future studies literature has identified that creating a defensible storyline in the topic area is important for scenario development processes (Hanspach et al., 2014, Palomo et al., 2011, Bishop et al., 2007). Kaljonen et al. (2012) emphasised the importance of defining a storyline in scenario analysis when making informed decisions, while Giljum et al. (2008) highlighted the potential of scenario analysis in assessing the consequences caused by alternative strategies and policy directions. Kok (2009) distinguished the difference between a qualitative narrative storyline and a quantitative mathematical model storyline while highlighting the following key characteristics of mathematical modelling storylines: based on scientific judgements; depending on model architecture; data-driven; plausible; and internally consistent.

Quantitative scenario analysis has potential for system modelling enhancements, particularly in the area of sensitivity analysis which creates a systematic framework for understanding the relative importance of different parameter inputs on model outcomes (Saltelli, 2002, Pannell, 1997, Verburg and Bouma, 1999). In system modelling, sensitivity analysis uses boundary conditions to represent variables with multiple plausible values that are based on subjective area knowledge assumptions. Bishop et al. (2007) showed the advantage of sensitivity analysis for system modelling as it generates the most suitable quantitative variable combinations for demonstrating future system arrangements. However, when using sensitivity analysis in modelling decisions, Pannell (1997) emphasised the importance of focusing on the research objectives to optimise the model strategies. These points demonstrate the importance of focusing on variable selection and model objective functions when developing sensitivity analysis scenarios for system modelling.

The integration of spatial analytics (multi-criteria spatially-explicit quantifications) and scenario analysis in modelling incorporates spatial intelligence into modelling results by distinguishing and identifying scenario effects in a spatial context. Land-use research has used spatially-explicit plausible scenario analysis to find solutions for possible future land transformation challenges (Bryan et al., 2011, Seppelt et al., 2013, Kropp and Lein, 2013, Jiang et al., 2016, Lauf et al., 2016, Sohl et al., 2007). Based on scenario models, land-use research has identified the advantage of integrating socio-economic, land-use regulations and urban growth variables in a single consistent framework for the mapping of future land use (de Nijs et al., 2004). Moreover, researchers have integrated different land-use models, such as the CLUE (conversion of land-use change and its effects) model and system dynamics models, for creating multi-criteria, spatially-explicit scenarios to investigate future land-use change analysis on different scales and at different time resolutions (Luo et al., 2010). Although the view has been expressed among researchers that scenario-based modelling predictions are non-realistic, an investigation on spatial data ambiguities in LULCC scenarios by Dendoncker et al. (2008) showed that scenario-based model results (spatial patterns) varied on different scales due to varying spatial data quality rather than due to scenario variations along the scales.

2.4 PERI-URBAN FARMERS' LAND-USE DECISIONS

The land-use decision behaviours of peri-urban farmers are important in understanding agricultural land transitions on the fringes, as they are the primary decision makers on farmlands that occupy a larger portion of the land use. These decisions spatially and functionally change peri-urban landscape structures while introducing multi-stakeholder engagements as a substitute for the heritage farming that has been practised for generations (Duvernoy et al., 2018). However, the previous literature on urban-centric land-use planning, policy and LULCC has paid little attention to farmers' land-use decisions when investigating the impacts on landscapes. This may be due to the complexity associated with the functionalities in these land systems which are characterized by rapid landscape changes and unseen socio-economic and land governance interactions occurring on the fringes (Davoudi and Stead, 2002, Galli et al., 2010). Recent peri-urban studies have demonstrated that the research community has a growing interest in exploring farmers' land-use decisions in land transitions (Nualnoom et al., 2016, Akimowicz et al., 2016, Nguyen et al., 2017b). At the same time, land-use policy makers are realising the importance of having comprehensive knowledge on peri-urban farming functionalities when proposing sustainable land management on the fringes (Duvernoy et al., 2018, Rutten et al., 2014). In focusing on the land-system approach, LSS has recognized the necessity of including agricultural land-use functions in peri-urban land system domains, as this enables exploration of the connections between urban sprawl effects and agricultural land extinction which primarily depend on farmers' land-use decisions (Fragkias et al., 2012, Duangjai et al., 2015, Seto et al., 2012b).

2.4.1 Land-use decision cognitive behaviour

The cognitive behaviour behind farmers' (human) land-use decisions is complex and varies, depending on their own experiences and psychological aspects (Sterman, 2001) in relation to their farming business. As Hertwig et al. (2004) explained, people make decisions based on their personal encounters stored as experience in their memory. Their study further described the distinguishable differences between experience-based decisions and description-based decisions (providing a summary of possible consequences), emphasising that people often tend to make decisions based on their experiences. The validity of this fact in the farming industry is confirmed by the social study of Vanclay (2004) on agricultural extension, emphasising that farmers, as individuals or as groups, make decisions based on their experiences, rather than on information, knowledge or their own beliefs. Moreover, a study on farm diversification determinants by Meraner et al. (2015) identified that farmers' personal attitudes on land-use change—"land-use diversifications"—are highly influenced by their personal psychological aspects. Pichón (1997) identified similar assumptions made in land-use-related studies on farmers' land-use decisions: production-based decisions based on physical and socio-economic aspects; trade-offs between business opportunities and constraints; and seeking to minimize the risk and uncertainties.

However, Vanclay (2004) argued that farmers have unique interests and behaviour in relation to land-use decisions: "[p]rofit is not the main driving force of farmers, Farmers are not all the same, Farmers construct their own knowledge, Farmers' attitudes are not the problem" (p.214). These statements emphasise that farmers' land-use decisions—individually or as groups—based on their own theorisation, expectations or limitations of their farming business, have insights into socio-economic and physical set-ups (Aalders, 2008).

The land-use decisions of peri-urban farmers are concerned with exogenous (external) and endogenous (internal) factors that farmers experience in the farm environment. The individual farmer's land-use decisions are important in understanding land use (Aalders, 2008) which is governed by those decisions, with this varying from person to person under specific circumstances (Chambers and Conway, 1992). Northcote and Alonso (2011) described farmers' concerns about their land-use decisions: "[d]ecision-making is shown to involve an assessment of risk, which is shaped by their appraisal of economic conditions, market opportunities, access to resources (including labour) and lifestyle factors" (p.237).

In peri-urban landscapes, farmers experience a series of influential external factors, namely, socio-economic, environmental and institutional regulations, while confronting a wider range of influential internal factors when making their land-use decisions (Nguyen et al., 2017b, Akimowicz et al., 2016). Land-use researchers have recognized external factors that influence farmers' land-use decisions such as: financial markets, credit and market opportunities (Northcote and Alonso, 2011, Seppelt et al., 2012); socio-structural and industry engagements (McNally, 2001); access to new technology (Bowman and Zilberman, 2013); bio-physical (soil and water) or geographic limitations (Stoorvogel et al., 2004, Deng et al., 2015); institutional land-use regulations; and farmers' perceptions of climate variability (Rutten et al., 2014, Thulstrup, 2015) including extreme weather events (McCord et al., 2015). Moreover, researchers have identified internal factors such as: family-oriented decisions (Hansson et al., 2013); limited accessibility to knowledge and skills (Stoorvogel et al., 2004, Nualnoom et al., 2016); lifestyle objectives; and psychological stress associated with farm income and maintenance expenditure (Hansson et al., 2013), as well as demographic concerns including age succession, education and farming business engagements (full-time/part-time) (Huber et al., 2015).

Arneth et al. (2014) emphasised the importance of the inclusion of the individual's decision in land-use modelling

> Most importantly, current state-of-the art modelling tools are unable to represent human agency which underpins individual behaviour, decision making and adaptive learning and hence is important for understanding how societies will respond to challenges (p.2).

However, limited knowledge has been developed in the land-use literature on the inclusion of underlying factors (drivers of land-use change) that govern the individual farmer's land-use decisions, when investigating community-scale land-use transitions (Rindfuss et al., 2004). Land-use researchers have identified the advantage of incorporating the individual farmers' decision behaviours in LSS by conceptualising agent-centric models to investigate the dynamics of land systems and their feedback on these land systems. Land-use researchers are often confronted with the challenge of isolating the key factors that drive farmers' land-use decisions, from the series of factors that are present in the land system. To develop comprehensive agent-centric models based on farmers' decision-making behaviour, it is vital to understand decision drivers and the behaviour of decision-making profiles, that is, groups of farmers with similar patterns of decision-making. Today, land-use modellers are often challenged when incorporating individual farmers' decision behaviours in LSS as such behaviours are complex and require a larger amount of comprehensive data to investigate farmers' concerns, motivations and perspectives towards land management. Based on the above points, the author acknowledges that identifying the underlying factors that drive peri-urban farmers' land-use decisions is one of the major knowledge gaps in the LSS literature. The peri-urban farmers' land-use decision behaviours need to be incorporated to investigate agricultural land-transition phenomena on city fringes.

2.4.2 Land-use decision drivers and profiles

Factor dimension reduction methods are useful in exploring latent factors from a series of indicative factors in complex systems. Latent (hidden) factor analysis is an effective exploratory factor analytical (EFA) method for reducing the series of factors into a manageable set of variables while describing underlying latent factors (Colantoni et al., 2016). In land-change science, exploratory data analytical methods have been used to reduce the number of factors while describing and ranking their importance in land-system changes (Lesschen et al., 2005, Salvati et al., 2017a, Veldkamp and Fresco, 1997). Moreover, LSS has recognized the advantage of using factor reduction methods in land-use modelling when investigating the underlying factors in complex land systems (Veldkamp and Lambin, 2001). Therefore, the author recognizes the advantage of using exploratory factor analysis (EFA) for investigating underlying factors (key influences) behind peri-urban farmers' land-use decisions. This will assist in building the knowledge on peri-urban farmers' land-use decisions, enabling justifiable estimates—parameter assumptions—to be made for agent-centric land-use modelling (i.e. agent-based modelling [ABM]).

In terms of exploring peri-urban farmers' land-use decision patterns, it is essential that they are classified into groups based on their responses. Clustering (exploratory cluster analysis [ECA]) is an unsupervised data analytical method that is used to partition the response-objectives into groups, that is, clusters (Cornuéjols et al., 2018). Land-use researchers have identified the advantage of using cluster analysis to group farmers based on their land-management objectives for further investigation (Lesschen et al., 2005). Land-use research has implemented hierarchical cluster analysis (HCA) to investigate similar groups of farmers with different behaviours in structured land systems (Handayani, 2013, Köbrich et al., 2003). These groups of farmers (decision-making profiles) exhibit different attributes in terms of their land-use change decision behaviours. In contrast, non-hierarchical cluster analysis has been used to explore a similar group of behaviours or strategies in complex un-structured land systems (Thompson et al., 2002, Hietel et al., 2004, Rasul et al., 2004). The author identifies the advantage of using non-hierarchical (*k*-mean) cluster analysis over hierarchical clustering to explore peri-urban farmers' land-use decision patterns, as peri-urban areas consist of unstructured and complex land systems.

Principal component analysis (PCA) is another structure reduction method extensively used in land system science (LSS) when conducting land-use research to understand land structures (Lesschen et al., 2005). The PCA applications are often based on a vital set of variables on continuous scales for data analysis. The use of categorical variables (factors on common scales) in EFA assist in identifying the key drivers, while grouping participants based on their decision patterns (profiles) by ECA and their associated behaviour under the assigned categorical scale. The categorical variables are very useful in cluster analysis in partitioning the data as groups (Seo and Gordish-Dressman, 2007). The classification approach based on categorical variables advances the development of agent-centric models as it enables the data for groups to be partitioned and identifies the categorical responses of the grouped participants using a common scale.

Halkidi et al. (2001) stated the importance of cluster result validations and interpretations for improving the knowledge of grouped behaviours. In conceptualising agent-centric models for understanding peri-urban agricultural land transition phenomena, the author identifies the need to develop knowledge on the following aspects: underlying factors behind farmers' land-use decisions; land-use decision-making profiles; and land-use change decision commonalities to make assumptions for modelling.

Based on the points above in subsections 2.4.1 and 2.4.2, the author identified two major knowledge gaps in the land-use science literature in the incorporation of peri-urban farmers' land-use decision behaviours when investigating agricultural land-transition phenomena. These gaps were due to the absence of methodological approaches in:

- Identifying the underlying factors driving peri-urban farmers' land-use decisions.
- Identifying peri-urban farmers' land-use decision patterns and land-use decision-making profiles.

2.5 MODELLING AGRICULTURAL LAND TRANSITIONS

2.5.1 Land-use modelling

Land-use modelling has been developed as a methodological approach for exploring LULCC and its impact on the surrounding landscapes. With its foundation in ecological modelling, land-use modelling has become popular among researchers as it can represent a wider range of parameter inputs, ranging from socio-economic to bio-physical aspects, from human–environmental land systems. Over the last few decades, many diverse land-use modelling techniques have been developed to understand land-change processes through theoretical models and model simulations (Verburg et al., 2006, Verburg et al., 2004, Brown et al., 2013, Lambin et al., 2000). The land-use modelling literature has identified several challenges that exist in land-change modelling with these including the choices of: spatial or non-spatial modelling; causality or empirical modelling; scale dependency of the models; equation-based or agent-centric modelling; and model uncertainties or validations (Verburg et al., 2006, Koomen and Stillwell, 2007, Brown et al., 2004).

Verburg et al. (2015) demonstrated the purpose of developing land-change models: “[w]hile some models are targeted as learning-tools to test alternative conceptualisations of land system dynamics, other models are specifically designed to evaluate alternative policy proposals to support decision making ...” (p.33). The above study demonstrates the advantage of incorporating land-use modelling in land-use planning for informed policy directions while transferring scientific knowledge into practice. In their review of land-change models, Verburg et al. (2004) emphasised the importance of prioritising multi-scale analysis, spatio-temporal dynamics and neighbourhood effect quantifications in land-use model development as they address the future LSS challenges. Sterman (2002) emphasised the importance of having a systematic approach in modelling, stating that though all models are not necessarily accurate, some models assist us to understand complex systems. In an agricultural-based model analysis, Lambin et al. (2000) highlighted the advantage of using cross-sectoral integrative modelling approaches in exploring complex land-transitional processes while emphasising that the three major aspects of “why, where and when” should be the focus in land-change modelling. In addition to these three aspects, Sterman (2002) identified “to whom” the (target audience/ client) as an important aspect in land-change model development as it assists in improving mental maps of model uses. Although land-change models have shown significant improvement in the last few years, the LSS experts on the National Research Council (NRC)’s Committee on Needs and Research Requirements for Land-Change Modelling (2014) have recognized that the following aspects need to be strengthened in future land-use modelling: “… spatio-temporal representation of land use decision making, cross-scale dynamics, and a stronger link to empirical data collection for parameterisation and validation” (p.15).

2.5.2 Land-system complexity

Land-change science has recognized various aspects of land-system modelling complexities, namely, the spatial, scale, behavioural and temporal dynamics associated with human-coupled land systems. Gutman (2004) emphasised that LSS has realised the connections between social and ecological systems, and land-change dynamics and land-agents’ (land-users’) behavioural interactions with these systems. Consequently, LSS has focused on exploring the underlying drivers behind land-system changes; land-use agents (multi-actors) and their connections with system dynamics; socio-environmental feedback; land-use change patterns; and non-linear land-system dynamics (Ligtenberg et al., 2001, Messina and Walsh, 2001, Verburg et al., 1999, Meyfroidt, 2016).

System analytics often focus on the key features of complex systems analysis: non-linearity, endogenous and exogenous effects on land systems, feedback, self-organization and path dependencies (Müller, 2016, Sterman, 1994). These characteristics of complex systems have been widely addressed by LSS in many land-use modelling studies (Brown et al., 2005b, Verburg, 2006). In their analytical study on complexity, with land-use modelling combined with human dimensions, Parker et al. (2008b) emphasised the need to divert the land-use modelling focus from human decisions to human interactions with social and bio-physical processes when seeking to understand complex system outcomes. Sterman (2002) recognized the advantage of using empirical information-based model simulations to understand these systems: "… qualitative modelling exposes us to one of the most fundamental bounds on human cognition: our inability to simulate mentally the dynamics of complex nonlinear systems (p.525).

Liu et al. (2007) demonstrated that integrated social and bio-physical modelling is superior to individual model attempts as it provides descriptive statistics of complex system dynamics comprising: "nonlinear dynamics with thresholds, reciprocal feedback loops, time lags, resilience, heterogeneity, and surprises" (p.1513). The investigative land-use research on complex system characteristics by Brown et al. (2008) demonstrated the advantage of using the conceptual inheritance from complexity science to create "bottom-up" agent-based models for exploring complex land-change features: micro-scale decisions and patterns, heterogeneity, cross-scale interactions and system feedback. Reviews of the land-change modelling literature have shown that LSS has focused on the calibration and validation of land-use model simulations, due to their contribution to scientific advancements and acceptance (van Vliet et al., 2016). However, validating these models (which comprise a wider range of assumptions) is a challenge as it requires reliable data sources from within the actual land system (Messina et al., 2008).

2.5.3 Agent-based model simulations

Land-use researchers have realised the benefit of using agent-centric models—agent-based models (ABMs)—to explore land-system dynamics, as the aggregated behaviour data of individual decisions are used to simulate complex land-system processes (Parker et al., 2003, Rounsevell et al., 2012). The philosophical investigation by Brown et al. (2016) demonstrated the advantage of using a "bottom-up" over a "top-down" approach in developing process-based land-use modelling, as it uses more realistic assumptions and evidence on land-system dynamics. However, land-use modellers have identified many challenges in capturing agent properties, behaviours, their sensitivity to model environments, model verification and validation, all of which consume a large amount of empirical information in model development processes (Filatova et al., 2013, Villamor et al., 2013).

Parker et al. (2008b) stated that land agents employ a diverse set of strategies and experience a range of influences in making land-use decisions. They further explained how these decisions are heavily dependent on land-change drivers, both spatially and temporally. In addition, Parker et al. (2003) introduced an integrated multi-agent system (MAS) approach with LULCC, emphasising that it is suitable for representing complex spatial interactions under heterogeneous conditions and for developing decentralized, autonomous decision-making modelling. Edwards-Jones et al. (1998) claimed that a considerable benefit can be gained from integrating economic and psychological variables in models in a smaller-scale behaviour prediction. This has been further confirmed in recent literature on comparative approaches for developing ABMs for landscape change studies (Millington and Wainwright, 2016). The above points confirm the effectiveness of using an integrated agent-based modelling method to capture agents' land-use change phenomena on a micro-scale.

Another popular modelling method among the environment and land-use research communities (Verburg and Overmars, 2007, Berberoğlu et al., 2016, Fuglsang et al., 2013, de Almeida et al., 2003) is cellular automata (CA). Crooks and Heppenstall (2012) defined cellular automata (CA) as a "… discrete dynamic system, the behaviour of which is specified in terms of local relations" (p.91). However, Takeyama and Couclelis (1997) argued that, despite the theoretical interest, CA have not been widely used in applications, mainly due to the difficulties of adapting a strict formalism to the demands of modelling real-world phenomena. Furthermore, the authors explained that the assumptions made in CA—standards of regularity, homogeneity, universality and closeness—are difficult to match with the real world. Birkin and Wu (2012) showed the difference between CA and ABMs:

> CA model social dynamics with a focus on the emergence of properties from local interactions while ABMs simulate more complex situations than the CA where the 'agents' control their own actions based on their perceptions of the environment (p.52).

The comparison of land-use case studies by Parker et al. (2008a) showed that the CA model had difficulties when incorporating human decision making into land-use modelling. It was further explained that, even though CA models successfully replicate aspects of ecological and bio-geophysical phenomena, they are not suited to the development of decision-making models. In 2010, Liu explained the distinctions between CA and MASs such as an agent's autonomous features, and agents and environmental mobility and interactions (Liu, 2010). Gilbert (2008) identified the advantage of using an ABM over CA, as it would help to isolate ethical problems with regard to human systems in virtual environments.

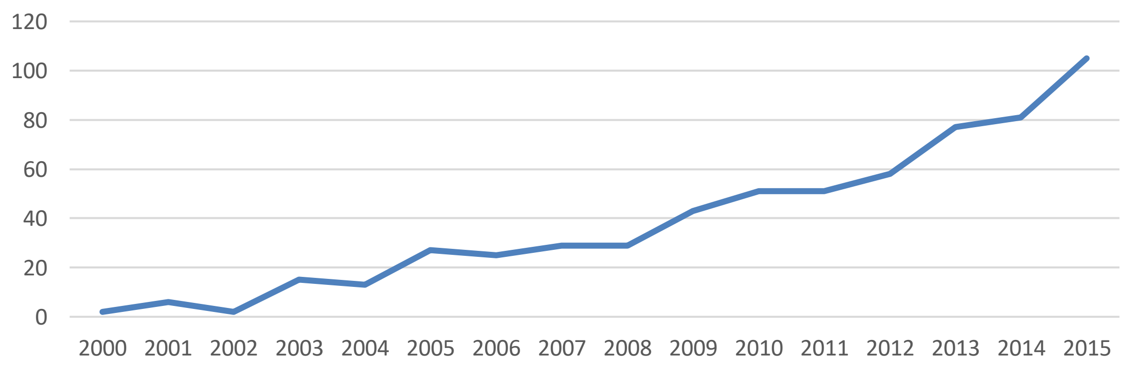


Figure 2.1: Results of topic search for: (Land) AND (Agent-based model)
Note: In total, 614 records were listed for 2000–2015 in this search on the Web of Science database.

Agent-based modelling (ABM) is a computational method that enables the creation and analysis of, and experimentation with, models composed of agents that interact within an environment (Gilbert, 2008). Agent-based simulation has become increasingly popular as a modelling approach in the social sciences and land-change analysis as it enables the building of models in which individual entities and their interactions are directly represented (Rindfuss et al., 2008, Gilbert, 2008). Assigning suitable properties and behavioural characteristics (decision rules) of agents as well as defining the interaction between agents and environments are the most important aspects in developing agent-based models (ABMs).

Land-change analysis shows that ABMs are more effective over equation-based land-use models. Parker et al. (2003) explained that the major drawback of equation-based mathematical modelling is that a numerical or analytical solution to the system must be obtained, limiting the level of complexity that can be built into such models. Compared to the structural equation modelling (SEM) (variable-based) approaches, agent-based simulation (in system-based approaches) provides advanced capabilities for capturing the heterogeneity of individuals (agents), explicitly representing agents' decision rules, and situating agents in a geographic or any other type of analysis (Gilbert, 2008). The above points reveal the importance of capturing the complexities of a land system, such as the scale, spatial, behavioural and time complexities, in the modelling process.

The fundamental importance of integrating human decisions into agent-centric models representing human-coupled systems has been demonstrated in many land-use studies (Polasky et al., 2011, Schlueter et al., 2012, Müller, 2016). Particularly in land-change studies of cases at the micro-level, land-change patterns experience a substantial influence from assumptions made on human decisions and the decision rules they follow (Parker et al., 2008b, Parker et al., 2003, Jager and Mosler, 2007). However, only a limited number of studies have focused on introducing protocols for the integration of human-decision behaviour into land-system modelling. Land-use modellers have identified significant knowledge gaps in the current literature in relation to incorporating human decisions into ABMs such as: provision of an insufficient theoretical or empirical foundation and non-transparent reproducibility of the models and their outcomes (Müller et al., 2013). Land-use modellers have also identified the importance of providing a complete description of models to maintain transparency in modelling processes, thus providing evidence so models can be reproduced in different environments (Parker et al., 2008b, Richiardi et al., 2006).

The definition of a standard protocol for the ABM that originated from ecological modelling to become the ODD (overview, design concepts and details of the model) protocol received a higher level of acceptance from the scientific community as it provided a solid structure for developing ABMs (Grimm et al., 2010, Grimm et al., 2005). Although the ODD protocol is not supported for addressing human decision making in ABMs, Polhill et al.'s (2008) study showed the advantage of using the ODD protocol in land-change studies as it provides useful standards for result communications and for competition between the models.

Consisting of the structural elements (overview, design concepts and details) of models with guiding questions for the sub-topic areas of these key elements, the ODD protocol provides a comprehensive understanding of the modelling process (Grimm et al., 2005). However, modellers have identified the necessity of incorporating human decisions into the ODD protocol to address the challenges in ABM in gaining an understanding of socio-ecological complex systems (Müller et al., 2013, An, 2012). Müller et al. (2013) particularly showed the advantage of focusing on human decision making, and the adaptation and learning of the modelled agents in integrating human decisions into the ODD standard protocols when modelling human-based complex processes.

Tesfatsion (2006) defined "agents" in ABM as "[b]undled data and behavioural methods representing an entity constituting part of a computationally constructed world" that allow modellers to identify a group of humans by their properties, social groups or bio-physical elements, or institutions as entities that represent agents in complex systems. Müller et al. (2013) provided guidance for incorporating human decisions into the ODD protocols by introducing the ODD + D protocol to represent the agent's characteristics and decision behaviour in ABM development. This particularly highlights the importance of focusing on the following areas: spatial aspects in model overview; design concepts with human decision behaviours; theoretical and empirical outlines with system complexity; and the implementation of models.

The current study mainly focuses on investigating peri-urban agricultural land-transition phenomena through the target farming group's land-use decision-making behaviours in a highly dynamic land system. Therefore, it is important to investigate the agricultural agents' characteristics such as: their heterogeneity, decision rules, dependencies and experiences when making assumptions for parameterising the agents (peri-urban farming land-use decision-making profiles) in the modelling process.

In terms of evaluating peri-urban agricultural land-transition phenomena, the author identifies the following significant knowledge gaps in developing agent-centric models in the land-change science literature:

- Capturing information from empirical observations to identify and define the key land-change drivers, the agents in the system (groups of farmers that make decisions in a similar pattern [decision-making profiles]), their decision-making behaviour and interaction with other agents, in these complex human-coupled land systems on city fringes.

- Capturing land-transition system dynamics and their feedback under different land administrative policy directions.

To address these gaps, the author focuses on developing an ABM to evaluate agricultural land-transition phenomena while exploring the target group's (agricultural land-use) variations in alternative scenarios, concentrating on theoretical considerations in land system science (LSS). The author uses the knowledge developed in the following sections of this research: agricultural land in peri-urban landscapes, agricultural land vulnerability and farmers' decision behaviours to define the assumptions when developing the ABM in the final stage of this study.

Figure 2.2: Word cloud produced by keyword search in NVivo

Note: The word cloud provides a relative description of journal articles, book chapters and reports referred to in this thesis.

CHAPTER 3 – LAND-USE ANALYSIS OF URBAN FRINGES

This chapter explores the physical land-parcel arrangements of Adelaide city's peri-urban landscapes using urban–rural (U–R) gradient analysis from the city centre in three directions (north, east and south) towards rural landscapes. Furthermore, this study analyses the interactions of two landscape metrics to explore the land fragmentation zones along these transects. The final stage of the research described in this chapter focuses on spatially quantifying the extent of agricultural land in the derived land fragmentation zones, instead of the entire farmland as a buffer, to target the agricultural land that is highly vulnerable to urban sprawl.

Contributions to knowledge:

- Identified land fragmentation zones in peri-urban landscapes.
- Showed the advantage of spatially quantifying agricultural land in land fragmentation zones for making informed land management decisions.

This chapter was published as a journal paper "Agricultural Land Fragmentation at [sic] Urban Fringes" (Wadduwage et al., 2017) at the time of completion of this thesis. The author of the thesis designed the study, analysed the data, wrote the final write-up and prepared the research paper for publication. This section of the thesis (Chapter 3) had the benefit of input from supervisors and co-authors and from the *LAND* journal's peer-review process. The author acknowledges their valuable and important contributions.

3.1 ABSTRACT

One of the major consequences of expansive urban growth is the degradation and loss of productive agricultural land and agro-ecosystem functions. Four landscape metrics—percentage of land (PLAND), mean parcel size (MPS), parcel density (PD) and the Modified Simpson's Diversity Index (MSDI)—were calculated for cells (1 km × 1 km in area) along three 50 km-long transects that extend out from the central business district (CBD) of Adelaide, South Australia, in order to analyse variations in landscape structures. Each transect has different land uses beyond the built-up area, and they differ in topography, soils and rates of urban expansion. Our new findings are that zones of agricultural land fragmentation can be identified by the relationships between MPS and PD, that these occur in areas where PD ranges from 7–35 N/km^2, and that these occur regardless of distance along the transect, land use, topography, soils or rates of urban growth. This suggests that the geometry of fragmentation may be consistent and indicates that quantification of both land use and land-use change in zones of fragmentation is potentially important in planning.

3.2 INTRODUCTION

Projections suggest that over two-thirds of the world's population will live in urban centres by 2050 (UN, 2015), and that a major part to this growth will be due to people migrating from the countryside (Seto et al., 2011, Schneider et al., 2015, Fragkias et al., 2012). Over the last 30 years, the global rate of urban land occupation (Angel et al., 2011, Bringezu et al., 2014) has been double the rate of urban population growth (Seto et al., 2012a). Agricultural land loss due to urbanization has been highlighted by a number of researchers (Shi et al., 2012, Debolini et al., 2015, Handayani, 2013, Appiah et al., 2014, Malaque and Yokohari, 2007, Piorr, 2011, Piorr et al., 2011), and has raised a number of environmental concerns, for example: declining quality of soil and water assets; loss of natural habitat; decreased plant and animal diversity; and compromised ecological functions (Matson et al., 1997, Flynn et al., 2009). The urban sprawl that can be anticipated (given urban population projections) will increase demands for land for housing, industry and infrastructure, thereby, consuming more agricultural land on the edges of cities (Xiao et al., 2006, Liu et al., 2013, Seto et al., 2011). This will lead to irreversible and unsustainable land-use transitions at the cost of productive agricultural land in peri-urban areas (Jiang and Swallow, 2015, Pham et al., 2014, d'Amour et al., 2016), where open spaces and scarce remnant ecosystems with high ecological and conservation values are already threatened (Crossman et al., 2007).

Urban fringes—the transitional zones between urban and rural areas (Thapa and Murayama, 2008)—are characterized by highly dynamic, spatially heterogeneous land-use and land-cover changes (LULCC) (Seto et al., 2010, Nagendra et al., 2013). This takes place due to the relatively lower land prices in these zones and the high frequency of land tenure change (Rauws and De Roo, 2011, Liu et al., 2014). Compared to urban environments, the faster rates of housing and infrastructure growth and the higher proportion of remnant 'green' spaces lead to different landscape structures on the fringe. Research has also demonstrated that urban growth leads to increased land fragmentation (Irwin and Bockstael, 2007) and landscape diversity (Lambin et al., 2001) in these areas. The diverse arrays of land uses that result from these processes create spatially heterogeneous, complex land-use configurations (Allan, 2004, Luck and Wu, 2002, Kuang et al., 2016, Lambin and Meyfroidt, 2010, Haase and Nuissl, 2010). However, a concern for planners and people implementing land management policies in urban fringe environments is that the quantitative land-use data they require are often accompanied by relatively low levels of accuracy (Bunker and Houston, 2003, Houston, 2005).

A recent development in understanding the influence of urbanization on land use has been the use of urban-to-rural (U–R) gradient analysis (Kroll et al., 2012, Andersson et al., 2009, Haase and Nuissl, 2010). This concept originated as a combination of elements drawn from landscape ecology and urban ecology (McGarigal and Cushman, 2005, Godron and Forman, 1983), and has been used to synthesize complex anthropogenic land transitions worldwide (Haase and Nuissl, 2010, McDonnell et al., 1997, Luck and Wu, 2002, Weng, 2007, McDonnell and Hahs, 2008, Larondelle and Haase, 2013, Vizzari et al., 2015, Forman and Godron, 1986, McDonnell et al., 1993). The continuous representation of land-use intensity and the spatial arrangement of land use along gradients are more effective in land-use planning than conventional, discrete spatial measurements (Vizzari and Sigura, 2015). Urban-to-rural (U–R) gradient analysis is also useful for examining gradual landscape change on urban fringes. The approach has other advantages; for example, in environmental modelling, it is used to minimize subjectivity in categorizing variability and in describing ecological processes at urban fringes (Bridges et al., 2007). It is also used to represent land use as a gradient and for measuring the spatial attributes of land parcels along gradients, both of which improve our ability to interpret landscapes (Luck and Wu, 2002, Warren et al., 2011). Geographically-referenced points along gradients enable spatial and non-spatial data to be aggregated for systematic landscape comparisons (Shkaruba et al., 2016, Joo et al., 2011, Díaz-Varela et al., 2016). Finally, these continuous information gradients can be utilized to understand landscape structures and potential land-use variations in complex land systems.

Landscape metrics calculated along these gradients have been used to identify land-structure elements and their changing patterns, and to describe the effects of urban development on the margins of several cities (Luck and Wu, 2002, Haase and Nuissl, 2010, Weng, 2007). Vizzari and Sigura (2015) claimed that gradient analyses enable interactions between land-use types to be identified precisely when exploring land transitions. In the current research, landscape structure is defined as the spatial configuration of land parcels (i.e. their size and spatial arrangement) and their composition (land-use presence and amount of each land parcel in the landscape) (McGarigal and Marks, 1995).

This paper (chapter) reports on the application of urban-to-rural (U–R) gradient analysis to understand agricultural land fragmentation on the urban fringes of Adelaide. In previous research, landscape metrics have been plotted along transects, but the relationships between them have not been integrated into gradient analyses. Four landscape metrics—parcel density (PD), mean parcel size (MPS), percentage of land (PLAND) and the Modified Simpson's Diversity Index (MSDI)—were used to quantify and characterize land fragmentation along transects extending from the Adelaide CBD into surrounding rural areas. A novel element of the research is the quantitative analysis of agricultural land-use presence in zones of active land fragmentation on the urban fringe. In this context, urban-to-rural (U–R) transects were used as geo-referenced land-use information gradients that integrate measurements of land use, while simultaneously examining landscape structure and land-use changes.

3.3 MATERIAL AND METHODS

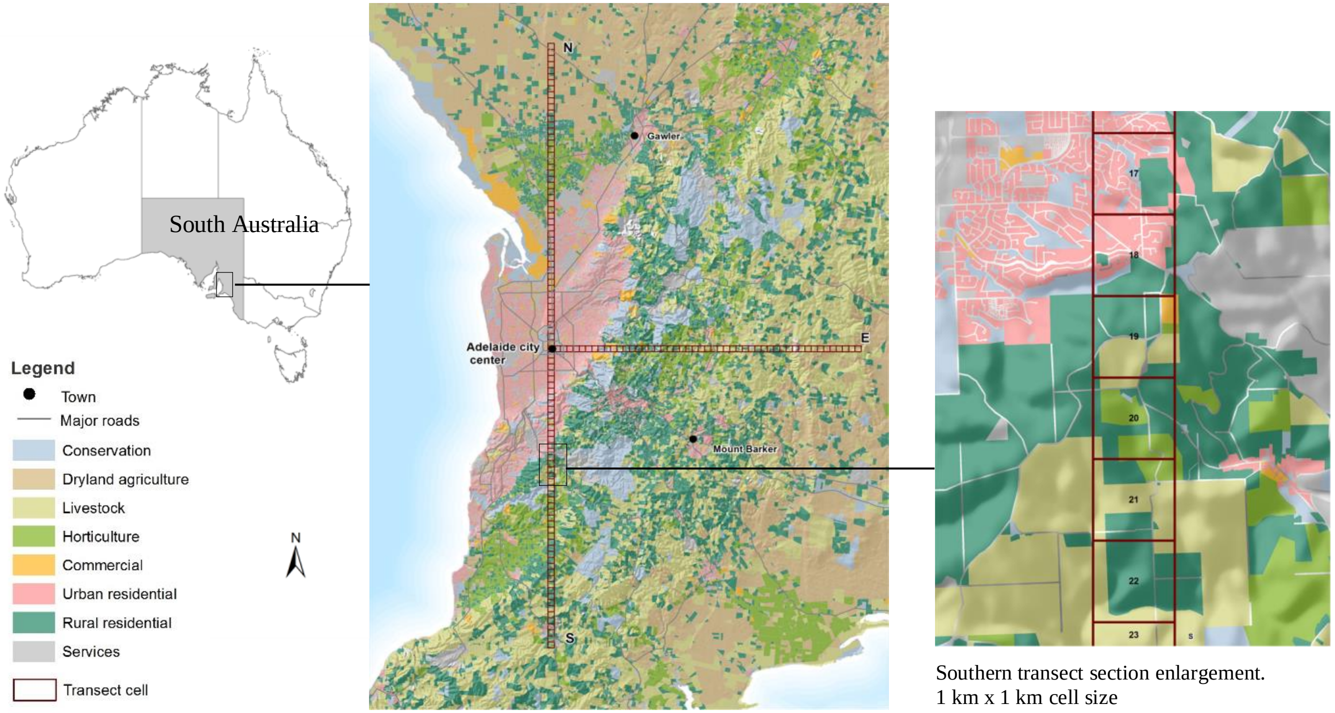
3.3.1 Study area

Adelaide—the capital of South Australia—is a coastal city surrounded by sprawling residential and modern industrial suburbs to the north and south. In addition, satellite towns to the east and north, Mount Barker and Gawler (Figure 3.1), respectively, are being incorporated into the urban fabric of the metropolitan area. Adelaide's fringes are urban frontiers that impinge on intensive horticulture and dryland agriculture on the northern plains; a conservation green belt with mixed agricultural land use in the Adelaide Hills to the east; and traditional agricultural areas focused around high-value, globally-recognized wine regions to the south (McLaren Vale) and north-east (Barossa Valley). Population growth and economic diversification are increasing the demand for land for housing, transport and industrial infrastructure. In turn, this has led to significant pressure on adjacent productive agricultural land.

The variations in rural land use on Adelaide's northern, eastern and southern margins provide a heterogeneous setting in which to test urban-to-rural (U–R) gradient analysis. Land-use gradients 50 km-long were sampled in transects in northerly, easterly and southerly directions outwards from the Adelaide central business district (CBD) (Figure 3.1).

Previous researchers using gradient analysis (Zhang et al., 2016, Luck and Wu, 2002) have mapped urban-to-rural (U–R) gradients along transport corridors. It is probable that this leads to a bias towards the investigation of urban land use. However, as this paper (chapter)'s research focus is on the incorporation of different types of agricultural land into an expanding urban area, it was decided to maximize the agricultural land uses considered in the gradient analysis. Therefore, the transects were not oriented along main routes out of Adelaide, but in three cardinal directions. In fact, many routes out of Adelaide are possible, with these routes orientated in a variety of directions. Therefore, each transect has some transport corridor influence.

The transects were sampled over 50 km so they are comparable and long enough to cover all types of parcels where agricultural land is being incorporated into the urban fabric of the city.



Southern transect section enlargement.
1 km x 1 km cell size

1a: Land use on Adelaide city fringes.

Figure 3.1: Land-use distribution in Adelaide and its surrounding areas
Source: Department of Planning, Transport and Infrastructure (DPTI) (2014)
Note: Urban-to-rural (U–R) transects are overlaid in red. The inset map to the right shows an enlargement of the urban-to-rural (U–R) transect south of the city.

The current study uses a single statewide cadastral data set produced by the South Australian Government's Department of Planning, Transport and Infrastructure (DPTI) in 2014, which is publicly available online at <http://data.sa.gov.au>. The primary purpose of this data set is to assess council rates and levies based on land-parcel valuations. The attributes of the data set pertinent to this research are: land-parcel identity codes; land-use categories; and the land-use classes occurring in each of the land parcels. It contains 19 land-use categories (Table 3.1) which were regrouped into eight land-use classes for the purposes of this research. Sixteen (16) categories were regrouped into five land-use classes—conservation, urban residential, rural residential, commercial and services. Three land-use classes—dryland agriculture, livestock land and horticultural land—were not changed.

Table 3.1: Reclassification of cadastral data set's (2014) land-use categories to study's land-use classes

Original Land-Use Categories*	**Reclassified Land-Use Classes** (numbers in parentheses are used in subsequent graphs)
Reserve, Forestry, Vacant	Conservation (1)
Agriculture	Dryland agriculture (2)
Livestock	Livestock (3)
Horticulture	Horticulture (4)
Commercial, Food industry, Mine and Quarry, Public institution	Commercial (5)
Residential, Non-private residential, Vacant residential	Urban residential (6)
Rural residential	Rural residential (7)
Education, Golf, Recreation, Utility industry	Services (8)

*Land-use categories defined in the South Australian Government DPTI's cadastral data set in 2014.

3.3.2 Urban-to-rural gradients on urban fringes

Urban-to-rural (U–R) gradients (Haase and Nuissl, 2010) were used to visualize and analyse land use along three 50 km-long transects, each of which comprised 50 cells 1 km × 1 km. ArcGIS© 10.2.1 (ESRI: Redlands, CA, USA) was used for all spatial data analyses. The cell-based transects (1 km^2 in area) were produced using the Fishnet tool by defining the spatial areas for cell references. They were overlaid on the cadastral data set and land-use information was extracted for each cell. These data were then compiled using the tabulation tool in the ArcGIS spatial analyst extension. Each cell in the resulting data set included a unique identifier and the areas of each land-use class (Table 3.1) within each cell.

Landscape metrics have been used extensively in conservation biology, but their application in land-use research to measure, characterize, analyse and visualize landscape structure is far less common, particularly in urban areas (Liu et al., 2016, McDonnell et al., 1997, Wrbka et al., 2004, Millington et al., 2003). Four landscape metrics were calculated from the attributes for each cell in the three transects (Table 3.2). The percentage of each land-use class in each cell (PLAND) provided data on compositional changes in land use along the gradients. Key spatial features along the three transects were measured by mean parcel size (MPS) and parcel density (PD). Finally, the Modified Simpson's Diversity Index (MSDI) was used as a measure of the proportional abundance of land-use classes in each cell and as an indicator of land-use diversity. Plots of each of the metrics for each gradient enabled the landscape structures to be visualized and analysed.

Table 3.2: Landscape metrics used for spatial feature characterization

Metric	Description	Range	Equation
Percent of land-use coverage (PLAND) [%]	Proportion of total area occupied by a particular land-use class.	0 < PLAND ≤ 100	$P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} (100)$
Modified Simpson's Diversity Index (MSDI)	Measurement of land-use diversity in a cell determined by distribution of the proportional abundance of different land-use types (parcel richness) extensively.	MSDI ≥ 0	$\text{MSDI} = -ln \sum_{i=1}^{n} {P_i}^2$
Mean parcel size (MPS) [ha]	Average area of all land parcels in the landscape.	MPS > 0	$\text{MPS} = \frac{\sum_{j=1}^{N} a_j}{\text{N}} \frac{1}{10{,}000}$
Parcel density (PD) [N/km²]	Number of land parcels per 100 ha.	PD > 1	$\text{PD} = \frac{N}{A}(10{,}000)(100)$

Notes: P_i = proportion of landscape occupied by parcel land-use type *i*; a_{ij} = area (m^2) of parcel *ij*; a_j = area (m^2) of parcel *j*; *A* = total area of landscape (m^2) (cell); *i* = land-use class (1–8); *j* = number of parcels; *n* = n_i = number of parcels in landscape (cell) of parcel land-use type *I*; and *N* = number of parcels in landscape (McGarigal and Marks, 1995).

3.3.3 Landscape matrix analysis

The relationship between mean parcel size (MPS) and parcel density (PD) was investigated to examine the extent of land fragmentation in relation to the distance along each transect. The association between MPS and PD demonstrated probable land-structure variations in the landscape, and trend lines were used to visualize the nature of the MPS–PD relationship.

The study area contained the following median land-parcel areas: LL (livestock land) (59 ha); DL (dryland agriculture) (50 ha); and HL (horticultural land) (12 ha). The minimum size of HL was 2.5 ha which probably represents intensive irrigated vegetable cultivation or small vineyards. The median (12 ha) to minimum (2.5 ha) size of HL parcels allowed the estimation of the range of the number of agriculture-based land parcels likely to occur in a 1 km^2 (100 ha) cell. Horticultural land (HL) was used to define the PD range between 7 and 35 N/km^2 as it is the agricultural land-use type with the smallest median parcel size. Therefore, it is the land-use class that would provide the maximum number of land parcels in a 1 km^2 (100 ha) cell. This range of values is believed to indicate high potential for transforming agricultural land-uses to urban land-uses on urban fringes. This is due to high property values, proximity to built-up areas, and frequent experience of government-promoted land subdivision and land re-zoning for urban development. Rauws and De Roo (2011) identified these land-use change drivers as “push factors” which are influenced by urban economies converting non-urban land uses to an urban form on peri-urban areas. Therefore, in the current study’s scatter diagrams, the common PD range used was from 7–35 N/km^2; where a 1 km^2 cell could have 7–35 land parcels (N)/km^2 that are highly vulnerable to changes in land use. The agriculture-based land-parcel information associated with cells from the land cadastral data set was extracted within this range of patch (parcel) densities.

3.4 RESULTS

The landscape metric values were plotted along the three urban-to-rural (U–R) gradients, north, east and south, with PLAND shown in Figure 3.2, MPS and PD in Figure 3.3, and MSDI in Figure 3.4. The PLAND values for the eight land-use types (Figure 3.2) illustrate the variations in land-use composition along the three transects, thereby demonstrating the urban, peri-urban and rural characteristics of these transects. The PLAND values along these three transects show high percentages of urban land uses near the city centre, a gradual change to higher percentages of agricultural land uses at the end of the transects, and a heterogeneous mix of land-use types in the peri-urban areas. The MPS–PD relationship is a negative relationship (Figure 3.3), with higher MPS values being associated with lower PD values. Figure 3.5(a) illustrates the association between MPS and PD for the land parcels along each transect. Figure 3.5(b) shows the relationship between PD and MPS in the ranges 0–40 N/km^2 and 0–80 ha, respectively, for each transect. The MSDI is somewhat similar between transects (Figure 3.4) and shows that diversity generally declines with distance from the central business district (CBD). However, it is noteworthy that the southern transect has relatively lower landscape diversity than the other two.

3.4.1 Agricultural land-use presence

The PLAND values for dryland agriculture (DL), livestock land (LL) and horticultural land (HL) along the three transects are shown in Figure 3.6. The northern transect shows three distinctly different zones of land use. The built-up area, between 0–15 km from the CBD, has low agricultural PLAND for the three agricultural land uses, with the value for PD high while the value for MPS is low. From 15–37 km, the agricultural land-use percentages are HL (61.4%), DL (31.6%), and LL (6.8%). These represent mainly intensive vegetable production, rain-fed cereal cultivation, and sheep and horse grazing, respectively. This

22 km-long zone presents a typical urban fringe landscape structure, with increasing MPS while PD is decreasing. The landscape beyond the fringe (> 37 km) is dominated by dryland agriculture, and mainly comprises rain-fed wheat, barley and olive groves, which occupy large land parcels in a rural landscape. The land-use presence in zones of high fragmentation is shown in Figure 3.7.

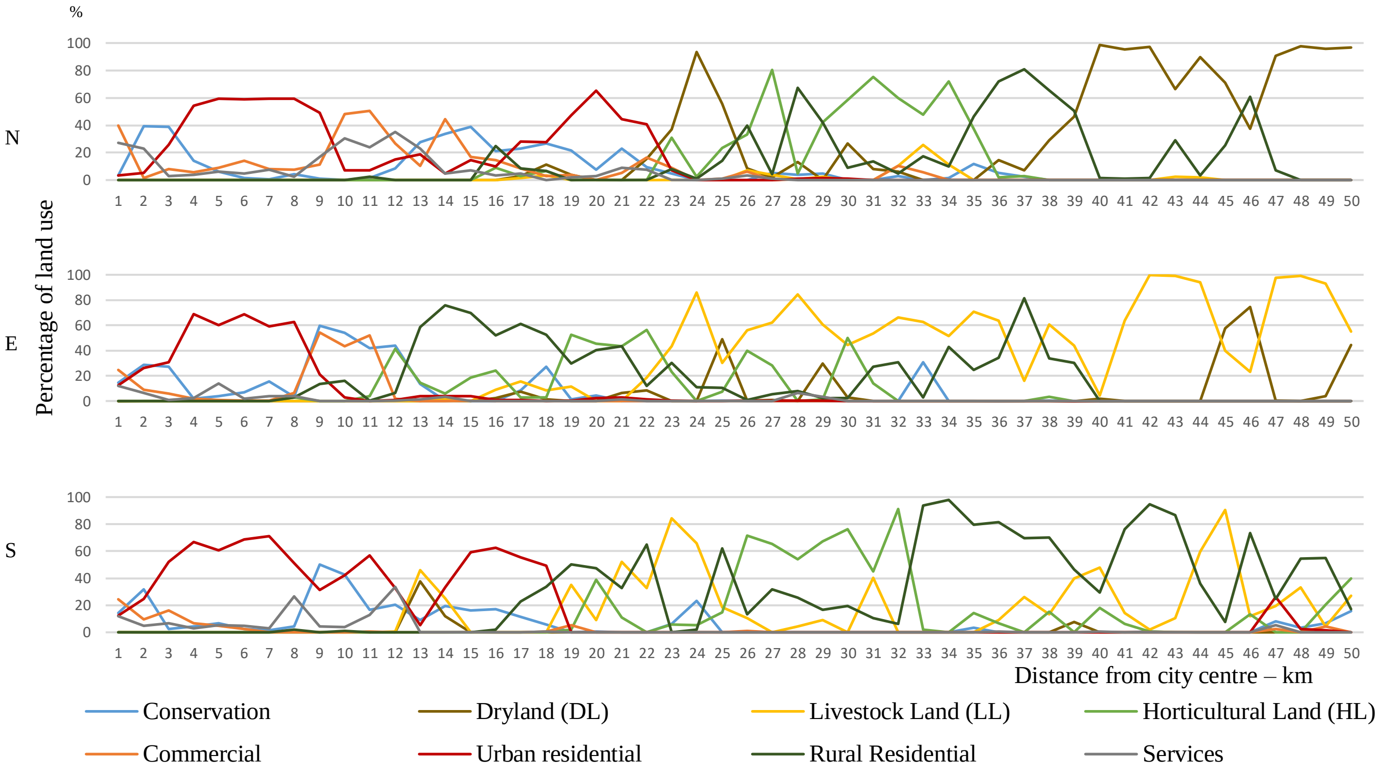


Figure 3.2: Percentage of land (PLAND) along north, east and south transects

Note: N=north; E=east; S=south

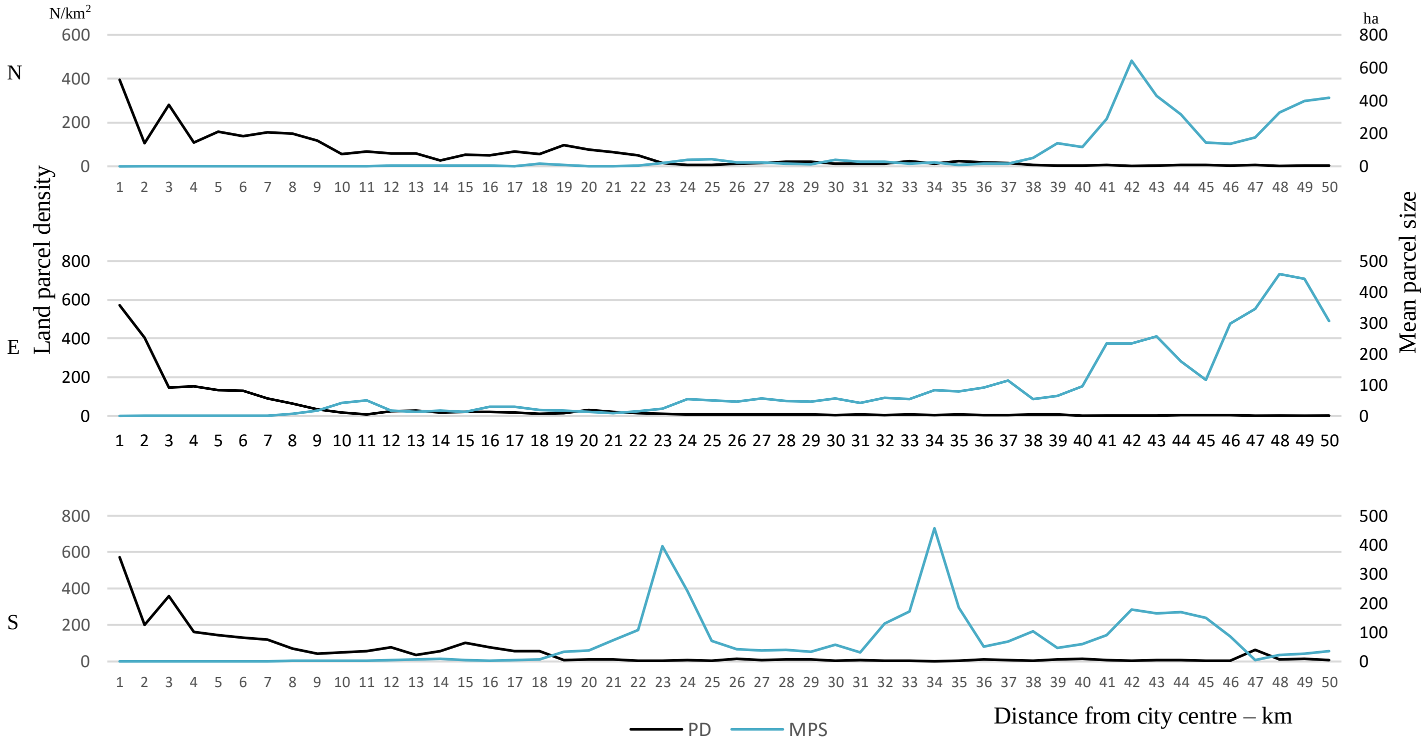


Figure 3.3: Parcel density (PD) and mean parcel size (MPS) along north, east and south transects

Note: N=north; E=east; S=south

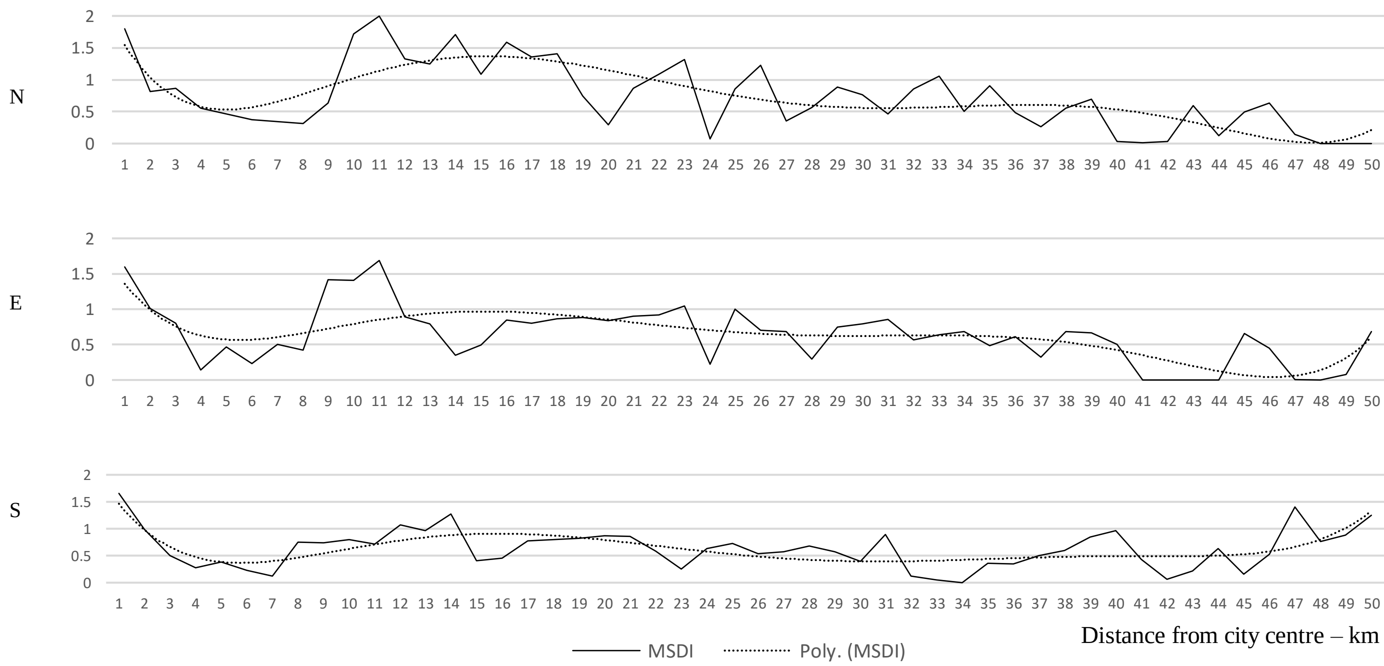


Figure 3.4: Modified Simpson's Diversity Index along north, east and south transects

Note: N=north; E=east; S=south

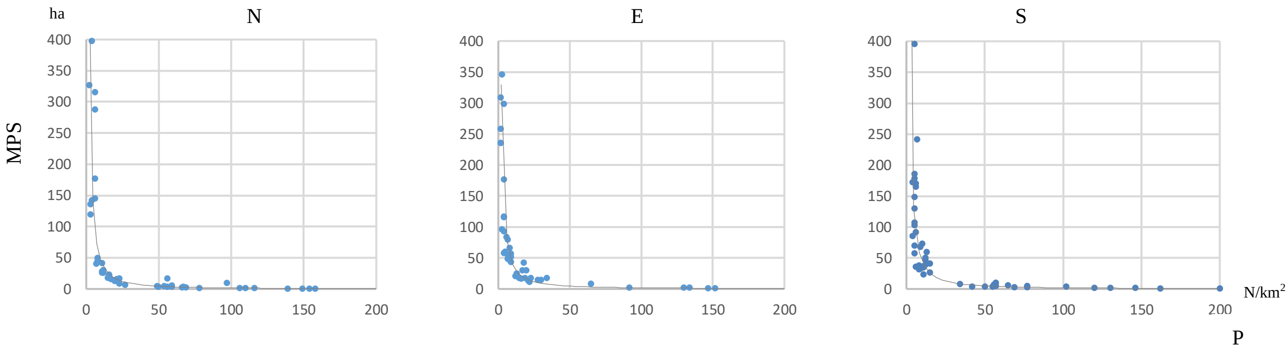


Figure 3.5(a): Scatter diagrams of MPS and PD along north, east and south transects

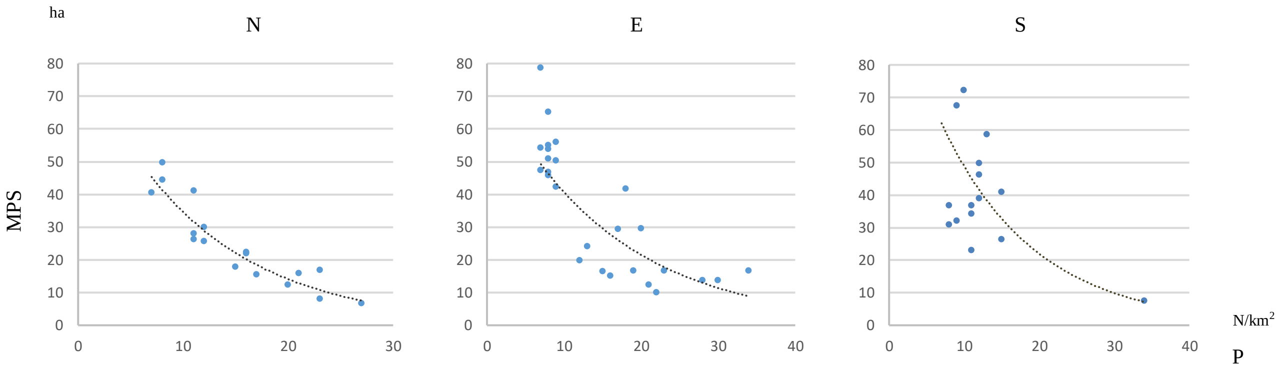


Figure 3.5(b): Enlargements of MPS and PD scatter diagrams for 7 N/km^2 < PD < 35 N/km^2 range

Note: N=north; E=east; S=south

Figure 3.6: Percentage of total land area occupied by each agricultural land-use type along north, east and south transects

Note: N=north; E=east; S=south

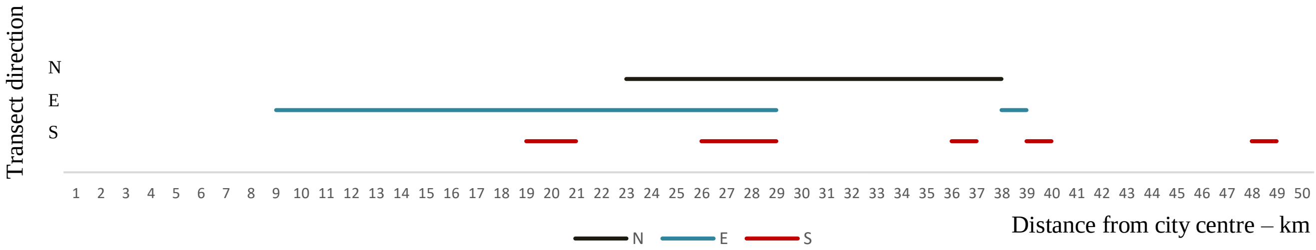


Figure 3.7: Areas prone to land fragmentation (7 N/km^2 < PD < 35 N/km^2) along each transect

Note: N=north; E=east; S=south

The first 10 km of the eastern transect represents the built-up areas of eastern Adelaide. From 11–32 km, the transect is characterized by the three agricultural land uses of the Adelaide Hills—sheep and cattle rearing (LL, 52.7%); vegetable cultivation, fruit orchards and wineries (HL, 38.5%); and rain-fed crops (DL, 8.7%). The MPS values of land parcels in this hilly terrain are relatively small. The transect beyond 33 km is dominated by livestock land (LL) and dryland agriculture (cultivation) (DL).

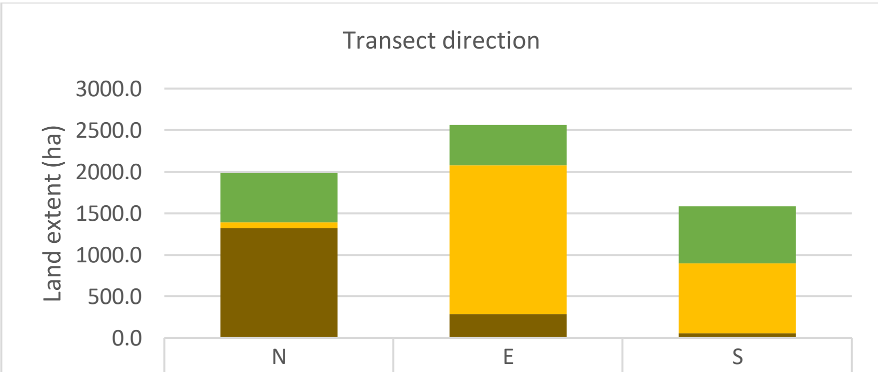
The southern transect is significantly different from the northern and eastern transects in terms of agricultural land use. After the built-up area, which comprises the first 18 km along the transect, LL and HL have much higher shares than DL of the overall land use. The landscape from 18–33 km has an agricultural land-use split of HL (60.1%), LL (39.2%), and DL (0.7%). This combination characterizes the complex land uses of McLaren Vale, which has transitioned from a mixed grazing and horticultural region, to one of vineyards and olive groves, with some grazing being retained on the margins. The amount of LL increases in the landscape beyond 33 km. However, in these final 17 km, the PLAND values of rural residential land and urban residential land increase, leading to correspondingly higher MSDI values. The changes in these metrics demonstrate the influence of the town of Victor Harbor, which is located beyond the end of the transect. Table 3.3 summarizes the agricultural land presence along the three transects:

Table 3.3: Summary of agricultural land along the three gradients

Transect	Built-Up Area	Urban Fringe Areas	Rural Areas
North	0–15 km. Low PLAND, high PD and low MPS for DL, LL and HL	15–37 km. HL (61.4%), DL (31.6%) and LL (6.8%), representing mainly intensive vegetable production, rain-fed cereal cultivation, and sheep and horse grazing, respectively.	> 37 km. Dominated by DL (rain-fed wheat, barley and olives) which occupies large land parcels.

Transect	Built-Up Area	Urban Fringe Areas	Rural Areas
East	0–10 km. Low PLAND, high PD and low MPS for DL, LL, HL.	11–32 km. LL (52.7%), HL (38.5%) and DL (8.7%) representing sheep and cattle rearing; vegetable cultivation, orchards and wineries; and rain-fed crops, respectively. Relatively small MPS compared to other rural areas due to hilly terrain.	> 32 km. Dominated by LL and DL.
South	0–18 km. Low PLAND, high PD and low MPS for DL, LL, HL.	18–33 km. HL (60.1%), LL (39.2%) and DL (0.7%) representing the complex land uses of McLaren Vale which has transitioned from a mixed grazing and horticultural region to vineyards and olive groves with some grazing retained on the margins.	> 33 km. High proportions of land in LL (cattle grazing). Increase in PLAND for residential land uses, and higher MSDI values at the end of the transect due to influence of the town of Victor Harbor.

The total amount of agricultural land in each transect is summarized in Figure 3.8. The eastern transect has the highest amount of agricultural land (2,558 ha, 51.2%), comprised of 11% DL, 70% LL and 19% HL. The southern transect has the lowest amount of agricultural land (1,583 ha, 31.6%: comprising 4% DL, 53% LL and 3% HL). The northern transect has 1,979 ha (39.6%) under the three types of agricultural land use, and is dominated by dryland agriculture (cultivation) (DL), accounting for 66% of all agricultural land.



	N	E	S
%HL	591.6	481.7	684.9
%LL	70.9	1786.4	840.9
%DL	1317.3	289.9	57.6

Figure 3.8: Total agricultural land extent and land-use type percentages in north, east and south transects

3.4.2 Agricultural land fragmentation

Along each transect, MPS and PD values were used to characterize agricultural land fragmentation. In considering the zone where PD ranged from 7–35 N/km^2, the critical zones for land fragmentation in the northern and eastern gradients extended for 15 km and 20 km, respectively (Figure 3.7). In the southern transect, however, this zone is disjunctive and extends from 19 km to the end of the transect. Figure 3.9 shows the amount of land occupied by agricultural land uses in the zones of land fragmentation for each transect, and the corresponding percentage data. The total amounts of agricultural land of all types in the zones of high fragmentation are: 935.1 ha, 1,311.9 ha and 825.7 ha along the northern, eastern and southern transects, respectively. Figure 3.10 displays the amount of each class of agricultural land in the zones of fragmentation. Horticultural land (HL) comprises a large component in each transect and dominates the northern transect. Livestock grazing (LL) accounts for the highest proportions of agricultural land in the zones of high fragmentation in the eastern and southern transects but is a minor element in the northern transect. Dryland agriculture (DL) has a low presence in the zones of fragmentation in all three transects. This agricultural use is only encountered with any frequency in the northern transect where a significant contemporary urban fringe formation has developed on land formerly used for rain-fed cereal cultivation on the northern Adelaide Plains.

	N	E	S
%HL	572.91	428.83	385.46
%LL	61.27	777.85	394.84
%DL	301.01	105.24	45.45

Figure 3.9: Agricultural land extent and land-use type percentages in zones of high land fragmentation

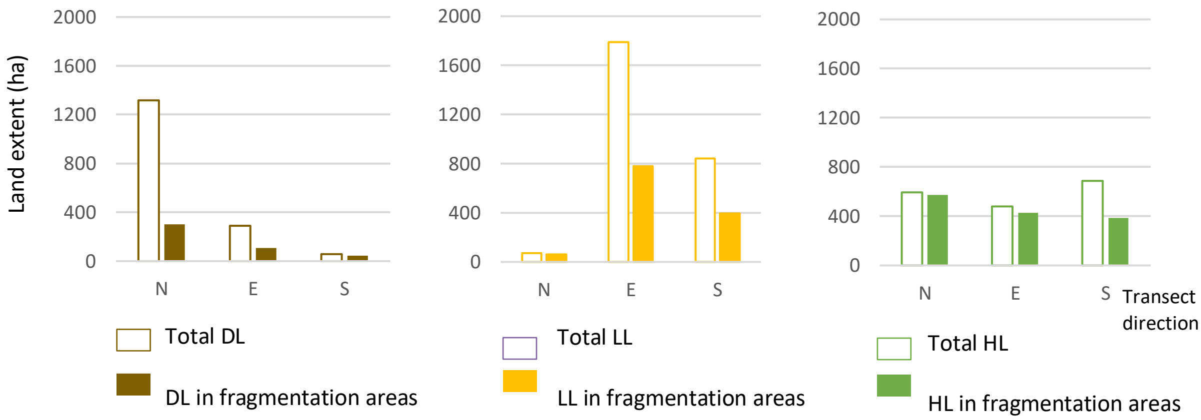


Figure 3.10: Extent of DL, LL and HL in zones of high land fragmentation: north, east and south transects

3.5 DISCUSSION

By applying gradient analysis, Weng (2007) found that landscape fragmentation was positively correlated with the degree of urbanization, and that it resulted in the loss of agricultural land on urban fringes. Therefore, as agricultural land is generally the major land-use category beyond the fringe, it is the major land reserve for meeting the land demands of urban development in sprawling cities such as Adelaide. Moreover, land fragmentation is the key spatial manifestation of the process of incorporating agricultural land into transitional, urban fringe landscapes.

The current research confirms the presence of agricultural land along all three gradients, and that land fragmentation can be easily visualized and quantified using a combination of gradient analysis and landscape metrics. This is the first application of these techniques in the Australian context. More importantly, this research provides an advance on previous analyses of the incorporation of agricultural land into the urban fabric of cities, by comparing the conversion processes acting on three types of agricultural land (dryland agriculture [DL], livestock land [grazing] [LL] and horticultural land [HL]).

3.5.1 Land-structure analysis along gradients

This research presents a novel method for investigating agricultural land fragmentation on the urban fringe, by analysing the associations between mean patch (parcel) size and patch (parcel) density. Notwithstanding the differences in land-use geographies along the transects, scatter plots of MPS and PD for the three transects showed similar patterns of cell organization with respect to patch (parcel) density and mean patch (parcel) size. Cells associated with the horizontal parts of the trend lines (Figure 3.5[a]) indicated low levels of association between MPS and PD; for example, a decline in MPS from 400 ha to approximately 100 ha led to very little increase in PD which remained at < 7 N/km^2. When PD reached approximately 35 N/km^2, further increases were not accompanied by significant changes in MPS, that is, the vertical parts of the trend lines shown in Figure 3.5. This means that the zone bounded by PD values of 7–35 km^2 is a critical land fragmentation zone in which the relationship between MPS and PD is very sensitive. For example, in the current study, a decrease of one hectare (1 ha) in MPS leads to an increase in PD of 0.52 N/km^2 (in the northern transect), 0.54 N/km^2 (eastern transect) and 0.33 N/km^2 (southern transect).

In the northern and eastern transects, the cell values corresponding to the high fragmentation zone are well distributed (Figure 3.5[b]). This indicates that large land parcels are being fragmented in a regular and incremental manner to create progressively smaller parcels, and that the resulting increases in PD are responses to rapid urban development to the north and east of Adelaide. More clustered cell values in the southern transect indicate a differently organized landscape structure. The corresponding cell values in the southern transect cluster between an MPS value of 22–70 ha and a PD value of 7–15 N/km^2. This pattern is believed to be derived from an urban fringe characterized by larger land parcels that can be attributed to the size of vineyards and to the planning restrictions on post-sale use of vineyards due to the implementation of the *Character Preservation (McLaren Vale) Act 2012* (South Australian Government, 2013). That is, land fragmentation is not occurring at the same rate or in the same way as it is on the eastern and northern fringes of the city.

Overall, the results demonstrate that it is the contemporary land-use transformation processes that explain the landscapes measured by the metrics. This validates the use of landscape metrics derived for cells along transects to characterize landscape structures. For example, the urban fringe to the south of Adelaide has a lower MPS for agricultural land than the fringes to the north and east, with the difference due to the high frequency of vineyards in the south compared to the dominance of dryland cereal fields in the north, and extensive grazing areas and fruit orchards in the east. Furthermore, this method can be used to understand the influences of regional towns on land-use transitions—a point that is rarely considered in peri-urban studies (Vizzari and Sigura, 2015). For example, in the southern transect, the influence of the town of Victor Harbor on land fragmentation and land-use changes near the end of the transect is clear in comparison to the other two transects.

If landscape metrics are to be used effectively in assessing land fragmentation on urban fringes, it is imperative that they are calculated for all cells and plotted along the entire transect, rather than simply focusing on the peri-urban areas. This allows the emerging and existing areas of fragmentation to be identified objectively through the behaviour of metrics.

The land fragmentation zones identified through landscape metrics value changes (the combination of PD and MPS values) represent the areas undergoing significant spatial and structural land-use changes which convert larger land parcels into smaller plots. Land fragmentation often decreases the landscape's connectivity and increases its spatial heterogeneity (Guastella and Pareglio, 2016). Many land-use case studies demonstrate that land fragmentation areas facilitate the conversion of non-urban land uses into urban form on the city fringes by bringing urban sprawl into peri-urban landscapes (Irwin and Bockstael, 2007, Gbanie et al., 2018, Weng, 2007). However, rapidly developing cities in countries like China show a limited loss of cropland within land fragmentation zones on city fringes due to government-led land development processes (Yu et al., 2018). Separate from this exceptional experience, many cities around the world experience land-use and land-cover changes (LULCC) in land-fragmented zones due to land-use functional changes, such as housing development, farmland intensification/abandonment or unstable multi-functional farming practices on the city fringes. In a south-eastern Michigan case study to investigate land-cover fragmentation, Robinson (2012) showed that the smaller land parcels in land fragmentation areas make a significant contribution to changing land uses due to the higher degree of land-use differences. Agricultural practices established in smaller land parcels within these fragmenting zones have less sustainability, due to the frequent economic demand fluctuations and deteriorating natural resources (poor soil and water qualities) that lead to land abandonment or use for non-agricultural practices. The focus area of this case study—Adelaide's peri-urban regions—often experiences land fragmentation which converts larger agricultural land parcels (larger areas of grazing land in the north and vegetable farmland in eastern hilly areas) and breaks them into smaller land parcels by subdivisions. These subdivisions are often allocated for intensive farming practices (i.e. hydroponic shed farms) and unstable small-scale multi-functional farming practices with higher potential for ultimate conversion into non-agricultural land uses on the city fringes. The utilization of these smaller land parcels within land fragmentation zones in peri-urban regions for long-term stable agricultural investments such as wineries is very rare.

3.5.2 Agricultural land in areas of fragmentation

The agricultural land types in the zones of high land fragmentation were, in order of decreasing area, horticultural land (HL), livestock land (grazing) (LL) and dryland agriculture (cultivation) (DL). This differed from the total distribution of agricultural land along the three transects which, in order of decreasing area, were livestock land (grazing) (LL), horticultural land (HL) and dryland agriculture (cultivation) (DL). This change in order highlights the importance of quantifying agricultural land in high fragmentation zones, rather than analysing agricultural land along an entire transect—particularly if the results are being used to make strategic land-use decisions regarding urban fringes.

It can be argued that quantifying agricultural land in fragmentation areas, instead of the total land presence, will improve planners' understanding of the vulnerability of agricultural land in these transitional landscapes. For example, land under dryland cultivation (DL) has the highest land-use presence in the northern transect, although, in that transect, only 20% of that land-use class is prone to fragmentation. The fact that agricultural land fragmentation occurring on the fringes of Adelaide can be identified and characterized using gradient analysis and landscape metrics (regardless of the different characteristics of the northern, eastern and southern transects) is testament to the robustness of the method. Moreover, different spatial configurations of land-parcel arrangements can be identified. Figure 3.10 provides data on the proportions of different land-use classes in the three transects. These data reveal the importance of quantifying individual land-use class measurements to identify the detailed land-structure elements in these complex landscapes. Vizzari and Sigura (2015) argued that whole gradient analysis is required in rural-to-urban (R–U) analyses. Urban expansion in Australian cities occurs in less complex landscapes than in world regions characterized by high levels of urbanization or rapid urbanization and unprecedented levels of development in tangled webs of complex rural–urban (R–U) transitions (Handayani, 2013), for example, in Japan, eastern China, south-east Asia, western Europe and parts of North America. Nevertheless, the usefulness of whole gradient analysis is again emphasised in the current research.

Land-use responses to urbanization stimuli are dependent on geographic location, with land ownership and land-use policies as integral parts of complex land systems (Ornetsmüller et al., 2016). Although the current research illustrates a higher probability of land fragmentation in some types of horticultural land, other areas are much less affected, for example, protected heritage wine-making regions with large capital investments. This indicates that other attributes of land-use classes are important in determining the extent of land fragmentation. In the northern transect, many intensively-cultivated vegetable farms are proximate to built-up areas, currently have relatively small investments, are operated by ageing landowners who are contemplating selling their farms, and are located in areas where local councils are actively re-zoning land. These land attributes are what leads to fragmentation, rather than simply the land's spatial characteristics. This demonstrates the importance of integrating local knowledge and current urban development policies into future urban-to-rural (U–R) gradient analyses to improve outcomes.

The method outlined in this paper (chapter) can be applied to different geographies, provided a land data set (or land-use maps derived from remotely sensed data) with land-use attributes is available to provide justifiable evidence for probable agricultural land transitions. An analytical approach, such as the one in the current research which uses a single data set, could overcome the issues of analyses based on multiple data sets (Walcott et al., 2013), for example, data incompatibility, error generation and variations in data definitions associated with previous landscape studies. However, some limitations would still exist, such as human error in data collection and spatial analysis.

The integration of the gradient method with the analysis of landscape metrics leads to two main advances. Firstly, it improves the interpretability of transitional processes of agricultural land on city fringes by focusing measurements on specific areas (e.g. agricultural land within zones of fragmentation), while still analysing the landscape structure in an urban-to-rural (U–R) continuum. Secondly, it enhances information richness for improved peri-urban land-use planning strategies within planning and policy-making groups at different levels of land governance (e.g. from local government to State government level), as well as for other stakeholder groups who share common interests in the effective management of peri-urban land. These include primary industries, biological conservation, natural resource management and recreational opportunities.

3.6 CONCLUSIONS

The current research has integrated landscape metrics into urban-to-rural (U–R) gradient analysis to deepen our understanding of the geographies of agricultural land-use change on the urban fringes of Adelaide. The study reveals that less well-regulated horticultural land uses are the most vulnerable to urban expansion, with well-protected horticultural land experiencing much lower levels of conversion and fragmentation. Land uses related to livestock grazing and rearing have a larger presence than horticulture but are less likely to change. Dryland agriculture is the least vulnerable to urban sprawl.

The research findings confirm that integrating landscape metrics and urban-to-rural (U–R) gradient analysis provides a robust method that works equally well under different natural environments, rates of urban growth and types of land use. A new finding is that MPS and PD can be used to identify zones with high rates of agricultural land fragmentation. Land fragmentation occurs when PD ranges from 7–35 N/km^2, regardless of distance from the city centre, land use, topography, soils and rates of urban growth, with this suggesting a fragmentation geometry that may be consistent.

The integration of landscape metrics into gradient analysis has the potential to provide a wide range of stakeholders, ranging from planners to conservation and primary production groups, with a rich source of information on agricultural land-use configurations and their interdependencies. Furthermore, it can provide them with the ability to systematically compare spatially quantifiable land-use metrics along urban-to-rural (U–R) gradients. Nonetheless, the current study suggests that further opportunities should be pursued to test the robustness of this method in urban fringe landscapes in different types of cities around the world.

CHAPTER 4 – AGRICULTURAL LAND VULNERABILITY ON URBAN FRINGES

A MULTI-CRITERIA SPATIALLY-EXPLICIT SCENARIO ANALYSIS

This chapter explores peri-urban agricultural land vulnerability to urban sprawl by developing multi-criteria spatially-explicit analysis grounded on six indicative parameters of land change that represent the study area. Furthermore, this approach focuses on exploring land vulnerability variations in three scenarios that targeted land-management policies ranging from economic development to environmental protection. Finally, the chapter demonstrates the advantage of spatially quantifying peri-urban agricultural land in local land administration areas when making informed land-management decisions.

Contributions to knowledge:

- Spatially quantified Agricultural Land Vulnerability Index (ALVI) values in three scenarios; representing land-management policy directions ranging from economic development to environmental protection.

- Identified agricultural land vulnerability variations in local land administrative areas.

4.1 ABSTRACT

The loss of agricultural land on urban fringes is often monitored but rarely analysed under different scenarios of urban sprawl. This study adopts a multi-criteria spatially-explicit approach to investigate agricultural land vulnerability to urban sprawl under opposing policy directions in the Adelaide metropolitan area. Six land-use change parameters (proposed land development and regulated areas; demand for land; steep areas in the terrain; land fragmentation zones; and resistance by agricultural production types), representing socio-economic and land-use planning effects, were analysed under a business-as-usual (BAU) scenario, an accelerated economic development scenario (EDS) and a high environmental protection scenario (EPS). Spatial grids were used to upscale the parameter inputs to a common geographic scale. Vulnerability was identified for different local government areas. Under each scenario, the study showed that agricultural land has a high level of vulnerability to change on the northern Adelaide Plains and around the small town of Gawler. In the EDS, vulnerability extended further into the conservation area to the east and displayed a leap-frog effect, with this confirming the need to sacrifice farmland uses to maintain land supply for urban development. The local government area-based results enable the transfer of knowledge into practice by identifying high priority areas for land-management interventions and by specifying which types of

agricultural land should be managed strategically to ensure sustainable land-use transformations in these urban fringe landscapes.

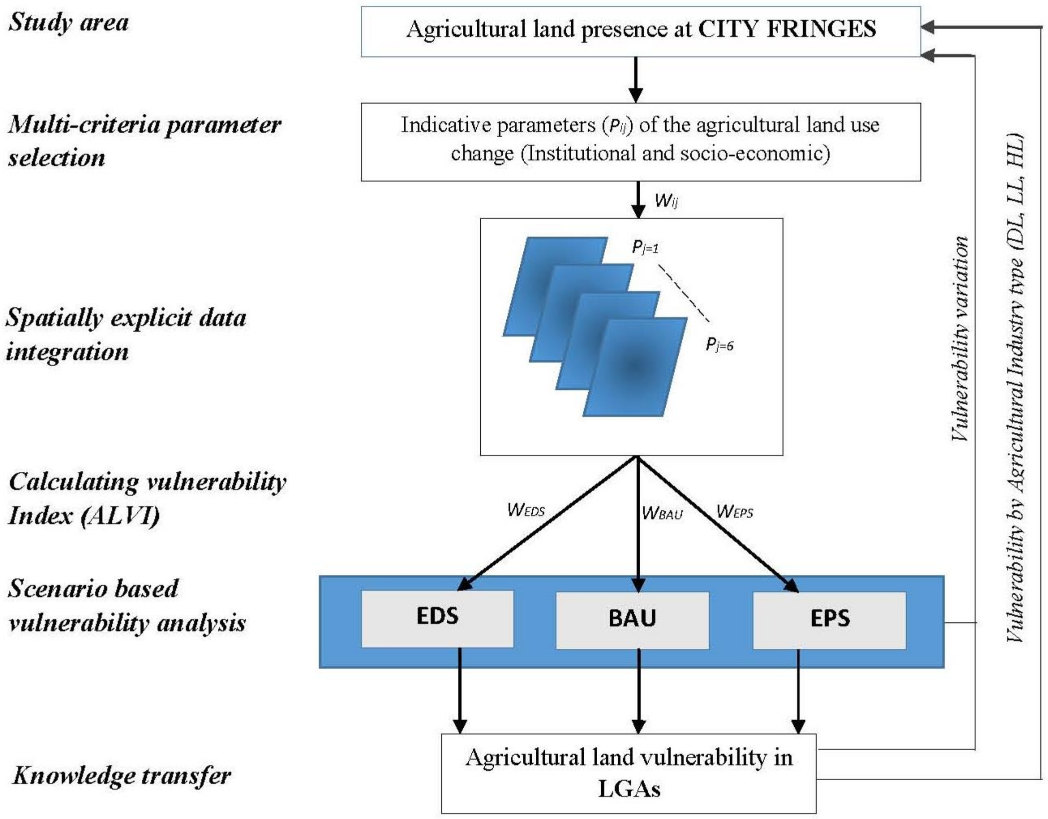


Figure 4.1: Graphical abstract

4.2 INTRODUCTION

Australian cities have expanded significantly since the 1950s as the national economy has transitioned from being dominated by agriculture to a mix of agriculture and urban-based manufacturing and service industries. This has occurred in parallel with significant demographic changes in the form of rural-to-urban (R–U) migration and immigration. Presently, nearly 90% of the Australian population lives in urban areas (ABS, 2013), a proportion that is predicted to increase to 94% by 2050. Urban expansion has consumed large areas of land for dwellings, commercial buildings and infrastructure, with the significant demand for land continuing.

The Australian ‘big country’ psyche has created an unsustainable issue and seemingly unfettered expansion on urban fringes (Buxton et al., 2011a) at the expense of highly productive agricultural land (Ives and Kendal, 2013, Johnson et al., 1998). This is not uncommon globally, despite commentaries about the loss of agricultural land on urban fringes creating an irreversible drain on natural resources (Sali et al., 2016, Jiang et al., 2016, Feng and Liu, 2016, Galli et al., 2010, Lee et al., 2015); compromised food security (Galli et al., 2010, Sali et al., 2016, Pham et al., 2014, McFarland, 2015); and impacts on people's lives (Thebo et al., 2014, Pham et al., 2014, James, 2014, Ives and Kendal, 2013). Furthermore, transport infrastructure and the provision of services often lag behind the development of commercial premises and house building. These are all major issues for sustainable development.

Agriculture is highly vulnerable to urban sprawl on the fringes of Australian cities (Ashton and Weragoda, 2017). The economic context of this is critical. Houston (2005) estimated that 25% of the gross value of agricultural production in Australia was generated from the 3% of total land area that constituted peri-urban agricultural land in 2004. This ratio may be relatively stable: Mewett (2013) reported that 13.4% of the value of agricultural commodities in Victoria in 2010–2011 was generated by peri-urban farmers around Melbourne who occupied 2% of the State's land area. Bunker and Houston (2003) demonstrated that the vulnerability to conversion of agricultural land in peri-urban areas was significantly influenced by the focus on urban development in Australia in the 1980s and 1990s. Since the turn of the millennium, land governance policies have recognized the importance of maintaining natural resources in peri-urban landscapes, although agricultural land is still being lost due to urban sprawl. Land on the fringes of cities is subject to the interests of an array of actors on a spectrum from land developers to those advocating strong landscape protections. Peri-urban farmers' land-use decisions—to continue farming practices or change the land use—are always subjected to these stakeholder influences and land-management policies.

The conversion of farmland to urban form on city fringes occurs as a result of various factors (drivers and the influencing proxies) such as land-governing institutional considerations; market forces and land-use conversion patterns; physical barriers to land-use change; and present agricultural land-use practices on these landscapes. The LGAs on city fringes make decisions on areas suitable for development and areas to be protected from the conversion of natural or heritage agricultural practices to urban sprawl. Therefore, the land-governing institutional decisions represented by land-use zoning have a significant impact on accommodating urban sprawl in peri-urban landscapes with agricultural practices. Market forces, such as land market value, also have a significant impact on the purchase of land with agricultural practices for housing/commercial land use, with this contributing to rapid land fragmentation (farmland subdivision) which appears as smaller land parcels on urban fringes. However, physical barriers, such as steep terrain, substantially reduce the possibility of converting farmland to housing/commercial practices due to higher engineering and utility servicing costs. Although land fragmentation is not a key driving force, it is a proxy that influences farm landowners to convert their land use to intensive agricultural use or abandonment that eventually converts to non-agricultural use. In general, land parcels that are subject to subdivision remain stable for longer periods. However, agricultural land in the form of smaller land parcels has a higher tendency towards converting into non-agricultural practices due to higher market values for land and the disappearance of support services for conventional farming practices. Therefore, farming practices on grazing land (livestock with less economic returns) on urban fringes are more vulnerable towards land-use conversions compared to dryland agricultural practices (such as growing wheat and barley) at the rural end of these fringes.

The local government authorities (LGAs) face many challenges in trying to achieve sustainable urban development while preserving privately-owned farmland and green spaces on urban fringes. As they are the primary land-governing authorities, the LGA planners and policy makers seek precise and spatially-explicit information on land assets to decide on the trade-offs between urban development, agricultural productivity and environmental preservation. Inaccurate spatial estimates of agricultural land-use vulnerabilities on the margins of cities around the world have complicated strategic land-management decisions (Galli et al., 2010, Henderson, 2003, Duvernoy et al., 2018).

Scenario representations—hypothetical situations with alternative policy set-ups—are widely used by land-use scientists to synthesize complex land-use transitions (Sohl et al., 2016, Lauf et al., 2016, Johnson et al., 2016, Jiang et al., 2016, Houet et al., 2016, Feng and Liu, 2016) and are developed around relevant storylines (Priess and Hauck, 2014). Scenarios can be developed to examine specific outcomes under defined conditions (McCarthy, 2001, Kaljonen et al., 2012, Haasnoot and Middelkoop, 2012). In scenario analysis, alternative combinations of parameters create situations which conceptualise how different groups of land managers behave under different policy arrangements. A comparison of the responses of different groups of land managers/farmers to a range of scenarios describes the variations in plausible responses in any land system being investigated. The quantitative parameter-based land-change model scenarios enable the examination of land-use change trends by adjusting variables according to the defined scenario storyline (Veldkamp and Lambin, 2001). These policy-responsive scenarios can be linked to probable future directions in land-system investigations (McCarthy, 2001). A number of multi-disciplinary studies (Johnson et al., 2016, Jiang et al., 2016, Mahmoud et al., 2009, Haasnoot and Middelkoop, 2012) have confirmed the importance of using scenario-based methods for assessing the consequences of land-use policies and strategies.

In the current study, the author has used a spatially-explicit, multi-criteria index approach to calculate the vulnerability of agricultural land to urban sprawl around Adelaide. A spatial grid method was used to transfer the positive and negative influences of socio-economic and institutional effects on land-use change, using parameter weights to calculate the Agricultural Land Vulnerability Index (ALVI) values for the situation of the business-as-usual (BAU) scenario. Alternatively, another two plausible scenarios, an accelerated economic development scenario (EDS) and a high environmental protection scenario (EPS), were developed to investigate the ALVI value variations, under the extremes of land-use policy directions. Based on the above three scenarios, spatial quantifications were used to examine the overall agricultural land vulnerabilities in the local government areas of the study area.

4.3 MATERIALS AND METHODS

4.3.1 Study area

This study focuses on the Adelaide metropolitan area in South Australia. Adelaide is a coastal city of 1.32 million people (ABS, 2016) surrounded by sprawling metropolitan areas to the north and south. Urbanization is encroaching on arable cereal farms and intensive vegetable growing and horticultural areas on the Adelaide Plains to the north; a conservation green belt (the Hills Face Zone) beyond which is a mixed farming belt to the east and the south east; and traditional wine-producing areas to the south, east and north east (McLaren Vale, the Adelaide Hills and Barossa Valley, respectively). Wadduwage et al. (2017) identified three broad agricultural land-use types in this region: dryland agriculture (DL), land devoted to rearing livestock (LL) and horticultural areas (HL) (Figure 4.2). The classes account for 0.3, 0.23 and 0.07 million ha, respectively. The median sizes of the dryland agriculture (DL) and livestock land (LL) parcels are similar, and both are much greater in area than horticultural land (HL) parcels (Table 4.1).

Table 4.1: Agricultural land-use categories in study **area**

Data from Wadduwage et al. (2017)

Land-use code	**Land-use type**	**Dominant agriculture**	**Land-use type** (%)	**Total land extent (1000ha)**	**Number of land parcels**	**Median land parcel size (ha)**
DL	Dryland agricultural	Wheat, barley and canola cropping. Olive groves.	51	315	2645	50.3
LL	Livestock land	Pasture.	36	239	3442	59.0
HL	Horticultural land	Vineyards. Intensive vegetable production.	13	75	2231	12.2

An expanding economy and a growing population have increased the demand for land on the fringes of Adelaide (Liu and Robinson, 2016). While town planners and property developers are seeking new land in the peri-urban zone, natural resource stakeholders, such as primary industry professionals and natural resource managers, are trying to protect productive agricultural landscapes and conservation areas from urban sprawl (Liu and Robinson, 2016, Gant et al., 2011). In 2012, the South Australian Government launched a 30-year plan for Greater Adelaide, in which future development and preservation areas are identified (Planning SA, 2010). In addition, the two world-class wine-producing areas of the Barossa Valley and McLaren Vale benefit from protection afforded by the *Character Preservation (Barossa Valley)* and *Character Preservation (McLaren Vale) Acts of 2012* (South Australian Government, 2013).

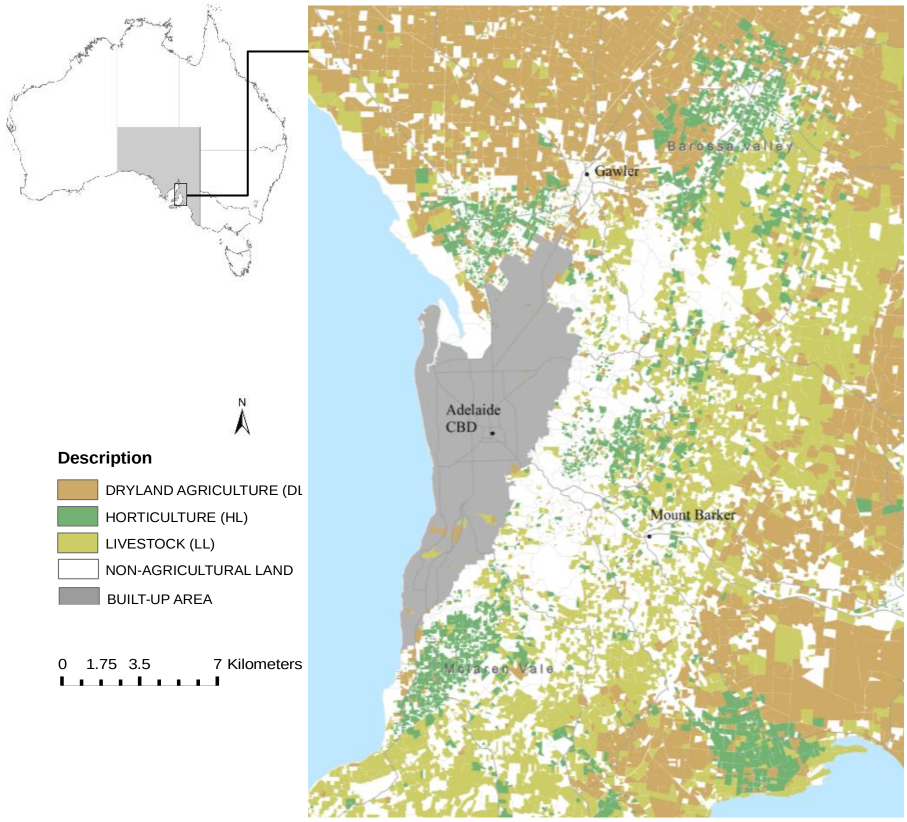
Agricultural land is the most cost-effective and widely available land-use type and can easily accommodate the rising demand for urban expansions on these fringes. Land-use researchers recognize the advantage of integrating natural resource management plans—particularly for water management—with local land-use planning, which leads to information-driven land-management practices for preserving agricultural landscapes (Bunker and Houston, 2003). The LGAs in the Greater Adelaide region are primarily responsible for land governance (i.e. development planning, subdivisions and regulating natural landscapes). The LGAs are prioritising land-management strategies while maintaining a balance between land supply for development and landscape protection, within council boundaries on the fringes of Adelaide city.

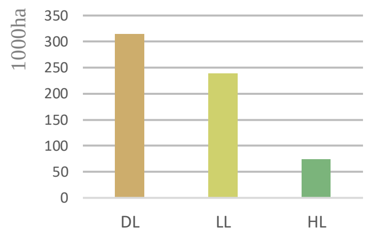
a) DL = Dryland agriculture (rain-fed cereal crops)

b) LL = Livestock land (grazing pasture)

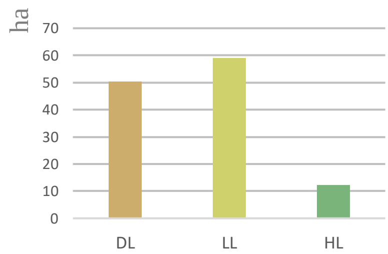
c) HL = Horticultural land (irrigated cultivations with farm dams)

Figure 4.2: Aerial imagery of the three broad land-use types identified in this region
Note: a) DL= dryland agriculture; b) LL = livestock land; and c) HL = horticultural land





a) Total agricultural land area by land-use category



b) Median land parcel size (ha) by land-use category

Figure 4.3: Agricultural land use in Greater Adelaide
(Wadduwage et al., 2017)

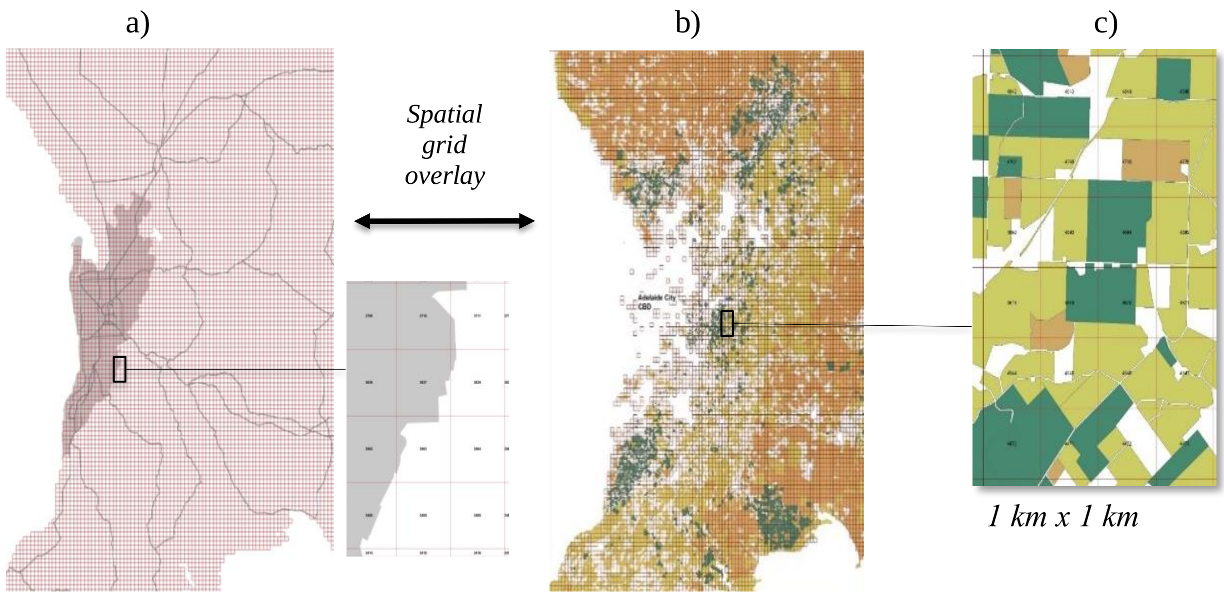


Figure 4.4: Spatial grid overlay
Note: a) shows the grid overlaid on the entire area investigated (light pink) without land-use data. The dark pink area is urban; b) shows the grid overlaid on land-use classes for the inset area in Figure 4.4(a); and c) is a 1x1 km area extracted from Figure 4.4(b). The key to land-use classes in Figure 4.4(b) and 4.4(c) is in Figure 4.3.

The current study uses South Australian Government planning data sets from the *30-Year Plan for Greater Adelaide* (Planning SA, 2010) to identify planned zones for development and primary production. These zones identified by spatial areas are recognized for future urban development—land development zones—and primary production areas include legislatively protected zones under the *Character Preservation Act 2012*. The SA Government land cadastral data with land-use information (Department of Planning, Transport and Infrastructure [DPTI], 2016) are used to identify land-parcel boundaries and agricultural land uses, respectively (data source <http://location.sa.gov.au>). This land cadastral data set is maintained for local government levy collection purposes in the study area. A generalized agricultural land-use data set was derived from the land cadastral land-use data to represent the broad agricultural land-use categories, DL, HL and LL, defined by production type.

A digital elevation model (DEM), with 30 m resolution (data source: Geoscience Australia, <http://data.gov.au>), was used to derive the steeper areas of the landscapes. The steeper areas are identified by the slope map (over 50% of the terrain in the study area is elevated) generated through the DEM using ArcGIS Desktop 10.4 (ESRI Corp.). Zones under land fragmentation are identified through land-parcel analysis of the landscape (Wadduwage et al., 2017), and are used to represent land fragmentation in the study area. Local government administrative boundaries were used to spatially identify agricultural land vulnerabilities within local government areas on the Adelaide city fringes.

The research on which this paper (chapter) reports used the following data sets:

Table 4.2: Spatial data used for this research

Description of data	Spatial Resolution	Date	Source	Reference	How used in this research
Land use Generalized	10 m	June 2016	http://location.sa.gov.au	Department of Planning, Transport and Infrastructure (DPTI) (SA)	To identify development zones and primary production zones (reported in *30-Year Plan for Greater Adelaide*)
Land Use South Australia (ACLUMP) – land cadastral data	10 m	June 2016	http://location.sa.gov.au	Department of Environment, Water and Natural Resources (DEWNR) (SA)	To identify land parcel boundaries and agricultural land use
Digital elevation model	30 m	June 2010	http://data.gov.au	Geoscience Australia	To derive steep areas of the landscapes
Generalized Agricultural land-use data	10 m	June 2016	Spatial data extraction from State govt. land cadastral data	The main agricultural land-use categories: DL, HL and LL.	To identify agricultural land use by production type: DL, HL and LL
Land fragmented zones	10 m	June 2016	Spatial data analysis results derived from State govt. land cadastral data	Extracted from land cadastral data with land-use information. (Wadduwage et al., 2017)	To represent the land-fragmented areas
Local government areas	10 m	June 2016	http://location.sa.gov.au	Department of Planning, Transport and Infrastructure (DPTI) (SA)	To identify local government area land boundaries on the fringes

4.3.2 Agricultural land vulnerability parameters

Six parameters (PM1–PM6) which can either negatively or positively affect the loss of agricultural land in peri-urban areas (Table 4.3) were used to calculate agricultural land vulnerability in the study area. They reflected the effects of land-use planning, the socio-economic situation, and physical constraints on land transitions on the urban fringes. Spatial layers were created for these parameters from the source data described in Table 4.2. A 1 km^2 grid was used as a common scale for all parameters. This was overlaid on the land-use maps using the ArcGIS version 10.2.1 Fishnet tool (Figure 4.4).

Table 4.3: Parameter (PM) consideration for calculating ALVI values

Parameter	Description	Data source
PM1–Proposed development areas	Land scheduled for development [b]	Land Use Generalized
PM2–Proposed regulated areas	Planning and legislative provision for primary industries [b]	Land Use Generalized
PM3–Demand for land	Land values based on distance to built-up area and transport corridors	Land Use South Australia
PM4–Physical barriers to infrastructure development and building	Probability of construction	Digital elevation model
PM5–Land fragmentation	Probability of land-use change	Land fragmented zones
PM6–Resistance by production type	DL > HL > LL	Generalized Agricultural land-use data

[b] *30-Year Plan for Greater Adelaide* (2010), [c] Land cadastral data with land-use information in 2016 (SA government [DPTI])

The following methods were used to map the six parameters. Areas scheduled for land development (PM1) or protection (PM2) were mapped for each cell in the spatial grid from the *30-Year Plan for Greater Adelaide* (Planning SA, 2010). Land demand (PM3) was mapped for each cell using spatial proximity analysis between the centroids of each land parcel and built-up areas or major transportation corridors. Steep areas unsuitable for urban development (PM4) were mapped from a raster DEM by extracting cells where the gradient was > 50%. Cells with high levels of land parcel fragmentation (PM5) were mapped from maps of land-parcel density (PD) and mean land parcel size (MPS). Wadduwage et al. (2017) identified high fragmentation areas in the Adelaide region as locations where MPS increases in areas where the PD is between 7 N/km^2 and 35 N/km^2. Landowner resistance to land-use change was identified in relation to the dominant agricultural production types in the broad land uses in the area: DL, HL and LL (Wadduwage et al., 2017). These data were acquired from the Land Use South Australia (ACLUMP) land cadastral map (Table 4.1). The highest resistance was found in dryland agricultural (DL) areas, which are dominated by large commercial farms with high economic returns, and the lowest was in grazing lands (LL), where economic returns are relatively low, and many farms are heritage properties, that is, family farms with ageing landowners, or hobby farms. Medium resistance was found in horticultural enterprises (HL), such as vineyards and vegetable farms, which generate high economic returns from relatively small land parcels.

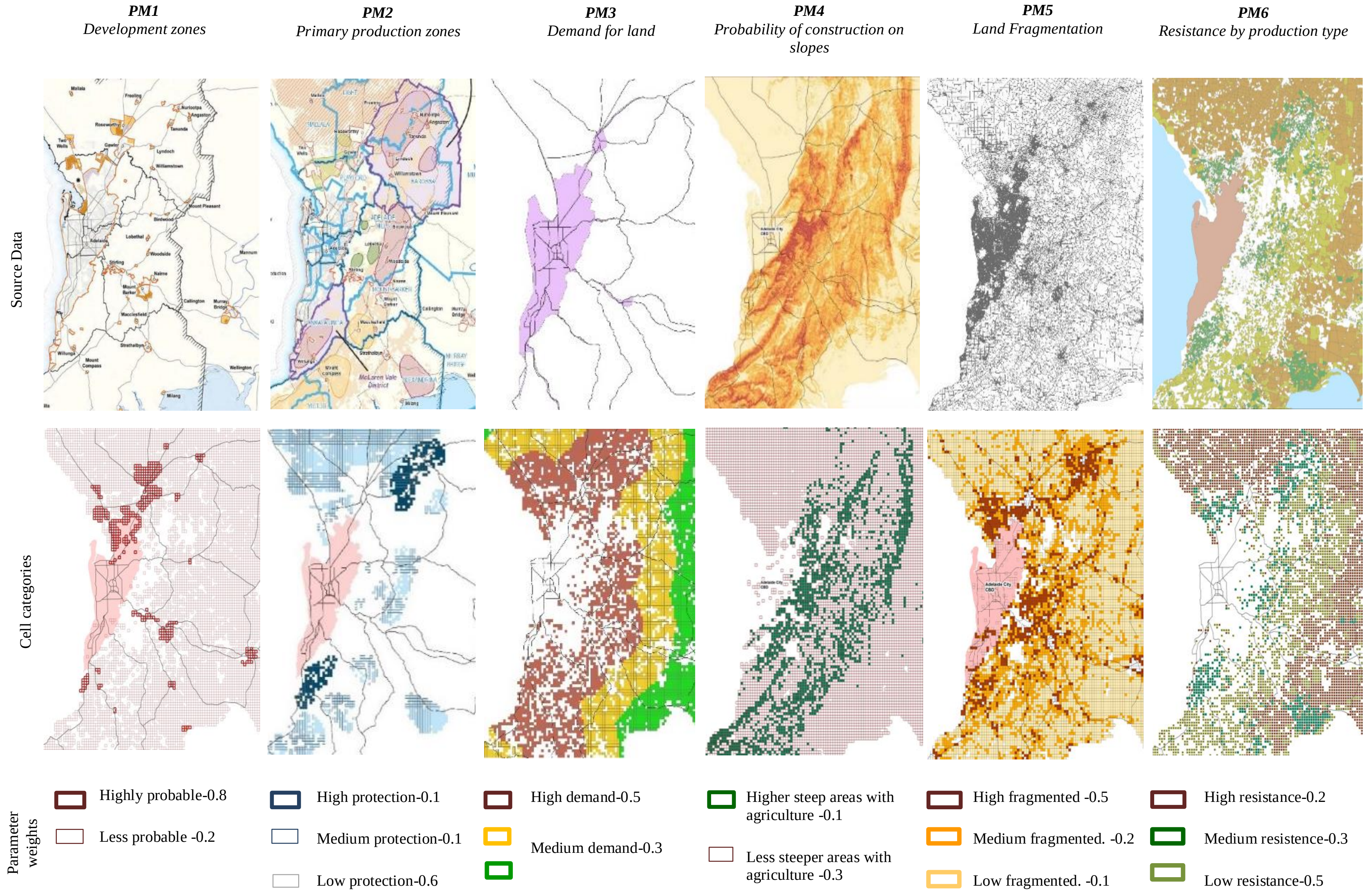


Figure 4.5: Maps of parameters used to calculate agricultural land vulnerability in Greater Adelaide

4.3.3 Scenario development and land vulnerability analysis

Three land-change scenarios, each with a clear storyline, were developed: a business-as-usual (BAU) scenario, an accelerated economic development scenario (EDS) and a high environmental protection scenario (EPS). The BAU scenario assumed the continuation of current economic and population growth trends within existing land governance policies, as identified by the proposed development and preservation areas in the region. Implicit in this scenario was the assumption of the continuation of current land-change trends and the behaviour of local land markets to satisfy the demand for land on the periphery of Adelaide. In this situation, the vulnerability of agricultural land can be assumed to follow a sequence where grazing land is the most vulnerable and dryland agriculture the least vulnerable.

The EDS represents an expanding local economy with large investments in industry, commerce and services, and increased population growth. This would lead to increased demand for land for housing and infrastructure development and may be accompanied by more relaxed planning controls. It would lead to more land becoming vulnerable to urban sprawl and increased land fragmentation. Furthermore, it would adversely affect natural systems; therefore, strong land-use management practices would exist for regulating natural resources, while accommodating land development in the proposed areas as a land governance policy. In this situation, farmland with low economic returns would be highly vulnerable to urban sprawl in efforts to satisfy land demand for housing and infrastructure development in the study area.

The EPS is the opposite scenario to that presented in EDS, with strict adherence to wide-ranging land governance and natural resource management policies while allowing sustainable land development and management practices on the fringe of the city, for example, retaining green spaces, heritage and conservation areas. Compared to the other two scenarios, the EPS would be characterized by a relatively low amount of land development as it would be attracting land uses with lower economic returns while the environment would be highly regulated. Due to the combined effects of low economic growth and higher regulation for environmental management, less demand would be created for land—for housing, infrastructure and commercial facilities—while limiting land fragmentation. Although less pressure would be exerted on non-regulated agricultural landscapes for land-use changes (by land-use planning), the HL use (e.g. vegetable growers) would face increasing land vulnerability as businesses would not be financially viable under the higher level of water, waste and land management regulations.

Land-use research has extensively used parameter weights to represent parameter sensitivity to the defined scenario storylines (Long and Zhang, 2015, Salvati and Carlucci, 2013, Estoque and Murayama, 2012, Buxton et al., 2011a). Contemporary land-use studies have utilized the weights on parameters in various forms: as indicators in urban studies (Lauf et al., 2016, Thapa and Murayama, 2012); as parameter inputs in CLUMondo and CLUE (conversion of land-use change and its effects) models (Liu et al., 2017, Ornetsmüller et al., 2016, Jiang et al., 2016); as factors in cellular automata (CA) models (Feng and Liu, 2016); and as parameter weights in land-use trade-offs (LUTO) models (Bryan et al., 2016) to represent parameter sensitivity parallel to the defined scenario storylines. In the current study's integrated approach, parameter weights represented the parameter sensitivity to each scenario storyline while using a spatially-explicit grid approach to calculate ALVI values in a spatial context.

Table 4.4: Spatial weights used for scenario development

	EDS (Economic Development)			BAU (Bussiness as usual)			EPS (Environmental Protection)		
Parameter	*weight (Low -high)*			*weight (Low -high)*			*weight (Low -high)*		
PM1 Proposed development areas	0.1	0.9		0.2	0.8		0.3		0.7
PM2 Proposed regulated areas	0.7	0.2	0.1	0.6	0.1	0.1	0.4	0.1	0
PM3 Demand for land	0.1	0.2	0.7	0.2	0.3	0.5	0.2	0.4	0.4
PM4 Physical barriers on land-use change	0.4	0.2		0.3	0.1		0.1	0	
PM5 Land fragmentation	0.1	0.2	0.7	0.1	0.2	0.5	0	0.1	0.2
PM6 Resistance by production type (DL>HL>LL)	0.1	0.2	0.7	0.2	0.3	0.5	0.2	0.4	0.4

In the three land-change scenarios (EDS, BAU, EPS), parameter weights were assigned according to the assumptions made in the defined storylines (Table 4.4). The parameter weights in Table 4.4 represent the relative effect of the six parameters on land vulnerabilities in each scenario while representing the proportional differences between the scenarios. All weights were assigned between 0 (zero) and 1 (one) (where 0 is the least important and 1 is the most important) but were not normalized to represent the relative importance among the parameters.

The six parameters (PM1–PM6) were weighted for each of the three scenarios based on local knowledge of land-management practices (Table 4.4). Higher weightings represented the higher importance of their effect on land vulnerabilities in the study area. Higher weights were assigned to the proposed development areas (0.8), less regulated areas (0.6), high land-demand areas (0.5), higher land-fragmentation areas (0.5) and low-resistance LL areas (0.5). The steep areas in P4 were assigned a relatively low weight (0.3) compared to the other parameters, as they were not of equal importance when land markets were competitive, that is, higher land demand for proposed development areas.

The ALVI values were calculated for each cell using the following equation:

$$Agricultural\ Land\ Vulnerability\ Index\ (ALVI)\ = \frac{\sum_{j=1}^{6} w_i p_{ij}}{N} \quad (1)$$

where

p_{ij} = *Parameter representation of the i-th cell;* w_j = *Spatial weight of the i-th cell; and N = Number of parameters.*

For every cell in the spatial grid, each parameter (*p*) was represented by a value of 1 or 0 and the assigned weight (*w*) from Table 4.4. Figure 4.5 illustrates cell categories derived from the source data and the associated weights for each parameter that were used to calculate ALVI values. For ease of comparison, the actual ALVI values for each cell in each scenario were categorized into the following variability classes: Very low < 0.1; Low 0.11–0.3; Medium 0.31–0.4; High 0.41–0.5; and Very high > 0.51.

Local government area boundaries were overlaid on the land vulnerability grid layer and the land-use spatial data in ArcGIS to quantify the land vulnerabilities of the land-use types—three generalized land-use types; LL, DL and HL—derived for each of the three scenarios for local government areas in Adelaide's peri-urban zone. The attribute tables of the land vulnerability spatial quantifications created in ArcGIS were used to analyse the spatial variation in land vulnerability for each scenario and to calculate the amounts of each of the general land-use types located within the highly vulnerable areas.

4.4 RESULTS

4.4.1 Agricultural land vulnerability in contrast

Figure 4.6 illustrates the agricultural land vulnerabilities in the area under investigation for the three different scenarios, within the common ranges of ALVI values for better comparisons. The maps in Figure 4.6 interpret the spatial distribution of agricultural land vulnerability in each scenario on the Adelaide city fringes.

The EDS, which represents high levels of economic development, leads to very high ALVI values of 0.5–0.7 for the northern Adelaide Plains and the eastern fringes, beyond the hilly conservation areas. These values indicate that agricultural land in these two areas is highly vulnerable to conversion to urban land uses. Furthermore, this scenario shows a clustering of areas with high ALVI values close to the current built-up area. Horticultural land in McLaren Vale to the south has significantly lower vulnerability to conversion to urban land uses compared to agricultural land closer to the current built-up area. These areas of economically productive multi-functional land (vineyards in the McLaren Vale area) show higher resistance to urban pressure on the southern fringes. The larger dryland agricultural land parcels and the winery land at the rural edge of the city shows lower land vulnerabilities (ALVI: 0.1–0.2) even under enhanced urban development.

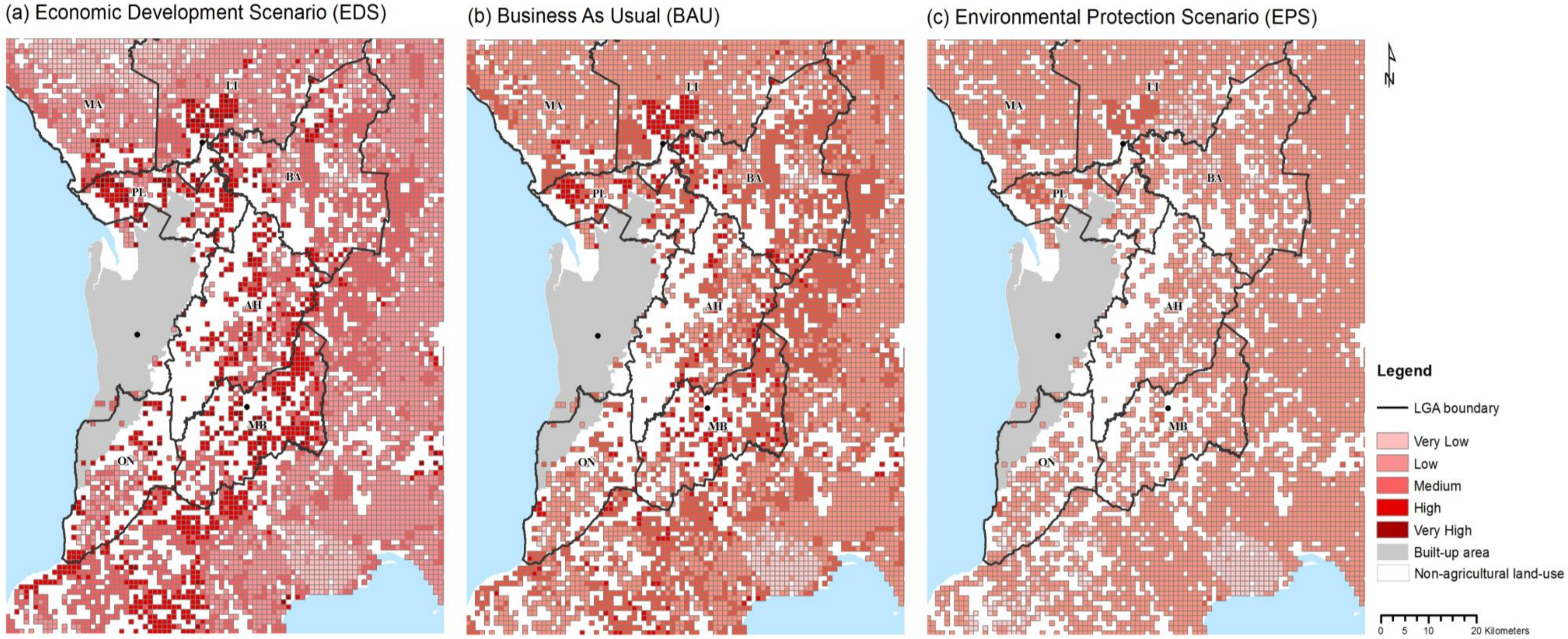


Figure 4.6: Agricultural land vulnerability variations in the three scenarios

Notes: a) EDS; b) BAU; c) EPS;

Agricultural Land Vulnerability Index (ALVI) values classified in the ranges of 0.1 < Very low < 0.2 < Low < 0.3 < Medium < 0.4 < High < 0.5 < Very high < 0.7.

The business-as-usual (BAU) scenario shows the high vulnerability of agricultural land (ALVI: 0.4–0.5) to the north of the city. These areas mainly comprise land for livestock rearing around the town of Gawler and areas of intensive horticulture, mainly vegetable cultivation, along transport corridors on the northern Adelaide Plains. The patchy agricultural land on the eastern fringes of the city has moderate levels of vulnerability to urban sprawl. However, within this part of the Adelaide urban fringe, land used for stock raising around the fast-growing town of Mount Barker has high ALVI values (0.4–0.5) in this scenario. Agricultural land to the south of the city has only low vulnerability to urban development in the BAU scenario.

The EPS, which represents high levels of landscape protection, only generates moderate levels of agricultural land vulnerability to urban sprawl (ALVI: 0.3–0.4) around Gawler and Mount Barker. Most agricultural land is characterized by lower agricultural land vulnerabilities with livestock farms to the south of the city and vineyards in McLaren Vale having very low ALVI values of 0.1–0.2.

Figure 4.7 presents a summary of the variation in agricultural land vulnerability classes in the study area for the three different scenarios. Very high vulnerability of agricultural land to urban sprawl is only found under the EDS, whereas high levels of vulnerability are found in both EDS and the BAU scenario. Medium levels of vulnerability are very similar in the EDS and the BAU scenario but, in the EPS, decline markedly. The largest proportion of land in each scenario falls in the low vulnerability class. The EPS is the only scenario in which land with very low ALVI values occurs.

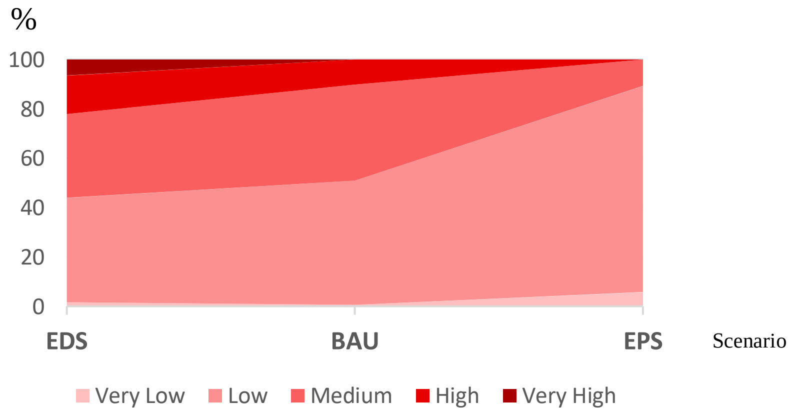
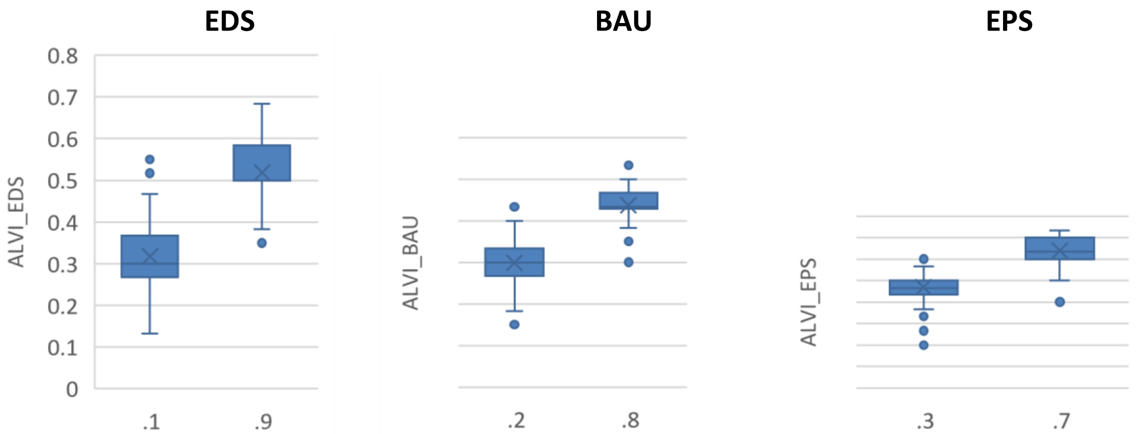
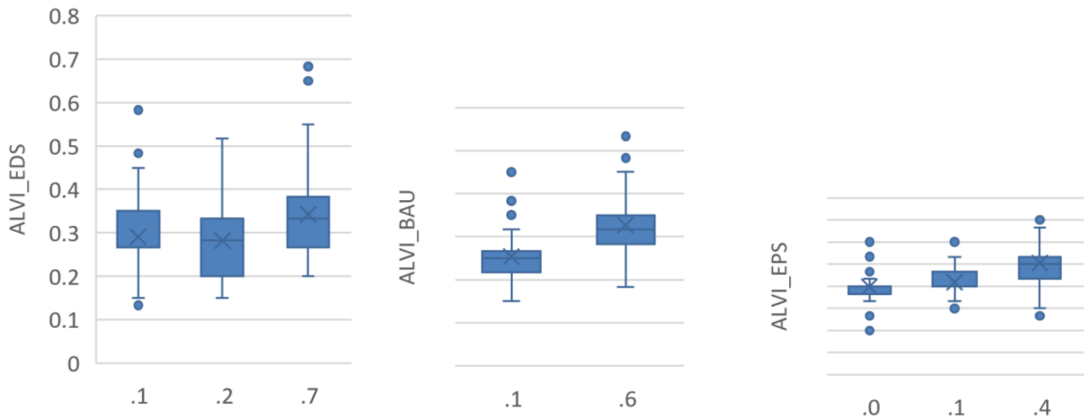


Figure 4.7(a): Level of agricultural land vulnerability variations in the three scenarios (EDS, BAU and EPS)

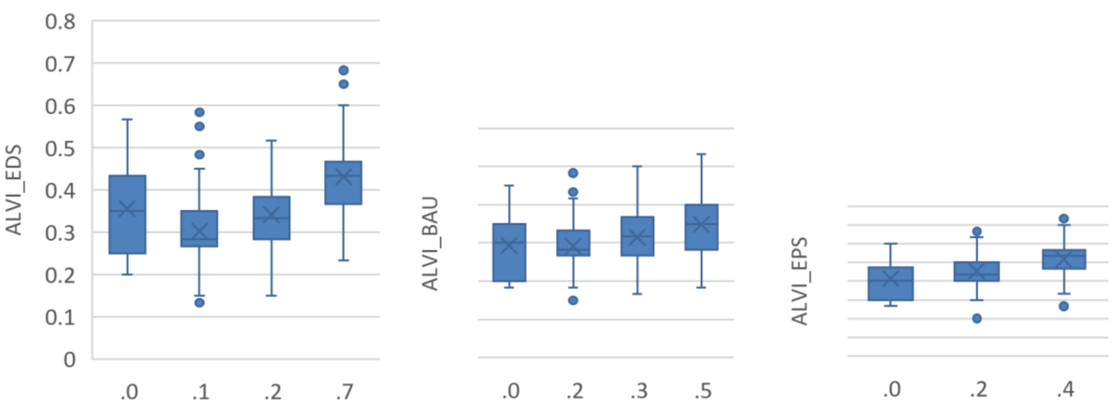
Sensitivity analysis was used to find the impact of each input parameter on the calculated Agricultural Land Vulnerability Index (ALVI) values. By using the statistical data set in SPSS (# 5916 data records associated with cells, including parameter input values and the calculated ALVI values for the three scenarios), the sensitivity of ALVI for each parameter (independent variables PM1 to PM6) was tested by developing explorative data descriptive statistics through statistical analysis to visualize the overall results in box plots (with 95% confidence intervals [CIs] for received mean values). These box plots show the ALVI variations against the assigned weights (ascending order) for each parameter type (PM1–PM6) in the three tested scenarios (EDS, BAU, EPS).



PM1 Proposed development areas



PM2 Proposed regulated areas



PM3 Demand for land

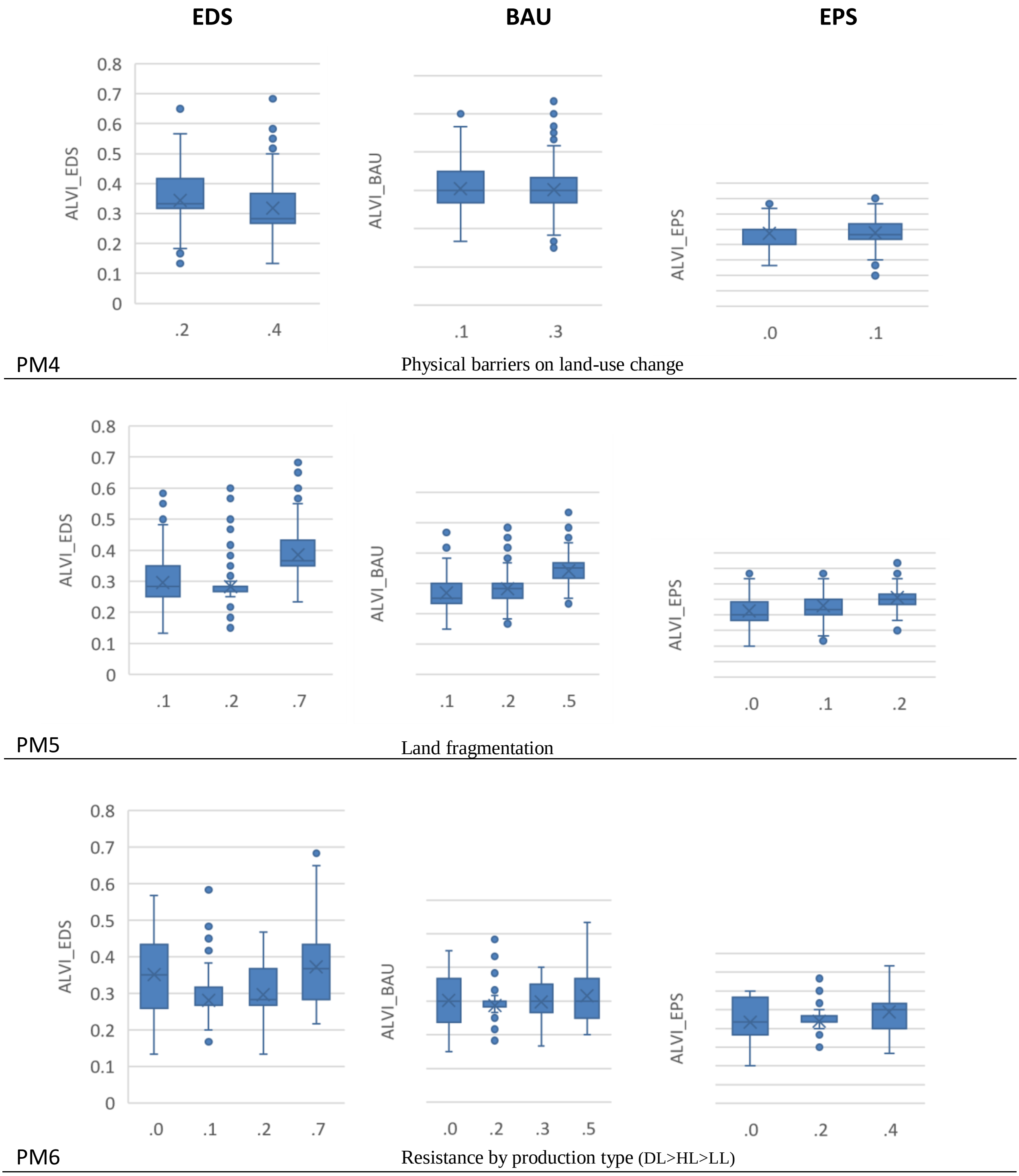


Figure 4.7(b): Parameter weight descriptive statistics

Notes: This figure presents the independent variables PM1–PM6 and the ALVI values received in each scenario (EDS, BAU and EPS). Box plots present the mean values of the ALVI values received with 95% confidence intervals (CIs) while visualizing error bars and extreme outliers with dots. For each parameter, the y-axis represents the units of ALVI values in each scenario.

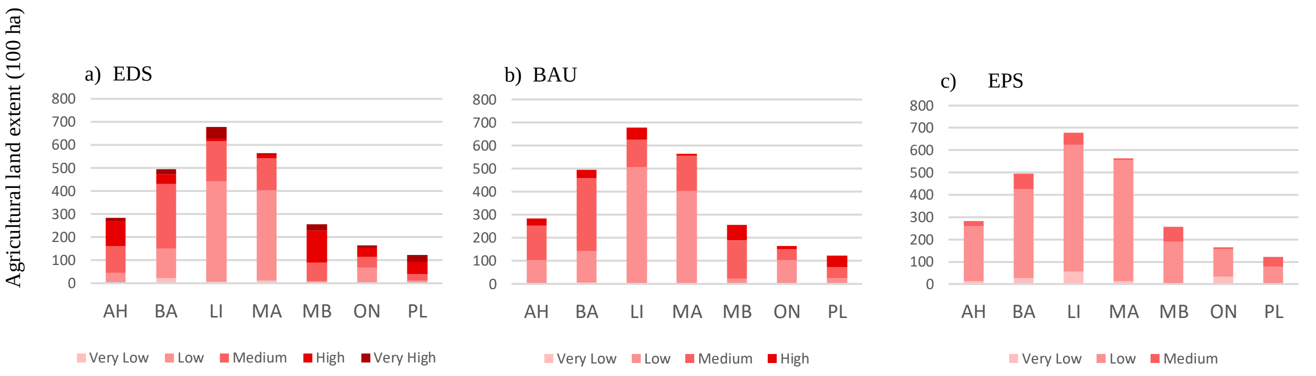


Figure 4.8: Extent of agricultural land by vulnerability class by local government areas for each scenario

Note: This figure presents the seven local government areas surrounding Adelaide in relation to each scenario: (a) EDS, (b) BAU and (c) EPS. The key to the local government areas is as follows: AH = Adelaide Hills, BA = Barossa; LI = Light; MA = Mallala; MB = Mount Barker; ON = Onkaparinga; and PL = Playford.

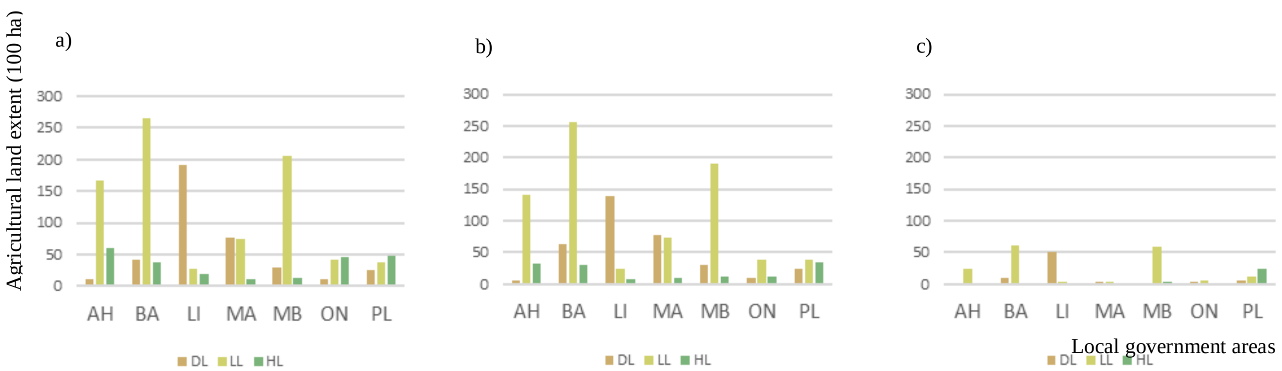


Figure 4.9: Local government area-based agricultural land vulnerability by production type

Note: In a) EDS; b) BAU; and c) EPS within the ALVI range of medium (0.3) to very high (0.7).

Table 4.5: Agricultural land-use vulnerability by local government area on Adelaide city fringes

LGA Code	LGA Name	Description	Total land (1000 ha)	Land use of DL (1000 ha)	Land use of LL (1000 ha)	Land use of HL (1000 ha)
AH	Adelaide Hills (DC)	Reserve	79,027	1,658	19,837	10,255
BA	Barossa (DC)	Agriculture	88,670	9,972	31,611	12,666
LI	Light (RC)	Livestock	126,676	92,099	6,171	8,124
MA	Mallala (DC)	Horticulture	92,514	57,639	9,388	1,996
MB	Mount Barker (DC)	Institution	59,169	4,166	22,287	1,741
ON	Onkaparinga (C)	residential	51,598	1,423	6,135	11,253
PL	Playford (C)	residential	34,256	3,073	4,791	6,003

Note: DC = District Council; C = Council; and RC = Regional Council

4.4.2 Agricultural land vulnerability in local government areas

Figure 4.8 illustrates the extent of the different levels of agricultural land vulnerability to urban growth for the seven local government areas that surround Adelaide. The figure provides a comparative view of scenario-based land vulnerability variations in each local government area, considering the constant land extents. Overall, the local government areas on Adelaide's northern rural fringes (i.e. Light Regional Council [LI]; Mallala District Council [MA] and Barossa District Council [BA]) show a substantially higher extent of agricultural land that is vulnerable to urban sprawl in comparison to the lesser extent of vulnerable agricultural land in the local government areas to the city's north (Playford Council [PL]) and the city's south (Onkaparinga Council [ON]). In terms of vulnerability, the PL, MB and AH local government areas show higher percentages of higher extents of vulnerable agricultural land, compared to the total agricultural land presence within these local government areas.

Table 4.5 summarizes the local government area-based statistics for total agricultural land presence and the land extent occupied by each production type on Adelaide's city fringes. Agricultural land with medium to very high (ALVI: 0.3–0.7) vulnerability by production type was quantified in each local government area, with the results for the three scenarios shown in Figure 4.9. The comparative representation of the local government area-based agricultural land vulnerability variations under the three scenarios demonstrates how each local government area is affected by the influence of extreme policy directions.

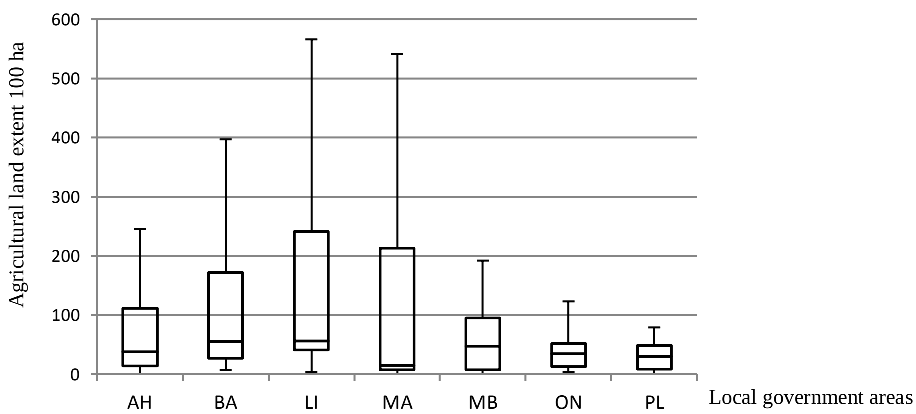


Figure 4.10: Block plots of overall agricultural land vulnerability variances in each local government area on Adelaide's city fringes
Note: These block plots illustrate the extent of the land form: minimum, lower quartile, median, upper quartile and maximum.

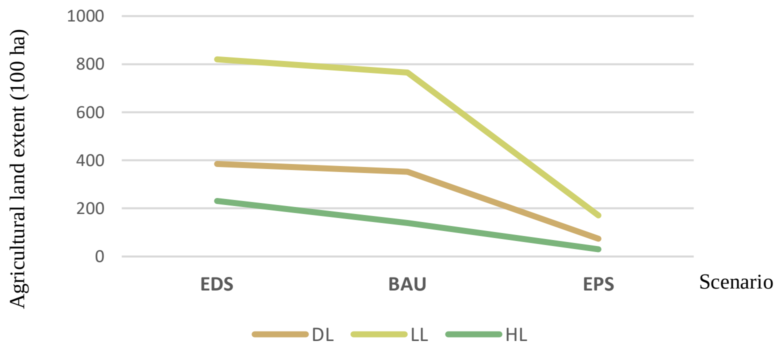


Figure 4.11: Agricultural land vulnerability by production type in EDS, BAU and EPS
Note: The values presented are within the ALVI range of medium (0.3) to very high (0.7).

Figure 4.10 illustrates the overall agricultural land vulnerability variances in each local government area. These results show distinct agricultural land vulnerability ranges in local government areas in the study area. Figure 4.11 shows the extent of distinct agricultural land occupied by each production type under the three defined scenarios, where vulnerability ranges from medium to very high. The agricultural land-use type LL shows higher vulnerabilities in the EDS and the BAU scenario, but it shows a significant reduction in the EPS compared to DL and HL, the other two types of land use.

4.5 DISCUSSION

The multi-criteria approach employed in the current research addresses the methodological challenges of integrating land-use change drivers, such as land-use planning, economic behaviour and physical constraints, with the spatial arrangement of land to quantitatively assess the vulnerability of agricultural land to urbanization on the edge of cities. In land-use planning, spatially-explicit land-use planning instruments are regarded as a popular method for developing sustainable urban development strategies (Lauf et al., 2016). Nevertheless, their use requires a thorough understanding of land-change drivers and the extent of the land to strengthen land-management policies (Thebo et al., 2014). The spatially-explicit method employed in this research captures parameter magnitudes as spatial weights that are used to calculate the vulnerability of agricultural land to conversion to urban land use in each cell. The approach enables the visualization of the spatial distribution of agricultural land's vulnerability to encroaching urbanization.

The quantification and visualization of agricultural land's vulnerability to urban sprawl have been given less attention in land-change studies, despite the amount of research on monitoring land use on the fringes of cities (Lauf et al., 2016, Colantoni et al., 2016, Ju et al., 2016, Deng et al., 2015, Kuang et al., 2016). The quantification of land use and land-use change is important in understanding the impact of phenomena like urbanization on landscapes, and it can strengthen existing land-use management policies (Lambin et al., 2000) in peri-urban zones. This is important as contemporary land-use research perspectives have changed from a focus on land use and land cover to one on land systems which incorporate socio-economic interdependencies to try to capture the complexity of land transformation processes (Ornetsmüller et al., 2016, Lauf et al., 2016, Grau et al., 2013, Lambin et al., 2000). The visual representation of the spatial variability of agricultural land vulnerability can improve our interpretation of the causes of agricultural land's transformation to urban land uses in these complex land systems. The facts developed in this approach (evidence-based) enable justifiable land-management decisions while improving the knowledge on agricultural land-transition phenomena under different policy settings.

Scenario-based land-use analysis is widely used for predicting future land-use and land-cover changes (LULCCs) (Lauf et al., 2016, Yang et al., 2016, Sohl et al., 2016, Ornetsmüller et al., 2016, Jiang et al., 2016, Houet et al., 2016) but occasionally it is used to synthesize complex land transformations (Priess and Hauck, 2014). In addition, scenario analysis can be used to investigate the socio-economic policy implications of land-use change (Sali et al., 2016, Lauf et al., 2016, Yang et al., 2016, Koomen et al., 2005, Booth et al., 2016). Many studies have illustrated that scenario analysis stimulates creative thinking and knowledge exchange amongst a wide range of stakeholder groups (Sali et al., 2016, Kaljonen et al., 2012, Haasnoot and Middelkoop, 2012, Sleeter et al., 2012, Zurek and Henrichs, 2007), as it capable of capturing land-system sensitivity under different parameter set-ups. The integration of two different modelling techniques—parameter-based land-use models with scenario analysis—provides rich information on land transitional processes (Lambin et al., 2000). The continuous representation of land vulnerability variations in opposing scenarios (Figure 4.7) demonstrates the possibility of synthesizing the increasing agricultural land vulnerabilities in excessive urban development conditions, as well as the decreasing trends in landscape-protected situations.

4.5.1 Agricultural land vulnerability under different scenarios

The two extreme scenarios developed to represent the vulnerability of agricultural land to urban growth under opposing policy directions—high levels of economic development and strong environmental protection—enabled the relationships between land vulnerability and policy directions to be investigated. The ALVI values calculated for the EDS and the EPS demonstrated how the vulnerability of farmland to urban sprawl varies spatially under these two scenarios, while illustrating the farmland vulnerabilities in the BAU scenario under the continuation of current socio-economic and land administrative policy trends.

The overall results showed significantly higher levels of agricultural land vulnerability under the EDS (very high 5%; high 15%; medium 30%; and low 50%) while showing relatively low levels of land vulnerability in the EPS (medium 10%; low 85%; and very low 5%). These results demonstrated that land-management policies targeting economic development (the EDS) cause significantly higher levels of land vulnerability compared to those of the EPS on the city fringes. The spatial variations of these results demonstrate the spatial heterogeneity of these land vulnerabilities in a spatial context (Figure 4.6). Agricultural land in closer proximity to the current built-up area shows significantly higher vulnerability to urban sprawl under strong urban development policy directions (the EDS) while, in the EPS, vulnerability is significantly reduced. However, agricultural land to the north of the city, which includes farmland around the neighbouring town of Gawler, shows relatively high vulnerability to urban growth even under the EPS with its implied high levels of environmental protection. This demonstrates the inevitability of transformations from agricultural land use to urban land use in the northern peri-urban zone.

Under conditions of high levels of economic and urban development, that is, the EDS, the location of farmland that is highly vulnerable to conversion from agricultural to urban land use on the fringes east and south of Adelaide demonstrates a leap-frog effect in which land with high ALVI values is generated beyond the Hills Face Conservation Zone and McLaren Vale, both of which benefit from protection through planning laws. This scenario also reveals that agricultural landowners in these more distant areas to the east and south would sacrifice their farmland to meet the demand for land under policies that promote high levels of urban growth. The results also confirm that some economically productive, multi-functional agricultural practices are more resilient than others to urban sprawl on urban fringes (Zasada, 2011); for example, horticulture, based on vines and olives, is less vulnerable to land-use change than dairy production and stock rearing. However, this argument may have limited wider application because McLaren Vale also benefits from a global profile and protection under the *Character Preservation (McLaren Vale) Act of 2012* (South Australian Government, 2013).

As parameter weights were assigned according to the assumptions made in the defined storylines (EDS, BAU and EPS), these weights represent the relative differences expected for each scenario. For example, in the EPS with a situation of less economic growth, parameter weights assigned for PM3 (demand for land) were in the range of *Low–high* (0.1–0.4) compared to the EDS which had higher market demand for land and a range of *Low–high* (0.1–0.7). This result demonstrates the maintenance of relative importance between the parameter weights in each scenario. The overall results show that the lowest level of farmland vulnerabilities was under the EPS as, in this scenario, it experiences less urban pressure (represented by weights) in accordance with the defined storyline.

The sensitivity analysis results show the ALVI values received for each parameter type (Figure 4.7[b]). The results for PM1 show a significant increase in ALVI values (3.2–5.1) of farmland vulnerabilities with the increase of parameter weights (0.1–0.9) in the EDS (Figure 4.7[b] ALVI_EDS vs. PM1), representing future development zones proposed by the land administration. Moreover, a similar trend was also experienced in the other two scenarios (BAU and the EPS) although, overall, they received lower ALVI values. These results demonstrate the significant impact of PM1, that is, development zones on farmland vulnerabilities in peri-urban areas. The ALVI values for PM2 show limited changes over the increase of weights in the EDS (Figure 4.7[b] ALVI_EDS vs. PM2), while the BAU scenario and the EPS displayed similar patterns. This result demonstrates the minimal importance of PM2 (i.e. proposed land-use regulated areas) for calculating farmland vulnerabilities on the city fringes. The calculated ALVI values for PM3 display an average level (3.0–4.1) of an increasing trend (Figure 4.7[b] ALVI_EDS vs. PM3), with an increase in PM3 weights (0.1–0.7) displaying a similar trend in the other two scenarios. This result shows that higher weights in economic growth situations (i.e. the EDS) have a greater impact on the calculated ALVI values, due to the increasing demand for land to facilitate farmland conversions on city fringes.

The PM4 results exhibit an interesting outcome by showing a decreasing trend (3.8–3.1) of ALVI values with an increase in the parameter weights (0.2–0.4) in the EDS (Figure 4.7[b] ALVI_EDS vs. PM4). This result demonstrates that higher weights for PM4 have less impact on land vulnerabilities in an economic development situation (i.e. the EDS), as the cumulative weight of the other parameters (PM1–development zones and PM3–demand for land) have a greater influence on increasing the ALVI values in the study area. In these extensive growth situations, physical barriers to land development on steeper terrain have less influence in restraining urban sprawl due to a larger investment in engineering and infrastructure development. Although ALVI values for PM5 (land fragmentation) show an increasing trend over increasing weights (3.0–3.8), scattered outliers of ALVI values (Figure 4.7[b] ALVI_EDS vs. PM5) demonstrate its weakened influence on land vulnerabilities in the low weights for PM5: for the EDS, this was particularly the case. The results also show that in high economic growth situations, farmland vulnerabilities can be triggered in low fragmenting areas due to other more significant influencing factors, such as a higher demand for land within the proposed development area. The ALVI values for PM6 show limited changes with the increase of weights in the EDS (Figure 4.7[b] ALVI_EDS vs. PM6) with scattered ALVI values at low weights, while displaying similar patterns in the EPS and the BAU scenario. This demonstrates the decreased importance of the type of farmland use (PM2–resistance by production type DL > HL >LL) for calculating farmland vulnerabilities especially at the lower weights in the EDS, as other parameters (PM1 and PM3) have a substantial influence over PM6 for converting farmland to non-agricultural land use.

4.5.2 Agricultural to urban land-use transformation by local government areas

Dependencies in land-system changes are created by geographic location and spatial configuration of the land use (Ornetsmüller et al., 2016). Estimates of land vulnerability by local government area have the advantage of improving local knowledge, in the context of rural-to-urban (R–U) land transformation, among stakeholders such as planners and policy makers, urban developers, and primary production and natural resource management professionals. Houston (2005) highlighted the importance of quantifying physical land occupancy on the fringes of Australian cities to understand the effects of urban sprawl on agricultural land uses. In the current research, estimates on the vulnerability of land under three broad types of production—dryland agriculture (DL), livestock land (grazing and rearing) (LL) and horticulture (HL)—provide detailed information that should be assessed to improve industry-specific land-management strategies in local government areas.

The amount of agricultural land in a local government area itself is not an indicator of vulnerability to change. For example, the part of the Mallala District Council area covered by this study has over 92,500 ha of agricultural land, most of which is used for broad-acre cereal farming (part of the dryland agriculture [DL] category). However, it demonstrates less vulnerability to urban sprawl than agricultural land in the Playford Council area which only has 34,256 ha of agricultural land but has a higher level of vulnerability due to the presence of intensive vegetable gardens in the proposed development land-use zones.

The agricultural land area derived by production type in the higher vulnerability ranges—medium to very high—in Figure 4.9, demonstrates that local government area land vulnerabilities are non-linear and unique. Moreover, the results demonstrate the overall land extent occupied by the production types: LL > DL > HL, where LL represents a significantly higher level of land vulnerability on Adelaide's city fringes. In particular, the results show significant land vulnerability increments in the eastern and south-eastern local government areas (Adelaide Hills [AH] and Mt Barker [MB]—beyond the hilly conservation areas) under excessive urban development policies as these create suitable environments for accommodating urban sprawl by converting the majority of LL and HL agricultural land uses to urban form. Overall, the livestock land (LL) uses (Figure 4.11) show a significant reduction in vulnerability in higher environmental protection conditions (i.e. the EPS), although, under EDS and its higher urban development conditions, these land uses show a slight increase in vulnerability. This demonstrates that higher environmental protection policies have a significant impact on protecting livestock farmland from the sprawl on urban fringes.

These facts were further confirmed by the unique overall land vulnerability variances. In all three scenarios in local government areas (Figure 4.10), these contrasted with the significant differences in land vulnerability variances—the higher variances with larger outliers (Light [LI], Mallala [MA]) and the local government areas with low variances (Onkaparinga [ON], Playford [PL]. This proves the necessity of capturing local-scale agricultural land vulnerability details for making informed land-management decisions.

4.5.3 Methodological advances and limitations

Studies of land-use transformation on the urban fringes of many cities have found that peri-urban agricultural land is under pressure and vulnerable to urban sprawl (Zasada, 2011, Robinson, 2004, Vizzari, 2011, Malaque and Yokohari, 2007, Heimlich and Anderson, 2001, Lee et al., 2015, Jiang et al., 2013, McFarland, 2015). The current study confirms this general finding under various policy directions. In addition, the patchy land vulnerability feature presented in the study's scenarios confirms the non-linear nature of peri-urban land-use transformations (Ornetsmüller et al., 2016, Brown and Robinson, 2006).

The spatially-explicit maps and analyses of the vulnerability of farmland to urbanization using a scenario approach have enabled the likely outcomes of different land-management policies to be compared. Although this research focuses on agricultural land on the fringes of one city—Adelaide–the approach adopted could readily be applied to other Australian cities that are encroaching onto highly productive agricultural land (MacLachlan et al., 2017, Buxton et al., 2011a, McFarland, 2015, James and O'Neill, 2016) and to cities elsewhere with similar land-use configurations.

Successful applications of this method are dependent on selecting the correct parameters, accurate integration of spatial data, and quantification of results at various levels of local government administration. Correct parameter selection is the most critical of these aspects. Parameters are highly case-dependent (Thapa and Murayama, 2008) and the type, magnitude and location of land-use transformations generated from each scenario are highly dependent on parameter assumptions about local land-use policy settings (Bryan et al., 2016, Koomen et al., 2005). The selection of parameters that are the most influential drivers on the target land-use group, that is, agricultural land uses in the current study, is superior to using a wide range of parameters (Sali et al., 2016). The parameters selected in the current research project have been widely used by the land-use research community to describe land transformation processes on urban fringe landscapes. Institutional land policies have been shown to have a substantial impact on agricultural land-use transformations on the urban fringe (Malaque and Yokohari, 2007, Lambin et al., 2001). Declared land development zones in peri-urban areas attract land developers, while regulating development on primary production land in protected land-use zones. The growing economies of urban centres have a significant impact on peri-urban agricultural land uses—agricultural infrastructure, production cost, income (Wu et al., 2011)—and relate to the associated complex social interactions on the city fringes (Ives and Kendal, 2013, Parrott and Meyer, 2012). Agricultural land managers/farmers in peri-urban areas often sell land for non-agricultural uses due to the high prices generated by the high demand for land (Szabo, 2015). The rate of land transformation is often enhanced in areas where land fragmentation is high (Su et al., 2011), while it is restricted by physical barriers such as steep terrain on urban fringes. Agricultural landowners' land-use decisions depend on these factors. The agricultural land-change driver-focused parameter representation improves model effectiveness, while limiting the uncertainties associated with the policy-responsive scenario development process.

The main limitation of this approach involves the uncertainties generated during modelling and the development of scenarios. The fundamental cause of the uncertainties in these scenarios is that land-change processes exhibit spatial, temporal and behavioural complexities that are not fully understood (Parker et al., 2008b). This is certainly the case for Adelaide due to the limited amount of research that has been conducted (Houston, 2005, Liu and Robinson, 2016) and can only be partially resolved by the limited number of studies from other large Australian cities (Bunker and Houston, 2003, James, 2014, Sinclair et al., 2004).

In addition, scenario development in modelling increases the level of further uncertainties in the model results. Mahmoud et al. (2009) highlighted the importance of addressing three areas of uncertainty—understanding sources, estimating magnitudes and communicating uncertainties to stakeholders—to create modelling scenarios that will perform well. Although uncertainties are unavoidable in creating scenarios, accounting for these propagated errors at each stage can improve the precision of the targeted land-use change.

The current research attempts to address the challenge of transferring knowledge about land-use change into practice, by quantifying land vulnerability information for different local government areas. These local government area-based results demonstrate the importance of identifying the hotspots where significant amounts of agricultural land are vulnerable to change, and of quantifying the land vulnerability information. This should lead to more informed decisions; however, local government authorities (LGAs) in Australia must adhere to State-level planning recommendations for land development. This results in local-scale land-use changes collectively contributing to changing land use on a metropolitan scale. Therefore, quantification of the vulnerability of farmland to transformation to urban land uses at the level of local government areas is superior to estimates for entire cities or metropolitan areas when informed decisions must be made.

In this research, firstly, the multi-criteria approach was used to transfer the parameter-based land-use information into knowledge by systematic data compilations and analysis. Secondly, this knowledge was transferred into practice by calculating the associated agricultural land vulnerabilities and land extents by production type at the level of local government areas. This research demonstrates the success of using a multi-criteria spatially-explicit method together with scenario-based analyses to explore agricultural land vulnerabilities in these complex urban fringe land systems.

4.6 CONCLUSION

Agricultural land vulnerability is an effect of complex land-use transformation processes occurring on urban fringes. The level of vulnerability is non-linear and is highly dependent on the geographic location. Scenario-based analysis enables an understanding of the land system vulnerability responses under opposing policy directions in a policy spectrum ranging from economic development to environmental protection. The contrasting results demonstrate that the sacrifice of farmland to urban sprawl is inevitable under economic development policy directions in Adelaide, as confirmed in worldwide city-scale case studies.

The quantification and analysis of agricultural land vulnerability at the level of local government areas minimize information gaps among stakeholder policy networks when selecting strategic trade-offs between urban development and environmental protection. A step forwards is taken by transforming the acquired knowledge to practice on a local scale and is ultimately accountable for creating less land vulnerability on a metropolitan scale. Although this study has used a comprehensive parameter representation of the land-use change drivers—institutional and socio-economic—a substantial information gap continues to exist in the area of integrating the social aspects—agricultural landowners' land-use decision-making behaviours—for precise land vulnerability estimations on the city fringes.

The advanced version of this approach can achieve highly accurate results by incorporating empirically-validated socially-indicative parameters, regardless of the uncertainties associated with data integration and scenario development.

CHAPTER 5 – DRIVERS OF PERI-URBAN FARMERS' LAND-USE DECISIONS

This chapter focuses on exploring the key factors that govern farmers' land-use decisions in peri-urban land systems. It analyses a series of primary factors identified in previous land-change studies to investigate the factors that drive farmers' land-use decisions on Adelaide city's fringes. A survey is conducted on farmers' rankings of each factor's importance for their farm's success or for changing the land use/ownership. Statistical analysis factor reduction techniques were used to investigate the factors that drive farmers' land-change decisions while identifying farmers' descriptive statistics in these peri-urban landscapes.

Contributions to knowledge:

- Explored peri-urban farmers' characteristics and land-use decision preferences in the study area.
- Derived key factors that drive peri-urban farmers' land-change decisions while demonstrating the linkages between primary factors and latent factors (drivers) in the study area.

5.1 ABSTRACT

The loss of agricultural land due to urban sprawl has negative impacts on community lifestyles and green landscapes in peri-urban areas. However, researchers have rarely investigated the complex decisions made by landowners and land managers about changes in farmland use on the fringes of cities. The author sent a postal questionnaire to 1,650 farm landowners and managers on the fringes of Adelaide, South Australia, to elicit information on internal and external factors driving their land-use decisions. Descriptive statistics were developed for farmers' demographics, farming life, industry and motivations in managing land while investigating 28 primary factors representing the socio-economic, environmental and institutional land-governance influences on land-use decisions. These factors consist of 16 influences on farm success (IFSs) and 12 influences on land-use change (ILUCs). Exploratory factor analysis (EFA) was used to identify the key drivers from the above primary factors. Results demonstrate the advantage of deriving latent factors to identify key drivers, as this process identifies a different set of factors with higher loadings than is provided by farmers' recommendations. These findings can improve the knowledge about farmers' land-use decision-making behaviour to model complex land-use transitions on city fringes.

5.2 INTRODUCTION

Peri-urban agricultural landscape transformation is a complex land-change phenomenon which significantly affects people and environmental systems on the edge of cities. Contemporary urban expansion is accelerating the rates of agricultural land transformation in many peri-urban areas around the world (Ives and Kendal, 2013, van der Zanden et al., 2016, Pandey and Seto, 2015, Wang and Qiu, 2017). The loss of agricultural land on these fringes has a significant impact on landscapes and their provision of agro-ecosystem services, in general, and food security, in particular, on urban–rural frontiers (Lee et al., 2015, d'Amour et al., 2016, Sali et al., 2016, Thebo et al., 2014, Malaque and Yokohari, 2007, Praweenwongwuthi et al., 2017). The land-management decisions of peri-urban farmers (primary decision makers) often lead to frequent land-use and land-cover changes (LULCC) in these landscapes. However, knowledge is lacking about the factors underlying this kind of decision making and their effects on these land-use transformations. This creates challenges for current land-use planning and sustainable land-management practices on the fringes of many cities (van der Zanden et al., Thebo et al., 2014, James, 2014).

Peri-urban landscapes are characterized by land-use heterogeneity (Zasada, 2011) and exhibit substantial spatial variations in the world's regions (Schneider and Woodcock, 2008, Galli et al., 2010, Moreira et al., 2016), while their land systems are highly commercialized and diversified in comparison with rural agricultural land systems (Galli et al., 2010). The agricultural land uses in these diverse landscapes are characterized by crops, livestock and multi-functional farming practices (Thebo et al., 2014, Zasada, 2011). Agricultural landowners in these land systems have diverse motivations ranging from profit maximization to environmental protection for managing their land uses (Ward et al., 2007). In addition, these farm management practices vary from individual heritage farming practices to larger farming investments with export markets (Liu et al., 2013, Thebo et al., 2014). Land-use research has identified the advantages of using empirical information which includes local landowners' motivations, behaviours and perspectives towards land-use decisions to explore complex land-transition processes (Kennedy and Veregin, 2016, Nualnoom et al., 2016, Murray-Rust et al., 2014, Bakker and van Doorn, 2009, Tesfahunegn et al., 2016, Liang et al., 2016, Solano et al., 2003).

As a human-dominant land system, peri-urban areas represent these geographies in terms of social, economic and environmental insights (Lee et al., 2015, Wu et al., 2011). Peri-urban farmers' land-use decisions have a significant impact on agricultural land transitions on city fringes (Burchfield and Gilligan, 2016). Yet many land-use researchers focus on exploring land-use transitions through geographic exploratory factors (Thapa and Murayama, 2008), rarely investigating landowners' land-use decision behaviours in terms of multi-dimensional factors, such as the social, economic, environmental and institutional regulations associated with these land transitions (Kennedy and Veregin, 2016, Nualnoom et al., 2016). Apart from these external factors, internal factors, such as landowners’ demographics, livelihood, expectations, motivations and perceptions on externalities have a substantial influence on their land-use decision behaviours (Adelaja et al., 2011, Lambin et al., 2003, Ward et al., 2007, Nguyen et al., 2017a, Nguyen et al., 2017b). Furthermore, Sengupta et al. (2000) highlighted that farmers use non-economic motivation for their land-use decisions. Land-use research has highlighted several primary factors that affect peri-urban farmers’ land-use decisions (Wu, 2008, Lambin et al., 2003). In varying situations, farmers have unique trade-offs between internalities and externalities (Nualnoom et al., 2016), represented by the combined effect of latent factors on their land-use decisions leading to complex land-use transitions (Parker et al., 2008b).

Statistical analysis is an effective tool that is capable of testing hypotheses, theoretical assumptions and relevant factor rankings for building models to understand complex processes (Hooten and Wikle, 2010). The integration of statistical analysis in land-use and land-cover change (LULCC) models improves the potential to identify relative factor effects under controlled environments (Munroe and Müller, 2007). In non-hierarchical systems, empirical information representing land-use decision factors provides investigative pathways for exploring farming land-use decision behaviours (Bakker and van Doorn, 2009, Nualnoom et al., 2016). In land system science (LSS), exploratory data analysis methods are used to reduce the number of factors, describing the underlying latent factors and classifying the variables into groups (Lesschen et al., 2005). Latent factor analysis (LFA) is an effective exploratory factor analytical method for reducing the series of factors to a manageable set of variables while describing underlying latent factors.

The current research investigates the social, economic and environmental factors underpinning the decision-making behaviour of peri-urban farmers—the primary land-use decision makers—for the farmland around the city of Adelaide in South Australia. The specific research questions are:

1. What are the characteristics of land-use decision makers in terms of participants’ age, education, income, production, farming life and motivations towards land management and land-use change?
2. What are the latent factors governing farmers’ land-use decisions in this land system?

5.3 MATERIALS AND METHODS

5.3.1 Study area

This study analyses the input of agricultural landowners in peri-urban landscapes within a 60-km radius of Adelaide's city centre (Figure 5.1 [a] [b]). Adelaide, with a population of 1.32 million (2016) is surrounded by agricultural landscapes to the north, south and, beyond the Hills Face Conservation zone, to the east. Rain-fed wheat, barley and canola; vineyards; olive orchards; irrigated vegetable cultivation; and pastures are the dominant agricultural land uses, and the land can be divided into zones of dryland (rain-fed) (DL) cultivation, horticultural land (HL) and grazing (LL) practices (Figure 5.1 [a] [b]), Wadduwage et al., 2017). Agricultural land parcels adjacent to the city vary from approximately 0.5–3000 ha. When South Australia was colonized from 1836 onwards, Adelaide was initially surrounded by large agricultural land parcels: over time, these have progressively increased through farm amalgamations and fragmentation as land has been incorporated into the city's urban fabric with the expansion of the city's peripheries (Figure 5.1 [a] [b]); Williams, 1966, Williams, 2017).

Economic expansion has accelerated agricultural intensification and land fragmentation in these spatially heterogeneous landscapes (Bunker and Houston, 2003, Wadduwage et al., 2017, Ford, 1997). This heterogeneity extends to returns on investments (ROIs): business-oriented horticulturalists, vignerons and irrigated vegetable farmers receive higher economic returns per unit of land area (Houston, 2003) than either heritage or hobby farmers who are mainly engaged with livestock and dryland cultivation. Land-management practices vary in response to markets and industries: different farms are also linked, for example, wine-overseas, organic, cereals-export, premium food and wine.

Farmers in these areas have inherited diverse cultural and farming practices (Mediterranean, Asian) since the generation of migrant settlers that first came to Adelaide. The age of individual farmers, the nature of their unique farm businesses, and their individual preferences in terms of land management create internal influences in land-management decision making. Farmers in these areas are exposed to saline soils and experience extreme climatic conditions, such as storms and droughts, with a limited annual mean precipitation of 600–820mm (Australian Bureau of Meteorology, 2017). The limited accessibility of water in these areas has increased the demand for water resource management in State government land-governance policies (Bunker and Houston, 2003). In addition to these socio-economic and environmental externalities, local government land administration policies—restrictions on land uses, land subdivisions and increasing council rates—have had a substantial institutional impact on farmers' land-use decisions. In 2012, the South Australian Government introduced a road map for city development (*The 30-Year Plan for Greater*

Adelaide) highlighting land-use allocations in peri-urban areas for urban development and primary production (Planning SA, 2010). Overall, Adelaide's peri-urban farmers have their own trade-offs for making land-use decisions on their farm businesses, under the influence of both external and internal factors.

a) b)

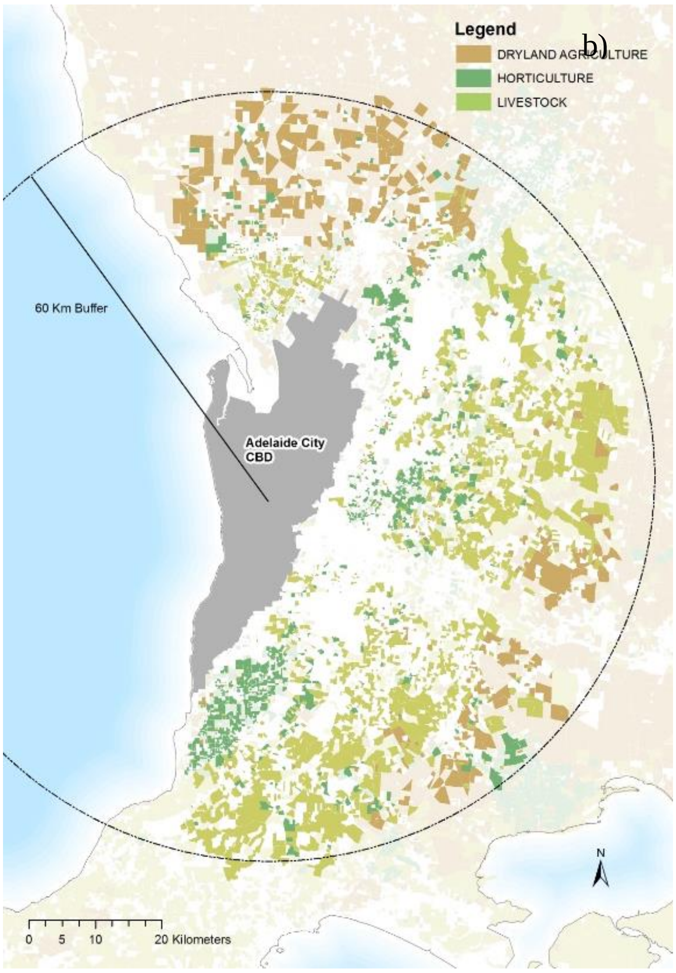


Figure 5.1: a) Agricultural land use around the Adelaide city fringes categorized into three classes; and b) Farmers and other land managers sent questionnaires within 60 km of Adelaide CBD in three sectors

Note: For (a), see Wadduwage et al. (2017)

Photograph has been removed due to copyright restrictions

Urban sprawl threat to food bowls

a) Vegetable grower from Adelaide south-eastern city fringes – Mt Barker Brussels sprouts grower Leigh Samwell. A freeway exit loop is planned for part of his farm. *The Advertiser* (2011)

Photograph has been removed due to copyright restrictions

Lettuce use foreign skills to grow

b) Hydroponic farmer from northern Adelaide fringes close to the built-up area – South Australian grower Dino Musolino says the government fails to understand the skills needed to operate a hydroponic farm. *The Australian* (2013)

Figure 5.2: Local newspaper articles reflecting Adelaide peri-urban farmers' concerns on urban sprawl and labour on farms
Note: a) Vegetable grower from Adelaide's south-eastern fringes, b) Hydroponic farmer from Adelaide's northern fringes close to the built-up area.

5.3.2 Primary data collection and analysis

The questionnaire were designed to collect information on the farmers' age, education, income, production, farming life and land-management motivations together with their land-use change preferences (Nulty, 2008) (Appendix C5). Their farming heritage, farming experience and their anticipation regarding their farms' continuation were the key focus areas for the farming life, while three land-management motivations were provided for their ranking: (i) making good profit from the farm; (ii) caring for the farm environment; and (iii) being part of the local community, with these having been identified in agricultural land-use research (Vanclay, 2004, Hammond et al., 2017, Guillem et al., 2015). In addition, their perceptions were collected of 28 influences that may have affected either the success of their farming enterprises (Table 5.1) or their decisions about land use (Table 5.2) (DiStefano and Morgan, 2014). Questionnaires were completed by people aged over 18 years who were managing a property on the land in question. The questionnaire adhered to a comprehensive set of standard ethical considerations which apply to social science research and was approved as Project 7043 by Flinders University Social and Behavioural Research Ethics Committee (Appendix C5).

The questionnaire was posted to a sample of 1,650 agricultural landowners—550 farmers in the north, and 550 each in the east and south sectors (Figure 5.1[b])—from a population of over 5,200. The recipients were identified from trade directories while the land parcels corresponding to their farms were obtained from the State government's land cadastral database (Department of Planning, Transport and Infrastructure, 2016). The overall response rate was 11.1% (183 responses), including 16 incomplete responses which were omitted from analysis. All questionnaires were coded with a unique ID representing the property location, so all responses could be linked to a geographic location. ArcGIS software (ESRI Corp.) was used to identify information about the corresponding land parcels (land use and land-parcel size) to cross-validate participants' responses (Nulty, 2008). The 167 completed responses were used as a sample for statistical data analysis—north (40), east (60) and south (68)—from the Adelaide peri-urban areas, while representing a wider variety of farmers by production, land-use types and land-parcel sizes.

Exploratory data analysis techniques in SPSS (IBM SPSS Statistics, Version 24 [formerly Statistical Package for the Social Sciences]) were used to analyse: (i) how landowners managed their land; (ii) land-use preferences amongst landowners and their motivations behind changing land uses; and (iii) farming life. In line with the two research questions, these exploratory statistical data analysis techniques were used to examine the sampled population (Figure 5.3) as follows:

- Descriptive statistics and cross-tabulations were used to examine sample frequencies and dependencies among the prominent variables.

- Exploratory factor analysis (EFA) was used to identify the underlying factors which affect farm success or land-use change.

The EFA correlations or similarities between the variables were examined to discover the data patterns (Muthén and Muthén, 2009). A parallel analytical technique—polychoric correlation matrix (factor rotations in SPSS [see Appendix C5, 1])—was used to investigate participants' responses by targeting the number of components that cause higher variance instead of random selections represented by eigenvalues, which are widely used in the research community (O'Connor, 2000). The primary data (influences) used for this analysis (Tables 5.1 and 5.2) were considered as independent variables. Mplus statistical software was used to investigate latent factors and corresponding factor loadings using the parallel analytical technique, Geomin rotated loadings (Klinke et al., 2010), which is based on weighted least squares means and variance adjustments (WLSMV), and regarded as superior to the maximum likelihood (ML) method (Beauducel and Herzberg, 2006). Two sets of latent factors were derived from two sets of primary influences: IFS: 16f for farm success (Table 5.1) and ILUC: 12f for land-use changes (Table 5.2) (Appendix C5, 2, 4). This separation assisted in maintaining the ratio of the number of factors: number of observations at above 1:10 for this analysis (Arrindell and Van der Ende, 1985).

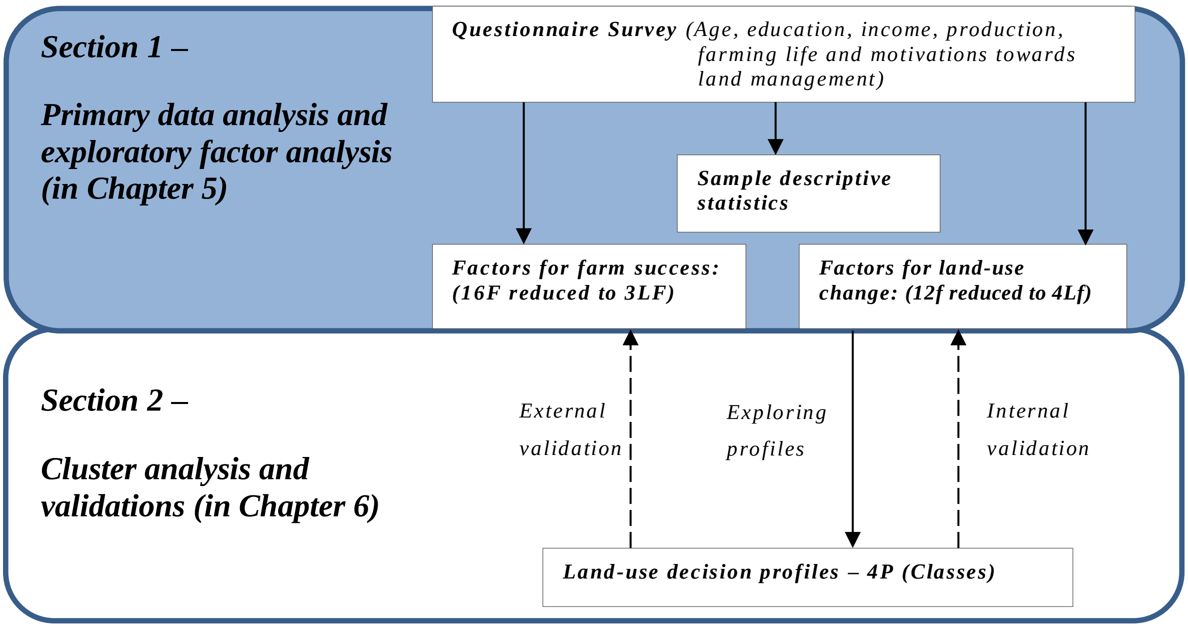


Figure 5.3: Conceptual framework of the statistical data analysis

Note: Section 1 consists of the primary data analysis (sample descriptive statistics) and EFA for factor reductions in Chapter 5. Section 2 consists of cluster analysis for profile identifications and validations in Chapter 6.

Table 5.1: Influence on farm success (IFS)

Factors (16F)
1. Labour costs
2. Farm maintenance costs
3. Investments in new technologies
4. Overall financial return on investment (ROI)
5. Access to finance
6. Crop insurance
7. Water accessibility
8. Soil fertility
9. Long-term climate changes
10. Severe climate events
11. Selection of crop/livestock type
12. Previous farming experience
13. Neighbouring farmers' crop/livestock choices
14. Farming heritage of your family
15. Having your own land
16. Being part of a cooperative farming group

Table 5.2: Influence on land-use change (ILUC)

Factors (12f)
1. Demand for your crop/livestock
2. Infrastructure development
3. Water price
4. High market value for your land
5. Other farmers willing to purchase land in your area
6. Costs of changing land use
7. Increasing water accessibility
8. Drought conditions
9. Decline in number of farmers from your ethnic group
10. Encroaching urbanization in your area
11. Government regulations on waste water or on farming practices
12. Government land-use planning regulations

5.4 RESULTS

5.4.1 Characteristics of farm landowners in sample

Descriptive statistics encompassing demography, livelihoods, farming experience, preferences, motivations and beliefs were used to identify the characteristics of the 167 farm landowners (139 male, 26 female) who completed the questionnaire. Eighty-two percent (82%) were born in Australia. Participants' ages ranged from 25 to over 75, with the most frequently occurring age band being 55–64 (Figure 5.4[a]). Over 89% had completed schooling to Year 10 as shown in Figure 5.4(b), while 73% had post-secondary qualifications. Many farmers participating in this survey resided in off-farm (Adelaide metropolitan) areas, while managing their farms on city fringes. People rearing livestock (37.2%) and owning vineyards (27.9%) comprised over half of the farmers surveyed (Figure 5.5[a]). One hundred and fifteen (115) participants sold their production at local markets, with almost equal numbers, 69 and 60, focused on national and export markets, respectively (Figure 5.5[b]).

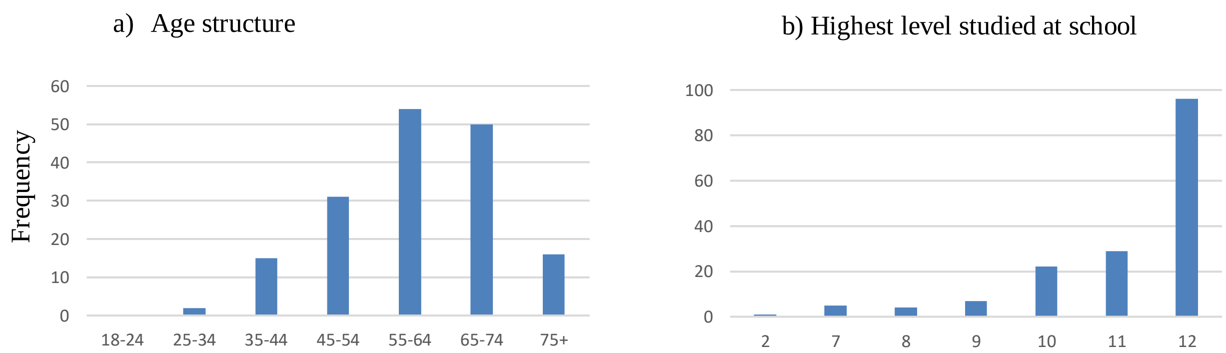


Figure 5.4: Sample's descriptive statistics: a) age structure by year ranges; and b) highest level studied at school by year

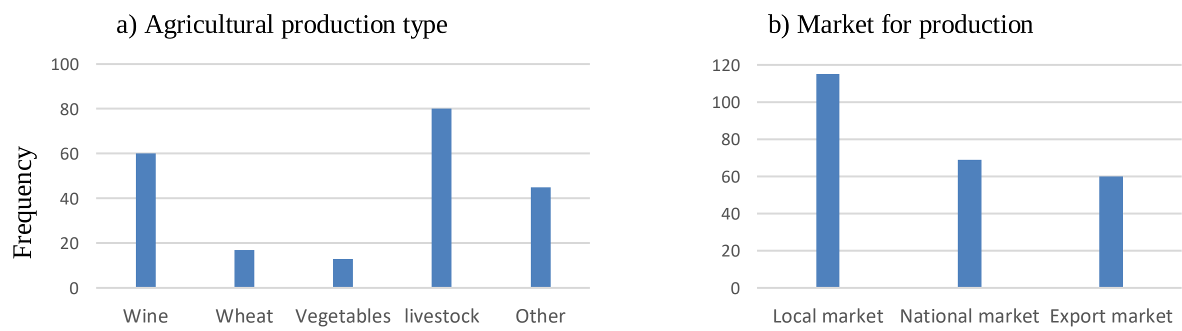


Figure 5.5: Sample's descriptive statistics: a) frequency of agricultural production type; and b) frequency of primary market for their production

The land-parcel sizes varied between 0.5 and 1,000 ha, with a median area of 18.5 ha. The two outliers of

2,000 and 3,000 ha represented large cereal farms at the outer limits of the 60-km buffer zone in the northern sector. Out of 167 participants, 140 confirmed that their production had single or multiple markets: the sample frequencies were single market (58); two markets (44); and three markets (38).

Half of the participants were from farming families. Their farming industry experience varied from one year to more than 70 years (mean=29), while the number of years they had lived in the area varied from one year to 84 years (mean=31). Participants described their farming industry engagement as full-time commercial (48 participants); part-time commercial (44); traditional (43); and hobby farmers (67). Unsurprisingly, given this breakdown, over 47% of participants confirmed that less than 25% of their household income was generated off farm. In total, 60% of participants were either "somewhat certain", "certain" or "very certain" about remaining in farming for the rest of their lives (Figure 5.6[a]), with "somewhat certain" being the most frequent response. Correspondingly, participants expected their engagement in farming in the future would be from one to 55 years (mean=13.5). In all, 57 participants (35%, n=162) stated that it was very unlikely that a family member would continue their farm business after their retirement (Figure 5.6[b]). In all, 41% (44, n=107) of participants who were aged over 54 years confirmed that it was very unlikely that their farm business would be continued by any of their family members (Table 5.4).

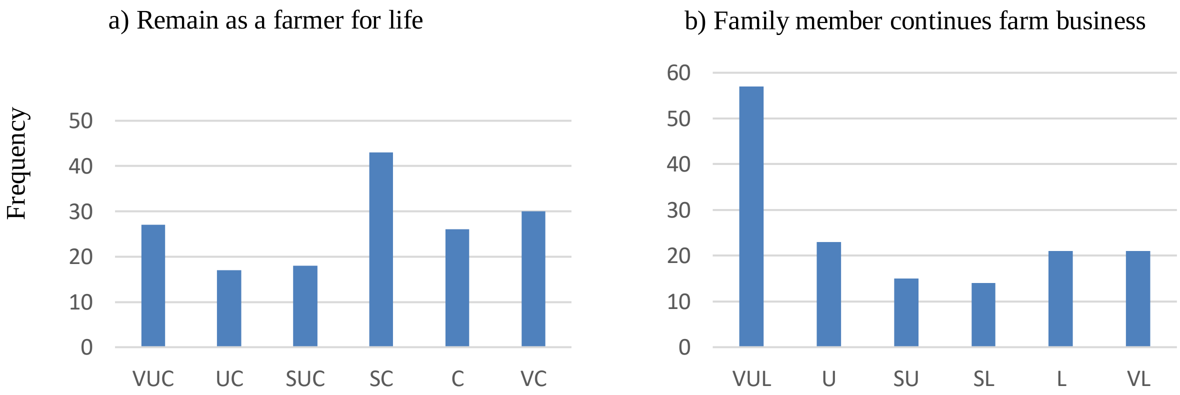


Figure 5.6: Descriptive statistics of the farming life

Notes: a) Remain as a farmer for life (VUC = very uncertain, UC = uncertain, SUC = somewhat uncertain, SC = somewhat certain, C = certain, VC = very certain); and b) Family member continues the farm business (VUL = very unlikely, U = unlikely, SU = somewhat unlikely, SL = somewhat likely, L = likely, VL = very likely)

Table 5.3: Cross-tabulation of observed count for: Age ranges vs. Family member continues the farm business

		Any of your family member will continue your farm business after you retire							Total
		NA	VUL	U	SU	SL	L	VL	
Age ranges	25-34	0	0	0	0	0	1	1	2
	35-44	1	4	0	1	3	4	2	15
	45-54	2	9	6	7	3	1	2	30
	55-64	3	21	7	3	2	11	6	53
	65-74	4	19	9	2	6	3	4	47
	75+	1	4	1	2	0	1	6	15
Total		11	57	23	15	14	21	21	162

Participants ranked the importance of the three land-management motivations provided, namely, "making good profit from the farm", "caring for the farm environment" and "being part of the local community" in a range of unimportant to very important (Figure 5.7). All three were ranked I=important or VI=very important by most landowners. Interestingly, VI=very important dominated the responses of "making good profit" from the farm and "caring for the farm environment", while receiving substantially lower numbers for "being part of the local community". In addition, only one participant considered "caring for the farm environment" as unimportant, though 20 and 8 participants considered "making a profit" and "being part of the community" unimportant, respectively.

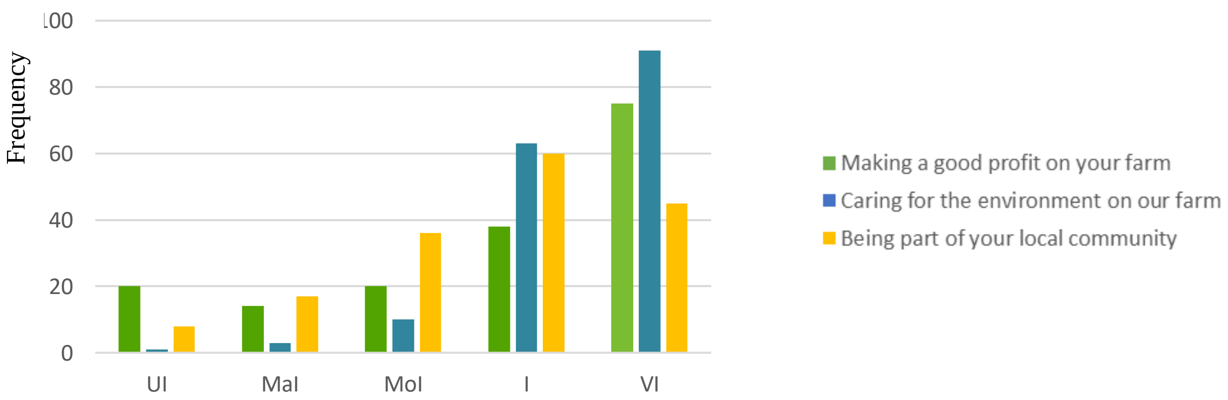


Figure 5.7: Land management motivations

Note: The motivations: "making good profit from the farm", "caring for the farm environment" and "being part of the local community" were ranked as UI = unimportant, MaI = marginally important, MoI = moderately important, I = important and VI = very important.

5.4.2 Land-use decisions

Using a 4-point Likert scale ("unlikely", "somewhat unlikely", "somewhat likely" and "likely"), participants were asked to describe which of the following land-use decisions they would make—change farming practices, sell the whole farm, subdivide and sell a part of their land, or lease the land—if, in a hypothetical situation, their farming business was unsuccessful.

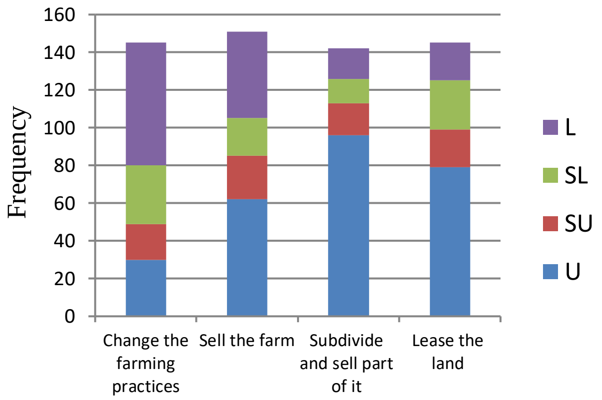


Figure 5.8: Land-use change decisions on the farm being unsuccessful
Note: U = unlikely, SU = somewhat unlikely, SL = somewhat likely and L = likely.

The highest preference was to retain their land by changing their farming practices, although selling the land was the second-most likely option (Figure 5.8). Few landowners opted to subdivide and sell part of their farms or to lease their land. This suggests a dichotomy between keepers and sellers, which is picked up in the following discussion. The relationships between the two most frequent responses—changing farming practices and selling the entire farm—and participants' ages are illustrated in Figures 5.9(a) and 5.9 (b). Overall, landowners of all ages exhibited a higher preference for changing farming practices rather than selling. The tendency to change farming practices was most marked in age groups from 34–44 and 55–64; however, among landowners older than 65, the gap between "likely to change" and "unlikely to change" narrowed (Figure 5.9[a]). Figure 5.9(b) shows that the relationship was more complicated between selling the farm and participants' age groups. Most of the younger landowners (25–44) and older landowners (> 55) were unlikely to sell their land, while those aged between 45 and 54 would most likely sell their entire farm. Despite these qualitative trends, χ^2 test results with likelihood ratios > α=0.05 demonstrated that no significant relationships existed between participants' age groups and their land-use decisions.

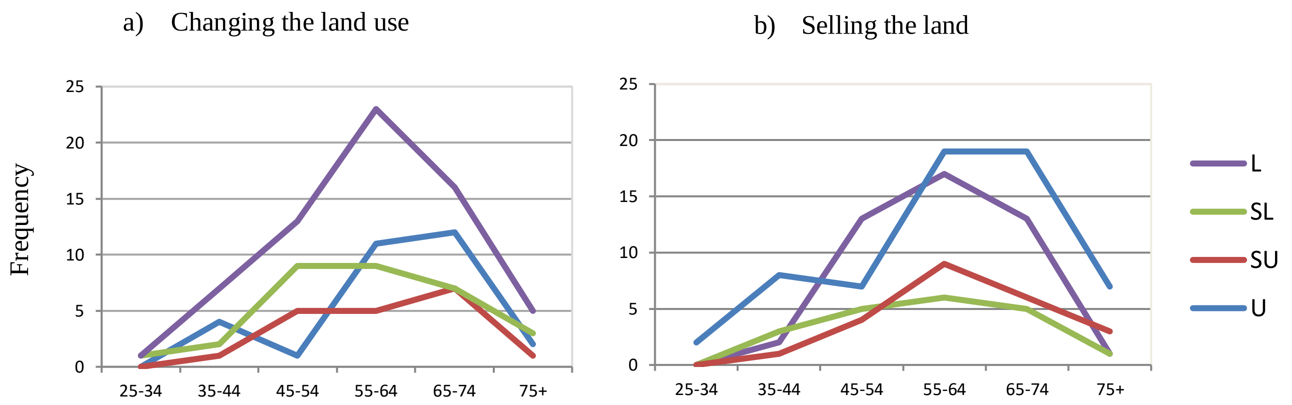


Figure 5.9: Participants' land-use decisions by age group

Note: a) Changing the land use, b) Selling the land: U = unlikely, SU = somewhat unlikely, SL = somewhat likely, L = likely.

Figure 5.10 illustrates the variations in participants' land-use decisions by production type. A significant number of participants in all four production types indicated a relatively high tendency to make land-use-change decisions if the farm were unsuccessful. Livestock owners and vineyard owners showed the least preference for changing land-use practices, while vegetable growers had the highest tendency to change. However, regardless of production type, landowners were more likely to change farming practices rather than sell their farms (Figure 5.10). Yet again, χ^2 tests with likelihood ratios > α=0.05 demonstrated that no significant direct relationships existed between participants' production types and their land-use decisions.

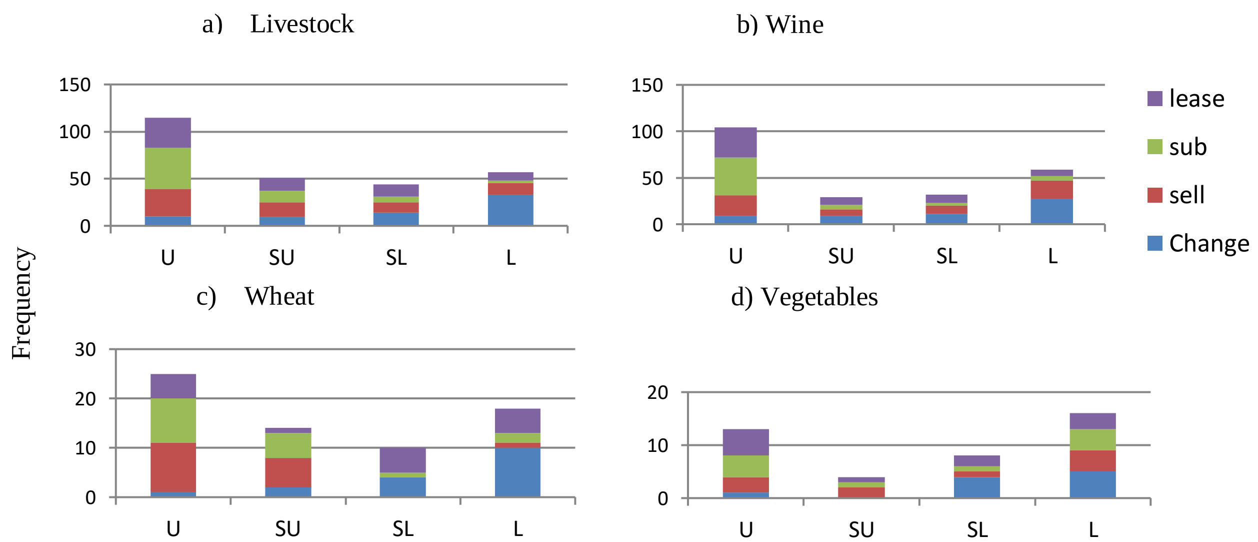


Figure 5.10: Land-use decisions by agricultural industry production type

Note: a) Livestock, b) Wine, c) Wheat, d) Vegetables: (U = unlikely, SU = somewhat unlikely, SL = somewhat likely, L = likely).

5.4.3 Factors with influence on farm success (IFS) and land-use change (LUC)

Participants were asked to describe the importance of 16 factors (IFS) in terms of success in their farm enterprise on a Likert scale ranging from "unimportant" (1) to "very important" (5). Mean scores were calculated and plotted on a radar diagram (Figure 5.11). Participants identified three economic factors ("farm maintenance costs" [F2], "overall financial return on investment" [ROI] [F4] and "having your own land" [F15]); environmental factors ("water accessibility" [F7], "soil fertility" [F8] and "long-term climate changes" [F9]); and industry-specific factors ("selection of crop/livestock type" [F11] and "previous farming experience" [F12]) as the most important in managing a successful farm.

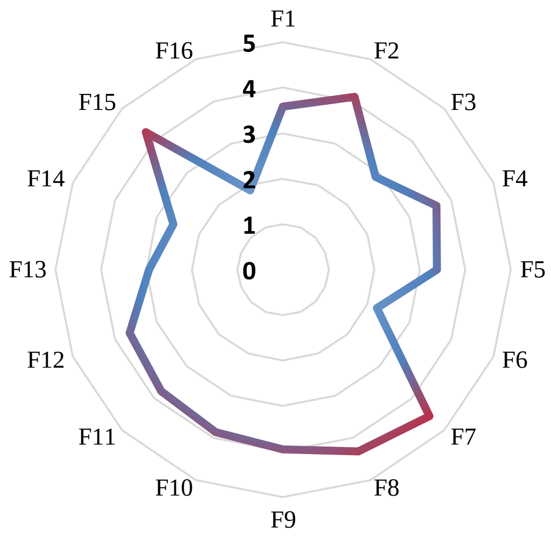


Figure 5.11: Mean responses for 16 factors (16F) considered for farm success

Note: 1 = unimportant, 2 = marginally important, 3 = moderately important, 4 = important, 5 = very important

Table 5.4: Influence on farm success (IFS)

Factors (16F)
F1. Labour costs
F2. Farm maintenance costs
F3. Investments in new technology
F4. Overall financial return on investment (ROI)
F5. Access to finance
F6. Crop insurance
F7. Water accessibility
F8. Soil fertility
F9. Long-term climate changes
F10. Severe climate events
F11. Selection of crop/livestock type
F12. Previous farming experience
F13. Neighbouring farmers' crop/livestock choices
F14. Farming heritage of the family
F15. Having your own land
F16. Being part of a cooperative farming group

Figure 5.11 illustrates the variations in participants' responses for each factor in its influence on farm success (IFS), within a common range of minimum ("unimportant" = 1) and maximum ("very important" = 5). The inter-quartile ranges (IQRs) in the box plots represent the clustered responses between Q1 and Q3 (Q1 = 25th percentile and Q3 = 75th percentile), indicating the precision of participants' responses for each factor. For example; variations in participants' responses for F2 ("farm maintenance costs") and F16 ("being part of a cooperative farming group") were limited to the two extreme ratings, "very important" (5) and "unimportant" (1), respectively. This is also shown in the comparison of returns on investment (ROIs) in F2 ("farm maintenance costs") and F7 ("water accessibility"). Although the IQRs of F2 and F7 are between "important" (4) and "very important" (5), most responses to F7 indicated the stronger rating of "very important" (5), unlike participants' responses to F2, with the F7 median greater than the median for F2.

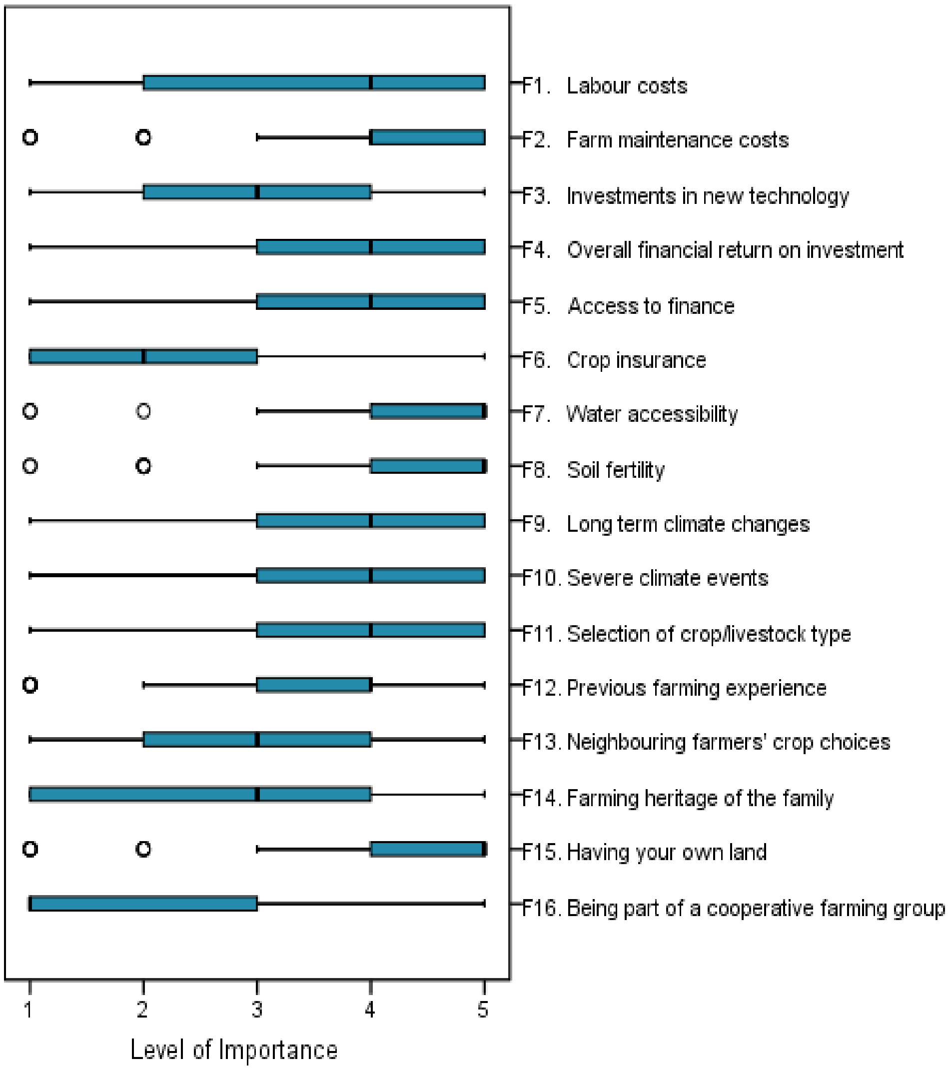


Figure 5.12: Factors influencing farm success with upper (Q3) and lower quartiles (Q1)

Note: Importance ranges from 1 = unimportant, 2 = marginally important, 3 = moderately important, 4 = important, 5 = Very Important.

Participants also rated the importance of 12 factors in influencing their decisions about land use if the farm were unsuccessful, again using a Likert scale ranging from “unimportant” (1) to “very important” (5), with these illustrated on a radar diagram (Figure 5.13). Two economic factors (“water price” [f3] and “high market value for your land” [f4]); two environmental factors (“increasing water accessibility” [f7] and “drought conditions” [f8]); and an institutional factor (“government land-use planning regulations” [f12]) were highly important in participants’ land-use decisions if the farm were unsuccessful.

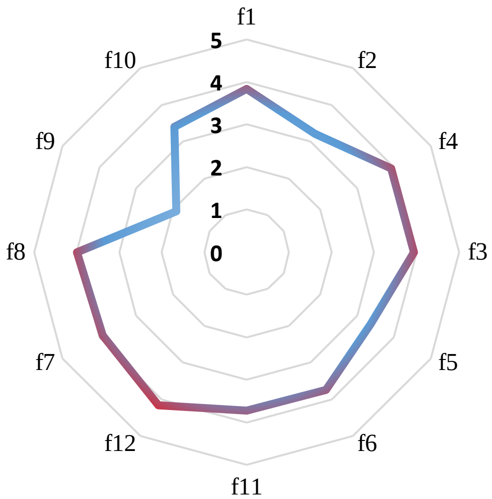


Figure 5.13: Mean responses for 12 factors considered important in land use decision-making if a farm is unsuccessful

Note: 1 = unimportant, 2 = marginally important, 3 = moderately important, 4 = important, 5 = very important

Table 5.5: Influence on land-use change (ILUC)

Factors (12f)
f1. Demand for your crop/livestock
f2. Infrastructure development
f3. Water price
f4. High market value for your land
f5. Other farmers willing to purchase land in your area
f6. Costs of changing land use
f7. Increasing water accessibility
f8. Drought conditions
f9. Decline in number of farmers from your ethnic group
f10. Encroaching urbanization in your area
f11. Government regulations on waste water or on farming practices.
f12.Government land-use planning regulations

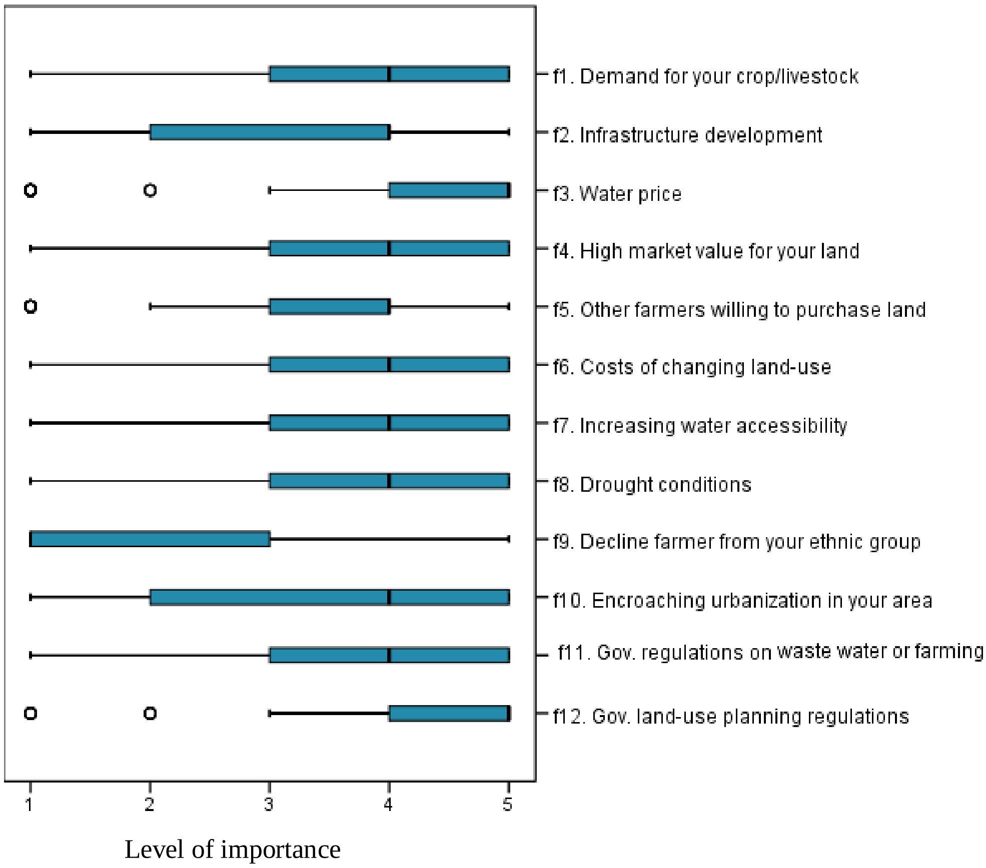


Figure 5.14: Factors influencing land-use change with upper (Q3) and lower quartiles (Q1)

Note: Importance ranges from 1 = unimportant, 2 = marginally important, 3 = moderately important, 4 = important, 5 = very important.

Figure 5.14 uses box plots to illustrate the variations in participants' responses for each factor influencing land-use change (ILUC) with responses ranging from minimum ("unimportant" [1]) to maximum ("very important" [5]). For example, in the comparison of f1 ("demand for crops/livestock") and f2 ("infrastructure development"), although both factors showed median responses in the "important" scale as (4) "likely", the more clustered responses in "very important" (5) for f1 showed that participants selected f1 over f2, for their land-use change decisions. Also, in the comparison of f3 ("water price") with f4 ("high market value for the land") shows that participants rated f3 as being more important than f4, as the higher number of responses were clustered in the 4–5 range on the "likely" scale which was further confirmed by the f3 median being greater than the f4 median.

5.4.4 Latent factor dimensions

Using EFA, three latent factors were identified from the 16 variables (factors) that are concerned with having an influence on farming enterprise success (IFS). These latent factors can be defined by considering their correlation patterns with the IFS's different factor groups (Table 5.6).

- Latent factor 1 (LF1) primarily has high factor loadings for economic factors (F1–F6), ranging from 0.56 for "farm maintenance costs" to 0.77 for "labour costs", "investments in new technology" and "overall financial return on investment". It also has moderate loadings for being "part of a cooperative farming group", the "farming heritage of the family" and the "selection of crop/livestock type". It has no loadings greater than 0.25 on any of the environmental factors.

- Latent factor 2 (LF2) has very high loadings on three of the four environmental factors— "water accessibility" (F7), "long-term climate changes" (F9) and "severe climate events" (F10)—as well as a moderate loading (0.48) on "soil fertility". It also has moderate loadings on "farm maintenance costs" (F2) and "neighbouring farmers' crop choices" (F13).

- Latent factor 3 (LF3) has high factor loadings on F12 ("previous farming experience") and F14 ("farming heritage of the family"), although neither are as high as the highest loadings for LF1 and LF2. Interestingly, in line with LF2, it also has moderate loadings on "soil fertility", "farm maintenance costs" and "farming heritage of the family".

Table 5.6: Factor reduction from 16F to 3LF with influence on farm success (IFS)

Factor rotation matrix (Geomin rotated loadings)

Latent Factor Classification				
LF1	LF2	LF3	F-ID	Factors (IFS)
0.77			F1.	Labour costs
0.77			F3.	Investments in new technology
0.77			F4.	Overall financial return on invest
0.71			F5.	Access to finance
0.66			F6.	Crop insurance
0.56	0.27		F2.	Farm maintenance costs
0.47			F16.	Being part of a cooperative farming
0.45			F11.	Selection of crop/livestock type
	0.87		F9.	Long term climate changes
	0.82		F10.	Severe climate events
	0.76		F7.	Water accessibility
	0.48	0.30	F8.	Soil fertility
0.30		0.62	F14.	Farming heritage of the family
		0.60	F12.	Previous farming experience
	0.45	0.34	F13.	Neighbouring farmers' crop/livestoc
	0.29	0.27	F15.	Having your own land

Note: Factor loadings < 0.25 are suppressed

Table 5.7: Factor reduction from 12f to 4Lf with influence on land-use change (ILUC)

Factor rotation matrix (Geomin rotated loadings)

Latent Factor Classification					
Lf 1	*Lf 2*	*Lf 3*	*Lf 4*	F-ID	Factors (ILUC)
0.99				f7.	Increasing water accessibility
0.67				f2.	Infrastructure development
0.62				f3.	Water price
	0.99			f4.	High market value for your land
	0.77			f5.	Other farmers willing to purchase land
0.30			0.74	f11.	Government regulations on waste wate
		0.36	0.61	f12.	Government land-use planning regulatio
		0.84		f8.	Drought conditions
		0.72		f10.	Encroaching urbanization in your area
	0.26	0.60		f6.	Costs of changing land-use
N/A	N/A	N/A	N/A	f1.	Demand for your crop/livestock
N/A	N/A	N/A	N/A	f9.	Decline farmer from your ethnic group

Note: Factor loadings < 0.25 are suppressed
N/A = not applicable for identifying the latent factors.

Four latent factors were identified from the 12 factors which participants considered in the context of land-use decision-making, under influence on land-use change (ILUC) (Table 5.7). These four factors are as follows:

- Latent factor 1 (Lf1) has very high factor loadings ranging from 0.62–0.99 on “infrastructure development” (f2), “water price” (f3) and “increasing water accessibility” (f7). It also has a moderate loading on “government regulations on waste water or farming practices” (f11), representing the high level of concerns of multi-functional farmers about water accessibility and infrastructure development in the area.

- Latent factor (Lf2) has two very high factor loadings of 0.77 for “other farmers willing to purchase land in the area” (f5) and 0.99 “high market value for your land” (f4), as well as a moderate value for the “costs of changing land use” (f6), representing factors that agricultural land sellers consider, such as land market prices and the availability of buyers in the area.

- Latent factor (Lf3) obtained a correlation factor loading greater than 0.6 for “costs of changing land use” (f6), “drought conditions” (f8) and “encroaching urbanization in the area” (f10), with these factors representing the mixed importance of land-change cost, droughts and urbanization that are of significant concern among heritage farmers with larger rain-fed cereal crops and grazing farmland.

- The fourth factor (Lf4) obtained high loadings on institutional factors (government regulations on waste water or farming practices (f11) and government land-use planning regulations (f12), respectively) reflecting the factors that are considered significant by farmers involved in intensive farming practices—hydroponic and poultry industries—in the study area.

a) Heritage vineyard

b) Commercial farmland

c) Intensive horticultural – hydroponic farm

d) Multi-functional farmland

Figure 5.15: Aerial imagery of identified major land-use categories

Note: a) Heritage; b) commercial; c) intensive; and d) multi-functional farming practices on the fringes of Adelaide.

5.5 DISCUSSION

5.5.1 Characteristics of peri-urban farmers

Most survey participants from the peri-urban areas of Adelaide were Australian-born males aged between 55 and 74 who had completed their secondary schooling. Even though farmers had competitive commercial interests on the fringes (Wu et al., 2011), they had a median of 30 years of farming experience and 26 years of farming history in their current farm areas, demonstrating their agricultural heritage and attachment to farming. Currently, however, a significant proportion (over 50%) of farmers in the areas around Adelaide do not reside on the land they are managing. The argument on heritage and attachment is supported by the fact that 47% of participants generate less than 25% of their household income from their farms. This might suggest that profitability is not a major motivation; however, 67% of the same participants indicated that making a good profit on one's farm was either "very important" or "important" to them (Figure 5.6).

The dominant types of land use in the sample—grazing land for livestock rearing and vineyards for wine production—accounted for 65% of farms. The wide range of land-parcel area (0.5–1000 ha) indicates the heterogeneous nature of land use in the peri-urban zone. The smaller median land-parcel size of 18.5 ha represented intensive vegetable cultivation and vineyards with higher economic returns than the more extensive grazing land and cereal fields. In addition, Figure 5.4(b)'s results confirmed the contribution of peri-urban farmers to the local food supply in Adelaide—feeding more than 1.3 million people—by the highest number of participants confirming that their production has a local market.

Prior land-use research (Zasada, 2011, Jat et al., 2017, Irwin and Bockstael, 2007, Brown and McCarty, 2018, Serra et al., 2017) has highlighted the heterogeneous characteristics of peri-urban land use with its intensive and specialised farming elements, and multi-functional agricultural practices and heritage farms contrasting strongly with rural agricultural landscapes. The findings of this research indicated the high presence of hobby farmers, multi-functional horticultural land uses and elderly heritage farmers, confirming these peri-urban agricultural land-use characteristics on Adelaide's fringes. Walcott et al. (2013) demonstrated that Australian agricultural production patterns are the result of complex human–environment land systems, which depend on underlying non-random processes and structural set-ups in different geographies. The overall reluctance showed by participants regarding changing land use or selling the land in a situation in which their farm was not financially viable (Figure 5.9, all four production types) demonstrates the unique structural and functional arrangements that are entangled with socio-economic factors and long-term heritage farming; for example, two well-known world winery heritage regions (the Barossa Valley and McLaren Vale) are located on the Adelaide city fringes. Furthermore, proven long-term living (0–84 years, mean = 31), farming industry experience (0 to > 70 years, mean = 29) and the mix of farming industry engagements (commercial, traditional and hobby farming) provide evidence of the unique nature of farming on the fringes of Adelaide.

Individual landowners' expectations and motivations are important in understanding the accumulated land-use decision-making behaviour on any one farm or land parcel (Bakker and van Doorn, 2009), with the sum of these aspects leading to complex land-transition processes on urban fringe landscapes. Participants in this research indicated their limited expectations for active farming (median of 10 years) but had a higher expectation of remaining in the farming business for the rest of their lives. This, in turn, would lead to increasing demand for labour, automation and agricultural intensification—for example, land leased for higher economic returns—to maintain the future sustainability of their farming business. Moreover, participants (particularly 44% of the participants who were aged over 54, as shown in Table 5.3) had a high level of uncertainty about the continuation of their farming business by any of their family members, thus exposing these land uses to the anticipated urban sprawl. Other factors considered in landowners' land-use decisions—lifestyle, health and family—further added to their uncertainty about the continuation of their farming business. This demonstrates the effect of farmers' land-use decisions on both local socio-economic transitions and accommodation of urban sprawl on the city fringes.

Of the three tested land-management motivations, the overall interest in "caring for the farm environment" (Figure 5.6) and the existence of different farmer groups (commercial, traditional and hobby) in the study area, complied with Vanclay's (2004) statements "profit is not the main driving forces of farmers" and "farmers are not all the same", respectively. In contrast, the lower level of responses by participants who believed in the importance of being in a local farming community showed that the statement "farming is a social practice" is invalid in peri-urban areas. Correspondingly, this point was reconfirmed by participants who ranked the factor "being part of a cooperative farming group" as unimportant as an influence on farm success (IFS) (Figure 5.10). This further describes the peri-urban farmers' individuality compared to that of rural farmers, as peri-urban farmers operate under the extremes of the urban economy and institutional regulations on land-management practices (Wu, 2008).

The land-use decision preferences of participants varied with their age and farming industry engagement in the hypothetical situation of a farm being unsuccessful. The overall higher preference for changing farming practices and remaining on the land indicates that these farmers were reluctant, as a first priority, to consider selling their land if their farm were not financially viable or if they were unable to continue farming due to personal circumstances. In addition, their responses reconfirm their attachment to farming and a rural lifestyle.

Although statistically no significant relationship exists between participants' age groups and their land-use decisions, landowners aged between 45 and 74 years tended to make more land-use change decisions, compared to younger and older farmers. This proves their limited expectation of continuing farming in the study area. The propensity for the older group to sell is most likely based on their desire to retire and raise capital for their retirement by selling their farms, especially as many of them already live elsewhere. For younger farmers, a wider range of reasons is possible, ranging from, for example, inheriting land they do not wish to farm, through to needing to raise capital for another enterprise, for a house purchase, or to attain some level of financial stability.

The resistance demonstrated by participants in all production types to selling their farmland as the first choice in this situation reconfirms the existence of heritage and hobby farmers. Although the Chi-square test confirmed the non-existence of any direct relationship between land-use decisions and representative production types, results indicate that vegetable landowners are more likely to make land-use change decisions if their farm is unsuccessful, compared to landowners with livestock or winery land uses on larger land parcels. The land-use characteristics of the intensive vegetable production group—with small land-parcel sizes and the associated lower land-use change cost—demonstrate the feasibility of the implementation of new land-management practices by this group compared to the other production groups.

5.5.2 Latent factors

In terms of the 16 IFS factors, participants identified farm maintenance cost, accessibility for natural resources and farm ownership as factors of higher importance for their land-use decisions (Figure 5.10), reflecting the key challenges experienced by farmers on the Adelaide city fringes. The rising cost for farm maintenance was due to competitive markets and highly regulated land-management practices on the fringes. As Adelaide is a city experiencing water scarcity and soil salinity, farmers in these areas have their farming opportunities confined by the limited accessibility of natural resources. Land ownership has a significant impact on farmers surviving in a long-term agri-business as they experience frequent income fluctuations under highly regulated planning restrictions.

The emergence of these three latent factors (LFs) through the EFA-3LF process (Table 5.6) demonstrates the importance of additional factors which participants did not rank under IFS as being the most significant. The economic aspects of LF1—labour cost, investment in new technology and overall return on investments (ROIs); the environmental aspects of LF2—long-term climate changes and severe climate events; and the social aspect of LF3—heritage farming experience—have a higher impact on farmers' land-use decisions. These socio-economic and environmental aspects are the key considerations for long-term sustainable farming on city fringes under conditions of an expanding economy with urban sprawl.

Based on participants' consideration of the 12 ILUC factors (Figure 5.12), the following factors were identified as needing higher consideration for their land-use decisions—rising property values and demand for natural resources—reflecting the common challenges experienced by landowners on the fringes. The higher mean values provided by participants for economic factors (water price) and environmental factors (water accessibility and droughts) demonstrate the effect of limited water availability for agricultural practices in Adelaide, as recorded by Bunker and Houston (2003) on water-regulated land-management practices in the greater Adelaide areas. This is an example of peri-urban farmers prioritising environmental and economic factors in their land-use decisions, as described by Wu et al. (2011). In addition, the higher values provided for government planning regulations on land-use management reflect participants' higher concern about these factors in their land-use decisions, compared to less regulated rural agricultural practices.

However, the four emergent latent classes (4Lf) (Table 5.7), based on ILUC, demonstrate the connections between the factor with higher loadings and peri-urban farmers' land-use decision priorities in Adelaide. Latent factor 1 (Lf1) showed the combined effect of the primary factors—demand for water, infrastructure development and land-governing regulations—mostly considered by landowners involved in large-scale farming businesses/multi-functional farming, such as wineries with cellar doors, in their land-use decisions. The factors of concern to farmers intending to sell their farmland were demonstrated by the latent factor 2 (Lf2) which showed the combined effect of higher property values and the availability of farm buyers in these areas (Zasada, 2011). The third latent factor (Lf3) showed prominent higher factor loadings for urban sprawl, drought conditions and costs of changing land use which are highly considered by heritage farmers engaged in long-term stable farming practices (Adelaja et al., 2011). The fourth latent factor (Lf4) showed the combined effect of local government regulations on waste water and land-use planning with higher factor loadings, which were of high concern to landowners with intensified vegetable garden practices in their land-use decisions in the proximity of built-up areas (Bunker and Houston, 2003).

From the 28 factors considered, the factor reduction techniques assisted in successfully identifying seven latent classes. The statistical representation of participants' preference for these factors in both situations (IFS and ILUC) did not recognize those factors that emerged through the latent factors as important. Overall, these facts demonstrate the importance of identifying latent factors in exploring the drivers behind farmers' decisions, as this process provides additional factors which have substantial impacts on land-use decisions on city fringes.

5.5.3 Opportunities and limitations

The derived connections between the factors (IFS and ILUC) and the latent factors are useful for underpinning the key drivers behind peri-urban farmers' land-use decisions that lead to complex land-transitional processes. Identification of these drivers and the associated primary factor influence have potential contributions to make in describing complex land-use changes on city fringes through the understanding gained on the relevant causes and effects. Furthermore, the knowledge of these key drivers is essential for addressing the methodological challenges in modelling complex land-use changes by improving the parameter inputs for justifiable results.

The main limitations of this approach are the limited response rate received from participants due to their off-farm residences and the competitive nature of farming businesses in these peri-urban areas that can also be experienced in similar geographies. The limited responses (the ratio of primary factors: number of responses < 1:10) can restrict the use of statistical analysis tools—for example, EFA—by violating the required preconditions. The multiple data-collection techniques—direct contact in market gatherings, corporate farmers' meetings and cultural events—proved to be useful in increasing the response rate. In terms of distributing the survey questionnaires, the use of email was less effective than postal surveys (Shih and Fan, 2009, Nulty, 2008).

5.6 CONCLUSION

In human-coupled land systems, land-use change decisions determine the complex land transitions leading to land-use change and cover change (LULCC) in these landscapes (Parker et al., 2008b). This study focuses on peri-urban farmers' land-use decisions on city peripheries predominantly surrounded by farmland under the pressure of urban sprawl. Limited understanding of key drivers behind farmers' land-use decisions, with both internal and external insights, forms the methodological challenges in conceptualising the land-use change model simulations under unclear parameter inputs.

This study's statistical investigations confirm the non-significant relationships between landowners' land-use decisions and their age group or production type, while providing descriptive statistics to demonstrate the general characteristics of farmers on the Adelaide city fringes. The factor dimension reduction methods used in this exploratory approach show the possibility of identifying latent factors in terms of the primary influencing factors (IFS and ILUC) considered for the analysis. The connections developed between the primary influencing factors and the derived latent factors are important in identifying the key drivers behind farmers' land-use decisions on city fringes.

Therefore, this study demonstrates the advantage of using EFA for improving knowledge of the factors which drive farmers' land-use decisions, while ensuring justifiable inputs for farmers' land-use decision behaviours in modelling complex agricultural transitions. Despite the current study being restricted to Adelaide, this approach can be used in different geographies by identifying the associated primary factors that influence farmers' land-use decisions.

CHAPTER 6 – PERI-URBAN FARMERS' LAND-USE DECISION-MAKING PROFILES

As a continuation of the previous research approach in Chapter 5, this chapter investigates peri-urban farmers' land-use decision-making profiles and the associated decision rules for conceptualising the agent-centric models targeting the exploration of agricultural land-transition phenomena on the Adelaide city fringes. By considering the questionnaire survey responses (in Chapter 5) as the source data, this chapter statistically investigates the suitable number of decision-making profiles and decision behaviours in connection with the previously identified latent factors and the primary influences on land-use change decisions.

Contributions to knowledge:

- Derived land-use decision-making profiles in terms of farmers' land-management motivations.
- Identified the profiles' land-change decision behaviours in terms of their properties and the decision rules for complex land-system modelling.

6.1 ABSTRACT

The decisions of peri-urban farmers about land use make substantial contributions to urban sprawl in farming landscapes on the fringes of cities. These decisions are fundamental in developing agent-centric bottom-up models of complex land transitions in peri-urban geographies. Therefore, the identification of target agents and their decision-making behaviours is a key methodological challenge for developing agent-based model (ABM) simulations of peri-urban farmland transitions. In this study, non-hierarchical cluster analysis was used to identify and characterize the profiles of groups of farmers through their anticipated land-use decision behaviours based on an analysis of farmers on the urban fringes of Adelaide. The profiles derived were validated internally and externally using the primary land-change factors selected by survey participants. Moreover, empirical justifications were used to cross-reference the profile properties and decision behaviours. The four farming profiles derived were: P1 = heritage farming interest; P2 = commercial farming interest; P3 = selling the farmland; and P4 = multi-functional/hobby farming interest. A multiple cluster comparison post hoc test provided evidence of a significant difference in characteristics of the P3 profile (P3)—selling the farm—compared to the other profiles, with this having the highest impact on peri-urban land transitions. In this approach, the results demonstrate the possibility of identifying land-use decision-making profiles by farmers' motivations toward land management, instead of their demography, production

type or financial status that have generally been used in land-change studies. This method can be replicated in different peri-urban geographies for exploring land-use decision-making profiles based on farmers' response patterns.

6.2 INTRODUCTION

Contemporary land systems research identifies the human and bio-physical processes that drive land-change processes in diverse socio-economic, cultural and environmental situations (Lambin et al., 2000, Lambin et al., 2003, Parker et al., 2008b, Liu et al., 2007). Agent-based models (ABMs), which are often represented as agent-centric land-use models in land-change science, capture human decisions through the definition of the agents and their decision-making behaviours (Sterman, 1989). These models have methodological advances over conventional land-change models, as improvements are incorporated in the empirical, behavioural and heuristic knowledge of the modelled land systems (Axelrod and Tesfatsion, 2006, Filatova et al., 2013). The definition of target agents' areas of autonomy (their properties and functions, as well as the decision rules) are important in developing ABMs, as this oversees agents' interactions and decision behaviours in the associated model environments (Parker et al., 2003). In terms of modelling the behaviour of a target group, improved knowledge about the heterogeneity of agents in the group, that is, differences between agents in terms of their properties and decision rules, are key to making assumptions when developing ABMs (Kaye-Blake et al., 2010). However, the capture of these data is challenging in peri-urban complex land systems, as farmers (agents) experience multi-dimensional influences ranging from socio-economic to psychological variables when making their land-use decisions.

Research on farmers' land-management decisions has shown that they have different priorities, understandings, issues and values (Vanclay, 2004, Wu, 2008) which interplay with their individual experiences and the opportunities provided by farmland resources (Aalders, 2008). Generally speaking, peri-urban farmers have specific land-use decision behaviours with multiple priorities for managing their farms (James, 2014, Bakker and van Doorn, 2009). Exploring farmers' land-use decision-making profiles and decision similarities—decision patterns—is important in understanding the rationalities behind farmers' land-change decision behaviours (Magliocca et al., 2013). However, the concerns behind farmers' land-use decisions are often unseen and difficult to identify due to privacy matters (Aalders, 2008).

Land-use change research has shown that primary factors, such as the socio-economic and environmental setting, and land-use regulations, strongly influence land-use decision making (Wu, 2008, Lambin et al., 2003). This includes the non-economic motivations for farmers' land-use decisions, such as maintaining the farm lifestyle, their past experience and observations of neighbouring farmers (Sengupta et al., 2000). In the peri-urban complex land systems, farmers' heterogeneous land-use decisions are not organized in a decision tree with a sequence of actions. In these non-hierarchical land systems, decision-pattern identification amongst land agents has two main methodological challenges: (i) identify the groups of farmers that make similar patterns of decisions—the decision-making profiles; and (ii) identify the decision-making behaviours of the derived profiles.

The land-use modelling experts recognize the importance of adapting the data, parameters and validation to the modelling processes to increase the user's confidence in the models. However, many land-use modelling applications have given less attention to model verification and validation than they might have done (van Vliet et al., 2016, Robinson, 1997), while few studies have acknowledged the practical difficulties of incorporating new data for validation (Mörtberg et al., 2013, Verburg et al., 2012). Many agent-centric land-change models have demonstrated the advantages of conducting internal and external validations through the use of empirical data (Caillou, 2012, Ligtenberg et al., 2010, Villamor et al., 2013). In particular, ABM research targeting the high process accuracy of system dynamics has emphasised the importance of empirical validation (Berger and Schreinemachers, 2006), as the validity of these models is contingent on the modelling outputs matching real-world processes (Brown et al., 2005b). As this study focused on identifying a set of representative land-use decision-making profiles for an anticipated ABM with higher process accuracies, the profile validations are important for identifying the agents' areas of autonomy in order to parameterise the agents in the land system. Validation through the data used for deriving the profiles analysed (internal validation) and validation through the data not used in deriving the profiles (external validation) were incorporated in this research.

The study focuses on the identification of peri-urban farmers' land-use decision-making profiles and their decision-making behaviour in the context of peri-urban land systems, to identify the agents' areas of autonomy in the anticipated ABM in order to parameterise the agents. The farmer—the land agent—is defined in this research as the individual or group of people who make the primary decisions on land use, including land managers, tenants or off-farm landowners.

The specific research objectives are to:

i) Identify the land-use decision-making profiles to represent the farming population.
ii) Identify the decision-making behaviour of these derived profiles
iii) Internal and external validation of the decision-making behaviours of these derived profiles.

In this approach, the decision-making profiles were investigated by survey participants' decision patterns, while exploring the decision-making behaviours through responses of the corresponding grouped participants. Statistical data analytical methods were used to identify the decision-making profiles and the decision-making behaviours while using the primary factors and the previously derived latent factor connections for internal and external validations.

6.3 METHODS

Responses to a survey questionnaire about farmers' land-use decisions completed by 167 farmers located on the fringes of Adelaide (Chapter 5) were used to derive the profiles of land-use decision-making behaviour. Figure 6.1, Section 2 'Cluster Analysis and Validations' mainly focuses on responses to participants' primary concerns (Influence of Farm Success [IFS] in Table 6.1 and Influence on Land-Use Change [ILUC] in Table 6.2), their motivations in managing their farms, and their preferred land-use decisions given the hypothetical situation that their farm became unsuccessful, that is, not financially viable for continuing the farming business (i.e. survey questionnaire questions 4, 8, 9 and 10 [Appendix C5]). Furthermore, the derived latent factors in Section 1 (Chapter 5, Table 5.6 'Factor reduction from 16F to 3LF' and Table 5.7 'Factor reduction from 12f to 4Lf') make connections between the primary factors and the identified decision preferences of the profiles.

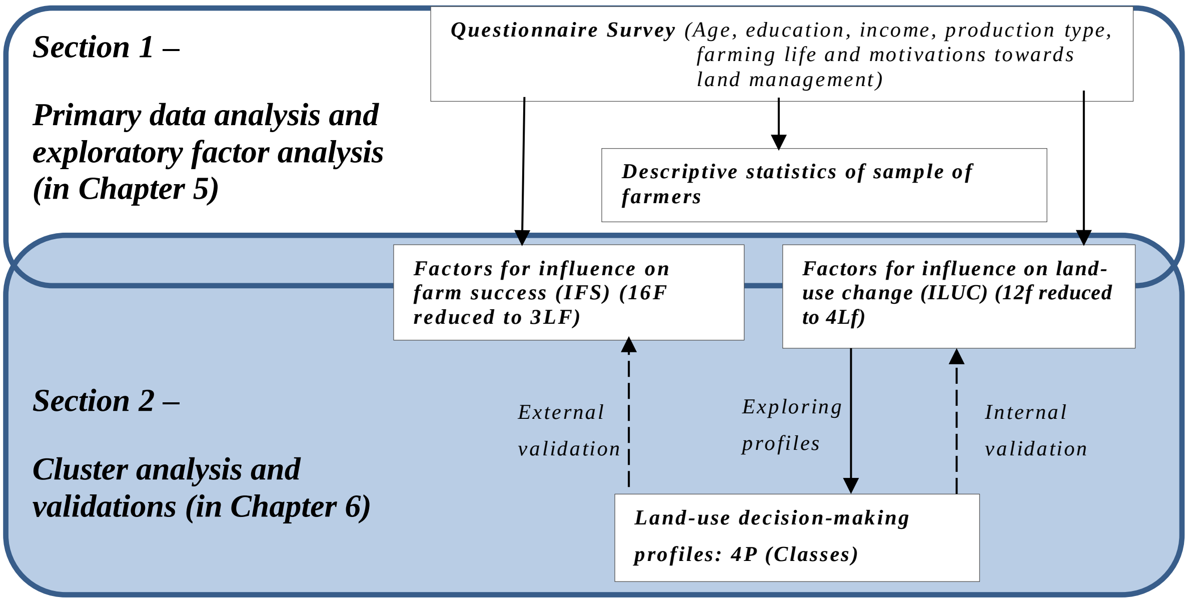


Figure 6.1: Conceptual framework of the statistical data analysis

Notes: Section 1: consists of primary data analysis (sample descriptive statistics) and EFA for factor reduction in Chapter 5. Section 2: consists of cluster analysis for profile identifications and validations in Chapter 6.

Table 6.1: Influence on farm success (IFS)

Factors (16F)
1. Labour costs
2. Farm maintenance costs
3. Investments in new technologies
4. Overall financial return on investment
5. Access to finance
6. Crop insurance
7. Water accessibility
8. Soil fertility
9. Long-term climate changes
10. Severe climate events
11. Selection of crop/livestock type
12. Previous farming experience
13. Neighbouring farmers' crop/livestock choices
14. Farming heritage of your family
15. Having your own land
16. Being part of a cooperative farming group

Table 6.2: Influence on land-use change (ILUC)

Factors (12f)
1. Demand for your crop/livestock
2. Infrastructure development
3. Water price
4. High market value for your land
5. Other farmers willing to purchase land in your area
6. Costs of changing land use
7. Increasing water accessibility
8. Drought conditions
9. Decline in number of farmers from your ethnic group
10. Encroaching urbanization in your area
11. Government regulations on waste water or on farming practices
12. Government land-use planning regulations

Exploratory cluster analysis (ECA) is a method of investigating patterns among participants—across a set of categorical variables—for grouping them into class variables (profiles/groups of participants) (Kaufman and Rousseeuw, 2009, Halkidi et al., 2001) with this process also categorical (Hadzi-Pavlovic, 2009). In land system science (LSS), ECA has been used to identify land-use decision-making profiles (farming groups) in complex land systems that consist of non-linear and non-hierarchical land-change processes (Bakker and van Doorn, 2009, Ward et al., 2007). The non-hierarchical ECA method—K-mean classification—enables the exploration of a similar group of participants in unstructured decision processes, while investigating the appropriate number of clusters (k). However, in non-hierarchical cluster analysis, class selection (number of classes=k) is a subjective decision that focuses on the objectives of the analysis (Nylund et al., 2007, Kaufman and Rousseeuw, 2009). The varying K numbers in ECA therefore open investigative pathways for exploring the most appropriate number of groups that have similar decision behaviours in these complex human-dominant land systems. Hence, this study utilized ECA to identify statistically similar decision-making profiles in the peri-urban zones of Adelaide.

Exploratory data analysis was used to examine the farmers' responses as follows.

- Firstly, the number of decision-making profiles of the farmers sampled (classes) was determined from the primary factors (ILUC in Table 6.2), using non-hierarchical cluster analysis (ECA) (K varies from 3–5, based on the key number of classes identified by cluster analysis).

- Secondly, the types of land-use decision-making behaviour for each class were determined by comparing the mean behaviour of the members of a class with their individual profiles (using post hoc test results [Appendix C6, 3]).

- Finally, internal validation (using F values in the analysis of variance [ANOVA]: k=3, k=4 and k=5 [Appendix C6, 1[a], 1[b])] and 1[c]) and external validation (using F values in ANOVA of the primary factors considered for farm success [Appendix C6, 9]) were undertaken to cross-reference the profile's behavioural concerns with the primary factors.

Non-hierarchical cluster analysis (in SPSS, version 24) was used to derive the profile classes. In using this technique, it is assumed that no hierarchical organization of the variables exists (i.e., peri-urban farmers' land-use decisions are not structured or following a sequence of actions) in the studied land system. A one-way ANOVA was used to identify class memberships (farming participants grouped into classes) and the land-use decision-making behaviours of these classes (profiles, see Appendix C6, 2). Three sets of cluster options (where k=3, k=4 and k=5) were investigated to identify the highest suitable cluster grouping, demonstrating the connections with the derived latent factors (in Chapter 5). In these three options, the factor variabilities of ILUC were examined by the F values derived in ANOVA (Appendix C6, 1[a], 1[b] and 1[c]).

The primary factors in Table 6.2 (ILUC), utilized to derive the profile classes, were used to internally validate the derived class behaviours. External validation was accomplished by using the factors concerned with farm success (IFS) in Table 6.1.

6.4 RESULTS

6.4.1 Land-use decision-making profiles and internal validation

Figure 6.2(a) shows the number of participants in each classified option that was used to identify the decision-making profiles. The classified classes, C3, C4 and C5, are where k is equal to 3, 4 and 5, respectively. The variations in participant responses, calculated by ANOVA for each classification, for each of the primary factors are shown in Figure 6.2(b). The F values derived in ANOVA (Appendix C6, 1[a], 1[b] and 1[c]) were only used to describe the variability of the primary factors, as the clusters had already been selected to maximize the differences between cases. In this analysis, the higher the F means, the higher the response variability of the class participants (Figure 6.2[b]). The factor f3 (water price) in the C3 class shows a significantly higher level of response variations compared to the other two classes, C4 and C5. The factor f9 ("decline in the number of farmers from a participant's ethnic group") in C5 displays the highest level of response variations, compared to the other two least-response variations observed in classified classes C3 and C4.

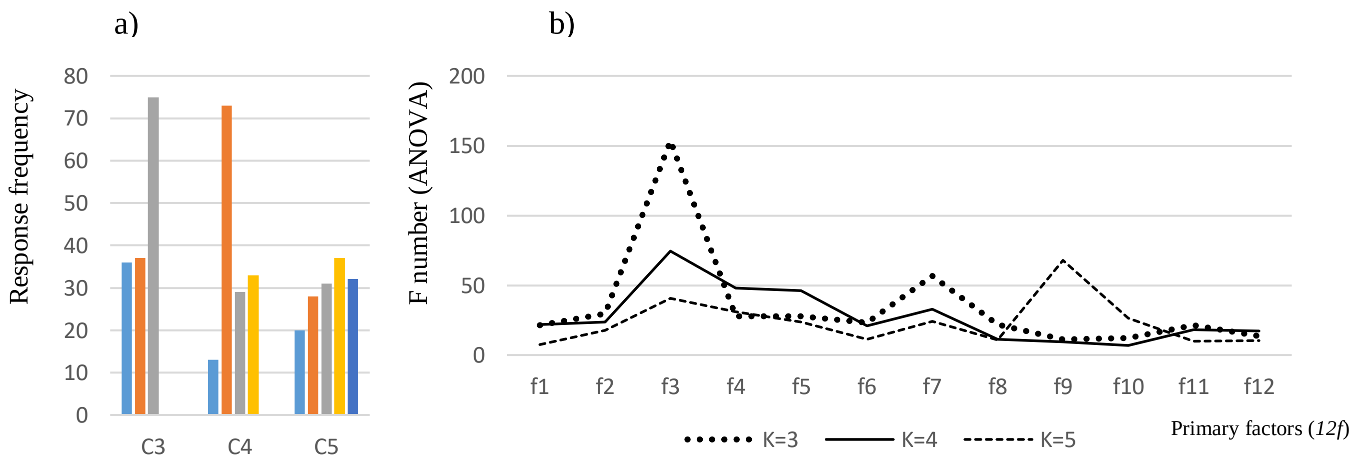


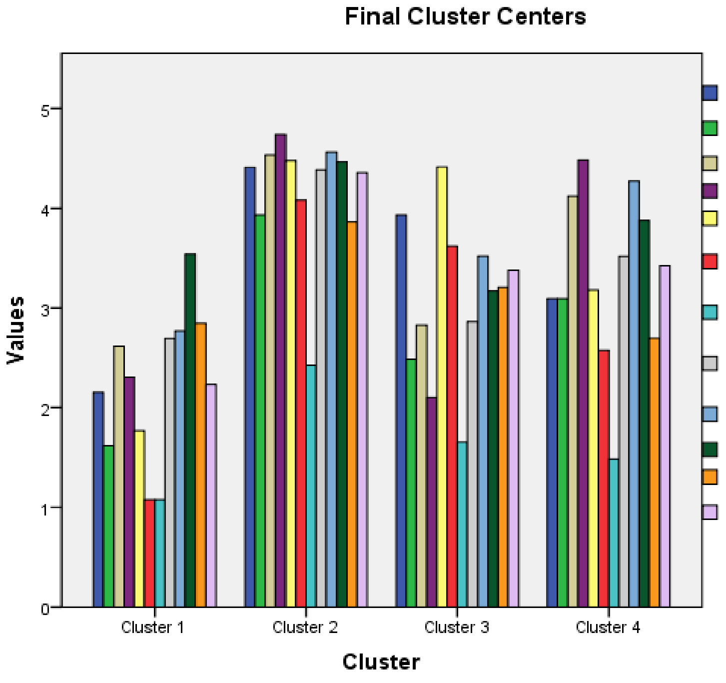
Figure 6.2: Cluster group frequencies and F values derived for each factor

Notes: a) Cluster group frequencies of the three classifications (C3 [k=3]; C4 [k=4] and C5 [k=5]) demonstrate the number of farmers classified into classes in each option; and b) F values derived for each factor (from the ANOVA), carried out on each classification demonstrate class members' response variability for each ILUC factor. The higher the F means, the higher the response variability of class members.

The 12 factors (means of responses) associated with each classification were mapped against each final cluster centre (mean value of the 12 factors, see Appendix C6 1[a], 1[b] and 1[c]). The final cluster centres of the C4 classification (in Figure 6.3) demonstrate the highest interpretability of the derived classes (profiles [4Ps]) in terms of the corresponding factors (12f). As an example, participants in Cluster 1 (Class P1) showed heritage farming interest with higher concerns about the factors of drought conditions (f8) and urban sprawl (f10). Table 6.3 shows the highly correlated primary factors for all the derived clusters in C4 (P1, P2 P3 and P4). These points suggest that C4 was the most representative class for land-use decision-making profiles in the study area, as this class demonstrated higher interpretability of primary influences with less variances (Figure 6.2[b], k=4) in participants' responses.

The mapped correlations between the derived profiles (P1–P4), latent factors and the associated primary factors for land-use change decisions with higher factor loadings, as in Table 6.3, demonstrate the association of these profiles and the primary factor considerations of these grouped participants. The primary factors identified in each cluster group (profiles P1–P4) in Figure 6.3 display similar results with higher importance (average mean values). That is, in Cluster 1 (P1), the grouped participants had higher average mean values for the two primary factors, drought conditions (f8) and urban sprawl (f10), that were highly considered by heritage farmers (farmers on rain-fed land) with larger land parcels on the city fringes. Moreover, participants in Cluster 3 (P3) identified the primary factors of higher importance as being: high market value for land (f4); demand for your crop/livestock (f1) and availability of land buyers in the area (f5). In other words, these were the key concerns of highly profit-oriented landowners with less attachment to the farmland or environment. In addition, participants in Cluster 4 (P4) identified the primary factors of higher importance as water price (f3), water accessibility for farming (f7) and decline in the number of farmers from their ethnic group (f9). These factors were highly concerning to long-term farmland holders with commercial/hobby farming interests and who depended on irrigation for multi-functional farming practices on the fringes. These points further confirm the land management motivational characteristics of the derived classes (profiles) and their connections with latent factors and primary factors prioritised by the profiles for their land-use decisions when their farm's continuation was not viable.

Average mean values of responses



f1- Demand for your crop/livestock
f2- Infrastructure development in the area
f7- Increasing water accessibility
f3- Water price
f4- High market value for land
f5- Other farmers willing to purchase land
f9- Decline in the number of farmers from your ethnic group
f11- Government regulations on farming
f12- Government land-use planning
f8- Drought conditions
f10- Encroaching urbanization in the area
f6- Costs of changing land use

Clusters in C4 (k=4) classification

Figure 6.3: Frequencies of 12 constructive factors in four cluster groups

Table 6.3: Derived profile correlations with latent factors and correspondent primary factors

Cluster Group	Latent Factor Correspondents	Correlated Primary factors (with higher factor loading)
Cluster 1-(P1)	Lf3	Drought (f8), urban sprawl (f10)
Cluster 2-(P2)	Lf4	Gov. regulations on farming (f11), Gov. planning regulations (f12)
Cluster 3-(P3)	Lf2	High market value for land (f4), availability of land buyers (f5)
Cluster 4-(P4)	Lf1	Water accessibility for farming (f7), infrastructure development (f2)

Note: The derived profile correlations with latent factors and the correspondent primary factors (with higher factor loadings) concerned with land-use change decisions. P=profile

Figure 6.4 illustrates the spatial distribution of the derived cluster participants as land-use decision-making profiles (P1 = heritage farming interest; P2 = commercial interest; P3 = selling the farmland and P4 = multi-functional/hobby farming interest) in the study area. Although these land-use decision-making profiles were difficult to understand by land-use type, the land-management motivational differences were identified as follows.

P1 (Heritage interest):	Highly attached to the farmland and less profit-oriented.
P2 (Commercial interest):	Large-scale commercial farming businesses (profit-oriented but caring for the farm environment).
P3 (Selling interest):	Highly profit-oriented (intensive farming), less attachment to the farmland and less caring of the farm environment.
P4 (Multi-functional/ hobby farming interest)	Farmers with commercial interest/hobby farmers (less profit-oriented but highly caring for the farm environment).

These classified profiles (n=148, the clustered participants) were mapped based on the geographic location identified through a survey ID that referred to the physical location of participants' farms. This showed the heterogeneous distribution of this sample of profiles in these peri-urban landscapes.

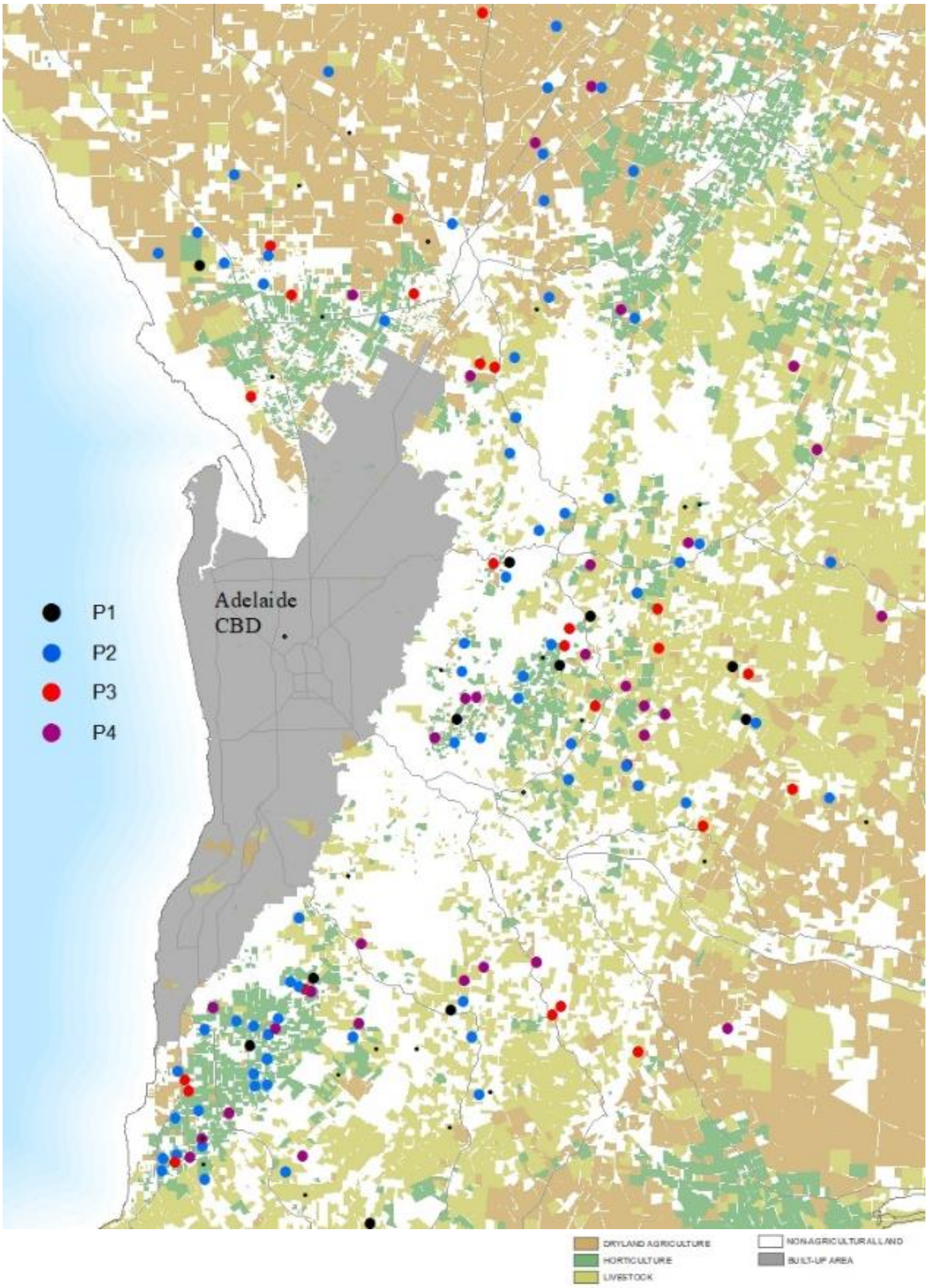


Figure 6.4: Land-use decision-making profile overlay on land use on the Adelaide city fringes

Notes: Key profile interests identified if the farm is viewed as not viable: P1 = Heritage farming interest, P2 = Commercial interest; P3 = Selling the farmland and P4 = Multi-functional/hobby farming interest. The three land use types in the background are: horticultural land (HL) (green), dryland agriculture (DL) (brown) and livestock land (LL) (light green).

6.4.2 External validation of derived profiles

Figure 6.5 illustrates the mean response variation of each primary factor (Table 6.1 'Influence on farm success [IFS]') of the clustered profiles. All 16 primary factors were found to be statistically significant in the ANOVA test (Appendix C6, 9). However, the factors representing substantially higher F values where F is greater than 8—F1 ("labour cost"), F2 ("farm maintenance"), F3 ("investment in new technologies"), F4 ("return on investment [ROI]"), F5 ("demand for land") and F7 ("water accessibility")—with higher response variability between groups, demonstrate a higher possibility of contrasting responses between the derived profiles.

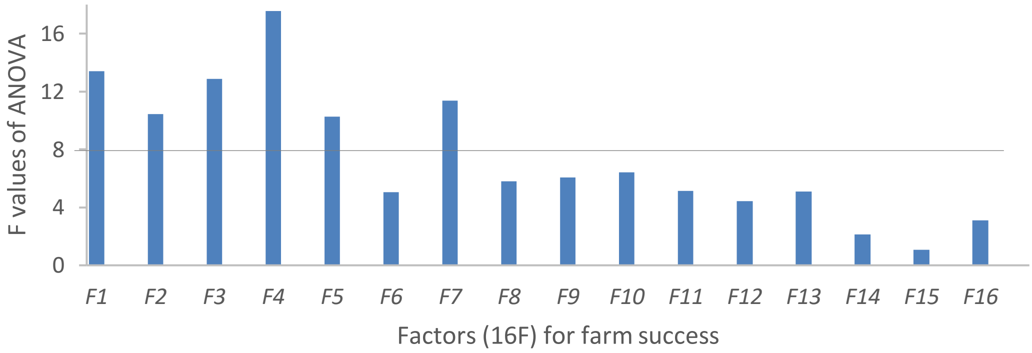


Figure 6.5: Primary factor response variability (for external validation of profiles)

6.4.3 Land-use change decision-making behaviours of profiles

Figure 6.6 shows the land-use change action preferences of the participants grouped into four land-use profiles (P1–P4). The mean preference variations of these land-use change decisions were in contrast with the land-use change decision behaviour of the derived land-use profiles. All four profiles (4Ps) exhibited a high preference for changing the land use in a situation where the farm was unsuccessful. Participants in P3 showed the highest preference for selling the land, with those in P2 the second highest and participants in P1 showed the least preference for giving up agricultural land-use practices in the study area. These results confirmed that the grouped participants in P3 had the highest interest in selling their land, with higher concerns about the "market value of their land" (f4) and the "availability of land buyers in their farming area" (f5), as shown in Table 6.3.

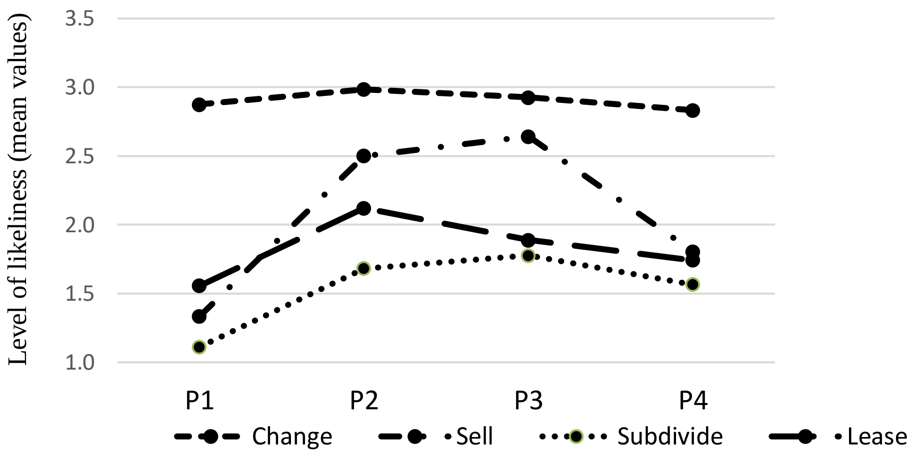


Figure 6.6: Mean responses of land-use decision-making profiles (4Ps)

Notes: P1 = heritage farming interest; P2 = commercial interest; P3 = Selling the farmland and P4 = Multi-functional/hobby farming interest). On the y-axis – increases likeliness: 1-Unlikely, 2-Somewhat Unlikely, 3-Somewhat likely, 4-Likely

6.4.4 Land-use decision-making profile contrasts

The mean comparison test—one-way ANOVA—confirms that the profile descriptive statistics—age group, gender, household income, farmer type and industry experience—demonstrate non-significant differences between the profiles—that is, the grouped participants—in the sample, with this recorded with non-significant *p*-values ($p > 0.05$) (Appendix C6, 8, 10, 11). Although the vegetable-cultivation land use showed a significantly lower *p*-value in ANOVA ($p = 0.024$) (Appendix C6, 5), the post hoc test results showed the difference between P2 and P3 to be non-significant ($p > 0.051$) with respect to the vegetable cultivation land use, as it was not less than $p = 0.05$ (Appendix C6, 3).

In the mean comparison tests, the lower *p*-values ($p < 0.05$) of land-management motivations, “making good profit from the farm” ($p = 0.001$) and “caring for the farm environment” (p = 0.008), showed a significant difference between these two land-use profile motivations while the third motivation “being part of the local community” ($p = 0.084$) was non-significant among the profiles (Appendix C6, 6).

Table 6.4 lists the results from the mean comparison test (ANOVA) by land-use change decisions within and between the profiles in order to explore the decision preferences. The significantly higher F value and the lower *p*-value ($p < 0.05$) in the option to sell the land (P3) confirmed that participants had a significantly higher preference (95% confidence interval [CI]) for selling the land in a situation where the farm was financially unsuccessful/it was not viable to continue the farming business. The mean responses of participants grouped in Profile 3 (Figure 6.6) demonstrated a significantly higher land-use change decision behaviour for the option of selling the land in contrast to the other profiles (P1, P2 and P4).

Table 6.4: ANOVA of land-use change decisions between different cluster groups

Option		Sum of Squares	*df*	Mean Squared	F	(*p*) Sig.
Change the farming practices	Between groups	0.503	3	0.168	.121	0.948
	Within groups	175.878	127	1.385		
	Total	176.382	130			
Sell the farm	Between groups	21.968	3	7.323	4.732	0.004
	Within groups	204.267	132	1.547		
	Total	226.235	135			
Subdivide and sell part of the farm	Between groups	3.303	3	1.101	0.993	0.398
	Within groups	138.573	125	1.109		
	Total	141.876	128			
Lease the land	Between groups	4.777	3	1.592	1.195	0.314
	Within groups	171.855	129	1.332		
	Total	176.632	132			

In addition, the current study used a multiple cluster comparison based on the Benferroni method as the post hoc test recorded a statistically significant mean difference between P1 and P3 and between P2 and P1 in terms of participants' preferences for the option of selling the farmland (Appendix C6, 4). In comparison to profiles P1, P2 and P4, the above results contrast the land-selling preferences of P3 which has the highest impact on the conversion of farmland into non-agricultural land-use practices in the study area.

6.5 DISCUSSION

The quantitative analytical methods used in this study address the methodological challenges faced when trying to identify land-use decision-making profiles of farmers on city fringes. In this exploratory approach, the primary factors affecting farmers' land-use decisions were mapped into clusters of farmers with statistically similar decision-making profiles in the peri-urban zones of Adelaide. This section discusses the study results and the methodological aspects of this approach.

6.5.3 Opportunities and limitations

The derived connections between the primary factors of land-use change, latent factors and land-use decision-making profiles are useful in deconstructing the complex land-transitional processes through their associated causes and effects. The latent factors redraw the linkages between the essential parameter arrangements—primary factor influences—and the probable land-use decision behaviours of the profiles to demonstrate the micro-scale land-use conversions which accumulate to macro-scale complex land-transitional processes on urban fringes (Kim and Batty, 2011). These cause-and-effect linkages are useful in bottom-to-top land-use change modelling approaches, such as ABM simulations constructed on agents' functional behaviours to explore the complex system process characteristics, such as self-organization and path dependencies (Rauws and De Roo, 2011, Millington, 2012b, Rindfuss et al., 2008), in dynamic environments. Although the current study is not solely designed for this purpose, the conceptual similarities of the multi-agent system principles demonstrate the possibility of using profile decision-making behaviour as an optimising agent in land-use modelling (Schreinemachers and Berger, 2006) while, in ABMs, the agents are parameterised.

The non-standard number selection for group classification (k value) in non-hierarchical cluster analysis is a major limitation for exploring the target decision-making profiles and the decision behaviours of the representative farming populations. The preliminary data investigation, expert knowledge integration and empirical validation are useful in selecting the representative number of profiles to avoid result diversion from the target research objectives. The internal validation technique used in this method is an effective way of selecting the required number of farming profiles based on the associated primary factor response variations of participants, with this having the potential to apply in different geographies.

6.5.1 Land-use decision-making profiles

Figure 6.2(a) illustrates the number of participants classified into classes at each clustering option: C3, C4 and C5. The uniquely identified primary factor response variabilities for the three classifications (where k=3, k=4 and k=5) in Figure 6.2(b) demonstrate the strengths and weaknesses of the classified group responses at each primary factor. The primary factors, f2 (“infrastructure development”), f8 (“drought conditions”) and F11(“government regulations on waste water or farming practices”), show strong responses with lower variability, while f3 (“water price”) and f9 (“decline in the number of farmers from a participant’s ethnic group”) demonstrate weaker responses with higher variability. After comparing the three clustering options, C4 was selected to identify the profiles as it demonstrated lower response variability overall for the important factors (shown in Figure 6.3) of “water price” (f3), “property values” (f4) and the “potential for selling land” (f5) which were highly considered by farmers in farmland ownership changes on the city fringes (Zasada, 2011). Furthermore, compared to the other two options, C4 demonstrated the highest degree of interpretability of the observed primary factor responses (Figure 6.3) and the associated latent factors (Table 6.3) for farmers’ land-use decisions in the study area. For example, C3 (P3) showed higher response frequencies for the factors, “market values” and “potential farmland buyers”, achieving higher factor loadings for Lf2, thus being of high concern to the farmland-selling profiles (in Figure 6.3). Moreover, C1 (P1) showed higher response frequencies for the factors, “drought conditions” and “urban sprawl”, both of which were associated with Lf3 thus being of high concern to heritage farmers on the Adelaide fringes. In the C4 classification, the profile P2 showed the highest number of similar participants (Figure 6.2(a), where P2 = 73, P4 = 33, P3 = 29 and P1 = 13), representing farmers engaged in commercial agri-businesses who had higher concerns about “government regulations on farming”, “land management”, “water price” and “water accessibility”. These connections were further confirmed by the correspondent latent factor Lf4 which showed similar concerns on land-use decisions (Table 6.3).

In summary, Table 6.3 shows the mapped farming profiles against the correspondent latent factors with higher factor loadings, constructing the linkages between the classified farming profiles and the latent factors used for their land-use decisions. These internal validations demonstrate the representative strengths of the correspondent latent factors against the classified land-use decision-making profiles. This enhances the interpretability of these land-use decision-making profiles in terms of their unique latent factor consideration patterns for land-use decisions in situations where the farm is financially unsuccessful/not viable due to personal circumstances (such as age, health and long-term debts).

Halkidi et al. (2001) stated the importance of cluster result validations and interpretations in the process of clustering data—quality assessment—for maintaining the validity of results. The external validation results shown in Figure 6.5 demonstrate higher primary factor variabilities (higher F numbers) for the factors with higher factor loadings for the correspondent latent factors derived in Chapter 5 (economic [LF1], environmental [LF2] and social [LF3] in terms of the primary factors [IFS] considered for their farm success). The correspondent latent factors were associated with “economic consideration” and “water accessibility” which were the prominent issues experienced by farmers in the study area. These cross-validated results—by external and internal examinations—justified the validity of the land-use decision-making profile classifications in terms of the latent factors that influenced the farmer profiles’ collective land-use decisions, but acted as hidden land-change drivers.

The spatial distribution of the profiles overlaid on the land-use classifications (Figure 6.4) demonstrates the profile of agri-industry involvement in the spatial context. Although the classified profiles were restricted to the clustered sample of participants (n = 148), this distribution shows the area-specific connection between decision-making profiles and associated land-use types. The derived profile P2 with its commercial agri-business interests shows a substantial engagement with the horticultural land-use types in Adelaide’s southern McLaren Vale wine-producing areas and vegetable gardens beyond the eastern hilly conservation zone. The decision-making profile participants with higher interest in selling their farmland (P3) showed a mix of land-use representation and were mostly located in the rural areas of the Adelaide fringes. The higher number of P3 profile participants in the eastern livestock lands—landscapes beyond the Adelaide Hills conservation areas—demonstrates the higher land vulnerability risk of livestock agri-businesses in these areas to accommodating the urban sprawl. Most P4 profile participants had higher interests in hobby farming and multi-functional agri-businesses and were located closer to built-up areas, while the limited number of P1 profile participants—represented by heritage farmers—were dispersed around the study area.

6.5.2 Land use decision-making behaviours of profiles

Vanclay (2004) described farmers' land-management practices based on motivational factors. The current study results confirm this point, indicating that classified land-use decision-making profiles identify a range of motivations ranging from agricultural land preservation to selling the land, in terms of their decision making. The land-use decision-making profile P3 shows the highest preference for selling the land, while the profile P1 (heritage farming interest) shows the least motivation for changing the land's ownership and/or subdividing. The mean response variations of the grouped participants in Figure 6.6 demonstrate the distinguishable land-use decision-making behaviours of the profiles: P1, P2, P3 and P4. The post hoc test results (Appendix C6, 4) contrasted the land-selling preferences among the profiles P1, P2 and P3, while the ANOVA test results confirmed a significantly higher preference for selling the land by the P3 profile in a situation where the farm was unsuccessful (Table 6.4). The above points reveal a range of profile preferences on land-use decision-making behaviours in the order of least to most likely to sell their land—P1 < P4 < P2 < P3—where the P3 profile (land sellers) has the highest impact on the extinction of peri-urban agricultural land due to urban sprawl (Hussain and Hanisch, 2013).

The two extremes of the profiles, P3 (selling the farmland) and P1 (heritage farming), demonstrate the contrast through the motivational differences of farmers' land-use decision-making behaviour in profit maximization and their attachment to the land, respectively. Overall, the results confirm Ajzen's (1991) statement of potential, using behavioural attitudes to predict the profiles' decision-making behaviours. Based on these points, the author argues that the farmers' land-management motivations should be prioritised, instead of using conventional biophysical or socio-economic measurements, when investigating peri-urban agricultural land transitional processes in terms of farmers' land-use decision-making behaviours.

In focusing on the research objectives, the investigative cluster selection process followed in ECA demonstrates the advantage of examining the response variability of primary factors for deriving land-use decision-making profiles. The post hoc test results improve the understanding of the linkages between the derived profiles and the associated land-use decision motivations while demonstrating the distinguishable differences between the profiles in terms of their land-management motivations. These points reveal the possibility of using sample inferences to statistically examine these land-use decision-making profiles and their land-use decision-making behaviour to represent the entire farming population in the study area.

6.6 CONCLUSION

Peri-urban farmers' land-use decision-making behaviour has a significant impact on farmland transitions on city fringes. The limited understanding of farmers' decision-making profiles—that is, a group of farmers who show similar decision-making patterns—and their decision-making behaviours are the major challenges experienced by land-use modellers when parameterising objects in their models to examine complex agricultural land transitional processes (Bakker and van Doorn, 2009).

The exploratory clustering techniques used on the analysis of participants' responses—the questionnaire survey data set—demonstrate the possibility of identifying farmers' land-use decision-making profiles and their decision-making behaviours in relation to their land-management motivations. Although this study focused on a set of primary factors relevant to Adelaide, the incorporation of the area's specific land-use influences and the study's empirical justifications can further improve the knowledge of peri-urban farmers' land-use decision-making profiles and decision-making behaviours in different geographies. Targeting the collection of detailed information on farmers' land-management motivational aspects in questionnaire surveys can improve the profile classifications. The derived land-use decision-making profiles and decision-making behaviours are used as information sources to make assumptions for parameterising the agents—spatial agents with properties and decision rules—in the anticipated ABM simulations (in Chapter 7) on the Adelaide city fringes.

CHAPTER 7 – ABM SIMULATIONS OF PERI-URBAN AGRICULTURAL LAND TRANSITIONS

This chapter explains the proposed agent-based model (ABM) in detail, including the agent profiles used, their properties and decision-making behaviours. It identifies land vulnerability variations as the model environment, which represents the combinational effects of socio-economic and biophysical aspects of peri-urban agricultural land transitions. The ABM utilizes empirically validated decision profiles and decision-making behaviours, as described in Chapter 6, to identify agents and decision rules, while using the Agricultural Land Vulnerability Index (ALVI) values found in Chapter 4 for creating the model environment. The spatially-explicit model environments represent three land-management policy scenarios for analysis. Finally, the ABM simulations evaluate peri-urban agricultural land-transition processes in terms of land-system feedback and land-transition trends based on farmers' land-change decision-making behaviours.

Contributions to knowledge:

- Developed an agent-based model (ABM) using the farmer decision-making profiles to investigate peri-urban agricultural land-transition phenomena.
- Evaluated the agricultural land transition dynamics in three different scenarios, representing the farmer population, using agent-based models (ABMs).

7.1 INTRODUCTION

In human-dominated land systems, the use of agent-centric or agent-based model (ABM) simulations has been shown to have many advantages as a learning tool for understanding the complex land transition processes associated with land-use decisions made by people (Magliocca et al., 2014). For example, ABM simulations are useful in complex system analysis as they provide insight into system interdependencies, heterogeneity and feedback (Wise et al., 2016). Agent-based model (ABM) simulations can also capture non-linear land system dynamics and spatially-explicit changes that enable land transitions to be evaluated in terms of feedback in land systems, as well as trends in land transitions associated with complex system processes (Brown and Xie, 2006, Borshchev and Filippov, 2004). These simulations can simultaneously reduce the complexity that is explicit in land-system processes (Murray-Rust et al., 2014b).

Contemporary land-use research has identified the advantages of capturing the behaviour, actions and responses of people within land systems, in particular, to address behavioural questions that are rarely implemented in biophysical land-change models (Brown et al., 2014, Malanson and Walsh, 2015). Land system science (LSS) researchers have emphasised the advantage of representing endogenous drivers in land-change modelling to evaluate the complex land-system feedback in dynamic environments (Verburg et al., 2015). In complex urban systems, ABM is superior to biophysical modelling as it has capabilities that cannot be accomplished through improvements in numerical biophysical models (Zou et al., 2012).

In socio-ecological systems modelling, ABM simulations explain the causal effects of human decisions on landscape level changes, while also representing human decision-making behaviour, for example, decision preferences and priorities (Murray-Rust et al., 2011, Ford, 1999, Simon, 1957). In ABM, the decision behaviour of heterogeneous agents is used to describe heterogeneous land-transition processes in land systems (Bakker et al., 2015, Malanson and Walsh, 2015, Murray-Rust et al., 2014b, Arneth et al., 2014, Macal and North, 2005). The land-change models grounded on rural agricultural land uses demonstrate a significant knowledge gap in capturing farmers' decision-making behaviour, and the decision rules applied in land-change decisions (Morgan and Daigneault, 2015, Kennedy and Veregin, 2016).

The research problem in ABM needs to be addressed by carefully selecting the agents, the interactions between agents, and the model environments that are sensitive to agent behaviour (O'Sullivan et al., 2016, Macal and North, 2005). As well as exploring land-transition processes, human behaviour and the underlying drivers of land change, ABMs are also useful when defining precise local-scale decision behaviour to assess spatial land-transition patterns and trends on a macro scale (Kelley and Evans, 2011). As the ABM is research purpose-dependent, agent-centric model descriptions need to be developed in parallel to the research objectives in ABM applications (Müller et al., 2014, Castle and Crooks, 2006). Overall, these models require appropriate attention in the stages of model design and experimentation, as well as the effective communication of results in parallel to the research objectives (Dorin and Geard, 2014) by visualizing the targeted system feedback (Grignard and Drogoul, 2017).

Agent-based models (ABMs) are often challenged due to their complex parameterisation of human behaviour and local land-transition processes (Murray-Rust et al., 2014a). Empirically-validated parameterisations are important in these models which heavily depend on agents' decision rules based on assumptions about the characteristics of agent behaviour (Smajgl and Barreteau, 2017). Agent-targeted data collection approaches—tailored to the research objectives—are effective in ABM, as they enhance the empirical evidence about assumptions made on local agents' parameters (Robinson et al., 2007). Questionnaire-based surveys are a useful way of collecting behavioural information about agents: also useful, is the empirical validation of the assumptions made about the agents' areas of autonomy, that is, their perception and capabilities, and the decision rules (Kelley and Evans, 2011). Moreover, surveys focusing on specific population groups in land systems improve the capture of the behaviour of target groups among the mass of heterogeneous agents (Jokar Arsanjani et al., 2013, Robinson and Brown, 2009). Research has identified the importance of having empirical assumptions and validations in ABM to understanding complex land-transition processes (Kelley and Evans, 2011, Hulse et al., 2016, Heckbert et al., 2011).

The integration of scenario analysis in ABM enhances the interpretability of complex system feedback under different model environments. Land-use research has demonstrated the advances accumulated from the integration of scenario analyses in ABM, as it demonstrates system dynamics and model sensitivity under alternative parameter arrangements (Morgan and Daigneault, 2015, Valbuena et al., 2010, Long and Zhang, 2015, Hosseinali et al., 2015, Ligtenberg et al., 2004). Although these integrative models are often used to simulate future land-use transitions, some authors have utilized ABM as a learning tool for understanding LSS theories associated with complex land-transition processes (Murray-Rust et al., 2013, Parker et al., 2003, Grimm et al., 2005). These points demonstrate the improved comparability of system feedback between different scenarios when integrating scenario analysis into agent-based modelling (ABM).

The integration of GIS data into ABM carries location intelligence to the model simulations while enabling visualization of the results in a spatial context (Brown et al., 2006). The spatial representation of system feedback is important in understanding complex land transitions, particularly when addressing the methodological question of “where they occur” (Cioffi-Revilla et al., 2011). The integration of GIS data with the object-oriented data modelling capacities in the ABM provides advanced computational facilities for entities in all models by identifying agents as “instrumental computing agents” (Brown and Xie, 2006, Sengupta et al., 2000). A spatially-explicit ABM has many advantages over other types of models in exploring, for example: spatial interactions among target agents (Hywood et al., 2016); complex adaptive systems (Tang and Bennett, 2010); the scale dependency of system feedback (An et al., 2005, Evans and Kelley, 2004); and the spatio-temporal phenomenon of land transitions (Brown et al., 2005), and in analysing model sensitivity while explaining the uncertainties generated in modelling processes (Ligmann-Zielinska, 2013). Spatially-explicit ABM is popular among the LSS community as it adds location intelligence to the results and enhances research communication between land-use researchers and land administrative practitioners (Millington and Wainwright, 2016, O’Sullivan et al., 2016, Crooks, 2006). The modelling software used in this study, NetLogo, uses notions of object-oriented data modelling and is capable of integration with GIS data (Dahal and Chow, 2014, Berryman, 2008). Geographic information system (GIS)-integrated NetLogo applications improve ABM simulations, as they use information in the spatial feature-attribute tables in the GIS for model computations and for visualizing simulations (Hosseinali et al., 2015, Anderson et al., 2017, Grignard and Drogoul, 2017).

Agent-based modelling (ABM) simulations have been used extensively in analysing urban sprawl (Malik and Abdalla, 2017, Brown and Robinson, 2006, Parker and Meretsky, 2004) and land-use changes associated with agricultural practices and policies (Millington and Wainwright, 2016, Murray-Rust et al., 2014b, Alam et al., 2013, Matthews et al., 2007, d'Aquino et al., 2002). Agent-based modelling (ABM) has been successfully used to explore agricultural land-use change by considering the decision-making behaviour of heterogeneous farmers or groups of farmers as agents which significantly affects complex land-transition processes on city fringes (Valbuena et al., 2010, Smajgl et al., 2011, Bakker and van Doorn, 2009, Matthews et al., 2007). Agricultural land-change research has also explored the possibility of defining agent typologies—that is, defining and identifying groups of farmers likely to behave in a similar manner—for agent-based analysis in rural landscapes (Valbuena et al., 2008). However, less attention has been given to the use of ABM simulations to better understand agricultural land transitions in peri-urban landscapes when exploring the loss of agricultural land due to urban sprawl.

This study focuses on developing ABM to target peri-urban agricultural land loss due to urban sprawl on the fringes of Adelaide, South Australia. The study uses the land-use decision-making behaviour of peri-urban farmers as the key driver of land transitions, while identifying four types of farmland decision profile autonomy to simulate the process dynamics in a spatial context. Spatially-explicit land vulnerability indexes, which represent exogenous socio-economic and biophysical effects on agents' decision-making behaviours, were used as the model environment. The two main research objectives in applying ABM were:

1. To explore agricultural land-use transition phenomena through the decision-making behaviour of agents (land-use decision-making profiles) in the peri-urban land system.
2. To explore farmers' land-use decisions that lead to agricultural land loss trends in the peri-urban land system under varying land-governing policy directions in the three scenarios of economic development (EDS), business-as-usual (BAU) and environmental protection (EPS).

7.2 MATERIALS AND METHODS

7.2.1 Data

The knowledge gained in Chapters 3, 4, 5 and 6 (see Figure 7.1) was used to define the agents, their characteristics and decision rules, and the interactions between them and the model environment to make assumptions for building the models. Four peri-urban farmer land-use decision-making typologies (P1 = heritage farming interest, P2 = commercial interest, P3 = selling farmland interest and P4 = multi-functional/hobby farming interest) were derived from information gathered in a questionnaire survey of farmers/landowners in the study area (Chapter 6). Participants were geo-located using the geographic coordinates of their farmland, which were obtained from South Australian government land cadastral data and used to develop a data set named *Sample of Farming Agents* (Table 7.1). The profile-based spatial data set was manipulated to create the *Entire Population of Farming Agents* data set by spatially analysing the centroids of agricultural land parcels in the land cadastral data in Adelaide. An alternative agent data set (*Alternative Entire Population of Farming Agents*) was created by changing the profile configuration to represent the agents' increased spatial heterogeneity in the land system. The Agricultural Land Vulnerability Index (ALVI) values for the three scenarios (EDS, BAU and EPS) (Chapter 4) were attributed to the polygons in a grid laid over the study area. All the spatial data sets were created and managed in the ESRI-ArcGIS 10.4.1 desktop platform while assigning the profile parameters: properties, sensitivity to model environment (weights) and exposure to exogenous vulnerabilities (ALVI) in the attribute tables. Table 7.1 outlines these data sets.

Figure 7.2 shows the spatial distribution of the sample of farming agents (Figure 7.2[a]) and the entire population of farming agents (Figure 7.2[b]), with these points identified in the developed ABMs as the farming agents that represented the decision profiles. The properties and associated decision rules of these agents—farming decision profiles—were linked to the associated attribute tables in GIS and as the agents' parameter inputs.

As demonstrated in Figure 7.1, the land vulnerabilities identified in Chapter 4, in association with the explored land fragmentation zones in Chapter 3, were used as the spatially distributed land vulnerability data to representing the ABM environment. Furthermore, the questionnaire survey results used to identify the drivers of land change in this land system (Chapter 5) were also used to validate the decision profiles, as described in Chapter 6, and, in the developed ABMs, to make assumptions about the agents.

Table 7.1: Spatial data with agents' (profile) properties and exposure to land vulnerabilities

	Data Sets	Data Type	No. of records	Fields in attribute tables
1.	*Sample of Farming Agents* (**Vdata**) Farmers who responded to the questionnaire survey, each of whom had geo-located information and was assigned to one of the four profiles (P1–P4) (Chapter 6).	Points	144	**ProfCODE, WV, WN, RT, STAGE, V1, V2, V3**
2.	*Entire Population of Farming Agents* (**VdataALL**) The profile information assigned to the entire farming population: a manipulated spatial data set (Data Set 1) of points derived through spatial analysis of the agricultural land-parcel centroids.	Points	6525	**ProfCODE, WV, WN, RT, STAGE, V1, V2, V3**
3.	*Alternative Entire Population of Farming Agents* (**VdataALL_2**) Manipulated data from Data Set 2, with alternative profile type allocations for the farming population.	Points	6525	**ProfCODE, WV, WN, RT, STAGE, V1, V2, V3**
4.	*Agricultural Land Vulnerability Index* (ALVI) Spatial representation of land vulnerability under different scenarios: EDS, BAU and EPS (Chapter 4).	Grids	5916	EDS (**V1**), BAU (**V2**), EPS (**V3**)

Notes: The text in **bold font** represents the data labels used in the NetLogo code for ABM development; Data fields: ProfCODE = profile type; WV= vulnerability weight; WN = neighbourhood weight; STAGE = Starting age of the profile; V1 = vulnerability in EDS scenario; V2 = vulnerability in BAU scenario; V3 = vulnerability in EPS scenario.

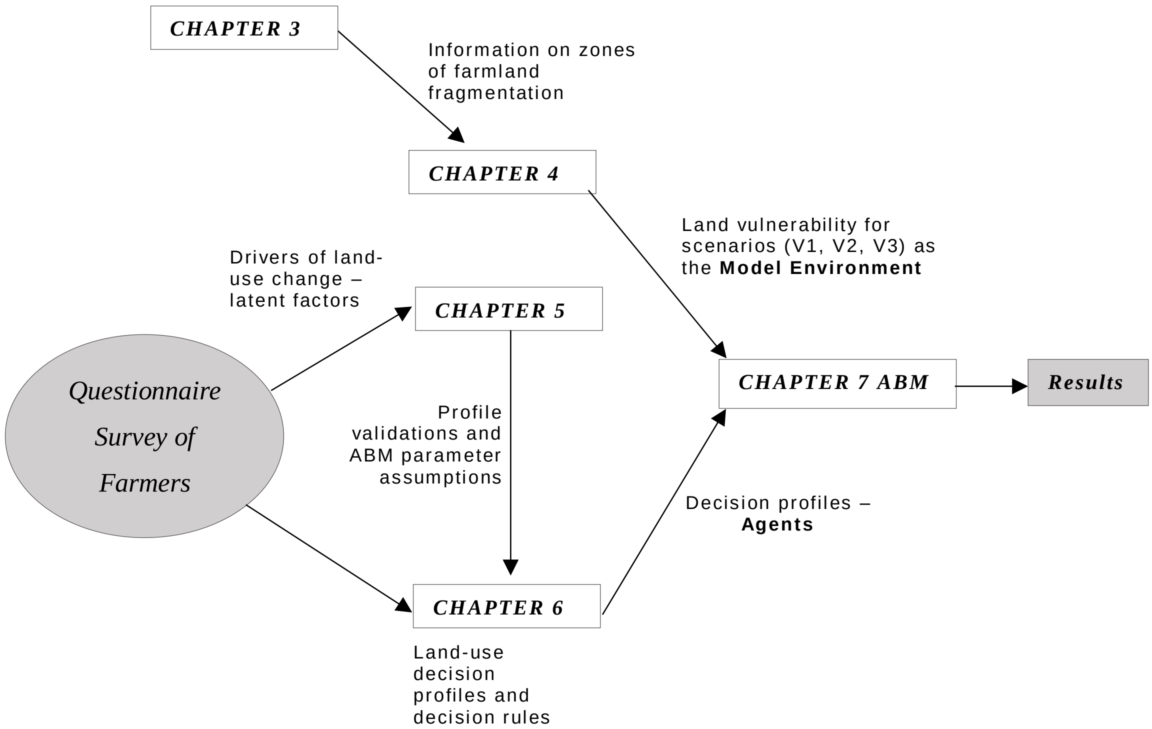


Figure 7.1: Development of ABM represented as an information flow diagram

a) Sample of farming agent profiles

b) Entire population of farming agent profiles

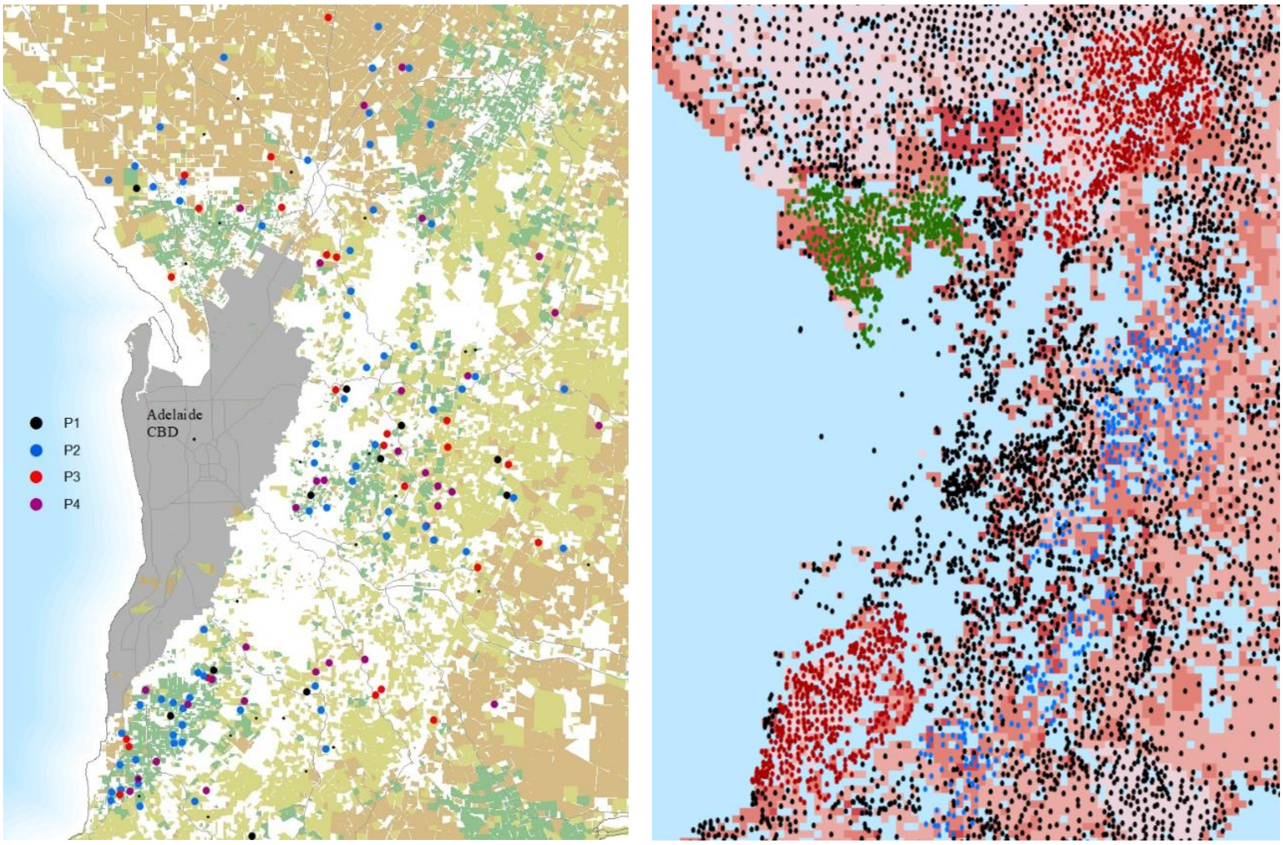


Figure 7.2: Spatial distribution of sample and entire population of farming agents
a) Sample of farming agents (Data Set 1) overlaid on land-use classes; b) Entire population of farming agents (Data Set 2) overlaid on agricultural land vulnerability data from BAU scenario

7.2.2 Methods

In the current study, the ABM has been structured to focus on agents' land-use change decision-making behaviour, and on the interactions between similar type of agents and between agents and the model environment. The four farming profiles (P1, P2, P3 and P4, see Chapter 6) were used to define the types of decision-making agents in the land system. The agents' properties and their autonomous decision-making behaviour, as shown in Table 7.2, describe the agents, that is, their dominant land uses, starting age and resilience to different types of vulnerability (the resilience threshold [RT]); the weights that indicate each of the four profiles' sensitivity (exposure to land vulnerability [WV] and to neighbouring agents [WN]); and the behavioural action (change of profile type), based on the derived profiles' decision-making behaviours and their empirical justifications in Chapters 5 and 6. As an example, when comparing P1 (heritage farmers) with P2 (commercial farmers), P1 has a higher sensitivity to land vulnerability (WV) and to the neighbourhood

(WN), due to expectations of lower economic returns from the farmland, and higher attachments to the neighbouring farming community, respectively. In addition, P1 was assigned higher resilience threshold values and a higher starting age representing the less profit-oriented, ageing heritage farming community on the Adelaide city fringes.

Table 7.2: Parameter assumptions and weights for agent profiles (P1 to P4)

	Profile types	**"ProfCODE"**	**P1**	**P2**	**P3**	**P4**
	Dominant land uses for agents in each profile	-	**Heritage farming**	**Commercial farming**	**Selling farmland**	**Multi-functional /hobby farming**
Agent sensitivity to the model environment	For land vulnerability	**WV**	0.8	0.3	0.5	0.6
Agent sensitivity to other agents	For the neighbourhood	**WN**	0.6	0.1	0.1	0.2
Decision pathway	Profile change		P1 to P2	P2 to P4	**Die**	P4 to P3
Memory of previous state	Resilience threshold (RT)	**RT**	50	30	20	40
Decision rule	Condition for action	-	IF R >= RT OR age >= maxage	*IF R >= RT* OR age >= maxage	*IF R >= RT OR age >= maxage*	*IF R >= RT OR age >= maxage*
	Starting age	**ST_AGE**	60	35	40	50

Notes: Weights: WV and WN have possible ranges of 0 to 1; WN is applicable only IF # same type of profile agents >= 3 within a proximity of radius (= r); maximum age of an agent = 85; profile memory (R) updates at each model iteration; Die = disappear from the land system (i.e., land sold to a developer); Profile change = land sold to another farmer

In the ABM, two profile attributes, agents' age (Age) and resilience to land vulnerability (Memory R), were set up for all the profiles, so they would update endogenously for each iteration of the model, using the ALVI values for agent memory updates. The profile memory calculations were based on Equation [1]:

$$Memory\ (R) = R_0 + \mathrm{V}(\ \mathrm{WV} - \ \mathrm{WN}\ ) \qquad [1]$$

Where,

WV = *Land vulnerability weight*
WN = *Neighbourhood effect weight*
V = *Agricultural Land Vulnerability Index (ALVI) value*
R0 = *Previous record value*
R = *New memory*

In this approach, agent mobility was excluded, with this decision based on the assumption that agents do not move within the area modelled—an assumption supported by the questionnaire responses. Moreover, agent mobility is not relevant to achieving the objectives of the research. In the model, agent mobility is replaced by the agent actions of “Profile change” (where the land is sold to another farmer) or “Die” (where the land is sold to a land developer). This approach allowed the dynamics of farmland extinction in the ABM to be examined. Although these profiles were not set up for any goal directions or system adaptations, their action performance was dependent on the set conditions (Table 7.2).

All changes in a profile follow a sequential rule of actions that change the status of the profile types from P1 to “Die” (Figure 7.3). This sequence was identified in parallel to the occurrence of land transition common practices in the study area, with this supported by responses from questionnaire participants. Heritage farmers often sold their farms to new agricultural farming investments due to the lack of labour, their age and the generational shift for other employment which represented the conversion of P1 to P2. Following that, large-scale commercial practices (P2) were often converted to multi-functional/hobby farmland uses (P4) due to the lower economic returns which characterized farmland subdivisions for multiple farmland uses. Furthermore, converting P4 (multi-functional/hobby farmland) into P3 (intensive farming practices) was prevalent to achieve higher economic returns from smaller land parcels (i.e. shed farming) on city fringes. These intensive agricultural land uses located closer to built-up areas were highly vulnerable to urban sprawl due to higher land market values and also, often due to land abandonment owing to frequent crop price fluctuations.

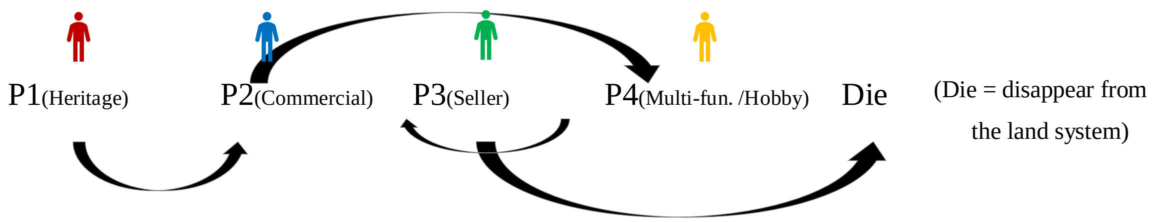


Figure 7.3: Sequential rule for profile changes in ABMs

The ABMs were set up to represent a calendar year at each tick (loop) in the simulations. At each tick, every agent in each profile updates memory (R) and age (Age) with these being attributes in the ABM results (agent attributes are provided in Appendix C7, 2). The dynamic interaction of these agents with neighbouring agents belonging to the same profile type is represented by the assigned weighting “WN” that reduces the memory increments (representing the negativity of the neighbourhood effect for land vulnerability). This is also subject to the condition of having at least three agents of the same profile within a radius of *r* (units) in the system. This approach provides land parcel-level detail for the agents, with land-transition trends emerging on the scale of the entire study area. This model is supported by adding new agents to the system when the agent type converts from P2 to P4, representing subdivision of larger farmland parcels into several medium-sized farming practices, which is often observed in Australian peri-urban land systems. To provide a detailed description of the ABM, the "overview, design concepts and details + decision" (ODD + D) protocol standards were used, focusing on these key ABM structural elements and the model development details, as guided by modelling experts (Müller et al., 2013, Grimm et al., 2010).

Table 7.3: ODD + D protocol including comprehensive model description

Structural Elements of ABM		Description
I) **Overview**	I(i) Purpose	The purpose of this study is to explore agricultural land-use transition phenomena through the decision behaviour of the agents (land-use decision-making profiles) in the peri-urban land system. The study aims to explore farmers' land-use decisions that lead to agricultural land loss trends in the peri-urban land system, under varying land-governing policy directions in the three scenarios of economic development (EDS), business-as-usual (BAU) and environmental protection (EPS). This model is designed for peri-urban agricultural stakeholder groups (land-use planners, land administrative policy groups, primary production land-use stakeholder networks and the academic research community).
	I(ii) Entities, state variables and scales	This model contains four types of agents (land-use decision-making profiles) behaving in the model world (domain) sensitive to the model environment (with set Agricultural Land Vulnerability Index [ALVI] values). Each model entity, that is, each agent type (land-use decision-making profile) is attributed a starting age and parameters for decision rules; sensitivity to the model environment; previous memory; and the same type of neighbouring agents, as well as decision rules and action pathways, as summarized in Table 7.2. The factors/drivers of the model (the ALVI values) are defined at each geographic location representing the economic, physical and land administrative influences (as described in Chapter 4) driving land transitions on the city fringes This model world (space) represents the entire study area—peri-urban Adelaide—by identifying the farmers within their property as points of data while the background represents the land vulnerability with a gradient pixel colour range where darker red represents a higher level of vulnerability. On each iteration, one "tick" represents annual changes in the land system.
	I(iii) Process overview and scheduling	In every iteration, each agent type (P1–P4) behaves according to the defined action pathway (Figure 7.3) by checking the pre-conditions and previous memory, as described in Table 7.2. The new agents added to the system (P4s – when the profile type changes from P2 to P4) use the same assumptions made with the existing agent type P4.

II) **Design Concepts**	II(i) Theoretical and empirical background	This model's rationale is based on using the empirical approach (the questionnaire survey) to identify land-use decision-making profiles (groups of farmers making similar decisions, P1–P4) and behaviours to explore complex land-use transitional processes on city fringes. The assumptions about agents' decisions (represented by parameters in Table 7.2) were based on the results in Chapter 6 derived through cluster analysis and its empirical observations. The aggregated data for each agent-type (land-use decision-making profile type) represent each agent's properties, interaction with neighbouring agents and sensitivity to the model environment (land vulnerability), through the weighted parameter effects at each iteration at each point (over 6500 points in the entire study area). The ABM was particularly used to model the land-use transitional processes as this model is superior to conventional numerical or cellular automata (CA)-based models to address land-system complexities as described in Chapter 2's literature review.
	II(ii) Individual decision making	The agents in these models make decisions to change their land use with this represented by a change of profile type. This is in accordance with the sequential rule in Figure 7.3 (selling/leasing the farm to another farmer = "Profile Change"; or selling the farm to non-agricultural practices = "Die") which represents land transitions depending on agents' accumulated exposure to externalities (interaction with other agents and the model environment) in the land system. These decisions rules were defined based on the empirical justifications provided in Chapter 6, including the uncertainties. The behaviour of the agents (four profile types [4Ps]) responds to the changing endogenous (neighbourhood) and exogenous (land vulnerability) effects in the model. On each iteration, a combination of the four different types of agents (over 6500 agents) in the system calculates the Memory (R) while checking the preconditions (threshold value [RT] and maximum age ["maxage"]) before executing the profile action to change the profile type or "Die" in the entire land system. Therefore, this model represents city-level agricultural land transitions focusing on the peri-urban areas of Adelaide.
	II(iii) Learning	The "resilience to vulnerability", represented by Memory (R) in Equation (1) with unique threshold values for each agent type (Table 7.2), is aggregated as a combination of the parameter weights of WV (agricultural land vulnerability exposure) and WN (neighbourhood effect), with spatial rules and accumulated experience (RO) from previous model iterations as the agents' learning mechanism that is used to decide the change of profile type or "Die" (removal) from the land system.
	II(iv) Individual sensing	The agents (decision-making profiles) have a uniquely defined way of sensing the model environment (land vulnerabilities are obtained in a spatially-explicit way from the model environment) and of sensing a similar type of agent in their spatial proximity to check preconditions (neighbourhood effects) at each agent point, before making a decision for behavioural action in the land system. Therefore, each agent in the

		model individually senses other agents' spatial proximities and the model environment to continuously update their learning memory to decide upon their action.
	II(v) Individual prediction	The agents in these models do not utilize any existing data to predict future conditions; however, they use the ALVI values, reflecting their consideration of land-use zoning, socio-economic effects and physical conditions that influence agricultural land transition on the fringes, with these used to calculate the agents' resilience for making land-use change decisions. The models focus on the accuracy of the land-use change process over the predictions; therefore, agents' actions depend on the values calculated on each iteration. Moreover, the unique differences of each agent type are represented by the weighted values, starting age and the resilience threshold (RT) values as defined in Table 7.2.
	II(vi) Interaction	On each iteration of the model, the interaction of the similar type of agent depends on spatial proximities (30 units) in the model's spatial domain to identify the neighbourhood effect.
	II(vii) Collectives	The emerging aggregations during the model simulations, formed by the affected individual agents in the system, capture the path dependencies in the land-transition processes to represent the collective form of trends.
	II(viii) Heterogeneity	The different agent types (land-use decision profiles: P1–P4) represent the heterogeneity of agents in terms of their properties, interactions, sensitivity to the model environment and the decision action rules. Furthermore, the agent data set created for ABM-3, representing agents with increased spatial heterogeneity, was used to explore the land-transitional processes in this complex land system.
	II(ix) Stochasticity	This model was not tested for stochasticity as it used statistically derived sample information (questionnaire survey responses, with ECA to identify the profile types) to represent the entire peri-urban farming population. In this approach, ABM-1 used the sample raw agents for model initialization, while ABM-2 and ABM-3 used the extrapolated data set for modelling.
	II(x) Observation	These models observed the total number of that agent type (P1–P4) remaining in the land system at each iteration (the "tick" point representing the land-use composition on that occasion). During the simulations in each tested scenario, the overall trends of the decision profiles (through all iterations) emerged, providing land-transitional patterns over time. These trends are important when understanding land-transition phenomena on city fringes under different land-management policy directions that are represented as land vulnerabilities in the scenario-based models.
III) Details	III(i) Implementation details	The ABMs were developed and implemented using NetLogo software according to the following key steps (Figure 7.4 'Information flow diagram') that are undergone on each iteration. The NetLogo code for this model (including the code descriptions) is available in Appendix C7, 3, for reference and future modifications.

	III(ii) Initialisation	The initial state of the model "world" of the ABMs represented the entire study area with all the agents in their geographic locations. The initialisation of the model always remained the same, but it allowed parameter variations in the model environment and proximities (i.e., selecting vulnerability with respect to the considered scenarios and changing proximities to neighbouring agents) between simulations. In these models, the initial values chosen (at "Setup") were based on the provided data sets.
	III(iii) Input data	These models used external spatial data sources from GIS software (agent geographic coordinates and land vulnerability pixel values) to represent agent information and the model environment.
	III(iv) Sub-models	Three different agent-based sub-models were created with different agent data sets as follows. The vulnerability information remained the same. 1. *Sample of Farming Agents* (Vdata) 2. *Entire Population of Farming Agents* (VdataAll) 3. *Alternative Entire Population of Farming Agents* (VdataAll_2)

7.2.3 ABM development in NetLogo

The software NetLogo version 5.3.1 (https://ccl.northwestern.edu/netlogo/) was used as the agent-based modelling (ABM) environment in this research, in addition to the NetLogo GIS extension which facilitates the transfer of spatial data sets (ArcGIS Geo-database files) to the NetLogo modelling environment. All spatial data layers were projected and visualized on the NetLogo display, in accordance with the GDA 1994 South Australia Lambert coordinate system. The agents in the spatial data sets (Vdata, VdataALL, VdataALL_2) were represented as points (Figure 7.5), using GIS to link the agents' properties and their status in the attribute tables. The grid-based Agricultural Land Vulnerability Index (ALVI) values were spatially joined to the agent point data sets using the ArcGIS spatial join function. This technique simplifies ABM development in NetLogo as the agents' attributes and vulnerability information for different scenarios are stored in a single attribute table in the agent point data layers.

The flow diagram of ABM development in NetLogo is shown in Figure 7.4 and the graphical user interface (GUI) in Figure 7.5. Initially, the model defined the model domains, the agents (as turtles) and the connections to the GIS spatial data sets. The ABM used object-based programming concepts, with the common profile class (p) defined in the NetLogo programming code, while uniquely identifying the profile types (as objects) and the associated decision-making behaviours of the agents in the land system (Appendix C7, 3 'ABM Code'). The model was initiated by "Setup" and ran with "Go", executing the agents' defined functions (profile-based decision rules and behavioural action) repeatedly over each "tick".

These iterations continuously calculated the agents' Memory (R) and age (Age) at each "tick". Looped execution in the model simulated the behaviour of agents, and the interactions between them and the model environment for the set time period.

Three ABMs were developed. The first, ABM-1, focused on the first research objective, while ABM-2 and ABM-3 addressed the second objective:

ABM-1 Analyses land transitions using the *Sample of Farming Agents* (Vdata) for all three scenarios: EDS (V1), BAU (V2) and EPS (V3). The numbers of agents in the four profiles (sampled profiles) at the start of ABM-1 model runs were set at P1 = 12, P2 = 72, P3 = 27 and P4 = 33.

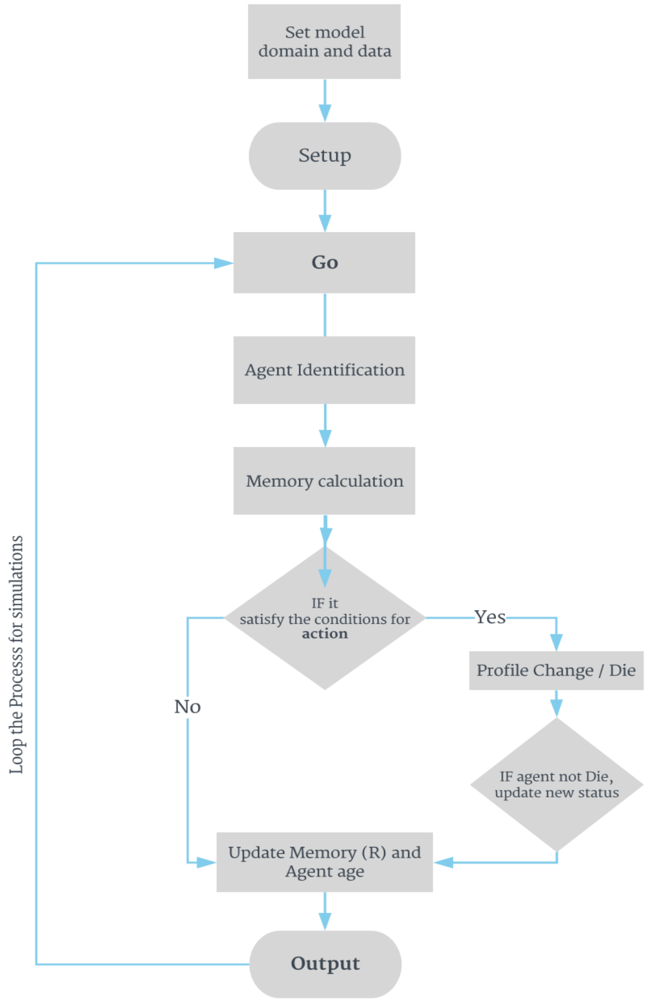
ABM-2 Analyses the land transitions using the *Entire Population of Farming Agents* (VdataALL) for all three scenarios and investigates the neighbourhood effect caused by interactions between agents using three radiuses (10, 30 and 50 units). The numbers of agents in the four profiles at the start of ABM-2 model runs were set at P1 = 2319, P2 = 2839, P3 = 486 and P4 = 881(Figure 7.6[a]).

ABM-3 Repeats the analyses in ABM-2 using the *Alternative Entire Population of Farming Agents* (VdataALL_2) for the three scenarios with increased numbers of agents in P2 and P4 (with increased spatial heterogeneity of the agents in the system) at the start of the model runs, that is, P1 = 1236, P2 = 3600, P3 = 486 and P4 = 1200) (Figure 7.6[b]).

An agent data set was created for the entire farming population—*Entire Population of Farming Agents*—by identifying the farmland location (centroids of each land parcel) and the land use of the representative farming population on the city fringes. The profile types were allocated (P1 = heritage, P2 = commercial, P3 = intensive and P4 = multi-functional/hobby farming) for these farmers by identifying their agricultural land functions and the area-specific empirical observations from the study area. Farmers engaged in agricultural practices, such as olives or grazing on medium-sized land parcels were allocated to P1 (heritage); farmers in areas with commercially operated agricultural companies were allocated to P2 (commercial); farmers in areas dominated by intensive farming practices (e.g., hydroponic or shed farming) on smaller land parcels were allocated to P3; and the observed multi-functional farming practices on single land parcels/less profit-oriented farmlands were allocated to P4. These profiles were allocated to the entire farming population while considering the maintenance of proportional differences between farming groups in the study area (i.e., clustered P3 profiles comprising farmers with intensive agricultural practices on the northern fringes closer to built-up areas) and representing the spatial heterogeneity of the study area's farming population.

The profile configuration data set used in ABM-2, called the *Entire Population of Farming Agents*

(VdataALL), was changed to an *Alternative Entire Population of Farming Agents* (VdataALL_2) to test the effects of different preconditions on the existing ABM-3 farming profile. This alternative profile configuration was mainly created by increasing the P2 (commercial) count and decreasing the P1 (heritage) count in the data set, while increasing the spatial heterogeneity of the agents (the diversity of profile types in specific geographic areas within the land system). The ABM-3 simulation results, based on the *Alternative Entire Population of Farming Agents* (VdataALL_2) data set, enabled the comparison of land transitional process changes under alternative preconditions with higher spatial land-use heterogeneity in the land system.



Define the model domain and the spatial data storage.

Set up model by clearing all previous data records.

Ask Profile Class (P) to identify the defined agent categories.

Agent Identification.

Calculate Agent Memory.

IF the selected Profile Memory satisfies the condition, execute action of Profile Change/Die.

If changing to new Profile, update to new status.

Update Memory and age according to the agent status.

Use this information to initiate the next process through looping.

Figure 7.4: Flow chart of ABM development in NetLogo

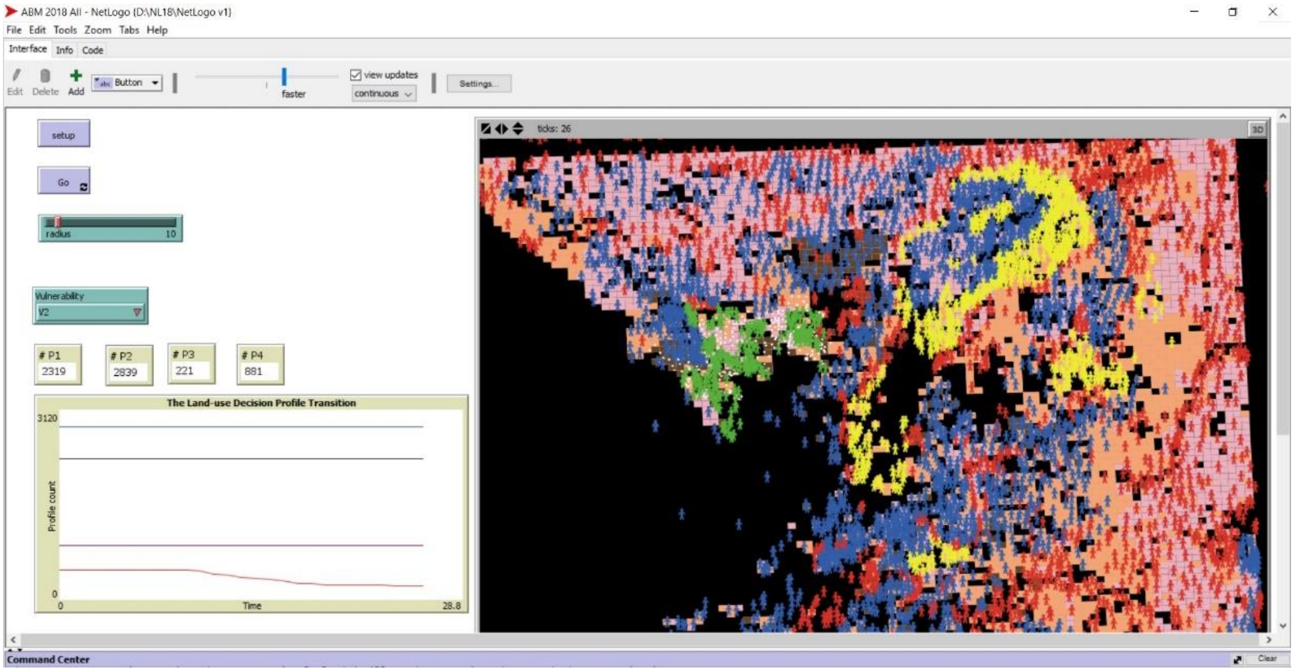


Figure 7.5: ABM-2 GUI showing agents as profiles-spatial interface

Notes: Buttons—"Setup" (to initiate the ABM); "Go" (to run); "Radius" (to select radius 1–100); "Vulnerability" (to select V1, V2 or V3); the profile boxes— "#P1", "#P2", "#P3", "#P4"—to show profile number change over time; and "Plotter" to show the plotted profile variations over time.

a) *Entire Population of Farming Agents*

b) *Alternative Entire Population of Farming Agents*.

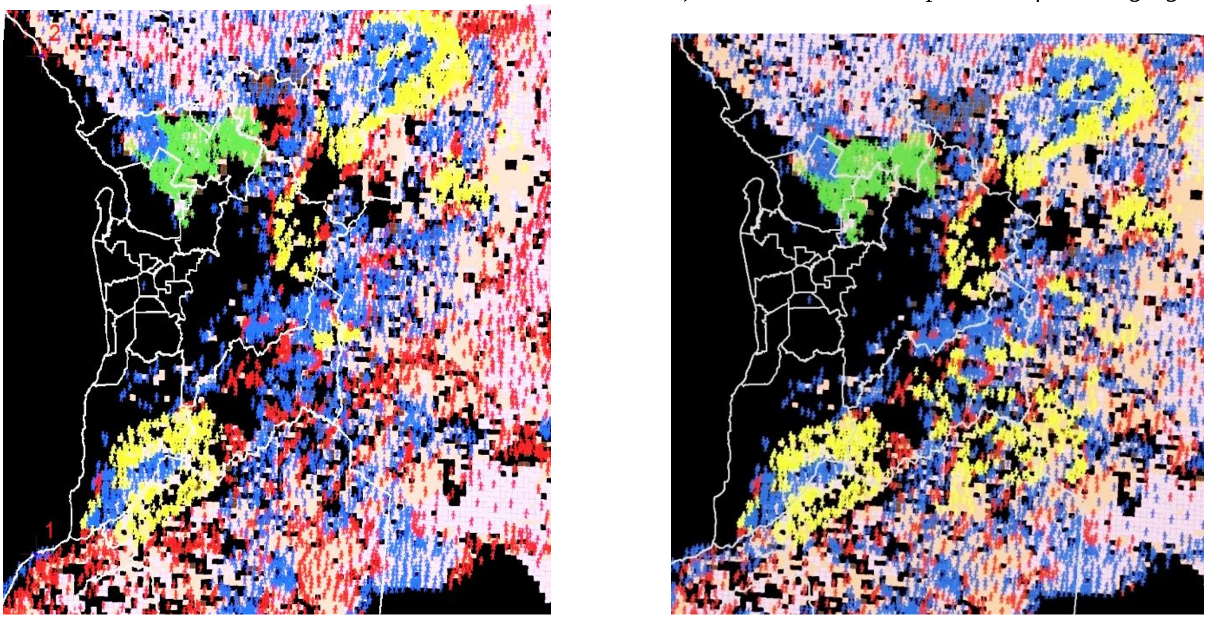


Figure 7.6: Representation of agent-profile display

a) Agents in ABM-2 *Entire Population of Farming Agents*; b) Agents in ABM-3 *Alternative Entire Population of Farming Agents.*

Notes: Four profile types: P1 (Red – heritage), P2 (Blue – commercial), P3 (Green – sellers) and P4 (yellow – multi-function/hobby) at the start of ABM ("Setup"); local government area boundaries only for visualization.

7.3 RESULTS

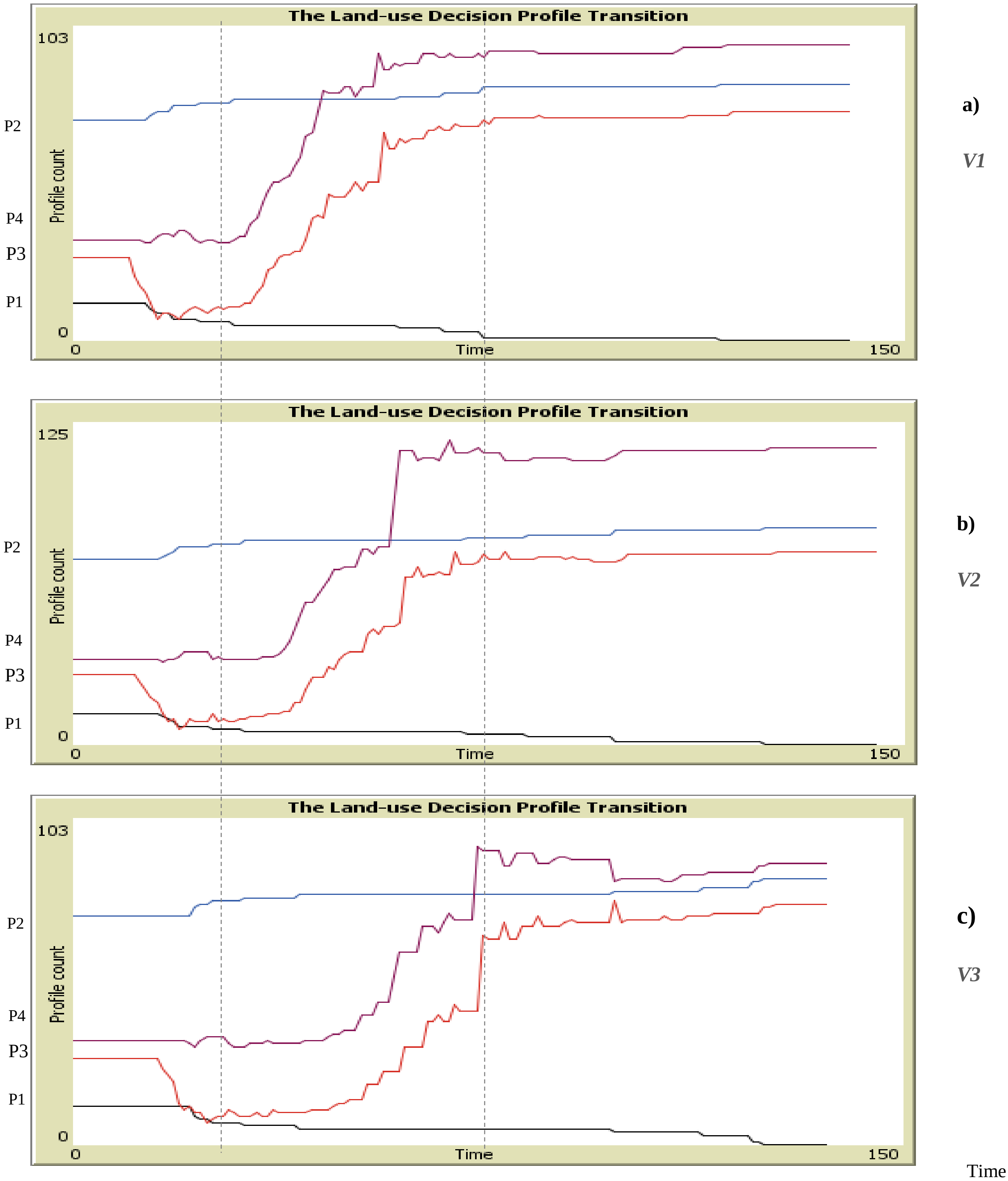


Figure 7.7: Sample profile count changes by profile type in three scenarios in ABM-1

Notes: a) EDS (V1); b) BAU (V2); and c) EPS (V3) where the radius = 50 units considered for WN; these are the profile dynamic curves from the raw data of NetLogo Plotter results (Appendix C7, 3).

7.3.1 ABM simulation of sampled farmers – ABM-1

The ABM-1 simulated results in Figure 7.7(b) illustrate the profile extinction trends by the profile types (P1, P2, P3 and P4) in the BAU scenario. In this analysis, the land-use decision-making profile P1—generally represented by heritage farmers—showed the shortest lifespan, dropping over 50% of its numbers midway to its extinction. This result represented the heritage farmer generational shift to non-farming businesses on the fringes. Although P3—commonly characterized by farmers of intensified agriculture—showed a sudden drop at the initial stage of the simulation, it maintained a lower number of farmers in the land system for long periods, compared to P1 and P4. The profile P4—multi-functional/hobby farmers—showed stable numbers and longer lifespans over the heritage farmer profile (P1) as most of these farmers were financially stable, even though they were not fully dependent on their farming businesses. The profile P2—commonly characterized by commercial farmers—showed the longest lifespan even when losing numbers, and it maintained constant numbers through profile changes in the system (from P1 to P2; in other words, heritage farmers selling their land for commercial farming practices on the fringes). The long-term stability of P2, compared to the intensified farming group P3, would be faced with extinction as they were not expecting higher economic returns from their farmland. These simulation results demonstrated the profiles' ascending lifespans from P1 < P4 < P3 < P2, while demonstrating the unique profile number extinction rates in the land system.

The ABM-1 simulated results for the other two scenarios, the EDS (V1) and EPS (V3), demonstrated the comparative result of the profile type extinctions, as seen in Figure 7.7(a) and Figure 7.7(c), respectively. The profile P3 showed a rapid drop in numbers and a shorter lifespan in V1 compared to the results in V3, due to the rising demand for land in the EDS causing the conversion of intensified farming land located closer to the built-up areas. The profile P4 showed a higher reduction rate in numbers with constant lifespans in V1, compared to the results in V3, due to the higher sensitivity of multi-functional farming practices to the economy, and the possibility of hobby farmers making quick decisions to sell the land for higher economic returns. The profile P2 showed constant profile numbers in both scenarios (V1 and V3) as these profiles were less sensitive to externalities due to their financial stability. The profile P1 maintained slightly higher profile numbers in V3, due to the land-governing policies in the EPS that focused on environmental sustainability, reducing the heritage farming extinction rate in peri-urban landscapes.

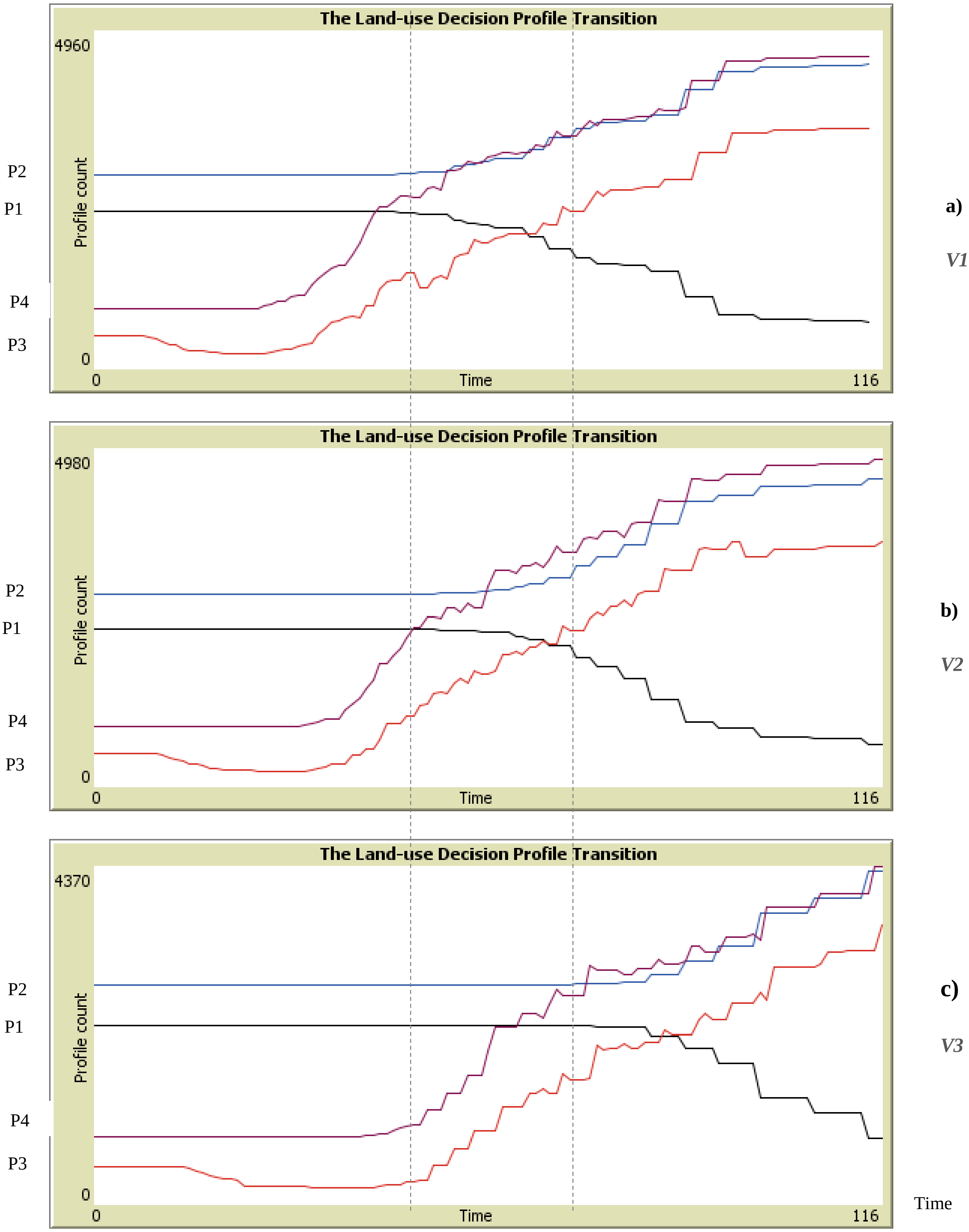


Figure 7.8: Total profile count changes (VdataALL) by profile type in three scenarios in ABM-2

Notes: EDS (V1); b) BAU (V2); and c) EPS (V3) where the radius = 50 units considered for WN; these are the profile dynamic curves from the raw data of NetLogo Plotter results (Appendix C7, 3).

7.3.2 ABM simulation of entire farmer population – ABM-2

The ABM-2 simulated results in the BAU scenario (Figure 7.8[b]) demonstrated similar profile extinction patterns in parallel to those of ABM-1. The profiles' lifespans in ABM-2 (V2) followed the ascending order P1 < P4 < P3 < P2 with unique profile number extinction rates which were particularly featured in the later parts of the extinction curves (Figure 7.8[b]). The heritage group profile P1 showed shorter lifespans as was the case in the ABM-1 results, demonstrating the heritage farming generational shift, even though higher P1 profile numbers existed in the model's initial stage. In this total farming ABM simulation in the BAU scenario, the profiles P3 and P4 were able to maintain long-term stable profile numbers due to the profile change processes (selling farmland to different farming practices or changing land-management/crop types representing the complex farmland transitions on the fringes). Overall, the ABM-1 results (Figure 7.7[b]) based on the sample of farmers represent the total farming population behavioural dynamics in ABM-2 (Figure 7.8[b]).

The ABM-2 simulated results for the other two scenarios, the EDS (V1) and EPS (V3), demonstrated the comparative results of the profile type extinctions in Figure 7.8[a] and Figure 7.8[c], respectively. The profile P3 showed a rapid drop in numbers and a shorter lifespan in V1 compared to the results in V3, due to the higher land demand for urban development that exerts pressure on intensified farming land located closer to built-up areas. The highest number of farmers represented in the P2 profile maintained a stable number of profiles for a longer lifespan and showed a sudden increase, or a "tipping point", where it attracts many farmers for commercial farming practices parallel to the economic development trends in these geographic locations. As P1 showed constant lifespans in both scenarios (V1 and V3), this profile extinctions in this land system were demonstrated as being inevitable during land transition processes.

The profile dynamics in the BAU scenario (Figure 7.8[b]) were tested for changes in the spatial interaction effects between agents in ABM-2 (radius options; 10, 30 and 50 units considered to be assigned to neighbourhood weights [WN] in agent memory calculations) and showed no effect on the profile dynamics. These non-significant changes in all three radius options demonstrated minor interactions between agents leading to land systems which had less neighbourhood effects contributing to their land-use decisions. The results for the other two scenarios (V1 and V2) utilizing the same investigation confirmed the point that neighbourhood effects were minimal.

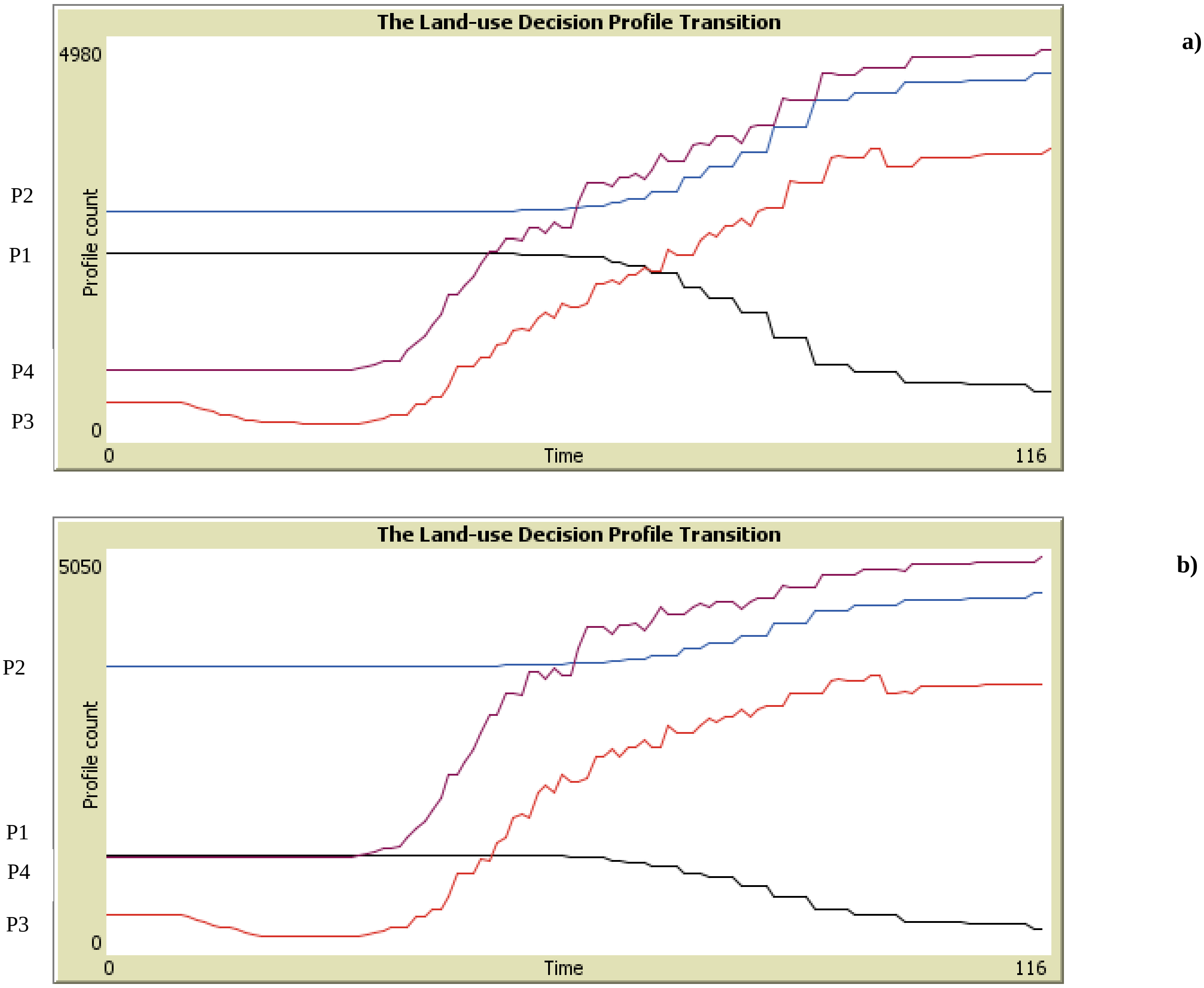


Figure 7.9: Total profile number changes by profile type under BAU (V2)

a) Total profile number changes (VdataALL) in ABM-2; and b) Total profile number changes (VdataALL-2) in ABM-3
Notes: where the radius = 50 units considered for WN; profile configuration in VdataALL (P1 = 2319, P2 = 2839, P3 = 486, P4 = 881) and in VdataALL_2 (P1 = 1236, P2 = 3600, P3 = 486, P4 = 1200).

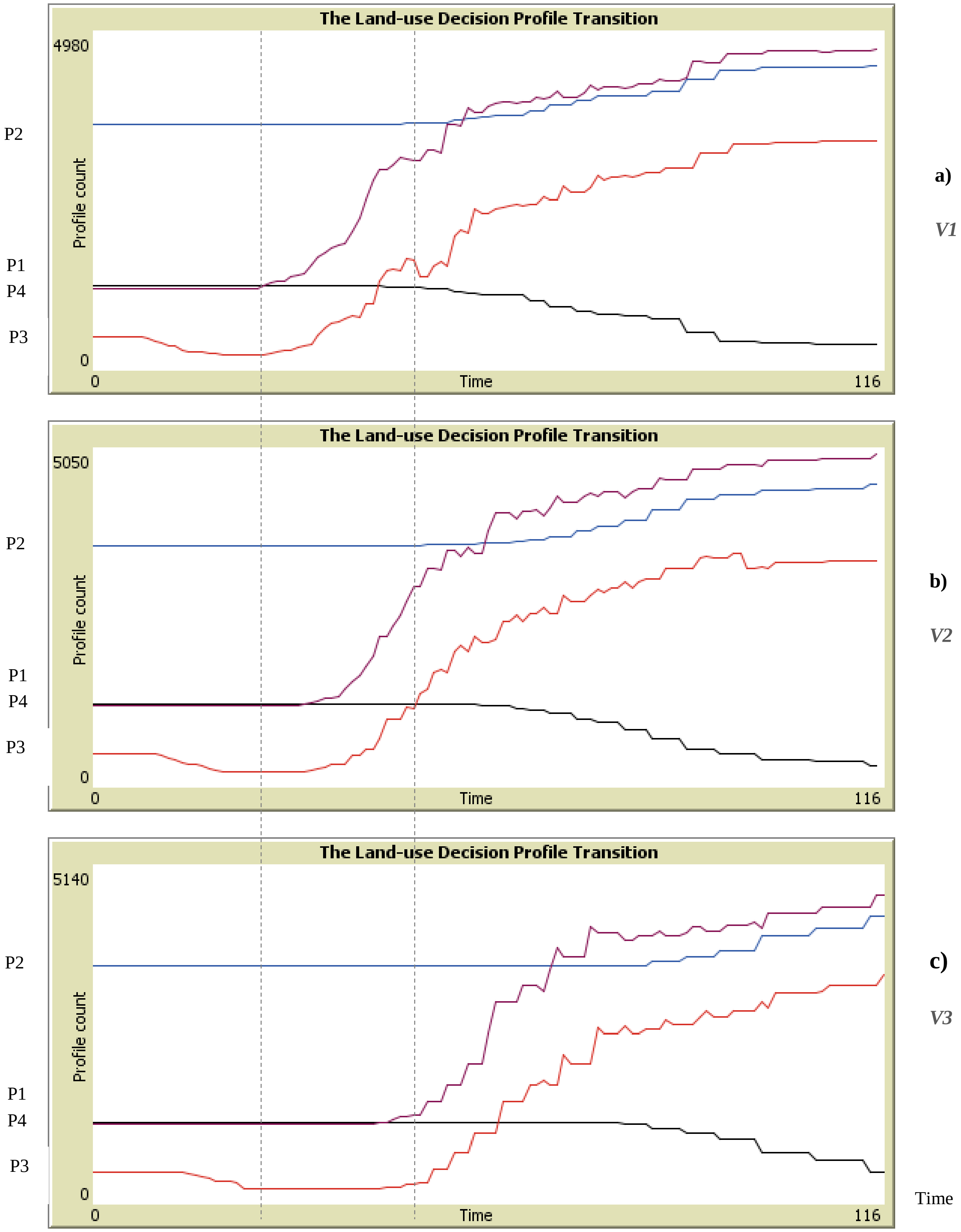


Figure 7.10: Total profile number changes (VdataALL-2) by profile type in three scenarios in ABM-3
Notes: EDS (V1); b) BAU (V2); and c) EPS (V3) where the radius = 50 units considered for WN; these are the profile dynamic curves from the raw data of NetLogo Plotter results (Appendix C7, 3).

7.3.3 ABM simulation with alternative profile configuration of population – ABM-3

The results in ABM-3 (Figure 7.10) demonstrated similar profile count changing patterns in parallel to the ABM-2 results, while illustrating slightly different lifespan variations in all profile types. Although the profile configuration changed in the ABM-3 agent data set (P2 and P4 increased by 800 and 500 agents, respectively), the profile lifespans in ABM-3 (V2) followed the same order as in ABM-2 (V2) as demonstrated in Figure 7.9. However, the varied profile extinction rates in the profile P4 (see P4 dynamic curves in Figure 7.9[b]) demonstrated its contribution differently to the configuration of peri-urban agricultural landscapes. It demonstrated the initial condition of some decision-making profiles (the profile numbers) having an influence on profile dynamics of these land transitional processes. Although P1 and P2 were illustrated with stable profile numbers and constant lifespans in both simulations (Figure 7.9), these profiles would experience sudden changes, demonstrating that they can only survive or stable for a certain period and that the occurrence of urban sprawl into these areas is inevitable.

The comparative results of ABM-3 (Figure 7.10) in the three scenarios (V1, V2 and V3), showed distinguishably shorter lifespans for the profile P3 in V1, compared to V2 and V3, demonstrating the fact that land-governing policies directed in the EDS can affect the decision-making profiles of intensified agriculture farmers over the rest of the farming community on the fringes. On the other hand, it showed the possibility of maintaining higher P4 profiles (less extinction rates) in V1 even under the EDS scenario policy directions. Overall, these results illustrated the following points: these profiles make different configurations in static points in peri-urban landscapes, are continually subject to sudden changes as a system and are retained only within the period of the profiles' lifespans.

7.4 DISCUSSION

Although ABM has been utilized in land-use research to analyse urban expansions, less attention has been given to utilizing farmers as central decision agents when seeking to understand farmland extinction processes in peri-urban agricultural landscapes due to urban sprawl. The novelty of this approach involved using farming decision-making profiles as primary agents, instead of farming groups identified by their physical status (income level, production type, land use, farm ownership or land-parcel extent) as commonly utilized in ABM development. In this approach, the developed ABMs were grounded on peri-urban farming decision profiles that explored the profile type change processes in three land-governing scenarios to capture land-system transitions under different land-governing policy directions on the city fringes of Adelaide.

7.4.1 Decision-making profile sample representation in ABM

The ABM-1, developed based on the sampled decision profiles, derived from farmers' survey response clusters in Chapter 6, showed the possibility of parameterising the decision profile behavioural characteristics to develop agent-centric models. In ABM development, the sampled profile's sensitivity to the model environment (land vulnerability), to other agents (other agents in the same profile group—the neighbourhood effect) and behavioural actions (associated with decision rules and conditions) are the important relative aspects when making assumptions on the profiles' land-use decisions (presented in detail in Figure 7.3 with the ODD + D protocol). These uniquely identified profile characteristics and dynamic circumstances for agents' decisions (Table 7.2) at each agent location and time unit ("tick") in ABM continually updated agents' memory and age, demonstrating the model's capability of capturing the heterogeneous autonomy of agents' dependency on their previous state. The model environment, consisting of spatially varied ALVI values (in Chapter 4, based on socio-economic and environmental indicators), captured the spatial heterogeneity of land vulnerabilities in the studied land system. Due to these points, the developed ABM was based on sample agents' decision-making behavioural characteristics and the spatially varied model environment, creating an artificial model that represented the areas of agents' autonomous actions and spatial heterogeneity over time. It was useful to deconstruct the complex land transitional processes that originated through the farming profile decisions (individual/as a group) in these peri-urban land systems. Moreover, the empirical justifications of the profile behaviours—the clustered farmer grouped responses in Chapter 6—were useful for interpreting the profile dynamics (the profile extinction patterns), as illustrated through the ABM simulations.

As described in the previous section (ABM-1 simulation results), the sample profiles showed the autonomous behavioural dynamics characterized by the unique profile lifespans and the profile number changing patterns in the simulated graphs. These distinguishable profile curves demonstrated the represented farmers' land-use decision behaviour that ultimately caused farmland transitions based on the profile count, while emphasising the causal interdependencies between profiles in the land system. Furthermore, these profile dynamic curves provided the combinational profile count at each tick point, indicating the land-use decision-making profile configuration dynamics in the land system. Although these dynamic curves were not aligned solely with the study area land-use changes, they improved the knowledge on profile-changing mechanisms (profile lifespans, increasing (or extinction) rates and patterns) that ultimately created non-linear complex farmland transitions in peri-urban landscapes.

The integration of scenario analysis in ABM showed plausible agent behavioural trends in various land systems. Comparison of the profile dynamic curves under these three scenarios, namely, the EDS, the BAU scenario and the EPS, considered for this analysis (as described in Chapter 4), demonstrated the effects of land vulnerability variations (between V1, V2 and V3) for each profile type. The ABM-1 results demonstrated the possibility of connecting the profile land-use decision-making characteristics with the scenario storylines to justify the profile dynamic curves. These connections improved the knowledge of unique profile dynamics (changing lifespans, extinctions and sudden drops) under the vulnerabilities created in the scenario storylines. For example, the dynamic curves of profile type P3—the majority of intensified agriculture farmers—in the EDS showed a quicker "tipping point" profile count drop compared to the EPS, due to the higher land demands (higher property markets) created in the EDS which can, compared to the EPS, potentially transform intensified farmland to urban form more quickly. Alternatively, these scenario analyses could be used to identify the long-term profile count dynamic curves in response to different land-management policy directions which eventually described the probable farmland transition processes in the studied land system. For example, the dynamic curves of profile type P2—the majority of commercial farmers—in the three scenarios showed an increasing pattern in the farmer count in EDS (V1) > BAU (V2) > EPS (V3). It also showed the same pattern of decreasing numbers of the P1 profile (heritage farming) in the land system, confirming the point that quick heritage farmland conversions to commercial practices would occur more rapidly under the EDS compared to the EPS, as a result of land-management policy directions that favoured economic development.

7.4.2 Developing ABM based on sample profiles

The demonstrated similar patterns of the profile dynamic curves in ABM-1 and ABM-2 emphasised the possibility of using sample data assumptions grounded on empirical observations (farmer survey information) to develop an ABM for the entire peri-urban farming community (like ABM-2). The agent classifications, based on the sample profile information, created knowledge of the individual farming agents' land-use decision-making behaviours in the entire farming population. The ABMs developed based on these spatially distributed agent data sets consisted of agents' areas of autonomy that are useful in simulating the entire farming population dynamics (targeted at the agent type changing patterns) in the land system. As seen in the ABM-2 results displayed in Figure 7.8, these simulations provide rich information on the profile type land-use transitional trends and lifespans, as well as the emergent land transitional patterns in specific geographic areas in the landscapes. As an example, the intensified vegetable gardens (P3) clustered to the north of Adelaide and bounded by built-up areas, showed a rapid farmland extinction hotspot that was accommodating urban sprawl into these northern peri-urban landscapes. Furthermore, the ABM-2 simulated results (Figure 7.8[a], [b] and [c) confirmed the capture of the profile dynamic curve differences under the defined scenarios represented by the unique land vulnerability model environments (V1, V2 and V3).

In addition to information provided by the profile dynamic curves, the detailed spatial data integration (spatial data manipulated from the land cadastral GIS data) in ABM provided spatially-explicit dynamic profile extinction information on the land system by visualizing the area-specific land transitional processes. The spatially-explicit visualization of the profile dynamics in ABM-2 (Figure 7.8) demonstrated the dynamics of the intensified agricultural land extinctions on the northern fringes and the landscape configuration dynamics of the eastern agricultural landscapes, reflecting the non-linear agricultural land transitional processes in a spatial context. Spatially dynamic information in these specific areas is important for interpreting land transitions that have connections with local empirical justifications.

7.4.3 Peri-urban agricultural land system feedback

In ABM simulations, the incorporation of spatial interactions between agents was found to be useful when capturing the dynamic spatial heterogeneity in land-transitional processes. These interactions have the potential to change the associated profile decision-making behaviour when it is highly sensitive to land-use decisions of the profiles. As an example, the profile P1—heritage farmers—showed a higher level of sensitivity to the neighbouring community than was the case with the profit-oriented farmers, mostly represented by P2 and P3, when making land-use decisions (assumptions based on survey results from Chapter 6). These neighbourhood effects were however less effective when retaining peri-urban farming industries over time, as these profiles were continually exposed to highly competitive markets, thus diverting their concerns to financial priorities (rising property values, new market opportunities and labour cost) over neighbourhood influences. The ABM-2 (BAU scenario) tested simulated results for neighbourhood effects (WN) in three radius buffering zones (spatial analysis radius = 10, 30, 50 units, around the agents at each "tick") confirming that no significant impact had occurred on profile decisions in these simulations, as similar profile dynamic curves were maintained under the three spatial analysis options. These results also confirmed the occurrence of weakened neighbourhood effects in peri-urban land system dynamics, influenced by the existence of neighbouring urban land use, due to urban sprawl (Wu, 2008). Some geographic locations, displayed with clustered land transition dynamics in the ABM-2 simulations, were mainly due to the decision profile type: properties, sensitivity to the model environment (land vulnerability) and resilience thresholds (RTs), represented based on socio-economic status, while having a minimal neighbourhood effect. This finding demonstrated the point that, overall, this land system was less self-organized in terms of farmland transitions due to the minimal neighbourhood effects involved in the profile's land-use decision processes.

The ABMs tested for alternative profile configurations (ABM-3 vs. ABM-2 in Figure 7.9) showed that some profiles (i.e., P4 and P1) demonstrated the effects of the initial profile numbers on the profile dynamics in the land system. Furthermore, the comparative results of ABM-2 (Figure 7.8) and ABM-3 (Figure 7.10) in the three scenarios showed that the alternative profile configurations simulated in ABM-3 were illustrated, in comparison with ABM-2, with different profile configurations in the simulations. These points emphasised the path-dependent characteristics of the overall land system, represented by unpredictable non-linear farmland transitions and sudden profile number changes that were influenced by the profile pre-conditions represented by parameter inputs. The comparative results further demonstrated the processes associated with the agents' (profile) land-change decisions and behavioural autonomy, while being sensitive to the model environment which addressed the complexity in these path-dependent land systems.

In the ABM simulation results, based on the three scenarios (Figure 7.8 and Figure 7.10), some profile dynamic curves showed significant variations in the EDS that, compared to the BAU scenario and the EPS, created more demand for land and frequent land fragmentation. In both model simulations (ABM-2 and ABM-3), profile P3 (sellers with intensive farming interest) and P4 (multi-functional/hobby farming interest) in the EDS showed rapid profile count increases within shorter periods, demonstrating their higher sensitivity to situations with substantial economic development policies (the EDS). These quicker profile count increases in the land system were mostly influenced by the rising demand for land and the tightening land-use regulations imposed by land administration on the city fringes. These points demonstrated the anticipated profile land-change decision-making behaviours influenced by the EDS, leading to higher land vulnerability on the fringes. Overall, the ABM simulation results revealed that the profiles in this land system, under the EDS, had a higher sensitivity to land vulnerability.

7.5 CONCLUSION

Peri-urban farmers' land-use decisions drive agricultural land extinctions in the urban fringe land systems and consist of complex land-transitional processes. However, limited knowledge has been developed on their land-use decision-making behaviours to help in understanding these complex land extinction processes under different land-governing policy directions.

This study focused on exploring the extinction trends of predefined land-use decision profiles (derived from farmers' land-use decision-making behaviours), while examining system feedback in three land-governing policy scenarios. Spatially-explicit ABM simulations were used to analyse agricultural land transitional processes while exposing the profiles to land vulnerabilities created in the three scenarios (EDS, BAU and EPS). The ABM simulation results demonstrated the agricultural land transitional processes as being highly path-dependent but less self-organized and largely dependent on the land administration and economic effects prevalent on the Adelaide city fringes. Furthermore, the simulated results demonstrated that the sacrifice of farmland for urban sprawl was inevitable under all three scenarios in Adelaide. The results also sounded the alert to the rapidity of farmland transitions (the conversion of heritage farmland to commercial practices and intensive farming land uses ultimately increasing farmland fragmentation) in the land system, under accelerated financial growth in the EDS that focused on land-governing policies targeting economic development. This study shows the possibility of effectively using sampled profile land-use decision-making characteristics for developing ABM to understand the complex peri-urban agricultural land transitions. However, the limited accessibility of information for farmers' land-change decision-making behaviours (external and internal) for agents' parameterisations has been identified as the major limitation of developing ABM based on farmers' motivations towards land management on the city fringes.

The results show the advantage of focusing in land-management policies on the decision profiles which were mostly represented by intensified farming and multi-functional/hobby farmers that were highly sensitive to the urban sprawl on the Adelaide city fringes. This agent-based modelling (ABM) approach, based on farmers' decision profiles, can be further improved by underpinning farmers' concerns on market mechanisms in peri-urban areas (Bakker et al., 2015). Although this ABM approach has focused on the process accuracies of peri-urban land transitions, it can be further improved by validating the simulations through area-specific empirical justifications.

CHAPTER 8 – CONCLUDING DISCUSSION

As the final section of the thesis, this stand-alone chapter discusses the overall knowledge improvements achieved in the topic area where the knowledge gaps identified in the literature review (Chapter 2) exist, in parallel to the set objectives. Although the previous chapters (Chapters 3 to 7) provided detailed discussion on chapter-specific methods and results with reference to the study area, this chapter addresses the overall research problem in the context of land system science (LSS) focusing on the topic area "Peri-urban agricultural land transitional processes" through examples from Adelaide. The final part of this chapter focuses on concluding the thesis by presenting the overall argument, the research approach strengths and recommendations grounded on the findings for future improvements in the knowledge of these land transitions in peri-urban landscapes.

8.1 INTRODUCTION

Overall, this study focused on deepening our knowledge of peri-urban agricultural land transition phenomena due to urban sprawl, which has caused significant impact on ecological services, food security and the community lifestyle in peri-urban landscapes. A combination of contemporary socio-economic changes, deteriorating eco-system services and the influences of dynamic land administration policies has created complex land transitional processes in peri-urban land systems. This has caused major challenges for the land-use research community when deconstructing these complex land transitions to underpin the causes and subsequent effects of agricultural land extinctions in these peri-urban land systems. Moreover, these land transitions demonstrate the effects of spatially heterogeneous farmland extinction in peri-urban landscapes, further complicating the possibilities of understanding farmland conversions. To address this problem, the current study has attempted to improve knowledge in the specific areas that show information gaps within the land-system literature.

This study was mainly designed to explore agricultural land transition phenomena in peri-urban landscapes under the following sub-topics: agricultural land presence in land fragmentation zones; land vulnerability to urban sprawl; drivers behind land transitions; behaviours of land-use decision-making profiles; and overall agricultural land-system dynamics on the Adelaide city fringes.

The specific objectives established for this study were

Objective 1: To analyse the peri-urban land-parcel structure and land-use compositional arrangement to investigate the agricultural land presence in land fragmentation zones.

Objective 2: To analyse peri-urban agricultural land vulnerability at a local level, under opposing policy directions.

Objective 3: To explore peri-urban farmer characteristics, the drivers behind land-use decisions, the decision-making profiles and their land-use decision behaviours.

Objective 4: To explore agricultural land transition process characteristics and responses of land system dynamics under varying agent-based model (ABM) environments.

By reviewing over 330 referenced articles (see Chapter 2) in the area of land system science (LSS) and associated sub-topics, several information gaps were identified, while suitable methods used to address these gaps were evaluated. Furthermore, this literature review evaluated the advantages of the methods selected for this research over the techniques commonly used in land-change science—such as remote sensing, cellular automata (CA) and numerical modelling methods—for exploring the implications of urbanization on peri-urban land-use transitions. Parallel to the above research objectives, the following information gaps were identified through the literature review in Chapter 2:

- Agricultural land presence in land fragmentation areas.
- Peri-urban agricultural land vulnerability in local government administrative areas.
- Underlying factors which drive peri-urban farmers' land-use decisions.
- Farmers' land-use decision-making profiles and the decision rules.
- Agricultural land transition processes in peri-urban landscapes under the dynamics of land-management policy directions.

The study's key empirical findings are summarized within their respective chapters (Chapters 3 to 7). The knowledge obtained through these empirical findings with reference to the Adelaide city fringes are listed against each chapter topic area in Table 8.1 below.

This is the author's original contribution to the knowledge of land system science (LSS) in the area of peri-urban agricultural land systems.

Table 8.1: Contribution to the knowledge of land system science (LSS) in each chapter of thesis

Chapter	Topic	Contribution to LSS knowledge improvement
3	Analysis of land use on urban fringes	• Identified land fragmentation zones in the peri-urban landscapes. • Showed the advantage of spatially quantifying agricultural land in the land fragmentation zones, for informed land-management decisions.
4	Agricultural land vulnerability on urban fringes	• Spatially quantified the ALVI in three scenarios, representing land-management policy directions ranging from economic development to environmental protection. • Identified variations in agricultural land vulnerability in local government administrative areas.
5	Drivers of peri-urban farmers' land-use decisions	• Explored peri-urban farmers' characteristics and land-use decision preferences in the study area. • Derived key factors driving peri-urban farmers' land-use change decisions while demonstrating links between primary and latent factors (drivers) in the study area.
6	Peri-urban farmers' land-use decision-making profiles and decision behaviours	• Derived land-use decision profiles in terms of peri-urban farmers' land-management motivations. • Identified the profiles' land-change decision behaviours in terms of their properties and decision rules for complex land-system modelling.
7	Agent-based simulations of peri-urban land transitions	• Developed an ABM using farmer decision-making profiles for investigating peri-urban agricultural land transition phenomena. • Evaluated agricultural land transition dynamics in three different scenarios using ABMs representing the farmer population of the Adelaide city fringes.

The following section synthesises the empirical findings from the Adelaide city fringes to address the specific research objectives of this study.

8.2 IMPLICATIONS OF URBANIZATION ON PERI-URBAN AGRICULTURAL LAND EXTINCTION

Australian cities are highly urbanized. As is the case with the other major Australian cities, Adelaide is subject to urbanization due to population growth (external migration) and employment opportunities created during the past few decades. Adelaide's rising need for infrastructure development, dwellings and commercial facilities has created a significant demand for peri-urban land predominantly consisting of agricultural farmland. Contemporary socio-economic changes and local land management have a substantial effect on land-parcel arrangements (land cadastre) in peri-urban landscapes that display a range of high to low land-parcel densities. Peri-urban land closer to commercial facilities, major road networks and housing development areas shows a higher possibility of changing the spatial structure of its land-parcel arrangement (by land subdivisions), compared to the larger land parcels surrounded by medium and large agricultural land parcels in rural areas (Pearson et al., 2010). However, these spatially heterogeneous differences are indistinguishable in land cadastral data sets when identifying the land fragmentation zones in Adelaide.

Chapter 3 addressed this issue by proposing urban-to-rural (U–R) gradient transects in combination with landscape metrics (parcel density [PD] vs. mean parcel density [MPS]) to examine the extremely fragmented areas within the study area. When considering the land-parcel arrangement along the three transects from the city centre to peri-urban areas, the results demonstrated a common range of 7 $N/km^2 < PD < 35\ N/km^2$ in the land fragmentation zones on Adelaide's fringes. Furthermore, these ranges were used to identify the land fragmentation zones along the three transects and to spatially quantify the agricultural land within the zones and total transect cells. The results demonstrated a significant difference in agricultural land presence within the fragmentation zones compared to the total extent of agricultural land within the transects. These results clearly indicate the advantage of identifying farmland (primary industries) within the fragmentation zones for targeted land-management practices with the higher possibility of converting this farmland to non-agricultural land uses in these peri-urban landscapes. By classifying land uses by production type, the less-regulated horticultural land uses are concluded as being the land-use type exposed to the highest possible degree to urban sprawl, compared to the larger presence of livestock land in the Adelaide peri-urban areas. To improve the robustness of this method, the author suggests applying it in urban fringe landscapes in different geographies.

In this attempt, urban-to-rural (U–R) gradient analysis was applied on the Adelaide city fringes that are arranged with larger areas of farmland in the rural hinterland without any larger cities existing closer to these fringes, with this like the North American urban fringe land-parcel arrangements. However, application of this urban-to-rural (U–R) transect method can vary in alternative urban fringe landscapes, such as the city peripheries of European nations which are mostly characterized by fragmented and small-scale farmland as well as closer cities that share common peri-urban areas (Verburg et al., 2008, Corbelle-Rico et al., 2012) and city fringes in eastern Europe with limited information on landscapes (Plieninger et al., 2016). The application of this urban-to-rural (U–R) gradient technique in developing nations, such as the countries of East/South-east Asia with cities of high population densities and limited smaller areas of farmland (Wang et al., 2017, Schneider et al., 2015, Anseeuw et al., 2012, Hassan, 2017); highly dense African cities with abundant/smaller areas of farmland (Murayama et al., 2015, Makita et al., 2010, Hou et al., 2016); or cities in South America commonly characterized by high elevated terrain and limited agricultural land presence due to rural–urban migration (Aide and Grau, 2004), can be varied based on specific spatial land-parcel arrangements in these geographic areas.

Variations in application could occur in terms of the transect length; PD versus MPS dependencies (the definition of a unique PD range to identify land fragmentation zones); and empirical evidence of land use in the studied geographies. Therefore, this method could be used to investigate specific-area land fragmentation zones, while identifying farmland located within these zones when prioritising land-management practices. The author also identifies the likelihood of integrating this technique with environmental impact assessments (EIAs), as it is highly regarded in peri-urban land management, to identify urban fringe farmland with a greater exposure to urban sprawl.

The urban-to-rural (U–R) gradients have been widely applied on North American city fringes to understand land transitions and associated effects due to the expanding cities nearby (McDonnell and Hahs, 2008, Weng, 2007, Bridges et al., 2007, Luck and Wu, 2002). Moreover, on many occasions, the urban-to-rural (U–R) gradient analysis has been successfully used in European cities to investigate land-use changes due to urban sprawl (Haase and Nuissl, 2010, Vizzari et al., 2015, Larondelle and Haase, 2013). However, very few research attempts have considered using urban-to-rural (U–R) gradients with landscape metrics to understand the effect of urbanization on peri-urban agricultural land transitions around the cities of eastern Europe, Asia (except for eastern China [Zhang et al., 2016]), Africa and South America. To improve the knowledge on anticipated farmland extinctions from urban expansion, the author highlights the importance of applying this method in cities experiencing rapid urban growth and exhibiting limited concern for farmland preservation. Overall, this method has the potential to improve the understanding of the effects of urbanization on peri-urban agricultural landscapes by spatially quantifying the extent of farmland within fragmentation zones. Furthermore, the plotted land-use configurations embedded within the urban-to-rural (U–R) gradients present a visualization of the changing patterns of land use along the gradients, with this useful for developing area-specific information for land-use analysis. These quantifications are important for land-use researchers and land-management practitioners to identify the magnitude of current urbanization impacts on peri-urban landscapes, ecological services and local community lifestyles.

8.3 LOCAL LAND ADMINISTRATIVE POLICIES AND AGRICULTURAL LAND TRANSITIONS IN PERI-URBAN AREAS

The local land administrative policies play a major part in land-use planning and management in peri-urban areas. As a result of urban pressure from nearby cities, land in peri-urban zones is frequently subject to land-use changes due to "push" factors (i.e., increasing employment opportunities, property value, future development zones, services and expanding infrastructure to rural areas), while restraining the sprawl with "pull" factors (i.e. land zones conserved by legislation, farmland with higher economic returns). This leads to non-linear land-use transitions on the city fringes. Land-use planners and policy makers seek justifiable evidence to select strategic land-management solutions in these landscapes when maintaining peri-urban landscape sustainability. As one of the major land-use types on the city fringes, agricultural land uses are often subject to conversion into non-agricultural practices to satisfy the growing demand for land (Pannell and Vanclay, 2011, Ichikawa et al., 2006, Lee et al., 2009). However, only limited attempts have been undertaken to identify land vulnerability (land-use conversion) to urban sprawl and to estimate the risk of agricultural land conversions in a spatial context.

Chapter 4 addressed this issue by proposing spatially-explicit multi-criteria methods integrated with scenario analysis, using the Adelaide city fringes as a testing site. Although Chapter 3 was focused on three transects, Chapter 4 considered the entire peri-urban area of Adelaide as a study area for investigating land vulnerabilities in a spatial context. In this attempt, the Agricultural Land Vulnerability Index (ALVI) values were derived through six geographically weighted indicative parameters that significantly impacted on agricultural land extinction in Adelaide. By focusing on the major aspects of urban sprawl on city fringes (i.e., institutional effects such as land-use planning/management, and socio-economic and physical land-use/land-parcel arrangements), the parameters were classified as follows: institutional effects (development and protected zones); socio-economic influences (property market value, financial strength by agricultural-production type); and physical land arrangement (steep terrain and land fragmentation zones). However, applying this method in different peri-urban/geographic areas would benefit from selecting parameters based on the effects of institutional, socio-economic and physical status specific to the study areas. A detailed reflection of the socio-economic effects in parameter representations could also more precisely identify land vulnerabilities.

The spatially-explicit results of the current study demonstrates the spatial heterogeneity of land vulnerabilities in the studied landscapes. In peri-urban land systems, the trade-offs between urban expansion ("push") and the power to restrain urban sprawl ("pull") create spatially heterogeneous land vulnerabilities in specific locations. This provides evidence for the patchy evolution of land-use changes on urban fringes, due to area-specific complex land transitions. These non-homogeneous land vulnerability estimates are important in identifying locations where agricultural land is at risk due to urban sprawl. This provides grounds for exploring connections between the causes and the effects occurring at specific geographic areas. The knowledge developed on land vulnerability is useful when identifying the risk of farmland conversions to non-farmland uses, under different land-management policy directions.

The plausible scenario representation of this analysis has demonstrated the situation-based land vulnerability variations in a spatial context, answering the question “in what situations does urban sprawl accelerate and where is land vulnerability significantly increased?” by demonstrating the initial set-up of the land system and the magnitude of the impact under these situations in different locations. This helps in understanding the location-specific trade-offs (“push” and “pull”) and the effects under different land-management policy set-ups. This information is highly regarded by land-use planners and policy makers to identify what type of land management strategies affect peri-urban landscapes and where it can occur in different magnitudes.

Land-use researchers have identified the advantage of using scenario analysis for evaluating land-management policies in complex land systems (Verburg et al., 2010, Thapa and Murayama, 2012, Adams et al., 2016). Although this study has investigated land vulnerabilities in three scenarios under the spectrum of land-management policy options (the EDS, the BAU scenario and the EPS), there is the possibility of expanding this method to investigate scenario-based land vulnerabilities with temporal dynamics for future predictions. However, in this attempt, the author focused on developing three sets of land vulnerability model environments for the ABM, representing the spatially-explicit impact on agricultural land uses under the selected land-management policy directions.

The development of a scenario’s storyline provides a foundation for analysis. Although this study defined the scenarios based on study area-specific local knowledge and planning reports, this method could be further improved at a different study site by incorporating the broader view of stakeholder engagements. As an example, a recent scenario’s planning attempt in the northern coastal areas of the same study area has successfully used broader representation of stakeholder participation to define the storyline for its scenario analysis (Sandhu et al., 2018). The importance of wider stakeholder engagement and strong empirical justifications in a developed storyline in land-system analysis is also demonstrated through the studies of other authors (Griewald et al., 2017, Westhoek et al., 2006, Patel et al., 2007, Herrero et al., 2014).

In this analysis, the unique land vulnerabilities exhibited in the local government areas emphasised the advantage of developing local government area-based knowledge of the farmland at risk, to select strategic land-management policies at the level of local peri-urban land administration. Transferring the knowledge (spatially-explicit land vulnerability information) into land-use planning or land-management practices is challenging in local government land administration. The author has identified the advantage of incorporating this land vulnerability information into spatial data sets (GIS layers): these are readily available for integration with the current local government area land-use planning spatial-analysis tools to offer evidence for strategic policy decisions. Moreover, spatial information on land vulnerability can fulfil the need for common information media to be used to identify the implications of location-based urban sprawl on productive agricultural landscapes, among local government land administration and stakeholder policy groups represented at different levels (Bateman et al., 2013). Overall, this study (in Chapter 4) was an attempt to improve the level of knowledge of peri-urban agricultural land vulnerabilities under different land-management policy directions, through the views of land-use planners and policy makers.

8.4 DRIVERS FOR PERI-URBAN FARMERS' LAND-USE CHANGE DECISIONS AND DECISION BEHAVIOURS

Peri-urban farmers' land-use change decisions make a significant contribution to the transformation of peri-urban farming landscapes into non-farming land uses by deciding on the continuation of farming businesses or to sell the farmland, under their own land-management implications. These decisions affect the rate of urban sprawl into peri-urban landscapes. Understanding the rationale behind these decisions is a complex task due to wider insights of external considerations (such as markets for their production, water accessibility and climate changes) and internal considerations (such as labour, return on investment [ROI], debts, family and health). The investigation of key drivers behind these complex land-use decisions is important to reveal the factors which have greater influence on land transitions. The land system science (LSS) literature shows that only limited knowledge has been developed on farmers' land-use decisions in these peri-urban areas that demonstrate substantial human–environment interactions.

Chapter 5 addressed this knowledge gap by surveying a sample of farmers representing the peri-urban farming population in Adelaide, South Australia, while statistically investigating their farming characteristics and the key drivers behind their land-use change decisions. The initial statistical tests confirmed the absence of any significant correlations between the farmers' land-use decisions and their age group or industry type, demonstrating the complexity of the land-change decision processes in these peri-urban areas. The latent factors derived through EFA over the 16 factors considered by the farmers to influence farm success showed higher factor loadings for the following primary factors: climate change (long-term/severe conditions), labour cost, return on investments (ROIs), investment in new technologies and water accessibility on the fringes of Adelaide. The emergence of internal economic factors, such as labour cost and investment in new technologies which were not identified as priority concerns by the farmers for their farming business success, demonstrated the advantage of using EFA to investigate the key drivers behind farmers' land-use decisions. Furthermore, the latent factors derived from 12 primary factors (considered for land-use change decisions in the situation where their farming business was not considered viable) showed higher factor loadings for the following primary factors: water accessibility, property market value, availability of buyers in the area, drought conditions and government regulations on waste water or farming practices. These results demonstrate that the local economy, the environment and local land administration play a major role in farmers' land-use decisions on the Adelaide fringes. Overall, the above points reveal that the key drivers behind farmers' land-use decisions have internal and external considerations for farmland transitions on Adelaide city fringes, which could potentially change in different geographies with area-specific land-system arrangements.

Applying this technique in contemporary peri-urban land systems can be especially challenging due to the substantially varied local conditions that drive agricultural land-change decisions. As an example, in the contemporary peri-urbanization occurring due to rapid government-led land-use changes on the fringes of eastern Chinese cities (Shanghai, Tianjin and Shenzhen) (Bai et al., 2011, Tian et al., 2017), peri-urban farmers (including heritage farmers) have limited options when deciding to continue their farming practices on their heritage farmland (Tian, 2015). In this situation, the government-led land-change policies will appear to be the key driver controlling the land transitional processes while leaving very limited room for farmers to decide whether to remain in their farming businesses in these rapidly developing peri-urban zones. Also, when applying this exploratory approach in developing nations (city peripheries of South-East Asian and African cities) that are commonly characterized by less regulated land, farms with low economic returns and abandoned farmland (Mertes et al., 2015, Murayama et al., 2015), it is necessary to carefully select the evident area-specific factors for farmland transitions including the economic shift from farming to small-scale industries. Furthermore, when applying this method to research on the fringes of heritage cities that exhibit teleconnections and higher concerns about climate change (such as cities in the European Union having direct trade relationships with other world nations [Roberts, 2014]), it is necessary to represent the variety of socio-economic factors that have a substantial influence on local farmland transitions.

Chapter 6 addressed another key knowledge gap that emerged through this study's literature review: "what are the farmers' land-use change decision-making profiles and their decision rules in peri-urban land systems?" Based on the peri-urban farmers' questionnaire survey in Adelaide, four land-use change decision-making profiles were derived by clustering the farmers' responses (grouping them by response patterns), while exploring the decision behaviours of the grouped participants. In this approach, the author demonstrated the possibility of classifying the land-change decision-making profiles in terms of their motivation towards land management. The derived four profiles were as follows:

P1 (Heritage interest): Highly attached to the farmland and less profit-oriented.

P2 (Commercial interest): Large-scale commercial farming businesses (profit-oriented but caring for the farm environment).

P3 (Selling interest): Highly profit-oriented (intensive farming), less attachment to the farmland and less caring of the farm environment.

P4 (Multi-func./hobby interest): Farmers with commercial interest/hobby farmers' involvements (less profit-oriented but highly caring for the environment).

These derived profiles distinguished the targeted differences in land management of their respective types of farmers in the peri-urban areas. These results carried the different dimension of identifying the decision-making profiles and the land-change decision rules to deconstruct the complexity associated with their farmland transitions.

By grouping the farmers based on similar objectives for their farming businesses, these emerging clusters helped to identify their decision-making profiles as farmers with similar attitudes and opinions on land-change decisions were grouped together. Once the grouped participants were identified as a profile, their land-use change decision behaviours could be uniquely identified in these land systems. In this exploratory approach, statistical investigations demonstrated that the profile P3 (farmland sellers) had tight clusters (less cluster variability between participants) while the other three profiles (P1, P2, P4) showed loose clusters. However, each of these three profiles was characterized by distinguishable behavioural differences. The demonstrated strong clustering of the farming participants in profile P3 (farmland sellers)—their land-change decisions having the highest impact on land conversions—shows the robustness of this approach in understanding farmland transitional processes in complex peri-urban land systems.

8.5 EVALUATION OF FARMLAND TRANSITIONAL PROCESSES ON CITY FRINGES

Land-use modellers are often challenged by the complexity associated with land transitional processes in peri-urban landscapes with extensive human–environment interactions. The LSS literature is developing, but limited knowledge on peri-urban farmland transition dynamics is often experienced in many city peripheries around the world. Chapter 7 of this thesis has addressed this gap by developing agent-based models (ABMs), representing the "agents" of the derived farmland decision-making profiles and using spatially-explicit land vulnerabilities as the "model environment" in which to evaluate the complex farmland transitional processes in the study area on the peripheries of Adelaide. To understand the transitional processes, the developed ABMs were focused on maintaining the accuracy of land transitional processes by defining the properties of the agents (groups of farmers/farmland decision-making profiles) and the behavioural functions, with these represented by information from the farmers' survey and local empirical observations. Furthermore, this study was extended to examine farmland transitions under different land-management policy directions to explore the sensitivity of the decision-making profiles (agents) to the model environment through these tailored ABM simulations.

The developed ABMs were focused on addressing major complexity challenges: spatial, behavioural and temporal dynamics associated with these farmland transitional processes. In this modelling exercise, spatial complexities were addressed by focusing on the following: spatial auto-correlations (by examining agents with similar profiles in defined proximities with a set radius), spatial dependency (by integrating spatially distributed land vulnerability in the model environment) and spatial heterogeneity (by changing the spatial diversity of agents in the system in ABM-3) in these farmland transitions. In many instances, the system behavioural complexities were addressed, by measures such as: path dependency (PD) of the agents (by maintaining the agents' previous knowledge as "memory" that was updated at each model iteration) and agents' behavioural complexities (by identifying the derived profile agents as specific class-based objects in NetLogo—with code to represent the unique decision rules for their actions and to capture the multiple goals of these profiles through the assigned conditions for their actions). Furthermore, the behavioural complexity (path dependency) of this land system was examined by incorporating varying model environments through meaningful scenario analysis in a spectrum of policy directions (the EDS to the EPS). This scenario-based analysis helped in developing an understanding of the path-dependent trajectories of the alternative land-management policy implications for farmland transitions. In the ABM simulations, the temporal complexities of the agents (profiles) were addressed by assigning unique life expectancies and a "starting age" while assigning constant (annual) periods for the iterations. Overall, the spatial, behavioural and temporal complexities of the farmland transitional processes were represented in the developed ABM simulations.

The ABM simulation results demonstrated the opportunity of using the farmers' land-use decision-making profiles as the agents in these land systems to gain an understanding of the farmland extinction processes represented by the disappearance of farmers and conversion of their farmland to different land-use practices over time. Although some profiles showed constant and stable lifespans in the profile dynamic curves (P1 [heritage] and P2 [commercial]), the developed tipping-points midway into the simulations demonstrated that the farmers' extinction (P1 [heritage]) or increased commercial farming (P2 [commercial]) in this land system were inevitable, after a certain time. Furthermore, the unique profile's dynamic curve patterns of the profiles P3 (sellers, intensive farmers) and P4 (multi-functional/hobby farmers) significantly increased the profile count midway into the simulations. This showed subjective variabilities in the land extinction processes that explained the higher risk of increasing these types of land uses in the land system, as they can easily be converted into non-farming practices due to the pressure of urban sprawl in Adelaide. This path-dependent feedback demonstrated the profiles' behavioural dependencies with the initial/previously experienced situations in the simulations.

The unaffected dynamic curves of all four profiles in varied spatial proximities of the neighbourhood (varying radiuses – analysing the spatial correlations between individual agents belonging to the same profile type) demonstrated the farmers' individuality in their land-change decision-making behaviours that had the least effect on farmland transitions. This provided evidence for less self-organization of the profiles in land transitions, indicating their autonomous adaptive preferences for their-land-change decisions. This was further confirmed by the higher percentage of farmers residing off site, with less consideration for their neighbourhood when making land-use decisions on the Adelaide city fringes.

In the study's scenario-based simulations, the sensitivity of the tested profiles to the three land-management policy trajectories indicated that profiles P3 (intensive farmers) and P4 (multi-functional/hobby farmers) were highly sensitive to these policies, compared to the profiles of heritage or commercial farmers who were represented with stable and constant lifespans. The rapidly increasing profile count represented by these types of farmers (P3 [intensive], P4 [multi-functional and hobby farmers]) in a high economic development scenario (EDS), demonstrated that the expected urban sprawl into these landscapes would occur, particularly at the cost of heritage and larger commercial farmland with less economic returns. The conversions of these types of farmland are highly dependent on the emergent economies in these peri-urban areas due to rising property market values and local demand for their production. Due to the small scale of their farming practices, these farmers can make quick decisions to sell the farm, in comparison to heritage farmers or large-scale commercial farming businesses. Therefore, these land conversions latently, but substantially, contribute towards the peri-urban landscape transition.

The accelerated farmland transitional trends on the northern Adelaide fringes provide indicative evidence for converting these types of farmland (characterized by grazing and intensive farming) into housing development. Furthermore, hobby farmers and multi-functional farmers with lower economic returns, whose farms are located beyond the eastern hilly conservation areas, also indicate a higher tendency for transforming their farmland into non-agricultural practices to maintain their wealth. The land-governing authorities have the legal mandate to manage these farmlands by regulating land use, subdivisions and natural resources within the farms. However, these authorities have given less attention to the evaluation of alternative land-use policies when assessing the impact of these farming practices on the Adelaide city fringes. These points show the advantage of evaluating alternative land-management policies to identify the farmlands with a major contribution to make in transforming productive agricultural landscapes into urban form on the fringes of Adelaide.

In this approach, the knowledge, developed in the ABM simulations that captured the complexities of the farmers' land-use change decisions, was used to examine the farmland extinction phenomenon on the

Adelaide city fringes. However, the method and application of this approach in different peri-urban areas needs to be tailored to represent area-specific profiles (based on farming motivations) and farmers' autonomous decision behaviours while focusing on the sensitivity of the profiles to the tested model environments. The identification of these sensitive profiles is important for targeting strategic land-management policies for specific farmland uses and effective land management on urban fringes.

8.6 CONCLUSION AND RECOMMENDATIONS

This study was mainly designed to explore peri-urban agricultural land transition phenomena due to urban sprawl using Adelaide, South Australia, as a study area. In parallel with the key research objectives, this study developed the knowledge on the agricultural land areas; their presence in land fragmentation zones; farmland vulnerability in specific local government areas; farmers' land-use change decision-making behaviours; land system transitions; and feedback under plausible scenarios. In the developed ABMs, the identification of agents as decision-making profiles in terms of their land management motivations (heritage, commercial, sellers with intensive farming interest and multi-functional/hobby farming interest) brings a new dimension to exploring the complex land transitions on the city fringes.

The ABM simulation system feedback showed that the extinction of agricultural land on the fringes of Adelaide due to urban sprawl is unavoidable over time. Specifically, the results demonstrated the advantage of managing long-term commercial farming businesses and heritage farms to restrain urban sprawl from entering the peri-urban landscapes in Adelaide. By facilitating the gradual conversion of heritage farms with shorter lifespans to stable commercial farming investments with longer lifespans, the power of this land system to restrain urban sprawl could also be increased. Furthermore, the study's results showed the urgent need to focus on land administration policies that affect farmland consisting of intensive, multi-functional and hobby farms with these exhibiting a higher risk of conversion to non-agricultural practices on the urban fringes.

Based on the knowledge developed in this research, the author has identified the advantage of "preparing the peri-urban" for the anticipated urban sprawl in the near future by establishing long-term sustainable land-management goals to avoid irreversible changes to the current peri-urban landscapes. To prepare "the peri-urban" for such future challenges, a broader dialogue needs to exist with wider stakeholder participation (including land-governing agencies, planners, politicians, community leaders and academics) to evaluate the plausible land-transitional options that aim to increase human well-being, economic development and ecological services in the peri-urban regions. This will assist stakeholders to agree on sustainable, area-specific goals (i.e., the kinds of landscapes required in these areas in the future) and to establish long-term development goals in State and local government development plans and legislation to streamline future peri-urban land-use transitions.

A major limitation experienced in this research was the requirement to collect a large amount of information on farmers' socio-economic factors, their properties and land-use change decision-making behaviours in order to parameterise the agents in the ABM development processes. Although this study was focused on the Adelaide city fringes, diverse case studies targeting the area-specific complex peri-urban farmland transitional processes could further improve the knowledge in different geographies. The LSS research community could further explore these peri-urban farmland transitions by focusing on farmland vulnerabilities and policy implications in local government areas as well as by undertaking detailed examinations of social and micro-economic factors driving farmers' land-change decisions. Identification of farmers' land-change decision-making profiles could also be investigated by focusing on their land-management motivations for the ABM simulations, as profiles extremely sensitive to plausible peri-urban scenarios were prioritised for land-system analysis.

APPENDICES

APPENDIX C3:

Homing in on city fringe land use

Small-scale livestock agistment and hobby farms near city fringes are most vulnerable to development, says Flinders GIS researcher Suranga (Sam) Wadduwage.

Pockets of small landholdings used for hobby farms and grazing are most susceptible to urban infill and industrial development, leaving larger horticultural and dryland farms for food production, according to Flinders University researchers.

A new spatial planning tool, based on maps of Adelaide and its surrounding areas, could be adapted and used in rapidly growing cities in Australia and overseas to improve urban planning and major infrastructure development, says Professor Andrew Millington, an expert in Geographic Information System (GIS) and land science at Flinders University's School of the Environment.

"We've used this GIS mapping technique to draw up a vulnerability map of the Adelaide region. It shows a number of highly fragmented peri-urban areas which could be targeted for land development as the city grows," Professor Millington says.

"According to our metrics of State Government data, there are several areas with marginal economic value which are most susceptible to development, including hobby farms to the south and north of Adelaide.

"They could be the focus of development in order to preserve those valuable and often more economically viable food production farming areas in the future."

While smaller horticultural and livestock grazing land is increasingly falling prey to housing, roads and other development on Adelaide's urban fringes, dryland farming, larger-scale horticultural enterprises and heritage-protected vineyards are generally less vulnerable.

Around Adelaide, the researchers identified several key areas currently most vulnerable to development, including:

- To the north of Adelaide – the Gawler Belt, north of Virginia and the western end of the new Northern Expressway, between Edinburgh and Virginia.
- To the south – the O'Halloran Hill-Black Rd and Kangarilla areas
- To the east – some patches around Mt Barker and the Littlehampton hills-face zone.

"The test of this technique would be to apply it to another city which is expanding rapidly to see the potential hotspots which could be rezoned to encourage industry and developers to concentrate on acquiring these areas," Professor Millington says.

However, these peri-urban agricultural lands which are more vulnerable for fragmentation can be protected with community engagement and other support, says the lead researcher Suranga Wadduwage.

Major city urban planning to reduce urban sprawl would benefit from close examination of underutilised, less productive land over more valuable, capital intensive food and wine agricultural land.

Apart from the planning authorities, these peri-urban areas come under the radar of different stakeholder policy networks, such as primary production, NRM boards and conservation groups, Mr Wadduwage says.

"It is possible to take an alternative view and rally the support of these stakeholder networks in collective planning strategies.

"These landholdings subject to lower economic returns can have a sustainable and enduring future rather than be consumed by urban developments, which has irreversible consequences for a city's future."

Urban sprawl puts hobby farms in the firing line

https://indaily.com.au/news/local/2017/04/28/urban-sprawl-puts-hobby-farms-firing-line/

APPENDIX C5:

Ethics approval for data collection

FINAL APPROVAL NOTICE

Project No.:	**7043**		
Project Title:	Agricultural Land Dynamics at the Urban Fringe: Adelaide		
Principal Researcher:	Mr Suranga Wadduwage		
Email:	wadd0025@flinders.edu.au		
Approval Date:	9 November 2015	Ethics Approval Expiry Date:	**1 January 2019**

The above proposed project has been **approved** on the basis of the information contained in the application, its attachments and the information subsequently provided with the addition of the following comment(s):

Additional information required following commencement of research:

1. Permissions
   Please ensure that copies of the correspondence granting permission to conduct the research from the individuals and/or organisations involved (i.e., Mayor, City of Playford; Mayor, City of Onkaparinga; Mayor, Adelaide Hills Council) are submitted to the Committee *on receipt.* Please ensure that the SBREC project number is included in the subject line of any permission emails forwarded to the Committee. Please note that data collection should not commence until the researcher has received the relevant permissions (item D8 and Conditional approval response – number 7).

Survey introductory letter

Flinders UNIVERSITY

Prof. Andrew Millington

School of Environment

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Tel: +61 8 82017577

Email: andrew.millington@flinders.edu.au

CRICOS Provider No. 00114A

LETTER OF INTRODUCTION

Dear Sir/Madam:

This letter is to introduce Suranga Wadduwage who is a research higher degree student in the School of the Environment at Flinders University. He is undertaking research leading to the production of a PhD thesis or other publications on the subject of '**Evaluation of agricultural land dynamics at the urban fringe: Adelaide**'.

He would be most grateful if you would volunteer to assist in this project, by completing questionnaires which covers certain aspects of this topic. No more than 15 minutes on one occasion would be required.

Be assured that any information provided will be treated in the strictest confidence and none of the participants will be individually identifiable in the resulting thesis, report or other publications. You are, of course, entirely free to discontinue your participation at any time or to decline to answer particular questions.

Any enquiries you may have concerning this project should be directed to me at the address given above or by telephone on +61 8 8201 7577, by fax on +61 (08) 8201 3300, by e-mail (andrew.millington@flinders.edu.au)

Thank you for your attention and assistance.

Yours sincerely

Andrew C Millington

Prof. Andrew Millington

Professor of Land Change Science
Distinguished Professor in GIS, School of the Environment.

This research project has been approved by the Flinders University Social and Behavioural Research Ethics Committee (Project No: 7043). For more information regarding ethical approval of the project the Secretary of the Committee can be contacted by telephone on 8201 5962, by fax on 8201 2035 or by email human.researchethics@flinders.edu.au

Updated 28 September 2007

inspiring achievement

Questionnaire survey form

Return Form | Survey Ref No:

Questionnaire Survey for Agricultural land Owners

First, I would like to ask some questions about your farm

1. What is the approximate area of your farm? ☐☐☐ …... hectares ☐ acres ☐
2. What are you producing/have produced in the last 12 months in your farm?

   Grapes/Wine -Yes☐ No☐ , **Wheat** -Yes☐ No☐, **Vegetables** -Yes☐ No☐ ,

   Livestock -Yes☐ No ☐, **Other** Yes☐ No ☐ If yes, please specify ………………………………….
3. As you are aware, where does your production go to?

   Local market-Yes☐ No☐, National market-Yes☐ No☐, Export market -Yes☐ No☐.
4. How important are the following to you?

		Very Important	Important	Moderately important	Marginally important	Unimportant
4.1	Making a good profit from your farm	☐	☐	☐	☐	☐
4.2	Caring for the environment on your farm	☐	☐	☐	☐	☐
4.3	Being part of your local community	☐	☐	☐	☐	☐

5. During the last production season, how many full time equivalent employees work in your farm, including yourself? ☐☐ persons
6. Have you implemented a long-term farm management plan for your farm? Yes☐ No ☐
7. Approximately what proportion of your household's income has **NOT** come from Farm (In the last five years)? none ☐, less than 25% ☐, 25-50% ☐, 51-75% ☐, 76-100% ☐, all ☐
8. From your experience, how do you rate the importance of following **factors** in the **success** of your farm?

		Very Important	Important	Moderately important	Marginally important	Unimportant
8.1	Labour costs	☐	☐	☐	☐	☐
8.2	Overall maintenance costs (running cost)	☐	☐	☐	☐	☐
8.3	Investments in new technology	☐	☐	☐	☐	☐
8.4	Selection of crop/livestock type	☐	☐	☐	☐	☐
8.5	Overall financial return on investment (ROI)	☐	☐	☐	☐	☐
8.6	Water accessibility	☐	☐	☐	☐	☐

1

8.7	Soil fertility	☐	☐	☐	☐	☐
8.8	long term climate changes (eg. increased frequency of drought)	☐	☐	☐	☐	☐
8.9	Severe climate events (eg. freak storm)	☐	☐	☐	☐	☐
8.10	Previous farming experience	☐	☐	☐	☐	☐
8.11	Neighbouring farmers' crop/livestock choices	☐	☐	☐	☐	☐
8.12	Farming heritage of your family	☐	☐	☐	☐	☐
8.13	Having your own land (not a leased property)	☐	☐	☐	☐	☐
8.14	Being part of a cooperative farming group	☐	☐	☐	☐	☐
8.15	Access to finance (eg. Bank loans, savings)	☐	☐	☐	☐	☐
8.16	Crop insurance	☐	☐	☐	☐	☐

9. In a hypothetical situation of your farm being **unsuccessful**, what is your most likely decision?

	likely	**somewhat likely**	**somewhat unlikely**	**unlikely**
Change the farming practices	☐	☐	☐	☐
Sell the farm	☐	☐	☐	☐
Subdivide and sell part of it	☐	☐	☐	☐
Lease the land	☐	☐	☐	☐

Not applicable ☐

10. In such a hypothetical situation (your farm being **unsuccessful**), how do you rate the importance of the following **factors** on your future **land-use decisions**?

		Very Important	**Important**	**Moderately important**	**Marginally important**	**Unimportant**
10.1	Increasing demand for your crop/livestock	☐	☐	☐	☐	☐
10.2	Infrastructure development in your area (transport, energy and water)	☐	☐	☐	☐	☐
10.3	Increasing water accessibility	☐	☐	☐	☐	☐
10.4	Water price	☐	☐	☐	☐	☐
10.5	High market value for your land (high selling price)	☐	☐	☐	☐	☐

10.6	Other farmers willing to purchase land in your area	☐	☐	☐	☐	☐
10.7	Decline in the number of farmer from your ethnic group in your area.	☐	☐	☐	☐	☐
10.8	State or Local government regulations on waste water or farming practices.	☐	☐	☐	☐	☐
10.9	State or Local government planning restrictions on land-use	☐	☐	☐	☐	☐
10.10	Drought conditions	☐	☐	☐	☐	☐
10.11	Encroaching urbanization in your area	☐	☐	☐	☐	☐
10.12	Costs of changing land-use	☐	☐	☐	☐	☐

I would like to ask some questions about your farming life

11. Would you describe yourself as any of these?

    Full-time commercial farmer Yes☐ No☐, Part-time commercial farmer Yes☐ No☐,

    Traditional farmer Yes☐ No☐, Hobby farmer Yes☐ No☐, Other- please specify ……………………..

12. Do you believe that you come from a "farming family"? Yes☐ No☐
13. Approximately how many years have you worked in the farming industry? ☐☐ years
14. Approximately how many years have you lived in this area? ☐☐ years
15. How many years more would you like to actively farm? ☐☐ years
16. How would you judge that any of your family member will continue your farm business after you retire?

    Very unlikely☐, unlikely☐, somewhat unlikely☐, somewhat likely☐, likely☐, very likely ☐,

    Not applicable ☐

17. How would you judge that you will remain as a farmer for the rest of your working life?

    Very uncertain☐, uncertain☐, somewhat uncertain☐, somewhat certain☐, certain☐, very certain☐

I would like to ask you some questions about yourself.

18. Which of these age ranges do you fall into?

    (18-24) ☐, (25-34) ☐, (35-44) ☐, (45-54) ☐, (55-64) ☐, (65-74) ☐, (75+) ☐

19. Are you male ☐, or female ☐
20. Were you born in Australia? No☐ Yes☐ If Yes, go to Question 23
21. When did you migrate to Australia?

    1-5 years ago ☐, 6-20years ☐, 20-40 years ☐, over 40 ☐

22. Which country did you migrate from? ………………………………………………………….
23. How many years of primary school and secondary school have you completed? (Grade 1-12) ☐☐
24. Have you done any post-secondary education? Yes☐ No☐

Exploratory factor analysis results

1. Latent factor analysis (LFA) in SPSS for Question 8

Initial factor analysis results in SPSS - Q8 for 16 Primary Factor analysis

Pattern Matrix[a]

	Component 1	Component 2	Component 3	Component 4	Component 5	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Labour cost	.780	.182	.073	-.083	-.154	-.095	.625	.090	.081	.028	.634	.133	.039	.105	-.197
Maintenance cost	.670	.234	-.063	-.004	.086	.127	.631	.161	.028	.054	.548	.213	-.025	.148	-.037
Investments in new machinery or technology	-.022	.052	.843	-.096	.250	-.106	.028	.025	.016	.603	.035	.026	.677	.044	-.018
Selection of crop type or farming practise	.480	-.131	-.236	-.152	.169	.090	.372	.011	.199	-.123	.394	-.018	-.143	.196	.087
Overall financial return on investment (ROI)	.868	.074	-.039	-.110	-.131	-.109	.884	-.045	.031	-.099	.854	.024	-.068	.084	-.229
Water accessibility	.126	.746	-.227	.082	.007	-.083	.057	.754	-.122	-.182	-.010	.828	-.161	-.012	-.160
Soil fertility	.246	.236	-.531	.000	.150	-.021	.048	.383	.247	-.449	.111	.293	-.372	.189	.091
Climate change	-.149	.610	-.103	-.275	.322	.136	.003	.590	-.042	.040	.060	.535	.019	-.109	.342
Severe climate events	.120	.658	.151	.043	-.006	-.006	.063	.341	.009	.034	.058	.345	.053	.009	.021
Previous farming experience	.657	-.061	.054	.387	.335	-.098	.198	.029	.519	-.028	.068	.048	.005	.748	-.156
Neighbouring farmer crop/livestock choices	-.004	.252	.148	-.043	.772	.156	-.055	.423	.308	.220	-.042	.327	.183	.335	.319
Farming heritage of your family	.534	-.253	-.031	.094	.476	.086	.065	-.125	.805	-.033	.204	-.167	-.037	.604	.181
Having your owned land	-.109	.016	-.544	-.164	.480	.955	.079	.008	-.002	-.151	.067	.086	-.312	.057	.451
Being part of a cooperative and/or farming	.106	.030	.002	-.787	-.021	.039	.268	.115	.003	.023	.384	.049	.030	-.112	.167
Access to finance	.684	.001	-.084	-.213	-.053	.096	.806	-.085	-.082	.014	.724	-.036	-.056	.003	.004
Crop insurance	.388	-.151	.143	-.506	.155	-.032	.371	-.023	.214	.062	.479	-.085	.099	.085	.135

Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 18 iterations.

Extraction Method: Maximum Likelihood. Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 7 iterations.

Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 18 iterations.

Component Correlation Matrix

Component	1	2	3	4	5
1	1.000	.108	-.121	-.190	.282
2	.108	1.000	-.103	-.109	.126
3	-.121	-.103	1.000	.090	-.117
4	-.190	-.109	.090	1.000	-.124
5	.282	.126	-.117	-.124	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

	1	2	3	4	5
1	1.000	.153	.267	.146	-.097
2	.153	1.000	.360	.564	-.101
3	.267	.360	1.000	.235	-.067
4	.146	.564	.235	1.000	-.005
5	-.097	-.101	-.067	-.005	1.000

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

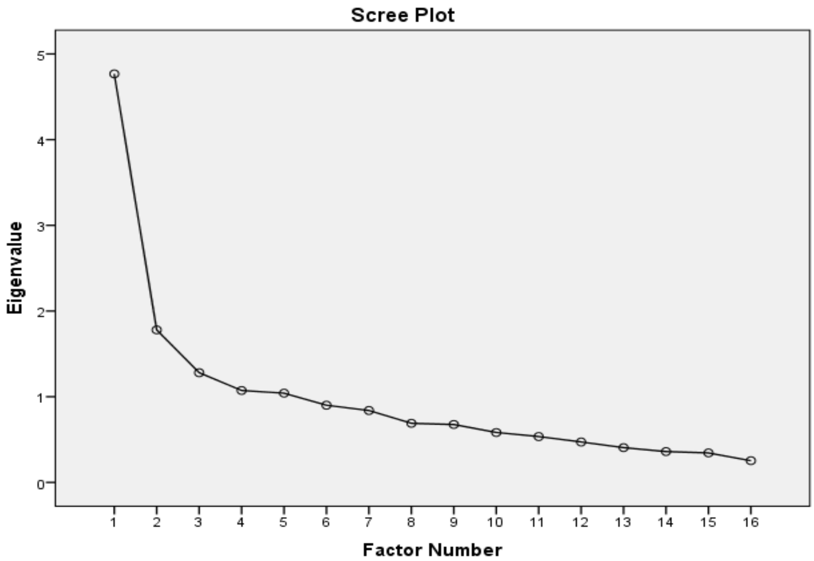
Factor Correlation Matrix

	1	2	3	4	5
1	1.000	.308	-.118	.506	.230
2	.308	1.000	-.117	.193	.260
3	-.118	-.117	1.000	-.079	-.034
4	.506	.193	-.079	1.000	.102
5	.230	.260	-.034	.102	1.000

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

2. Latent factor analysis (LFA) in Mplus: Question 8 for analysis of 16 primary factors

Represent 3 significant factors Eigenvalue > 1



Total Variance Explained

Factor	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	4.768	29.797	29.797
2	1.780	11.124	40.921
3	1.280	8.002	48.923
4	1.073	6.706	55.629
5	1.042	6.510	62.139
6	.901	5.630	67.769
7	.839	5.243	73.012
8	.690	4.311	77.322
9	.676	4.226	81.548
10	.582	3.640	85.189
11	.535	3.344	88.532
12	.472	2.949	91.482
13	.406	2.536	94.018
14	.360	2.249	96.267
15	.344	2.150	98.416
16	.253	1.584	100.000

Extraction Method: Principal Axis Factoring.

		Option-1			Option-2			Option-3		
F-ID	Factor	LF1	LF2	LF3	LF1	LF2	LF3	LF1	LF2	LF3
F1	Labour cost	0.774	0.06	-0.006	0.744	0.066	0.018	0.742	0.099	0.024
F2	Maintenance cost	0.556	0.266	0.217	0.524	0.304	0.149	0.625	0.317	-0.028
F3	Investments in new machinery	0.766	-0.04	-0.173	0.827	-0.116	-0.179	0.721	-0.108	0.162
F4	Selection of crop type	0.453	0.026	0.212	0.449	0.049	0.185	0.548	0.063	-0.114
F5	Financial return on investment	0.772	0.007	0.083	0.721	0.037	0.131	0.77	0.084	-0.08
F6	Water accessibility	-0.013	0.755	0.117	-0.134	0.86	0.001	-0.013	0.789	0.235
F7	Soil fertility	0.085	0.482	0.3	-0.01	0.598	0.207	0.182	0.564	0.006
F8	Climate change	0.007	0.874	-0.08	0.045	0.857	-0.352	0.006	0.746	0.557
F9	Severe climate events	0.037	0.819	-0.016	-0.025	0.869	-0.186	0.004	0.798	0.405
F10	Previous farming experience	0.241	0.01	0.599	0.048	0.211	0.712	0.443	0.226	-0.525
F11	Neighbouring farmer crop choices	-0.007	0.449	0.338	0.002	0.5	0.158			
F12	Farming heritage of your family	0.301	-0.133	0.62	0.275	-0.015	0.568	0.584	-0.024	-0.433
F13	Having your owned land	-0.046	0.286	0.269						
F14	Being part of a cooperative groups	0.469	0.091	-0.163	0.527	0.024	-0.211	0.43	0.004	0.219
F15	Access to finance	0.706	0.008	-0.004	0.718	-0.023	0.004	0.69	0.024	0.003
F16	Crop insurance	0.658	-0.121	0.007	0.718	-0.165	-0.006	0.726	-0.212	0.029

Factor reduction (16F to 3F) Factors influence on farm access.

MPlus results for **Option – 1 (selected factor reduction option)**

EXPLORATORY FACTOR ANALYSIS WITH 3 FACTOR(S):

MODEL FIT INFORMATION

Number of Free Parameters 45

Chi-Square Test of Model Fit

Value 108.607*
Degrees of Freedom 75
P-Value 0.0068

* The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and WLSMV cannot be used for chi-square difference testing in the regular way. MLM, MLR and WLSM chi-square difference testing is described on the Mplus website. MLMV, WLSMV, and ULSMV difference testing is done using the DIFFTEST option.

RMSEA (Root Mean Square Error Of Approximation)

Estimate 0.052
90 Percent C.I. 0.028 0.073
Probability RMSEA <= .05 0.417

CFI/TLI
CFI 0.981
TLI 0.969

Chi-Square Test of Model Fit for the Baseline Model

Value 1847.081
Degrees of Freedom 120
P-Value 0.0000

SRMR (Standardized Root Mean Square Residual)

Value 0.052

MINIMUM ROTATION FUNCTION VALUE 0.53964

GEOMIN ROTATED LOADINGS (* significant at 5% level)

	1	2	3
Q8_1	0.774*	0.060	-0.006
Q8_2	0.556*	0.266*	0.217
Q8_3	0.766*	-0.040	-0.173
Q8_4	0.453*	0.026	0.212
Q8_5	0.772*	0.007	0.083
Q8_6	-0.013	0.755*	0.117
Q8_7	0.085	0.482*	0.300
Q8_8	0.007	0.874*	-0.080

Q8_9	0.037	0.819*	-0.016
Q8_10	0.241	0.010	0.599*
Q8_11	-0.007	0.449*	0.338*
Q8_12	0.301	-0.133	0.620*
Q8_13	-0.046	0.286*	0.269
Q8_14	0.469*	0.091	-0.163
Q8_15	0.706*	0.008	-0.004
Q8_16	0.658*	-0.121	0.007

3. Latent factor analysis (LFA) in SPSS for Question 10

Initial factor analysis results in SPSS – Q10 for 12 Primary Factor analysis

Pattern Matrix[a]

	Component			
	1	2	3	4
Increasing demand for your	.092	.349	.053	-.264
Infrastructure development in	.725	.101	-.058	-.099
Increasing water accessibility	.910	.032	-.041	.037
Water price	.710	-.071	.074	-.199
High market value for land	-.149	.938	.010	.008
Other farmers willing to	.005	.925	-.005	.097
Decline in the number of	.202	.377	-.003	-.042
State or Local government	.167	-.017	-.091	-.852
State or Local government	-.001	.032	.249	-.752
Drought conditions (UnS)	.458	-.018	.661	.272
Encroaching urbanization in	-.209	-.018	.810	-.143
Costs of changing land-use	.084	.244	.546	-.201

Extraction Method: Principal Component Analysis.
a. Rotation converged in 11 iterations.

Pattern Matrix[a]

Factor			
1	2	3	4
.063	-.150	.219	.181
.566	-.044	.063	.071
1.051	.053	.041	-.164
.583	-.194	-.029	.057
-.075	.063	1.010	-.043
.044	.010	.752	.004
.172	-.064	.211	.063
.055	-1.023	-.045	-.085
.022	-.421	.083	.331
.334	.103	-.069	.450
-.096	-.020	.016	.525
.063	-.076	.129	.601

Extraction Method: Maximum Likelihood.
a. Rotation converged in 6 iterations.

Pattern Matrix[a]

Factor			
1	2	3	4
.095	.243	.155	.121
.555	.075	.103	.041
1.034	.015	-.058	-.106
.556	-.022	.189	.075
-.107	.923	-.025	-.020
.039	.845	-.065	-.024
.156	.225	.086	.042
.115	-.011	.825	-.086
-.009	.046	.563	.277
.327	-.027	-.154	.512
-.118	.005	.075	.531
.061	.180	.127	.523

Extraction Method: Principal Axis Factoring.
a. Rotation converged in 11 iterations.

Component Correlation Matrix

Component	1	2	3	4
1	1.000	.280	.207	-.241
2	.280	1.000	.203	-.314
3	.207	.203	1.000	-.211
4	-.241	-.314	-.211	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

Factor Correlation Matrix

1	2	3	4
1.000	-.323	.273	.358
-.323	1.000	-.355	-.352
.273	-.355	1.000	.363
.358	-.352	.363	1.000

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

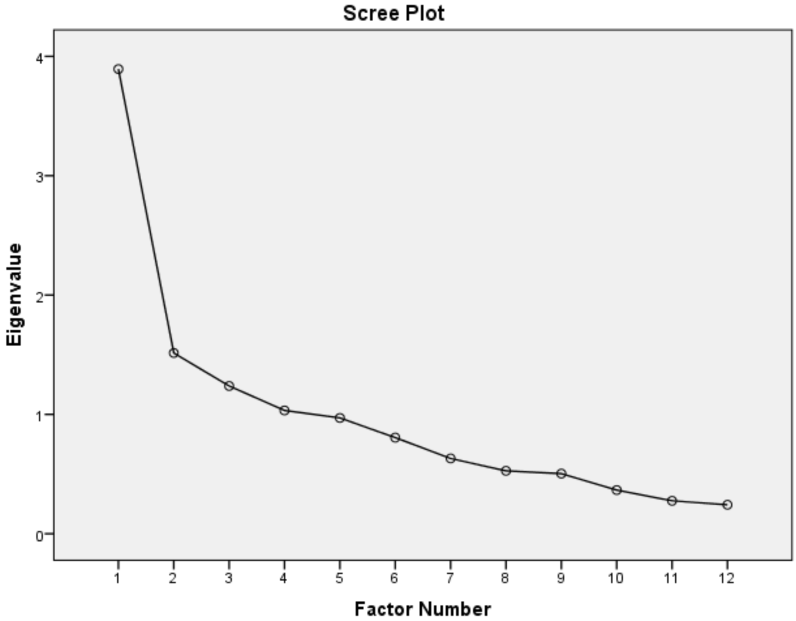
Factor Correlation Matrix

1	2	3	4
1.000	.299	.317	.322
.299	1.000	.380	.325
.317	.380	1.000	.364
.322	.325	.364	1.000

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

Latent Factor Analysis in M-Plus

4. Latent factor analysis (LFA) in Mplus: Question 10 for analysis of 12 primary factors



	Initial Eigenvalues		
Factor	Total	% of Variance	Cumulative %
1	3.894	32.448	32.448
2	1.514	12.620	45.067
3	1.238	10.316	55.383
4	1.033	8.606	63.990
5	.971	8.088	72.077
6	.805	6.711	78.788
7	.631	5.256	84.044
8	.527	4.391	88.435
9	.504	4.196	92.631
10	.366	3.049	95.680
11	.276	2.300	97.979
12	.243	2.021	100.000

Extraction Method: Principal Axis Factoring.

		Option-1				Option-2				Option-3			
F-ID	Factor	LF1	LF2	LF3	LF4	LF1	LF2	LF3	LF4	LF1	LF2	LF3	LF4
F1	Increasing demand for your crop/livestock	0.131	0.233	0.25	0.023	0.146	0.244	0.237	0.032				
F2	Infrastructure development in your area	0.695	0.099	-0.027	0.064	0.684	0.08	-0.017	0.069	0.671	0.062	-0.024	0.093
F3	Increasing water accessibility	0.976	-0.004	0.015	-0.06	0.978	-0.012	0.008	-0.045	0.992	-0.006	0.012	-0.04
F4	Water price	0.633	-0.04	0.194	0.141	0.635	-0.031	0.182	0.157	0.619	-0.027	0.19	0.173
F5	High market value for land	-0.034	0.95	-0.041	0.049	-0.031	0.947	-0.039	0.052	-0.024	0.989	-0.037	0.048
F6	Other farmers willing to purchase	0.053	0.819	0.064	-0.081	0.057	0.818	0.055	-0.07	0.069	0.77	0.082	-0.061
F7	Decline farmer from your ethnic group	0.238	0.224	0.01	0.085								
F8	Government regulations on waste water	0.314	-0.008	0.014	0.714	0.31	-0.005	0.008	0.741	0.304	-0.008	0.008	0.743
F9	Government planning restrictions on land	0.029	0.048	0.35	0.614	0.025	0.051	0.363	0.596	0.023	0.055	0.361	0.608
F10	Drought conditions	0.056	0.008	0.881	-0.394	0.071	0.016	0.841	-0.367	0.075	0.015	0.84	-0.356
F11	Encroaching urbanization in your area	-0.345	-0.029	0.698	0.047	-0.368	-0.044	0.733	0.034	-0.357	-0.039	0.715	0.037
F12	Costs of changing land-use	-0.05	0.267	0.603	0.019	-0.048	0.266	0.604	0.02	-0.04	0.259	0.6	0.029

Factor reduction (12F to 4F) Factors influence on land use change.

MPlus results of the **Option – 3 (selected factor reduction option)**

EXPLORATORY FACTOR ANALYSIS WITH 4 FACTOR(S):

MODEL FIT INFORMATION

Number of Free Parameters 34

Chi-Square Test of Model Fit

Value	13.220*
Degrees of Freedom	11
P-Value	0.2792

* The chi-square value for MLM, MLMV, MLR, ULSMV, WLSM and WLSMV cannot be used for chi-square difference testing in the regular way. MLM, MLR and WLSM chi-square difference testing is described on the Mplus website. MLMV, WLSMV, and ULSMV difference testing is done using the DIFFTEST option.

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.035
90 Percent C.I.	0.000 0.093
Probability RMSEA <= .05	0.596

CFI/TLI

CFI	0.998
TLI	0.992

Chi-Square Test of Model Fit for the Baseline Model

Value	1135.272
Degrees of Freedom	45
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value	0.019

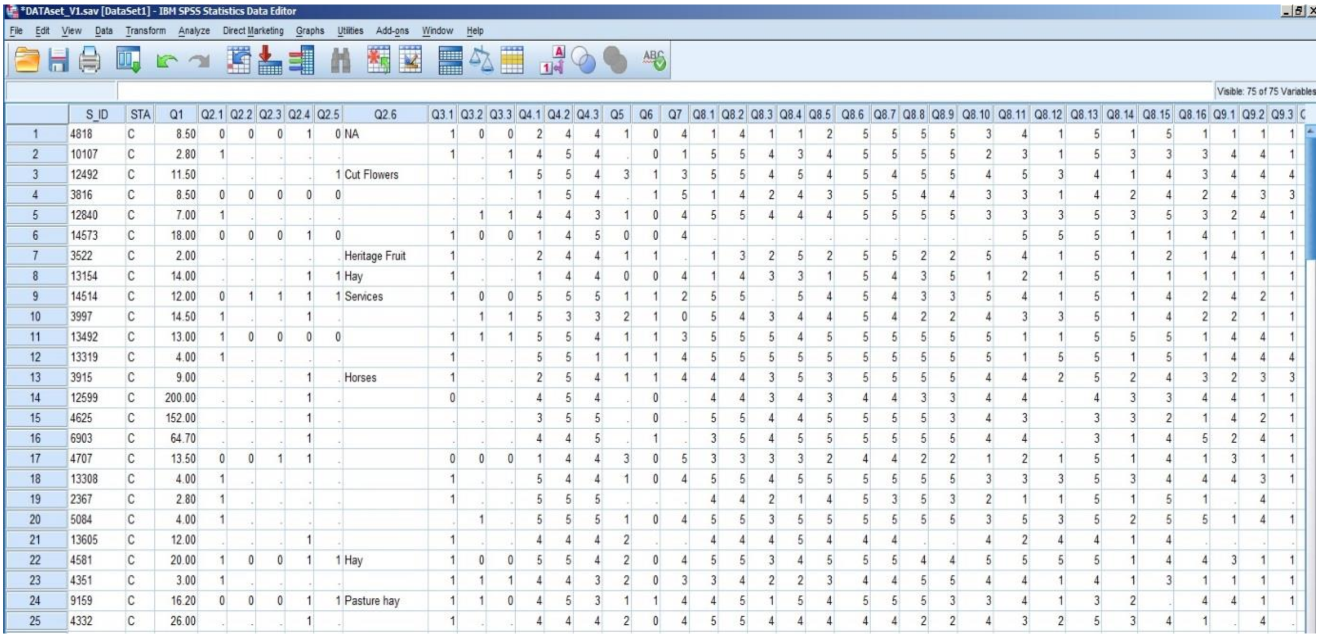
MINIMUM ROTATION FUNCTION VALUE 0.45465

GEOMIN ROTATED LOADINGS (* significant at 5% level)

	1	2	3	4
Q10_2	0.671*	0.062	-0.024	0.093
Q10_3	0.992*	-0.006	0.012	-0.040
Q10_4	0.619*	-0.027	0.190	0.173
Q10_5	-0.024	0.989*	-0.037	0.048
Q10_6	0.069	0.770*	0.082	-0.061
Q10_8	0.304*	-0.008	0.008	0.743*
Q10_9	0.023	0.055	0.361*	0.608*
Q10_10	0.075	0.015	0.840*	-0.356*
Q10_11	-0.357*	-0.039	0.715*	0.037
Q10_12	-0.040	0.259*	0.600*	0.029

Data in SPSS

Screen shots of a) data and b) variable



	S_ID	STA	Q1	Q2.1	Q2.2	Q2.3	Q2.4	Q2.5	Q2.6	Q3.1	Q3.2	Q3.3	Q4.1	Q4.2	Q4.3	Q5
1	4818	C	8.50	0	0	0	1	0	NA	1	0	0	2	4	4	1
2	10107	C	2.80	1	.	.	.	.		1	.	1	4	5	4	.
3	12492	C	11.50	.	.	.	.	1	Cut Flowers	.	.	1	5	5	4	3
4	3816	C	8.50	0	0	0	0	0		.	.	.	1	5	4	.
5	12840	C	7.00	1	.	.	.	.		.	1	1	4	4	3	1
6	14573	C	18.00	0	0	0	1	0		1	0	0	1	4	5	0
7	3522	C	2.00	.	.	.	.	.	Heritage Fruit	1	.	.	2	4	4	1
8	13154	C	14.00	.	.	.	1	1	Hay	1	.	.	1	4	4	0
9	14514	C	12.00	0	1	1	1	1	Services	1	0	0	5	5	5	1
10	3997	C	14.50	1	.	.	1	.		.	1	1	5	3	3	2
11	13492	C	13.00	1	0	0	0	0		1	1	1	5	5	4	1
12	13319	C	4.00	1	.	.	.	.		1	.	.	5	5	1	1
13	3915	C	9.00	.	.	.	1	.	Horses	1	.	.	2	5	4	1
14	12599	C	200.00	.	.	.	1	.		0	.	.	4	5	4	.
15	4625	C	152.00	.	.	.	1	.		.	.	.	3	5	5	.
16	6903	C	64.70	.	.	.	1	.		.	.	.	4	4	5	.
17	4707	C	13.50	0	0	1	1	.		0	0	0	1	4	4	3
18	13308	C	4.00	1	.	.	.	.		1	.	.	5	4	4	1
19	2367	C	2.80	1	.	.	.	.		1	.	.	5	5	5	.
20	5084	C	4.00	1	.	.	.	.		.	1	.	5	5	5	1
21	13605	C	12.00	.	.	.	1	.		1	.	.	4	4	4	2
22	4581	C	20.00	1	0	0	1	1	Hay	1	0	0	5	5	4	2
23	4351	C	3.00	1	.	.	.	.		1	1	1	4	4	3	2
24	9159	C	16.20	0	0	0	1	1	Pasture hay	1	1	0	4	5	3	1
25	4332	C	26.00	.	.	.	1	.		1	.	.	4	4	4	2

	Q6	Q7	Q8.1	Q8.2	Q8.3	Q8.4	Q8.5	Q8.6	Q8.7	Q8.8	Q8.9	Q8.10	Q8.11	Q8.12	Q8.13	Q8.14	Q8.15	Q8.16	Q9.1	Q9.2	Q9.3
1	0	4	1	4	1	1	2	5	5	5	5	3	4	1	5	1	5	1	1	1	1
2	0	1	5	5	4	3	4	5	5	5	5	2	3	1	5	3	3	3	4	4	1
3	1	3	5	5	4	5	4	5	4	5	5	4	5	3	4	1	4	3	4	4	4
4	1	5	1	4	2	4	3	5	5	4	4	3	3	1	4	2	4	2	4	3	3
5	0	4	5	5	4	4	4	5	5	5	5	3	3	3	5	3	5	3	2	4	1
6	0	4	.	.	.	.	.	.	.	.	.	.	5	5	5	1	1	4	1	1	1
7	1	.	1	3	2	5	2	5	5	2	2	5	4	1	5	1	2	1	4	1	1
8	0	4	1	4	3	3	1	5	4	3	5	1	2	1	5	1	1	1	1	1	1
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18	0	4	5	5	4	5	5	5	5	5	5	3	3	3	5	3	4	4	4	3	1
19	.	.	4	4	2	1	4	5	3	5	3	2	1	1	5	1	5	1	.	4	.
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21	.	.	4	4	4	5	4	4	4	.	.	4	2	4	4	1	4	.	.	.	.
22	0	4	5	5	3	4	5	5	5	4	4	5	5	5	5	1	4	4	3	1	1
23	0	3	3	4	2	2	3	4	4	5	5	4	4	1	4	1	3	1	1	1	1
24	1	4	4	5	1	5	4	5	5	5	3	3	4	1	3	2	.	4	4	1	1
25	0	4	5	5	4	4	4	4	4	2	2	4	3	2	5	3	4	1	.	4	.

*DATAset V1.sav [DataSet1] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Direct Marketing Graphs Utilities Add-ons Window Help

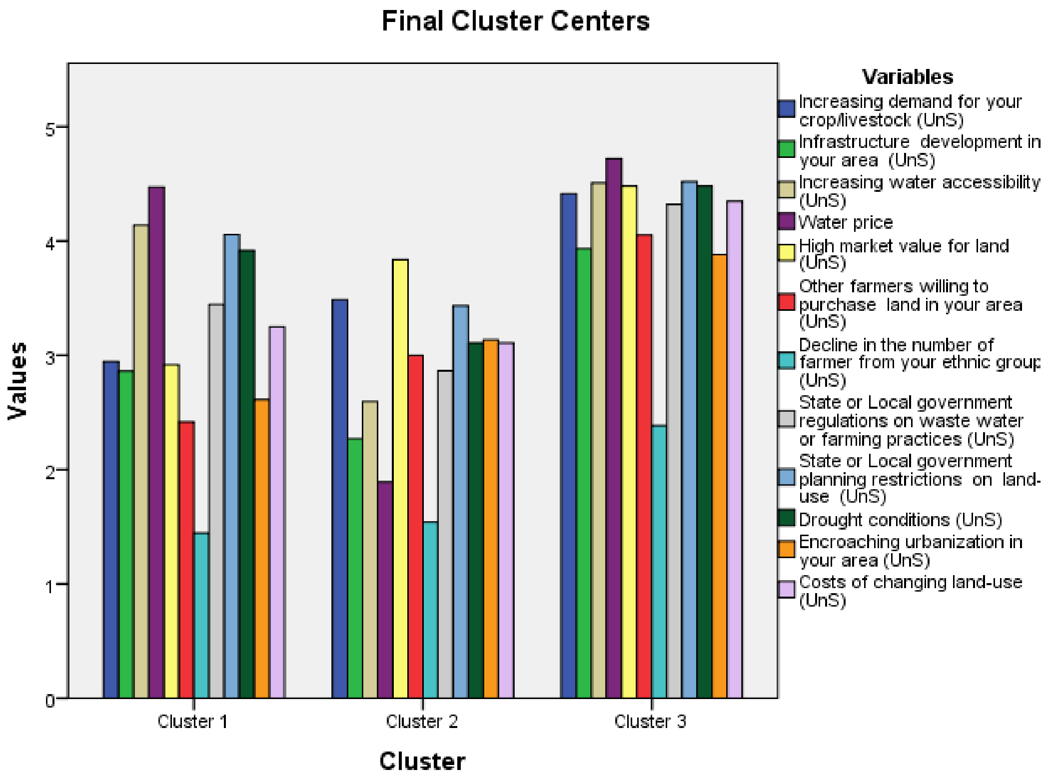
	Name	Type	Width	De...	Label	Values	Missing	Columns	Align	Measure	Role
33	Q8.15	Numeric	8	0	Access to finance	{1, UI}...	None	4	Right	Ordinal	Input
34	Q8.16	Numeric	8	0	Crop insurance	{1, UI}...	None	4	Right	Ordinal	Input
35	Q9.1	Numeric	8	0	Change the farming practices (when farm is unsucce	{1, U}	None	3	Right	Ordinal	Input
36	Q9.2	Numeric	8	0	Sell the farm (UnS)	{1, U}...	None	3	Right	Ordinal	Input
37	Q9.3	Numeric	8	0	Subdivide and sell part of it (UnS)	{1, U}...	None	3	Right	Ordinal	Input
38	Q9.4	Numeric	8	0	Lease the land (UnS)	{1, U}...	None	3	Right	Ordinal	Input
39	Q9.5	Numeric	8	0	Not applicable (UnS)	{0, NA}...	None	3	Right	Nominal	Input
40	Q10.1	Numeric	8	0	Increasing demand for your crop/livestock (UnS)	{1, UI}	None	5	Right	Ordinal	Input
41	Q10.2	Numeric	8	0	Infrastructure development in your area (UnS)	{1, UI}...	None	6	Right	Ordinal	Input
42	Q10.3	Numeric	8	0	Increasing water accessibility (UnS)	{1, UI}...	None	4	Right	Ordinal	Input
43	Q10.4	Numeric	8	0	Water price	{1, UI}...	None	4	Right	Ordinal	Input
44	Q10.5	Numeric	8	0	High market value for land (UnS)	{1, UI}...	None	4	Right	Ordinal	Input
45	Q10.6	Numeric	8	0	Other farmers willing to purchase land in your area (	{1, UI}	None	4	Right	Ordinal	Input
46	Q10.7	Numeric	8	0	Decline in the number of farmer from your ethnic gro...	{1, UI}...	None	5	Right	Ordinal	Input
47	Q10.8	Numeric	8	0	State or Local government regulations on waste wat...	{1, UI}...	None	5	Right	Ordinal	Input
48	Q10.9	Numeric	8	0	State or Local government planning restrictions on l...	{1, UI}...	None	5	Right	Ordinal	Input
49	Q10.10	Numeric	8	0	Drought conditions (UnS)	{1, UI}...	None	5	Right	Ordinal	Input
50	Q10.11	Numeric	8	0	Encroaching urbanization in your area (UnS)	{1, UI}	None	4	Right	Ordinal	Input
51	Q10.12	Numeric	8	0	Costs of changing land-use (UnS)	{1, UI}...	None	4	Right	Ordinal	Input
52	Q11.1	Numeric	8	0	Full-time commercial farmer	{0, No}...	None	4	Right	Nominal	Input
53	Q11.2	Numeric	8	0	Part-time commercial farmer	{0, No}...	None	4	Right	Nominal	Input
54	Q11.3	Numeric	8	0	Traditional farmer	{0, No}...	None	4	Right	Nominal	Input
55	Q11.4	Numeric	8	0	Hobby farmer	{0, No}	None	4	Right	Nominal	Input
56	Q11.5	String	8100	0	Other	None	None	12	Left	Nominal	Input
57	Q12	Numeric	8	0	You come from a "farming family"	{0, No}...	None	3	Right	Nominal	Input
58	Q13	Numeric	8	0	How many years have you worked in the farming ind...	None	None	3	Right	Scale	Input
59	Q14	Numeric	8	0	How many years have you lived in this area	None	None	3	Right	Scale	Input
60	Q15	Numeric	8	0	How many years more would you like to actively farm	None	None	3	Right	Scale	Input
61	Q16	Numeric	8	0	Any of your family member will continue your farm b...	{0, NA}...	None	3	Right	Ordinal	Input
62	Q17	Numeric	8	0	you will remain as a farmer for the rest of your work...	{1, VC}...	None	3	Right	Ordinal	Input
63	Q18	Numeric	8	0	Age ranges	{1, 18-24}...	None	2	Right	Ordinal	Input
64	Q19	Numeric	8	0	male /Female	{1, MALE}...	None	4	Right	Nominal	Input
65	Q20	Numeric	8	0	Were you born in Australia	{0, No}	None	2	Right	Nominal	Input
66	Q21	Numeric	8	0	When did you migrate to Australia	{1, 1-5}...	None	3	Right	Scale	Input
67	Q22	String	972	0	Which country did you migrate from	None	None	8	Left	Nominal	Input
68	Q23	Numeric	8	0	Primary and secondary school have you completed	None	None	3	Right	Ordinal	Input
69	Q24	Numeric	8	0	Have you done any post-secondary education	{0, No}...	None	3	Right	Nominal	Input
70	Q25	String	8100	0	Other important things for land-use decisions	None	None	23	Left	Nominal	Input

Data View Variable View

APPENDIX C6:

Exploratory cluster analysis results

1(a) Classification k=3 (primary factor variations against the three clusters)



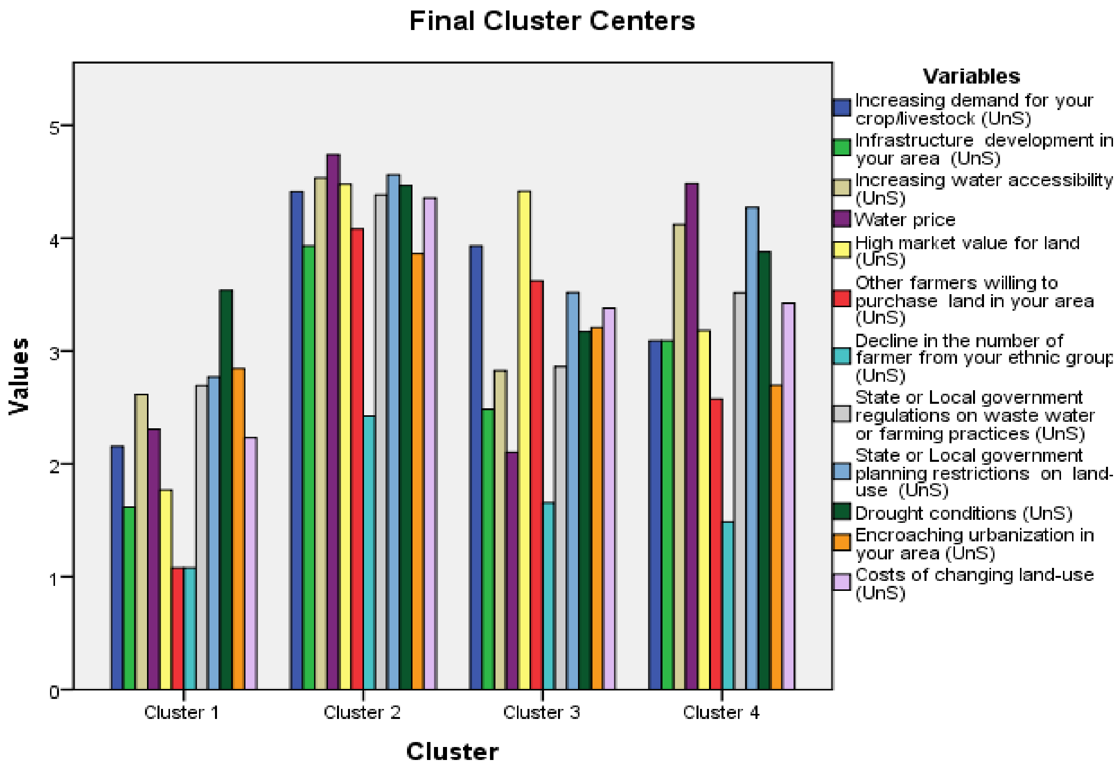
ANOVA

	Cluster Mean Square	Cluster df	Error Mean Square	Error df	F	Sig.
Increasing demand for your crop/livestock	29.057	2	1.361	145	21.352	.000
Infrastructure development in your area	37.987	2	1.285	145	29.571	.000
Increasing water accessibility	46.241	2	.814	145	56.835	.000
Water price	105.505	2	.687	145	153.504	.000
High market value for land	29.978	2	1.079	145	27.776	.000
Other farmers willing to purchase land in your area	36.367	2	1.300	145	27.969	.000
Decline in the number of farmer from your ethnic group	14.851	2	1.323	145	11.224	.000

State or Local government regulations on waste water or farming practices	28.355	2	1.335	145	21.244	.000
State or Local government planning restrictions on land-use	14.804	2	1.088	145	13.612	.000
Drought conditions	23.481	2	1.083	145	21.681	.000
Encroaching urbanization in your area	21.124	2	1.743	145	12.116	.000
Costs of changing land-use	25.442	2	1.099	145	23.158	.000

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

1(b) Classification k=4 (primary factor variations against the four clusters)



Final Cluster Centers

	Cluster			
	1	2	3	4
Increasing demand for your crop/livestock	2	4	4	3
Infrastructure development in your area	2	4	2	3
Increasing water accessibility	3	5	3	4

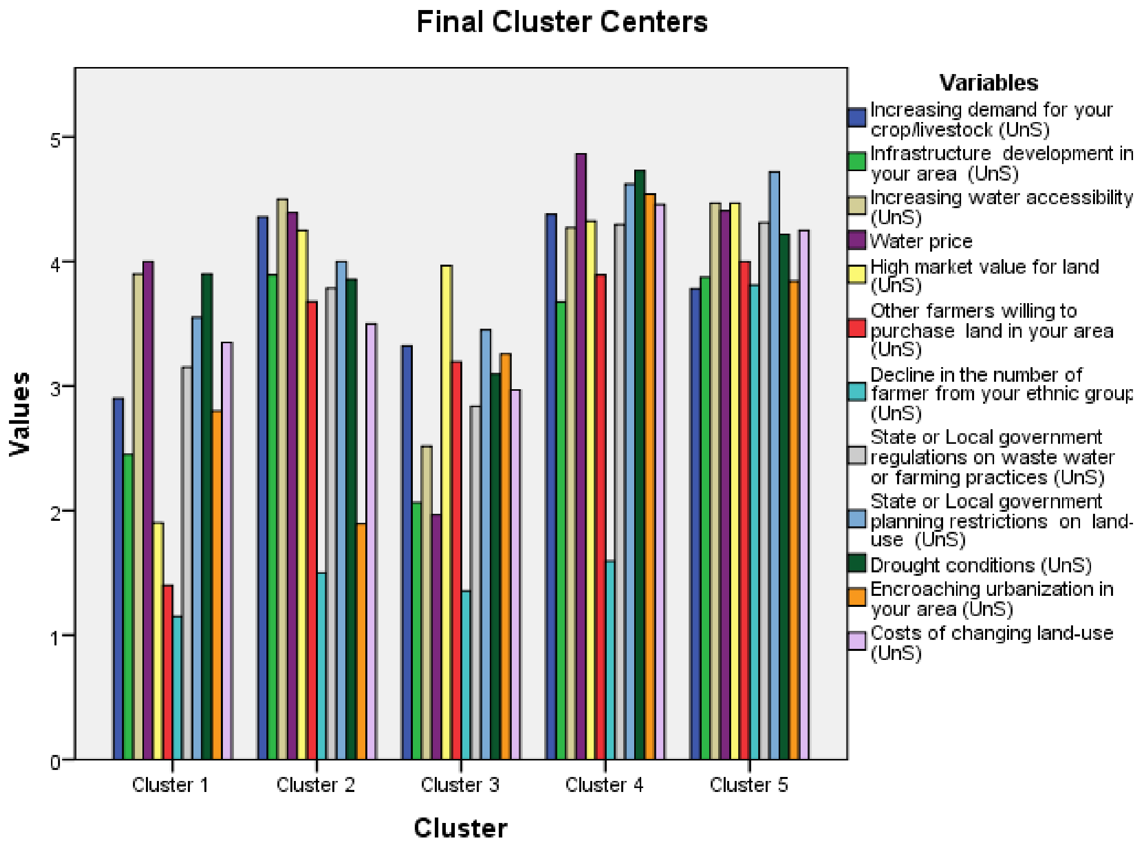
Water price	2	5	2	4
High market value for land	2	4	4	3
Other farmers willing to purchase land in your area	1	4	4	3
Decline in the number of farmer from your ethnic group	1	2	2	1
State or Local government regulations on waste water or farming practices	3	4	3	4
State or Local government planning restrictions on land-use	3	5	4	4
Drought conditions	4	4	3	4
Encroaching urbanization in your area	3	4	3	3
Costs of changing land-use	2	4	3	3

ANOVA

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Increasing demand for your crop/livestock	26.493	3	1.222	144	21.682	.000
Infrastructure development in your area	28.847	3	1.220	144	23.642	.000
Increasing water accessibility	28.519	3	.867	144	32.882	.000
Water price	62.971	3	.846	144	74.475	.000
High market value for land	35.994	3	.753	144	47.784	.000
Other farmers willing to purchase land in your area	42.651	3	.926	144	46.068	.000
Decline in the number of farmer from your ethnic group	12.005	3	1.289	144	9.317	.000
State or Local government regulations on waste water or farming practices	22.841	3	1.262	144	18.100	.000
State or Local government planning restrictions on land-use	16.410	3	.959	144	17.115	.000
Drought conditions	12.984	3	1.146	144	11.328	.000
Encroaching urbanization in your area	12.332	3	1.792	144	6.882	.000
Costs of changing land-use	21.418	3	1.013	144	21.134	.000

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

1(c) Classification k=5 (primary factor variations against the five clusters)



Final Cluster Centres

	Cluster				
	1	2	3	4	5
Increasing demand for your crop/livestock	3	4	3	4	4
Infrastructure development in your area	2	4	2	4	4
Increasing water accessibility	4	5	3	4	4
Water price	4	4	2	5	4
High market value for land	2	4	4	4	4
Other farmers willing to purchase land in your area	1	4	3	4	4

Decline in the number of farmer from your ethnic group	1	2	1	2	4
State or Local government regulations on waste water or farming practices	3	4	3	4	4
Government planning restrictions on land-use	4	4	3	5	5
Drought conditions	4	4	3	5	4
Encroaching urbanization in your area	3	2	3	5	4
Costs of changing land-use	3	4	3	4	4

ANOVA

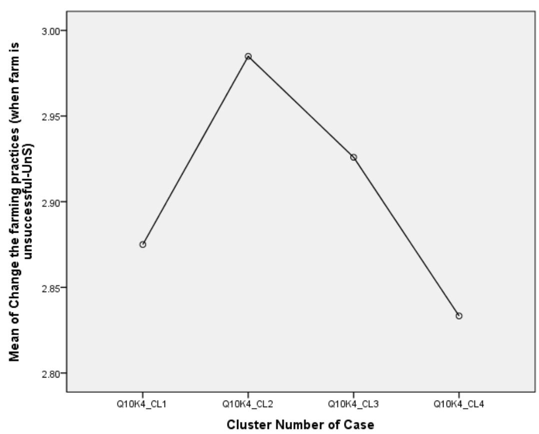
	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Increasing demand for your crop/livestock	11.065	4	1.477	143	7.493	.000
Infrastructure development in your area	21.784	4	1.225	143	17.790	.000
Increasing water accessibility	21.161	4	.880	143	24.053	.000
Water price	41.245	4	1.019	143	40.484	.000
High market value for land	25.090	4	.812	143	30.904	.000
Other farmers willing to purchase land in your area	25.989	4	1.100	143	23.625	.000
Decline in the number of farmer from your ethnic group	36.282	4	.535	143	67.873	.000
State or Local government regulations on waste water or farming practices	13.545	4	1.371	143	9.879	.000
State or Local government planning restrictions on land-use	10.375	4	1.020	143	10.175	.000
Drought conditions	11.824	4	1.096	143	10.790	.000
Encroaching urbanization in your area	31.456	4	1.183	143	26.582	.000
Costs of changing land-use	12.621	4	1.117	143	11.300	.000

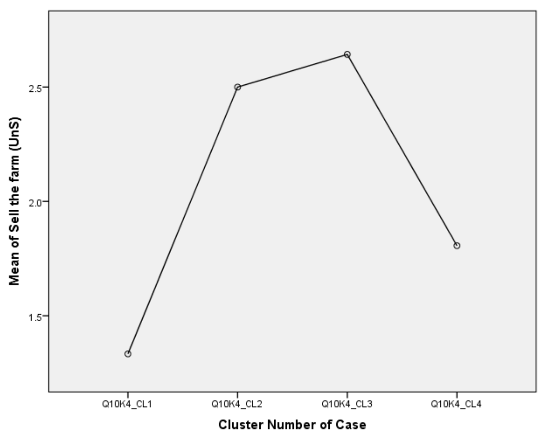
The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

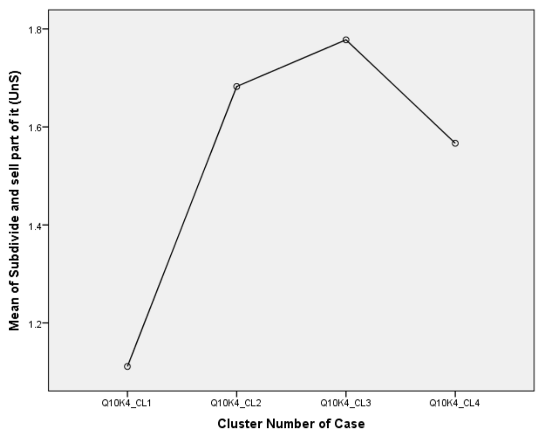
2. Mean comparison of land use change actions (if the farming is not viable)

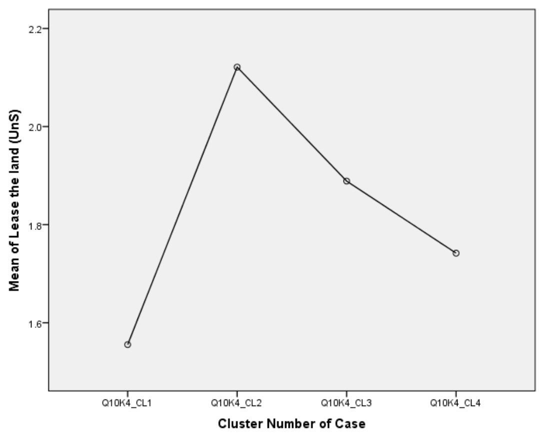
ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Change the farming practices	Between Groups	.503	3	.168	.121	.948
	Within Groups	175.878	127	1.385		
	Total	176.382	130			
Sell the farm	Between Groups	21.968	3	7.323	4.732	.004
	Within Groups	204.267	132	1.547		
	Total	226.235	135			
Subdivide and sell part of it	Between Groups	3.303	3	1.101	.993	.398
	Within Groups	138.573	125	1.109		
	Total	141.876	128			
Lease the land	Between Groups	4.777	3	1.592	1.195	.314
	Within Groups	171.855	129	1.332		
	Total	176.632	132			









3. Post hoc test results of land use change descriptive statistics vs classified profiles (4 clusters, k=4)

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
						Lower Bound	Upper Bound
Change the farming practices	Q10K4_CL1	8	2.88	1.553	.549	1.58	4.17
	Q10K4_CL2	66	2.98	1.143	.141	2.70	3.27
	Q10K4_CL3	27	2.93	1.107	.213	2.49	3.36
	Q10K4_CL4	30	2.83	1.206	.220	2.38	3.28
	Total	131	2.93	1.165	.102	2.73	3.13
Sell the farm	Q10K4_CL1	9	1.33	.707	.236	.79	1.88
	Q10K4_CL2	68	2.50	1.264	.153	2.19	2.81
	Q10K4_CL3	28	2.64	1.339	.253	2.12	3.16
	Q10K4_CL4	31	1.81	1.223	.220	1.36	2.25
	Total	136	2.29	1.295	.111	2.07	2.51
Subdivide and sell part of it	Q10K4_CL1	9	1.11	.333	.111	.85	1.37
	Q10K4_CL2	63	1.68	1.045	.132	1.42	1.95
	Q10K4_CL3	27	1.78	1.281	.247	1.27	2.28
	Q10K4_CL4	30	1.57	.971	.177	1.20	1.93
	Total	129	1.64	1.053	.093	1.45	1.82
Lease the land	Q10K4_CL1	9	1.56	1.130	.377	.69	2.42
	Q10K4_CL2	66	2.12	1.196	.147	1.83	2.42
	Q10K4_CL3	27	1.89	1.155	.222	1.43	2.35
	Q10K4_CL4	31	1.74	1.064	.191	1.35	2.13
	Total	133	1.95	1.157	.100	1.75	2.15

4. Post hoc test results of land use change actions (if farm is not viable)

Multiple Comparisons

Bonferroni

Dependent Variable	(I) Cluster Number of Case	(J) Cluster Number of Case	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Change the farming practices	Q10K4_CL1	Q10K4_CL2	-.110	.441	1.000	-1.29	1.07
		Q10K4_CL3	-.051	.474	1.000	-1.32	1.22
		Q10K4_CL4	.042	.468	1.000	-1.21	1.30
	Q10K4_CL2	Q10K4_CL1	.110	.441	1.000	-1.07	1.29
		Q10K4_CL3	.059	.269	1.000	-.66	.78
		Q10K4_CL4	.152	.259	1.000	-.54	.85
	Q10K4_CL3	Q10K4_CL1	.051	.474	1.000	-1.22	1.32
		Q10K4_CL2	-.059	.269	1.000	-.78	.66
		Q10K4_CL4	.093	.312	1.000	-.74	.93
	Q10K4_CL4	Q10K4_CL1	-.042	.468	1.000	-1.30	1.21
		Q10K4_CL2	-.152	.259	1.000	-.85	.54
		Q10K4_CL3	-.093	.312	1.000	-.93	.74
Sell the farm	Q10K4_CL1	Q10K4_CL2	-1.167	.441	.055	-2.35	.02
		Q10K4_CL3	-1.310*	.477	.041	-2.59	-.03
		Q10K4_CL4	-.473	.471	1.000	-1.73	.79
	Q10K4_CL2	Q10K4_CL1	1.167	.441	.055	-.02	2.35
		Q10K4_CL3	-.143	.279	1.000	-.89	.61
		Q10K4_CL4	.694	.270	.067	-.03	1.42
	Q10K4_CL3	Q10K4_CL1	1.310*	.477	.041	.03	2.59
		Q10K4_CL2	.143	.279	1.000	-.61	.89
		Q10K4_CL4	.836	.324	.066	-.03	1.71
	Q10K4_CL4	Q10K4_CL1	.473	.471	1.000	-.79	1.73
		Q10K4_CL2	-.694	.270	.067	-1.42	.03
		Q10K4_CL3	-.836	.324	.066	-1.71	.03
Subdivide and sell part of it	Q10K4_CL1	Q10K4_CL2	-.571	.375	.782	-1.58	.43
		Q10K4_CL3	-.667	.405	.615	-1.75	.42
		Q10K4_CL4	-.456	.400	1.000	-1.53	.62
	Q10K4_CL2	Q10K4_CL1	.571	.375	.782	-.43	1.58
		Q10K4_CL3	-.095	.242	1.000	-.74	.55
		Q10K4_CL4	.116	.234	1.000	-.51	.74
	Q10K4_CL3	Q10K4_CL1	.667	.405	.615	-.42	1.75
		Q10K4_CL2	.095	.242	1.000	-.55	.74

		Q10K4_CL4	.211	.279	1.000	-.54	.96
		Q10K4_CL1	.456	.400	1.000	-.62	1.53
	Q10K4_CL4	Q10K4_CL2	-.116	.234	1.000	-.74	.51
		Q10K4_CL3	-.211	.279	1.000	-.96	.54
Lease the land	Q10K4_CL1	Q10K4_CL2	-.566	.410	1.000	-1.66	.53
		Q10K4_CL3	-.333	.444	1.000	-1.52	.86
		Q10K4_CL4	-.186	.437	1.000	-1.36	.98
	Q10K4_CL2	Q10K4_CL1	.566	.410	1.000	-.53	1.66
		Q10K4_CL3	.232	.264	1.000	-.47	.94
		Q10K4_CL4	.379	.251	.802	-.29	1.05
	Q10K4_CL3	Q10K4_CL1	.333	.444	1.000	-.86	1.52
		Q10K4_CL2	-.232	.264	1.000	-.94	.47
		Q10K4_CL4	.147	.304	1.000	-.67	.96
	Q10K4_CL4	Q10K4_CL1	.186	.437	1.000	-.98	1.36
		Q10K4_CL2	-.379	.251	.802	-1.05	.29
		Q10K4_CL3	-.147	.304	1.000	-.96	.67

*. The mean difference is significant at the 0.05 level.

5. Mean comparison of production types

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Main production-Wine	Between Groups	1.247	3	.416	1.749	.163
	Within Groups	21.391	90	.238		
	Total	22.638	93			
Main production-Wheat	Between Groups	.449	3	.150	.787	.506
	Within Groups	11.612	61	.190		
	Total	12.062	64			
Main production-Vegetables	Between Groups	1.460	3	.487	3.393	.024
	Within Groups	8.179	57	.143		
	Total	9.639	60			
Main production-livestock	Between Groups	.191	3	.064	.285	.836
	Within Groups	21.003	94	.223		
	Total	21.194	97			
Main production-Other	Between Groups	.446	3	.149	.634	.596
	Within Groups	14.539	62	.235		
	Total	14.985	65			

6. Mean comparison of farming motivations

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Making a good profit on your farm	Between Groups	58.625	3	19.542	11.872	.000
	Within Groups	235.375	143	1.646		
	Total	294.000	146			
Caring for the environment on our farm	Between Groups	6.505	3	2.168	4.111	.008
	Within Groups	75.948	144	.527		
	Total	82.453	147			
Being part of your local community	Between Groups	8.360	3	2.787	2.256	.084
	Within Groups	176.633	143	1.235		
	Total	184.993	146			

7. Mean comparison of defined farmer type

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Full-time commercial farmer	Between Groups	1.308	3	.436	1.844	.144
	Within Groups	25.772	109	.236		
	Total	27.080	112			
Part-time commercial farmer	Between Groups	.187	3	.062	.240	.869
	Within Groups	21.060	81	.260		
	Total	21.247	84			
Traditional farmer	Between Groups	1.914	3	.638	2.678	.052
	Within Groups	19.539	82	.238		
	Total	21.453	85			
Hobby farmer	Between Groups	1.414	3	.471	2.363	.078
	Within Groups	15.561	78	.200		
	Total	16.976	81			

8. Mean comparison of age and sex

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Age ranges	Between Groups	3.930	3	1.310	1.034	.380
	Within Groups	182.523	144	1.268		
	Total	186.453	147			
male /Female	Between Groups	.235	3	.078	.532	.661
	Within Groups	21.044	143	.147		
	Total	21.279	146			

9. Mean comparison of primary factors considered for farm success (IFU-16F)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Labour cost	Between Groups	71.732	3	23.911	13.411	.000
	Within Groups	247.821	139	1.783		
	Total	319.552	142			
Maintenance cost	Between Groups	26.436	3	8.812	10.426	.000
	Within Groups	117.480	139	.845		
	Total	143.916	142			
Investments in new machinery or technology	Between Groups	39.196	3	13.065	12.869	.000
	Within Groups	140.100	138	1.015		
	Total	179.296	141			
Selection of crop type or farming practise	Between Groups	24.054	3	8.018	5.139	.002
	Within Groups	218.439	140	1.560		
	Total	242.493	143			
Overall financial return on investment (ROI)	Between Groups	62.057	3	20.686	17.564	.000
	Within Groups	164.880	140	1.178		
	Total	226.938	143			
Water accessibility	Between Groups	19.000	3	6.333	11.348	.000
	Within Groups	79.253	142	.558		
	Total	98.253	145			
Soil fertility	Between Groups	12.512	3	4.171	5.793	.001
	Within Groups	100.794	140	.720		
	Total	113.306	143			
Climate change	Between Groups	24.914	3	8.305	6.059	.001

	Within Groups	193.251	141	1.371		
	Total	218.166	144			
Severe climate events	Between Groups	24.038	3	8.013	6.422	.000
	Within Groups	175.920	141	1.248		
	Total	199.959	144			
Previous farming experience	Between Groups	15.859	3	5.286	4.409	.005
	Within Groups	166.658	139	1.199		
	Total	182.517	142			
Neighbouring farmer crop/livestock choices	Between Groups	23.897	3	7.966	5.093	.002
	Within Groups	220.544	141	1.564		
	Total	244.441	144			
Farming heritage of your family	Between Groups	13.983	3	4.661	2.115	.101
	Within Groups	312.976	142	2.204		
	Total	326.959	145			
Having your owned land	Between Groups	3.085	3	1.028	1.066	.366
	Within Groups	137.025	142	.965		
	Total	140.110	145			
Being part of a cooperative and/or farming group	Between Groups	10.228	3	3.409	3.116	.028
	Within Groups	154.282	141	1.094		
	Total	164.510	144			
Access to finance	Between Groups	46.746	3	15.582	10.246	.000
	Within Groups	214.427	141	1.521		
	Total	261.172	144			
Crop insurance	Between Groups	28.012	3	9.337	5.038	.002
	Within Groups	259.481	140	1.853		
	Total	287.493	143			

10. Mean comparison of farming industry experience

ANOVA

How many years have you worked in the farming industry

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	759.112	3	253.037	.967	.410
Within Groups	36909.550	141	261.770		
Total	37668.662	144			

11. Mean comparison of household income

ANOVA

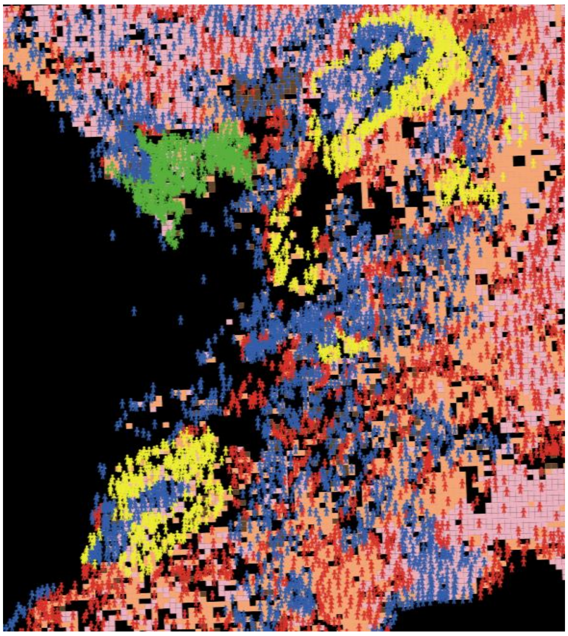
Proportion of your household's income

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	10.152	3	3.384	1.112	.346
Within Groups	431.958	142	3.042		
Total	442.110	145			

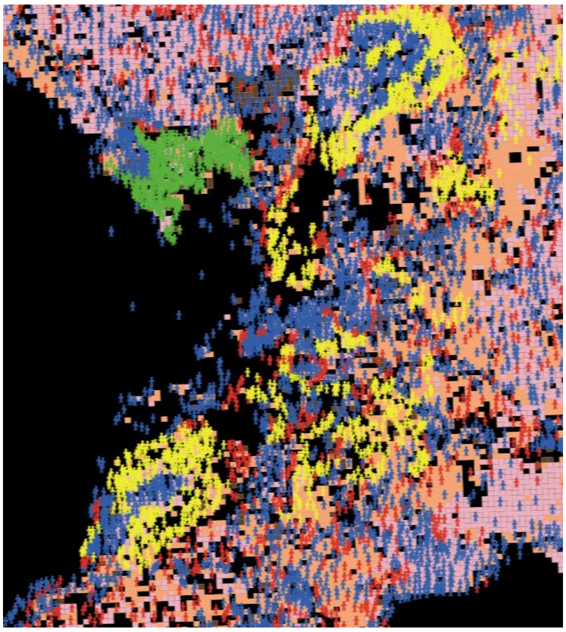
APPENDIX C7:

1. Agent (profile) in ABM-2 and ABM-3

a)



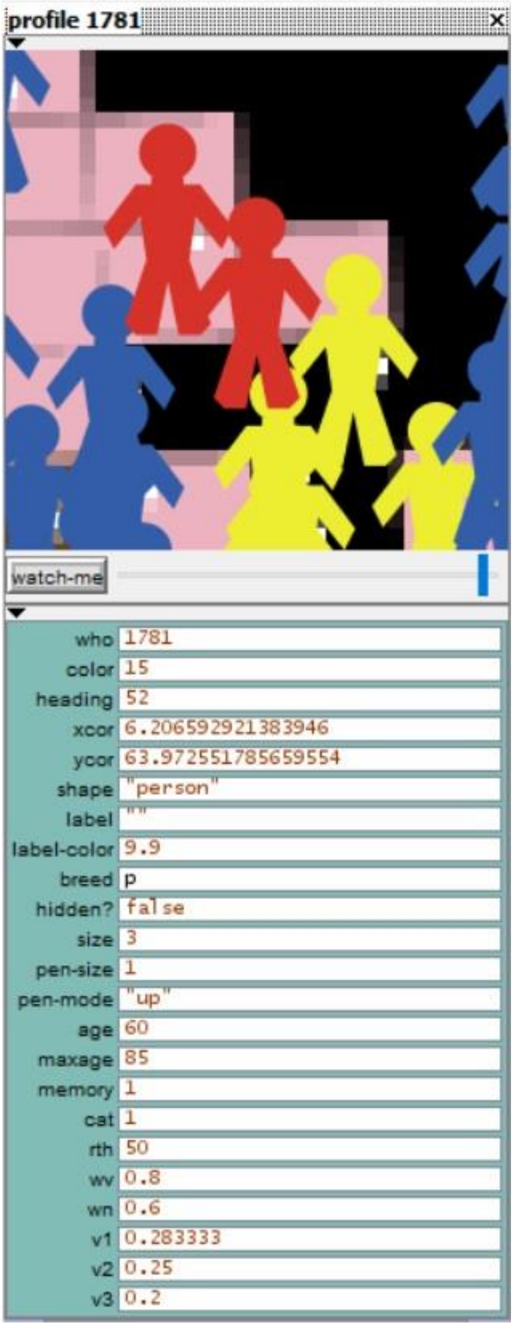
b)



Four profile types P1(Red-heritage), P2 (Blue-commercial), P3(Green-sellers), P4(yellow-multi-function/hobby).

a) Agents in ABM-2 *Entire Population of Farming Agents*.
b) Agents in ABM-3 *Alternative Entire Population of Farming Agents.*

2. Agent (profile) identifier with parameter monitoring interface



In each tick, every agent in each profile updates memory (R) and age (Age),

3. NetLogo code for ABM-1

```
extensions [gis]
;GIS extension
turtles-own [age maxage memory cat RTH WV WN V1 V2 V3 ]
;;Agent variables

globals
[
  vdata
  vdataA
  vdataSA
  agentcount
  subset
  pcat
  V
]
;Global variables
breed [P profile]
to setup
  clear-all
  setup-patches
  reset-ticks
end
; Clear all the previous agents patches or tick results
to go
  ask P
  [
    ;get same Category agents in-radius
    set subset turtles in-radius 30
    set pcat cat
    set agentcount count subset with [cat = pcat]
    ;show agentcount
    ; number of agents within the circle
    ifelse agentcount < 3
    [
      set WN 0
    ]
    [
      ifelse cat = 1
      [
        set WN 0.6
      ]
      [
        ifelse cat = 2 or cat = 3
        [
          set WN 0.1
        ]
        [
          set WN 0.4
        ]
      ]
    ]
    ;condition for excluding WN in the function

    ifelse vulnerability = "V1"
    [
      set V V1
```

```
    ]
    [
      ifelse vulnerability = "V2"
      [
        set V V2
      ]
      [
        set V V3
      ]
    ]
   ; defining the vulnerabilities for the scenarios
    set memory (memory + (V * 10 * WV) - ( V * 10 * WN ))
    ; function for calculating the agent memory (R)
    set age age + 0.5
    ; Agent age increases 0.5 at each tick
    ; condition for profile change
      if (memory >= RTH or age >= maxage)
      [
        ifelse cat = 1
        [
          set cat 2
          set color blue
        ]
        [
          ifelse cat = 2
          [
            set cat 4
            set color yellow
          ]
          [
            ifelse cat = 4
            [
              set cat 3
              set color green
            ]
            [
               die
            ]
          ]
        ]
       ]
      ];;end of profile change
  tick
end
to move
end
to setup-patches
  clear-all
  gis:load-coordinate-system "D:/NL18/GIS/Test4/AgentFull_LamGDA.prj"
  set vdata gis:load-dataset "D:/NL18/GIS/Test4/Vul_LamGDA.shp"
  set vdataSA gis:load-dataset "D:/NL18/GIS/SA_144_Vinfo.shp"
  ;;drawing map
  ;;gis:set-world-envelope-ds gis:envelope-of vdata
  foreach gis:feature-list-of vdata
  [
    if gis:property-value ? "V2" >= 0.1  [gis:set-drawing-color 137 gis:fill ? WHITE]
    if gis:property-value ? "V2" >= 0.3 [gis:set-drawing-color 27 gis:fill ? WHITE]
    if gis:property-value ? "V2" >= 0.4 [gis:set-drawing-color 33 gis:fill ? WHITE]
```

```
 ]
 gis:set-world-envelope-ds gis:envelope-of vdataSA
 gis:set-drawing-color white
  ;;drawing map
 ;;gis:set-world-envelope-ds gis:envelope-of vdataSA
 gis:draw vdataSA 1
 foreach gis:feature-list-of vdataSA
 [
   let col red
   if gis:property-value ? "ProfCODE" = 1
   [
     set col  red
   ]
   if gis:property-value ? "ProfCODE" = 2
   [
     set col  blue
   ]
   if gis:property-value ? "ProfCODE" = 3
   [
     set col  green
   ]
   if gis:property-value ? "ProfCODE" = 4
   [
     set col  yellow
   ]
   ;;let location gis:location-of (first (first (gis:vertex-lists-of ?)))
   let location gis:location-of gis:centroid-of ?
   let xp 0
   let yp 0
   if not empty? location
   [
     set xp item 0 location
     set yp item 1 location
   ]
   create-P 1
   [
      set color  col
      set shape "person"
      set size 5
      set xcor xp
      set ycor yp
      set memory 1
      set cat gis:property-value ? "ProfCODE"
      set maxage 85
      set age gis:property-value ? "STAGE"
      set RTH gis:property-value ? "RT"
      set WV gis:property-value ? "WV"
      set WN gis:property-value ? "WN"
      set V1 gis:property-value ? "V1"
      set V2 gis:property-value ? "V2"
      set V3 gis:property-value ? "V3"
   ]
 ]
gis:set-world-envelope-ds gis:envelope-of vdataSA
end
```

REFERENCES

AALDERS, I. 2008. Modeling land-use decision behavior with Bayesian belief networks. *Ecology and Society,* 13.

ABARES (AUSTRALIAN BUREAU OF AGRICULTURAL AND RESOURCE ECONOMICS AND SCIENCES) 2018. *Agricultural commodities.* 4.0 March Quarter. Canberra: ABARES.

ABS (AUSTRALIAN BUREAU OF STATISTICS). 2013. *4102.0–Australian Social Trends, April 2013* [Online]. Australian Bureau of Statistics. Available: http://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/4102.0Main+Features30April+2013 [Accessed 2018].

ABS (AUSTRALIAN BUREAU OF STATISTICS). 2016. *South Australia State Summary* [Online]. Australian Bureau of Statistics. Available: http://www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/3218.0Main%20Features352014-15?opendocument&tabname=Summary&prodno=3218.0&issue=2014-15&num=&view= [Accessed 3218.0–Regional Population Growth, Australia, 2014-15].

ABS (AUSTRALIAN BUREAU OF STATISTICS). 2018. *Agricultural Commodities* [Online]. Australian Bureau of Statistics. Available: http://www.abs.gov.au/Agriculture [Accessed].

ACREMAN, M. 2005. Linking science and decision-making: features and experience from environmental river flow setting. *Environmental Modelling & Software,* 20**,** 99-109.

ACUTO, M. 2015. Implosions/explosions. Towards a study of planetary urbanization, edited by Neil Brenner. *Urban Geography,* 36**,** 154-156.

ADAMS, V. M., PRESSEY, R. L. & ÁLVAREZ-ROMERO, J. G. 2016. Using optimal land-use scenarios to assess trade-offs between conservation, development, and social values. *PloS one,* 11**,** e0158350.

ADELAJA, A., SULLIVAN, K. & HAILU, Y. G. 2011. Endogenizing the planning horizon in urban fringe agriculture. *Land Use Policy,* 28**,** 66-75.

AGUILERA, F., VALENZUELA, L. M. & BOTEQUILHA-LEITÃO, A. 2011. Landscape metrics in the analysis of urban land use patterns: A case study in a Spanish metropolitan area. *Landscape and Urban Planning,* 99**,** 226-238.

AIDE, T. M. & GRAU, H. R. 2004. Globalization, migration, and Latin American ecosystems. *Science,* 305**,** 1915-1916.

AJZEN, I. 1991. The theory of planned behavior. *Organizational behavior and human decision processes,* 50**,** 179-211.

AKIMOWICZ, M., CUMMINGS, H. & LANDMAN, K. 2016. Green lights in the Greenbelt? A qualitative analysis of farm investment decision-making in peri-urban Southern Ontario. *Land Use Policy,* 55**,** 24-36.

ALAM, S. J., BAKKER, M. M., KARALI, E., VAN DIJK, J. & ROUNSEVELL, M. D. Simulating the expansion of large-sized farms in rural Netherlands: a land exchange model. International Workshop on Multi-Agent Systems and Agent-Based Simulation, 2013. Springer, 115-128.

ALEXANDER, P., BROWN, C., ARNETH, A., FINNIGAN, J. & ROUNSEVELL, M. D. 2016. Human appropriation of land for food: The role of diet. *Global Environmental Change,* 41**,** 88-98.

ALLAN, J. D. 2004. Landscapes and riverscapes: the influence of land use on stream ecosystems. *Annual review of ecology, evolution, and systematics***,** 257-284.

ALLEN, A. 2003. Environmental planning and management of the peri-urban interface:

perspectives on an emerging field. *Environment and urbanization,* 15**,** 135-148.
AMIRINEJAD, G., DONEHUE, P. & BAKER, D. 2018. Ambiguity at the peri-urban interface in Australia. *Land Use Policy,* 78**,** 472-480.
AN, L. 2012. Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling,* 229**,** 25-36.
AN, L., LINDERMAN, M., QI, J., SHORTRIDGE, A. & LIU, J. 2005. Exploring complexity in a human–environment system: an agent-based spatial model for multidisciplinary and multiscale integration. *Annals of the association of American geographers,* 95**,** 54-79.
ANDERSON, J. H., DOWNS, J. A., LORAAMM, R. & READER, S. 2017. Agent-based simulation of Muscovy duck movements using observed habitat transition and distance frequencies. *Computers, Environment and Urban Systems,* 61**,** 49-55.
ANDERSSON, E., AHRNÉ, K., PYYKÖNEN, M. & ELMQVIST, T. 2009. Patterns and scale relations among urbanization measures in Stockholm, Sweden. *Landscape ecology,* 24**,** 1331-1339.
ANGEL, S., PARENT, J., CIVCO, D. L., BLEI, A. & POTERE, D. 2011. The dimensions of global urban expansion: Estimates and projections for all countries, 2000–2050. *Progress in Planning,* 75**,** 53-107.
ANSEEUW, W., BOCHE, M., BREU, T., GIGER, M., LAY, J. & MESSERLI, P. 2012. K. Nolte (2012): Transnational Land Deals for Agriculture in the Global South. Analytical Report based on the Land Matrix Database. CDE/CIRAD/GIGA, Bern/Montpellier/Hamburg.
APPIAH, D. O., BUGRI, J. T., FORKUOR, E. K. & BOATENG, P. K. 2014. Determinants of Peri-Urbanization and Land Use Change Patterns in Peri-Urban Ghana. *Journal of Sustainable Development,* 7**,** p95.
ARNETH, A., BROWN, C. & ROUNSEVELL, M. D. A. 2014. Global models of human decision-making for land-based mitigation and adaptation assessment. *Nature Clim. Change,* 4**,** 550-557.
ARRINDELL, W. A. & VAN DER ENDE, J. 1985. An empirical test of the utility of the observations-to-variables ratio in factor and components analysis. *Applied Psychological Measurement,* 9**,** 165-178.
ARSENAULT, A., NOLAN, J., SCHONEY, R. & GILCHRIST, D. 2012. Outstanding in the field: Evaluating auction markets for farmland using multi-agent simulation. *Journal of Artificial Societies and Social Simulation,* 15**,** 11.
ASHTON, D. & WERAGODA, A. 2017. Australian vegetable-growing farms. Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra.
AUSTRALIAN BUREAU OF METEOROLOGY. 2017. *Annual Climate Summary for South Australia*. Australian Government
AXELROD, R. & TESFATSION, L. 2006. Appendix AA guide for newcomers to agent-based modeling in the social sciences. *Handbook of computational economics,* 2**,** 1647-1659.
BAI, X., CHEN, J. & SHI, P. 2011. Landscape urbanization and economic growth in China: Positive feedbacks and sustainability dilemmas. *Environmental Science & Technology,* 46**,** 132-139.
BAKKER, M. M., ALAM, S. J., VAN DIJK, J. & ROUNSEVELL, M. D. 2015. Land-use change arising from rural land exchange: an agent-based simulation model. *Landscape ecology,* 30**,** 273-286.
BAKKER, M. M. & VAN DOORN, A. M. 2009. Farmer-specific relationships between land use change and landscape factors: Introducing agents in empirical land use modelling. *Land Use Policy,* 26**,** 809-817.
BARÓ, F., HAASE, D., GÓMEZ-BAGGETHUN, E. & FRANTZESKAKI, N. 2015. Mismatches

between ecosystem services supply and demand in urban areas: A quantitative assessment in five European cities. *Ecological Indicators,* 55**,** 146-158.

BATEMAN, I. J., HARWOOD, A. R., MACE, G. M., WATSON, R. T., ABSON, D. J., ANDREWS, B., BINNER, A., CROWE, A., DAY, B. H. & DUGDALE, S. 2013. Bringing Ecosystem Services into Economic Decision-Making: Land Use in the United Kingdom. *Science,* 341.

BATTY, M. 2009. Cities as Complex Systems: Scaling, Interaction, Networks, Dynamics and Urban Morphologies.

BATTY, M. 2015. Optimal cities, ideal cities. *Environment and Planning B-Planning & Design,* 42**,** 571-573.

BATTY, M., XIE, Y. & SUN, Z. 1999. Modeling urban dynamics through GIS-based cellular automata. *Computers, Environment and Urban Systems,* 23**,** 205-233.

BAXTER, J., GRAY, M. & HAYES, A. 2010. Families in regional, rural and remote Australia. *Statistics [ABS],* 3.

BEAUDUCEL, A. & HERZBERG, P. Y. 2006. On the performance of maximum likelihood versus means and variance adjusted weighted least squares estimation in CFA. *Structural Equation Modeling,* 13**,** 186-203.

BERBEROĞLU, S., AKıN, A. & CLARKE, K. C. 2016. Cellular automata modeling approaches to forecast urban growth for adana, Turkey: A comparative approach. *Landscape and Urban Planning,* 153**,** 11-27.

BERGER, T. & SCHREINEMACHERS, P. 2006. Creating agents and landscapes for multiagent systems from random samples. *Ecology and Society,* 11.

BERKE, P. R. & CONROY, M. M. 2000. Are we planning for sustainable development? An evaluation of 30 comprehensive plans. *Journal of the American planning association,* 66**,** 21-33.

BERRYMAN, M. 2008. Review of software platforms for agent based models. Land Operations Division DSTO Defence Science and Technology Organisation, Australia.

BEZEMER, D. & HEADEY, D. 2008. Agriculture, development, and urban bias. *World Development,* 36**,** 1342-1364.

BHATTI, S. S., TRIPATHI, N. K., NITIVATTANANON, V., RANA, I. A. & MOZUMDER, C. 2015. A multi-scale modeling approach for simulating urbanization in a metropolitan region. *Habitat International,* 50**,** 354-365.

BIAN, Z.-X., WANG, S., WANG, Q.-B., YU, M. & QIAN, F.-K. 2018. Effects of urban sprawl on arthropod communities in peri-urban farmed landscape in Shenbei New District, Shenyang, Liaoning Province, China. *Scientific reports,* 8**,** 101.

BIGGS, R., RAUDSEPP-HEARNE, C., ATKINSON-PALOMBO, C., BOHENSKY, E., BOYD, E., CUNDILL, G., FOX, H., INGRAM, S., KOK, K. & SPEHAR, S. 2007. Linking futures across scales: a dialog on multiscale scenarios. *Ecology and Society,* 12.

BIRKIN, M. & WU, B. 2012. A review of microsimulation and hybrid agent-based approaches. *Agent-based models of geographical systems.* Springer.

BISHOP, P., HINES, A. & COLLINS, T. 2007. The current state of scenario development: an overview of techniques. *foresight,* 9**,** 5-25.

BOOTH, E. G., QIU, J., CARPENTER, S. R., SCHATZ, J., CHEN, X., KUCHARIK, C. J., LOHEIDE, S. P., MOTEW, M. M., SEIFERT, J. M. & TURNER, M. G. 2016. From qualitative to quantitative environmental scenarios: Translating storylines into biophysical modeling inputs at the watershed scale. *Environmental Modelling & Software,* 85**,** 80-97.

BÖRJESON, L., HÖJER, M., DREBORG, K.-H., EKVALL, T. & FINNVEDEN, G. 2006. Scenario types and techniques: towards a user's guide. *Futures,* 38**,** 723-739.

BORSHCHEV, A. & FILIPPOV. 2004. A. From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. *Proceedings of the 22nd International Conference of the System Dynamics Society.*

BOWMAN, M. S. & ZILBERMAN, D. 2013. Economic factors affecting diversified farming systems. *Ecology and Society,* 18**,** 33.

BRENNER, N. & SCHMID, C. 2015. Towards a new epistemology of the urban? *City,* 19**,** 151-182.

BRIDGES, L. M., CROMPTON, A. E. & SCHAEFER, J. A. 2007. Landscapes as gradients: the spatial structure of terrestrial ecosystem components in southern Ontario, Canada. *ecological complexity,* 4**,** 34-41.

BRINGEZU, S., SCHÜTZ, H., PENGUE, W., O'BRIEN, M., GARCIA, F., SIMS, R., HOWARTH R. W., KAUPPI, L., SWILLING, M., & HERRICK, J. 2014. *Assessing Global Land Use: Balancing Consumption with Sustainable Supply*. UNEP Publication, 131.

BRINKLEY, C. 2018. High rugosity cities: The geographic, economic and regulatory pathology of America's most non-concentric urban areas. *Land Use Policy,* 73**,** 215-224.

BROOK, R. & DÁVILA, J. 2000. *The peri-urban interface: a tale of two cities,* Development Planning Unit, UCL & University of Wales at Bangor.

BROWN, C., BROWN, K. & ROUNSEVELL, M. 2016. A philosophical case for process-based modelling of land use change. *Modeling Earth Systems and Environment,* 2**,** 1-12.

BROWN, C., MURRAY-RUST, D., VAN VLIET, J., ALAM, S. J., VERBURG, P. H. & ROUNSEVELL, M. D. 2014. Globalisation, regionalisation and behavioural responses of land use agents. *Multi-Agent-Based Simulation XIV.* Springer.

BROWN, D. G., ASPINALL, R. & BENNETT, D. A. 2006. Landscape models and explanation in landscape ecology—A space for generative landscape science? *The Professional Geographer,* 58**,** 369-382.

BROWN, D. G., JOHNSON, K. M., LOVELAND, T. R. & THEOBALD, D. M. 2005a. Rural land-use trends in the conterminous United States, 1950–2000. *Ecological Applications,* 15**,** 1851-1863.

BROWN, D. G., PAGE, S., RIOLO, R., ZELLNER, M. & RAND, W. 2005b. Path dependence and the validation of agent-based spatial models of land use. *International Journal of Geographical Information Science,* 19**,** 153-174.

BROWN, D. G., RIOLO, R., ROBINSON, D. T., NORTH, M. & RAND, W. 2005. Spatial process and data models: Toward integration of agent-based models and GIS. *Journal of Geographical Systems,* 7**,** 25-47.

BROWN, D. G. & ROBINSON, D. T. 2006. Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. *Ecology and society,* 11**,** 46.

BROWN, D. G., ROBINSON, D. T., AN, L., NASSAUER, J. I., ZELLNER, M., RAND, W., RIOLO, R., PAGE, S. E., LOW, B. & WANG, Z. 2008. Exurbia from the bottom-up: Confronting empirical challenges to characterizing a complex system. *Geoforum,* 39**,** 805-818.

BROWN, D. G., VERBURG, P. H., PONTIUS JR, R. G. & LANGE, M. D. 2013. Opportunities to improve impact, integration, and evaluation of land change models. *Current Opinion in Environmental Sustainability,* 5**,** 452-457.

BROWN, D. G., WALKER, R., MANSON, S. & SETO, K. 2004. Modeling land use and land cover change. *Land Change Science.* Springer.

BROWN, D. G. & XIE, Y. 2006. Spatial agent-based modelling. *International Journal of Geographical Information Science,* 20**,** 941-943.

BROWN, M. & MCCARTY, J. 2018. Remote Sensing Data and Methods for Identifying Urban and

Peri-Urban Smallholder Agriculture in Developing Countries and in the United States.
BRUECKNER, J. K. 2000. Urban sprawl: diagnosis and remedies. *International regional science review,* 23**,** 160-171.
BRUECKNER, J. K. & FANSLER, D. A. 1983. The economics of urban sprawl: Theory and evidence on the spatial sizes of cities. *The Review of Economics and Statistics***,** 479-482.
BRUECKNER, J. K. & HELSLEY, R. W. 2011. Sprawl and blight. *Journal of Urban Economics,* 69**,** 205-213.
BRUEGMANN, R. 2001. Urban sprawl. International Encyclopedia of the Social & Behavioral Sciences. Online Edition. Elsevier Science, Ltd.
BRUNDTLAND, G. H. 1987. *Report of the World Commission on environment and development:" our common future.",* United Nations.
BRYAN, B. A., CROSSMAN, N. D., KING, D. & MEYER, W. S. 2011. Landscape futures analysis: assessing the impacts of environmental targets under alternative spatial policy options and future scenarios. *Environmental Modelling & Software,* 26**,** 83-91.
BRYAN, B. A., NOLAN, M., MCKELLAR, L., CONNOR, J. D., NEWTH, D., HARWOOD, T., KING, D., NAVARRO, J., CAI, Y. & GAO, L. 2016. Land-use and sustainability under intersecting global change and domestic policy scenarios: trajectories for Australia to 2050. *Global Environmental Change,* 38**,** 130-152.
BRYANT, C. & CHARVET, J.-P. 2003. Introduction: the peri-urban zone: the structure and dynamics of a strategic component of metropolitan regions/Introduction: la zone periurbaine: structure et dynamiques d'une composante strategique des regions metropolitaines. *Canadian Journal of Regional Science,* 26**,** 231-250.
BUNKER, R. & HOUSTON, P. 2003. Prospects for the Rural-Urban Fringe in Australia: Observations from a Brief History of the Landscapes around Sydney and Adelaide. *Australian geographical studies,* 41**,** 303-323.
BURCHFIELD, E. K. & GILLIGAN, J. M. 2016. Dynamics of Individual and Collective Agricultural Adaptation to Water Scarcity. *In Winter Simulation Conference (WSC).*
BURNLEY, I. H. 2001. *The impact of immigration on Australia: a demographic approach*, Oxford University Press, USA.
BURNLEY, I. H. & MURPHY, P. A. 1995. Residential location choice in Sydney's perimetropolitan region. *Urban Geography,* 16**,** 123-143.
BUXTON, M., ALVAREZ, A., BUTT, A., FARRELL, S., PELIKAN, M., DENSLEY, L. & O'NEILL, D. 2011a. Scenario planning for Melbourne's peri-urban region,' RMIT University, Melbourne. *Case study,* 9**,** 335.
BUXTON, M. & CHOY, D. L. 2007. Change in peri-urban Australia: implications for land use policies. *State of Australian Cities' Conference*, Adelaide, 28-30 November.
BUXTON, M., HAYNES, R., MERCER, D. & BUTT, A. 2011b. Vulnerability to bushfire risk at Melbourne's urban fringe: the failure of regulatory land use planning. *Geographical Research,* 49**,** 1-12.
CAILLOU, P. 2012. Automated multi-agent simulation generation and validation. *Principles and Practice of Multi-Agent Systems.* Springer.
CASTLE, C. J. & CROOKS, A. T. 2006. *Principles and concepts of agent-based modelling for developing geospatial simulations*, Centre for Advanced Spatial Analysis, University College London.
CHAMBERS, R. & CONWAY, G. 1992. *Sustainable rural livelihoods: practical concepts for the 21st century*, Institute of Development Studies (UK).
CIOFFI-REVILLA, C., ROGERS, J. D. & HAILEGIORGIS, A. 2011. Geographic information systems and spatial agent-based model simulations for sustainable development. *ACM*

Transactions on Intelligent Systems and Technology (TIST), 3**,** 10.
COLANTONI, A., GRIGORIADIS, E., SATERIANO, A., VENANZONI, G. & SALVATI, L. 2016. Cities as selective land predators? A lesson on urban growth, deregulated planning and sprawl containment. *Science of the Total Environment,* 545**,** 329-339.
CORBELLE-RICO, E., CRECENTE-MASEDA, R. & SANTÉ-RIVEIRA, I. 2012. Multi-scale assessment and spatial modelling of agricultural land abandonment in a European peripheral region: Galicia (Spain), 1956–2004. *Land Use Policy,* 29**,** 493-501.
CORNUÉJOLS, A., WEMMERT, C., GANÇARSKI, P. & BENNANI, Y. 2018. Collaborative clustering: Why, when, what and how. *Information Fusion,* 39**,** 81-95.
CROOKS, A. T. 2006. *Exploring cities using agent-based models and GIS*, Centre for Advanced Spatial Analysis, University College London.
CROOKS, A., CASTLE, C. & BATTY, M. 2008. Key challenges in agent-based modelling for geo-spatial simulation. *Computers Environment and Urban Systems,* 32**,** 417-430.
CROOKS, A. T. & HEPPENSTALL, A. J. 2012. Introduction to agent-based modelling. *Agent-based models of geographical systems.* Springer.
CROSSMAN, N. D., BRYAN, B. A., DE GROOT, R. S., LIN, Y.-P. & MINANG, P. A. 2013. Land science contributions to ecosystem services. *Current Opinion in Environmental Sustainability,* 5**,** 509-514.
CROSSMAN, N. D., BRYAN, B. A., OSTENDORF, B. & COLLINS, S. 2007. Systematic landscape restoration in the rural–urban fringe: meeting conservation planning and policy goals. *Biodiversity and Conservation,* 16**,** 3781-3802.
CUADRADO-CIURANETA, S., DURÀ-GUIMERÀ, A. & SALVATI, L. 2017. Not only tourism: unravelling suburbanization, second-home expansion and “rural” sprawl in Catalonia, Spain. *Urban Geography,* 38**,** 66-89.
D’AMOUR, C. B., REITSMA, F., BAIOCCHI, G., BARTHEL, S., GÜNERALP, B., ERB, K.-H., HABERL, H., CREUTZIG, F. & SETO, K. C. 2016. Future urban land expansion and implications for global croplands. *Proceedings of the National Academy of Sciences***,** 1606036114
D’AQUINO, P., AUGUST, P., BALMANN, A., BERGER, T., BOUSQUET, F., BRONDÍZIO, E., BROWN, D. G., COUCLELIS, H., DEADMAN, P. & GOODCHILD, M. F. 2002. Agent-based models of land-use and land-cover change. *Proceedings of an International Workshop,* 4-7.
DAHAL, K. R. & CHOW, T. E. 2014. An agent-integrated irregular automata model of urban land-use dynamics. *International Journal of Geographical Information Science,* 28**,** 2281-2303.
DAVOUDI, S. & STEAD, D. 2002. Urban-rural relationships: an introduction and brief history. *Built Environment*, 28**,** 269-277.
DE ALMEIDA, C. M., BATTY, M., MONTEIRO, A. M. V., CAMARA, G., SOARES-FILHO, B. S., CERQUEIRA, G. C. & PENNACHIN, C. L. 2003. Stochastic cellular automata modeling of urban land use dynamics: empirical development and estimation. *Computers, Environment and Urban Systems,* 27**,** 481-509.
DE NIJS, T. C., DE NIET, R. & CROMMENTUIJN, L. 2004. Constructing land-use maps of the Netherlands in 2030. *Journal of environmental management,* 72**,** 35-42.
DEBOLINI, M., VALETTE, E., FRANÇOIS, M. & CHÉRY, J.-P. 2015. Mapping land use competition in the rural–urban fringe and future perspectives on land policies: A case study of Meknès (Morocco). *Land Use Policy,* 47**,** 373-381.
DEL MAR LÓPEZ, T., AIDE, T. M. & THOMLINSON, J. R. 2001. Urban expansion and the loss of prime agricultural lands in Puerto Rico. *Ambio: a Journal of the Human environment,* 30**,** 49-54.

DENDONCKER, N., SCHMIT, C. & ROUNSEVELL, M. 2008. Exploring spatial data uncertainties in land-use change scenarios. *International Journal of Geographical Information Science,* 22**,** 1013-1030.
DENG, F. F. & HUANG, Y. 2004. Uneven land reform and urban sprawl in China: the case of Beijing. *Progress in Planning,* 61**,** 211-236.
DENG, X., HUANG, J., ROZELLE, S., ZHANG, J. & LI, Z. 2015. Impact of urbanization on cultivated land changes in China. *Land Use Policy,* 45**,** 1-7.
DENG, X., LI, Z. & GIBSON, J. 2016. A review on trade-off analysis of ecosystem services for sustainable land-use management. *Journal of Geographical Sciences,* 26**,** 953-968.
DEPARTMENT OF INFRASTRUCTURE AND TRANSPORT. 2011. Our Cities National Urban Policy Paper. Department of Infrastructure and Transport, Commonwealth of Australia.
DEPARTMENT OF PLANNING, TRANSPORT AND INFRASTRUCTURE (DPTI). 2016. *Land Use Generalised* [Online]. SA Government. Available: https://data.sa.gov.au/data/dataset/3d1fc5f0-ce19-4b68-a7cd-191ded177f5e [Accessed 01/12/2016 2016].
DÍAZ-VARELA, E., ROCES-DÍAZ, J. V. & ÁLVAREZ-ÁLVAREZ, P. 2016. Detection of landscape heterogeneity at multiple scales: Use of the Quadratic Entropy Index. *Landscape and Urban Planning,* 153**,** 149-159.
DIBARI, J. N. 2007. Evaluation of five landscape-level metrics for measuring the effects of urbanization on landscape structure: the case of Tucson, Arizona, USA. *Landscape and Urban Planning,* 79**,** 308-313.
DISTEFANO, C. & MORGAN, G. B. 2014. A comparison of diagonal weighted least squares robust estimation techniques for ordinal data. *Structural Equation Modeling: A Multidisciplinary Journal,* 21**,** 425-438.
DOCKING, A. & SREEKUMAR, C. 2008. Planning for Food Production within the Sydney Metropolitan Region. *International Cities, Towns, Centres and Communities Society Conference,* 7-10.
DORIN, A. & GEARD, N. 2014. The practice of agent-based model visualization. *Artificial life,* 20**,** 271-289.
DOUGLAS, I. 2006. Peri-urban ecosystems and societies transitional zones and contrasting values. In: McGregor, D., Simon, D. & Thompson, D. (Eds.). *The peri-urban interface: Approaches to sustainable natural and human resource use* (pp. 18-29) London: Earthscan.
DUANGJAI, W., SCHMIDT-VOGT, D. & SHRESTHA, R. P. 2015. Farmers' land use decision-making in the context of changing land and conservation policies: A case study of Doi Mae Salong in Chiang Rai Province, Northern Thailand. *Land Use Policy,* 48**,** 179-189.
DUVERNOY, I., ZAMBON, I., SATERIANO, A. & SALVATI, L. 2018. Pictures from the other side of the fringe: Urban growth and peri-urban agriculture in a post-industrial city (Toulouse, France). *Journal of Rural Studies,* 57**,** 25-35.
EDWARDS-JONES, G., DEARY, I. & WILLOCK, J. 1998. Incorporating psychological variables in models of farmer behaviour: Does it make for better predictions? *Etudes et Recherches sur les Systemes Agraires et le Dêveloppement***,** 153-173.
ELHADARY, Y. A. E., SAMAT, N. & OBENG-ODOOM, F. 2013. Development at the Peri-urban area and its impact on agricultural activities: An example from the Seberang Perai Region, Penang State, Malaysia. *Agroecology and sustainable food systems,* 37**,** 834-856.
ELLIS, E. C. 2011. Anthropogenic transformation of the terrestrial biosphere. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences,* 369**,** 1010-1035.
ELMQVIST, T., FRAGKIAS, M., GOODNESS, J., GÜNERALP, B., MARCOTULLIO, P. J.,

MCDONALD, R. I., PARNELL, S., SCHEWENIUS, M., SENDSTAD, M. & SETO, K. C. 2013a. Stewardship of the biosphere in the urban era. In *Urbanization, biodiversity and ecosystem services: Challenges and opportunities: A global assessment.* Springer.

ELMQVIST, T., FRAGKIAS, M., GOODNESS, J., GÜNERALP, B., MARCOTULLIO, P. J., MCDONALD, R. I., PARNELL, S., SCHEWENIUS, M., SENDSTAD, M. & SETO, K. C. 2013b. *Urbanization, biodiversity and ecosystem services: Challenges and opportunities: A global assessment*, Springer.

ELTON CONSULTING. 2009. Sydney's Agriculture—Planning for the Future (Forum Outcomes Report). Sydney, New South Wales: Department of Primary Industries.

ESTOQUE, R. C. & MURAYAMA, Y. 2012. Examining the potential impact of land use/cover changes on the ecosystem services of Baguio city, the Philippines: A scenario-based analysis. *Applied Geography,* 35**,** 316-326.

EVANS, T. P. & KELLEY, H. 2004. Multi-scale analysis of a household level agent-based model of landcover change. *Journal of Environmental Management,* 72**,** 57-72.

FENG, L., DU, P., LI, H. & ZHU, L. 2015. Measurement of Urban Fringe Sprawl in Nanjing between 1984 and 2010 Using Multidimensional Indicators. *Geographical Research,* 53**,** 184-198.

FENG, Y. & LIU, Y. 2015. Fractal dimension as an indicator for quantifying the effects of changing spatial scales on landscape metrics. *Ecological Indicators,* 53**,** 18-27.

FENG, Y. & LIU, Y. 2016. Scenario prediction of emerging coastal city using CA modeling under different environmental conditions: a case study of Lingang New City, China. *Environmental monitoring and assessment,* 188**,** 540.

FILATOVA, T., VERBURG, P. H., PARKER, D. C. & STANNARD, C. A. 2013. Spatial agent-based models for socio-ecological systems: Challenges and prospects. *Environmental Modelling & Software,* 45**,** 1-7.

FINCHER, R. 2011. Population growth in Australia: views and policy talk for possible futures. *Geographical Research,* 49**,** 336-347.

FLYNN, D. F., GOGOL-PROKURAT, M., NOGEIRE, T., MOLINARI, N., RICHERS, B. T., LIN, B. B., SIMPSON, N., MAYFIELD, M. M. & DECLERCK, F. 2009. Loss of functional diversity under land use intensification across multiple taxa. *Ecology letters,* 12**,** 22-33.

FOLEY, J. A., DEFRIES, R., ASNER, G. P., BARFORD, C., BONAN, G., CARPENTER, S. R., CHAPIN, F. S., COE, M. T., DAILY, G. C. & GIBBS, H. K. 2005. Global consequences of land use. *science,* 309**,** 570-574.

FOLKE, C., JANSSON, Å., ROCKSTRÖM, J., OLSSON, P., CARPENTER, S. R., STUART CHAPIN III, F., CRÉPIN, A.-S., DAILY, G., DANELL, K. & EBBESSON, J. 2011. Reconnecting to the biosphere. *AMBIO: A Journal of the Human Environment,* 40**,** 719-738.

FORD, T. 1997. *Population Trends in Adelaide's Peri-urban Region,* Master's thesis, University of Adelaide.

FORD, T. 1999. Understanding population growth in the peri-urban region. *International Journal of Population Geography,* 5**,** 297-311.

FORMAN, R. T. & GODRON, M. 1986. *Landscape ecology*. John Wiley & Sons, New York.

FORSTER, C. 2006. The challenge of change: Australian cities and urban planning in the new millennium. *Geographical research,* 44**,** 173-182.

FRAGKIAS, M., LANGANKE, T., BOONE, C., HAASE, D., MARCOTULLIO, P. J., MUNROE, D., OLAH, B., REENBERG, A., SETO, K. C. & SIMON, D. 2012. Land teleconnections in an urbanizing world. *GLP [Global Land Project] and UGEC [Urbanization and Global Environmental Change] workshop report***,** 22.

FUGLSANG, M., MÜNIER, B. & HANSEN, H. S. 2013. Modelling land-use effects of future

urbanization using cellular automata: An Eastern Danish case. *Environmental Modelling & Software,* 50**,** 1-11.
GALLI, M., LARDON, S., MARRACCINI, E. & BONARI, E. Agricultural management in peri-urban areas. The experience of an international workshop. Felici, Pisa, 2010.
GANT, R. L., ROBINSON, G. M. & FAZAL, S. 2011. Land-use change in the 'edgelands': Policies and pressures in London's rural–urban fringe. *Land Use Policy,* 28**,** 266-279.
GARDINER, R. & LE GOULVEN, K. 2001. Sustaining our global public goods. *Economic Briefing*.
GBANIE, S. P., GRIFFIN, A. L. & THORNTON, A. 2018. Impacts on the Urban Environment: Land Cover Change Trajectories and Landscape Fragmentation in Post-War Western Area, Sierra Leone. *Remote Sensing,* 10**,** 129.
GILBERT, N. 2008. *Agent-based models,* Sage.
GILJUM, S., BEHRENS, A., HINTERBERGER, F., LUTZ, C. & MEYER, B. 2008. Modelling scenarios towards a sustainable use of natural resources in Europe. *Environmental Science & Policy,* 11**,** 204-216.
GIMBLETT, R., DANIEL, T., CHERRY, S. & MEITNER, M. J. 2001. The simulation and visualization of complex human–environment interactions. *Landscape and Urban Planning,* 54**,** 63-79.
GLOBAL LAND PROJECT (GLP). 2005. *Science Plan and Implementation Strategy.* International Geosphere-Biosphere Programme (IGBP) Secretariat, IGBP Report No. 53/IHDP Report No. 19, Stockholm.
GODRON, M. & FORMAN, R. 1983. Landscape modification and changing ecological characteristics. *Disturbance and ecosystems.* Springer.
GOTTMANN, J. 1957. Megalopolis or the Urbanization of the Northeastern Seaboard. *Economic geography,* 33**,** 189-200.
GOTTMANN, J. 1966. *Metropolis on the move: Geographers look at urban sprawl,* Wiley.
GOUNARIDIS, D., CHORIANOPOULOS, I. & KOUKOULAS, S. 2018. Exploring prospective urban growth trends under different economic outlooks and land-use planning scenarios: The case of Athens. *Applied Geography,* 90**,** 134-144.
GRAU, R., KUEMMERLE, T. & MACCHI, L. 2013. Beyond 'land sparing versus land sharing': environmental heterogeneity, globalization and the balance between agricultural production and nature conservation. *Current Opinion in Environmental Sustainability,* 5**,** 477-483.
GREENE, R. P. & STAGER, J. 2001. Rangeland to cropland conversions as replacement land for prime farmland lost to urban development. *The Social Science Journal,* 38**,** 543-555.
GRIEWALD, Y., CLEMENS, G., KAMP, J., GLADUN, E., HÖLZEL, N. & VON DRESSLER, H. 2017. Developing land use scenarios for stakeholder participation in Russia. *Land Use Policy,* 68**,** 264-276.
GRIGNARD, A. & DROGOUL, A. 2017. Agent-Based Visualization: A Real-Time Visualization Tool Applied Both to Data and Simulation Outputs. *The AAAI-17, Human-Machine Collaborative Learning.* WS.
GRIMM, N. B., FAETH, S. H., GOLUBIEWSKI, N. E., REDMAN, C. L., WU, J., BAI, X. & BRIGGS, J. M. 2008. Global change and the ecology of cities. *science,* 319**,** 756-760.
GRIMM, V., BERGER, U., DEANGELIS, D. L., POLHILL, J. G., GISKE, J. & RAILSBACK, S. F. 2010. The ODD protocol: a review and first update. *Ecological modelling,* 221**,** 2760-2768.
GRIMM, V., REVILLA, E., BERGER, U., JELTSCH, F., MOOIJ, W. M., RAILSBACK, S. F., THULKE, H.-H., WEINER, J., WIEGAND, T. & DEANGELIS, D. L. 2005. Pattern-oriented modeling of agent-based complex systems: lessons from ecology. *science,* 310**,**

987-991..
GUASTELLA, G. & PAREGLIO, S. 2016. Urban spatial structure and land use fragmentation: the case of Milan FUA. *Aestimum*, 153.
GUILLEM, E., MURRAY-RUST, D., ROBINSON, D., BARNES, A. & ROUNSEVELL, M. 2015. Modelling farmer decision-making to anticipate tradeoffs between provisioning ecosystem services and biodiversity. *Agricultural Systems,* 137, 12-23.
GÜNERALP, B. & SETO, K. 2013. Futures of global urban expansion: Uncertainties and implications for biodiversity conservation. *Environmental Research Letters,* 8, 014025.
GÜNERALP, B., SETO, K. C. & RAMACHANDRAN, M. 2013. Evidence of urban land teleconnections and impacts on hinterlands. *Current Opinion in Environmental Sustainability,* 5, 445-451.
GUTMAN, G. 2004. *Land Change Science: Observing, Monitoring and Undeerstanding Trajectories of Change on the Earth's Surface*, Springer.
HAASE, D. & NUISSL, H. 2010. The urban-to-rural gradient of land use change and impervious cover: a long-term trajectory for the city of Leipzig. *Journal of Land Use Science,* 5, 123-141.
HAASNOOT, M. & MIDDELKOOP, H. 2012. A history of futures: a review of scenario use in water policy studies in the Netherlands. *Environmental science & policy,* 19, 108-120.
HADZI-PAVLOVIC, D. 2009. Finding patterns and groupings: I. Introduction to latent class analysis. *Acta Neuropsychiatrica,* 21, 312-313.
HALKIDI, M., BATISTAKIS, Y. & VAZIRGIANNIS, M. 2001. On clustering validation techniques. *Journal of intelligent information systems,* 17, 107-145.
HALLER, A. 2014. The "sowing of concrete": Peri-urban smallholder perceptions of rural–urban land change in the Central Peruvian Andes. *Land Use Policy,* 38, 239-247.
HAMMOND, J., VAN WIJK, M. T., SMAJGL, A., WARD, J., PAGELLA, T., XU, J., SU, Y., YI, Z. & HARRISON, R. D. 2017. Farm types and farmer motivations to adapt: Implications for design of sustainable agricultural interventions in the rubber plantations of South West China. *Agricultural Systems,* 154, 1-12.
HANDAYANI, W. 2013. Rural-urban transition in Central Java: Population and economic structural changes based on cluster analysis. *Land,* 2, 419-436.
HANSPACH, J., HARTEL, T., MILCU, A., MIKULCAK, F., DORRESTEIJN, I., KOVÁCS-HOSTYÁNSZKI, A. & BÁLDI, A. 2014. A holistic approach to studying social-ecological systems and its application to southern Transylvania. *Ecology and Society*, &.
HANSSON, H., FERGUSON, R., OLOFSSON, C. & RANTAMÄKI-LAHTINEN, L. 2013. Farmers' motives for diversifying their farm business–The influence of family. *Journal of Rural Studies,* 32, 240-250.
HARVEY, R. O. & CLARK, W. A. 1965. The nature and economics of urban sprawl. *Land Economics,* 41, 1-9.
HASSAN, M. M. 2017. Monitoring land use/land cover change, urban growth dynamics and landscape pattern analysis in five fastest urbanized cities in Bangladesh. *Remote Sensing Applications: Society and Environment,* 7, 69-83.
HASSE, J. E. & LATHROP, R. G. 2003. Land resource impact indicators of urban sprawl. *Applied geography,* 23, 159-175.
HAYEK, U. W., EFTHYMIOU, D., FAROOQ, B., VON WIRTH, T., TEICH, M., NEUENSCHWANDER, N. & GRÊT-REGAMEY, A. 2015. Quality of urban patterns: Spatially explicit evidence for multiple scales. *Landscape and Urban Planning,* 142, 47-62.
HAYTER, R., BARNES, T. J. & BRADSHAW, M. J. 2003. Relocating resource peripheries to the core of economic geography's theorizing: rationale and agenda. *Area,* 35, 15-23.

HECKBERT, S., BISHOP, I., MARCEAU, D. & BENESON, I. 2011. Empirical calibration of spatially explicit agent-based models. *Advanced Geosimulation. Bentham*, 92-110.
HEDBLOM, M., ANDERSSON, E. & BORGSTRÖM, S. 2017. Flexible land-use and undefined governance: From threats to potentials in peri-urban landscape planning. *Land Use Policy,* 63, 523-527.
HEIMLICH, R. E. & ANDERSON, W. D. 2001. Development at the urban fringe and beyond: Impacts on agriculture and rural land. United States Department of Agriculture, Economic Research Service.
HENDERSON, S. R. 2003. Agricultural Adaptation to Real Regulation on the Urban Fringe: The Chicken Meat Industry's Response to Land-use Conflict in the Western Port Region of Victoria, Australia. *Australian Geographical Studies,* 41, 156-170.
HENRICHS, T., ZUREK, M., EICKHOUT, B., KOK, K., RAUDSEPP-HEARNE, C., RIBEIRO, T., VAN VUUREN, D. & VOLKERY, A. 2010. Scenario development and analysis for forward-looking ecosystem assessments. *Human Well-Being*, 151.
HEROLD, M., COUCLELIS, H. & CLARKE, K. C. 2005. The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, Environment and Urban Systems,* 29, 369-399.
HERRERO, M., THORNTON, P. K., BERNUÉS, A., BALTENWECK, I., VERVOORT, J., VAN DE STEEG, J., MAKOKHA, S., VAN WIJK, M. T., KARANJA, S., RUFINO, M. C. & STAAL, S. J. 2014. Exploring future changes in smallholder farming systems by linking socio-economic scenarios with regional and household models. *Global Environmental Change,* 24, 165-182.
HERSPERGER, A. M. & BÜRGI, M. 2009. Going beyond landscape change description: quantifying the importance of driving forces of landscape change in a Central Europe case study. *Land Use Policy,* 26, 640-648.
HERTWIG, R., BARRON, G., WEBER, E. U. & EREV, I. 2004. Decisions from experience and the effect of rare events in risky choice. *Psychological science,* 15, 534-539.
HIETEL, E., WALDHARDT, R. & OTTE, A. 2004. Analysing land-cover changes in relation to environmental variables in Hesse, Germany. *Landscape ecology,* 19, 473-489.
HOLLOWAY, D. & BUNKER, R. 2003. Using GIS as an aid to understanding urban consolidation. *Australian Geographical Studies,* 41, 44-57.
HOOTEN, M. B. & WIKLE, C. K. 2010. Statistical agent-based models for discrete spatio-temporal systems. *Journal of the American Statistical Association,* 105, 236-248.
HOSSEINALI, F., ALESHEIKH, A. A. & NOURIAN, F. 2015. Assessing urban land-use development: Developing an agent-based model. *KSCE Journal of Civil Engineering,* 19, 285-295.
HOU, H., ESTOQUE, R. C. & MURAYAMA, Y. 2016. Spatiotemporal analysis of urban growth in three African capital cities: A grid-cell-based analysis using remote sensing data. *Journal of African Earth Sciences,* 123, 381-391.
HOUET, T., MARCHADIER, C., BRETAGNE, G., MOINE, M., AGUEJDAD, R., VIGUIÉ, V., BONHOMME, M., LEMONSU, A., AVNER, P. & HIDALGO, J. 2016. Combining narratives and modelling approaches to simulate fine scale and long-term urban growth scenarios for climate adaptation. *Environmental Modelling & Software,* 86, 1-13.
HOUSTON, P. 2003. The national audit of Peri-urban agriculture. *Australian Planner,,* 40.
HOUSTON, P. 2005. Re-valuing the Fringe: Some Findings on the Value of Agricultural Production in Australia's Peri-Urban Regions. *Geographical Research,* 43, 209-223.
HUANG, S.-L., WANG, S.-H. & BUDD, W. W. 2009. Sprawl in Taipei’s peri-urban zone: Responses to spatial planning and implications for adapting global environmental change.

Landscape and Urban Planning, 90**,** 20-32.
HUBER, R., FLURY, C. & FINGER, R. 2015. Factors affecting farm growth intentions of family farms in mountain regions: Empirical evidence for Central Switzerland. *Land Use Policy,* 47**,** 188-197.
HULSE, D., BRANSCOMB, A., ENRIGHT, C., JOHNSON, B., EVERS, C., BOLTE, J. & AGER, A. 2016. Anticipating Surprise: using agent-based alternative futures simulation modeling to identify and map surprising fires in the Willamette Valley, Oregon USA. *Landscape and Urban Planning*.
HUMPHREYS, A., WRIGHT, M., FOWLER, A., TINSLAY, P., GOJAK, D. & TOOKER, M. 2001. Rockdale market gardens conservation management plan. *NSW Department of Urban Affairs and Planning Architectural History Services, Sydney Google Scholar*.
HUSSAIN, Z. & HANISCH, M. 2013. Dynamics of peri-urban agricultural development and farmers' adaptive behaviour in the emerging megacity of Hyderabad, India. *Journal of Environmental Planning and Management***,** 1-21.
HYWOOD, J. D., READ, M. N. & RICE, G. 2016. Statistical analysis of spatially homogeneous dynamic agent-based processes using functional time series analysis. *Spatial Statistics,* 17**,** 199-219.I
ICHIKAWA, K., OKUBO, N., OKUBO, S. & TAKEUCHI, K. 2006. Transition of the satoyama landscape in the urban fringe of the Tokyo metropolitan area from 1880 to 2001. *Landscape and Urban Planning,* 78**,** 398-410.
IRWIN, E. G. & BOCKSTAEL, N. E. 2007. The evolution of urban sprawl: evidence of spatial heterogeneity and increasing land fragmentation. *Proceedings of the National Academy of Sciences,* 104**,** 20672-20677.
IVES, C. D. & KENDAL, D. 2013. Values and attitudes of the urban public towards peri-urban agricultural land. *Land Use Policy,* 34**,** 80-90.
JAEGER, J. A., BERTILLER, R., SCHWICK, C. & KIENAST, F. 2010. Suitability criteria for measures of urban sprawl. *Ecological indicators,* 10**,** 397-406.
JAGER, W. & MOSLER, H. J. 2007. Simulating human behavior for understanding and managing environmental resource use. *Journal of Social Issues,* 63**,** 97-116.
JAIN, A. 2008. Urban growth centres on the periphery: ad hoc policy vision and research neglect.
JAMES, S. W. 2014. Protecting Sydney's Peri-Urban Agriculture: Moving beyond a Housing/Farming Dichotomy. *Geographical Research,* 52**,** 377-386.
JAMES, S. 2016. *Farming on the Fringe: Peri-urban Agriculture, Cultural Diversity and Sustainability in Sydney,* Springer.
JAMES, S. W. & O'NEILL, P. M. 2016. Planning for Peri-urban Agriculture: a geographically-specific, evidence-based approach from Sydney. *Australian Geographer,* 47**,** 179-194.
JAT, M. K., CHOUDHARY, M. & SAXENA, A. 2017. Application of geo-spatial techniques and cellular automata for modelling urban growth of a heterogeneous urban fringe. *The Egyptian Journal of Remote Sensing and Space Science,* 20**,** 223-241.
JIANG, L., DENG, X. & SETO, K. C. 2013. The impact of urban expansion on agricultural land use intensity in China. *Land Use Policy,* 35**,** 33-39.
JIANG, W., CHEN, Z., LEI, X., HE, B., JIA, K. & ZHANG, Y. 2016. Simulation of urban agglomeration ecosystem spatial distributions under different scenarios: A case study of the Changsha–Zhuzhou–Xiangtan urban agglomeration. *Ecological Engineering,* 88**,** 112-121.
JIANG, Y. & SWALLOW, S. K. 2015. Providing an ecologically sound community landscape at the urban–rural fringe: a conceptual, integrated model. *Journal of Land Use Science,* 10**,** 323-341.
JOHNSON, M. L., BELL, K. P. & TEISL, M. F. 2016. Does reading scenarios of future land use

changes affect willingness to participate in land use planning? *Land Use Policy*, 57**,** 44-52.
JOHNSON, N., KELLEHER, F. & CHANT, J. 1998. The future of agriculture in the peri-urban fringe of Sydney. *Proceedings of the 9th Australian Agronomy Conference,* Wagga Wagga Australia, 613-616.
JOKAR ARSANJANI, J., HELBICH, M. & DE NORONHA VAZ, E. 2013. Spatiotemporal simulation of urban growth patterns using agent-based modeling: The case of Tehran. *Cities,* 32**,** 33-42
JOO, W., GAGE, S. H. & KASTEN, E. P. 2011. Analysis and interpretation of variability in soundscapes along an urban–rural gradient. *Landscape and Urban Planning,* 103**,** 259-276.
JU, H., ZHANG, Z., ZUO, L., WANG, J., ZHANG, S., WANG, X. & ZHAO, X. 2016. Driving forces and their interactions of built-up land expansion based on the geographical detector–a case study of Beijing, China. *International Journal of Geographical Information Science***,** 1-20.
KAIN, J.-H., LARONDELLE, N., HAASE, D. & KACZOROWSKA, A. 2016. Exploring local consequences of two land-use alternatives for the supply of urban ecosystem services in Stockholm year 2050. *Ecological Indicators*.
KALJONEN, M., VARJOPURO, R., GIEŁCZEWSKI, M. & IITAL, A. 2012. Seeking policy-relevant knowledge: a comparative study of the contextualisation of participatory scenarios for the Narew River and Lake Peipsi. *Environmental Science & Policy,* 15**,** 72-81.
KAPHENGST, T. 2014. Towards a definition of global sustainable land use? A discussion on theory, concepts and implications for governance. Globalands Discussion Paper AP 3.1.
KAUFMAN, L. & ROUSSEEUW, P. J. 2009. *Finding groups in data: an introduction to cluster analysis,* John Wiley & Sons.
KAYE-BLAKE, W., LI, F. Y., MARTIN, A. M., MCDERMOTT, A., RAINS, S., SINCLAIR, S. & KIRA, A. 2010. *Multi-agent simulation models in agriculture: a review of their construction and uses*, Lincoln University. Agribusiness and Economics Research Unit.
KELLEY, H. & EVANS, T. 2011. The relative influences of land-owner and landscape heterogeneity in an agent-based model of land-use. *Ecological Economics,* 70**,** 1075-1087.
KENNEDY, A. 1993. Agriculture in the Sydney region: A fringe activity critical to the regional economy. *Planning for Harmony, Royal Australian Planning Institute (NSW) Annual Conference.*
KENNEDY, T. T. & VEREGIN, H. 2016. Parcelization in rural agricultural and forested landscapes in Wisconsin, 1972–2007: evaluating multiple dimensions of human decision-making over time. *Journal of Land Use Science*.
KIM, D. & BATTY, M. 2011. Modeling Urban Growth: An Agent Based Microeconomic Approach to Urban Dynamics and Spatial Policy Simulation. UCL Working Papers Series.
KLINKE, S., MIHOCI, A. & HÄRDLE, W. 2010. Exploratory factor analysis in MPlus, R and SPSS. *Invited paper ICOTS8 of the International Association of Statistical Education*.
KÖBRICH, C., REHMAN, T. & KHAN, M. 2003. Typification of farming systems for constructing representative farm models: two illustrations of the application of multi-variate analyses in Chile and Pakistan. *Agricultural systems,* 76**,** 141-157.
KOK, K. 2009. The potential of Fuzzy Cognitive Maps for semi-quantitative scenario development, with an example from Brazil. *Global Environmental Change,* 19**,** 122-133.
KOOMEN, E., KUHLMAN, T., GROEN, J. & BOUWMAN, A. 2005. Simulating the future of agricultural land use in the Netherlands. *Tijdschrift voor economische en sociale geografie,* 96**,** 218-224.
KOOMEN, E. & STILLWELL, J. 2007. *Modelling land-use change,* Springer.
KOSCHKE, L., FUERST, C., FRANK, S. & MAKESCHIN, F. 2012. A multi-criteria approach for

an integrated land-cover-based assessment of ecosystem services provision to support landscape planning. *Ecological Indicators,* 21**,** 54-66.
KROLL, F., MÜLLER, F., HAASE, D. & FOHRER, N. 2012. Rural–urban gradient analysis of ecosystem services supply and demand dynamics. *Land Use Policy,* 29**,** 521-535.
KROPP, W. W. & LEIN, J. K. 2013. Scenario analysis for urban sustainability assessment: A spatial multicriteria decision-analysis approach. *Environmental Practice,* 15**,** 133-146.
KUANG, W., LIU, J., DONG, J., CHI, W. & ZHANG, C. 2016. The rapid and massive urban and industrial land expansions in China between 1990 and 2010: A CLUD-based analysis of their trajectories, patterns, and drivers. *Landscape and Urban Planning,* 145**,** 21-33.
LAMBIN, E. F. & GEIST, H. J. 2006. *Land-use and land-cover change*, Springer.
LAMBIN, E. F., GEIST, H. J. & LEPERS, E. 2003. Dynamics of land-use and land-cover change in tropical regions. *Annual review of environment and resources,* 28**,** 205-241.
LAMBIN, E. F. & MEYFROIDT, P. 2010. Land use transitions: Socio-ecological feedback versus socio-economic change. *Land use policy,* 27**,** 108-118.
LAMBIN, E. F. & MEYFROIDT, P. 2011. Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences,* 108**,** 3465-3472.
LAMBIN, E. F., ROUNSEVELL, M. & GEIST, H. 2000. Are agricultural land-use models able to predict changes in land-use intensity? *Agriculture, Ecosystems & Environment,* 82**,** 321-331.
LAMBIN, E. F., TURNER, B. L., GEIST, H. J., AGBOLA, S. B., ANGELSEN, A., BRUCE, J. W., COOMES, O. T., DIRZO, R., FISCHER, G. & FOLKE, C. 2001. The causes of land-use and land-cover change: moving beyond the myths. *Global environmental change,* 11**,** 261-269.
LARONDELLE, N. & HAASE, D. 2013. Urban ecosystem services assessment along a rural–urban gradient: A cross-analysis of European cities. *Ecological Indicators,* 29**,** 179-190.
LARONDELLE, N. & LAUF, S. 2016. Balancing demand and supply of multiple urban ecosystem services on different spatial scales. *Ecosystem Services,* 22**,** 18-31.
LAUF, S., HAASE, D. & KLEINSCHMIT, B. 2014. Linkages between ecosystem services provisioning, urban growth and shrinkage–A modeling approach assessing ecosystem service trade-offs. *Ecological Indicators,* 42**,** 73-94.
LAUF, S., HAASE, D. & KLEINSCHMIT, B. 2016. The effects of growth, shrinkage, population aging and preference shifts on urban development—A spatial scenario analysis of Berlin, Germany. *Land Use Policy,* 52**,** 240-254.
LEE, C.-L., HUANG, S.-L. & CHAN, S.-L. 2009. Synthesis and spatial dynamics of socio-economic metabolism and land use change of Taipei Metropolitan Region. *Ecological Modelling,* 220**,** 2940-2959.
LEE, Y.-C., AHERN, J. & YEH, C.-T. 2015. Ecosystem services in peri-urban landscapes: The effects of agricultural landscape change on ecosystem services in Taiwan's western coastal plain. *Landscape and Urban Planning,* 139**,** 137-148.
LESSCHEN, J. P., VERBURG, P. H. & STAAL, S. J. 2005. *Statistical methods for analysing the spatial dimension of changes in land use and farming systems*, Citeseer.
LIANG, X., CHEN, H., WANG, Y. & SONG, S. 2016. Design and application of a CA-BDI model to determine farmers' land-use behavior. *SpringerPlus,* 5**,** 1581.
LIGMANN-ZIELINSKA, A. 2013. Spatially-explicit sensitivity analysis of an agent-based model of land use change. *International Journal of Geographical Information Science,* 27**,** 1764-1781.
LIGTENBERG, A., BREGT, A. K. & VAN LAMMEREN, R. 2001. Multi-actor-based land use modelling: spatial planning using agents. *Landscape and urban planning,* 56**,** 21-33.

LIGTENBERG, A., VAN LAMMEREN, R. J., BREGT, A. K. & BEULENS, A. J. 2010. Validation of an agent-based model for spatial planning: A role-playing approach. *Computers, Environment and Urban Systems,* 34**,** 424-434.
LIGTENBERG, A., WACHOWICZ, M., BREGT, A. K., BEULENS, A. & KETTENIS, D. L. 2004. A design and application of a multi-agent system for simulation of multi-actor spatial planning. *Journal of environmental management,* 72**,** 43-55.
LIU, C. & LI, Y. 2016. GIS-based dynamic modelling and analysis of flash floods considering land-use planning. *International Journal of Geographical Information Science***,** 1-18.
LIU, J. 2014. Forest sustainability in China and implications for a telecoupled world. *Asia & the Pacific Policy Studies,* 1**,** 230-250.
LIU, J., DIETZ, T., CARPENTER, S. R., ALBERTI, M., FOLKE, C., MORAN, E., PELL, A. N., DEADMAN, P., KRATZ, T. & LUBCHENCO, J. 2007. Complexity of coupled human and natural systems. *science,* 317**,** 1513-1516.
LIU, J., HULL, V., BATISTELLA, M., DEFRIES, R., DIETZ, T., FU, F., HERTEL, T. W., IZAURRALDE, R. C., LAMBIN, E. F. & LI, S. 2013. Framing sustainability in a telecoupled world. *Ecology and Society,* 18.
LIU, Y. 2010. *Modelling urban development with geographical information systems and cellular automata*, CRC Press.
LIU, Y., FENG, Y. & PONTIUS, R. G. 2014. Spatially-explicit simulation of urban growth through self-adaptive genetic algorithm and cellular automata modelling. *Land,* 3**,** 719-738.
LIU, Y., GUPTA, H., SPRINGER, E. & WAGENER, T. 2008. Linking science with environmental decision making: Experiences from an integrated modeling approach to supporting sustainable water resources management. *Environmental Modelling & Software,* 23**,** 846-858.
LIU, Z., HE, C. & WU, J. 2016. The Relationship between Habitat Loss and Fragmentation during Urbanization: An Empirical Evaluation from 16 World Cities. *PloS one,* 11**,** e0154613.
LIU, Z. & ROBINSON, G. M. 2016. Residential development in the peri-urban fringe: The example of Adelaide, South Australia. *Land Use Policy,* 57**,** 179-192.
LIU, Z., VERBURG, P. H., WU, J. & HE, C. 2017. Understanding land system change through scenario-based simulations: a case study from the drylands in northern China. *Environmental management,* 59**,** 440-454.
LIVANIS, G., MOSS, C. B., BRENEMAN, V. E. & NEHRING, R. F. 2006. Urban sprawl and farmland prices. *American Journal of Agricultural Economics,* 88**,** 915-929.
LONG, Y. & ZHANG, Y. 2015. Land-use pattern scenario analysis using planner agents. *Environment and Planning B: Planning and Design,* 42**,** 615-637.
LOW CHOY, D., SUTHERLAND, C., GLEESON, B., SIPE, N. & DODSON, J. 2008. Change and continuity in peri-urban Australia: peri-urban futures and sustainable development. *Griffith University, Brisbane*.
LUCK, M. & WU, J. 2002. A gradient analysis of urban landscape pattern: a case study from the Phoenix metropolitan region, Arizona, USA. *Landscape ecology,* 17**,** 327-339.
LUO, G., YIN, C., CHEN, X., XU, W. & LU, L. 2010. Combining system dynamic model and CLUE-S model to improve land use scenario analyses at regional scale: A case study of Sangong watershed in Xinjiang, China. *Ecological Complexity,* 7**,** 198-207.
MACAL, C. M. & NORTH, M. J. 2005. Tutorial on agent-based modeling and simulation. *Proceedings of the 37th Winter Simulation Conference,* 2-15.
MAGLIOCCA, N. R., BROWN, D. G. & ELLIS, E. C. 2013. Exploring Agricultural Livelihood Transitions with an Agent-Based Virtual Laboratory: Global Forces to Local Decision-Making. *PloS one,* 8**,** e73241.

MAGLIOCCA, N. R., BROWN, D. G. & ELLIS, E. C. 2014. Cross-site comparison of land-use decision-making and its consequences across land systems with a generalized agent-based model. *PLoS One,* 9**,** e86179.
MAHMOUD, M., LIU, Y., HARTMANN, H., STEWART, S., WAGENER, T., SEMMENS, D., STEWART, R., GUPTA, H., DOMINGUEZ, D. & DOMINGUEZ, F. 2009. A formal framework for scenario development in support of environmental decision-making. *Environmental Modelling & Software,* 24**,** 798-808.
MAIER, H., GUILLAUME, J., VAN DELDEN, H., RIDDELL, G., HAASNOOT, M. & KWAKKEL, J. 2016. An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? *Environmental Modelling & Software,* 81**,** 154-164.
MAKITA, K., FÈVRE, E., WAISWA, C., BRONSVOORT, M., EISLER, M. & WELBURN, S. 2010. Population-dynamics focussed rapid rural mapping and characterisation of the peri-urban interface of Kampala, Uganda. *Land Use Policy,* 27**,** 888-897.
MACLACHLAN, A., BIGGS, E., ROBERTS, G. & BORUFF, B. 2017. Urban Growth Dynamics in Perth, Western Australia: Using Applied Remote Sensing for Sustainable Future Planning. *Land,* 6**,** 9.
MALANSON, G. P. & WALSH, S. J. 2015. Agent-based models: Individuals interacting in space. *Applied Geography***,** 95-98.
MALAQUE, I. R. & YOKOHARI, M. 2007. Urbanization process and the changing agricultural landscape pattern in the urban fringe of Metro Manila, Philippines. *Environment and Urbanization,* 19**,** 191-206.
MALIK, A. & ABDALLA, R. 2017. Agent-based modelling for urban sprawl in the region of Waterloo, Ontario, Canada. *Modeling Earth Systems and Environment,* 3**,** 7.
MANCEBO, F. Coping with urban sprawl: toward a sustainable peri-urbanization, giving way to residential path. *Les Annales de la Recherche Urbaine,* 2008. 51-57.
MASON, D. & KNOWD, I. 2010. The emergence of urban agriculture: Sydney, Australia. *International journal of agricultural sustainability,* 8**,** 62-71.
MATANLE, P. & RAUSCH, A. 2011. Japan's shrinking regions in the 21st century: contemporary responses to depopulation and socioeconomic decline.
MATSON, P. A., PARTON, W. J., POWER, A. & SWIFT, M. 1997. Agricultural intensification and ecosystem properties. *Science,* 277**,** 504-509.
MATTHEWS, R. B., GILBERT, N. G., ROACH, A., POLHILL, J. G. & GOTTS, N. M. 2007. Agent-based land-use models: a review of applications. *Landscape Ecology,* 22**,** 1447-1459.
MCCARTHY, J. J. 2001. *Climate change 2001: impacts, adaptation, and vulnerability*. Contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change, Cambridge University Press.
MCCORD, P. F., COX, M., SCHMITT-HARSH, M. & EVANS, T. 2015. Crop diversification as a smallholder livelihood strategy within semi-arid agricultural systems near Mount Kenya. *Land Use Policy,* 42**,** 738-750.
MCDONNELL, M. J. & HAHS, A. K. 2008. The use of gradient analysis studies in advancing our understanding of the ecology of urbanizing landscapes: current status and future directions. *Landscape Ecology,* 23**,** 1143-1155.
MCDONNELL, M. J., PICKETT, S. T., GROFFMAN, P., BOHLEN, P., POUYAT, R. V., ZIPPERER, W. C., PARMELEE, R. W., CARREIRO, M. M. & MEDLEY, K. 1997. Ecosystem processes along an urban-to-rural gradient. *Urban Ecosystems,* 1**,** 21-36.
MCDONNELL, M. J., PICKETT, S. T. & POUYAT, R. V. 1993. The application of the ecological gradient paradigm to the study of urban effects. *Humans as components of ecosystems.* Springer.

MCFARLAND, P. 2015. The Peri-urban Land-Use Planning Tangle: An Australian Perspective. *International Planning Studies,* 20**,** 161-179.
MCGARIGAL, K. 2002. Landscape pattern metrics. *Encyclopedia of environmetrics*.
MCGARIGAL, K. & CUSHMAN, S. 2005. The gradient concept of landscape structure [Chapter 12].
MCGARIGAL, K. & MARKS, B. J. 1995. Spatial pattern analysis program for quantifying landscape structure. *Gen. Tech. Rep. PNW-GTR-351. US Department of Agriculture, Forest Service, Pacific Northwest Research Station*.
MCGRANAHAN, G., SATTERTHWAITE, D. & TACOLI, C. 2004. Rural-urban change, boundary problems and environmental burdens. *IIED Rural Urban Working Paper 10,* International Institute for Environment and Development (IIED).
MCGUIRK, P. & ARGENT, N. 2011. Population growth and change: implications for Australia's cities and regions. *Geographical Research,* 49**,** 317-335.
MCNALLY, S. 2001. Farm diversification in England and Wales—what can we learn from the farm business survey? *Journal of rural studies,* 17**,** 247-257.
MERANER, M., HEIJMAN, W., KUHLMAN, T. & FINGER, R. 2015. Determinants of farm diversification in the Netherlands. *Land Use Policy,* 42**,** 767-780.
MERTES, C. M., SCHNEIDER, A., SULLA-MENASHE, D., TATEM, A. & TAN, B. 2015. Detecting change in urban areas at continental scales with MODIS data. *Remote Sensing of Environment,* 158**,** 331-347.
MESSINA, J., EVANS, T., MANSON, S., SHORTRIDGE, A., DEADMAN, P. & VERBURG, P. 2008. Complex systems models and the management of error and uncertainty. *Journal of Land Use Science,* 3**,** 11-25.
MESSINA, J. P. & WALSH, S. J. 2001. Simulating land use and land cover dynamics in the Ecuadorian Amazon through cellular automata approaches and an integrated GIS. *Open Meeting of the Human Dimensions of Global Environmental Change Research Community,* Rio de Janeiro, Brazil, 6-8.
MEWETT, J. 2013. Towards national reporting on agricultural land use change in Australia.
MEYFROIDT, P. 2016. Approaches and terminology for causal analysis in land systems science. *Journal of Land Use Science,* 11**,** 501-522.
MEYFROIDT, P., LAMBIN, E. F., ERB, K.-H. & HERTEL, T. W. 2013. Globalization of land use: distant drivers of land change and geographic displacement of land use. *Current Opinion in Environmental Sustainability,* 5**,** 438-444.
MILLINGTON, A. 2012a. Land—A multidisciplinary journal addressing issues at the land use and sustainability nexus. *Land,* 1**,** 1-4.
MILLINGTON, A. C., VELEZ-LIENDO, X. M. & BRADLEY, A. V. 2003. Scale dependence in multitemporal mapping of forest fragmentation in Bolivia: implications for explaining temporal trends in landscape ecology and applications to biodiversity conservation. *ISPRS Journal of Photogrammetry and Remote Sensing,* 57**,** 289-299.
MILLINGTON, J. D. 2012b. Using social psychology theory for modelling farmer decision-making. *International Congress on Environmental Modelling and Software.*
MILLINGTON, J. D. & WAINWRIGHT, J. 2016. Comparative Approaches for Innovation in Agent-Based Modelling of Landscape Change. *Land,* 5**,** 13.
MILLS, D. E. 1981. Growth, speculation and sprawl in a monocentric city. *Journal of Urban Economics,* 10**,** 201-226.
MITCHELL, M., LOCKWOOD, M., MOORE, S. A., CLEMENT, S., GILFEDDER, L. & ANDERSON, G. 2016. Using scenario planning to assess governance reforms for enhancing biodiversity outcomes. *Land Use Policy,* 50**,** 559-572.

MONONEN, L., AUVINEN, A.-P., AHOKUMPU, A.-L., RÖNKÄ, M., AARRAS, N., TOLVANEN, H., KAMPPINEN, M., VIIRRET, E., KUMPULA, T. & VIHERVAARA, P. 2016. National ecosystem service indicators: Measures of social–ecological sustainability. *Ecological Indicators,* 61**,** 27-37.

MOREIRA, F., FONTES, I., DIAS, S., E SILVA, J. B. & LOUPA-RAMOS, I. 2016. Contrasting static versus dynamic-based typologies of land cover patterns in the Lisbon metropolitan area: Towards a better understanding of peri-urban areas. *Applied Geography,* 75**,** 49-59.

MORGAN, F. J. & DAIGNEAULT, A. J. 2015. Estimating impacts of climate change policy on land use: An agent-based modelling approach. *PloS one,* 10**,** e0127317.

MÖRTBERG, U., HAAS, J., ZETTERBERG, A., FRANKLIN, J. P., JONSSON, D. & DEAL, B. 2013. Urban ecosystems and sustainable urban development—analysing and assessing interacting systems in the Stockholm region. *Urban ecosystems,* 16**,** 763-782.

MOUGEOT, L. J. 2000. Urban agriculture: Definition, presence, potentials and risks, and policy challenges. *Cities feeding people series; rept. 31*.

MÜLLER, B., BALBI, S., BUCHMANN, C. M., DE SOUSA, L., DRESSLER, G., GROENEVELD, J., KLASSERT, C. J., LE, Q. B., MILLINGTON, J. D. & NOLZEN, H. 2014. Standardised and transparent model descriptions for agent-based models: Current status and prospects. *Environmental Modelling & Software,* 55**,** 156-163.

MÜLLER, B., BOHN, F., DREßLER, G., GROENEVELD, J., KLASSERT, C., MARTIN, R., SCHLÜTER, M., SCHULZE, J., WEISE, H. & SCHWARZ, N. 2013. Describing human decisions in agent-based models–ODD+ D, an extension of the ODD protocol. *Environmental Modelling & Software,* 48**,** 37-48.

MÜLLER, D. 2016. Research frontiers in land use science. *Journal of Land Use Science,* 11.

MUNROE, D. K. & MÜLLER, D. 2007. Issues in spatially explicit statistical land-use/cover change (LUCC) models: Examples from western Honduras and the Central Highlands of Vietnam. *Land Use Policy,* 24**,** 521-530.

MURAYAMA, Y., ESTOQUE, R. C., SUBASINGHE, S., HOU, H. & GONG, H. 2015. Land-use/Land-Cover changes in Major Asian and African Cities. *Annual report on the multi-use social and economy data bank,* 92.

MURAYAMA, Y. & THAPA, R. B. 2011. *Spatial analysis and modeling in geographical transformation process: GIS-based applications,* Springer Science & Business Media.

MURRAY-RUST, D., BROWN, C., VAN VLIET, J., ALAM, S. J., ROBINSON, D. T., VERBURG, P. H. & ROUNSEVELL, M. 2014a. Combining agent functional types, capitals and services to model land use dynamics. *Environmental Modelling & Software,* 59**,** 187-201.

MURRAY-RUST, D., DENDONCKER, N., DAWSON, T. P., ACOSTA-MICHLIK, L., KARALI, E., GUILLEM, E. & ROUNSEVELL, M. 2011. Conceptualising the analysis of socio-ecological systems through ecosystem services and agent-based modelling. *Journal of Land Use Science,* 6**,** 83-99.

MURRAY-RUST, D., RIESER, V., ROBINSON, D. T., MILIČIČ, V. & ROUNSEVELL, M. 2013. Agent-based modelling of land use dynamics and residential quality of life for future scenarios. *Environmental Modelling & Software,* 46**,** 75-89.

MURRAY-RUST, D., ROBINSON, D. T., GUILLEM, E., KARALI, E. & ROUNSEVELL, M. 2014b. An open framework for agent based modelling of agricultural land use change. *Environmental Modelling & Software,* 61**,** 19-38.

MUTHÉN, B. & MUTHÉN, B. O. 2009. *Statistical analysis with latent variables,* Wiley New York.

NAGENDRA, H., UNNIKRISHNAN, H. & SEN, S. 2013. Villages in the city: spatial and

temporal heterogeneity in rurality and urbanity in Bangalore, India. *Land,* 3**,** 1-18.
NATIONAL RESEARCH COUNCIL (NRC) 1998. *People and pixels: Linking remote sensing and social science,* National Academies Press.
NATIONAL RESEARCH COUNCIL (NRC), COMMITTEE ON NEEDS AND RESEARCH REQUIREMENTS FOR LAND CHANGE MODELLING. 2014. Advancing land change modeling: opportunities and research requirements. National Academies Press.
NGUYEN, P., VAN WESTEN, A. & ZOOMERS, A. 2017a. Compulsory land acquisition for urban expansion: livelihood reconstruction after land loss in Hue's peri-urban areas, Central Vietnam. *International Development Planning Review,* 39**,** 99-121.
NGUYEN, T. T., NGUYEN, L. D., LIPPE, R. S. & GROTE, U. 2017b. Determinants of Farmers' Land Use Decision-Making: Comparative Evidence From Thailand and Vietnam. *World Development,* 89**,** 199-213.
NORTHCOTE, J. & ALONSO, A. D. 2011. Factors underlying farm diversification: the case of Western Australia's olive farmers. *Agriculture and Human Values,* 28**,** 237-246.
NUALNOOM, P., WEHRMEYER, W. & MORSE, S. 2016. Analysing household decision-making on oil palm cultivation in Thailand. *Journal of Land Use Science,* 11**,** 560-578.
NUGENT, R. 1999. Is Urban Agriculture Sustainable in Hartford, Connecticut (USA). *Contested Countryside: The Rural Urban Fringe in North America. Ashgate, London*.
NUGENT, R. 2000. The impact of urban agriculture on the household and local economies. In Bakker N., Dubbeling M., Gündel S., Sabel-Koshella U., de Zeeuw H. *Growing cities, growing food. Urban agriculture on the policy agenda.* Feldafing, Germany: Zentralstelle für Ernährung und Landwirtschaft (ZEL)**,** 67-95.
NULTY, D. D. 2008. The adequacy of response rates to online and paper surveys: what can be done? *Assessment & evaluation in higher education,* 33**,** 301-314.
NYLUND, K. L., ASPAROUHOV, T. & MUTHÉN, B. O. 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural equation modeling,* 14**,** 535-569.
O'CONNOR, B. P. 2000. SPSS and SAS programs for determining the number of components using parallel analysis and Velicer's MAP test. *Behavior Research Methods,* 32**,** 396-402.
OLOFSSON, P., FOODY, G. M., STEHMAN, S. V. & WOODCOCK, C. E. 2013. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment,* 129**,** 122-131.
ORNETSMÜLLER, C., VERBURG, P. H. & HEINIMANN, A. 2016. Scenarios of land system change in the Lao PDR: Transitions in response to alternative demands on goods and services provided by the land. *Applied Geography,* 75**,** 1-11.
O'SULLIVAN, D., EVANS, T., MANSON, S., METCALF, S., LIGMANN-ZIELINSKA, A. & BONE, C. 2016. Strategic directions for agent-based modeling: avoiding the YAAWN syndrome. *Journal of land use science,* 11**,** 177-187.
PALOMO, I., MARTÍN-LÓPEZ, B., LÓPEZ-SANTIAGO, C. & MONTES, C. 2011. Participatory scenario planning for protected areas management under the ecosystem services framework: the Doñana social-ecological system in southwestern Spain. *Ecology and Society,* 16.
PANDEY, B. & SETO, K. C. 2015. Urbanization and agricultural land loss in India: Comparing satellite estimates with census data. *Journal of Environmental Management,* 148**,** 53-66.
PANNELL, D. J. 1997. Sensitivity analysis: strategies, methods, concepts, examples. *Agric Econ,* 16**,** 139-152.
PANNELL, D. J. & VANCLAY, F. 2011. *Changing land management: Adoption of new practices by rural landholders,* CSIRO Publishing.
PARKER, D. C., ENTWISLE, B., RINDFUSS, R. R., VANWEY, L. K., MANSON, S. M.,

MORAN, E., AN, L., DEADMAN, P., EVANS, T. P. & LINDERMAN, M. 2008a. Case studies, cross-site comparisons, and the challenge of generalization: comparing agent-based models of land-use change in frontier regions. *Journal of land use science,* 3**,** 41-72.
PARKER, D. C., HESSL, A. & DAVIS, S. C. 2008b. Complexity, land-use modeling, and the human dimension: Fundamental challenges for mapping unknown outcome spaces. *Geoforum,* 39**,** 789-804.
PARKER, D. C., MANSON, S. M., JANSSEN, M. A., HOFFMANN, M. J. & DEADMAN, P. 2003. Multi-agent systems for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers,* 93**,** 314-337.
PARKER, D. C. & MERETSKY, V. 2004. Measuring pattern outcomes in an agent-based model of edge-effect externalities using spatial metrics. *Agriculture, Ecosystems & Environment,* 101**,** 233-250.
PARKER, F. & JARECKI, S. 2004. Transitions at the rural/urban interface:" moving in"," moving out" and" staying put". *State of Australian Cities National Conference 03*.
PARROTT, L. & MEYER, W. S. 2012. Future landscapes: managing within complexity. *Frontiers in Ecology and the Environment,* 10**,** 382-389.
PATEL, M., KOK, K. & ROTHMAN, D. S. 2007. Participatory scenario construction in land use analysis: an insight into the experiences created by stakeholder involvement in the Northern Mediterranean. *Land Use Policy,* 24**,** 546-561.
PEARSON, L. J., PARK, S., HARMAN, B. & HEYENGA, S. 2010. Sustainable land use scenario framework: Framework and outcomes from peri-urban South-East Queensland, Australia. *Landscape and Urban Planning,* 96**,** 88-97.
PEARSON, L. J., PEARSON, L. & PEARSON, C. J. 2010. Sustainable urban agriculture: stocktake and opportunities. *International Journal of Agricultural Sustainability,* 8**,** 7-19.
PEISER, R. B. 1989. Density and urban sprawl. *Land Economics,* 65**,** 193-204.
PHAM, V. C., PHAM, T.-T.-H., TONG, T. H. A., NGUYEN, T. T. H. & PHAM, N. H. 2014. The conversion of agricultural land in the peri-urban areas of Hanoi:(Vietnam): Patterns in space and time. *Journal of Land Use Science*.
PICHÓN, F. J. 1997. Colonist land-allocation decisions, land use, and deforestation in the Ecuadorian Amazon frontier. *Economic Development and Cultural Change,* 45**,** 707-744.
PILI, S., GRIGORIADIS, E., CARLUCCI, M., CLEMENTE, M. & SALVATI, L. 2017. Towards sustainable growth? A multi-criteria assessment of (changing) urban forms. *Ecological Indicators,* 76**,** 71-80.
PIORR, A. 2011. Peri-urbanisation in Europe: towards European policies to sustain urban-rural futures. *Synthesis report; PLUREL [Sixth Framework Programme],* Forest & Landscape, University of Copenhagen.
PIORR, A., RAVETZ, J., TOSICS, I. & PLUREL. 2011. *Peri-urbanisation in Europe: Towards European Policies to Sustain Urban-rural Futures: Synthesis Report,* Forest & Landscape.
PLANNING SA. 2010. *The 30-Year Plan for Greater Adelaide*. Government of South Australia, Adelaide.
PLIENINGER, T., DRAUX, H., FAGERHOLM, N., BIELING, C., BÜRGI, M., KIZOS, T., KUEMMERLE, T., PRIMDAHL, J. & VERBURG, P. H. 2016. The driving forces of landscape change in Europe: A systematic review of the evidence. *Land Use Policy,* 57**,** 204-214.
POLASKY, S., CARPENTER, S. R., FOLKE, C. & KEELER, B. 2011. Decision-making under great uncertainty: environmental management in an era of global change. *Trends in ecology & evolution,* 26**,** 398-404.
POLHILL, J. G., PARKER, D., BROWN, D. & GRIMM, V. 2008. Using the ODD protocol for

describing three agent-based social simulation models of land-use change. *Journal of Artificial Societies and Social Simulation,* 11**,** 3.
POZOUKIDOU, G. & NTRIANKOS, I. 2017. Measuring and assessing urban sprawl: A proposed indicator system for the city of Thessaloniki, Greece. *Remote Sensing Applications: Society and Environment,* 8**,** 30-40.
PRAWEENWONGWUTHI, S., KAEWMUANGMOON, T., CHOENKWAN, S. & RAMBO, A. T. 2017. Recent Changes in Agricultural Land Use in the Riverine Area of Nakhon Phanom Province, Northeast Thailand. *Southeast Asian Studies,* 6**,** 357-365.
PRIBADI, D. O. & PAULEIT, S. 2015. The dynamics of peri-urban agriculture during rapid urbanization of Jabodetabek Metropolitan Area. *Land Use Policy,* 48**,** 13-24.
PRIBADI, D. O. & PAULEIT, S. 2016. Peri-urban agriculture in Jabodetabek Metropolitan Area and its relationship with the urban socioeconomic system. *Land Use Policy,* 55**,** 265-274.
PRIESS, J. A. & HAUCK, J. 2014. Integrative scenario development. *Ecol Soc,* 19**,** 12.
PRIMARY INDUSTRIES AND REGIONS SA (PIRSA). 2017. The Measure of the Land [Online]. Primary Industries and Regions SA (PIRSA). Available: http://pir.sa.gov.au/aghistory/land_settlement_in_sa/the_measure_of_land [Accessed 13/01/2018 2018].
RAMALHO, C. E. & HOBBS, R. J. 2012. Time for a change: dynamic urban ecology. *Trends in ecology & evolution,* 27**,** 179-188.
RAMANKUTTY, N. & FOLEY, J. A. 1998. Characterizing patterns of global land use: An analysis of global croplands data. *Global Biogeochemical Cycles,* 12**,** 667-685.
RAMANKUTTY, N., FOLEY, J. A. & OLEJNICZAK, N. J. 2002. People on the land: Changes in global population and croplands during the 20th century. *AMBIO: A Journal of the Human Environment,* 31**,** 251-257.
RAMANKUTTY, N., GRAUMLICH, L., ACHARD, F., ALVES, D., CHHABRA, A., DEFRIES, R. S., FOLEY, J. A., GEIST, H., HOUGHTON, R. A. & GOLDEWIJK, K. K. 2006. Global land-cover change: Recent progress, remaining challenges. *Land-use and land-cover change.* Springer.
RASUL, G., THAPA, G. B. & ZOEBISCH, M. A. 2004. Determinants of land-use changes in the Chittagong Hill Tracts of Bangladesh. *Applied geography,* 24**,** 217-240.
RAUWS, W. & DE ROO, G. 2011. Exploring transitions in the peri-urban area. *Planning Theory & Practice,* 12**,** 269-284.
RAVETZ, J., FERTNER, C. & NIELSEN, T. S. 2013. The dynamics of peri-urbanization. *Peri-urban futures: Scenarios and models for land use change in Europe.* Springer.
RICHIARDI, M., LEOMBRUNI, R., SAAM, N. & SONNESSA, M. 2006. A common protocol for agent-based social simulation.
RINDFUSS, R. R., ENTWISLE, B., WALSH, S. J., AN, L., BADENOCH, N., BROWN, D. G., DEADMAN, P., EVANS, T. P., FOX, J. & GEOGHEGAN, J. 2008. Land use change: complexity and comparisons. *Journal of land use science,* 3**,** 1-10.
RINDFUSS, R. R., WALSH, S. J., TURNER, B., FOX, J. & MISHRA, V. 2004. Developing a science of land change: challenges and methodological issues. *Proceedings of the National Academy of Sciences of the United States of America,* 101**,** 13976-13981.
ROBERTS, B. H. 2007. Changes in urban density: its implications on the sustainable development of Australian cities. *Proceedings of the State of Australian Cities National Conference*. Citeseer, 720-739.
ROBERTS, B. H. 2014. Managing systems of secondary cities. *Policy Reponses in International*. *Development*. Cities Alliance.
ROBINSON, D. T. 2012. Land-cover fragmentation and configuration of ownership parcels in an

exurban landscape. *Urban Ecosystems,* 15**,** 53-69.
ROBINSON, D. T. & BROWN, D. G. 2009. Evaluating the effects of land-use development policies on ex-urban forest cover: An integrated agent-based GIS approach. *International Journal of Geographical Information Science,* 23**,** 1211-1232.
ROBINSON, D., BROWN, D. & CURRIE, W. 2009. Modelling carbon storage in highly fragmented and human-dominated landscapes: linking land-cover patterns and ecosystem models. *Ecological Modelling,* 220**,** 1325-1338.
ROBINSON, D. T., BROWN, D. G., PARKER, D. C., SCHREINEMACHERS, P., JANSSEN, M. A., HUIGEN, M., WITTMER, H., GOTTS, N., PROMBUROM, P. & IRWIN, E. 2007. Comparison of empirical methods for building agent-based models in land use science. *Journal of Land Use Science,* 2**,** 31-55.
ROBINSON, G. M. 2004. *Geographies of agriculture: globalisation, restructuring and sustainability,* Pearson Education.
ROBINSON, G. M. & CARSON, D. A. 2015. 1. The globalisation of agriculture: introducing the Handbook. *Handbook on the Globalisation of Agriculture***,** 1.
ROBINSON, S. 1997. Simulation model verification and validation: increasing the users' confidence. *Proceedings of the Winter Simulation Conference*. IEEE Computer Society, 53-59.
ROLF, W., PETERS, D., LENZ, R. & PAULEIT, S. 2017. Farmland–an Elephant in the Room of Urban Green Infrastructure? Lessons learned from connectivity analysis in three German cities. *Ecological Indicators*.
ROUNSEVELL, M., REGINSTER, I., ARAÚJO, M. B., CARTER, T., DENDONCKER, N., EWERT, F., HOUSE, J., KANKAANPÄÄ, S., LEEMANS, R. & METZGER, M. 2006. A coherent set of future land use change scenarios for Europe. *Agriculture, Ecosystems & Environment,* 114**,** 57-68.
ROUNSEVELL, M., ROBINSON, D. & MURRAY-RUST, D. 2012. From actors to agents in socio-ecological systems models. *Philosophical Transactions of the Royal Society B: Biological Sciences,* 367**,** 259-269.
RUSK, D. 1993. *Cities without suburbs*.
RUTTEN, M., VAN DIJK, M., VAN ROOIJ, W. & HILDERINK, H. 2014. Land use dynamics, climate change, and food security in Vietnam: A global-to-local modeling approach. *World Development,* 59**,** 29-46.
SALI, G., MONACO, F., MAZZOCCHI, C. & CORSI, S. 2016. Exploring land use scenarios in metropolitan areas: food balance in a local agricultural system by using a multi-objective optimization model. *Agriculture and Agricultural Science Procedia,* 8**,** 211-221.
SALTELLI, A. 2002. Sensitivity analysis for importance assessment. *Risk analysis,* 22**,** 579-590.
SALVATI, L. & CARLUCCI, M. 2013. The impact of Mediterranean land degradation on agricultural income: a short-term scenario. *Land Use Policy,* 32**,** 302-308.
SALVATI, L., FERRARA, A. & CHELLI, F. 2017a. Long-term growth and metropolitan spatial structures: an analysis of factors influencing urban patch size under different economic cycles. *Geografisk Tidsskrift-Danish Journal of Geography***,** 1-16.
SALVATI, L., GITAS, I., DI GIACOMO, T. V., SARADAKOU, E. & CARLUCCI, M. 2017b. Sprawl matters: the evolution of fringe land, natural amenities and disposable income in a Mediterranean urban area. *Environment, Development and Sustainability***,** 1-17.
SALVATI, L., RANALLI, F., CARLUCCI, M., IPPOLITO, A., FERRARA, A. & CORONA, P. 2017c. Forest and the city: A multivariate analysis of peri-urban forest land cover patterns in 283 European metropolitan areas. *Ecological Indicators,* 73**,** 369-377.
SÁNCHEZ-LOZANO, J. M., TERUEL-SOLANO, J., SOTO-ELVIRA, P. L. & GARCÍA-

CASCALES, M. S. 2013. Geographical Information Systems (GIS) and Multi-Criteria Decision Making (MCDM) methods for the evaluation of solar farms locations: Case study in south-eastern Spain. *Renewable and Sustainable Energy Reviews,* 24**,** 544-556.

SANDHU, H., CLARKE, B., BARING, R., ANDERSON, S., FISK, C., DITTMANN, S., WALKER, S., SUTTON, P., KUBISZEWSKI, I. & COSTANZA, R. 2018. Scenario planning including ecosystem services for a coastal region in South Australia. *Ecosystem Services,* 31**,** 194-207.

SANDHU, H. S., CROSSMAN, N. D. & SMITH, F. P. 2012. Ecosystem services and Australian agricultural enterprises. *Ecological Economics,* 74**,** 19-26.

SCHLUETER, M., MCALLISTER, R., ARLINGHAUS, R., BUNNEFELD, N., EISENACK, K., HOELKER, F., MILNER-GULLAND, E., MÜLLER, B., NICHOLSON, E. & QUAAS, M. 2012. New horizons for managing the environment: A review of coupled social-ecological systems modeling. *Natural Resource Modeling,* 25**,** 219-272.

SCHNEIDER, A., MERTES, C., TATEM, A., TAN, B., SULLA-MENASHE, D., GRAVES, S., PATEL, N., HORTON, J., GAUGHAN, A. & ROLLO, J. 2015. A new urban landscape in East–Southeast Asia, 2000–2010. *Environmental Research Letters,* 10**,** 034002.

SCHNEIDER, A. & WOODCOCK, C. E. 2008. Compact, dispersed, fragmented, extensive? A comparison of urban growth in twenty-five global cities using remotely sensed data, pattern metrics and census information. *Urban Studies,* 45**,** 659-692.

SCHREINEMACHERS, P. & BERGER, T. 2006. Land use decisions in developing countries and their representation in multi-agent systems. *Journal of land use science,* 1**,** 29-44.

SCOTT, A., CARTER, C., REED, M., LARKHAM, P., ADAMS, D., MORTON, N., WATERS, R., COLLIER, D., CREAN, C. & CURZON, R. 2013. Disintegrated development at the rural–urban fringe: Re-connecting spatial planning theory and practice. *Progress in Planning,* 83**,** 1-52.

SENGUPTA, R., LOFTUS, T. & SHCHERBANIUK, M. 2000. *Agent-based modeling of human decision-making behavior within Spatial Decision Support Systems,* Department of Geography, Southern Illinois University. Carbondale, Illinois.

SEO, J. & GORDISH-DRESSMAN, H. 2007. Exploratory data analysis with categorical variables: An improved rank-by-feature framework and a case study. *International Journal of Human-Computer Interaction,* 23**,** 287-314.

SEPPELT, R., LAUTENBACH, S. & VOLK, M. 2013. Identifying trade-offs between ecosystem services, land use, and biodiversity: a plea for combining scenario analysis and optimization on different spatial scales. *Current Opinion in Environmental Sustainability,* 5**,** 458-463.

SEPPELT, R., VOINOV, A., LANGE, S. & BANKAMP, D. 2012. Using social psychology theory for modelling farmer decision-making. *International Congress on Environmental Modelling and Software, Sixth Biennial Meeting*, Leipzig, Germany.

SERNA-CHAVEZ, H., SCHULP, C., VAN BODEGOM, P., BOUTEN, W., VERBURG, P. & DAVIDSON, M. 2014. A quantitative framework for assessing spatial flows of ecosystem services. *Ecological Indicators,* 39**,** 24-33.

SERRA, P., SAURÍ, D. & SALVATI, L. 2017. Peri-urban agriculture in Barcelona: outlining landscape dynamics vis à vis socio-environmental functions. *Landscape Research***,** 1-19.

SERRA, P., VERA, A., TULLA, A. F. & SALVATI, L. 2014. Beyond urban–rural dichotomy: Exploring socioeconomic and land-use processes of change in Spain (1991–2011). *Applied Geography,* 55**,** 71-81.

SETO, K. C., FRAGKIAS, M., GÜNERALP, B. & REILLY, M. K. 2011. A meta-analysis of global urban land expansion. *PloS one,* 6**,** e23777.

SETO, K. C., GÜNERALP, B. & HUTYRA, L. R. 2012a. Global forecasts of urban expansion to

2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences,* 109**,** 16083-16088.
SETO, K. C. & REENBERG, A. 2014. *Rethinking global land use in an urban era,* MIT Press.
SETO, K. C., REENBERG, A., BOONE, C. G., FRAGKIAS, M., HAASE, D., LANGANKE, T., MARCOTULLIO, P., MUNROE, D. K., OLAH, B. & SIMON, D. 2012b. Urban land teleconnections and sustainability. *Proceedings of the National Academy of Sciences,* 109**,** 7687-7692.
SETO, K. C., SÁNCHEZ-RODRÍGUEZ, R. & FRAGKIAS, M. 2010. The new geography of contemporary urbanization and the environment. *Annual review of environment and resources,* 35**,** 167-194.
SETO, K. C. & SATTERTHWAITE, D. 2010. Interactions between urbanization and global environmental change. *Current Opinion in Environmental Sustainability,* 2**,** 127-128.
SHARMA-WALLACE, L. 2016. Toward an environmental justice of the rural-urban interface. *Geoforum,* 77**,** 174-177.
SHAW, K. 2013. Australia's Unintended Cities: The Impact of Housing on Urban Redevelopment. *Urban Policy and Research,* 31**,** 379-383.
SHI, Y., SUN, X., ZHU, X., LI, Y. & MEI, L. 2012. Characterizing growth types and analyzing growth density distribution in response to urban growth patterns in peri-urban areas of Lianyungang City. *Landscape and Urban Planning,* 105**,** 425-433.
SHI, Y. J., PHIPPS, T. T. & COLYER, D. 1997. Agricultural land values under urbanizing influences. *Land economics***,** 90-100.
SHIH, M. 2017. Rethinking displacement in peri-urban transformation in China. *Environment and Planning A,* 49**,** 389-406.
SHIH, T.-H. & FAN, X. 2009. Comparing response rates in e-mail and paper surveys: A meta-analysis. *Educational Research Review,* 4**,** 26-40.
SHKARUBA, A., KIREYEU, V. & LIKHACHEVA, O. 2016. Rural–urban peripheries under socioeconomic transitions: Changing planning contexts, lasting legacies, and growing pressure. *Landscape and Urban Planning*.
SIEVERTS, T. 2003. *Cities without cities: an interpretation of the Zwischenstadt,* Routledge.
SIMON, D. 2008. Urban environments: issues on the peri-urban fringe. *Annual Review of Environment and Resources,* 33**,** 167-185.
SIMON, H. A. 1957. *Models of man; social and rational,* New York: John Wiley and Sons, Inc.
SINCLAIR, I., DOCKING, A., JARECKI, S., PARKER, F. & SAVILLE, L. 2004. From the outside looking in: The future of Sydney's rural land. *University of Western Sydney, Hawkesbury, Australia*.
SLEETER, B. M., SOHL, T. L., BOUCHARD, M. A., REKER, R. R., SOULARD, C. E., ACEVEDO, W., GRIFFITH, G. E., SLEETER, R. R., AUCH, R. F. & SAYLER, K. L. 2012. Scenarios of land use and land cover change in the conterminous United States: utilizing the special report on emission scenarios at ecoregional scales. *Global Environmental Change,* 22**,** 896-914.
SMAJGL, A. & BARRETEAU, O. 2017. Framing options for characterising and parameterising human agents in empirical ABM. *Environmental Modelling & Software,* 93**,** 29-41.
SMAJGL, A., BROWN, D. G., VALBUENA, D. & HUIGEN, M. G. A. 2011. Empirical characterisation of agent behaviours in socio-ecological systems. *Environmental Modelling & Software,* 26**,** 837-844.
SOHL, T. L., SAYLER, K. L., DRUMMOND, M. A. & LOVELAND, T. R. 2007. The FORE-SCE model: a practical approach for projecting land cover change using scenario-based modeling. *Journal of Land Use Science,* 2**,** 103-126.

SOHL, T. L., WIMBERLY, M. C., RADELOFF, V. C., THEOBALD, D. M. & SLEETER, B. M. 2016. Divergent projections of future land use in the United States arising from different models and scenarios. *Ecological Modelling,* 337**,** 281-297.
SOLANO, C., LEON, H., PEREZ, E. & HERRERO, M. 2003. The role of personal information sources on the decision-making process of Costa Rican dairy farmers. *Agricultural Systems,* 76**,** 3-18.
SONTER, L., BARRETT, D., MORAN, C. & SOARES-FILHO, B. 2015. A Land System Science meta-analysis suggests we underestimate intensive land uses in land use change dynamics. *Journal of Land Use Science,* 10**,** 191-204.
SOUTH AUSTRALIAN GOVERNMENT 2013. *Character Preservation (McLaren Vale) Act 2012*. Government of South Australia.
STEEL, G., VAN NOORLOOS, F. & KLAUFUS, C. 2017. The urban land debate in the global South: New avenues for research. *Geoforum*.
STERMAN, J. D. 1989. Misperceptions of feedback in dynamic decision making. *Organizational behavior and human decision processes,* 43**,** 301-335.
STERMAN, J. D. 1994. Learning in and about complex systems. *System Dynamics Review,* 10**,** 291-330.
STERMAN, J. D. 2001. System dynamics modeling: tools for learning in a complex world. *California management review,* 43**,** 8-25.
STERMAN, J. D. 2002. All models are wrong: reflections on becoming a systems scientist. *System Dynamics Review,* 18**,** 501-531.
STOORVOGEL, J., ANTLE, J., CRISSMAN, C. & BOWEN, W. 2004. The tradeoff analysis model: integrated bio-physical and economic modeling of agricultural production systems. *Agricultural systems,* 80**,** 43-66.
STÜRCK, J. & VERBURG, P. H. 2017. Multifunctionality at what scale? A landscape multifunctionality assessment for the European Union under conditions of land use change. *Landscape Ecology,* 32**,** 481-500.
SU, S., JIANG, Z., ZHANG, Q. & ZHANG, Y. 2011. Transformation of agricultural landscapes under rapid urbanization: a threat to sustainability in Hang-Jia-Hu region, China. *Applied Geography,* 31**,** 439-449.
SU, S., XIAO, R. & ZHANG, Y. 2012. Multi-scale analysis of spatially varying relationships between agricultural landscape patterns and urbanization using geographically weighted regression. *Applied Geography,* 32**,** 360-375.
SUBASINGHE, S., ESTOQUE, R. C. & MURAYAMA, Y. 2016. Spatiotemporal Analysis of Urban Growth Using GIS and Remote Sensing: A Case Study of the Colombo Metropolitan Area, Sri Lanka. *ISPRS International Journal of Geo-Information,* 5**,** 197.
SUBASINGHE, S. & MURAYAMA, Y. 2017. Urban Growth Evaluation: A New Approach Using Neighborhood Characteristics of Remotely Sensed Land Use Data. *Spatial Data Handling in Big Data Era.* Springer.
SUN, S., PARKER, D. C., HUANG, Q., FILATOVA, T., ROBINSON, D. T., RIOLO, R. L., HUTCHINS, M. & BROWN, D. G. 2014. Market impacts on land-use change: An agent-based experiment. *Annals of the Association of American Geographers,* 104**,** 460-484.
SZABO, S. 2015. Urbanization and food insecurity risks: assessing the role of human development. *Oxford Development Studies,* 43**,** 1-22.
SZABÓ, S., BERTALAN, L., KEREKES, Á. & NOVÁK, T. J. 2016. Possibilities of land use change analysis in a mountainous rural area: a methodological approach. *International Journal of Geographical Information Science,* 30**,** 708-726.
TAKEYAMA, M. & COUCLELIS, H. 1997. Map dynamics: integrating cellular automata and GIS

through Geo-Algebra. *International Journal of Geographical Information Science,* 11**,** 73-91.
TALEAI, M., SLIUZAS, R. & FLACKE, J. 2014. An integrated framework to evaluate the equity of urban public facilities using spatial multi-criteria analysis. *Cities,* 40**,** 56-69.
TANG, W. & BENNETT, D. A. 2010. The explicit representation of context in agent-based models of complex adaptive spatial systems. *Annals of the Association of American Geographers,* 100**,** 1128-1155.
TAYYEBI, A., PIJANOWSKI, B. C., LINDERMAN, M. & GRATTON, C. 2014. Comparing three global parametric and local non-parametric models to simulate land use change in diverse areas of the world. *Environmental Modelling & Software,* 59**,** 202-221.
TESFAHUNEGN, G. B., MEKONEN, K. & TEKLE, A. 2016. Farmers' perception on causes, indicators and determinants of climate change in northern Ethiopia: Implication for developing adaptation strategies. *Applied Geography,* 73**,** 1-12.
TESFATSION, L. 2006. Agent-based computational economics: A constructive approach to economic theory. *Handbook of computational economics,* 2**,** 831-880.
THAPA, R. B. & MURAYAMA, Y. 2008. Land evaluation for peri-urban agriculture using analytical hierarchical process and geographic information system techniques: A case study of Hanoi. *Land use policy,* 25**,** 225-239.
THAPA, R. B. & MURAYAMA, Y. 2012. Scenario based urban growth allocation in Kathmandu Valley, Nepal. *Landscape and Urban Planning,* 105**,** 140-148.
THEBO, A., DRECHSEL, P. & LAMBIN, E. 2014. Global assessment of urban and peri-urban agriculture: irrigated and rainfed croplands. *Environmental Research Letters,* 9**,** 114002.
THOMPSON, D. M., SERNEELS, S. & LAMBIN, E. F. 2002. Land use strategies in the Mara ecosystem: A spatial analysis linking socio-economic data with landscape variables. *Linking People, Place, and Policy.* Springer.
THULSTRUP, A. W. 2015. Livelihood resilience and adaptive capacity: Tracing changes in household access to capital in Central Vietnam. *World Development,* 74**,** 352-362.
TIAN, L. 2015. Land use dynamics driven by rural industrialization and land finance in the peri-urban areas of China:"The examples of Jiangyin and Shunde". *Land Use Policy,* 45**,** 117-127.
TIAN, L., GE, B. & LI, Y. 2017. Impacts of state-led and bottom-up urbanization on land use change in the peri-urban areas of Shanghai: Planned growth or uncontrolled sprawl? *Cities,* 60**,** 476-486.
TIAN, L., LI, Y., YAN, Y. & WANG, B. 2017b. Measuring urban sprawl and exploring the role planning plays: A shanghai case study. *Land Use Policy,* 67**,** 426-435.
TITEUX, N., HENLE, K., MIHOUB, J. B., REGOS, A., GEIJZENDORFFER, I. R., CRAMER, W., VERBURG, P. H. & BROTONS, L. 2016. Biodiversity scenarios neglect future land use changes. *Global change biology*.
TRUBKA, R. & GLACKIN, S. 2016. Modelling housing typologies for urban redevelopment scenario planning. *Computers, Environment and Urban Systems,* 57**,** 199-211.
TSCHARNTKE, T., CLOUGH, Y., WANGER, T. C., JACKSON, L., MOTZKE, I., PERFECTO, I., VANDERMEER, J. & WHITBREAD, A. 2012. Global food security, biodiversity conservation and the future of agricultural intensification. *Biological conservation,* 151**,** 53-59.
TSUCHIYA, K., HARA, Y. & THAITAKOO, D. 2015. Linking food and land systems for sustainable peri-urban agriculture in Bangkok Metropolitan Region. *Landscape and urban planning,* 143**,** 192-204.
TURNER, B. L., LAMBIN, E. F. & REENBERG, A. 2007. The emergence of land change science

for global environmental change and sustainability. *Proceedings of the National Academy of Sciences,* 104**,** 20666-20671.
TURNER, B., MEYER, W. B. & SKOLE, D. L. 1994. Global land-use/land-cover change: towards an integrated study. AMBIO-STOCKHOLM-, 23, 91-91.
TURNER II, B. 2016. Land system architecture for urban sustainability: new directions for land system science illustrated by application to the urban heat island problem. *Journal of Land Use Science,* 11**,** 689-697.
UN (UNITED NATIONS). 2012. *World Urbanization Prospects 2011 Revision: Highlights*. United Nations, New York. Online at http://esa.un.org/unpd/wup/pdf/WUP2011_Highlights.pdf
UN (UNITED NATIONS) 2015. *The State of Asian and Pacific Cities: Urban Transformations Shifting from Quantity to Quality*. United Nations.
UUEMAA, E., ROOSAARE, J. & MANDER, Ü. 2005. Scale dependence of landscape metrics and their indicatory value for nutrient and organic matter losses from catchments. *Ecological Indicators,* 5**,** 350-369.
VÁCLAVÍK, T., LAUTENBACH, S., KUEMMERLE, T. & SEPPELT, R. 2013. Mapping global land system archetypes. *Global Environmental Change,* 23**,** 1637-1647.
VALBUENA, D., BREGT, A. K., MCALPINE, C., VERBURG, P. H. & SEABROOK, L. 2010. An agent-based approach to explore the effect of voluntary mechanisms on land use change: A case in rural Queensland, Australia. *Journal of environmental management,* 91**,** 2615-2625.
VALBUENA, D., VERBURG, P. H. & BREGT, A. K. 2008. A method to define a typology for agent-based analysis in regional land-use research. *Agriculture, ecosystems & environment,* 128**,** 27-36.
VAN DER ZANDEN, E. H., LEVERS, C., VERBURG, P. H. & KUEMMERLE, T. 2016. Representing composition, spatial structure and management intensity of European agricultural landscapes: A new typology. *Landscape and Urban Planning,* 150**,** 36-49.
VAN NOTTEN, P. W., ROTMANS, J., VAN ASSELT, M. B. & ROTHMAN, D. S. 2003. An updated scenario typology. *Futures,* 35**,** 423-443.
VAN VLIET, J., BREGT, A. K., BROWN, D. G., VAN DELDEN, H., HECKBERT, S. & VERBURG, P. H. 2016. A review of current calibration and validation practices in land-change modeling. *Environmental Modelling & Software,* 82**,** 174-182.
VAN VLIET, J., DE GROOT, H. L., RIETVELD, P. & VERBURG, P. H. 2015. Manifestations and underlying drivers of agricultural land use change in Europe. *Landscape and Urban Planning,* 133**,** 24-36.
VAN VLIET, J., EITELBERG, D. A. & VERBURG, P. H. 2017. A global analysis of land take in cropland areas and production displacement from urbanization. *Global Environmental Change,* 43**,** 107-115.
VANCLAY, F. 2004. Social principles for agricultural extension to assist in the promotion of natural resource management. *Animal Production Science,* 44**,** 213-222.
VELDKAMP, A. & FRESCO, L. 1997. Reconstructing land use drivers and their spatial scale dependence for Costa Rica (1973 and 1984). *Agricultural systems,* 55**,** 19-43.
VELDKAMP, A. & LAMBIN, E. F. 2001. Predicting land-use change. *Agriculture, ecosystems & environment,* 85**,** 1-6.
VERBURG, P. H. 2006. Simulating feedbacks in land use and land cover change models. *Landscape Ecology,* 21**,** 1171-1183.
VERBURG, P. H. & BOUMA, J. 1999. Land use change under conditions of high population pressure: the case of Java. *Global environmental change,* 9**,** 303-312.
VERBURG, P. H., CROSSMAN, N., ELLIS, E. C., HEINIMANN, A., HOSTERT, P., MERTZ,

O., NAGENDRA, H., SIKOR, T., ERB, K.-H. & GOLUBIEWSKI, N. 2015. Land system science and sustainable development of the earth system: A global land project perspective. *Anthropocene,* 12**,** 29-41.
VERBURG, P. H., DEARING, J. A., DYKE, J. G., VAN DER LEEUW, S., SEITZINGER, S., STEFFEN, W. & SYVITSKI, J. 2015. Methods and approaches to modelling the Anthropocene. *Global Environmental Change*.
VERBURG, P. H., DE KONING, G., KOK, K., VELDKAMP, A. & BOUMA, J. 1999. A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use. *Ecological modelling,* 116**,** 45-61.
VERBURG, P. H., EICKHOUT, B. & VAN MEIJL, H. 2008. A multi-scale, multi-model approach for analyzing the future dynamics of European land use. *The Annals of Regional Science,* 42**,** 57-77.
VERBURG, P. H., ERB, K.-H., MERTZ, O. & ESPINDOLA, G. 2013. Land System Science: between global challenges and local realities. *Current opinion in environmental sustainability,* 5**,** 433-437.
VERBURG, P. H., KOK, K., PONTIUS JR, R. G. & VELDKAMP, A. 2006. Modeling land-use and land-cover change. *Land-use and Land-cover Change.* Springer.
VERBURG, P. H., KOOMEN, E., HILFERINK, M., PÉREZ-SOBA, M. & LESSCHEN, J. P. 2012. An assessment of the impact of climate adaptation measures to reduce flood risk on ecosystem services. *Landscape ecology,* 27**,** 473-486.
VERBURG, P. H., NEUMANN, K. & NOL, L. 2011. Challenges in using land use and land cover data for global change studies. *Global Change Biology,* 17**,** 974-989.
VERBURG, P. & OVERMARS, K. 2007. Dynamic simulation of land-use change trajectories with the CLUE-s model. In *Modelling land-use change.* Springer.
VERBURG, P. H., SCHOT, P. P., DIJST, M. J. & VELDKAMP, A. 2004. Land use change modelling: current practice and research priorities. *GeoJournal,* 61**,** 309-324.
VERBURG, P. H., VAN BERKEL, D. B., VAN DOORN, A. M., VAN EUPEN, M. & VAN DEN HEILIGENBERG, H. A. 2010. Trajectories of land use change in Europe: a model-based exploration of rural futures. *Landscape ecology,* 25**,** 217-232
VILLAMOR, G. B., TROITZSCH, K. G. & VAN NOORDWIJK, M. 2013. Validating human decision making in an agent-based land-use model. *MODSIM2013: 20th International Congress on Modelling and Simulation*. Modelling and Simulation Society of Australia and New Zealand, Adelaide, Australia, 211.
VIZZARI, M. 2011. Peri-urban transformations in agricultural landscapes of Perugia, Italy. *Journal of Geographic Information System,* 3**,** 145.
VIZZARI, M., ANTOGNELLI, S., HILAL, M., SIGURA, M. & JOLY, D. 2015. Ecosystem Services Along the Urban–Rural–Natural Gradient: An Approach for a Wide Area Assessment and Mapping. *Computational Science and Its Applications--ICCSA 2015.* Springer.
VIZZARI, M. & SIGURA, M. 2015. Landscape sequences along the urban–rural–natural gradient: A novel geospatial approach for identification and analysis. *Landscape and Urban Planning,* 140**,** 42-55.
VIZZARI, M., SIGURA, M., ANTOGNELLI, S. & KOVAČEV, I. 2015. Ecosystem services demand, supply and budget along the urban-rural-natural gradient. *Proceedings of the 43rd International Symposium on Agricultural Engineering, Actual Tasks on Agricultural Engineering*, Opatija, Croatia, 24-27 February. University of Zagreb, 473-484.
WADDUWAGE, S., MILLINGTON, A., CROSSMAN, N. D. & SANDHU, H. 2017. Agricultural Land Fragmentation at Urban Fringes: An Application of Urban-To-Rural Gradient Analysis

in Adelaide. *Land,* 6**,** 28.
WALCOTT, J. J., ZUO, H., LOCH, A. D. & SMART, R. V. 2013. Patterns and trends in Australian agriculture: a consistent set of agricultural statistics at small areas for analysing regional changes. *Journal of Land Use Science,* 9**,** 453-473.
WANDL, A. & MAGONI, M. 2017. Sustainable planning of peri-urban areas: introduction to the special issue. Taylor & Francis.
WANG, A., CHAN, E. H., YEUNG, S. C. & HAN, J. 2017. Urban Fringe Land Use Transitions in Hong Kong: From New Towns to New Development Areas. *Procedia Engineering,* 198**,** 707-719.
WANG, H. & QIU, F. 2017. Investigation of the dynamics of agricultural land at the urban fringe: A comparison of two peri-urban areas in Canada. *The Canadian Geographer/Le Géographe canadien,* 61**,** 457-470.
WARD, J., BRYAN, B., CROSSMAN, N. & KING, D. 2007. The potential for carbon trading in the SA Murray Darling Basin: modelling farmer decision making. *MODSIM 2007 International Congress on Modelling and Simulation.* Canberra, Australia: Modelling and Simulation Society of Australia and New Zealand.
WARREN, P. S., RYAN, R. L., LERMAN, S. B. & TOOKE, K. A. 2011. Social and institutional factors associated with land use and forest conservation along two urban gradients in Massachusetts. *Landscape and Urban Planning,* 102**,** 82-92.
WEI, Y. D. & EWING, R. 2018. *Urban expansion, sprawl and inequality*. Elsevier.
WENG, Y. 2007. Spatiotemporal changes of landscape pattern in response to urbanization. *Landscape and Urban Planning,* 81**,** 341-353.
WENTZ, E. A., ANDERSON, S., FRAGKIAS, M., NETZBAND, M., MESEV, V., MYINT, S. W., QUATTROCHI, D., RAHMAN, A. & SETO, K. C. 2014. Supporting global environmental change research: a review of trends and knowledge gaps in urban remote sensing. *Remote Sensing,* 6**,** 3879-3905.
WESTHOEK, H., VAN DEN BERG, M. & BAKKES, J. 2006. Scenario development to explore the future of Europe's rural areas. *Agriculture, ecosystems & environment,* 114**,** 7-20.
WILLIAMS, M. 1966. Delimiting the Spread of Settlement: An Examination of Evidence in South Australia. *Economic Geography,* 42**,** 336-355.
WILLIS, A.-M. 2007. From peri-urban to unknown territory. *Design Philosophy Papers,* 5**,** 79-90.
WINARSO, H., HUDALAH, D. & FIRMAN, T. 2015. Peri-urban transformation in the Jakarta metropolitan area. *Habitat International,* 49**,** 221-229.
WISE, S., CROOKS, A. & BATTY, M. 2016. Transportation in Agent-Based Urban Modelling. *International Workshop on Agent-Based Modelling of Urban Systems*. Springer, 129-148.
WRBKA, T., ERB, K.-H., SCHULZ, N. B., PETERSEIL, J., HAHN, C. & HABERL, H. 2004. Linking pattern and process in cultural landscapes. An empirical study based on spatially explicit indicators. *Land use policy,* 21**,** 289-306.
WU, J. 2008. Land use changes: Economic, social, and environmental impacts. *Agricultural and Applied Economics Association,* 23**,** 6-10.
WU, J. 2013. Landscape sustainability science: ecosystem services and human well-being in changing landscapes. *Landscape Ecology,* 28**,** 999-1023.
WU, J. 2014. Urban ecology and sustainability: the state-of-the-science and future directions. *Landscape and Urban Planning,* 125**,** 209-221.
WU, J., FISHER, M. & PASCUAL, U. 2011. Urbanization and the viability of local agricultural economies. *Land Economics,* 87**,** 109-125.
WU, Q., ZHANG, X., XU, Y. & LI, T. 2016. Dualities of semi-urbanization villages in social-spatial transition: A case study of Zhoucun village in suburban Nanjing, China. *Journal of*

Rural Studies, 47**,** 657-664.
XIAO, J., SHEN, Y., GE, J., TATEISHI, R., TANG, C., LIANG, Y. & HUANG, Z. 2006. Evaluating urban expansion and land use change in Shijiazhuang, China, by using GIS and remote sensing. *Landscape and urban planning,* 75**,** 69-80.
YANG, H., VILLAMOR, G. B., SU, Y., WANG, M. & XU, J. 2016. Land-use response to drought scenarios and water policy intervention in Lijiang, SW China. *Land Use Policy,* 57**,** 377-387.
YEH, A. G.-O. & LI, X. 1998. Sustainable land development model for rapid growth areas using GIS. *International Journal of Geographical Information Science,* 12**,** 169-189.
YU, J., CHEN, Y., WU, J. & KHAN, S. 2011. Cellular automata-based spatial multi-criteria land suitability simulation for irrigated agriculture. *International journal of geographical information science,* 25**,** 131-148.
YU, Q., HU, Q., VAN VLIET, J., VERBURG, P. H. & WU, W. 2018. GlobeLand30 shows little cropland area loss but greater fragmentation in China. *International Journal of Applied Earth Observation and Geoinformation,* 66**,** 37-45.
YU, X. J. & NG, C. N. 2007. Spatial and temporal dynamics of urban sprawl along two urban–rural transects: A case study of Guangzhou, China. *Landscape and Urban Planning,* 79**,** 96-109.
YU, Y., FENG, K. & HUBACEK, K. 2013. Tele-connecting local consumption to global land use. *Global Environmental Change,* 23**,** 1178-1186.
ZASADA, I. 2011. Multifunctional peri-urban agriculture—A review of societal demands and the provision of goods and services by farming. *Land Use Policy,* 28**,** 639-648.
ZHANG, Y., WANG, C., XIE, H., ZHANG, J. & WU, J. 2017. Analyzing spatial variations in land use/cover distributions: A case study of Nanchang area, China. *Ecological Indicators,* 76**,** 52-63.
ZHANG, Z., TU, Y. & LI, X. 2016. Quantifying the Spatiotemporal Patterns of Urbanization along Urban-Rural Gradient with a Roadscape Transect Approach: A Case Study in Shanghai, China. *Sustainability,* 8**,** 862.
ZHENG, H. W., SHEN, G. Q. & WANG, H. 2014. A review of recent studies on sustainable urban renewal. *Habitat International,* 41**,** 272-279.
ZHU, Y.-G., REID, B. J., MEHARG, A. A., BANWART, S. A. & FU, B.-J. 2017. Optimizing Peri-URban Ecosystems (PURE) to re-couple urban-rural symbiosis. *Science of the Total Environment*.
ZHU, Z., WOODCOCK, C. E., ROGAN, J. & KELLNDORFER, J. 2012. Assessment of spectral, polarimetric, temporal, and spatial dimensions for urban and peri-urban land cover classification using Landsat and SAR data. *Remote Sensing of Environment,* 117**,** 72-82.
ZOU, Y., TORRENS, P. M., GHANEM, R. G. & KEVREKIDIS, I. G. 2012. Accelerating agent-based computation of complex urban systems. *International Journal of Geographical Information Science,* 26**,** 1917-1937.
ZUREK, M. B. & HENRICHS, T. 2007. Linking scenarios across geographical scales in international environmental assessments. *Technological forecasting and social change,* 74**,** 1282-1295.