Impact of Spatial Resolution on Mapping Urban Vegetation from Space

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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 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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ABSTRACT

Vegetation is a part of liveable human society. This means that grass, shrubs and trees, which are visible in parks and gardens, are present in human communities and urban areas. Vegetation has a number of tangible benefits to humans, so, the mapping of vegetation in urban environments, whether it be small or large areas, is very important. Vegetation maps can be used for several purposes ranging from, but not limited to, monitoring street trees to conducting analysis of impact on human health. Recently, the use of satellite remote sensing techniques has become popular in mapping urban vegetation due to a huge archive of data and its free availability, at least for medium and lower spatial resolutions. Different satellite imagery is available, with differing resolutions (spatial, spectral, swath and temporal) and as there always has been a tension between accuracy and cost when it comes to mapping the focus of this project is to explore this tension when mapping urban vegetation. The research focuses on information accuracy of vegetation mapping which should be interest when researchers are not from the field of remote sensing and who used remote sensing techniques to map urban vegetation often using indices like Normalised Difference Vegetation Index (NDVI). These researchers often do not disclose or discuss the values of the selected NDVI threshold. So, the main objective of this research is to compare the results which are obtained from using different types of satellite imagery, along with their respective resolutions and different methods with ground truth. This comparison will help to provide an insight on how the accuracy differs over different images, with different resolutions and different processes used. For this comparison varying vegetation maps were obtained by using the Thresholded Normalised Difference Vegetation Index (THNDVI) and supervised classification methods on multispectral satellite images with a spatial resolution varying from 2 metres to 30 metres. The results from this thesis indicate that when THNDVI is used on Pleiades imagery (high-resolution imagery) it yields most accurate result. This thesis also indicates the major cost drivers while mapping urban vegetation. This study not only helps to determine which method is accurate, but also what resolution of satellite imagery can be used to obtain the desired results. In addition, this research demonstrates the critical importance of setting the correct threshold in NDVI when classifying vegetation on the basis of NDVI.

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Dedication

I dedicate this work to all my friends and family, who stood by me all these times and supported me. I would also like to dedicate this thesis especially to my parents, who made me who I am now and made me capable enough to reach this platform and perform such a feat.

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LIST OF ACRONYMS

AUD Australian Dollars

AVHRR Advanced Very-High-Resolution Radiometer

CBD Central Business District

DSM Digital Surface Model

DVI Difference Vegetation Index

EnMAP Environmental Mapping and Analysis Program

ESRI Environmental System Research Institute

GCP Ground Control Points

GIS Geographic Information System

IR Infra-Red

LAI Leaf Area Index

MODIS Moderate Resolution Imaging Spectroradiometer

MSI Multi Spectral Imagery

NDVI Normalized Difference Vegetation Index

NDWI Normalized Difference Water Index

NIR Near Infra-Red

NOAA National Oceanic and Atmospheric Administration

PCA Principal Component Analysis

RVI Ratio Vegetation Index

SA South Australia

SD Standard Deviation

SPOT Satellite Pour l'Observation de la Terre (Satellite for observation of Earth)

SVM Support Vector Machine

TA Test Area

TCT Tasselled Cap Transformation

THNDVI Thresholded Normalized Difference Vegetation Index

1.0 INTRODUCTION

1.1 Background

As vegetation plays a very important role in all social, economic, environmental and cultural aspects of life, many researchers have been mapping vegetation extending from small to large scale for various purposes ever since the introduction of GIS technologies (Ekkel and de Vries, 2017, Xie et al., 2008, Yuan and Bauer, 2006). Vegetation, often referred to as "greenness", is a part of liveable society. This means that grass, shrubs and trees, often exhibiting in parks, are present in human communities, or in other words urban areas. So, the mapping of vegetation in urban environments, whether it be small or large areas, is very popular (Zhang et al., 2010, Van de Voorde et al., 2008). These urban vegetation maps are used by many stakeholders such as urban planners, health researchers, professionals and engineers. These people use urban vegetation maps for different purposes. The uses of urban vegetation maps can range from monitoring heat islands (Weng et al., 2004, Yuan and Bauer, 2007) and conducting research into the effect of greenness on human health and the longevity of humans who are exposed to greenness in urban areas (Dadvand et al., 2012, Kuo and Sullivan, 2001, Takano et al., 2002) and may also be used by city councils to monitor street trees and urban vegetation.

Although mapping urban areas would be beneficial for many stakeholders, such areas are both very heterogeneous and can be large in spatial extent. Heterogeneity between the urban features present includes impervious surfaces such as roads, footpaths, building roofs, concrete etc. and pervious features such as soil, grass, shrubs and trees. In other words, the features present in small spatial extents change very rapidly over short distances, making it difficult to map, especially over very large urban extents (Weng, 2012). Figure 1 is a spatial profile of a typical urban residential block inside the Adelaide metropolitan area.

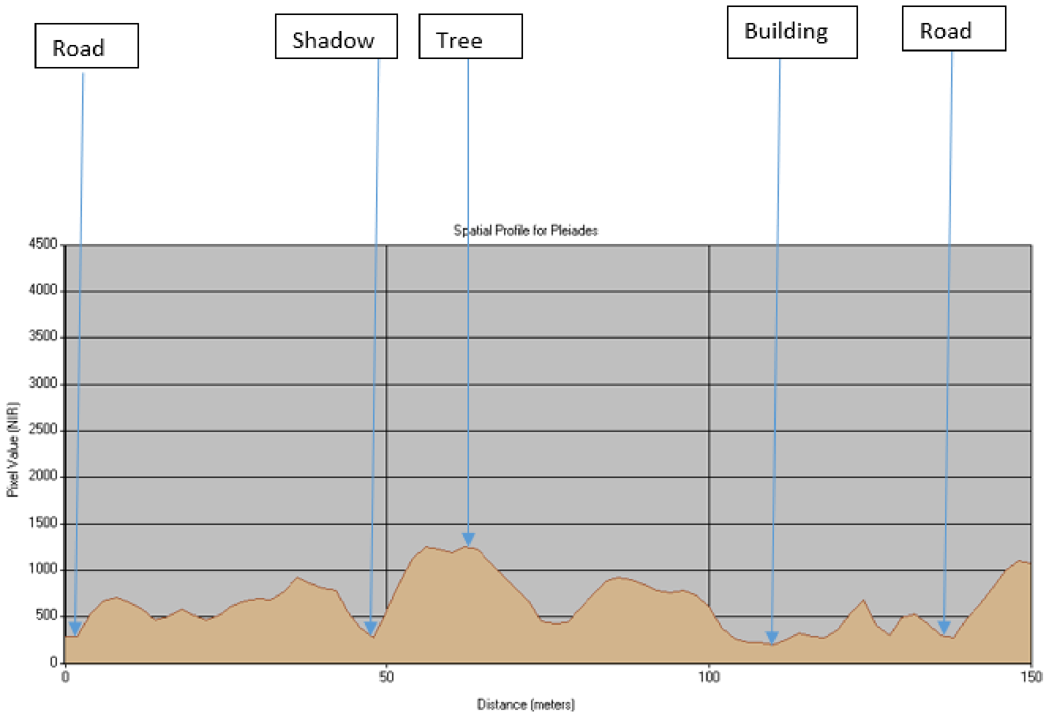

Figure 1: Spatial profile or heterogenous urban area

Some potential vegetation such as street trees, small parks and small gardens are potentially eclipsed if mapping occurs over a very large spatial area. In Figure 1, in such a short distance such as from 50 m to 100 m the reflectance changes dramatically from a pixel value of 500 to 1300 to again less than 500. This implies that per spatial unit (metre) there is a lot of change in urban features, hence making the urban area heterogenous. Therefore, mapping vegetation which is present in an urban area, which already has a large heterogeneity throughout a large spatial extent, will be time consuming and extremely costly. Moreover, these rapid changes over a very short distance can only be perceived if a higher resolution image is used.

Vegetation can be mapped through different techniques. such as through a land survey. However, the cost incurred through this method will be high due to the extent of the area, labour costs and time required. Yet a benefit of this is that every small patch of grass can be mapped, making it highly accurate. On the other hand, if a lower accuracy is acceptable then vegetation can be mapped by relatively less expensive methods such as aerial remote sensing. But when it comes to vegetation consisting of trees, grass and shrubs, their phenology should also be considered when mapping. Some non-native vegetation present in South Australia are deciduous, meaning they will shed their leaves annually and the grass and shrubs are much greener during the rainy season (late August/early September) than in summer (mid-February/Late March). Therefore, to obtain an accurate urban vegetation map the process should be applied to different seasons considering the above factors. Creating two urban vegetation maps for different seasons will increase the total cost incurred in mapping urban vegetation.

There is another process of obtaining an urban vegetation map, besides those two mentioned above, which is cheaper and may even be free of cost (data only) in some cases; the process is satellite remote sensing. There are a number of image providers that supply satellite images for various times free of charge such as Landsat and Sentinel 2, which can be used to map vegetation in urban areas. The main issue regarding this method is what is the accuracy of satellite remote sensing?

Due to difficulties in mapping vegetation using a land survey, vegetation was usually mapped using aerial or remotely sensed imagery (Fensham and Fairfax, 2002, Xie et al., 2008, Skowno and Bond, 2003). Previously aerial photography used to be the primary source of data for urban vegetation mapping (Feng et al., 2015, Li and Shao, 2013). Aerial imagery provides the best resolution of the image, further resulting in a higher accuracy for the end map produced. However, it is very expensive. Aerial imagery was previously just simple colour imagery (RGB image) and thus its capacity was limited to creating a vegetation map, as simple RGB cannot differentiate between green tones of natural vegetation and artificial objects such as synthetic fields, artificial grass, green roofs etc. This limitation can be removed by introducing an infra-red band in the imagery. Recently an infra-red band has been introduced in aerial imagery, but satellite images have already had infra-red capability for a very long time, which makes more automated mapping possible. Another factor is that vegetation does not tend to remain the same throughout the year. It changes with the seasons and the cost of acquiring an aerial image throughout the year (say once per season) will be very high. But current methods of mapping using remotely sensed images are becoming more popular due to the increased availability of images and higher quality of imagery, with some images also being freely available (Weng, 2012). Since better resolution (spatial and spectral) satellite imagery started to become freely available, the tendency towards the use of satellite imagery for urban vegetation mapping has increased (Hill et al., 2010, Lefebvre et al., 2016, Mathieu et al., 2007, Tigges et al., 2013, Nichol and Lee, 2005). It is logical that high spatial resolution satellite imagery will produce better results than lower spatial resolution imagery, even for the smallest unit of urban vegetation such as street trees, lawns or gardens (Mathieu et al., 2007). But high resolution (both spatial and spectral) satellite images such as Pleiades 1, Planetscope and SuperView 1, do not come free of charge and can be as much as \$24 per km^2. So as usual the trade-off between accuracy and cost starts here; in other words, the higher the accuracy and resolution the higher the cost. As the accuracy of the map will potentially depend on the resolution of the imagery used, and since the freely available imagery is not of a high resolution, it is of research interest to consider the relationship between vegetation mapping accuracy, resolution and cost.

1.2 Aim and Objectives

The main aim of this research is to investigate how cost, accuracy and resolution are interrelated when mapping urban vegetation from satellite remote sensing instruments. The objectives which will assist in reaching the above-mentioned aim are:

a. Investigate the impact of sensor resolution on the accuracy of mapping urban vegetation.
b. Explore different computer-based image analysis methods for mapping urban vegetation and what impacts these have on accuracy.
c. Discover the major drivers of cost for producing maps of vegetation in large urban areas.
d. Obtain the most accurate urban vegetation map for the lowest possible cost.

The total cost for the completion of the project does not only include the cost incurred for the imagery used. There are also costs incurred for software, human labour and the computer system used. Yet most of the cost is incurred through the imagery used. if the imagery is of a high resolution. High-resolution imagery is usually expensive, especially for commercial purposes. Commercially available satellite imagery a has spatial resolution that ranges from 40 cm to 2 km. The cost for the image with a high spectral resolution is also high; the price increases as the resolution increases. However, when the spatial resolution is high the spectral resolution is often low. For instance, recently launched spaceborne satellites such as Ikonos and Quickbird have spatial resolutions of 4m and 2.4m for multispectral images respectively, yet their spectral resolution is limited to 4 bands in multispectral (Herold et al., 2003). Although in order to carry out this project it is only required that the spectral bands that differentiate between vegetation and non- vegetation components in the image. Therefore spectral resolution will not be an issue, as all the images used have at least 4 bands including RGB and infrared. Among these four bands, the two bands of red and Infra-Red (IR) are commonly used to identify vegetation. This is because the higher the chlorophyll content in the leaf, the healthier the leaf is and a healthier leaf absorbs more red and reflects Near Infra-Red (NIR) (Dall'Olmo et al., 2005, Gitelson and Merzlyak, 1997, Tucker, 1979). However, if different types of vegetation are to be mapped, such as different species of tree, it is not sufficient to only use red and NIR band. In that case a multiple number of spectral bands besides red and NIR are required.

The images with a higher spatial resolution are larger in data size. These occupy more disk space than lower resolution images, and as more disk space is occupied the processing time also increases. Another noticeable factor to consider is that images with a higher spatial resolution usually have smaller spatial extents compared to lower spatial resolution images; so, mosaicking of many small images must be undertaken to achieve a single combined image. Furthermore, as spatial resolution increases then in the context of an image of an urban area the heterogeneity will become more pronounced, meaning an increase in spatial resolution will also increase the internal variability of what appear to be homogenous classes at a lower spatial resolution (Carleer et al., 2005, Thomas et al., 2003). In other words, an increase in spatial resolution can potentially result in an increase in classification errors (Carleer et al., 2005). It will create a salt and pepper effect when classifying a heterogenous urban area due to spectral mixing and blurring, as the spectral resolution is usually low when spatial resolution is high. Yet this all depends on the perception of the user, as it is human nature to aggregate all complexities into one homogenous division such as vegetation and non-vegetation.

To achieve the above-mentioned aim, the Adelaide metropolitan area was chosen as the study area. As the Adelaide metropolitan area has a very large extent (3258 Km^2), with a vast amount of vegetation in hilly parts and these exhibit predominant land covers of agriculture and native vegetation or conservation areas. However, those hilly areas are not urban vegetation and so are not areas of interest to this research. So, to achieve the aims of this research, Adelaide Metropolitan City has been chosen as the study area for the following reasons:

a. The structure or organisation of features such as buildings, road network, parks etc. in Adelaide is typical of several large Australian cities.
b. It is easy and economical for any sort of field verifications, as the researcher is based at Flinders University.
c. The amount of vegetation present in the urban area is aligned with planning policy. According to the Planning, Development and Infrastructure Act 2016, 12.5% of the area vested in council should be open space. There are land use and landcover maps of Adelaide available, which can help determine if the area is green space or not. But the land use map cannot help to determine if the green space is open space or private space. Moreover, the land use map also cannot determine if the green space contains natural (real) vegetation or artificial vegetation such as artificial grass or turfs.

In Figure 2 the extent of the study area can be seen with respect to Adelaide, and later in Figure 7 the selected Test Areas inside the study area can also be seen. The Test Areas were selected empirically by calculating the Normalised Difference Vegetation Index (NDVI) from a medium spatial resolution satellite, Sentinel 2 (see Figure 5), of the study area and then applying zonal statistics using suburb boundaries as zones to obtain the average NDVI value for each suburb inside study area. The suburbs with high, moderate and low vegetation present in them were chosen and were named Test Area 1 (TA 1), Test Area 2 (TA 2) and Test Area 3 (TA 3) respectively. In Figure 2 below, the tentative boundary of Adelaide Metropolitan City can be seen.

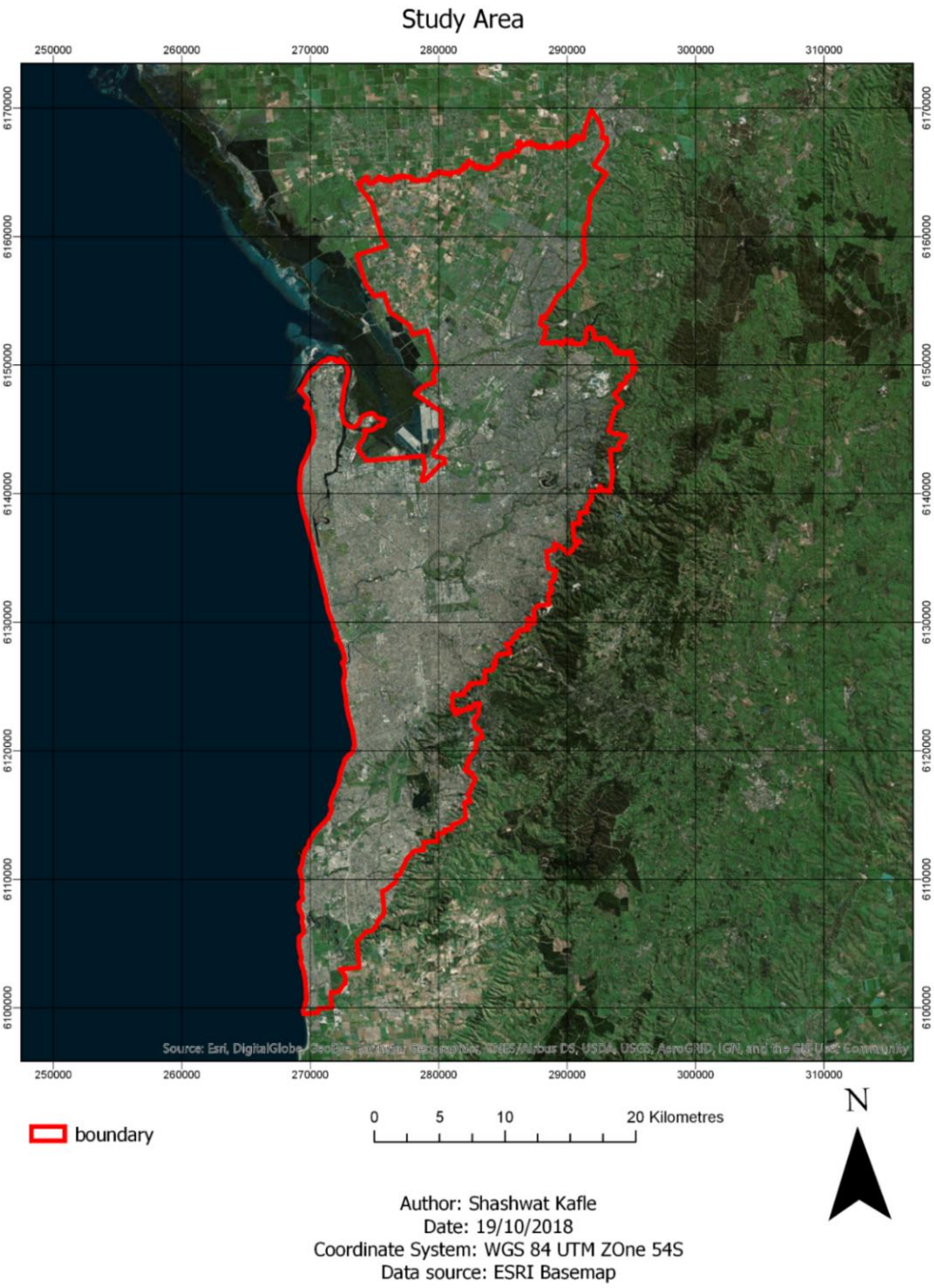

Figure 2: Study Area Extent

Although the ground truth collection cannot be done for the whole metropolitan area, three test areas (TA) were selected based on the abundance of vegetation in that area, with the help of NDVI (high, medium and low).

The cost does not increase significantly relative to accuracy up to a certain point. However, it increases rapidly at higher levels of accuracy (Jensen, 2016, Mumby and Edwards, 2002). This means that a small increase in accuracy can potentially lead to a significant increase in cost.

1.3 Research in wider context

As discussed in section 1.2, the aim of this research is to determine what image spatial resolution and what methods will be the most accurate to use for mapping vegetation in an urban area from space, and their relationship to cost. This will give a result in a metropolitan city such as Adelaide as to what resolution, what method, and at what minimal cost will prove to provide the best result. But that is not all there is to this research. It can be applied to a very large area of vegetation (dense or sparse vegetation) in order to obtain the vegetation map with the best accuracy achievable. This will assist many other areas of research which will require a vegetation map to proceed, such as in the health sector, urban planning sector, construction management etc.

1.4 Outline of Thesis

The thesis has 5 chapters. Chapter 1 introduces the research, the need for urban vegetation mapping, the issues in constructing vegetation maps of large spatial extents, the use of satellite remote sensing, the tension between cost and accuracy, and the impact of image resolution on accuracy. The chapter includes the overall research aim and objectives. Chapter 2 presents a review of critical literature where relevant literature is viewed and compared to this research. The review ranges from vegetation mapping using remote sensing to various methods used to map vegetation and various imagery used to map vegetation, along with their accuracy. The review concludes with a summary of key findings and identifies a gap in the literature, which is that the literature rarely explores the appropriate image spatial resolution for the application in question. The next chapter, Methods, delivers a description of various methods undertaken based on the literature in order to answer the research objectives as posed in Chapter 1. Step-by-step processes by which each objective is achieved are laid out. Other issues explored in Chapter 3 are the selection of the study area, the selection of test areas within the study area, the choice of data, image processing procedures, development of ground truth, accuracy assessment methods and documentation of costs. Results are presented in Chapter 4, which displays key results obtained from the application of the methods which were taken into account for the research. A comparison of results obtained from different image processing is outlined here. Then the final chapter, Chapter 5, provides a discussion and draws conclusions from the research, relating this back to critical findings from the literature. After a full list of references, Appendices are provided.

2.0 REVIEW OF LITERATURE

2.1 Vegetation Mapping using Remote Sensing

Vegetation plays a very important role in the ecosystem and overall environment (Simonich and Hites, 1994). Not only does it protect and preserve the environment, but it also plays a vital role in many other ecological phenomena. Looking at the context of urban vegetation, an urban vegetation map can be used in a variety of ways. It can be used in micro climatic analysis (Dimoudi and Nikolopoulou, 2003), and can be used for research about how vegetation influences human health (Takano et al., 2002, Dadvand et al., 2012). It can also be used to research how a resident of a particular area responds positively or negatively (aggression, theft, other crimes etc.) to the amount of greenness present in the area (Kuo and Sullivan, 2001). Digital vegetation maps can also be used to measure vegetation units, their distribution and composition (Walker et al., 2005). A critical concern is what level of accuracy is required for the vegetation map. The accuracy of the map depends on what purpose it is being used for.

Much research has been conducted in the field of remote sensing, where it is used to map vegetation (Bauer and Yuan 2006; Weng 2012; Xie, Sha and Yu 2008). Mapping vegetation for various purposes using remote sensing instruments is a very promising technique. Aerial photographs used to be the primary source of data for mapping vegetation (Seidling 1998; Freeman and Buck 2003). But despite its high accuracy and amazing detail, the main problem with the aerial photograph is that it is harder to obtain and process than satellite imagery and is more time consuming. Moreover, the IR band that is required to map vegetation did not used to be included in aerial imagery. However, in more recent times most of the aerial images have started to include an IR band. Whereas satellite imagery has included at least one IR band for a long time, in comparison aerial imagery has only recently started to include IR. Since satellite imagery includes an IR band and some of the satellite imagery, such as Sentinel 2 (medium resolution satellite 10 m spatial resolution), are even available free of charge, it can be said that satellite imagery, depending on the purpose and extent of the research, might be more useful in mapping vegetation using remote sensing (Weng, 2012). That being said, some satellite imagery such as Landsat and MODIS, which are also freely available, also have a coarse spatial resolution. They can still map vegetation, but they may not be the most suitable for the purpose of mapping vegetation, especially in urban areas. There is a considerable amount of literature that mentions the use of satellite imagery (high resolution) compared to literature mentioning the use of aerial imagery or drones to map vegetation in urban areas.

2.2 Phenology

There is a very limited amount of literature that mentions the seasonal vegetation phenology that might affect the result of urban vegetation mapping, because image classification generally uses data from a single date rather than multiple dates (e.g. Hills et al. 2010, Tigges et al. 2013). As a result of this, image classification does not take into account the variation in vegetation throughout different seasons and variation in spectra caused by it (Dennison and Roberts, 2003). Seasonal phenology in the vegetation is mainly induced by weather changes, environment, human activity etc. (Hill et al., 2010, Zhang et al., 2001). However, the phenology is mostly affected by seasonal weather fluctuation. In the case of Adelaide Metropolitan City, which lies in the Southern Hemisphere, the plants and grass are mostly green at the end of August or the beginning of September due to the continuous rainfall since the end of March. And the end of senescence usually occurs from almost mid- February until mid-March, as there is minimal precipitation during these times and the atmospheric temperature is higher than at any other time of the year, according to the meteorology data of SA. So, the amount of greenness will depend on the season or the date of the image acquired. This vegetation phenology can be monitored by satellite, which has a frequent revisit period. Most of the fine spatial resolution satellites do not have this quick revisit period, and besides that the high cost of new high-resolution satellite data is another problem. Tucker and Townshend 1980 used meteorological satellite data (AVHRR of NOAA satellite) to classify land use and monitor the vegetation dynamics of Africa during a 19-month period. They used satellite data which was acquired weekly over a period of 12 months to produce a remotely sensed estimate of production based on the duration and density of green leaf. Although AVHRR had a coarse resolution, it had a frequent revisit capability (weekly) which enabled it to be used to monitor the seasonal variation of vegetation (Tucker et al., 1985). However, while the resolution of AVHRR data was fit for Tucker and Townshend 1980 to estimate the production over Africa, the same data might not be suitable for mapping vegetation in urban areas such as Adelaide metropolitan city. Seasonal phenology is usually useful in detecting the vegetation type. However, in case of this research, in order to obtain the optimum result for overall greenness the analysis should be done in multidate data. This is because using the data acquired in multiple seasons can help to identify the variation in greenness (Tigges et al., 2013).

2.3 Sensor resolution

A vegetation map can be used to solve many problems and answer many questions. But it is obvious that the sensor resolution plays an important role in the end map.

In the case of satellite imagery there are different types of resolution. There are basically five different types of resolution that affect the imagery, those being spatial, spectral, temporal, radiometric and swath resolution respectively (Bruce, 2018). There are many satellite sensors currently available, some of the popular sensors in the literature being Rapid Eye, Sentinel 2, Landsat, Ikonos, Quickbird and Pleiades. These sensors have spatial resolution ranges from 30 metres to 2 metres and spectral resolution ranges from 13 bands to 4 bands. Moreover, different bands have different spatial resolutions as well, which can be seen on Table 3. The main concern of this research is spatial resolution, but as the purpose is to map vegetation then spectral resolution must be considered to some extent as well.

However, there is a tension involved in the resolution of a satellite. The tension is in the relationship between resolution (Bruce, 2018). Generally, the higher the resolution a satellite has, the smaller the swath width. Since the swath width of a high-resolution satellite is smaller in comparison to a low-resolution satellite, this will result in a huge number of images being required to cover the region of interest. This vast number of images will also increase the cost of the research, as it is obvious that more images of an expensive high-resolution satellite will incur a greater cost. Even if all those images are acquired, the processing will also be difficult as all those images will have to undergo all the pre-processing or atmospheric and geometric correction and finally mosaicking in order to obtain one single flawless image. This will result in an increase in the processing cost as well. There is another tension between the spatial and spectral resolution of an image. A higher spatial resolution usually results in a lower spectral resolution, as most of the high-resolution images used in the literature have a low spectral resolution. So not does the number of images increase as we increase the spatial resolution, but the spectral resolution also decreases. However, there is some satellite imagery, such as WorldView 2 with 1.8-metre multispectral spatial resolution and 8 bands, which has a high spatial and a reasonably high spectral resolution as well. There are also satellites such as the soon to be launched German Hyperspectral satellite mission called EnMAP (Environmental Mapping and Analysis Program), which has 30 metres spatial resolution and 230 spectral bands. There are many satellites with either good spatial resolution or good spectral resolution, but a perfect satellite with perfect resolution (including spatial, swath and spectral) is not out there yet.

The resolution of the imagery usually depends on the application and scale of the project. Some research or applications can be conducted using low resolution imagery (Tucker et al., 1985, Van de Voorde et al., 2008) while some applications and research requires very high-resolution imagery (Mathieu et al., 2007, Tigges et al., 2013, Zhang et al., 2010). Since there is no perfect imagery or satellite which fulfils the requirements of all the applications, the satellite imagery is chosen based on what is most suitable for the application, context and scale of the project or research.

Van de Voorde et al. 2008 mapped urban vegetation using Landsat ETM+ Data, which has a spatial resolution of 30 metres and produced a resulting accuracy of around 65%. They even had an average of 4% geometric shift and an RMS error on the control point, which they noted to be around 5.7 metres in the data, meaning that while acceptable there was still a shift error in the images. Looking at the research conducted by Van de Voorde et al., it potentially shows that lower resolution images end up providing lower accuracy. The method they used was a sub-pixel classification technique that measured vegetation using NDVI. Mathieu et al. 2007 used two IKONOS imagery, one being a panchromatic stereo pair with a 1-meter resolution which was used to generate DSM and the other being multispectral imagery with a four-metre resolution obtained in mid-summer and used to map the urban vegetation of Dunedin city in New Zealand. They had an average of 1.4-metre geolocation error, which is better than that achieved by Van de Voorde et al. However, the overall accuracy of the classification for Mathieu et al. was a moderate 63.6%.

Mapping vegetation in an area where the principal component, which is vegetation, is homogenous is comparatively easier than mapping vegetation in an urban area due to urban heterogeneity. It can be can be said that increasing the spatial resolution of images does not always lead to an increase in classification accuracy, because of an increase in heterogeneity in the image. Most of the literature where an urban vegetation map is produced by means of free satellite imagery, such as Van de Voorde et al. 2008, use Landsat images because of its huge archive while other literature where high-resolution imagery is used to map urban vegetation, such as Mathieu et al. or Tooke et al. (Tooke et al., 2009) prefer using IKONOS or Quickbird imagery. Since imagery with a better resolution than Landsat, and also free of cost as is Landsat, was not available at that time, such as Sentinel 2 with a resolution of ten metres, this provides an opportunity in t the present context to use that imagery and potentially yield better results. So, the question is still what image and what resolution is the least required in order to obtain the best possible or, in other words, accurate result, which remains a key research objective of this project.

For what purpose an image analysis is being conducted will determine how much accuracy is considered acceptable, because accuracy and cost are closely related. High levels of accuracy usually mean a high cost and vice versa; the other consideration is whether the image is readily available. Most of the literature does not explain how important the purpose of the end map is or explain in simple language the threshold of accuracy. For some purpose 70% accuracy is more than adequate, while some cases may require at least 85% accuracy, such as in areas like construction, hydropower etc. It is clear that the higher the resolution the higher the accuracy, yet at the same time high resolution imagery might not be readily available or might not be affordable within the project budget. So, the choice of imagery must be done while considering what level of accuracy is desired and what image is available.

2.4 Relevant Methods

Various literature discusses different methods used to map urban vegetation. Those methods usually vary depending on the different purposes of an urban vegetation map. Bauer and Yuan 2007 used NDVI in Landsat imagery to analyse the relationship between land temperature, impervious surface, and vegetation. Besides Bauer and Yuan 2007, others such as Small, Sobrino and Verhoef 2006, and Nichol and Lee 2005 have also used NDVI to either monitor vegetation in urban areas or to estimate change in vegetation in order to monitor land surface temperature. In majority of the literature NDVI is generally used for a quantitative assessment of vegetation, such as Nichol and Lee 2005, where NDVI was used to determine how effective it is to model urban biomass. Similarly, Small, Sobrino and Verhoef 2006 used NDVI and the land surface temperature algorithm to estimate change in vegetation. Yuan and Bauer 2007 used NDVI to determine the fraction of vegetation in a pixel, which further helped them to investigate its relationship with the land surface temperature of that pixel. NDVI is itself not an image classification technique but is instead an index that provides quantitative index information on the greenness of vegetation, which can be further used to indicate plant health, fractional cover, determine biomass etc.

NDVI is robust and commonly used in much literature, and only the band ratio-based vegetation index was considered because other indices like perpendicular based indices are more sensitive to soil than to the vegetation (Chlorophyll) (Nichol and Lee, 2005). However, while NDVI is a popular index, it might not be a suitable indicator in a sparsely vegetated area, because NDVI also depends on the reflectance of the bare soil, which may not be present in environments such as a city or urban area. Moreover, NDVI is also affected by non-photosynthetically active components such as aged vegetation, which might lead to an inaccurate estimation of the index (Carlson and Ripley, 1997). However, in the case of deciduous nature and phenology of vegetation in urban areas such as trees, grass etc., NDVI is a good indicator of vegetation at those times when all the vegetation is green due to high precipitation (Carlson and Ripley, 1997). Moreover, if a threshold is set on the NDVI index range then anything below the threshold is classified as non-vegetation and anything above the threshold can be classified as vegetation. For instance, during their case study at Beijing, Gamba and Aldrighi 2012, used threshold in NDVI Value to detect wrongly associated vegetated area. They set the threshold by analysing the histogram of NDVI Value on urban area (Gamba and Aldrighi, 2012). However, their objective was to obtain Landuse-Landcover map which can be used to monitor urban sprawl. Moreover, Amiri et al., 2009 also used threshold on NDVI values to differentiate between vegetation and non-vegetation area (Amiri et al., 2009). But they also fail to maintain the threshold value used for that purpose. This is one way to use thresholding to differentiate between vegetated and non-vegetated areas in an NDVI image. Dadvand etl al. 2012 used an NDVI map obtained from Landsat to determine the greenspace around the maternal place of residence. They used an NDVI map to determine how greenness around pregnant women impacts on the birth weight, head circumference and gestational age at delivery. But they did not mention the thresholding of the indices in order to obtain an accurate vegetation map that would show actual vegetated and non-vegetated areas. This might have caused a misrepresentation, with actual green areas such as garden, parks and trees being confused with artificial green areas such as turfs and artificial grass, and therefore the decisions and conclusions made using this vegetation map might not be entirely correct. This issue can be overcome by thresholding the index value of NDVI in order to obtain a map that differentiates between vegetation and non-vegetation areas. Since THNDVI can help to overcome the issue of how to separate vegetated areas from non-vegetated areas, this can prove useful to many researchers who are not from a geospatial field but are simply using NDVI to identify vegetation. It is worth investigating what degree of accuracy can be obtained and how effective it is to map vegetation using THNDVI

Another popular method among the literature is classification. Since an urban area is a heterogeneous area, the classification that does not require training data does not provide the best result in this case (Zha et al., 2003). Nancy et al. 2003 used different techniques of image classification to classify vegetation, which included supervised and unsupervised classification but also included automated classification and spatial model-based classification. While classifying an image using supervised classification, Nancy et al. obtained a 90% producer accuracy for the vegetation class, which is a very impressive result considering how heterogeneous the urban environment of the City of Scottsdale, their study area, is. However, the image used by them was obtained from an ADAR 5500 digital multispectral scanner, which is an airborne sensor with a 4 spectral band and a resolution of 1 m. That this was not a satellite remote sensing instrument is not relevant to this thesis. However, the process used to classify the image in an urban area is potentially useful to this research, as high-resolution satellite imagery with a resolution almost equal to that of the ADAS 5500 are also available and can potentially be used to map vegetation. Since major advances in the spatial resolution of satellite imagery strains the usefulness of supervised image classification in such images because the heterogeneity is clearly visible, this further enables the user to provide even better training data that will be of further use in supervised classification in highly heterogeneous areas such as urban areas (Thomas et al., 2003). Since the accuracy of the result obtained from the supervised classification of high-resolution imagery to map vegetation is high, it is worth investigating the result that will be obtained by this method in this research.

Another new approach to mapping urban vegetation is automated classification, also known as machine learning. This classification technique provides promising results for extracting information from very high-resolution satellite imagery (Mathieu et al., 2007). Initially it involves segmentation of the image to divide the image into a number of groups of homogenous and meaningful features such as roads, gardens, canopy, rooftops etc., and those features are then further used to classify the image (Mathieu et al., 2007). There is some literature that discusses about and shows the results of mapping urban vegetation using machine learning with the help of a high-resolution satellite. Mathieu et al. used IKONOS imagery and obtained a 63.6% accuracy, while Tigges et al. used a high-resolution rapid eye imagery to obtain an urban vegetation map of Berlin and obtained an 87.71% accuracy. However, because most of the high-resolution satellite imagery, such as Pleiades is not available free of cost and are very expensive to purchase (See Table 1), this may be a limitation to using this process to map urban vegetation. Machine learning in a medium or low-resolution satellite is very difficult as low spatial resolution creates different challenges and errors in image segmentation, which further create inaccuracy in image classification (Mathieu et al., 2007, Tigges et al., 2013).

The accuracy of the map obtained is the most crucial part of mapping almost anything. Most of the literature used NDVI to identify the vegetation in the area of interest, which was further used to establish relationships with other factors such as land surface temperature or vegetation cover in a pixel or for regression analysis (Nichol and Lee, 2005, Otukei and Blaschke, 2010). However, if a threshold value is set on NDVI, it can be used to classify vegetation (Geerken et al., 2005). This thresholding is the part that most of the literature does not mention weather it was used or not and if it was used what threshold they set. The accuracy of any classified image is assessed based on the ground truth (Geerken et al., 2005, Mathieu et al., 2007). The accuracy of statistics such as overall accuracy, classification accuracy, producer's accuracy and user's accuracy are obtained after the resulting classified image is assessed with the help of ground truth. Most of the accuracy assessment in the literature is carried out using error matrix, where all the classified and reference component are sorted in rows and columns and used to establish several accuracies of classification. For instance, Thomas et al. 2003 used error matrix to calculate the error in their classification.

2.5 Other Methods of Mapping Vegetation

Besides NDVI and classification, there are other methods which help us to map vegetation including Leaf Area Index (LAI), Ratio Vegetation Index (RVI), Difference Vegetation Index (DVI) and Normalized Difference Water Index (NDWI), or instead of using index other features such as Tasselled Cap Transformation (TCT), Principal Component Analysis (PCA) can also be used. All the above indices use the spectral value that is present in the pixel. Based on the value of red and infra-red, most of the vegetation indices are calculated. But in some contexts, there might be a problem, such as in NDVI where the index can be altered because of various photosynthetically inactive features. In such cases, many of the analysts prefer the process of object-based image classification. Supervised and unsupervised classification generally causes salt and pepper effect in the classified objects (Li and Shao, 2013). Even in the high-resolution imagery, at the edge of each object there are mixed pixels which increase the rate of misclassification. This misclassification has been overcome by object based image analysis, which is also popular in much of the literature (Li and Shao, 2013, Mathieu and Aryal, 2007, Zhang et al., 2010). While Object Based Image Analysis is usually performed on high resolution imagery such as IKONOS and Quick Bird, it is not always necessary for high resolution imagery to be used for these purposes. Sometimes even medium to coarse resolution satellites can be used to good effect if fit for purpose and if they fit the scale. Moreover, there is another popular method usually used in medium resolution imagery, known as Sub-Pixel Classification. Due to heterogeneity of the surface and different surface structures, it is difficult to map urban areas (MacLachlan et al., 2017). It is even tedious when the imagery is of medium resolution because of a lot of mixed pixels (Arif et al., 2015). Due to this heterogeneity and mixed pixels in the context of medium resolution satellite imagery, sub-pixel classification is being used widely to represent land use (Arif et al., 2015, MacLachlan et al., 2017, Weng and Pu, 2013). This is important to consider, as this research has a research question of what is a suitable resolution for mapping vegetation with the best accuracy? The methods discussed above use different resolutions. MacLachlan et al. 2017 use Landsat 7 imagery, while Mathieu and Aryal 2007 use IKONOS imagery, which are very different in terms of resolution. The imagery selected by them was based on what was most suitable for the purpose of their research. Mathieu and Aryal, 2007 used IKONOS imagery to map large scale vegetation communities in urban areas and obtained a moderate overall accuracy of 63.6%. MacLachlan et al. 2007, mentions achieving an 85.4% accuracy. These two examples give an insight that the accuracy and resolution depend on the purpose, methods and scale of the research.

2.6 Spatial Resolution and Cost

The accuracy of the map depends on the accuracy of the materials used to produce the map and the methods used. The total cost includes the cost incurred by imagery, software used, hardware used and the labour cost. Image is a very important aspect of remote sensing analysis, as most of the errors in the remote sensing process are caused by the image itself, as well as the processing and user's interpretation technique (Story and Congalton, 1986)

Table 1: Pricelist of Various Images

Platform	Name of Platform	Spatial Resolution (m)	Price AUD per sq. km.	Total price in AUD[1] for 3257 Sq. Km.	Disk Storage (in GB)
Aerial	Aerometrex	0.5	15-24 (Depending on date of acquisition)	11,000	97
Satellite	WV4	1.24	24.32	79,225	15
Satellite	Plaiedes	2	17.3	52,590	6
Satellite	Superview 1	2	19.5	63,511	6
Satellite	Spot	6	6.5	21,496	0.7
Satellite	Sentinel-2	10	0	0[2]	0.8
Satellite	Landsat	30	0	0	0.2

In Table 1 above, the price per Sq. Km of the archived image with high resolution is expensive. It becomes even more expensive, with price increases of around 10 AUD if the image

[1] Prices are rounded off to significant number

[2] Only for academic purpose

acquisition is a new task (depends on type of tasking), meaning the image is not in archive and therefore it must be freshly sensed via satellite. So if any of the imagery outlined in Table 1 or other relevant images that are also expensive are used in the processing, it can be concluded that image acquisition will be the major cost driver. It is even more expensive in aerial platform than satellite platform because the user must bear the total cost for the dedicated flight and image acquisition. Also, according to the literature, using a map with a high resolution for analysis potentially yields higher accuracy (Mathieu and Aryal, 2007, Mathieu et al., 2007). So it can be said that the accuracy and the cost are highly correlated, as higher accuracy usually incurs a higher cost. But there are still some cases where higher accuracy can be achieved using low cost or sometimes free imagery, such as Landsat, depending on the imagery purpose and scale of the study. For instance, if pervious versus impervious surface are to be mapped, then Landsat or Spot 6 can be used and can also yield high accuracy. But if every street tree must be mapped, then higher resolution data such as Aerometrex data might be required.

The cost also varies depending on what body is conducting the research. If the organisation or personnel conducting the analysis/research is a private or commercial organisation, then the cost will be almost as much as that outlined in Table 1. But if the research is conducted for academic purposes such as university research, or a thesis in this case, the cost of the image and software incurred will not be nil but it will still be minimal. For research purposes conducted through an academic institution such as a university, the software is either freely available to the researchers or available at a lower cost, while similarly the image provider usually provides the images free or at a negligible cost.

2.7 Gap in Literature

In all the literature viewed, most of the literature defines the accuracy of the map produced using the methods and resolution for the respective research. Tim Van de Voorde et al. 2008 used Landsat image, which at 30 m in resolution is a very low-resolution image in comparison to that used in other literature. Yet they do not mention how much accuracy was required for them to carry out their research. Similarly, others such as Mathieu et al. 2007, Tigges et al. 2013, Zhang et al. 2010 used a very fine resolution imagery (3, 5 and 3m respectively). But while they obtained a higher accuracy level due to the resolution of the imagery they used, they fail to mention the cost they incurred to conduct the analysis. Besides that, most of the literature fails to mention the errors and issues caused by any geometric distortion of the image, threshold used in NDVI, and shadows in the images, while some of the literature even fails to discuss the accuracy of the methods used For instance, Dadvand et al. 2012 used an

NDVI image created from Landsat image, but does not mention the distortions in the image or any geometric correction applied to the image.

Another factor is that most of the literature does not focus on the importance of multidate image analysis. However, some of them do focus on that. Tigges, Lakes and Hostert 2013, focused on multidate imagery from RapidEye. As a multi temporal image would help to identify tree species-specific characteristics, which would further help in classifying different tree species in the urban environment of Berlin. As multidate image analysis in the case of vegetation can potentially be useful, especially in a temperate climate such as Adelaide, where the variation in greenness can be observed during the change in seasons. The literature that focused on multidate image analysis often used high resolution imagery such as Rapid Eye (Tigges et al., 2013). This also indicated that multidate imagery is potentially useful when a high-resolution image is used, because changes in vegetation might be significantly clear only in high resolution imagery. But in this research, due to a lack of multidate images for high resolution imagery and the inclusion of low-resolution imagery such as Landsat, unfortunately this concept cannot be pursued. These gaps in the literature helped to formulate the tasks for this research, which are listed below:

a. Investigate the impact of sensor resolution on the accuracy of mapping urban vegetation.
b. Explore different methods for mapping urban vegetation and what impacts these have on accuracy and cost.
c. Discover the major drivers of cost for producing maps of vegetation of large urban areas (cost of resources).
d. Obtain the most accurate urban vegetation map.

3.0 METHODS

3.1 Overview

An overall flow chart of the processes that were carried out in this research is provided in Figure 3:

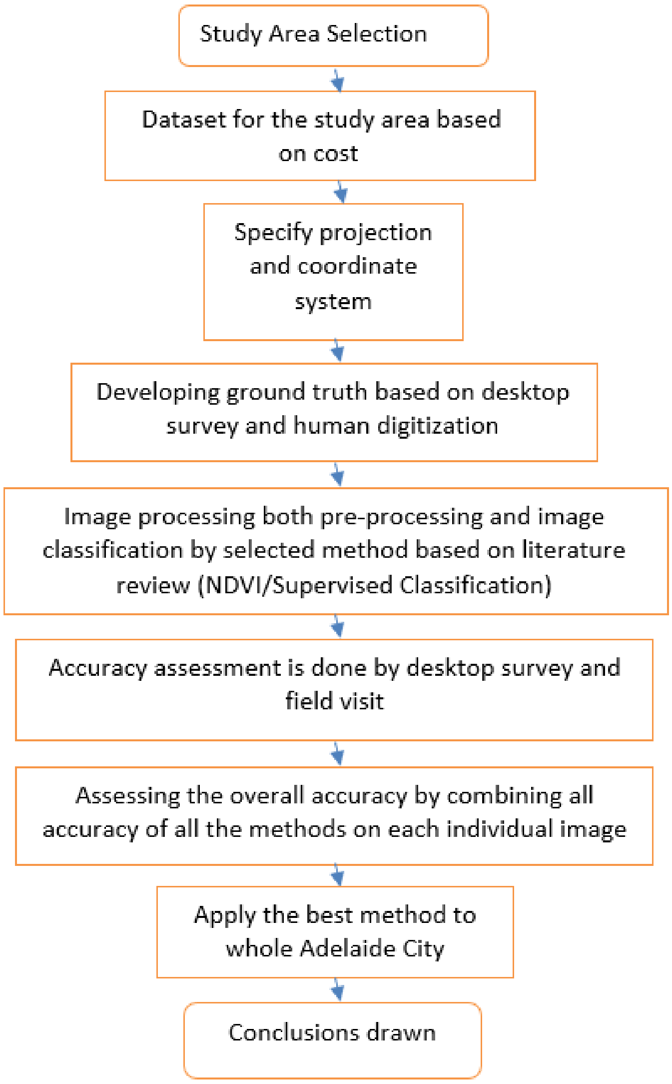

Figure 3: Flowchart of Methods

3.2 Selection of Study Area

The overall study area for mapping urban vegetation was Adelaide metropolitan city. The main reason for choosing Adelaide metropolitan city is accessibility to the area. As the accuracy assessment based on the field verification might be done, this is the main reason why accessibility to the area was an important consideration. Another reason to justify the selection of Adelaide metropolitan city as the study area is the availability of the data and Adelaide metropolitan city being an ideal city to perform this analysis due to its layout, structure and the way this city is built. Of course, there are many other possible cities to study, but the spatial extent and extent heterogeneity must also be considered. For instance, Delhi could also be chosen as a study area, but the structure of the city and density of buildings and population gives rise to more spatial heterogeneity, which might later create various challenges and also give rise to many errors.

To test the methods on different images of different resolution, test suburbs was chosen. The empirical method of choosing the test suburbs was to perform NDVI on the whole study area and use zonal statistics (where the zones are different suburbs). This was carried out so that suburbs based on high, medium and low NDVI values can be chosen. The NDVI value does not represent the density of vegetation in the area, but rather the overall greenness of vegetation present in the area. So, after comparing NDVI with visual interpretation, the test areas were chosen.

Table 2: Sample table of Zonal Statistics of Postcodes Based on NDVI

POSTCODE	SUBURB NAME	SUBURB_NUM	NDVI_MEAN
	WELLAND	500704	
	BOWDEN	500701	
	WEST HINDMARSH	500705	
	BROMPTON	500702	
5007 (TA3)	HINDMARSH	500703	0.16
	CLARENCE GARDENS	503901	
	EDWARDSTOWN	503902	
5039 (TA1)	MELROSE PARK	503903	0.23
	HYDE PARK	506101	
	MALVERN	506102	
	UNLEY	506103	
5061 (TA2)	UNLEY PARK	506104	0.31

The above suburbs were chosen not only with the help of statistics, but also with the help of visual interpretation with consideration of factors such as:

a. Should not have too many parks in it.
b. Must have a majority of residential area in it, with the presence of vegetation such as trees, small parks, gardens etc.
c. Should not be an industrial area with abundant impervious surfaces only.

The test suburb 5007 was named as Test Area 3 (TA3), which has a low mean NDVI in it. Similarly, 5039 was named TA2, which has a moderate mean NDVI in it, while finally 5061 was named TA1, which has a high mean NDVI in it.

3.3 Selection of datasets

After the study area and its extent was set, the main challenge was to select a dataset or images on which the further processing was to be conducted. As the literature review indicates that the accuracy of the map is higher when the resolution of the dataset or image used to obtain the map is also high (spatial resolution), consequently all the potential image providers with different resolutions (spectral and spatial) were compared based on their resolution and cost (see Table 1).

It is clear from Table 1 that the higher the resolution of the image (spatial resolution), the more expensive the image becomes. Moreover, if processing involves the use of multi date images the cost will be double that which is outlined in Table 1, but it is also understood that some of the image providers such as Sentinel and Landsat provide images free of charge for research or academic purposes. Sentinel 2 MSI images have a moderate spatial resolution of 10 metres and has 13 band spectral bands, whereas Landsat 5 has a lower spatial resolution of 30 metres and has spectral band of 7. The reason for choosing Landsat 5 over Landsat 7 ETM+ or Landsat 8 is that since 2003 there has been an error on the Landsat & ETM+ scan line sensor which results in a data loss of 12-14%. The error which occurs by scan line may be corrected in pre-processing, but even then, the resulting image will not be as good as one with no error, with the error in the image likely to be around 14% with a spatial resolution 30 m, which is unaffordable. Moreover, the data on Landsat 8 was very hazy and cloud coverage was high.

But in Landsat 5 there is no scanline error and a dataset with almost no haze and cloud was also available.

Based on this calculation it would be suitable to consider Sentinel-2A imagery, as it has a 13 band and is of 10 m resolution, while I also have access to Pleiades Multi Spectral Imagery thanks to my supervisor who has allowed to use that imagery for this research. The Landsat 5 Image was also used since it freely available and has a good spectral resolution as many very old archives of images, which may be useful to investigate if it is fit for purpose.

3.4 Development of ground truth

In order to assess the accuracy of the methods used to classify and map the vegetation in an urban area, ground truth is required. Ground truth is a very crucial part of the image processing as it determines how accurate the generated data will be by cross-referencing the resulting map with this data. To obtain the ground truth, there were basically two different approaches taken. These approaches were based on an interpretation of the data to identify the change between ground truth and the dataset acquired and the collection of the ground truth digitally. The following steps were undertaken to acquire ground truth:

a. Desktop survey: Since the images acquired from different image providers were from different dates ranging from 2014 to 2017, those images had to be checked using high resolution imagery such as google earth in order to find out if there are any dominant changes in the images over the respective periods of time. This was carried out in order to confirm that the ground truth in the different TA's at the present time is not affected by what may have been in the respective TA at the time of the dataset. For instance, if there was a big park in the image that might no longer be present at the current time in the same place, this might create a problem as the ground truth and the result obtained from the image using a different method might differ.

b. Human digitisation: After a desktop survey was done and it was concluded that there are not any major changes inside the TA's landscape between the imagery and the present context, the acquisition of ground truth of different features was carried out by human digitisation using an ESRI base map in ArcGIS Pro. The TA in the ESRI base map was also checked with the TA in recent google earth images and no significant changes were found. The desktop survey for the ESRI basemap was also important because the ground truth was digitised using the ESRI basemap, and that ground truth will be used to assess the accuracy of the vegetation map produced from the further image processing and classification of various datasets. After all the images were verified and found to be suitable for collecting ground truth, including features such as trees, shrubs, gardens, roads, buildings (rooftops) and shadows, the boundaries of those respective features were digitised and extracted from the ESRI basemap.

3.5 Image Processing

The main part of this research is image processing, as this is where all the methods and processes undertaken to obtain the result are discussed. There are various factors to be considered from the literature and other studies when processing the image. These factors inform an understanding of what processing is mandatory and what processing is not. Every aspect of this research relies on this part being carried out correctly, and many processes were undertaken while processing the image. However, to make the process more comprehensible, the Image processing will be divided into two basics parts as discussed below:

a. Pre-processing: Any image obtained must be corrected geometrically and radio metrically, also known as restoration of image, before it is ready to go to further processing. This corrects the distortion caused by the sensor and platform (Schowengerdt, 2006, Pohl and Van Genderen, 1998). All the pre-processing varies according to the sensor and platform. Therefore, it can be said that the pre-processing for every image is different. The pre-processing of the image that was carried out in this research can also be divided into two major parts:

   i. **Atmospheric correction**: This is done to remove the scattering and absorbing effect of the atmosphere to obtain the correct ground reflectance. But this is usually only in the context of a single image from each image provider being used, while in this case atmospheric correction was not necessary as the image used was not hazy or cloudy and moreover, all the pixel values if influenced will be influenced to the same degree and will therefore still provide a good result while classifying it.

   ii. **Geometric correction**: When the image was overlayed on top of the ESRI basemap in ArcGIS Pro the image did not completely align to the basemap, which required all the images to undergo geometric correction. Because if the images do not align, the information of the satellite data will not correspond exactly to ground truth, as the basemap was considered as ground truth and so the geometric correction had to be done. The ESRI basemap was considered as ground truth because it was the only high-resolution dataset available. Another reason was that due to a bug in both ArcMap and ArcGIS Pro, the Google Earth image (another high-resolution image) could not be georeferenced for digitisation.

Figure 4: Geometric Shift in Pleiades

The imagery was geometrically corrected using GCP from the base map and the resampling method used was bilinear interpolation. The first-degree polynomial did not yield worthy results. However, the second degree polynomial yielded a result that although not exact, still significantly improved the image that almost aligned with the base map, while the resampling method bilinear interpolation was used in order to avoid the “stair stepped” effect caused by the nearest neighbourhood and to obtain a smoother and more accurate result.

b. Image Analysis: This was the most crucial part of this investigation. This part determines the overall result and output, which is the map (Schowengerdt, 2006) or overall research. Since the main objective of this project was to obtain an (urban) vegetation map, this was undertaken based on an understanding from the literature, the accuracy obtained by researchers, and the popularity of methods which are widely used, the following methods were used to process and classify and hence map the urban vegetation. They are as follows:

i. **NDVI**: The threshold here is used to define anything that falls below the threshold as being non-vegetation. Although NDVI has a broader use in agriculture and land use, to use it to differentiate between vegetated and non-vegetated areas in an urban environment, it needs to be thresholded (Geerken et al., 2005). After the computation of NDVI on all the images obtained after pre-processing, threshold on NDVI was applied using a spatial modeler in ERDAS Imagine obtaining thresholded NDVI raster. The threshold was set differently for different images as the range of NDVI values was different for all the images. This difference in NDVI values was a result of a different wavelength of red and NIR bands in different imagery. Furthermore, three different thresholds were set for each individual image to identify which threshold would yield satisfactory results.

ii. **Supervised Classification**: Supervised classification is also popular in much of the literature (Myint, 2006, Thomas et al., 2003, Zha et al., 2003). The main feature of this method is the classification of features based on user trained data or user defined signatures. All the datasets were classified using this method. Parallelepiped was used as a non-parametric rule and maximum likelihood was used as a parametric rule, while the unclassified rule was set to unclassified to ensure that most of the unclassified features could again be trained to obtain their signature such that unclassified features could be reduced to a minimum. For parallelepiped surface, the standard deviation was set to reduce the number of outliers, while setting standard deviation also helps in reducing incidences of misclassification; it is like setting threshold to maximum likelihood classification. Parallelepiped is used instead of maximum likelihood because it is faster; the main limitation is that maximum likelihood is said to be more accurate although slower than parallelepiped, assuming that all the signatures selected are correct and the input data follows a Gaussian distribution, which might not always be the case. However, assuming the specified signatures are correct and use a standard deviation (3 SD was set for all images) to parallelepiped each side's dimension, then the result from using parallelepiped rule will also be highly accurate. There is also a sub-pixel classification method that can be used to classify an image with greater accuracy, but as with Sentinel 2 and Landsat the spectral resolution of Pleiades is also not high (only 4 bands). As the sub-pixel classification approach exploits the spectral information of the image, and as the literature review informs an understanding that there is a trade-off between increased spatial resolution and decreased spectral resolution, consequently the sub-pixel classification method was not used in this case. In this research the supervised classification signatures for four different features (grass, tree, non-vegetation and shadow) were specified. For the parallelepiped sides, a 2.5 standard deviation was set. After the classification, the raster was compared with the satellite imagery and most of the major unclassified patches were noted. For those unclassified features, again the signature was trained, and the image reclassified. This process was repeated several times to minimise the unclassified features. After classifying an image that depicts four different features, classification was again performed in order to depict just two features, namely vegetation and non-vegetation.

3.6 Accuracy Assessment

This is another crucial part of the overall image analysis. Each of the resulting rasters underwent this procedure, as one of the main objectives of this research is to find out what process and which image yields the highest accuracy amongst all the available methods and images, and therefore this can help to establish a relationship between image and accuracy. The ground truth collected will play the most critical role in this process, as this will serve as reference data to assess the accuracy of all the results obtained.

For the purposes of THNDVI, a fishnet (or GIS square polygon layer) related to the pixel size of individual images was created. Zonal statistics were extracted from the higher resolution vector ground truth. Using the zonal statistics, where the zone was the fishnet for an individual image, all the NDVI values of corresponding fishnets were calculated. A similar fishnet was intersected with all the higher resolution vector ground truth. The intersected fishnet contained the detail on how much of each feature, such as shadows, grass, non-vegetation or trees, were present in an area of that fishnet while the individual NDVI value of these respective fishnets was used to assess the accuracy of classification. So, after obtaining the fishnet, with its respective NDVI value for each cell that corresponding to satellite imagery and containing the information regarding the content of each individual fishnet, the data was analysed in a tabular form in Excel. The analysis was conducted based on the following simple principles and logic:

i. At least 50% of the individual fishnet's area should be covered by vegetation.
ii. The corresponding fishnet has an NDVI value greater than the thresholded value.

After using the formulas created on Excel, based on this straightforward reasoning the accuracy of each TA for each image and each threshold was computed, the results of which will be reported in the results section.

For the supervised classification accuracy assessment, the first step was that the ground truth in digital format (Figure 11) was merged and converted into raster (Figure 12) using an ERDAS vector to raster function. It was noted in conversion that in order to capture most of the digitised features, the cell size during conversion was set to 0.5 metres so as to preserve most of the details and assess their accuracy. After obtaining the raster of ground truth data, a thematic matrix union tool was used to obtain an error matrix for all 3 TA's across all the images. The classification error, error of commission, error of omission and overall accuracy were all calculated with the assistance of this matrix.

3.7 Selecting best method

The individual accuracy of each method for each image was obtained and assessed across all 3 TA's. Following this, the average accuracy was calculated using the accuracy of all 3 TA's recorded individually for each. After determining the overall accuracy through this method, the method and image which displayed the highest accuracy was considered to be the best method and imagery, and that method shall be applied to the imagery of the whole study area, which is Adelaide metropolitan city, to map the urban vegetation.

4.0 RESULTS

4.1 Study area selection

Based on the results listed below, obtained from zonal statistics using suburbs as zones and the NDVI obtained from a Sentinel 2 image for the Adelaide metropolitan city, 3 TA's were chosen. The zonal statistics of NDVI for different suburbs are outlined in Figure 5:

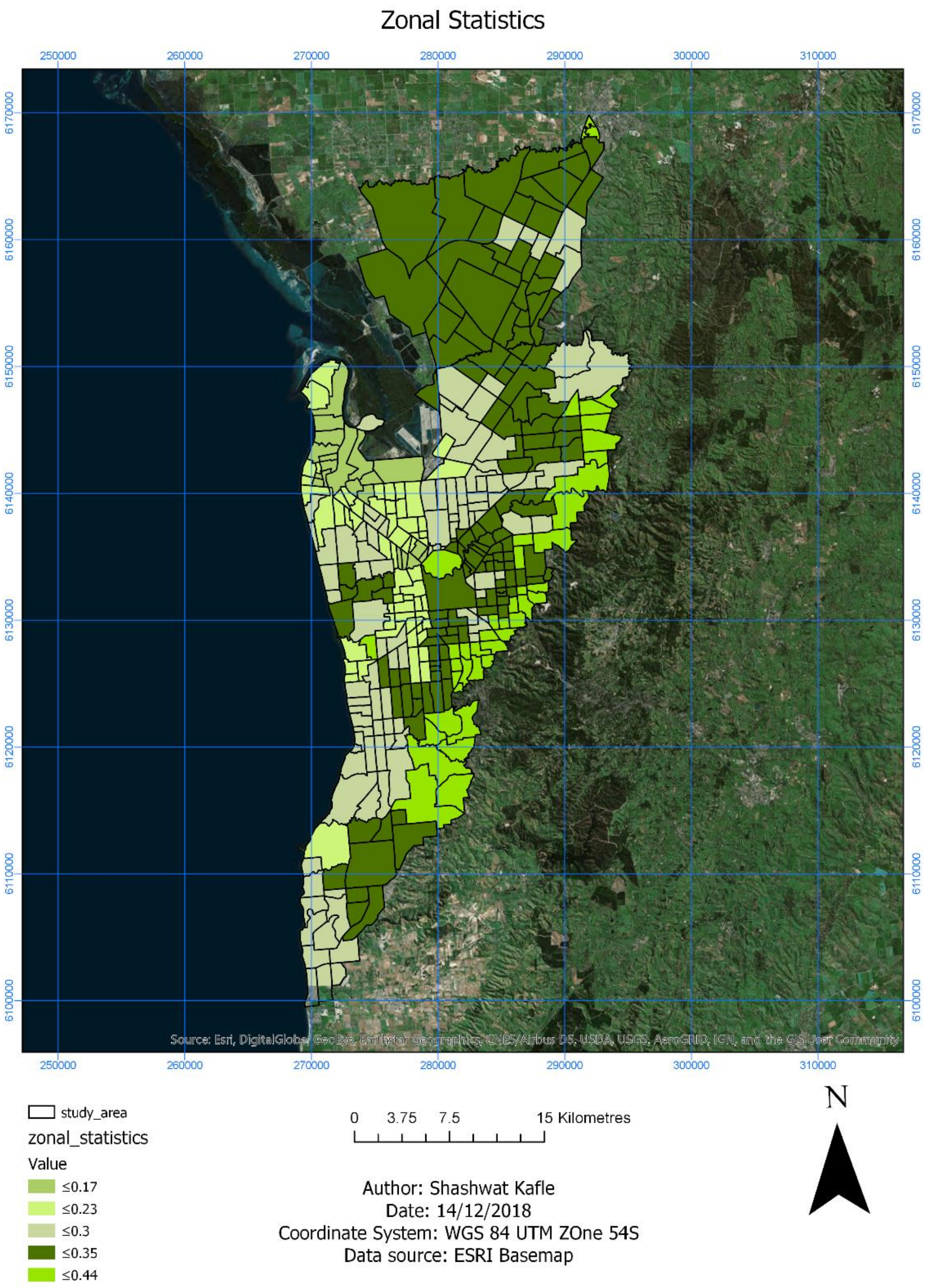

Figure 5: NDVI of different suburb

On the basis of the zonal statistics listed in Figure 5, it was concluded that the highest NDVI value in the study area was 0.49 recorded at 5052, Belair, with this high value largely a result of the presence of a vast amount of greenness such as trees and plants, and with fewer buildings and impervious surfaces present in the suburb. The lowest NDVI value was 0.091 recorded at 5015, Port Adelaide, where the greenness was comparatively less than in all other suburbs. Below is the histogram that represents the distribution of NDVI values.

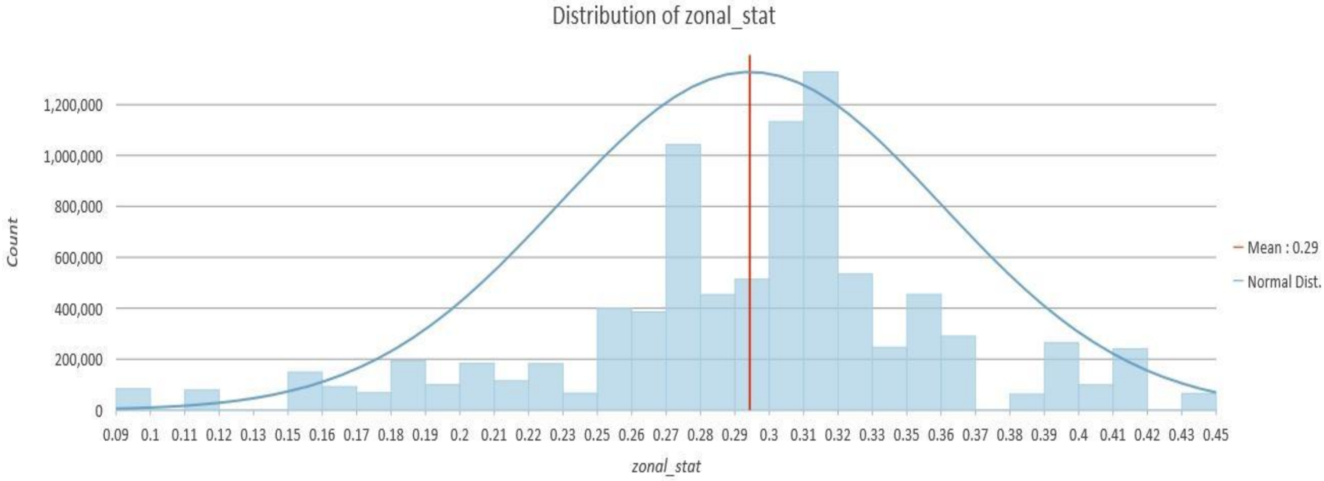

Figure 6: Histogram of Mean NDVI value

The tails of the curve show extreme NDVI values. The suburbs that represent extreme values of NDVI cannot be selected as a study area because the regions with extreme values are not a typical urban area, with the low NDVI denoting a suburb with a lot of industry and building while the one with a higher NDVI denotes an area with too much vegetation. Moreover, it is both empirically and visually clear that they have either most of the greenness or a majority of photosynthetically inactive features such as houses, buildings or pavement in them. So those suburbs that had extreme values could not be selected. In order to overcome this problem, the suburbs were selected based on a visual interpretation and examination of NDVI zonal statistics, such that an area chosen is an urban area with residents but also with an ample amount of greenness present in them, excluding national parks and excessive forest and plantations. Consequently, the suburb with postcode 5007 and a low mean NDVI, postcode 5039 with an average mean NDVI, and postcode 5061 with a high mean NDVI, were selected as set out in Figure 7 below. These study areas were not just selected based on visual interpretation but were also assessed empirically using zonal statistics of NDVI for each suburb.

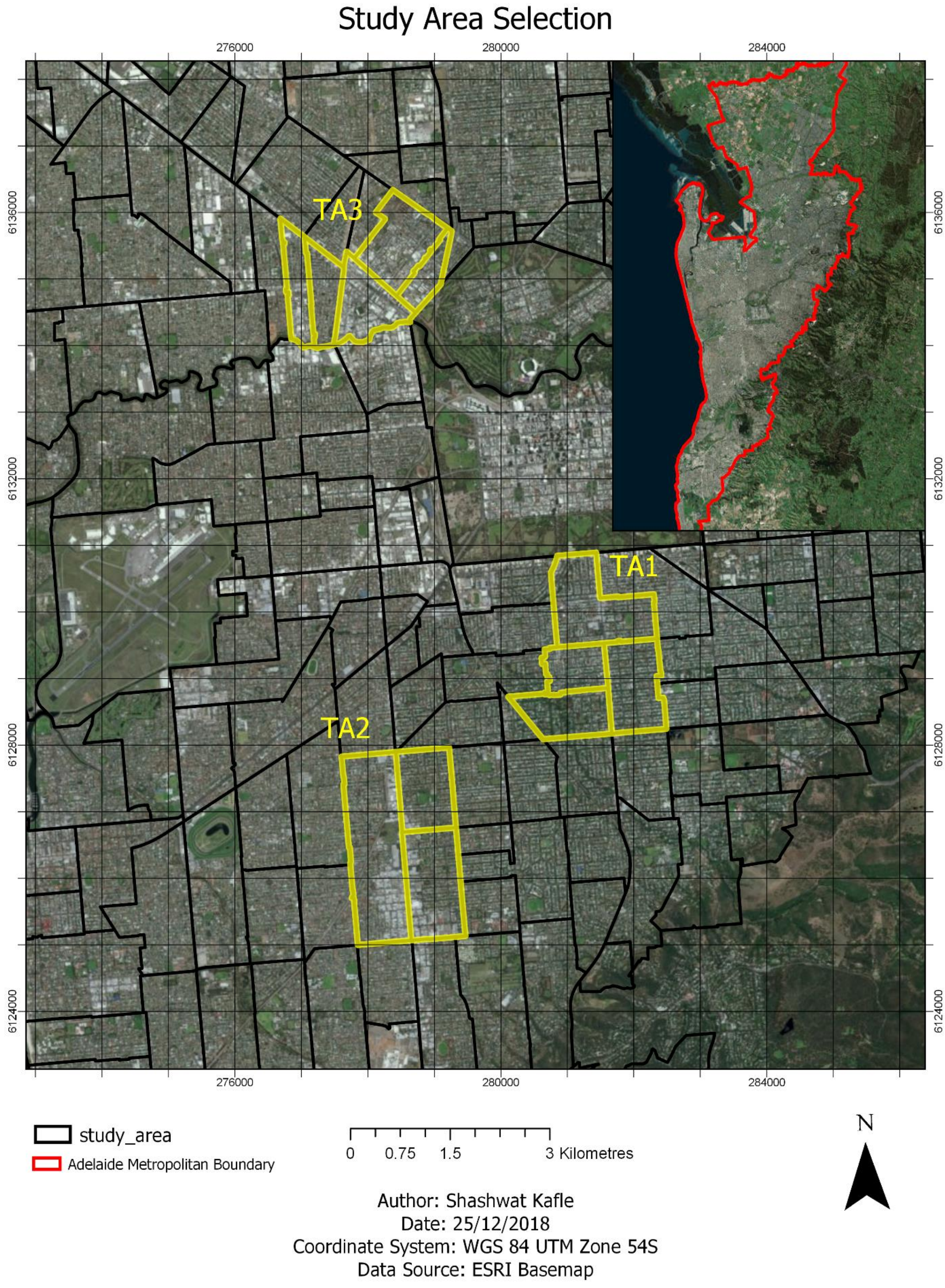

Figure 7: 3 Study Area selected as Test Areas

4.2 Dataset selection

In contrast to the research aim and objective, three datasets (multi-spectral satellite imagery) were selected based on their spatial resolution. The imagery selected were Landsat 5 (30 m), Sentinel 2 (10 m) and Pleiades (2 m). These three particular data sets were specifically selected due to their varying resolution. The different spectral and spatial resolution and wavelength of each spectra can be seen in Table 3 and Figure 8:

Table 3: List of images used with their band content and resolution

	Pleiades	Sentinel 2	Landsat 5
Spatial Resolution	2 metres	Varying from 10 m to 60 m depending on bands used	30 metres
Spectral resolution	4 Band	13 Bands	7 Bands
Band composition	Blue: 0.43-0.55µm Green: 0.49-0.61µm Red: 0.6-0.72µm NIR: 0.75-0.95 µm	B1-Coastal Aerosol: 0.443µm (60 m) B2-Blue: 0.49 µm (10 m) B3-Green: 0.56 µm (10 m) B4- Red: 0.665 µm (10 m) B5- Vegetation Red Edge: 0.705 µm(20m) B6- Vegetation Red Edge: 0.740 µm (20m) B7- Vegetation Red Edge: 0.783 µm(20m) B8- NIR: 0.842 µm (10 m) B8A- Vegetation: 0.865 µm (20m) B9- Water Vapour: 0.945 µm (60 m) B10- SWIR- Cirrus: 1.375 µm (60 m) B11- SWIR: 1.610 µm (20m) B12- SWIR: 2.190 µm (20m)	B1-Blue: 0.49 µm B2-Green:0.56 µm B3- Red: 0.665 µm B4- NIR: 0.705 µm B5- SWIR1: 0.740 µm B6-Thermal:0.783 µm B7- SWIR2: 0.740 µm

The result obtained from all these images will help to inform an understanding of what is the relationship between image resolution and the accuracy obtained using that particular image.

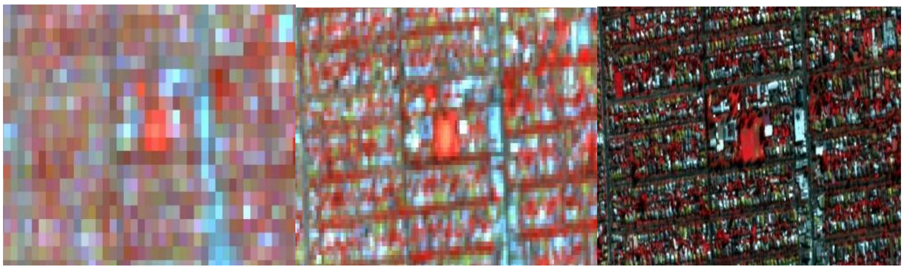

Figure 8: Comparison of resolution of Landsat 5(left), Sentinel 2 (middle) and Pleiades (right)

From Table 3 it is clear that although Sentinel 2 has a spatial resolution that depends on the bands used, which may vary from 10 metres to 60 metres, the bands used in this research (red, green, blue and NIR) were all of 10 m resolution. It can also be seen from Table 3 that the wavelength for same bands in different imagery is also different, especially for red and NIR. Because of the difference in the value of wavelengths, the indices calculated using these wavelengths also result in different values for different images, which will be further discussed in section 5.

4.3 Development of Ground Truth

A desktop survey was conducted to establish if there were any significant changes in the vegetation or non-vegetated impervious surfaces such as pavements, houses or buildings in the images. This was necessary because the images acquired were not the latest images. As the images acquired for the purpose of analysis were three to nine years old, due to the only available image for Pleiades being from March 2015 while for Landsat the image with the least cloud coverage and haze was from as far back as March 2009. As the images were significantly older than the present time, it must be checked to determine if there have been any significant changes in the images since then, so as to ensure that the accuracy assessment was not affected by changes in ground truth. In the case of Landsat 5, as the resolution was coarser than that of Sentinel 2 and Pleiades, changes in small spatial extent were not very clear, but there was no evidence of major changes. Since different images were acquired at different times, Google Earth's timeline was used to detect any significant changes between that time and the present. This was more helpful in the case of Landsat 5, as the low resolution meant that small features such as buildings, trees etc. in the image itself were not clear. In this case, Google Earth's timeline was used to match the time of the image acquired, and the Google Earth image from that time was compared to the present time to identify any significant changes

After undertaking a thorough desktop survey for different imagery, Google Earth was used to determine if there were any significant changes in the vegetation inside the TA's. With the exception of some changes in a couple of residential homes, there were no significant changes in vegetation in all three TA's. These findings further confirmed the accuracy of the dataset, which could then be finalised for further processing.

Figure 9: Digitization inside TA1

After all the features were extracted, there were some cases where either one or multiple features were inside another feature and donut polygons had to be created.

Figure 10: Creating donut polygon

After digitising the features in separate layers for all the TA's, the features were merged in each TA and used in further analysis for an accuracy assessment of the result obtained from all the image processing.

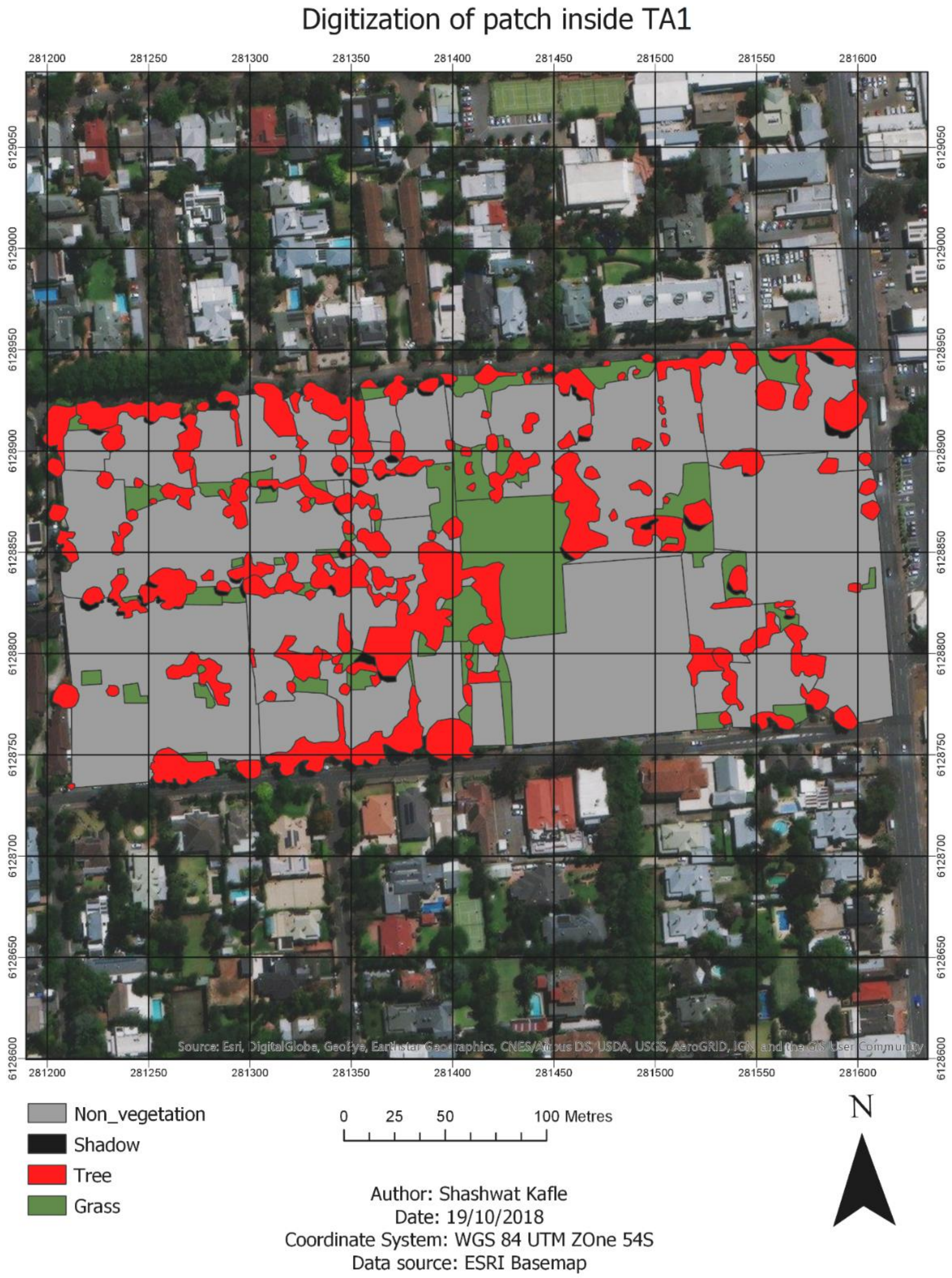

Figure 11: Digitization of patch inside TA1

The digitised patch of TA1 was merged and then converted into raster using a vector to raster function in ERDAS Imagine 2018 to obtain a raster as shown in Figure 12:

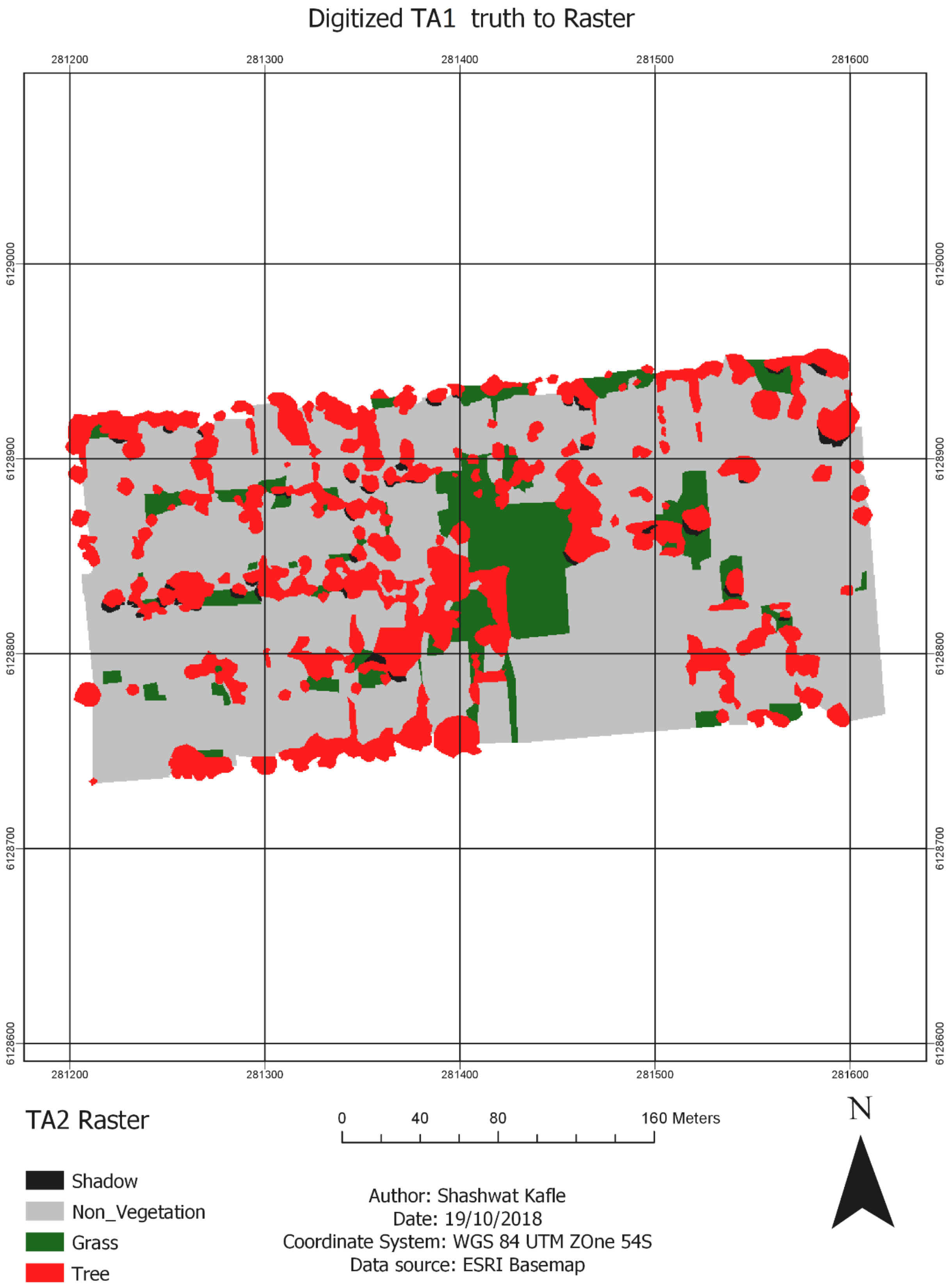

Figure 12: TA 1 digitised Vector converted to raster

This process was similarly applied to TA2 and TA3.

4.4 Image processing

As discussed in the methods, the two steps to the image processing were pre-processing and image classification. As a certain shift is clearly visible in Figure 4, when all the images were analysed it was noted that the actual basemap of Adelaide did not align with any of the satellite images, so all the satellite images had to be geometrically resampled to align as much as possible. Figure 13 shows the result obtained after geometric correcting was applied and the image was resampled for Pleiades:

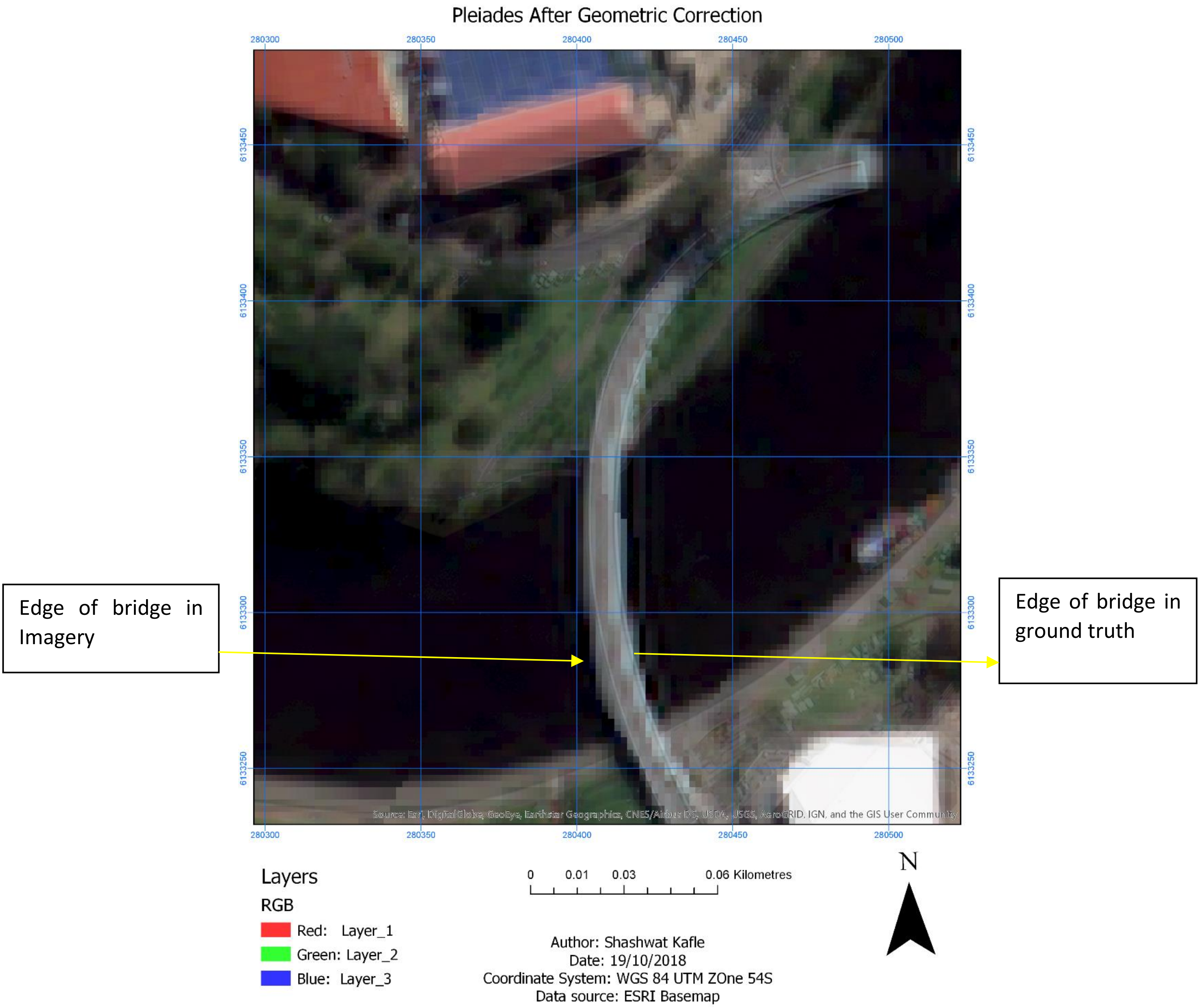

Figure 13:Image obtained after Geometric Correction (Image pixels align on the basemap bridge after correction)

In comparison to the shift seen on Figure 4, in Figure 13 the shift has been reduced as much as possible, such that the values computed using the satellite image corresponds very closely to the ground truth collected.

After the Pleiades image was corrected geometrically, it was used to compute the NDVI raster of the respective image. The NDVI obtained at the beginning had values that ranged from -1 to +1, while the range of the values were different for different images as illustrated in Appendixes 4 and 6.

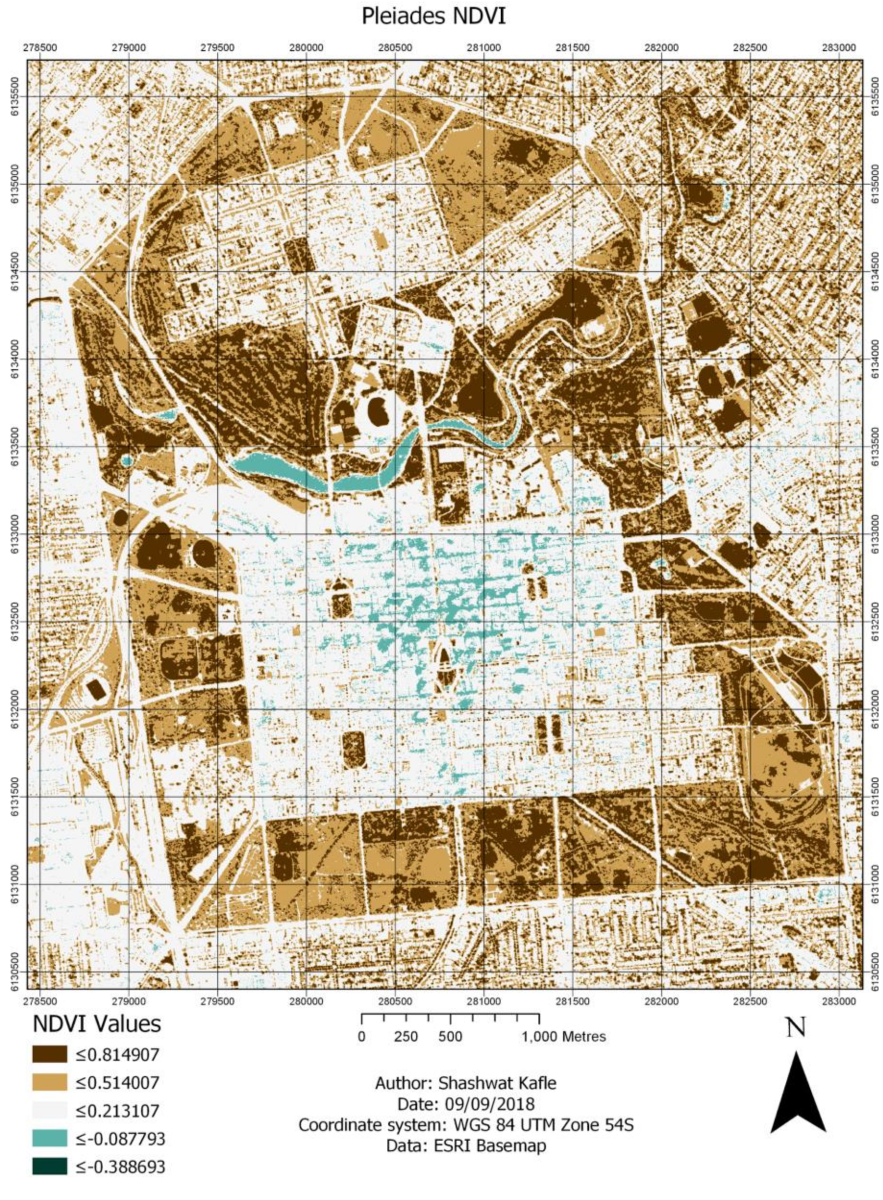

Figure 14: Pleiades NDVI

After computing the NDVI raster for all the geometrically corrected images, thresholding was applied to get a classified image. THNDVI for Sentinel 2 and Landsat 5 can be seen in Appendixes 5 and 7 respectively.

Figure 15:Pleiades THNDVI

After computing the THNDVI raster for all the images, supervised classification was performed on all the images. The result for the supervised classification with five classes for Pleiades can be seen on Figure 16:

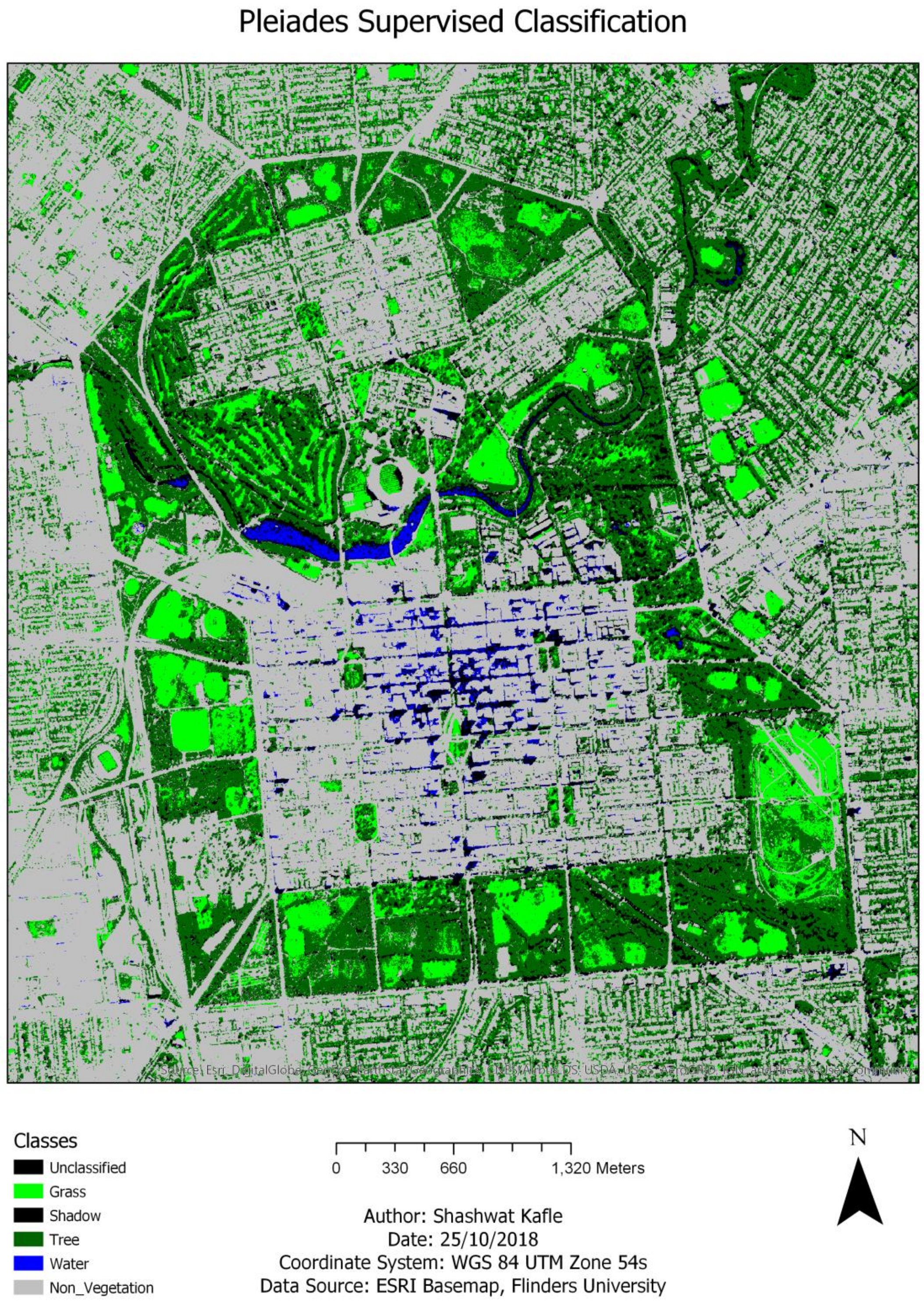

Figure 16: Pleiades Supervised classification

Similarly, the result for Sentinel 2 supervised classification using four classes can be seen in Appendix 1. After supervised classification was performed using training data for four classes (and water) as mentioned in the method, it was further classified for only two features and the result for Pleiades was obtained in Figure 17 (see also Appendix 2 and 3 for Sentinel 2 and Landsat classified using two classes):

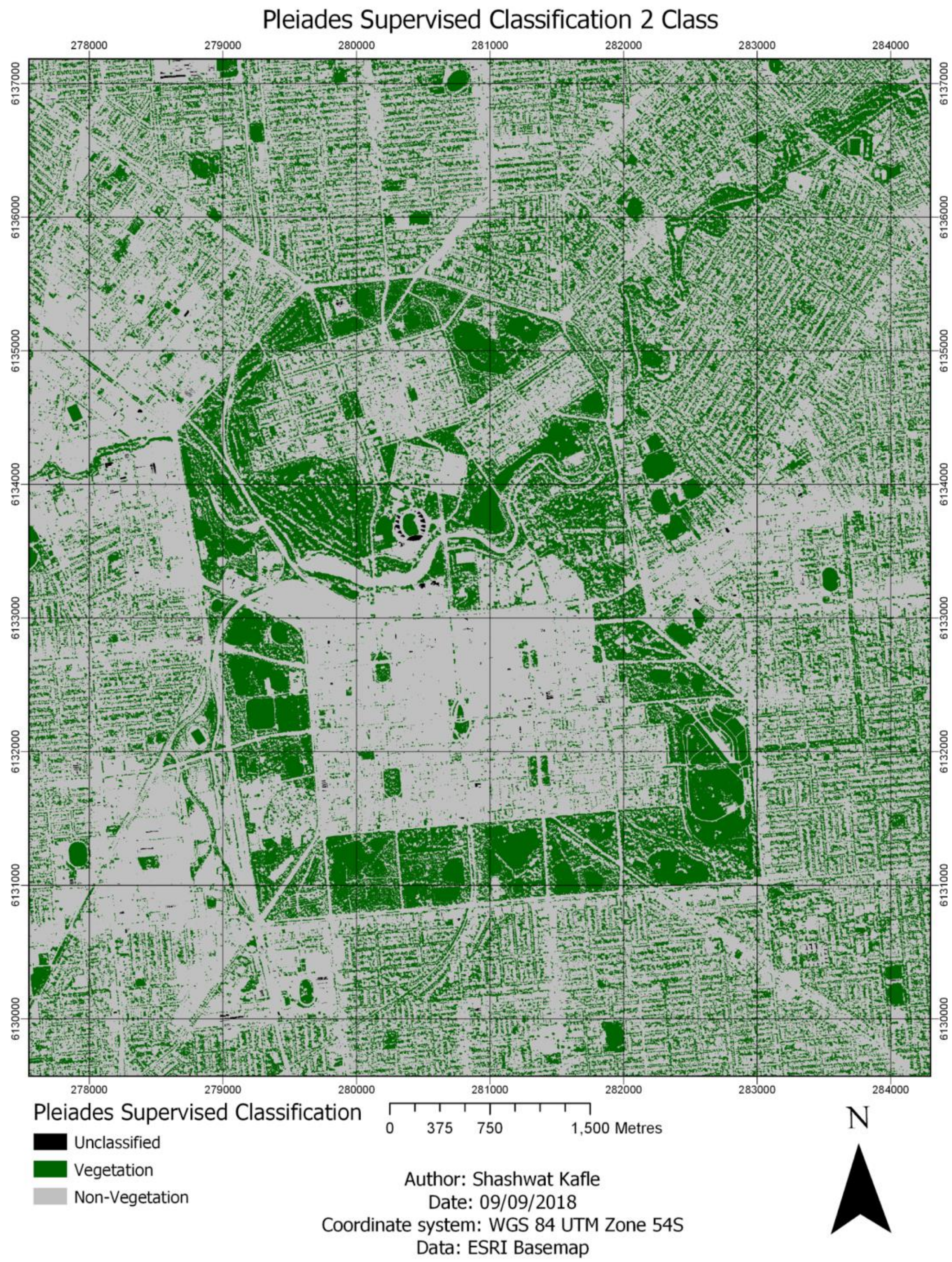

Figure 17: Pleiades Supervised classification for 2 class

4.5 Accuracy Assessment

The accuracy assessment for THNDVI was conducted mathematically using expressions in Excel. Table 4 shows the classification accuracy using thresholded NDVI for all the satellite imagery. For a more detailed accuracy assessment, error matrices for all satellite imagery and all test areas are provided from Appendix 9 to Appendix 23.

Table 4: Accuracy for THNDVI for potentially best threshold

	Accuracy		
Satellite	TA1	TA2	TA3
Pleiades	95.66%	99.36%	90.28%
Sentinel 2	92.19%	70.02%	83.66%
Landsat	92.82%	99.43%	35.7%

The accuracy for the supervised classification was calculated using the matrix obtained from the thematic matrix union, while the fifth class (water) was merged with non-vegetation, as the only area of classification interest was vegetation and non-vegetation. The accuracy obtained for the supervised classifications for four classes and two classes respectively are listed in Table 5:

Table 5: Accuracy for different image classification

Test Area	Satellite	Accuracy for 4 classes	Accuracy for 2 classes
TA1(High Vegetation)	Pleiades	65.70%	72.48%
	Sentinel 2	60.33%	71.90%
	Landsat	NA	69.13%
TA2 (Medium Vegetation)	Pleiades	67.96%	80.08%
	Sentinel 2	61.87%	70.36%
	Landsat	NA	67.13%
TA3 (Low Vegetation)	Pleiades	72.88%	78.50%
	Sentinel 2	72.76%	77.78%
	Landsat	NA	77.32%

Pleiades recorded an average accuracy for THNDVI of 95%, Sentinel 2 recorded 82% accuracy and Landsat recorded 75% accuracy. However, where a supervised classification using four classes (excluding water) was conducted, Pleiades recorded an accuracy of 68.8% and Sentinel 2 recorded 64.98% accuracy. Similarly, the classification accuracy for only two classes was 77.02% for Pleiades, 73.34% for Sentinel 2, and 71.19% for Landsat respectively. Figures 18 and Figure 19 show the error maps obtained for TA 1 for Pleiades and Sentinel 2 images, while the Landsat error map can be seen in Appendix 8. This raster and the above accuracy result were obtained using the thematic matrix union function in ERDAS Imagine 2018. In all the error maps, red represents correctly classified pixels while yellow represents wrongly classified pixels (Commision and Ommission error):

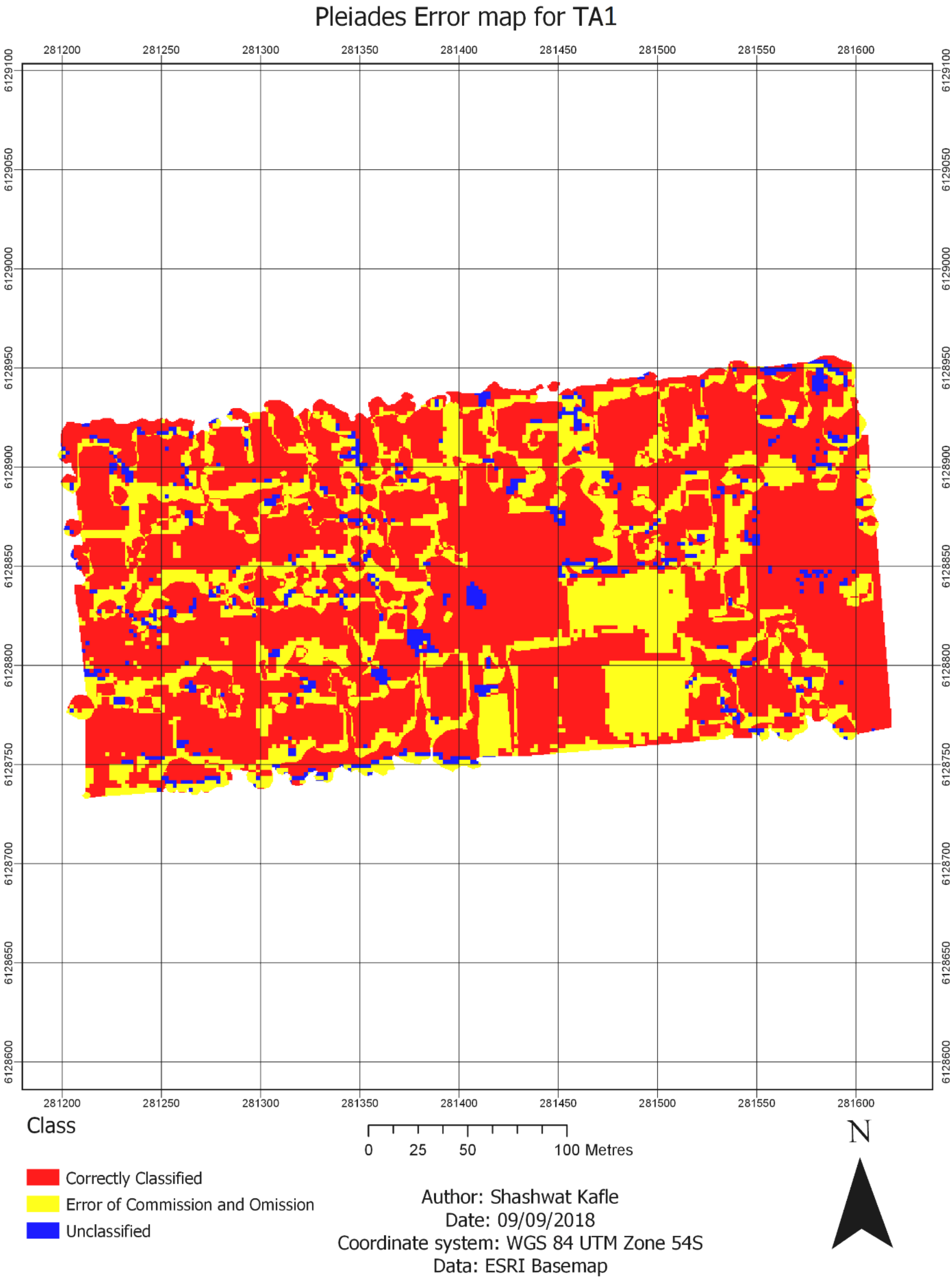

Figure 18: Error map for Pleiades for TA 1

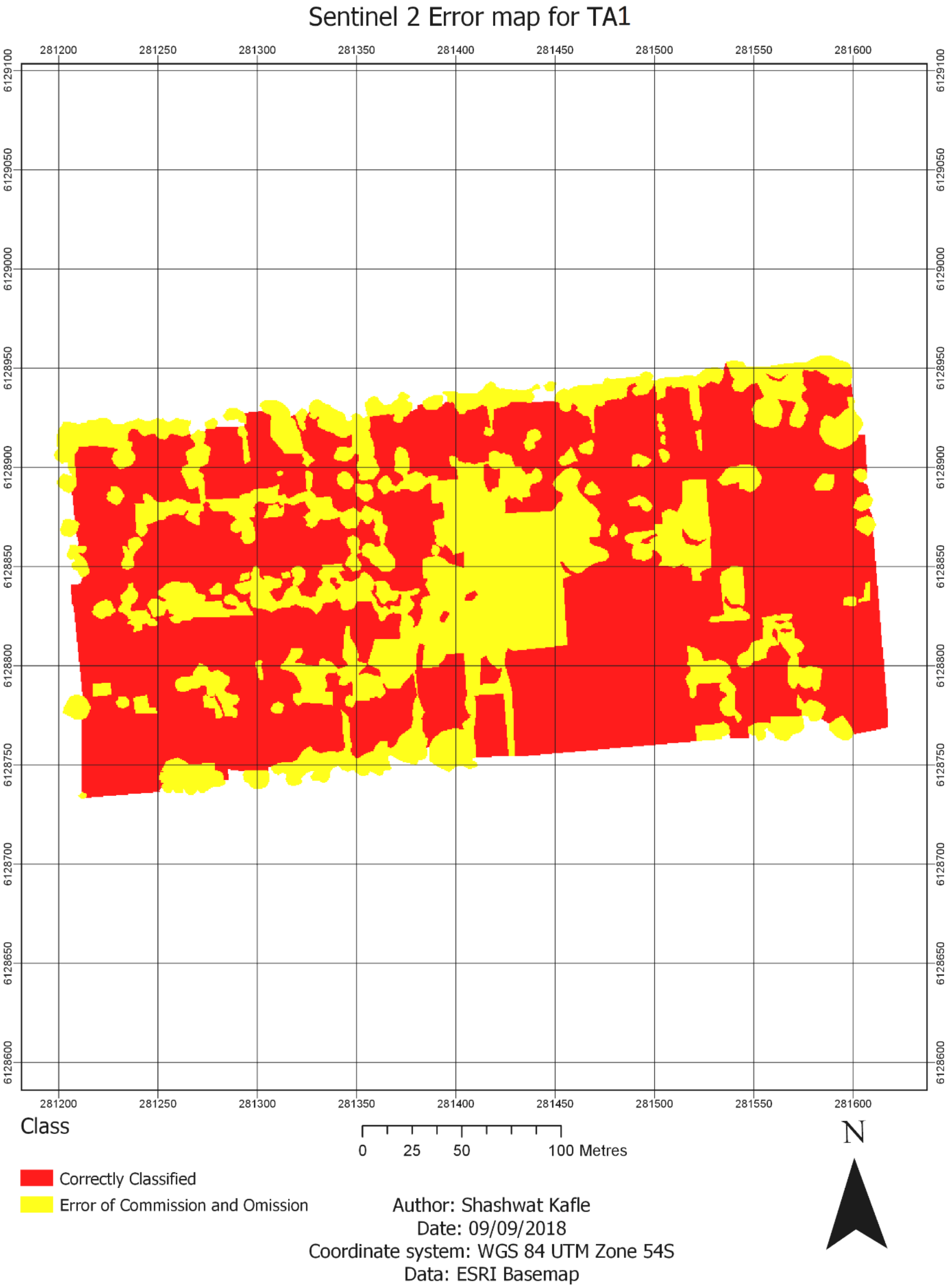

Figure 19: Error Map Sentinel 2

5.0 Discussion

5.1 THNDVI

Although the accuracy for various methods used to map urban vegetation were produced, most of the time they strongly indicated a higher accuracy for the higher spatial resolution imagery, while the accuracy decreased as the spatial resolution decreased. This general trend is observable in Figure 20, though there is less accuracy variation between satellites when the vegetated area is high.

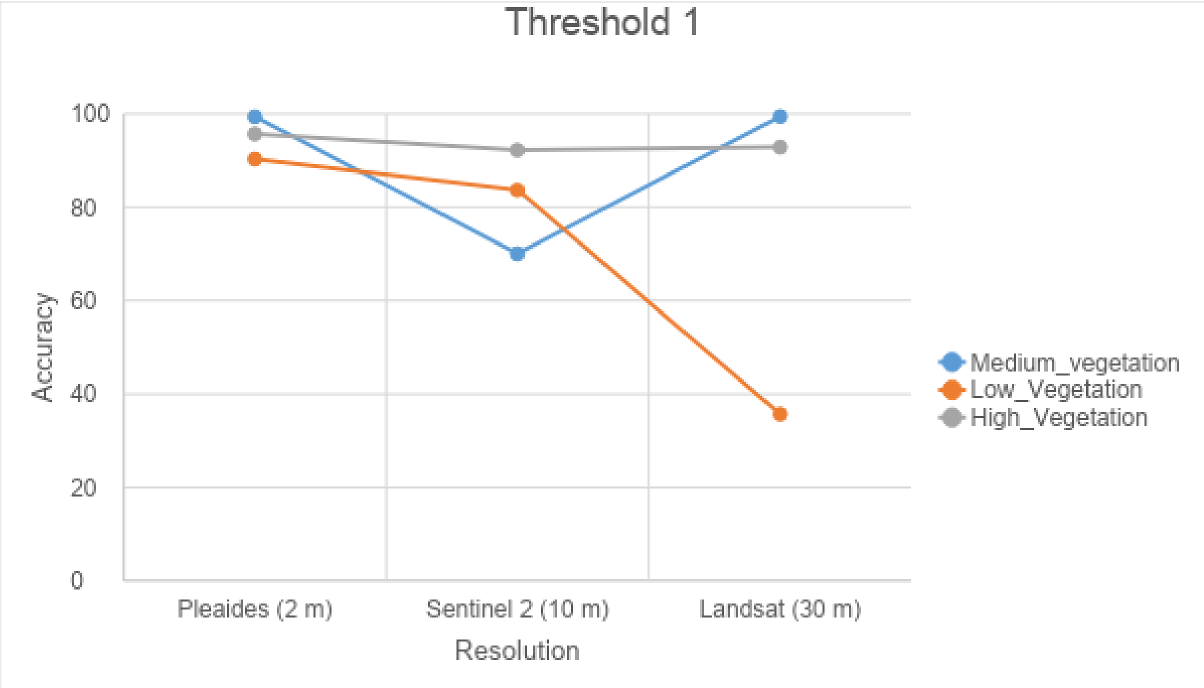

Figure 20: Accuracy vs Resolution for THNDVI

It was clear from the results obtained that different images yielded different values for NDVI due to the reflectance and the size of the pixel, insofar as the smaller is the pixel the greater the probability is that the pixel will have no mixed reflectance values. For instance, the 2 m resolution of Pleiades where the area of each pixel is 4 sq. m is significantly smaller than the Landsat pixel of 900 sq. m. It is because of this that Pleiades imagery had more pixels that were "spectrally pure" (containing just one feature) instead of mixed pixels (containing more than one feature), which affects its reflectance, and which further affects NDVI values as the NDVI value is calculated based on the reflectance of NIR and Red band. For this reason, all three images yielded different ranges of NDVI values, and so the threshold for each of them was different.

The difference in NDVI value between all three images indicated that there is a difference between red and NIR value for the same feature in all the images. As a different sensor and a different atmosphere in a different satellite gives rise to different values of red and NIR, this eventually results in different NDVI values. To some extent in this context, NDVI itself normalises the atmospheric difference issue. But in some cases, these variation in the NDVI value in different sensors might affect applications such as monitoring, change detection etc. Besides that, it will mainly affect the time series trend such as the annual, long-term trend derived from remote sensing methods which help to monitor and detect change in land cover (Bradley et al., 2007). NDVI derived phenological data might not be reliable as NDVI itself may be inaccurate due to atmospheric effects and the sensor effect (Bradley et al., 2007, Trishchenko et al., 2002, Van Leeuwen et al., 2006).

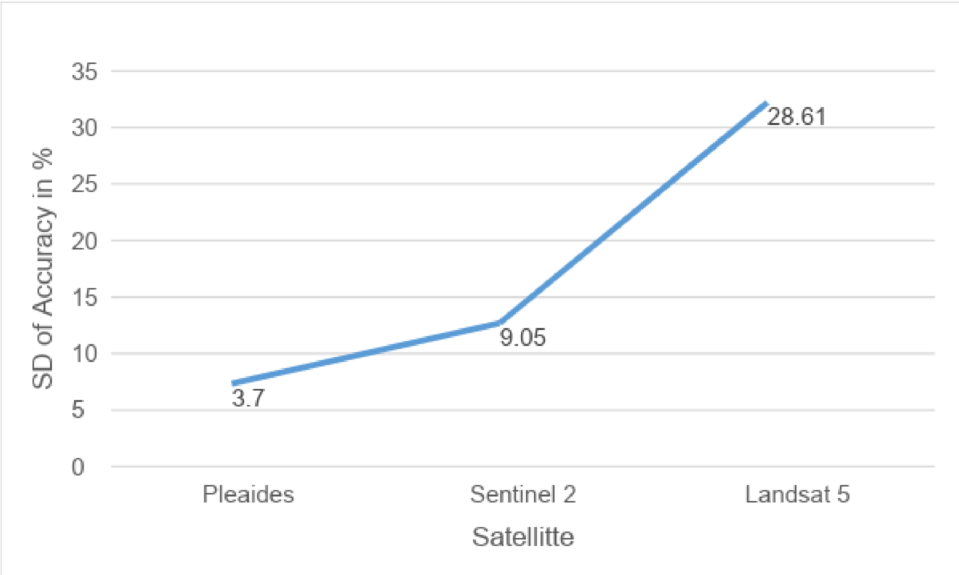

Figure 21: Plot of SD of accuracy (%) for different satellites

In Figure 21, it was discovered that the standard deviation (SD) for the accuracy of Pleiades was 3.7 %, for Sentinel 2 it was 9.05 %, while Landsat was very high at 28.61 %. This statistic illustrates that although Landsat in some points shows a result with very high accuracy, such as in this case of medium vegetation where it recorded an accuracy of almost 99.5%, comparable to that of Pleiades, Pleiades remains 225 times better than Landsat in terms of spatial resolution. The SD of Landsat is significantly higher in comparison to Pleiades and Sentinel 2; a higher SD means more uncertainty in the results. Although Landsat provides astonishing results in some instances, it is still not as reliable as other medium or high-resolution images because it is inconsistent. There could be a number of potential reasons for Landsat images yielding this result, such as a smaller number of pure pixels. As the vegetation in an urban area is being mapped, this vegetation includes not only canopies but also grass, gardens and small trees inside residential premises. Since there is a heterogeneity that changes rapidly per spatial unit in the context of an urban area, a pixel as large as 30 m might include other features in addition to the vegetation present at that point. This heavily impacts the reflectance of the pixel, which further affects the NDVI. In contrast, Sentinel 2 and Pleiades have a medium (10 m) and high (2 m) spatial resolution respectively, which potentially produces a higher number of "pure" pixels (in comparison to Landsat's 30 m pixel that purely represents vegetation without any other features present in it). Consequently, when there are other non-vegetation surfaces (but which still show some reflectance in NIR and red band) alongside some real vegetation, such as grass or a canopy of trees (which give high reflectance in NIR and red band) present in the same pixels in Landsat due to these mixed pixels the NDVI value of the pixel will be quite high. This leads to classifying the mixed pixel as pure vegetation or as a pixel with a majority of vegetation present within it. Many researchers using this method and this image are not taking this problem into consideration when formulating a hypothesis (Dadvand et al., 2012, Van de Voorde et al., 2008). Therefore, any conclusion drawn without considering the effects of mixed pixels on NDVI might be significantly inaccurate.

Another issue is determining the correct threshold for THNDVI. Although THNDVI showed remarkable accuracy in order to obtain that accuracy the proper threshold must be set. In this research, the threshold was decided based on GIS data, which was the ground truth. Setting the threshold also introduced errors of both commission and omission. For instance, in Figure 22 the tennis court (an artificial feature which was verified after a field visit) had no vegetation present in it but was classified as vegetation (error of commission). Yet in other cases some vegetation was classified as non-vegetation (error of omission). Proper thresholds should be selected in order to achieve minimal errors of both commission and omission, as these errors also determine the accuracy of the map, not just overall accuracy. If a very high threshold is set, a high level of errors of omission will be introduced, while if a very low threshold is set a high error of commission rate is introduced. Errors of both commission and omission should be checked using various GIS statistics and the threshold. A plot between the threshold and accuracy (accuracy for each different threshold) can help in deciding what is the best threshold for the NDVI values. The threshold will also differ in a different satellite image, as the NDVI for different satellites is different, so determining the correct threshold must be done carefully. In this case the threshold for Pleiades was 0.15, at which point the map had a maximum accuracy level in comparison to any other map produced from any other methods. Table 6 shows the threshold used for different imagery and their respective accuracies in 3 Test Areas.

Table 6: Threshold for all 3 Imagery with their Accuracy

Image	Test Area	Accuracy	Threshold
Sentinel 2	TA1	92.19	0.3
	TA2	70.02	
	TA3	83.66	
Pleaides	TA1	95.66	0.15
	TA2	99.36	
	TA3	90.28	
Landsat	TA1	92.82	0.1
	TA2	99.43	
	TA3	35.7	

Besides the ambiguity created by a larger pixel size or low spatial resolution imagery and the problem in setting the correct threshold, there is another consideration that may explain why images of low spatial resolution, such as Landsat, cannot be completely relied on for such analysis, which is geometric shift. As is clear from Figure 4 and as discussed in section 4.4, the acquired satellite images did not align properly to the basemap which was assumed to have the correct geometry. Moreover, the geometric correction was important as the ground truth was collected from the basemap, which, if referenced with a geometrically incorrect image, will not align either. However, during geometric correction the satellite images were resampled by confining the GCP residuals to half of their individual pixel size. Even after this correction, it was a close fit rather than a perfect fit. In other words, the images were resampled to show a minimum geometric shift. However, the RMS error on Landsat was around 5 m - 6 m, the best available result but still far from perfect. For this reason, it was also the case that the cells in the Landsat might possibly not align properly to the ground truth, on which the accuracy assessed for individual images was based. However, in the case of Sentinel and Pleiades the residual was low, due to which most of the pixels aligned with the ground truth and resulted in greater accuracy than that of low resolution Landsat. Aside from the mixed pixels and spatial resolution issues, there was also an issue in the spectral side of the imagery.

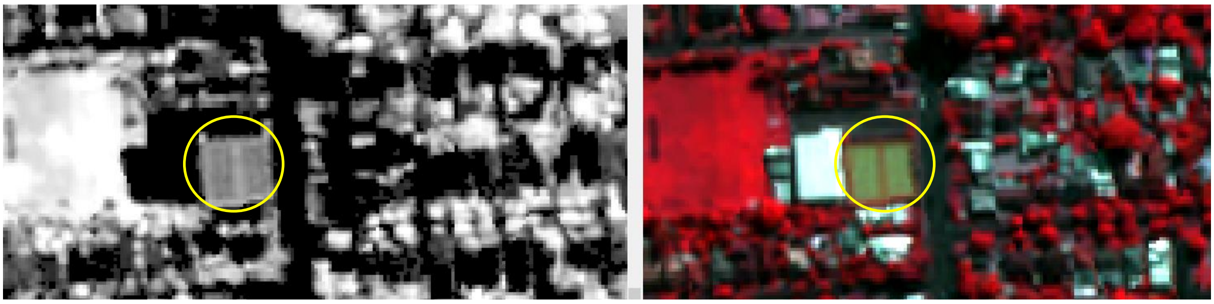

Figure 22: Comparison of NDVI value and real features (THNDVI Raster on left and Pleiades Image on right)

In Figure 22, the area inside the yellow circle on the right is a tennis court made of synthetic grass; this is an artificial feature with probably no chlorophyll present in it which was checked and confirmed after site visit. However, it still has some reflectance in the NIR band due to which it also displays some NDVI value. This may have happened because those are synthetic turfs with artificial grass and sand in them. If these turfs are not taken care of and cleaned properly, mosses might start to develop due to a build-up of dirt and moisture. These mosses have chlorophyll present in them, which exhibits some positive NDVI value. Hence, artificial features like these which ordinarily should not show any NDVI values present some NDVI value, which may well be above the threshold. If that is the case, then such features will be classified as vegetation. Yet it cannot be defined as vegetation, which might cause problems for researchers in fields related to health that use this method to map vegetation and conclude that everything with an NDVI value above a certain threshold is green vegetation (Dadvand et al., 2012, Van de Voorde et al., 2008).

Some of the literature (Carlson and Ripley, 1997, Nichol and Lee, 2005, Van de Voorde et al., 2008) deals with this problem. For instance, Van de Voorde et al 2008 mentions comparing pixels of Landsat satellite imagery to high resolution IKONOS imagery, in order to detect any land use change between the timespan of acquisition of the Landsat and IKONOS imagery. However, in this instance they fail to mention how accurately the Landsat image aligned with the IKONOS image, so that the pixels can be compared accurately and precisely. Moreover, researchers who use this method to map vegetation in order to analyse it in relation to other factors such as human health fail to mention geometric shifts, atmospheric corrections and the error induced by these things on the final map acquired. Without considering these factors, they may also come to an inaccurate conclusion.

5.2 Supervised Classification

In the context of supervised classification, in the case Sentinel 2 and Pleiades images, acquiring the signature to classify the image was not a problem due to its medium and high resolution. The signature of canopies and grass present in residential and commercial objects such as houses, buildings and factories could be easily extracted due to the resolution of the image. However, in the case of Landsat this could not be done as easily. The reason is that the pixel size was too large and in order to identify a canopy or a grass of the size of one third of the pixel, or even smaller features such as gardens or small trees, was visually challenging. In order to overcome this difficulty, the classification of the Landsat image was based on only two classes, vegetation and non-vegetation. However, as mentioned in section 3.5 of Methods, sub-pixel classification is one of the methods which can potentially overcome this issue as it exploits the spectral properties of pixel. Support Vector Machine (SVM) spectral unmixing might be one of the applicable methods for classifying an image with a high degree of heterogeneity, provided that there is a large training sample (MacLachlan et al., 2017). Although, as discussed above, sub-pixel classification is not applicable due to the low spectral resolution of Pleiades, which was used for the image analysis in this research. In comparison to Sentinel 2, Pleiades classified features such as tree and grass with a higher accuracy level due to its spatial resolution, indicating that even though features such as trees or grass are visually identifiable in Sentinel 2 images they may not be able tom be accurately classified. However, contrary to Pleiades, Sentinel 2 still has a number of mixed pixels which may confuse the classification algorithm and eventually lead to some misclassification of such features. Yet to compare the results between all imagery, even Pleiades and Sentinel 2 were classified in two classes as was Landsat. The accuracy obtained for each satellite for different classifications can be seen in Tables 4 and 5. In either case of classification, Pleiades had the highest average accuracy in comparison to Sentinel 2 and Landsat. Nevertheless, Sentinel, despite its medium resolution of 10 m, also displayed a result that was on par with Pleiades in terms of accuracy. However, at a high resolution the spatial heterogeneity of Pleiades imagery was clearer than the other two, where even features such as shadows were very difficult to identify in Sentinel 2 and almost impossible to identify in Landsat but were clearly visible and prominent in Pleiades.

Figure 23: Shadows around building in Adelaide CBD

Due to these shadows, an example of which can be seen in Figure 23, many features were eclipsed beneath the shadow and moreover, those features were wrongly classified as water as can be seen in Figure 25. Since shadows and deep water have similar reflectance properties, in that they absorb most of the bands and appear dark visually, there arises many instances of potential misclassification between shadows and water. In some instances (such as in Figure 24), the water bodies were misclassified as shadows in some places.

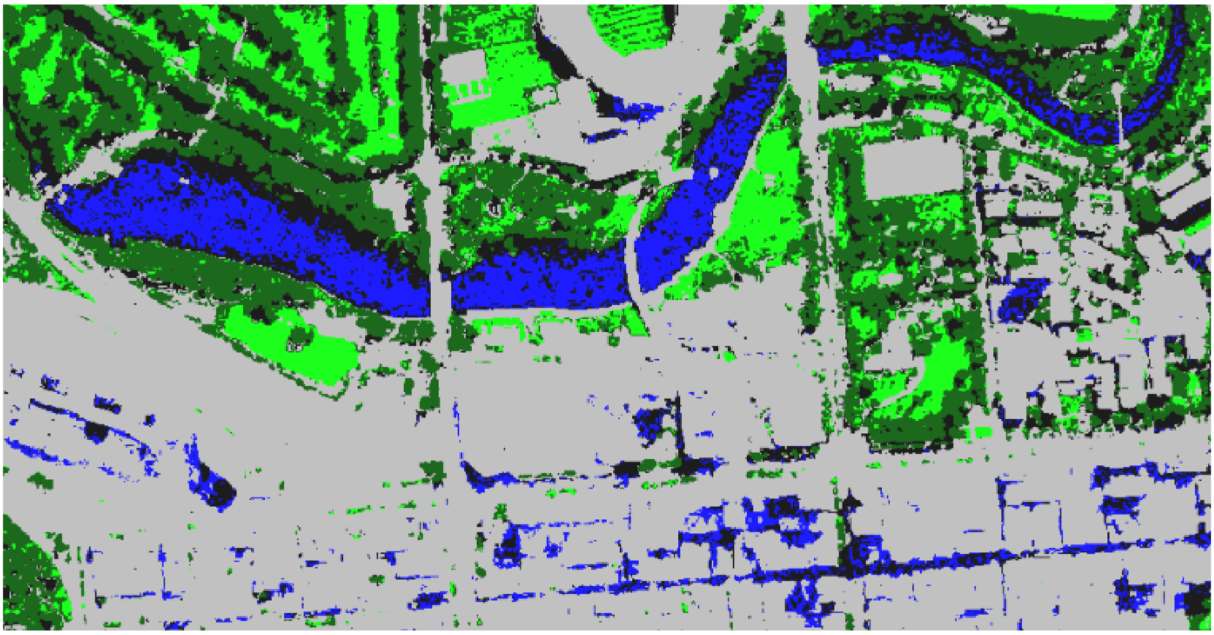

Figure 24: Water body misclassified as shadow and shadow misclassified as water (Dark Green=Tree, Light Green=Grass, Blue=Water, Black=Shadow, Grey=Non-Vegetation, Yellow=Unclassified)

This may be a possible explanation for the almost equal accuracy recorded between Pleiades and Sentinel 2, as in the above picture the shadows of the structure are clearly visible. The features present beneath the shadows there, such as trees, grass and non-vegetation features, were classified as shadow/water, leading to a misclassification. As a result, this misclassification leads to a decrease in the overall accuracy of the classified map. The misclassification and loss of details due to misclassification can be seen below:

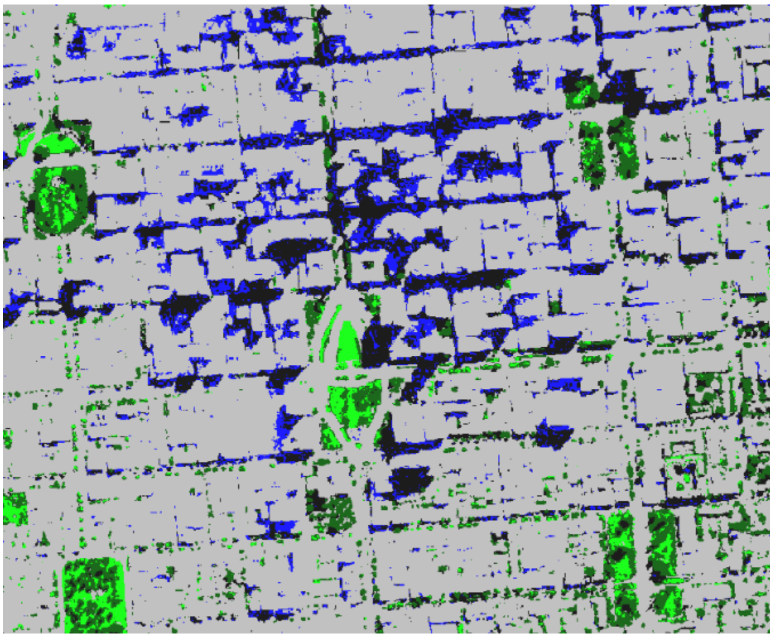

Figure 25: Misclassification of shadow around the Adelaide CBD (Dark Green=Tree, Light Green=Grass, Blue=Water, Black=Shadow, Grey=Non-Vegetation)

The misclassification is clear in Figure 25, where the majority of important features underneath the shadow are classified as shadow or water, ultimately leading to a diminishing of the overall accuracy of the classification. The cause of this problem is that satellite imagery, which was used in this research, is sun synchronous meaning that the elevation of the sun between different images is different, despite having the same azimuth. Due to this there will be shadows, as in an urban area such as Adelaide there are a lot of tall buildings which will cast wide shadows. The only possible solution to this problem is acquiring the image at the time of the summer solstice, which is 22nd December in the southern hemisphere, yet even at that time there will be minimal shadow to the south (with no shadow only at 23.5 degrees south latitude).

However, an analysis based on a single image is possible but not reliable for extrapolating as to the overall extent of vegetation present in an urban area, as some might be deciduous and if plant phenology is to be considered then a multidate image analysis should be conducted in order to obtain a more reliable result. Furthermore, in this case due to a lack of availability of multidate images for Pleaides, a multidate image analysis was not done. Furthermore, multidate image analysis is only reliable if the image is of a high resolution, so as to detect any change in vegetation (Tigges et al., 2013). Therefore, a multidate image analysis on medium and low-resolution satellite imagery might not yield a useful result either.

Table 7: Error of Commission in Pleiades for TA 1

	Number of classified pixels	Total Row	Error (%)
Shadow	13565	15745	86.15
Non_vegetation	36293	369373	9.83
Grass	16892	47671	35.43
Tree	141849	218349	64.97

Table 6 illustrates the error of commission when classifying Pleiades in four classes. Although the overall accuracy for this patch was found to be almost 68%, it shows a high level of error of commission on three classes. Also listed below are the errors of omission for the same patch for the same satellite image:

Table 8: Error of omission for TA1 for Pleiades Classification

	Number of classified pixels	Total Column	Error (%)
Shadow	3589	5769	62.21
Non_vegetation	93268	426348	21.88
Grass	94066	124845	75.35
Tree	17676	94176	18.77

It is clear from Table 8 that not only are errors of commission high, but errors of omission are also high, because of which it may be concluded that although the classification accuracy for this patch was found to be 68%, this classification may not be sufficient for it to be considered for the purpose of mapping vegetation in an urban area. But this is not the case when the classification is done using only two classes where shadow is included in the non-vegetation class while trees and grass are included in the vegetation class.

Table 9: Error of Commission in Pleiades for TA 1 (Only 2 classes)

	Number of classified pixels	Total Row	Error (%)
Non_vegetation	88187	432632	20.38
Veg	41583	218869	18.99

Table 10: Error of Omission in Pleiades for TA1 (only 2 classes)

	Number of classified pixels	Total Column	Error (%)
Non_vegetation	41583	386028	10.77
Veg	88187	265473	33.22

It is clear from Table 9 and Table 10 that the errors of both omission and commission may be significantly reduced to a satisfactory level when the image is classified for only two distinct classes and the accuracy for this classification is obtained at 80%. When the number of classes is reduced, it is more logical and less ambiguous to train the data so that the classification yielded a high accuracy in comparison to where there were multiple classes. Similarly, when the number of classes was reduced during the classification in Sentinel 2 the accuracy also increased significantly. But at the extremes of the spectrum, the classification accuracy of supervised classification also depends on the user's knowledge and interpretation, because if the signature acquired is not correct then the classification will be inaccurate regardless of the overall accuracy of classification. Therefore, the accuracy of supervised classification depends not only upon the available statistics but is also heavily dependent on the skills of the user in identifying on the image exactly what they are classifying.

As the results obtained from different methods and images showed different levels of accuracy, these accuracy levels are to be considered according to their use. For instance, if the objective of the research is to monitor street trees, then a high level of accuracy is required as street trees have a comparatively small canopy size compared to that of trees in parks. In this case, if a low accuracy is used then most of the street trees will be mixed in with the street due to mixed pixels (error of omission). However, in the event that someone requires an urban vegetation map in order to plan land plotting, where the plotting is planned based on the distance from parks and vegetation in the area, the map must be highly accurate. On the other hand, if a vegetation map is being used to determine greenness levels in a suburb, then a medium level of accuracy is acceptable. The bottom line is that importance of accuracy levels varies for different applications and, moreover, higher accuracy levels are required for a smaller study extent such as TA's in this research, while medium accuracy levels might be acceptable for a larger study area such as a state, country etc. If a low accuracy level is used on an area that requires greater attention to details, then the result may not be acceptable for the purpose.

5.3 Costs Incurred

When the results were evaluated at the end and considering all the efforts and problems that were encountered, there were three main costs encountered: (1) Data acquisition, (2) set-up costs and (3) time spent on analysis and image processing. The highest cost incurred during this academic research was the set-up costs. The software used for this research can potentially run on an ordinary computer system, but a faster processor and good storage system can provide additional benefits. A faster processor and HDD would result in faster processing and save a lot of time. Such a high-end system with a faster processor can handle all the tasks simultaneously and provide storage which is faster than a traditional hard drive, and can load images and the software quickly and efficiently. Another set-up cost incurred was the license fee for the software; as this was academic research, educational licensed software was used. As the software was provided by the university for research purposes, it was free of charge but only for student use. However, if this was a commercial project a huge license fee would need to have been paid for acquiring software such as ArcGIS Pro or ERDAS Imagine. The fee for the license does not only include the licensing price, it also includes an annual maintenance fee. The next highest cost incurred was (3) time spent on analysis and image processing. This section includes tasks such as processing images, using various tools to perform an analysis and obtain various statistics, the user's exploration on different methods to be used and finding suitable ways to use those methods which requires a lot of study in areas including findings, the literature review, field visits for accuracy assessments and validation of the results, time spent on interpretation of the data, preparing more than a dozen maps etc.

The cost incurred on data acquisition depends on the objective of the research. In this case, two satellite images used were free of charge (Sentinel 2 and Landsat), whereas Pleiades is not freely available. The cost for Pleiades per Sq. Km is AUD 15-24 (refer to Table 1). As has been mentioned previously, the satellite imagery is selected based on the objective of the research. If that objective can be met using a medium resolution satellite such as Sentinel 2, then the price incurred for data acquisition can be reduced to nil. However, if the objective requires a very fine resolution image, such as that of SuperView or Pleiades, the cost for data acquisition will surpass other costs such as the set-up cost and will further increase as the extent of the study area in the research increases. So the cost incurred for data acquisition varies considerably depending on the scope, objective and study area of the research.

In this research, three different datasets were used. Among the three datasets used, Landsat was free of charge, Sentinel 2 was also free of charge for academic and research purpose, while Pleiades was not normally freely available like Sentinel 2 and Landsat, but thanks to my supervisor it was made available for this research but was not available free of charge when my supervisor acquired access to it. The processing for all the images was carried out in the same system. However, the processing time was longer for Pleiades than it was for the other two. So, for the three major cost drivers, the set-up cost was consistent across all data sources used, while the data acquisition cost and time spent on analysis and processing was comparatively higher for Pleiades imagery. This difference in major cost drivers between the three different data sources used indicates a trade-off between cost and accuracy. It was clear that Pleaides allowed the most accurate map to be obtained, but in terms of cost drivers was costlier than the other two, while Sentinel 2 and Landsat were comparatively less accurate but incurred minimal costs. So, there is clearly a trade-off between accuracy and cost incurred in image processing.

6.0 CONCLUSION

After analysing all the results obtained using various methods on various imagery of different resolutions, the most accurate and effective method for mapping urban vegetation was found to be the THNDVI method. The satellite image for the THNDVI Method with the lowest spatial resolution had an average accuracy of 75%. Moreover, the dataset or image that provided the best accuracy was Pleiades imagery due to its high resolution. The average accuracy was 95% for THNDVI in the case of Pleiades. However, in the context of supervised classification the accuracy varied when the number of classes also varied (see Tables 6,7,8 and 9). For the purposes of this research, due to its high resolution, Pleiades had the highest accuracy amongst all the images used. Yet although the results for supervised classification seemed to be promising, the number of errors of commission and omission was high enough to potentially call into question whether the results obtained were accurate enough. Even in some instances of supervised classification, Pleiades and Sentinel 2 had a very similar level of accuracy despite their being on a completely different level of resolution (spatial). That may have occurred because Pleiades has a low spectral resolution of 4 bands compared to 13 bands for Sentinel 2. As the supervised classification is based on the signatures of the training data, the high spectral resolution of Sentinel 2 might have an advantage over Pleiades in this respect. Similar results were recorded for THNDVI between Pleiades and Sentinel 2. Although Pleiades had an outstanding accuracy of 95%, Sentinel also had an accuracy of 82% which was quite acceptable considering the scope and objective of this research. However, the result achieved from supervised classification, although the classification controlled for just two different features (vegetation and non-vegetation) which were visually appealing, was not accurate enough considering the number of errors or omission and commission. Even in the high-resolution Pleiades, where the errors of commission and omission were comparatively lower than that of Sentinel 2 and Landsat, and which showed a higher average accuracy, still had errors of commission and omission which were potentially unacceptable. In the context of THNDVI, despite a higher accuracy level than supervised classification, many features exhibit NDVI value which is also a type of classification error in the case of THNDVI (classifying artificial features as vegetation/greenness). But in comparison to the supervised classification errors of omission and commission in THNDVI, such misclassifications were less frequent. However, if a specified signature or quality of training data can be improved, the likelihood is that supervised classification can also potentially yield greater accuracy with fewer misclassification errors.

In the context of cost, as discussed in section 5.3, there is a clear trade-off between accuracy and cost. The results obtained in section 4.0 clearly show that Pleiades, with the highest resolution, demonstrated a higher degree of accuracy than the other two medium and low-resolution images across all the methods. Despite that, Sentinel 2 as a medium-resolution satellite displayed some promising results, which might be acceptable in the context of many potential research objectives. Even for THNDVI, Sentinel 2 achieved a notable accuracy of 82%, but still fell well short of the 95% accuracy achieved by Pleiades. Yet it must be understood that high-resolution imagery such as Pleiades or Superview are not freely available. The higher accuracy results obtained clearly come at a cost. A similar pattern emerges in the case of supervised classification. Pleiades recorded the highest overall classification accuracy here as well. So there is a clear trade-off between accuracy and cost. Although the cost of high resolution imagery is also high, it pays off in terms of the accuracy obtained after image classification, yet some freely available medium resolution satellites such as Sentinel 2 also show promising accuracy. So the answer to the research question is that the best method among the two was found to be THNDVI, while the most accurate map was the one obtained from Pleiades. This result also indicates that the highest accuracy and best results cannot be obtained at a low cost, but depending on the objective of the research, free and medium resolution images such as Sentinel 2 can also provide acceptable results. For the purposes of commercial use, Sentinel 2 is also not free but will be significantly less costly than other available high-resolution imagery.

7.0 FUTURE RESEARCH

There are a number of other popular methods besides either NDVI or supervised classification, which could potentially be used to attempt to verify the results. Since the introduction of ERDAS Imagine 2018, machine learning is becoming increasingly popular, although it was still somewhat popular under earlier available software. However, there is very little literature that deals specifically with machine learning for mapping vegetation in an urban area but there are substantial literature using Machine Learning to map vegetation. With many methods machine learning segments, the image, which creates many difficulties, particularly in urban areas such as Adelaide as these areas have a high degree of spatial heterogeneity, and that spatial heterogeneity becomes even more distinct in high resolution imagery such as Pleiades. The results obtained from machine learning are worthy of further investigation, as some of the researchers who have used it mentioned getting surprising results using this algorithm. Due to time constraints, this algorithm could not be applied to this research, but this method represents a promising potential area for similar research in future.

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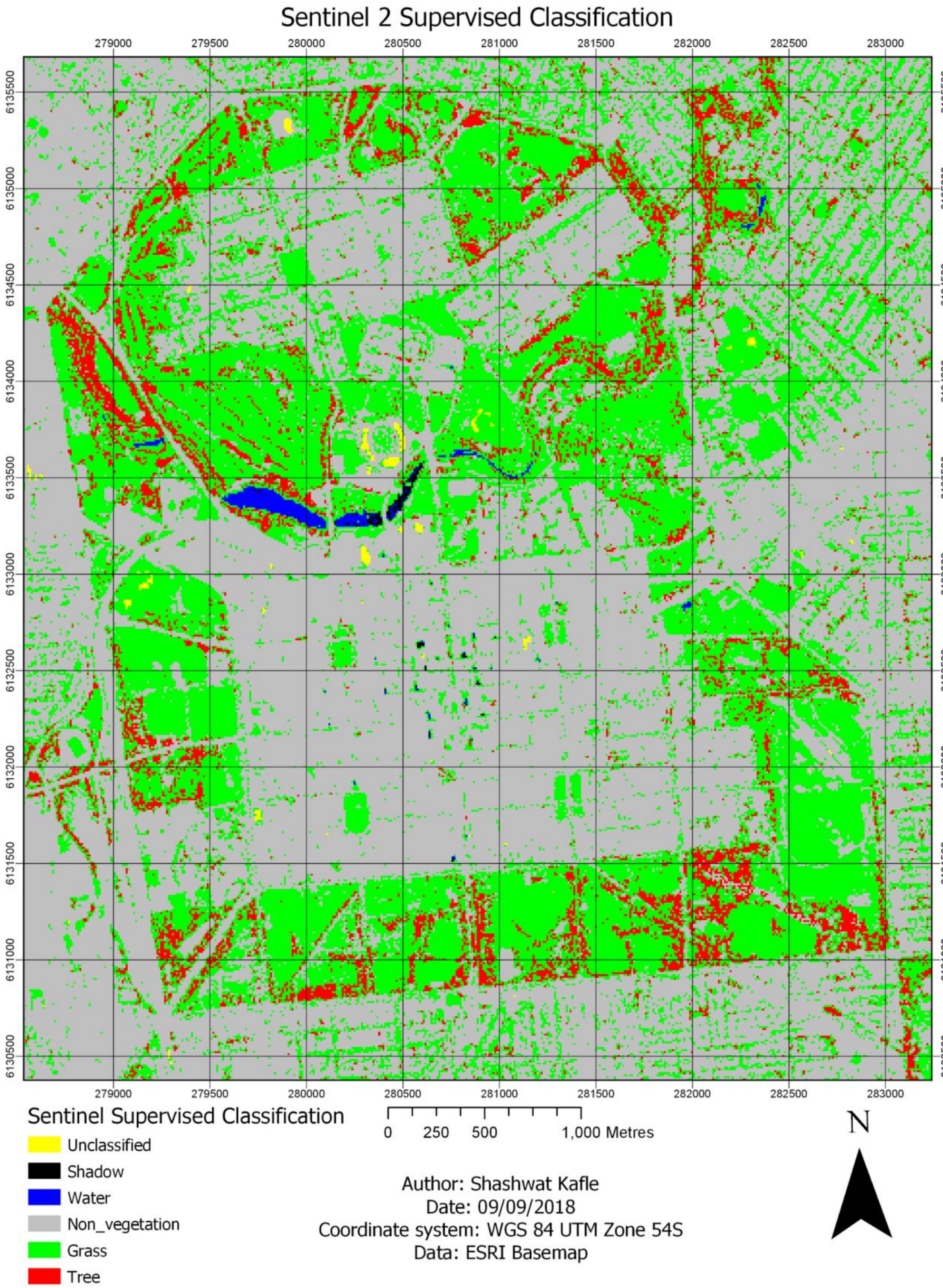
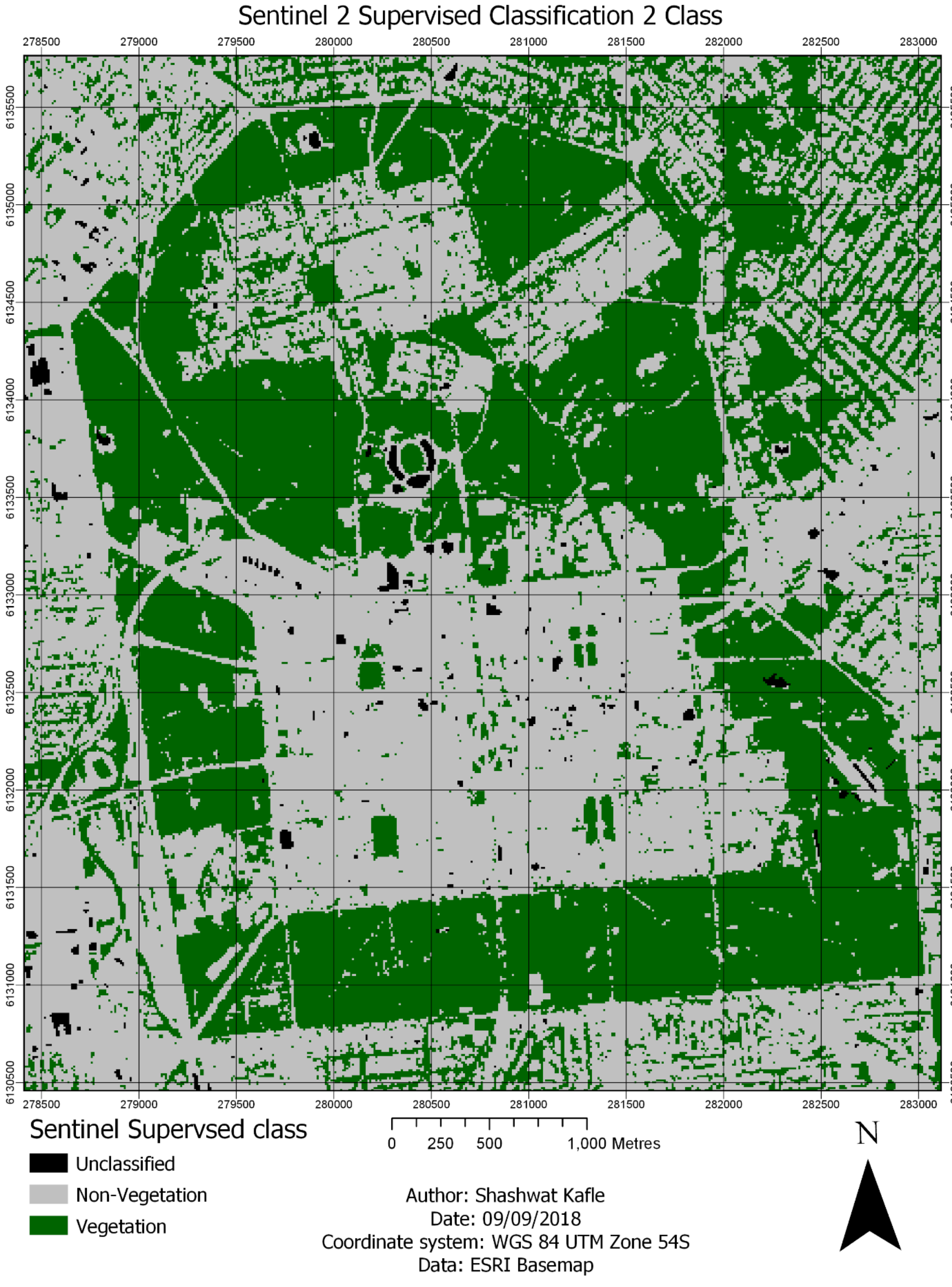
APPENDICES

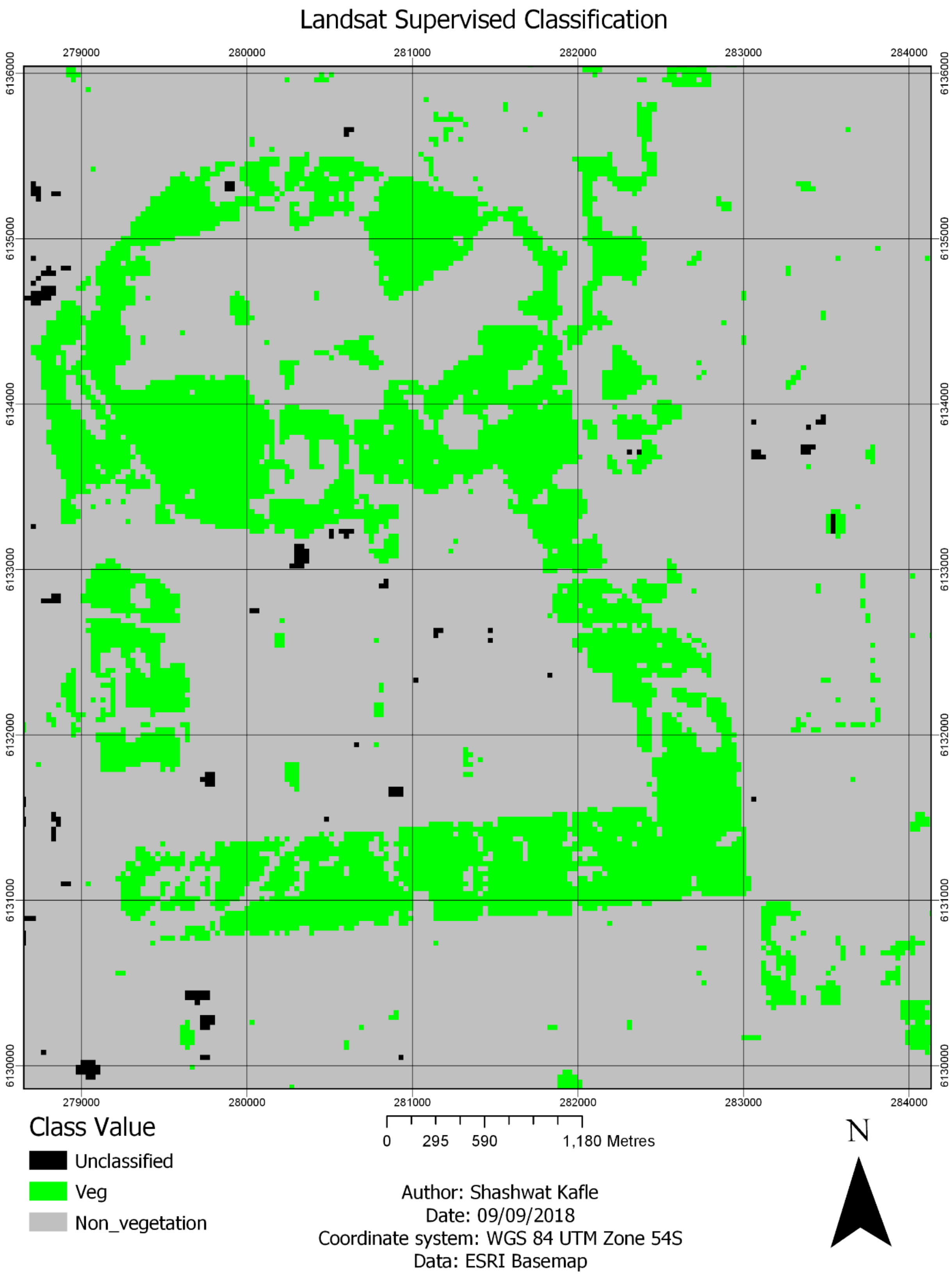
Appendix 1: Sentinel Supervised Classification for 5 classes



Appendix 2: Sentinel 2 supervised classification for 2 class



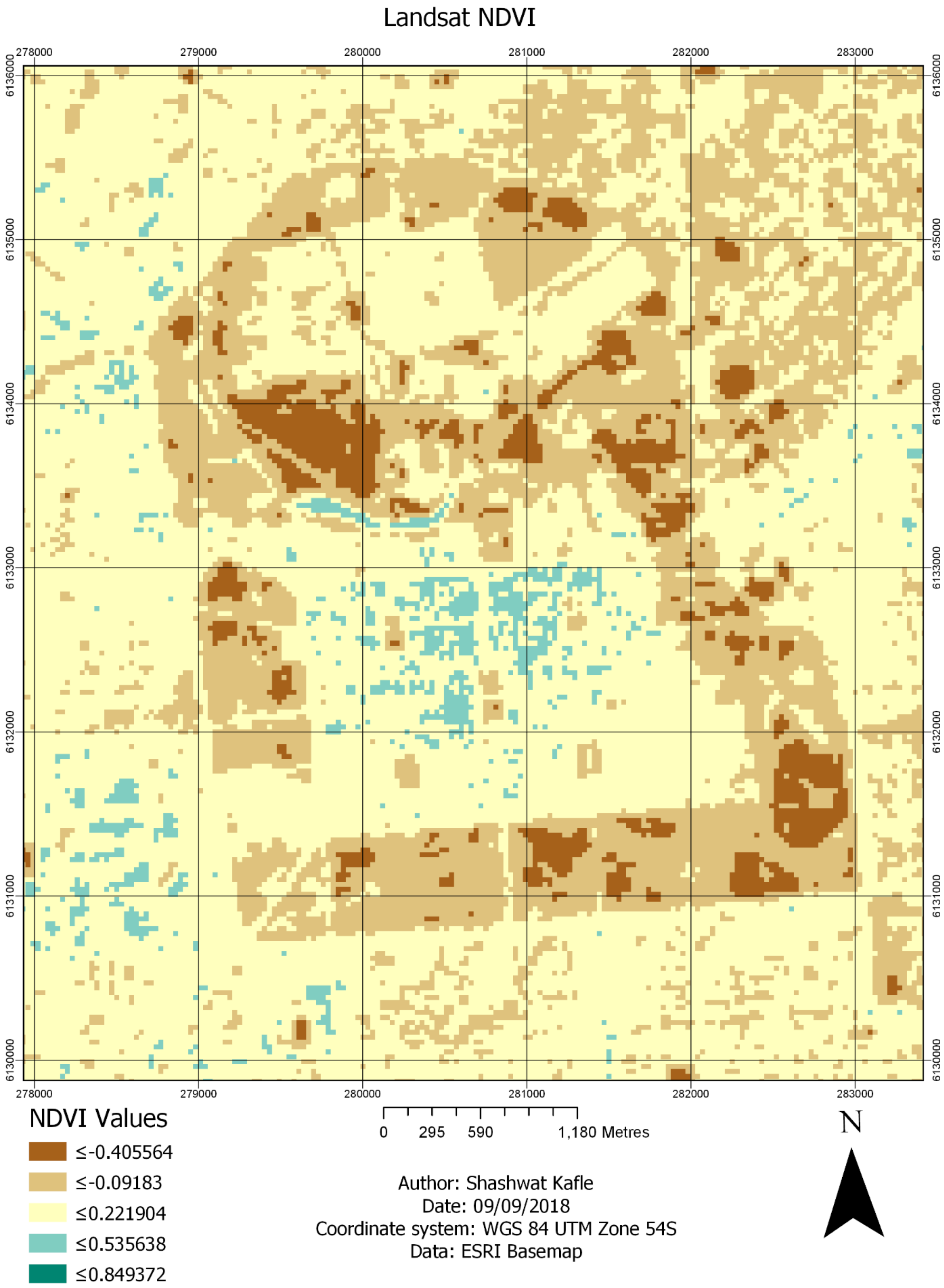
Appendix 3: Landsat supervised classification for 2 class



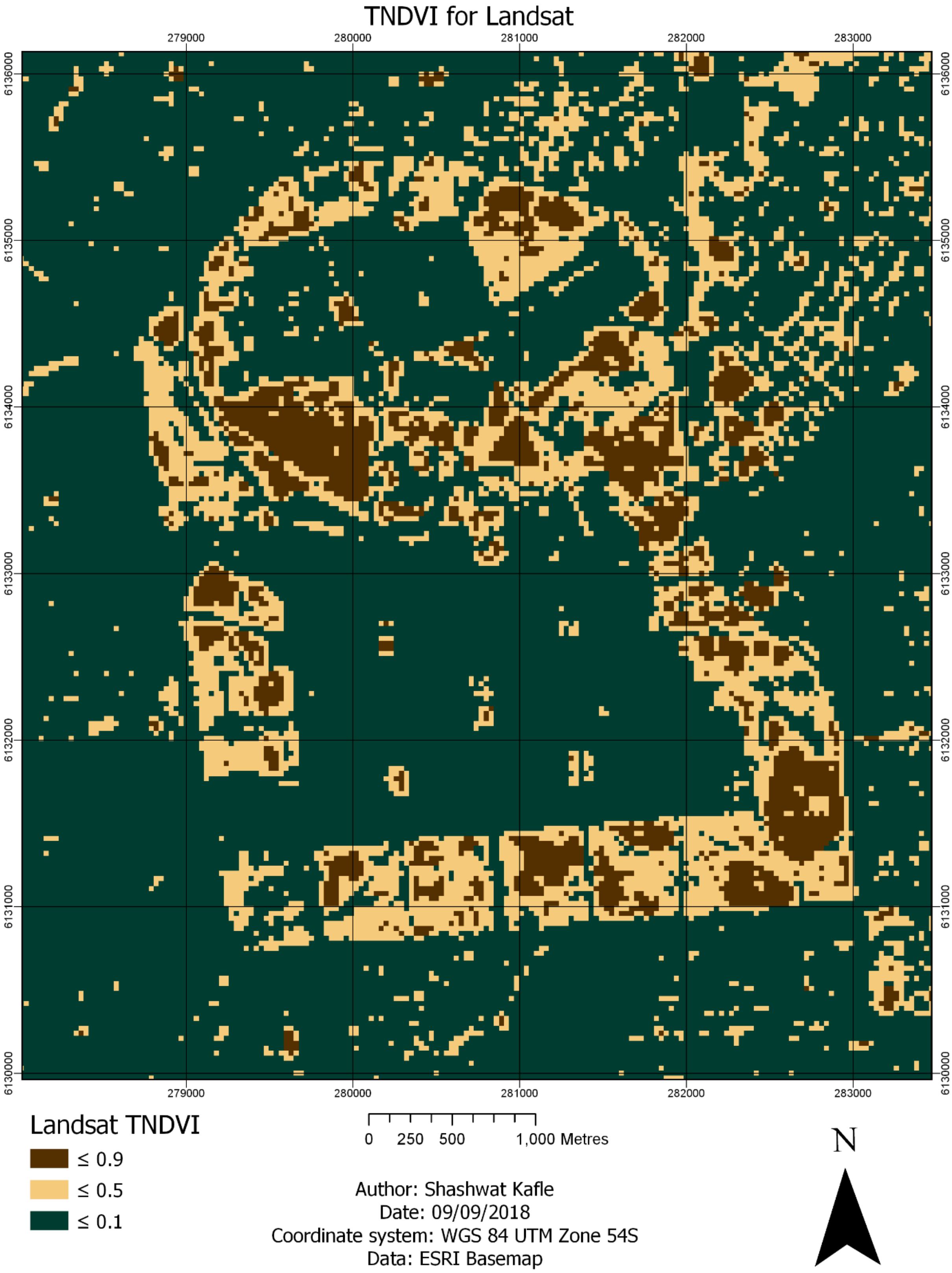
Appendix 4: Sentinel NDVI

Appendix 5: Sentinel 2 THNDVI

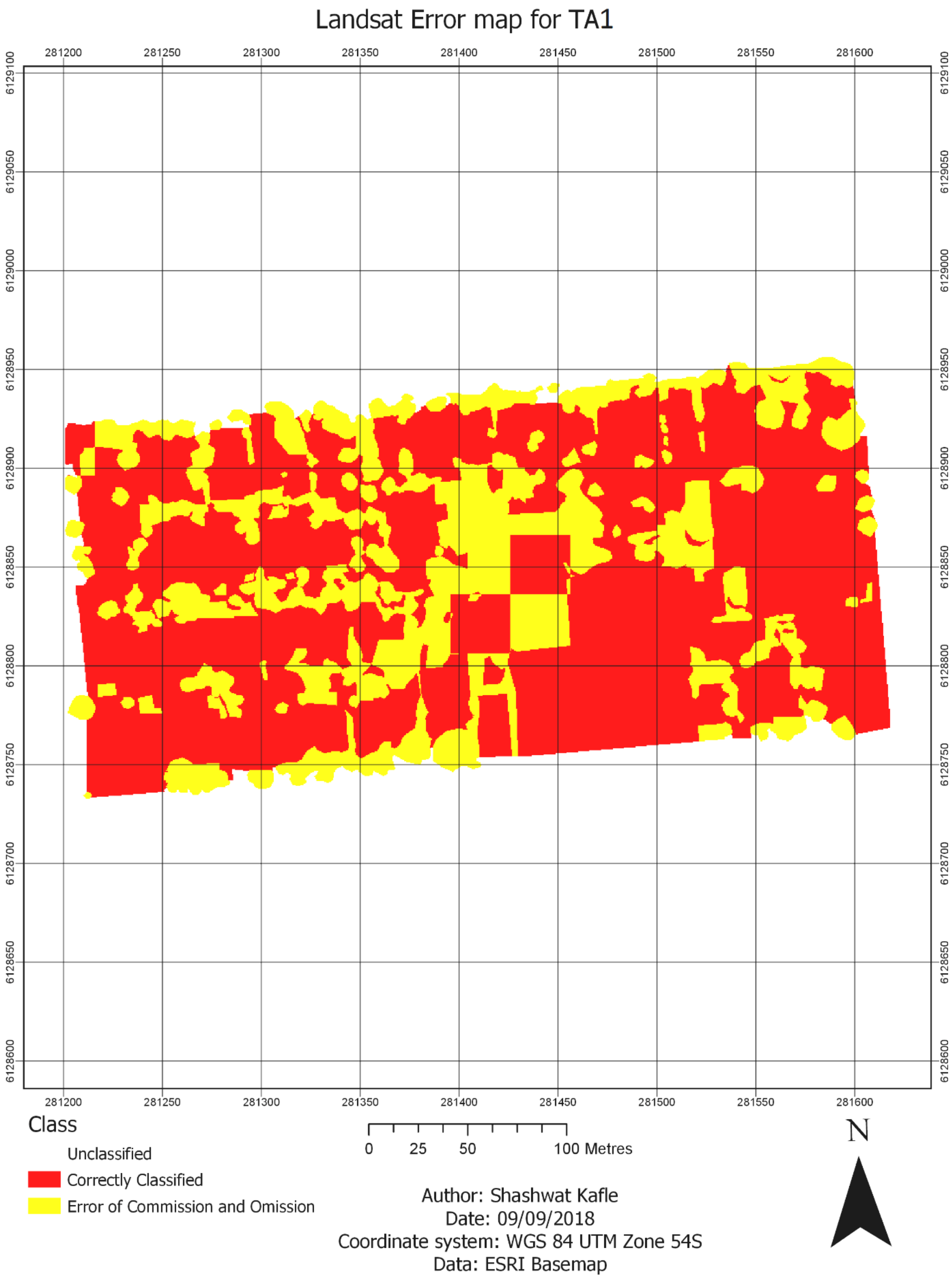
Appendix 6: Landsat NDVI



Appendix 7: Landsat THNDVI



Appendix 8: Landsat Error map for Supervised Classification



Appendix 9: Error matrix for Sentinel for 4 class of TA2

		Reference				
		Shadow	Non_veg	Grass	Tree	Total
Classified	Shadow	0	0	0	0	0
	Non_veg	2129	342977	66274	35285	446665
	Grass	3500	81952	62194	49695	197341
	Tree	2089	12780	5585	15643	36097
	Total	7718	437709	134053	100623	420814

Appendix 10: Error matrix of Sentinel for 2 class of TA2

		Reference Data		
		Non_veg	Veg	Total
Classified Data	Non_veg	345322	100118	445440
	Veg	101445	133231	234676
	Total	446767	233349	478553

Appendix 11: Error matrix of Pleiades for 2 class of TA2

		Reference Data		
		Non_veg	Veg	Total
Classified Data	Non_veg	344445	88187	432632
	Veg	41583	177286	218869
	Total	386028	265473	521731

Appendix 12: Error matrix of Pleiades for 4 class of TA2

		Reference Data				
		Shadow	Non_veg	Grass	Tree	Total
Classified Data	Shadow	2180	8631	3312	1622	15745
	Non_veg	1554	333080	22813	11926	369373
	Grass	95	12669	30779	4128	47671
	Tree	1940	71968	67941	76500	218349
	Total	5769	426348	124845	94176	442539

Appendix 13: Error matrix of Landsat for 2 class of TA2

		Reference Data		
		Non_veg	Vegetation	total
Classified Data	Non_Veg	425441	210505	635946
	Vegetation	9561	24174	33735
	total	435002	234679	449615

Appendix 14: Error matrix of Sentinel 2 for 4 class of TA1

		Reference Data				
		Shadow	Non-Veg	Grasss	Trees	Total
Classified Data	Shadow	0	0	0	0	0
	Non-Veg	864	170288	20795	35127	227074
	Grass	1234	25792	7906	33312	68244
	Trees	158	1146	434	2596	4334
	Total	2256	197226	29135	71035	299652

Appendix 15: Error matrix of Sentinel 2 for 2 class of TA1

		Reference Data		
		Non_Veg	Veg	Total
Classified Data	Non_Veg	171294	28183	199477
	Veg	55871	44298	100169
	Total	227165	72481	215592

Appendix 16: Error matrix of Landsat for 2 class of TA1

		Referenced Data		
		Non_veg	Veg	total
Classified Data	Non_veg	198912	565	199477
	Veg	91883	8156	100039
	total	290795	8721	207068

Appendix 17: Error matrix of Pleiades for 4 class of TA1

		Referenced Data				
		shadow	non_veg	Grass	Tree	total
Classified Data	shadow	357	2085	86	2723	5251
	non_veg	667	130689	4694	11349	147399
	Grass	22	11847	10399	3423	25691
	Tree	805	47282	13267	46830	108184
	total	1851	191903	28446	64325	188275

Appendix 18: Error matrix of Pleiades for 2 class of TA1

		Reference Data		
		Non_Veg	Veg	total
Classified Data	Non_Veg	133960	18911	152871
	Veg	60023	74000	134023
	total	193983	92911	207960

Appendix 19: Error matrix of Pleiades for 2 class of TA3

		Reference Data		
		Non_veg	Veg	total
Classified Data	Non_veg	62986	8653	71639
	Veg	13362	17421	30783
	total	76348	26074	80407

Appendix 20: Error matrix of Pleiades for 4 class of TA3

		Reference Data				
		shadow	Non_veg	Grass	Tree	total
Classified Data	shadow	0	558	0	98	656
	Non_veg	0	61997	4540	9137	75674
	Grass	0	2473	4324	2455	9252
	Tree	0	6622	1886	8323	16831
	total	0	71650	10750	20013	74644

Appendix 21: Error matrix of Sentinel 2 for 4 class of TA3

		Reference Data				
		shadow	Non_veg	Grass	Tree	total
Classified Data	shadow	0	323	94	276	693
	Non_veg	0	71236	4298	172	75706
	Grass	0	6185	3052	36	9273
	Tree	0	11750	4787	316	16853
	total	0	89494	12231	800	74604

Appendix 22: Error matrix of Sentinel 2 for 2 class of TA3

		Reference Data		
		Non_veg	Veg	total
Classified Data	Non_veg	71559	4840	76399
	Veg	17935	8191	26126
	total	89494	13031	79750

Appendix 23: Error matrix of Landsat for 2 class of TA3

		Reference Data		
		Non_veg	Veg	total
Classified Data	Non_veg	74277	461	74738
	Veg	22247	3139	25386
	total	96524	3600	77416