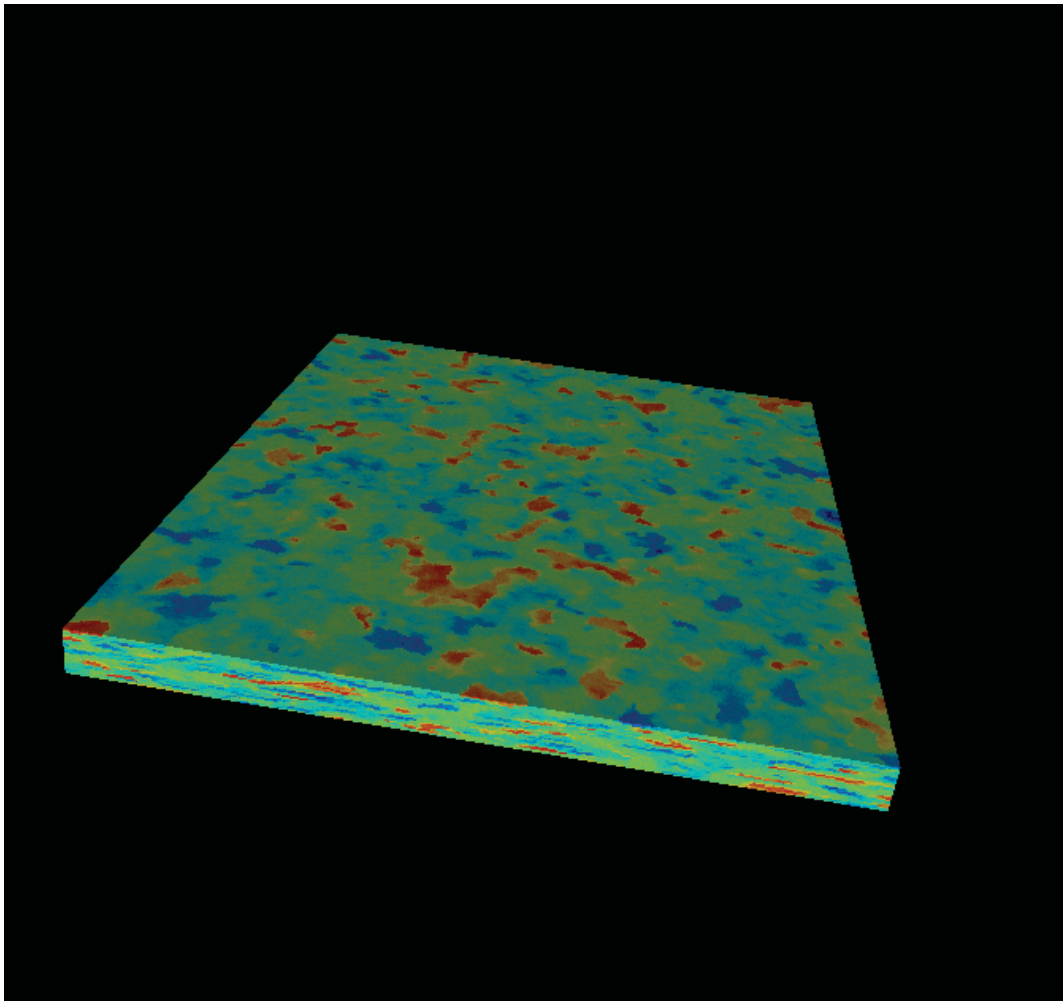


# Quantifying Groundwater Ages in Heterogeneous Environments



**James L. McCallum**

BSc. EnvSci. (Honours).

As a requirement in full for the degree of Doctor of Philosophy in the School of the Environment, Flinders University, South Australia



## **Declaration**

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

James L. McCallum

## **Co-authorship**

James McCallum is the primary author on all manuscripts in this thesis. On all submitted papers, the co-authors provided intellectual supervision and editorial content.

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## Summary

The age of groundwater is of great interest as it infers the timescales of groundwater flow and solute transport. As such, a number of methods exist for determining the age of groundwater in simple groundwater systems where flow and transport properties are constant in space. These methods include the use of naturally occurring and anthropogenic compounds (from this point collectively referred to as environmental tracers) to estimate groundwater age, and the use of numerical simulation techniques. The applicability of these methods outside of these contexts have been demonstrated to be limited. Hence, there is a need to assess how these methods may be applied in non-ideal contexts.

This body of work addresses the quantification of groundwater ages in complex environments where flow and transport properties are highly spatially variable. Specifically, this work investigates: (1) The bias of traditional “apparent age” estimates in heterogeneous environments. (2) The accuracy of correction schemes to correct for errors in age estimates encountered in complex environments. (3) How the choice of a geostatistical model can impact on the estimates of numerically simulated groundwater age distributions in heterogeneous environments. (4) A new method for estimating groundwater age distributions without the assumption of a prior model.

In the first part of this research, we used numerical simulations of synthetic two-dimensional aquifers to investigate the bias of age dating techniques. We simulated synthetic aquifers by varying both the range of hydraulic conductivity values and the structure of the hydraulic conductivity fields. Numerical flow simulations were undertaken and environmental tracer concentrations were simulated. We hypothesised that errors in apparent ages may behave as a correctable bias rather than as a random error. These biases are due to non-linear temporal variations in the concentrations of the compounds used for dating, and the mixing arising from the variations of flow-paths in these systems. The findings of this study suggest that using multiple tracers with differing biases may allow for mean ages to be determined.

The second part of this we assessed the accuracy of techniques that account for biases. These techniques include the use of correction factors based on aquifer structures, the use of mean transit times derived from lumped parameter models, and techniques using ages from multiple tracers. The study was also implemented in a numerical context allowing comparisons to be made. Simulations comprised of four aquifers - a homogeneous aquifer, an aquifer with high conductivity lenses and two aquifer/aquitard systems. Environmental tracer concentrations were then used in conjunction with correction schemes. The research highlighted some of the limitations regarding the use of environmental tracers to infer groundwater “age”. The correction schemes require some knowledge of the aquifers limiting the usefulness of adding such data to studies. Additionally, many of the correction schemes are not applicable outside of the context of their explicit assumptions. This work has implications for the use of environmental tracers outside of ideal contexts, in that using apparent ages in conjunction with models of mean or advective ages will produce erroneous results.

The third study investigated the numerical simulation of groundwater age distributions in heterogeneous aquifers. The study involved testing the ability of a number of geostatistical techniques to re-create the groundwater age distribution of a two-dimensional synthetic aquifer with varying levels of hydraulic conductivity data. Generally, in practice, values of hydraulic conductivity are only known at discrete locations. To simulate an entire K-field, a simulation technique is required. The study demonstrated the importance of the geostatistical model when estimating residence time distributions. Generally, a larger amount of conditioning data and a method able to recreate multiple scales of features will improve the estimate.

The final study proposed a new method for estimating groundwater age distributions with environmental tracer data. The use of lumped parameter models to estimate groundwater age distributions is limited by the simple assumptions of the model. Numerical simulation techniques, whilst able to simulate more complex systems, are limited by the required detail of spatially variable parameters. In this approach we assumed that the relationship between historic concentrations and measured groundwater concentrations could be fully explained by the convolution relationship. We used this to assess how various levels of concentration data are able to inform the groundwater residence time distribution. We demonstrate that even with large amounts of environmental tracer data, estimates of residence time distributions are highly non-unique. This has implications for the use of lumped parameter models, as the ability of a model to fit environmental tracer concentration data does not necessarily validate its choice.





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