MODELLING FUTURE LAND-USE CHANGE AND ASSESSING RESULTANT STREAMFLOW RESPONSES: A CASE STUDY OF TWO DIVERSE SOUTHERN AFRICAN CATCHMENTS

by

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Submitted in fulfilment of the academic requirements for the degree of

Master of Science

in Environmental Science

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July 2022

ABSTRACT

Land-use and land cover (LULC) is a crucial constitute of the terrestrial ecosystem, impacting on numerous fundamental processes and characteristics such as land productivity, geomorphological process and the hydrological cycle. Assessing the hydrological impacts of land-use and land cover changes (LULCCs) has become one of many challenges in hydrological research. LULCCs modify hydrological processes such as evapotranspiration, infiltration and interception, consequently impacting on the hydrological regimes of a catchment. Understanding the implications of LULCCs on catchment hydrology is therefore fundamental for effective water resource planning and management, and land-use planning. Globally, numerous studies have documented the impacts of LULCCs on catchment hydrology, however in Southern Africa there exists a knowledge gap on the impacts of LULCCs on catchment hydrology, specifically future land-use and land cover change (LULCC). Therefore, the aim of this study was to simulate potential future land-use within two diverse South African catchments using an appropriate land-use change model and thereafter to assess streamflow responses to these future land-use scenarios using the ACRU hydrological model.

Future land-use was simulated utilizing the Cellular Automata Markov (CA-Markov) model. The CA-Markov model is a hybrid land-use change model that integrates Markov chain, CA, Multi-Objective Land Allocation (MOLA) and Multi-Criteria Evaluation (MCE) concepts. CA-Markov simulated future land-use through the creation of conditional probability and transition probability matrices, suitability images and the utilization of a CA contiguity filter and socio-economic and biophysical drivers of LULCC. The results illustrated that within both catchments, increasing growth of anthropogenically driven LULC classes such as urban, agroforestry and agrarian areas inevitability contribute to the fragmentation, modification and deterioration of natural land-cover types. The model's reliability and capability was assessed by running a validation, which was conducted by simulating changes between t_1 (1990) and t_2 (2013/14) to predict for t_3 (2018). The predicted map produced for 2018 was then compared against the actual 2018 reclassified map, which served as a reference map. The obtained kappa values (Kstandard, Klocation and Kno) achieved during the validation were all above 80%, thus indicating the model's reliability and capability in successfully predicting future LULC in the study sites.

The assessment of future LULCC impacts on streamflow responses was achieved by utilizing the ACRU model. Historical and future scenarios of land-use were utilized as inputs into a pre-existing ACRU model where all input parameters (e.g. climate, soils) remained constant with only changes made to the land cover parameters and area occupied by each land cover. The results illustrated that due to anthropogenic induced LULCC, the hydrological regime within the uMngeni catchment has been altered when compared to the baseline hydrological regime. Patterns of low (1:10 driest year) and high (1:10 wettest year) flows have changed significantly between the baseline and 1990. However, between 1990 and the future hydrological regime (2030 LU scenario) only a slight amplification of these impacts was evident. Mean annual streamflow increases and decreases were present in majority of Water Management Units (WMU's), however, the Table Mountain, Pietermaritzburg, and Henley WMU's illustrated greater increases in mean annual accumulated streamflows compared to other WMU's while the New Hanover New Hanover and Karkloof WMU's illustrated the greatest decreases in mean annual accumulated streamflows.

Furthermore, results indicated that streamflow responses significantly increase in the presence of urban land-use. The impacts become evident as streamflows cascade through the catchment. The results also illustrated that streamflow responses were due to the nature of LULCC, *viz* urban land-use, commercial forestry, and agriculture combined with the location and extent of LULCCs.

These results are beneficial for the implementation of proactive and sustainable water resource planning and land-use planning. Moreover, considering the simulated streamflow responses in relation to varying land-use scenarios, it is essential that water resource planning incorporate land-use location, nature and scale from not only the perspective of land-use effects, but also on hydrological responses in a catchment. Given the interdependence between streamflow responses and changes in land-use, water resource and land-use planning should not occur in silos. Overall, this study illustrated the importance of understanding and assessing land-use and water interactions in a water stressed region such as South Africa.

Keywords: land-use and land cover changes, hybrid land-use change model, streamflow responses, land-use and water interactions, sustainable water resource planning

PREFACE

The research in this dissertation was completed by the candidate while based in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg under the supervision of Dr. Michele Toucher and Dr. Romano Trent Lottering. The Durban Research Action Partnership (DRAP) GEC Phase 3 program and the National Research Fund financially supported the research.

This studies represent original work by the author and have not otherwise been submitted in any form for any degree or diploma to any other tertiary institution. Where use has been made of the work of others it is duly acknowledged in the text.

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DECLARATION 1 – PLAGIARISM

I, ***Kimara Moodley***, declare that

(i) the research reported in this dissertation, except where otherwise indicated or acknowledged, is my original work;

(ii) this dissertation has not been submitted in full or in part for any degree or examination to any other university;

(iii) this dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons;

(iv) this dissertation does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

  a) their words have been re-written, but the general information attributed to them has been referenced;

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(v) where I have used material for which publications followed, I have indicated in detail my role in the work;

(vi) this dissertation is primarily a collection of material, prepared by myself, published as journal articles or presented as a poster and oral presentations at conferences. In some cases, additional material has been included;

(vii) this dissertation does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the dissertation and in the References sections.

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Signed: Kimara Moodley

Date: 19/07/2022

DECLARATION 2 – PUBLICATIONS

Details of contribution to publications that form part of and/or include research presented in this thesis (includes publications in preparation, submitted, in press and published and give details of the contributions of each author to the experimental work and writing of each publication).

Publication 1 – Chapter 2 of this thesis

Moodley, K., Toucher, M.L., and Lottering, R. **Under Review**: Simulating future land-use within two diverse catchments in Southern Africa. *Scientific African*

The work and analysis for this publication was conducted by K. Moodley with technical advice from M.L. Toucher and R. Lottering. The publication was written in its entirety by K. Moodley, and all figures, tables and graphs were produced by the same, unless otherwise referenced in the text of the paper. Editing and advice regarding interpretation was provided by M.L. Toucher and R. Lottering

Publication 2 – Chapter 3 of this thesis

Moodley, K., Toucher, M.L., and Lottering, R. **Under preparation**: Assessing the impacts of future land-use changes on streamflow responses within the uMngeni catchment.

The work and analysis for this publication was conducted by K. Moodley with technical advice from M.L. Toucher and R. Lottering. The publication was written in its entirety by K. Moodley, and all figures, tables and graphs were produced by the same, unless otherwise referenced in the text of the paper. Editing and advice regarding interpretation was provided by M.L. Toucher and R. Lottering.

ACKNOWLEDGEMENTS

I wish to extend my thanks and gratitude to the Durban Research Action Partnership (DRA'P) for providing me with top-up funding under the Global Environmental Change Research (GEC phase 3) Programme.

Thanks also goes out to the National Research Fund (NRF) for providing financial support during my final year of study.

I would like to extend my gratitude and acknowledge the below persons for their involvement and support during this research:

Dr Michele Toucher, South African Observation Network (SAEON) and School of Agricultural, Earth and Environmental Sciences (SAEES), University of KwaZulu-Natal, Pietermaritzburg for her undivided assistance, supervision, guidance and advice, this dissertation would have not been successful if it was not for her efforts. Dr Romano Trent Lottering, School of Agricultural, Earth and Environmental Sciences (SAEES), University of KwaZulu-Natal, Pietermaritzburg for his co-supervision and support.

Mrs Alize Le Roux**, Council for Scientific and Industrial Research (CSIR)** for her technical assistance with the land-use modelling issues.

Dr Michael S. Aduah, Department of Geomatics Engineering, University of Mines and Technology, Tarkwa, Ghana for his technical assistance and advice with hydrological modelling queries.

Mr Odebiri Omosalewa and Dr Trylee Nyasha Matongera PhD candidates, School of Agricultural, Earth and Environmental Sciences (SAEES), University of KwaZulu-Natal, Pietermaritzburg for their technical assistance, advice, help and continuous emotional support throughout this research.

Thanks also goes out to Mr Jeremy Naidoo and Mrs Susette Martin, Department of Water and sanitation for their assistance in providing me with digital spatial datasets.

Kerushen Chetty for his endless encouragement, love and understanding and friends and family for their unyielding motivation and support.

DEDICATION

Dedicated to my beloved grandmother Mrs Mavis Mapaith, your legacy lives on.

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ACRONYMS AND ABBREVIATIONS

AHP	Analytical hierarchy process
CA	Cellular Automata
DWA	Department of Water Affairs
EGIS	Environmental Affairs GIS
ET	Evapotranspiration
GDP	Gross Domestic Product
GIS	Geographic Information Systems
KZN	KwaZulu-Natal
LULC	Land-use and land-cover
LULCC	Land-use and land-cover change
LULCCs	Land-use/cover changes
MAP	Mean annual precipitation
MCE	Multi-criteria evaluation
MMTS	Mooi-uMngeni Transfer Scheme
PGDP	Provincial Growth and Development Plan
RS	Remote sensing
SANLC	South African National Land-Cover
SIP’s	Strategic Integrated Projects
WLC	Weighted Linear Combination function
WMU’s	Water Management Units

CHAPTER ONE: BACKGROUND AND INTRODUCTION

Land-use and land-cover change (LULCC) are significant contributors to global environmental change (Li *et al.* 2018) and impact on various aspects of the environment including hydrology (Scanlon *et al.* 2007). Land-use and land-cover (LULC) are two terms that are interrelated but have different meanings (Rawat and Kumar 2015). “Land-cover” can be referred to as the identifiable landscapes on the earth’s surface, namely forests, grassland and waterbodies. In contrast, the term “land-use”, makes reference to the utilization of land by humans for activities such as commercial forestry and cropping (Keys and McConnell 2005; Lambin 2006; Ellis and Pontius 2007).

Land-cover change can take one of two forms: modification or conversion. Modification is altering the land’s attributes but not its overall classification, for example, the modification of forests due to logging. Conversion refers to land being transformed from one land-cover category to another, for example, natural forest clearing for cropland (Lambin *et al*. 2003). LULCC occurs due to conversions of, or the intensification of present LULC (Turner *et al.* 1995), as a result of complex interactions between the physical environment and society (Pielke *et al*. 2011).

The environment and its associated ecologies are one of the first areas to be impacted by changes in land-use (Aspinall and Hill 2008; Ellis and Pontius 2007). Excessive pressure exerted on land resources for the purpose of food, shelter and water provision, has resulted in drastic LULCC, which has consequently altered hydrological regimes and water resources (Githui *et al.* 2009; Savenije *et al.* 2014; Gyamfi *et al.* 2016). Even though studies have investigated the relationship between hydrological processes and LULCC (Beighley and Moglen 2002; Wei *et al*. 2005; Chaves *et al*. 2008), limited hydro-climatological data coupled with the differences in catchment characteristics, creates challenges in fully understanding this relationship (Li and Sivapalan 2011; Tekleab *et al.* 2014).

Within South Africa, a primary factor impacting catchment hydrology, is LULCC (Albhaisi *et al*. 2013). Internationally, the impacts of LULCC on hydrology have been well documented (Brook *et al.* 2011; Baker *et al*. 2013; Yang *et al.* 2014; Ahn and Merwade 2017), and LULCC models are being implemented and utilized for the purpose of land-use planning and water resource planning related decisions. However, within South Africa there is sparse evidence indicating the implementation of land-use modelling applications accompanied with limited

LULC research (Wray *et al*. 2013; Tizora *et al*. 2016). There is no standard modelling approach to model land-use (Verburg *et al*. 2006), as selecting a land-use change model depends on study site, characteristics, data availability and research questions. After consulting various academic papers and comparative literature on LULCC models, two widely used and extensively cited cellular automata models were shortlisted to conduct a comparative study to determine the most suitable LULCC model to simulate future LULCC in the respective study sites. The CA (Cellular Automata) - Markov and Dyna-CLUE models were shortlisted based on their extensive applications and benefits when modelling LULCC in a developing country and local context (Aduah *et al*. 2017; Tizora *et al*. 2018; Aliani *et al*. 2019; Das *et al*. 2019; Pokojska 2019; Zhou *et al*. 2020; Tadese *et al*. 2021; Youneszadeh *et al*. 2021). Furthermore, these models employ sound mathematical and statistical techniques and theories, thus enabling them to simulate LULCC annually and provide the user with flexibility regarding data acquisition, inputs and processing (Le Roux 2012).

The CA-Markov model, which is an integration of the CA and Markov models, combines concepts of Multi-Objective Land Allocation (MOLA), Multi-Criteria Evaluation (MCE), Markov chains and Cellular automata (CA) (Ruben *et al.* 2020). The CA model controls the changes and evolution in the cells while the Markov chain produces the transition probability matrix (Kamusoko *et al*. 2009). Besides simulating two-way transitions between multiple LULC categories, the model also predicts changes among multiple LULC categories (Ye and Bai 2008), thus making it a spatially explicit robust LULCC model.

The Dynamic Conversion of Land-Use and its Effects model (Dyna-CLUE) developed by Fresco and Veldkamp (1996), is utilised to simulated future LULCC scenarios based on historical land-use (Verburg and Veldkamp 2004). The model has two distinctive modules, namely, a spatial allocation module and a non-spatial demand module. The model requires various inputs to dynamically model land-use change, *viz*; location characteristics, land-use demands (requirements), specific land-use conversions and spatial restrictions and policies.

As highlighted, both models are robust and capable of modelling LULCC within the study sites. Despite Dyna-Clues’ appealing advantages it was not used in this study due to the data requirements associated with the model. The model requires conversion elasticity values for each land-use this requires expert knowledge, visual interpretation and the analysis of historical LULC data. Moreover, spatial restrictions and policies were not applicable in this study. Land-use demand values require calculations which are produced independently from the model either through the integration of economic and macro-demographic models or through historical land-use trend extrapolation and require advanced spatial analysis knowledge. Therefore, the CA-Markov model was chosen and implemented as the most appropriate land-use change model based on the models reduced processing time, ease of use, data requirements and extensive application.

Simulating future LULCC through a land-use model, assists in evaluating and predicting LULCC impacts and providing solutions to LULCC impacts (Agarwal *et al*. 2002). Thereafter, a hydrological model can be utilised to determine hydrological responses to changing LULC. The KwaZulu-Natal (KZN) province is prone to high levels of ecological disturbances as a result of anthropogenic activities (Beires 2010). The uThukela river basin, the largest river in KwaZulu-Natal and the second largest river basin within South Africa (DWAF 2003) and the uMngeni river system, is characterized by rurality, lack of resources, poor catchment management and uneven water distribution (Van Der Kwast *et al*. 2013; PSEDS 2008). It is anticipated that changes in LULC will continue into the future. Several land-use change studies have been conducted in both catchments (Smith *et al*. 2010; Schulze and Horan 2007; Blignaut *et al*. 2010; Toucher *et al*. 2012; Mauck and Warburton 2013; Namugize *et al*. 2018). However, none of these studies have investigated how plausible scenarios of future changes in the land-use would impact streamflow. Hence, a study that is capable of determining the effects of future land-use on catchment hydrology within these catchments, will not only be beneficial in adding to the limited LULC studies within South Africa but will also enhance the understanding of the effects and dynamics of future land-use change on local catchment hydrology, which will facilitate better resource management, land-use planning and catchment services. The land-water nexus will be discussed and analysed further in sections 1.1 – 1.4

1.1 Interactions between LULCC and hydrology

A catchment's hydrological responses are related, amongst others, to the catchment land-use and are reactive to land-use changes (Schulze 2000; Bewket and Sterk 2005) as LULCC modifies the way in which precipitation is partitioned into the water budget components of inception, infiltration, soil water, evapotranspiration and runoff (Chen and Li 2004; DeFries and Eshleman 2004; Li *et al*. 2009; Moa and Cherkauer 2009). LULCC impacts on hydrological processes vary with catchment scale, are site specific (Gebremicael *et al.* 2019) and often threshold related.

The land-use location in a catchment, the degree of intrinsic land cover modification by anthropogenic effects and the severity of LULCC, all determine the degree to which land-use governs a catchment's hydrological response (Warburton *et al*. 2012). Catchment size also has an influence on the streamflow response to LULCC, for example, precipitation conversion into streamflow within a large catchment is usually more complex as a result of the increased variation with regards to properties of a specific catchment, such as geology, soils and land-use (Ashagrie *et al.* 2006). Blöschl *et al.* (2007) explained that any impact as a result of changes in land-use, will likely decrease with an increase in catchment size. The theory was confirmed by Peel (2009), who highlighted that land-use impacts on streamflow responses are more prevalent at smaller temporal and spatial scales (<1000 km^2).

Three land-uses that have a noteworthy influence on hydrological responses in a South African context are; intensification of agriculture via irrigation (Schulze 2003), urbanization (Choi and Deal 2008) and afforestation (Jewitt *et al*. 2009). The means by which the aforementioned land-uses impact hydrological responses differ from each other. For instance, urbanization affects hydrological responses through the substitution of vegetation with impermeable surfaces such as pavements, roads and artificial structures, which hinder rainfall infiltration and result in increased streamflow and surface runoff (Robinson *et al*. 2000; Marsalek *et al.* 2006). Zhang and Schiling (2006) showed that a transformation of land from seasonal vegetation cover to seasonal line crops resulted in a reduction in evapotranspiration. While Baker and Miller (2013) found that decreasing forest area also reduced evapotranspiration.

Therefore, investigating land-use change impacts on hydrological responses is crucial to better inform effective management of water resources and land-use planning (Memarian *et al.* 2014; Singh *et al.* 2014). Methods for analyzing land-use change impacts on hydrological responses include, statistical analysis, experimental catchment comparative analysis and modelling (Elfert and Bormann 2010). Modelling is one of many methods in a wide range of approaches and techniques available to reveal the dynamics of a land-use system (Verburg *et al*. 2006) and is the most commonly used method for the assessment of LULCC impacts on hydrology.

1.2 LULCC modelling and the role of land-use change models in LULCC studies

LULC patterns within a region are determined by economic, environmental and demographic driving factors (Verburg *et al.* 1999; Castella *et al.* 2007) that operate at local and regional scales. LULCC can be triggered by numerous factors such as biophysical conditions (Alemayehu *et al*. 2009; Yalew *et al*. 2016) and interactions between demographic and socio-economic changes (Bewket 2002; Jacob *et al.* 2016). Understanding these patterns and factors are essential for sustainable resource management (Castella *et al.* 2007) and robust land-use planning (Dietzel and Clarke 2006). However, this requires data relating to the place, time, rate and type of change together with the physical and social forces that propel these changes (Lambin and Ehrlich 1997). Interactions among these factors quite often can only be achieved through the use of land-use change models. The development of LULCC models have been influenced by three pertinent issues; theoretical developments in various fields accompanied by diverse perspectives and approaches around what should be modelled, data availability and the need for planning and policy (Batty 2008).

Land-use change models provide spatio-temporal and non-linearity analysis of LULCC as they utilize different methods to better understand spatial relationships between LULCC and their associated drivers (Verburg and Veldkamp 2004). In addition, these models also evaluate, predict, explain and support land-use policy and planning and help to improve understanding relating to land-use system functioning (Verburg *et al*. 2004). Moreover, land-use change models can represent plausible ways that the future might unfold through scenario developments (Dalla-Nora *et al*. 2014). LULCC models are capable of exploring dynamic processes linked to the land-use system, simulating LULCC trajectories and feedback loops via land-use scenario implementation and lastly, predicting the future development of land-use over space and time (Basse *et al*. 2014). LULCC modelling, especially when undertaken using an approach that is spatially explicit, serves as an important technique for conducting experiments that aid in LULCC understanding, describing key LULCC processes quantitatively, exploring and projecting future LULCC scenarios (Veldkamp and Lambin 2001). Modelling future land-use consists of applying artificial interactions to a specific land-use system to investigate anticipated future land-use dynamics and developments (Lambin and Geist 2006). It also aids in the determination of future land-use trends and provides useful information regarding probable future land-use conditions under varying scenarios (Koomen and Stillwell 2007). A variety of land-use change models exist and are classified into different categories for different applications.

1.3 Classifying land-use change models

Various classifications of land-use change models have been proposed in literature. For example, Briassoulis (2000) classified models according to (i) integration models, (ii) econometric and statistical models (iii), optimization models and (iv) spatial interaction models (Figure 1.1). Verburg *et al.* (2004) examined land-use change models with reference to seven features, namely, level of integration, driving factors, level of analysis, temporal dynamics, cross-scale dynamics, neighbourhood effects and spatial integration, for the purpose of describing numerous features of land-use change models that need to be taken into consideration when modelling. In a similar approach, Lambin *et al.* (2000) distinguished between integrated, stochastic, empirical statistical, dynamic simulation and optimization modelling approaches. More recently, Silva and Wu (2012) categorized land-use models by grouping them into six different benchmarks of modelling approaches: planning tasks, levels of analysis, spatial dimensions, temporal scales and spatial scales.

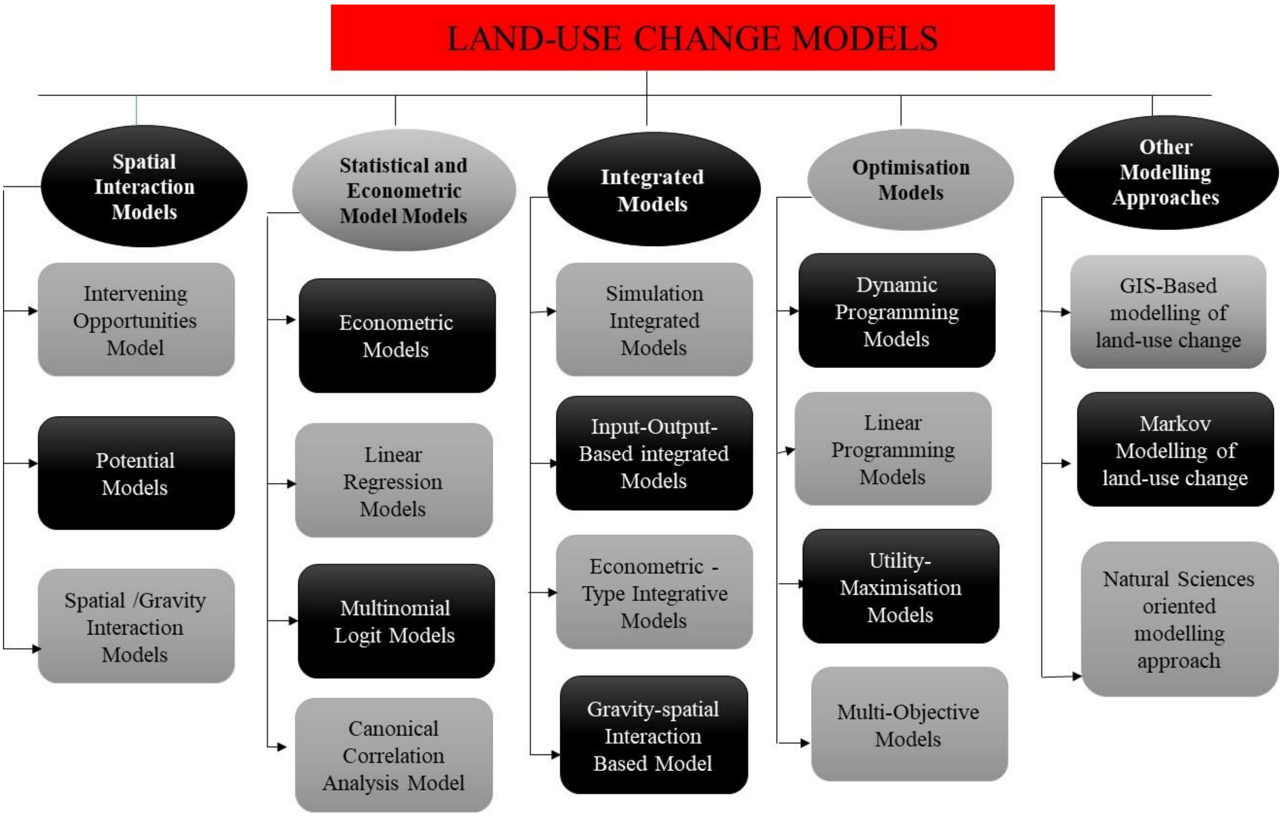

Figure 1.1: Common classifications of land-use change models (adapted from Briassoulis, 2000).

Literature has identified two main model structure types, *viz*.: top-down and bottom-up models (Table 1.1). Top down-models are based on remote sensing data and originate from landscape ecology (Castella and Verburg, 2007). The models are used when determining the aggregate land-use change rate for a region by statistical or mathematical means (Verburg, 2006). As opposed to top-down models, bottom-up models describe how actors in land-use change interact with the environment. Bottom-up models also known as agent-based models consist of autonomous decision-making entities, rules dictating action sequence in the model, rules determining interactions among the environment and agents and an environment in which the agent's function (Parker et al. 2002; Castella and Verburg 2007).

Top-down models include DINAMICA (Soares-Filho *et al*. 2002), Environment Explorer (White and Engelen 2000), Conversion of Land Use and its Effects (CLUE) (Veldkamp and Fresco 1996) and CA-Markov (Eastman 2012). Bottom-up models, on the other hand, require extensive fieldwork in order to collect data regarding agents' behaviour and to develop rules that govern their interactions with the environment. The SLEUTH model (Clarke and Gaydos 1998) is a popular bottom-up approach that takes into account local drivers of LULC. A variety of models only implement a top-down or bottom-up approach, yet some integrate these approaches to produce hybrid models. Examples of hybrid models include Dyna-Clue (Verburg and Overmars 2009), Markov and CA-Markov. The main benefit of hybrid models is that they overcome the limitations of individual modelling approaches while leveraging their strengths (National Research Council, 2014).

Land-use change models should address land-use system characteristics on a multiscale basis and place more attention on the interaction between driving factors of LULCC. Thus, the selection of an appropriate land-use change model is crucial (Han *et al*. 2015).

1.4 Review of LULCC modelling studies

In recent years, land-use change studies utilizing GIS and RS approaches based on LULCC modelling techniques has become increasingly common and abundant (Munthali *et al.* 2020). Literature has shown the benefits of land-use change models over traditional approaches. As stated by Verburg *et al*. (2004) land-use change models are useful tools for separating the complex web of biophysical and socio-economic forces responsible for influencing land-use and its spatial pattern and for estimating LULCC impacts. Globally, various researchers have utilized an array of models to simulate and predict LULCC.

Table 1.1: Examples of land-use change models

MODEL NAME	MODEL TYPE	PURPOSE
CLUE **(Veldkamp and Fresco,1996)**	Top-down	Combines various biophysical and human land-use drivers as well as their interactions to determine land-use.
CLUE-s **(Verburg *et al*., 2002)**	Top-down	Dynamically simulates competition among different types of land-use to model land-use change.
Dyna-CLUE **(Verburg and Overmars, 2009)**	Hybrid	Used to test conversions of land-use and its associated impacts using current and historical land-use patterns related to biophysical and socio-economic driving factors at different scales using logistic regression equations.
CA-Markov **(Clarks Labs,2010)**	Top-down	LULC forecasting model that simulates two-way transitions between multiple LULC categories and predicts transitions between multiple categories of LULC. Integrates the benefits of both CA and Markov models.
SLUETH **(Clarke and Gaydos,1998)**	Bottom-up	Projects urban growth and analyses how newly developed urban areas impact the surrounding environment and replace surrounding land-use.
LUCAS **(Berry *et al*., 1996)**	Hybrid	Examines anthropogenic impact on land-use and the subsequent impacts on resource sustainability and the natural environment.
LTM **(Pijanowski, 1997**)	Top-down	Analyses the spatio-temporal aspects of land-use change drivers and determines the spatial interactions of drivers.

Hybrid models have become a popular approach in simulating and predicting future LULC patterns and changes. The CA-Markov model, which was used in this study, is an example of a hybrid modelling approach. The CA-Markov model has been extensively used in many regions of the world. For example, Hoet and Hubert-Moy (2006), used the CA-Markov model to analyse LULC trajectories within a catchment located in Central Brittaney, France. In order to support water resource management, the model predicted plausible LULCC for the years 2015 and 2030. Applying the model as a planning support tool, Nouri *et al*. (2014) predicted urban LULCC within Anzali, Iran. As a result, the authors concluded that utilizing CA-Markov to simulate future LULCC provided an opportunity to improve environmental management in order to strike a better balance between ecological protection and urban development. The CA-Markov model has been widely applied and has shown to produce reliable results for sustainable planning in countries such as Tanzania, India, Iraq, and Malaysia (Memarian *et al*. 2012; Singh *et al*. 2015; Hyandye and Martz 2017; Hamad *et al*. 2018).

Within Southern Africa, the application of the CA-Markov model is limited. Matlhodi *et al*. (2021) employed the CA-Markov model to predict future LULCC within Gaborone dam catchment, Botswana. The results demonstrated the model's reliability and efficiency in simulating LULCC by producing realistic future LULC patterns. Daniels (2021) simulated future spatio-temporal expansion of informal settlements between 2011 and 2051 within the city of Cape Town, South Africa utilising the CA-Markov model. The study concluded that the hybrid CA-Markov model produced credible simulation outputs and served as a functioning decision making-facilitator. In a different study, Ikegwuoha *et al.* (2021) predicted future LULC within the Olifants river basin, South Africa. The model simulated LULCC for the year 2040 and served as a suitable decision support system for the formulation of sustainable land-use planning policies. Based on previous studies, the hybrid CA-Markov model was deemed to be suitable for use in this study.

1.5 Research Aim and Objectives

The aim of this study was to simulate potential future land-use/cover of the uThukela and uMngeni catchments for the assessment of streamflow responses. In order to achieve this aim, four objectives were set:

1. Undertake a comprehensive literature review to determine the most suitable land-use change model.
2. Simulate future land-use for the uThukela and uMngeni catchment utilizing the most appropriate land- use change model and collected data.
3. Assess changes in streamflow responses in the uMngeni catchment under plausible future land-use scenarios utilizing the ACRU agrohydrological model.

In order to address the aforementioned aim and associated objectives, a systematic research approach was followed which is outlined below.

The research approach followed in this study together with the delineation of the chapters is provided in Figure 1.2. The main research chapters (Chapters 2 and 3) were written as independent papers and in accordance with the guidelines provided by the School of Agricultural, Earth and Environmental Science, University of KwaZulu-Natal.

A comprehensive introduction (Chapter 1) is followed by the simulation of future land-use under three different plausible future development scenarios for the uThukela and uMngeni catchments (Chapter 2), thereafter the assessment and impact analysis of future land-use change on streamflow responses is presented (Chapter 3). Finally, the dissertation concludes with a synthesis chapter (Chapter 4), which synthesises key research findings to foster future recommendations and research, which is geared towards improved catchment management and land-use planning.

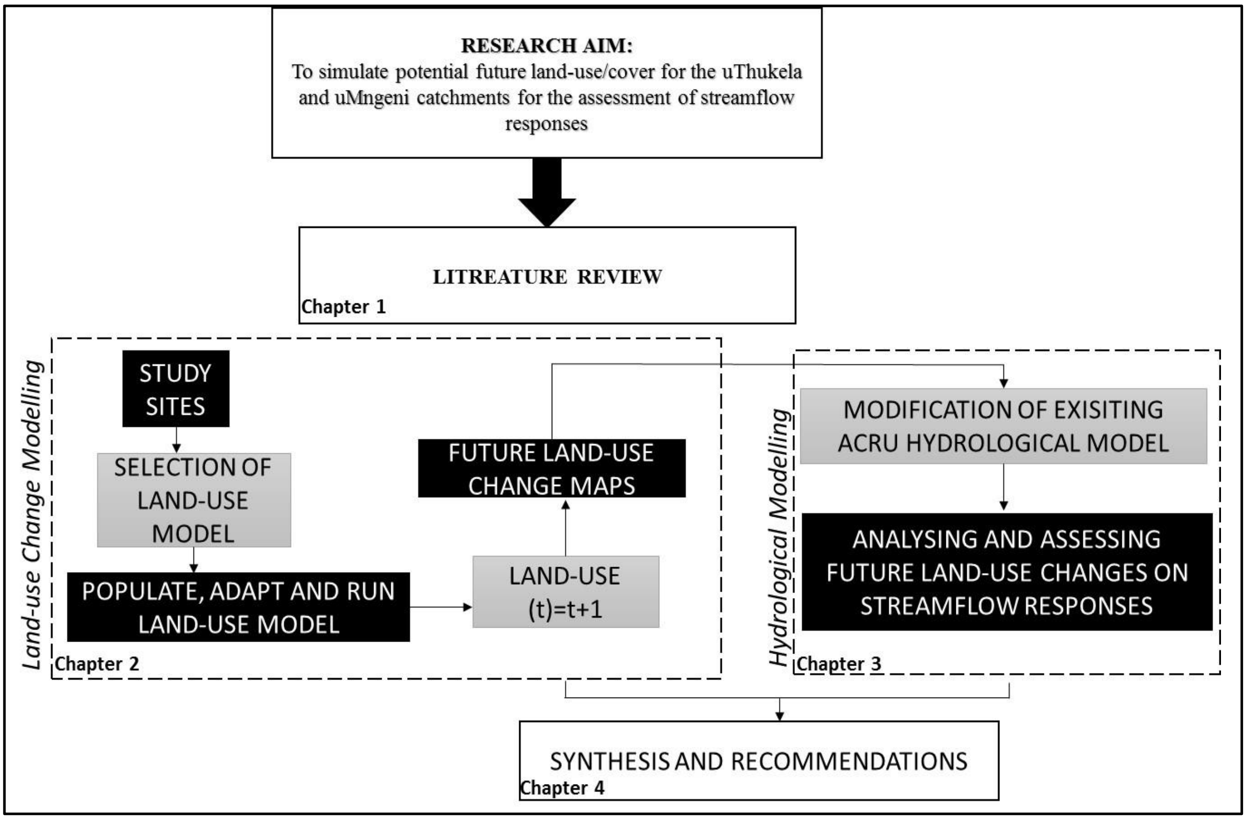

Figure 1.2: Research approach adopted in study

1.6 References

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CHAPTER TWO: SIMULATING FUTURE LAND-USE WITHIN THE UTHUKELA AND UMNGENI CATCHMENTS IN KWAZULU-NATAL

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Abstract

Due to anthropogenic activities, the earth's surface is constantly being altered. These alterations take the form of Land-use/cover change (LULCC), which is a fundamental driver of global, regional and local environmental change. LULCC studies have become pivotal in supplementing our understanding and observations of environmental change. However, understanding the past and present spatial-temporal variability of LULCC characteristics and their link to future land-use/cover trajectories at a catchment scale is limited, particularly in Southern Africa. As a contribution to addressing this limitation, this study simulated future land-use change utilizing a spatially distributed, empirical land-use modelling approach, for the uThukela and uMngeni catchments in the KwaZulu-Natal province, South Africa. The CA-Markov model, a popular and frequently utilized model employed in LULC predictive modelling, was selected to simulate LULCC conjointly with Geographic Information Systems (GIS) techniques. The obtained kappa values (Kstandard, Klocation and Kno) achieved during the validation were all above 80%, thus indicating the model's reliability and capability in predicting future LULC in the study sites. Future projections indicated that both study areas are anticipated to experience anthropogenic induced LULCC which further fragments the landscape configuration, functionality and ecological stability. With an understanding of the extent of projected LULCC by 2030 within both catchments, proactive planning and management within the framework of sustainable water resource management and land-use planning in the respective catchments can be undertaken.

Keywords: LULCC, CA-Markov model, environmental change, sustainable land-use planning

2.1 Introduction

Land-use and land cover change (LULC), which can be described as modifications to the biological and physical cover of the Earth's surface (Pielke *et al.* 2011), significantly impact natural resources, the environment and threaten societal and ecosystem functionality (Palang *et al*. 2000; Nagendra *et al*. 2004). Land-use/cover change (LULCC) is rooted in the spatio-temporal interactions between biophysical and socio-economic aspects (Veldkamp and Verburg 2004; Poelmans and Van Rompaey 2009; Arsanjani *et al.* 2013). LULCC is predominately attributed to anthropogenic factors, such as escalating population growth, industrialization, and urban sprawl (Agarwal *et al.* 2002; Hishe *et al.* 2021), which consequently alters earth-atmospheric interactions (Mahmood *et al.* 2010) and the associated demand on environmental resources (Lambin *et al*. 2006; Bewket and Abebe 2013).

Wood *et al.* (2004) identified agricultural expansion as a primary driver of LULCC within parts of Africa; and South Africa does not deviate from this. Highly fragmented land is omnipresent as a result of population growth where land redistribution was a common during the pre- and post-apartheid era (Gelderblom 2004; Atkinson and Marais 2006). Many stable and productive landscapes were modified and converted into settlements and cultivated land to satisfy shelter and food demands of society.

Even though land-use provides various socio-economic benefits, it is accompanied by substantial socio-economic and environmental implications. Conversions of natural vegetation to facilitate agricultural expansion and urban development, contributes to soil erosion, degradation and deteriorating ecosystem services and processes (Lubowski *et al*. 2006; Wu and Irwin 2008). Furthermore, LULCC influences the hydrological cycle and water supply (Schilling *et al*. 2010; Garg *et al*. 2019). Therefore, understanding processes, patterns and the magnitude of LULCC, is mandatory for the sustainable management of natural resources, which may include improved land-use policies, determining future developmental pressure points, effective and proactive land-use planning and integrated land-water resource management strategies (Dietzel and Clarke 2006; Castella *et al.* 2007; Taubenbock *et al.* 2009).

The complexities of LULCC necessitate the utilization of tools and technologies that are capable of systematically understanding, analyzing and simulating LULC dynamics. Integrating various geospatial technologies such as Geographic Information Systems (GIS) and Remote Sensing (RS) provide a useful platform from which LULC dynamics can be ascertained and LULCC processes, patterns and impacts can be analysed and better understood

(Luo *et al.* 2010; Nouri *et al.* 2014). The recent advancement and unprecedented growth of these technologies have given rise to the development of prediction techniques, comprehensive computing and spatial simulation models (Benenson and Torrens 2004). Various approaches have been utilized to simulate LULCC, such as statistical models (regression), evolutionary models (neural networks), mathematical models (static and linear), systems models (flow and stock) and cellular models (Cellular Automata (CA) and Markov Chains) (Agarwal *et al*. 2002; Parker *et al*. 2003; Poelmans and Van Rompaey 2010; Subedi *et al.* 2013). Generally, these approaches are integrated to produce a hybrid model, which are widely utilized because of their flexibility, simulation capabilities and bottom-up approach (Nejadi *et al*. 2012; Amini Parsa, *et al*. 2015).

The CA-Markov model, which combines CA techniques and Markov chain procedures, has been the most universally employed model in simulating future LULCC dynamics (Ebrahimipour *et al.* 2016; Gidey *et al.* 2017; Li *et al*. 2020). This model can simulate LULCC among multiple categories and takes into consideration LULCC suitability and the impact of natural drivers of LULCC (Eastman 2003; Mas *et al.* 2014; Sang *et al*. 2011). The Markov chain process governs temporal changes in LULC classification founded on conversion probabilities (Lopez *et al*. 2001; Guan *et al.* 2011; Yang *et al*. 2012), while spatial changes are governed by local rules controlled by suitability maps or the CA spatial filter (Wu 2002; He *et al*. 2008; Yang *et al*. 2012). Several studies have proven the efficiency and success of the CA-Markov model to simulate spatial and temporal LULCC (Samat 2009; Memarian *et al.* 2012; Fu *et al*. 2018; Faichia *et al*. 2020). Moreover, the quantitative, spatially detailed outputs of future LULC trends produced by the model, provide information relating to the magnitude and direction of LULCC, which can assist in climate change studies and strategies, biodiversity conservation and land management policies (Weng,2002).

Although several land-use modelling studies (Cillers 2010; Mauck and Warburton 2012; Abu-taleb *et al*. 2013; Shoko and Smit 2013; Le Roux 2012; Tizora *et al.* 2018) have been conducted within South Africa, only four studies have incorporated future land-use modelling into their research. For example, Shoko and Smit (2013) suggested the development of a conceptual model for implementing an agent-based prototype that is empirically informed and capable of simulating future trends and patterns in changes in land occupation over time, with focus on informal settlement proliferation within the city of Cape Town. Abu-taleb *et al.* (2013), conversely, utilized a cellular automata model to model future urban growth in the Gauteng province. Whereas, Tizora *et al.* (2018) showed the Dyna-CLUE model to be suitable for simulating LULCC at a provincial level in a Southern African context. While Mauck and Warburton (2012) used an urban growth model (SLEUTH) to model future urban growth within the uMngeni catchment. In assessing the LULCC modelling initiatives within South Africa, Wray *et al*. (2013) stated that provincial and local LULCC modelling initiatives are predominantly GIS based and centred around tracking trends as opposed to the simulation of future LULCC under scenario developments, with the use of future modelling mainly being utilized for population prediction. Whereas, within the academic sphere, an analysis of historical land cover change was more common.

Given the limited attempts to understand future land-use change patterns, processes and their associated driving forces across South Africa and for the province of KwaZulu-Natal in particular, this paper set out to quantify and simulate future land-use change utilizing a spatially distributed, empirical land-use modelling approach, for two South African catchments in the KwaZulu-Natal province, namely the uMngeni and uThukela catchments. LULC modification within these catchments is occurring at unprecedented rates, placing increasing pressure on natural resources, particularly water resources (Mauck and Warburton 2013; Namugize *et al*. 2018). Hence, simulating future LULCC within these catchments will be crucial in fostering better land-use planning, decisions and improving land-use policies and water resource management.

2.2 Description of Study Areas

Located within the province of KwaZulu-Natal, South Africa, the uThukela and uMngeni catchments (Figure 2.1) are two highly water stressed systems (Mauck 2013; De Lecea and Cooper 2016) in the summer rainfall area that are inter-connected via the Mooi-uMngeni Transfer Scheme (MMTS). The MMTS was developed to ensure that the assurance of water-supply to approximately five million downstream water users within the catchment remained high (uMngeni Water Infrastructure Master plan, 2019).

The uMngeni catchment (4 349 km^2) not only houses the country's largest trade port and the second largest economic hub, but also drives 65% of the province's economic production (Karar and Seetal 2000) and supports 15% of South Africa's total population (Warburton *et al*. 2010). The catchment supplies water to the Durban-Pietermaritzburg corridor, which are two prominent urban areas that produce close to 1/5 of the country's Gross Domestic Product (GDP) (Warburton *et al*. 2010). The uMngeni catchment (Figure 2.1), experiences a warm subtropical climate, with mean annual temperatures (MAT) that range from 20ºC near the coast to 12ºC towards the escarpment (Mauck and Warburton 2012). In the drier reaches of the catchment, mean annual precipitation (MAP) varies from 700 mm to 1 550 mm in the wetter reaches of the catchment (Warburton *et al*. 2010). Land-cover within the catchment is diverse, predominately consisting of commercial and small-scale agriculture, natural forests, plantations and urban areas (Ghile and Schulze 2010).

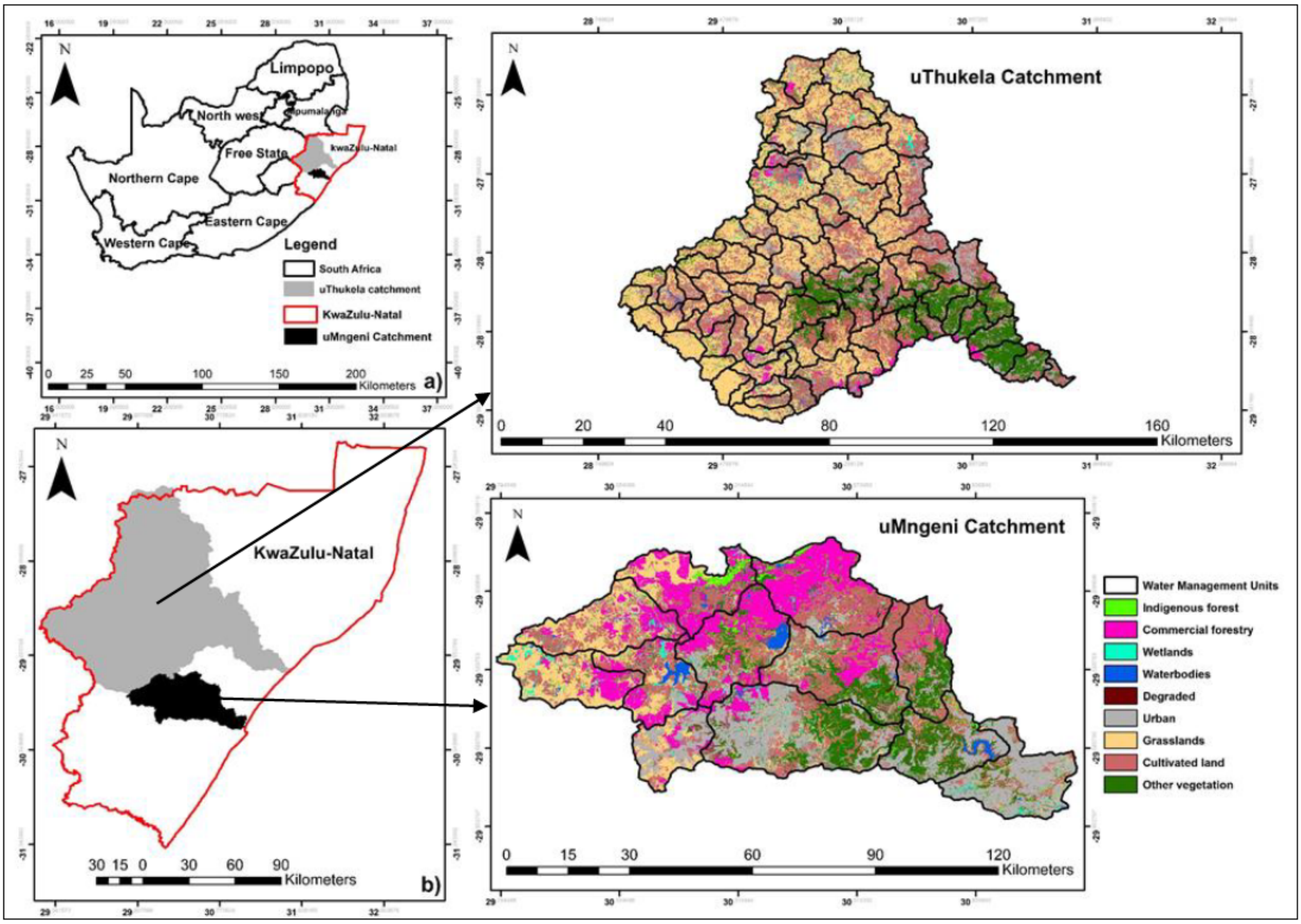

Figure 2.1: Maps showing geographic distribution of respective study catchments with respect to a) South Africa and b) KwaZulu-Natal (Source: https://egis.environment.gov.za/data_egis/data_download/current)

The uThukela catchment (29 036 km^2) contributes to South Africa's food production and is a prime tourism hotspot as it encompasses the World Heritage uKhahlamba-Drakensberg Park (uThukela District Municipality 2019). The catchment is diverse, from being a water rich catchment in the high rainfall (MAP = 1 520 mm) headwater areas (Northern Drakensberg Strategic Water Source Area), accommodating the Tugela-Vaal inter-basin transfer scheme, to having areas of water poverty lower down in the catchment (MAP = 650 mm). Land-use in the catchment is highly variable, with large areas of natural vegetation, 15% of the catchment is utilized for agriculture, 8% is considered degraded and approximately 1% is classified as urban (EDTEA 2017; Anderson *et al*.2009).

Both these catchments were selected due to the pressures they are currently under and the planned development trajectories. The "National Development Plan 2010: Vision for 2030" and the "KwaZulu-Natal Provincial Growth and Development Plan (PGDP) 2018" provide a reference point for the national and provincial developmental goals and objectives that are relevant to the catchments. Designed to progressively move the country towards addressing socioeconomic challenges, eliminating poverty and reducing inequality, the goals and objectives include developing and promoting the agricultural potential of KwaZulu-Natal, upgrading all informal settlements on suitable and well-located land by 2030 (NDP 2012), enhancing spatial economic development and enhancing the resilience of new and existing cities, towns and rural nodes (PGDP 2018). Strategic Integrated Projects (SIP's) have been designed to assist in achieving these goals and objectives. Three SIPs are relevant to the study areas, one speaks to a logistics and industrial corridor running through the uMngeni catchment, another to node and corridor development spanning the KwaZulu-Natal province from south to east, and the last to agri-logistics and rural infrastructure. These SIP's will modify pre-existing LULC, with the future LULC trajectory of the uThukela catchment likely to include the increasing conversion of natural vegetation to accommodate the proliferation of agriculture, while in the uMngeni catchment, is likely that the future LULC trajectory is likely to include significant expansions in urban and agriculture LULC classes at the expense of natural land-cover types. Undertaking future LULCC mapping will serve as a management tool for the identification of potential conflicts among dominate land-uses, allow the potential to determine the consequences on ecosystem services and implement sustainable land-use strategies and improved agricultural policy action plans.

2.3 Methodology

Prior to modelling future land-use change, LULC data was sourced, verified and prepared before using in the CA-Markov model.

2.3.1 LULC Data

The land-use maps for the years 1990, 2013/14 and 2018 produced by GEOTERRAIMAGE Pty Ltd were obtained from the Department of Environmental Affairs GIS (EGIS) webpage (https://egis.environment.gov.za/data_egis/data_download/current). The 1990 and 2013/14 land-cover datasets were generated using the same operationally proven, semi-automated modelling procedures and methodologies. The 1990 DEA/CARDNO SANLC dataset was produced utilizing Landsat-5 multispectral and multi-seasonal imagery obtained between 1990 and 1991, while the 2013/14 LULC was produced using Landsat 8 multi-seasonal imagery. The national dataset is in raster format, map corrected based on 30 x 30 m cells and ideally suited for ± 1: 75,000 - 1: 250,000 scale GIS based mapping and modelling applications (GEOTERRA Image Data User Report and Metadata, 2015).

The SANLC 2018 dataset was generated using automated mapping models as opposed to general procedures of image classification, from 20m resolution multi-seasonal Sentinel-2 satellite imagery for the period of 1st January 2018 to 31st December 2018 (GEOTERRA Image Data User Report and Metadata, 2019). The automated mapping models and associated procedures, used cloud-based geo-data computing capabilities and image archives, although the merging and final compilation of the LULC classes, was achieved utilizing automated modelling capabilities embedded in commercial mapping software in a traditional desktop environment. The SANLC 2018 dataset, which is presented in a GeoTIFF raster format, depicts South Africa's full spatial extent, in addition to 100 m into neighbouring countries, and 10 km's into coastal waters.

Accuracy assessments for the datasets were independently conducted by GEOTERRAIMAGE Pty Ltd. Due to insufficient suitable historical reference data, an accuracy assessment on the historical 1990 DEA/CARDNO SANLC dataset was not conducted (GEOTERRA Image Data User Report and Metadata 2015). The 2013/14 dataset was verified visually through a desk-top approach, against high resolution photography and imagery in Google Earth © (GEOTERRA Image Data User Report and MetaData, 2015) and accuracies reported using industry standard confusion (error) matrices which included user, producer and kappa values.

Overall map accuracy for the 2013/14 dataset was reported as 82.53% with a mean LULC class accuracy of 88.36%. A reported Kappa Index value of 0.81 indicated that the results were highly unlikely to be attributed to chance occurrence (GEOTERRA Image Data User Report and MetaData, 2015). The overall map accuracy reported for the SANLC 2018 dataset, was 90.14%, with an 89.63% mean LULC class accuracy and 90% confidence limits of 89.65 – 90.62 %. The reported Kappa index was 0.89 (GEOTERRA Image Data User Report and MetaData, 2019).

2.3.2 Data Preparation

In order to model future LULCC, the Markov and CA-Markov modules and Land Change Modeler (LCM) in the TerrSet software version 18.31 requires the LULC images to have identical sequential categorical legends and spatial dimensions with the backgrounds assigned a value of zero. The LULC images were therefore resampled to a 100 x 100 m (1 ha) resolution and clipped to the extent of the respective study sites. This resolution was compatible with the input data, yielded the highest accuracy and maintained the morphology of LULC types. The 1990, 2013/14 and 2018 land-use maps were reclassified into 9 classes (Table 2.1) to achieve commonality across the different LULC images and for the simplification of land-use classes.

Table 2.1: Description of land-cover classes used in study (adapted from DEA / CARDNO SCFP002: Implementation of Land-Use Maps for South Africa, 2016)

LULC class	Description
Indigenous Forest	Natural or semi-natural indigenous forest, which is dominated by tall trees, where tree canopy densities are generally > ± 75% and tree canopy heights are typically > ± 5m, associated with multiple understory vegetation canopies.
Commercial Forestry	Forestry plantations utilized for cultivating commercial timber tree species. Represents a combination of young, temporary and mature, clear-felled stands. Comprises of spatially smaller woodlots and windbreaks with the same cover characteristics
Grassland	Natural / semi-natural areas dominated by grass, where bush and/or tree densities are generally < ± 20% but may include localised denser areas up to ± 40%, regardless of canopy heights.
Other Vegetation	Includes natural / semi-natural tree and / or bush dominated areas, such as thicket, tall, dense shrubs and bush, closed and open woodland and bushland and transitional wooded grassland areas. Where typically canopy heights are between 2 - 5 m, and canopy density is typically > ± 75%,
Cultivated Land	Cultivated lands utilized primarily for rain-fed, annual crop production for commercial markets or home use and/or local markets. Generally represented by large or small field units, typically in a dense local or regional cluster
Urban	Includes all built-up areas. Typically represented as a single class, including but not limited to residential land-uses (formal and informal), transport networks, religious, educational, industrial, health and commercial infrastructure across a range of structural densities ranging from high to low. Includes agricultural smallholdings located on the urban periphery.
Wetlands	Primarily vegetated areas on a seasonal or permanent basis. Identifiable by surface vegetation patterns. Wetland vegetation is either rooted or floating and is predominately herbaceous. Includes but is not limited to wetlands associated with, marshes, seeps/springs, lakes/pans, floodplains, swamps, some riparian areas and estuaries.
Waterbodies	Areas of open surface water. Includes man-made or natural bodies of water, which can either be flowing, static, fresh water or saltwater.
Degraded/Bare areas	Bare and/or sparsely vegetated areas (typically < ± 5 - 10% vegetation cover). Includes but not limited to dry riverbeds, erosion areas, dry pans, natural rock exposures, rocky and sandy desert areas, beaches and coastal dunes, very sparse, low grasslands and shrublands. Includes mining activity footprints, which comprise of sand mines, open cast pits, tailings, waste dumps, flooded pits, extraction pits, quarries and borrow pits

2.3.3 Modelling LULCC Framework

The modelling framework adopted in this study is depicted in Figure 2.2. The processes and applications were conducted utilizing RS and GIS based software and applications in a GIS data environment. A 5x5 CA filter and Markov chain modelling approach, jointly known as CA-Markov was used to simulate future LULCC within the respective study sites. The CA-Markov model is based on the evaluation and utilization of historical land-use combined with predictions of the spatial distribution of LULC in the future (Sang *et al*. 2011).

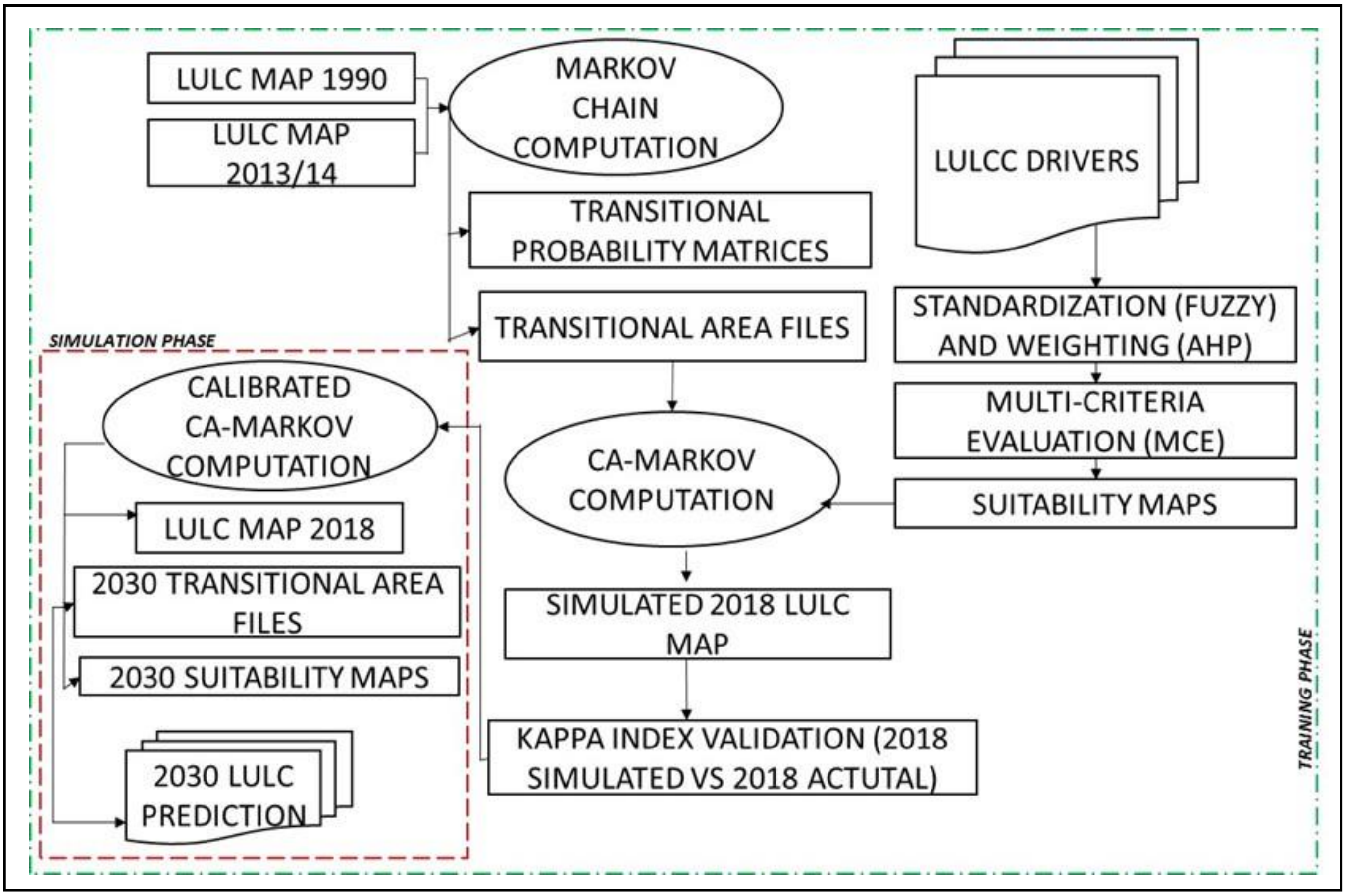

Figure 2.2: Modelling framework adopted in study

2.3.3.1 Cellular Automata (CA) Model

The cellular Automata (CA) model, expressed in equation 2.1, can be described as a cellular entity, which can change and control complex spatially distributed processes (Gidey *et al*. 2017). The CA model independently varies from a new state based on its immediate neighbours and preceding state (Surabudin *et al*. 2013; Omar *et al.* 2014).

$$\mathbf{S}(\boldsymbol{t},\boldsymbol{t}+\mathbf{1}) = \boldsymbol{f}\,(\mathbf{S}(\boldsymbol{t}), \boldsymbol{N}) \qquad \textbf{(2.1)}$$

Where:

S = Set of discrete and limited cellular states, ***N*** = Cellular field, ***t* and *t*+1** = Different time steps**,** ***f*** = transformation rule of cellular states

CA encompasses a regular lattice framework in which any given cell within the lattice is in one of a defined number of states, with the states either changing at every time step (or iteration) or remaining in the current state (O'Sullivan and Unwin 2003). Changes are facilitated by deterministic rules which are defined before the execution of the CA process. The model performs as an analytical engine that facilitates dynamic LULC modelling within remote-sensing and GIS environments (Rendana *et al*. 2015). A disadvantage of the model is its inability to define transition rules (Rocha *et al*. 2007). However, this can be compensated for by integrating other empirical and spatial models such as CA-Markov (Halmy *et al*. 2015).

2.3.3.2 Markov Chain Model

The Markov chain model is a stochastic model (Equation 2.2) in which the future state of one system (t_2) can be predicted according to the probability of transition and its previous state (t_1) (Houet and Hubert-Moy 2006; Thomas and Laurence 2006; Adhikari and SouthWorth 2012), making it suitable for LULCC modelling studies (Sang *at al*. 2011). The model analyses LULC images from two time periods to derive a transition probability matrix, a set of conditional probability images and a transition areas matrix (Mishra *et al*. 2014; Ebrahimipour *et al*. 2016).

$$\mathbf{S\ (t,\ t+1)} = \boldsymbol{P}_{\mathbf{ij}}\mathbf{*\ S(t)} \qquad \textbf{(2.2)}$$

Where:

S(t) = The system status at time t, S (t+1) = The system status at time (t+); and P_{ij} = Transition probability matrix in a given state and is calculated as follows:

$$P_{ij} = \begin{Vmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,n} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n,1} & p_{n,2} & \cdots & p_{n,n} \end{Vmatrix}, \ (0 \leq p_{ij} \leq 1)$$

Where:

P **=** Transition probability, P_{ij} = Probability of converting from i (current state) to another state j, P_n = State probability of any given time

An inherent issue with the Markov chain model, is that although the transition probabilities are generally accurate on a LULC category basis, it is unable to delineate the quantity of conversion state between different LULC classes (Bozkaya *et al*. 2015; Ghosh *et al.* 2017), thus fails as a spatial distribution model (Nouri *et al*. 2014).

2.3.3.3. CA-Markov Model

The CA-Markov model combines the strengthens of CA and Markov chain models and overcomes the disadvantages of the two separate models making it robust and reliable (Eastman 2003; Arsanjani *et al*. 2011; Yang *et al*. 2012; Singh *et al*. 2015; Aburas *et al*. 2021). The integrative CA-Markov modelling approach is able to simulate two-way transitions between multiple categories, predict any transition between multiple categories and control space dynamics via local principles utilizing transition probabilities of each LULC class utilizing Markov Chain procedures and CA mechanisms (Pontius and Spencer 2005; Ye and Bai 2008; Behera *et al*. 2012).

The CA-Markov model has been widely applied and has shown to produce reliable results for sustainable planning in countries such as Tanzania, India, Iraq and Malaysia (Memarian et al. 2012; Singh et al. 2015; Hyandye and Martz 2017; Hamad et al. 2018). Moreover, the model is one of few design support tools used to analyse the spatio-temporal distribution of LULC (Hua 2017). In addition, the model has been widely used to simulate urban sprawl, forest cover, LULC dynamics and watershed management. When analysing historical LULC changes, this model develops an empirical explanation of the association between LULC transitions and a set of explanatory variables (Matlhodi et al 2021; Nouri et al. 2014). Markov chains have good statistical power to predict change probabilities, and cellular automata are considered to be a powerful method for reading spatial patterns of change (Ghosh et al. 2017; Gidey et al. 2017). Compared to methods that are only capable of handling changes in a single land type, CA-Markov is straightforward, user-friendly, easy to set up, has a pre-defined calibration process, can simulate multi-class land changes and has been proved to be a simple but effective approach to model the evolution of LU patterns in areas with intense human activity and dynamicity (Eastman 2012).

The CA-Markov modelling process, conducted within the IDRISI Selva v.17 software, required three inputs: (i) base land-cover image, (ii) transition suitability image collection, (iii) Markov transition areas file and (iv) number of cellular iterations. These inputs were derived using various applications, modules and functions within the IDRISI Selva v.17 software.

2.3.3.4 Generating Transition Area files and Transition Probability Matrices

The Markov chain model was applied to derive transition probability matrices and transition area files between 1990 to 2013/14 and 2013/14 to 2018 using the Markov-Markovian transition estimator (MARKOV module) in TerrSet 19.0 The MARKOV module analyses a pair of land cover images and outputs a transition probability matrix, a transition areas matrix, and a set of conditional probability images. The transition probability matrix file records the probability that each land cover category will change to every other category, while the transition areas matrix file records the number of pixels that are expected to change from each land cover type to each other land cover type over the specified time (Regmi *et al*. 2014; Adhikari and SouthWorth 2012). The conditional probability images report the probability that each land cover type would be found at each pixel after the specified time. These images are calculated as projections from the later of the two input land cover images and is expressed as follows:

$$\chi = \sum (O\text{-}E)^2/E \qquad \textbf{(2.3)}$$

Where:

χ = Transition probability matrix, O = Observed number of transitions and E = Expected number of transitions

In order to validate the CA-Markov model and predict a future LULCC scenario, the LULC image of 1990 for the uMngeni catchment was used as a base map while the 2013/14 LULC image was used as second LULC to obtain a transition probability matrix and a transition areas matrix between 1990 and 2013/14 to run a simulation for 2018.

2.3.3.5 Fuzzy Standardisation and Analytic Hierarchy Process (AHP)

An accurate indicator and prime driver of LULC dynamics is the proximity to socio-economic factors such as distance to main road networks, city centres and waterbodies as societies residing in close proximity to these socio-economic influences have the freedom to expand and/or create new settlements and clear existing vegetation at various spatial-temporal scales (Subedi *et al*. 2013; Gidey *et al*. 2017). In this study, elevation, slope and aspect coupled with socio-economic factors of distance to main routes and primary rivers were taken into consideration as drivers based on literature findings. The analytical hierarchy process (AHP) was applied to determine the weights of these drivers in conjunction with a pairwise comparison matrix (Memarian *et al.* 2012 and Rimal *et al.* 2018). AHP, a common and popular mathematical, multi-purpose decision-making technique, is a measurement theory based on expert judgement formulated to analyse complex decision issues utilizing pairwise comparison methods (Satty 1980; Memarian *et al*. 2012). In this method, a pairwise comparison matrix is used, where comparisons are developed with reference to a scale of absolute judgement that illustrates how much more an element dominates over the other for a specific attribute. Given the symmetrical nature of the matrix, only the lower half is filled.

While many different standardisation methods exist, this study used fuzzy membership applications, which provides a variety of membership functions as opposed to other standardisation methods (Myint and Wang 2006). The IDRISI MOLA environment was used to execute fuzzy standardization and used various fuzzy membership function types and shapes.

2.3.3.6 Suitability Map Generation

Individual suitability maps for land-cover classes are a pre-requisite for the development of the transition suitability image collection, which is used as an input for the CA-Markov model. Suitability maps were generated using the multi-criteria evaluation (MCE) tool in IDRISI version 17.01, which evaluated the drivers of LULCC using the Weighted Linear Combination (WLC) function (Saaty 1980; Eastman 2003, Dengiz and Usul 2018). WLC (equation 2.4) multiplies each individual standardized driver map by its driver weight then aggregates the results (Eastman 2003). The higher the score the higher the suitability for that specific LULC.

$$\mathbf{S} = \sum W_i X_i * \mathbf{\Pi} C_j \qquad \mathbf{(2.4)}$$

Where:

S= Suitability, W_i= Factor i weight, X_i= Factor i score, C_j= Boolean value of constraint j

2.2.4 Validation Method

The Kappa statistic index has become accepted as the standard to quantify image classification accuracy (Yang *et al*. 2014; Halmy *et al*. 2015; Gidey *et al*. 2017; Singh *et al*. 2017; Mondal *et al*. 2019). However, according to Pontius Jr and Millones (2001) kappa indices are often misleading, flawed and impractical, hence they encourage the use of components of agreement and disagreement as the foremost validation technique. Both agreement and disagreement components and kappa statistics were thus considered. These were obtained from the VALIDATE module imbedded in the TerrSet 19.0 software.

The VALIDATE module computes seven different statistical calculations, which form the premise of components of agreement and disagreement (Pontius Jr and Chen 2006). Ascertained by Pontius and Millones (2011) components of agreement and disagreement are more beneficial validation techniques and offer a comprehensive statistical analysis. Components of agreement and disagreement statistics are based on the commonality and variability between the simulated and reference map. Components of agreement describe agreement characteristics between the reference map and simulated map, while components of disagreement describe disagreement characteristics between the reference and simulated map. (Pontius *et al*. 2007). The module also provides traditional Kappa Index of Agreement (*KIA*) statistics and other useful variations such as *Kstandard Kquantity, Klocation and Kno. Kstandard* denotes overall *KIA*, *Kquantity* illustrates the level of agreement relating to quantity, given the models capability to identify location; *Klocation* gives the level of agreement related to location, given a specific quantity and *Kno* indicates the overall simulation run accuracy. The aforementioned variants complement the standard kappa index, which is defined as (Keshtkar and Voigt 2016):

$$\boldsymbol{K=(P_a-P_e)/(P_i-P_e)} \qquad \textbf{(2.5)}$$

Where:

K= Kappa index, P_a= Actual accuracy, P_e= Expected prediction accuracy; and P_i= Ideal accuracy (100%)

When Kappa index equals 1, the agreement is perfect and when equal to 0 agreement is expected by chance (Pontius 2000), however, Kappa index values of above 0.61 can be considered to display substantial agreement (Cohen 1960). According to literature acceptable values for components of agreement and disagreement range from ≤ 0 indicating no agreement; 0.01–0.20 indicating none to slight; 0.21–0.40 indicating fair; 0.41– 0.60 as moderate; 0.61–

0.80 indicating substantial and 0.81–1.00 indicating near perfect agreement (McHugh 2012). In terms of values for disagreement, Wundram and Loffler (2008) stated that an overall disagreement above 23% is not satisfactory.

2.4 Results

2.4.1 Validation Results

Prior to producing LULC maps for the future, a validation of the model was undertaken for the uMngeni catchment to determine its adequacy and accuracy. The validation was conducted by simulating changes in the uMngeni catchment between t_1 (1990) and t_2 (2013/14) to predict for t_3 (2018). The predicted map produced for t_3 (2018) was then compared against the actual 2018 reclassified map (Figure 2.3). The traditional KIA statistics (*Kstandard, Kquantity, Klocation* and *Kno*) were all above 0.8 (Table 2.2), indicating a high level of agreement between the simulated and predicted map and a satisfactory accuracy level. The components of agreement and disagreement were also considered (Table 2.2). Interpreting overall agreement and disagreement is considered more beneficial when validating prediction accuracy. Based on the overall agreement and disagreement values, overall agreement (0.8715) illustrated a higher value compared to overall disagreement (0.1285). Low map disagreement was mainly a result of location errors (0.0906) rather than quantity errors (0.0379), indicating the model's high ability to predict LULCCs in quantity rather than location. The combined Kappa statistics and components of agreement and disagreements confirm the CA-Markov model can be considered valid and suitable to predict future LULCC within the respective study sites.

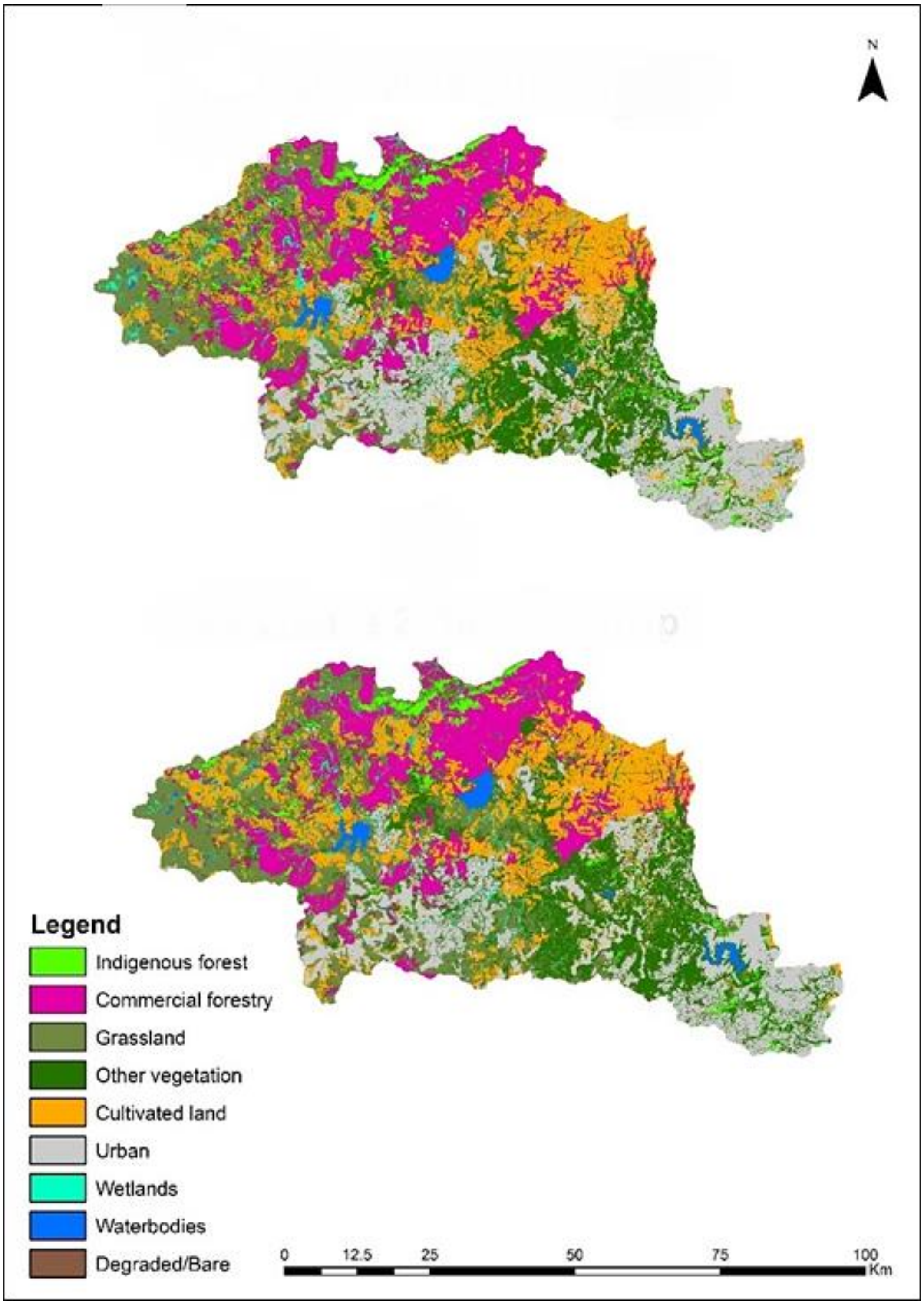

Figure 2.3: Map showing a) simulated 2018 LULC map and b) actual 2018 LULC map for the uMngeni catchment

Table 2.2: Summary of Kappa statistics, components of agreement and disagreement considered in model validation

		Statistic	**%**
Kappa statistic	Kstandard	0.8107	81
	Kno	0.8572	85
	Klocation	0.8586	85
	Klocationstrata	0.8586	85
Component of Disagreement	Disagreement due to location	0.0906	9
	Disagreement due to quantity	0.0379	3
	Overall Disagreement	0.1285	12
Component of Agreement	Agreement due to location	0.5504	55
	Agreement due to quantity	0.2211	22
	Agreement due to chance	0.100	10
	Overall Agreement	0.8715	87

2.4.2 Markov Chain Analysis

Transition probability matrices produced for 2030 through the utilization of the Markov chain model for the uMngeni and uThukela catchments (Table 2.3 and 2.4) are a result of cross-tabulation of the 2014 and 2018 LULC images. These results present possible LULC conversions that are likely to occur in 2030. They are not necessarily representative of the realistic LULCC in the study areas, but rather are direct equivalents of LULCC that have occurred between 2014 and 2018 and therefore due to their new mutualistic independence, they may be directly compared.

In the uMngeni catchment a significant proportion of predicted LULCC for 2030 appears to be distinct with exception to waterbodies, wetlands and degraded LULC types. Similarly, the predicted LULCC for 2030 for the uThukela catchment is distinctive and well dispersed. Within both catchments, major transitions mainly occurred in natural vegetation classes (other vegetation, grasslands and indigenous forest). Notably, in both catchments, grasslands (uMngeni = 42.34%; uThukela = 58.96%) had the highest probability of being converted to the urban land class, followed by indigenous forest, cultivated areas and other vegetation having a similar probability of transitioning to urban land-use. The high demand for the urban land-use class projected in 2030 can be attributed to the catchments economic and agricultural productivity. Less significant classes such as waterbodies, wetlands and degraded/bare areas showed a high probability of remaining unchanged. Urban land-uses displayed the highest probability (uMngeni=79.69%; uThukela= 78.23%) of remaining unchanged.

Table 2.3: 2030 Transitional probability matrix for the uMngeni catchment

PROBABILITY OF CHANGING INTO:

		Indig. Forest	Other Veg.	Grass	Comm. Forestry	Cultivated	Urban	Wetlands	Waterbodies	Degraded
	Indig.Forest	9.74	0.25	0.02	27.84	14.93	33.67	0.77	0.01	12.77
	Other Veg.	0.14	12.66	0.03	26.03	13.77	35.23	1.02	0.69	10.43
	Grassland	0.01	0.15	19.92	0.06	28.37	42.34	0.33	0.01	8.81
GIVEN:	**Comm.Forestry**	0.07	7.98	0.15	45.36	20.35	21.22	0.03	0.00	4.84
	Cultivated	0.04	9.68	0.06	14.44	35.42	31.62	0.01	0.00	8.73
	Urban	0.00	3.31	0.00	0.00	3.07	79.96	0.00	0.00	13.66
	Wetlands	0.05	17.55	0.09	0.00	9.55	11.52	28.14	13.13	19.97
	Waterbodies	0.02	5.84	0.04	0.00	0.00	4.89	3.98	78.41	6.82
	Degraded	0.03	9.14	0.02	10.20	15.10	21.79	5.56	7.04	31.12

Table 2.4: 2030 Transitional probability matrix for the uThukela catchment

PROBABILITY OF CHANGING INTO

		Indig. Forest	Other Veg.	Grass	Comm. Forestry	Cultivated	Urban	Wetlands	Waterbodies	Degraded
	Indig. Forest	**3.74**	0.04	0.08	26.48	21.58	35.40	0.68	0.03	11.97
	Other Veg.	0.15	**12.55**	0.07	27.39	15.34	37.96	0.06	0.28	6 20
	Grassland	0.02	0.37	**10.73**	0.01	18.72	58.69	0.21	0.00	11.25
GIVEN:	**Comm.Forestry**	0.09	6.22	0.04	**47.13**	17.35	21.54	0.07	0.00	7 56
	Cultivated	0.55	8.52	0.06	13.68	**31.02**	35.42	0.01	0.00	10.74
	Urban	0.03	7.59	0.01	0.11	4.88	**78.23**	0.00	0.00	9 15
	Wetlands	0.01	17.76	0 30	0.00	8.84	11.06	**28.22**	15.12	18.69
	Waterbodies	0.05	8.84	0 14	0.00	0.00	3.33	5.66	**76.25**	5.73
	Degraded	0.07	7.20	0.02	9.19	11.79	28.37	2.17	3.26	**37.93**

2.4.3 Spatial-temporal analysis of historical land-use patterns and simulated 2030 LULCC

2.4.3.1 uMngeni Catchment

The historical spatial distribution of LULC classes in the uMngeni remains fairly consistent between 1990 and 2018 (Figure 2.4), with the upper reaches occupied by cultivated land, grasslands and commercial forestry, the middle reaches of the catchment dominated by commercial forestry and urban, while the lower reaches are predominately occupied by urban and other vegetation LULC classes. Between 1990 and 2018, notable and visible changes in LULC areas was the loss in grasslands and gains in cultivated land (Table 2.5). Whereas other vegetation, urban and indigenous forestry showed small net increases between 1990 and 2018. The waterbodies, wetlands and degraded LULC classes remained relatively constant, with negligible changes in their distribution. The overall LULC of the uMngeni catchment from 1990 to 2018 depicts a decline in grasslands in favour of agricultural and urban land-uses.

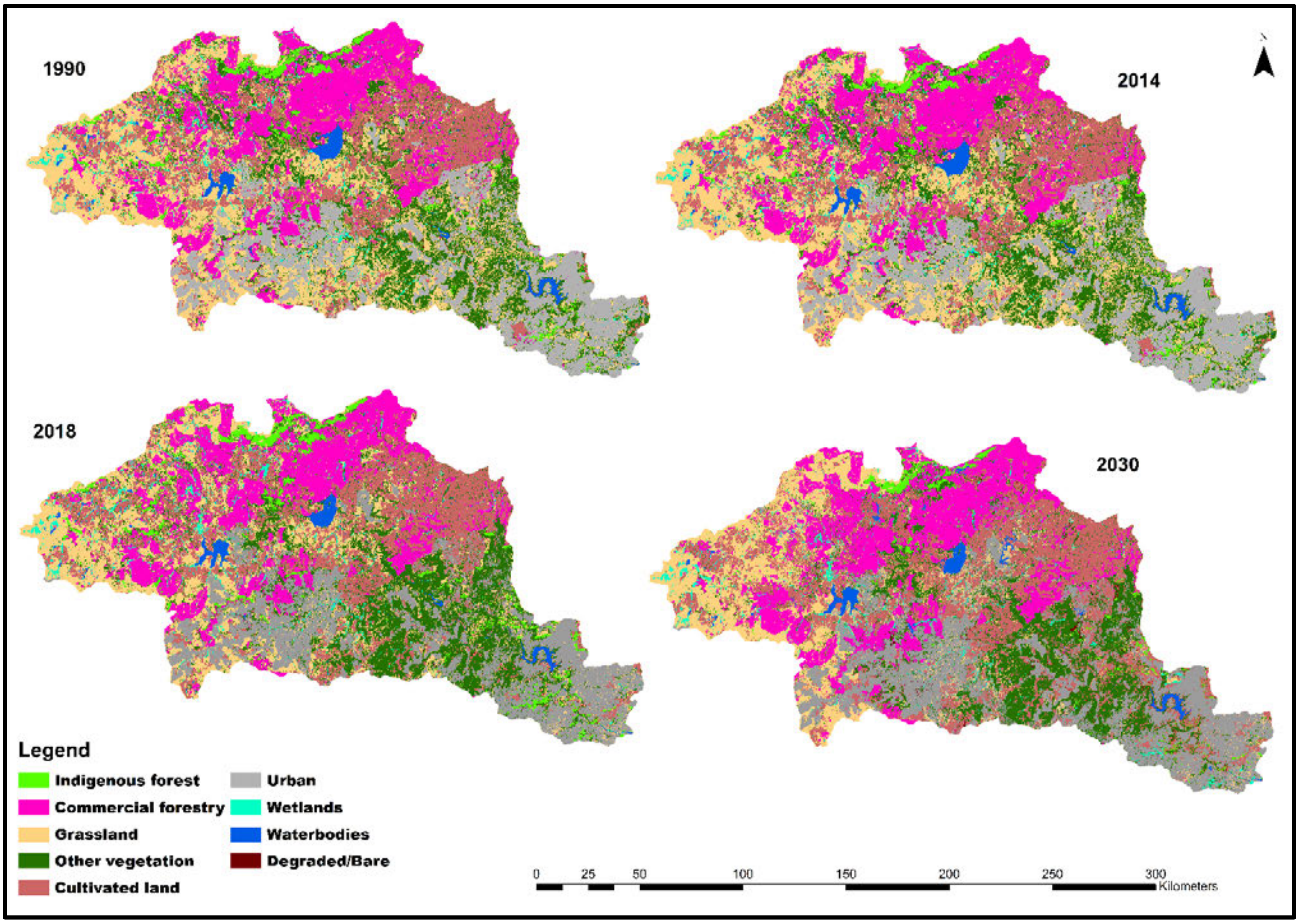

Figure 2.4: Spatio-temporal distribution of historical and simulated future LULC within the uMngeni catchment

Table 2.5: Area statistics for historical and future LULC in the uMngeni catchment

	1990		*2013/14*		*2018*		*2030*		*Δ(90-2018)*	*Δ(90-2030)*
	km^2	**%**	**km^2**	**%**	**km^2**	**%**	**km^2**	**%**	**%**	**%**
Grassland	1192.14	26.81	1007.08	22.65	864.63	19.45	698.22	15.70	-7.36	-11.12
Comm. forestry	790 16	17.77	714.65	16.07	759.10	17.07	842.96	18.96	-0.70	1.20
Urban	785 11	17.66	785.60	17.67	837.48	18.84	945.46	21.26	1.18	3.60
Other vegetation	752 53	16.93	891.68	20.05	828.59	18.64	691.40	15.55	1.71	-1.36
Cultivated land	664 51	14.95	770.66	17.33	846.50	19.04	1033.27	23.24	4.09	8.28
Indigenous forest	93.76	2.11	116.51	2.62	136.76	3.08	65.81	1.48	0.98	-0.64
Wetlands	91.58	2.06	83.44	1.88	94.46	2.12	83.75	1.88	0.06	-0.16
Waterbodies	68.79	1.55	66.32	1.49	67.60	1.52	67.83	1.53	-0.03	-0.04
Degraded/Bare	7.57	0.17	10.21	0.23	11.04	0.25	17.46	0.9	0.08	0.24
Total	**4446.15**	**100.00**	**4446.15**	**100.00**	**4446.15**	**100.00**	**4446.15**	**100.00**		

The predicted LULC results for 2030 for the uMngeni catchment (Figure 2.4) indicated that the LULC pattern did not differ greatly from 2018, however, dominating LULC classes and their occurrences within the catchment are well defined and resemble an increasingly anthropogenically altered landscape. Among all nine LULC classes, cultivated land, urban and the commercial forestry LULC classes showed the greatest net gain between 1990 and 2030 (Table 2.5). Cultivated land had the highest net gain and is expected to be densely clustered in the upper areas of the catchment, with sparse distributions in the south-east region. Projected net gains in urban land-uses were clustered in the south-east regions of the catchment whilst areas with smaller gains appeared in the middle reaches of catchment along the economic corridor. Commercial forestry areas also increased in the projected 2030 land cover map relative to 1990, with these gains occurring in the upper reaches and south-west areas of the catchment. These gains in agricultural land, urban areas and commercial forestry were primarily at the expense of grasslands and other vegetation, and to a lesser extent indigenous forestry. These areas declined in area by -11.12%, -1.36% and -0.64%, respectively. Wetlands experienced relatively smaller net losses in area, while negligible increases in degraded areas occurred. The declines in grassland and other vegetation (essentially a natural vegetation class) indicated that between 1990 and 2030 the LULC has become increasingly anthropogenically altered.

Table 2.6 summaries the annual rates of change in percentage for each LULC class within the uMngeni catchment. Grasslands were the only LULC class to exhibit constant declining annual rate of change during the periods of observation. Cultivated land, urban and degraded/bare

LULC classes experienced a constant increase during the observation periods. Urban land-use did not experience any growth or decline during the first time period, as the areas during this period did not experience any significant change (Table 2.5). Commercial forestry underwent minuscule decreases in the first time period with considerable increases in the second and third periods. Indigenous forest gained substantial area during the first two observation periods but suffered a significant annual decrease in the last period.

Table 2.6: Annual rate of change (%) of LULC classes in the uMngeni catchment during the periods under study

LULC Class	**1990-2014**	**2014-2018**	**2018-2030**
Grassland	-0.17	-0.80	-0.31
Commercial forestry	-0.07	0.25	0.16
Urban	0.00	0.30	0.20
Other vegetation	0.13	-0.36	-0.26
Cultivated land	0.10	0.43	0.35
Indigenous forest	0.02	0.11	-0.13
Wetlands	-0.01	0.06	-0.02
Waterbodies	-0.00	0.01	0.00
Degraded/Bare	0.00	0.01	0.01

2.4.3.2 uThukela Catchment

The uThukela catchment is dominated by grasslands, with cultivated land and natural vegetated areas being present in the lower, middle and upper reaches of the catchment (Figure 2.5). Between 1990 and 2018, grasslands declined while an increase in cultivated land occurred (Table 2.7). Less significant changes (>1%) were displayed in the other vegetation class, including net gains in indigenous forest, commercial forestry and urban areas. Waterbodies, wetlands and degraded areas experienced insignificant changes, thus making them relatively stable over the 24-year observation period. The overall LULC scenario for the uThukela catchment illustrates a decrease of natural vegetation in favour of agricultural expansion.

Figure 2.5 depicts the spatial distribution for 2030 in the uThukela catchment. As represented in Table 2.7, cultivated land, urban together with the least dominating classes (wetlands and degraded/bare) encountered the highest gains over the 24-year observation period. Whilst natural classes such as grassland, other vegetation and indigenous forest suffered the greatest net losses from 1990 to 2030. Commercial forestry underwent a slight but considerable net gain.

Grasslands, cultivated land, other vegetation and urban areas are projected to be the prime LULC class types within the uThukela catchment in 2030, dominating areal extents of 43.08%, 29.06%, 12.59% and 8.62% of the total study area, respectively. Even though more than 50% of the study area is expected to remain naturally vegetated mainly by grasslands, the increase in urban and cultivated land-use at the cost of grasslands and other vegetation land-uses, will likely leave much of the natural vegetation fragmented. Areas of cultivated land which experienced the highest net gain, are projected to be distributed throughout the catchment with dense clusters south-east and south-west of the catchment, and in the middle reaches of the catchment. Predicted net gains in urban land-uses are primarily in the south-east region, in the edge of the north-east region and around Newcastle and Ladysmith. Natural vegetation classes such as indigenous forest and other vegetation are projected to be densely aggregated in the south-east region and in the lower right reaches of the catchment. Projected gains in commercial forestry are expected to be clustered as one long continuous strip on the edge of the catchment extending from south to east with patches also evident in the south-west of the catchment. Wetlands underwent relatively smaller net gains in area, while negligible increases in water bodies occurred. Degraded/bare areas are scattered throughout the landscape and are mainly concentrated in the south-eastern parts of the catchment.

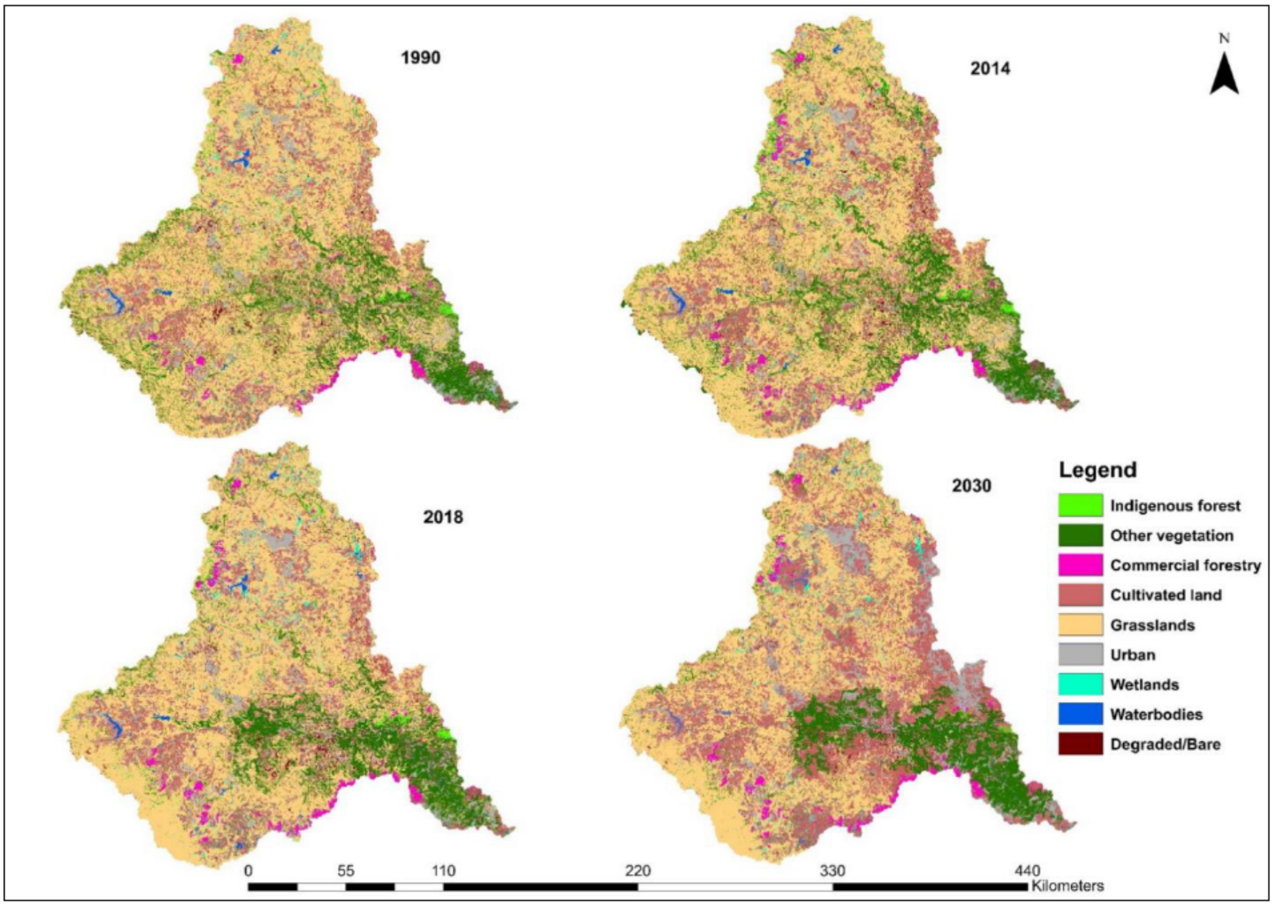

Figure 2.5: Spatio-temporal distribution of historical and simulated future LULC distribution in the uThukela catchment

Table 2.7: Area statistics for historical and future LULC in the uThukela catchment

	1990		*2013/14*		*2018*		*2030*		*Δ(1990-2018)*	*Δ(1990-2030)*
	km²	**%**	**km²**	**%**	**km²**	**%**	**km²**	**%**	**%**	**%**
Grassland	17608.06	60.55	16451.05	56.57	15319.80	52.68	12528.34	43.08	-7.87	-17.48
Comm. forestry	545.74	1.88	616.68	2.12	659.74	2.27	654.57	2.25	0.39	0.36
Urban	1571.68	5.40	1518.18	5.22	1769.40	6.08	2505.86	8.62	0.68	3.20
Other vegetation	4490.72	15.44	4973.71	17.10	4217.17	14.50	3661.99	12.59	-0.95	-2.84
Cultivated land	3281.65	11.28	3963.32	13.63	5381.06	18.50	8451.24	29.06	7.22	17.76
Indigenous forest	149.79	0.52	201.00	0.69	163.01	0.56	87.05	0.30	0.06	-0.20
Wetlands	576.20	1.98	481.66	1.66	694.14	2.39	670.31	2.30	0.39	0.32
Waterbodies	177.93	0.61	182.13	0.63	256.35	0.88	146.63	0.50	0.28	-0.12
Degraded/Bare	679.07	2.34	693.10	2.38	620.17	2.13	374.84	1.29	-0.20	-1.04
Total	**29080.84**	**100.00**	**29080.84**	**100.00**	**29080.84**	**100.00**	**29080.84**	**100.00**		

Relative to 1990, the uThukela catchment is projected to experience changes in its land-use morphology. As demonstrated in Table 2.8, it is evident that the catchment is likely to continue being subjected to spatial-temporal LULC disturbances. Noteworthy annual increases in cultivated land and increases in commercial forestry and urban areas, can be attributed to the significant annual deceases in grasslands and decreases in other vegetation and indigenous forest classes. Wetlands and waterbodies underwent minimal annual changes with noticeable increases during period two and decreases in period three. Urban land-uses showed significant annual increases in period two and three while degraded/bare areas demonstrated a considerable annual decrease in periods two and three.

Table 2.8: Annual rate of change (%) of LULC classes in the uThukela catchment during the periods under study.

LULC class	1990-2013/14	2014-2018	2018-2030
Grassland	-0.17	-0.97	-0.80
Commercial forestry	0.01	0.04	-0.00
Urban	-0.01	0.22	0.21
Other vegetation	0.07	-0.65	-0.16
Cultivated land	0.10	1.22	0.88
Indigenous forest	0.01	-0.03	-0.02
Wetlands	-0.01	0.18	-0.01
Waterbodies	0.00	0.06	-0.03
Degraded/Bare	0.00	-0.06	-0.07

2.5 Discussion

The CA-Markov model was shown to be a reliable and robust model for simulating future LULC as the kappa index values (*Kstandard, Kno and Klocation*) were all over 0.8 and the components of agreement had higher values (0.8715) compared to overall disagreement (0.1285). Furthermore, disagreement was largely a result of allocation errors (0.0906) rather than quantity errors (0.0379), indicating the model's high ability to predict LULCCs in quantity rather than location. Similarly, Munthali *et al*. (2019) obtained kappa index values over 0.8 and found that disagreement was mainly attributed to allocation error as opposed to quantity errors when modelling future land-use dynamics for Malawi. Singh *et al.* (2018) modelling LULCC dynamics for India and Rimal *et al.* (2017) modelling urban expansion in the Jhapa district in Nepal, reported similar statistics with all kappa index values over 0.8 further supporting the suitability of the CA-Markov model in modelling LULCC dynamics in developing countries. The CA-Markov model takes precedence over other land-use change models based on its simple calibration, effective explicit simulation capabilities, high data efficiency and ability to simulate complex LULC patterns and LULC types (Mermarian *et al.* 2012; Singh *et al.* 2015; Hyandye and Martz 2017).

Several Southern Africa studies have noted significant transformation of South Africa's landscape (StatsSA, 2004; Schoeman, 2013; Niedertscheider 2012; Jewitt 2012; Gillson *et al.* 2012; Halpern and Meadows 2013; Jewitt *et al*. 2015; Gibson 2018). For example, Jewitt *et al.* (2015) found 7.6% loss of natural vegetation across the KwaZulu-Natal province between 2005 and 2011, due to anthropogenic landscape transformation. Analysing the historical LULC maps available for the two catchments between 1990 and 2018, revealed similar trends in LULCC in the uMngeni and uThukela catchments of considerable declines in the areas under grassland and indigenous forest, while the areas under cultivated land, commercial forestry and urban LULC classes increased. These trends indicate a disintegration of natural LULC classes due to the expanding anthropogenic-induced activities such as agricultural and urban intensification. Waterbodies, wetlands and degraded areas remained relatively stable over the 28-year period, while the extent of commercial forestry increased slowly at a steady rate. These findings agree with Namugize *et al.* (2018) who noted that natural vegetation within the uMngeni catchment has been significantly modified due to anthropogenic activities and Van Der Kwast *et al*. (2013) who noted that the uThukela catchment was degrading due to anthropogenic driven LULC transformations and unsustainable land-use practices. The LULC simulated in this study for 2030 exhibited similar trends with the natural land-use classes such as grassland, other vegetation and indigenous forest declining in spatial extent across both catchments, with expansion in agricultural and urban areas. Similarly, Selomane and Reyers (2020) projected significant LULCC's by 2030 across South Africa of increases in agriculture, urbanisation and commercial forestry areas, and decreases in all other land-uses.

The projected urban, agricultural and commercial forestry expansion will most likely result in a fragmented landscape functionality and configuration. The landscape stability is also negatively affected by modifying the functionality, connectivity and composition of adjacent land through the loss and removal of natural vegetation cover and biodiversity. Ultimately, the projection is towards a progressive landscape homogenization and low diversification of the natural landscape (Prokopová *et al.* 2019). The altered landscape configuration, connectivity and composition leads to dysfunctionality in ecosystem system services and functions, and a reduction in ecological stability (Jongman 2002; Fondoni *et al.* 2011). Thereby affecting the societies who are reliant on these ecosystem services (Kerr and Ostrovsky 2003). In a country such as South Africa, and in the uMngeni and uThukela catchments, where many people are heavily reliant on the services provided by the ecosystem, these trends of continued fragmentation and the resultant negative impact on ecosystem services is highly concerning.

Globally LULCC's are largely driven by interactions between environmental factors (climate and topography) and socio-economic factors (e.g. population) (Lambin and Geist 2008). Hence, LULCC can be expressed as a function of environmental and socio-economic factors. These factors are known as "driving factors" and are categorised into underlying (indirect changes at a regional level) or proximate (direct modifications by individuals at a local level) drivers of LULCC (Lambin and Geist 2008). Even though this study did not explicitly determine the drivers contributing to LULC trends within the study sites, applicable underlying and proximate drivers within the study catchments include agricultural and infrastructure expansion, socio-economic factors (population growth, population distribution, poverty and related factors), institutional and policy factors and agro-technological change. This is supported by Geist and Helmut (2002), who stated that within Southern Africa there is a recurrent set of underlying socio-economic, socio-political, institutional and policy and technological driving forces. These forces produce at the proximate level, a limited set of direct outcomes such as agrarian expansion, infrastructure extension and wood extraction which bear immediate consequences.

Due to data scarcity relating to LULC drivers, only topographic variables (slope and elevation) and distance to primary roads and rivers were taken into consideration. These drivers served as a proxy in describing the spatial distribution of LULC classes in relation to the natural landscape. The absence of biophysical and socio-economic data resulted in transition inconsistencies between validation and calibration intervals. For the purposes of this study, LULC transitions between 1990 and 2014 were used as prototypal LULC patterns within the CA-Markov model. Using LULC transitions from one-time period can result in the projection of discontinued trends or the miss projection of short-term trends as long-term trends. For example, transitional matrices based on a decline or strong growth trend can result in the model either undershooting or overshooting its predictions (Iacono *et al.*2015).

2.6 Conclusion and Future Research

This study aimed to investigate the historical and future LULCC dynamics within two diverse Southern African catchments. An integration of GIS and RS was utilized in conjunction with a spatially distributed empirical land-use change model to explore the spatial-temporal LULC dynamics and simulate future LULCC. The research findings inferred the following:

- The hybrid CA-Markov model was able to successfully simulate future LULCC within the study catchments utilizing historical LULC data, transition matrices, and suitability maps. The reliability and predictive power of the model was illustrated during the model validation process.
- Based on historical and future LULC trends and patterns, spatial-temporal LULC dynamics within the study catchments are primarily attributed to anthropogenic induced landscape modifications. These modifications significantly altered landscape patterns and take the form of rapid socio-economic development in the form of urbanisation and agricultural intensification. Moreover, these LULC dynamics are an outcome of the interplay between socio-economic, institutional and biophysical drivers governing the study areas. By analysing spatial-temporal LULCC dynamics, trends and patterns, preventative interventions can be put into place to reverse the projected direction of LULC changes and help manage LULC variability within the study areas.
- The incessant and rapid LULC transformations occurring within the study catchments pose consequential impacts. The analysis illustrates significant removal of natural vegetation as well as increasing rates of urban and agricultural growth. Predicted LULC dynamics illustrated the continuation of this trend. This will negatively impact the

social-ecological system within the catchments and foster unsustainable development. These predicted LULC dynamics should be a forewarning to policy makers, natural resource planners and manages, stakeholders and the local government to formulate proactive and effective land-use policies to curb the unmannered growth of artificial LULC classes to help reduce or mitigate adverse environmental effects.

The findings of this study not only contextualised the LULCC dynamics and future LULC trajectories within two Southern African catchments, but also demonstrated the importance and advantages of utilizing GIS and RS technologies in land-use analysis and prediction. The study has also provided vital insights on LULCC's and their associated impacts on the natural environment in the study landscape. Considering that the study was conducted at a catchment scale, future studies should conduct comparative research and adapt the CA-Markov model across different landscapes at a regional and local level. This will contribute towards the retrieval of comprehensive and informative reference LULC datasets. Although the utilization of multi-spectral imagery, was adequate in achieving the study's aim and objectives, future studies should consider using hyperspectral datasets. These datasets effectively evaluate LULC issues at thematic levels that are higher order where 5m or higher spatial resolutions are required. Furthermore, it is recommended that future studies investigate the potential for the CA-Markov model to accommodate socio-economic conditions as it forms a vital part of LULCC studies, especially in instances where the results can be utilized to inform and supplement land planning and policy.

With the ability of the CA-Markov land-use change model to effectively simulate future land-use change under different catchment land-uses and given the implications of changing land-use on hydrological responses such as streamflow, an enhanced understanding of the complex dynamics between land-use and hydrological responses is necessary. To achieve this understanding, the selection of an appropriate hydrological model is required and confirmation of the model's ability to represent hydrological responses such as streamflow under varying land-uses needs to be achieved.

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CHAPTER THREE: ASSESSING THE IMPACTS OF FUTURE LAND-USE CHANGES ON STREAMFLOW RESPONSES WITHIN THE UMGENI CATCHMENT

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Abstract

An essential prerequisite for proactive land-use planning and water resource management is the impact analysis of actual and future land-use/cover change (LULCC) on hydrological regimes. The aim of this study was to assess the changes in streamflow responses as a result of historical and future land-use change in the uMngeni catchment. Changes in streamflow responses were assessed utilizing the ACRU hydrological model combined with baseline, historical and plausible future land-use scenarios. The results illustrated extensive streamflow changes in a number of Water Management Units (WMUs) by 1990. Increases and decreases in mean annual streamflows were present in many of these areas; however, the Pietermaritzburg, Table Mountain and Henley WMUs were shown to have greater increases in mean annual accumulated streamflows compared to other areas while the Karkloof and New Hanover WMUs illustrated the greatest decreases in mean annual accumulated streamflow. However, between 1990 and 2030 the changes in mean annual accumulated streamflow under the land-uses for 2014, 2018 and projected land-use for 2030 were limited. Furthermore, the results indicated that urban land-use has a significant effect on streamflow responses. These impacts are evident as streamflows cascade through the catchment. Changes in the 1:10 wettest year and 1:10 driest year accumulated streamflows have shown the greatest change between the baseline and the 1990 LU scenario.

Keywords: Water Management Units, ACRU hydrological model, land-use/cover change, water resources management

3.1 Introduction

Pressure exerted on land resources for the purpose of food, shelter and water provision, has resulted in extensive modification of the natural landscape through both natural processes and anthropogenic activities (Coppin *et al*. 2004; Cohen and Goward 2004; Hu *et al*. 2005; D'Orgeval *et al*. 2008). The resultant land-use and land cover change (LULCC) has altered hydrological regimes and available water resources (Githui *et al.* 2009; Savenije *et al.* 2014; Gyamfi *et al.* 2016), becoming a key driver of alterations in hydrologic responses within catchments (Wada *et al*. 2011; Chawla and Mujumdar 2018; Kabite and Gessesse 2018). LULCC impacts water resource availability by altering the rainwater partitioning through the soil and vegetation into the hydrological components of surface runoff, interception, evapotranspiration (ET) and infiltration, thus modifying the water balance of a catchment (Falkenmark *et al*. 1999; Rose and Peters 2001; Costa *et al*. 2003; Scanlon *et al*. 2007; D'Orgeval and Polcher 2008; Rientjes *et al*. 2011). Therefore, a catchments hydrological response is responsive to LULCC and is reliant on the land-use within the catchment (Schulze 2002; Bewket and Sterk 2005).

The degree to which LULCC alters the hydrological responses within a catchment, is dictated by the degree of LULCC, the extent of modification and location within the catchment. Land-water interactions vary significantly both in space and time, due to water fluctuations in a catchment, which move laterally (via soils, rivers and aquifers) and vertically (via evapotranspiration). Hence, as water is transmitted through the catchment, any LULCC impacts will subsequently be transferred through the catchment (Falkenmark 2003). In addition, land-use induced impacts are generally threshold related as individual catchments have their own unique feedback mechanisms between catchment components and processes, with varied stable states existing in each (Warburton *et al*. 2012). Hydrological responses differ according to different LULCCs. Land-use changes that significantly impact hydrological responses include, agricultural intensification via irrigation, urbanization and commercial afforestation (Choi and Deal 2008; Jewitt *et al*. 2009). Thus, in order to achieve effective water resource management, the interdependence between a hydrological system and land-use needs recognition, as land-use and water decisions are intrinsically linked (Molden 2007). An appropriate and accepted way to assess LULCC effects on catchment hydrological responses is through the utilization of a hydrological model, which is sensitive to LULCCs and structured to adequately represent and conceptualize hydrological processes (Warburton *et al*. 2012).

Within South Africa, rapid LULCC driven by unprecedented population growth and development in conjunction with macro and regional developmental and economic policies has led to significant landscape transformation and fragmentation (Warburton *et al*. 2012; Niedertscheider *et al*. 2012; Gillson *et al.* 2012; Halpern and Meadows 2013; Jewitt *et al*. 2015; Mauck and Warburton 2014; Gibson *et al*. 2018; Moodley *et al*. under review, Chapter 2) Thus, as land management decisions are ultimately water management decisions, it is imperative to analyse and determine the implications of future LULCC projections on hydrological responses for adaptive and resilient land-use planning and water resource management. The uMngeni catchment is one of many catchments within South Africa heavily impacted by unsustainable LULCC. Within six years (2005-2011) the uMngeni catchment lost approximately 7.6 % of its natural land-cover, consequently bringing the total loss of natural land-cover in the catchment to 48 % (Hughes *et al*. 2018). This loss is the result of rapid urbanization and economic stimulus in the form of agriculture, trade and tourism (KZN Provincial Planning Commission, 2012). Several studies have investigated the impact of LULCC's on hydrology within the catchment. For example, Mauck and Warburton (2013), mapped future areas of urban expansion within the uMngeni catchment with results showing that areas around the cities of Durban and Pietermaritzburg will experience the highest growth in urban areas by 2050. Following this, Mauck and Warburton (2013) modelled the impact of future urban expansion on streamflow responses within the uMngeni catchment, showing that the Water Management Units (WMUs) around Pietermaritzburg (Table Mountain, Pietermaritzburg and Henley) would experience the greatest increase in mean annual streamflow. Namugize *et al*. (2018), assessed the relationship between LULCC and water quality deterioration using Geographic Information System (GIS) techniques and water quality parameters. Their Findings revealed that urban LULC are linked to water quality deterioration. Warburton *et al*. (2012) used a hydrological model to enhance the understanding of land-water dynamics in the uMngeni catchment, and showed that LULC areas, contributions and location impact streamflow responses differently.

Although previous studies have evaluated the impact of LULCC on hydrology, these have focused particularly on urban land-use and no assessment of the impacts of future projections of LULCC on hydrology have been undertaken for the uMngeni catchment. Moodley *et al*. (under review, Chapter 2) modelled projected future LULCC for the uMngeni using the CA-Markov model, thus allowing for the hydrological impacts of these future LULCC to be assessed. Assessing the impact of these land-use changes in the uMngeni catchment will quantify and provide insights on the extent and severity of land-use induced hydrological impacts, allowing for proactive management of water resources and land-use planning at catchment level. This study will make use of the future LULCC projection made by Moodley *et al*. (under review, Chapter 2) as input to the ACRU agrohydrological model (Schulze 1995) to assess the hydrological responses of the uMngeni catchment to LULCC over time. The ACRU Agrohydrological Model (Schulze 1995) was developed in South Africa, specifically for South African conditions and is sensitive to land cover and changes thereof. The ACRU model has been successfully used to assess the impacts of land-use change on hydrology within South Africa and internationally (Herpertz 1994; Makoni *et al*. 2001; Schulze 2004; Schmidt *et al*. 2009; Aduah *et al*. 2017). More importantly, the model has been extensively applied in the uMngeni catchment for both climate change and LULCC impact studies (Kienzle and Schulze 1995; Schulze 1997; Schulze *et al*. 2005; Warburton *et al*. 2012; Mauck 2012).

3.2 The uMngeni Catchment

The uMngeni catchment (4 349 km^2), situated within the province of KwaZulu-Natal, South Africa, comprises of 13 Water Management Units (WMUs) as shown in Figure 3.1. The Msunduzi and uMngeni river are the two primary rivers within the catchment which converge in the Inanda WMU and exit the catchment via the Durban WMU into the Indian ocean (Figure 4.1). The catchment receives between 600 and 1 550 mm of rainfall per annum, with majority of rainfall occurring during summer (October to March) (Mauck and Warburton 2014). The mean annual temperature ranges between 12 to 20 °C (Warburton *et al*. 2012). The uMngeni catchment houses four primary dams, making it a highly water engineered system. The Inanda and Nagle dam supply water to Durban while Albert falls and Midmar provide the city of Pietermaritzburg alongside parts of Durban (Summerton 2008). Furthermore, 300 farm dams supply irrigation water to 18 500 hectares of land within the middle to upper reaches of the catchment. Summerton (2008) defines the uMngeni as a stressed system that, for the foreseeable future, is closed to new streamflow reduction activities.

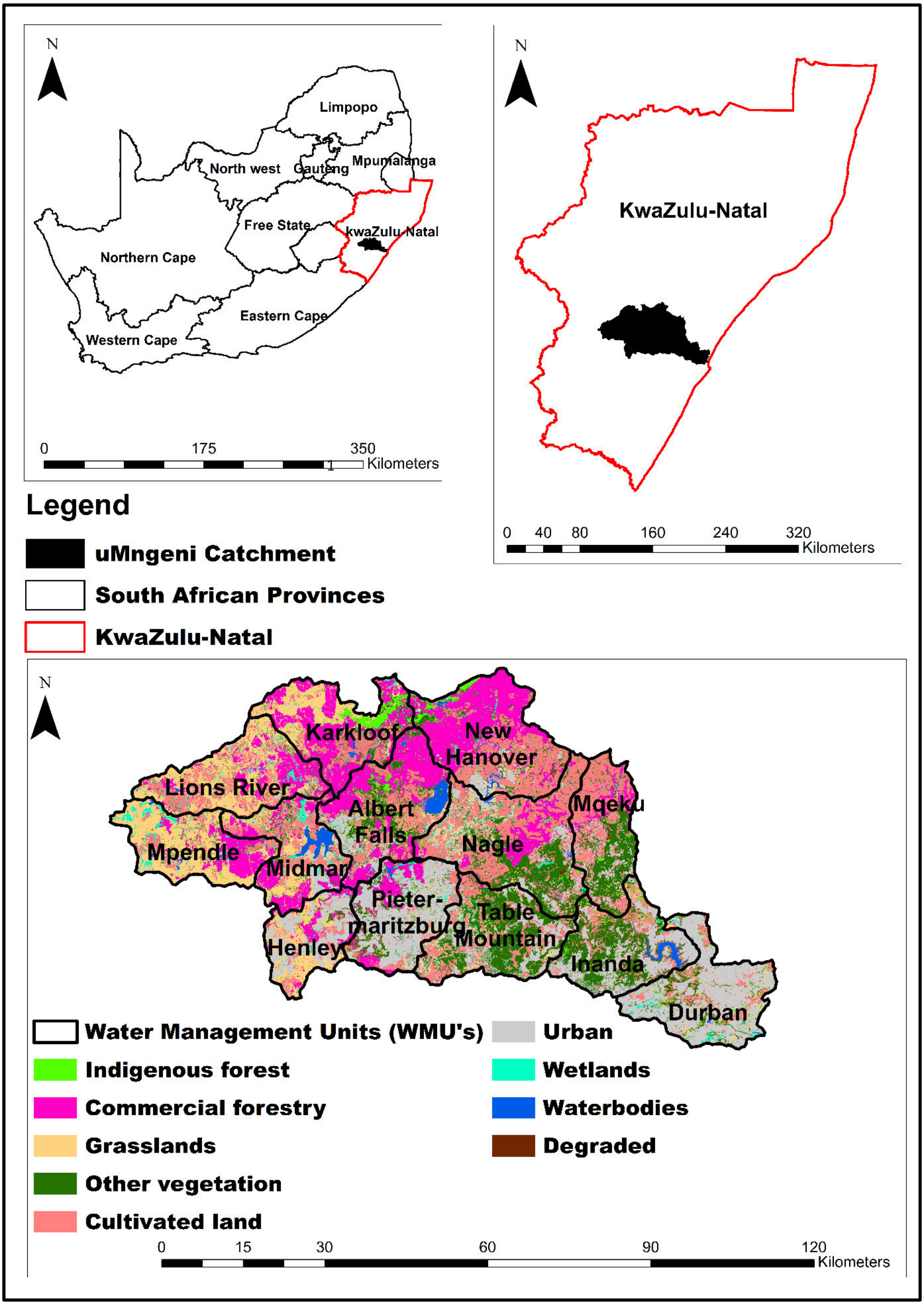

Figure 3.1: Locality of the uMngeni catchment with LULC distributions within WMU'S

(source: https://egis.environment.gov.za/data_egis/data_download/current)

Historical land-use within the catchment varies, with a significant portion of the catchment covered by natural vegetation. Plantation forestry is a dominant land-use within the upper reaches of the catchment, while commercial and small-scale agriculture is practiced within the middle and upper reaches and the lower reaches are predominantly occupied by urban areas (Figure 3.1) (Geoterraimage (Pty) Ltd., 2010). Future LULC within the uMngeni catchment will resemble an increasingly artificial landscape with much of the natural vegetation within the catchment being transformed to accommodate the expansion of anthropogenic activities such as commercial forestry and urbanization Moodley *et al*. (under review, Chapter 2) In addition, as a region with high economic growth and development, the catchment is also expected to see a rise in urban development in the future (PSEDS, 2008). Socio-economic challenges such as rapid population growth, unemployment and poverty also plague the catchment (Mauck and Warburton 2014). The eThekwini and Msunduzi water services authorities (WSAs) currently supply more than 4 million residents with water. Thus, water is a vital asset for sanitation, human use and consumption as well as for commercial, agricultural and industrial activities within the catchment (Mauck and Warburton 2014).

3.3 The ACRU agrohydrological model

The ACRU Model (Schulze 1995) was developed in the School of Bioresources Engineering and Environmental Hydrology at the University of KwaZulu-Natal, South Africa for the purpose of simulating catchment hydrological responses to land management. It is an agro-hydrological, physical-conceptual, daily time-step model (Schulze 1995; Smithers and Schulze 2004). The model operates around a multi-layer soil water budget based on total evaporation and accounts for the redistribution and partitioning of soil water (Smithers and Schulze, 2004). The input variables are derived from the physical properties of a catchment, rather than the model relying on calibrating parameters to provide “the best fit” between observed and simulated data (Smithers and Schulze 2004).

ACRU conceptualizes land cover based on water use and vegetation input parameters that describe LULC processes and how vegetation governs hydrological processes. In the ACRU model, the three processes that are considered when modelling the land-use component are canopy interception loss, evaporation from vegetated surfaces and soil water extraction by plant roots (Schulze, 1995). For each process monthly input values are required and these account for vegetation genetic and environmental factors affecting transpiration, for example spring regrowth, winter dormancy, senescence, planting date and growth rates (Schulze, 1995). Total evaporation comprises of transpiration, soil water evaporation and canopy interception loss

(Schulze 1995). For the purposes of this study canopy interception losses per rainday values were set using the interception loss parameter for each month of the year for each land-use considered. The interception loss parameter values accounted for intra-annual differences in interception loss with growth stage and dormancy. The parameters ranged from 3.5 mm per rainday for mature trees grown for commercial timber production to zero for freshly ploughed land.

Transpiration is described using the water use coefficient (K_{cm}) within the *ACRU* model. K_{cm} is expressed as the ratio of maximum evaporation from the plant at a given stage of plant growth to a reference potential evaporation (Schulze, 1995). When the soil water content of both the top and subsoil horizons falls below 40% of plant available water, transpiration losses are reduced in proportion to the level of plant stress. When plant available water increases to above 40% in either soil horizon, the plant stress is relieved, and the evaporative losses recover to the optimum value at a rate dependent on the ambient temperature (Schulze, 1995). Monthly values of K_{cm} for each land-use are used to compute daily values internally in the model using Fourier Analysis (Schulze, 1995).

Soil water extraction occurs simultaneously from both soil horizons and is distributed in relation to the number of active roots in each soil horizon. Therefore, monthly values of the fraction of active roots in the topsoil horizon are a required input and the fraction in the lower soil horizon is computed internally from this. Under stressed soil water conditions, soil water extraction from the subsoil's contribution to total evaporation will be enhanced beyond that computed for its root mass fraction if the subsoil is not stressed and the topsoil is similarly, the reverse is true (Schulze, 1995). Evaporation of soil water under wet conditions is suppressed by a surface or litter cover, such that there is a linear relationship between surface cover and soil water evaporation, with 100% surface cover allowing 20% of maximum evaporation from the soil water. Soil moisture, structure, texture and soil depth factors are necessary model inputs. These variables govern the rate of water infiltration into the soil, therefore deciding components of runoff, ground water recharge and soil water storage.

In ACRU impervious areas within urban LULC units are accounted for by needing the impervious portion of the subcatchment. In the subcatchment, adjunct impervious areas (i.e. impervious areas which are connected directly to a stormwater or stream system) are differentiated from areas disjunct impervious surfaces (i.e. areas adjacent to pervious areas) (Schulze 1995). For the purpose of this study, conventional values for various urbanization types produced by Tarboton and Schulze (1992) were utilized. Recent LULC studies undertaken in the uMngeni catchment by Warburton *et al*. (2010), Warburton *et al.* (2012) and Mauck (2012) have also used these values.

3.4 ACRU model Configuration and Data Acquisition

As the ACRU model has been extensively used in the uMngeni catchment, an existing ACRU model configuration for the uMngeni catchment as detailed in Warburton *et al*. (2010) was utilized. A short summary is given here with more details available in Warburton *et al*. (2010).

3.4.1 Sub-catchment delineation and configuration

The 13 WMUs (Figure 3.1) were initially delineated as Quaternary Catchments by the Department of Water Affairs and Forestry according to altitude, topography, soil properties, land cover and streamflow gauging stations and these have been used in major studies by Tarboton and Schulze (1992), Smithers et al. (1997) and Summerton (2008). Warburton *et al*. (2010) further delineated these WMU's into 145 relatively homogenous catchments based on terrain, climate and soils. However, the LULC within these 145 catchments varied. Thus, each catchment was further delineated according to LULC into hydrological response units (HRUs). The HRUs were configured to flow in a logical sequence typical of river flow.

3.4.2 Climate, soils and streamflow response variables

Warburton *et al*. (2010) selected fifteen driver rainfall stations for the uMngeni catchment based on the location of the station, the altitude of the rainfall station within the catchment and the reliability of the record. Daily rainfall data for a 40-year time period (1960-1999) was extracted from the Lynch (2004) rainfall database. To improve the rainfall stations representativeness of the catchment, the daily rainfall was adjusted using a month-by-month correction factor as described in Warburton *et al*. (2010). Daily maximum and minimum temperatures were extracted from a database organized by Schulze and Maharaj (2004) and used to compute daily reference evaporation using the daily A-pan equivalent reference evaporation equation by Hargreaves and Samani (1985).

Soil information, such as water holding characteristics, including wilting point and the field capacity and subsoil and topsoil depth, were obtained from the 'South African Atlas of Climatology and Agrohydrology' database (Schulze *et al*. 2008). This source also provided estimations for the fraction of the daily movement of water from the A to B horizons and B horizons to groundwater. As per Warburton *et al*. (2010) it was assumed that 30% of the total stormflow generated in a sub-catchment would exit the same day as the rainfall event which generated the stormflow, and it was assumed that 0.9 % of the groundwater store will become base flow each day.

As this study was particularly concerned with the land cover and land-use, more detail is provided on the land cover and land-use used as well as the parameters to represent them. In the simulations undertaken, all input parameters (e.g. climate, soils) remained constant with only changes made to the land cover parameters and area occupied by each land cover.

3.4.3 LULC Scenarios

Several land cover scenarios were considered, these included reference or benchmark scenarios against which comparisons could be made, historical and current land cover scenarios and the future projections.

3.4.3.1 Reference Land-use: A means of comparison

The determination of land-use impacts on hydrological responses, requires a reference condition or baseline land-cover against which LULCC can be assessed (Warburton *et al.*2012). The South African Department of Water Affairs (DWA) has accepted and supported natural vegetation in the form of Acocks' (1988) Veld Types, as the reference or reasonable standard land cover against which to assess land-use impacts (Schulze 2004; Jewitt *et al*. 2009). The baseline or reference land cover can be considered the natural vegetation of the catchment and depicts a period before significant LULCC occurred. Therefore, streamflow simulated under the baseline land cover is assumed to be representative of the natural flow regimes of the uMngeni river. For the purpose of this study, the Acocks (1988) Veld Types was utilized as the reference land cover against which historical and future LULCC are assessed to establish their hydrological impacts. It must be acknowledged that the utilization of a specific reference or baseline land-cover can cause variations when assessing the extent of land-use change impacts on hydrological responses, which increases the complexity that exists when assessing how changes in land-use impact on hydrological responses.

3.4.3.2 Historical land-use

Historical LULC data used in this study was based on the SANLC datasets developed by GEOTERRAIMAGE Pty Ltd. Historical land-use at three periods were considered, *viz.* 1990, 2013/14 and 2018 (Figure 3.2). LULC within the catchment was categorized into nine distinct LULC classes *viz*; commercial forestry plantations, indigenous forest, grasslands, cultivated land typically for subsistence or commercial purposes, urban, wetlands, waterbodies, degraded/bare and other vegetation classes which includes natural, semi-natural tree and / or bush dominated areas, such as thicket and tall, dense shrubs.

Historical spatial distribution of LULC within the uMngeni catchment remained largely unchanged between 1990 and 2018 with commercial forestry and agriculture occurring in the upper areas of the catchment, and urbanization in lower reaches. Over time, however, the percentage of natural vegetation declined and became more fragmented by anthropogenic activities such as agriculture and urbanization (Figure 3.2). The historical spatio-temporal changes within the various WMUs are shown in Table 3.1. WMUs located at the upper reaches of the catchment were predominately under commercial forestry production while WMUs located in the middle reaches were occupied by cultivated areas and grasslands. WMUs situated in the lower reaches were dominated by urban areas. Significant LULCCs have occurred within the Inanda, Durban, Henley, Karkloof, Pietermaritzburg, and Nagle WMUs. These WMUs have been subjected to significant anthropogenic modifications via the transformation and conversion of natural vegetation for the expansion of urban, cultivated and commercial forestry land-uses.

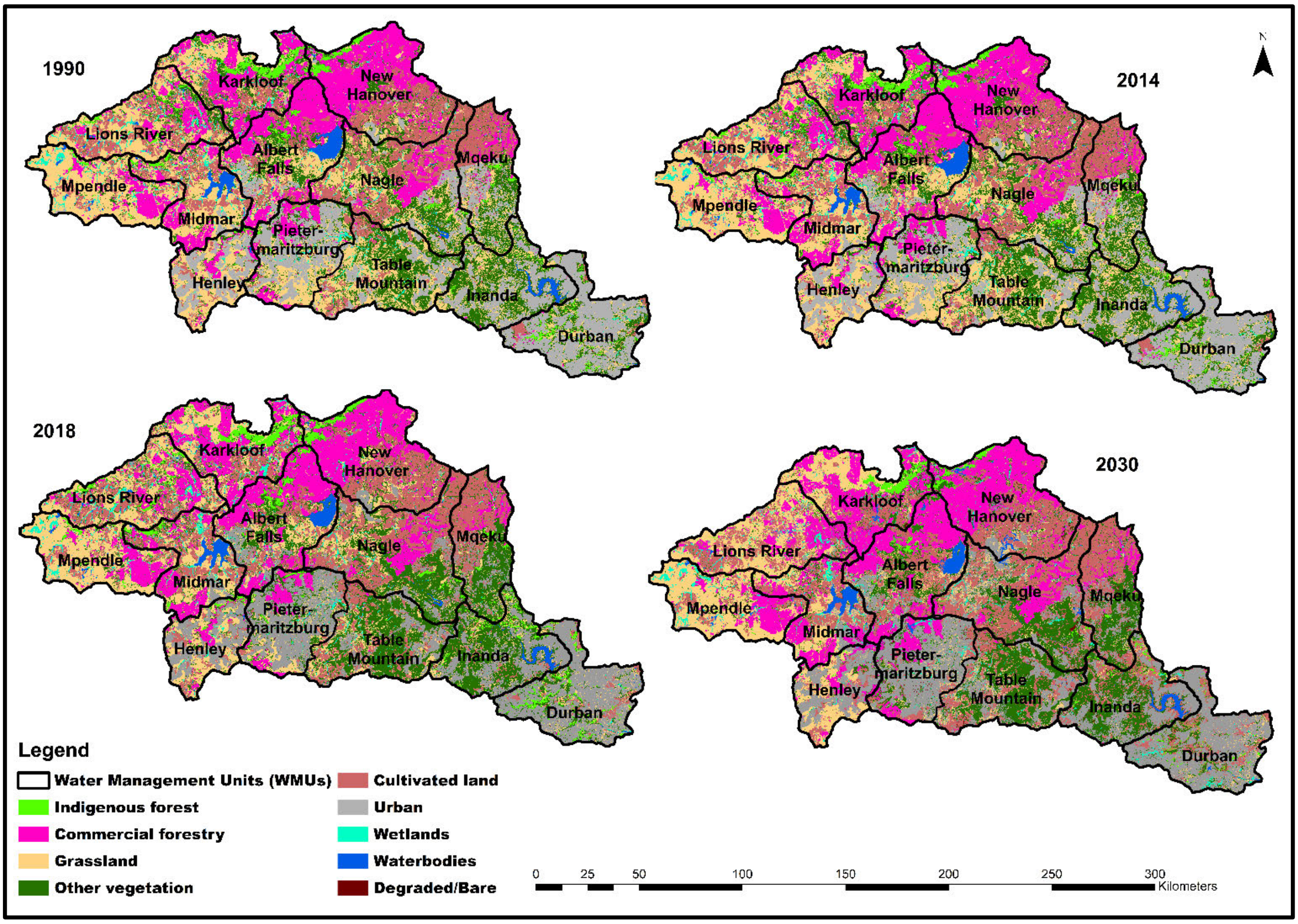

Figure 3.2: Historical LULCC within the uMngeni catchment (Source: https://egis.environment.gov.za/data_egis/data_download/current) and 2030 LULC produced by the CA-Markov model (Moodley *et al*. under review, Chapter 3)

3.4.3.3 Future LULC modelling

The future land-use scenario for 2030 modelled by Moodley *et al*. (under review, Chapter 2) for the uMngeni using the CA-Markov model were used to inform the future LULC hydrological modelling scenario. The CA-Markov model was deemed suitable for modelling future LULCC for utilization in hydrological applications as confirmed by recent studies conducted by Marhaento *et al.* (2018), Gao *et al*. (2020) and Matlhodi *et al*. (2021). The model provided a future LULC map for the year 2030 based on historical land-use, transitional probabilities and applicable LULCC drivers (Figure 3.2). Moreover, the CA-Markov model produces the required spatial location and extent of LULCC needed as input for hydrological applications. The projected LULCC for 2030 for the uMngeni catchment are shown spatially in Figure 3.2 with the areas provided in Table 3.2.

Projected land-use for the year 2030 within the uMngeni catchment resembles an increasingly anthropogenically altered landscape (Figure 3.2). Reductions in the spatial extent of natural vegetation classes such as grasslands and other vegetation are expected within most WMUs. WMUs located in the lower and middle reaches of the catchment, specifically the Durban, Henley, Inanda, Nagle, New Hanover, Pietermaritzburg, Albert Falls and Table Mountain WMUs are anticipated to experience an expansion in cultivated, urban and commercial forestry land-use classes. These simulated land-use trajectories are likely to prevail as a result of historical LULCC trends.

Table 3.1: Change (km^2) in land-uses and land covers within the uMngeni WMUs between 1990 and 2018. A positive value indicates an increase in the land-use/land cover between 1990 and 2018, a negative value a decrease.

	Δ1990-2018 (Km^2)								
WMUS	**Indigenous forest**	**Commercial Forestry**	**Grassland**	**Other vegetation**	**Cultivated land**	**Urban**	**Wetlands**	**Waterbodies**	**Degraded/Bare**
Albert Falls	6.0	-8.0	-16.9	1.9	16.8	4.5	-0.4	-3.9	-0.1
Durban	9.4	-2.0	-9.0	-19.6	9.5	11.4	-0.5	0.3	0.4
Henley	2.4	-2.1	-19.9	2.1	8.9	6.9	1.6	-0.1	0.1
Inanda	7.8	-0.6	-33.9	20.6	10.1	-3.5	-0.5	-1.8	1.6
Karkloof	4.6	6.9	-0.3	-22.7	5.4	1.8	3.8	0.4	0.2
Lions River	3.3	4.4	-14.9	-3.1	4.8	4.9	0.3	0.4	0.0
Midmar	1.7	5.3	-31.2	7.0	8.2	5.8	1.2	2.0	0.0
Mpendle	2.1	5.6	-16.0	5.1	2.9	0.8	-0.4	0.0	0.0
Mqeku	0.5	-5.3	-23.1	21.2	28.0	-22.1	0.2	0.0	0.6
Nagle	0.3	-5.1	-50.0	26.5	29.9	-0.9	-1.2	0.2	0.2
New Hanover	2.7	-20.3	3.0	-8.9	17.0	4.1	2.1	-0.1	0.4
Pietermaritzburg	2.1	-8.6	-39.6	4.2	5.9	37.2	-1.1	0.1	-0.2
Table Mountain	0.1	-1.6	-72.6	41.0	33.1	1.3	-2.2	0.8	0.1

Table 3.2: Predicted areas and percentages of each LULC in each WMU of the uMngeni catchment in 2030 as well as the total area and percentage of each LULC across the uMngeni catchment

	Indigenous forest		**Commercial forestry**		**Grassland**		**Other veg**		**Cultivated land**		**Urban**		**Wetlands**		**Waterbodies**		**Degraded/ Bare**	
	km²	**%**	**km²**	**%**	**km²**	**%**	**km²**	**%**	**km²**	**%**	**km²**	**%**	**km²**	**%**	**km²**	**%**	**km²**	**%**
Albert falls	7.5	1.9	142.7	36.5	28.7	7.3	61.6	15.7	88.1	22.5	37.9	9.7	5.0	1.3	18.8	4.8	0.8	0.2
Durban	7.7	2.2	0.3	0.1	16.6	4.6	29.2	8.2	48.8	13.6	246.7	68.9	6.2	1.7	1.1	0.3	1.4	0.4
Henley	3.4	1.4	28.4	11.6	70.0	28.7	10.2	4.2	28.4	11.6	92.5	37.9	5.5	2.2	2.9	1.2	3.0	1.2
Inanda	6.4	2.0	0.1	0.0	9.2	2.8	115.6	35.1	61.4	18.7	120.1	36.5	2.1	0.6	11.2	3.4	2.7	0.8
Karkloof	21.7	6.4	142.4	42.0	87.4	25.8	22.9	6.8	52.6	15.5	2.7	0.8	6.5	1.9	2.1	0.6	0.8	0.2
Lions' river	2.3	0.6	73.6	20.8	156.5	44.3	13.2	3.7	87.2	24.7	7.1	2.0	11.0	3.1	2.6	0.7	0.2	0.1
Midmar	0.3	0.1	71.7	25.7	67.7	24.3	16.0	5.7	69.3	24.8	24.2	8.7	11.8	4.2	17.7	6.3	0.3	0.1
Mpendle	1.2	0.4	57.6	19.8	165.4	56.7	10.1	3.5	34.5	11.8	2.0	0.7	17.4	6.0	3.0	1.0	0.2	0.1
Mqeku	2.3	0.8	22.2	8.2	5.6	2.1	84.7	31.2	121.6	44.8	31.1	11.5	1.3	0.5	0.2	0.1	2.3	0.9
Nagle	1.9	0.4	56.2	11.3	33.9	6.8	124.8	25.2	193.0	39.0	72.1	14.6	6.9	1.4	3.5	0.7	2.7	0.5
New Hanover	12.3	2.8	205.8	47.2	14.7	3.4	29.0	6.7	134.9	30.9	27.8	6.4	3.4	0.8	5.9	1.4	2.2	0.5
Pietermaritzburg	1.2	0.4	42.8	13.4	16.8	5.3	30.5	9.6	29.2	9.2	189.0	59.4	5.1	1.6	1.5	0.5	2.0	0.6
Table Mountain	0.2	0.1	0.9	0.3	25.1	7.4	141.1	41.5	82.3	24.2	84.9	24.9	4.5	1.3	0.2	0.1	1.3	0.4
UMngeni	68.4	1.5	844.6	19.0	697.5	15.7	688.9	15.5	1031.2	23.2	938.2	21.1	86.6	1.9	70.6	1.6	20.0	0.5

3.5 Results

Simulated streamflows under historical (1990, 2013/14 and 2018) and future (2030) LULCC scenarios were compared against the Acocks' (1988) baseline vegetation scenario. It should be noted that dams and irrigation were not considered in the model. This was done to allow for the LULC impacts to be evident, rather than the effects of the catchments water engineered system and irrigation demand being dominant.

3.5.1 Changes in the mean annual accumulated streamflows simulated under historical and future land-use scenarios

The absolute and percentage change in the mean annual accumulated streamflow simulated under historical and future land-use relative to the streamflow simulated under baseline vegetation at the WMU outlets is given in Table 3.3. The spatial pattern of change within the WMU's are shown in Figure 3.3. As the results are presented as the accumulation of streamflow through the catchment, the Durban WMU also represents the simulated flows for the entire uMngeni catchment. The mean annual accumulated streamflows simulated under the 1990 land cover reflects the significant land-use change that had occurred in the uMngeni catchment by 1990. For example, by 1990 the accumulated flow at the outlets of the Karkloof and New Hanover WMUs had decreased by 30 and 18 %, respectively relative to the accumulated streamflows under the baseline land cover. These decreases are attributable to the large areas under commercial afforestation in those WMUs (Figure 3.3). While increases in accumulated flows of 16, 24 and 23 % were evident for the Henley, Pietermaritzburg and Table Mountain WMUs respectively. These increases in flows are attributable to the urban areas in the Henley and Pietermaritzburg WMUs whose flows are then routed through the Table Mountain WMU.

The changes in accumulated streamflow under the 2014 and 2018 land-uses relative to the baseline streamflow are similar to those observed under the 1990 land-use, however the increases in the Henley, Pietermaritzburg, Table Mountain and Inanda WMUs become greater due to the expansion of urban areas in 2014 and 2018. Further at the outlet of the UMngeni catchment, an increase in flow of 13.7 and 17 % relative to the baseline is seen under the 2014 and 2018 land covers respectively. This is attributable to the expansion of urban areas in the Durban WMU as well as the increase in urban areas in the upstream WMUs already highlighted.

Table 3.3: Absolute (mm) and percentage change in mean annual accumulated streamflows simulated under historical and future land-use scenarios relative to the Acocks'1988 baseline at the outlets of the uMngeni water management units

WMU	1990		2014		2018		2030	
	mm	%	mm	%	mm	%	mm	%
Mpendle	-8.1	-3.2	-8.2	-3.2	-9.1	-3.5	-10.5	-4.1
Lions River	0.5	0.2	4.0	1.9	2.2	1.0	-0.9	-0.4
Karkloof	-85.2	-30.4	-82.6	-29.4	-85.0	-30.3	-88.9	-31.7
Midmar	-2.4	-1.1	-1.0	-0.5	-1.9	-0.9	-3.0	-1.4
Albert Falls	-21.4	-9.7	-19.2	-8.7	-20.2	-9.1	-21.0	-9.5
New Hanover	-35.1	-18.2	-32.0	-16.6	-31.0	-16.1	-30.6	-15.9
Nagle	-17.9	-8.9	-15.5	-7.7	-16.0	-8.0	-14.8	-7.4
Pietermaritzburg	52.2	24.2	58.1	26.9	66.4	30.7	70.5	32.6
Table Mountain	43.0	23.6	46.6	25.6	52.5	28.9	59.7	32.8
Henley	37.1	16.0	40.1	17.2	42.0	18.1	41.1	17.7
Inanda	4.3	2.2	6.2	3.2	6.9	3.6	10.1	5.3
Mqeku	20.2	13.2	19.6	12.8	11.2	7.3	10.6	6.9
Durban/uMngeni	10.9	5.6	12.4	6.4	13.7	7.0	17.0	8.7

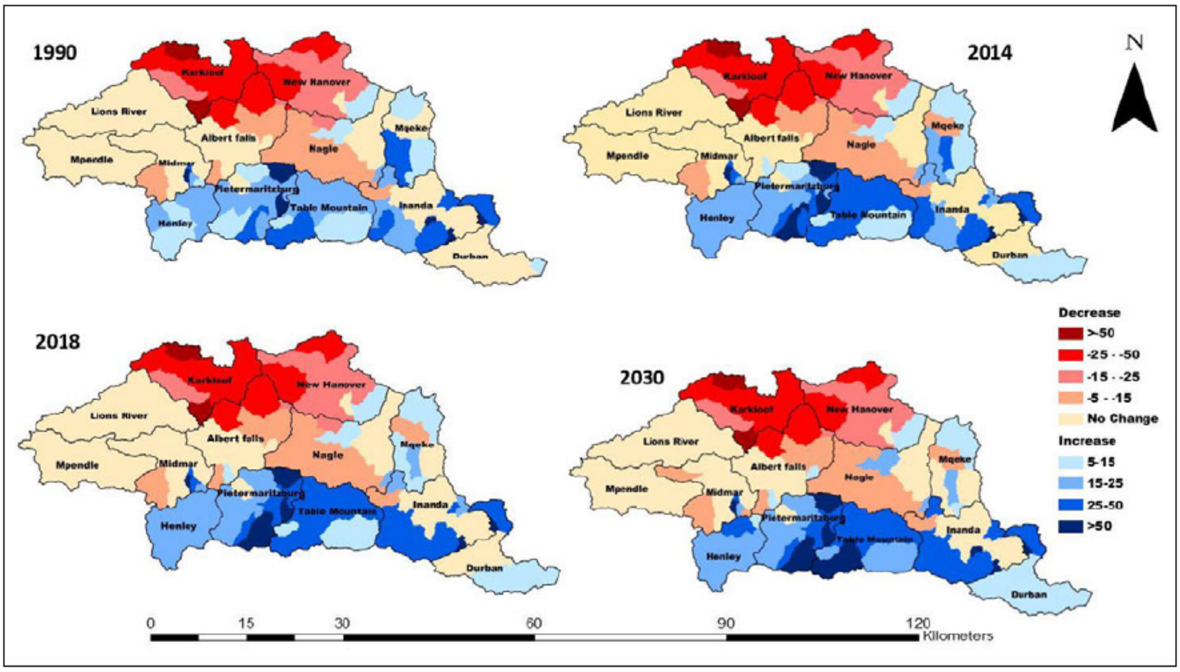

Figure 3.3: Percentage change maps of mean annual accumulated streamflow simulated under historical and future land-use relative to the Acocks (1988) baseline vegetation

Under the 2030 projected land cover the accumulated streamflows relative to the baseline show similar changes as under the 2018 land cover, due to the extent of land cover change that had already taken place. However, the increases in flow in the Henley, Pietermaritzburg, Table Mountain, Inanda and Durban WMUs become even greater under the 2030 land cover due to the projected expansions in urban areas

3.5.2 Changes in the 1:10 wettest year accumulated streamflows simulated under historical and future land-use scenarios

Given the variability in the climate of the uMngeni, considering the influence on the mean average streamflow needs to be supplemented with understanding the influence during wet and dry periods. Table 3.4 show the absolute and percentage change and Figure 3.4 the spatial pattern of change in the 1:10 wettest year accumulated streamflow under historical and future land-use scenarios relative to the baseline within the 13 WMU's. The results show that under 1990 land-use notable decreases are evident in the Karkloof, New Hanover, Albert Falls and Nagle WMU's which decreased by 22, 14, 7 and 6% respectively. These decreases are attributable to the commercial forestry and sugarcane areas in these WMU's, particularly the large areas in the Karkloof and New Hanover WMUs. Whereas significant increases were apparent in the Table Mountain, Pietermaritzburg, Mqeku and Henley WMU's with increased flows of 12, 9, 7 and 5% respectively. These increased flows are attributable to the presence of urban areas and small farming towns in these parts of the catchment. Changes in the 1:10 wettest year accumulated streamflows under the 2014 and 2018 land-use are similar to those under the 1990 land-use, however, increases within the Pietermaritzburg and Table Mountain WMU's grew as a result of increasing urbanisation. At the catchment outlet (Durban WMU), changes in the 1:10 wettest year accumulated streamflows under the 1990, 2014 and 2018 land-use experienced an increase in flow of 4.3, 4.8 and 5.3 % respectively. These increases are due to high-density residential development and commercial and industrial expansions combined with the accumulated influences of upstream impacts.

Table 3.4: Absolute (mm) and percentage change in 1:10 wettest year accumulated streamflows simulated under historical and future land-use scenarios relative to the Acocks'1988 baseline at the outlets of the uMngeni water management units

WMU	1990		2014		2018		2030	
	mm	%	mm	%	mm	%	Mm	%
Mpendle	-8.7	-1.9	-9.1	-2.0	-10.4	-2.3	-12.1	-2.7
Lions River	0.8	0.2	6.5	1.8	2.6	0.7	-1.4	-0.4
Karkloof	-109.8	-22.2	-104.7	-21.2	-109.7	-22.2	-117.1	-23.7
Midmar	-3.9	-1.0	-1.9	-0.5	-4.3	-1.1	-6.9	-1.7
Albert Falls	-31.0	-7.4	-27.2	-6.5	-29.6	-7.1	-31.7	-7.6
New Hanover	-48.7	-14.4	-44.3	-13.1	-43.0	-12.7	-42.8	-12.6
Nagle	-24.5	-6.3	-20.9	-5.4	-22.2	-5.7	-22.2	-5.7
Pietermaritzburg	42.9	8.9	50.3	10.4	58.6	12.1	61.9	12.8
Table Mountain	50.5	11.9	54.9	13.0	61.9	14.6	70.9	16.8
Henley	28.7	5.2	33.4	6.0	35.2	6.4	32.5	5.9
Inanda	8.1	2.1	10.7	2.7	12.1	3.1	17.5	4.5
Mqeku	25.5	7.1	25.7	7.1	16.7	4.6	15.7	4.3
Durban/uMngeni	16.8	4.3	18.9	4.8	20.9	5.3	26.5	6.7

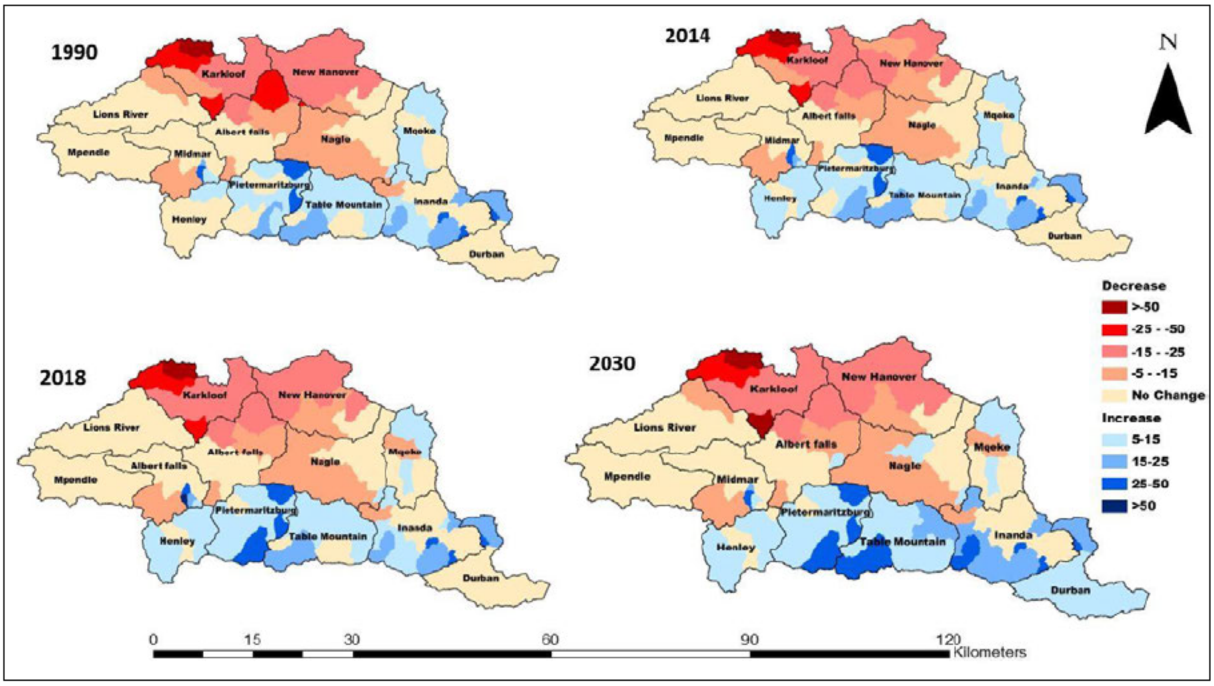

Figure 3.4: Percentage change maps of 1:10 wettest year accumulated streamflows simulated under historical and future land-use relative to the Acocks (1988) baseline vegetation

Changes in the spatial pattern of the 1:10 wettest year accumulated streamflows due to land-use change under the simulated 2030 land-cover is similar to the 2018 land-use scenario, however the magnitude of change in streamflow slightly varies. This is a consequence of the preceding LULCC which has altered the catchments land-use configuration and composition. However, decreases have been amplified within the Karkloof and Albert Falls WMU's due to the increases in commercial forestry expected in these areas. Increases grew under the 2030 simulated land-cover scenario within the Pietermaritzburg and Table Mountain WMU's which cascades downstream increasing streamflows in the Inanda and Durban WMU's. These increases are due to projected urban sprawl.

3.5.3 Changes in the 1:10 driest year accumulated streamflows simulated under historical and future land-use scenarios

A comparison of the spatio-temporal changes for the 1 in 10 dry year percentile streamflows under historical and future simulated land-use scenarios relative to the streamflow simulated under baseline vegetation are shown in Figure 3.5 with absolute and percentage changes shown in Table 3.5 at the outlets of the uMngeni WMUs. Percentage changes in 1:10 driest year accumulated streamflows under the 1990 land-use have resulted in significant decreases by 43, 24, 11 and 10% respectively at the Karkloof, New Hanover, Nagle and Albert Falls WMUs outlets. These decreases are the consequence of commercial forestry impacts during these dry years using a greater percentage of the flows than during wetter years. While increases of 50, 50, 52, 64 and 14% were apparent in the Pietermaritzburg, Table Mountain, Henley, Mqeku and Durban WMUs respectively. Within the Pietermaritzburg, Table Mountain, Henley and Mqeku WMUs, increases are attributable to the presence of towns and urban areas.

Changes in the 1:10 driest year accumulated streamflows under the 2014 and 2018 land-uses relative to the baseline streamflows are similar to those under the 1990 land-use as experienced in the mean annual accumulated streamflows and the 1:10 wettest year accumulated streamflows. Increases experienced in the Pietermaritzburg, Table Mountain, Henley and Durban WMU's became between 1990 and 2014/2013 were due to increased urban expansion, with the impacts remaining constant under the 2018 land cover. The Mqeku WMU experienced a significant 23% decrease between 2014 and 2018 due to the expansion of commercial afforestation as well as cultivated land.

Table 3.5: Absolute (mm) and percentage change in 1:10 driest year accumulated streamflows simulated under historical and future land-use scenarios relative to the Acocks'1988 baseline at the outlets of the uMngeni water management units

WMU	1990		2014		2018		2030	
	mm	%	mm	%	mm	%	Mm	%
Mpendle	-4.6	-4.4	-4.7	-4.5	-4.9	-4.6	-5.7	-5.4
Lions River	1.2	1.6	2.6	3.4	2.3	3.0	0.6	0.8
Karkloof	-41.9	-42.6	-40.8	-41.5	-41.5	-42.2	-43.1	-43.8
Midmar	-2.8	-2.9	-2.5	-2.6	-2.5	-2.6	-2.8	-2.9
Albert Falls	-7.9	-9.8	-7.3	-9.0	-7.3	-9.0	-7.3	-9.0
New Hanover	-20.8	-24.0	-19.3	-22.2	-18.7	-21.5	-17.9	-20.6
Nagle	-8.3	-10.8	-7.2	-9.4	-7.1	-9.3	-5.6	-7.3
Pietermaritzburg	34.6	50.0	37.3	53.9	42.5	61.4	48.3	69.8
Table Mountain	34.6	50.0	37.3	53.9	42.5	61.4	48.3	69.8
Henley	30.9	52.0	32.3	54.4	33.9	57.1	33.5	56.4
Inanda	5.9	7.0	7.0	8.4	7.6	9.1	10.3	12.3
Mqeku	17.5	69.2	16.3	64.4	10.4	41.1	10.4	41.1
Durban/uMngeni	12.3	14.2	13.0	15.0	14.2	16.4	17.3	20.0

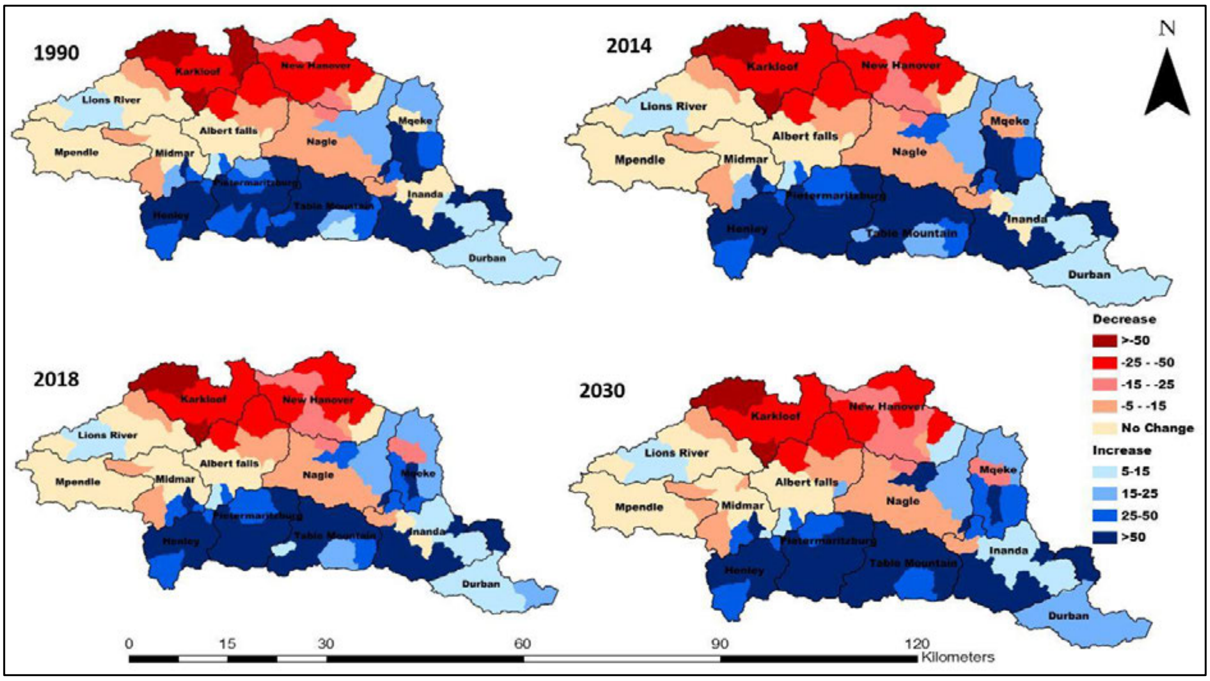

Figure 3.5: Percentage change maps of in 1:10 driest year accumulated streamflows simulated under historical (1990, 2014 and 2018) and future (2030) land-use relative to the Acocks (1988) baseline vegetation

The 1:10 driest year accumulated streamflows simulated under the 2030 land-use does not differ greatly from the 2018 land-use scenario as land-uses were generally similar due to land-use proportions in the scenarios been relatively similar. However increased flows within the Pietermaritzburg, Table Mountain, Inanda and Durban WMUs become greater. Decreases in the Karkloof WMU become larger, while some sub catchments within the New Hanover and Nagle WMUs showed increased flows.

3.6 Discussion

The aim of this study was to assess the hydrological impact of historical and future LULC in the uMngeni catchment using the ACRU agrohydrological model. The study utilized simulated future and historical LULC maps as inputs into a pre-existing ACRU agrohydrological model to simulate streamflow responses under historical and future land-use scenarios.

The results illustrate that due to anthropogenic induced LULCC, the hydrological regime within the uMngeni catchment has been altered when compared to the baseline hydrological regime. Previous studies have illustrated the successful application of the ACRU hydrological model in assessing hydrological impacts of LULCC (Warburton *et al*. 2010; Mauck 2012;

Aduah *et al*. 2017; McNamara and Warburton 2018). The uMngeni catchment has two major tributaries *viz*; the Lions River tributary which is located in the upper catchment and the Msunduzi tributary located in the lower reaches of the catchment. The Lions River tributary converges with the uMngeni River upstream of Midmar Dam whilst the Msunduzi River joins the uMngeni River upstream of the Inanda Dam. The confluence of the Lions River tributary and the Umgeni River within the Midmar WMU illustrates a decrease in mean annual accumulated, 1:10 wettest year and 1:10 driest year streamflow responses. This is a result of the presence of streamflow attenuating land-uses such as commercial forestry. The convergence of the Msunduzi River with the uMngeni River in the Inanda WMU shows increases in mean annual accumulated, 1:10 wettest year and 1:10 driest year streamflow responses. These increases are attributable to the presence of urban areas.

Patterns of low (1:10 driest year) and high flows (1:10 wettest year) have changed significantly between the baseline and 1990. However, between 1990 and the future hydrological regime (2030 LU scenario) only a slight amplification of these impacts is evident. The further change in flows expected in the future hydrological regime is attributable to the anticipated expansion of urban areas, commercial forestry and cultivated land (Moodley *et al*. under review, Chapter 2).

Land-uses within the uMngeni catchment are diverse with multiple land-uses dominating the different WMUs. The land-use impacts on mean annual accumulated streamflows are notable at both an accumulated catchment scale and subcatchment scale (Figure 4.5). As streamflow moves through the catchment, associated streamflow impacts vary in magnitude and extent. In the upper reaches of the catchment there are significant decreases in streamflow responses, however these impacts are attenuated in the downstream WMU's due to the impact of urban areas and impervious surfaces which increase flows. Mean annual accumulated streamflows simulated under historical and future projections of land-use relative to the baseline land-use scenario, take into account effects of various hydrologically sensitive LULC types such as commercial forestry, urban, agricultural land-use and cultivated land. The type of LULC and its location within a catchment significantly contributes to the streamflow responses of the catchment (Warburton *et al*. 2012).

WMU's within the upper reaches of the catchment experienced no changes or decreases between 5 and > 50% in mean annual accumulated streamflows attributable to large scale commercial sugarcane production and forestry. Increases in the WMU's located in the middle and lower reaches are due to high volumes of residential and built-up urban areas. The streamflow response at the outlet of the uMngeni catchment (Durban WMU) reflects the different land-uses evident within the catchment. Furthermore, specific LULC types exert varying impacts on streamflow responses. For example, built-up formal urban land-use which can be found in the Durban WMU has a greater influence on increasing mean annual accumulated streamflow responses while commercial forestry which is evident in the Karkloof WMU have a reduced effect on streamflow. By 2030, significant increases in mean annual accumulated streamflow within the Henley, Pietermaritzburg and Table Mountain WMUs were evident. These increases are attributable to the anticipated sprawling urban growth and urban expansion along transportation routes.

Historical and future spatial-temporal changes of patterns of low (1:10 wettest year) and high (1:10 driest year) streamflow responses (Figures 4.6 and 4.7) relative to the baseline scenario are a result of the nature of LULCC, *viz* urban land-use, commercial forestry and agriculture, combined with the location and extent of LULCCs. Under historical and future land-use scenarios WMU's in the upper reaches of the catchment displayed the greatest decreases attributed to the high proportion of commercial plantation forestry. According to a study conducted by Scott et al (1998) commercial forestry plantations are estimated to reduce low flows by 7.8% and mean annual streamflow by 3.2%. The middle and lower reaches of the catchment experienced the greatest increases as a result of the high percentage of informal and formal residential areas as well as built-up urban areas. These findings are supported by Mauck and Warburton (2014).

When analysing LULCC and its resultant hydrological effects, the preceding LULC condition needs to be recognized before taking into account future land-use scenarios (Quilbé *et al.* 2008). The extent of change from a preceding LULC to a new LULC, dictates the extent of change in the catchment's hydrological regime (Robinson *et al.* 2000). For example, within the uMngeni catchment the resultant increases in flows as a result of urban land-use within the Henley, Inanda, Pietermaritzburg and Durban WMUs are attributed to the conversion of the preceding land-use, which was mainly natural vegetation and commercial forestry to residential urban land-use and built-up land-use. This conversion has the greatest impact on hydrological responses due to the varying physiological characteristics of natural vegetation and commercial forestry (Falkenmark *et al*. 1999). At the catchment outlet streamflow, increases are evident as a result of substantial urban land-use with 1:10 driest year accumulated streamflows showing the greatest increase. This is due to the low of precipitation during the dry year and the small quantity in increases in absolute values of percentage change in streamflow.

The results indicate that the conversion of land-cover to urban land-use will exert the greatest impact on catchment streamflow responses within the 21% of the catchment expected to be urbanized by 2030. A change in LULC to urban is accompanied by the total replacement of natural ecosystems, hence it poses one of the largest impacts on a catchment's hydrological responses (Schulze 2004). Thus, this calls for land-use management planning and land-use policies to be more sustainable and proactive by attempting to accommodate land-use to a sites original attributes as opposed to changing the sites qualities to accommodate land-use adapt land-use to the qualities of a site, rather than adapting these qualities to land-use, and implementing urban growth management programs, while ensuring uncontrolled urban sprawl (Nuissl and Siedentop 2021). Considering the simulated streamflow responses to the different land-use scenarios, it is essential that water resource planning incorporate land-use location, nature and scale from not only the perspective of land-use impacts but also on catchment hydrological responses. Moreover, given the interdependence between streamflow responses and land-use change, water resource and land-use planning should not occur in silos. Utilizing historical and plausible future scenarios of land-use change can be utilized to advise planning and development of water related policies and assist in decision-making within catchment management in the context of catchment land-use planning.

3.7 Conclusion

Quantitatively assessing land-use change impacts on streamflow responses utilizing historical and future plausible land-use change scenarios provided beneficial insights for sustainable water resources management. The results revealed that historical land-use change relative to the baseline significantly impacted mean annual, dry and wet year flows. It also illustrates that potential future land-use changes are likely to increase mean annual accumulated streamflows within most WMU's. At a localized HRU scale land-use impacts on hydrological responses are easily discernible while at a catchment scale the impacts of land-use change become difficult to distinguish as a result of the balancing or amplification effects of present land-uses in the catchment. Furthermore, at the WMU scale the impacts becomes less likely discernible however, only at this scale are the accumulated streamflows able to reflect the combined impacts of land-use changes. This study has shown that the spatial variability of streamflow changes has been shown to be higher at the WMU scale than at the catchment scale.

Moreover, the study has demonstrated the advantages of utilizing a daily time step and land-use sensitive model which possess a substantial level of confidence in its capability to produce realistic outputs to enhance understanding around the complex interactions of land-use change at varying spatio-temporal scales. The results also revealed that specific land-use types have varying impacts on mean annual, winter and summer accumulated streamflow changes. It is these land-use types which will require evaluation and consideration during policy development and planning regarding land-use planning and its associated effects on streamflow.

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CHAPTER FOUR: SYNTHESIS

4.1 Introduction

This research focused on assessing the modelling of future LULCC in two diverse South African catchments and then illustrating the impacts of these future LULCC on streamflow responses within one of these catchments. In this chapter, the research aim and objectives formulated in chapter one will be examined and assessed against research conclusions and results. In addition, key conclusions will be highlighted, limitations and recommendations for future research will also be identified together with contributions that this research has made to new knowledge.

4.2 Aim and associated objectives evaluation

4.2.1 Aim

The aim of this study was to model future land-use under different plausible future developmental scenarios for the uThukela and uMngeni catchments and thereof to assess the hydrological impact of future LULCC on streamflow responses within the uMngeni catchment utilizing the ACRU model. The aim was achieved by deriving four primary objectives. The four objectives are described and evaluated below.

4.2.2 Evaluation of objectives

In this section, the four objectives will be evaluated and assessed to determine the studies capability in achieving the objectives. The four objectives are listed below:

1. **Undertake a comprehensive literature review to determine the most suitable land-use change model**.

In order to achieve the first objective, the study conducted an extensive literature review highlighting and identifying various land-use change models. The selection and identification of an appropriate land-use change model was conducted by reviewing articles and literature through a systematic literature search. Information obtained pertained to model categorization, analysis, functionalities, limitations and applications. Appropriate models were then selected and compared to each other based on model characteristics such as data requirements and modelling techniques. Once this was complete shortlisted models were further assessed based on a selection criterion.

The CA-Markov model was selected as the most suitable land-use change model to be used in the land-use change modelling process due to the models attractive advantages such as its ability to combine CA techniques and Markov chain procedures, it was also the most universally employed LULCC model in simulating future LULCC dynamics, has the capability to simulate LULCC among multiple categories and takes into consideration LULCC suitability and the impact of socio-economic and natural drivers of LULCC.

2. **Source data which may inform the land-use simulation process, including historical land-use maps, policy documents, spatial development plans and climate change scenarios**.

Objective two was met by obtaining relevant data which was utilized to inform the simulation process and populate the selected land-use change model. Data took the form of historical land-use maps, policy documents, spatial development plans and drivers of land-use change. Land-use change maps which were utilized as input data for the land-use simulation process were obtained from https://egis.environment.gov.za/ for the years 1990, 2013/14 and 2018. Policy documents and development documents such as integrated development plans and spatial development plans, which informed the scenario development process were acquired from various sources including: http://www.uthukela.gov.za/, http://www.durban.gov.za/ and https://www.umgeni.co.za/infrastructure-master-plans/.

3. **Simulate future land-use for the uThukela and uMngeni catchment utilizing the most appropriate land-use change model and collected data.**

The third objective was achieved by employing the integrative CA-Markov model and associated IDRISI applications. Future LULCC was simulated for the year 2030 utilizing a standard cellular automata 5x5 contiguity filter, a cellular automata iteration of 12 years, taking into consideration historical LULCC data from 1990 to 2018 as a baseline and identifying socio-economic and biophysical drivers of LULCC. The performance of the CA-Markov model was tested by running a validation, which was conducted by simulating changes between t_1 (1990) and t_2 (2013/14) to predict for t_3 (2018). The predicted map produced for 2018 was than compared against the actual 2018 reclassified map, which served as a reference map. The obtained kappa values (Kstandard, Klocation and Kno) achieved during the validation were all above 80%, thus indicating the model's reliability and capability to successfully predict plausible future LULC in the study sites. The results obtained illustrated that within both catchments, increasing growth of artificial LULC classes such as urban, agroforestry and agrarian areas inevitability contribute to the fragmentation, modification and deterioration of natural land-cover types leading to increasingly anthropogenically altered landscape.

4. **Assess changes in streamflow responses within the uMngeni catchment under plausible future land-use scenarios utilizing the ACRU agrohydrological model**

The last objective was met by utilizing historical land-use maps and modelled future land-use as inputs to the ACRU model within the pre-existing configuration, only modifying land-use parameters and keeping all other parameters constant. The Acocks (1988) Veld Types was utilized as the reference land cover against which historical and future LULCC were evaluated to establish their hydrological impacts. The results revealed substantial streamflow changes in majority of Water Management Units (WMUs) within the uMngeni catchment by 1990. Increases and decreases in mean annual streamflows were evident in many of these areas; however, the Pietermaritzburg, Table Mountain and Henley WMUs were shown to have pronounced increases in mean annual accumulated streamflows compared to other areas while the Karkloof and New Hanover WMUs displayed the greatest decreases in mean annual accumulated streamflow. These changes in streamflow responses were attributable to different LULC types and its location within the catchment. However, between 1990 and 2030 the changes in mean annual accumulated streamflow under the land-uses for 2014, 2018 and projected land-use for 2030 were limited due to the fairly consistent LULC pattern between 2018 and 2030. Urban land-use was shown to have the greatest impact streamflow responses.

4.3 Limitations and Recommendations

This section will identify relevant limitations evident in the study and render possible recommendations for future research. Limitations associated with this study include, but are not limited, to the following:

1. **Uncertainties in LULCC and hydrological modelling**

Models attempt to be representations of real-world processes such as LULCC, thus utilizing any model will be accompanied by uncertainties. Uncertainties present in land-use change and hydrological modelling arise as a result of lack of understanding of hydrological and LULCC processes, inaccurate and/or insufficient input data and errors in the model structure. It is suggested that data processing methodologies such as suitable ground truthing and image processing procedures can be undertaken to minimise uncertainty in LULC input data. Furthermore, a sensitivity analysis can be performed to reduce parameter space uncertainty.

2. **Lack of accurate LULC Classification Scheme and Methodology**

Not only does South Africa lack comparable and consistent LULC datasets at regional and local levels, but also the lack of a consistent LULC classification system used to classify satellite imagery used to produce the maps, made LULCC assessment difficult. It is proposed that additional investments be directed towards the development of a consistent and reliable LULC classification system for LULC maps in the country, so that LULCC can be identify with high levels of accuracy and confidence. The classification system should be capable of accounting for improved satellite imagery resolution whilst creating LULC layers which are consistent with previous classifications. It is also recommended that the National Geo-Spatial Information (NGI) organization actively engage with local municipalities to ensure the successful development of methodologies and standards of a National LULC classification system.

3. **Absence of CA-Markov applications in LULCC studies in South Africa**

To the researcher's knowledge there has not been any previous or current LULCC studies conducted in South African that has employed the CA-Markov land-use change model to simulate future LULCC. Increased application of the CA-Markov model in regional, local and catchment scale studies in South Africa will be beneficial in validating the model's applicability within South Africa. Testing the applicability of the model in a South African context will be advantageous in future research to determine future LULC dynamics, processes and patterns on a national scale.

4. **Inapplicability of selected land-use drivers**

A crucial limitation is that, over several decades, certain drivers that assumed to be applicable in the past may not necessarily be effective in the future. Consequently, in a structured modelling environment, it is not feasible to dynamically make changes to the chosen modelling approach to accommodate current trends. Moreover, the hybrid CA-Markov model assumes that historical patterns of LULCC will persist into the future.

4.4 Future Research

Future studies on LULCC modelling should incorporate more census and socio-economic data for a holistic understanding and analysis of LULCC processes. Moreover, future work should attempt to reduce uncertainties pertaining to hydrological and LULCC modelling. This can be achieved by utilizing optical satellite images with high spectral and spatial resolution obtained at frequent time intervals to observe LULCC dynamics within South Africa. Studies should also conduct independent data collection such as soil surveys and water consumption of different LULC types such as commercial forestry to reduce uncertainties as a result of unreliable input data during the hydrological modelling process. Future studies should also examine the usefulness of utilizing streamflow gauges at various sites for hydrological modelling validation. Utilizing streamflow gauges located at various sites in a catchment such as in the interior will enable accurate determination of modifications in river ecology and the spatial variability of water resources and effectively monitor restoration efforts. Future research should also consider applying the CA-Markov land-use change model on a provincial and regional scale to identify similarities and differences in LULCC patterns.

4.5 Key Conclusions and Contribution to Knowledge

This research aimed to understand the associated implications of LULCC on streamflow responses at a catchment level and highlighted the complexity of the dynamics between land-use and hydrological responses. Chapter 2 demonstrated the capability of a land-use change model (CA-Markov) in simulating future LULCC at a catchment scale for the assessment on hydrological responses, specifically streamflow responses. Chapter 3 described the resultant impact of future LULCC on streamflow responses, while considering LULCC and streamflow response dynamics. The research yielded the following key conclusions and contributions:

- The CA-Markov land-use change model proved to be effective and reliable in simulating future LULCC, as it was capable of spatially simulating multiple LULC classes based on suitable socio-economic and biophysical drivers;
- Analysing historical LULCC and modelling future LULCC are vital components in providing information to better understand the land-use change process and aids in the implementation of effective natural resources management and land-use planning;

- The CA-Markov and ACRU models can be integrated to be effective tools in impact studies to provide data on the hydrological impacts of LULCC;
- The study catchments have heterogeneous feedback mechanisms, complexities and land-water dynamics, thus each have unique thresholds of where LULCC starts to significantly influence hydrological responses such as streamflow;
- Streamflow responses are dependent on the location and extent of certain LULC within the catchment. WMU's dominated by urban land-use illustrated the greatest increase in streamflow responses while WMU's occupied by hydrologically sensitive land-uses such as commercial forestry illustrated decreases in streamflow responses.
- Urban land-use poses the greatest effect on a catchment's hydrological responses especially streamflow responses. Impervious and artificial surfaces impede groundwater seepage and increase streamflows.
- A catchment's hydrological responses are reliant on the land-use present and are reactive to LULCC.