Quantifying the hydrological benefits of investing in ecological infrastructure through the use of ecological and hydrological models

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ABSTRACT

Ecosystems are vital for the survival of all life on earth. Healthy ecosystems in turn provide invaluable goods and services that contribute to sustainable growth. Therefore, in order to produce and deliver goods and services at an optimum, ecosystems need to be managed, maintained and protected to remain within functioning capacity. There are many stresses that impact ecosystems functioning, examples of these include, growing population, climate change and land use/land cover (LULC) changes. These stressors alter ecological infrastructure (EI), which is the base from which ecosystem services (ES) are derived. EI is the natural equivalent of built infrastructure, e.g. dams, and provides beneficial services to society.

Previously, attention had been centred on supply-sided interventions which focused mainly on built infrastructure investments. Despite their importance, the focus needs to shift to integrate investments between both built infrastructure and EI, this owes to built-infrastructure sites becoming scarce, and the majority of water resources already being allocated. The benefits of EI investments are generally not easily or explicitly demonstrated therefore there remains a reluctance to adopt EI investment approaches.

To inform investment decisions pertaining to water resources management, tools such as ecological and hydrological models can be used. Thus, the aim of the study was to demonstrate how both ecological and hydrological can be used in tandem with each other to result in making more well-informed water resources management decisions. The novelty of the research was thus twofold: (1) demonstrating how LULC changes impact EI functionality in producing and delivering HES, (2) identifying how both ecological and hydrological models can be applied synergistically to reveal the full potential benefits of investments in EI.

The study was conducted across the uMkhomazi catchment with a focus on the proposed Smithfield. A major concern within the catchment is the high degree of soil erosion which could potentially impact the functionality of the dam. Based on the dominant LULC within the catchment, i.e., grasslands, the targeted land management intervention selected was grassland restoration of degraded surfaces, with the protection/management of grasslands currently in good health. Grasslands provide a wide array of ecosystem benefits but are often disregarded in value therefore, it was assumed that changes to this LULC would result in significant impacts on HES.

To effectively demonstrate the importance of management/protection vs. the absence of management/protection practices, the selected intervention was modelled under three scenario cases, i.e. baseline conditions, best-case conditions (protection/management/restoration) and worst-case conditions (no protection/management), for both water and sediment yield, using the InVEST ecological model and ACRU hydrological model. Comparisons were done on an annual time step across models to keep on par with ecological model capabilities. The results from the modelling activity demonstrated that upon the implementation of the intervention there was a decrease in water and sediment yield, water yield decreased by 2% using the ACRU model and by 0.3% using the InVEST model. Sediment yield decreased by 6% using the ACRU model and by 66% using the InVEST model. For the worst-case scenario (no protection/management practices), water yield increased with more pronounced effects on sediment yield. Water yield increased by 13% and 2%, using the ACRU and InVEST model, respectively, and sediment yield increased by 28% using the ACRU model and by more than 100% using the InVEST model.

The independent use of models demonstrated their respective strengths and limitations more clearly, allowing for an improved understanding of model capabilities, which served as the theoretical basis for the synergistic application of ecological and hydrological models. Isolated use of models often leads to over/under estimation of EI investment values, therefore using these models in tandem with each other can aid in revealing the full potential benefits of EI investments across multiple intervention techniques in an efficient and effective manner.

PLAGIARISM DECLARATION

I, ***Sayuri Tasha Srikissan*** declare that:

(a) The research reported in this dissertation, except where otherwise indicated, is my original work.

(b) This dissertation has not been submitted for any degree or examination at any other university.

(c) This dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

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DEDICATION

I dedicate this dissertation to my daughter Ariah and to my parents Ajesh Srikissan (late) and Sholay Srikissan.

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LIST OF ABBREVIATIONS

ACRU	Agricultural Catchments Research Unit
ARC	Agricultural Research Council
ARIES	Artificial Intelligence for Ecosystem Services
DWS	Department of Water and Sanitation
EI	Ecological Infrastructure
ES	Ecosystem Services
FC	Field Capacity
HBV	Hydrologiska Byråns Vattenbalansavdelning
HES	Hydrological Ecosystem Services
InVEST	Integrated Valuation of Ecosystems Services and Trade-offs
L-THIA	Long-Term Hydrological Impact Assessment
LUCI	Land Utilization Capability Indicator
LULC	Land Use Land Cover
MIMES	Multiscale Integrated Model of Ecosystems Services
MUSLE	Modified Universal Soil Loss Equation
NSE	Nash Sutcliff co-efficient of efficiency
PES	Payment for Ecosystem Services
PMD	Percentage Mean Difference
PO	Porosity
RIOS	Resource Investments Optimization Systems
SANBI	South African National Biodiversity Institute
SWAT	Soil Water and Assessment Tool
USLE	Universal Soil Loss Equation
WP	Wilting Point

1. INTRODUCTION

Ecosystems provide unique sets of services that are essential for human well-being (Ureta *et al*., 2020; Delpy *et al*., 2021; Perschke *et al*., 2023), contributing to sustainable growth within the economy, environment and society (Duarte *et al*., 2016; Grizzetti *et al*. 2016; Benra *et al*., 2021). The longevity of ecosystems depends primarily on water resources. Functioning of the agricultural, industrial and domestic sectors are all dependent on water resources. Immense pressure is brought upon the already limited natural resources due to external pressures (Perschke *et al*., 2023), which necessitates the need for additional protection and maintenance (SANBI, 2014; Benra *et al*., 2021).

With water security problems being witnessed globally, numerous countries are required to improve the assurance of supply for future generations. This has become increasingly challenging given the impacts of climate change, population growth and land use/land cover (LULC) changes (Ureta *et al*., 2020; Delpy *et al*., 2021; Perschke *et al*., 2023). The 'solution' to securing water supplies in most instances is to invest in grey or built infrastructure (Gokool and Jewitt, 2019). As crucial as built infrastructure may be and often cannot be substituted for, there remains limited options for investment due to over-allocation of majority of the water supplies and limited potential sites for further development (Gokool and Jewitt, 2019). Furthermore, unabated development focusing purely on enhancing socio-economic growth at the expense of the environment can deteriorate catchments to a point where they can no longer render crucial hydrological ecosystem services (HES) at an optimum rate (Gokool and Jewitt, 2019; Perschke *et al*., 2023). Subsequently, continuous investment in built infrastructure to secure water supplies is not considered the most feasible option, especially for the future where there are many uncertainties (Gokool and Jewitt, 2019; Perschke *et al*., 2023).

Considering this situation, investments into ecological infrastructure (EI) have been gaining prominence as a complement and in some instances as an alternative to built infrastructure. From a South African perspective, investing in EI has become increasingly attractive (SANBI, 2014), indirectly supporting poverty alleviation (Cumming *et al*., 2017 and SANBI, 2014), job creation and the continuous supply of benefits from ecosystems to people (Hughes *et al*., 2018). As per the definition by SANBI (2014), EI is defined as the "naturally functioning ecosystems that are able to produce and deliver a suite of valuable services to people." EI is a nature-based equivalent of built infrastructure as both are able to provide beneficial services, such as;

reduction of flood effects, improved water quality and reduced soil erosion, *inter alia* (SANBI, 2014; Duarte *et al*., 2016).

Despite sufficient research around investment in EI, there remains a reluctance to adopt the approach. This could be due to the inability to effectively demonstrate the associated benefits and value of investment. Demonstrating the benefits of EI protection and management is vital for demonstrating the rewards thereafter and attracting investments. Since EI and the services that flow from it can provide invaluable benefits to sustaining and improving human well-being, there is a need to better understand and quantify the benefits that potential investments into EI may have to support management, policy and decision making (Guswa *et al*., 2014; Francesconi *et al*., 2016; Hughes *et al*., 2018). To gain an improved understanding of the complex relationships between ecosystems and their interactions with anthropogenic activities, quantitative tools are required (Bagstad *et al*., 2011), with hydrological and ecological models being amongst the most popular.

Ecological and hydrological models are used to assist in predicting the consequences of various management decisions amongst many other applications (Sharps *et al*., 2017; Schuwirth *et al*., 2019), in order to answer questions related to the availability and quantity of water resources (Gichamo *et al*., 2020), and in doing so assisting water resources management (Dang *et al*., 2020; Gichamo *et al*., 2020). Models can be used as tools to assess changes to water resources caused by LULC and climate changes, *inter alia*. They allow for the quantification and spatial mapping of ES (Sharps *et al*., 2017), which is beneficial depending on the desired outcome of the modelling activity. Multiple modelling approaches are available to answer questions related to water resources management, however, the selection of a suitable approach depends on user-identified criteria such as data availability and knowledge, amongst others (Schuwirth *et al*., 2019). Subsequently, there may exist trade-offs between the requirements and capabilities of the models that can be used to understand and quantify the benefits of investing in EI, which in turn impacts decisions relating to planning and management.

The study will be undertaken across the uMkhomazi catchment, with a focus on the Smithfield dam. The construction of the dam will be for the planned water transfer scheme between the uMkhomazi and uMngeni catchment to meet the projected water demands of the uMngeni catchment. A major concern within the uMkhomazi catchment which poses a threat to the functionality of the Smithfield dam is the high degree of soil erosion (UW, 2014), therefore the application of ecological and hydrological models in this regard to reveal the full potential benefits of investments in EI to guide water resources management decisions.

1.1 Problem Statement

Traditionally, sophisticated hydrological models were used to reveal the potential HES benefits that can be achieved through investing in EI. However, capacity constraints such as a lack of finances, limited access to data and skilled personnel, *inter alia*, may limit the feasibility and efficacy of adopting these approaches, especially in resource poor and data-scarce environments. Whilst comprehensive analysis of EI intervention impacts on HES are limited using ecological models, it is a quick and easy tool to use with limited time and practical application efforts. Due to the simple nature of ecological models, high spatial and temporal variability is not required, as the model also has lower input data requirements and process knowledge (Luke and Hack, 2017), in comparison to hydrological models.

To avoid concentrating unnecessary efforts with in-depth modelling approaches or alternatively producing vague results for problems at hand, models can be applied synergistically to more effectively and efficiently facilitate the quantification of the HES benefits derived from EI investments (Schuwirth *et al*., 2019).

1.2 Aims and Objectives

The study is thus two-fold, firstly demonstrating how LULC changes impact EI functionality in producing and delivering HES, and secondly identifying how both ecological and hydrological models can be applied synergistically to reveal the full potential benefits of investments in EI.

Aim: To demonstrate how both ecological and hydrological models can be used in tandem with each other to result in making more well-informed water resources management decisions.

Objectives:

- Evaluating available literature on the use of models for demonstrating the benefits of investing in EI.
- Evaluate impacts of management vs. no management practices on delivery and provision of HES.
- Assess strengths and limitations associated with each of the models.

- Determine how ecological and hydrological models can be used in conjunction with each other, to demonstrate the full potential benefits of HES.

1.3 Research Questions

- What are the respective strengths and limitations of applying ecological and hydrological model/s to demonstrate the benefits of investing in EI?
- How can ecological and hydrological models be coupled to maximise their respective strengths and overcome the challenges of implementing these approaches independently?

1.4 Research Hypothesis

- Ho: The combined use of ecological and hydrological models will aid in maximizing their respective strengths and overcome the challenges of implementing these approaches independently.
- Ha: The combined use of ecological and hydrological models will not aid in maximizing their respective strengths and overcome the challenges of implementing these approaches independently.

1.5 Organization of dissertation

The dissertation consists of six chapters. Chapter One provides the significance and motivation for the study together with the aim, objectives, and research questions. A literature review and evaluation of literature is performed in Chapter Two, which provides comprehensive understanding of the study and insight to knowledge gaps. The methodology which was implemented in this study is covered in Chapter Three, along with the study site description and model configurations. Results and description are provided in Chapter Four, followed by the respective discussion of model results in Chapter Five. Chapter Six provides concluding remarks and recommendations that can be used for future research.

2. LITERATURE REVIEW

This section entails a review of literature pertaining to ecosystems, ecosystem services, EI and EI investments. Various hydrological and ecological models are reviewed to determine which models are most appropriate for the study.

2.1 Hydrological Ecosystem Services

There are a variety of ecosystems that exist, each of which have their own unique attributes. Ecosystems include *inter alia* agricultural lands, forests, wetlands and riparian areas (Grizzetti *et al*., 2016). Although ES may be defined differently depending on the context of the study, in this study ES will be categorized based upon the two definitions described below.

Guswa *et al*., (2014), defines ES as "the conditions and processes through which ecosystems, and the species that make them up, sustain and fulfil human life", essentially it is the collection of benefits from nature provided to humans (Francesconi *et al*., 2016). Bagstad *et al*., (2011), defines ES as 'the economic benefits that nature provides to people'. Biophysical processes on the landscape are explained through ES and are organized in different categories (Guswa *et et al*., 2014). There are four such ES categories, that is, provisioning services, cultural services, supporting services and regulating services (Christie and Rayment, 2012; Francesconi *et al*., 2016; Anley *et al*., 2022). Provisioning services include food and fibre. Pollination, climate and water regulation falls under regulating services. Cultural services include recreation, aesthetic characteristics, ecotourism and religious values. Nutrient cycling and soil formation are supporting services (Christie and Rayment, 2012; Francesconi et al., 2016; Ureta *et al*., 2020; Delpy *et al*., 2021).

The concept of ES draws attention to the multi-functionality of water systems and recognises the benefits that ecosystems provide to the people (Perschke *et al*., 2023), which is used to justify/argue the costs that go into protection and restoration of nature (Duarte *et al*., 2016; Grizzetti *et al*., 2016). Hydrologic ecosystem services (HES) are "freshwater benefits to people generated by terrestrial ecosystems" (Qiu and Turner, 2015). Each of these services are characterised by quality, quantity (Qiu and Turner, 2015), timing and location. Examples of these services include water purification and climate regulation amongst many others (Grizzetti *et al*., 2016). There are many ES associated with water resources, one for example, is naturally occurring water retention, which has the ability to reduce the harmful effects associated with floods and droughts (Qiu and Turner, 2015; Grizzetti *et al.*, 2016), ensuring safe guarding ecosystems. These services provided by river basins are essential for the survival of human life and biodiversity support.

Important as ES are, scientists are reluctant to incorporate the concept into their work due to varying definitions and approaches for their valuation and quantification (Grizzetti *et al.*, 2016). Thus, there is a need to understand the relationship between anthropogenic forces and ES, in an attempt to provide the most effective measures to achieve acceptable ecosystem conditions in relation to the hydrology of the area (Grizzetti *et al.*, 2016). Stressors and pressures stemming from anthropogenic forces alter ecosystems and their ability to contribute to hydrologic processes, such alterations include water quality and quantity changes and are not only limited to the physical habitat change (Qiu and Turner, 2015).

In an attempt to buffer these changes and maintain ecosystems in the most natural state, studying the anthropogenic effects on ecosystems is needed (Christie and Rayment, 2012; Grizzetti *et al.*, 2016; Ureta *et al.*, 2020). Figure 2.1 represents how humans and ecosystems interact with one another (Grizzetti *et al.*, 2016), pressures are caused by human activities, if ecosystems are altered, in turn biodiversity within these ecosystems are also affected, services rendered are changed along with the economic value of these services (Christie and Rayment, 2012; Grizzetti *et al.*, 2016). This ripple effect of changes necessitates the need to account for the resilience of the ecosystem to promote sustainable delivery of services (Grizzetti *et al.*, 2016).

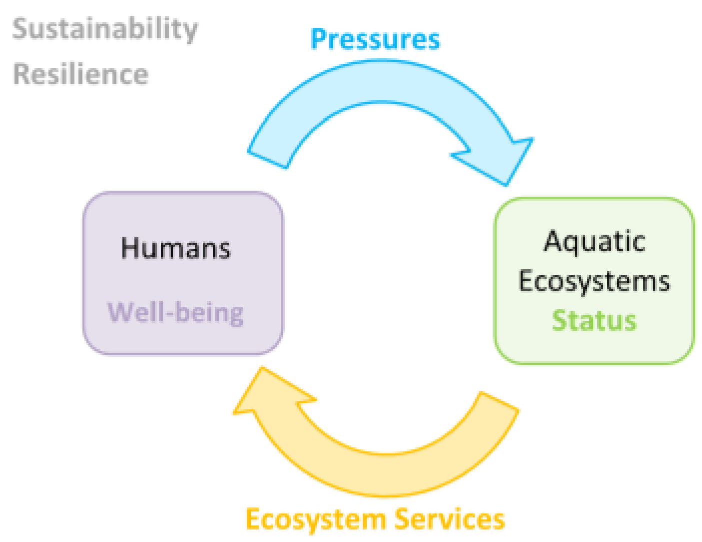

Figure 2.1 The relationship between humans and ecosystems (Grizzetti *et al.*, 2016).

A detailed illustration of the links between drivers, pressures, ecosystem status and ES are shown in Figure 2.2, it must be noted that each study will have its own unique links and this is not a set standard. These links demonstrate how a single change or combination of changes can result in a ripple effect on the greater society and environment.

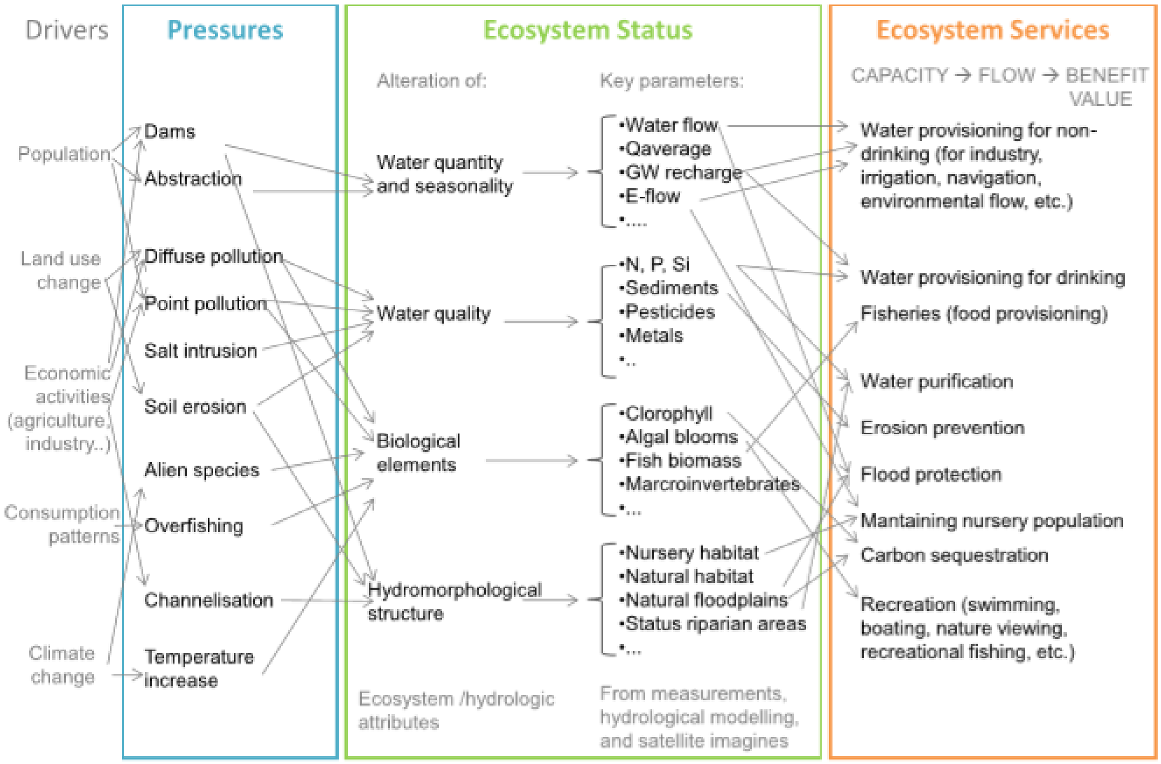

Figure 2.2 The links between drivers, pressures, ecosystem status and ES (Grizzetti *et al*., 2016).

Important factors to takes into consideration, is the ‘capacity’ of an ecosystem to deliver services, the flow of the services and the benefits that the services provide to people (Perschke *et al*., 2023). The ecosystem’s ability to provide services is known as ‘capacity’ and use of the service is the ‘flow’. Capacity is derived from biophysical data and flow from socio-economic data. In some instances, information regarding flow and capacity is limited and more often than not the full capacity of an ecosystem is unknown (Grizzetti *et al*., 2016). This makes it increasingly challenging to know to what extent services can be used.

Incorporating ES in management approaches is becoming increasingly popular as it suggests as to why there should be concern around the management and conservation of ecosystems (Guswa *et al*., 2014) and biodiversity. Valuing ES in terms of monetisation is just one way in which value can be measured (Guswa et al., 2014), and is commonly seen as the simplest way of comprehending the concept, especially during decision-making. Valuing ES can range from simply recognising the fact that an area provides services that benefits the local community to economic valuation of the services (Guswa *et al*., 2014).

2.2 Ecological Infrastructure

According to the definition from SANBI (2014) ecological infrastructure (EI) refers to "naturally functioning ecosystems that deliver a suite of valuable services to people", or alternatively EI is the base from which ES are derived and flow from (Perschke *et al*., 2023). These include healthy mountain catchments, wetlands, rivers and many more, which work together to provide benefits. EI is "the nature-based equivalent of built infrastructure" (Cumming et al., 2017 and SANBI, 2014), and plays a crucial role in providing services that can enhance socio-economic and environmental development (SANBI, 2014; Cumming *et al*., 2017; Gokool and Jewitt, 2019).

2.2.1 History of EI in South Africa

Investments into EI initially started off as a pilot project focusing on a model called "payment for ecosystem services" (PES) (SANBI, 2014), in South Africa in 2011. This did not prove to be viable as it was more off a supply and demand approach (SANBI, 2014). The approach was focused with the sale of services to potential buyers and lacked mutual benefit between role players and ecosystems. It is for this reason that this project was not successful (SANBI, 2014). With much experimentation of alternate ideas to a variety of stakeholders, shifting in model thinking began which resulted in the emergence of a new model called "investing in ecological infrastructure" (SANBI, 2014). This model has a different approach to understanding and communicating the intentions behind the maintenance and restoration of ecosystems, with focus on those that provide valuable services (SANBI, 2014).

The "investing in ecological infrastructure" model pays attention to identifying important services stemming from naturally functioning ecosystems and recognising the organisations/stakeholders that would gain benefits from it or be the ones to invest in these systems. The primary stakeholders that are recognised include government and the private sector (SANBI, 2014). The new model "investing in ecological infrastructure" was more appealing to stakeholders as it was an easier concept to grasp on ecological infrastructure than ES, being a more tangible concept (SANBI, 2014; Perschke *et al*., 2023).

2.2.2 Investing in EI

Investing in EI implies a long-term commitment to nature (Perschke *et al.*, 2023), as opposed to simply buying ES, which occurs once-off. Investing in EI yields returns to the investor through the provision of services (SANBI, 2014). The analogy of ecosystems being the natural equivalent of built infrastructure persuades one into thinking that just as built infrastructure requires initial investments for optimum functioning (Cumming *et al*., 2017), and thereafter, continuous investments for maintenance, the same applies to EI, for optimum service delivery (Cumming *et al*., 2017). Comparing EI to built infrastructure makes it easier for investors to grasp the concept of investing in nature. Table 2.1 provides a list of 7 principles set out by SANBI (2014) to guide EI investment, in a strategic framework. This is important to all interested stakeholders, to provide them with the necessary information required for EI investment.

Table 2.1 7 Principles set out by SANBI for investment in EI (SANBI, 2014).

No.	Principle
1	Investment in EI should focus on achieving clearly defined benefits and outcomes.
2	Investment in EI should focus on systematically identified spatially strategic areas.
3	Investment in EI will be strengthened by a transdisciplinary approach.
4	Investment in EI should build on and learn from existing experience and programmes.
5	Investment in EI should optimise its contribution to job creation, poverty alleviation and rural development.
6	Investment in EI should take place in a participatory and socially sensitive manner.
7	Investment in EI should include monitoring and evaluation.

Devotion of time, effort and finances in order to see a worthwhile result in the future is what investment is, according to the "Framework for Investing in Ecological Infrastructure in South Africa" (SANBI, 2014). With regards to investing in EI, a few of the common examples are maintenance and restoration of degraded EI. There are several ways in which EI investment can be done, as shown in Figure 2.3 (SANBI, 2014).

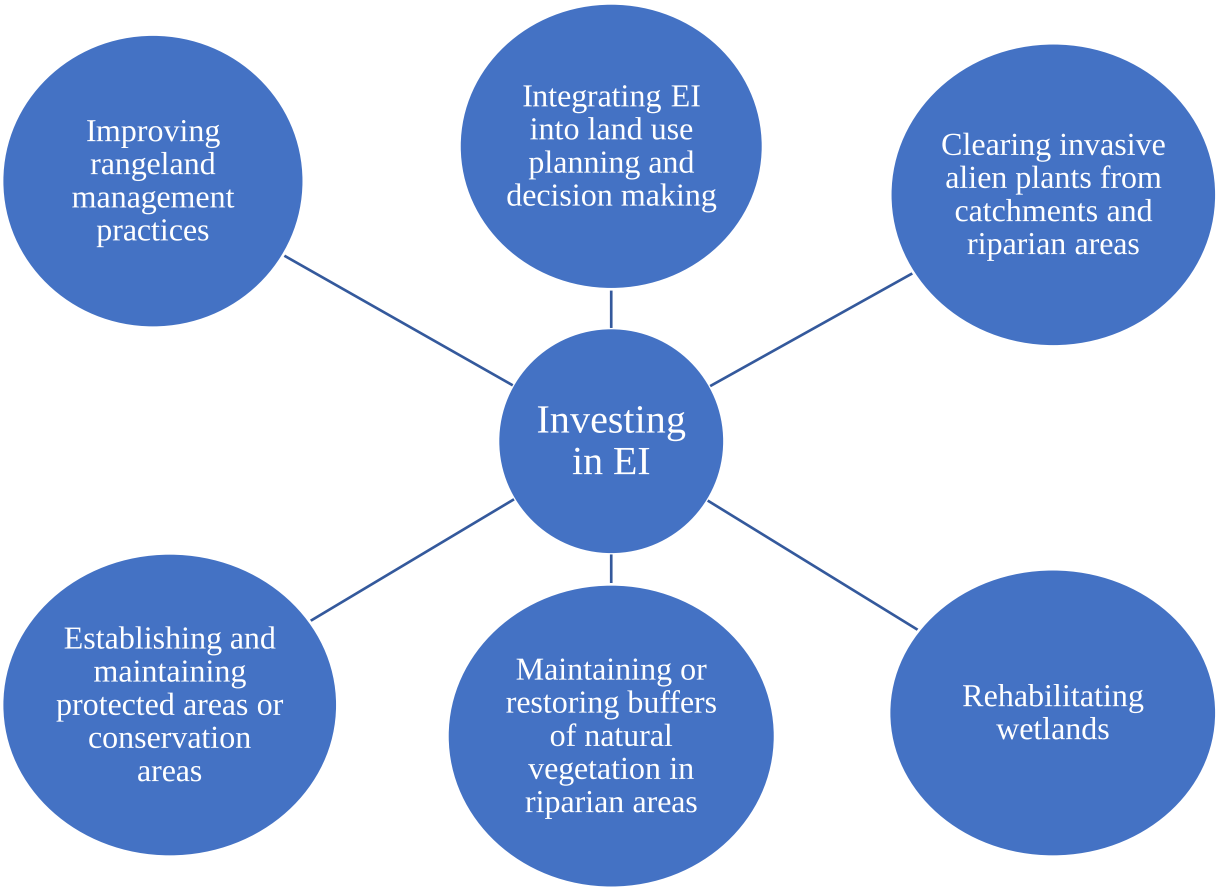

Figure 2.3 Examples of potential EI interventions (SANBI, 2014).

Upon the implementation of an intervention a ripple effect of positive change results (Figure 2.4). The main advantage of investing in EI is that it is able to improve the flow of services to people (SANBI, 2014; Gokool and Jewitt, 2019; Perschke *et al*., 2023), which in turn contributes to improving human well-being. EI investments directly contribute to achieving sustainable development goals one, two and six (SANBI, 2014; Cumming *et al*., 2017; Gokool and Jewitt, 2019), i.e. poverty alleviation, food security and water provision, respectively.

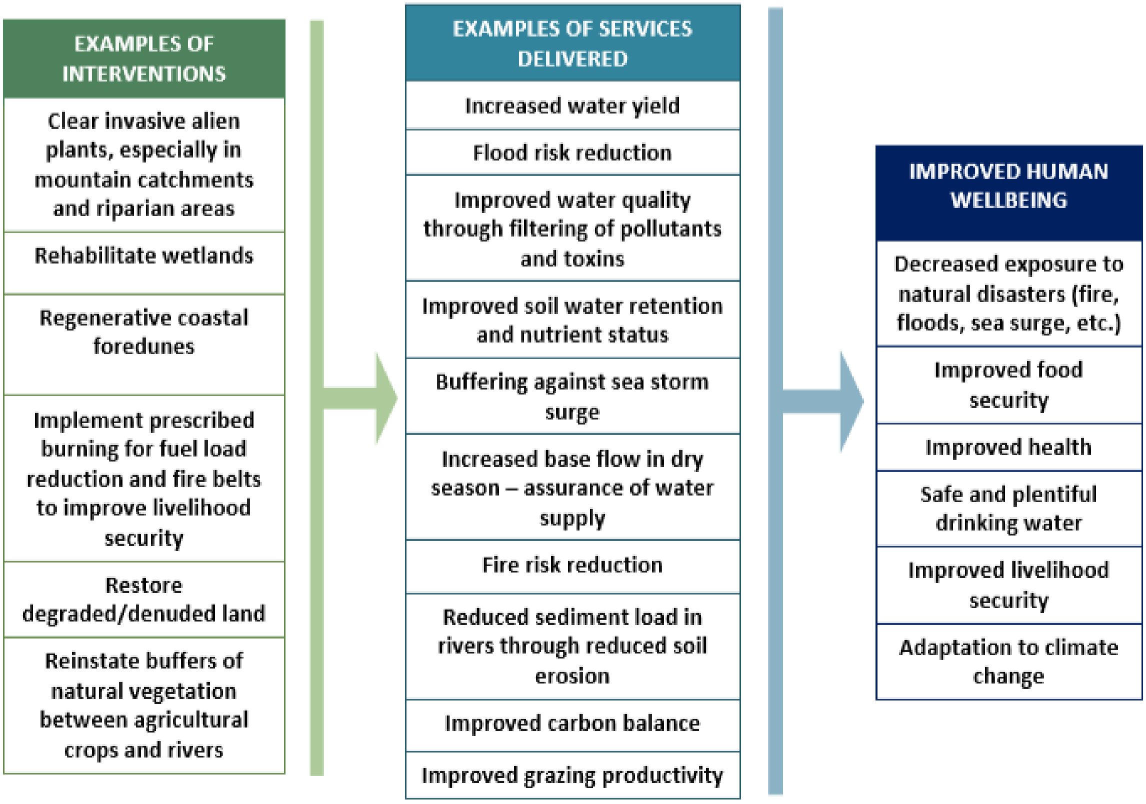

Figure 2.4 Examples of the services delivered, and benefits received from investing in EI (SANBI, 2014).

Recognizing the value of nature could potentially promote investments in conservation, which would have a direct impact on increased human welfare (Sanchez-Canales *et al.*, 2012; Perschke *et al.*, 2023). This can be done by demonstrating the benefits associated with managing ecosystems. This is where ES modelling comes into practice by providing a means of knowledge to enable one to address concerns caused by anthropogenic activities (Francesconi *et al.*, 2016; Gokool and Jewitt, 2019).

2.3 Models used to quantify the hydrological benefits of investing in EI

Modelling enables the prediction of what would occur if certain hypothetical changes were to happen within a catchment, such as, the impact on drinking water from the conversion of forest to agriculture, determining the value of restoration of areas, or determining the effects of management practices (Guswa *et al.*, 2014). Models aim to test user specified hypotheses for future ecosystem conditions, in attempts to predict future scenarios. Modelling tools each possess their own unique strengths and features and thus, the tool chosen depends on the objectives of the study at hand (Sharps *et al.*, 2017).

2.3.1 Ecological/Ecosystem services models

Ecological models attempt to incorporate components and processes of ecosystems into a single modelling framework (Geary *et al*., 2020). Ecological models are tools which provide estimates of various ES, e.g. carbon storage, water yield, crop pollination, *inter alia*, and are able to provide economic values, biophysical measures or maps that illustrate economic or biophysical model outputs. These models are generally associated with low data requirements, quick run time and minimal expertise requirements (Luke and Hack, 2017), which is advantageous for studies limited by funding and time. Although these are relatively simplistic models, in comparison to their hydrological counterparts, they allow for efficient and effective modelling despite the lack of comprehensive analysis of catchment response. These models have been extensively used in marine and fisheries context however, they are now being increasingly adopted in terrestrial ecosystems management (Geary *et al*., 2020). There are a number of models available globally however, in this study only a select few of the most commonly applied models globally are described. Examples of these models are provided in Table 2.2. The models reviewed are most commonly used in studies determining the effects of LULC changes on components of the hydrological cycle.

Table 2.2 Review of commonly used ecological models.

Models	Description	Advantages	Disadvantages	References
Resource Investment Optimization System (RIOS)	• It is an open-source, standalone software tool, running on an annual and longer timestep. • It is supported by any Windows operating software. • The model is able to identify areas providing the greatest returns for EI investment (priority areas). • The model utilises biophysical data, i.e., soils, topography and land uses, to locate priority areas of concern. • The model is made up of two sub-models, i.e. Investment Portfolio Advisor and a Portfolio Translator.	• The model works independently of scale and location thus, can be applied on a regional, national or continental scale. • The model is able to operate on widely available data (global or local datasets). • The model can determine how funds should be used between transition activities.	• Due to only working on annual/longer timesteps, the model leaves out important seasonal variations. • Limitations arise when attempting to apply results at very fine scales. • No longer supported by the developer thus, reluctance for use.	• Goldstein *et al.*, 2017; • Luke and Hack, 2017; • Gokool and Jewitt, 2019
Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST)	• The model can map, quantify, and value services provided by a landscape, using simplified representations of hydrological relationships. • It is an open-source, standalone tool.	• Able to work on local, regional and global scale. • Easily accessible, free to download and accompanied by detailed documentation, i.e. easy to comprehend user manual and each sub-model accompanied by input data.	• Works on an annual time-step, thus leaving out important seasonal variations.	• Sanchez-Canales *et al.*, 2012; • Bagstad et al., 2013; • Guswa *et al.*, 2014; • Zhang *et al.*, 2016;

	• It is a physically based, spatially explicit model. • Demonstrates how LULC/ climate changes alter the delivery of ES.	• Easy to use, thus allows for quick analysis. • Majority of the requisite data is freely available. • The model is applicable to marine, freshwater and terrestrial environments. • The model provides quantitative mapped outputs, which can be applicable to varying contexts. • Can be used in regions lacking in-situ data due to majority of the datasets being freely available global data sets.		• Luke and Hack, 2017; • Sharps *et al*., 2017; • Gokool and Jewitt, 2019
Artificial Intelligence for Ecosystem Services (ARIES)	• The model represents the flow of ES from source to users, with the possibility of interruption by sinks. • Sources include: precipitation and inter-basin transfers (main features of model). • The model is spatially explicit and open source. • The model can value and quantify ES, by a combination of many complex ES models, rather than using a single model,	• Automatically negotiates differences in input data, units and scales between component models. • ARIES can run remotely through any web browser, therefore no need to purchase any software. Data, model storage, processing, model runs and results are managed by the server. • Uncertainty is included in all calculations.	• The model requires skilled personnel for the addition of models to ARIES and new algorithms. • Nutrient retention and water models work on an annual time-step thus, miss the detailed temporal changes in water supply, hydropower production and nutrient concentration.	• Villa *et al*., 2009; • Bagstad *et al*., 2011; • Guswa *et al*., 2014; • Sharps *et al*., 2017; • Delpy *et al*., 2021

	accomplished through an intelligent modelling platform.	• Maps are provided with associated uncertainty due to the probabilistic approach used to cope with data gaps. • The model can be used in data scarce cases, using a probabilistic approach. • Free to download. • Does not require high resolution topographic data as the model is able to aggregate outputs at catchment and sub-catchment scale.	• Interactions between the surface and groundwater is not accounted for by the water models.	
Land Utilization Capability Indicator (LUCI)	• It is an integrated land management decision support model, which is gaining traction for mapping areas rendering ES and goods. • Spatially explicit model, depicting both biophysical properties and configuration of individual landscape elements. • Three basic model requirements: land cover information, a digital elevation model and soil information.	• Provides a proxy measure for the quantity of diffuse pollution retention, with other ES models being incapable of portraying. • Comprehensive outputs are produced, i.e., colour coded maps, with green representing good opportunities and red indicating where restoration and preservation activities should be concentrated. • Built in trade-off tool identifies priority areas	• Unable to report for uncertainty. • Soils data such as soil hydraulic properties are scarce and costly to measure.	• Delpy *et al*., 2021; • Thomas *et al*., 2020; • Dang *et al*., 2021

	• It is a GIS-based framework modelling various land management scenarios to determine where changes would produce the best improvements for ES.	where interventions would render the most benefits. • Easily accessible for public use. • Currently recognized as the only ecological tool able to simultaneously model range of varying spatial scales, while representing small scale connectivity. • Able to compare multiple ES at once and identify trade-offs. • Generates in-depth information even in the absence of detailed input data, at local scale. • A LUCI toolbox available for affordable data acquisition.		
Multiscale Integrated Model of Ecosystems Services (MIMES)	• An analytical framework used for assessing the relationship between ES and human activities. • The model allows for explanation of how ES benefits are gained and lost. • The model is run on user defined transformations of materials between human, built, natural and social capitals.	• The model understands coupled system behaviour across different spatial and temporal scales. • MIMES performs as a Geospatial Information System as well, accounting for links between human and economic systems to be accounted for.	• Extremely complex model to use, requiring costly and challenging training of researchers. • A main requirement is that multiple ecological and human dynamics need to be specified. • Outputs are complex and can be difficult to	• Boumans *et al.*, 2015; • Oliveira, 2021

	• Outputs are a result of 'what if' conditions, identifying trade-offs amongst human interactions and economic services. • The model produces spatially explicit outputs.	• The model is able to make the most of any and available data.	comprehend as much as the real world.	

2.3.2 Hydrological models

Hydrological models attempt to simulate complex hydrological processes on the surface and sub-surface, using mathematical representations to predict the behaviour of water balance components. Hydrological models can be classified as either conceptual or physically based models. Conceptual models simplify complex hydrological processes and physical models aim to represent physical catchment characteristics in greater detail. These models aim to explicitly demonstrate the impacts of various management interventions on HES, enabling in-depth analysis to be conducted, and thereafter allowing for informed detailed conclusions to be drawn. Despite the significant amount of time and effort allocated to input data processing and model configuration (Gichamo *et al*., 2020), outputs produced are good estimations of what could potentially occur under future scenarios.

The common concerns of hydrological models are issues of scale, alongside skills of the modeller and high data input demands (Guswa *et al*., 2014), which impact model selection. Table 2.3 provides examples of commonly used hydrological models that are available for HES simulations.

Table 2.3 Review of commonly used hydrological models for HES simulations.

Models	Description	Advantages	Disadvantages	References
Soil Water and Assessment Tool (SWAT)	• The model has been adapted for ES valuation and quantification. • SWAT is an open access model and is well documented which allows for successful implementation and can be utilised extensively. • It is a physically based, spatially distributed model. • Runoff is calculated using a modified Soil Service-Curve Number (SCS CN).	• The model can function on a daily time step. • Hydrologic response can be isolated to a single variable, for example LULC change. This allows for changes to be isolated and studied, to determine its effects on hydrologic response. • The model is non-stationary; thus, it is able to account for changes over time.	• Multiple input parameters are required for the model to run. • Time consuming model setup.	• Baker and Miller, 2013; • Guswa *et al*., 2014; • Francesconi *et al*., 2016; • Liu *et al*., 2022

Agricultural Catchments Research Unit (ACRU)	• It is a multi-purpose agrohydrological model and revolves around a multi-layer soil water balance. • It is a physical conceptual model. • Parameters are estimated from physical characteristics of the catchment.	• Operates on a daily basis. • The model can output a variety of hydrological responses, such as, daily values of stormflows, baseflows, total streamflow, soil water evaporation, peak discharge and sediment yields within the catchment. • Accounts for seasonal variations. • Able to simulate the effects that different management practices would have on the hydrological responses of the catchment, i.e. sediment yield, water yield, and so on, and able to link with the economic sectors of water resource management. • Used extensively within a South African context.	• It is a data intensive model requiring much expertise for data processing and model configuration. • Time consuming model configuration.	• Schulze, 1995; • Mander *et al*., 2017; • Hughes *et al*., 2018; • Schulze and Schütte, 2019; • UW, 2019; • Otim *et al*., 2020

MIKE SHE	• The model is a spatially distributed physically based, deterministic model developed by the European Hydrological System- Systeme Hydrologique Europeen. • Evapotranspiration calculations make use of the Kristensens and Jensen method, which is based on leaf area index, potential evaporation, and root depth for each vegetation type. • Apart from simulating water flow, the model can simulate the transport of solutes. • The same output is produced for the same set of inputs, regardless of the time period.	• The model covers the complete extent of the hydrological system in a catchment. • The catchment area is discretised into a large number of grids, which allows for spatial variability to be accounted for input data, i.e. soil type, slope, land cover *inter alia*. • The model can provide hydrologic information at any given point within the catchment enabling in-depth investigations to be conducted. • Useful to predict varying scenarios where different time periods are used.	• The model requires much training effort/ expertise for setup. • Timely model setup process. • Not freely available.	• Christiaens and Feyen, 2001; • Ramteke *et al*., 2020; • Aredo *et al*., 2021

Hydrologiska Byråns Vattenbalans avdelning (HBV)	• The model was developed in Sweden in 1972 by the Swedish Meteorological and Hydrological Institute. • The model is a semi-distributed and conceptual rainfall-runoff model using rainfall, temperature and estimates of potential evaporation to simulate discharge which is most readily available data in most catchments. • There are various applications of the model, but are not limited to, climate change studies, computation of design floods or to compute hydrological forecasts.	• Its simple structure allows for easy set up and calibration. • It is a freely available software advantageous for developing countries where funds are scarce. • Its simple nature allowed for the development of multiple versions of the model, each for specific applications. • Since its development the model has been used worldwide due to its robust nature allowing for its application in various regions.	• Several versions available, making model selection difficult. • Limited application within a South African context.	• Grillakis *et al*., 2010; • Bergström and Lindström, 2015; • Tibangayuka *et al*., 2022; • Wang *et al*., 2023

Long-Term Hydrological Impact Assessment (L-THIA)	• L-THIA is an analytical tool useful for determining the impact of LULC changes on the hydrology of a catchment. • Rapid development of the tool to investigate the long-term effects of LULC changes based on climatic data and spatial land use pattern. • The model comprises of two components. i.e. hydrological and water quality component. • The model simulates the volume of direct runoff coming off each cell. In response to different land use changes.	• It is a simple rainfall-runoff model. • The model is able to identify which is the optimum sites for a particular land use associated with minimal environmental impacts *inter alia*, destruction of groundwater resources and flooding. • The model uses past experiences to determine the long-term impacts on future profiles.	• The model is only capable of handling 8 land use classes, i.e. agriculture, low-density residential areas, high-density residential areas, water bodies, grasslands/rangelands and industrial areas. • Classes falling out of these are categorised according to similar runoff production characteristics. • Severe climatic changes are missed due to the model simulation process being performed using averages of long-term changes.	• Jahanishakib *et al*., 2023; • Mehrani *et al*., 2023

2.4 Review of Case Studies

Numerous studies have been reviewed studying the impacts of various LULC changes on HES. A detailed review of selected studies follows with additional studies found in Table 2.4. Generally, studies were conducted to analyse and thus address concerns within catchments, to inevitably improve catchment management. Majority of the studies looked at the influence that LULC has on components of the hydrological cycle and ES.

A study conducted by Gokool and Jewitt (2019), within the uMngeni catchment, made use of the InVEST and RIOS ecological models. The study was conducted to demonstrate how ES modelling could be utilized to aid decision making with interest around EI investments. Datasets used included, digital elevation models, LULC, soils, biophysical data and economic data amongst many others. The results demonstrated that investing in EI resulted in a reduction in sediment yield by approximately 47%, and a reduction of water yield by 1.25% in cases of protection/maintenance activities. This was a trade-off identified by the study. Although there is a reduction of water yield with the implementation of the investment portfolio, reduction in sediment export is associated as a net benefit.

For the LULC scenario with no protection, bare soil coverage would increase across the catchment, as natural vegetation would degrade, resulting in sediment and water yield to increase. The absence of protection may result in a reduction on the return of investment on HES. This study demonstrates that protection provides a greater impact on sediment export than restoration and riparian management. However, this case does not always hold true, this relies on the current LULC and what it will transition to. Seasonal dynamics also play a role in influencing the results (Gokool and Jewitt, 2019), which was overlooked with the InVEST model. Although there were limitations associated with local data sets and the models itself, the study was still able to demonstrate how both models were able to aid EI investment decision making. The models were not validated due to a lack of observed data, thus the results produced were only indicative of relative change (Gokool and Jewitt, 2019). Gokool and Jewitt (2019), recommend the use of a more spatially and temporally explicit hydrological model in conjunction to using RIOS, to evaluate the spatio-temporal impact of management practices on the delivery of HES.

A study conducted by Bagstad *et al*., (2013), in San Pedro River, Arizona and northern Sonora, Mexico aimed to compare two ES models, i.e. ARIES and InVEST. Bagstad *et al*., (2013), suggested that conducting studies in different geographic context can aid in improving the understanding of the strength and weaknesses of these models and other ES models, therefore supporting resource management. The models were used to simulate carbon storage and water yield in open and constrained urban development. The results indicated that there were similar gains and losses of ES across different scenarios. For open and constrained urban development both InVEST and ARIES results demonstrated a loss of carbon storage and an increase in water yield. Management scenarios showed increased water yields, due to grasslands having lower evapotranspiration rates (Bagstad *et al*., 2013). Both InVEST and ARIES were successful at modelling the changes due to urban growth and management practices. Similar results were produced for both models over a larger spatial extent in the case of urban growth scenarios. Over a smaller spatial extent such as the management scenarios the results are different (Bagstad *et al*., 2013). It was also found that ARIES is a time-consuming model to use. ARIES and InVEST were selected as other models were qualitative and not spatially explicit, some require commercial licenses and certain models were place specific. Sensitivity analysis was not conducted in the study, as it would have been time consuming to perform (Bagstad *et al*., 2013), recommendations include conducting further comparative studies to determine where each modelling platform will be best applied.

Mander *et al*., (2017), conducted a study using the ACRU model to demonstrate the hydrological returns from EI investment, within the Baviaanskloof-Tsitsikamma catchment and uMngeni catchment. Results demonstrated that protection, maintenance and rehabilitation of priority EI produced significant hydrological gains. With rehabilitation, both baseflow and streamflow would improve in the catchments. The ACRU model was successful at demonstrating the HES that would be gained under different management scenarios and which areas within the catchment are the main water source areas/ priority areas. Economic modelling provided valuation of HES in terms of monetization to demonstrate the costs involved in the various management techniques. There was a lack of uncertainty analyses for model verification, due to limited streamflow data (Mander *et al*., 2017), however, the ACRU model has been extensively used and verified.

de Oliveira Serrao *et al*., (2022), conducted a study in a basin in the Brazilian Amazon using the SWAT hydrological model. The purpose of the study was to determine the impact of historical LULC changes on hydrological processes and sediment yield. The historical changes resulted in significant impacts on the hydrological balance within the basin, such as, increasing mean flow, surface runoff and sediment yield. Sub-basins which were dominated with pasture-land resulted in increased surface runoff and sediment yield. On the other hand, sub-basins primarily constituting of forests had homogeneity in the time series however, if 19% of the existing forests were to be lost it would result in a collapse of the water balance. It was found that changing land use altered the water balance, which had both positive and negative impacts on society. These changes inevitably impact human activities, such as, livestock, energy production, food security and water supply. Validation studies of the SWAT model revealed that the model performed well in simulating sediment yield.

Table 2.4 Review of additional case studies.

Study site and model used	Intended purpose of study	Key research findings	Recommendations	References
• Vietnamese Mekong River Delta • LUCI ecological model	Supporting natured-based flood water management in river deltas though the use of ES modelling.	• Successful in contributing to nature-based solutions implementation. • The model performed well in simulating ES, i.e. flood mitigation, agricultural productivity, etc.	• Limited applicability to new agro-hydrological regime. Thus, a reconceptualization of model mechanisms is required for water-tolerant crops.	Dang *et al.*, 2020
• Himachal Pradesh, India • InVEST and RIOS ecological model	Manage forest ES for hydropower production.	• Soil and water conservation increased sediment retention, with a slight decline in water yielded. • InVEST does not account for extremes. • The model performed with greater reliability using local data. • ES modelling with multiple parties increases relevance in policy making.	• To incorporate economic valuation for the quantification of the value of ES. • Use a hydrological model to account for seasonal changes.	Vogl *et al.*, 2016
• Global, watershed and marine application • MIMES ecological model	To simulate the interactions between human and natural systems	• Validation studies revealed that the model performed well under all scenario cases with regards to flow and generation of ES over space and time. • Increased urbanisation reduced ES production, however reforestation resulted in an increase in ES production.	• Sustainable future planning requires sophisticated and spatially explicit approaches, dynamic modelling of ES and having local modelling being scaled to watershed, national and global scales.	Boumans *et al.*, 2015

		• Effective modelling of trade-offs and synergies		
• Cagayan de Ora watershed, Philippines. • LUCI ecological model	To improve predictions of the effects of extreme events, climate change and LULC changes on hydrology, with focus on flood mitigation measures.	• The model was effective for long-term land use planning. • The model was able capture the abrupt changes of floods well. • The model identified priority areas for management to further improve flood mitigation ES. • Results demonstrate that small-scale rehabilitation provides greater flood mitigation measures as compared to large scale reforestation.	• To model various other ES, identify trade-offs and apply the model to multiple land cover scenarios.	Benavidez *et al*., 2016
• Shaya Catchment, Ethiopia • MIKE SHE hydrological model	To determine the impact of LULC change on streamflow.	• No significant trends or shifts in rainfall, however streamflow increased significantly. • LULC change resulted in streamflow to increase during the wet season and decrease during the dry season, due to the expansion of settlement and agricultural area, accompanied by a decrease of forest, bush and bare land. • Based on statistics such as the correlation coefficient, root mean square error and Nash Sutcliff co-efficient of efficiency, the model exhibited very good performance.	• Monitor and control LULC change to maintain balance in the ecosystem. • Management and policy makers to regulate changes to prevent impacting hydrologic system.	Aredo *et al*., 2021

• Gumara catchment, Ethiopia • HBV hydrological model	Determining the impact of LULC changes on water balance components, i.e. evapotranspiration, soil moisture, groundwater recharge and runoff. To quantify the rate of LULC changes.	• Forest and grassland area decreased from 11% and 18%, respectively to 5% and 10%, respectively between 1986 to 201, with cultivated land increasing. The model indicated a minor change in water balance components +/- 5%. • The model was incapable of demonstrating certain observed changes in the catchments. • There was good model performance suggested by validation studies. • Limitations associated with simple rainfall-runoff models.	• Use of a modelling approach consisting of physical and statistical characteristics, along with a good spatial and process-based representation of LULC.	Birhanu *et al.*, 2019
• Gharesou watershed, Iran • L-THIA hydrological model	Determining hydrological responses to spatial-temporal LULC changes, concentrating on annual runoff for flood prevention.	• Lowest runoff produced under forest/grassland cluster. High-density residential land cover generated the highest runoff values. • Runoff was predicted to increase due to forest degradation and fragmentation, with an increase in settlement. Land degradation resulted in a loss of hydrological connectivity. • Statistical analysis revealed good model performance in simulating the effects of LULC change on runoff.	• Connectivity of natural areas should be conserved, with minimal artificial land uses in the catchment. • Perform studies on finer scales and shorter time periods.	Jahanishakib *et al.*, 2023
• Lake Victoria Basin, East Africa	Assessing hydrological impacts of LULC	• Increased runoff due to grassland and forest degradation and	• The effect of LULC changes, e.g. deforestation,	Liu *et al.*, 2022

• SWAT hydrological model	changes. Focus on seasonal runoff and hydrological droughts.	expansion of agricultural and urban land. • Increased groundwater promotes surface runoff during the short rainy season, and vice versa for the long rainy season. • The model performed well in simulating seasonality runoff.	on climate requires investigations.	
• Upper Awash Subbasin, Oromia, Ethiopia. • SWAT + hydrological model	To determine the response of runoff and sediment yield to sensitive changes in the watershed.	• The model made use of land use maps from 2000, 2010 and 2020, along with continuous climate data from 1992 to 2020. • It was found that agriculture and urbanization both increased, however, forest and shrubland decreased in area. • LULC changes had significant impacts on surface runoff and soil erosion. • Results from the model indicated that with the LULC both water and sediment yield increased. Due to increased bare soils, agricultural land and urban areas over the years. • The model performed well in simulating flows and sediment yield. The results were as follows: R^2 = 0.88 and NSE=0.9 for streamflow, and R^2 = 0.82 and NSE= 0.86 for sediment yield.	• Land use managers to take actions due the high degree of sediments generated by the catchment, resulting in negative implications on the downstream reservoir.	Tumsa, 2023

• Nanjuma River Basin, Northern China • HBV hydrological model	Determining the applicability of the HBV to model a catchment influenced by humans. As well as analysing the impact of a changing environment on the hydrological regime.	• The study was conducted from 1961 to 2017 and was split into 3 periods of change, i.e., natural period, moderate human influence and intensive human activities. The model performed best under a predominantly natural period, for both daily and monthly discharge simulations. • The model performs moderately well when there were moderate human influences. • Under intensive human influences the model was almost incapable of capturing the hydrological regime. • Significant decrease in streamflow under climate changes and human influences.	• Further hydrologic modelling for operational flow forecasting under a changing environment, for water resources management.	Wang *et al.*, 2023
• Beijing-Tianjin-Hebei, China • L-THIA hydrological model	To determine the impact of climate change and urban growth in large-scale urban agglomeration, in China in 2030.	• Climate change and urban growth both impact hydrological processes, results showed that there was an increase in surface runoff. • The main influence of change was climate change within regional and city scales. • Urban growth had the greatest impact within the sub-city scale. From the results produced it was indicative that a single factor cannot	• The analytical framework developed within this study to be applied to other large-scale urbanized areas, for similar assessments.	Ju *et al.*, 2023

		be used for managing water resources effectively in megacities. Integrated solutions are required for effective management across the large scale. • Validation studies suggested that the model provided accurate simulations of surface runoff.		
• uMngeni catchment, South Africa • ACRU hydrological model	To aid EI investments by demonstrating the impacts of EI investments on water and sediment yield.	• The results indicated that there were significant gains in ES by rehabilitation of overgrazed lands. • Dry season baseflow and accumulated streamflow could be increased by rehabilitation of overgrazed land. Rehabilitation of overgrazed lands proved to be the solution for improving dry season baseflows. • Removal of alien invasive plants improved streamflow. However, sediment reduction improved under the rehabilitation of overgrazed lands. • A validation study conducted by Warburton *et al*., (2010), confirmed the applicability of the ACRU model to simulate streamflow in the catchment.	• An approach such as this is recommended for the efficient supply of clean water to society, for land use planning and for catchment infrastructure.	Hughes *et al*., 2018

2.5 Evaluation of Literature

Regardless of the conservation efforts that are currently practiced, ecosystems and ES continue to decline, mainly due to the inability to fully recognise the value and variety of benefits stemming from ecosystems. One of the main impactors on change is human influences which include land modifications, climate change, population and economic growth. These influences alter the ecosystem's capacity to produce and deliver services, that are required for one's livelihood (Christie and Rayment, 2012). This motivates for conservation measures and/or management practices that will protect and maintain ecosystems and ensure the flow of services (Christie and Rayment, 2012).

A general consensus that can be made, is that EI plays significant role in water resources management, as they produce and deliver HES. To demonstrate the hydrological benefits that investing in EI can have, hydrological and ecological models are often utilized. These models are able to identify areas of concern and aid in identifying which management practices will render the greatest returns on investment. While these models possess their inherent strengths and weaknesses there are potentially synergies that exist between them that warrant further investigation, specifically in relation to developing an approach to maximise the strengths of these models, in order to adequately describe the benefits of investing in EI.

From the various studies that were reviewed the key takeaway was that LULC changes played a significant role in impacting the production and delivery of HES, therefore further research into improving the predictions of LULC change impacts on HES is recommended. The recommendations from the studies reviewed suggested that modelling should be done at finer scales, various models should be evaluated to determine which performs best in a certain region, and the use of more complex models in addition to using ecological models, amongst others.

One of the main knowledge gaps identified includes the limited studies with combined use of hydrological and ecological models for understanding HES response to LULC changes. The majority of studies used either hydrological or ecological models but rarely a combination of the two for analysis purposes.

Thus, research into approaches that utilise the combination of ecological and hydrological models is required. Also, it was identified that there are limited ecological model studies conducted in a South African context, as well as limited recent ecological model studies.

Integrated approaches are required to recognise the full potential benefits of EI. Thus, the study will aim to demonstrate how both ecological and hydrological models can potentially be used in conjunction with each other to inevitably improve the modelling arena. From the literature that was reviewed, it can be concluded that low modelling efforts are associated with ecological models however, comprehensive analysis is limited.

Alternatively, hydrological models can provide detailed representations of the impacts of change but are data intensive and can be complex and time-consuming to adequately configure. Collectively these tools have the potential to improve the modelling arena substantially.

3. METHODOLOGY

From the literature that was reviewed, it was identified that HES benefits aren't explicitly demonstrated in studies pertaining to investments in EI, resulting in its significance being undervalued. In the majority of studies reviewed, independent use of ecological and hydrological models was made but rarely a combination of both. The study aims to address the above-mentioned gap in research. This section describes the manner in which the study was conducted and includes the study site description, data requirements, and model configuration.

3.1 General Methodology

From the aforementioned model selection criteria in Chapter 2.5, the models that were selected for this study were the InVEST and ACRU models. From the literature that was reviewed model selection for the study was based on the following criteria: ease of application, accessible data, model capabilities, freely available, currently supported by developer, applicability of models to selected regions, and practical application effort. There are various models currently available for understanding catchment response to LULC changes, however, models selected for this study were based on the aforementioned criteria.

The selected study site was the uMkhomazi catchment. The proposed Smithfield dam within the uMkhomazi catchment is required for water transfers between the uMkhomazi and uMngeni catchment. Therefore, it is imperative to investigate the impacts of LULC changes on the catchment's response to the production and delivery of HES.

According to Umgeni Water (UW) Phase 1 (2014), within the uMkhomazi catchment soil erosion stemming mainly from anthropogenic sources, namely, overgrazing, alien invasives, forestry, removal of trees, as well as the combined influence of high intensity rainfall within the region (UW, 2014), is a major concern. The high degree of soil erosion would result in the lifespan of the dam being reduced (UW, 2016), as well as potentially degrading the water quality within the dam. Therefore, it is of critical importance to understand how current and future catchment management practices can or will affect the lifespan and functioning of the dam to facilitate improved decision-making.

Water yield modelling is significant in determining water supply within a catchment and to predict availability for the present and future. Together with the concern of soil erosion, this reasoning has led to the following set objectives for the study, i.e. (i) water yield enhancement, (ii) erosion control (sediment yield reduction).

The general workflow of the study can be found in Figure 3.1.

The objectives provided in Chapter one to achieve the aim of the study are as follows:

- Evaluating available literature on the use of models for demonstrating the benefits of investing in EI.
- Evaluate impacts of management vs. no management practices on delivery and provision of HES.
- Assess strengths and limitations associated with each of the models.
- Determine how ecological and hydrological models can be used in conjunction with each other, to demonstrate the full potential benefits of HES.

The initial step was to select an intervention technique corresponding to Smithfield dam concerns. The selected intervention technique was grassland restoration of degraded grasslands and the protection of grasslands that are in currently good condition. Grasslands are the dominant LULC class within the uMkhomazi catchment therefore, it was assumed that changes to this LULC would result in significant changes to HES delivery and production. The next step was to source the required data for the InVEST and ACRU model. Most of the datasets used for InVEST were from global datasets, with biophysical data being from local datasets, where applicable. All required inputs were unified in ArcGIS with a single co-ordinate system in accordance with model requirements. For the ACRU model, pre-processing of rainfall, evaporation and temperature data was required. Both models were run independently to demonstrate their respective strengths and weaknesses.

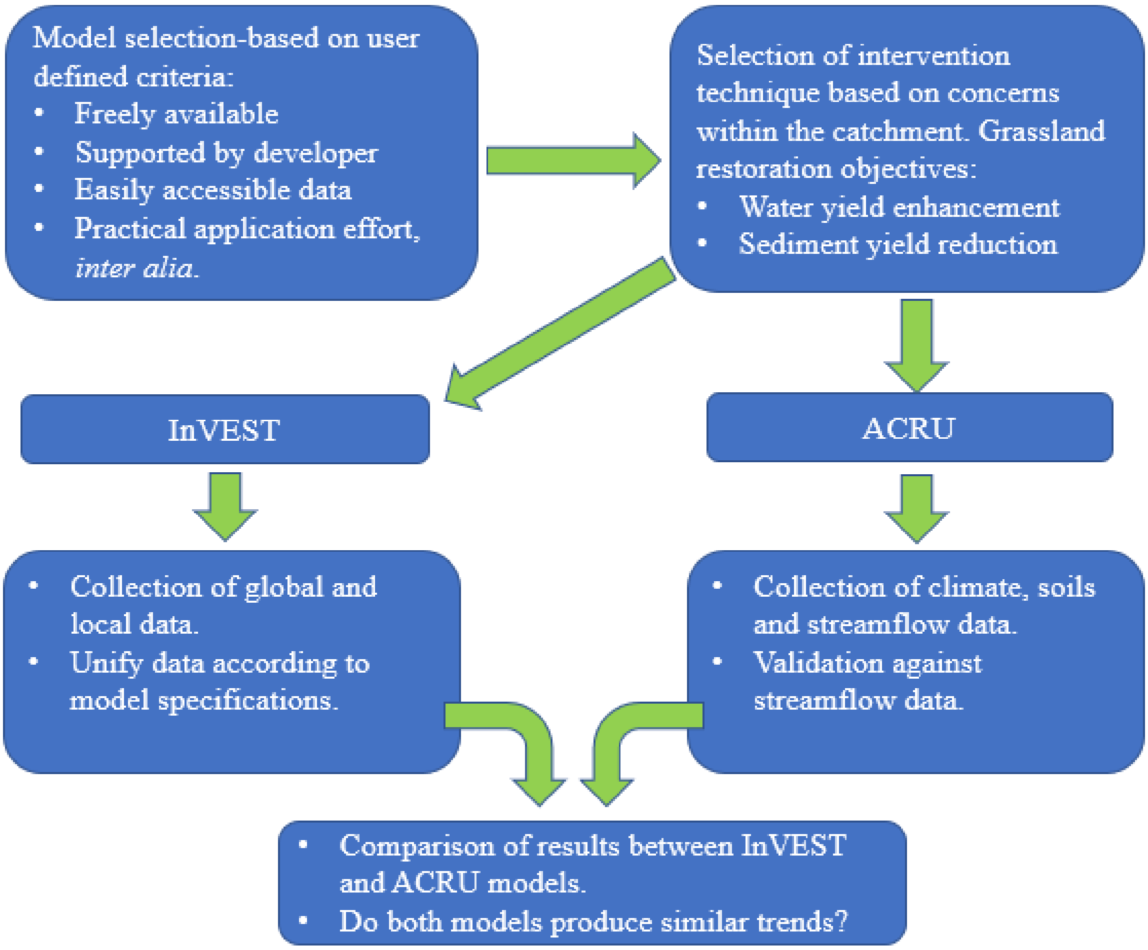

Figure 3.1 General methodology for evaluating performance of ecological and hydrological models.

The targeted land management was derived from the dominant LULC class within the catchment, i.e. grasslands. Grasslands are amongst the largest terrestrial biomes, contributing to biodiversity hotspots that carry high value for ecosystems. Despite their relevance and value, it has not received much attention as compared to forestry and freshwater (Carbutt and Kirkman, 2022). Restoration of grasslands provides a host of benefits: stabilising ecosystem integrity, improving the quality of life for humans, buffering climate change effects, *inter alia*. There is a need to promote awareness on the value of grasslands and the HES they provide, for ES and climate change mitigation. Nature-based solutions are promoted in these instances. There are multiple ways in which restoration can be achieved; management after clear felling, control of alien plant species, assisted natural regeneration such as, revegetation with grasses, plugs, sods, seeding, forbs, use of fire regimes, temporary use of restricted access, the establishment of management and monitoring and the implementation of penalties for unlawful conversion of grasslands (Carbutt and Kirkman, 2022). Figure 3.2 demonstrates an example of the landscape under baseline conditions and management vs. no management practices.

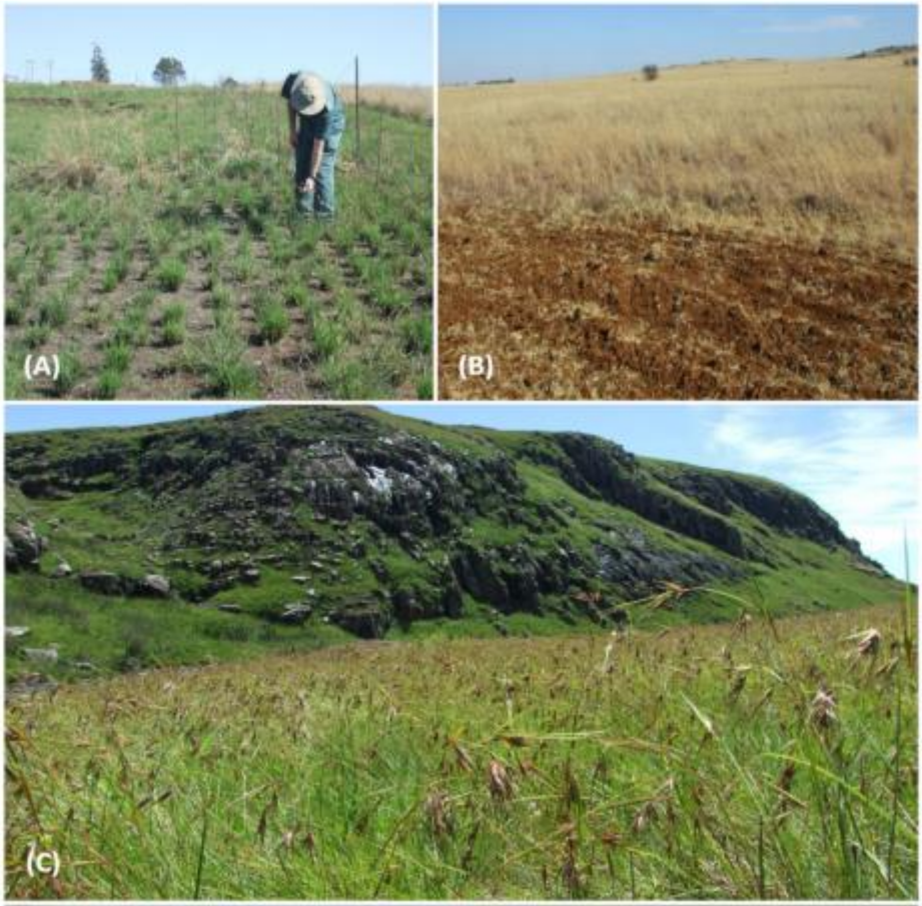

Figure 3.2 South African grasslands: (A) preparation of land for restoration with assisted regeneration; (B) degraded grasslands; (C) pristine grasslands (Carbutt and Kirkman, 2022).

3.2 Study Site Description

The uMkhomazi catchment covers an area of 4388 km^2 and receives a mean annual precipitation of 981 mm (UW, 2017). It is situated in KwaZulu-Natal, South Africa (UW, 2016), as seen in Figure 3.3. The source of the uMkhomazi River is found at an altitude of 3000m and located in the Drakensburg Mountains (UW, 2016). The catchment consists of small towns which have low water requirements (UW, 2016). The majority of the catchment is underdeveloped, with noticeably developed areas being large areas of commercial forestry and irrigated areas in the central catchment area. Currently there are no major water resource infrastructures along the uMkhomazi river (UW, 2016), besides the water abstractions for

SAPPI SAICCOR mill, small towns, rural settlements, dry-land sugarcane and invasive alien plants (DWS, 2019). The combined water users only consume a net total of 159 million $m^3.year^{-1}$ of water, which equates to a total of 15% of the total mean annual runoff for the catchment (DWS, 2019). Wetlands are widely distributed across the catchment, with most of these wetlands connected to the river channels. Although most of the wetlands have been drained and lost to agriculture the 48% that remain are in moderate to good condition with minimal disturbance to their functional behaviour.

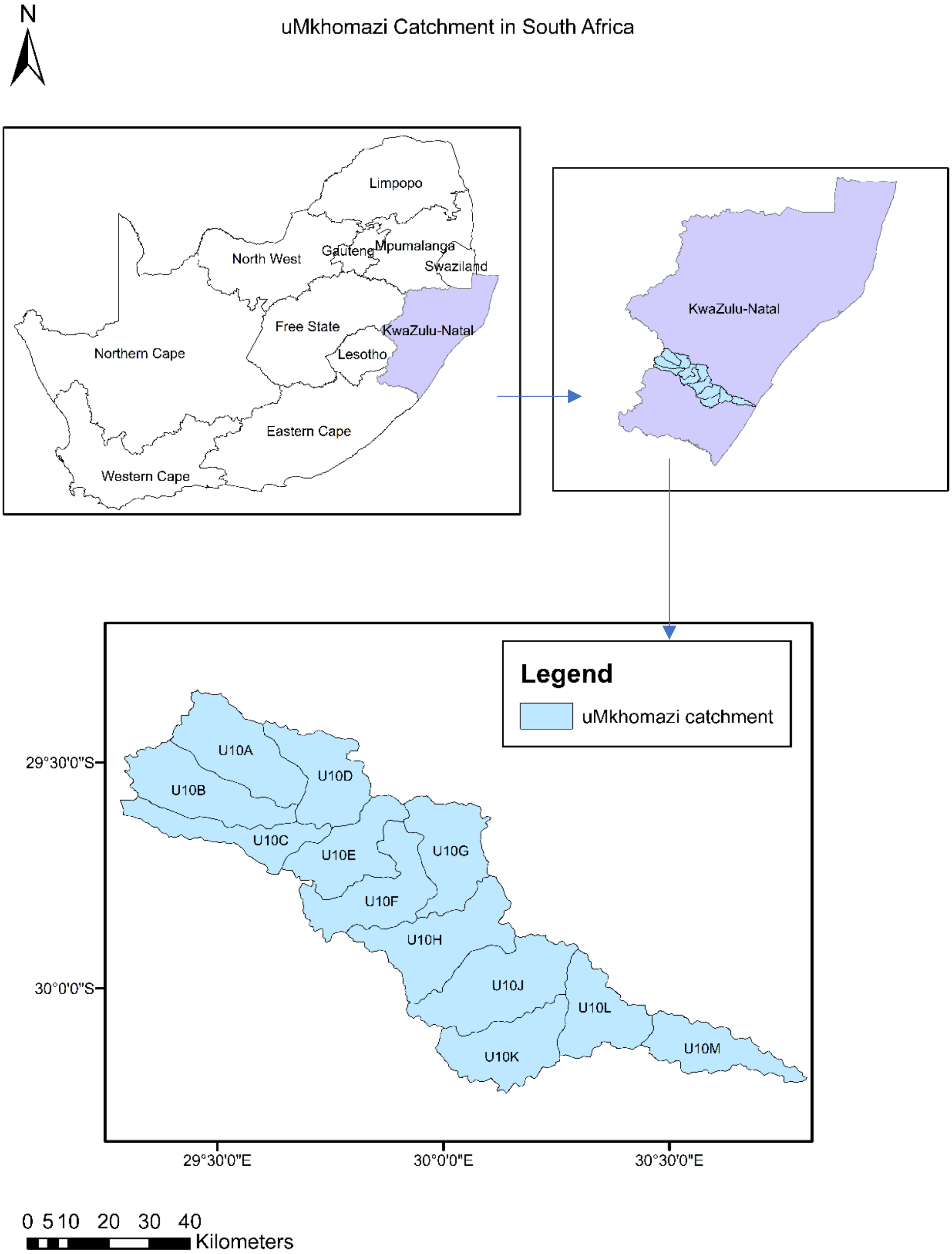

Figure 3.3 The uMkhomazi catchment within Kwa-Zulu Natal, South Africa.

The uMkhomazi-Mngeni transfer scheme comprises of the transfer of water from the underdeveloped uMkhomazi River to the Mngeni system (UW, 2016). The proposed Smithfield dam, seen in Figure 3.4, is required to meet the demands of both the uMngeni and uMkhomazi catchments. The uMngeni catchment is vital to 15% of South Africa's population, being the main water supplier to two major cities, i.e., Pietermaritzburg and Durban (Mander *et al*., 2017, Kusangaya *et al*., 2018, Namugize *et al*., 2018). In the long term the uMngeni system is projected to have insufficient water resources to meet demands (DWS, 2019). The transfer of water resources from the Smithfield dam would be independent of the existing uMngeni system, and thus be able to provide a back-up storage supply when required (DWS, 2019). The underdeveloped Umkhomazi catchments' main concern with the development of the new dam is the degree of sedimentation that would occur in the dam from upstream activities within the catchment (UW, 2017).

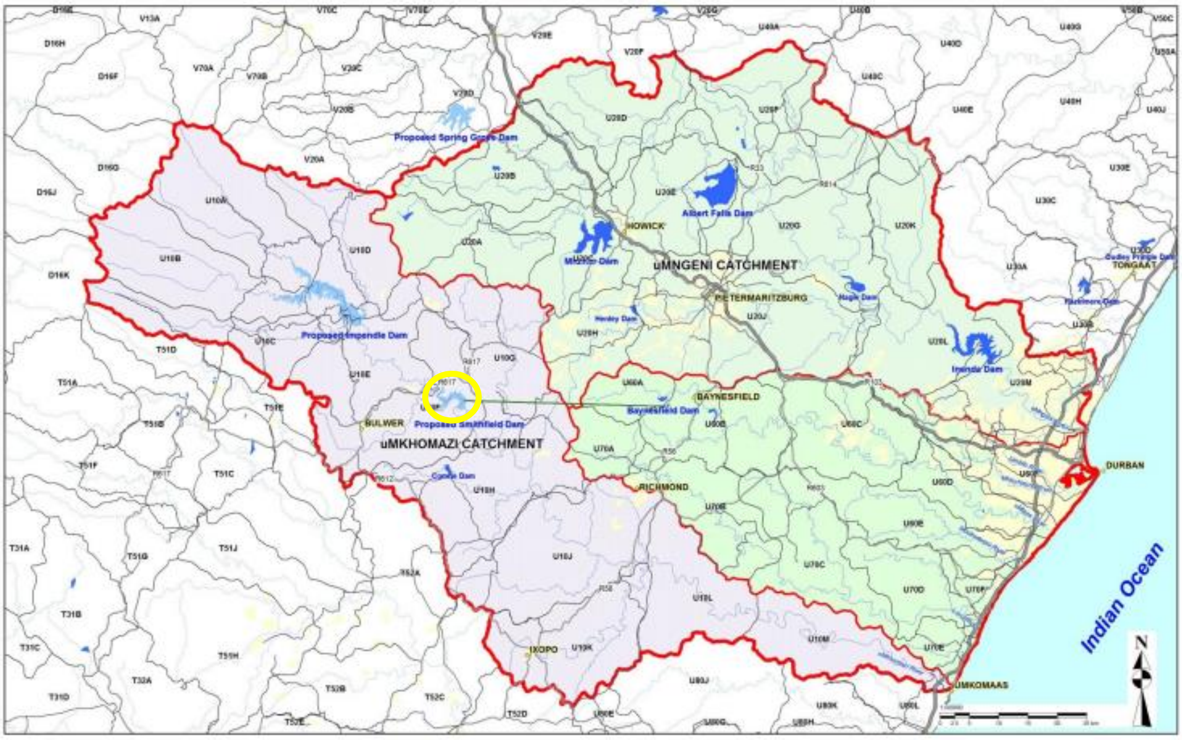

Figure 3.4 The proposed Smithfield Dam within the uMkhomazi catchment (quaternary catchment U10F) along the uMkhomazi River (UW, 2017).

3.3 InVEST Model

In this study, the Water Yield and Sediment Delivery Ratio sub-models were selected for application purposes, to achieve the selected modelling objectives. Each sub-model within InVEST required its own unique data requirements to run and produce outputs. Water yield volume results are essential to be known to provide an indication of water resource quantities within the catchment for the desired purpose of a water transfer scheme.

3.3.1 InVEST model data collection

The data requirements for the InVEST model depend on which sub-model is selected, i.e. water supply or water purification model, amongst others. Common data needed for the InVEST model included the number of sub-catchments, LULC information, digital elevation model and threshold flow accumulation (Jorda-Capdevila *et al*., 2019), amongst others. Most of the data inputs were derived from global datasets (Sharp *et al*., 2020), with a few derived from local datasets (Table 3.1).

Table 3.1 Characteristics of input data for the Water Yield sub-model and Sediment Ratio Delivery sub-model.

Data needs (InVEST model)	Source	Format	Characteristics
LULC map	Ezemvelo KZN Wildlife, 2017	Raster	Local
Digital Elevation model	NASA JPL, 2013	Raster	Global
Soil erodibility	Panagos *et al*., 2012	Raster	Global
LULC biophysical co-efficients	Adapted from default values in Vogl *et al*., 2016	.csv	Global
Rainfall Erosivity Index	Panagos *et al*., 2017	Raster	Global
Precipitation	Schulze, 1995	Raster	Local
Reference evapotranspiration	Schulze, 1995	Raster	Local
Root restricting layer depth	Hengl *et al*., 2017	Raster	Global
Plant available water content	Hengl *et al*., 2017	Raster	Global

Input data for the InVEST sub-models were unified using ArcMap 10.5.1. The majority of datasets were global datasets which were projected to 1984 Hartebeesthoek and clipped for the catchment boundary (Figures 3.5-3.11).

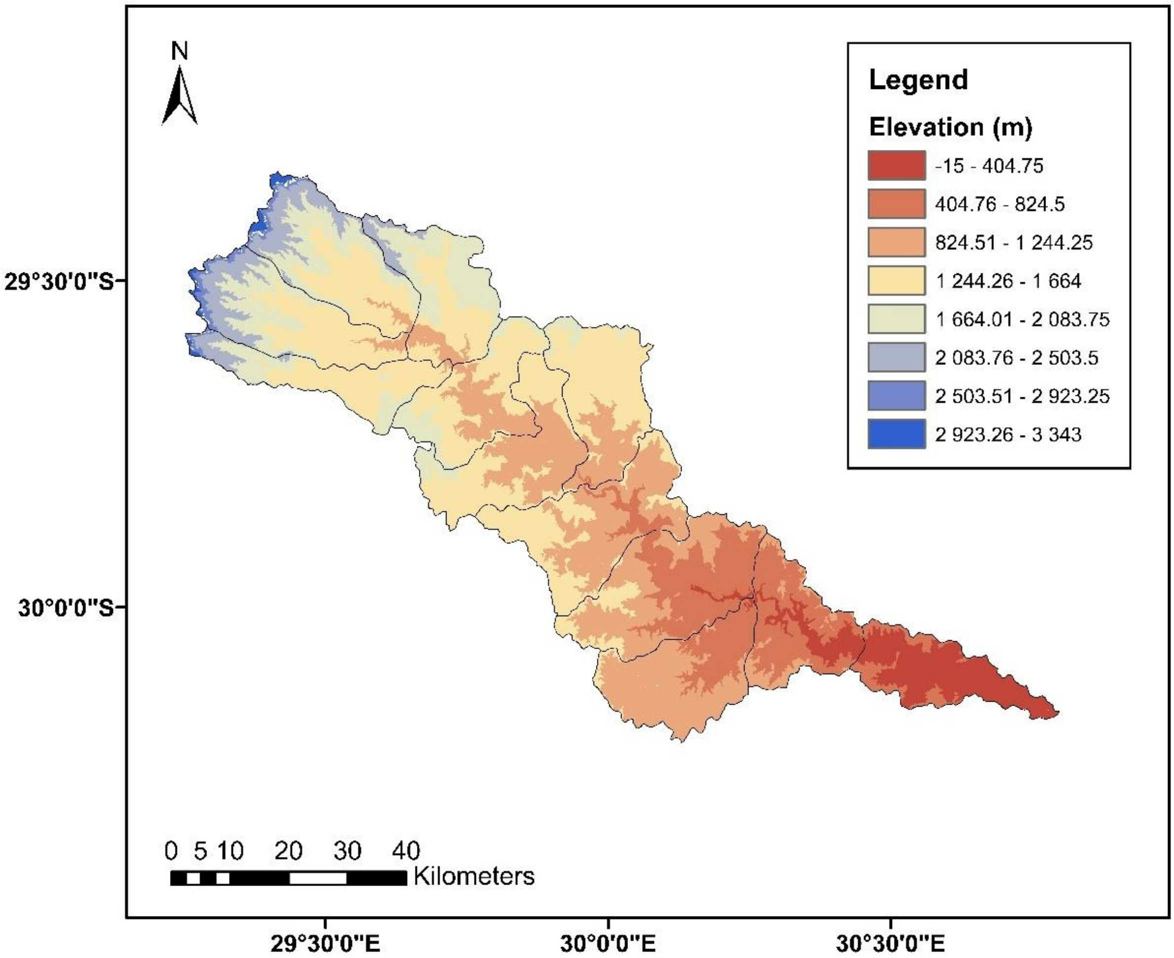

Figure 3.5 Digital Elevation Model input for the Water Yield sub-model (NASA JPL, 2013).

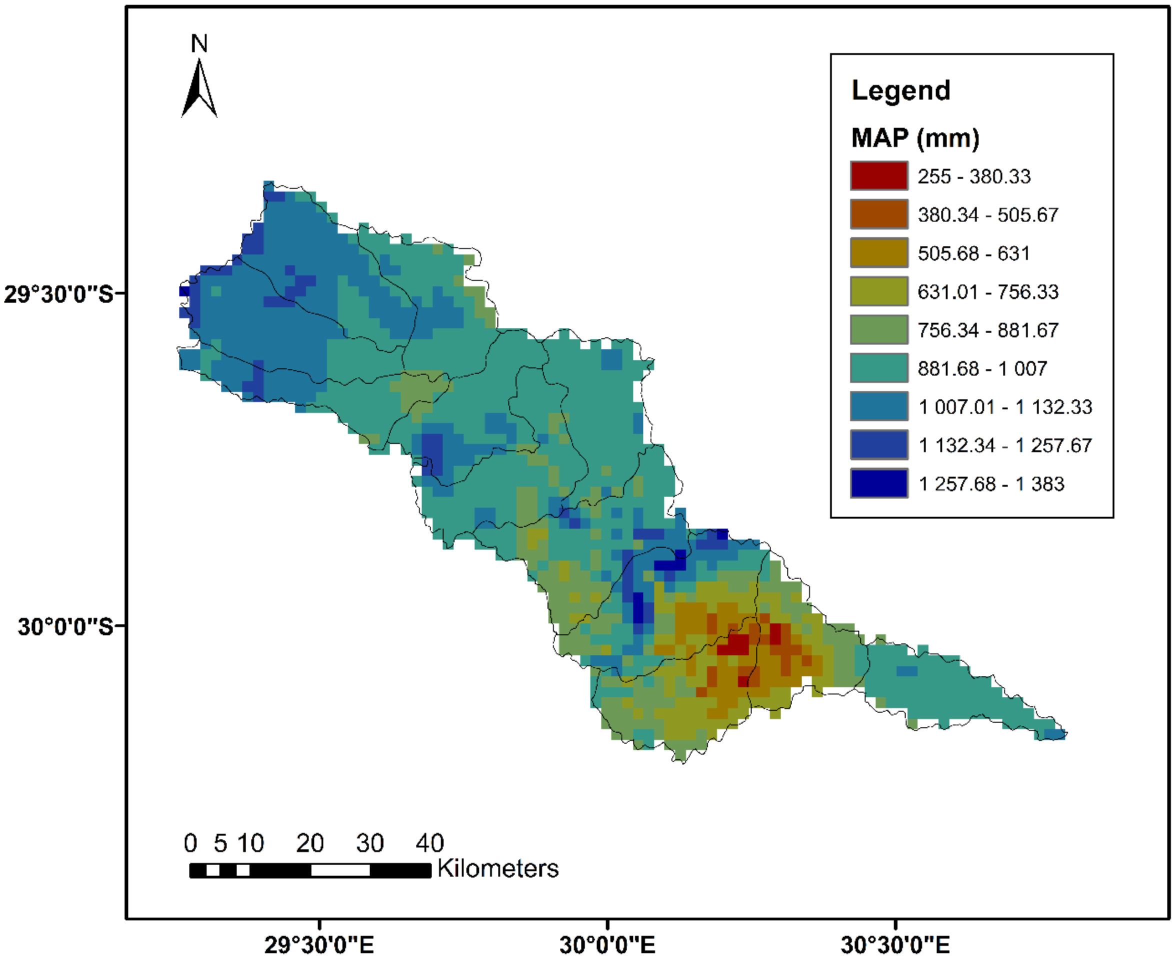

Figure 3.6 Mean Annual Precipitation across the uMkhomazi catchment (Schulze, 1995).

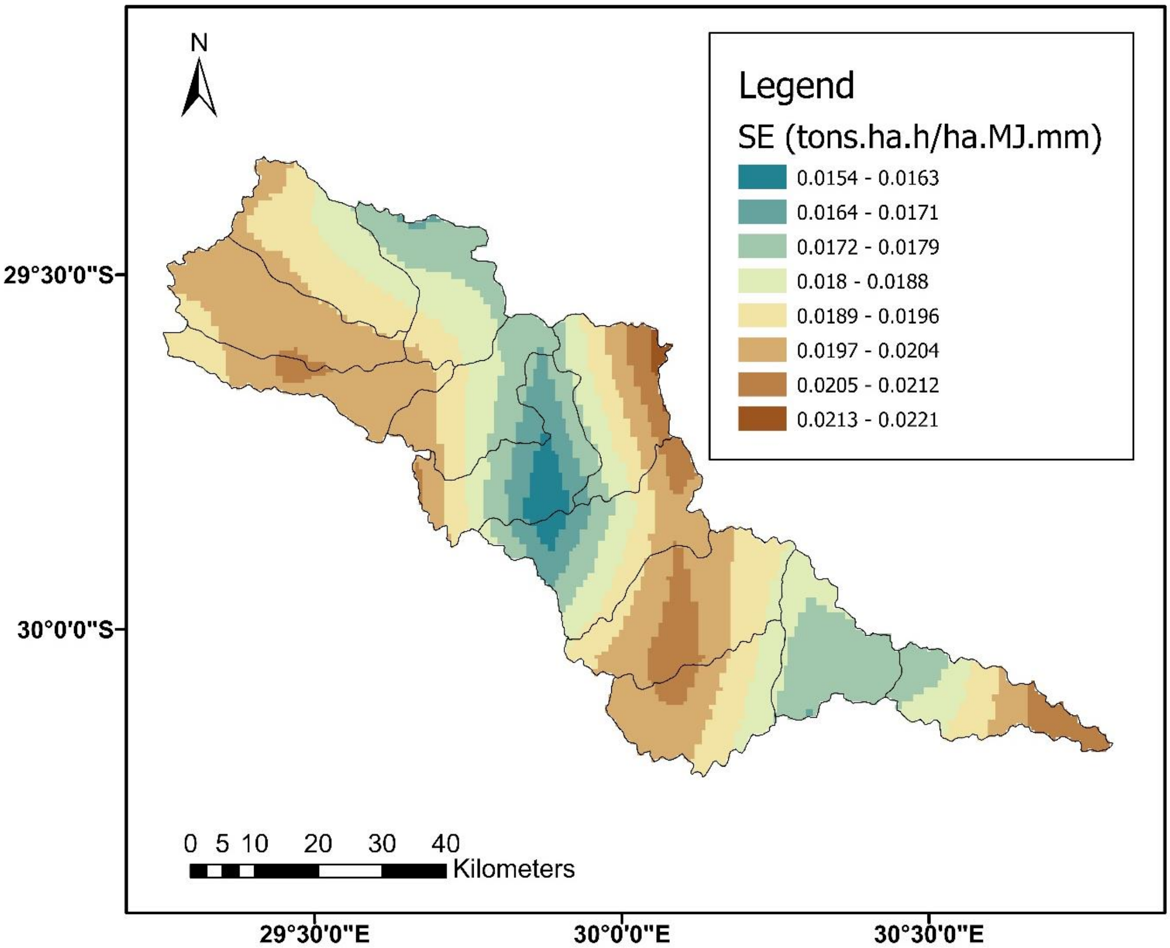

Figure 3.7 Soil erodibility factor for the uMkhomazi catchment (Panagos *et al*., 2012).

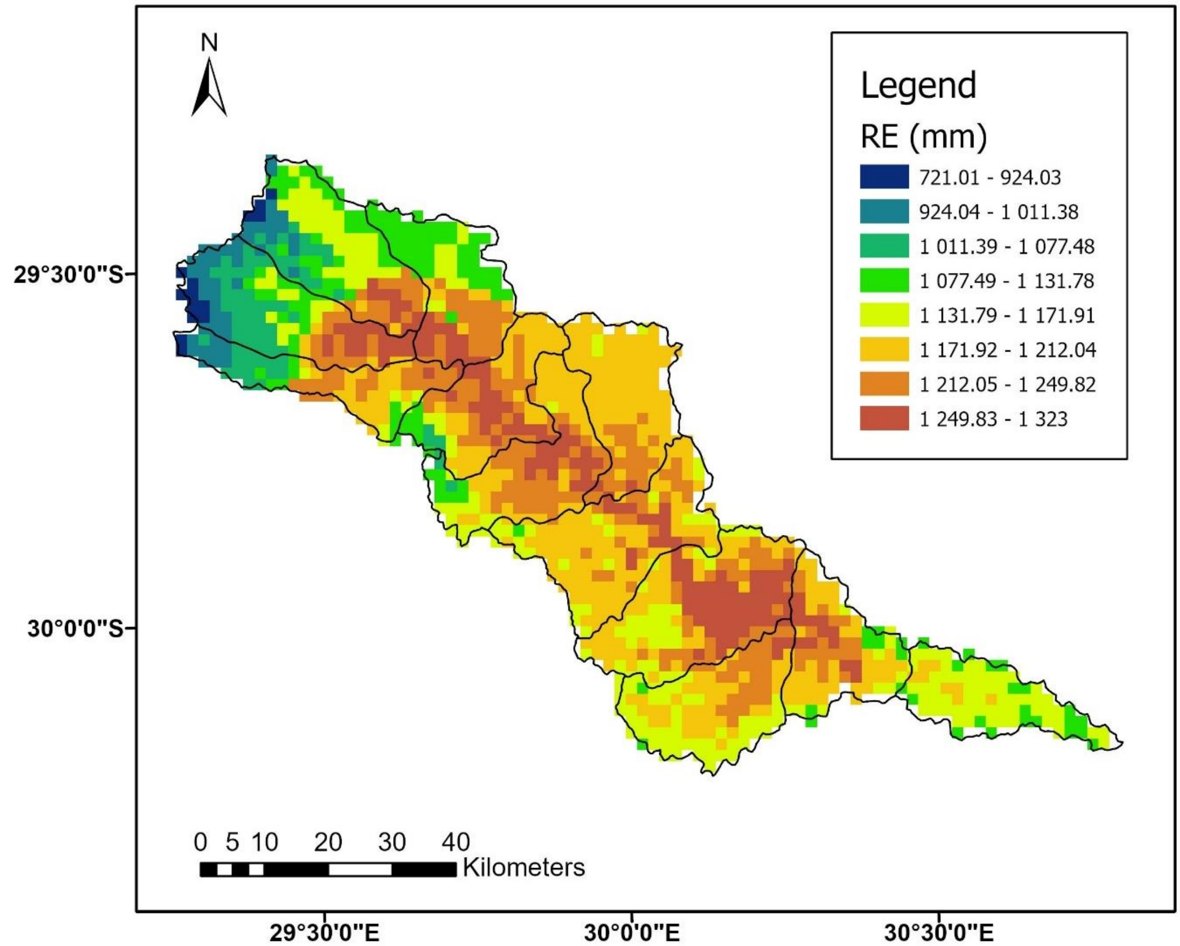

Figure 3.8 Penman-Monteith reference evapotranspiration across the uMkhomazi catchment (Schulze, 1995).

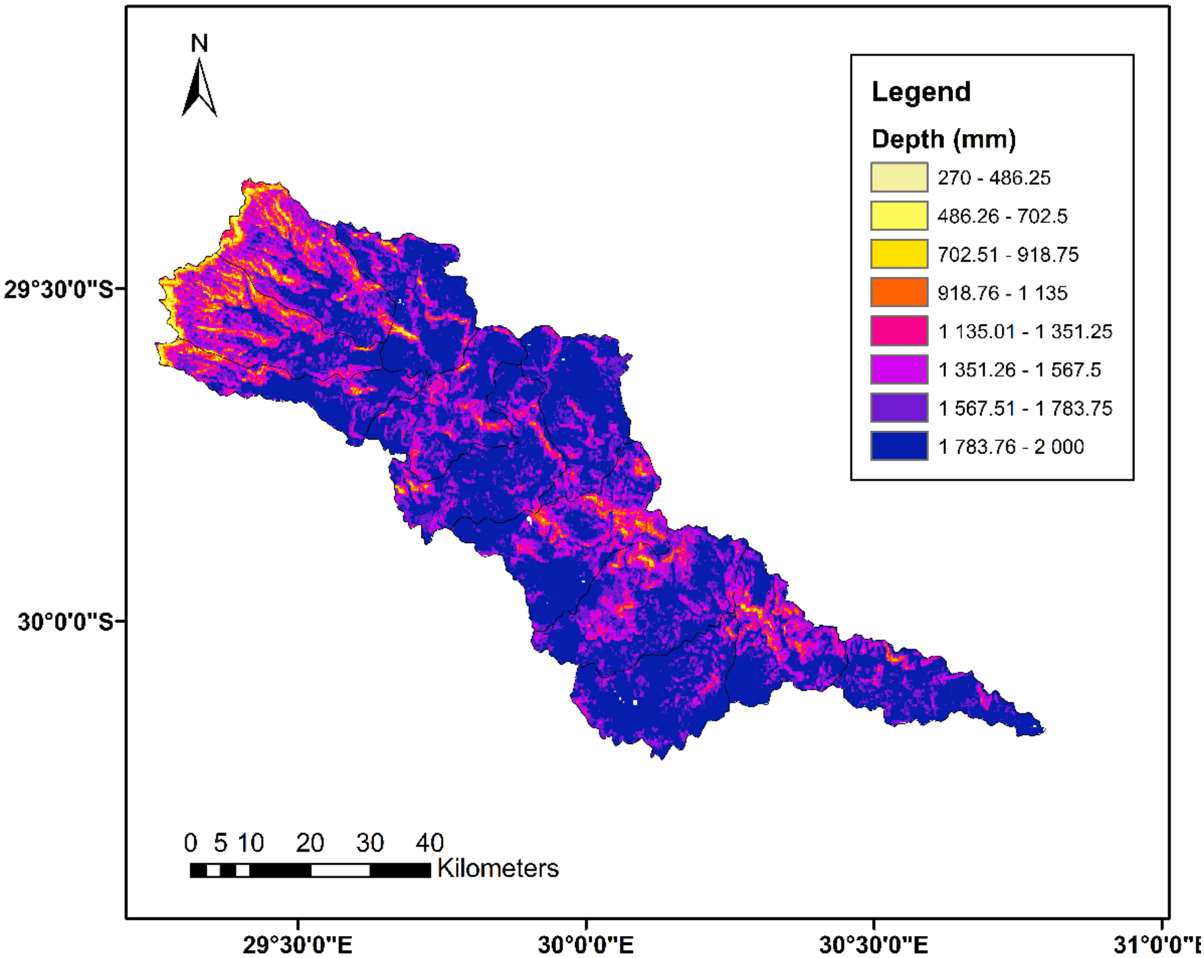

Figure 3.9 Depth to root restricting layer (Hengl *et al*., 2017).

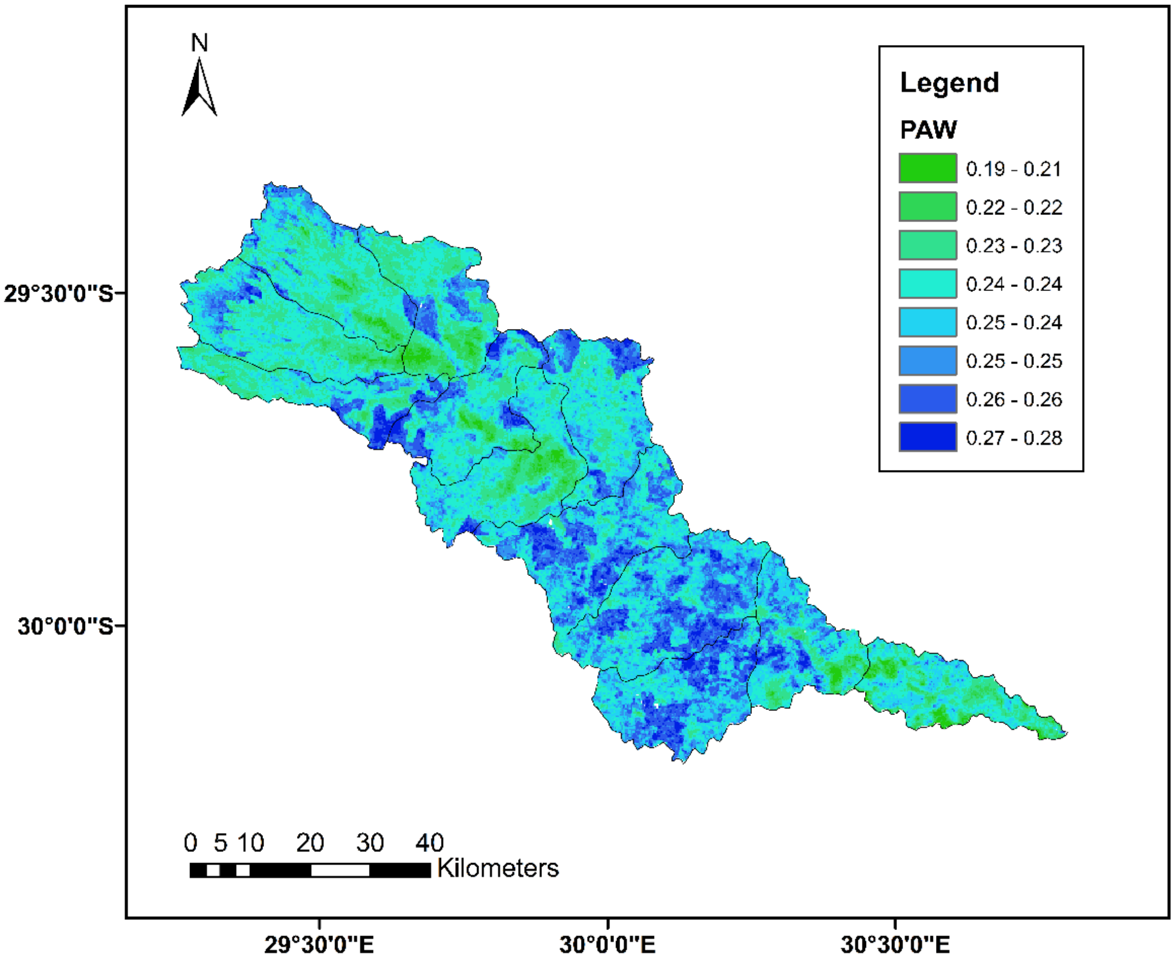

Figure 3.10 Plant available water fraction (Hengl *et al*., 2017).

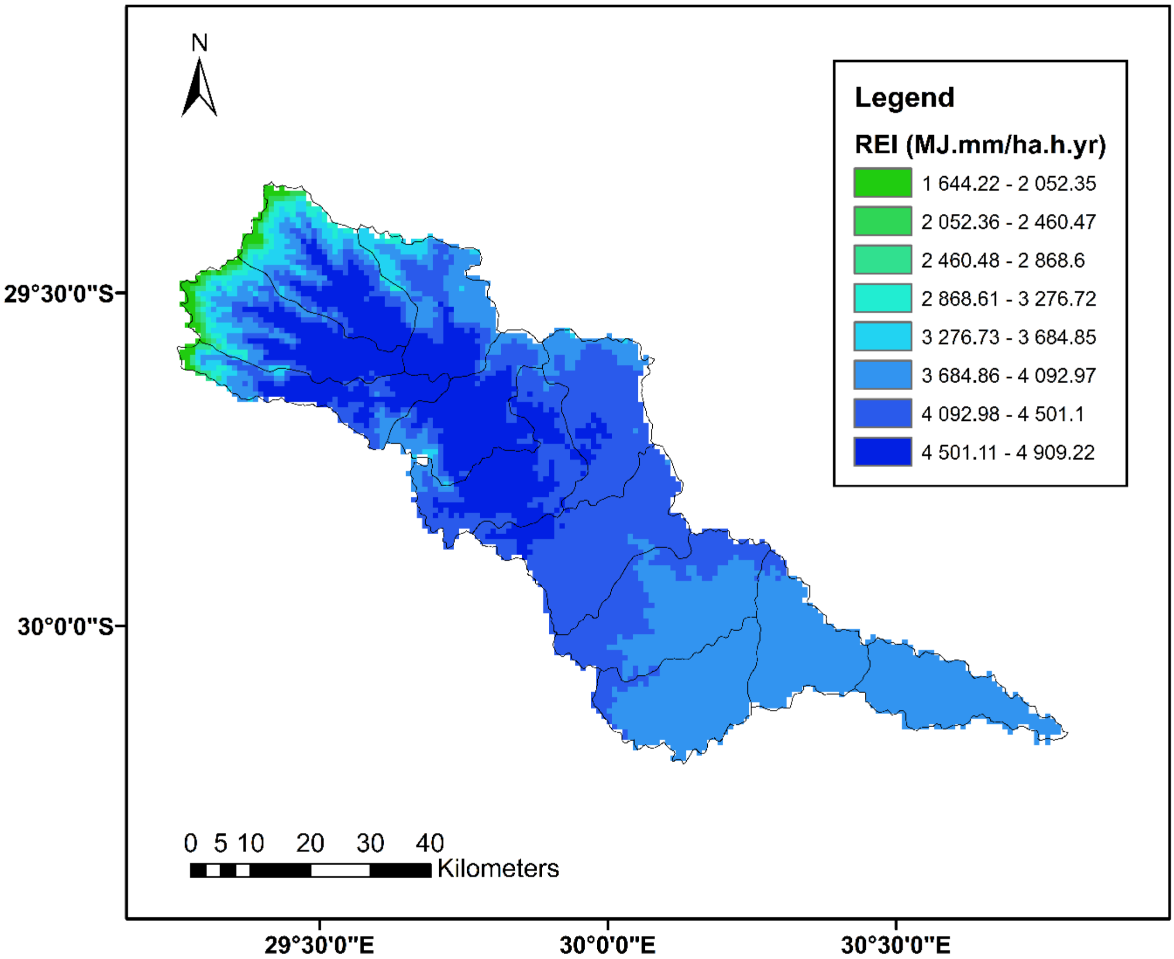

Figure 3.11 Rainfall Erosivity Index (Panagos *et al*., 2017).

The Z parameter required for the Water Yield sub-model captures the hydrogeological characteristics and local precipitation pattern and is given as:

$$Z = \frac{(w-1.25)P}{AWC} \quad (3.1)$$

$$AWC = Min\,(Rest.Layer.Depth, root.depth)xPAWC \quad (3.2)$$

where: w = 2.6 (Xu *et al*., 2013), P = Mean Annual Precipitation, AWC = Available Water Capacity, Rest. Layer. Depth, root. depth = Root restricting layer depth, PAWC = Plant Available Water Capacity (Sharp *et al*., 2020).

3.3.2 InVEST model configuration

The LULC map obtained from Ezemvelo KZN Wildlife (2017), illustrates that the uMkhomazi catchment has approximately 43 different LULC classes (Figure 3.12). For the scope of this study not all LULC classes were modelled as the LULC classes were grouped for ease of modelling. Gokool and Jewitt (2019) LULC reclassification was used as a basis for the 2017 Ezemvelo LULC map reclassification, in this study. Reclassification was conducted for simplification purposes of modelling and was done by placing similar LULC classes in a single group, shown in Table 3.2. ArcMap 10.5.1 was used for the reclassification processes. The reclassified LULC map for the uMkhomazi catchment is shown in Figure 3.13.

The catchment was disaggregated into two sub-catchments i.e., the upper and lower sub-catchments. For this study the lower sub-catchment was ignored as it lies below the Smithfield dam and any LULC changes below the dam would have little to no impact on the dam.

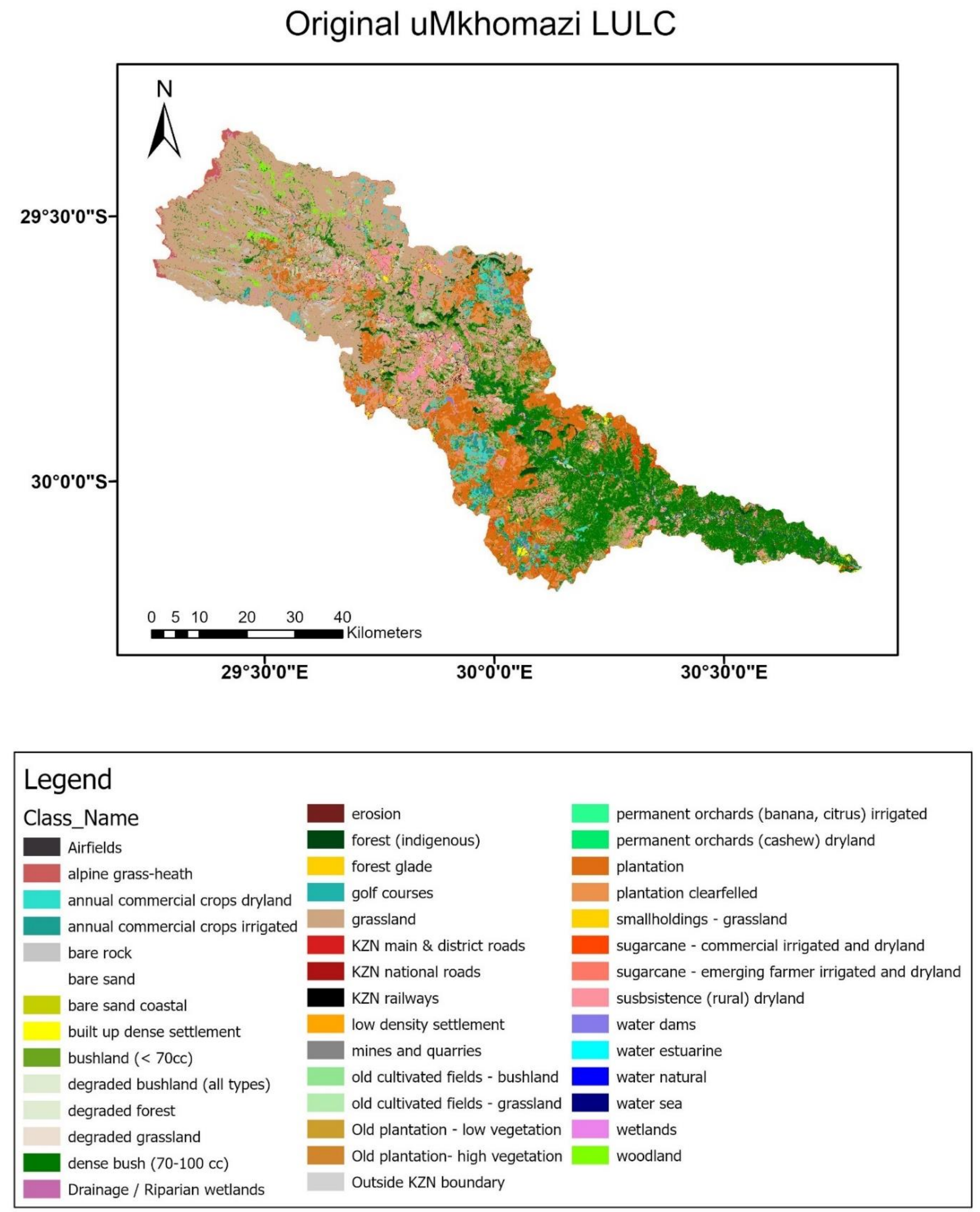

Figure 3.12 Approximately 43 LULC classes within the uMkhomazi catchment (Ezemvelo KZN Wildlife, 2017).

Table 3.2 Reclassification of the current LULC classes within the uMkhomazi Catchment.

Reclassified LULC	Original LULC
1: Water	Water, water estuarine, water dams, water sea
2: Commercial Agriculture	Permanent orchards (cashew) dryland, permanent orchards (banana, citrus) irrigated, sugarcane - commercial irrigated and dryland, sugarcane - emerging farmer irrigated and dryland, annual commercial crops irrigated, annual commercial crops dryland
3: Commercial Forestry	Plantation, Old plantation- high vegetation, Old plantation - low vegetation
4: Natural Forest	Forest (Indigenous)
5: Wetlands	Wetlands, Drainage/Riparian wetlands
6: Bare Soil	Plantation clear-felled, mines and quarries, degraded forest, bare sand, degraded grassland, degraded bushland, erosion, bare rock, bare sand coastal
7: Urban	Built up dense settlement, KZN national roads, KZN main & district roads, KZN railways, Outside KZN boundary
8: Mixed Urban	Low density settlement, subsistence (rural) dryland
9: Grassland	Golf courses, grassland, smallholdings - grassland, old cultivated fields – grassland, alpine grass-heath, forest glade, airfields
10: Bushland	Dense bush (70-100 cc), bushland (< 70cc), old cultivated fields – bushland, woodland

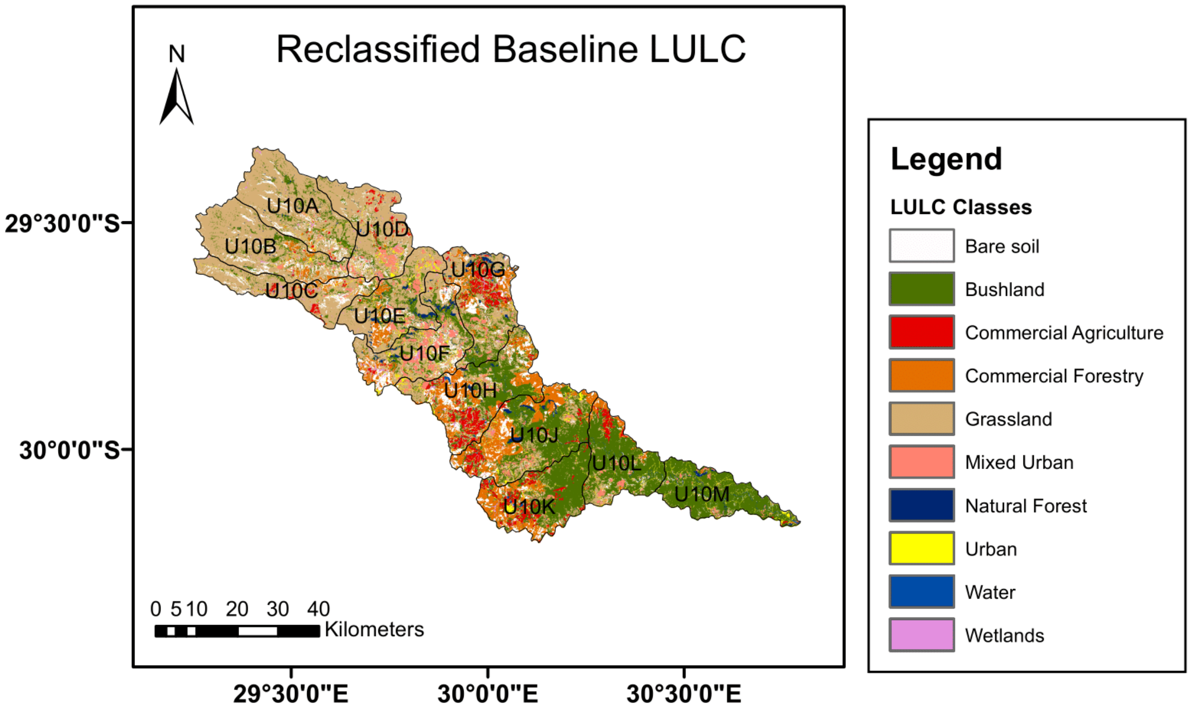

Figure 3.13 Reclassified LULC map for the uMkhomazi catchment.

In this study, only a single management intervention was modelled to demonstrate the effects that protection/maintenance and restoration versus no protection/maintenance would have on the hydrological response of a catchment. The dominant LULC in the surrounding region is grassland. It was assumed that any change to the grasslands would result in the greatest impact on HES delivery. It was for this reason that the selected intervention technique was grassland restoration.

Generating hypothetical future scenarios was undertaken using the "InVEST model user application: Scenario Generator." The Scenario Generator works based on the Biophysical table, with LULC represented by a numerical code seen in Table 3.3. The Scenario Generator was run with user-identified LULC changes (what can occur in the most realistic time frame, e.g. 10 years). The intervention technique had three scenarios: (i) baseline conditions, (ii) best-case scenario (protection/maintenance/restoration) and (iii) worst-case scenario (no protection/maintenance). The worst-case scenario demonstrates what would occur in the absence of management practices. The reclassified maps (Figure 3.14) which were produced using the Scenario Generator, demonstrate the reclassified LULC for the three aforementioned scenarios.

The following scenarios for the grassland restoration intervention were run to account for the impact that protection/maintenance/restoration vs. no protection/maintenance would have on the catchment's response to water and sediment yield. The best-case scenario was characterised by currently bare soil surfaces being transitioned to restored grassland, with the protection of grasslands that are currently in good health, and the worst-case scenario was characterised by grasslands being transitioned to bare soil surfaces.

Although these are targeted land management scenarios, they still provide a means for decision-making despite their accuracy and reliability being questionable. The scope of the study was not to demonstrate absolute changes but rather to inform how models can be used in tandem with each other to enhance outputs, for decision-making, planning purposes and adoption into policy.

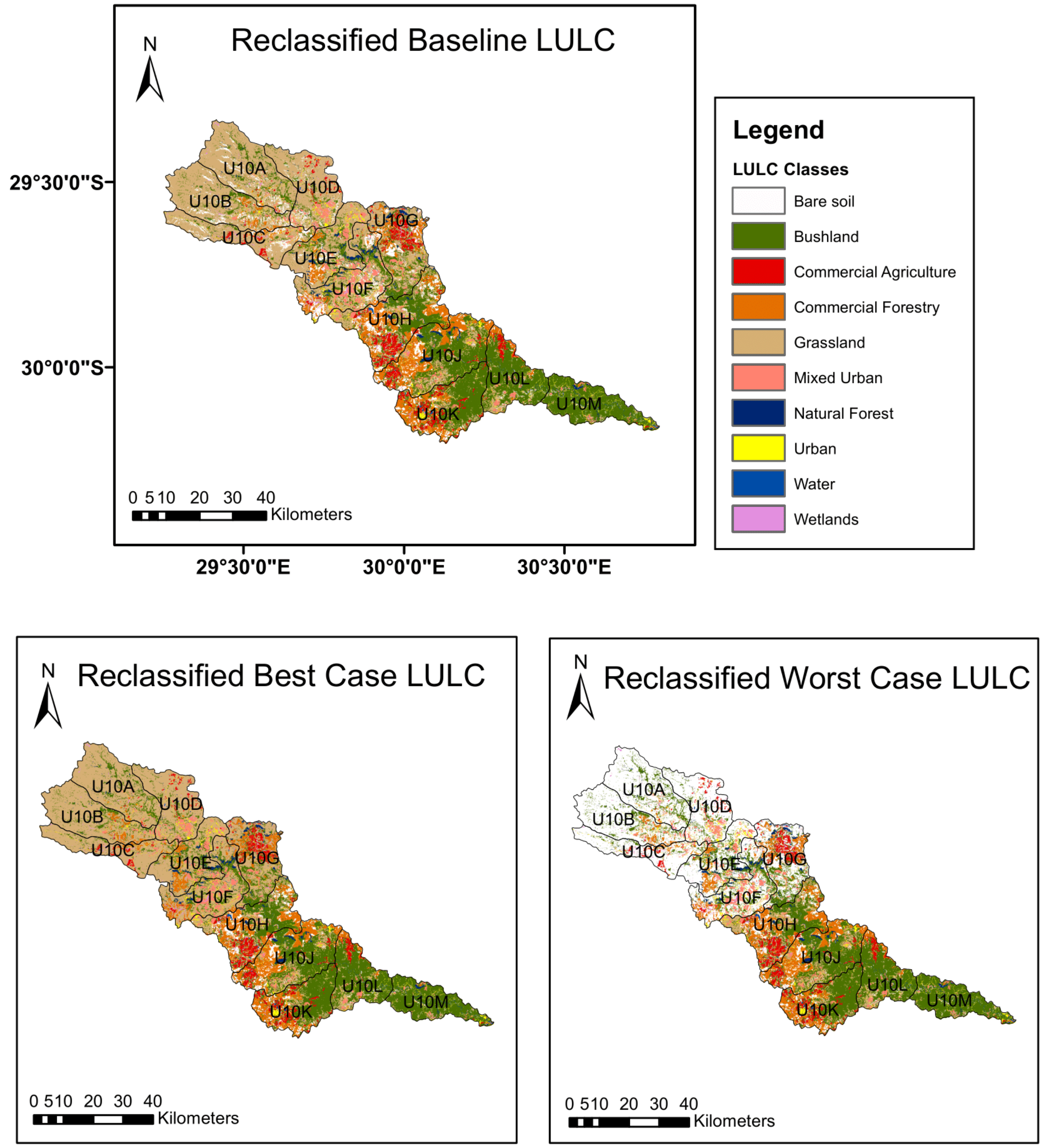

Figure 3.14 Baseline, best and worst-case scenarios within the uMkhomazi catchment, using the reclassified LULC classes.

The InVEST model required a biophysical table from which important biophysical characteristics of a catchment are provided. Each LULC from the LULC raster data was represented using a unique integer in the biophysical table, accompanied by a corresponding descriptive name, root depth, cover management factor, support practice factor and crop co-efficient value. A subset of the biophysical table is provided in Table 3.3. The LULC co-efficients were obtained from default values provided within the model, where applicable localised data from ACRU's Compoveg database (Smithers and Schulze, 2004), was used for crop co-efficient values (Kc).

Table 3.3 Biophysical Table for the uMkhomazi catchment.

Lucode	LULC_desc	LULC_veg	usle_c	usle_p	root_depth	Kc
1	Water	0	0.04	1	1	1
2	Commercial Agriculture	1	0.19	1	1550	1.02
3	Commercial Forestry	1	0.003	1	1920	1.106

3.4 ACRU model

3.4.1 Climate and streamflow data acquisition

Daily rainfall, evaporation and temperature data was acquired from the Cobham Automatic Weather Station (AWS) and was provided by the Agricultural Research Council. This AWS is located at a latitude and longitude of -29.7014° S and 29.41183° E, respectively, and at an elevation of 1625 m.a.s.l. From the available data, the selected AWS was the closest in proximity to the upper catchment, therefore only one AWS was used.

Data that was missing for each climatic variable was infilled using either monthly or annual averages. Temperature and evaporation data that was missing for the month was infilled using annual averages for the respective year (Table 3.4). Rainfall, evaporation, maximum temperature and minimum temperature data that was missing for specific days within a month, was infilled using monthly averages, seen in Table 3.5, 3.6, 3.7 and 3.8, respectively. The number of days infilled for rainfall, evaporation, maximum temperature and minimum temperature data was 97, 1403, 349 and 472, respectively.

Table 3.4 Months in the respective years that were infilled for either temperature or evaporation data or both, using annual averages.

Year/Month	Variables infilled (Temperature or A-pan Evaporation)
1992/12	Maximum and minimum temperature, A-pan evaporation
1993/01 – 1993/02	Maximum and minimum temperature, A-pan evaporation
1996/01	A-pan evaporation
1994/01 – 1994/03	A-pan evaporation
1994/11	Maximum and minimum temperature, A-pan evaporation
1995/01 – 1995/03	Maximum and minimum temperature
1995/06	Minimum temperature
1995/11	Maximum and minimum temperature, A-pan evaporation
1995/12	A-pan evaporation
1996/01	A-pan evaporation
1999/08	Maximum and minimum temperature, A-pan evaporation
2000/10 – 2000/12	Maximum and minimum temperature
2001/01 – 2001/05	Maximum and minimum temperature
2005/10	A-pan evaporation
2010/12	Minimum temperature

Table 3.5 The number of days infilled in a month using monthly averages for rainfall data.

Year/Month	No. of days infilled	Year/Month	No. of days infilled
1997/12	2	2010/11	2
1998/01	1	2010/12	12
1998/03	1	2011/05	7
2005/05	2	2011/11	3
2000/06	5	2011/12	4
2005/10	2	2012/03	7
2005/12	13	2012/04	7
2006/01	1	2012/07	14
2010/01	7	2014/07	7

Table 3.6 The number of days infilled in a year using monthly averages for evaporation data.

Year	No. of days infilled	Year	No. of days infilled
1980	12	1998	58
1981	10	1999	66
1982	14	2000	61
1983	17	2001	15
1984	24	2002	16
1985	19	2003	29
1986	30	2004	26
1987	32	2005	45
1988	21	2006	67
1989	31	2007	34
1990	33	2008	34
1991	37	2009	54
1992	29	2010	66
1993	54	2011	83
1994	39	2012	64
1995	78	2013	35
1996	59	2014	39
1997	72		

Table 3.7 The number of days infilled in a year using monthly averages for maximum temperature data.

Year	No. of days infilled	Year	No. of days infilled
1985	1	2000	34
1986	1	2001	1
1992	4	2003	7
1993	11	2005	20
1994	15	2006	1
1995	73	2009	1
1996	25	2010	22
1997	48	2011	29
1998	15	2012	28
1999	5	2014	8

Table 3.8 The number of days infilled in a year using monthly averages for minimum temperature data.

Year	No. of days infilled	Year	No. of days infilled
1980	13	1998	15
1981	12	1999	5
1982	16	2000	35
1983	12	2003	7
1984	7	2005	18
1985	9	2006	2
1988	1	2009	9
1992	31	2010	11
1993	16	2011	45
1994	15	2012	28
1995	74	2013	3
1996	33	2014	9
1997	46		

Daily streamflow data abstracted in $m^3.s^{-1}$ from the Department of Water and Sanitation (2023) was used for observed streamflow data input into the model. In-situ streamflow data from Lot93 gauge found along the Mkhomazi river was used, Figure 3.15. Lot93 gauge is located at a latitude and longitude of -29.74369° S, 29.90494° E and an elevation of 1334 m.a.s.l.

Figure 3.15 Location of the Cobham Automatic Weather Station and Lot 93 streamflow gauge within the uMkhomazi catchment.

3.4.2 Soil characteristics

Hydrologic response units (HRU's) were selected based on dominant land types (Figure 3.16) and LULC. Within each of the 7 sub-catchments, the dominant land types were Ac, Ab and Fa.

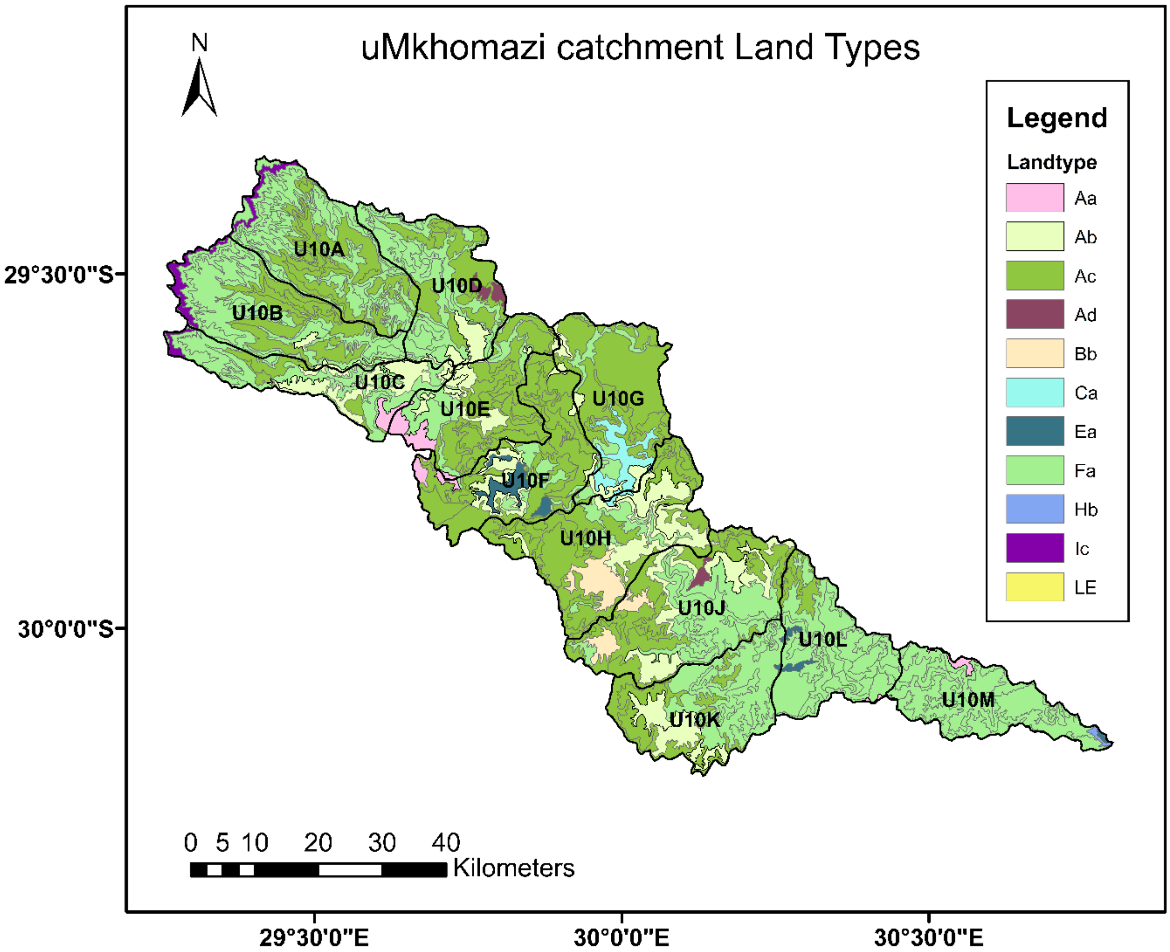

Figure 3.16 Land types within the uMkhomazi catchment (Schulze, 1995).

The soil characteristics of each land type required for the ACRU model are provided in Table 3.9. Depth, wilting point (WP), field capacity (FC), porosity (PO) and soil layer response were provided for both the A and B horizons for each respective land type.

Table 3.9 Soil characteristics of each land type (Schulze, 1995).

	Ac		Fa		Ab	
	A	**B**	**A**	**B**	**A**	**B**
Depth	0.30	0.57	0.291	0.234	0.3	0.55
WP	0.154	0.193	0.146	0.158	0.150	0.187
FC	0.247	0.287	0.236	0.250	0.244	0.2810
PO	0.424	0.415	0.437	0.417	0.422	0.412
AB/BFRESP	0.384	0.384	0.336	0.336	0.387	0.387

The catchment was delineated according to the dominant LULC and land types. Different land types have a varying impact on the hydrology of a catchment due to the varying associated characteristics. ArcMap was used to perform the intersect function of LULC and land types to determine the coverage of each LULC and land type.

3.4.3 Dam characteristics

The area/volume relationships were unavailable for the catchment thus, the default area/volume relationship was used, similar to the study conducted by Taylor (2001). There are no major dams within the uMkhomazi catchment thus, all small dams were combined to produce a single dam to be modelled. It was assumed that there were no legal flow requirements to be released from the dam. Seepage was calculated as described in Taylor (2001) as:

$$0.0006 \ x \ storage \ capacity \tag{3.3}$$

Dam characteristics abstracted from DWS and Taylor (2001).

$$\begin{aligned} \text{Seepage} &= 0.0006 \text{ x } 7940000 \\ &= 4764 \text{ m}^3.\text{day}^{-1} \end{aligned} \tag{3.4}$$

3.4.4 ACRU model calibration

An iterative process was used to attain an optimal simulation, i.e. closest to reality. Various variables were evaluated (Table 3.10), such as critical stormflow depth (m), initial soil moisture percent (%), quick flow response (fraction), amongst others. To determine which parameters cause the most significant changes to simulations sensitivity analyses were performed, analyses were performed by increments of 0.1.

Table 3.10 ACRU variables for an optimum validation within this study.

Variables	Values
Quick flow response	0.2
Coefficient of baseflow response	0.009
Critical stormflow depth	0.3 m
Soil layer response (A horizon)	0.2
Soil layer response (B horizon)	0.2
Initial soil moisture percent (A horizon)	40%
Initial soil moisture percent (B horizon)	40%

3.4.5 Sediment yield modelling using the ACRU model

Sediment yield was simulated using the Modified Universal Soil Loss Equation (MUSLE). MUSLE is used to estimate the sediment yield produced after a rain event. The MUSLE equation used to determine the sediment yield off the catchment, is given by equation 3.5:

$$y = \alpha.(Q.p)^{\beta}.K.LS.CP \tag{3.5}$$

where y = sediment yield from an individual event (tonne), Q = stormflow volume for the event (m^3), q = peak discharge for the event ($m^3.s^{-1}$), K = soil erodibility factor (tonne h $N^{-1}.ha^{-1}$), α and β = MUSLE co-efficients 8.934 and 0.56 respectively (Schulze, 1995).

Maximum and minimum soil erodibility factors (K), Table 3.11, were used as input for the MUSLE equation.

Table 3.11 Maximum and minimum soil erodibility factors.

Soil Type	Kmax	Kmin
Fa	0.34	0.34
Ac	0.25	0.25
Ab	0.25	0.25

The ACRU model required a runoff lag method when the MUSLE equation was used, the chosen runoff method was the Schmidt and Schulze equation which required the average slope and two-year, 30-minute (2yr30min) rain intensity (I30), taken from the Design Rainfall

Estimation for South Africa (Schulze and Schmidt, 1995). It was assumed that all HRU's had the same slope, due to modelling based on LULC HRU's and not sub-catchments. The two-year, one-day (2yr1day) rain intensity was obtained from the map (Figure 3.17), which was a value of 60 $mm.h^{-1}$ (Schulze and Schmidt, 1987). A multiplication factor was used to get the 2yr1day rain intensity to 2yr30min rain intensity for the Umkhomazi catchment which falls under rainfall distribution zone 4 (eqn. 3.6). Thus, a multiplication factor of 1.236 (Table 3.12).

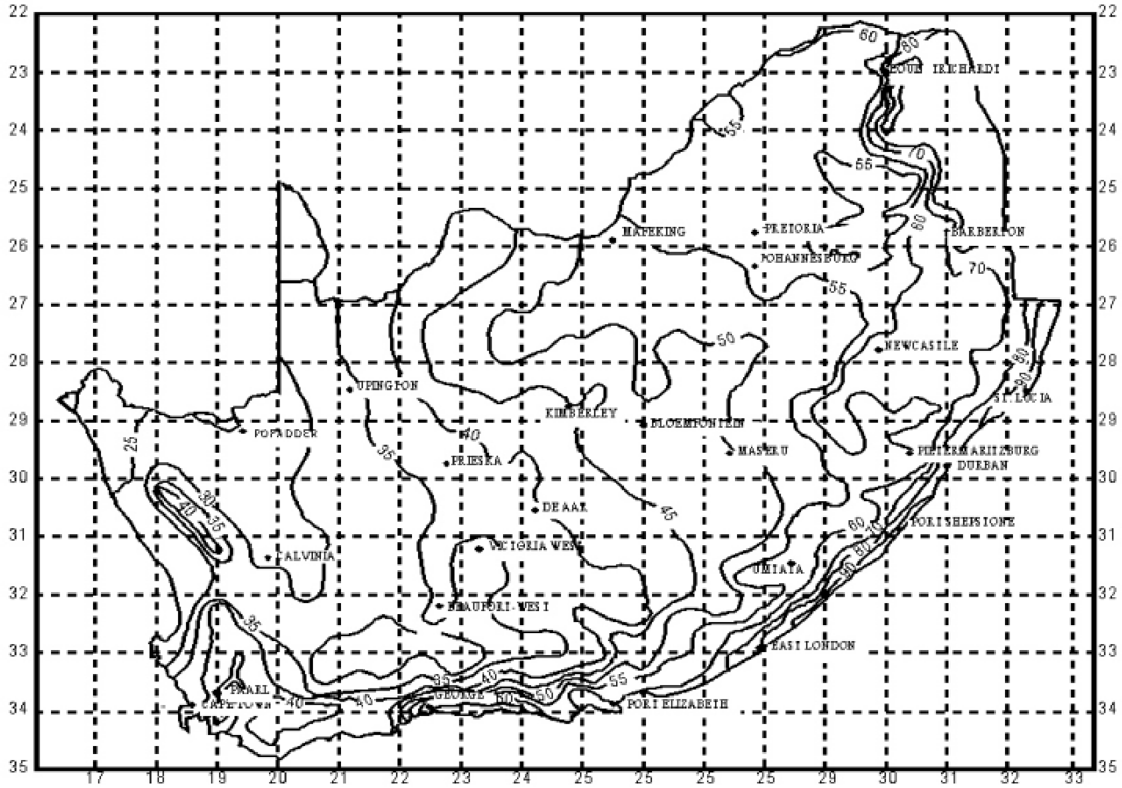

Figure 3.17 Expected maximum one-day rainfall in Southern Africa for 2-year return periods (after Schulze and Schmidt, 1987).

Table 3.12 Intensity multiplication factor for specific rainfall distribution zones (Schulze and Schmidt, 1995).

Intensity Multiplication Factor	Rainfall Distribution Zone			
	1	2	3	4
	0.430	0.664	0.974	1.236

Thus, the I30 (2yr30min) value was calculated using equation 3.6.

$$\mathrm{I30} = 60 \text{ x } 1.236 \qquad (3.6)$$

$$= 74.16 \text{ mm.h}^{-1}$$

Data for specific locations and climate zones were input to the model to determine the amount of sediment that could potentially run off the catchment, under the varying LULC scenarios (Lorentz and Schulze, 1995).

4. RESULTS

Results from the InVEST ecological model and ACRU hydrological model under varying LULC changes are provided and described in this section, with regards to the selected modelling objectives, i.e. water yield enhancement and sediment yield reduction over the uMkhomazi catchment for the three different scenarios. This section is structured as follows:

i. Surface streamflow results from the InVEST model under baseline, best and worst-case scenarios.
ii. Sediment yield results from the InVEST model under baseline, best and worst-case scenarios.
iii. Validation of the ACRU model under baseline conditions.
iv. ACRU streamflow model results under baseline, best and worst-case scenarios.
v. ACRU sediment yield results under baseline, best and worst-case scenarios.

4.1 InVEST model

Water yield and sediment yield simulations results were produced per sub-catchment using the InVEST model, for quaternary catchments U10A to U10G. Simulations were only conducted on sub-catchments above and surrounding the proposed Smithfield dam, to be built in U10F. Water and sediment yield values are given in million $m^3.year^{-1}$ and million $ton.year^{-1}$, respectively.

4.1.1 Streamflow modelling using the InVEST model

The best-case scenario was characterised by bare soil transitioning to restored grassland, with grassland that was currently in good condition being maintained/protected. Provided there is proper management and/or protection, this could potentially promote the regrowth of grasslands. The worst-case scenario was characterised by grassland being degraded to bare soil, if left unprotected. Visually, there are no apparent changes in water yield across the three scenarios (Figure 4.1), however there are differences in values. The differences were minimal and therefore fell within the same range, thus visually it appeared as if the water yield remained the same.

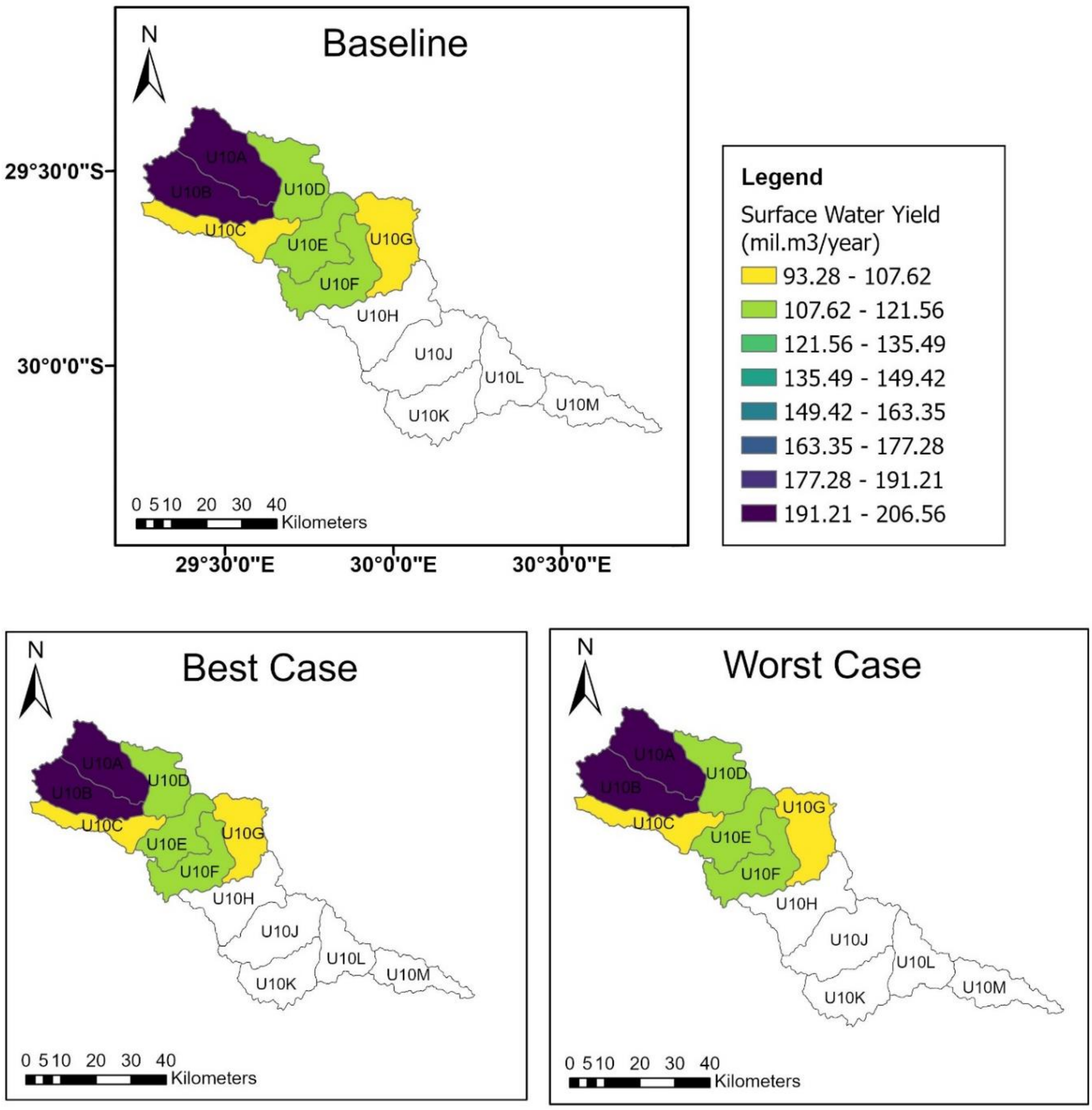

Figure 4.1 Surface water yield in mil.m^3.$year^{-1}$ for the baseline, worst and best-case scenarios for the selected intervention technique using the InVEST model, within the uMkhomazi catchment.

4.1.2 Sediment yield modelling using the InVEST model

Sediment yield for all quaternary catchments were found within the range of 0.46-5 mil.ton.$year^{-1}$, for baseline conditions (Figure 4.2). The best-case scenario produced the lowest volume of sediments per annum and the worst-case scenario produced the greatest volume of sediments per annum.

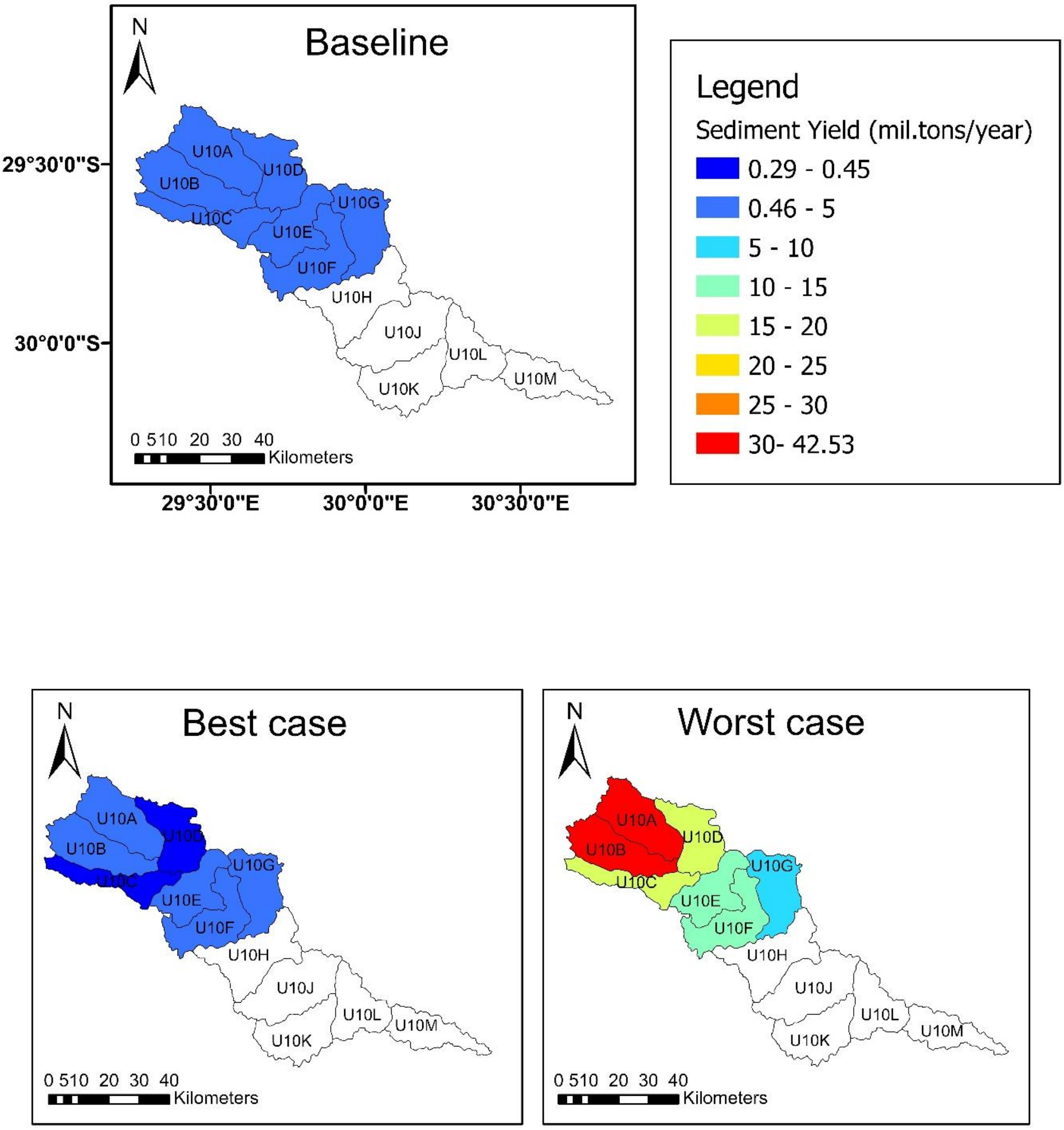

Figure 4.2 Sediment yield in mil.tons.year^{-1} for the baseline, best and worst-case scenarios for the selected intervention, within the uMkhomazi catchment.

The InVEST model results provide annual totals of the water and sediment yield within the uMkhomazi catchment. Table 4.1, provides annual totals for water and sediment yield for quaternary catchments U10A to U10G.

Table 4.1 Comparison table of water and sediment yield within the uMkhomazi catchment for the baseline, worst and best-case scenarios.

	Baseline	Best case	Worst case
Water Yield (mil.m^3/year)	933.5	931.1	953.5
Sediment Yield (mil.ton/year)	14.1	7.1	152.1

Although the InVEST model results are illustrated per sub-catchment, conclusions were drawn based on totals across the entire upper catchment for both water yield and sediment yield. The Water Yield sub-model within InVEST was run to determine the volume of water yield under the varying LULC scenarios across the uMkhomazi catchment (Figure 4.1). LULC for the best and worst-case scenarios, results in approximately a 0.3% and 2% deviation of water yielded respectively, compared to baseline conditions. Water yield reduced for the best-case scenario and increased for the worst-case scenario.

In contrast, sediment yield was impacted substantially by changing LULC. Baseline conditions produced a sediment yield of 14.1 mil.tons.$year^{-1}$ given by the Sediment Delivery Ratio (SDR) sub-model. The best-case scenario results imply a reduction in sediment yield, Table 4.1. Sediment yield is greatly exacerbated for the worst-case scenario, increasing from 14.1 mil.tons.$year^{-1}$ to 152.1 mil.tons.$year^{-1}$.

4.2 ACRU model

The ACRU model was used to simulate water and sediment yield over the uMkhomazi catchment, under the varying LULC scenarios. The model was run for a period of 35 years.

4.2.1 Validation of the ACRU model

The scatter plot for the baseline scenario in Figure 4.3, provides an indication of how well the model performed against reality. Verification studies were conducted for the ACRU model using the co-efficient of determination (R^2) and Nash Sutcliff co-efficient of efficiency (NSE). The baseline conditions produced an R^2 value of 0.52 which indicated a fair degree of model performance. However, the NSE value of 0.1 (Table 4.2), suggests a poor/weak correlation between simulated and observed streamflow, as a value less than 0.36, suggests poor model performance (Eryani *et al*., 2022).

The flow duration curve and log distribution of flows, Figure 4.4 and 4.5, respectively, provides an indication of model performance with regards to simulating flows, i.e., high, low and medium flows. The baseline scenario streamflow simulation depicts an overall over-simulation (Figure 4.4), which is also supported numerically by the percentage mean difference (PMD) between daily flows, (Table 4.2). The PMD provides the difference between averages of simulated and observed values in terms of a percentage. The PMD for the baseline scenario was -32.5%. The negative value of the PMD indicated that streamflow was over-simulated in comparison to observed flows.

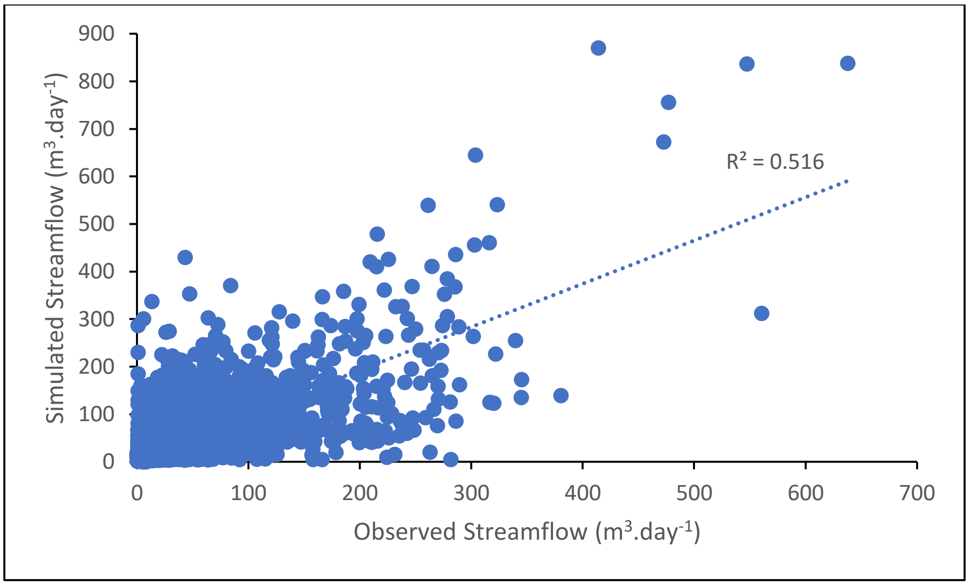

Figure 4.3 Scatter plot of observed and simulated daily streamflow values for the baseline scenario within uMkhomazi catchment from 1980 to 2014.

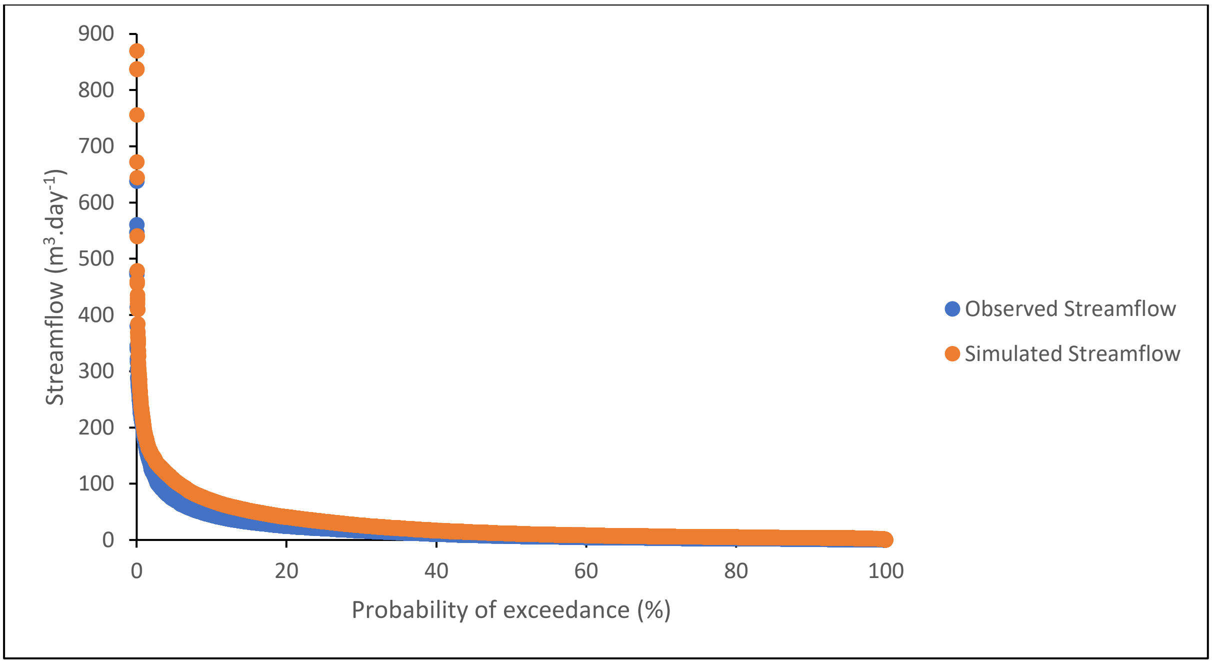

Figure 4.4 Flow duration curve of observed vs. simulated streamflow within the uMkhomazi catchment from 1980 to 2014, for the baseline scenario.

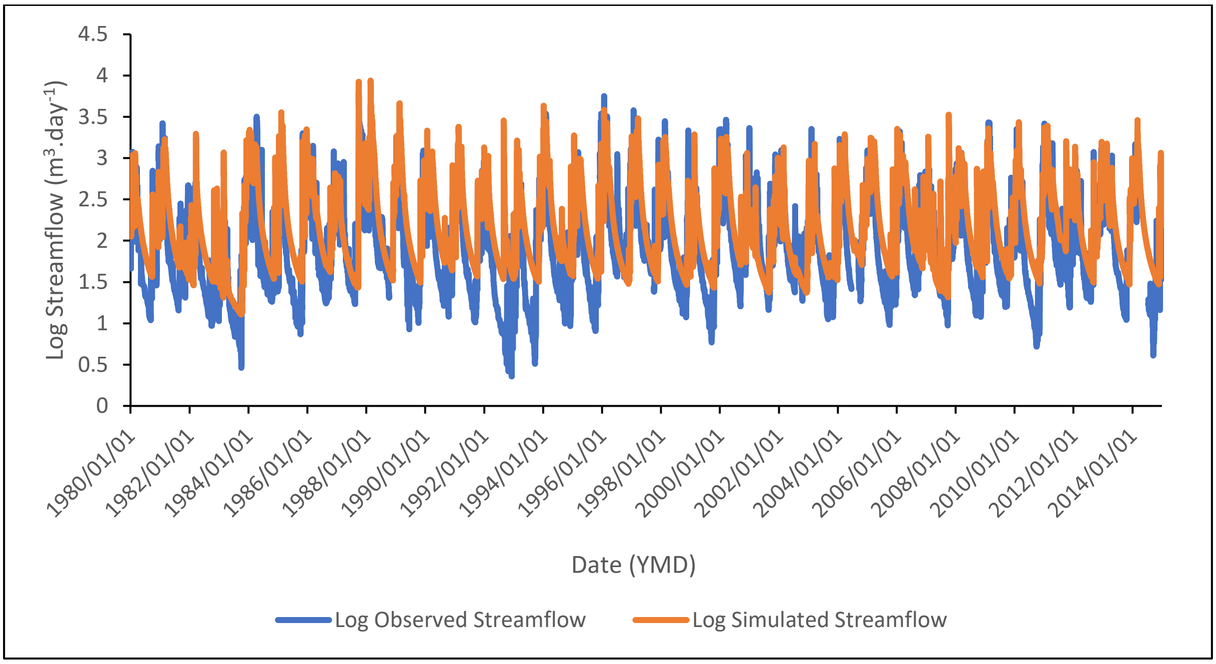

Figure 4.5 Log of observed and simulated streamflow for baseline conditions within the uMkhomazi catchment from 1980 to 2014, for the baseline scenario.

4.2.2 Streamflow model results from the ACRU model

The baseline, best and worst-case scenario water yield, Figure 4.6, all followed similar trends. Although, their absolute values differ there is a similar trend identified, with high water yield flows during high rain events (summer) and low flows occurring during low rain events (winter).

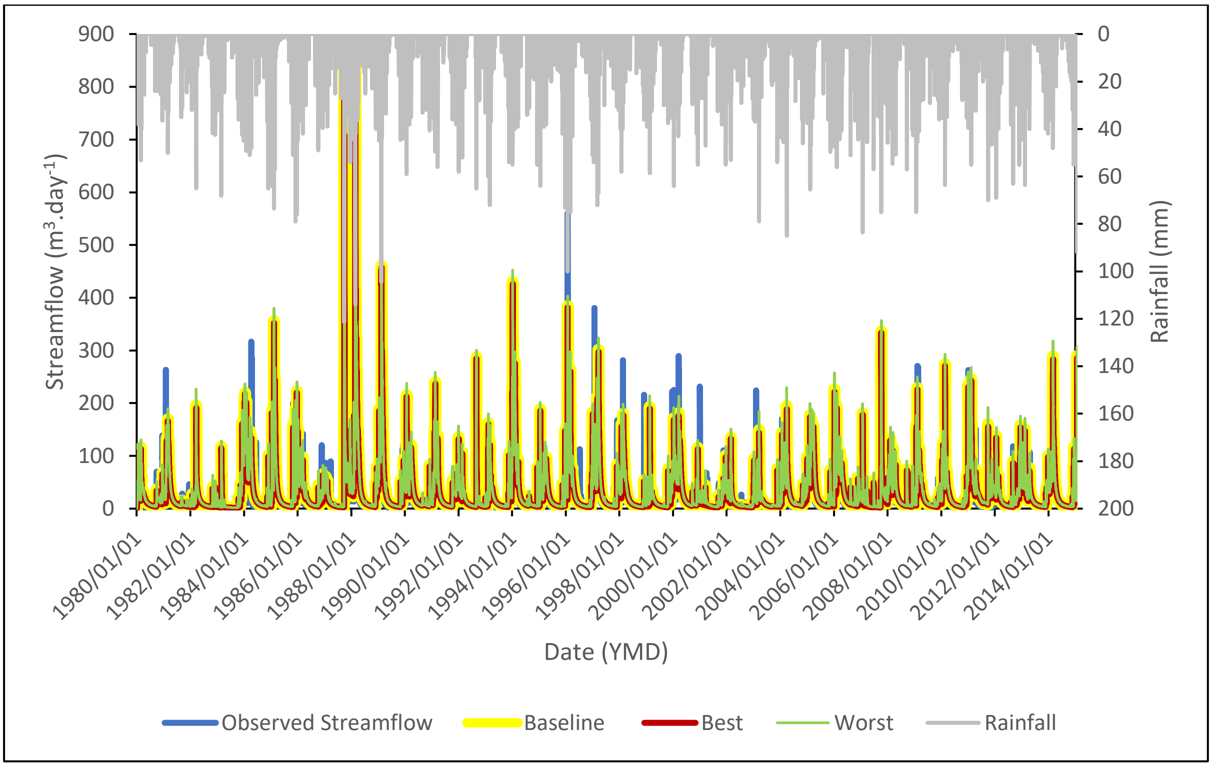

Figure 4.6 Time series of observed and simulated streamflow for baseline, best and worst LULC scenarios within the uMkhomazi catchment from 1980 to 2014.

Conservation statistics for the baseline, best and worst-case scenarios are provided in Table 4.2. The worst-case scenario produced the greatest water yield, and the lowest water yield was produced under the best-case scenario. In comparison to observed streamflow all scenarios over-simulated streamflow.

Table 4.2 Conservation statistics for baseline, best and worst-case scenarios within the uMkhomazi catchment between 1980 and 2014.

	Observed	Baseline case	Best-case	Worst-case
Total flow ($m^3.day^{-1}$)	229999.4	353530.8	346119.3	404138.9
Mean daily flow ($m^3.day^{-1}$)	18.7	27.7	27.1	31.6
PMD (%)		-32.5	N/A	N/A
NSE		0.1	N/A	N/A

4.2.3 Sediment yield results from the ACRU model

Time series of sediment yield is shown in Figure 4.7, for baseline, best and worst-case scenarios across the uMkhomazi catchment, from 1980 to 2014. The sediment yield for all three scenarios followed a similar trend, with the highest sediment yield during summer rainfall months and the lowest during winter months. Apart from LULC change impact on sediment yield, rainfall is a major contributing factor to soil erosion.

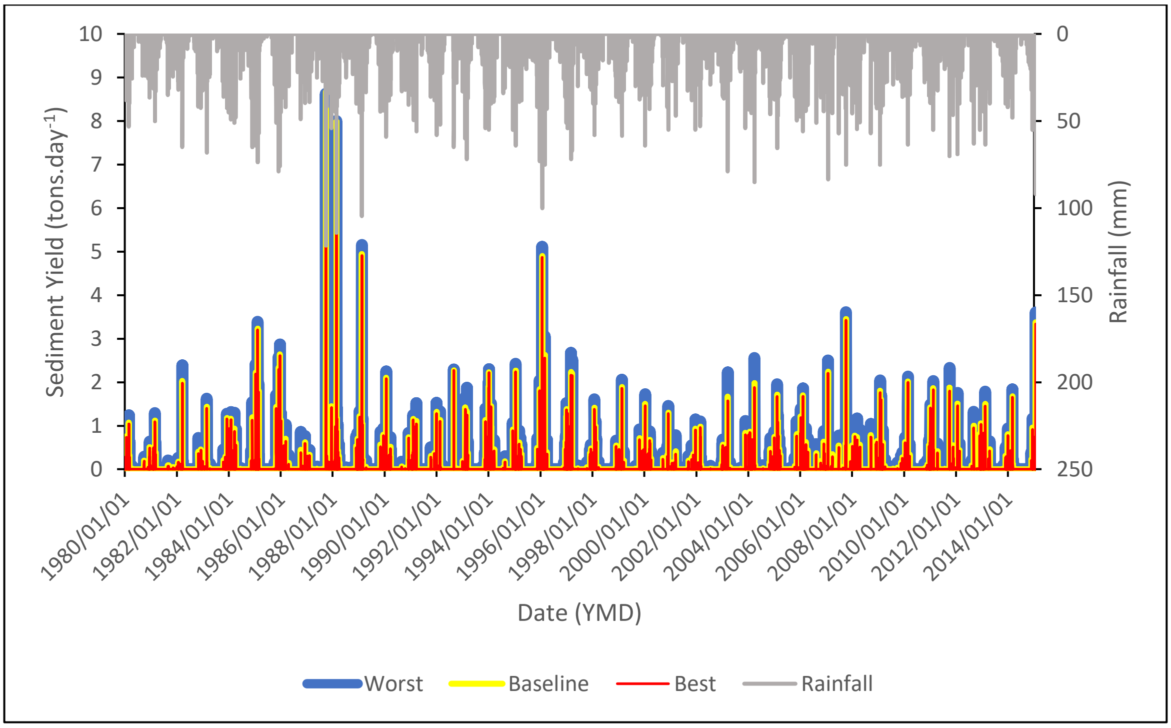

Figure 4.7 Sediment yield for the baseline, best and worst-case scenario within the uMkhomazi catchment from 1980 to 2014.

The average annual water and sediment yield from 1980 to 2014 is shown in Table 4.3. This is for comparison purposes against the InVEST model, which only runs on an annual time step. The worst-case scenario has the highest sediment yield, 11.8 million tons.year^{-1}, accompanied with the highest water yield and the best-case scenario has the lowest sediment yield which is 8.4 million tons.year^{-1}, along with the lowest water yield. As the catchment stands at present the sediment yield coming of per year is 8.9 million tons.

Both models produced similar trends in results, with water and sediment yield both decreasing for the best-case scenario and increasing for the worst-case scenario (Table 4.3 and 4.4). The differences in results between the scenarios are provided in Table 4.5. The accuracy and reliability of results produced was subject to the accuracy of input data.

Table 4.3 Average annual ACRU sediment and water yield over the uMkhomazi catchment.

	Baseline	Best	Worst
Annual Sediment Yield (mil.tons)	8.9	8.4	11.8
Annual water yield (mil.m^3)	10100.9	9889.1	11546.8

Table 4.4 InVEST sediment and water yield over the uMkhomazi catchment.

	Baseline	Best	Worst
Annual Sediment Yield (mil.tons)	14.1	7.1	152.1
Annual water yield (mil.m^3)	933.5	931.1	953.5

Table 4.5 The differences between the best and worst-case scenarios' water and sediment yield, relative to the baseline scenario, expressed as a percentage.

InVEST	Best-case	Worst-case
Water Yield	0.3% decrease	2% increase
Sediment Yield	66% decrease	More than 100% increase
ACRU		
Water Yield	2% decrease	13% increase
Sediment Yield	6% decrease	28% increase

5. DISCUSSION

The study aimed to explore the potential synergies and identify how ecological and hydrological models can be coupled to result in making more well-informed water resources management decisions. The study was carried out using the InVEST ecological model and ACRU hydrological model. The research questions provided at the outset of the study are addressed in this section. It is important to take note that these are user-generated scenarios and are not definite changes that will occur within a catchment, rather these are assumptions of what could potentially occur under management/protection vs. no management/protection practices.

5.1 The InVEST model validation against similar studies

In this study the InVEST model was not validated, due to limited in-situ data however, similar studies conducted across various regions of the world suggest good model performance with regards to both the InVEST Water Yield and Sediment yield sub-models. Water yield studies conducted by Belete *et al*., (2018), Srichaichana *et al*., (2019), Yang *et al*., (2020), Wei *et al*., (2021), and Basha *et al*., (2024)**,** all suggest that the InVEST model can be applied with confidence, as the respective validation studies undertaken suggested that the observed data corresponded well with simulated data. Belete *et al*., (2018), was able to effectively model annual water yield in a region that does not have flow meters thus, findings from this study confirm that the InVEST model can also be applied with confidence in data-scarce regions.

Further supporting the successful application of the model in data-scarce regions was a study conducted by Yang *et al*., (2020), in which the Water Yield sub-model revealed good model performance under changing LULC and precipitation. Validation results from Wei *et al*., (2021), suggested that there was a strong linear relationship between simulated and observed water yield values, implying satisfactory model performance in simulating water yield under climate and LULC changes. Further studies by Basha *et al*., (2024), demonstrated that the Water Yield sub-model performed well even at the pixel level, under changing LULC scenarios.

The Sediment Yield sub-model of InVEST can also be applied with confidence according to findings by Srichaichana *et al*., (2019), Degife *et al*., (2021), Gashaw *et al.*, (2021) and Yadav *et al*., (2023). The Sediment yield sub-model validation study by Srichaichana *et al*., (2019), suggested that the model performed well against reality, under changing LULC, further supported by Yadav *et al*., (2023). Further studies conducted by both Degife *et al*., (2021) and Gashaw *et al*., (2021), suggested that the Sediment Yield sub-model exhibits good performance and is useful for estimating sediment yield in data-scarce regions.

Nedkov *et al*., (2022), performed a study to determine the appropriateness of various models for the analysis of different ES, findings from the study suggested that the InVEST soil erosion model was the most developed tool, compared to the other models analysed. From the various studies that Nedkov *et al*., (2022) reviewed, overall, the InVEST model ranked first for being the most used ecological model for ES modelling (Nedkov *et al*., 2022). Further supporting the reliability of the InVEST model was Decsi *et al*., (2022), in which the InVEST model was also found to be the most efficient, compared to other models, with regards to result reliability even when compared to hydrological models (Decsi *et al*., 2022), therefore its use is highly recommended.

From the various aforementioned studies in which the InVEST model was applied and validated, there is a certain level of confidence that can be coupled with InVEST model use in this study, as the InVEST model has proven to simulate water and sediment yield well globally (Belete *et al*., 2018; Srichaichana *et al*., 2019; Yang et al., 2020; Degife *et al*., 2021; Gashaw *et al.*, 2021; Wei *et al*., 2021; Decsi *et al*., 2022; Nedkov *et al*., 2022; Yadav *et al*., 2023; Basha *et al*., 2024).

5.2 Validation of the ACRU model

The ACRU model performance was validated against observed streamflow data, as this was the only parameter with an available and acceptable record length. Statistical analysis performed demonstrated an overall over-simulation of flows. Due to the scale that was used for streamflow in the flow duration curve (Figure 4.4), it appeared as if low flows are simulated well however, log transformed data (Figure 4.5), revealed that low flows are just as poorly simulated as medium flows. Medium and low flows are more poorly simulated as compared to high flows. Multiple reasons could be owing to the over-simulation of flows; the critical stormflow depth being too shallow, rainfall errors, streamflow errors, quick flow response fraction being too high, *inter alia.* Parameters within ACRU were changed to attain an optimum simulation ‘closest to reality’, which was constrained by the data and information available to configure the model.

The performance of the model is not only dependent on its capabilities, but it is also as a function of input data, performance evaluation data, and decisions of the modeller (Glenday *et* *al*., 2022). The sensitivity of the model to rainfall and climate variability could have been one of the main contributors to the poor performance of the ACRU model as only one weather station was used to simulate the entire catchment, whereas these conditions are likely to vary spatially in reality, furthermore, the distance between the weather station and streamflow gauge (error in values could also exist) and the difference in altitudes between the two locations, could have also impacted model performance as meteorological variables change with altitude, therefore the use of one weather station may not adequately represent the climatic spatio-temporal variability across the catchment. Furthermore, other factors that could have also contributed to the poor performance of the ACRU model include: the infilling method chosen for rainfall, temperature and evaporation data, *inter alia*. Also, user errors may be more easily introduced with complex model configurations (Glenday *et al*., 2022), thus contributing to the shortcomings of model performance. Furthermore, inadequate consideration of LULC changes resulting from the reclassification of the LULC map may have also influenced the model's performance; the reclassification of the LULC map resulted in the spatial heterogeneity of the LULC within the catchment not being well captured and therefore resulted in variables, i.e. crop co-efficients, *inter alia*, contributing to streamflow being inadequately accounted for. In this study, the focus was on the effects of LULC changes on HES, rather than the absolute values produced therefore, although the model exhibits poor performance, consistent errors have been carried through the various scenario cases.

5.3 Water and sediment yield simulations using the InVEST and ACRU model

The best-case scenario could be attained through targeted land management, the ACRU and InVEST models both demonstrated that if bare soil surfaces transitioned to grasslands (best-case scenario), it would result in a decrease in water yielded by the catchment, a 2% decrease identified using the ACRU model and a 0.3% decrease using the InVEST model. These changes are as a result of vegetation type, infiltration rates, evapotranspiration rates, *inter alia*. It was expected for the water yield to decrease for the 'best-case' scenario as the land cover was being replaced with a higher water using vegetation cover. The crop co-efficient (Kc) of LULC plays an integral role in influencing the water yield in a catchment, essentially Kc is a factor that relates the evapotranspiration of a specific crop to the evapotranspiration of a reference crop and is an important component in estimating the water requirements of a crop. Grasslands have a higher Kc value (0.605), than bare soils (Kc = 0.485), and thus, have greater water demands compared to bare soil surfaces. Similar findings by Hughes *et al*., (2018) demonstrated that effective rehabilitation of grasslands resulted in improved vegetation cover resulting in increased interception, infiltration and percolation of precipitation to lower soil layers. Which is particularly important for baseflow generation during dry periods (Bagstad *et al*., 2013). Although the overall water yield was reduced, there would be more water available for low flows due to the improved retention capacity, which is better identified with a daily time step-model, such as ACRU.

The vice versa is true for the worst-case scenario, the transition from grasslands to bare soil resulted in water yield increasing by 13% using the ACRU model and by 2% using the InVEST model. The lower Kc value of bare soil implied less water was lost due to evapotranspiration thus, leaving a greater volume of water available for surface runoff (Vogl *et al*., 2016; Tumsa, 2023). Infiltration would be reduced thus, more water would be available for runoff (Vogl *et al*., 2016; Gokool and Jewitt, 2019). Although there was a greater volume of water produced under the worst-case scenario, there would be less water available during the drier periods. The reduced retention time associated with surface roughness of bare soil surfaces would result in the majority of rainfall becoming runoff. Additionally, the absence of vegetation root systems to absorb and infiltrate water to lower soil layers also promotes runoff.

The ACRU model results indicated that sediment yield decreased by 6% for the best-case scenario, whilst the InVEST model identified a 66% reduction in sediment yield, in comparison to the baseline scenario. Grasslands have a vast root system that tends to hold soil particles with greater bonds (UW, 2014), thus preventing easy dislodgement. Less surface runoff accompanied by the best-case scenario implied less energy being available to dislodge and transport sediments thus, sediment yield was reduced.

The worst-case scenario produced the highest sediment yield identified by both the InVEST and ACRU models, as a result of limited vegetation cover exposing more surface to soil erosion, coupled with a limited vegetative root system to aggregate soil particles. The worst-case scenarios' sediment yield increased from 14.1 mil.tons.year^{-1} to 152.1 mil.tons.year^{-1}, compared to the baseline LULC, identified by the InVEST model and increased by 28% using the ACRU model. In the absence of protection/management practices, grasslands could potentially degrade to this worst-case scenario. The greater water yield produced under the worst-case scenario results in more water being made available for particle dislodgement and transport.

LULC change results from the InVEST model demonstrated minimal changes to water yield however, its impacts on sediment yield were more pronounced. This could potentially be due to baseline conditions currently having a lower proportion of bare soil surfaces, therefore when transitioned to grassland, there was less area of LULC changes thus, resulting in soil erosion reducing by only half the initial yield. However, under baseline conditions there was a high proportion of grassland surfaces, therefore when transitioned to bare soil, it resulted in exaggerated effects on sediment yield, also true for the ACRU model. Degraded landscapes produce higher sediment yields per area compared to natural vegetation (Hughes *et al*., 2018), thus, increased sediment yield produced under the worst-case scenario. The increased sediment export under the worst-case scenario would impact dam characteristics, i.e. life span, water quality and dam functioning (Msadala *et al*., 2010; Hughes *et al*., 2018).

Therefore, reducing the amount of sediment that runs off a catchment will help to prevent siltation and contamination of dams and rivers. Studies conducted by Vogl *et al* (2016) and Gokool and Jewitt (2019), found that there was an increase in water and sediment yield associated with degraded landscapes, similar to the findings from this study. Although water yield increased under the degraded vegetation cover, the negative impacts outweigh the positive gains, as quick-flow increases, the risk of floods, erosion and nutrient mobilisation increases along with it (Hughes *et al*., 2018). The minimal changes in water yield for the InVEST model could potentially be due to the model being unable to account for baseflow, as improved vegetation cover has the capacity to store more water therefore, the water yield is only representative of surface flow (Cong *et al*., 2020), thus, appearing as if there were minimal changes to water yield from the baseline scenario to the best-case scenario. The ACRU model demonstrates greater changes to water yield as compared to the InVEST model, as ACRU is able to account for both surface and sub-surface flows, therefore providing more detailed results.

The ACRU model helped to identify when high flows and low flows occur. Streamflow was the greatest under summer rainfall conditions (Figure 4.6). Similar trends were seen for all scenario cases, as all follow the same rainfall regime. The lowest flows occurred during June to August and the highest flows occurred during December to March.

Water and sediment yield share a close relationship with rainfall patterns (Tian *et al*., 2022). Sediment yield was dominant during summer rainfall periods (December to March), Figure 4.7, for the baseline, best and worst-case scenarios. During this period there were more frequent and higher magnitude rain events providing sufficient energy for the dislodgement of soil particles. During winter rainfall months (June to August) minimal sediment yield was produced. Winter rain events are attributed with light rains (drizzle), which does not possess sufficient energy to promote high rates of soil erosion. Summer rain events are attributed with heavy downpours in a short period of time (Tian *et al*., 2022), promoting high soil erosion rates (Tian *et al*., 2022).

During peaks of rain events sediment yield was the greatest due to peak rainfall having the greatest amount of energy for particle dislodgement. The same trend was seen across all scenario cases.

Soil erosion is predominantly a major concern within the uMkhomazi catchment. From the model results produced, water resources managers would concentrate their efforts on scenarios that yield the lowest sediment yield, and in doing so attempt to prevent reaching the worst-case scenario. With regard to the proposed Smithfield dam, it is useful to have these modelling scenarios in play to aid decision making.

Trends identified by both models are the same and thus, provide a similar frame of reference for water resources management, the model results suggest that the user-identified 'best-case' scenario does in fact result in reduced sediment yield for the uMkhomazi catchment. The scenario demonstrated how HES can be safeguarded with protection/management and restoration practices in place. Associated with reduced sediment yield would be reduced costs required for water purification processes, dredging of dams and maintenance of pumping equipment, allowing for the catchment to deliver and render HES within functioning capacity.

Furthermore, an important factor to take into consideration in addition to the measures of minimising soil erosion is the Ecological Reserve or environmental flow requirements (Tanner *et al*., 2022). Satisfying the ecological reserve helps to safeguard aquatic ecosystems (Tanner *et al*., 2022), thus, ensuring the protection and delivery of services rendered from ecosystems. Hughes *et al*., (2014), suggested that environmental flow requirement determinations should adopt a holistic approach incorporating hydrology, channel hydraulics and ecological response. The consideration of the aforementioned aspects that impact flow would provide more representative estimates for environmental flow assessments. The ecological reserve should be met and managed to ensure the long-term sustainability of rivers and ecosystems. Priority is given to the reserve and thereafter all other water users and uses can be satisfied, this is to ensure protection of water resources and biota.

Managing the soil erosion across the uMkhomazi catchment through implementation of the intervention technique would result in the sediment yield being reduced, resulting in a ripple effect of benefits, i.e. reduced siltation of the dam, therefore water holding capacity and water quality would be safeguarded, and thus, ensuring that the dam has sufficient water for release to meet the ecological reserve of the river. Although the overall water yield is reduced with the intervention technique, this is a relatively marginal decrease and is compensated for by the greater water volume of water available for important baseflow generation (Vogl *et al*., 2016).

The consideration of Flagship Free Flowing Rivers is also of great importance. Although the Mkomazi River is not identified as a Flagship Free Flowing River, it has been marked as a high value aquatic conservation area, by a provincial scale assessment conducted by Rivers-Moore *et al*., (2011). Freshwater conservation areas aim to protect aquatic biodiversity, and thus protecting HES rendered. The consideration of freshwater conservation areas (Rivers-Moore *et al*., 2011) plays a significant role in determining the type and extent of intervention techniques that can be implemented in a region. The consideration of the Freshwater Ecosystem Priority Areas maps for EI protection and management can aid in determining where efforts should be concentrated (Driver *et al*., 2011), to provide the greatest returns on investment.

5.4 Differences between the InVEST and ACRU model outputs

The functionality of a model influences the output produced (Lüke and Hack, 2018), models vary in their application, theoretical concept and consequently in their results (Lüke and Hack, 2018). The differences in model output between the InVEST and ACRU models are inherent, and to highlight a few reasons; the poor calibration of the ACRU model, the inability of the InVEST model to capture seasonality (Ureta *et al*., 2021; Gokool and Jewitt, 2019, Vogl *et al*., 2016), outputs of models being produced on different temporal scales, and the use of only one weather station to simulate the entire catchment for the ACRU model.

Global datasets were used for the configuration of the InVEST model which could have also introduced errors in the results, resulting in over/under estimations, making the output's reliability and accuracy questionable. Data pre-processing and the different algorithms used for calculations also contribute to different output results (Cong *et al*., 2020). The differences in water yield simulated between the InVEST and ACRU models are essentially due to their respective conceptualization, with the former being based on a simplified water cycle, i.e. precipitation less evapotranspiration. (Lüke and Hack, 2018), while the latter is conceptualized to comprehensively account for all hydrological processes (Cong *et al.*, 2020). The InVEST model is also unable to account for baseflow therefore, only simulating a portion of the total water yield (Cong *et al*., 2020), thus, resulting in different absolute values produced.

The algorithms used to calculate sediment yield values are different between the two models, the ACRU model calculates sediment yield using the MUSLE equation, whereas InVEST utilises the Universal Soil Loss Equation (USLE) equation. The models operate on different temporal scales which could also impact the output produced. Although differences in absolute values exist, consistent predictions/trends are identified by both ecological and hydrological models, similar findings reported by Lüke and Hack (2018). Furthermore, direct comparisons of results can only be made when the same input data is used for all models (Lüke and Hack, 2018; Cong *et al*., 2020). Direct comparisons are not recommended as these are different modelling approaches and produce outputs based of different ES metrics (Lüke and Hack, 2018). Although both models produce different absolute values, the models still provide a similar frame of reference (Cong *et al*., 2020), for water resources management and policy-making.

5.5 Strengths and limitations of each modelling approach

InVEST played a significant role in providing estimates of soil erosion, as there were limited in situ data available, therefore its use is particularly advantageous for data-scarce regions such as the uMkhomazi catchment, further supported by studies conducted by Belete *et al*., (2018), Yang *et al*., (2020) and Degife *et al*., (2021). An advantage of the InVEST model, in addition to simulating sediment export, is the model's ability to also simulate sediment retention, comparison of the two outputs can be used to determine which areas are considered priority for protection (Lüke and Hack, 2018). The sediment retention capacity of the baseline scenario can be used to determine areas with the potential to improve HES. The InVEST model can run on global data sets with most being readily available at no cost, which is beneficial as one can initially run a quick and simple model that does not require complex input data processing and setup, as well as minimal expertise requirements, promoting model application (Srichaichana *et al*., 2019; Degife *et al*., 2021; Gashaw *et al.*, 2021; Yadav *et al*., 2023), as an alternative to initially running complex hydrological models, saving both time and effort. The model is also advantageous for studies conducted at larger scales, making the most of its spatial visualization (Cong *et al*., 2020).

Although, the response of both models to water and sediment yield followed a similar trend to LULC changes there are in model specifications which impacted the absolute values simulated. The annual time step of the InVEST model neglects extreme events, missing important seasonal changes (Vogl *et al*., 2016; Gokool and Jewitt, 2019; Ureta *et al*., 2021).

The Water Yield sub-model does not possess the capability to differentiate between surface runoff and the volume that infiltrates, it is also unable to account for the various growth stages of the crop (Gokool and Jewitt, 2019; Ureta *et al*., 2021). Therefore, the sub-model provides a simplistic overview of water yield within the catchment under the various scenarios (Vogl *et al*., 2016). The intended purpose of the sub-model is not for detailed water plans but rather to demonstrate how changes in the catchment impact water yield.

Global data used in the InVEST model has a coarse resolution which is particularly disadvantageous for modelling on regional or local scales, therefore results produced are only reliable at sub-watershed and watershed scales (Lüke and Hack, 2018; Cong *et al*., 2020), thus unable to provide reliable results at finer temporal/spatial scales (Nedkov *et al*., 2022). Furthermore, the spatial distribution of LULC is also not well captured by the model (Sharp *et al*., 2020). The simplicity of the model and low input data demands, result in the model being sensitive to most of the parameters, impacting the output produced (Sharp *et al*., 2020). A major limitation of the Sediment Delivery Ratio model is its reliance on the USLE equation which does not take processes such as gully erosion into consideration (Gokool and Jewitt, 2019; Sharp *et al*., 2020), thus, only a portion of the actual sediment load is being simulated. To overcome the limitations associated with the USLE equation Gwapedza *et al*., (2021), suggests using the MUSLE equation for improved sediment yield estimations, as it is a simple way of estimating sediment yield and has proven to be successful (Gwapedza *et al*., 2021).

The catchment response to seasonality can be followed with a daily time step model such as ACRU, which is important for understanding baseflow, streamflow and sediment dynamics, necessary to make well-informed water resources management decisions. ACRU provides an indication of when extreme events occur, not just providing overall totals for the catchment. This level of detail provided by the ACRU model can be used to inform when appropriate times are for abstractions, which is particularly important during winter months when streamflow depends primarily on baseflows. This information can be useful for pumping regimes between catchments and to determine dam health with regard to levels of sedimentation that may occur. Being able to follow seasonal dynamics and trends informs better management decisions and implementation of more sound activities, enabling decision-makers to act accordingly and to protect the catchment from repetitive issues.

Results produced by the InVEST model were unable to explicitly demonstrate the value of EI investments, hence the need for hydrological models to explore the full potential benefits derived from EI investments. From the study it is evident that both models are able to complement each other. The ACRU model was able to overcome many of the aforementioned limitations of the InVEST model and vice versa. ACRU accounts for evapotranspiration losses, interception losses and surface cover during the various growth stages of a crop, also accounting for groundwater availability for evapotranspiration demands of vegetation.

From the modelling activity performed, it was found that a major limitation associated with the ACRU model was the difficulty experienced in retrieving quality in-situ data at finer scales. The model is also not an optimising model (Otim *et al*., 2020). Since ACRU models hydrological processes in detail, application efforts are much greater, associated with input data preprocessing, training effort and post-processing to quantify and visualize HES. Although the model itself is freely available, cost implications may arise with the acquisition of lengthy climate data and the training of researchers.

The ACRU model also does not account for gulley erosion or provide for temporary storage; therefore, sediment yield is only representative of erosion characteristics (Lodenkemper *et al*, 2021). The sensitivity of the model to rainfall data plays a significant role in the results produced therefore, vital for good model performance is quality rainfall data, thus, the infill method selected is important. In this study, monthly averages were used for infilling of rainfall data which could have resulted in errors, as rainfall is not an everyday occurrence. The model could be accounting for rain events that didn't occur or completely miss events that did occur. Therefore, it is important to adopt an approach that provides the closest representations of reality as far as possible.

5.6 How ecological and hydrological models can be used in conjunction with each other to maximise modelling capabilities.

The scope of the study was not to demonstrate absolute changes that would occur within the catchment but rather to demonstrate relative changes that would result from the implementation of the intervention technique versus the absence of management/protection. Although having scientifically sound results would have been of immense benefit to the study, the exact figures were not of main concern. Rather the modelling exercise undertaken was to attain an understanding of how both hydrological and ecological models could potentially be applied to aid in making well-informed water resources management decisions.

The majority of studies conducted to date provide the theoretical basis of model use, with only a few assessing the practical application of models for ES studies (Cong *et al*., 2020), whereas this study aimed to develop a framework for the synergistic application of hydrological and ecological models. Various frameworks have been developed for model selection and application (Harrison-Atlas *et al*., 2016; Nedkov *et al*., 2022), which can be used as a basis to aid decision-making and appropriate model selection for HES analysis. However, these frameworks (Harrison-Atlas *et al*., 2016; Nedkov *et al*., 2022), assess hydrological and ecological model applicability but seldom reveal how these models can be used in tandem to maximise their respective strengths and minimize their limitations. Most of the studies reviewed provided comparisons of models determining the appropriateness of each for various ES-related concerns and the suitability of models for various regions however, this study aimed to determine how these very disparate models can be applied in real case scenarios.

From the modelling exercise undertaken, the application of the InVEST model was quick and efficient, as most datasets used were readily available global datasets, as compared to the application of the ACRU model, in which data acquisition, pre-processing and model set-up was much more complex. It may be argued that the need for ecological models, with regard to the modelling approach, provides limited comprehensive analysis, however, the model was found to be beneficial under time availability, funding and expertise constraints. Despite the model's limitations, the model still serves as a useful means for providing estimates of relative change for water resources planning and management (Belete *et al*., 2018; Srichaichana *et al*., 2019; Degife *et al*., 2021; Gashaw *et al.*, 2021; Wei *et al*., 2021; Yadav *et al*., 2023; Basha *et al*., 2024; Yang et al., 2020). Under favourable conditions (i.e. sufficient funding, time and expertise) the use of more complex models can be applied alongside ecological models, allowing for explicit modelling of the impacts of LULC changes on HES, and thus providing a greater understanding of catchment dynamics.

Although there were large differences in outputs produced between InVEST and ACRU both models followed similar trends in results, for example, both models demonstrated that if grasslands were not protected and were to degrade, water yield would increase resulting in sediment yield to increase as well, and vice versa for the best-case scenario. Despite the differences in absolute values produced, the models still provide a similar frame of reference for decision-making (Lüke and Hack, 2018).

From the modelling activity undertaken the synergistic application of models can thus be derived; if multiple intervention techniques need to be evaluated within a relatively short time frame, and under limited funding and expertise, initially a quick analysis can be performed using a simple ecological model that is not data-intensive, such as the InVEST model, to provide estimates of relative changes that would result. All intervention techniques in question can be modelled as compared to only evaluating a select few, due to the aforementioned constraints. This approach will allow for multiple interventions to be explored efficiently and effectively and thereafter, from the results produced the interventions which demonstrate the most significant impacts on HES can be modelled in depth using a complex hydrological model such as ACRU, to reveal the full potential benefits of the interventions on HES.

For example, if 10 interventions are to be evaluated it would be easier to first run all interventions using a simple model which will allow for quick analysis to be conducted, thereafter, the top three or four interventions which demonstrate the most significant changes to HES can be modelled in depth using a hydrological model. This allows for effective and efficient modelling to be conducted. This is a useful way of optimising model use, as compared to modelling all 10 interventions in depth which would require a substantial amount of time, expertise and funding. The synergistic use of the models will allow for multiple EI intervention techniques to be explored as compared to modelling only a select few, resulting in efficient and effective water resources management conclusions to be drawn. Saving both time and effort and still providing results informed by science.

6. CONCLUSION AND RECOMMENDATIONS

Ecological infrastructure is the base from which goods and services required for social, economic and environmental survival are derived, thus, protection and maintenance of EI is vital. An effective means of demonstrating the benefits associated with EI investments is needed, in order to reveal the full potential benefits of investments. This can be achieved through the use of ecological and hydrological models. To promote EI investment adoption in policy-making and water resources management, an adequate demonstration of the value of EI is required.

Not to completely ignore the benefits that built infrastructure has been providing over the years but the degradation of EI and further degradation that would occur if there were continual built infrastructure development would result in catchments being unable to provide services at their optimum. However, built infrastructure is still essential for providing the bulk of the water supply. Moving forward, to incorporate EI investments into planning and policy-making rather than solely investing in built infrastructure, can be achieved by effectively demonstrating the value of EI and services rendered. Quantifying the hydrological benefits associated with investing in EI has the potential to attract investors and promote adoption in water resources management and policy-making. There is seldom consideration of EI to augment water security issues, due to inadequate understanding of associated benefits. By demonstrating the full potential of EI investments water resource managers will be attracted to the concept and adopt the approach.

Thus, the study aimed to demonstrate how ecological and hydrological models can potentially be applied to complement each other, to enhance the understanding of hydrological responses under changing LULC. From the modelling activities undertaken in this study, it was deduced that if both models were to be used in tandem with each other they would have the potential to contribute to making more well-informed water resources management decisions. Overall, both models were able to demonstrate the relative changes to water and sediment yield, upon the implementation of the intervention technique vs. the absence of any intervention, within the uMkhomazi catchment.

The magnitude of water yield changes were minimal with the given LULC changes however, its impact on sediment export/yield were more pronounced, which is important to take cognisance of for water resources planning and management. Although absolute values produced by both models were different, the overall trends identified by both models to catchment response were similar, e.g. the water and sediment yield decreased for the best-case scenario, and increased for the worst-case scenario, identified by both models, thus providing a similar frame of reference for decision making. The varying results were mainly attributed to model functionality in terms of input data requirements, theoretical concepts, applications, and algorithms used for calculations.

Optimum conditions for the uMkhomazi catchment should be associated with reduced sediment yield and acceptable water yield, possible with the best-case scenario. The user-identified best-case scenario resulted in an overall net benefit of reduced sediment yield, however in the absence of protection/management, the catchment could potentially reach the worst-case scenario, thus emphasising the importance of management and protection within the uMkhomazi catchment. Suitable management techniques can result in achieving the ‘best-case’ scenario. Grassland restoration can be achieved with the correct farming techniques, i.e, periodic ploughing of land and grazing, educated use of land and water sources, amongst others. Quantifying HES under varying scenario cases provides a good opportunity for the protection and management of HES and inevitably EI.

Independent use of InVEST and ACRU against each other demonstrated their respective strengths and weaknesses clearly. The ACRU model was able to overcome the major limitation associated with InVEST model, i.e., being unable to account for seasonality. Understanding of seasonal changes is important for making predictions and for planning and management purposes. Failure to account for seasonality results in poorly informed management decisions.

Alternatively, InVEST was efficient in producing results for water resources planning, particularly under time constraints, which is more difficult to achieve using the ACRU model. The ACRU model allows for the effects of LULC changes to be analysed at a finer spatial resolution and produces higher temporal resolution outputs, allowing for in depth analysis to be conducted, which was the major limitation associated with the InVEST model. Thus, the combined use of models will enable predictions to be made with greater confidence, provided both models produce similar output trends. It is important to note that the model output is only as good as the model input. Also, improved complexity does not necessarily translate to improved simulations, therefore model capabilities and limitations need to be well understood in order to be applied effectively.

The scope of the study was not to demonstrate what would precisely occur in the future and where, but rather to demonstrate how the use of both hydrological and ecological models can be used as a tool to portray in depth what could potentially happen to HES under changing LULC. In the event of needing to analyse multiple intervention techniques under funding, time availability and expertise constraints, models can be applied synergistically to quantify the LULC change impacts on EI functionality in producing HES, revealing the full potential benefits of investments in EI.

The InVEST model can be used an initial indicator tool to determine if a certain intervention technique would result in significant impacts in the catchment and thereafter, determining if further investigations would be necessary, which can then be done using a complex hydrological model to reveal the full potential benefits of the intervention technique. This application of models is both time and cost-efficient, also preventing running the risk of complex model setup for multiple intervention techniques only to reveal minimal changes to ES. Therefore, this study can serve as the theoretical basis for the synergistic application of hydrological and ecological models enabling effective and efficient evaluation of multiple intervention techniques.

The associated limitations of the study can be used as recommendations to be considered for future studies. Models that demonstrate where (priority areas) in the catchment management practices would have the greatest returns on investments can be used, aiding in making even more well-informed water resources management decisions. Also incorporating economic value into decision-making plays a significant role, as funding is crucial in determining which interventions can be adopted for a specific catchment. It would be beneficial to use a range of ecological and hydrological models, to determine which model performs best within certain regions. Studies examining a combination of models that work 'best' within a particular region/catchment would be of immense benefit to interested parties. Multiple intervention techniques can be explored, demonstrating the impact of various interventions on the delivery and production of HES. Modelling can be performed at a finer scale, with more LULC classes resulting in more representative outputs. There are multiple ES available, but in this study, focus was on HES, moving forward future research can be conducted around various other ES.

In the plethora of models available, difficulty arises with regard to model choice and application. Findings from the study can contribute to developing a streamlined approach for model application, saving both time and effort. Effective demonstration of the value of EI investments can potentially be achieved through the combined use of models, promoting the adoption of EI investments in catchment management actions and policy. Thus, using these models in tandem with each other has the potential to improve the modelling arena significantly.

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