IMPACTS OF LAND USE AND LAND COVER CHANGES ON LAND DEGRADATION AND HYDROLOGY IN A CHANGING CLIMATE: A CASE OF LIMPOPO RIVER BASIN IN SOUTH AFRICA

Reported to the

Water Research Commission

by

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EXECUTIVE SUMMARY

Introduction

One of the most socioeconomically significant transboundary basins in Southern Africa, the Limpopo River Basin (LRB), is under increasing strain from changing land use and land cover (LULC), growing soil degradation, and worsening hydroclimatic extremes. The ecological resilience and hydrological functioning of the basin have been profoundly impacted in recent decades by rapid agricultural development, mining operations, urban growth, and climate-driven environmental changes. In one of the most vulnerable areas of South Africa, protecting water security, guaranteeing sustainable land management, and fostering climate change resilience all depend on an understanding of these processes. This project, titled "*Impacts of Land Use and Land Cover Changes on Land Degradation and Hydrology in a Changing Climate: A Case of Limpopo River Basin in South Africa",* aimed to generate an evidence-based understanding of the interactions between LULC transitions, land degradation processes, and hydrological responses in two catchment areas of the LRB (i.e., Mokolo and Lephalala River Catchments). The study integrated remote sensing, hydrological modelling, climate project analysis, drought and soils analysis, and participatory adaptation planning to provide holistic insights for policy, water governance, and improved local livelihoods. The goal of the project was to evaluate land degradation in the Limpopo River Basin driven by drought, soil erosion and the consequent impacts on hydrology in a changing climate. The specific aims of the project (as reflected in the signed MoA with an addition of iv as recommended by the reference group) are defined as follows:

i. To characterise and quantify LULC changes using remote sensing and GIS in the Limpopo River Basin between 1980 and 2020.

ii. To evaluate the spatial-temporal distribution of drought and soil erosion in the basin.

iii. To model the impacts of LULC changes and climate change on land degradation and hydrology.

iv. To co-develop a site-specific climate change adaptation plan for the Mokolo and Lephalale river catchments.

Methodological Approach

To achieve the goals of the study, remotely sensed imagery was acquired using Landsat Multispectral Scanner 1–5 for the classification of LULC changes in 1980, 1990, 2000 and 2010. Additionally, Landsat Operational Land Imager (OLI-2) and Thermal Infrared Sensor (TIRS-2) 9 were used to classify LULC for 2024. The random forest algorithm was used, with 80% of the total sample used for training and calibrating the model, and the remaining 20% for validation and testing the accuracy of the classification for each period. To improve the accuracy of the classification, the Normalised Difference Vegetation Index and the Normalised Difference Built-up Index were incorporated into the Google Earth Engine (GEE) code as key spectral indices to enhance the distinction between vegetation and urban built-up areas. Six land use classes were of interest in this classification, and these include bare surfaces, woodlands, water bodies, forests, agriculture and built-up areas. Standardised indices (i.e., Standardised Precipitation Index (SPI), Standardised Precipitation Evaporation Index (SPEI) and Standardised Streamflow Index (SSI)) were used to assess drought characteristics (i.e., frequency, duration, intensity and severity) in the two catchment areas. These were computed at three timescales: 6-, 12- and 24 months. Historical drought trends were determined using the Mann-Kendall, and the sequential Mann-Kendall was further employed to detect changes in trend points. A reconnaissance survey was conducted across the two catchments to visually inspect soils and possible gully development due to runoff, which assisted in determining soil erodibility. Water samples were collected for further laboratory sediment load. In addition to the primary data collection, digital soil data at a scale of 1:1 million were acquired from the Global Environment Facility Soil Organic Carbon database. This dataset is an upgraded version developed by national experts from the global Soil and Terrain (SOTER) database. The data were reclassified into the major hydrological soil groups (HSG) of the catchments using the FAO/UNESCO revised manual for soil maps of the world, based on drainage characteristics. Additional resources, such as the World Reference Base for Soil Resources, were used to complement reference group soil descriptions.

For the climate projection, the Delta Statistical Downscaling method was applied to downscale projections of future regional rainfall and temperature using data from the CORDEX-Africa project. The downscaling was to 0.5 degrees, and the data were bias corrected using a quantile mapping approach for the key climatic variables of interest. This study used five GCMs (MPI-ESM1-2-HR, GFDL-ESM4, MRI-ESM2-0, IPSL-CM6A-LR, and UKESM1-0-LL). The downscaled data used in this study for the five models considered two emission scenarios, Shared Socio-economic Pathways (SSPs), SSP2-4.5 (intermediate level of emissions) and SSP5-8.5 (a high emission scenario). Variability and linear trends were determined for future rainfall as well as minimum and maximum temperatures over the study area. The SSPs' climate change projections were also used to evaluate climate change impacts on water resources availability and to inform local adaptation plans. The bias-corrected GCM data were divided into three periods: the base period (1980–2019), near-future (2020–2049) and far-future (2050–2099).

For the quantification of current and future water resources, SWAT was used. The steps included delineating the catchment (step 1), creating HRUs (step 2), and activating the SWAT editor (step 3). The SWAT2012 editor also required several steps to complete before simulating the model. These include creating a weather generation station, batch files and importing the databases into the editor. The weather generation .csv file contained statistics on climate data, station names, elevation, and the location; it was imported into the SWAT2012 reference database. The results from the model were read into the project databases by importing them to the project database. For this study, the output files chosen were output.rch (for streamflow) and output.sub (for the water balance components, i.e., surface runoff and evapotranspiration). Three water users' stakeholder engagement workshops were conducted in Shongoane and Martinique villages under the Lephalale Local

Municipality. This was to aid the development of context-specific climate change adaptation measures that are locally relevant and feasible. Water users considered were domestic and agricultural. The first workshop focused on communicating the study's findings on climate change projections, followed by the completion of questionnaires. The ClimACT Prio Tool was then employed to prioritise the different options put forward by the water user groups. This prioritising, scoring and ranking were done in collaboration with the stakeholders to achieve an adaptation plan.

Results and Discussion

The results of the study are presented in chapters 3-8. Chapter 3 details the LULC classification, Chapter 4 discusses historical drought assessment and trends, Chapter 5 presents the soil erosion analysis and sedimentation, Chapter 6 details the future projections of rainfall and temperature in the two catchment areas together with future drought projections, while Chapter 7 presents the modelled current and future climate water resources availability and Chapter 8 captures the localised climate change adaptation co-development process and findings. The project key findings for each aim are summarised below.

Characterising and Quantifying LULC Changes

Using multi-decadal remote sensing datasets (Landsat) and GIS-based classification methods, the project mapped and quantified spatial patterns of LULC change across the two catchment areas. This aim provided foundational evidence of how human and environmental pressures have reshaped the landscape over four decades. It has been determined that the two catchments within the LRB (i.e., Mokolo & Lephalala) have changed since the 1980s, due to 27% of missing data for 1980; the long-term change detection analysis was carried out from 1990 to avoid bias. Notably, the agricultural LU class area increased by approximately 57.14% over the study period, expanding from 2.1% in 1990 to 3.3% in 2024. This expansion occurred primarily at the expense of natural vegetation, which is mainly woodlands in the study area, with the most pronounced changes observed in the middle reaches of both catchment areas. The spatial analysis revealed that agricultural expansion was concentrated along river corridors and in areas with relatively favourable soil and water conditions. Areas classified as bareland or severely degraded increase by 33.3% (from 0.3% in 1990 to 1.3% in 2024). These areas exhibited signs of severe erosion, vegetation loss, and soil degradation. Built-up areas grew from 0.1% in 1990 to 0.7% in 2024, which is evident in newly established settlements around the town of Lephalale and within the communal lands. The two land use classes (i.e., water and forest) did not show any changes over the study period (i.e., 1990 and 2024). The maximum likelihood classifier yielded a substantial kappa index with overall accuracies as high as 99%. Changes in the bareland class and the built-up areas, while not as significant as agricultural expansion, indicate increased environmental pressure and the natural ecosystem's ability to render optimal ecological functions.

Assessment and characterising drought and soil erosion dynamics

By combining meteorological drought indicators (e.g., SPI, SPEI) with soil erosion analysis, the project evaluated how drought severity and land-surface degradation have evolved over the years. Historical drought in the Mokolo and Lephalala River Catchments between 1980 and 2023 was characterised using three standardised drought indices (SPI, SSI and SPEI) at the 6th, 12th and 24th timescales. The analysis revealed increasing drought frequency and severity over the four-decade period, with 15 major drought events identified, indicating intensification of water stress in recent decades. The 2015-2016 drought emerged as the most severe event on record, with SPEI values below -2.5 persisting for 18 months, resulting in severe agricultural losses, water supply restrictions, and ecological stress. Trend analysis using the Mann-Kendall test indicated statistically significant increasing trends in drought severity ($p < 0.05$) for all indices at the 12-month and 24-month timescales, confirming progressive intensification of water stress in both catchments. Soil analysis studies showed that the two catchments are characterised by young, shallow, and poorly developed soils, and as such, these soils can easily detach during rain. This is evident in the study area through several gully erosions, which are mainly near riverbanks. This alteration may not only translate to sedimentation of nearby water bodies but will also compromise the water chemistry of rivers. Sediment loads were noted in the upstream and downstream reaches of the Lephalala River, with the Mokolo being highly sedimented in the lower reaches of the river system.

Modelling the impacts of climate change on catchment hydrology

This chapter presents the Soil Water Assessment Tool (SWAT) modelling based on the current and future climate data in the study area. To enable the model setup and calibration, historical data were utilised, including climate, hydrological and LULC change data. The SWAT model was calibrated and validated using observed streamflow. Model performance metrics indicated good to very good agreement between simulated and observed values. The Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error-observations Standard deviation Ratio (RSR), and Percent Bias (%BIAS) ranged from 0.4-0.2, 0.75-0.90, and -14% to -13.8%, respectively. These performance metrics meet recommended guidelines for catchment hydrological modelling and provide confidence in the model's ability to simulate basin processes. These performance metrics meet recommended guidelines for catchment hydrological modelling and provide confidence in the model's ability to simulate basin processes. Climate change projections indicated reduced precipitation and increased temperature, with evapotranspiration increasing despite reduced precipitation. The increase in evapotranspiration may be driven by changes in vegetation composition and expansion of bare land. Climate change projections under both high- and low-emission scenarios indicated substantial future impacts.

Co-Developing a climate change adaptation plan for the Mokolo and Lephalale River Catchment

Through engagement with local municipalities, water managers, and community stakeholders, the project co-developed a localised climate change adaptation plan for the Mokolo and Lephalala River catchments in the Limpopo River Basin, using the ClimACT Prio to support transparent and evidence-based decision-making. The process responds to increasing climate risks in the region, including rising temperatures, more frequent droughts, variable rainfall, and growing pressure on water resources and livelihoods. The adaptation planning process combined climate data and stakeholder knowledge to ensure that proposed actions are both scientifically robust and locally relevant. Key climate risks affecting water resources, agriculture, ecosystems, and disaster management were identified and validated through stakeholder engagement, ensuring alignment with on-the-ground realities and existing priorities. The ClimACT Prio tool was applied in a series of participatory workshops to systematically identify and prioritise adaptation options. Stakeholders evaluated the proposed measures against agreed criteria, including effectiveness, feasibility, urgency, cost, and co-benefits. The chapter delivered a prioritised set of adaptation actions plan tailored to the Mokolo and Lephalala catchments. These actions emphasise strengthening water security; improving drought and flood preparedness; protecting critical ecosystems through pollution prevention, environmental conservation, and law enforcement; climate education, and information sharing between different sectors. The process also highlights enabling conditions required for successful implementation, including improved coordination across institutions, capacity building, and integration with existing catchments and municipalities' development planning processes. The adaptation plan integrates scientific modelling outputs with local knowledge and the proposed actionable measures, including water-saving technologies, environmental conservation, and public awareness, with information sharing between sectors highly encouraged.

Conclusions and Recommendations

This study investigated the impacts of LULC changes on land degradation and hydrology in the Mokolo and Lephalala river catchments under a changing climate over the period 1980-2024. The study offers thorough insights into the intricate relationships between LULC change, climate change, land degradation, and water resources in these semi-arid catchments through an integrated analysis that combines remote sensing, hydrological modelling, drought assessment, erosion evaluation, and participatory adaptation planning. While LULC change is the primary driver of degradation, climate change acts as a critical amplifier, exacerbating degradation processes and constraining recovery. Rising temperatures increase evaporative demand and drought stress; declining precipitation reduces water availability, and increased rainfall intensity generates higher erosive power on degraded lands. The study shows that climate change contributed to streamflow, highlighting its dominant role in altering water availability. Future climate projections indicate continued, and potentially accelerating degradation and water stress under both the low- and high-emission scenarios, with severe droughts becoming more frequent, further contributing to declining water yield. Without substantial interventions, the region faces threats to livelihoods, ecosystems, and development that could trigger social-ecological regime shifts with potentially irreversible consequences. Despite challenges experienced in the region, effective adaptation is both feasible and economically justified through integrated strategies that simultaneously address land and water management, and support livelihood. This study showed this through the multistakeholder engagement in co-developing contextually appropriate solutions for the context of Lephalala and Mokolo river catchment areas.

Based on the research findings and conclusions, the following recommendations are proposed for different stakeholder groups and decision-making levels. These recommendations are organised thematically and prioritised based on urgency, feasibility, and potential impact. The recommendations emphasise the need for strengthened institutional and financial support to enhance climate resilience and sustainable natural resource management in the Mokolo–Lephalala region. At the provincial level, LEDET and DAFF are encouraged to significantly scale up sustainable land management interventions through established programmes such as LandCare, Working for Water, and Working for Wetlands, supported by increased budget allocations. Targeted investment should focus on climate-vulnerable areas identified through risk mapping, particularly the middle and lower catchment zones and associated riparian areas that are highly susceptible to erosion during intense rainfall events. These resources should also support technical assistance, training, and extension services that promote local adoption of sustainable practices. In parallel, municipalities should mainstream climate change adaptation into Integrated Development Plans and Spatial Development Frameworks, supported by municipal-level climate vulnerability assessments and the implementation of co-developed adaptation plans. Dedicated, multi-stakeholder coordination units are recommended to ensure effective implementation, resource mobilisation, and partnerships across the catchments.

At the local level, the recommendations call for stronger enforcement of environmental bylaws and prioritisation of conservation and ecosystem restoration, particularly of wetlands and riparian zones, to improve river water quality and reduce sedimentation risks in the Mokolo and Lephalala rivers. As an immediate short-term intervention, the establishment of alternative domestic water supply systems is proposed for Ga-Shongoane and Martinique villages to address persistent household water insecurity. Decentralised solutions such as boreholes, rainwater harvesting, and storage infrastructure would enhance system redundancy, reduce reliance on vulnerable centralised supplies, and improve resilience to drought and infrastructure failure. Improved water access would yield direct benefits for household health, sanitation, and food preparation, while reducing socio-economic vulnerability, especially among women and the elderly. Supported by community engagement and capacity building, these interventions provide a practical transitional solution while longer-term integrated water resource management strategies are developed.

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CAPACITY BUILDING

The following postgraduate students were supported by this project.

1. Yandheya Kubayi (Honours, Graduated from the University of Venda)
2. Ndivheni Ravhura (MSc dissertation submitted to the University of Venda)
3. Enny Mkhonto (MSc dissertation submitted to the University of Venda)
4. PhD *

*The project was unable to recruit a PhD candidate since its inception. However, the PhD student has now been identified and was planning to enrol for a PhD at the University of Venda in the 2026 academic year. Budget allocation for PhD has been reserved to support the PhD registration, tuition, and operational expenses.

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The findings and outputs from this study have contributed to the following.

Published

Matimolane S., Madubye M. and **Mathivha F.I.** (2025). Variability and Impacts of Hydrometeorological Variables on Surface Water Resources in Mokolo River Catchment, South Africa. *Sustainable water resources management*. 11,106. http://doi.org/10.1007/s40899-025-01284-7

Conferences

Mathivha FI, Makungo R, Malahlela OE, Diko ML, Nkosi M, Matimolane S (2025). Co-Developing Climate Adaptation Strategies in Semi-Arid Environments: Lessons from Mokolo and Lephalala Catchments. *Climate change and futures in Africa conference series*. 29-31 October 2025. Windhoek, Namibia

Manuscripts in Preparation

Mathivha FI, Makungo R, Malahlela OE, Diko ML, Nkosi M, Matimolane S. Co-Developing Climate Adaptation Strategies in Semi-Arid Environments: Lessons from Mokolo and Lephalala Catchments.

Mathivha FI, and Nkosi M. The impacts of climate change on the Lephalale River Catchment in Limpopo Province, South Africa

Mathivha FI, and Matimolane S. Drought in the current and future climate: A case of Waterberg District Municipality

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACRONYMS & ABBREVIATIONS

ACRU	Agricultural Catchments Research Unit
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
ClimACT Prio	Climate Actions Prioritisation Tool
CMIP6	Coupled Model Intercomparison Project Phase 6
CSIR	Council for Scientific and Industrial Research
DAFF	Department of Agriculture, Forestry and Fisheries
DFFE	Department of Forestry Fisheries and the Environment
DWAF	Department of Water Affairs and Forestry
DWS	Department of Water and Sanitation
ERA5	European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis 5
ET	Evapotranspiration
EVC	Erosion Vulnerability Classification
EVI	Enhanced Vegetation Index
FAO	Food and Agricultural Organisation
FF	Far Future
GCMs	Global Circulation Models
GEE	Google Earth Engine
GIS	Geographical Information System
GHGs	Green House Gas Emissions
HRUs	Hydrological Response Units
HSG	Hydrological Soil Group
IPCC	Intergovernmental Panel on Climate Change
ISE	Inherent Soil Erodibility
KGE	Kling-Gupta Efficiency
LEDET	Limpopo Department of Economic Development, Environment and Tourism
LRB	Limpopo River Basin
LRC	Lephalala River Catchment
LULC	Land Use Land Cover
LULCC	Land Use Land Cover Change
MJJA	May June July August
MK	Mann Kendall
MMK	Modified Mann Kendall
ML	Maximum Likelihood
MRC	Mokolo River Catchment
MSI	Multispectral Instrument
NDBI	Normalised Difference Built-up Index
NDJF	November December January February
NDVI	Normalised Difference Vegetation Index
NF	Near Future
NSE	Nash–Sutcliffe Efficiency
OLI	Operational Land Imager
PA	Producer Accuracy
PDF	Probability Density Function
PDSI	Palmer Drought Severity Index
PET	Potential Evapotranspiration
QGIS	Quantum Geographic Information System
RF	Random Forest

RMSE	Root Mean Square Error
RSR	Root Mean Square Error-observations Standard Deviation Ratio
ROIs	Regions of Interest
RS	Remote Sensing
RUSLE	Revised Universal Soil Loss Equation
SAWS	South African Weather Service
SDGs	Sustainable Development Goals
SMI	Soil Moisture Index
SOTER	Global Soil and Terrain database
SPEI	Standardised Precipitation Evaporation Index
SPI	Standardised Precipitation Index
SQMK	Sequential Mann Kendall
SSP	Shared Socio-economic Pathway
SSI	Standardised Streamflow Index
SVM	Support Vector Machine
SWAT	Soil Water Assessment Tool
UA	User Accuracy
UNCCD	United Nations Convention to Combat Desertification
UNESCO	United Nations Educational, Scientific and Cultural Organisation
USGS	United States Geological Survey
VIC	Variable Infiltration Capacity
WMO	Work Meteorological Organisation
WRC	Water Research Commission

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

Potential impacts of climate change on water security include decreased quality and quantity of available water and increased inter-annual variability (Kusangaya et al., 2014; Seneviratne et al., 2012; Tabari, 2020); an increase in drought intensity and return period (Davis-Reddy et al., 2017; Tabari, 2020); and increased evapotranspiration (Wu et al., 2009). However, climate change is also projected to affect runoff and erosion rates in many parts of the world (Nearing et al., 2004; Mullan et al., 2012; Mullan, 2013; Simonneaux et al., 2015). Climate change is associated with increasing temperatures and alterations in the rainfall patterns, resulting in changes in streamflow patterns, increased frequency and severity of climate extremes linked to frequent floods and droughts with severe impacts on soil, water and the plant environment, affecting crop production and, by extension, human health and nutrition (Odiyo et al., 2021).

Over recent decades, frequent extreme weather events, such as thunderstorms, heavy rain, droughts, and heat waves, have been reported (Biggs et al., 2004; Kusanyaya et al., 2013; Simpson and Dyson, 2018; Mathivha, 2020), which is due to the wide projection of a warm planet, climate, and weather variability (Thornton et al., 2014). Kiem and Austin (2013) attributed the increased frequency, intensity, and duration of droughts to anthropogenic climate change and further stressed the need for robust drought adaptation strategies. Drought in the study area has serious ecological and economic consequences that pose an increasing challenge to communities as the global climate changes (Maponya and Mpandeli, 2012). The increased frequency of extreme weather events, coupled with a steadily increasing world population, may lead to the risk of severe land degradation. This is likely due to the need for increased food production and land use change, e.g., by deforestation and intensification of agricultural land use activities. Expansion of agriculture, urbanisation, deforestation, and the day-to-day activities of mankind have resulted in temporal and spatial change in land use/ land cover (LULC), which has affected water flow pathways and water balance (Rawat and Manish, 2015).

Land erosion fundamentally has an impact on the physical and chemical characteristics of soils and causes on-site nutrient loss and off-site sedimentation and nutrients enrichment of water resources (Upadhya et al., 2012). Furthermore, sediment deposition reduces the storage capacity and lifespan of reservoirs as well as river systems. Sedimentation remains one of the most important threats to river ecosystems around the world. The severity of such threats varies with watershed sediment yield, rate of transportation, and mode of deposition (Tundu et al., 2018; Borrelli et al., 2020). Such adverse effects may be exacerbated in drought-prone environments, compounded by anthropogenic activities. Major parts of the world's land surface are classified as 'dryland', comprising hyper-arid, arid, semi-arid, and dry sub-humid areas, and a substantial proportion of this is thought to be in various degrees of degradation (Meadows and Hoffman, 2003). Such degradation has negative implications for over a billion people who are dependent on the land for their livelihoods. Direct impacts of climate change on soil erosion include variations in rainfall erosivity, temporal changes in rainfall, changes in soil moisture content, and changes in wind erosion (Mullan et al., 2012). Indirectly, changes in temperature, solar radiation, and atmospheric CO_2 concentrations will affect plant biomass production, infiltration rates, soil moisture, land use and crop management, which, in turn, will affect runoff and soil erosion (Nearing et al., 2004). Climate change negatively impacts hydrology, resulting in reduced precipitation (Singh, 2006). This subsequently results in reduced runoff and water resources availability. Global trends in precipitation, humidity, drought, and runoff indicate that southern Africa is on a negative trajectory with respect to the changes associated with climate change (Kundzewicz et al., 2007).

The conversion of land from forest to agriculture and built-up area leads to an increase in hardened surface area, such as roads, parking lots, sidewalks, and rooftops. The impervious areas block rain from recharging groundwater, impair the ability of natural systems to cleanse runoff and protect wetlands and near-shore biota from contaminants, increase the potential for flooding and erosion, and contribute to the degradation of streams and lakes. Potential evapotranspiration is expected to increase in the Limpopo River Basin (LRB) due to climate change (Zhu and Ringler, 2012), leading to declines in water resources and soil moisture levels and frequent food insecurity at varying magnitudes. The problem is aggravated by increased demand for water resources due to population growth and industrial development. These problems are attributed to increased frequency, intensity, and duration of drought in the basin (Schulze et al., 2001; Schulze, 2011). A major challenge has been to scientifically identify the key factors influencing land degradation in the basin to plan appropriate mitigation measures and interventions, given a changing climate. Most land degradation studies have mainly focused on anthropogenic causes and have not linked degradation to climate extremes such as drought (Scholten and Seitz, 2019).

The above clearly indicates a significant gap in studies exploring the link between LULC changes, land degradation (drought and soil erosion), hydrology and climate change. Further to this, Theron et al. (2021) reported that there is a considerable lack of studies in the developing region of sub-Saharan Africa regarding the effects of climate change on soil erosion. This study aims to evaluate land degradation emanating from natural (drought) and anthropogenic (soil erosion) drivers and their implications on hydrology in two catchment areas of the LRB under a changing climate. This study builds on work that has been done in the LRB. Kundu et al. (2015) evaluated the impacts of LULC changes Luvuvhu River Catchment and Moeletsi et al. (2018) evaluated drought analysis and hydrological modelling, while Botai et al. (2020) evaluated the potential impacts of the projected future climate on water resources over the LRB. And further aligns with the WRC-funded research conducted in the LRB by Akanbi et al. (2025) and Abiodun et al. (2025). Further to this, the current study builds on the recommendations by Odiyo et al. (2021) on the need for modelling impacts of LULC changes on hydrology in a changing climate. Odiyo et al. (2021) modelled the impacts of climate change on the hydrology of the Luvuvhu River Catchment based on CCAM projection; however, their analysis did not include LULC in the hydrological modelling framework. Though LULC directly affects land degradation and hydrology, the extent of this in a changing environment is still not well understood. This study is essential for advancing knowledge on this, particularly in the Limpopo River Basin in South Africa. This study therefore contributes to an improved understanding of the land degradation over the years and how these changes have impacted hydrology and water availability at the catchment scale.

1.2 PROJECT AIMS

The goal of the project was to evaluate land degradation in the Limpopo River Basin driven by drought and soil erosion, and the consequent impacts on hydrology in a changing climate. The specific aims of the project were defined as follows:

i. To characterise and quantify LULC changes using remote sensing and GIS in the Limpopo River Basin between 1980 and 2020.
ii. To evaluate the spatial-temporal distribution of drought and soil erosion in the basin.
iii. To model the impacts of LULC changes and climate change on land degradation and hydrology.
iv. To co-develop a site-specific climate change adaptation plan for the Mokolo and Lephalale river catchments.

1.3 METHODOLOGICAL APPROACH

To achieve the aims of the study, the research team adopted the framework presented in Figure 1.1.

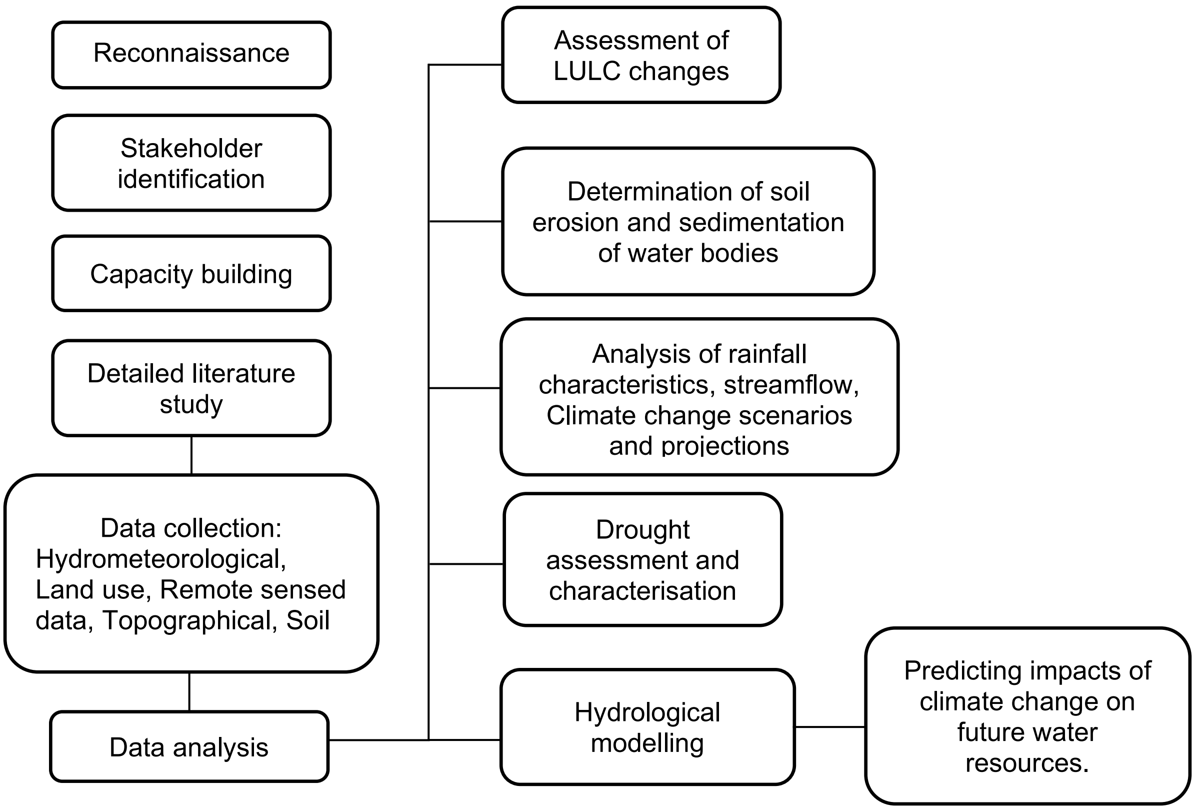

Figure 1.1. The framework adopted to achieve the goal of the study.

The approach followed for each aim is as follows:

- **Aim 1**: A pixel-based classification remote sensing approach was adopted to identify and classify major LULC changes in the Mokolo and Lephalala catchments from satellite imagery between 1980 and 2023.
- **Aim 2**: This objective has two parts, the first being a historical drought assessment and the other soil erosion & sedimentation. For the first part, drought indices were used as a drought quantifying parameter to assess and

characterise drought in terms of duration, magnitude, frequency and severity, while the second part of the objective analysed soils dominant in the study area and their susceptibility to erosion as well as determine sediment load of the two rivers in the study area.

- **Aim 3**: To achieve this objective, the Soil Water Assessment Tool was developed for the two study catchments. Outputs from GCMs were applied to developed SWAT hydrological models to simulate future climate change impacts on hydrology and water resources availability in the study area.
- **Aim 4**: To co-develop a climate change adaptation plan for the two catchment areas, three stakeholder engagement workshops were carried out, and the Climate Action Prioritisation (CLIMACT Prio) Tool was used to score, standardise and rank the different climate adaptation actions to finally come out with the top community preferred actions to assist the communities with adaptation.

1.4 THE STUDY AREA CONTEXT

In the western half of the Limpopo River basin (LRB) lies the Mokolo and Lephalala, River Catchments (MRC and LRC), which make up the Waterberg Water Management Area (WMA), including the Matlabas River Catchment. The two river catchments lie between 23.8400 and 24.45 °S, 27.20 and 28.1900 ° E, as shown in Figure 1.2, with the rivers draining the mountainous Waterberg complex and flowing north-westwards to join the Limpopo River, which forms the northern boundary between South Africa and Botswana. Before joining the Limpopo River near the Botswana-South Africa border, the MRC drains an area of about 8,387 km^2, originating from flat hills (koppies) on the north side of Alma town (DWAF,1996) with an elevation between 1200 and 1600 m.a.s.l. The main tributaries of MRC include Poer-se-Loop, Klein Heuningspruit, Sandspruit, Rietspruit, Grootspruit, and Malmanies Rivers. The entire MRC is from the Waterberg Mountains and runs down the Sand River. Spatially, the LRC has an area coverage of approximately 14 386 km^2 and rises at 788 m.a.s.l.

The two river catchments are situated in areas with varying rainfall patterns. Mean annual rainfall is relatively low, approximately 560 mm/yr, and most rainfall is received as thunderstorms during the austral summer months (NDJF), with no rainfall recorded during the dry winter months (MJJA). The region experiences a high annual rate of evaporation, averaging 1 900 mm/yr, which exceeds rainfall, and the area is considered to be arid (Schulze, 1997). The natural vegetation of the Lephalala catchment is dominated by savannah vegetation forms, with Waterberg Mountain Bushveld in the upper reaches grading gradually into arid Limpopo Sweet Bushveld closer to the Limpopo River (Mucina and Rutherford, 2006). The dominant land use in the upper catchment is cattle and game ranching, with small areas of irrigated agriculture. The lower reaches of the catchment support extensive areas of irrigated cotton and lucerne, as well as cattle and game ranching. The soils are medium- to deep sandy-clay loam soils in the upper reaches of the study area, grading moderately deep sandy loam soils along the valley bottoms and the lower reaches of the river basins (Midgley et al., 1994).

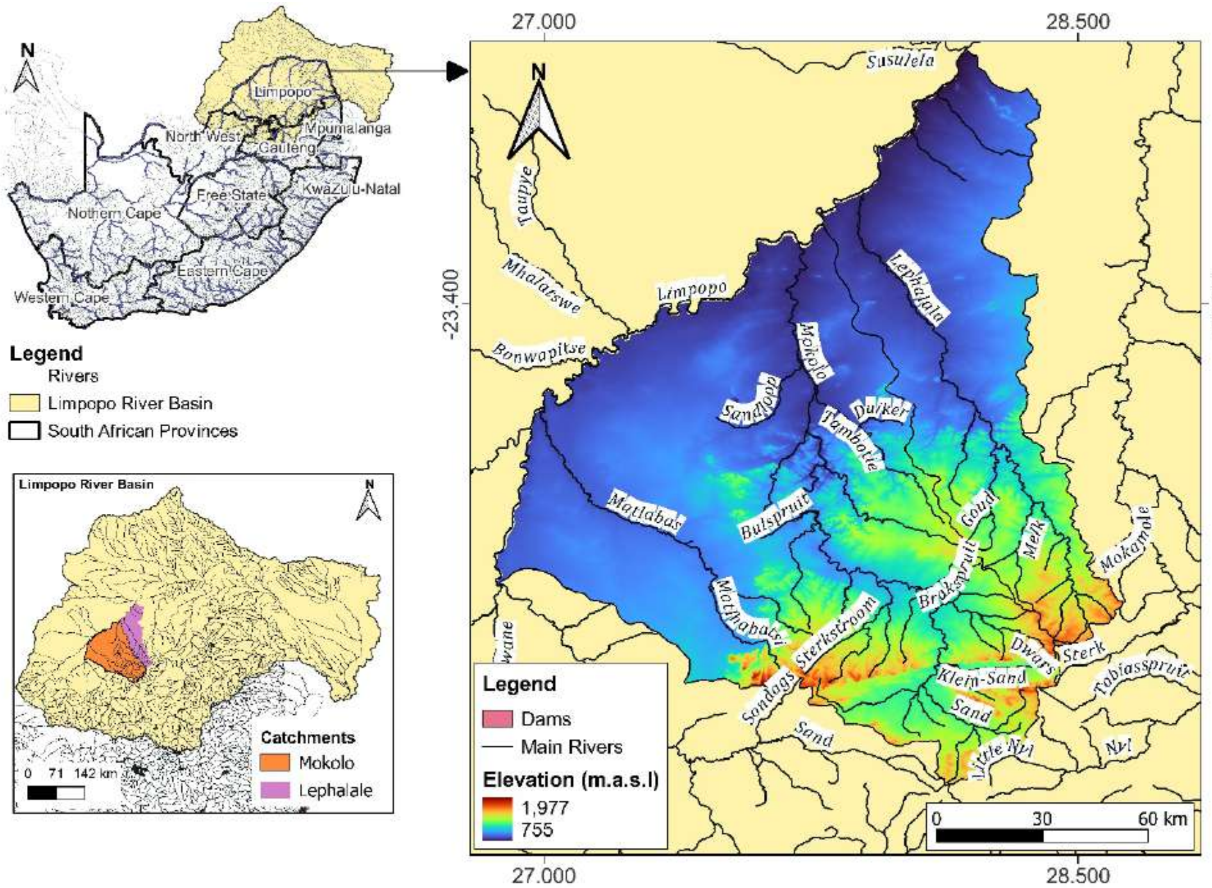

Figure 1.2. The Mokolo and Lephalala River Catchments in the context of Limpopo River Catchment and South Africa. The map further depicts the hydrology and elevation of the two catchment areas.

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CHAPTER 2: LITERATURE REVIEW

2.1 OVERVIEW OF LAND USE AND LAND COVER (LULC) CHANGES

Land Use and Land Cover (LULC) changes represent fundamental transformations in the Earth's surface, driven by human activities and natural processes. Land cover refers to the biophysical and anthropogenic characteristics of the Earth's surface, where land cover describes physical materials (e.g., vegetation, water, soil) and land use denotes human purposes (e.g., agriculture, settlement) (Ibrahim and Boru, 2025). According to Valencia-Gaspar et al. (2024), these changes have become one of the primary drivers of global environmental change and limiting factors of ecosystem services. Globally, LULC reportedly plays a crucial role in the hydrothermal cycle, the water-land-carbon cycle, and energy balance (Chang et al., 2018), owing to its direct influence on the Earth's surface coverage. Furthermore, LULC data is deemed important in the global change studies.

Driven by the need to understand and document these changes, there are multiple classification systems used for mapping and analysis. The Anderson scheme (1976), widely used by the United States Geological Survey (USGS), categorises LULC changes into nine hierarchical levels, from broad urban/rural divisions to specific crop types. While globally, the Food and Agriculture Organisation (FAO)'s Land Cover Classification System (LCCS) integrates modular components for satellite-derived products such as MODIS and Landsat, distinguishing 14 major thematic classes, including cultivated areas, forests, and bare surfaces (Di Gregorio and Jansen, 2000). The South African National Land Cover classification system uses a hierarchical structure that complies with the Spatial Data Infrastructure Act (SDI Act 54 of 2003). It features level 1 classification, which indicates the broad categories, and level 2, which presents the detailed classes (Stats SA, 2024).

Furthermore, due to advancements in Earth-observing satellite tools, awareness and understanding of LULC have been enhanced in many parts of the world. Several satellite tools and sensors have been used over the past decades to monitor these changes, and recent advancements have led to a better quality of data/satellite images produced for classification. For example, the CORINE Land Cover (Europe) and GlobeLand30 emphasise multi-spectral remote sensing for finer resolutions (10-30m), enabling distinctions between natural grasslands and managed pastures. The most used tools for LULC change monitoring are Landsat sensor data and Sentinel satellite data. Landsat and Sentinel sensors provide a multi-decadal, multispectral imagery essential for mapping, change detection, and monitoring degradation processes (Roy et al., 2014). The Landsat series offers long-term continuity since 1972, normally with a resolution of 30 m. Its combination with robust vegetation indices (NDVI, EVI) is vital for distinguishing crops from natural vegetation during classification. According to Roy et al. (2014), the first sentinel sensor was launched in 1972, and this was followed by Landsat 2, 3, 4, 5 and 7.

On the other hand, Sentinel-2 (10-20m resolution, 13 bands including red-edge) delivers greater spatial detail. The Earth is monitored at a 5-day revisit frequency, excelling in fine-scale urban-peri-urban delineation and erosion-prone bare soils, achieving 90-94% classification accuracies in Google Earth Engine. Nwagou et al. (2023) used Landsat 8 and Sentinel-2 to map the shift of the agricultural landscape in

Southern Cameroon. According to the latter study, Landsat 8 was launched in 2013 with a reduced wavelength of the reflective band and the Operational Land Imager (OLI) sensor producing images with greater radiometric resolution and a stronger signal-to-noise efficiency. Sentinel-2, equipped with the Multispectral Instrument (MSI) was launched in 2015. The images provide enhanced spectral, temporal and spatial resolution.

LULC classification relies on diverse supervised and unsupervised algorithms, each balancing accuracy, computational demands, and the handling of spectral variability from the satellite data. Some of the commonly used classifiers include the maximum likelihood (ML), Support Vector Machine (SVM) and Random Forest. The ML is an example of a parametric statistical classifier that assumes a Gaussian distribution of classes and assigns pixels to the highest-probability band. According to Rawat et al. (2024), ML is among the commonly used classifiers introduced in the 1960s based on statistical and probability theories. The SVM is an example of a non-parametric machine learning method. It constructs hyperplanes to maximise class margins in high-dimensional space via kernel tricks. The RF algorithm is an ensemble of decision trees that aggregates predictions to reduce overfitting and deliver top accuracies for multi-class LULC. There are other methods, such as object-based image analysis (OBIA), that segment pixels into objects for contextual classification (Blaschke et al., 2013). In a classifier comparison study by Nuthammachot and Ali (2025), ML was noted to have scored the lowest accuracy, amounting to a kappa of 64.86 and an overall accuracy of 79.81%, while the Random Forest and SVM had high accuracy results. The overall accuracy for SVM amounted to 87.97% and the kappa was 76.53%, while the random forest scored about 87.94% for overall accuracy, and the kappa coefficient results were 76.54%. Similarly, Rawat et al. (2024) observed the least accurate performance from MLC, while the machine learning algorithm scored higher.

Historically, LULC shifts trace to approximately 10,000 years ago, when agricultural activities led to about 5-10% clearance of global forests (Ritchie, 2025), but accelerated after the Industrial Revolution. From 1700 to 2020, global cropland expanded by 1,200 Mha, mainly at the expense of forests, per HYDE database reconstructions (Goldewijk et al., 2016). Forest cover declined from 5.5 billion ha in 1700 to approximately 4 billion ha today, with a net annual loss of 10 Mha (1990-2020), per FAO Global Forest Resources Assessments. Globally, urbanisation claimed 1.5 Mha/year (1992-2015), per ESA CCI datasets, concentrating in Asia (e.g., China's 20% urban growth 2000-2020) (Zhao et al., 2021). Grasslands shrank by 15% since 1700, fragmented into pastures, while wetlands were reduced by 35% since 1970. Recent trends (2000-2020) show cropland stabilisation in Europe/North America but reported an expansion of about 10% in Africa and 5% in South America, driven by biofuels (Vali et al., 2015). These patterns, quantified through annual 1km grids like those from Li et al. (2023) for CONUS, revealed cropland-urban gains and forest-shrub losses. South Asia saw 15 Mha deforestation for rice/palm, with urbanisation doubling built-up areas between 1990 and 2020. The Amazon in South America lost 20% forest cover between 1970 and 2020, approximately 450,000 km² to soy/cattle grazing.

Regionally, patterns diverge sharply. In sub-Saharan Africa, agriculture expanded by 20% between 1980 and 2020, worsened by the conversion of savannas. According to Afuye et al. (2024), this led to erosion in watersheds such as the Limpopo. Europe stabilised via the Common Agricultural Policy, with cropland contracting 5% but intensification rising; afforestation reclaimed 10 Mha. North America's CONUS transitioned from 60% forest/grassland in 1630 to 40% cropland/urban (2020), peaking 1850-1920 with 115 Mha conversions. Australia/Oceania shows shrub-to-pasture shifts, losing 10% native vegetation to mining/agriculture. Regional divergence underscores climate-biome interactions, e.g., boreal forests are resilient in Russia but vulnerable in Canada.

Human activities have been directly and indirectly linked to modifications of Earth's surface and climate since the mid-20th century (Lucas et al., 2022). For example, urbanisation, fuelled by population growth has driven annual built-up expansion of 1-2% annual built-up expansion in developing regions. In a study by Wang and Wang (2022). In China, cultivated areas reportedly decreased in cultivation lands between 2000 and 2020. While the drivers might be similar, underlying factors such as economic status also play a huge role in LULC change rates. For example, in developed areas, rapid change in urbanisation has been strongly driven by industrial growth and master plans, whereas in low-income countries, poverty and climate change have been identified as drivers of land use conversion (Kora et al., 2025).

Currently, it is estimated that about 38% of the Earth’s surface is allocated to cultivation land, while studies like Wang and Wang (2022) reported a low productivity being experienced worldwide. This demand for food production and agroecosystem services has driven increased cultivation in certain regions. It has been highlighted that agriculture accounts for 50 Mha net gain/decade globally, through intensification (e.g., Green Revolution) and extensification (e.g., Brazilian Cerrado). In some studies, it has been noted that population density correlates with 80% cropland expansion in Africa/Asia. Furthermore, agricultural-linked deforestation totals about 420 Mha loss (1990-2020), with 90% for cattle/commodities being in the tropics. In other instances, fires and logging are reportedly episodic drivers, such as the case of the Indonesian peat fires that cleared about 10 Mha of palm.

In countries like South Africa, policies, government development plans, and laws have been identified as drivers for LULC changes, particularly urbanisation and peri-urban expansion. Land reform (restitution, redistribution, tenure reform) and subsidised housing programmes have converted former agricultural and open lands into new settlements and mixed smallholder systems, reshaping rural and urban fringes (Mani et al., 2021). However, in the events of weak implementation, limited capacity and socio-economic pressures, it was highlighted that the same policies often lead to unplanned densification and settlement on marginal or sensitive land, further contributing to erosion, overgrazing and other forms of land degradation.

2.2 LAND DEGRADATION: CONCEPTS AND INDICATORS

Land degradation encompasses the decline in the capacity of the land to support ecosystems and human needs, primarily through human-induced processes. Globally, LULC changes have been identified as the primary driver of ecosystem loss and degradation (Lucas et al., 2022). The UNCCD defines land degradation as "a reduction or loss of the biological or economic productivity of land arising from human-induced or natural processes, including soil erosion, deterioration of soil properties, and long-term loss of natural vegetation". This aligns with the FAO perspective, emphasising diminished ecosystem goods and services resulting from land-use changes, contamination, or climate variability. It has been highlighted that LULC changes highly drive land degradation in sub-Saharan Africa. According to Assede et al. (2023), LULC changes have accelerated soil erosion in semi-arid regions of East Africa due to the reduction of woodlands and wooded grasslands, supporting observations by Mani et al. (2023) in South Africa.

Addressing land degradation has become imperative to ensure the sustainability and functioning of the environment and the ecosystem. This is further enabled by Sustainable Development Goals (SDGs) 11 and 15, which focus on addressing land degradation and desertification by promoting sustainable development through thorough planning (Valencia-Gaspar et al., 2024). Land degradation types can be categorised by processes: physical (e.g., erosion), chemical (e.g., salinisation), and biological (e.g., loss of biodiversity). Soil erosion, the most widespread type, involves the detachment and transport of soil particles by water or wind, classified as sheet, rill, gully, or mass movement erosion. Water erosion dominates in humid tropics, while wind erosion prevails in arid zones, reducing topsoil fertility by 1-2% annually in vulnerable areas. Salinisation occurs in irrigated lands, where poor drainage leads to salt accumulation, affecting 20% of global irrigated cropland and halving yields (Devkota et al., 2022). Desertification, often conflated but distinct, refers to the persistent decline in land productivity in drylands due to drought and mismanagement, encompassing vegetation loss and soil compaction.

Other types include acidification (pH drop from acid rain or fertilisers), nutrient depletion (via leaching or cropping without replenishment), and structural degradation (compaction from heavy machinery, reducing infiltration by 50-80%) (Sun, 2025). Biological degradation manifests as reduced organic matter (down 30-50% in tilled soils) and biodiversity loss, impairing resilience. In South Africa, soil erosion is among the predominant forms of land degradation (Le Roux et al., 2007). It has been reported that the combination of high rainfall erosivity, steep topography, human activities, and fragile soil makes the country prone to soil erosion. The Department of Forestry, Fisheries and the Environment (DFFE) confirmed that soil erosion was the primary form of degradation in the sloping communal lands of Limpopo, the Eastern Cape, and KwaZulu-Natal, followed by wind erosion as the secondary form (DFFE, 2018). Other forms of degradation experienced in other parts of the country include vegetation degradation encompassing bush encroachment and species loss, and biological degradation.

Monitoring land degradation employs multi-scale methods, such as field-based methods, remote sensing, and modelling (Nzuza et al., 2016; Jiang et al., 2023; D'Acunto et al., 2025). According to Jiang et al. (2023), expert opinion, remote sensing, abandoned croplands, and land-use change methods are currently the most widely used approaches to assess land degradation driven by intensive human activity and rapid climate change. Furthermore, there are four noteworthy indicators, i.e., soil organic carbon (SOC), net primary productivity, biodiversity and fractional vegetation cover, used to evaluate global land degradation. Dong et al. (2019) found that soil infiltration is highly influenced by soil bulk density, and water capacity increased with dry bulk density. For instance, an SOC loss threshold of <2% was reported to signal degradation, while a bulk density of >1.6 g/cm³ depicts high soil compaction, and infiltration rates of <10 mm/h show poor soil structure and slow water absorption (Njoloma et al., 2016).

Remote sensing tools and vegetation indices, such as the Normalised Difference Vegetation Index (NDVI), along with Landsat and Sentinel-2 imagery, and machine learning techniques such as Random Forests and Cellular Automata (CA) have proven valuable for monitoring and evaluating land degradation. Landsat and Sentinel-2 data enable change detection using pixel-based classifiers in platforms such as Google Earth Engine. Nzuza et al. (2020) predicted land degradation using Sentinel-2 imagery in combination with environmental variables, including rainfall, aspect, and slope, in the Greater Sekhukhune District. On the other hand, Kumar et al. (2022) used NDVI alongside land surface temperature (LST) and Landsat 8 OLI/TIR to assess land degradation. NDVI can be used to categorise between maximum vegetation cover and bare soil using a threshold, reflecting light in the visible and near-infrared bands to distinguish vegetated and non-vegetated areas.

In addition, tools such as hyperspectral sensors can quantify salinisation using salt indices. Neto et al. (2017) noted the ProSpecTIR-VS sensor as one such example. In addition, Xu et al. (2025) noted that microwave radar can penetrate clouds to map soil moisture. Soil moisture plays a vital role in binding soil particles and supporting plant life, thereby stabilising the soil and, consequently, preventing soil degradation. Other effective monitoring tools include drone-based LiDAR, which can provide high-resolution topographic data for gully detection with accuracy >90%. Modelling tools such as the Revised Universal Soil Loss Equation (RUSLE), the United States Department of Agriculture-Water Erosion Prediction Project (WEPP), and the European Soil Erosion Model (EUROSEM) have gained global recognition for their ability to estimate erosion. Musasa et al. (2025) is one of the studies in Africa to have applied the model to estimate soil erosion risk at the sub-catchment level. The study used the model to better understand the drivers of soil loss. On the other hand, Phinzi et al. (2020) used the model and a random forest to assess soil erosion risk in the Umzintlava Catchment, and the effects were categorised as “very low” to “extremely high” erosion risks.

Table 2.1 Summary of the key indicators and monitoring techniques, accompanied by their strengths and limitations.

Technique	**Key Indicators**	**Resolution/Spatial Scale**	**Strengths**	**Limitations**
Field Surveys	SOC, Bulk Density, Infiltration	Plot-level	High accuracy	Labour-intensive, local scale
Remote Sensing	Soil Moisture, vegetation Greenness, Bare soils	Landsat, Sentinel-2, NDVI, EVI	Synoptic, temporal series	Pre-data processing, Cloud cover, validation needed
Modeling	RUSLE, WEPP	Watershed-global	Predictive scenarios	Data/input uncertainty
Participatory	Farmer yield perceptions	Community	Socio-economic context	Subjective bias

It has been noted that places vulnerable to land degradation are often drylands, areas experiencing intensive agricultural activities, and areas with high population density (IUCN, 2017). According to IUCN (2017), drylands are places with evapotranspiration rates exceeding rainfall and high climate uncertainty. It was further noted that dry areas experience severe water scarcity, and they cover approximately 50% of the Earth and host over 2 billion people. Desertification is the predominant form of land degradation in these areas, and examples are commonly found in Africa and Asia, with bare soils being a common indicator (Costa et al., 2025). For instance, the Sahel region of Africa is noted for being heavily degraded and subject to desertification due to intense agricultural activities and wind erosion (Doso, 2014). Mani et al. (2021) reported that 60% of South Africa is degraded, while 91% of it is prone to desertification due to unsustainable land management and overgrazing, resulting in woody plant encroachment.

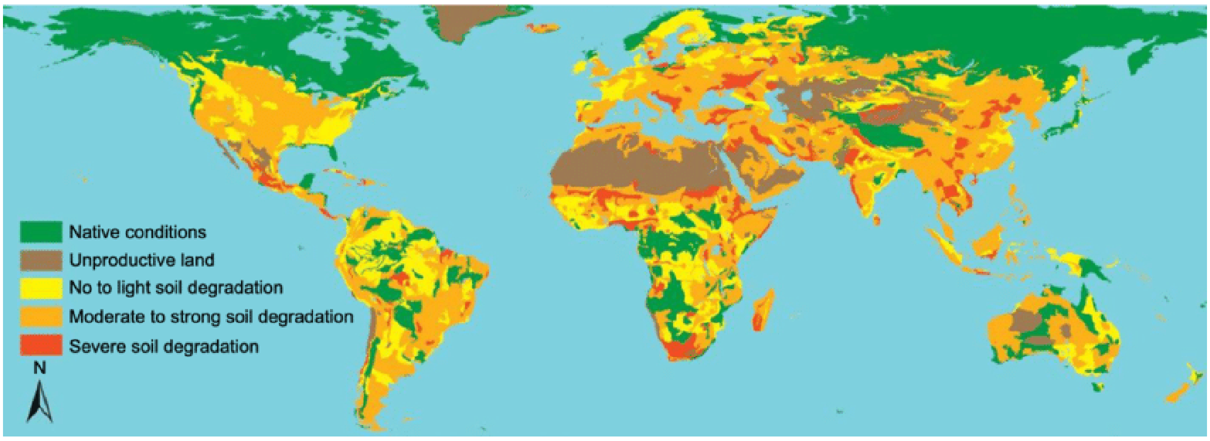

Figure 2. 1. Globally degraded areas (Schulte et al., 2017).

2.3 HYDROLOGICAL PROCESSES AFFECTED BY LULC CHANGE

Infiltration is the process by which water on the ground surface enters the soil, while runoff is water that flows on the Earth's surface as overland flow (Bronstert et al., 2023). These two processes describe two opposing water movements, and each plays a role in the recharge of water resources. For instance, infiltration is a critical component of groundwater recharge and subsurface flows, while runoff contributes greatly to the replenishment of surface water resources such as rivers, lakes, and wetlands (Gebreslassie et al., 2025). In addition to precipitation and soil properties, LULC characteristics greatly influence infiltration and runoff rates. For instance, Gebreslassie et al. (2025) further highlighted that converting forest cover to impermeable surfaces, such as pavement and buildings, prevents water from entering the ground, leading to increased runoff and reduced infiltration. Conversely, highly vegetated areas tend to have higher infiltration rates than bare soils. Green infrastructure (GI) practices, such as rain gardens and permeable pavements in urban areas, have been reported to enhance infiltration, thereby reducing the volume and peak flow of stormwater runoff (Liu et al., 2014). In this view, it can be concluded that areas dominated by runoff tend to have low infiltration rates, and vice versa. In some cases, runoff has been reported to occur when the precipitation exceeds the soil's infiltration capacity or when the soil is saturated (Bronstert et al., 2023). Thus, in addition to soil compaction and impermeable surfaces, saturated conditions can also lead to increased surface runoff.

In several studies, evapotranspiration (ET) has been described as the process by which water returns to the atmosphere (Katul and Novick, 2009; Ghiat et al., 2021; Wang et al., 2021). This can be water that infiltrates the ground or runoff water; thus, ET is defined as the sum of evaporation from the soil and water surfaces and transpiration from plants. Unlike runoff and infiltration, the factors affecting ET are more complex because it is also highly influenced by meteorological variables (i.e., temperature, humidity, wind, and solar radiation); however, LULC makeup still plays a role in its distribution. For instance, compared with bare areas, highly vegetated areas have higher ET because there is more leaf area for transpiration and higher soil moisture levels near the surface (Wang et al., 2021). Furthermore, ET has been highlighted as a significant mechanism for reducing runoff volumes; thus, systems such as green roofs and rain gardens rely on both infiltration and ET to manage stormwater (Sharma and Malaviya, 2021). However, quantifying ET in these systems is complex due to the dynamic interaction between soil, plants, and climate. It has also been argued that a large fraction of infiltrated water is eventually lost to the atmosphere through ET, while a smaller portion may recharge groundwater or reappear as surface water through baseflow or subsequent runoff events (Huffman et al., 2013). Thus, the balance between infiltration, runoff, and ET determines the fate of precipitation and the sustainability of water resources in both natural and built environments.

As mentioned above, changes in LULC alter the way precipitation is partitioned between infiltration, runoff, and ET, consequently influencing streamflow and groundwater. Studies like Zhu et al. (2019) reported an increase in streamflow following reductions in surface permeability due to surface sealing and hardening with impervious materials such as concrete and asphalt. This reduces infiltration and increases surface runoff, leading to higher peak flows and greater total streamflow. In addition, deforestation or conversion of natural vegetation to agriculture can also increase streamflow in the short term (Hou et al., 2022). With less vegetative cover to intercept rainfall and promote infiltration, more water runs off into streams. In addition, agricultural practices that compact the soil or remove ground cover can exacerbate this effect, further reduce infiltration and increase both the volume and variability of streamflow (Dias et al., 2015). In contrast, reforestation or the implementation of green infrastructure can moderate streamflow by enhancing infiltration and increasing ET, thus reducing the volume and speed of runoff entering streams. These practices help maintain baseflow during dry periods and reduce the risk of flash floods during storms.

Groundwater recharge is the process by which water moves downward from the surface to replenish aquifers. Land use changes can significantly alter recharge rates. Urban development, with its extensive impervious surfaces, dramatically reduces recharge by preventing water from soaking into the ground (Yu et al., 2024). On the other hand, agricultural expansion can have mixed effects on recharge. In some cases, irrigation and the removal of deep-rooted vegetation can increase recharge by allowing more water to percolate below the root zone (Jin et al., 2025). However, the reduction of infiltration, as stated by Yu et al. (2024), can often lead to reduced groundwater recharge. Natural landscapes, such as forests, typically promote higher recharge rates due to their permeable soils, which facilitate water movement into the subsurface.

Land use changes profoundly and multifacetedly affect how water flows, infiltrates, and interacts within a given watershed, significantly influencing its overall hydrological responses. These alterations have critical implications for water resources, environmental health, and climate resilience. Runoff, infiltration, percolation, ET and interception are some of the ways in which a catchment responds to rainfall input and are heavily influenced by LULC (Achugbu et al., 2022). For instance, in catchments lacking vegetation cover, the main form of response tends to be immediate runoff, whereas in heavily vegetated catchments promote infiltration. A study with a 75% increase in effective impervious area and a 50% decrease in forest area in a watershed projected a 69% increase in total yearly mean surface runoff, along with a 3% increase in annual streamflow (Talib and Randor, 2023). Deforestation and the conversion of forests to other land covers also diminish the land's ability to absorb water, increasing runoff and potential flooding. Conversely, land-use changes often reduce groundwater flow and recharge at the watershed scale. As surface runoff increases due to impervious surfaces or compacted soils, less water percolates into the ground, thereby reducing aquifer replenishment. This can result in decreased baseflows in streams between storm events, impacting perennial water availability. Studies have shown reductions in return flow and percolation to both shallow and deep aquifers due to land use changes and increased urbanisation (Kiprotich et al., 2021). Talib and Randir (2023) further reported that land-use changes also impact the energy balance of a watershed, thereby affecting the amount and timing of water loss to the atmosphere as ET. While the specific effect can vary, clearing vegetation and canopy cover, such as through deforestation or urbanisation, has been proven to increase ET and consequently increase runoff. For example, a decrease in ET due to increased impervious areas has been linked to an increase in winter storm events.

2.4 INTERACTIONS BETWEEN LULC CHANGE AND CLIMATE CHANGE

Global warming impacts the world and will continue to have an impact on humans and the ecosystem in the future in various ways across different regions (Ziervogel et al., 2014). The impacts of climatic fluctuation and change in South Africa are concerning, while most relevant questions around this topic are yet to be answered. Significant hydro-climatic variability across both temporal and spatial scales affects South Africa's water resources, posing risks to national economic growth and the livelihoods of the population (Schulze, 2011). Anthropogenic climate change primarily results from global warming, a gradual increase in Earth's temperature driven by human-induced intensification of the greenhouse effect. The primary driver of increasing greenhouse gas (GHG) concentrations is the combustion of fossil fuels, including coal, oil, and natural gas. Rising emissions of GHGs, including nitrous oxide (N_2O), methane (CH_4), carbon dioxide (CO_2), and chlorofluorocarbons (CFCs), are major contributors to global warming. These GHGs absorb thermal radiation from the Earth's surface, thereby reducing the net thermal radiation that leaves the atmosphere (Dube et al., 2014). The IPCC estimates that the temperature of the Earth's surface temperature has risen by 0.57 to 0.92°C over the past century due to global warming (IPCC, 2007). Although global warming raises global temperatures, these changes are not uniform; some regions experience increases in temperature, while others see decreases over the same period.

Anthropogenic activities such as waste management, agriculture, and changes in land use can exacerbate climate change by increasing emissions of CH_4 and N_2O (Tian et al., 2016). The combustion of fossil fuels and modifications to land use have caused a 40% increase in the concentration of GHGs, particularly CO_2, compared to preindustrial periods (Ntinyari and Gweyi-Onyango, 2021). On the other hand, it has been estimated that the agricultural sector accounts for 10% to 20% of all global anthropogenic GHG emissions. The IPCC Fifth Assessment Report (AR5) introduced a framework for scenario development, and the Representative Concentration Pathways (RCPs) encompass a range of plausible radiative forcing trajectories. In the scientific community, four RCPs have been developed according to the radioactive forcing target level for 2100 introduced by Van Vuuren et al. (2011) and these are RCP2.6, RCP4.5, RCP6.0, and RCP8.5.

Information on all radiative forcing components used as inputs in climate modelling up to 2100 years into the future can be estimated using the RCPs. Radiative forcing is projected to increase global temperatures above pre-industrial levels by less than 1°C under RCP2.6 and by nearly 7°C under RCP8.5, with the median estimate for RCP8.5 slightly below 5°C (Havlík et al., 2015). The Planbureau voor de Leefomgeving (PBL) Integrated Model to Assess the Global Environment (IMAGE) modelling team of the Netherlands Environmental Assessment Agency (NEAA) developed RCP 2.6. In this scenario, the atmospheric concentration of greenhouse gases is projected to reach approximately 450 parts per million (ppm) of CO_2 equivalent by 2100 (Van Vuuren et al., 2011). RCP4.5 was developed by the Global Change Assessment Model (GCAM) modelling team at Pacific Northwest National Laboratory, which is part of the United Nations (UN) Joint Global Change Research Institute (JGCRI). RCP6.0 was developed by the National Institute for Environmental Studies (NIES) modelling team using the Integrated Assessment Model (IAM). The Model for Energy Supply Systems and their General Environmental Impact (MESSAGE) and the Integrated Assessment Framework were used in the development of RCP8.5 by the International Institute for Applied Systems Analysis (IIASA), Austria. Its rising GHG emissions over time are indicative of scenarios that result in significantly higher GHG concentrations (Riahi et al., 2017). By 2100, the atmospheric concentration of GHGs would have increased to 1370 ppm of CO_2 equivalent under this scenario.

Recently, new Shared Socioeconomic Pathways (SSPs) (Riahi et al., 2017), have emerged from the latest CMIP6, improving traceability relative to CMIP5's RCPs, which are a set of five narratives that are set to replace RCPs. O'Neill et al. (2017) and Riahi et al. (2017) identify five SSP pathways representing different socioeconomic futures: SSP1 (sustainable development), SSP2 (middle-of-the-road), SSP3 (regional rivalry), SSP4 (inequality), and SSP5 (fossil fuel-driven development). The combined scenario names are SSP126 (SSP1-RCP2.6), SSP245 (SSP2-RCP4.5), SSP370 (SSP3-RCP7.0), and SSP585 (SSP5-RCP8.5). The selection and application of adaptation and mitigation strategies determine the future climate response in the SSP pathway. The latest CMIP6 combines both RCP and SSP to create more realistic, reliable, and accurate future scenarios. Given the new CO_2 concentration paths, CMIP6 must incorporate updated climate-state estimates. Because the medium emission scenario (SSP2-4.5) is considered the most likely to occur, while the low (SSP1-2.6) and high (SSP4-6.0-5-8.5) emission scenarios are seen as less probable and more uncertain (Wang et al., 2019).

Ning et al. (2022) chose SSP2-4.5 to run Global Climate Models (GCMs) for climate prediction. The SSP scenarios are divided into five socioeconomic SSP families as presented. Illustrative temperature levels, derived using the MAGICC7.0 default settings for generating greenhouse gas concentrations, within the range of Shared Socioeconomic Pathway (SSP) scenarios available from the Integrated Assessment Modeling (IAM) community at the time of benchmark scenario development, are depicted as small black horizontal bars on the 2100 pillars for each SSP. The SSP concentration scenarios for CO2 (a–c), CH4 (d–e), nitrous oxide (f), NF3 (CCMAg), and SF6 (i) were generated using the anthropogenic emission scenarios (Meinshausen et al., 2020). Long-term CMIP6 model evaluations are scheduled for the four SSP scenarios (bold lines with color-box names): SSP5-8.5 (red), SSP5-34-OS (orange), SSP1-2.6 (blue), and SSP1-1.9 (turquoise) as indicated. The RCP extensions (Meinshausen et al., 2011) and other SSP scenarios that follow the same design principles are examples of these.

Despite the specific design concepts for CO_2 emissions, it is anticipated that other gases from fossil and industrial sources will be phased out by 2225, while emissions associated with land use will remain constant at 2100 values. For the pre-2100 emission scenarios, standardised integrated assessment scenarios are used, whereas the post-2100 extensions are based on simple extension assumptions. Meinshausen et al. (2020) assume that all land use CO_2 emissions will linearly phase out between 2100 and 2150; however, because the continuous negative land use CO_2 emissions are incompatible with stable land use and land cover patterns in 2100. The initial scenario design proposal by O'Neill et al. (2017) maintained all non-CO_2 GHG emissions at 2100 levels. However, the ultimate extensions proposed by Meinshausen et al. (2020) are predicated on sector-specific differentiation in extension regulations. In particular, the linear phase-out of all fossil fuels by 2250 was predicated on assumptions about industrial non-CO_2 emissions, including aerosols. In a similar vein, it has been projected that synthetic industrial gases will cease to exist by 2250 instead of continuing to be emitted. For non-CO_2 emissions associated with land use, it has been assumed that 2100 emission levels remained unchanged.

2.5 MODELLING APPROACHES FOR ASSESSING IMPACTS

Hydrological models are among the most widely applied tools for understanding the relationship between LULC, Climate change, and water resources. According to Kiprotich et al. (2021), catchment-scale models are deterministic and can be categorised as lumped, semi-distributed, or distributed models. The study further described that lumped models model the catchment as a single unit, and in contrast, semi-distributed models partition the catchment into multiple components, such as hydrological response units (HRUs). Several models are used to simulate catchment hydrological response, including the Soil and Water Assessment Tool (SWAT), ACRU, VIC and HBV. SWAT is a physically based, semi-distributed, continuous-time model designed to simulate the impact of land management practices on water, sediment, and nutrient yields in large, complex watersheds over a long period (Neitsch et al., 2011). The model is widely used globally and is continuously under development (Alawi and Ozkul, 2023). SWAT subdivides watersheds into sub-basins and further into HRUs, which are homogeneous in land use, soil, and topography. It requires detailed inputs, including weather, soil properties, land use, and topography, making it suitable for ungauged basins and scenario analysis of land use and climate changes. It simulates hydrological processes such as surface runoff, infiltration, ET, groundwater flow, and nutrient cycling. SWAT is computationally efficient, user-friendly, and supported by various interfaces and tools (e.g., SWAT-CUP for calibration and uncertainty analysis) (Arnold et al., 2012). However, it has limitations in simulating groundwater in geologically heterogeneous basins and requires intensive calibration for complex catchments. Nonetheless, studies continue to rely on it to simulate the impacts of LULC and climate change on water resources. For instance, Xiao et al. (2023) employed the model to assess the impacts of LULC and climate on Xiaoxingkai Lake Basin. The study observed an increase in the lake volumes due to the coupled impacts of climate change and LULC. A similar study was conducted in Ethiopia at the Upper Gilgel Abbay Watershed by Abuhay et al. (2023). The study found increases in surface runoff and water yield, and a 37.9% decrease in groundwater between 1986 and 2003, driven by increased cultivation and a decrease in forest and grassland. The model performance in both studies achieved an NSE value above 0.5, demonstrating the model's ability to simulate complex systems.

The ACRU model is a conceptual, physically based rainfall-runoff model developed by Schulze (1995). It simulates daily, monthly, and annual components of the water balance, including interception, infiltration, surface runoff, soil moisture, ET, and groundwater recharge. ACRU is designed to assess the impacts of LULC, climate variability, and land management on hydrological responses at catchment scales. It is particularly useful for evaluating the effects of afforestation, agriculture, and urbanisation on streamflow and groundwater recharge. The model is based on the theory that runoff occurs after initial abstractions, including interception, depression storage and infiltration (Kusangaya et al., 2017). The model has been deemed suitable for data-scarce and ungauged catchments by studies such as Aduah et al. (2017). In addition, it has been established that the model was developed for South African conditions and the default values are based on local soil information (Graham et al., 2022), however, despite this fact, the model has been applied outside of South Africa. For example, Aduah et al. (2017) applied it in a West African basin to model hydrological changes of a rainforest catchment. Forbes et al. (2011) applied ACRU to simulate the hydrological response of the Beaver Creek Catchment to climate change between 2010 and 2070. A notable advantage of the model is that it does not require the calibration of input data because these are estimated from physical characteristics of the catchment using available geophysical information (Tetsoane, 2013). However, the limitation on catchment size and the seamless integration of the SWAT model with GIS make SWAT a much preferable option than ACRU (Scott-Shaw et al., 2022; Le Roux et al., 2023).

HBV is a conceptual, lumped hydrological model developed in Sweden for simulating runoff in catchments with limited data (Seibert, 1999). It operates at daily time steps and includes routines for accumulation and melt, soil moisture accounting, and runoff generation. The snow computation is dependent on temperature thresholds, and it is optional, depending on the region. HBV is widely used for climate change impact assessments and flood forecasting (Li et al., 2015). While it is simpler than SWAT and ACRU, it effectively captures streamflow dynamics in temperate and cold regions. HBV has limited spatial resolution, making it less suitable for detailed studies of land-use change impact studies. However, despite these limitations, it has been successfully applied in a study in Tanzania by Tibangayuka et al. (2022). The study aimed to evaluate the model performance in the Wami Ruvu basin. Although the model's performance was acceptable, the study revealed significant parameter uncertainty. A similar study was conducted by Ouatiki et al. (2020) at the Ait Ouchen watershed in Morocco. The study concluded that HBV can reasonably simulate daily streamflow and annual variability in reliability.

Variable Infiltration Capacity (VIC) is a macroscale, semi-distributed hydrological model that balances physical realism and computational efficiency. It simulates land surface processes, including infiltration, ET, soil moisture, and runoff generation, at grid scales (Wi et al, 2017). It can provide information on the quantity and timing of water resource availability. It is often used in climate and hydrological modelling at regional to continental scales. VIC incorporates vegetation and soil heterogeneity and can couple with atmospheric models (Devia et al., 2015). It is effective for studying climate variability impacts on hydrology, but it is less focused on detailed land management practices compared to SWAT. Furthermore, the notable limitation is the series of tasks required to prepare input data. According to Wi et al. (2017), the development and process of the required input data require a level of training not available to all users. Hai et al. (2024) found the model efficient in reconstructing streamflow for the Da River Basin in Vietnam from 1981 to 2020; however, they showed little reliability under human intervention. On the other hand, using a modified version of the mode, Sahi et al. (2024) were able to account for anthropogenic influence in hydrological simulation.

The Revised Universal Soil Loss Equation (RUSLE) extends the empirical USLE framework, estimating average annual soil loss (A) as $A = R \times K \times LS \times C \times P$, where R is rainfall erosivity, K is soil erodibility, LS is the slope length/steepness, C is cover-management, and P is the support practice. RUSLE2, its Windows-based iteration, incorporates sub-daily rainfall, detailed management sequences, and GIS integration, enhancing accuracy for cropland predictions by 20-30% over USLE. Validated with > 10,000 plot-years globally, it excels in data-scarce regions like sub-Saharan Africa, where it estimates 2-50 t/ha/yr losses in Limpopo Basin contexts. The Water Erosion Prediction Project (WEPP) offers a process-based alternative, simulating hydrology, soil detachment, and transport via fundamental equations for interrill (raindrop detachment) and rill (flow shear) erosion. WEPP models daily/event-based processes across hillslopes (up to 365m), predicting runoff, sediment yield, and deposition with modules for climate, soil, management, and topography. It outperforms RUSLE on complex profiles (e.g., varying slopes) and non-agricultural lands like rangelands, handling intrinsic site effects that are absent in RUSLE's empirical factors.

2.6 SUMMARY

This chapter examined the evolution and drivers of LULC changes and their implications for land degradation and hydrological systems. The reviewed literature demonstrates that human-induced LULC transformations, particularly deforestation, agricultural expansion, rangeland degradation, mining, and urbanisation have significantly altered terrestrial landscapes across diverse climatic regions. Land degradation is conceptualised as a multidimensional process, commonly assessed through indicators such as soil erosion, vegetation loss, soil fertility decline, sedimentation, and reduced ecosystem productivity. These indicators provide critical insights into the extent and severity of land degradation resulting from different LULC trajectories and land management practices.

The chapter further highlighted that hydrological processes are highly sensitive to LULC change, with substantial impacts on surface runoff, infiltration, ET, groundwater recharge, and streamflow dynamics. Changes in vegetation cover and soil properties influence water partitioning and flow pathways, often increasing hydrological extremes such as floods and droughts. Importantly, the interaction between LULC change and climate change was shown to exacerbate these impacts, as altered land surfaces amplify the effects of changing precipitation patterns, rising temperatures, and increased ET demand. The literature consistently indicates that climate variability acts as a reinforcing stressor, intensifying land degradation and hydrological instability, particularly in semi-arid and water-scarce environments.

Finally, the review underscored the growing use of modelling approaches to assess LULC, climate, and hydrology interactions, ranging from empirical and process-based models to remote sensing-driven and machine learning techniques capable of capturing complex, nonlinear relationships. While these tools have improved understanding and prediction of environmental responses, the chapter emphasised that effective assessment and management require integration of socioeconomic and policy dimensions. The literature converges on the need for integrated, multidisciplinary frameworks that combine biophysical modelling with socioeconomic analysis to inform sustainable land and water management under changing climatic conditions.

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CHAPTER 3: LAND USE AND LAND COVER CHANGE ASSESSMENT

3.1 INTRODUCTION

Land use land cover change (LULCC) has long been recognised as a major driver of environmental change at both spatial and temporal scales, with direct and indirect implications for sustainable development, livelihood systems, and biogeochemical cycle perturbation (Flato et al, 2013). Lambin et al. (2001) concluded that, in addition to population growth and poverty, LULC changes are driven by people's responses to economic opportunities, which are mediated by institutional factors that are either amplified or attenuated by global geopolitical and economic factors. Like many countries worldwide, South Africa is experiencing natural resource depletion due to extensive land use changes. These changes continue to occur due to unplanned settlement expansions (Wang et al., 2023), agricultural activities (Mohomi et al., 2024; Wang et al., 2023), illegal sand mining activities (Kgaphola et al., 2023) and climate change (Onaolapo et al., 2025), among other factors. Sadly, the persistent occurrence of these changes negatively affects the ability of the catchment areas to provide essential ecosystem services

Some of the implications of the LULC change include ecosystems to regulate climate change, environmental degradation, increased risk of natural hazards, and loss of crucial hydrological systems, among others. For example, Mabuda et al. (2024) demonstrated that a notable 7.3% rise in overall surface runoff from 1990 to 2020 was linked to the transformed land cover conditions in the Luvuvhu catchment in Limpopo Province of South Africa. Musetsho et al. (2021) found that this catchment is often affected by drivers of LULC changes associated with deforestation, sand and gravel mining activities, and agricultural practices in wetlands. This thus resulted in significant changes in the LULC classes, which could potentially disrupt the functioning of the natural ecosystem. The potential impacts of LULC changes vary across river catchments and are often caused by anthropogenic activities. Accurate quantification of such changes thus becomes crucial for informing policies and strategies aimed at increasing the resilience of the environment to potential changes and reducing the impacts of LULC changes on the natural environment.

The use of space-based technology has been lauded as one of the most effective tools for mapping LULC changes for decades. For example, Masiza et al. (2023) utilised long-term Landsat data for monitoring changes in LULC to ascertain the nature, causes and extent of degradation in the savannahs of Raymond Mhlaba Local Municipality, Eastern Cape, South Africa. Landsat data was used to assess the impact of LULC change on land degradation in rural semi-arid South Africa (Kgaphola et al., 2023). There are several studies in South Africa and globally that utilised the capabilities offered by Landsat data for assessing the LULC change due to its combined spectral and spatio-temporal capabilities. For example, the availability of Landsat data pre-1980, coupled with the recent launch of Landsat 9 in September 2021, ensures data continuity, which necessitates long-term monitoring of LULC changes and their potential drivers. Thus, the current study aimed at assessing changes in LULC in the Mokolo and Lephalale River Catchments using Landsat data from 1980 to 2024.

3.2 METHODOLOGY

3.2.1 Data collection and pre-processing

In this study, various datasets were employed to accurately map the land use and land cover change in the river catchments of Mokolo and Lephalale. Remotely sensed imagery acquired using Landsat Multispectral Scanner (MSS) 1–5 was used for the classification of LULC changes for 1980, 1990, 2000 and 2010. Additionally, Landsat Operational Land Imager (OLI-2) and Thermal Infrared Sensor (TIRS-2) 9 were used to classify LULC for to 2024. The Landsat satellite is an American satellite that was first launched in 1972 for the monitoring of Earth's resources, and its recent mission launch was done in September 2021 with the launch of Landsat 9. It has a 16-day temporal resolution, with the spatial resolution of 30 m for the multispectral bands. Data from Landsat is acquired in the spectral range of between 0.4–12.2 μm, including the coastal to thermal infrared bands. In total, the Landsat satellite can currently acquire up to 11 spectral bands in the visible (30 m) to thermal infrared (100 m). For this study, the Landsat data were obtained through the Google Earth Engine (GEE), a software that was used for the preprocessing, processing, and post-processing of all images. Figure 3.1 presents the GEE workflow adapted in this study. Only images with less than 10% cloud cover were selected and masked over the catchments.

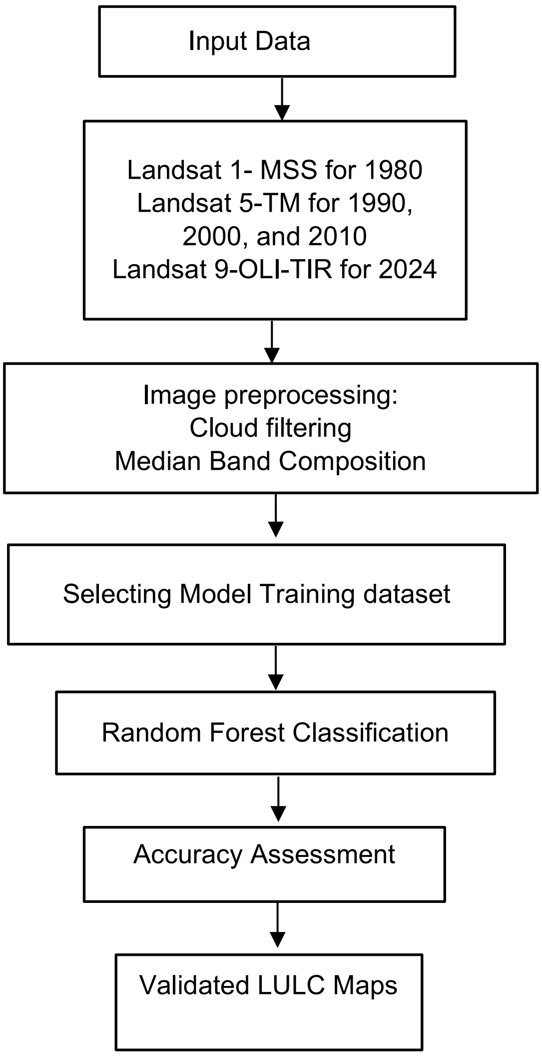

Figure 3. 1 The GEE workflow applied in the analysis and classification of LULC.

In addition to the remotely sensed data, in July 2022 and 2023, field data was collected, and it included (i) the geographic coordinates, (ii) information on the type of LULC, and (iii) general information on the activities common in the identified LULC class. Field data collection was conducted to include the areas in both catchments. The data collection followed a random sampling strategy and included sampling classes of built-up areas, agricultural lands, waterbodies, woodlands, bare areas, and forests. A total of 126 samples (n = 126). The data aided in the calibration and validation of classification. Furthermore, the virtual points played an important role in supplementing the LULC classes, whose points were insufficiently collected due to logistical difficulties associated with inaccessibility and land ownership.

3.2.2 Data analysis

This study used the random forest algorithm, in which 80% of the total sample (both virtually and physically collected points) was used for training and calibrating the model and the remaining 20% was used for validation and testing the accuracy of the classification for each period. The random forest has been successfully used in many previous studies and has proven to produce superior results than other algorithms, including the support vector machines, maximum likelihood, k-nearest neighbour classification, and spectral angle mapper (Adugna et al., 2021). The random forest is an ensemble classification method that combines hundreds of decision trees that decide on the output based on the plurality of votes by various trees. The common element in all of RF procedures is the generation of an independent prior random vector for each q-*th* tree, but with the same distribution. At each stage, the tree is grown using the training set to reduce generalisation error and the correlation between trees (Rodriguez-Galiano et al., 2012). To improve the accuracy of the classification, Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) were incorporated in the code during classification on GEE as key spectral indices to enhance the distinction of vegetation from urban built-up areas. NDVI highlights healthy vegetation by leveraging near-infrared reflectance, while NDBI emphasises impervious surfaces like buildings and roads (Thepvongs and Butar Butar, 2025), thus reducing confusion in heterogeneous landscapes like the South African urban-rural fringe. Table 3.1 shows the description of the major classes considered in this study.

Table 3.1. Major LULC classes considered for this research.

No.	LULC class	Description
1	Water	Areas of open waters that include rivers, puddles, lakes, dams and other man-made water bodies in mining areas
2	Woodlands	All wooded areas with indigenous woody vegetation growing under natural and semi-natural environments are found mostly in the protected areas.
3	Bare surfaces	Natural land and artificial non-vegetated areas, (excluding features such as bare agricultural fields) where the soil substrate is apparently visible.
4	Forests	Land with natural or planted vegetation (tall trees) whose trees have a height of >2.5 m. The forests in this category can be open- or closed-canopy, contiguous or dense.
5	Built-up areas	A class that includes all areas that are associated with human settlements, industrial areas, and the associated infrastructure
6	Agriculture	Cultivated lands with crops that are irrigated and non-irrigated.

3.2.3 Accuracy assessment

The accuracy assessment was conducted in the study area to determine the f reliability of the data model used. The producer accuracy (PA), user accuracy (UA), error matrix tables, overall accuracy (OA) and Cohen's Kappa (Kappa coefficient) were used as the measures of validation of the classified products in this study. They assessed both classification accuracy and the agreement between predicted classes and those obtained by random chance. The overall accuracy is the proportion of the correctly classified cases to the total number of reference cases (Equation 3.1). UA calculates the probability of correct results from the user's perspective and is given by Equation 1, while PA accounts for the probability of correctly classifying a reference class as shown in Equation 3.2. The Cohen's Kappa coefficient is a common measure employed to assess the level of agreement between different observers' ratings or between the same observer's ratings at various points in time for nominal-level items, calculated using Equation 3.4 (Feizizadeh et al., 2022). The rating criteria are listed in Table 3.2.

$$\text{User Accuracy } = \frac{\text{Correctly classified pixels in a class}}{\text{Total pixels classified in that class}} \quad (3.1)$$

$$\text{Porducer Accuracy } = \frac{\text{Correctly classified pixels in a class}}{\text{Total referemce pixels of that class}} \quad (3.2)$$

$$\text{Overall Acccuracy} = \frac{\text{Total correctly classified pixels}}{\text{Total refrence pixels}} \quad (3.3)$$

$$\text{Kappa coeffiecient} = \frac{P_a - P_e}{1 - P_e} \quad (3.4)$$

Where P_a presents the proportion of the actual LULC agreement an*d* P_e is the expected agreement

Table 3.2. The Cohen's kappa rating.

No.	Rating	Strength of agreement
1	< 0	Poor
2	0.00 – 0.20	Slight
3	0.21 – 0.40	Fair
4	0.41 – 0.60	Moderate
5	0.61 – 0.80	Substantial
6	0.81 – 1.00	Excellent

3.2.4 Post-classification processing

The determination of change between two analysis dates was conducted to quantify the extent of change noticeable in the Mokolo and Lephalala river catchments. The land use and land cover change were determined between the beginning and the end of the study period using Equation 3.5 as:

$$\text{Ch}_q = \frac{\text{At}_2 - \text{At}_1}{\text{At}_1} \times 100 \quad (3.5)$$

Where Ch_q represents the percentage of change in area (in ha), At_1 and At_2 represent the total area of a given class at initial and recent periods of study, respectively. Negative values describe a decrease, while positive values indicate an increase.

3.3 RESULTS

3.3.1 Land use and Land cover accuracy assessment

Generally, the random forest classification yielded good results, with the lowest overall accuracy being 0.97 for 2010 and the highest being 0.99 for 1990 and 2000. The Kappa coefficient achieved the highest of 0.99 for 1990 and 0.86 for 2024 (Table 6). During classification, it was noted that some imageries for 1980 were missing and this likely affected the classification accuracy. Overall, the lowest classification accuracy was obtained for imagery acquired in 1980 (0.95, kappa = 0.87) while the highest accuracy (0.99, kappa = 0.99) was obtained from the imagery acquired in 1990 (Table 3.3). Most of the accuracies in this study fall within the acceptable levels corresponding to the ‘Excellent agreement’ between classified and reference samples (Table 3.2). Based on the Error matrix tables (i.e., Table 3.4) for all the years, built-up areas had the lowest PA for 1990 and similarly with UA in 2000, 2010 and 2024; this class was commonly confused with bare areas. While a common confusion was observed between forests and woodlands.

Table 3.3. Accuracy assessment of the classified periods

Year	Overall accuracy	Kappa Coefficient
1980	0.95	0.87
1990	0.99	0.99
2000	0.99	0.95
2010	0.97	0.89
2024	0.96	0.86

Table 3.4. Matrix Error table for a) 1980, b) 1990, c) 2000, d) 2010 and e) 2024.

a) 1980							
	1-	**2-**	**3-**	**4-**	**5-**	**6-**	**Total**
1-	109	1	0	6	0	7	**123**
2-	0	31862	93	69	0	118	**32142**
3-	0	443	1467	0	0	29	**1939**
4-	0	412	0	2733	0	9	**3154**
5-	0	19	2	0	60	6	**87**
6-	1	982	83	12	0	5137	**6215**
Total	**110**	**33719**	**1645**	**2820**	**60**	**5306**	**43660**
PA	0.89	0.99	0.76	0.87	0.69	0.83	
UA	0.99	0.94	0.89	0.97	1.00	0.97	

b)1990

	1-	2-	3-	4-	5-	6-	Total
1-	1151	0	0	0	0	0	**1151**
2-	0	37744	0	0	0	0	**37744**
3-	0	0	1686	0	0	0	**1686**
4-	0	0	0	6690	0	0	**6690**
5-	0	2	0	0	572	0	**574**
6-	0	3	0	0	0	28731	**28734**
Total	**1151**	**37749**	**1686**	**6690**	**572**	**28731**	**76579**
OA	1.00	1.00	1.00	1.00	0.99	1.00	
PA	1.00	0.99	1.00	1.00	1.00	1.00	

c) 2000

	1-	2-	3-	4-	5-	6-	Total
1-	238	0	0	2	0	0	**240**
2-	0	14823	1	3	0	11	**14838**
3-	0	13	191	3	0	10	**217**
4-	0	7	4	313	0	10	**334**
5-	0	29	1	0	79	12	**121**
6-	0	114	3	1	1	1445	**1564**
Total	**238**	**14986**	**200**	**322**	**80**	**1488**	**17314**
PA	1.00	0.99	0.96	0.97	0.99	0.97	
UA	0.99	1.00	0.88	0.94	0.65	0.92	

d) 2010

	1-	2-	3-	4-	5-	6-	Total
1-	233	12	0	3	0	3	**251**
2-	0	15844	4	9	6	42	**15905**
3-	0	45	322	1	3	4	**375**
4-	2	41	5	367	0	0	**415**
5-	0	65	3	2	99	5	**174**
6-	0	248	0	8	2	1354	**1612**
Total	**235**	**16255**	**334**	**390**	**110**	**1408**	**18732**
PA	0.99	0.97	0.96	0.94	0.90	0.96	
UA	0.93	1.00	0.86	0.88	0.57	0.84	

e) 2024

	1-	2-	3-	4-	5-	6-	Total
1-	217	1	0	9	1	0	**228**
2-	0	16030	3	8	10	30	**16081**
3-	0	51	429	0	3	2	**485**
4-	0	29	0	386	3	1	**419**
5-	1	21	13	5	133	4	**177**
6-	0	492	0	3	2	1164	**1661**
Total	**218**	**16624**	**445**	**411**	**152**	**1201**	**19051**
PA	1.00	0.96	0.96	0.94	0.88	0.97	
UA	0.95	1.00	0.88	0.92	0.75	0.70	

*1-Waterbodies, 2-Woodlands, 3-Bareland areas, 4-Forests, 5-Build-up areas and 6-Agriculture. **PA**-Producer Accuracy, **UA**-User Accuracy.

3.3.2 Land Use and Land Cover validation/ accuracy assessment

The results of LULC classification are shown in Figures 3.2. The major LULC class is the woodlands (Savanna/bushland vegetation), and this is evidenced by the prevailing semi-arid climate. Furthermore, the results show that the southern part of the catchments is predominantly occupied by agricultural lands and forests, most of which are open canopy forest vegetation. It is also dominated by rural areas with a few suburban towns or mining towns, such Vaalwater and Lephalale. In the northern part of the catchments, there has been a noticeable change in LULC from 1980 to 2024. Currently, bare areas are commonly found in the study areas due to the combined effects of climate and anthropogenic engagements such as mining activities. For example, the imageries extracted during winter had more bare areas due to the lack of vegetation cover, leading to more exposed areas (e.g., 1980), while the LULC of 2000 is an example of LULC classified from images extracted in summer. The effects of climate change and anthropogenic activities such as mine have been noted to alter the ability of a catchment to offer sustainable ecosystem services and to regulate surface temperatures by increasing surface albedo (Santos Orozco et al., 2023; Scott et al., 2018). Table 3.5 and Figure 3.2 present a summary of LULC classes in this study.

Table 3.5. Accuracy assessment of classified Landsat imagery (n = 63).

	1980	**1990**	**2000**	**2010**	**2024**
1-Waterbodies (%)	0.0031	0.1	0.1	0.2	0.1
2-Woodlands (%)	62.7	92.3	91.5	93.2	89.7
3-Bare Areas (%)	2.8	0.3	0.6	0.4	1.3
4-Forests (%)	2.0	4.9	4.0	2.4	4.9
5-Built-up Areas (%)	0.0	0.1	0.3	0.5	0.7
6-Agricultural land (%)	4.9	2.1	3.5	3.3	3.3
7-No data (5)	27.5	-	-	-	-
Total	**100**	**100**	**100**	**100**	**100**

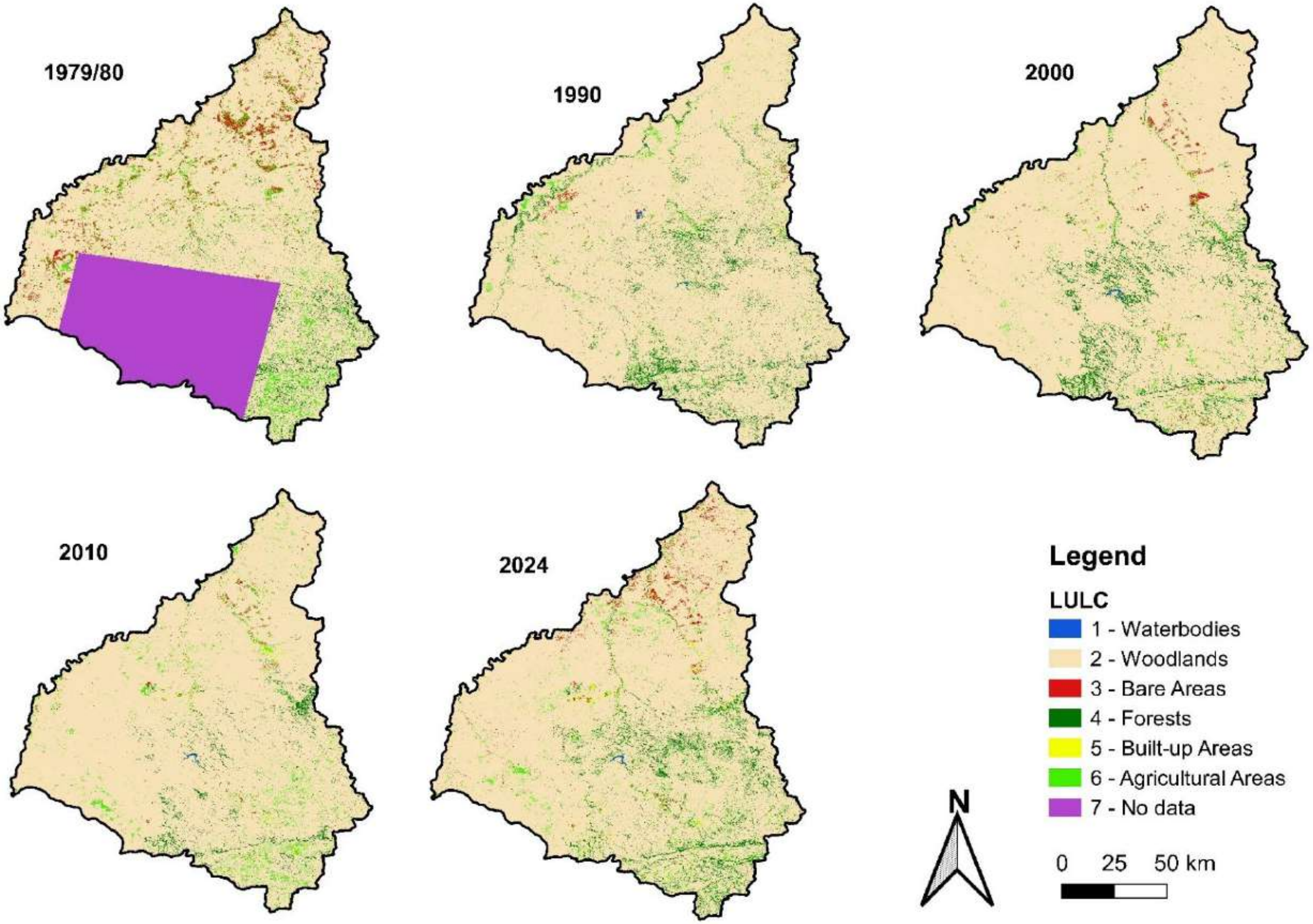

Figure 3.2 The LULC classification results from 1980, 1990, 2000, 2010 and 2024.

3.3.3 Change detection between 1980 and 2024

Due to 27% of missing data for 1980, the long-term change analysis was conducted from 1990 to avoid bias. Overall, Figure 3.3 indicated a great change in built-up areas and bare areas since 1980, which could have been fuelled by multiple mining activities and agricultural activities in the area. The increase in built-up areas is likely in response to associated expansions of mining activities, such as coal fields, and agricultural activities. The coal fields are thought to be a replacement of the Mpumalanga coalfields, which are currently exploited for the generation of electricity (Mathu and Chinomona, 2013). Ecologically, trends in forests (decreasing), bare lands (increasing) and woodlands (decreasing) show that the environmental sustainability will be threatened in the future if efforts are not put in place to address these challenges (Figure 3.4). The increase in bare areas is likely attributed to the combined effect of human activities, land policies, land degradation, and climate change (He et al., 2024). It should be noted that factors such as desertification, organic matter decomposition and erosion contribute to land degradation and thus the impact of LULC should be considered in conjunction with these factors (Liu et al., 2022). The woodlands class experienced a notable decline throughout the study period, suggesting persistent pressure on the provision of ecological functions and services in the catchment area.

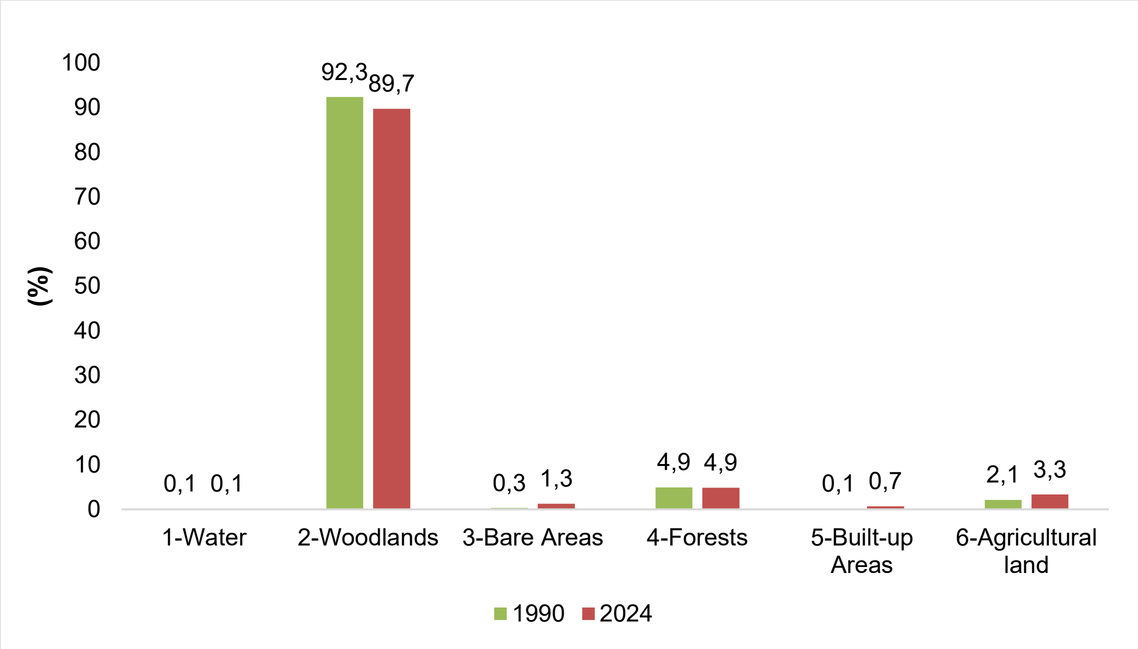

Figure 3.3 Land use and land cover change between 1990 and 2024.

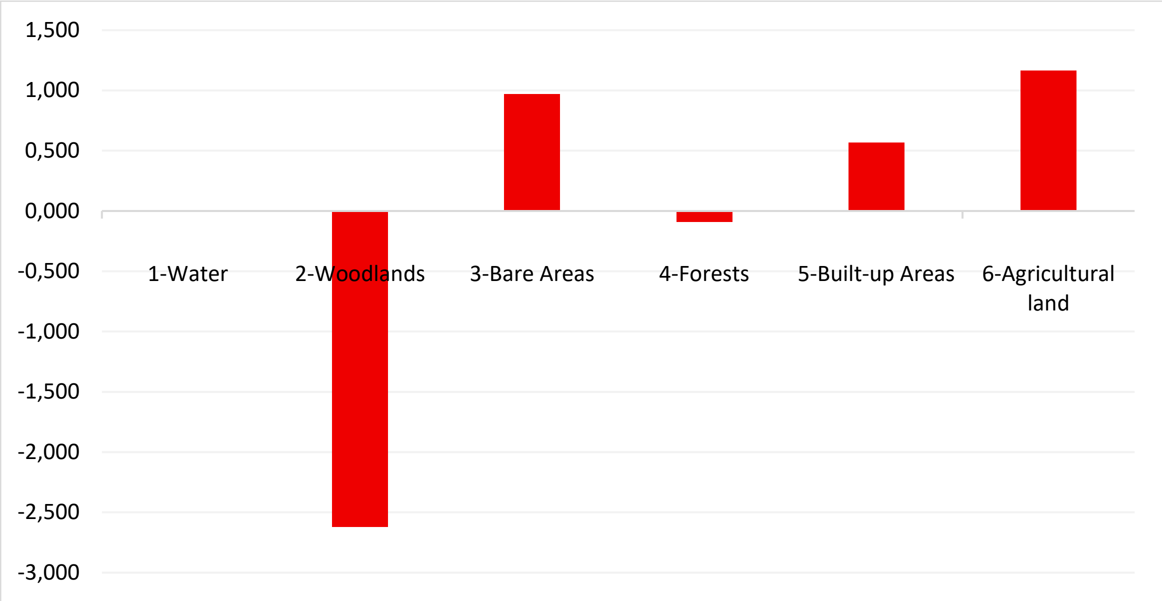

Figure 3.4 Change detection in the Mokolo and Lephalala river catchment between 1990 and 2024.

3.3 SUMMARY

Globally, unsustainable LULC changes have been proven to play a leading role in the degradation of natural resources, including soil, air, land and water. Furthermore, LULC has been noted to contribute to climate change and its effects. Thus, monitoring and assessing its pattern of change and expansion have become an integral part of sustainability studies, resource planning and policy development. This study used GEE for preprocessing, processing and post-processing of Landsat images used in the classification of LULC at Mokolo and Lephalale Catchment from the 80s to 2024. However, due to 27% of loss of data in the 1980s LULC class, the long trend was analysed from 1990. Overall, it has been determined that the catchments have changed, such as an increase in bare areas, agricultural lands, and the built-up areas with decreased woodland cover, indicating the increased environmental pressure on the ability of the natural ecosystem to render optimal ecological functions from the 1990s until the 21st century. The maximum likelihood classifier yielded an excellent kappa statistic, with overall accuracies exceeding 80%.

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CHAPTER 4: DROUGHT ASSESSMENT AND CHARACTERISATION, TREND ANALYSIS

4.1 INTRODUCTION

Drought is one of the most complex, costly, and least understood natural hazards, exerting profound impacts on water resources, food security, ecosystems, and socio-economic development worldwide. Unlike other hydro-meteorological extremes such as floods or storms, drought develops slowly, persists over extended periods, and often affects large spatial extents, making its detection, monitoring, and management particularly challenging (Wilhite, 2000; Mishra and Singh, 2010). In recent decades, the frequency, severity, and duration of droughts have increased in many regions, driven by climate variability and anthropogenic climate change (IPCC, 2021). These evolving dynamics underscore the growing importance of a robust framework for drought monitoring, assessment, and characterisation. Climate change is fundamentally altering the global hydrological cycle, influencing precipitation patterns, temperature regimes, evapotranspiration rates, and soil moisture dynamics (Trenberth et al., 2014). Rising temperatures intensify atmospheric water demand, exacerbating drought conditions even in regions where precipitation trends remain neutral or increase, a phenomenon often referred to as “hot drought” (AghaKouchak et al., 2014). Changes in rainfall seasonality, increased interannual variability, and the intensification of extreme events further complicate drought behaviour, challenging traditional drought monitoring approaches that rely solely on precipitation anomalies (Sheffield and Wood, 2011).

Drought is a multi-dimensional phenomenon commonly classified into meteorological, agricultural, hydrological, and socio-economic droughts, each reflecting different components of the climate–water–human system (Wilhite and Glantz, 1985). Effective drought characterisation, therefore, requires integrated approaches that capture atmospheric drivers, land surface processes, and hydrological responses across multiple temporal and spatial scales. To this end, a wide range of drought indices have been developed, including the Standardised Precipitation Index (SPI), Standardised Precipitation Evapotranspiration Index (SPEI), Palmer Drought Severity Index (PDSI), Standardised Runoff Index (SRI), and Soil Moisture Index (SMI) (McKee et al., 1993; Vicente-Serrano et al., 2010; Dai, 2011). Among these, standardised indices such as SPI and SPEI are widely adopted due to their flexibility, minimal data requirements, and ability to represent drought conditions across multiple accumulation periods. SPEI has gained prominence in the context of climate change because it explicitly incorporates temperature-driven evapotranspiration, making it more sensitive to warming trends (Vicente-Serrano et al., 2010). However, no single index can adequately capture the full complexity of drought processes, especially under non-stationary climate conditions. Consequently, multi-index and multi-scale approaches are increasingly recommended to improve drought assessment robustness and reduce uncertainty (Svoboda et al., 2012; Hao and Singh, 2015).

Statistical and trend-based techniques play a vital role in drought characterisation under changing climate conditions. Non-parametric methods such as the Mann–Kendall test, sequential Mann–Kendall (SQMK), and the Theil–Sen slope estimator are widely applied to detect monotonic trends, abrupt shifts, and long-term changes in drought indices (Yue et al., 2002; Hirsch et al., 1982). These methods are particularly well-suited for hydro-climatic data, which often violate assumptions of normality and stationarity. Emerging machine learning and hybrid approaches further enhance drought prediction and early warning by capturing nonlinear relationships between climatic drivers and drought responses (Mosavi et al., 2020). This chapter focuses on assessing and characterising historical drought, its trends, as well as exploring drought characteristics in the future climate.

4.2 METHODOLOGY

4.2.1 Datasets

The drought analysis in this study considered various hydrometeorological variables to provide a comprehensive drought assessment of the two selected catchments. To compute the different drought indices, the required data included rainfall, temperature, evaporation, streamflow, reservoir storage, and soil moisture. Station datasets were obtained from the South African Weather Service (SAWS) and the Department of Water and Sanitation (DWS). The study area has limited ground observed data, and as such, reanalysis data was used in conjunction with the data the research team managed to obtain. The drought analyses were conducted using *R Studio* software.

4.2.2 Drought indices formulation

- ***SPI computations***

The SPI was utilised to quantify rainfall deficit within the two catchments considered in the analysis. The procedure involved fitting the rainfall data into a Probability Density Function (PDF). A gamma distribution function was adopted because it fits well in rainfall time series data. The gamma distribution is expressed in terms of its PDF as shown in Equation (4.1).

$$f(x;\alpha,\beta) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{\frac{-x}{\beta}} \quad \text{for } ,\alpha,\beta > 0, \tag{4.1}$$

where *α* is the shape parameter, *β* is the scale parameter, *x* is the rainfall amount (mm), *Γ(α)* is the value taken by the Gamma function and $\underline{x}$ is the mean rainfall (mm). The *Γ(α)* is the value defined by a standard mathematical equation called Gamma function. This is given by Cacciamani et al. (2007) as indicated in Equation (4.2).

$$\Gamma(\alpha) = \int_0^{\alpha} x^{\alpha-1} e^{-y} dx, \tag{4.2}$$

where *Γ(α)*, *x* and *α* are defined in Equation (4.1). The above Gamma function was then evaluated using both the numerical method and tabulated values, depending on the value of the shape parameter *α.* A maximum probability is used to estimate the optimal values of *α* and *β* using the function given in the Equations (4.3) and (4.4), respectively.

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \tag{4.3}$$

$$\beta = \frac{\underline{x}}{\alpha} \tag{4.4}$$

where *α is* the shape parameter, *β* is the scale parameters, $\underline{x}$ is define above and *A* is the sample statistic. The sample statistic is defined by Equation (4.5).

$$A = ln\, ln\left(\underline{x}\right) - \frac{lnln\, x}{n} \tag{4.5}$$

where *n* is the number of observations. The calculated values are then used to compute the cumulative probability for non-zero rainfall using Equations (4.6) and (4.7), respectively.

$$f(x;\alpha,\beta) = \int_0^x f(x,\alpha,\beta)dx = \frac{1}{\beta^{\alpha}\Gamma(\alpha)}\int_0^x x^{\alpha-1}e^{\frac{-x}{\beta}}\,dx \tag{4.6}$$

Equation (4.6) parameters are as defined in Equation (4.4).

$$f(x;\alpha,\beta) = \frac{1}{\Gamma(\alpha)}\int_0^x t^{a-1}e^{-t}dt \text{ for } t = \frac{x}{\beta} \tag{4.7}$$

where *Γ(α)*, *x* and *β* are defined in Equations (4.1) and (4.4), respectively, while *t* is the time. The gamma function applies for values of rainfall *x* > 0 for the rainfall time series of the basin under study. In case of non-zero values, there was a need to compute the cumulative probability of both zero and non-zero values. This probability is represented by a function *H(x),* achieved by Equation (4.8).

$$H(x) = q + (1-q)f(x;\alpha,\beta) \tag{4.8}$$

where *H(x)* is the cumulative probability and *q* is the probability of zero rainfall. If m is the number of zeroes and n . The number of observations in the rainfall time series, then q is estimated by the ratio n. The cumulative probability is transformed into a standard normal distribution in such a way that the mean and variance of the *SPI* are zero and one, respectively. To carry out this step, an approximate transformation as per Mishra and Desai (2006) was adopted, as computed by Equation (4.9).

$$SPI = k - \frac{C_0 + C_1k + C_2k^2}{1 + d_1k + d_2k^2 + d_3k^3} \tag{4.9}$$

The value of *k* in Equations (4.9) was determined from the functions given in Equation (4.10)

$$k = \sqrt{ln\left(\frac{1}{1-H(x)^2}\right)} \tag{4.10}$$

where C_0 is 2.515517, C_1 is 0.802853, C_2 is 0.010328, d_1 is 1.432788, d_2 is 0.189269 and d_3 is 0.001308 (Bezdan et al., 2019), and these are constant values for computing the SPI. The SPI uses a classification system in which wet conditions are indicated by positive values, and negative values represent dry conditions (Table 4.1). This study only makes use of the negative values in its analysis, as they indicate drought.

Table 4.1 SPI drought classification (McKee et al., 1993).

SPI Values	Drought category
0 to -0.99	Mild/ Near normal
-1.00 to -1.49	Moderate
-1.50 to -1.99	Severe
≤ -2.0	Extreme

- ***SSI calculations***

For determining the SSI, this study followed the procedure as outlined in Faragman and Aghakouchak (2015), which derives the marginal probability of (i.e. precipitation and streamflow) using the empirical Gringorten plotting position (Gringorten, 1963) as shown in Equation (4.11).

$$P(x_i) = \frac{i-0.44}{n+0.12} \tag{4.11}$$

where, *n* is the sample size, *i* denotes the rank of non-zero streamflow data from the smallest, and $P(x_i)$ is the corresponding empirical probability. Making use of such an empirical approach, the original distribution (two-term gamma probability density function and the cumulative gamma distribution function) used in SPI for instance are not required to derive the parametric probabilities. Following the classical approximation as described by Abramowitz and Stegun (1965), Entekhabi et al. (1996), and Edwards and McKee (1997), SSI was computed using Equation (4.12).

$$SSI = t - \frac{C_0+C_1t+C_2t^2}{1+d_1t+d_2t^2+d_3t^3} \tag{4.12}$$

The constants C_0, C_1, C_2, d_1, d_2, and d_3 are as defined in Equation (4.9), while t is given by Equation (4.13).

$$t = \sqrt{ln\frac{1}{P^2}} \tag{4.13}$$

Since SSI is a standardised index, the SPI classification as described by McKee *et al*. (1993) was adopted to categorise the different drought events in the study area.

- ***SPEI computations***

The SPEI is based on the computation procedure of the original SPI. The index makes use of either the monthly or weekly difference between precipitation and Potential Evapotranspiration (PET) (Vicente-Serrano et al., 2010a). This study made use of Thornthwaite temperature-based method for PET estimation. The latter approach has the advantage of only requiring data on the monthly-mean temperature. The SPI methodology was modified by replacing the two-parameter distribution with a three-parameter distribution (i.e. SPEI requirement) (Vicente-Serrano et al., 2010a). The latter suggested getting the best fit three parameter distribution from L-moment and the detailed methodology for achieving this can be obtained in Hosking (1990). Following the classical approximation of Abramowitz and Stegun (1965), SPEI was computed as shown in Equation (4.14).

$$\mathrm{SPEI} = \mathrm{W} - (\mathrm{C_0} + \mathrm{C_1}\,\mathrm{W} + \mathrm{C_2}\,\mathrm{W}^2)/(1 + \mathrm{d_1}\,\mathrm{W} + \mathrm{d_2}\,\mathrm{W}^2 + \mathrm{d_3}\,\mathrm{W}^3) \tag{4.14}$$

where, W=√(-2ln(P)) for P≤0.5, and P is the probability of exceeding a threshold value denoted by D value, P=1-F(x). If P>0.5, then P is replaced by 1-P and the sign of the resultant SPEI is reversed. The constants C_0, C_1, C_2, d_1, d_2, and d_3 are as defined in Equation (9). For this study, SPEI was computed using a *CRAN Package "spei"* in *R Studio*. The SPEI drought classification is like that of SPI, therefore Table 4.1 was adopted to classify drought categories for the case of SPEI.

4.2.3 Trend analysis

The Mann–Kendall (MK) non-parametric trend test (Mann, 1945; Kendall, 1967) was used for drought trend analysis. This trend analysis method has been recommended by the WMO as an approach to computing trends of hydro-meteorological time series. The method has been widely applied in testing trends of climatological time series (Zhang et al., 2000). The test statistic S was calculated using Equation (4.15).

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sng\ (y_j - y_k) \tag{4.15}$$

$$Sng(y_j - y_k) = \left\{+1\ if\ \left(y_j - y_k\right) > 0\ 0\ if\ \left(y_j - y_k\right) = 0\ -1\ if\ \left(y_j - y_k\right) < 0\right\}$$

Mann (1945) and Kendall (1975) showed that when the number of observations is more than eight, S almost follows the normal distribution, and its mean and standard deviation are determined by Equations (4.16) and (4.17).

$$E(S) = 0 \tag{4.16}$$

$$V(S) = n(n-1)(2n+5) - \frac{\sum_{i=1}^{n} t_i(t_i-1)(2t_i+5)}{18} \tag{4.17}$$

where t_i is the number of identical data in the ith category. Kendall's standardised Z statistic is presented by Equation (4.18).

$$Z = \{S - \frac{1}{\sqrt{V(S)}} \quad S > 0\ \ 0 \qquad S = 0\ S + \frac{1}{\sqrt{V(S)}} \quad S < 0 \tag{4.18}$$

The Z statistic is a standardized Mann–Kendall test that follows a normal distribution and has a mean of 0 and a variance of 1. As a result of autocorrelation while dealing with hydro-meteorological variables, the analysis also considered the modified version of MK to further investigate the variation in trend significance between the two trend test methodologies. Kumar et al. (2009) improved the Mann–Kendall test by removing the effect of first-order autocorrelation. For this purpose, the autocorrelation coefficient of order k was obtained from the following relationship shown in Equation (4.19).

$$\mathrm{r_k} = \frac{(\frac{1}{\mathrm{n-k}}) \sum_{\mathrm{i-1}}^{\mathrm{n-k}} \left(\mathrm{y_i} - \underline{\mathrm{y}}\right)(\mathrm{y_{i-k}} - \underline{\mathrm{y}})}{(\frac{1}{\mathrm{n}}) \sum_{\mathrm{i-1}}^{\mathrm{n}} (\mathrm{y_i} - \underline{\mathrm{y}})^2} \tag{4.19}$$

By specifying the value of $k = 0$, the first-order autocorrelation coefficient was calculated. The significance test of the obtained function is that if the value of r_1 is between c_1 and c_2, respectively, it is assumed that the data are independent of each other at the 10% significance level. Otherwise, it is assumed that the data have autocorrelation, and their effect should be removed from the time series before performing the Mann–Kendall test. c_1 and c_2 given by Equations (4.20) and (4.21), respectively.

$$c_1 = \frac{-1+1/65\sqrt{n-2}}{n-2} \tag{4.20}$$

$$c_2 = \frac{-1-1/65\sqrt{n-2}}{n-2} \tag{4.21}$$

In the present study, this test is used for 95% confidence levels. If the Z statistic is positive, the trend of the data series is upward, and if it is negative, the trend is downward. To improve the test for monthly series that have autocorrelation, modifications to the Mann–Kendall test have been made (Yue et al. 2002). In this method, at first, the values of the S statistic are calculated for each year, and finally, the results of different years are added together as shown in Equation (4.22).

$$S' = \sum_{j=1}^{p} S_j \tag{4.22}$$

where S_j is the value of S for season j (j ¼ $1, 2, \ldots, p$). In the case that the time series has no autocorrelation, the variance of S' is determined using the following relationship:

$$S' = \sum_{j=1}^{p} Var(S_j') \tag{4.23}$$

The extended MK trend, known as the Sequential MK (SQMK) (Sneyers, 1990) is used to detect the turning points of trend in the time series. The SQMK creates two-time series, a progressive ($u(t)$) and a retrograde ($u'(t)$). Equation (4.24) defines the statistic t_i:

$$t_i = \sum_{j=1}^{i} n_i \tag{4.24}$$

Equations (4.25) and (4.26) were used in calculating the mean and variance t_i:

$$E(t_i) = \frac{i(i-1)}{4} \tag{4.25}$$

$$Var(t_i) = \frac{i(i-1)(2i-5)}{72} \tag{4.26}$$

Statistic $u(t_i)$ sequential values, which are standardised, were calculated by Equation (4.27).

$$u(t_i) = \frac{t_i - E(t_i)}{\sqrt{Var(t_i)}} \tag{4.27}$$

Equation (4.28) gives a forward sequential progressive statistic. To calculate the backward/retrograde statistic values ($u'(t)$), the same time series ($x_1, x_2, x_3, \ldots, x_n$) is used; however, the tail end of the time series is the starting point in this calculation. By combining the forward and backward sequential statistics, it makes it possible for the recognition of the estimated start of a developing trend (Jain et al., 2013). When plotted, if $(u(t))$ and $(u'(t))$ cross each other and diverge beyond the ±1.96 (95% confidence interval) threshold, a statistically significant trend exits in a time series. The region where they cross each other is the time where the trend turning point begins.

4.3 RESULTS

4.3.1 Historical drought assessment

Meteorological drought in the Mokolo and Lephalala River Catchments were analysed at three time series time scales (i.e., 6, 12 and 24 months) while hydrological drought represented by SSI was computed at 9, 12 and 24 months. Due to lack of primary station meteorological data, the study made use of CHIRPS rainfall and ERA5 temperature data for the base period from 1980 to 2020. Drought time series for the standardised indices at the different time scales are shown in Figures 4.1 to 4.5. Notable historic drought years 1987/88 (SPI/SSI/SPEI of -1.2), 1991/92 (SPI/SSI/SPEI of -1.46), 1994/96 (SPI/SSI/SPEI of -1.14), 2001/02 (SPI/SSI/SPEI of -1.54) and 2014/16 (SPI/SSI/SPEI < -2), were the focus regarding the historical assessment of drought in the catchment. The analysis of all SPI and further detected more drought years as depicted in Figures 4.1 to 4.5. Ground based station data showed the 1991/92 to be the most severe at the three timescales, while SPI derived from CHIRPS timeseries revealed 2002/03 to have experienced a more severe drought in the Beauty and downstream points of the Lephalala catchment. Drought in the study region is more pronounced between September and March as this is the period the area receives its rainfall and consequently, any deficit in precipitation will be notable over this period.

Considering the notable historical drought events reported in literature, SPEI detected all the drought years across the catchments at different SPEI time scales. The 2014 to 2016 drought dominated the severe category across the Mokolo catchment with the longest drought duration, and this is like the findings of Lephalala catchment upstream and downstream points. The SSI drought time series for all the streamflow stations (i.e. A4H002, A4H005 and A5H004) at 9-, 12- and 24-month timescales are shown in Figure 4.5. Like the SPI and the SPEI, SSI has managed to detect the reported historical drought events and quite notably depicted the 1991/92 drought in all stations in the severe category. Precipitation based indices showed that the 2014 to 2016 drought was the most extreme drought over the study period, and the SSI underestimated this drought event as it was categorised as moderate to near normal conditions. The behaviour of SSI compared to the precipitation-based indices might be because streamflow is dependent on precipitation; therefore, there is some lag between precipitation deficiency and reduced streamflow. Streamflow and base flow drought occur around 7 and 11 months, respectively after the end of a meteorological drought (Yang et al., 2017).

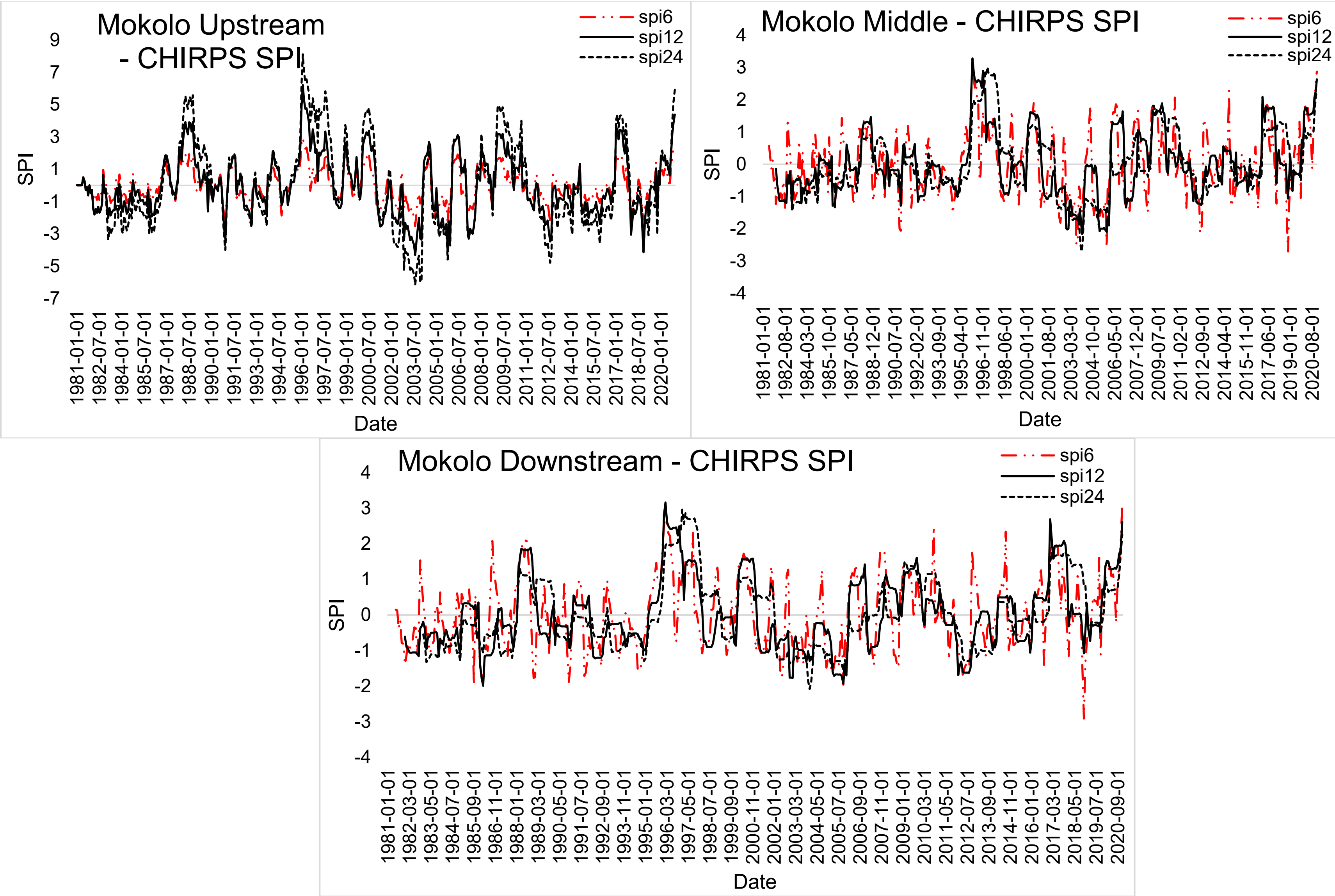


Figure 4.1 Mokolo River catchment CHIRPS SPI.

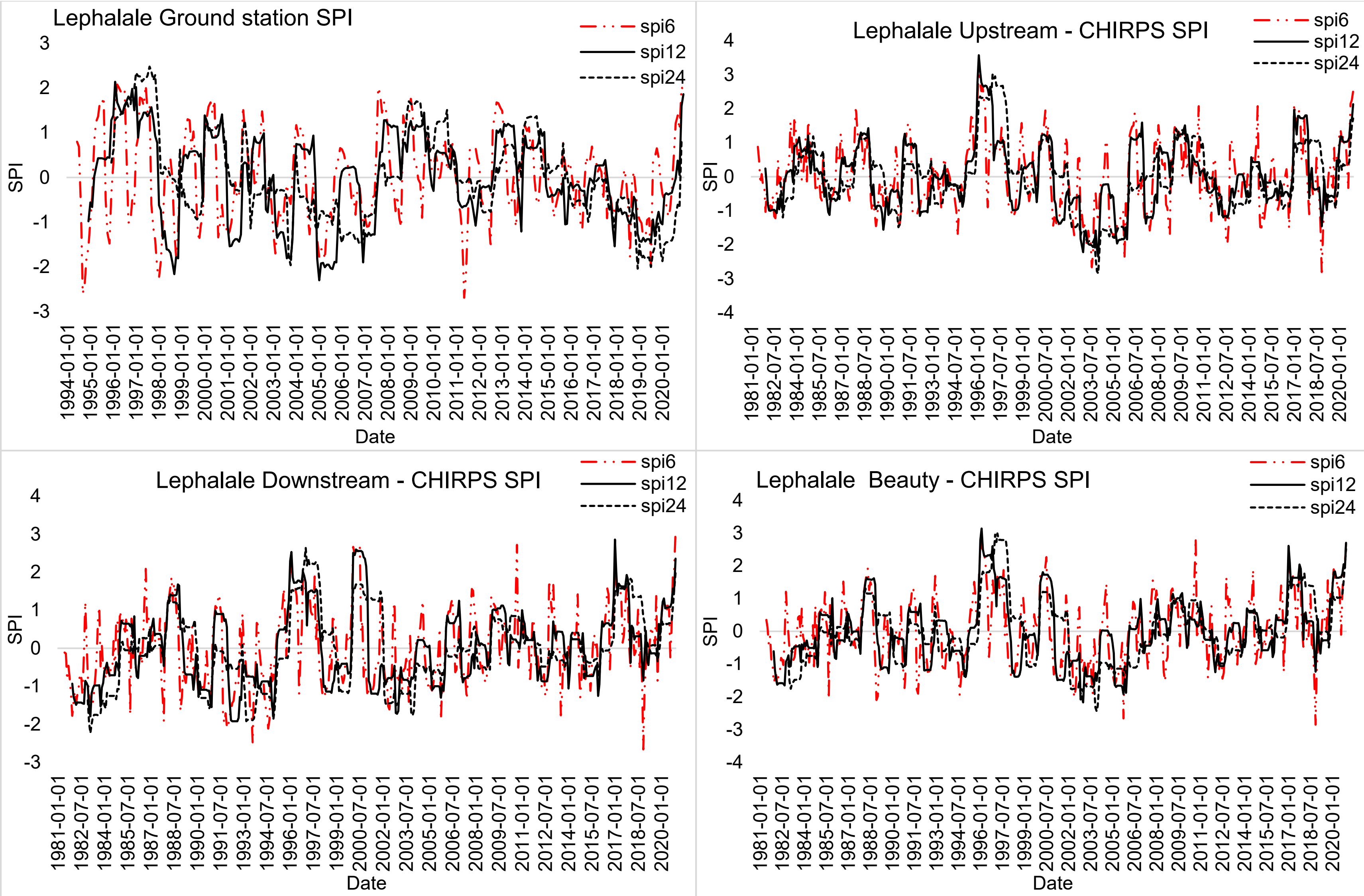


Figure 4.2 Lephalala River Catchment SPI.

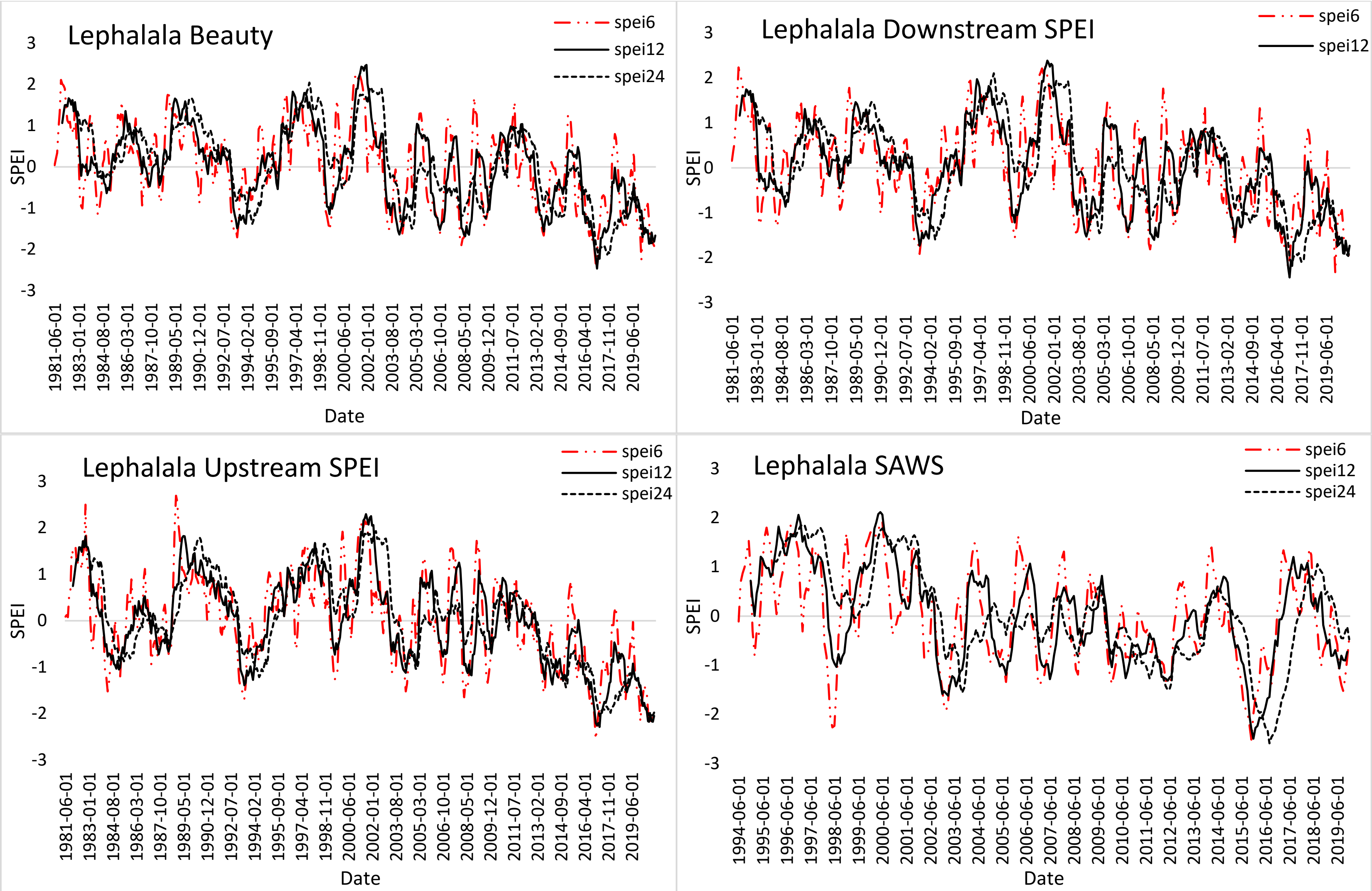


Figure 4.3 Lephalala River Catchment SPEI.

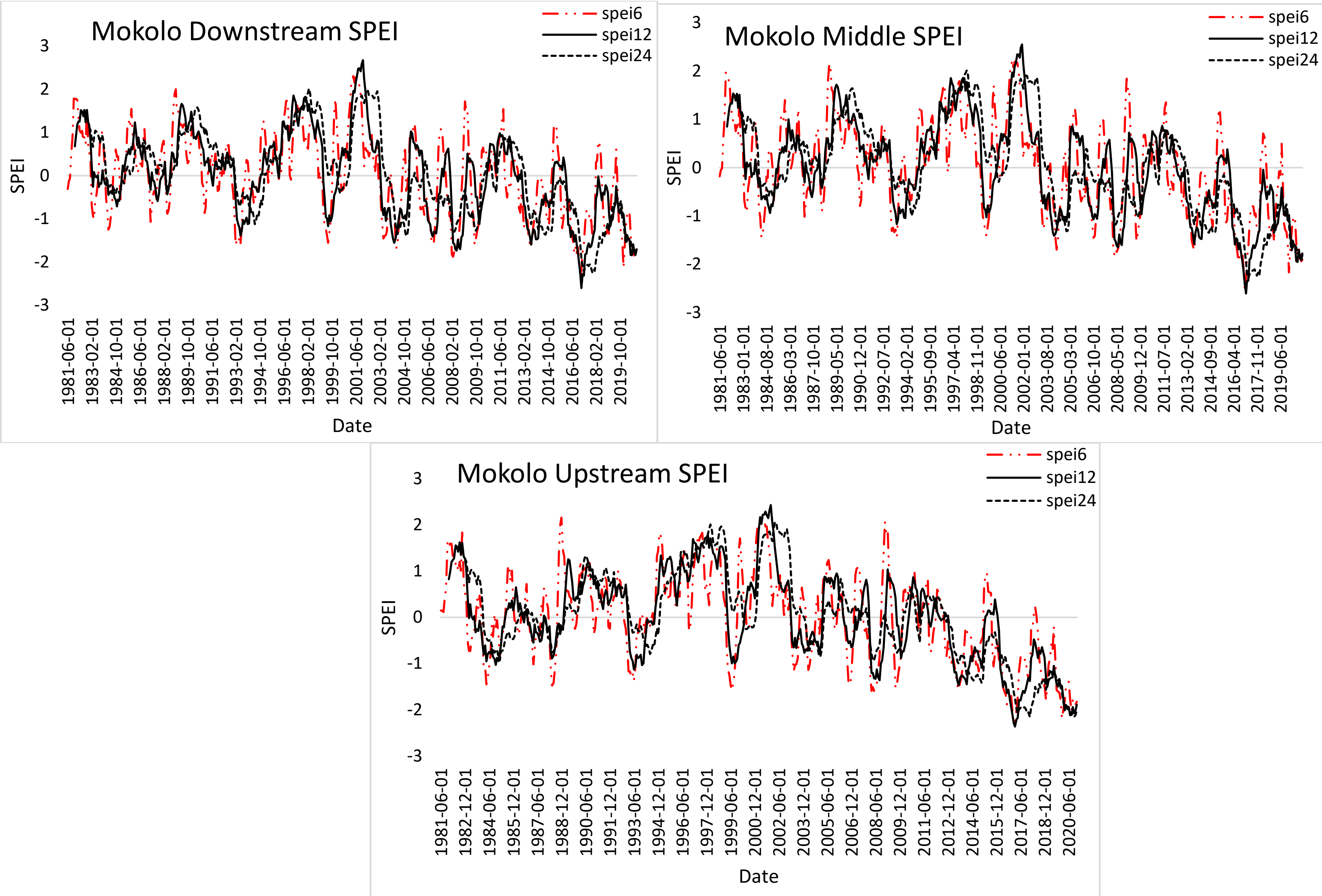


Figure 4.4 Mokolo River Catchment SPEI.

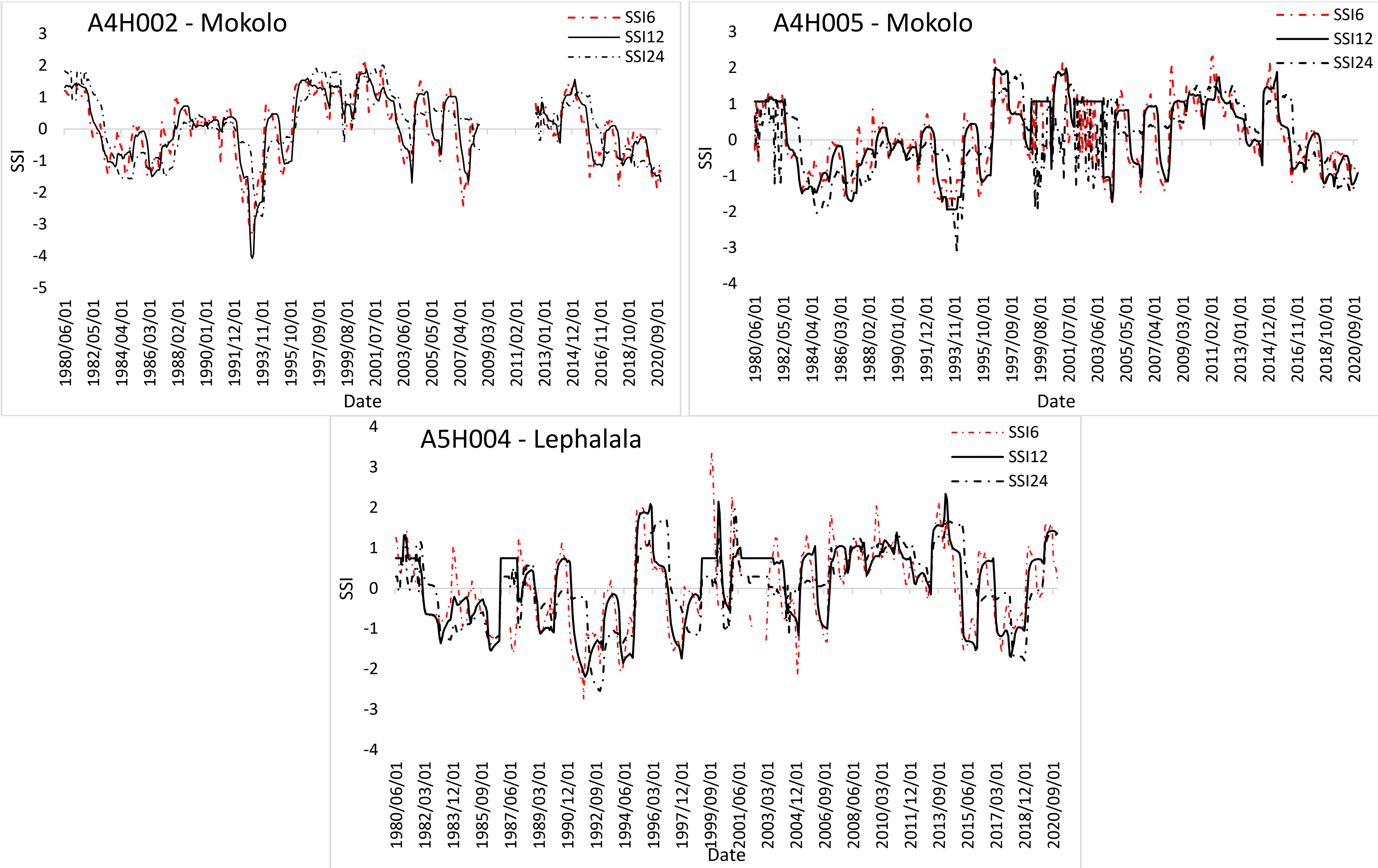


Figure 4.5 Lephalala and Mokolo River Catchments SSI.

4.3.3 Drought trends and their statistical significance

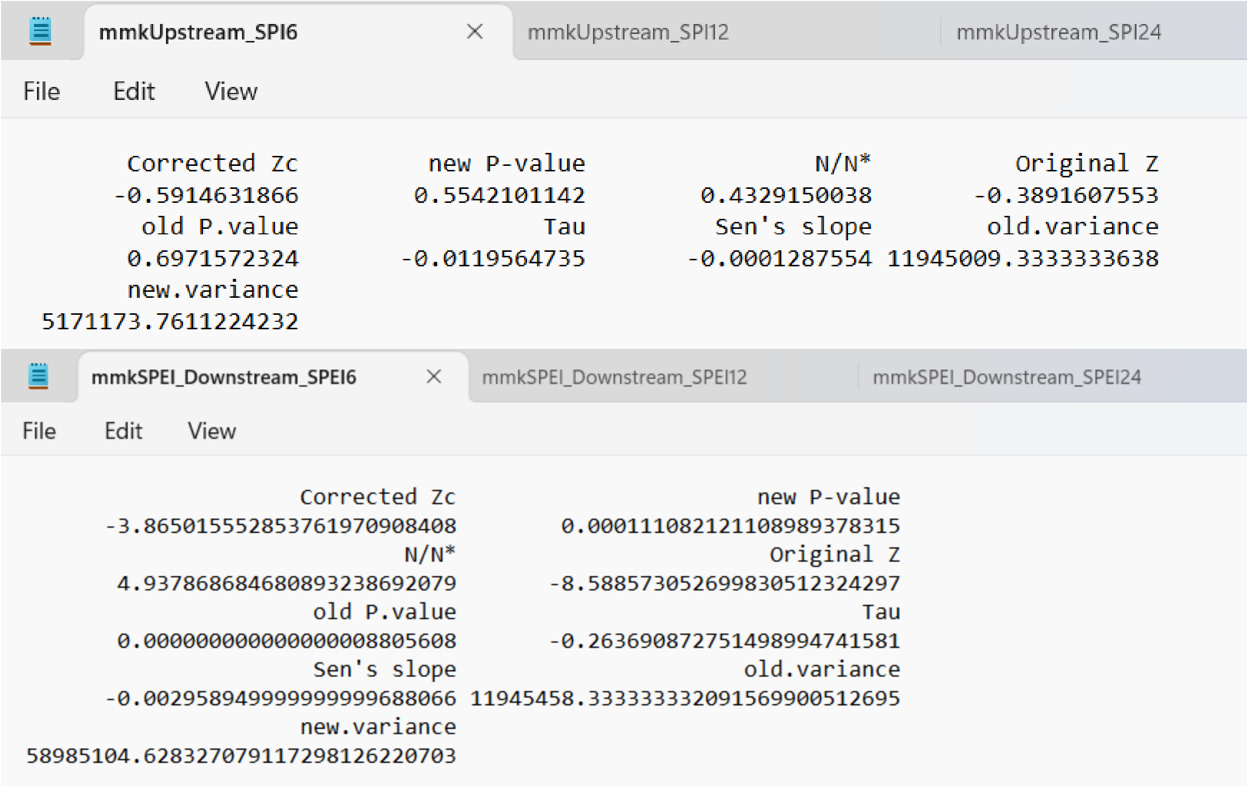
Considering the MK trend test, the SPI had a general positive trend across all timescales, as shown in Tables 4.2 & 4.3, and Figure 4.6 shows a sample of the modified MK output file from *R*. All the SPI points in Lephalala showed a positive SPI trend, with 33% (at the 6th and 24th time scale) negative trends detected by SPI in the Mokolo Catchment. The SSI across both catchments mainly experienced a negative trend over all timescales, with only streamflow station A4H005 detecting a positive trend across all timescales. In contrast to SPI and SSI, SPEI showed a negative across both catchments and timescales. This indicates that, according to SPEI, drought in the study area is on an increasing trend with varying magnitudes. The overall catchment drought in the Mokolo Catchment and Lephalala Catchment shows that drought conditions are decreasing over the study period, as it detected a positive MK trend. The difference between trend results for SPI, SSI and SPEI may be influenced by the variables used in the respective index formulation. For the case of SPEI, the index is an improvement of the SPI with the addition of evaporation and for this study, this was estimated using a temperature-based method, and temperature has been reported to play a significant role in the development of drought through its inherent nature to highly influence evaporation. Lenton et al. (2017) reported that sea surface temperature variability contributed to increased land temperature variability and autocorrelation, which ultimately contributed to persistent droughts in North America and the Mediterranean.

Table 4.2 Mokolo River Catchment SPI, SSI and SPEI MK trends.

Index		Time scale	S	Z	P_value	alpha	Trend
SPI	**Upstream**	6	-1557	-0.45	0.65	0.05	-ve
		12	506	0.15	0.88	0.05	+ve
		24	-2071	-0.64	0.53	0.05	-ve
	Middle	6	7202	2.08	0.04	0.05	+ve
		12	13453	3.97	7.3e-5	0.05	+ve
		24	16042	4.92	8.8e-7	0.05	+ve
	Downstream	6	10600	3.07	0.0022	0.05	+ve
		12	15909	4.69	2.7e-6	0.05	+ve
		24	16426	5.04	4.8e-7	0.05	+ve
SPEI	**Upstream**	6	-29703	-8.59	2.2e-16	0.05	-ve
		12	-31972	-9.43	2.2e-16	0.05	-ve
		24	-33470	-10.26	2.2e-16	0.05	-ve
	Middle	6	-31551	-9.13	2.2e-16	0.05	-ve
		12	-33878	-9.99	2.2e-16	0.05	-ve
		24	-38662	-11.85	2.2e-16	0.05	-ve
	Downstream	6	-29685	-8.59	2.2e-16	0.05	-ve
		12	-32492	-9.58	2.2e-16	0.05	-ve
		24	-38674	-11.86	2.2e-16	0.05	-ve
SSI	**A4H002**	9	2.59e+3	3.71	0.0002	0.05	+ve
		12	2.24e+3	-1.19	0.24	0.05	+ve
		24	1.93e+3	-1.48	0.003	0.05	+ve
	A4H005	9	-1.05e+3	-1.17	0.24	0.05	-ve
		12	-1.08e+3	-1.19	0.24	0.05	-ve
		24	-1.91e+3	-2.38	0.02	0.05	-ve

Table 4.3 Lephalala River Catchment SPI, SSI and SPEI MK trends.

Index		Time scale	S	z	P_value	alpha	Trend
SPI	**Upstream**	6	15680	4.54	5.72e-6	0.05	+ve
		12	21398	6.31	2.79e-10	0.05	+ve
		24	20378	6.25	4.17e-10	0.05	+ve
	Beauty	6	11651	3.37	7.5e-4	0.05	+ve
		12	15974	4.71	247e-6	0.05	+ve
		24	15224	4.67	3.05e-6	0.05	+ve
	Downstream	6	15680	4.54	5.72e-6	0.05	+ve
		12	21398	6.31	2.79e-10	0.05	+ve
		24	20378	6.25	4.17e-10	0.05	+ve
	SAWS	6	-1181	-0.62	0.54	0.05	-ve
		12	-8506	-4.6	4.29e-6	0.05	-ve
SPEI	**Upstream**	6	-32187	-9.31	2.2e-16	0.05	-ve
		12	-35594	-10.5	2.2e-16	0.05	-ve
		24	-34638	-10.62	2.2e-16	0.05	-ve
	Beauty	6	-11525	-6.41	1.44e-10	0.05	-ve
		12	-13478	-7.72	1.14e-14	0.05	-ve
		24	-16016	-9.75	2.2e-16	0.05	-ve
	Downstream	6	-29685	-8.59	2.2e-16	0.05	-ve
		12	-30588	-9.02	2.2e-16	0.05	-ve
	SAWS	6	-11563	-6.43	1.25e-10	0.05	-ve
		12	-13324	-7.67	1.68e-14	0.05	-ve
		24	-16064	-9.78	2.2e-16	0.05	-ve
SSI	**A5H004**	9	1.08e+3	1.17	0.24	0.05	+ve
		12	1.47e+3	1.67	0.095	0.05	+ve
		24	-1.5e+3	-1.48	0.14	0.05	-ve



mmkUpstream_SPI6 | mmkUpstream_SPI12 | mmkUpstream_SPI24

File Edit View

```
     Corrected Zc        new P-value              N/N*         Original Z
    -0.5914631866       0.5542101142      0.4329150038      -0.3891607553
      old P.value                Tau        Sen's slope       old.variance
     0.6971572324      -0.0119564735     -0.0001287554  11945009.3333333638
     new.variance
5171173.7611224232
```

mmkSPEI_Downstream_SPEI6 | mmkSPEI_Downstream_SPEI12 | mmkSPEI_Downstream_SPEI24

File Edit View

```
                     Corrected Zc                        new P-value
    -3.8650155528537619709084O8       0.000111082121108989378315
                             N/N*                         Original Z
      4.937868684680893238692079      -8.588573052699830512324297
                      old P.value                                Tau
      0.0000000000000000008805608      -0.263690872751498994741581
                       Sen's slope                       old.variance
    -0.0029589499999999999688066  11945458.3333333332091569900512695
                      new.variance
58985104.628327079117298126220703
```

Figure 4.6 Sample of the modified MK output for SPI and SPEI.

In addition to the MK and modified MK trend analysis, the sequential MK was conducted, and a sample of the results is presented in Figure 4.7. The direction of change is indicated when the forward and backward (Progressive and Retrograde) lines intersect, after which there is some stabilisation. From the presented samples, SPI shows a positive trend, as similarly observed by the MK and modified MK. Points of detection are only noted at the 6th and 24th timescale for SPI, while SPEI SQMK progressive and retrograde lines did not intersect. Like MK for SPI and SPEI, SQMK, is depicting a continuous negative trend likely driven by increasing temperatures in the study area over the considered period of study.

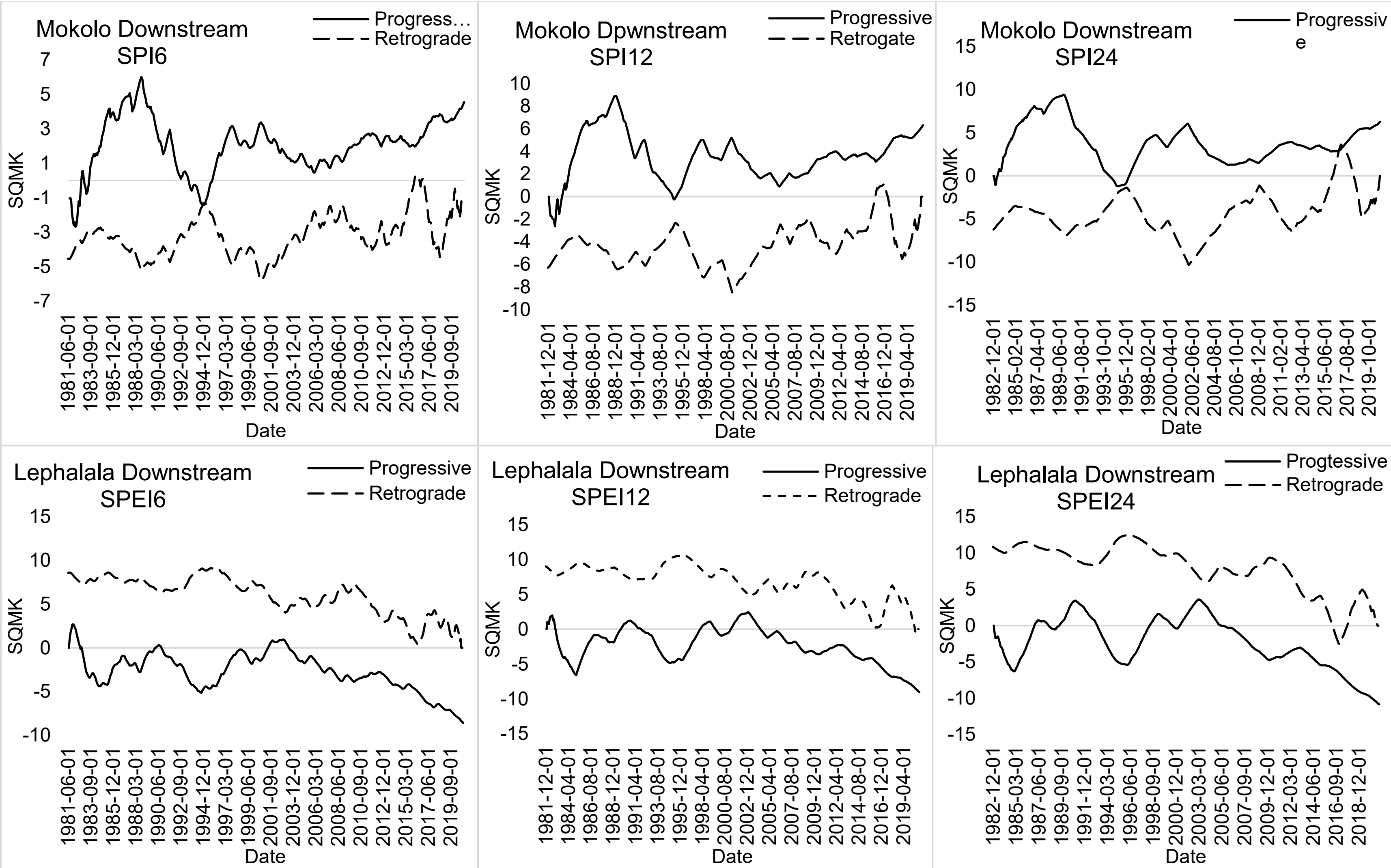


Figure 4.7 SQMK Lephalala and Mokolo catchments SPI and SPEI.

4.4 SUMMARY

This chapter assessed historical drought in the Mokolo and Lephalala River Catchments between 1980 and 2023 using three standardised drought indices (SPI, SSI, and SPEI) at the 6th, 12^{th,} and 24th timescales. The analysis revealed increasing drought frequency and severity over the four-decade period, with 15 major drought events identified, indicating intensification of water stress in recent decades. The SPEI, which incorporates temperature effects on evaporative demand, showed more pronounced drought trends compared to the precipitation-only SPI. It was noted that the Lephalale catchment experienced more frequent and severe droughts than the Mokolo catchment, reflecting higher evapotranspiration rates in this western region of the Limpopo River Basin. The 2015-2016 drought emerged as the most severe event on record, with SPEI values below -2.5 persisting for 18 months, resulting in severe agricultural losses, water supply restrictions, and ecological stress. Trend analysis using the Mann-Kendall test indicated statistically significant increasing trends in drought severity ($p < 0.05$) for all indices at the 12-month and 24-month timescales, confirming progressive water stress intensification in both catchments.

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CHAPTER 5: SOIL EROSION AND SEDIMENTATION

5.1 INTRODUCTION

One of the most common forms of land degradation worldwide is soil erosion and sedimentation, which seriously disturbs water supplies, ecological integrity, infrastructure stability, and agricultural output. Every year, some 75 billion tons of soil are lost worldwide, which results in decreased soil fertility, sedimentation of waterways, and heightened susceptibility of socioecological systems (Pimentel and Burgess, 2013). Although a variety of natural and man-made factors drive these processes, climate change is worsening them by changing vegetation patterns, intensifying extreme weather events, and altering rainfall regimes (IPCC, 2022; Nearing et al., 2004). Erosion dynamics are directly affected by how climate change alters the hydrological cycle. Particularly in dry and semi-arid regions, increased frequency and severity of high-magnitude rainfall events increase runoff generation and soil detachment rates. Arid and semi-arid regions with little vegetation cover, increased frequency and intensity of high-magnitude rainfall events increase runoff generation and soil detachment rates (Pruski and Nearing, 2002; Zhang and Nearing, 2005). Changes in rainfall seasonality and extended dry periods can cause soil surface crusting, decrease infiltration, and increase vulnerability to erosion once rain returns, even in humid and tropical areas (TLS et al., 2021). While wildfire intensification leaves soils bare and hydrophobic, significantly accelerating post-fire erosion and sediment yields, temperature increases also contribute to erosion through increased evapotranspiration, vegetation stress, and changed land cover conditions (Shakesby and Doerr, 2006; Prosser and Williams, 1998).

The sedimentation in rivers, reservoirs, and wetlands is a cascading consequence of upstream erosion. Sediment yields have increased significantly in many river basins worldwide due to land use change, agricultural expansion, deforestation, and extreme precipitation events (Walling, 2006). As climate change intensifies erosive forces, sedimentation threatens the longevity and functionality of hydraulic structures such as dams, irrigation canals, and water treatment systems critical infrastructures already under increasing pressure in drought-prone regions (Basson, 2008). Reservoir sedimentation reduces storage capacity, exacerbates water insecurity, and undermines hydropower generation, especially in regions with high interannual climate variability (Annandale et al., 2016). LULC changes interact synergistically with climate-induced erosion stresses. Expansion of cropland, overgrazing, urban development, and unsustainable tillage expose soils to erosive forces, while vegetation removal decreases surface roughness and protective cover (Southgate, 2020). In many developing regions, rapid population growth and economic pressures have driven unsustainable land conversion, intensifying erosion risks in marginal lands extremely sensitive to climatic fluctuations (FAO, 2019). The combined impact of climate and land use change creates complex feedback: eroded soils reduce productivity, prompting further land clearing and amplifying degradation pathways (Haregeweyn et al., 2017).

5.2 METHODOLOGY

Erosion and sediment delivery occur at extremely variable spatial and temporal scales, making it difficult and expensive to achieve representative observation (De Vente *et al*., 2007; Fryirs*, 2013*). Rooseboom and Annandale (1981) suggested methods of measuring suspended sediment loads in southern African rivers for catchments greater than 1 hectare. These include the bottle-sampling method and the measurement of sediment deposit volumes. The bottle sampling method used in this study involved lowering an open sampling bottle by hand 300 mm below the stream surface by hand and allowing it to fill (see Figure 5.1). Sampling was conducted in three sections of both the Mokolo and Lephalala Rivers, which constituted the upstream, middle and downstream (this was in the last accessible point before both rivers drain into the Limpopo River) reaches of the rivers. Figure 5.2 shows all the sampling points

Figure 5.1 Sediment sampling at Lephalala River @ Beauty.

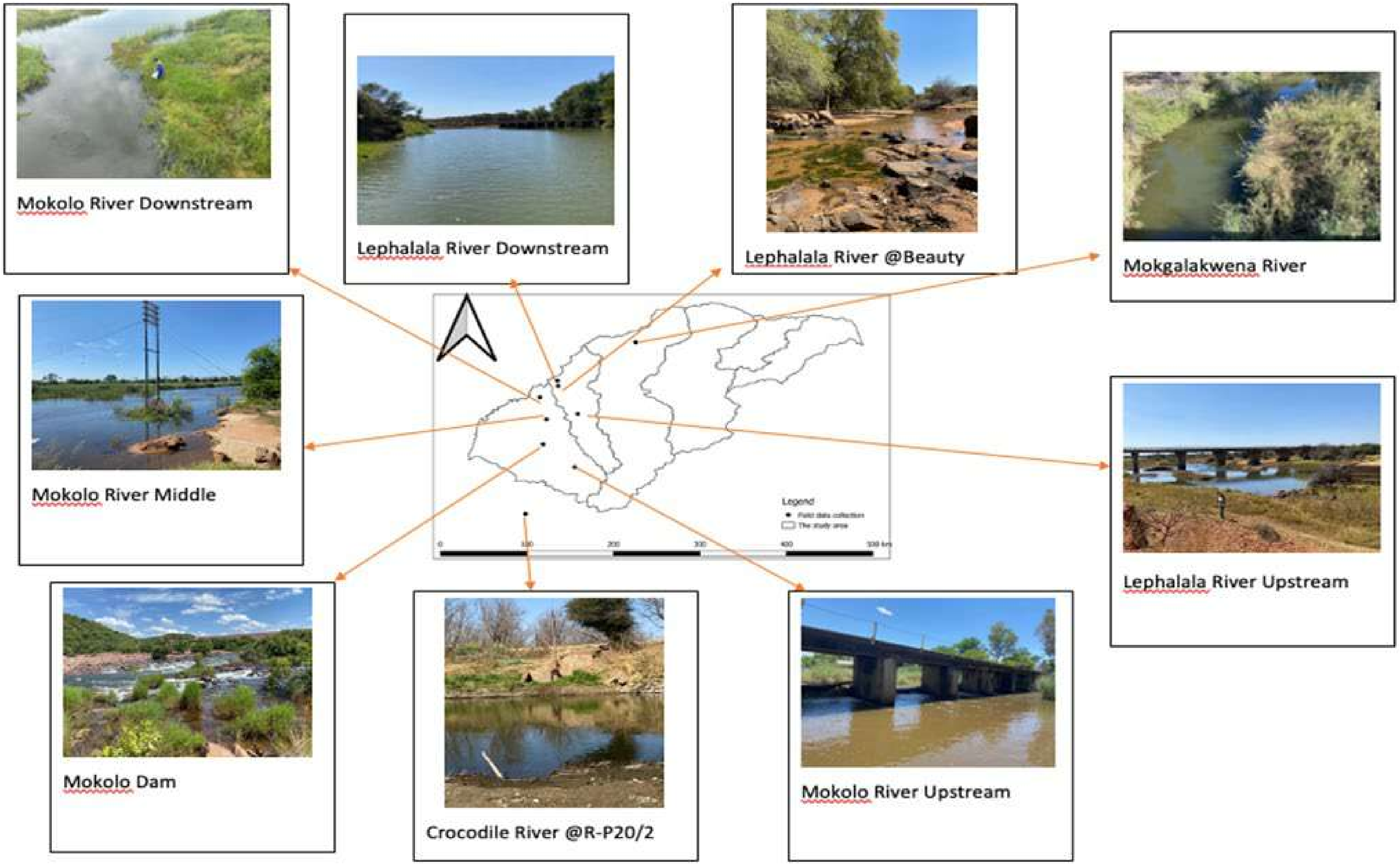

Figure 5.2 Water sampling points for sediment load analysis in the study area.

In the measurement of sediment deposit volumes, average sediment loads in rivers are measured indirectly by monitoring changes in the storage capacity of existing reservoirs. The water samples collected in the field for sediment analysis were separated in the Hydrology and Water Resources laboratory at the University of Venda. Figure 5.3 shows the sample preparation for sediment analysis.

Figure 5.3 Sediment separation and sediment sample preparation.

Digital soil data at a scale of 1:1 million were acquired from the Global Environment Facility Soil Organic Carbon database (URL: http://www.isric.org). This dataset was an upgraded version developed by national experts from the global Soil and Terrain (SOTER) database. The data were reclassified into the major hydrological soil groups (HSG) of the catchment with the help of the FAO/UNESCO revised manual for soil maps of the world based on their drainage characteristics. Additional resources, such as the World Reference Base for Soil Resources (IUSS Working Group WRB, 2015), were used to complement reference group soil descriptions.

Inherent soil erodibility (ISE) refers to the susceptibility of soils to detachment and transportation by erosive agents. It is a composite expression of those soil attributes (mechanical, chemical and physical) that affect the behaviour of a soil (Zund, 2017). The ISE assessment approach is biased towards the internal contributory factors (inherent to the soil) rather than the external triggering factors. The ISE combines surface soil stability (A Horizon) and subsoil (B Horizon) dispersiveness to classify soil erodibility categories, following the protocol outlined in the Soil Erodibility User Guide of the Department of Science, Information Technology, Innovation, Queensland Government, Brisbane (Zund, 2017). The full protocol and dataset can be accessed through www.data.qld.gov.au and http://qldspatial.information.qld.gov.au/catalogue/custom/index.page. Although the tool was developed for Australia, it can be applied to other study areas.

The ISE approach adopts a decision-tree-based model to elucidate the characteristics of surface soils and sub-soil interactions and their vulnerability to erosion (gully and rill). Surface soil stability is characterized based on soil texture (clay %), soil sodicity (ESP) and clay type (clay activity), while subsoil dispersity is categorised using soil texture (Clay %), soil sodicity (ESP), soil salinity (EC) and soil cation balance (Ca/Mg), simplified on a flow diagram (Figure 5.4). Reference data on diagnostic inherent soil characteristics with associated rating scores (Table 5.1), and an expert knowledge ranking system, based on 17 subcategories (Table 5.2), was used to classify erosion vulnerability (Table 5.3).

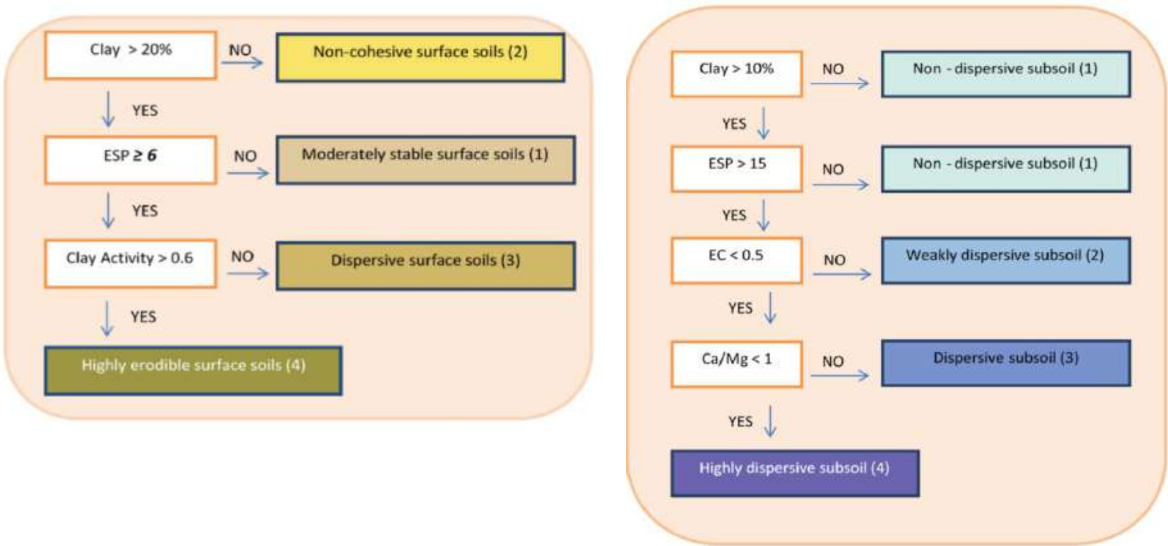

Figure 5.4. Surface soil erodibility and Subsoil dispersibility decision tree (after Zund, 2017).

Table 5.1. Classification of surface soil stability and sub-soil dispersibility. Source: Zund (2017).

Surface Soil Category	**Rating**
Moderately stable surface soils – soils that are unlikely to be dispersive. These are usually well-structured and resilient to degradation.	1
Non-cohesive surface soils – sandy soils that are non-structured or only weakly so and non-cohesive. These soils are easily eroded.	2
Dispersive surface soils – erodible loamy or clayey soils that are sodic, hard setting and likely to disperse in water.	3
Highly erodible surface soils – highly erodible clay soils that are sodic and dominated by expanding/swelling clays that disperse readily.	4
Sub-Soil Category	
Non-dispersive subsoils – non-sodic or weakly sodic subsoils that are unlikely to disperse.	1
Weakly dispersive subsoils – sodic subsoils that are saline or dominated by carbonate nodules that prevent these subsoils from dispersing readily.	2
Dispersive subsoils – sodic subsoils that disperse readily.	3
Highly dispersive subsoils – sodic soils that are also dominated by magnesium ions that enhances the dispersive affect.	4

Table 5.2 Overall inherent soil erodibility based on surface soil stability and subsoil dispersibility proposed by Zung (2017).

Subsoil dispersibility	Surface soil stability: Moderately stable surface soils	Non-cohesive surface soils	Dispersive surface soils	Highly erodible surface soils
No subsoil	1	5		8
Non-dispersive subsoils	2	4	11	14
Weakly dispersive subsoils	3	7		
Moderately dispersive subsoils	6	10	13	16
Highly dispersive subsoils	9	12	15	17

Table 5.3 Erosion vulnerability classification and inherent soil erosion descriptors (Modified after Zung, 2017).

Cell value	Soil characteristic	Vulnerability Classification (VC)
1	Moderately stable surface soils over rock or sediment	Very low erosion vulnerability
2	Moderately stable surface soils over non-dispersive subsoils	
3	Moderately stable surface soils over weakly dispersive subsoils	
4	Non-cohesive surface soils over non-dispersive subsoils	Low erosion vulnerability
5	Non-cohesive surface soils over rock or sediment	
6	Moderately stable surface soils over moderately dispersive subsoils	
7	Non-cohesive surface soils over weakly dispersive subsoils	
8	Clayey soils that erode and/or slake readily over rock or sediment	Moderate erosion vulnerability
9	Moderately stable surface soils over highly dispersive subsoils	
10	Non-cohesive surface soils over moderately dispersive subsoils	
11	Weakly dispersive clayey soils	
12	Non-cohesive surface soils over highly dispersive subsoils	High erosion vulnerability
13	Dispersive clayey soils	
14	Clayey surface soils that erode and/or slake over weakly dispersive subsoils	
15	Dispersive clayey surface soils over highly dispersive subsoils	Very high erosion vulnerability
16	Clayey surface soils that erode and/or slake over moderately dispersive subsoils	
17	Clayey surface soils that erode and/or slake over highly dispersive subsoils	

5.3 RESULTS

5.3.1 Field observation

Slopes of both transported and residual soils showed evidence of extreme erosion, manifested by irregular and disproportionate sizes of surface channels and gullies created by flowing water, as shown in Figure 5.4. Gullying displayed variable depths and was associated with areas with dispersive soils. In addition to overall land degradation and increased flood risks, the area's aesthetic features (particularly around Beauty Village) were seriously compromised. The channels served as dumping sites for the nearby residents in the Beauty community at Ga Seleka (Figure 5.5).


Figure 5.5 Development of gully erosion at Beauty (Mokolo); Left – bare land and steep slope contributing towards erosion, right – inherent soil erosion enhancing gully formation.

Tables 5.4 and 5.5 depict the sediment weight in each of the samples collected from the Lephalala and Mokolo rivers. The separated samples will be used further for sediment characterisation. Sediment load varies from 0.7 to 173 mg across all samples collected in all river reaches for the Lephalala River. Higher sedimentations, as shown in Table 5.4, were notable in the downstream reach of the Lephalala River. For the Mokolo River, the sediment load varied between 0.7 and 18.3. and like the Lephalala River, the highest load was notable in the downstream parts of the river. From this analysis, the Lephalala River shows higher sedimentation compared to the Mokolo River. This may be attributed to large-scale agriculture and subsistence farms adjacent to this river.

Table 5.4 Lephalala River sediment load.

	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**
Lephalala Upstream	Filter weight (F) =771.9 mg S+F= 789.0 mg Sediments weight= 17.1 mg	Filter weight=819.3 mg S+F= 820.0 mg Sediments weight= 0.7 mg	Filter weight= 794.3mg S+F= 795.8 mg Sediments weight= 1.5 mg	Filter weight=853.2 mg S+F=854.0 mg Sediments weight= 0.8 mg	Filter weight=830.5 mg S+F=832.1 mg Sediments weight= 1.6 mg
Lephalala Middle	Filter weight=816.6 mg S+F= 823.2 mg Sediments weight= 6.6 mg	Filter weight=783.5 mg S+F= 840.0 mg Sediments weight= 56.5 mg	Filter weight= 836.2 mg S+F= 988.8 mg Sediments weight= 152.6 mg	Filter weight=770.0 mg S+F=772.8 mg Sediments weight= 2.8 mg	Filter weight=806.4 mg S+F=807.9 mg Sediments weight= 1.5 mg
Lephalale Downstream	Filter weight=780.3 mg S+F= 953.7 Sediments weight= 173.4 mg	Filter weight=781.1 mg S+F= 782.8 Sediments weight= 1.7 mg	Filter weight= 821.4 mg S+F= 822.6 Sediments weight= 1.2 mg	Filter weight= 828.5 mg S+F=831.1 Sediments weight= 2.6 mg	Filter weight=782.2 mg S+F=785.5 Sediments weight= 3.3 mg

Table 5.5 Mokolo River sediment load.

	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**
Mokolo Upstream	Filter weight=812.1 mg S+F= 814.4 Sediments weight= 2.3 mg	Filter weight=803.8 mg S+F= 804.5 Sediments weight= 0.7 mg	Filter weight= 798.5 mg S+F= 799.7 Sediments weight= 1.2 mg	Filter weight= 814.3 mg S+F= 817.0 Sediments weight= 2.7 mg	Filter weight=799.9 mg S+F= 801.3 Sediments weight= 1.4 mg
Mokolo Middle		Filter weight= 779.9 mg S+F= 800.0 mg Sediments weight= 20.1 mg	Filter weight=817.1 mg S+F= 821.3 mg Sediments weight= 4.2 mg	Filter weight= 835.1 mg S+F=837.7 mg Sediments weight= 2.6 mg	Filter weight=801.8 mg S+F= 802.4 mg Sediments weight= 0.6 mg
Mokolo Downstream	Filter weight=807.7 mg S+F= 825.0 mg Sediments weight= 17.3 mg	Filter weight=824.9 mg S+F= 827.1 mg Sediments weight= 2.2 mg	Filter weight= 831.7mg S+F= 833.7 mg Sediments weight= 2 mg	Filter weight= 800.1 mg S+F= 801.9 mg Sediments weight= 1.8 mg	Filter weight=832.3 mg S+F=850.6 mg Sediments weight= 18.3 mg

5.3.2 Classification of inherent soil erodibility

The ISE appraisal focused mainly on the reference group soils. Eight main soil types were identified across both catchments. Results of pedogenic characteristics, texture, stability, and disability ratings, as well as erosion vulnerability classifications (EVC), are summarised in Table 5.4. The EVC for the study areas ranged from very low to very high, with 38% of the soil classified as high, and 25% as having very high vulnerability to erosion. These findings indicate that the soil types in Lephalala and Mokolo are inherently susceptible to erosion. The complexities of external triggering factors, such as high rainfall variability (frequency and intensity) within subcatchments, and LULC change, may further compound erosion risk in the study areas.

Table 5.6 Inherent Soil erodibility and erosion vulnerability classification for reference soils from Lephalale and Mokolo Catchments.

Soil type	Description	Soil Texture	Stability Rating	Dispersibility Rating	IE Rating	Vulnerability Classification
Acrisols (AC)	Pedogenetic differentiation of clay content (topsoil < subsoil) with argic subsoil horizon; advanced degree of weathering resulting to leaching of base cations.	Clay Loam	4	3	16	VH
Arenosols (AR)	Deep sandy soils (> 35% coarse fragments) exclusive of materials with fluvic or andic properties.	Sand	2	1	4	L
Cambisols (CM)	Young soils, with poorly developed horizon differentiation in the subsoil.	Sandy Loam	2	3	10	M
Leptosols (LP)	Very thin soils, extremely rich in coarse fragments including weathered calcareous materials	Sand	2	4	12	H
Luvisols (LV)	Pedogenetic differentiation of clay content (topsoil < subsoil) with argic subsoil horizon. High-activity clays and a high base saturation with low permeability	Clay Loam	3	3	13	H
Lixisols (LX)	Pedogenetic differentiation of clay content (topsoil < subsoil) with argic subsoil horizon. Low-activity clays and a high base saturation. Low aggregate stability.	Clay Loam	4	3	16	VH
Nitosols (NT)	Deep, well-drained, red to reddish-brown clayey soils with nitic horizon, typical angular blocky structure, high aggregate stability; rich in Fe and little water-dispersible clay (kaolinite)	Clay	1	2	3	VL
Regosols (RG)	Weakly developed soils in unconsolidated, generally fine-grained material. No diagnostic horizons. Low water holding capacity	Silt	2	4	12	H

IE – Inherent Erodibility, VH – Very High, H – High, M – Moderate, L – Low, VL – Very Low.

5.3.3 Implications of topsoil-subsoil interactions on erosion potential

The predominant reference group soils in the area (Figure 5.6) can be grouped into four major categories, namely, Group 1; young-shallow-poorly developed soils (Cambisols, Regosols, and Leptosols), and Group 2; soils with argic sub horizons, associated with high/low activity clays (Acrisolos, Luvisols and Lexisols), Group 3; Very coarse soils (Arenosols), and Group 4; well-drained low dispersible soils (Nitosols). Groups 1 and 2 contribute largely towards the high erosion susceptibility of the study areas, while Group 4 is the most stable pedologic unit (but of comparatively very small areal extent and therefore minimal implications for soil security).

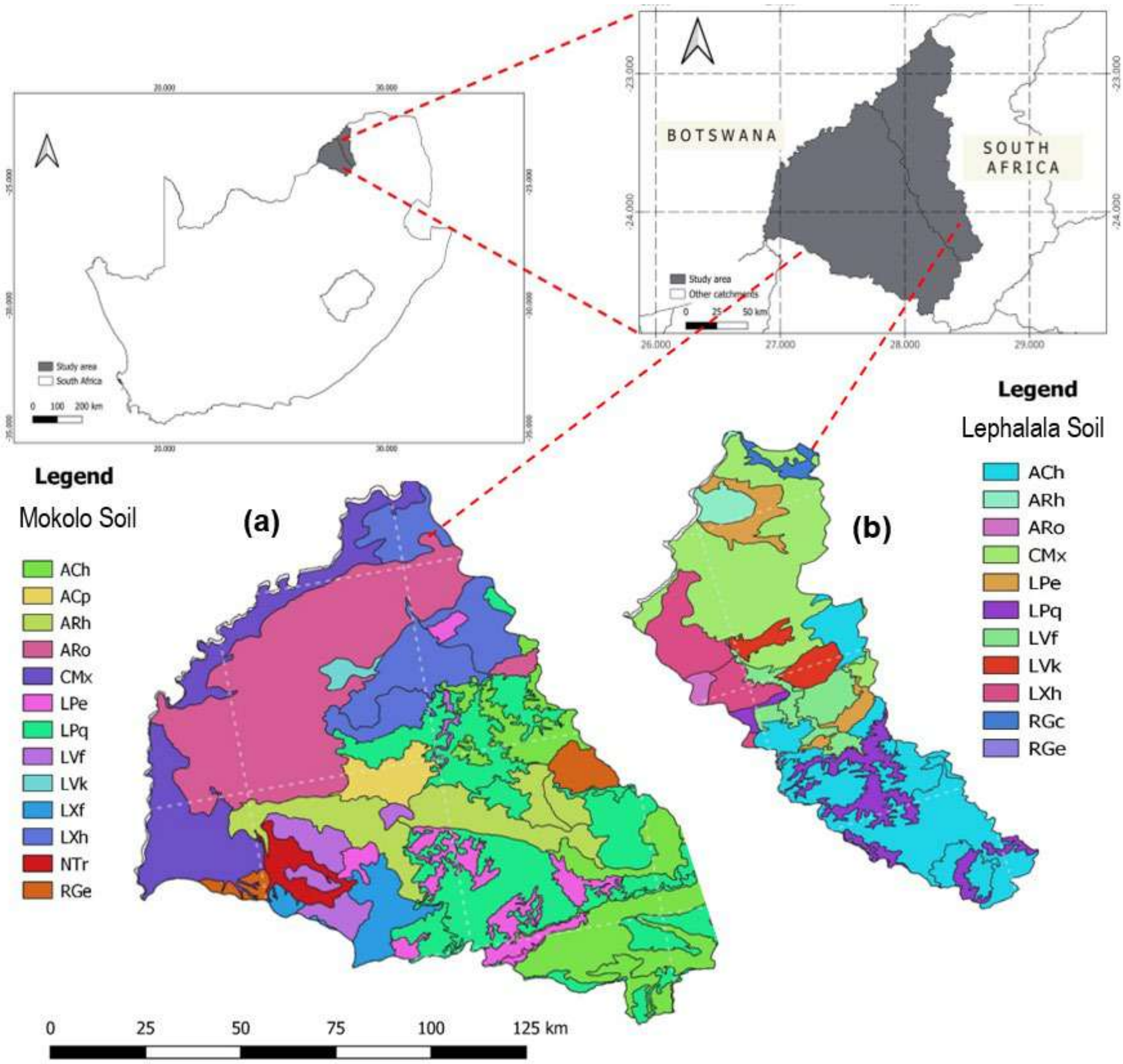

Figure 5.6 Soil typology maps for Mokolo and Lephalala catchments.

The development of argic sub-horizons is enhanced by the semi-arid to arid climate in the area, coupled with favourable parent materials (acidic igneous and metamorphic rocks). Alteration within the argic horizon may produce strongly acidic soils containing high-activity clay minerals such as vermiculite or smectites (such as Luvisols) or low activity clays such as kaolinite (Acrisols), as well as soils with high base saturation (Lixisols). Generally, soils with large amounts of high activity clays (> 24 $cmol^+/kg$

clay) are not highly weathered and have a high CEC under all pH levels. In contrast, low activity clays are more highly weathered due to their reduced surface area, low activity clays (< 24 $cmol^+$/kg clay) and lower capacity to retain and supply nutrients (IUSS Working Group WRB, 2015).

The literature further contends that soils high in clay have low erodibility factors (K values) of about 0.05 to 0.15 because they are resistant to detachment. Coarse-textured soils, such as sandy soils, have low K values, about 0.05 to 0.2, because of low runoff, even though these soils are easily detached (see *Technical Guide to RUSLE use in Michigan* – online resource). This online resource suggests that medium-textured soils, such as the silt loam soils, have a moderate K value, about 0.25 to 0.4, because they are moderately susceptible to detachment, and they produce moderate runoff. Soils having a high silt content are the most erodible of all soils. They are easily detached, tend to crust, and produce high rates of runoff. Values of K for these soils tend to exceed 0.4. The above observations are consistent with the characteristics of soil typologies from the Lephalala and Mokolo Catchments. However, further studies based on measured and empirically determined K values are ongoing to ascertain the proposed K classification scheme.

5.4 SUMMARY

Soil analysis studies showed that the two catchments are characterised by young, shallow, and poorly developed soils, and as such, these soils can easily detach during rain. This is evident in the study area by several gully erosions, which are mainly near riverbanks. Alteration within the argic horizon may produce strongly acidic soils containing high-activity clay minerals such as vermiculite or smectites (such as Luvisols) or low activity clays such as kaolinite (Acrisols), as well as soils with high base saturation (Lixisols). This alteration may not only result in sedimentation in nearby water bodies but also compromise the water chemistry of rivers. Sediment loads were noted in the upstream and downstream reaches of the Lephalala River, with the Mokolo being highly sedimented in the lower reaches of the river system.

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CHAPTER 6: FUTURE PROJECTION OF RAINFALL, TEMPERATURE AND DROUGHT CONDITIONS

6.1 INTRODUCTION

Climate change poses significant threats to water resources and agricultural productivity in semi-arid regions globally, with Sub-Saharan Africa identified as particularly vulnerable to projected climate variability and extremes (IPCC, 2021; Niang et al., 2014). South Africa, characterised by diverse climatic zones ranging from Mediterranean to semi-arid and arid conditions, faces substantial challenges in managing water resources under changing climatic conditions (Engelbrecht et al., 2015). The semi-arid regions of the country, which constitute approximately 70% of the land area, are especially susceptible to climate-induced hydrological stresses due to their marginal rainfall patterns, high evapotranspiration rates, and dependence on rainfed agriculture (Scholes and Biggs, 2005; Hoffman et al., 2018). Recent observational studies have documented significant warming trends across southern Africa, with temperature increases exceeding the global average, alongside shifts in rainfall patterns characterised by increased variability and changes in seasonal distribution (Kruger and Sekele, 2013; MacKellar et al., 2014). These observed changes have already manifested in more frequent and intense drought events, including the severe 2015-2017 drought that affected the Western Cape Province and the 2019-2020 drought in the Eastern Cape (Sousa et al., 2018; Mahlalela et al., 2019). Understanding future climate trajectories in semi-arid South Africa is therefore critical for developing effective adaptation strategies and informing water resource management, agricultural planning, and disaster risk reduction initiatives (Conway et al., 2015; Ziervogel et al., 2014).

Projected changes in temperature across southern Africa show robust agreement among climate models, with ensemble mean warming of 2-4°C by the end of the 21st century under RCP8.5, and 1-2°C under RCP4.5 (Engelbrecht et al., 2011; James and Washington, 2013). The semi-arid interior regions are projected to experience greater warming compared to coastal areas, with increases in the frequency and intensity of heatwaves and warm extremes (Dosio, 2017; Engelbrecht et al., 2013). In contrast, rainfall projections exhibit greater uncertainty and spatial heterogeneity, with some models projecting modest increases in summer rainfall over northeastern regions, while others suggest decreases, particularly during the austral winter months (Lazenby et al., 2016; Pinto et al., 2016). This uncertainty is partly due to the complex interactions between large-scale atmospheric circulation patterns, including the South Indian Ocean Convergence Zone, tropical-temperate troughs, and mid-latitude westerlies (Reason and Rouault, 2005; Hart et al., 2010). A major concern for semi-arid South Africa is the projected intensification of drought conditions, driven by the combined effects of reduced rainfall, increased evaporative demand due to higher temperatures, and shifts in rainfall seasonality (Dai, 2013; Cook et al., 2014). Climate model projections indicate an increase in both meteorological and agricultural drought frequency and severity, with implications for water security, food production, and ecosystem functioning.

This chapter presents future projections of rainfall, temperature, and drought in semi-arid South Africa, drawing on CORDEX-Africa regional climate model simulations and relevant literature. The analysis examines projected changes across multiple time horizons (near-term: 2021-2050 and far future 2051-2100) under moderate and high emission scenarios. By integrating climate model outputs with observed trends, this chapter aims to provide a comprehensive assessment of future climate outlook in the two sub-catchments of the LRB, thereby informing climate adaptation planning and resilience-building efforts in this vulnerable region (Ziervogel et al., 2016; Midgley and Thuiller. 2011).

6.2 METHODOLOGY

6.2.1 Climate change projections

In climate change scenarios studies, uncertainty arises from limitations such as the selection of future climate models, insufficient physical understanding of various feedback, and computational constraints (Martinex-Salvador et al., 2021). Therefore, efficient corrections are needed to make an appropriate choice in various climate change situations. The Delta Statistical Downscaling (DSD) method was applied to downscale projections of future regional rainfall and temperature using data from the CORDEX-Africa project. The downscaling was to 0.5 degrees and was bias-corrected using a quantile-mapping approach for the key climatic variables of interest. The CMhyd software (Rathjens et al., 2016) was used to adjust and eradicate bias for daily rainfall and temperature data. This study used five GCMs (MPI-ESM1-2-HR, GFDL-ESM4, MRI-ESM2-0, IPSL-CM6A-LR, and UKESM1-0-LL), details of which are shown in Table 6.1. The downscaled data used in this study for five models considered two emission scenarios, Shared Socio-economic Pathways (SSPs) SSP2-4.5 (intermediate level of emissions) and SSP5-8.5 (a high emission scenario). The selection of these climate models was informed by previous studies (Orkodjo et al., 2022) and their successful application in hydrological research in southern Africa (Angelina et al., 2015). SSPs' climate change projections and socio-economic scenarios were further used to evaluate climate change impacts on water resources availability and inform adaptation plans at the local level. The bias-corrected GCM data were divided into three periods: the base period (1980–2019), near-future (2020–2049) and far-future (2050–2099).

According to Tebaldi and Knutti (2007), a multi-model ensemble is a set of models created by combining multiple models called ensemble members. Multi-model ensembles frequently outperform single models (Duan and Phillips, 2010; Miao et al., 2012) and are thought to improve output skill, consistency, and dependability (Cantelaube and Terres, 2005). Simple Multi-model Averaging (SMA) (Equation 6.1) (Georgakakos et al., 2004) was used to characterise these model ensembles.

$$X_t = \overline{X_{obs}} + \sum_{i=N}^{N} \frac{(X_{sim})_{i,t} - (\bar{X}_{obs})_t}{N} \tag{6.1}$$

X_t is the multi-model variable simulation, such as rainfall or temperature, from the CORDEX-Africa model, derived using SMA at time t, and corresponds to the i^{th} model variable simulation at time t, X_{sim} is the time of the i^{th} model variable simulation, $\overline{X}_{obs}$ is the observed average, and N is the number of models under consideration.

Table 6.1 Details of the GCMs adopted for this study.

Modelling centre	ID	Literature
Geophysical Fluid Dynamics Laboratory, United States	GFDL-CM4	Huan et al. (2018)
Institut Pierre Simon Laplace Climate Modelling Centre, France	IPSL-CM6A	Boucher et al. (2020)
Max Planck Institute for Meteorology, Germany	MPI-ESM1	Gutjahr et al. (2019)
Meteorological Research Institute, Japan	MRI-ESM2	Yukomoto et al. (2019)
Met Office Hadley Centre, United Kingdom	UKESM1	Sellar et al. (2019)

6.2.2 Time series analysis

Time series of both near and far future climate data scenarios were analysed for seasonal cycles and variability. A linear trend was also fitted to the data to reveal the future rainfall, temperature and drought outlook of the two catchment areas.

6.3 RESULTS

Overall, historical trends analyses have been detailed for the study region. Studies such as Odiyo et al. (2021) reported that Limpopo Province is characterised by strong signals of climate change and global warming from observations and climate models. Maximum temperatures have risen by more than 2°C since 2000 above the 1981-2010 long-term mean, with five of the hottest years since records began from 2014, with 2016 being the hottest on record. This was further supported by Engelbrecht et al. (2015), who indicated that an increase in surface air temperatures over the African continent had risen at a rate more than double the global average. The continuously rising temperatures have negative impacts on surface water resources, the exposed topsoil, and environmental health. Therefore, this section will focus on the analysis of the near-future and far future climate.

6.3.1 Rainfall timeseries analysis

Figures 6.1 to 6.4 show selected interannual rainfall time series for near and far future climate under SSP585 and SSP245, respectively, for both catchment areas. Relatively high average monthly rainfall occurs in the rainfall months of November to February, while the dry seasons (April to September) have relatively low average monthly rainfall, with some dry months experiencing no rainfall. This is more notable in Figure 6.5, which indicates the mean monthly rainfall over the study area. There is a notable difference in rainfall across the months, for example, the months of February, April and October showed that the far future rainfall is much higher compared to near future rainfall for station A42A2 upstream. The same is noted for the downstream station, A50J2. This shows average rainfall is considered to be increasing over this region. It should be noted that the increase in rainfall does not translate to an increase in water resources availability as there are other variables at play, from water users and other climatic variables.

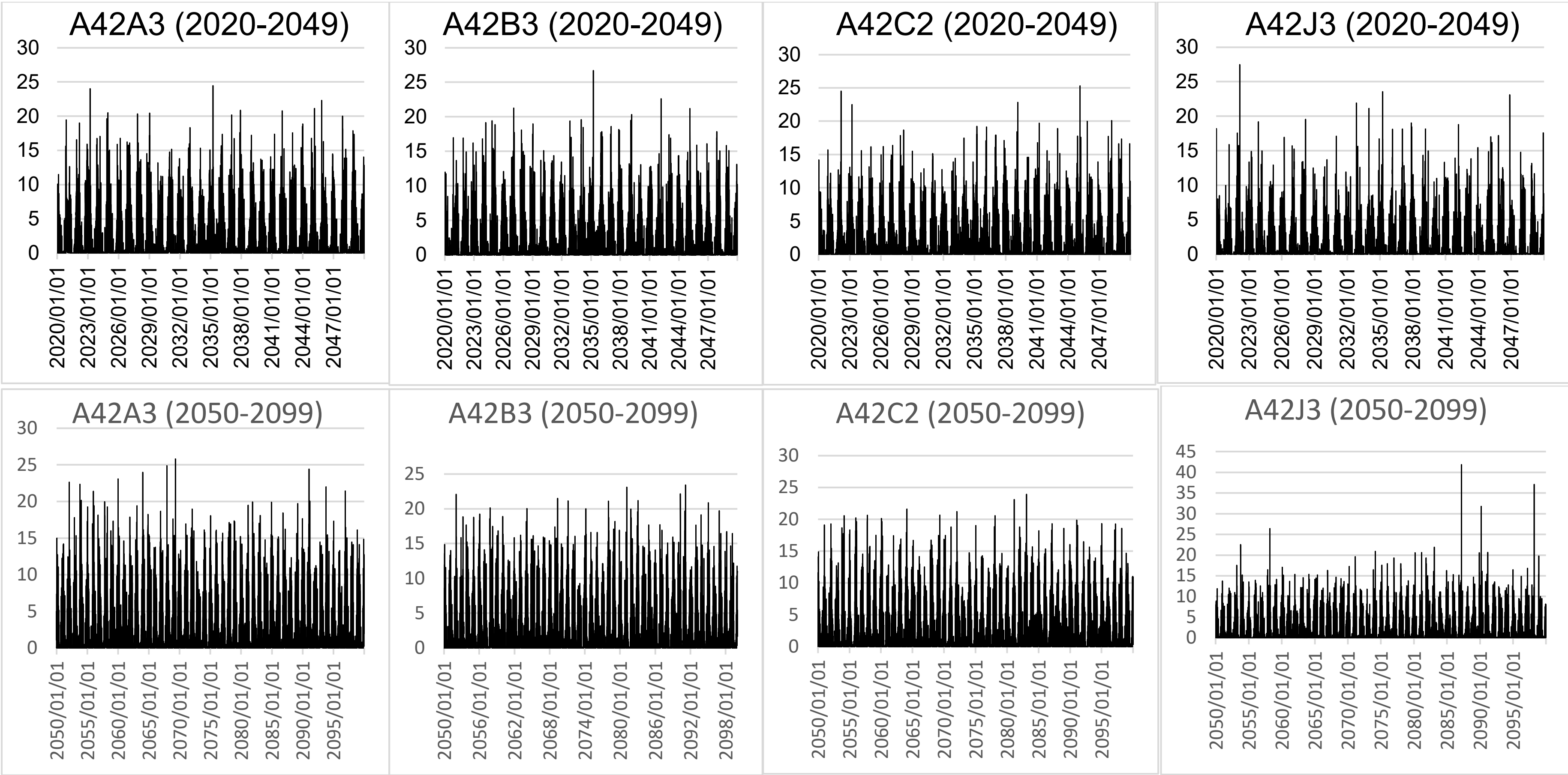

Figure 6.1 Mokolo River Catchment Near future and far future rainfall time series under SSP2-4.5 (moderate emission scenario).

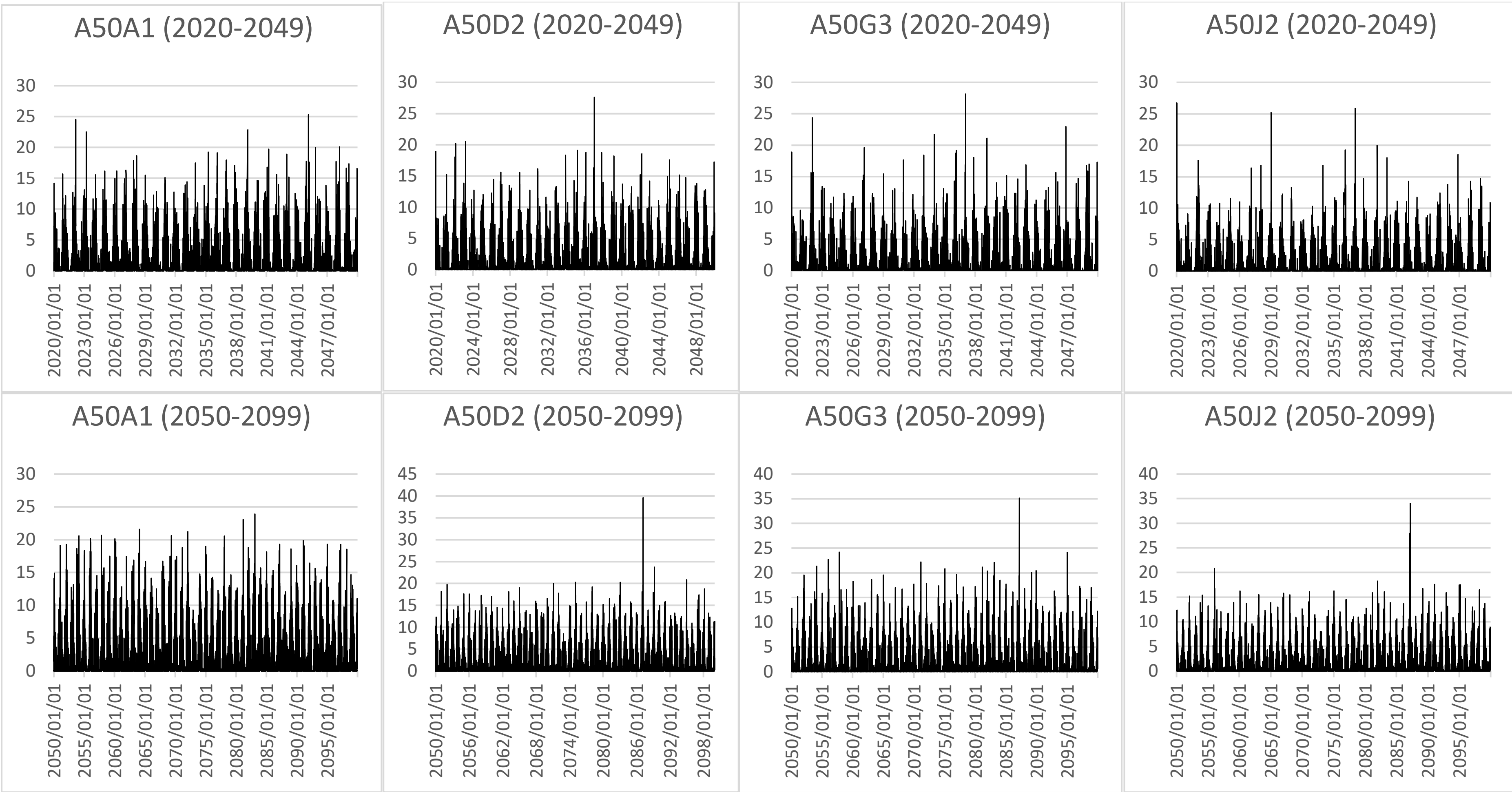

Figure 6.2 Lephalala River Catchment Near future and far future rainfall time series under SSP2-4.5 (moderate emission scenario).

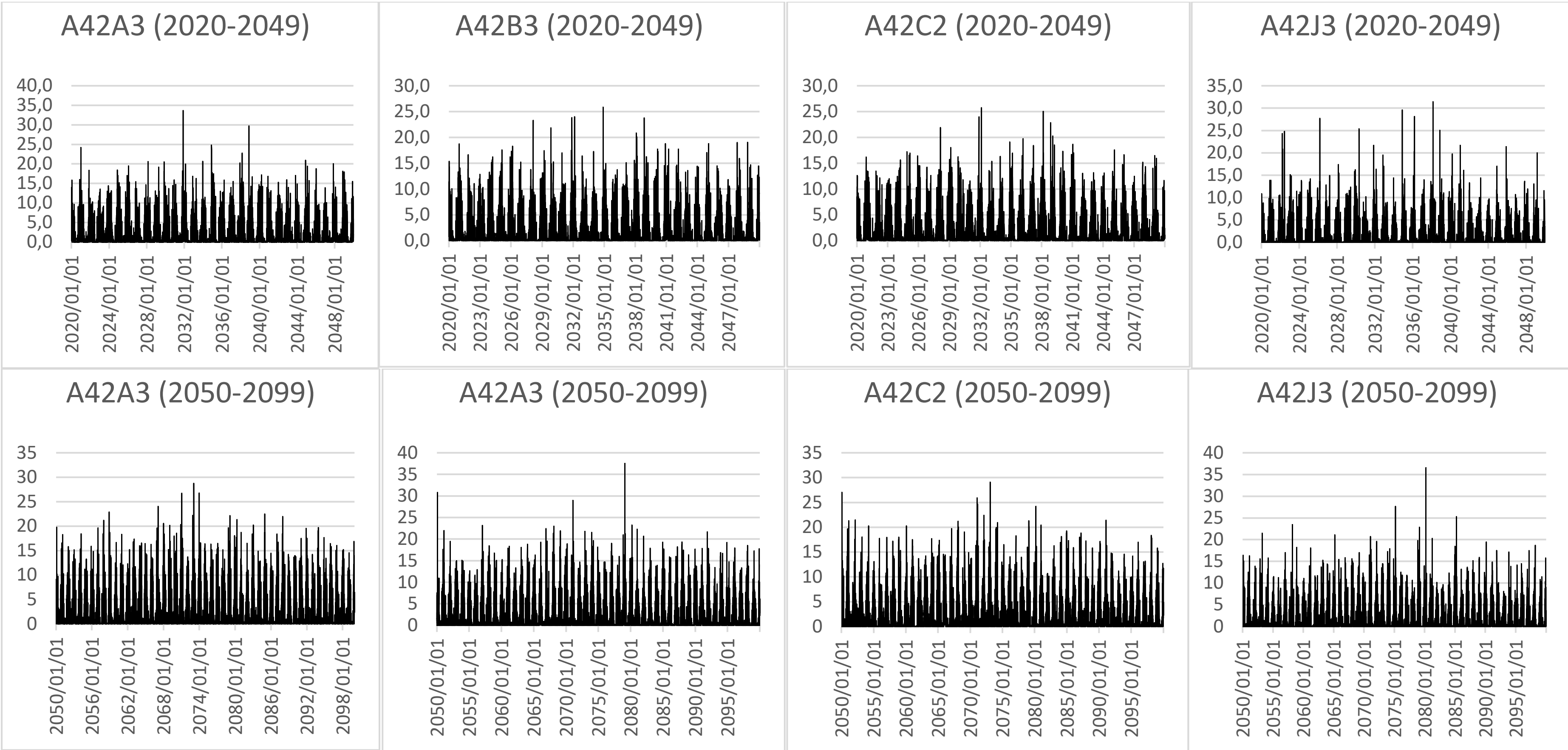

Figure 6.3 Mokolo River Catchment Near future and far future rainfall time series under SSP5-8.5 (high emission scenario).

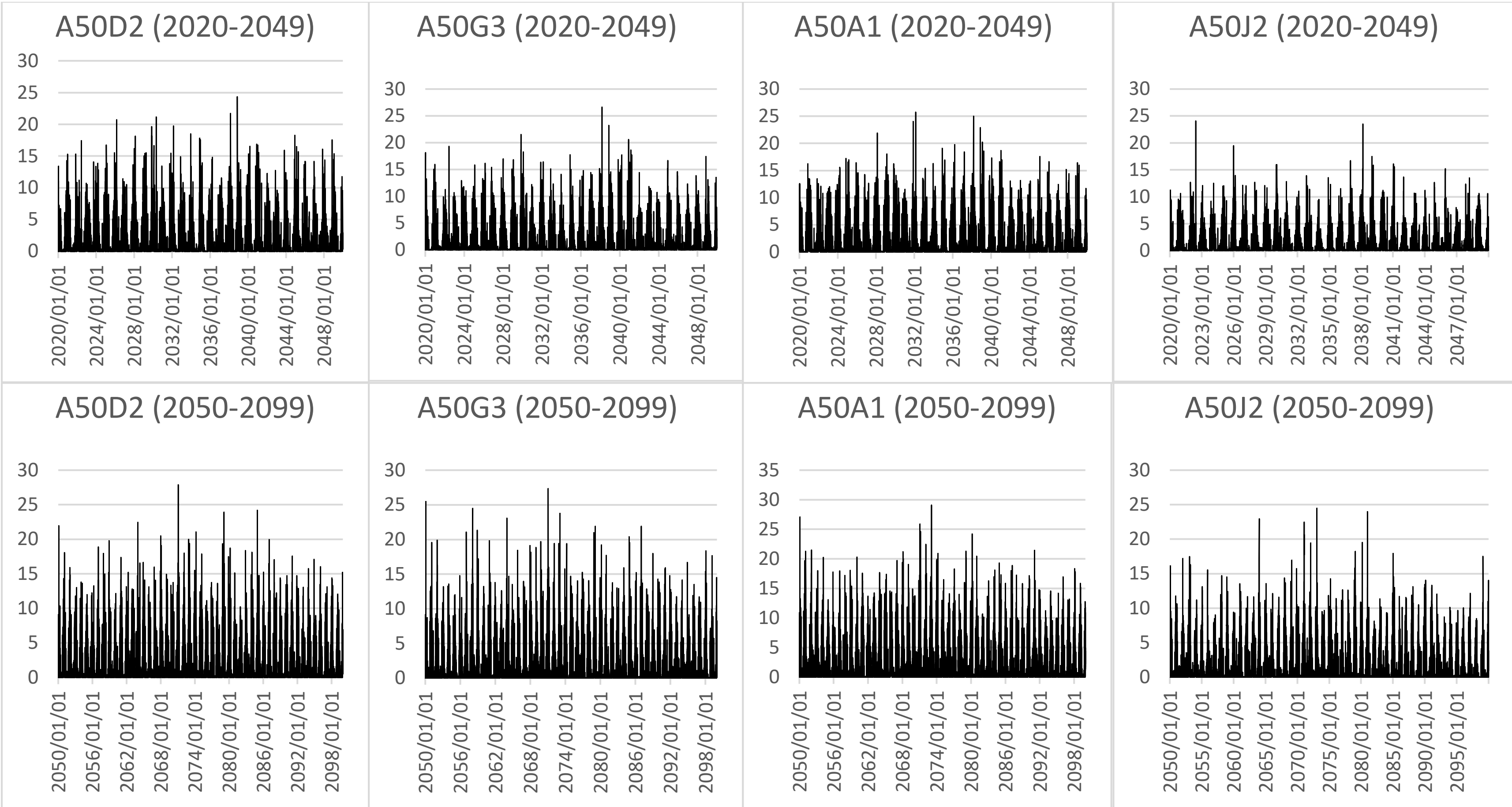

Figure 6.4 Lephalala River Catchment Near future and far future rainfall time series under SSP5-8.5 (moderate emission scenario).

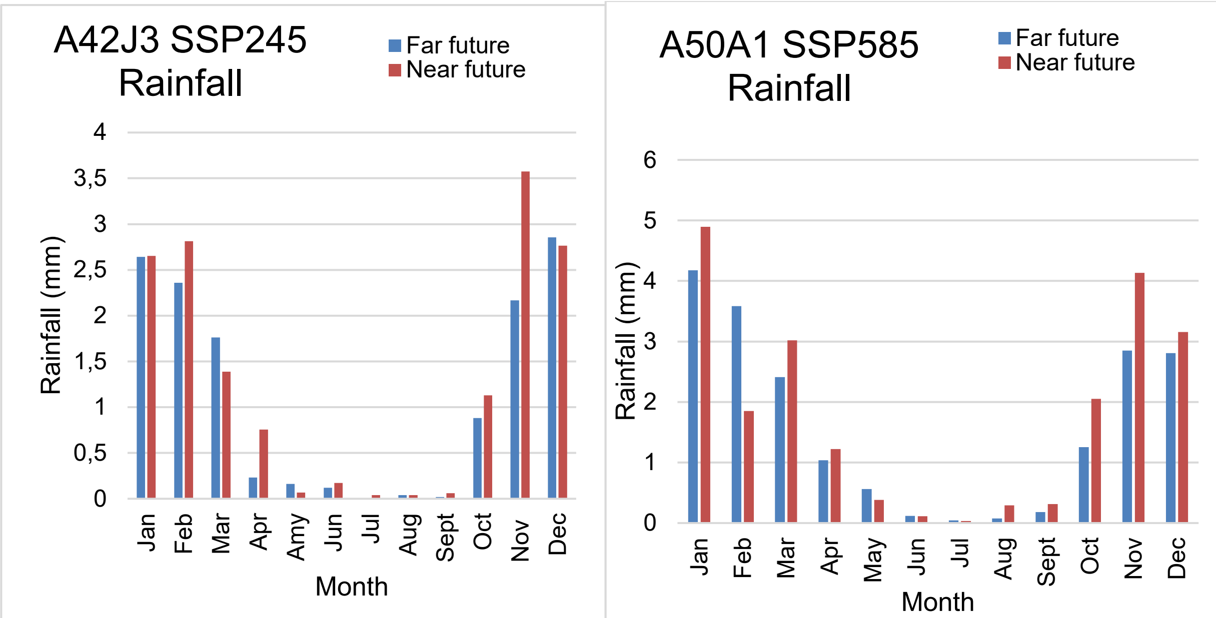

Figure 6.5 Near and far future mean monthly rainfall for SSP5-8.5 (high emission scenario) and SSP2-4.5 (moderate emission scenario).

6.3.2 Temperature time series analysis

The average minimum and maximum temperatures over the study area indicate a relatively warmer summer and cooler winter months. Figures 6.6 to 6.9 show the minimum and maximum temperatures for the near and future climate under SSP245 and SSP585. The upstream catchment shows a notable increasing trend in station A50A1, with the other stations and points in the catchment showing a rather stationary trend. The near-future monthly average across all months was higher than the far-future minimum and maximum temperatures. The near future results indicate variable behaviour in the future, where both extreme events (drought and floods) will prevail over the study area. Figure 10 depicts the monthly averaged near future and far future mean month minimum and maximum temperature time series for SSP5-8.5 (a high emission scenario) and SSP2-4.5 (moderate emission scenario).

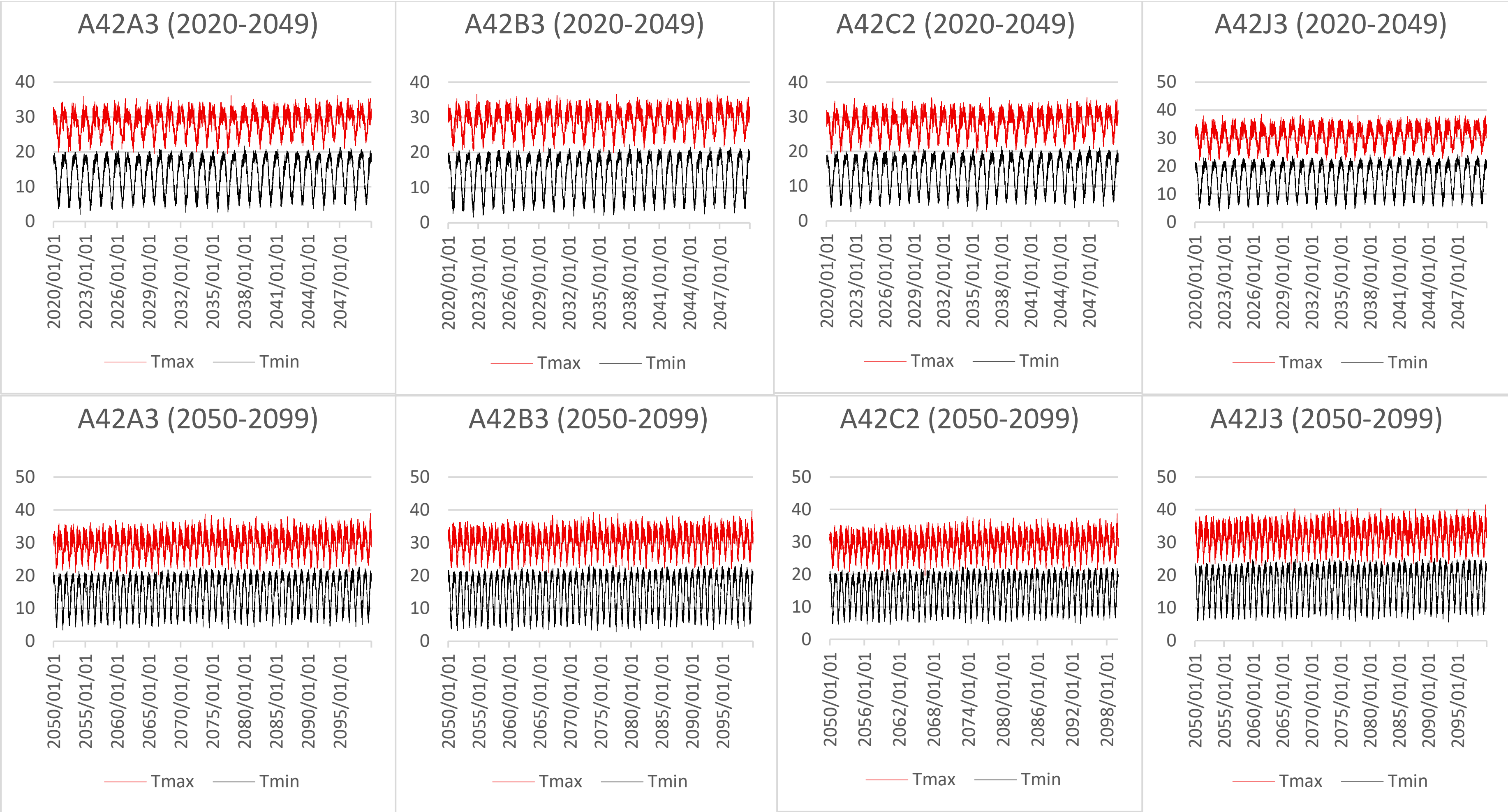

Figure 6.6 Mokolo River Catchment Near future and far future minimum and maximum temperature time series under SSP2-4.5 (moderate emission scenario)

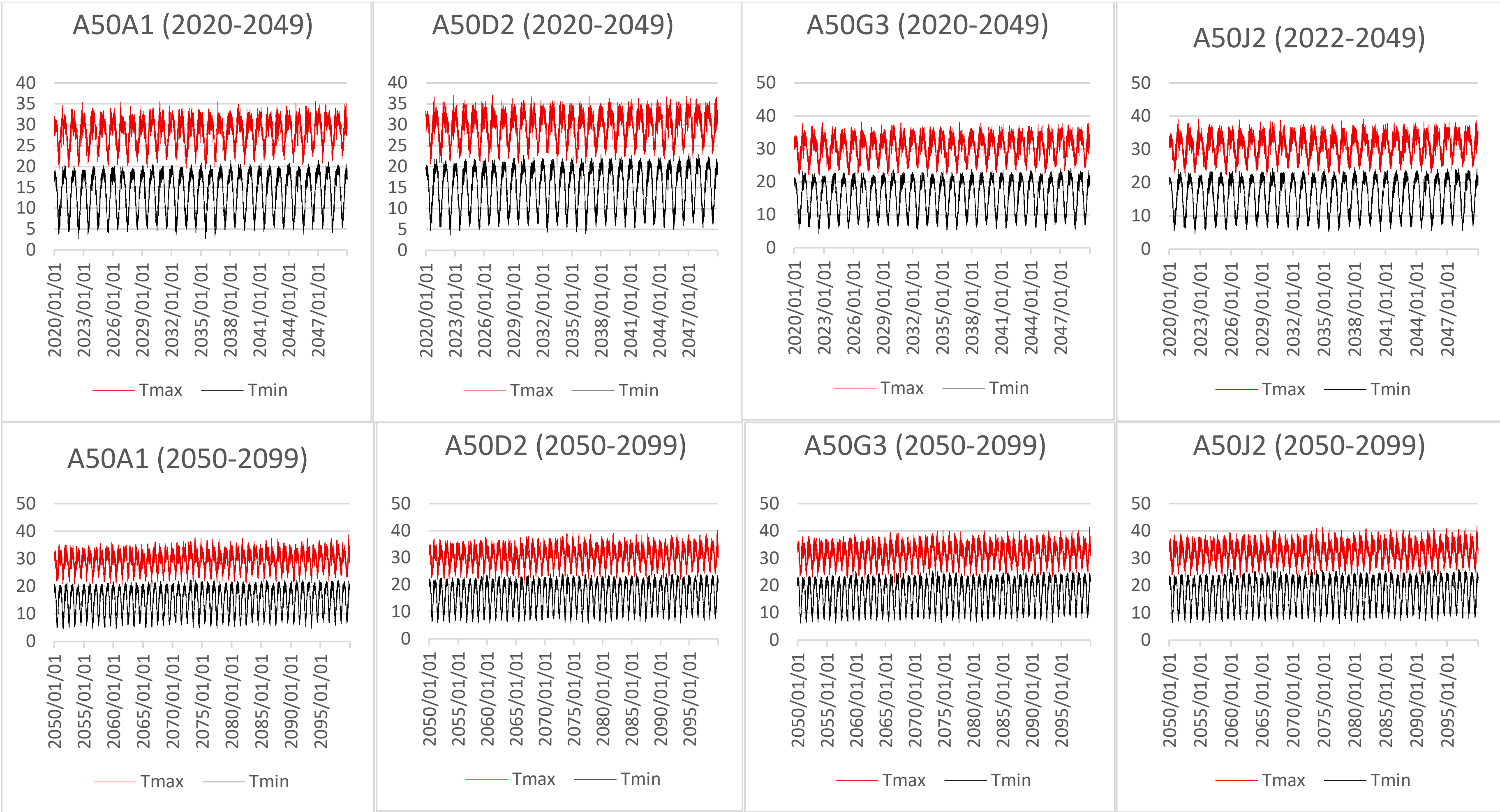

Figure 6.7 Lephalala River Catchment Near future and far future minimum and maximum temperature time series under SSP2-4.5 (moderate emission scenario).

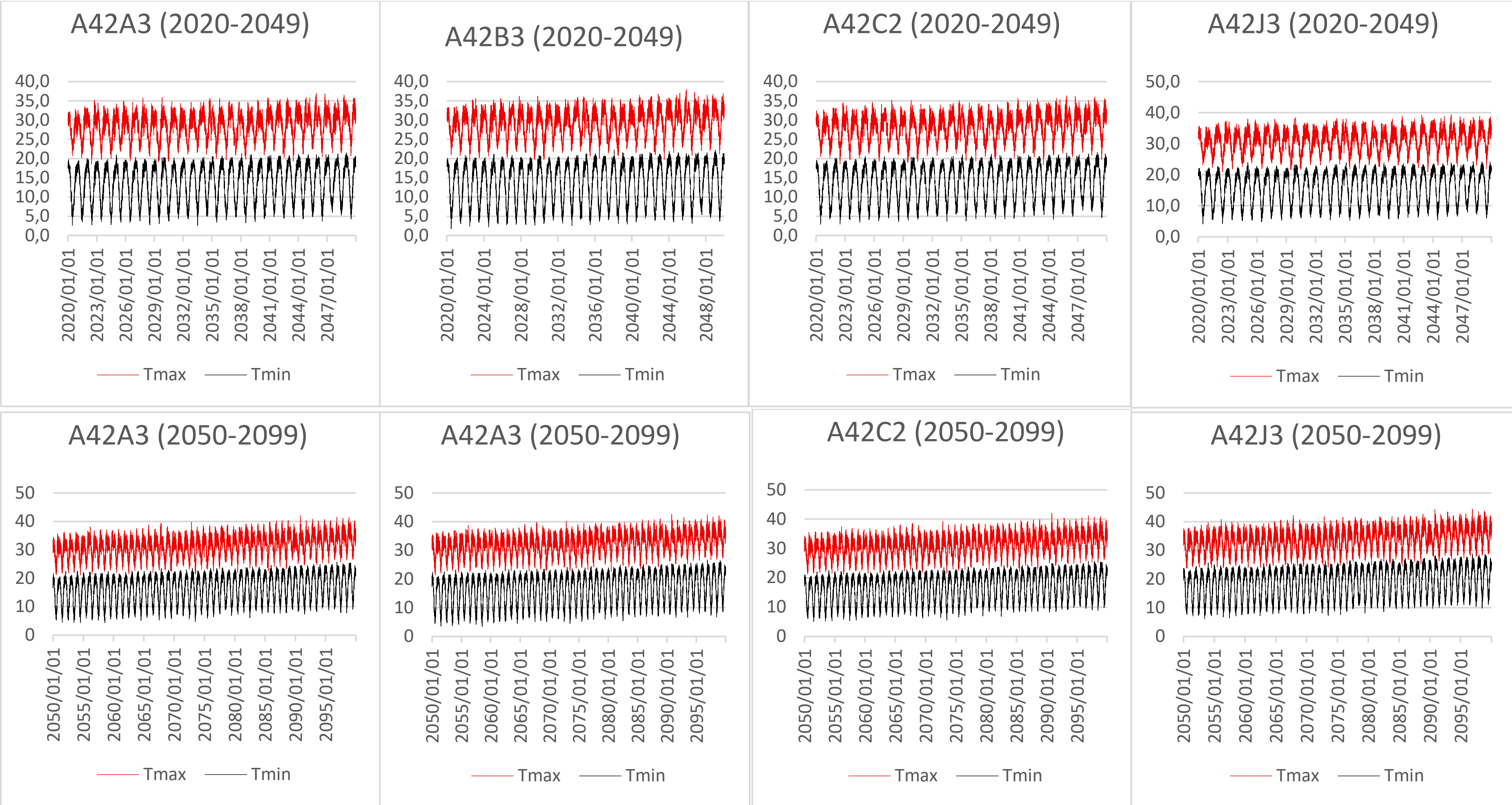

Figure 6.8 Mokolo River Catchment Near future and far future minimum and maximum temperature time series under SSP5-8.5 (high emission scenario).

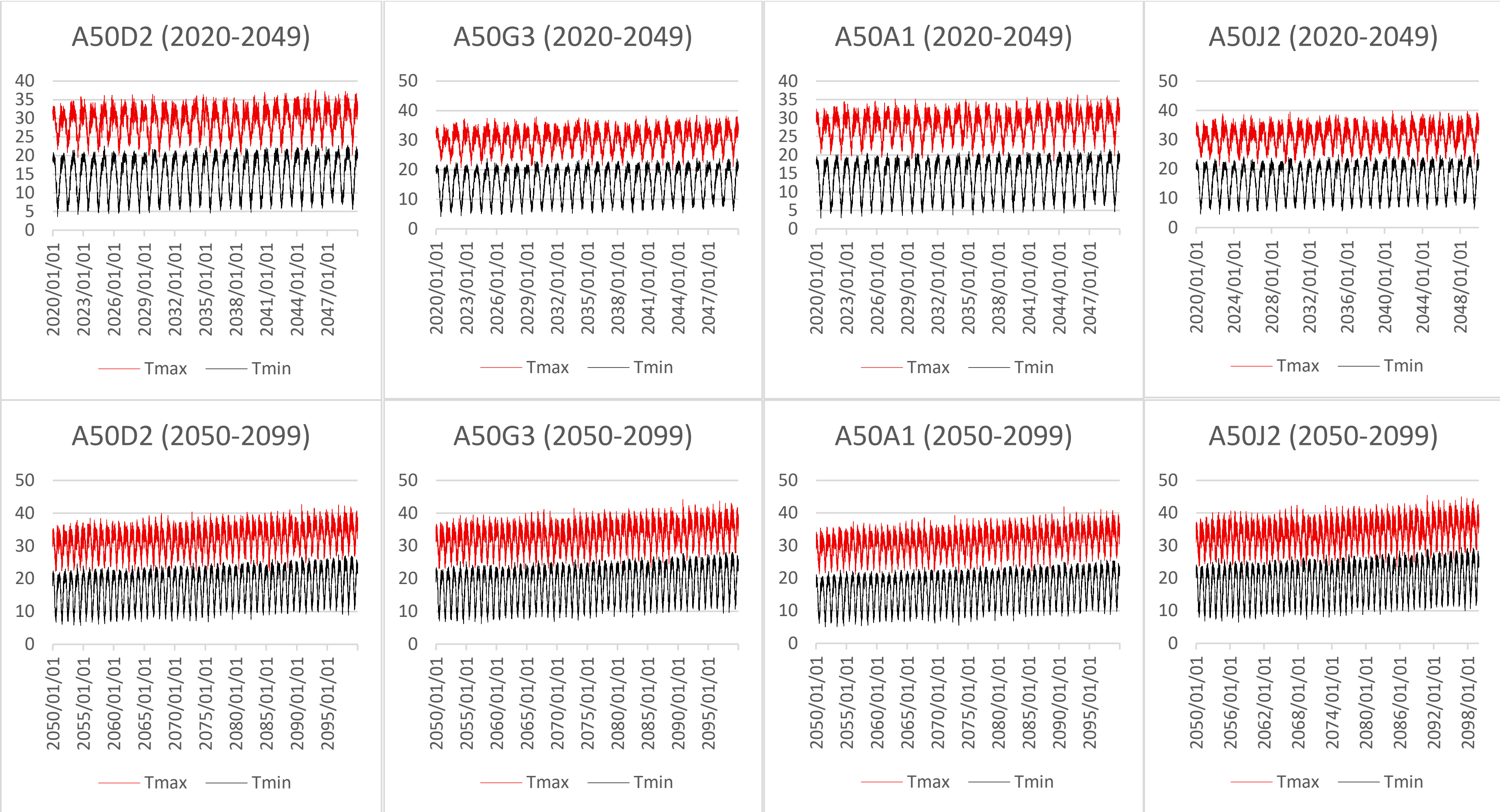

Figure 6.9 Lephalala River Catchment Near future and far future minimum and maximum temperature time series under SSP5-8.5 (high emission scenario).

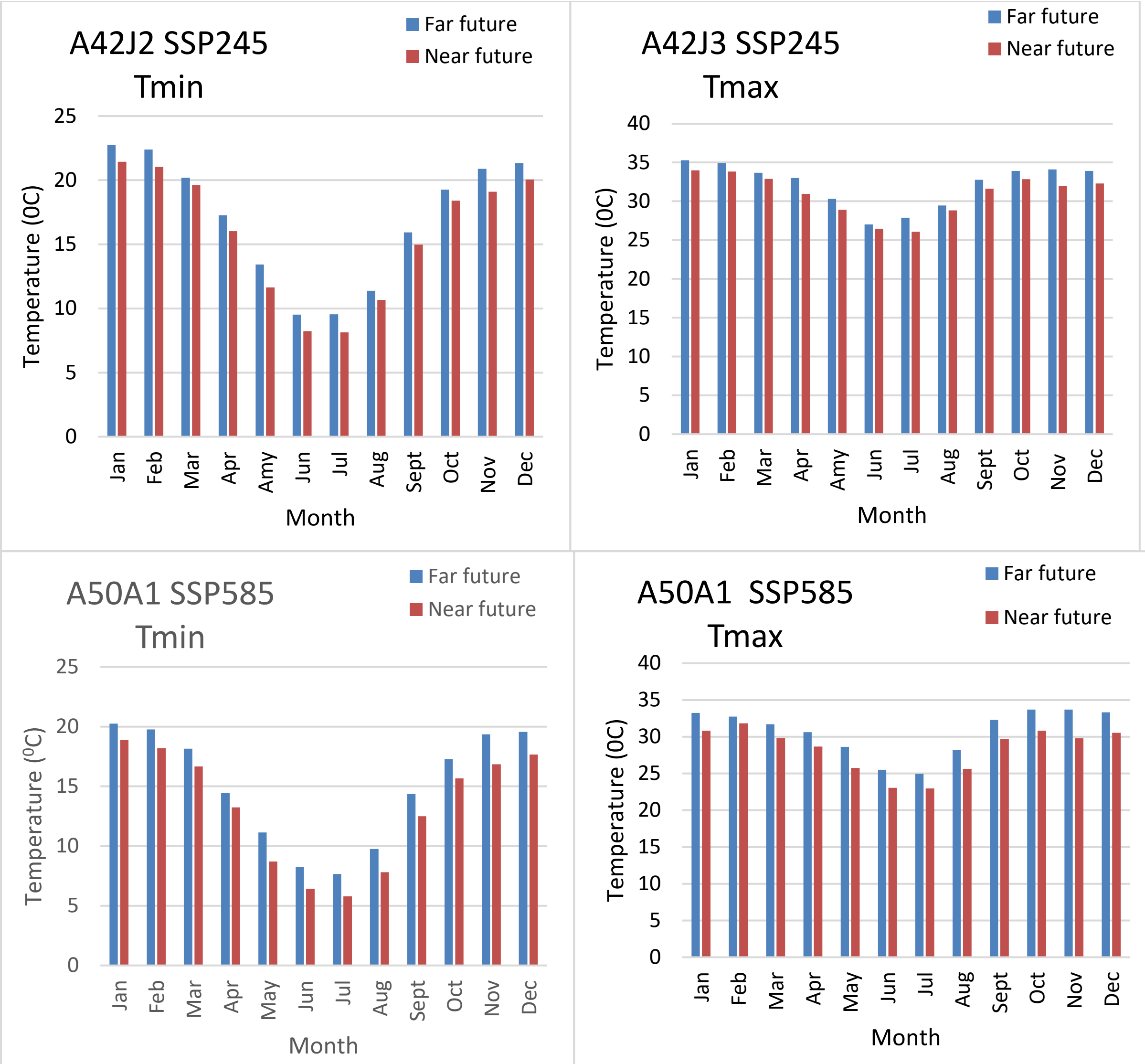

Figure 6.10. Near future and far future mean month minimum and maximum temperature time series for SSP5-8.5 (a high emission scenario) and SSP2-4.5 (moderate emission scenario).

6.4 FUTURE DROUGHT RISK IN MOKOLO AND LEPHALALA CATCHMENTS

Figures 8.11 to 8.14 depict projected future drought conditions in the Lephalala and Mokolo river catchment, for SSP2-4.5 and SSP5-8.5 in the near future (i.e., 2020-2049 and the far future (i.e., 2055-2099). The Standardized Precipitation Evapotranspiration Index (SPEI) has been used in this context as the drought quantifying parameter, and the index was computed at three time scales, 6-, 12- and 24 months. While there is some variability between wet and dry periods as depicted by the SPEI in all the figures, the majority of SPEI trends are predominantly negative, indicating a general shift toward increasing dryness within the two catchments.

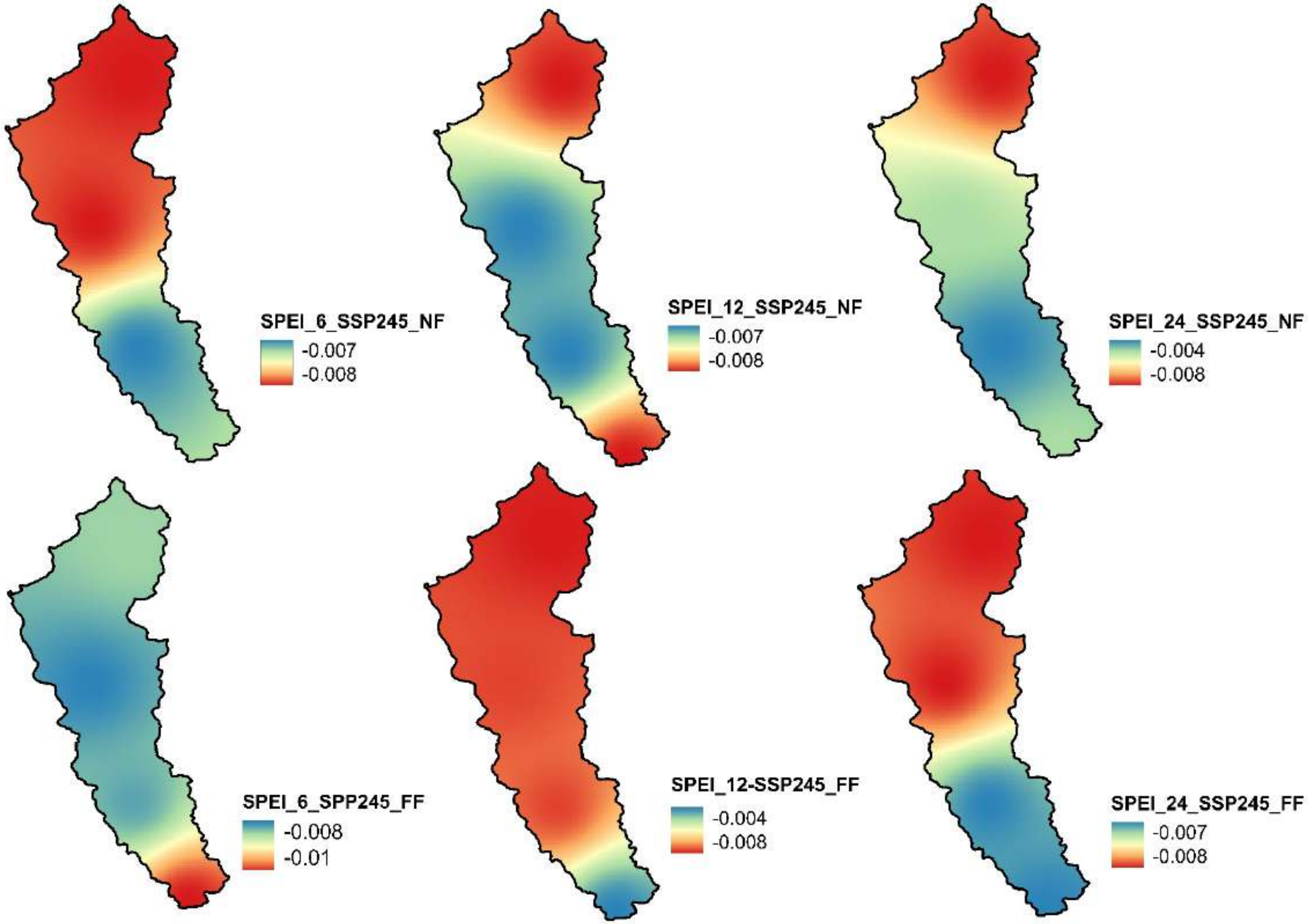

Figure 6.11 Projected spatial distribution drought risk maps for Lephalala River Catchment, depicting the SSP2-4.5 at varying SPEI timescales (i.e., 6-, 12- and 24 months). From the figure, SPEI is the Standardised Precipitation Evaporation Index, NF indicates Far Future and FF represents the Far Future.

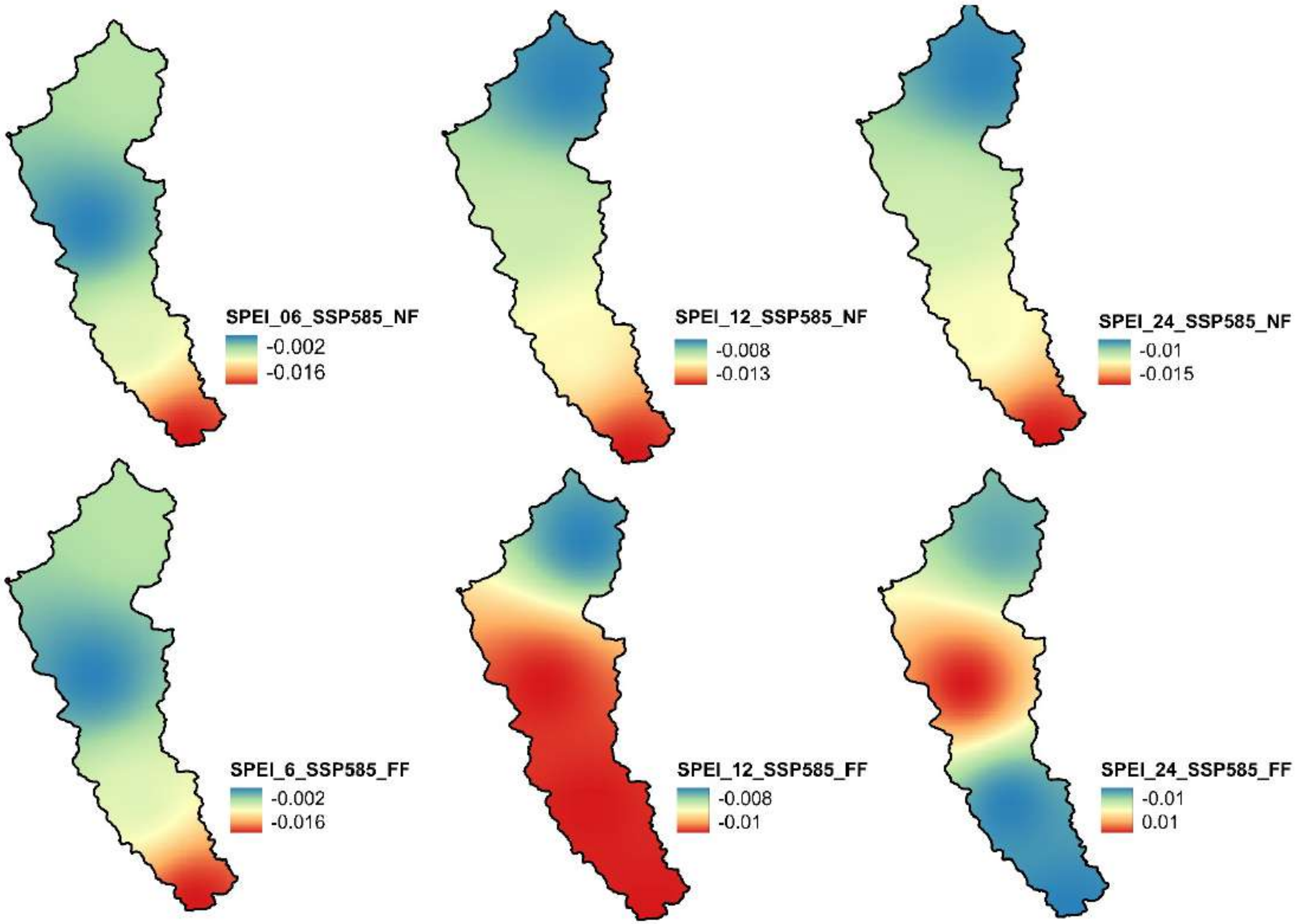

Figure 6.12 Projected spatial distribution drought risk maps for Lephalala River Catchment, depicting the SSP5-8.5 at varying SPEI timescales (i.e., 6-, 12- and 24 months). From the figure, SPEI is the Standardised Precipitation Evaporation Index, NF indicates Far Future and FF represents the Far Future.

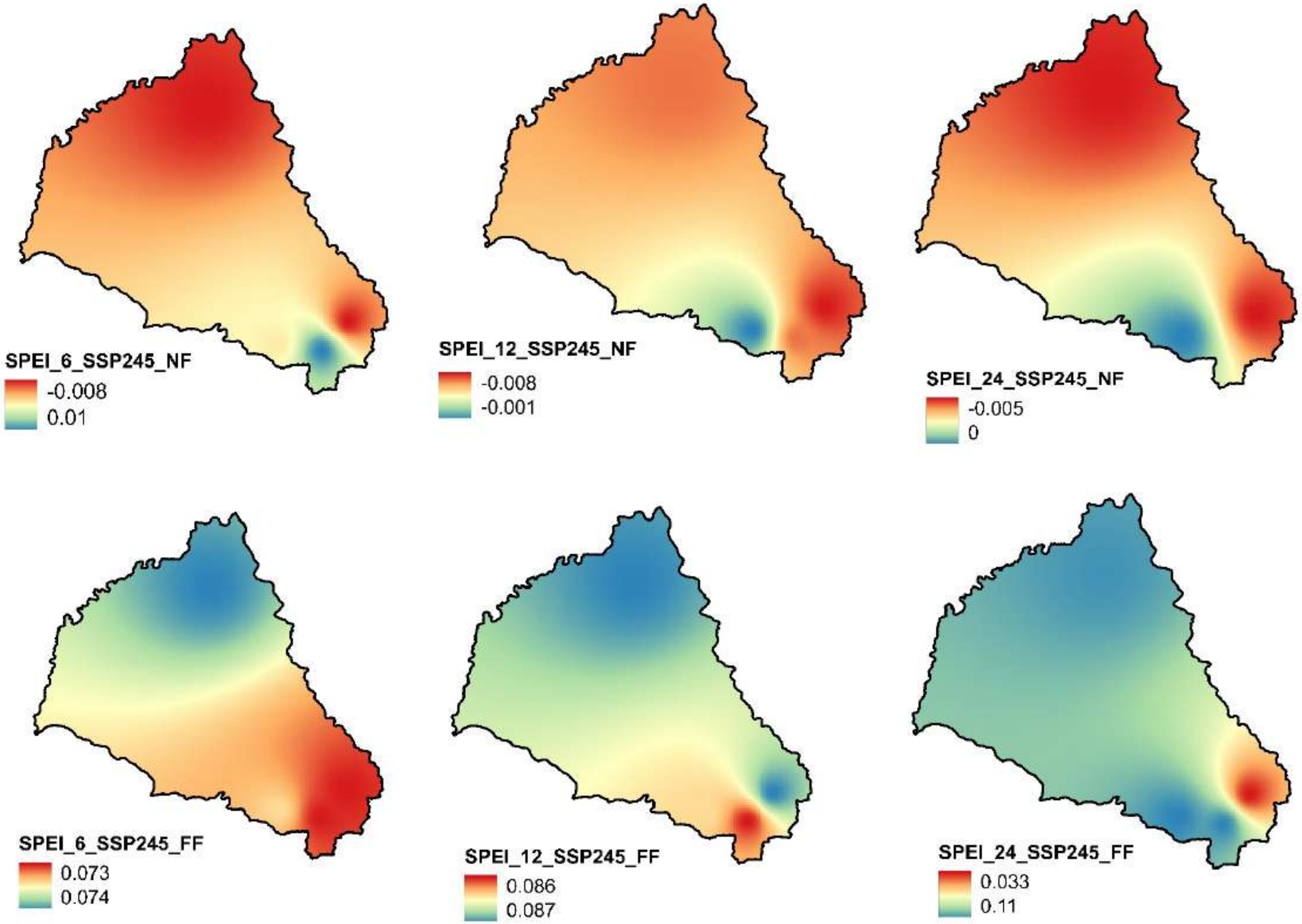

Figure 6.13 Projected spatial distribution drought risk maps for Mokolo River Catchment, depicting the SSP2-4.5 at varying SPEI timescales (i.e., 6-, 12- and 24 months). From the figure, SPEI is the Standardised Precipitation Evaporation Index, NF indicates Far Future and FF represents the Far Future.

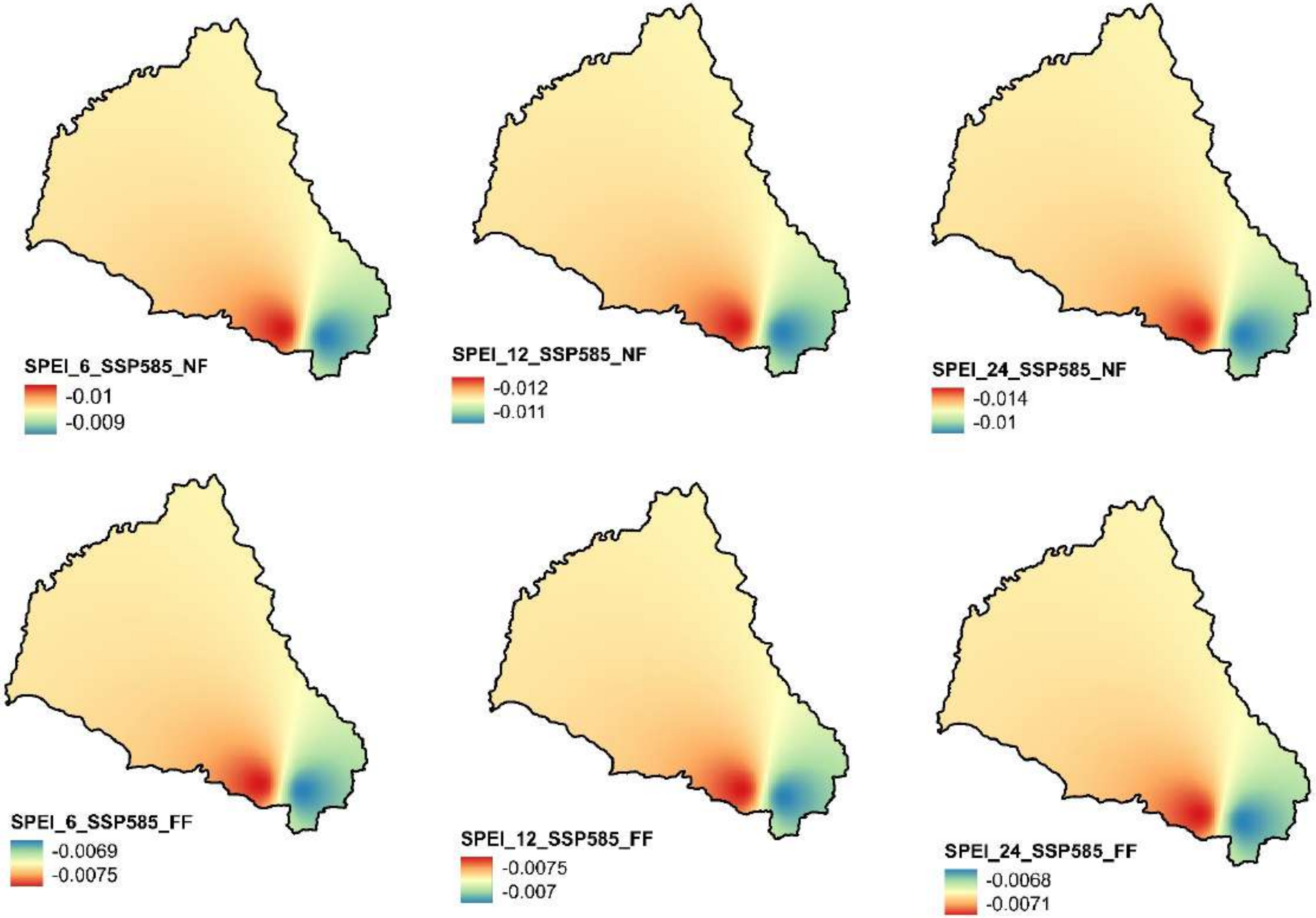

Figure 6.14 Projected spatial distribution drought risk maps for Mokolo River Catchment, depicting the SSP5-8.5 at varying SPEI timescales (i.e., 6-, 12- and 24 months). From the figure, SPEI is the Standardised Precipitation Evaporation Index, NF indicates Far Future and FF represents the Far Future.

Under near-future projects, for example, at SSP2-4.5, a pronounced latitudinal gradient is evident in the Lephalale Catchment. The northern section consistently shows stronger negative SPEI, particularly at the 6- and 12-month timescales, reflecting increasing short- to medium-term meteorological drought, which has the potential to translate into soil moisture deficit and water stress. Central areas exhibit comparatively weaker trends, while the southern portion shows moderate drying. At the 24-month scale, spatial contrasts become less distinct, suggesting that long-term hydrological drought under near-future conditions is more spatially integrated but still dominated by negative trends. In contrast, the far future condition reveals a marked intensification and spatial redistribution of drought signals. At the 6-month scale, negative trends strengthen in the southern part of the basin, indicating heightened short-term moisture deficits following fire disturbance. This pattern becomes more pronounced at the 12- and 24-month timescales, where large portions of the basin exhibit stronger and more spatially coherent negative SPEI trends compared to near-future conditions. The dominance of red and orange tones in the far future figures implies the intensification of evapotranspiration losses, reduced soil moisture retention, and disrupts vegetation recovery, thereby exacerbating drought persistence.

Mokolo Catchment SPEI maps at 6-, 12-, and 24-month timescales under the SSP5-8.5 scenario consistently show negative SPEI trend values across the catchment, indicating a progressive drying tendency under a high-emissions future climate. Across all timescales, stronger negative trends are concentrated in the south-eastern part of the catchment, while the central and north-western areas exhibit weaker declines. This spatial coherence suggests that the south-eastern zone is a hotspot of increasing drought severity, likely driven by the combined effects of reduced precipitation and increased evapotranspiration. In terms of timescale influence, at SPEI-6, drying signals are present but relatively moderate, reflecting short-term moisture stress, while SPEI-12 negative trends intensify and become more spatially coherent, indicating persistent annual-scale water balance deficits, with SPEI-24 patterns highlighting long-term hydrological drought risk, particularly in the south-eastern region of the Mokolo catchment area.

6.5 SUMMARY

Climate change projections analysis has shown that some parts of the catchments will experience increasing trends in minimum and maximum temperatures, both in the near and far future, while rainfall trends will remain relatively stable for most parts. While the current variability of rainfall and temperature still exists and there are not many changes in the seasons, there is a notable increase in both the rainfall and temperature variables in the far future. The projections further depict a clear linear increase in both minimum and maximum temperature in the far future, while temperature linear trends in the near future remain relatively stable. Rainfall projections, on the other hand, show an increase in the near future climate, with the far future period seeing rainfall declines. Such projections will influence the rate of land degradation and the availability of water resources. Regarding future drought risk, climate forcing under SSP2-4.5and SSP5-85 have depicted increasing dryness, intensifying both the magnitude and persistence of drought across multiple timescales. These results underscore the importance of climate-smart adaptation in water resources planning, drought risk assessment, and ecosystem management, particularly in semi-arid catchments vulnerable to land cover disturbance.

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CHAPTER 7: CLIMATE CHANGE IMPACTS ON HYDROLOGY AND WATER RESOURCES AVAILABILITY

7.1 INTRODUCTION

Hydrologic processes can be explained through developments in data collection and processing, concepts and theories, integration with allied sciences, computational and analysis tools, and models and model outputs (Singh, 2018). A hydrological model is an input–output model which mimics the evolution of water storage, water fluxes, and potentially related chemical and physical properties at the earth's surface and subsurface, based on the continuity equation (Horton et al., 2021). Hydrology plays a significant role in meeting twenty-first century challenges related to food, water, energy & ecosystem security for sustainable development. Hydrological models can be used in integration with Remote Sensing (RS) and Geographical Information Systems (GIS) or as a standalone. However, when integrated, the most reliable spatially distributed data for calibration and model inputs can be realised (Thakur et al., 2017). These models enhance the understanding of the environmental system behaviour and suggest solutions for long-term challenges in water resources management (Cuceloglu and Ozturk, 2019). Mengistu et al. (2019) further noted that this model enables users to manipulate the system’s variables and parameters to promote understanding of the interaction among the variables that make up a complex system.

Hydrology plays a central role in applied and fundamental environmental sciences, and there is an overwhelming diversity of models, particularly to simulate streamflow (Singh, 2018). Hydrological models are divided into three categories: Statistical models, conceptual and distributed hydrological models (Liu et al., 2017). Statistical models are based on the relationship between runoff, rainfall and air temperature but cannot project future resources, while conceptual models are based on hydrological scenarios, but the challenge is that a river basin is assumed to be an integral component; these groups of models do not account for spatial heterogeneity resulting from the difference in topography and vegetation. Distributed models are described as those that consider spatial and temporal data to simulate the hydrologic behaviour of a catchment (Iqbal et al., 2022; Cuceloglu and Ozturk, 2019). Furthermore, in distributed models, input variables can be easily obtained; they are large-scale basin models with high computational efficiency (Liu et al., 2017). Physical-based models play a significant role in predicting the effects of LULC changes on the hydrology of a river system (Jin et al., 2019).

A hydrological model should accurately depict the interactions among hydrological processes, be sensitive to land use, and provide a satisfactory representation of climate change (Warburton et al., 2010). Therefore, this makes model selection a pivotal step in hydrological modelling. Due to limited technical capacity for model simulation and funding constraints, developing countries such as South Africa rely largely on models developed elsewhere (Paul et al., 2022). Since no single model can work for all scenarios, to reduce uncertainties associated with the model structure and execution, it is important to apply different hydrological models (Moges et al., 2020). Except for the Agricultural Catchment Research Unit (ACRU) and the Pitman models developed in South Africa, several models have been applied to simulate catchment hydrological processes. Table 7.1 summarises some of these widely used hydrological models in South Africa, together with their advantages and disadvantages.

Table 7.1 Some widely used hydrological models in catchment process simulations in South Africa.

Model	Spatial structure	Advantages	Disadvantages
SWAT	Semi-distributed	• It can simulate missing weather information • It provides auto-calibration option • It can be used in QGIS interfaces • It accounts for soil, land-use and climate change • Open source	• Assumes the catchment dimensions remains static
MIKE-SHE	Distributed model	• It is applicable in any catchment size • It can produce a water budget for the hydrological cycle	• High computational demand • Large input data • Needs a licence • Over-paramaterisation
WEAP	Lumped continuous model	• Simulate a broad range of natural and engineered components of hydrologic systems • Provides a comprehensive, flexible and user-friendly framework for planning and policy analysis	• Does not account for stream attenuation. • Cannot model reservoir water quality. •
HEC-HMS	Semi-distributed	• Simplicity • Use of common methods • Open source	• HEC-GeoHMS requires the Spatial Analyst Extension from ArcGIS • It can only be applied in Dendritic catchments • Requires terrain pre-processing
ACRU	Distributed	• It accounts for climate, land use and soil changes • It does not require calibration and validation • Open source	• Least user friendly

Due to its ability to model finer-scale small sub-basins, the Soil and Water Assessment Tool (SWAT) was selected for application in this project. SWAT is classified as a semi-distributed model (Liu *et al*., 2017; Cuceloglu and Ozturk, 2019; Gabiri *et al*., 2019) and as a continuous-time model (Mengistu *et al*., 2019). Physically based semi-distributed hydrological models can provide a detailed representation of the fundamentals of the hydrologic process (Gabiri *et al*., 2019). The availability of the model and its applicability through the development of GIS-based interfaces, together with its easy integration with sensitivity, calibration, and uncertainty analysis tools, have contributed to the popularity of SWAT in global research (Mengistu, 2019). This project used Quantum GIS (QGIS) as the GIS interface for the model.

The model uses a daily time step and can produce long-term simulations (Ang and Oerng, 2018). The model subdivides the watershed into multiple sub-basins which are further subdivided into hydrologic response units (HRUs) (Dechmi *et al*., 2012). Each unit is characterised by a specific soil/ land use characteristic and the water balance for each unit is presented as four storage volumes (i.e., snow, soil profile, shallow aquifer, and deep aquifer (Dechmi *et al*., 2012). The soil profile is also subdivided into multiple layers that account for soil water processes such as infiltration, evaporation, plant uptake, lateral flow, and percolation. Model calibration and validation can be done manually or automatically using SWAT-CUP. According to Thavhana (2018), auto-calibration can minimise labour, frustration and the uncertainties that come with manual calibration. The SWAT model is driven by the water balance and is among the most widely used models to assess the impacts of land management and climate on hydrology and water resources (Sead, 2009; Liu et al., 2017). It also allows the simulation of conservation and land-use management. SWAT was used to analyse the response between the hydrological cycle and land use (Utamahadi, 2018).

Some studies have successfully applied it in simulating streamflow due to of LULC changes (Zhou *et al*., 2013; Baker and Miller, 2013; Shaffield *et al*., 2018). With a particular application in South Africa, studies such as Perry (2014), Thavhana (2018); Mengistu (2019), Nkosi (2020) and Scott-Shaw et al. (2022), amongst others, have successfully applied the SWAT model in different parts of the country. Perry (2014); successfully simulated runoff in mountainous environments of the Klaserie River Catchment, while Thavhana (2018) applied the model to simulate runoff for flood frequency analysis in the Luvuvhu River Catchment. Mengistu (2019) successfully conceptualised the major components of hydro-meteorological processes, with a focus on natural hydrological processes, using the SWAT Model; meanwhile, Nkosi (2020) simulated streamflow in the Crocodile River Catchment using the SWAT model. SWAT was further used to investigate the interactions among climate, land use, and soil on water use in natural and encroached wetlands in the uMngeni River Basin Quaternary Catchment U20G (Scott-Shaw et al., 2022).

7.2 METHODOLOGY

7.2.1 DATASETS

Table 7.2 shows the details of the SWAT model data used, including classified LULC, soil data, DEM, climate (i.e., temperatures, rainfall, humidity and wind speed), and streamflow data. All climate data were obtained from the South African Weather Service, while streamflow was obtained from the National Department of Water and Sanitation. Weather data was used as input for model simulation, and streamflow data was used for calibrating and validating the model. Spatial data required for the SWAT model includes DEM, LULC maps and soil maps. Table 7.3 shows the LULC classes used in the SWAT model set-up and calibration.

Table 7.2 Details of the climate and streamflow station data.

Climate data stations					
Station ID	**Latitude**	**Longitude**	**Elevation**	**Period**	**Data type**
Bulgerivier – pol	-24.12	27.70	1065	1968-2022	Rainfall
Dorset – pol	-24.06	28.16	1480	1950-2023	Rainfall
Doornplaas	-23.01	27.94	781	2001-2023	Rainfall
Ellisras-pol	-23.68	27.73	850	1967-2022	Rainfall
Grootgeluk-myn	-23.66	27.56	897	1976-2023	Rainfall
Hoopdal – pol	-24.27	27.50	1219	1980-2019	Rainfall
Jonkmansdrift	-24.18	28.54	1430	1980-2023	Rainfall
Lephalale	-23.68	27.71	839	1993-2023	Rainfall, Temperature, Humidity, wind speed
Steenbokfontein ars	-24.05	28.09	1317	2010-2023	Rainfall
Stockpoort – pol	-23.42	27.33	838	1950-2023	Rainfall
Villa nora – pol	-23.53	28.13	847	1950-2022	Rainfall
Streamflow stations					
Station ID	**Latitude**	**Longitude**	**Elevation**	**Period**	**Data type**
A5H004	-23.982	28.4	-	1955-2023	Streamflow
A5H006	-22.935	28.004	-	1971-2023	

Table 7.3 Land-use classes and SWAT codes.

LULC	**Description**	**SWAT Code**
1. Cultivation	Croplands, irrigated, dry crops, rotational crops, pastures	AGRR
2. Waterbodies	Dams, ponds, rivers	WATR
3. Built-up	All urban areas and settlements, commercial, mines, man-made structures	URLD
4. Bushland/Savanah	Bush, thickets, shrubs,	SAVA
5. Bare	No or little vegetation and exposed areas in cultivation areas, rocks, burnt areas, quarries areas	BSVR
6. Natural forest	Mixed indigenous forest and woodland	FRST

SWAT was used to simulate streamflow before and after LULC changes. Figure 7.1 shows the setup of SWAT as used in this study and the steps involved. The steps involve the delineation of the catchment (step 1), creation of HRUs (step 2), and activation of the SWAT editor (step 3). The SWAT2012 editor also required several steps before simulating the model. These include the creation of a weather generation station and batch files and importing the databases into the editor. The weather generation .csv file contained statistics on the climate data, station names, elevation, and location; it was imported to the SWAT2012 reference database. The model results are imported into the project database, or they can be viewed in SWAT using the visualise option. For this study, the output files chosen were *output.rch* (for streamflow) and *output.sub* (for the water balance components, i.e., surface runoff and evapotranspiration).

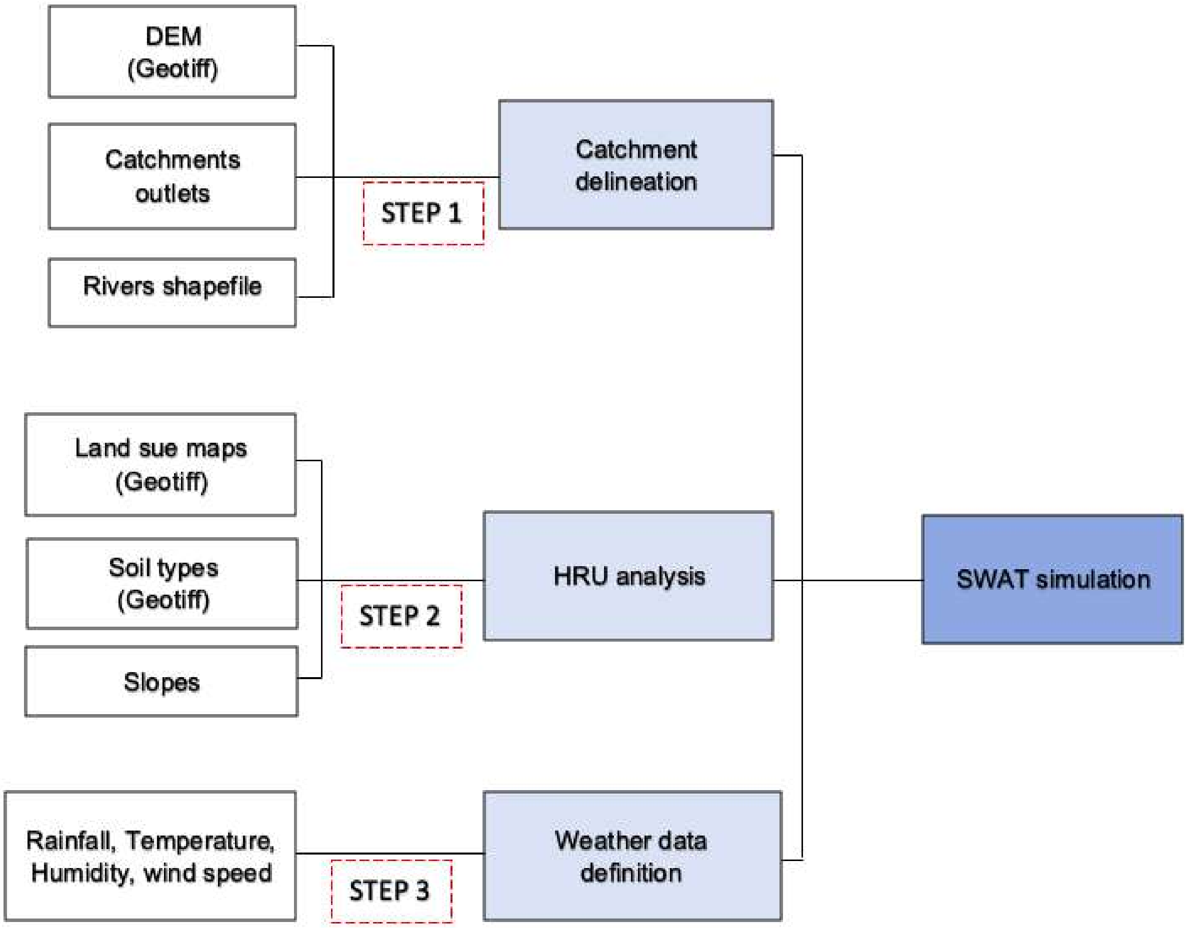


Figure 7.1 Schematic representation of the SWAT model (adapted from Phukoetphin et al., 2015).

7.2.2 Estimation of streamflow, surface runoff, and evapotranspiration in SWAT

Streamflow consists of the total flows from all HRUs to the sub-water level and can be rerouted via the variable-rate storage method or the Muskingum method. Both methods were indicated as a variation of the kinetic wave approach (Gassman *et al.*, 2007). For this study, the Muskingum routing method was used because it calculates the outflow downstream outflow hydrograph based on the upstream inflow hydrograph (Tassew et al., 2019).

Surface runoff is estimated from daily or sub-hourly rainfall, and it can be estimated through the modified soil conservation service (SCS) curve number (CN) or Green and Ampt infiltration method (Gassman et al., 2007; Jamil, 2020). The SCS-CN is modified based on the antecedent soil moisture content and LULC, the SWAT equation is given as shown by Equation (7.1) (Jamil, 2020).

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} - 0.8S)} \qquad 7.1$$

Runoff will occur when R_{day} > I_a. where Q_{surf} is the collected runoff (mm H_2O), R_{day} is the rainfall depth for the day (mm H_2O), I_a is the initial abstractions (including surface storage, interception) prior to runoff (mm H_2O) and S is the retention parameter (mm H_2O). SWAT uses three methods for estimating evapotranspiration: Penman-Monteith, Priestly-Taylor, and Hargreaves (Gassman *et al*., 2007). Since no solar radiation was available in the catchment area during the study period, the Hargreaves temperature-based method was used to estimate ET. This is because the Hargreaves only requires Temperature (Maximum and Minimum) data to estimate ET (Jung *et al*., 2016).

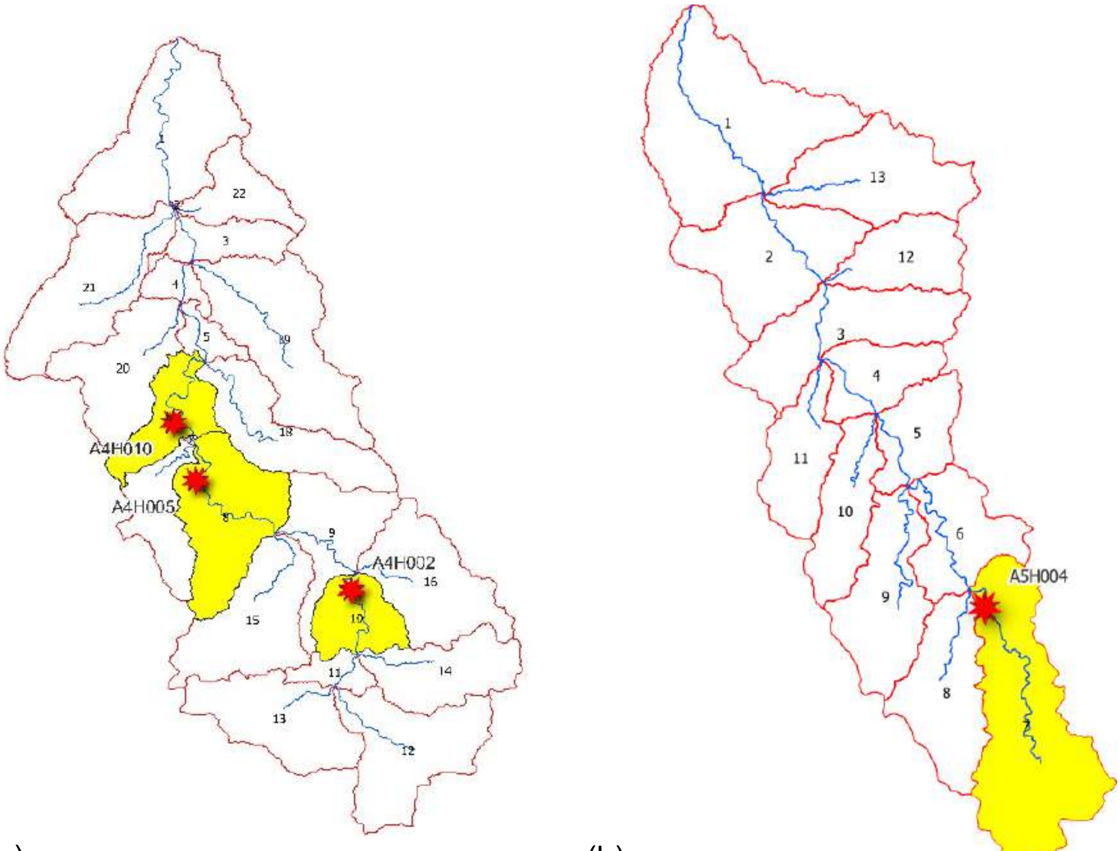
7.2.3 Calibration and validation

Model calibration is achieved by modifying parameter values and further comparing the model outputs with the observed data (Ang and Oeurng, 2018). The latter study further explained that model validation is used to determine whether the calibrated model can predict streamflow using the adjusted parameters. Model validation is usually done using later time periods. Calibration and Validation were done manually on the SWAT2012 editor window. Due to the lack of long-term continuous climate and streamflow data, the modelling period was restricted to 16 years. With a 40:60 data split, data from 2003 to 2009 were used for the calibration, and data from 2010 to 2019 for the validation run. The Nash–Sutcliffe Efficiency (NSE), Kling-Gupta Efficiency (KGE), Root Mean Square Error-Observations Standard Deviation Ratio (RSR), and the Percentage Bias (%BIAS) were used to evaluate model performance.

7.2 RESULTS

7.2.1 HRUs and streamflow

A total of 24 sub-catchments were created for Mokolo Catchment (Figure 7.2a) while 13 sub-catchments were created for Lephalale Catchment (see Figure 7.2b). Sub-catchment 6 and 9 was chosen for analysis in Mokolo Catchment because they coincided with streamflow stations A4H010 and A4H005, respectively, while Lephalala's sub-catchment 7 coincided with A5H004.



(a) (b)

Figure 7.2 Created sub-catchments and streamflow stations used in model simulations. (a) Mokolo River Catchment and (b) Lephalala River Catchment.

7.2.2 Sensitivity analysis, calibration and validation

Table 7.4 presents the adjusted parameters ranked in order of their sensitivity. The model was found to be more sensitive to parameters controlling groundwater than to those controlling surface runoff, and the best fit values are shown in Table 7.4.

Table 7.4 Model Parameters

Parameter	Description*	Rank	Fitted values		Default values	
			Mokolo Catchment	Lephalale Catchment	Abs_Min	Abs_Max
ALPHA_BF	Baseflow alpha factor (days)	1	0.3	0.048	0	1
CN2	Curve number for soil water	2	50	76.5	35	98
GW_DELAY	Groundwater delays (days)	3	200	31	0	500
SURLAG	Surface runoff lag time	4	2	2	0.05	24
GWQMN	Groundwater contribution to streamflow (mm)	5	1500	1000	0	50000
REVAPMN	Threshold depth of water in the shallow aquifer for percolation to occur (mm).	6	500	750	0	500
SHALLST_N	Initial depth of water in the shallow aquifer for "revap" to occur (mm)	7	1200	0.01	0	50000
GW_REVAP	Groundwater percolation coefficient	8	0.02	0.02	0.02	0.2
ESCO	Soil evaporation compensation factor	9	0.5	0.95	0	1
EPCO	Plant uptake compensation factor	10	0.67	1	0	1
OV_N	Manning's "n" value for overland flow	11	0.15	-	0.01	30

7.2.3 Test for model performance

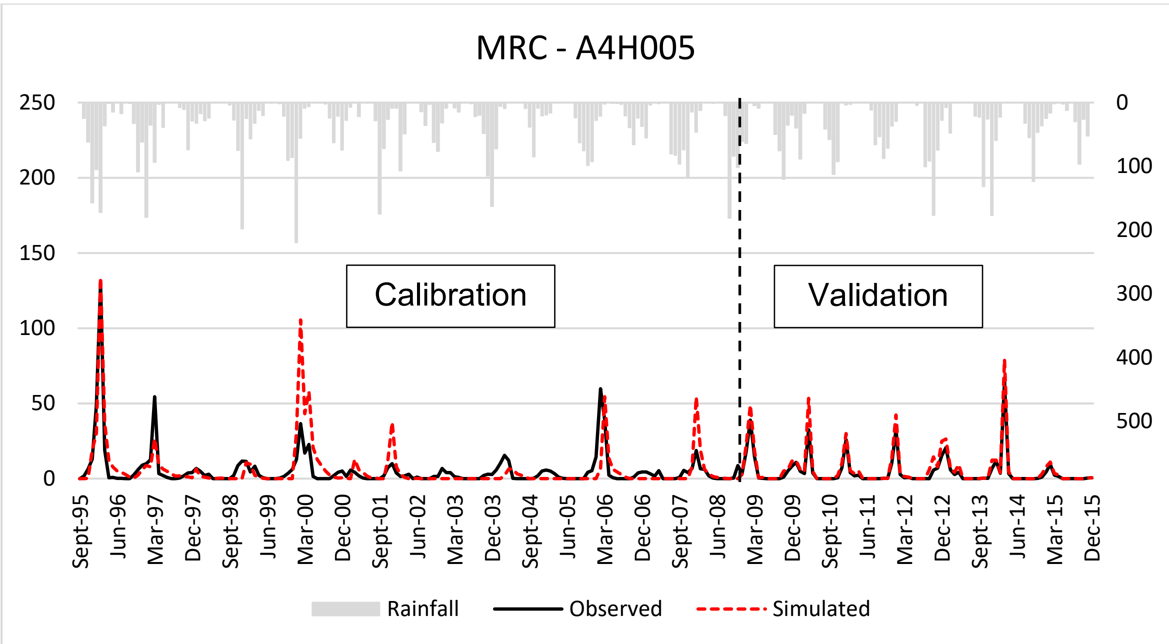
The model was calibrated and validated using observed streamflow data from the selected stations are shown in Table 7.5. For Mokolo Catchment, the model achieved an NSE of 0.6 (A4H005) and 0.5 (A4H010) for calibration and 0.7 (A4H005) and 0.5 (A4H010) for validation, while Lephalale Catchment, on the other hand, achieved an NSE of 0.6 for calibration and 0.5 for validation. According to Moriasi et al. (2007), NSE values between 0 and 1.0 are generally viewed as acceptable performance levels, while values less than zero indicate an unacceptable performance. Mendoza et al. (2021) further argued that values between 0.5 to 1 are considered satisfactory to very good. To overcome the shortcomings of the NSE and validate its results, KGE was also used to test the model performance. The KGE achieved values of 0.5 and above for all stations in both catchments. Knoben et al. (2019) reported that a KGE values greater than -0.41 are generally considered acceptable, with a KGE of 1 indicating a perfect match between simulated and observed data. A %BIAS value ranging between -50 and 50 has been described as acceptable; therefore, the model had a good PBIAS. RSR is used to standardise root mean square error (RMSE), lower RSR indicates good model performance. The model for both the catchments achieved an RSR ranging between 0.5 and 0.7. Mendoza et al. (2021) explained acceptable RSR values as those ranging between 0 and 0.7.

Table 7.5 Calibration and validation.

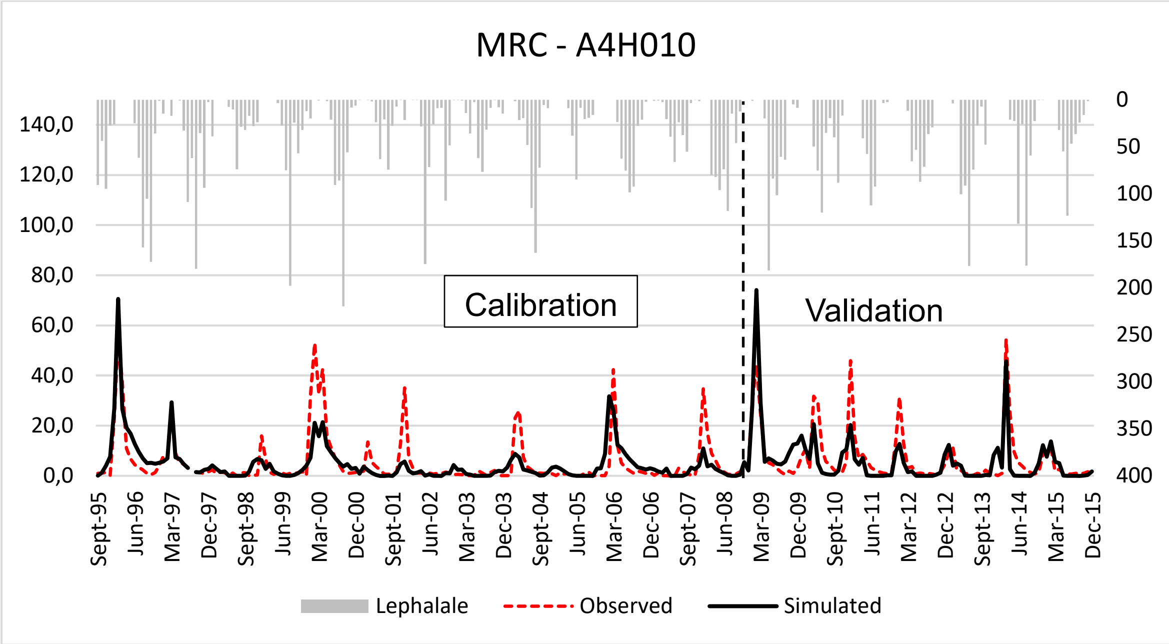
Performance Parameter	Period	Sub-catchment A4H005	Sub-catchment A4H010	Sub-catchment A5H004
NSE	Calibration	**0.6**	**0.5**	**0.6**
	Validation	**0.7**	**0.5**	**0.5**
%BIAS	Calibration	10	15	22
	Validation	19	12	-2
RSR	Calibration	**0.6**	**0.6**	**0.6**
	Validation	**0.5**	0.7	0.7
KGE	Calibration	**0.7**	**0.6**	**0.7**
	Validation	**0.7**	**0.6**	**0.8**

*Bold shows satisfactory to very good performance

Figures 7.3 and 7.4 compare the observed and simulated streamflow during calibration and validation periods. While the model did a better job in simulating the streamflow for both catchments, there were some underestimations and overestimations observed in simulating streamflow, with the most notable overestimation observed in the Mokolo catchment in the 1999/2000 hydrological year. This is largely due to the hydro-climate data availability in the region.



(a)



(b)

Figure 7.3 Calibration and validation of observed and simulated streamflow for the Mukolo River Catchment (a) A4H005 and (b) A4H010.

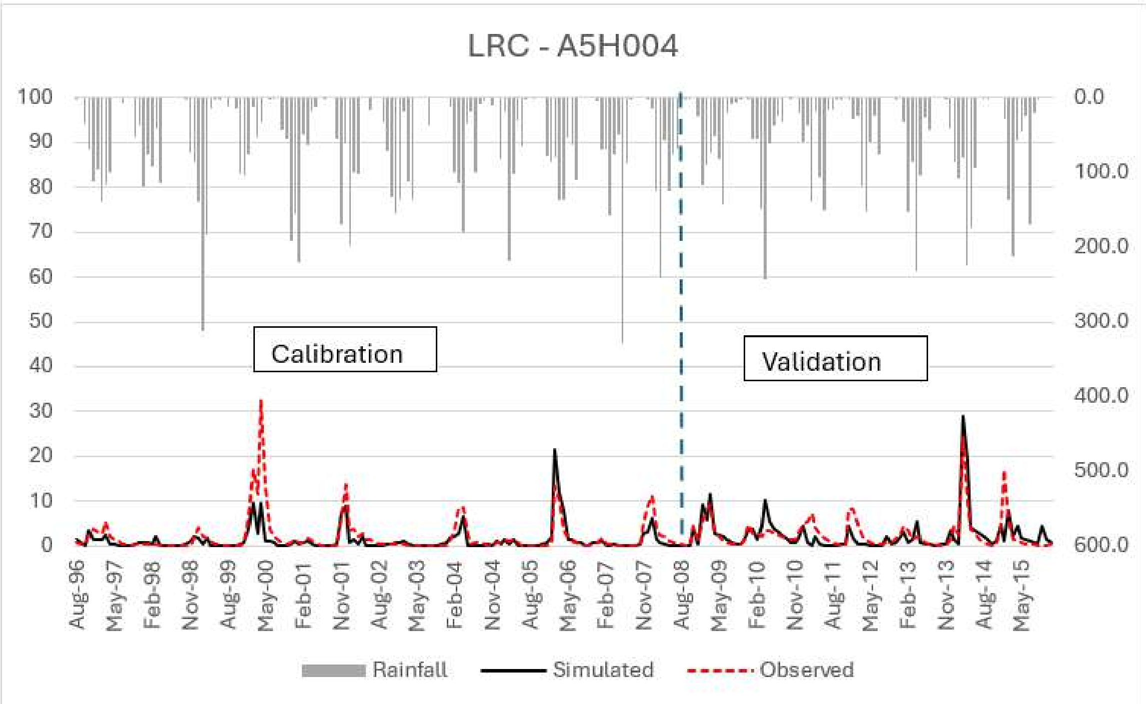


Figure 7.4 Calibration and validation of observed and simulated streamflow Lephalala River Catchment.

7.3 IMPLICATION OF LAND USE AND CLIMATE CHANGE ON HYDROLOGY

Figures 7.5 and 7.6 show the distribution of surface runoff for Mokolo and Lephalala catchments, respectively. The figures show the SWAT simulation using observed data (Figures 7.5(a) and 7.6(a)) and projection data (Figures 7.5(b-c) and 7.6(b-c). Surface runoff was simulated for the base period, near and far future periods. Surface water runoff or overland flow is an important aspect of the hydrological cycle that measures the excess water that flows on the surface when infiltration can no longer happen (Dong et al., 2019). This does not account for water flowing within confined channels, e.g., streamflow. From the simulated SWAT results, the highest surface runoff is mostly upstream for both the Mokolo River Catchment and Lephalale River Catchment, also in correspondence with the bare land. Most bare lands or areas with sparse vegetation do not support infiltration, thus leading to surface runoff (Erena and Worku, 2019). This was supported by Owuor (2016), where the study showed how the rehabilitation of previously bare areas reduced surface runoff from 7.3% to 5.2%. Both surface water and evaporation are mostly influenced by climate conditions such as temperatures, precipitation, and soil moisture.

Climate change projections for the base period (1993-2023) for the Mokolo River indicate low to moderate flows in the upper reaches of the river, which is inconsistent with the simulation of the base period using observation data (Figure 7.5). While this is the case for the Mokolo River, there is variation in the base period simulation using climate change projection and observed data for Lephalale. Climate change projections indicate high flows in the upper reaches of the Lephalala River, whereas observed data reveal moderate to low surface runoff in the lower reaches of the catchment. In the near future, the Lephalale river shows an increase in surface runoff of 16.14-16.02 mm compared to the base period simulation (6.29-14.06 mm). In far-future scenarios, the upstream and downstream regions show moderately low runoff, while the lower region will experience the lowest runoff. Surface runoff at the Mokolo River varies between high and low flows in both the near- and far-future scenarios. Of interest is a change from moderate runoff in the near future to low in the far future in the upstream reaches, while for the downstream reaches, runoff does not show Significant in the near future and the far future.

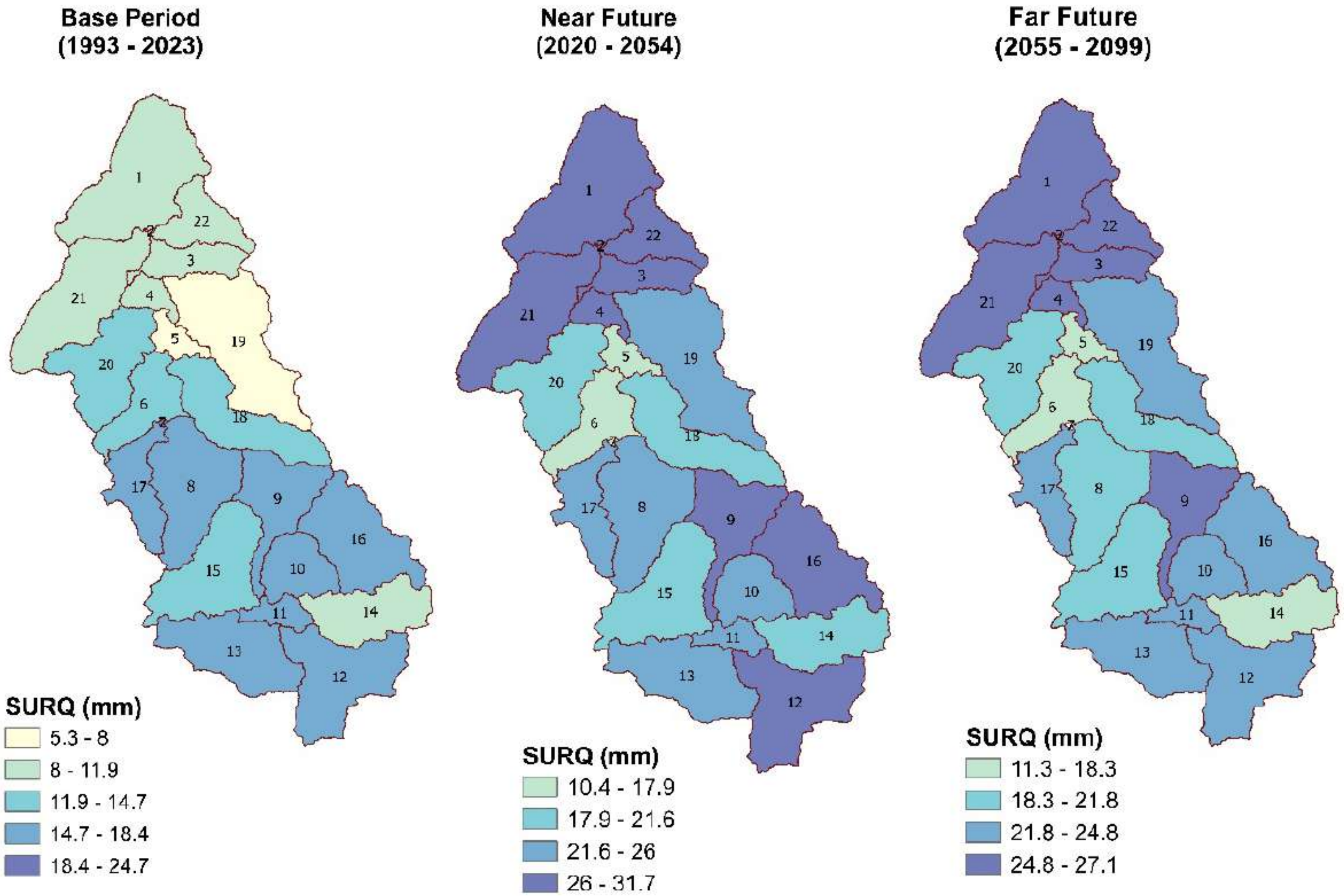


Figure 7.5 Surface water runoff for Mokolo River Catchment for the (a) base, (b) near, and (c) far future periods.

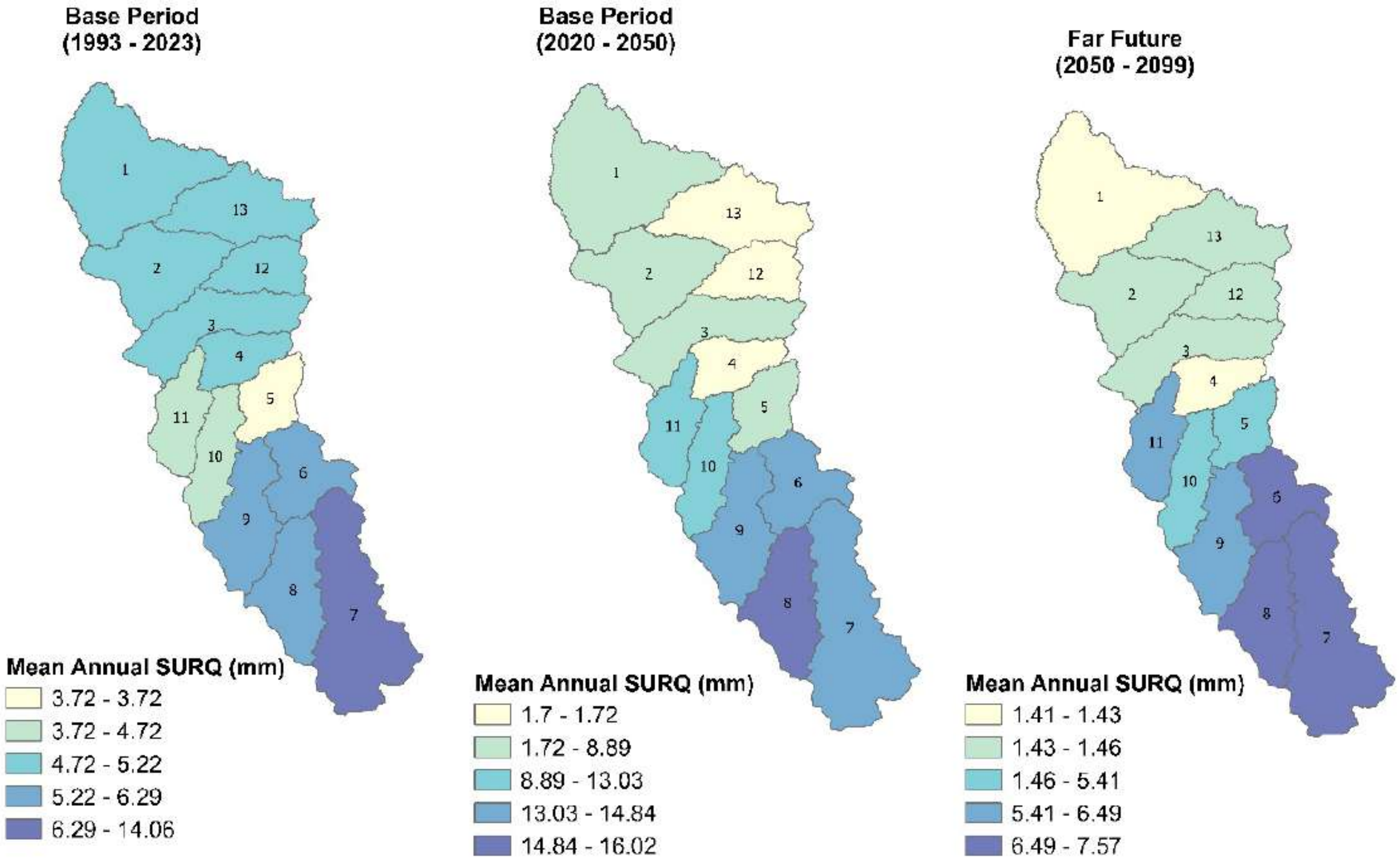


Figure 7.6 Surface water runoff for Lephalala River Catchment for the (a) base, (b) near, and (c) far future periods.

Figures 7.7 and 7.8 show the distribution of evapotranspiration (ET) for Mokolo and Lephalala River Catchments, respectively. The figures show the SWAT simulation using observed data (Figures 7.7(a) and 7.8(a)) and projection data (Figures 7.7(b-c) and 7.8(b-c)). Hydrology was simulated for the base period, near and far future periods. Based on the simulated SWAT results, the highest ET rates were distributed upstream of the Mokolo River Catchment and Lephalala River Catchment. ET has been defined as the water that evaporates from the surface (soil) and plant leaves to the atmosphere under existing weather conditions (Liu et al., 2022). Increased ET has been known to likely lead to decreased surface and subsurface flow and groundwater storage, consequently leading to water management challenges. Therefore, ET and PET are important aspects of surface water and energy balance and the hydrological cycle, and this also shows the impacts bare land likely has on the hydrological cycle. There is consistency in the simulated ET for both the near future and far future scenarios in the upstream section of the Lephalala River Catchment, which indicates that ET will be highest. For the Mokolo River Catchment, both the near and far future show a varying degree between high and low ET. The upstream of the catchment in the near future shows a higher ET, like the LRC, making this region prone to extreme events such as heatwaves and drought episodes.

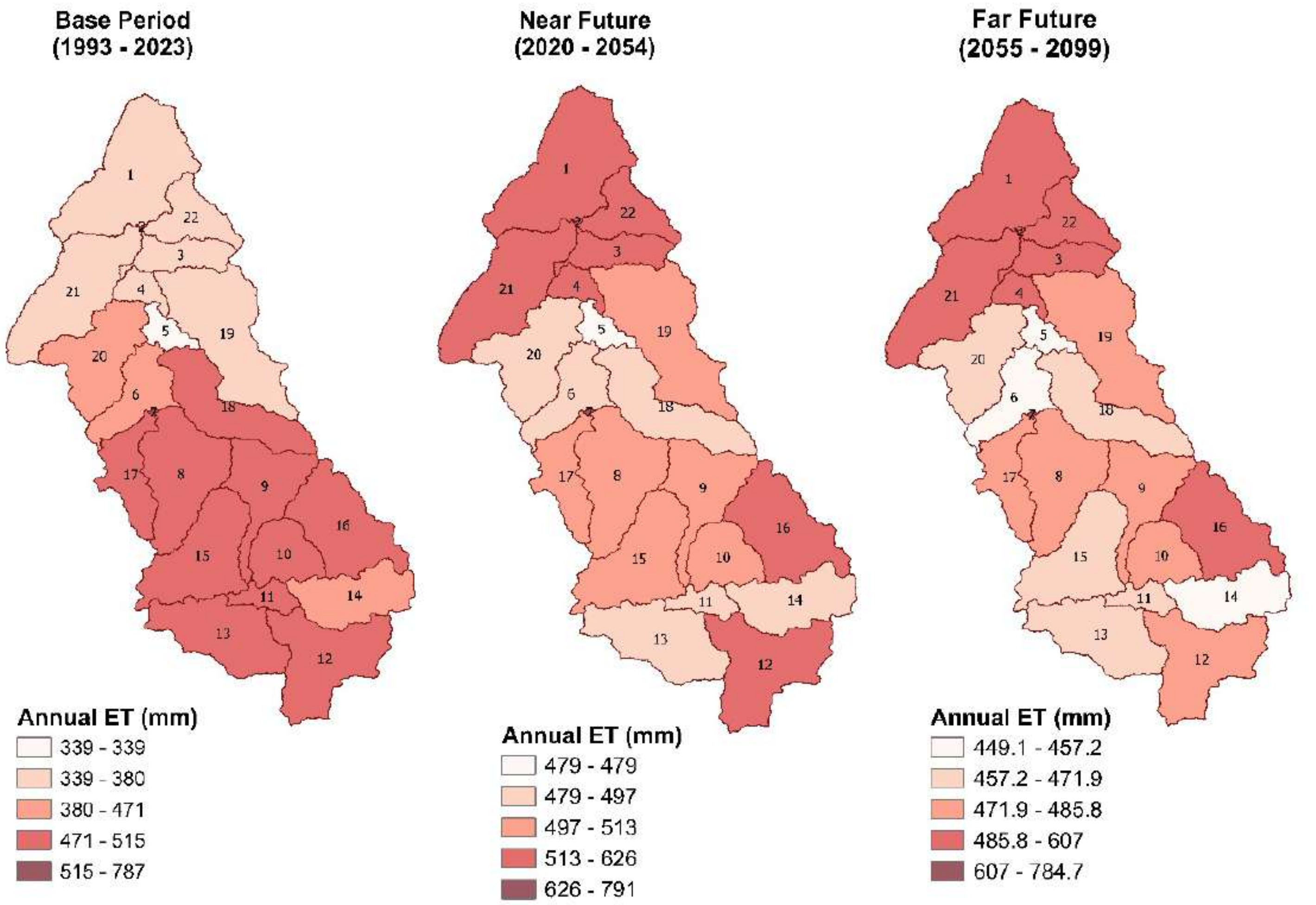


Figure 7.7 Evapotransipiration for Mokolo River Catchment in the (a) base, (b) near and (c) far future periods.

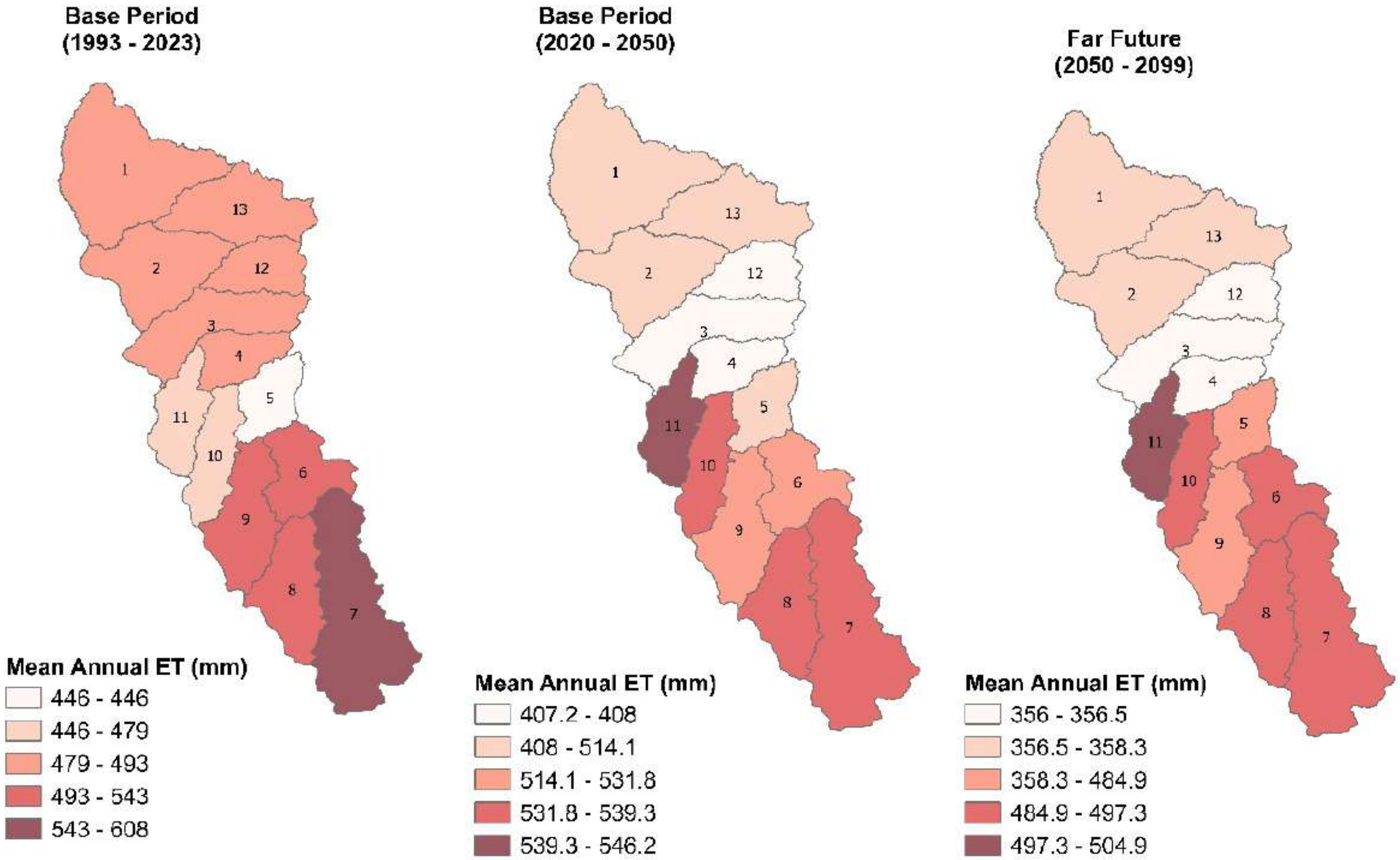


Figure 7.8 Evapotranspiration for Lephalala River Catchment for the (a) base, (b) near and (c) far future periods.

7.5 SUMMARY

This chapter presented the SWAT modelling based on the current and future climate over the study area. To enable the model set-up and calibration, historical data was utilised, and this included climate, hydrological and spatial data. The SWAT model was calibrated and validated using observed streamflow. Model performance metrics indicated good to very good agreement between simulated and observed values. The ranges of NSE = 0.5-0.7; KGE = 0.6-0.8, RSR = 0.5-0.7 and %BIAS = -2% to 22% were achieved. These performance metrics meet recommended guidelines for catchment hydrological modelling and provide confidence in the model's ability to simulate basin processes. The future water resources analysis showed that in the near future, surface runoff in both catchments will be high compared to the base period and the 1far future scenarios. This has the potential to translate into above-average water resources availability in the region, which can relieve water users of the current acute water shortages experienced in the catchment.

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CHAPTER 8: CO-DEVELOPMENT OF LOCALISED CLIMATE CHANGE ADAPTATION PLAN

8.1 INTRODUCTION

Climate change is a complex global challenge influencing various components of the ecological, environmental, socio-political, and socio-economic disciplines (Adger et al. 2005; Leal Filho et al. 2021; Feliciano et al. 2022). Climate change is characterised by long-term shifts in temperatures and precipitation patterns and other components such as pressure and humidity level in the surrounding environment (Abass et al., 2021) with adverse effects. The 21st-century challenge of climate change has been linked to the increase of natural hazards and disasters such as floods, heatwaves and cyclones, among others. Kelman (2015) reported that precipitation is expected to become more intense in many locations around the world due to climate change, and this is driven by warmer air that can hold more moisture, which means that quantity and intensity of rain can increase, with one likely consequence being increased rainfall-induced flooding overall. The adverse impacts of climate change have been projected to mainly affect developing regions of the world with limited adaptive capacity. For the case of the African continent, Climate Change (CC) impacts are multitudinous, with some regions experiencing severe, long-term drought, crop failures, and famine; others, heavy rains, sea-level rise, and both coastal and riparian flooding (Fonjong et al., 2024). Climate change poses a significant threat to South Africa’s water resources, food security, health, infrastructure, as well as its ecosystem services and biodiversity (Vogel et al., 2014) and this is exacerbated by the country's high levels of poverty and inequality.

Given heightened vulnerability to climate change impacts, it has become important to interrogate local-scale adaptation and resilience measures. This deliverable, therefore, presents the co-development of climate change adaptation strategies for the Lephalala and Mokolo river catchment areas in the Waterberg District Municipality. For the uptake of implementation and translational science, the scientific community is shifting the focus from pure scientific research to include translation and implementation of new scientific evidence in real-world practice settings (Grimshaw et al., 2012; Feldstein and Glasgow, 2008). Studies such as Yarborough et al. (2013), Wilkins et al. (2013), and Kost et al. (2012) suggested that stakeholder engagement is the key in both implementation and translational science, including tailoring best practices for a specific population. Stakeholders are individuals, organisations or communities that have a direct interest in the process and outcomes of a project or policy endeavours (Deverka et al., 2012).

8.2 CO-DEVELOPMENT OF CLIMATE CHANGE ADAPTATION OPTIONS

Odiyo et al. (2021) provided a review of existing climate change adaptation strategies including the National climate change response White Paper (DEA, 2010a), National Climate Change Response Green Paper of 2010 (DEA, 2010b), Long Term Adaptation Scenarios (LTAS) Flagship Research Programme (DEA, 2013), a strategy for adaptation to climate change specific to the South African water related sector (Schulze, 2011), South African national adaptation strategy (DEA, 2016b), climate change adaptation responses for rural areas DEA (2016a), Limpopo Province climate change adaptation strategy (DEA, 2015). The review indicated the existing commitment of the existing to build South Africa's resilience and adaptive capacity. It also noted a lack of implementation plans, clear responsibilities, and proposed budgets for each intervention.

Table 8.1 provides a summary of existing adaptation strategies for the Waterberg District Municipality (WDM), where stakeholder engagement for the current was undertaken. Like other adaptation strategies in South Africa, the WDM strategies also lack implementation plans, clear responsibilities, and proposed budgets for each intervention. Masonganye and Mukonza (2018) indicated that local municipalities acknowledge their responsibility to respond to climate change impact, but they are unable to act due to a lack of a clear mandate and procedures on how the implementation processes should be carried out.

Table 8.1 A summary of existing adaptation strategies for the WDM.

Reference	Adaptation strategies
Climate Change Vulnerability Assessment and Response Plan (WDM, 2016)	● Manage the increased impacts of floods due to litter blocking the sewer system ● Manage health impacts from increased storm events ● Manage the increasing waterborne and communicable diseases
WDM recommended adaptation goals (WDM, 2023)	● To prioritise the health and safety of communities in the face of a changing climate. ● To reduce the vulnerability and exposure of human and natural systems to climate ● change and extreme events such as flooding, wildfire and heat extremes. ● To ensure water security under a changing climate. ● To develop climate-resilient, low-carbon, diverse and inclusive local economies that are socially responsible, environmentally sustainable and provide opportunities for marginalised residents.

To guide and promote implementation of climate change strategies, it is important to involve stakeholders during the development process. Different stakeholders experience and adapt to climate change impacts in different ways. It therefore becomes crucial to involve all of them in the development of adaptation, particularly in cases where they are from the same catchment and share the same water resources. Krauß (2020) noted that the starting point for collaborative climate action should be to listening to stakeholder narratives about a changing climate. This can be achieved through engagement and co-development of local climate change adaptation strategies. Co-development is the process of working with stakeholders to develop new knowledge, tools, activities, products, or outcomes, or solve a specific problem (Fleming et al., 2023). Co-development of climate change adaptation strategies involves developing coping and adaptation measures in collaboration with diverse stakeholders. Co-development of climate change adaptation strategies ensures joint effort, buy-in, enhanced ownership, mutual learning, the development of effective and equitable measures, and acceptance and commitment to implementation. This ensures that the developed adaptation measures address the specific needs and vulnerabilities of those most affected by climate change. Terrado et al. (2023) noted that improving the co-development of case studies in climate services is key for making climate information actionable. In a study by Marengo et al. (2017), co-development of adaptation strategies provided a structured, transparent method for surfacing, discussing, and arriving at consensus on adaptation preferences.

8.3 METHODOLOGY

8.3.1 Stakeholder identification

A procedure followed by Odiyo et al. (2020) was adopted for stakeholder identification in the current study. This approach aims to achieve a self-mobilisation level of participation where stakeholders have a strong sense of ownership and can independently implement the developed adaptation strategies. Identified stakeholders were within the categories defined by André et al. (2012) (Table 8.2). Table 8.3 indicates stakeholders identified in this study, as well as their roles. The snowball method was used to identify and analyse stakeholders in the current study. In snowball sampling, participants are asked to recommend or nominate additional stakeholders in informal conversations, expert consultations, or interviews (Lemke et al., 2024). Makungo and Nkuna (2023) noted the wide application of the snowball method in climate change adaptation studies. Snowball sampling is a gradual process that continues until data saturation (Naderifar et al., 2017). It offers a practical solution for accessing hard-to-reach respondents, increasing response rates, and gaining deeper insights, making it a valuable tool for both qualitative and quantitative research (Ting et al., 2025).

Table 8.2 Stakeholder types and description (André et al., 2012).

Stakeholder type	Brief description/role
Functional (F)	Stakeholders who must make decisions on, prepare for and/or implement adaptation and those affected by decisions on adaptation actions
Geographical location (G)	Affected stakeholders within the boundaries of the study (Lephalala and Mokolo River Catchment)
Knowledge and abilities (K)	Stakeholders are assumed to have certain knowledge and skills related to adaptation or expert knowledge on the climate system and climate risks
Hierarchical level (H)	Decision-makers and other types of influential stakeholders who could indirectly facilitate or hinder adaptation

Table 8.3 Identified stakeholders and their roles.

Institution	Stakeholder role
Department of Water and Sanitation	F, H
Waterberg District Municipality (VDM)	F
Farmers Association	G, F
Communities within Lephalala and Mokolo River Catchment	G, F
LEDET	F, K
Tribal councils	G, H
Experts in field of study	K

8.3.2 Adaptation strategies co-development process

- ***Stakeholder consultation workshops***

To co-develop climate change adaptation measures, a series of four stakeholder consultation workshops was held in the study regions. The first consultation workshop was held on **05 July 2023** at the Waterberg Biosphere Reserve offices at Vaalwater. This workshop meeting aimed at introducing the project to key stakeholders in the region. The second consultation workshop (Figure 8.1) with a larger stakeholder group took place at Ga-Shongoane on **17 July 2024**. At this meeting, Prof Mathivha gave a presentation on the project's overview. She highlighted the objectives, summarised the key findings and their implications for the community. She emphasised that the project is bringing the community together to co-develop measures to address the challenges posed by climate change, i.e., making the community part of the solutions. The presentation alluded to the changes in climate and how they affect water quality and quantity, it highlighted the issue of land degradation and its impacts on the climate, soil erosion, and catchment hydrology, and explained the risk of climate change of hydrological extremes. "The increase in population, for example, leads to the increase in deforestation and water demand, thus resulting in a decline in water quantity and deterioration in water quality." Therefore, there is a need to plan for intervention and mitigation measures to adapt to the challenges posed by a changing climate.

Following the introduction of the project, Mr Musitha (on behalf of Prof Makungo) gave a presentation on the methodology the project is using to develop a climate change adaptation plan for the Mokolo and Lephalala catchments, i.e., the Multicriteria Decision Analysis method, which is the quickest and involves stakeholders in developing strategies. The presentation emphasised the importance of the stakeholders in the development of the strategy because they have first-hand experience with the impacts of climate change (i.e., increased frequency of drought and floods) in the area; therefore, their inputs and experiences are important. The presentation shared the following expectations from stakeholders:

- Strong sense of ownership of the strategies developed after the presentations.
- Be able to implement the strategies on your own and ensure that they are
- Implemented in the long term and see the benefits of the strategies.
- Request the stakeholders to be active and work together; and
- Give feedback in terms of the developed strategies through consultation workshops.

Figure 8.1 Stakeholder consultation workshop held at Ga-Shongoane on 17 July 2024.

The objective of this workshop was also for stakeholders to complete the questionnaires (Appendix 1 and 2). Stakeholders were divided into two groups; one group completed the domestic/ municipal questionnaire while the other completed the agriculture water use questionnaire. Figure 8.2 shows stakeholders working in sub-groups. The workshop participants emphasised noticing a shift in their communities, mainly in relation to weather and general environmental changes, during the discussions. In his closing remarks, Prof Diko encouraged everyone to come up with strategies that can be applicable given the socio-economic status of the two catchments. He further emphasised that all questionnaires will be analysed, and feedback will be provided in the upcoming stakeholder workshop.

Figure 8.2 Stakeholder consultation workshop: Stakeholders working in groups.

A stakeholder consultation workshop was held on **14 November 2024** (Figure 8.3) at the Martinique community hall. This workshop aimed to share with stakeholders the opinions on adaptation identified through the questionnaire completed during the July 2024 workshop. The research team analysed questionnaires completed in a workshop held in July 2024, including water/ municipal water users and agricultural water users. The analysis identified a total of 17 action and these included, (i) adjusting planning date, (ii) using drought resistant seeds, (iii) destocking during drought, (iv) rainwater harvesting, (v) increase water storage capacity, (vi) growing water efficient crops, (vii) environmental conservation, (viii) afforestation, (ix) water pollution prevention measures, (x) aggressive climate change awareness campaigns, (xi) investment in renewable energy sources, (xii) improved waste management, (xiii) explore groundwater as an alternative source of water supply, (xiv) water conservation, (xv) law enforcement, (xvi) information sharing between sectors, (xvi) sector specific planning and (xviii) energy efficient practices. In her address, Prof Makungo emphasised the importance of stakeholders in strategy development, as they have first-hand experience with the impacts of drought and floods in the area; therefore, their inputs are important.

Figure 8.3 Stakeholder consultation workshop held at Martinique Community Hall on 14 November 2024.

The last stakeholder consultation workshop was held on **18 March 2025** (Figure 8.4) at Martinique community hall. The aim of this workshop was to prioritise the identified adaptation actions.

Figure 8.4 Stakeholder consultation workshop held at Martinique Community Hall on 18 March 2025.

- ***Prioritising identified climate change adaptation strategies***

The Multi-Criteria Decision Analysis (MCDA) method within CLIMACT Prio tool Excel Spreadsheet, developed by HIS (2016), was used to prioritise the identified climate change adaptation strategies. MCDA is a decision support tool that allows consideration of quantitative and qualitative data in ranking alternative options and provides a systematic procedure for assessing and scoring options against a range of decisions (Werners, 2013). It was found to be suitable for this study because:

- It allows for consideration of stakeholders' preferences in the scoring and weighting of criteria, making it suitable for stakeholder engagement (Tröltzsch et al., 2016).
- It includes a full range of social, environmental, technical, economic, and financial criteria
- It incorporates the perspectives of local people who are the most affected, adaptation responses, and, therefore, aids in the acceptability of the developed strategies (Haque, 2016).

The procedures followed in MCDA are indicated in Figure 8.5 CLIMACT Prio procedures, which include feasibility assessment, selection of adaptation actions, criteria evaluation, scoring of adaptations (impact assessment matrix) and weighting of criteria were followed to prioritise and rank the identified climate change adaptation strategies.

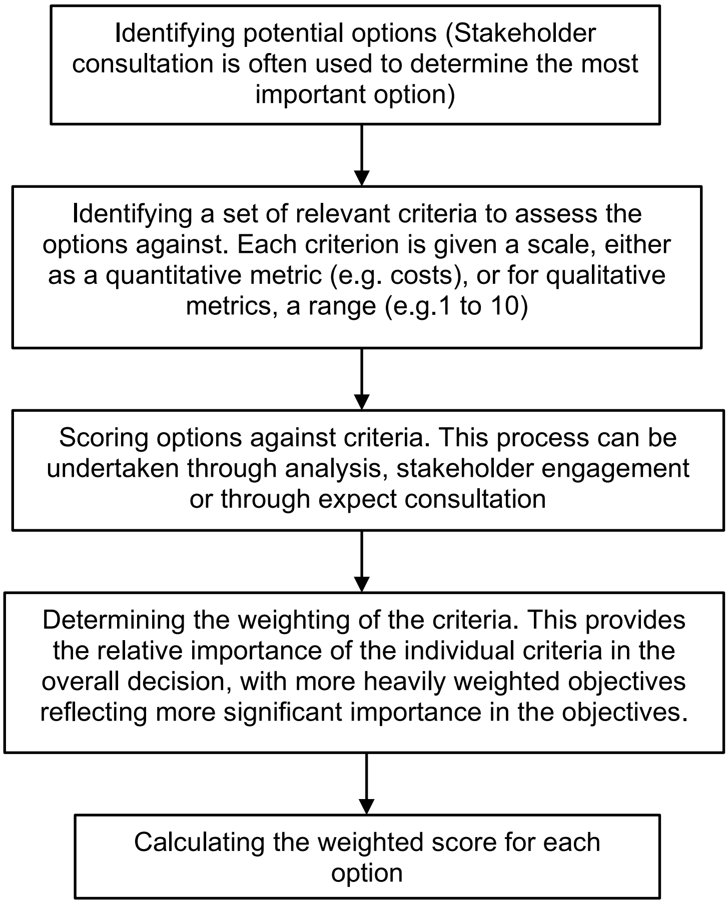

Figure 8.5 Multi-criteria decision analysis framework (adapted from, Tröltzsch et al. (2016).

8.4 CO-DEVELOPED ADAPTATION STRATEGY AND DRAFT IMPLEMENTATION PLAN

8.4.1 Feasibility assessment

From the identified action screened by stakeholders, a feasibility assessment was carried out for both municipal/domestic and agricultural water use. This involved further screening by stakeholders, following a predefined feasibility and impact assessment criteria (see Table 8.4). This is an important step, as this is where actions are to be taken further for assessment.

Table 8.4 Feasibility and impact assessment criteria.

	Criteria	High	Medium	Low
Feasibility Criteria				
	Stakeholder acceptability: *Would local residents accept it?*	Majority of residents in area	Limited majority	Low support
	Technical feasibility: *Will necessary design, implementation and maintenance support be available for the option?*	Design available	Resources to develop design, implement and maintain	No available resources to develop, design, implement and maintain
	Ease of implementation: *Can it be implemented at the local government level, or does it depend upon state/provincial or national support?*	Can be implemented without external support	Can implement this with some support	Cannot implement this without external support
	Financial viability: *Is it a financially realistic option? Does the city have funding or potential access to funding to cover the costs?*	Financially realistic with available funding	More limited funding opportunities	Expensive and limited funding opportunitie s
	Mainstreaming potential: *Could it be integrated with existing local government planning and policy development?*	Yes, easily and fully through many plans and strategies	Yes, partly but with more time and through more limited plans and strategies	Relatively limited potential, would require additional activities
Impact Criteria	**Effectiveness:** *How well would it work on reducing vulnerability (in relation to the other actions)?*	Vulnerability will be reduced to a large extent (in relation to the other actions)	Vulnerability will be reduced to a moderate extent (in relation to the other actions)	Vulnerability will be reduced to a limited extent (in relation to the other actions)
	Multi-sectoral and multiobjective: *Would it address objectives in other sectors?*	Yes, significant cross over with other sectors and objectives	Some cross over with other sectors and objectives	Little cross over with other sectors and limited impact on other objectives

Tables 8.5 and 8.6 present the feasibility ranking of the identified actions for agriculture and municipal/domestic water use, respectively. Each adaptation action was scored as high, medium, or low for each respective criterion. The scoring of high, medium, and low corresponds to numerical values of 3, 2 and 1, respectively, as shown in Tables 8.5 and 8.6.

Table 8.5 Feasibility assessment and ranking of adaptation for municipal/domestic water use.

	Feasibility criteria					Impact Criteria				
Adaptation Actions	Stakeholder Acceptability	Technical Feasibility	Ease of Implementation	Financial feasibility	Mainstreaming Potential	Effectiveness	Multi-sectoral/objective	Total	Ranking	Feasibility Index
Adjusting fertilisers	3	3	3	3	3	3	3	21	1	1.0
Practicing crop diversification	3	1	3	3	3	3	3	19	6	0.9
Food preservation	3	3	3	3	3	3	2	20	5	1.0
Adopting destocking during uncertainty period	3	3	3	3	1	2	1	16	11	0.9
Use of drought resistant seeds	3	3	1	1	1	3	3	15	12	0.6
Use early matured crop varieties	3	3	3	1	1	3	3	17	10	0.7
Changing farming practices	3	1	1	1	2	3	3	14	15	0.5
Use of seasonal climate forecasting	3	3	1	3	2	2	1	15	12	0.8
Planting high yielding crops varieties	3	3	3	3	3	3	3	21	1	1.0
Reducing production space to maximise irrigation	3	3	3	3	1	3	3	19	6	0.9
Commodity exchange	2	2	2	1	1	1	1	10	16	0.5
Reduce sand mining	3	1	3	3	3	3	3	19	6	0.9
Reduce illegal dumping	1	3	3	1	3	3	1	15	12	0.7
Reduce deforestation/forest fires	3	3	3	1	3	3	3	19	6	0.9
Reduce soil erosion	3	3	3	3	3	3	3	21	1	1.0
Enforcement of by-laws	3	3	3	3	3	3	3	21	1	1.0

Table 8.6 Feasibility assessment and ranking of adaptation for agricultural water use.

	Feasibility criteria					Impact Criteria				
Adaptation Actions	Stakeholder Acceptability	Technical Feasibility	Ease of Implementation	Financial feasibility	Mainstreaming Potential	Effectiveness	Multi-sectoral/objective	Total	Ranking	Feasibility Index
Adjusting planting date	3	3	3	1	3	3	3	19	5	0.9
Using drought resistant seeds	3	1	2	1	1	3	3	14	15	0.5
Adopt destocking over certain period (drought)	2	3	1	3	3	3	1	16	12	0.8
Rainwater harvesting	2	2	2	2	3	3	3	17	9	0.7
Increase water storage capacity	3	1	1	1	2	3	3	14	15	0.5
Growing water efficient crops/ plants	2	2	2	2	2	2	2	14	15	0.7
Environmental conservation	2	3	3	3	3	3	3	20	2	0.9
Afforestation	3	3	3	2	2	2	2	17	9	0.9
Water pollution prevention measures	3	3	3	3	3	3	3	21	1	1.0
Aggressive climate change awareness campaigns	3	3	3	3	3	3	2	20	2	1.0
Invest in renewable energy sources	1	2	2	1	2	2	2	12	18	0.5
Improved waste management	2	3	3	3	3	3	2	19	5	0.9
Explore alternative water sources (groundwater)	3	3	3	2	3	3	2	19	5	0.9
Water use efficiency/conservation/ reuse	2	3	3	2	3	3	2	18	8	0.9
Law enforcement	2	3	3	3	3	3	3	20	2	0.9
Information sharing between different sectors	2	2	2	3	3	2	3	17	9	0.8
Sector specific planning	1	2	2	2	3	2	3	15	13	0.7
Energy efficiency practices	2	2	3	2	2	2	2	15	13	0.7

From the list of adaptation actions presented in the feasibility assessment in Tables 8.5 and 8.6, the study ranked the actions from the highest to the lowest, and consideration was given to the seven and eight actions with the highest scores for the agricultural and municipal/domestic use, respectively. Table 8.7 and Table 8.8 show the top seven adaptation actions ranked for agricultural and municipal/domestic water use, respectively, and these were used for further evaluation. While information sharing is ranked eighth on Table 7, stakeholders conveyed that there is a lot of work to be done in the region; however, different activities are carried out and implemented in silos, therefore signalling the significance of information sharing among different sectors, i.e., academics, research, government, NGOs and private businesses.

Table 8.7 The top-ranked adaptation actions for agricultural water use.

No	Adaptation actions	Type	Sector	Time frame
1	Law enforcement	Non-structural	Disaster management	Long term
2	Environmental conservation	Non-structural	Ecological	Short term
3	Water pollution prevention measures	Non-structural	Water management	Short term
4	Aggressive climate change awareness campaigns	Non-structural	Disaster management	Short term
5	Explore alternative water sources (groundwater)	Non-structural	Water management	Short term
6	Water use efficiency/conservation/ reuse	Non-structural	Water management	Short term
7	Adopt destocking over certain period (drought)	Non-structural	Agriculture	Short term
8	Information sharing between different sectors	Non-structural	Disaster management	Long term

Table 8.8 The top seven ranked adaptation actions for municipal/domestic water use.

No	Adaptation actions	Type	Sector	Time frame
1	Water pollution prevention measures	Non-structural	Water management	Short term
2	Aggressive climate change awareness campaigns	Non-structural	Disaster management	Short term
3	Environmental conservation	Non-structural	Ecological	Short term
4	Water use efficiency/conservation/ reuse	Non-structural	Water management	Short term
5	Adjusting planting date	Non-structural	Agriculture	Short term
6	Improved waste management	Non-structural	Ecological	Medium term
7	Explore alternative water sources (groundwater)	Non-structural	Water management	Short term

8.4.2 Evaluation of the ranked adaptation actions

The evaluation criteria used to rank options for climate change adaptation in the municipal/domestic water usage sector and the agriculture sector are presented in Tables 8.9 and 8.10, respectively. In the stakeholder consultation workshops described in section 2, the various stakeholders were consulted to further discuss and validate these criteria, which were derived from De Bruin et al. (2009). Following the recommendations in the IHS (2016) user handbook, the stakeholders decided on the categories of criteria and their corresponding scales. A qualitative scale with 1 denoting the worst performance and 5 denoting the highest performance was employed. An action with a cost of 1 is the most expensive, and one with a cost of 5 is the least expensive.

Table 8.9 Evaluation criteria for agricultural water use.

Criteria	Category of Criteria	Units	Min/Max
Importance	Economic	"1-5"	Max
Urgency	Feasibility	"1-5"	Max
No regret characteristics	Economic	"1-5"	Min
Co-benefits	Environmental	"1-5"	Max
Effect of mitigation	Climate	"1-5"	Max
Public and political acceptability	Social	"1-5"	Max
Costs	Economic	"1-5"	Min
Job creation	Economic	"1-5"	Max

Table 8.10 Evaluation criteria for municipal/domestic water use.

Criteria	Category of Criteria	Units	Min/Max
Importance	Economic	"1-5"	Max
Urgency	Feasibility	"1-5"	Max
No regret characteristics	Economic	"1-5"	Min
Vulnerability	Social	"1-5"	Min
Public and political acceptability	Social	"1-5"	Max
Costs	Economic	"1-5"	Min
Job creation	Economic	"1-5"	Max

8.4.3 Impact assessment of the top ranked adaptation actions

Each adaptation action was given a score based on the evaluation criteria and each score was normalised to ensure that the selected criterion has the same scale and meaning. Climact Prio was normalised using linear interpolation, yielding a scale ranging from 0 to 1. Tables 8.11 and 8.12 present the findings of the impact assessment matrix, including evaluation criteria scores for each adaptation option, along together with their normalised values in brackets. Radar graphs (Figures 8.6 and 8.7) show the normalised scores for each adaptation option for agricultural and municipal/domestic water usage. For this study, water pollution prevention and adjusting of the planting were more expensive than the other adaptation actions for the municipal/domestic water use sector (see Table 8.10). The expenses are related to the water pollution prevention and adjusting of planting date are investments in infrastructure, research and development, and new equipment, labour, as well as potential changes in crop varieties, respectively. While adjustment of planting date is more aligned to the agriculture water use sector, the municipal/domestic water stakeholder group also indicated that they participate in subsistence agriculture. Tilahum (2021) reported a likelihood of 51.6% of farmers to adopt the planting date adjustment in Sekela district, West Gojjam zone, Ethiopia. This indicates that although there are some cost implications to this strategy, it is viable for most farmers as it ensures a return on investment.

Table 8.11 Impact assessment matrix for agricultural water use.

Options/Criteria	Importance	Urgency	No regret characteristics	Co-benefits	Effect of mitigation	Public and political acceptability	Costs	Job creation	Risk
	Max	**Max**	**Min**	**Max**	**Max**	**Max**	**Min**	**Max**	**Min**
Law enforcement	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	1 (0.2)	5 (1)	5 (1)	1 (0.2)
Environmental conservation	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	1 (0.2)	5 (1)	5 (1)	4 (0.8)
Water pollution prevention measures	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	1 (0.2)	**4** (1)	5 (1)	2 (0.4)
Aggressive climate change awareness campaigns	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	1 (0.2)	5 (1)	5 (1)	2 (0.4)
Explore alternative water sources (groundwater)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	**5 (1)**	5 (1)	5 (1)
Water use efficiency/conservation/ reuse	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	4 (0.8)
Adopt destocking over certain period (drought)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	4 (0.8)
Information sharing between different sectors	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)

Table 8.12 Impact assessment matrix for municipal/domestic water use.

Options/Criteria	Importance	Urgency	No regret characteristics	Vulnerability	Public and political acceptability	Costs	Job creation
	Max	**Max**	**Min**	**Min**	**Max**	**Min**	**Max**
Water pollution prevention measures	5 (1)	4 (0.8)	5 (1)	4 (0.8)	5 (1)	**1 (0.3)**	3 (0.6)
Aggressive climate change awareness campaigns	5 (1)	4 (0.8)	4 (0.8)	1 (0.2)	5 (1)	2 (0.7)	1 (0.2)
Environmental conservation	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	2 (0.7)	5 (1)
Water use efficiency/conservation/ reuse	5 (1)	5 (1)	5 (1)	4 (0.8)	5 (1)	2 (0.7)	5 (1)
Adjusting planting date	5 (1)	5 (1)	4 (0.8)	5 (1)	5 (1)	**1 (0.3)**	4 (0.8)
Improved waste management	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	3 (1)	5 (1)
Explore alternative water sources (groundwater)	5 (1)	5 (1)	5 (1)	5 (1)	5 (1)	3 (1)	5 (1)

Law enforcement, water pollution prevention measures, environmental conservation, and aggressive climate change awareness campaigns had low scores on political and public acceptance criteria, as shown in Table 8.11. This was driven by the lack of communication between different actors (i.e., NGOs, community structure, government, district and local municipalities, etc) as stated by some stakeholders during the consultation workshops. This lack of communication has the potential to hinder the effective implementation of the identified climate change adaptation options, as they are dependent on public and political acceptability. Cone et al. (2013) and Wibeck (2014) reported that effective communication is key to facilitating the implementation of adaptation measures by enhancing understanding of anticipated risks from climate change and the available options for adaptive responses among specific target groups. Public awareness encourages the local population to adapt and be prepared for the likely impacts of climate change and to foster community participation in decision-making (Sinay and Carter, 2020). For the no regret characteristics, five adaptation strategies for the municipal/domestic water usage sector received good scores (5), with two (i.e., adjusting planting date and aggressive climate change campaigns) getting a score of 4. According to de Bruin (2009), adaptation alternatives that have no regret features have the advantage that instances where climate change does not occur, if implemented, would result in environmental and economic gains that exceed their costs. It should be noted that a high urgency criteria score suggests that delaying action could lead to increased expenses or irreparable harm (de Bruin, 2011). Therefore, both water user groups, i.e., agriculture and municipal/domestic have noted all but two actions (aggressive climate change campaigns and water pollution prevention) as requiring urgent attention.

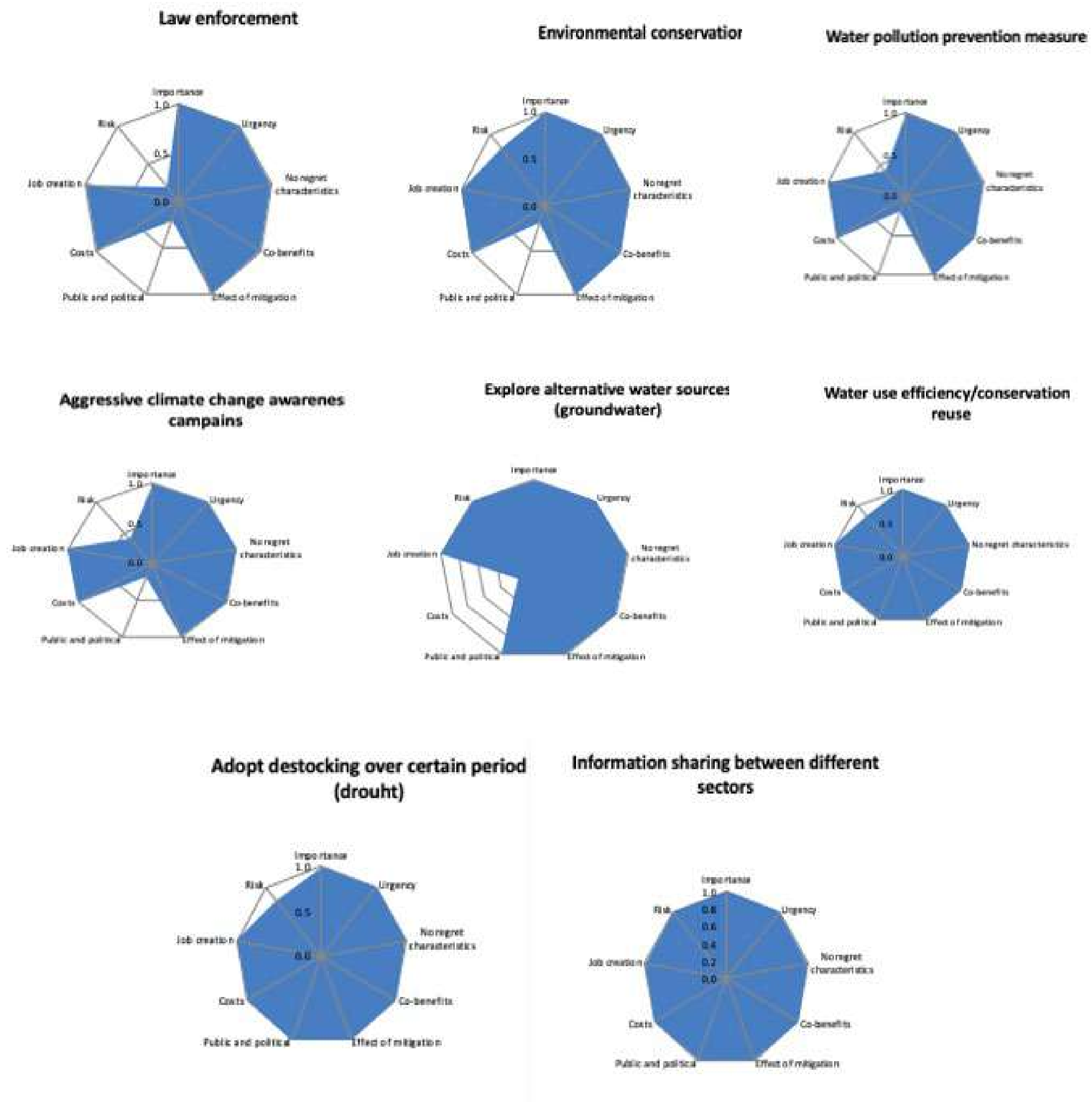

Figure 8.6 Normalised scores for each action for agricultural water use.

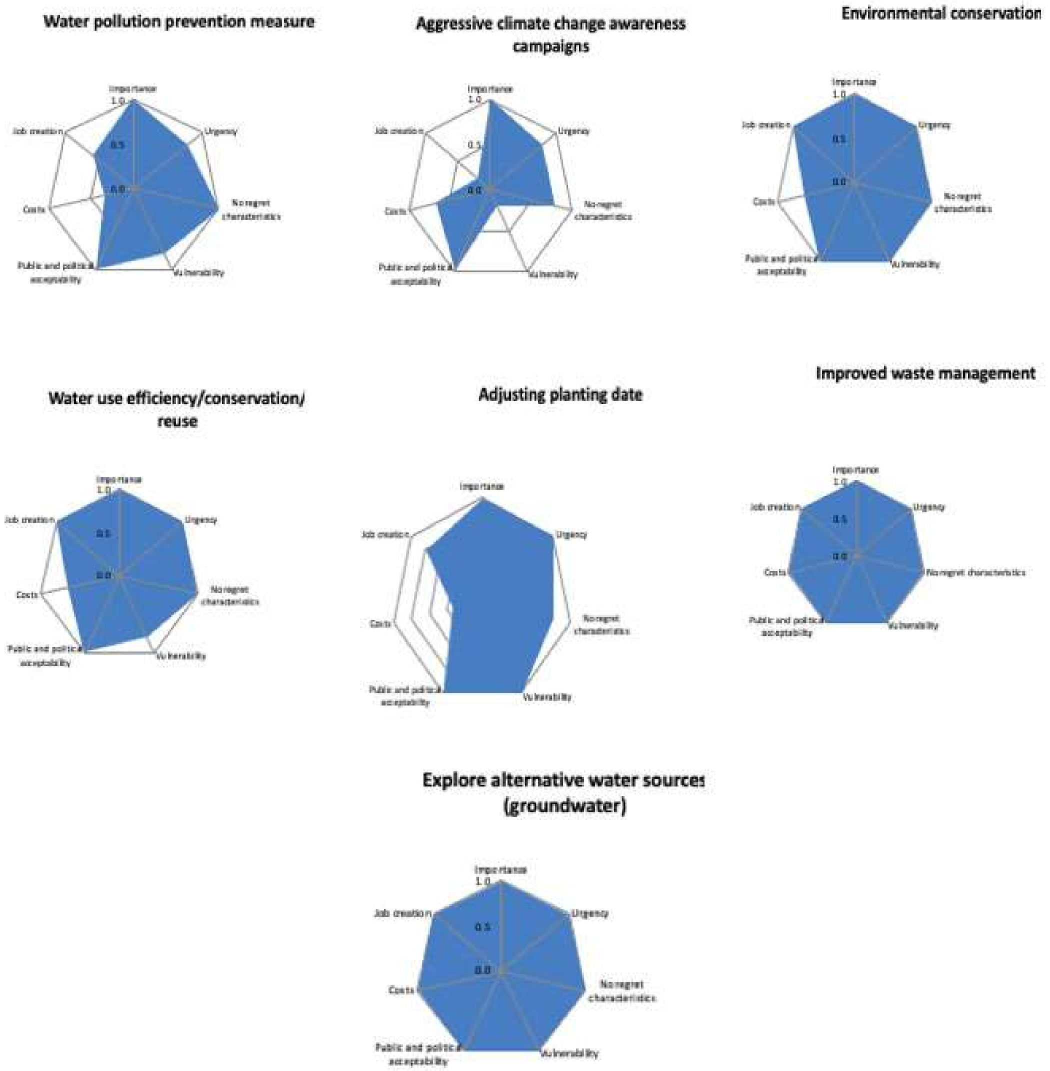

Figure 8.7 Normalised scores for each action for municipal/domestic water use.

8.4.4 Criteria weighting

There were 3 and 2 groups of stakeholders from the agricultural and municipal/domestic water use sectors, respectively. Depending on their perceived importance, these groups assigned weights to each criterion to determine which should be given a higher or lower weight than others. The weighting of the criterion was done using the procedures outlined in IHS (2016):

- The importance of each criterion was evaluated from highest to lowest. The most important (first-ranked) criterion was rated 1, the second most important criterion 2, until the lowest.
- Weighting preferences were defined verbally and arithmetically based on the scales from IHS (2016).
- CLIMACT Prio was used to calculate the average weights along with the standard deviations.

The criteria weightings for stakeholders from the agricultural and municipal/domestic water use sectors are presented in Tables 8.13 and 8.14, respectively. The deviation of the weightings from the respective water-use sector groups was measured by the standard deviation. The smaller the standard deviation the higher the convergence, implying that criteria with high standard deviations will need further consultations between stakeholders to avoid later conflicts. The standard deviations were generally low, indicating high convergence/agreement of the groups' opinions. The average weights for the agricultural and domestic water use sectors are in Figure 8.8.

Table 8.13 Criteria weighting by groups of stakeholders in the agriculture water use sector.

	Stakeholder 1				Stakeholder 2							
	Task 1	Task 2	Task 3		Task 1	Task 2	Task 3					
Criteria	Rank	Importance	Values	Weights	Rank	Importance	Values	Weights	Values Average	Mean	Median	St Deviation
Importance	5	Very High	90	13.6%	4	High	80	11.6%	85.0	12.6%	12.6%	1.4%
Urgency	2	High	80	12.1%	3	Very High	90	13.0%	85.0	12.6%	12.6%	0.7%
No regret characteristics	5	High	70	10.6%	6	High	70	10.1%	70.0	10.4%	10.4%	0.3%
Co-benefits	4	Very High	90	13.6%	5	High	70	10.1%	80.0	11.9%	11.9%	2.5%
Effect of mitigation	3	High	80	12.1%	4	High	90	13.0%	85.0	12.6%	12.6%	0.7%
Public and political	5	High	70	10.6%	4	Very High	100	14.5%	85.0	12.5%	12.5%	2.7%
Costs	2	High	80	12.1%	3	Very High	90	13.0%	85.0	12.6%	12.6%	0.7%
Job creation	3	Very High	100	15.2%	2	Very High	100	14.5%	100.0	14.8%	14.8%	0.5%

Table 8.14 Criteria weighting by groups of stakeholders in the municipal/domestic water use sector.

	Stakeholder 1				Stakeholder 2				Stakeholder 3							
	Task 1	Task 2	Task 3		Task 1	Task 2	Task 3		Task 1	Task 2	Task 3					
Criteria	Rank	Importance	Values	Weights	Rank	Importance	Values	Weights	Rank	Importance	Values	Weights	Values Average	Mean	Median	St Deviation
Importance	1	Very High	100	17.2%	4	High	80	13.8%	5	High	80	14.0%	86.7	15.0%	14.0%	1.9%
Urgency	2	High	70	12.1%	5	High	70	12.1%	1	Very High	90	15.8%	76.7	13.3%	12.1%	2.1%
No regret characteristics	7	High	80	13.8%	6	High	70	12.1%	6	High	70	12.3%	73.3	12.7%	12.3%	0.9%
Vulnerability	5	High	80	13.8%	3	Very High	100	17.2%	6	Very High	90	15.8%	90.0	15.6%	15.8%	1.7%
Public and political acceptability	3	High	70	12.1%	6	High	80	13.8%	5	High	70	12.3%	73.3	12.7%	12.3%	0.9%
Costs	5	Very High	100	17.2%	1	Very High	100	17.2%	2	High	80	14.0%	93.3	16.2%	17.2%	1.9%
Job creation	2	High	80	13.8%	2	High	80	13.8%	3	Very High	90	15.8%	83.3	14.5%	13.8%	1.2%

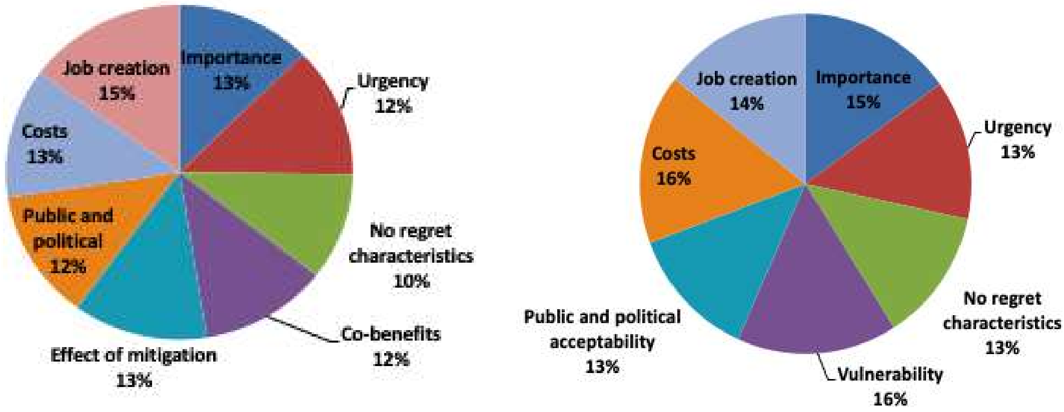

Figure 8.8 Weights assigned to the evaluation criteria for (a) Agriculture and (b) municipal/domestic water use sectors.

The weighted final scores were automatically calculated by combining the impact assessment matrix scores with the average weights requested by the stakeholders. The outcome of this computation is each option's ultimate score. The weighted summation formula served as the basis for the computation, and the program automatically ranked the adaptation choices. Figure 8.9 (a) and (b) depict the scores and ranking of climate change adaptation options for the agricultural and municipal/domestic water use sectors, respectively. Water conservation, destocking during drought periods, and information had an equal high score of 1 and ranked 1, while water pollution prevention measures, law enforcement, environmental conservation and climate change awareness campaigns had the minimum score (0.9) and were all equally ranked (4) in the agriculture water use sector (Figure 9a). The same sector ranked alternative water sources the lowest (8) with a score of 0.9. At a municipal/domestic water use level (Figure 8.9b), improved water management and alternative water sources had the highest score (1) with a rank of 1. Environmental conservation ranked (3) with a score of 0.95, water conservation ranked (4) with a score of 0.91, adjusting planning date ranked (5) with a score of 0.84, while water pollution prevention and climate change campaigns ranked (6) and (7), respectively, with the low scores of 0.78 and 0.65.

A high score of climate change adaptation options indicates that water users place a high priority on implementing them (Van Ierland et al., 2013). While other water user-specific options are important, this study found that water conservation and climate change adaptation options had the highest scores and priority for implementation for both agricultural and municipal/domestic water use sectors, respectively.

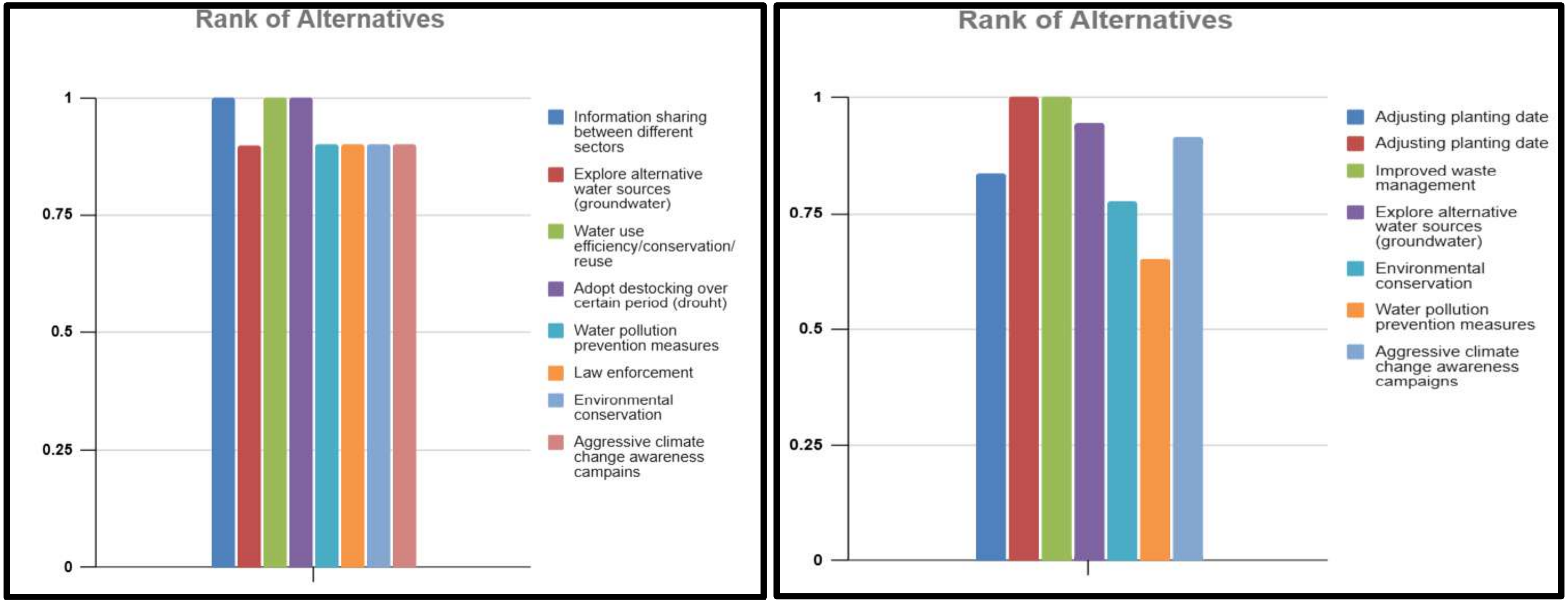

Figure 8.9 Scores of climate change adaptation strategies for the (a) agriculture and municipal/domestic water use sector.

8.4.5 Draft climate change adaptation plan

The draft climate change adaptation plans for Mokolo and Lephalala catchment areas' agricultural and municipal/domestic water use sectors are presented in Tables 8.15 and 8.16, respectively. Most of the climate change adaptation options for water use sectors had short time frames. Short-term adaptation alternatives have immediate effects following implementation (Champalle et al., 2015), which promotes community support. The effects of most of the climate change adaptation options in this study will therefore be felt immediately after implementation. Water conservation and exploration of alternative water sources, such as groundwater and rainwater harvesting, had medium-term implementation due to these adaptation options requiring the establishment of partnerships (i.e., between different stakeholders, including communities, universities and municipalities) and the infrastructure, respectively. The infrastructure required for alternative water sources will make the cost of implementation medium over the medium-term. While there is a need for support from other sectors, such as the LEDET, DEFF, DALRRD, DWS, and WDM, in implementing some of these adaptation actions, engagements with stakeholders revealed that they are already implementing some, such as water use efficiency and environmental conservation at an individual level.

Table 8.15. Draft climate change adaptation plan for the agricultural water use sector.

Adaptation Strategy	Explanation/ benefit	Institutional Responsibility	Time frame		Relative Cost	Implementation
			Short-term (1-5 years)	Medium-term (5-10 years)		
Law enforcement	The enforcement of municipal bylaws, mainly those that are linked to water and the general environment.	WDM, the local municipality, traditional authority and SANCO			Medium	Can be implemented over the medium term.
Environmental conservation	Awareness and education on the benefits of a clean environment.	WDM, the local municipality, traditional authority and SANCO			Low	Can be implemented over the short term.
Water pollution prevention measures	Awareness and education on the benefits of an improved water quality to communities' livelihoods	WDM, the local municipality, traditional authority and SANCO			Low	Can be implemented over the short term.
Aggressive climate change awareness campaigns	Awareness related to climate change impacts, water saving strategies, smart use of water resources, and illegal water connections	WDM, the local municipality, traditional authority and SANCO			Low	Can be implemented over the short term.
Explore alternative water sources (groundwater)	Groundwater exploration and borehole drilling and investment in rainwater harvesting infrastructure in the region.	WDM and DWS			Medium	Can be implemented over the medium term.
Water use efficiency/conservation/ reuse	Avoiding waste when collecting and using water from standpipes, controlling water use in home gardens, limiting water leaks and transmission losses and not utilising hose pipes for car washing, grass or vegetable watering	WDM, the local municipality, traditional authority and SANCO			Low	Can be implemented over the medium term.
Adopt destocking over a certain period (drought)	Reducing the number of livestock during drought periods to minimise loss due to water shortage.	DALRRD and DEFF			Low	Can be implemented over the short term.
Information sharing between different sectors	Avoid working in silos and share climate change-related information and frameworks with all interested and affected stakeholders in the region.	WDM, NGOs, researchers, and the local municipality			Low	Can be implemented over the short term.

Table 8.16 Draft climate change adaptation plan for the municipal/domestic water use sector.

Adaptation Strategy	Explanation	Institutional Responsibility	Time frame		Relative Cost	Implementation
			Short-term (1-5 years)	Medium-term (5-10 years)		
Water pollution prevention measures	Awareness and education on the benefits of an improved water quality to communities' livelihoods	WDM, the local municipality, traditional authority and SANCO			Low	Can be implemented over the short term.
Aggressive climate change awareness campaigns	Awareness related to climate change impacts, water saving strategies, smart use of water resources, and illegal water connections	WDM, the local municipality, traditional authority and SANCO			Low	Can be implemented over the short term.
Environmental conservation	Awareness and education on the benefits of a clean environment.	WDM, the local municipality, traditional authority and SANCO			Low	Can be implemented over the short term.
Water use efficiency/conservation/ reuse	Avoiding waste when collecting and using water from standpipes, controlling water use in home gardens, limiting water leaks and transmission losses and not utilising hose pipes for car washing, grass or vegetable watering	WDM, the local municipality, traditional authority and SANCO			Low	Can be implemented over the medium term.
Adjusting planting date	Changing the planting date according to the seasonal forecast for the specific year	Farmer			Low	Can be implemented over the medium term.
Improved waste management	Improving the management of household water through recycling and reusing water and other materials (plastic/paper) to reduce water pollution	WDM, SANCO and communities			Low	Can be implemented by communities in the short term.
Explore alternative water sources (groundwater)	Groundwater exploration and borehole drilling, and investment in rainwater harvesting infrastructure in the region.	WDM and DWS			Medium	Can be implemented over the medium term.

8.5 SUMMARY

This chapter presented the co-developed localised climate change adaptation plan for the Mokolo and Lephalala River catchments in the Limpopo River Basin, using the ClimACT Prio to support transparent and evidence-based decision-making. The process responds to increasing climate risks in the region, including rising temperatures, more frequent droughts, variable rainfall, and growing pressure on water resources and livelihoods. The adaptation planning process combined climate data and stakeholder knowledge to ensure that proposed actions are both scientifically robust and locally relevant. Key climate risks affecting water resources, agriculture, ecosystems, and disaster management were identified and validated through stakeholder engagement, ensuring alignment with on-the-ground realities and existing priorities. The ClimACT Prio tool was applied in a series of participatory workshops to systematically identify and prioritise adaptation options. Stakeholders evaluated the proposed measures against agreed criteria, including effectiveness, feasibility, urgency, cost, and co-benefits. The chapter delivers a prioritised set of adaptation actions plan tailored to the Mokolo and Lephalala catchments. These actions emphasise strengthening water security; improving drought and flood preparedness; protecting critical ecosystems through pollution prevention, environmental conservation, and law enforcement; climate education and wide information sharing across sectors. The process also highlights enabling conditions required for successful implementation, including improved coordination across institutions, capacity building, and integration with existing catchment as well as municipalities' development planning processes.

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CHAPTER 9: SYNTHESIS AND INTEGRATION

9.1 INTRODUCTION

The results of the multifaceted study of land use and land cover (LULC) changes, land degradation processes, and hydrological responses in two catchment areas of the Limpopo River Basin, South Africa, spanning the four-decade period from 1980 to 2024, are integrated in this synthesis chapter. This area is a crucial socio-ecological system that is under strain from several interrelated factors, including population growth, mining operations, urbanisation, agricultural development, and climate change (Scholes and Biggs, 2005). Developing effective adaptation measures and ensuring sustainable development in this semi-arid region requires an understanding of the intricate relationships among these factors and their cascading effects on water supplies and land degradation (Kusanyaya et al., 2014). To contribute to this understanding, the current study addressed four interconnected aims.

(i) characterising and quantifying LULC changes using remote sensing and GIS technologies
(ii) assessing and characterising drought and soil erosion
(iii) modelling the impacts of climate change on catchment hydrology as well as water resources availability; and
(iv) co-developing a site-specific climate change adaptation plan for the Mokolo and Lephalale river catchments.

Combining these goals results in a thorough understanding of the relationships between land, water, and climate as well as evidence-based interventions for managing the region's water resources sustainably. This synthesis chapter is structured to summarise key findings from each research aim and integrate the findings across aims to reveal patterns and synergies. This chapter attempts to offer a comprehensive knowledge of the opportunities and difficulties for sustainable resource management in a time of rapid environmental. The general study goals of understanding how hydrology and the availability of water resources are affected by land-use change and climate variability are further addressed in the synthesis.

9.2 SUMMARY OF KEY FINDINGS

9.2.1 Aim 1: LULC Change Characterisation and Quantification

Using multi-decadal remote sensing datasets (Landsat) and GIS-based classification methods, the project mapped and quantified spatial patterns of LULC change across the two catchment areas. This aim provided foundational evidence of how human and environmental pressures have reshaped the landscape over four decades. It has been determined that the two catchments within the LRB (i.e., Mokolo and Lephalala) have changed since the 1980s, due to 27% of missing data for 1980, the long-term change detection analysis was carried out from 1990 to avoid bias. Notably, the agricultural LU class area increased by approximately 57.14% over the study period, expanding from 2.1% in 1990 to 3.3% in 2024. This expansion occurred primarily at the expense of natural vegetation, which is mainly woodlands in the study area, with the most pronounced changes observed in the middle reaches of both catchment areas. The spatial analysis revealed that agricultural expansion was concentrated along river corridors and in areas with relatively favourable soil and water conditions. Areas classified as bareland or severely degraded increase by 33.3% (from 0.3% in 1990 to 1.3% in 2024). These areas exhibited signs of severe erosion, vegetation loss, and soil degradation. Built-up areas grew from 0.1% in 1990 to 0.7% in 2024, which is evident in newly established settlements around the town of Lephalale and within the communal lands. The two land use classes (i.e., water and forest) did not show any changes over the study period (i.e., 1990 and 2024). The maximum likelihood classifier yielded a substantial kappa index with overall accuracies as high as 99%. These accuracy levels are consistent with international standards and provide confidence in the change detection results (Congalton and Green, 2019; Olofsson et al., 2014).

9.2.2 Aim 2: Assessment and characteristics of Drought and Soil Erosion

The assessment of land degradation processes revealed complex spatial-temporal patterns of drought occurrence and soil erosion across the Mokolo and Lephalala catchment areas. Drought analysis using multiple indices, including the Standardised Precipitation Index (SPI), Standardised Precipitation Evapotranspiration Index (SPEI) and Standardised Streamflow Index (SSI), revealed increasing drought frequency, intensity, and duration over the study period. The region experienced 12 major drought events between 1980 and 2023, with seven occurring after 2000. Drought intensity increased significantly over time, with the 2015/2016 drought representing the most severe event recorded, affecting the majority of the study area (Botai et al., 2017). The average f drought duration increased from 4-6 months in the 1980s to 8-12 months in the 2010s, suggesting a change towards longer-lasting water shortages with dire economic and household consequences. Multi-year droughts have become common in recent years (Spinoni et al., 2012; Sheffield et al., 2012). The SPEI analysis, which incorporates temperature effects on evaporative demand, showed more multi-year drought trends than precipitation-only indices such as the SPI, indicating that rising temperatures are amplifying drought impacts through increased evapotranspiration (Dai, 2013; Naumann et al., 2018).

The soil erosion analysis using the Revised Universal Soil Loss Equation revealed widespread erosion problems across the study area, with strong linkages to LULC change patterns. Areas that underwent conversion from natural vegetation to agriculture or experienced vegetation degradation showed the most dramatic increases in erosion rates (García-Ruiz et al., 2015). The EVC for the study areas ranged from very low to very high, with 38% of the soil classified as high, and 25% as having very high vulnerability to erosion. These findings indicate that the soil types in Lephalala and Mokolo are inherently susceptible to erosion. High-intensity rainfall events, which have become more frequent in recent decades, will produce disproportionately high erosion in areas with degraded vegetation cover (Nearing et al., 2014), more so in the two catchments characterised by highly erosive soils. When eroded soil reaches water courses, it has significant implications for reservoir sedimentation, water quality, and aquatic ecosystems. Major reservoirs, including the Mokolo Dam, are likely to experience accelerated sedimentation rates.

9.2.3 Aim 3: Hydrological modelling in a changing climate

The integrated modelling approach, employing the Soil and Water Assessment Tool (SWAT), provided quantitative assessments of how climate change has affected, and will continue to affect hydrological processes. The SWAT model was calibrated and validated using observed streamflow. Model performance metrics indicated good to very good agreement between simulated and observed values. The ranges of NSE = 0.5-0.7; KGE = 0.6-0.8, RSR = 0.5-0.7 and %BIAS = -2% to 22% were achieved by the SWAT model in both calibration and validation. These performance metrics meet recommended guidelines for catchment hydrological modelling and provide confidence in the model's ability to simulate basin processes. Climate change reduced precipitation and increased temperature, with evapotranspiration increasing despite reduced precipitation, which may likely be driven by changes in vegetation composition and the increase in the bare land use class. Climate change projections under both high and low emission scenarios indicated substantial future impacts. Ensemble projections show high uncertainty but suggest modest declines in annual precipitation in the far future and some increase expected in the near future climate. The rainy season may become shorter but with more intense events (Pinto et al., 2016; Lazenby et al., 2015). Peak discharge events are expected to be moderate in the upper to middle reaches of both catchments, potentially worsened by LULC changes that reduced infiltration and increased runoff generation. This finding has important implications for flood risk management, more so as the recent floods in the Lephalala River resulted in missing children and loss of lives and livestock.

9.2.4 Aim 4: Co-development of Climate Change Adaptation Plan

The participatory process of co-developing a climate change adaptation plan for the Mokolo and Lephalale catchments engaged multiple stakeholder groups, including traditional authorities, community members, municipal officials, water managers, conservation practitioners, and research institutions. This process integrated scientific findings with local knowledge and stakeholder priorities to develop contextually appropriate and socially acceptable adaptation strategies. The process responds to increasing climate risks in the region, including rising temperatures, more frequent droughts, variable rainfall, and growing pressure on water resources and livelihoods. The adaptation planning process combined climate data and stakeholder knowledge to ensure that proposed actions are both scientifically robust and locally relevant. Key climate risks affecting water resources, agriculture, ecosystems, and disaster management were identified and validated through stakeholder engagement, ensuring alignment with on-the-ground realities and existing priorities. The ClimACT Prio tool was applied in a series of participatory workshops to systematically identify and prioritise adaptation options. Stakeholders evaluated the proposed measures against agreed criteria, including effectiveness, feasibility, urgency, cost, and co-benefits. The chapter delivers a prioritised set of adaptation actions plan tailored to the Mokolo and Lephalala catchments. These actions emphasise strengthening water security; improving drought and flood preparedness; protecting critical ecosystems through pollution prevention, environmental conservation, and law enforcement; climate education and wide information sharing across sectors. The process also highlights enabling conditions required for successful implementation, including improved coordination across institutions, capacity building, and integration with existing catchment as well as municipalities' development planning processes.

9.3 INTEGRATION OF FINDINGS: PATTERNS AND SYNERGIES

The integration of findings across objectives reveals LULC change as the dominant driver of land degradation in the region, operating through multiple pathways (direct and indirect). Direct Pathways includes, but is not limited to, removal of natural vegetation and overgrazing. Vegetation removal through agricultural expansion and deforestation directly exposes soils (as noted in the increase of bareland class over the LULC classification between 1980 and 2024). Overgrazing in communal rangelands reduces vegetation cover and soil organic matter. While the indirect Pathways would be the influence of LULC changes in the alteration of local and regional water balances, which affect groundwater recharge, streamflow patterns, contributing to ecosystem water availability. Clearing of vegetation, for example, will likely modify albedo, surface roughness, and energy partitioning, potentially affecting local climate and rainfall patterns. Land degradation reduces land productivity, potentially driving further expansion into marginal lands and creating self-reinforcing cycles of degradation. Reduced infiltration and groundwater recharge decrease water availability, intensifying competition for water resources and potentially driving unsustainable water use. Erosion and sedimentation degrade water quality and reservoir storage capacity, affecting water security and ecosystem health (Quinto et al., 2010).

While LULC change emerges as the primary driver of land degradation, climate change acts as a critical amplifier, exacerbating degradation processes and constraining recovery. Rising temperatures increase evaporative demand, reducing soil moisture availability and increasing drought stress on vegetation. These higher temperatures accelerate decomposition of organic matter, reducing soil carbon stocks and fertility. Declining annual precipitation reduces water availability for vegetation, agriculture, and ecosystem maintenance as well as domestic water use. Increased rainfall intensity generates higher erosive power, particularly on degraded lands with reduced infiltration capacity. This is particularly evident with notable gully developments in the Lephalala River Catchment. Greater rainfall variability in the two catchments, emulating the southern Africa variability, creates challenges for agricultural planning and water resource management. The combination of LULC change and climate change produces synergistic impacts exceeding the sum of individual effects. Degraded lands are more vulnerable to climate extremes, experiencing more severe drought impacts and higher erosion during intense rainfall. Climate change reduces the resilience and recovery capacity of degraded ecosystems (Zscheischler et al., 2018).

The temporal analysis identifies clearly differentiated phases of change, each shaped by interacting socio-political, economic, and climatic drivers. During the period 1980 to 1994, land use and land cover (LULC) change occurred at relatively low rates, largely constrained by apartheid-era policies and limited public and private investment in former homeland areas. This period was marked by gradual environmental degradation in communal lands due to high population pressure and insufficient land management support, alongside the expansion of commercial agriculture in more favourable areas. Climatic conditions were characterised by moderate drought frequency, with severe drought events in 1982/1984 and 1991/1992, the latter having significant adverse impacts on both agricultural production and domestic water supply, thereby intensifying pressures on water resource allocation (Kepe et al., 2014;

Hoffman and Todd, 2000). In contrast, the post-1994 period (1995 to the current period) reflects accelerated LULC dynamics following political transition and the implementation of land reform programmes. This phase saw the expansion of small-scale agriculture in former homelands, albeit with uneven outcomes, alongside rapid infrastructure development, urban growth, and increased mining activity in the Waterberg region. Climate variability intensified during this period, with severe droughts recorded in 1995/1996 and 2002/2003. From 2005 to the present, LULC change has further intensified, driven primarily by a mining boom, agricultural commercialisation, and continued urban expansion. This phase is associated with heightened degradation of natural landscapes, particularly in mining zones and communal rangelands, escalating water stress within the Mokolo and Lephalala catchment, and an increasing frequency and severity of droughts, including the extreme 2015/2016 event (Archer et al., 2017; Baudoin et al., 2017).

9.4 CHAPTER SUMMARY

The thorough analysis of the hydrological response, land degradation, and changes in land use and cover in the Mokolo and Lephalala catchments between 1980 and 2024 offers important insights into the opportunities and challenges for the sustainable management of semi-arid social-ecological systems under climate change. The study demonstrates that:

1. Across the two catchment areas, LULC changes have been significant and pervasive, with urbanisation and agricultural growth driving the conversion of natural lands and increasing the amount of bareland. These shifts result from intricate interactions among environmental, policy, economic, and demographic factors.
2. Drought and soil erosion have increased land degradation, endangering ecological integrity, water security, and agricultural output. Degradation is concentrated in community rangelands, steeply sloped cultivated areas, and mining sites, with notable interannual fluctuations driven by climate.
3. Land degradation and hydrology are impacted by the synergistic interactions between LULC change and climate change, with the combined effects outweighing the total of the individual effects. Climate change is the main cause of water supply loss, even though LULC change dominates erosion increases. For adaptation to be effective, both variables must be taken into consideration.
4. According to future projections, water stress is likely to persist, with the region potentially facing serious sustainability issues that will hinder development, ecosystems, and livelihoods in the absence of significant actions.
5. Effective adaptation requires integrated strategies addressing both land and water management, combining ecosystem-based approaches with livelihood support, and engaging multiple stakeholders in co-developing contextually appropriate solutions. The participatory adaptation planning process for the Mokolo-Lephalala catchments demonstrates viable pathways forward.
6. Furthermore, developing adaptation solutions that are both technically sound and socially acceptable requires knowledge integration, which combines scientific analysis with local knowledge, stakeholder values, and institutional realities. Research quality and implementation efficacy are both improved by transdisciplinary techniques.

Despite limitations and uncertainties, the study provides a robust foundation for addressing the interlinked challenges of land degradation, water security, and climate change in the Mokolo and Lephalala catchment areas. The co-developed adaptation plan offers a practical pathway forward, though successful implementation will require sustained commitment, adequate resources, improved governance, and adaptive management at all decision-making levels. The region's natural and human resources, combined with growing awareness of sustainability imperatives and emerging adaptation initiatives, provide a foundation for positive change.

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CHAPTER 10: CONCLUSIONS AND RECOMMENDATIONS

10.1 CONCLUSIONS

This study investigated the impacts of land use and land cover (LULC) changes on land degradation and hydrology in the Mokolo and Lephalala river catchments under a changing climate over the period 1980-2023. The study offers thorough insights into the intricate relationships between LULC change, climate change, land degradation, and water resources in these semi-arid catchments through an integrated analysis that combines remote sensing, hydrological modelling, drought assessment, erosion evaluation, and participatory adaptation planning. To improve the sustainability and resilience of the Mokolo and Lephalala system, this chapter offers broad conclusions as well as practical suggestions for researchers, policymakers, resource managers, and local communities. Through a variety of direct (vegetation removal, soil compaction, surface sealing, overgrazing) and indirect (altered water balances, modified microclimates, landscape fragmentation) pathways, LULC change emerges as the primary proximate driver of land degradation in the Mokolo and Lephalala catchments. The study shows that the observed erosion and hydrological changes over the study period were influenced by LULC change. These results highlight the need for sustainable land management to be at the heart of any plan for preserving the region's water security and ecosystem integrity. While LULC change is the primary driver of degradation, climate change acts as a critical amplifier, exacerbating degradation processes and constraining recovery. Rising temperatures increase evaporative demand and drought stress; declining precipitation reduces water availability; and increased rainfall intensity increases higher erosive power on degraded lands. The research shows that climate change contributed to streamflow, highlighting its dominant role in altering water availability.

Across the catchments, LULC variations, land degradation processes, and susceptibility exhibit significant temporal variation, revealing intricate relationships between biophysical gradients, land tenure systems, socioeconomic differentiation, and institutional capability. The Lephalala catchment is more severely affected by drought than Mokolo. Former homeland areas under community tenure exhibit more extensive degradation than commercial farming areas, and across different temporal eras, degradation rates and patterns of change vary. This variation necessitates locally based strategies that account for local circumstances and contexts to ensure equitable adaptation outcomes and target interventions.

The Mokolo and Lephalala catchments face increasing vulnerability to environmental change, with converging pressures from LULC change, climate change, and growing resource demands creating sustainability challenges. Future climate projections indicate continued, and potentially accelerating degradation, and water stress under both the low- and high- emission scenarios, with severe droughts becoming more frequent and water yield declining. Without substantial interventions, the region faces threats to livelihoods, ecosystems, and development that could trigger social-ecological regime shifts with potentially irreversible consequences. Despite the serious challenges faced in the region, effective adaptation is both feasible and economically justified through integrated strategies that address land and water management simultaneously, combine livelihood support, and engage multiple stakeholders in co-developing contextually appropriate solutions. The participatory adaptation planning process demonstrated viable pathways forward, with identified interventions being economically viable and some could be implemented in the short-term with little or no associated cost. Most of the stakeholders (many of whom were domestic water users) stressed the challenge of water supply for basic domestic chores. The proposed adaptation plan encourages information sharing among sectors active in the region, environmental conservation, and the establishment of use-efficiency systems.

10.2 RECOMMENDATIONS

Based on the research findings and conclusions, the following recommendations are proposed for different stakeholder groups and decision-making levels. These recommendations are organised thematically and prioritised based on urgency, feasibility, and potential impact.

- The provincial government (i.e., LEDET and DAFF) should significantly scale up support for sustainable land management through existing programs (i.e., LandCare, Working for Water, Working for Wetlands) and new initiatives in the region. This can be achieved by increasing budget allocations for sustainable land management programs, targeting support to high-priority areas which are vulnerable to future climate risk. These areas, according to the risk mapping, cut across both catchment areas, the middle and lower reaches of the two catchment areas, inclusive of riparian zones, which are highly exposed to erosion risks, especially during rainfall events. The budget allocation can further be used to provide technical assistance, training, and extension services to support adoption at the local level, using the local people.
- Municipalities in the region (Lephalale, Modimolle-Mookgophong, Mogalakwena, Blouberg) should mainstream climate adaptation into their Integrated Development Plans and Spatial Development Frameworks. This mainstreaming will compel managers at this level to conduct municipal climate vulnerability assessments and adopt the co-developed climate change adaptation plans. Additionally, managers can use the co-developed adaptation plan as a starting point to develop a robust plan applicable to the entire region. These should be done with specific, budgeted interventions and integrate climate considerations into land use planning, infrastructure development, and service delivery. Furthermore, the municipality should create a dedicated implementation unit to coordinate and support adaptation action across the catchments. This should be a multi-stakeholder governance structure with representation from government, private sector, civil society, and communities, with a clear mandate to coordinate adaptation implementation, mobilise resources, and facilitate partnerships.
- Local authorities should prioritise environmental conservation measures and strict adherence to environmental bylaws, and this should be enforced in the context of environmental law with law enforcement authorities. An emphasis at this level should also focus on restoration of wetlands and riparian zones, to enhance river water quality and reduce the risk of sedimentation to Lephalala and Mokolo rivers.
- This study further recommends, as an immediate short-term intervention, the establishment of an alternative domestic water supply system for the communities in the region of Ga-Shongoane and Martinique villages to address persistent

household-level water insecurity. The proposed intervention is necessitated by recurrent supply interruptions and declining reliability of existing water sources, which have been exacerbated by climatic variability and increasing demand pressures. An alternative supply system, such as decentralised boreholes, storage tanks or rainwater harvesting schemes, would enhance redundancy within the local water supply network. This approach would reduce dependence on vulnerable centralized systems and improve resilience to drought and infrastructure failure. Improved access to reliable domestic water would contribute directly to household health, sanitation, and food preparation needs. Furthermore, the intervention would mitigate socio-economic vulnerabilities associated with water scarcity, particularly to the vulnerable groups such as the elderly and women. In the short term, such systems can be implemented with relatively low capital investment and rapid deployment. Importantly, the initiative would provide a transitional solution while long-term integrated water resource management strategies are being developed. The intervention should be supported by community engagement and capacity building to ensure effective operation and maintenance. Collectively, the establishment of alternative domestic water supply systems represents a pragmatic and sustainable response to immediate water shortages in Shongoane and Martinique.

Appendix 1: Stakeholder Engagement Workshop Municipal Water Use Questionnaire

Impacts of land use and land cover changes on land degradation and hydrology in a changing climate: A case of Limpopo River Basin in South Africa (WRC Project no. C2022/2023-00906)

Questionnaire for collecting information on understanding of climate change, its impact and existing climate change adaptation strategies for municipalities: Municipal/Domestic water use

Interviewer : ……………………………………………………………

Date of interview : ……………………………………………………………

Purpose of interview: The purpose of the questionnaire is to obtain information on interviewee's understanding of climate change, its impact and existing climate change adaptation strategies in Mokolo and Lephalala river catchments for municipalities. This will assist in developing site specific practical climate change adaptation strategies for municipal/domestic water uses in the Mokolo and Lephalala river catchments.

1. **General information**

Gender	Male ☐ Femal ☐
Age group	<18 ☐ 21- 30 ☐ 31-40 ☐ 41-50 ☐ 51-69 ☐ 70 and abov ☐
Occupation	

Educational Level	**Mark with an X**
Did not go to school	
Primary School	
Secondary School	
Undergraduate Degree	
Postgraduate Degree	

2. Climate change, its impact, existing and/or suggested climate change adaptation strategies and mitigation

2.1 What is your understanding of the term "climate change"?

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2.2 How is climate change impacting on municipal/domestic water supply?

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2.3. Do you think that the impacts are going to be worse or better in the future?

Worse ☐

Better ☐

2.4. What is (are) the reason(s) for the answer you provided in question 2.3?

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2.5. What strategies do you have for adapting to climate change impacts?

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2.6. Are they working effectively?

Yes ☐

No ☐

2.7 What is (are) the reason(s) for the answer you provided in question 2.6?

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2.8 Have you documented the adaptation strategies that you are currently using?

Yes ☐

No ☐

If yes, please provide us with the document.

2.9 How often do you revise/update these strategies?

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2.10 What other climate change adaptation strategies can you suggest?

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2.11 What are the strategies that are there to mitigate or reduce climate change impacts?

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2.12 What other climate change mitigation strategies can you suggest?

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2.13 Is there any other relevant information you would want to share regarding climate change and climate change adaptation measures?

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THE END. THANK YOU FOR YOUR PARTICIPATION. YOUR INPUT IS VALUEABLE

Appendix 2: Stakeholder Engagement Workshop Agriculture Water Use Questionnaire

Impacts of land use and land cover changes on land degradation and hydrology in a changing climate: A case of Limpopo River Basin in South Africa (WRC Project no. C2022/2023-00906)

Questionnaire for collecting information on understanding of climate change, its impact and existing climate change adaptation strategies agricultural water use: Agricultural water use.

Interviewer : ……………………………………...............................

Date of interview : ……………………………………………………………

Purpose of interview: The purpose of the questionnaire is to obtain information on interviewee's understanding of climate change, its impact and existing climate change adaptation strategies in Mokolo and Lephalala river catchments for agricultural water use. This will assist in hydrological modelling of climate change impacts and developing practical site specific adaptation strategies for agricultural water uses in Mokolo and Lephalala river catchments.

2. **General information**

Gender	Male ☐ Femal☐
Age group	<18 ☐ 21- 30☐ 31-40 ☐ 41-50 ☐ 51-69 ☐ 70 and above☐
Occupation	

Educational Level	**Mark with an X**
Did not go to school	
Primary School	
Secondary School	
Undergraduate Degree	

Postgraduate Degree	

2. Agricultural water use

What is your role with respect to small scale agriculture?

…………………………………………………………………………………………….

What types of crops do you grow in your farm?

……………………………………………………………………………………………..

Do you keep records on water use in the farm or by small scale farmers?

Yes ☐

No ☐

If yes, please provide us with the information.

If no, please assist with information on planting and harvesting dates as well as irrigation schedules.

What are the main sources of water supply to the farms?

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How often are farmers able to meet the irrigation requirements?

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If there are periods where they fail to meet the irrigation requirements, what are the likely causes?

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2.7 How do you deal with water shortages, particularly during dry periods?

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3. Climate change, its impact and existing climate change adaptation strategies

3.1 What is your understanding of the term “climate change”?

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3.2 How is climate change impacting on small scale agriculture?

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3.3. Do you think that the impacts are going to be worse or better in the future?

Worse ☐

Better ☐

3.4. What is (are) the reason(s) for the answer you provided in question 3.3?

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3.5. Do you have strategies for adapting to climate change impacts?

Yes ☐

No ☐

3.6. If yes, are they working effectively?

Yes ☐

No ☐

3.6 What is (are) the reason(s) for the answer you provided in question 3.5?

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3.7 Have you documented the adaptation strategies that you are currently using?

Yes ☐

No ☐

If yes, please provide us with the document.

3.8 How often do you revise/update these strategies?

…………………………………………………………………………………………………

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3.9 Is there any other relevant information you would want to share regarding climate change and climate change adaptation measures?

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THE END. THANK YOU FOR YOUR PARTICIPATION. YOUR INPUT IS VALUEABLE.