FACULTY OF SCIENCE
SCHOOL OF GEOGRAPHY, ARCHAEOLOGY AND ENVIRONMENTAL STUDIES

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# AN ASSESSMENT OF THE IMPACTS OF CLIMATE CHANGE/ VARIABILITY AND LAND USE - LAND COVER CHANGES ON SURFACE RUNOFF IN THE UPPER MZINGWANE SUBCATCHMENT, ZIMBABWE

**By**

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# ABSTRACT

Climate change is one the most topical subjects in today’s world. Numerous studies have linked climate to increased incidence and severity of impacts of natural hazards such as droughts, floods and wildfires. To this end, climate science research has been and still continues to be one of the most active areas of scientific enquiry in a quest to better understand climate systems dynamics and more recently their interlink with other systems. In this study, the climate and land use – landcover change dynamics are explored and then their impacts on surface hydrological conditions in the upper Mzingwane subcatchment (UMS) of Zimbabwe assessed. Initially, an in-depth review of existing climate and hydrology published research in Zimbabwe over the past 29 years is undertaken using a systematic review approach. It emerged that of the 107 studies reviewed, the two predominant themes covered were climate impact (39%) and climate vulnerability, adaptation and mitigation (39%) while climate and hydrological modelling were the least covered themes at 4%. Most of the research is outdated in Zimbabwe and has limited use of more recent climate and hydrological modelling tools and techniques.

With regards to landscape degradation, historical land use and landcover changes and modelled future land use and landcover scenarios in UMS were explored the using Geographic Information Systems and Remote Sensing. It emerged that extensive deforestation has been taking place in the UMS with losses of over 700 km$^2$ between 1089 and 2018 and this trend is projected to continue into the future with over 40% of forest cover lost by 2038. These changes are most likely to be driven by increased human activities in the area especially small-scale and illegal gold mining.

To better understand historical precipitations conditions in the UMS, climate station historical precipitation records are used to assess twentieth century climate extreme events over UMS. Though results indicate statistically insignificant trends, indication is that high intensity and short period precipitation events have been increasing despite the overall decrease in total precipitation levels over the UMS. Generally, mean precipitation anomalies show a general negative trend of between -0.06 mm and - 6.36 mm in the northern and western region of the UMS suggesting general drying between 1920 and 2001. For example, results show declining trends in 5-day maximum precipitation (RX5Day), (mean = -0.879 mm/annum). Overall, the smoothed 5-year moving average trends for most index anomalies seem to reveal a near 20 to 30 year periodicity over the UMS.

Future climate projections in the UMS for the near future (2021 – 2040), mid-term future (2021-2060) and long term future (2061-2099) are explored using the Conformal Cubic Atmospheric Model (CCAM) data downscalings of 6 GCMs. Models show an overall anomaly signal ranging from -15 mm to +18 mm change in annual total precipitation over the UMS. Mid to long-term precipitation anomalies range between +3mm and +9mm compared to +3mm and +15mm in the near-future period suggesting decreases magnitude of change in total precipitation in the future. Four of the ensemble members generally show positive spatial patterns of change while two show the opposite trends in long term average of monthly precipitation though the is consensus on a south to north increasing gradient in precipitation in all future periods. The Max Plank Institute (MPI), the Geophysical Fluid Dynamics Laboratory Climate Model (GFDL CM2.5) and the National Centre for Meteorological Research Climate Model version 5 (CNRM-CM5) have highest competence in simulating monthly average precipitation while the Community Climate System Model Version 4 (CCSM4) has lowest performance. With regards to temperature projections, all ensemble members show a clear consensus on an increasing trend in both maximum and minimum temperature with magnitudes of changes varying between 1.1 °C up to 6.4 °C from the near to the long-term future. These changes translate to between +0.7 °C to +1.15 °C decade$^{-1}$ in mean temperature changes which shows consistent gradual warming over the UMS. This could have significant impacts on both human health, agriculture and water security.

For the first time in the Northern Limpopo basin, a physical, semi-distributed hydrological model is successfully applied to simulate stream run-off with satisfactory levels of accuracy using downscaled CCAM data. Majority of the ensemble members simulate simulated peak stream discharges ranging between 1244.8 m$^3$s$^{-1}$ and 42.9 m$^3$s$^{-1}$ though most (4) of the downscalings simulate a mean increase in peak discharge of ~620 m$^3$s$^{-1}$ i.e. ~7.83 m$^3$s$^{-1}$yr$^{-1}$ over the entire future period. The NorESMI and the GFDL-CM3 model project declining trends in peak stream discharge though the former simulates the highest peak discharge (1244.8 m$^3$s$^{-1}$) in the baseline period (1996 – 2015). The increases could be related to projected increases in precipitation by the CCAM ensemble members as earlier presented. The impact of land use and land cover changes on the stream peak and total volume discharge seems to be inconclusive in that in the 2018 (2038) LULC change forcing of the hydrological model show a decrease (increase) in stream peak discharge and volume in the UMS. The increase in discharge could relate to the projected increase in bareland/ impervious surfaces related to human development/ activities in the UMS.

Overall, the study manages to add new knowledge to fill gaps in historical and project future climate change/ variability scenarios in the UMS. The extent of past and future landscape degradation is quantified indicating extensive deforestation to continue into the future. With projected future climate projections of increasing total precipitation and temperatures, the projected impact is increased stream run-off and peak discharge. Novelty in this study is the first time use of downscaled, and/ bias-corrected high-resolution CCAM data together with simulated LULC scenarios to model future multi-temporal surface stream run-off at a subcatchment level. These study findings are consequential in understanding the climate-LULC-hydrology nexus and therefore valuable in planning for climate change impact mitigation, strategy and policy development so as to avert negative water security and livelihood impacts in the UMS and beyond.

***Keywords***

*Mzingwane catchment; Climate change; Land use - Land cover; GIS; Hydrological modelling; Zimbabwe*

# DECLARATION

I declare that this thesis report is my own unaided work. It is being submitted for the degree of Doctor of Philosophy at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other university.

……………………………………………

Auther Maviza

21st day of October in the year 2021

# DEDICATION

*~ To Gracsious, Adiel Wandile and Amaris Usanda*
*(my family, my life), with all my love. ~*

# PUBLICATIONS EMANATING FROM THIS RESEARCH

- Auther Maviza and Fethi Ahmed (2020), *Analysis of past and future multi-temporal land use and land cover changes in the semi-arid Upper-Mzingwane sub-catchment in the Matabeleland south province of Zimbabwe*, International Journal of Remote Sensing, 41:14, 5206-5227, DOI: https://doi.org/10.1080/01431161.2020.1731001

- Auther Maviza and Fethi. Ahmed (2021), *Climate Change/Variability and Hydrological Modelling Studies in Zimbabwe: A Review of Progress and Knowledge Gaps*, Springer Nature Applied Sciences, 3 549. DOI: https://doi.org/10.1007/s42452-021-04512-9

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# LIST OF ABBREVIATIONS AND ACRONYMS

AGCM - Atmosphere-only General Circulation Models
ANN - Artificial Neural Network
AOGCM - Coupled Atmosphere–Ocean General Circulation Models
CA - MC - Cellular Automata - Markov Chain
CA - Cellular Automata
CCAM - Conformal Cubic Atmospheric Model
CCCM - Canadian Climate Centre Model
CCSM4 - Community Climate System Model Version 4
CEDA - Centre for Environmental Data Analysis
CGCM3 - Coupled Global Climate Model
CORDEX - Coordinated Regional Climate Downscaling Experiment
COSMO-CLM - Consortium for Small-Scale Modelling and Regional Climate Model
CNRM-CM5 - Centre National de Recherches Météorologiques – Coupled Model version 5
CRU-TS - Climate Research Unit - Time Series
CSIRO Mk3 - Commonwealth Scientific and Industrial Research Organisation Mark 3
DEM - Digital Elevation Model
DN - Digital Numbers
DOS - Dark Object Subtraction
EBSCO - Elton B. Stephens Company
ENVI - Environment for Visualizing Images
EO - Earth observation
ESM - Earth System Models
ESRI - Environmental Systems Research Institute
FLAASH - Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes
GAD - Give-A-Dam
GCMs - Global Climate Models
GFDL CM2.5 - Geophysical Fluid Dynamics Laboratory Climate Model version 2.5
GIS - Geographic Information Systems
GISS - Goddard Institute of Space Studies
GoZ - Government of Zimbabwe
GS - Google Scholar
HadCM3 - Hadley Centre Coupled Model, version 3

HadGEM3-GC3.1 - Hadley Centre Global Environment Model 3 - Global Coupled version 3.1
HBV - Hydrologiska Byråns Vattenbalansavdelning model
HEC-GeoHMS - Hydrologic Engineering Center’s Geospatial Hydrologic Modelling Extension
HEC-HMS - Hydrologic Engineering Center’s Hydrologic Modelling System
IKS - Indigenous Knowledge Systems
IPCC - Intergovernmental Panel on Climate Change
ITCZ - Inter-tropical Convergence Zone
KIA - Kappa Index of Agreement
KNN - K-Nearest Neighbour
L5-TM - Landsat 5 Thematic Mapper
L8-OLI - Landsat 8 Operational Land Imager
LCM - Land Change Modeller
LP DAAC - United States Land Processes Distributed Active Archive Centre
LR - Logistic Regression
LULC - land use - land cover
LULCC - land use - land cover changes
MC - Markov chain
MIROC-ESM - Model for Interdisciplinary Research on Climate – Earth Systems Model
MLP - Multi-Layer Perceptron
MODHYDROLOG - MODified HYDROLOG model
MPI-ECHAM5 - Max Planck Institute for Meteorology European Centre Hamburg Model version 5
NAP - National Adaptation Plan
NCCRS - National Climate Change Response Strategy
NCP - National Climate Policy
NDVI - Normalised Difference Vegetation Index
OA - Overall Accuracy
OLR - Outgoing Longwave Radiation
PCM - Parallel Climate Model
QBO - Quasi-biennial Oscillation
QUAC - Quick Atmospheric Correction
RCD - Regional Climate Downscaling
RCMs - Regional Climate Models
RegCM4 - Regional Climate Model version 4

RF - Random Forest
RMSE - Root Mean Square Error
RS - Remote Sensing
SADC - Southern African Development Community
SARS-CoV-2 (COVID-19) - Severe Acute Respiratory Syndrome Coronavirus-2
SCS-CN - Soil Conservation Service - Curve Number
SDGs - Sustainable Development Goals
SEBS - Surface Energy Balance System
SOI - Southern Oscillation Index
SRCCL - Special Report on Climate Change and Land
SST - Sea-surface temperatures
STARDEX - Statistical and Regional dynamic Downscaling of Extremes for European regions
SVM - Support Vector Machine
SWAT - Soil and Water Assessment Tool
SWIR - Shortwave Infra-Red
TOA - Top-of-Atmosphere
TOPMODEL - Topographically-driven rainfall-runoff Model
TRMM - Tropical Rainfall Measuring Mission
UKMO - United Kingdom Meteorological Office
UMS - Upper Mzingwane sub-catchment
UNDP - United Nations Development Programme
UTM - Universal Transverse Mercator
VNIR - Visible Near Infra-Red
WCRP - World Climate Research Programme
ZCHPC - Zimbabwe Centre for High Performance Computing
ZINGSA - Zimbabwe National Geospatial and Space Agency
ZINWA - Zimbabwe National Water Authority

# CHAPTER 1: GENERAL INTRODUCTION

## 1.0 INTRODUCTION AND BACKGROUND OF THE STUDY

By 2025, it is estimated that 63% of the global projected population of 8 billion will be living in water stressed regions (Arnell, 1999) with climate change potentially exacerbating the pressures in these areas, which include semi-arid regions in Sub-Saharan Africa. Without any adaptation mechanisms in place, Hayashi et al. (2013) project a massive 83% increase in the global water-stressed population (i.e. 1.8 billion in 2000 to ~ 3.3 billion in 2050). Amidst this ongoing climate change discourse within the scientific community (Henderson-Sellers and McGuffie, 2012, Easterbrook, 2016), the 2015 state of the climate review by Blunden et al. (2016) revealed overwhelming shifts in global climatic conditions with some areas becoming either wetter or drier. This has bolstered the general consensus that climate change has negative impacts on various systems in the biosphere (Letcher, 2009, Boone et al., 2018). The changing or varying global, regional and local climatic trends have not only strongly influenced/impacted on water resource availability and accessibility, but also livelihoods in general (WaterNet, 2003, Love et al., 2010, Stigter and Ofori, 2014, Schilling et al., 2020). The broad range of present and future threats presented by climate change and/or variability extend to other most critical resources such as food, ecosystems, energy, and human-health (Pielke, 2013, Ngwenya et al., 2018b, Hayes et al., 2019, Nichols et al., 2020). This has over the years reinforced the widespread appreciation of the reciprocal feedback loops, complex patterns and non-linear dynamics exhibited by hydro-ecological processes with changing or varying climatic conditions (IPCC, 2001, Liu et al., 2007, Vicuna and Dracup, 2007), thus necessitating the need to expand scientific knowledge on the same.

Similarly, changes in landscape heterogeneities in space and time as a result of natural processes and primarily human activities (Liu et al., 2007), have been noted to have varying impacts on hydrological processes at different scales as well. Evidence from integrated studies of coupled human-natural systems (Gergel et al., 2002, Werner and McNamara, 2007, Li et al., 2019a) have revealed that population growth, emerging societal affluence and government policies have significant implications on landscape (land use-land cover) changes which tend to have an aggravating effect on the dynamics of natural hydrological processes in a given area (Klocking and Haberlandt, 2002).

As such, advancing scientific evidence and the theoretical understanding of complexities of mechanisms, patterns, magnitudes, and probability of incidence of various effects of climate change/variability and landscape change dynamics on hydrological systems has over the years become imperative. This has led to discovery of new connections between key factors and the formulation of pragmatic approaches to address intrinsic socio-economic challenges aimed at presenting contextual recommendations for ‘true’ sustainability (National Research, 2002). While some studies have focused on hydrological changes at long-term - macro-scale levels (Helmschrot and Flügel, 2002, Arnell, 2004), others have explored the same over transient to medium-term time periods at catchment and meso-scale levels in temperate and semi-arid regions of the world (Becker et al., 2004, Uhlenbrook et al., 2004, Yira et al., 2017). Over the years, there has also been an increasing interest in the integration of climate models in such studies in an attempt to understand future effects of climate change on catchment hydrology (Gleick, 1986, Bouwer et al., 2004, Maina et al., 2013, Chen et al., 2018), such as water yield and/or runoff (LaFontaine et al., 2015, Pokhrel et al., 2018, Falkland and White, 2020). Climate models have also proved useful in understanding dynamics and effects of important phenomena such as the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO) (Randall et al., 2007a, Christensen et al., 2013, IPCC, 2013, Manatsa et al., 2017).

Relative to climatic models, various hydrological modelling approaches have also been used to understand the mechanisms and driving forces behind changes in hydrological processes, so as to allow for reliable estimates of available water resources within river basins worldwide (Zhu and Ringler, 2012, Woldesenbet et al., 2016, Liu et al., 2017, Siderius et al., 2018). The models range from simple lumped and conceptual catchment models to the more complex distributed and physically based models, such as the Hydrologic Engineering Center’s Hydrologic Modelling System (HEC-HMS), Topographically-driven rainfall-runoff Model (TOPMODEL), and the Soil and Water Assessment Tool (SWAT). Such models have been widely used in numerous studies to better understand hydrological processes in different parts of the world (Fohrer et al., 2001, Gumindoga et al., 2015, Chen et al., 2018).

Further developments in the application of hydrological models have seen the emergence of what Xu (2016) referred to as state-of-the-art new generation distributed models integrating Geographic Information Systems (GIS), remotely sensed data and Global Climate Models. The advantage of such models has been their flexibility and ability to simulate different climatic and/or physiographic conditions and processes at various spatial scales in predicting future effects of climate and landscape changes (Andersen, 2008). However, though the exploitation of GIS and remote sensing techniques has increased within this domain in Sub-Saharan Africa, Murayama et al. (2011) found that gaps still remain in terms of streamlining policy formulation and implementation on the same with water resources monitoring and management.

Considering the prevailing semi-arid conditions therein, southern Africa is considered to be highly vulnerable to the effects of climate change (Ngcobo et al., 2013). Over and above the overarching effects of climate change, the region’s vulnerability according to SADC (2011) has been exacerbated by poor policy responses in the wake of socio-economic and environmental changes related to numerous anthropogenic activities such as agriculture, mining and deforestation in this region. As such, while numerous studies such as those by Gleick (1987), Hendrix and Glaser (2007), Farjad et al. (2017) and Moyo and Nangombe (2015) have explored these and other related challenges, critical knowledge gaps still exist concerning the potential future impacts of climate and landscape changes on those aspects most importance (e.g. water) to society and economies in southern Africa. Furthermore, despite the wide scope of application of Regional Climate Models (RCMs) in hydrological studies (Gangodagamage et al., 2001, Hewitson et al., 2004, Salathé et al., 2010, Daron, 2014), few studies have been undertaken within this domain in southern Africa. This necessitates the need for more multifaceted research to close such knowledge gaps and help identify opportunities for guided policy responses and innovative interventions aimed at building and/or strengthening climate resilience and adaptation in communities within the region.

In light of the earlier discussed aspects, the focus of this study is thus to explore the ‘climate-landscape change and surface hydrology’ nexus within the semi-arid upper-Mzingwane sub-catchment in Matabeleland South Province of Zimbabwe. This is achieved by integrating RCM data, a semi-distributed hydrological model and remotely sensed data to advance the understanding of, and predict future state of, surface water resources, and hence contributing to sustainable water resources management for better water security.

## 1.1 PROBLEM STATEMENT AND JUSTIFICATION OF STUDY

The upper Mzingwane sub-catchment (UMS) (Figure 3.1) is one of the most prolific sub-catchments in terms of capturing and storing water in the Northern Limpopo basin (Wu et al., 2006), with great economic value in and beyond the semi-arid Matabeleland South province of Zimbabwe. However, there are concerns about impacts of climate change and/or variability such as high rainfall variability in this and other lowveld catchments in Zimbabwe (Mazvimavi, 2010a). This sub-catchment has seen extensive though largely unquantified landscape/environmental transformations driven largely by socio-economic and political factors aimed at improving rural livelihoods e.g. the Government of Zimbabwe's accelerated land reform and black economic empowerment policies (Li and Yeh, 2004). Furthermore, despite having a functional Catchment Council (i.e. the Mzingwane Catchment Council) to manage the catchment, WaterNet (2003) noted that there was a general lack of integrated management approaches (aimed at linking agriculture, soil, water, climate), human capacities and weak institutional arrangements to bolster sustainable water resources within the catchment.

Furthermore, underlain by the vast Zimbabwean Craton greenstone belt (known to be a rich-gold bearing rock deposit) (Shadeed and Almasri, 2010), the environmental disturbances within the entire Mzingwane catchment have been exacerbated by an increase in both loosely regulated, legal and extensive illegal gold mining also espoused by the Zimbabwean government's black economic empowerment policies. The environmental degradation has also been compounded by poor land and agricultural practices, especially in communal and resettlement areas where land tenure systems are also poorly monitored (Love et al., 2005). Considering the already established intricate coupling of human-natural systems across space and time (Liu et al., 2007, Werner and McNamara, 2007), e.g. landuse and river run-off, the described scenarios indicate considerable land use-land cover changes (LULCC) over the years with possible impacts on the surface hydrological processes within the UMS (Ngigi et al., 2007, Thanapakpawin et al., 2007, Khare et al., 2015). Overarching this is the probable impact of climate change/variability on the sub-catchment's water resources which do not only sustain the local community's livelihoods but also supply water to Bulawayo (Zimbabwe's second largest city).

In light of the evident significance of the Mzingwane catchment, several climate-landuse-hydrology related studies have been undertaken over the years in an attempt to understand interlinkages of these key aspects so as to enhance formulation of sustainable land and water resources management policies and strategies for such a water-scarce catchment. Such studies have covered aspects such as (i) estimating and interpreting hydrological drought indices (Nyabeze, 2004), (ii) characterising catchment runoff vis-à-vis rainfall, interception, transpiration and evaporation (Unganai and Mason, 2001b), (iii) general environmental degradation (Shadeed and Almasri, 2010) and (iv) modelling the catchment's hydrological processes/ water balance using various statistical techniques (Love et al., 2001, Love et al., 2010) among others. The general conclusion from all these studies has been a confirmed impact of natural and human activities on the environment and water resources within this catchment.

GIS and Remote sensing have been widely used in LULCC and hydrological modelling studies globally (Finch, 1997, Gangodagamage et al., 2001, Ayad, 2005, Andersen, 2008, Deus et al., 2013), as also within the semi-arid catchments of southern Africa, such as the Musengezi and Manyame catchments in the Zambezi basin of Zimbabwe (Kite and Pietroniro, 1996, Rwasoka et al., 2011, Gumindoga et al., 2015, Dlamini et al., 2016, Gumindoga et al., 2016). However, only two known studies i.e. Mpala *et al.*, (2016) and Sawunyama *et al.* (2006) have attempted to use GIS and Remote sensing to explore hydrological dynamics within the Mzingwane catchment, albeit others (Love et al., 2001) that used the techniques in a rather simplistic cross-sectional manner showing a knowledge gap in use of these valuable techniques in the Mzingwane catchment in general.

Furthermore, little is known about surface runoff (stream flow) dynamics and its relationship to climate and LULCC in a spatio-temporal context within this sub-catchment, thus presenting a challenge in managing water resources in this area. In addition to this, no known study to date has been done to demonstrate the potential application of climatic models and hydrological models in this region (i.e. no attempt has been made to integrate downscaled RCM data, hydrological modelling techniques and remotely sensed data in a GIS environment to advance the understanding of the multi-temporal catchment landscape changes and to predict future surface run-off within the entire semi-arid Matabeleland region of Zimbabwe). Furthermore, quantifying hydrological changes within this sub-catchment under different climate and LULCC scenarios will provide a sound basis for understanding and predicting the influence of LULCC and climate on water security, and subsequently help identify landuse practices that might reduce negative impacts. For the first time in this region, the utility of medium-high resolution satellite remotely sensed data is demonstrated in the assessment of historic and future LULCC on multi-temporal scale over the UMS. The generation of new knowledge in this important sub-catchment is thus of unquestionable strategic importance at both local and national levels, hence the motivation to undertake this study.

## 1.2 AIM

The aim of this study was to assess changes and/ variability of climate and LULCC and their impacts on surface hydrological conditions (river run-off/ discharge) within the UMS, so as to understand future water security in this region.

## 1.3 SPECIFIC OBJECTIVES

1. To review published past literature on climate and surface hydrological conditions in Zimbabwe for the past 30 years; focusing on:
    - *Assessing key progress/ developments and knowledge gaps in climate and hydrology science research in Zimbabwe.*
2. To quantify past and future spatio-temporal land use-land cover (LULC) dynamics in the UMS.
3. To analyse historical climatic trends and identify any climate anomalies within the UMS; focusing on:
    - *Historical trends of precipitation extremes in the UMS using daily precipitation records*
4. To analyse future climate conditions in the UMS using a downscaled RCM; focusing on:
    - *Using bias corrected Conformal Cubic Atmospheric Model (CCAM) data to analyse future climatic conditions in the UMS.*

5. To predict future climate and LULC change impacts on surface run-off in the UMS; focusing on:
    - *Simulating future surface run-off in the UMS using the HEC-GeoHMS model (forced with future climatic and LULC variables from Objectives 2 and 4).*

## 1.4 STUDY CONCEPTUAL FRAMEWORK

This study was guided by two scientific theoretical constructs aimed at understanding the climate - land use change - surface hydrology nexus:

i. The Global Climate change theory: which seeks to present physical evidence of and explain the causes of global climate change through objective analyses of past and present scientific data concerning patterns of past climate changes, influences of ocean temperature and solar variations, and atmospheric carbon dioxide ($CO_2$) concentrations on global climate and possibly forecast future climates.
ii. Water balance modelling theory: which seeks to understand and/or explain the dynamics of and relationships between various components of the water balance such as evapotranspiration, surface and groundwater flow and discharge using mathematical representations of these processes and their characteristics at varying temporal and spatial scales.

The conceptual framework guiding this study is shown on Figure 1.1. It adapts some aspects of the frameworks proposed by Trenberth (1999) and Satake and Lin (2012), which attempt to explain the relationship between biophysical, socio-economic factors (not included in this study) and climate to hydrological systems processes in a given area.

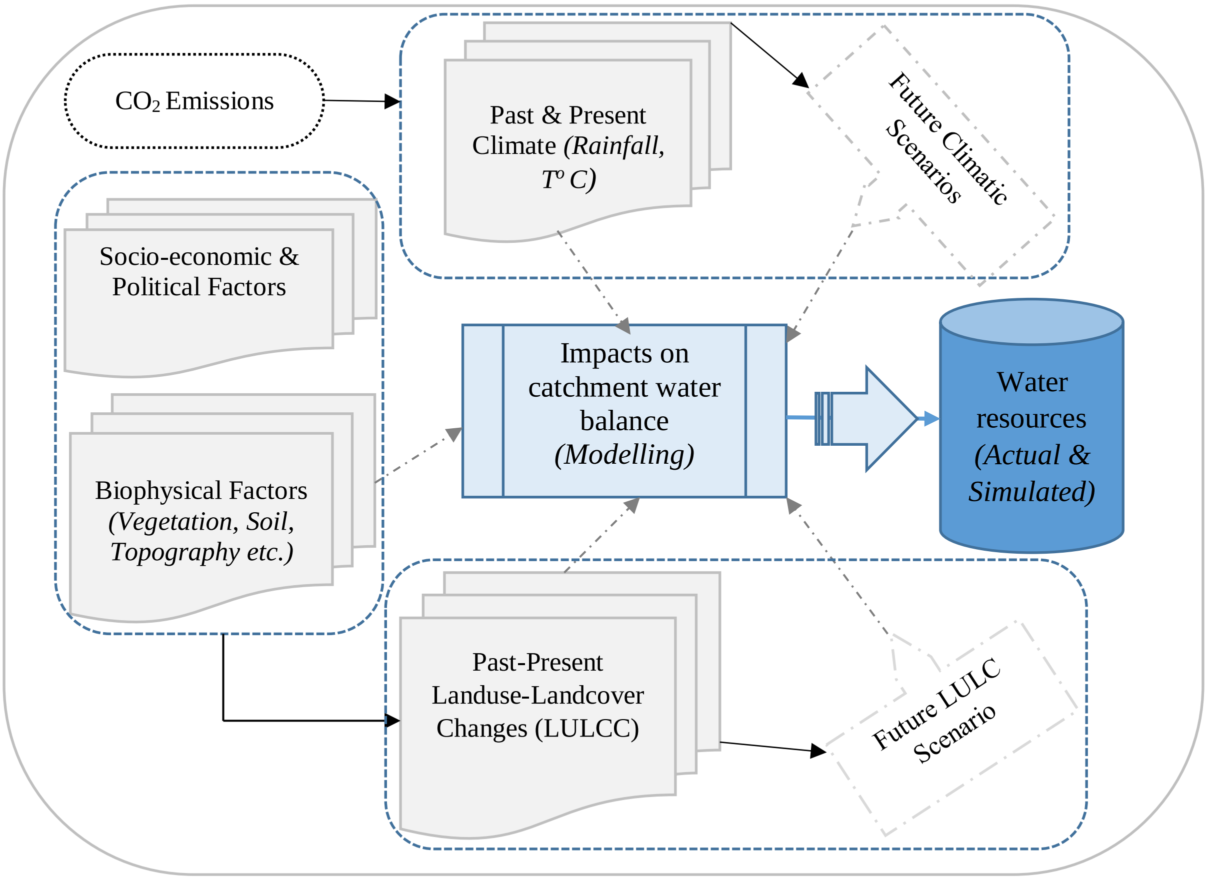

**Figure 1.1:** Study conceptual framework

## 1.5 MAIN STUDY DESIGN

The study followed a quantitative-catchment based approach in the assessment of the key elements of the research (i.e. analysis of historical and future climatic variations, multi-temporal quantification of LULCC and estimation of surface run-off characteristics of the Upper Mzingwane catchment). The approach adapted and integrated aspects of Vicuna and Dracup's (2007) two stage methodology, and components of Jack et al.'s (2016) cascading process of modelling, which involve (i) downscaling a selected RCM (statistically or dynamically) to resolve finer-scale features (at a scale less than 100km) and (ii) use of an impacts model to relate changes in climate to changes in specific phenomena such as crop yields and water availability (i.e. surface run-off in this study).

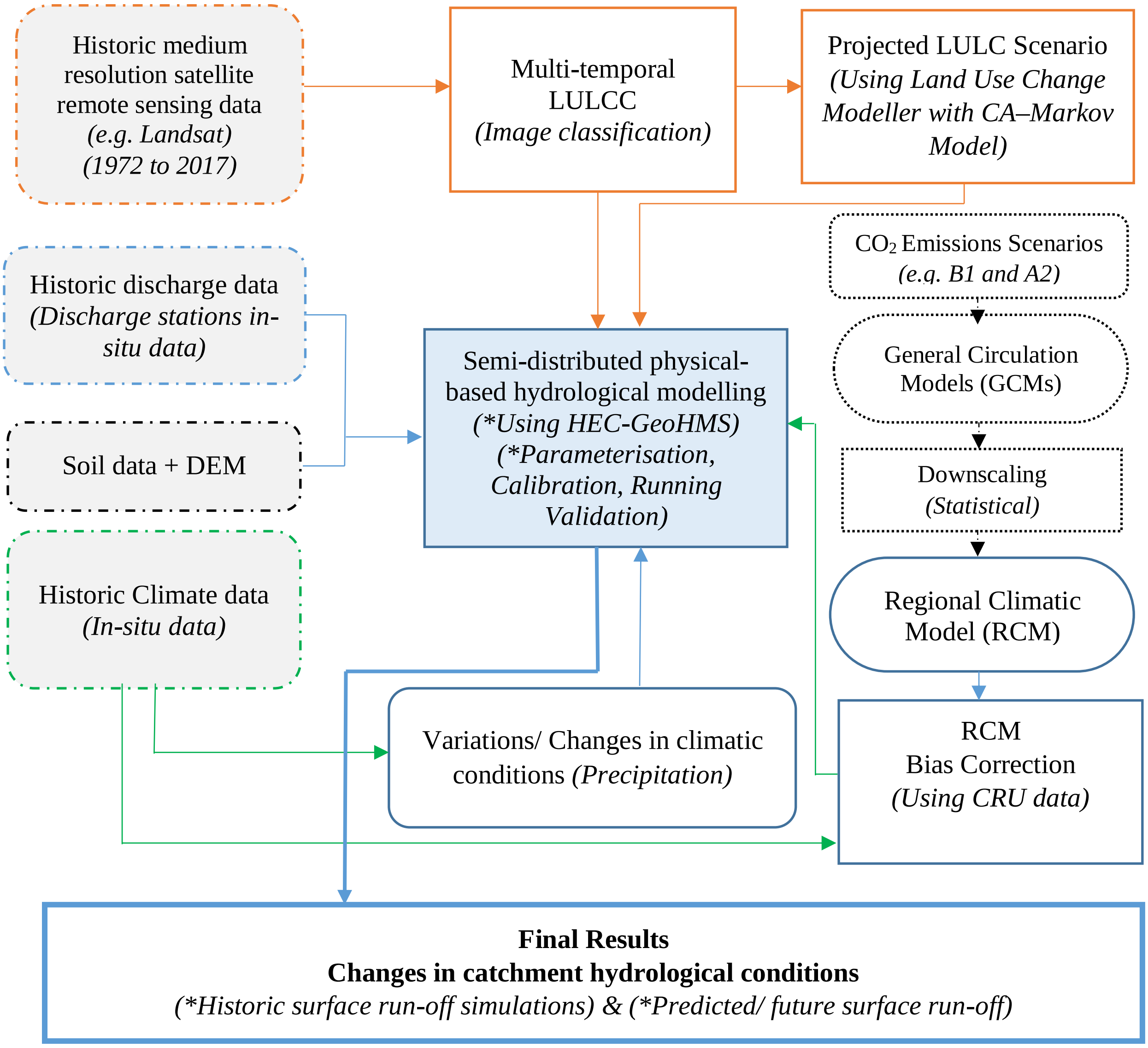

**Figure 1.2:** Overall study flow diagram showing the main steps to be followed in the entire study

The main steps in the study (shown on Figure 1.2) entailed firstly, a multi-temporal analysis of historical climatic trends and identification of climate anomalies, and secondly the quantification of the spatio-temporal LULCC dynamics within the UMS using Landsat satellite imagery, which formed the basis for simulating future LULC scenarios up to year 2038. Thirdly, future climatic scenarios were simulated using downscaled Conformal Cubic Atmospheric Model (CCAM) data to reveal future climate trends in the UMS. Lastly, the Hec-GeoHMS model was forced using future LULC scenarios and simulated climatic conditions to reveal likely (projected) future surface run-off in the study area.

## 1.6 THESIS STRUCTURE

**Chapter 1:** The context of the thesis is presented in this Chapter in the form of an introduction and background of the study. The problem statement (highlighting the research gap), the main study aim and specific objectives are also presented herein.

**Chapter 2:** This Chapter is a general literature review of the thesis. It explores progress and knowledge gaps in climate science and hydrological research in Zimbabwe against a global and regional overview of climate and hydrological research. The chapter is based on a manuscript submitted and currently under review in a scientific journal.

**Chapter 3:** This Chapter is based on a published paper analysing historical and modelling future land use and land cover changes in the UMS. It shows past land use and landcover changes from 1983 and 2018, and presents modelled land use and land cover scenarios from 2023 to 2038.

**Chapter 4:** An analysis of historical precipitation extremes and trends in the UMS using observed data is presented in this Chapter. An in-depth assessment of past precipitation scenarios and the associated climate anomalies in the study area are explored herein. The Chapter is also based on a manuscript submitted and under review in a scientific journal.

**Chapter 5:** In this Chapter, the bias corrected Conformal Cubic Atmospheric Model (CCAM) data are analysed to reveal future trends of climatic conditions (temperature, precipitation, humidity) in the UMS. The utility of the CCAM data in simulating future UMS climatology is also assessed.

**Chapter 6:** This Chapter presents and uses the CCAM future climatic scenarios together with future/modelled LULC scenarios (from the preceding Chapter 3 and 5 respectively) to force the hydrological model (HecHMS) to simulate future scenarios of stream flow in the UMS, thus revealing future water security scenarios in the study area.

**Chapter 7:** This is the final Chapter, which synthesises all findings from the preceding chapters, interprets and provides overall conclusions and recommendations.

# CHAPTER 2: STUDY LITERATURE REVIEW

*Based on a published paper:*
*Title: Climate change/variability and Hydrological modelling studies in Zimbabwe: A review of progress and knowledge gaps* [1]

## Abstract

This paper reviews developments in climate science and hydrological modelling studies in Zimbabwe over the past 29 years in an effort to expose knowledge gaps within this research domain. A global and regional overview is presented and then follows a systematic thematic approach in reviewing specifically online published, peer-reviewed journal articles on climate change/variability and hydrological modelling in Zimbabwe. The state and progress towards advanced integrated climate and hydrological modelling research is assessed, tracking benchmarks in the research methodologies (tools and techniques) used therein, including Geographic Information Systems (GIS) and Remote Sensing (RS). Descriptive summaries of key findings are presented, highlighting the main study themes (categories) and general conclusions arising from these studies while examining their implications on future climate and hydrological modelling research in Zimbabwe. Challenges associated with climate and hydrological modelling research in Zimbabwe are also briefly discussed and the main knowledge gaps in terms of research scope and methodologies employed in the reviewed studies are also exposed. In conclusion, plausible potential areas of focus in updating and advancing scientific knowledge to better understand the climate-landuse-hydrology nexus in Zimbabwe are presented. While this paper is primarily relevant for researchers, the general findings are also important for policy-makers, since it exposes potential areas for policy intervention or agenda setting in as far as climate and hydrology science research is concerned. This is done to effectively address pertinent questions in this domain in Zimbabwe.

**Keywords:** Zimbabwe, Climate change, Hydrology, Modelling, GIS, Remote sensing

## Article highlights

- Climate science research in Zimbabwe is outdated, especially studies focusing on predicting future climate conditions, though there are many new and advanced methods to achieve this in this field, regionally and globally.
- Over the past thirty years, climate impact studies and climate vulnerability, adaptation and mitigation studies have been the predominant type of climate studies in Zimbabwe, while studies focusing on predicting future surface water resources

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scenarios have also been lagging behind (i.e. having a limited coverage in term of length of time and location) in Zimbabwe.

- A knowledge gap exists in as far as understanding the relationship and the impacts of climate and land surface cover changes on water resources as revealed by the minimal research has been done in this domain. Therefore, this could have limited development of practical strategies and interventions to ensure future water security in Zimbabwe.

## 2.1 INTRODUCTION

A review of global climate changes since 1700 has revealed that over the centuries, twenty climatic events covering continental-scale temperature dips, hydroclimatic anomalies, stratospheric perturbations and general atmospheric composition changes have occurred, impacting millions of people in many ways (Zachos et al., 2001, Bronnimann, 2015, Easterbrook, 2016, Pecl et al., 2017). As such, understanding and predicting these inter-annual, and multi-decadal variations and changes in climate with resultant impacts has become a critical and active area of research globally over the decades. Several studies have been undertaken to quantify the extent of impacts and the dynamics (in space and time) of climate change on water resources (Arnell, 1999, Arnell, 2004, Hanson and Dettinger, 2005, Gurdak et al., 2009, Maina et al., 2012, Moumen et al., 2019, Bodansky et al., 2020), food security (Pielke, 2013, Reddy, 2014, Stigter and Ofori, 2014, Alberts, 2017, Soussana et al., 2019), ecosystems (National Research, 2002, Roberts et al., 2007, Thompson et al., 2017, Albrich et al., 2020), energy, and human health (Pedersen et al., 2014b, Sande et al., 2016, Haines and Ebi, 2019). All these studies have revealed that climate change is a significant factor to consider in holistic planning for community resilience and adaption, fostering global progress towards achieving the United Nations Sustainable Development Goals (UN SDGs), Agenda 2030 and Paris Agreement goals (Biermann et al., 2017, Silva, 2019, Zhenmin and Espinosa, 2019, Kawamoto and Kanie, 2020). These impacts are expected to vary in different countries in various regions of the world, considering the differences in climate-sensitivity of vulnerable populations with likely increases in poverty and inequities as a consequence of climate change, especially in developing countries (Hoegh - Guldberg et al., 2018, First, 2019).

In developing countries in Africa for example, where the impacts of climate system changes are predicted to be manifest in more uncertain terms (Rodo and Comin, 2003, Lemos and Rood, 2010, Daron, 2014, Giugni et al., 2015, Morioka et al., 2015, Scholes et al., 2015, Gumindoga et al., 2017, Ahmadalipour et al., 2019), expanding knowledge in this domain has become more pertinent, hence the steady developments in research therein. In southern Africa, studies also indicate a continued high climate variability (Grab and Nash, 2009, Neukom et al., 2014, Morioka et al., 2015) marked by recurrent and projected future droughts and floods (Van Wyk, 1998, Zengeya et al., 2011, Eccles et al., 2019, Emmanuel, 2019). The scope of these studies has been diverse, covering various focus areas such as climate modelling (Stouffer, 2006, Randall et al., 2007a, Engelbrecht and Engelbrecht, 2016, Sévellec et al., 2016), hydrological impacts (Mimikou et al., 1991, Abtew and Melesse, 2016, Abiodun et al., 2017, Farjad et al., 2017) and other general impact studies (Murwira and Skidmore, 2006, Maina et al., 2013, Wanders and Wada, 2014, Nešić, 2018).

Despite all the advances made in the aforementioned studies, knowledge gaps are well acknowledged, particularly considering the inherent uncertainties in the new developments in climate science modelling and climate impact assessment techniques (Creese et al., 2016). Tools and approaches are now available and more are being developed that allow for a better understanding and characterisation of the implications of climate change and variability to assist in better climate risk management strategy development (Zscheischler et al., 2018, Eckstein et al., 2019) in developing countries such as Zimbabwe. As such, the scientific community within and outside Zimbabwe has, over the past decades, been able to exploit various tools and techniques to generate new knowledge pertaining to local climate dynamics and impacts, so as to better guide decision making specifically tailored to local needs. One key area of focus has been the implications of climate change on water resources and hydrological systems, considering that a significant part of Zimbabwe is generally semi-arid in nature.

Furthermore, considering the acknowledgement of spatio-temporal land use and land cover change (LULCC) as an important factor (with both direct and indirect implications) on hydrological systems (Nie et al., 2011, Mishra et al., 2014, Khare et al., 2015, Boongaling et al., 2018, Birhanu et al., 2019, Gebrehiwot et al., 2019), attempts have also been made to explore the climate-LULCC-hydrology interlinkages using coupled systems approaches in various studies globally (Liu et al., 2007, Werner and McNamara, 2007, Nguyen et al., 2017, Pokhrel et al., 2018, Yan et al., 2019). All these studies indicate a wide scope of themes covered over the years, as mentioned earlier, and as such, it becomes important to explore and characterise these studies in a more systematic manner so as to better appreciate the advances made so far and identify the knowledge gaps therein. Very few known studies, apart from Brazier (2015) and Bhatasara (2017), have attempted to extensively review climate change research in Zimbabwe, albeit from a Foucauldian discourse perspective and general impacts and mitigation perspective, respectively. With regards to climate-hydrological modelling, no known studies have reviewed progress and gaps in this domain, hence in this paper, an attempt to expand the scope of review in these areas is made. This is achieved by presenting key research developments in climate science and hydrological modelling in Zimbabwe over the past three decades. The ultimate goal is to expose knowledge gaps and possible areas for further research in Zimbabwe.

## 2.2 METHODS

A systematic search for relevant peer reviewed literature from a range of databases searched using Google Scholar (GS) search engine was employed. The search leveraged GS's strength of cataloguing 100 million records of academic literature and most importantly being able to competently find potentially valuable grey literature (i.e. articles published by non-commercial academic publishers) (Haddaway et al., 2015). EBSCO Discovery Service within the University of Witwatersrand's e-library resources was used to augment the GS search and to widen the scope and depth of the online search. The search was limited to papers published in English between 1990 and 2019, on climate change and variability dynamics, climate modelling and hydrological modelling, covering briefly the global, continental, and regional perspectives, and then more extensively the Zimbabwean context. The literature search inclusion and exclusion criteria are summarised in Table 2.1. Thematic analysis adapting and integrating the approaches of Perkins et al. (2018) and Nichols et al. (2020) was used in assessing the content of the selected journal articles and categorising them according the study keywords and their dominant/predominant focus area/theme (e.g. general climate trends study, climate impact and climate modelling). Climate impact studies were further categorised according to impact areas (e.g. agricultural impacts, livelihood impacts, ecological impacts, hydrological impacts and energy impacts). We also identified and categorised studies specifically integrating hydrological modelling and climate modelling and leveraging GIS and RS techniques. The various hydrological and climate modelling techniques/ tools used in the selected studies were also assessed. General descriptive statistics (frequencies and proportions), tables and pie charts are used to present the findings of the study. Figure 2.1 summarises the main steps of the study methodology. However, it is important to note that some relevant published studies could have been missed, probably due to poor indexing or publication in unrated online journals and databases. Furthermore, some studies covered more than one theme, which meant that they had to be categorised in more than one group.

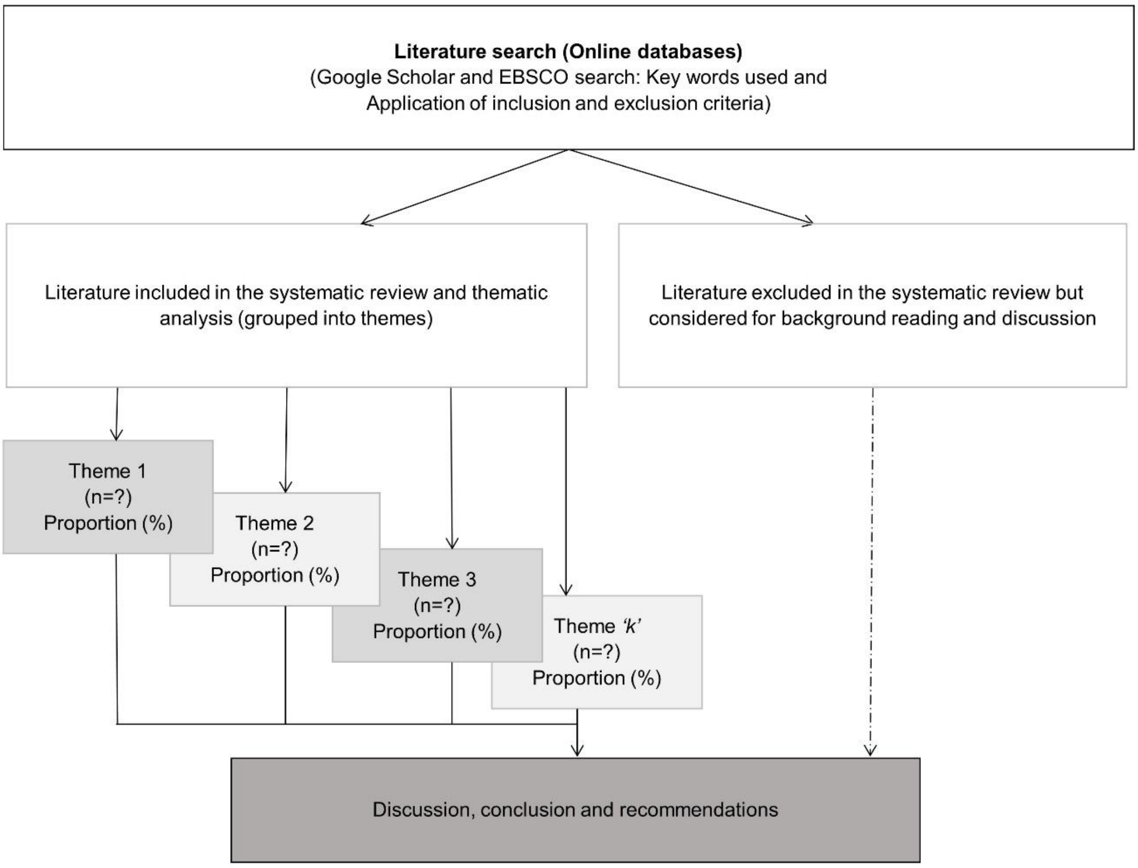

**Figure 2.1:** Methodological flow diagram showing the main steps of the study approach

*(Adapted from Nichols et al. (2020))*

**Table 2.1:** Literature inclusion and exclusion criteria summary used to select articles covered in the review

| *Inclusion criteria* | *Exclusion criteria* |
|---|---|
| Published, peer-reviewed academic journal articles on global, continental and regional scope on climate change and/ variability (trends) and hydrology. | Unpublished, non-peer reviewed materials |
| Published, peer-reviewed academic journal articles on climate change and/ variability, climate and hydrological modelling in general and specifically in Zimbabwe. | News articles, Unpublished thesis, Unofficial reports, Blog sites materials |
| Peer-reviewed journal articles on climate impacts in general and local (Zimbabwe) | Old publication (>15years) for global, continental and regional scope |
| Peer-reviewed journal articles published in English language from 1990 (for Zimbabwe scope) | Non-English language publications |
| Published book sections/chapters, ebooks, Reports (used in discussion only) | General, non-scientific reports |

Figure 2.2 is a map showing the main water catchments, settlements and the hydrology (rivers and dams) in Zimbabwe highlighting the location of the entire Mzingwane catchment (nesting the UMS in the northernmost extent of the catchment).

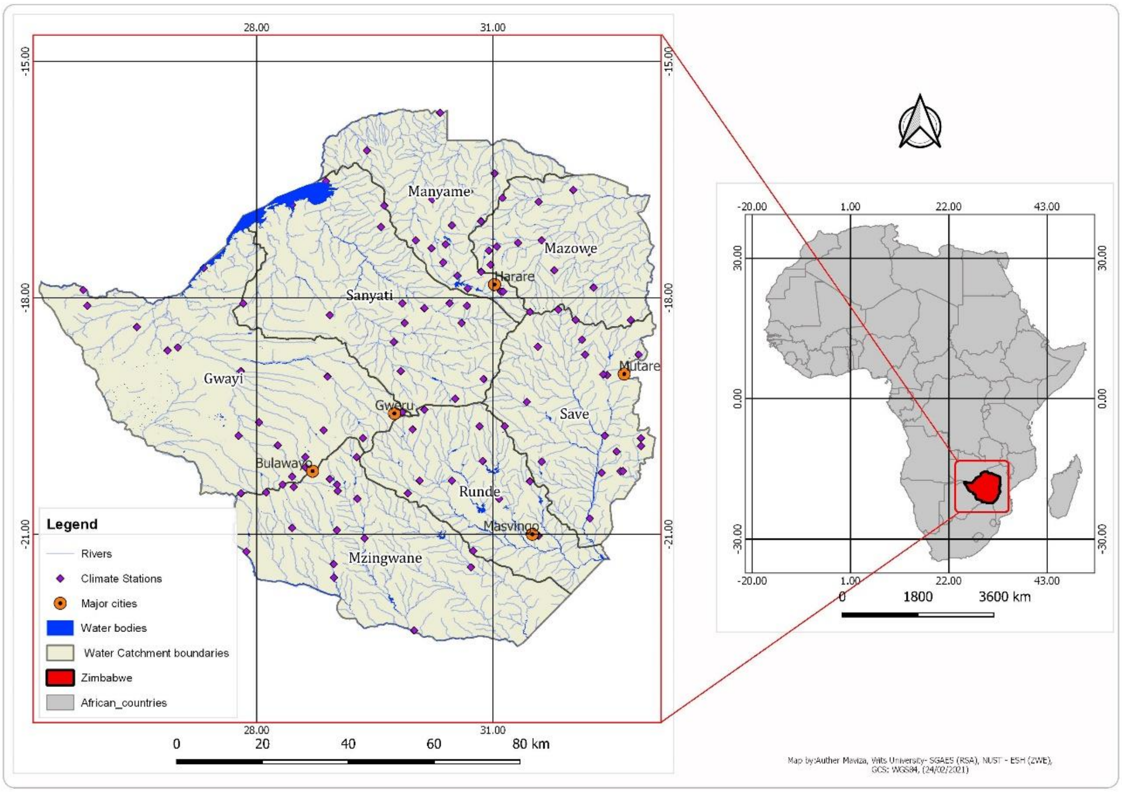

**Figure 2.2** : Map showing location of Zimbabwe relative to other countries in Africa and the main water catchments and climate stations

## 2.3 RESULTS AND DISCUSSION

### 2.3.1 Climate change/variability

#### *2.3.1.1 Global and regional climate change/variability studies – A brief overview*

Climate change refers to a statistically significant variation in either the mean state of the climate or in its variability, persisting for an extended period (typically decades or longer) due to natural internal processes or external forcings, or persistent anthropogenic changes in the composition of the atmosphere or in land use (IPCC, 2007). Most scientists have, however, settled to use the term ‘climate change’ to refer primarily to observed and predicted changes mainly as a result of human activities (Letcher, 2009, Maina et al., 2013, Nica et al., 2019, Li et al., 2020); although others suggest that climate changes are a result of natural cycles (Easterbrook, 2016). Over the years, the debate has evolved to include populist ideologies charged with political undertones (Dunlap and McCright, 2008, Antonio and Brulle, 2011, Dunlap et al., 2016, McCright et al., 2016, Huber, 2020), while some have presented alternative views in what has been termed the ‘climate change hiatus’ where scientists are beginning to re-interrogate if the temporary slowdown in the global average surface temperature warming trend observed between 1998 and 2013 is a genuine slowdown or a redistribution of energy in the earth system (Ferraro et al., 2015, Sévellec et al., 2016, Yan et al., 2016). Climate variability on the other hand has been defined as variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate on all temporal and spatial scales beyond that of individual weather events due to natural internal processes within the climate system (i.e. internal variability), or variations in natural or anthropogenic external forcing (i.e. external variability) (IPCC, 2007).

Studies by the Inter-governmental Panel on Climate Change (IPCC) experts (Hulme, 2016, IPCC, 2018, IPCC, 2019) and other studies such as Zachos et al. (2001), Stocker et al. (2013) and Scholes et al. (2015) indicate that the earth's climate has experienced complex evolution marked by periodic and anomalous variability both at global and regional scales with diverse impacts on populations throughout-time. Such changing climatic patterns have been linked with various extreme events or phenomena such as droughts and floods (WaterNet, 2003, Reddy, 2014, Wanders and Wada, 2014, Zscheischler et al., 2018, Emmanuel, 2019). This notion is also buttressed in a review of observed (1900–2000) and possible future (2000–2100) climatic conditions across Africa by Hulme *et al.* (2017), who concluded that the climate of Africa is warmer than it was 100 years ago, with some regions experiencing substantial inter-annual and multi-decadal rainfall variations with dramatic impacts on both the environment and some economies. Impacts of anthropogenic processes on the global carbon cycle and the resultant greenhouse effect have been acknowledged as directly linked to global and regional climatic systems perturbations, with the same devastating effects on numerous vulnerable communities around the world (IPCC, 2001, Kondratʹev et al., 2003, IPCC, 2007, Randall et al., 2007a, IPCC, 2014, Hulme, 2016, First, 2019). To mitigate against such impacts, 197 countries signed the 2015 Paris Climate Agreement in which signatories agreed to a goal of holding global temperatures well below 2°C above the pre-industrial levels and to pursue efforts to limit it to 1.5°C (Hulme, 2016). The IPCC further emphasised a dire need for drastic global action (Tollefson, 2018) to achieve this in light of a narrow window period of up to 2030 to stem catastrophic climate change projected by scientists such as Miller and Croft (2018). However, such global climate change governance efforts have not been without major drawbacks, as highlighted by the withdrawal of the United States of America (USA) in 2017 from the Paris Accord, citing unfairness of the agreement and possible threats to US economic interests (Cozier, 2017, Zhang et al., 2017, Nong and Siriwardana, 2018). Furthermore, it is worth mentioning that the recent SARS-CoV-2 (COVID-19) pandemic has also brought in a new dimension into the existing global climate change research and governance discourse (Caspi et al., 2020, Ficetola and Rubolini, 2020, O'Reilly et al., 2020), although this is not within of the scope of this review.

Numerous climate impact studies covering vulnerabilities and adaptation (Berrang-Ford et al., 2011, SADC, 2011, Pielke, 2013, Spalding-Fecher et al., 2016, Alberts, 2017, Hedlund et al., 2018, de Sherbinin et al., 2019, Shah et al., 2019, Fakhruddin et al., 2020) have been done and the general consensus is that climate change and variability presents serious vulnerability challenges for semi-arid regions (including those in southern Africa) that depend on rainfall for their primary production. In this regard, researchers such as Berrang-Ford et al. (2011) have explored human climate adaptation actions while others such as Anwar et al. (2013), Lennard et al. (2018) and Reddy (2014) have in this regard researched on modalities of developing frameworks for characterising and understanding community adaptation capacities to climatic variability and change *vis-à-vis* the spatio-temporal dynamics of climatic events such as the El Niño-Southern Oscillation (ENSO). Among other conclusions drawn, all these have revealed a need for pragmatic scientific evidence driven policy development to guide mitigation and adaptation strategies, especially in developing countries such as Zimbabwe (Ahmadalipour et al., 2019).

### *2.3.2 Climatic change and variability studies in Zimbabwe*

Climate in Zimbabwe is highly variable (Brown et al., 2013) and thus the country (with its limited coping capacity) is considered highly vulnerable to the impacts associated with climate change and variability, as is the case for most developing countries in Africa (Magadza, 1994, IPCC, 2001, Jack et al., 2016, Anderson et al., 2019, IPCC, 2019). In light of this, notable response initiatives have been taken by the Government of Zimbabwe (GoZ) in line with SADC climate policy directions. These include the adoption of a National Climate Policy (NCP) augmented by a National Climate Change

Response Strategy (NCCRS) and the setting up of a dedicated National Climate Change Management Department under the then Ministry of Environment, Water and Climate in 2013 (now Ministry of Environment, Tourism and Hospitality Industry). One of the six core objectives of the NCP was to strengthen climate research and modelling and promote relevant home-grown solutions to address the challenges of climate change (Brazier, 2015). Furthermore, the GoZ in partnership with the United Nations Development Programme (UNDP) implemented the National Adaptation Plan (NAP) in the year 2017, which aimed to analyse the country's short and long term climate risks and adaptation options. This was to help feed-into the country's NCP and NCCRS up-scaling of climate resilient development initiatives. In 2018, the GoZ set up and launched the Zimbabwe National Geospatial and Space Agency (ZINGSA) under the Ministry of Higher and Tertiary Education, Innovation, Science and Technology Development, with one of its mandates being to leverage exploitation of earth observation and geospatial technology in advancing climate science research among other focus areas. These developments have come against the backdrop of the GoZ launching the Zimbabwe Centre for High Performance Computing (ZCHPC) in 2015 with the goal of availing supercomputing capabilities to researchers in various field of science such as meteorology (e.g. numerical weather prediction/forecasting) and earth-system modelling in the country (ZCHPC, 2015). Despite these positive developments, not much research has been undertaken to expand knowledge and present updated scientific information on the evolution of past and future climatic conditions in Zimbabwe. A synergy in all these developments i.e. the ZINGSA, the ZCHPC and other relevant state agencies is critical to realise overall national climate objectives.

Figure 2.3 shows proportions of the five main identified thematic groups/ categories from the climate studies covered in this review, while Table 2.2 provides some examples of the 107 prominent climate studies undertaken in the past 29 years in Zimbabwe under each category. Climate impact and climate vulnerability, adaptation and mitigation studies are the co-predominant categories of all the studies reviewed (each with 39%), while climate modelling is the least covered theme (9%), followed by climate governance studies (8%). These results reveal a dearth of scientific knowledge, primarily within the themes of climate modelling, climate governance and general climatic trends respectively in Zimbabwe. Results show a publication rate of 3.7 (approximately 4) journal article publications per year over the study period, which shows relatively low research output on climate science in Zimbabwe.

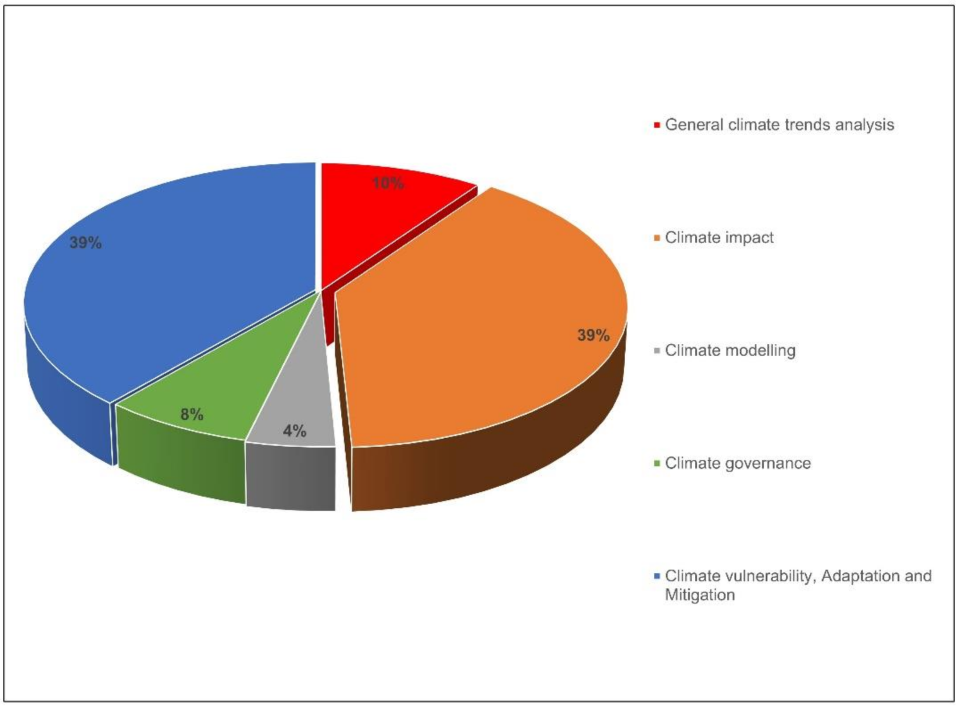

**Figure 2.3:** Proportions (%) of the various climate study themes (categories) covered in Zimbabwe in the past 29 years (n= 107)

**Table 2.2:** Climate study categorisation, examples and statistics for each category

| Study category | Frequency | % | Examples of studies |
|---|---|---|---|
| ***General climate trends analysis*** | 13 | 10 | *(Unganai, 1996)*, (Unganai, 1997)*, (Unganai and Mason, 2002)*, (Williams et al., 1994)*, (Mazvimavi, 2010a), (Nyoni et al., 2013), (Love et al., 2006), (Mushore et al., 2019), (Sibanda, 2018), (Mamombe et al., 2017a)* |
| ***Climate Impact*** | 52 | 39 | *(Booth et al., 1990), (Unganai, 1992), (Salewicz, 1995), (Kristensen et al., 2007), (Corbett and Carter, 1996)*, (Makadho, 1996b), (Hartman et al., 2002)*, (Chemura et al., 2016), (Matarira et al., 1995)*, (Nyanganyura, 1999), (Pilossof, 2016), (Ebi et al., 2005)*, (Brown et al., 2012), (Mutekwa, 2009)*, (Williams et al., 1994)*, (Gwimbi, 2009), (Mugandani et al., 2012), (Nyabako and Manzungu, 2012), (Gwitira et al., 2014), (Chapungu and Nhamo, 2016), (Ncube, 2010), (Love et al., 2006), (Phillips et al., 2002)*, (Manyeruke et al., 2013), (Davis and Hirji, 2014), (Sango and Nhamo, 2014)*, (Sande et al., 2016), (Pedersen et al., 2014a), (Beck and Bernauer, 2011), (Yamba et al., 2011), (Kutywayo et al., 2013), (Torr and Hargrove, 1999), (Svotwa et al., 2007), (Zinyengere et al., 2011), (Dube et al., 2017), (Bhatasara, 2018), (Zinyemba et al., 2018), (Bossuet and Thierfelder, 2019), (Magadza, 2011), (Gunda et al., 2017), (Descheemaeker et al., 2018)*,(Chikodzl and Mutowo, 2014), (Utete et al., 2019), (Mamombe, 2017), (Lord et al., 2018)* |
| ***Climate modelling*** | 6 | 5 | *(Unganai, 1996)*, (Ebi et al., 2005)*, (Mushore et al., 2019), (Chemura et al., 2016)*, (Mashonjowa et al., 2013), (Masanganise et al., 2012)* |
| ***Climate governance*** | 10 | 8 | *(Patt, 2001)*, (Patt and Gwata, 2002b), (Zinyengere et al., 2011)*, (Gutsa, 2014), (Mberego and Sanga-Ngoie, 2014), (Ngwenya et al., 2018b), (Bhatasara, 2017), (Mubaya and Mafongoya, 2017)* |
| ***Climate vulnerability, Adaptation and Mitigation*** | 51 | 39 | *(Matarira et al., 1995), (Matarira and Mwamuka, 1996), (Unganai, 2009)*, (Patt, 2001)*, (Thierfelder and Wall, 2010), (Rurinda et al., 2014), (Chifamba and Mashavira, 2011)*, (Gwimbi, 2009), (Mudombi-Rusinamhodzi et al., 2012), (Gwenzi et al., 2016), (Nhemachena et al., 2014), (Soropa et al., 2015), (Chifamba and Mashavira, 2011), (Dube et al., 2016), (Descheemaeker et al., 2018)*, (Chanza, 2017), , (Manyani et al., 2017), (Moyo, 2017), (Mbereko et al., 2018), (Musarandega et al., 2018), (Mubaya et al., 2017a)*, (Chanza et al., 2019), (Mushawemhuka et al., 2018),(Jiri et al., 2017) , (Mugambiwa, 2018), (Musarandega et al., 2018), (Katsaruware-Chapoto et al., 2017), (Mutandwa et al., 2019), (Jiri et al., 2018), (Mugambiwa, 2018), (Simba et al., 2012), (Nyahunda and Tirivangasi, 2019), (Nyahunda et al., 2019)* |

*NB: Twenty-five (25) of the studies marked with an asterisk (*) fall within at least two categories considering their scope).*

One prominent study shown in Table 2.2 that exclusively explored climate conditions in Zimbabwe is by Unganai (1996). This study revealed that over a 93 year period from the 1900s, daytime temperatures in Zimbabwe rose by about 0.8°C, translating to a 0.08°C rise per decade. Over the same time, precipitation was observed to have declined by up to 10% on average, which is about 1% per decade. These findings, however, were rebutted by Mazvimavi (2010a) in his study covering 40 rainfall stations across all the rainfall regions of Zimbabwe for periods 1892–1941 and 1942 to 2000. Mazvimavi (2010a) concluded that the purported climate change effects were not statistically significant within the time-series of total seasonal and annual rainfall in Zimbabwe, arguing that the findings of declining rainfall by Unganai (1996) were likely due to the presence of multi-decadal variability characterised by combining years with above and below average rainfall. This contrast between two prominent climate researchers presents a need for interrogation of data with new/ updated techniques to bring better clarity with regards to past climatic conditions/ trends in Zimbabwe. Since then, no known, published follow-up study has been done to build upon the existing knowledge in this regard.

On rainfall variability, studies have revealed that inter-annual rainfall variability in the country are largely influenced by external forcing of a near-global or hemispheric origin such as ENSO, the Inter-tropical Convergence Zone (ITCZ) to the North and the westerly cloud-bands to the south rather than regional or local-scale factors (Unganai, 1992, Unganai and Mason, 2001a, Mamombe et al., 2017a). On long-term predictability of rainfall trends, Unganai and Mason (2002) indicate that approximately 70% of the total summer rainfall variance in Zimbabwe is potentially predictable at long range. Over the years, climate-rainfall research has advanced to explore the teleconnectivity between summer rainfall patterns in Zimbabwe and sea-surface temperatures (SST), the Southern Oscillation Index (SOI), the Quasi-biennial Oscillation (QBO), Outgoing Longwave Radiation (OLR) and wind (Lemos and Rood, 2010). Nangombe *et al.* (2010) for example, concluded that there are strong correlations between severe droughts and circulation patterns and weather systems in the Indian Ocean and Equatorial Pacific Ocean (i.e. the ENSO SOI, the QBO and the Luni-solar tide at 20, 12.5, 3.2, and 2.7 year cycles). These studies have revealed the possibility of predicting drought occurrences using these established relationships. However, this knowledge is rather outdated and has not been fully utilised by decision makers in Zimbabwe for enhanced drought and other climate impact mitigation fore-planning (Gutsa, 2014, Ngwenya et al., 2018a). This is evidenced by poor preparation and the resultant recurrent adverse impacts experienced when such events occur.

Within the general climate studies reviewed in this paper, the predominant area of focus has been understanding rainfall dynamics (Sokona and Denton, 2001, Unganai and Mason, 2002, Thierfelder and Wall, 2010, Moyo et al., 2017), with less attention on temperature and other climatic parameters such as evaporation, humidity and solar radiation. Limited research on these other climatic parameters could be attributed to limited access to good quality data as revealed by Dlamini et al. (2016). However, some studies that have looked at other climatic parameters such a temperature and evapotranspiration (Gordon and O'Farrell, 1997, Allison et al., 2009, Brown et al., 2013, Kuri et al., 2014, Gumindoga et al., 2017) had limited detail and thus could not provide a comprehensive picture of the dynamics of these parameters in space and time over Zimbabwe. For example, although Unganai (1997) concluded a net warming of +0.3 to +0.5°C between 1897 and 1993, he could not attribute the observed warming trend to inherent climate variability even though similar trends have more recently been related to climate change (Watson et al., 1998, Brown et al., 2012) . Some of these studies have presented the climate dynamics in Zimbabwe in a general sense considering that the studies had a regional scope of coverage over southern Africa (Gordon and O'Farrell, 1997, Allison et al., 2009, Moyo and Nangombe, 2015, Scholes et al., 2015). Furthermore, studies such as that by Matarira and Jury (2005) had limited temporal resolution in their assessments since they used cross-sectional study designs and thus missed exploring the multi-temporal aspects of the climatic conditions in Zimbabwe. In other words, there is a need to build on this existing knowledge through longitudinal studies to capture a more recent picture of multi-temporal climatic trends in Zimbabwe.

While advances in climate research have seen the move towards the use of GIS and RS/ Earth observation (EO) technology to (1) augment climate data series, and (2) assist in better and advanced analyses of climate dynamics in space and time globally (Beniston and Verstraete, 2001, Turner et al., 2004, Gandhi et al., 2015, Suryabhagavan, 2017) and in southern African (Muhire et al., 2015a, Twumasi et al., 2017), progress in this direction has been limited in Zimbabwe. Only 8% of the reviewed studies in Zimbabwe over the past 29 years have directly or indirectly applied these tools and techniques at varying spatial and temporal scales. Examples include an assessment of inter-seasonal rainfall variability in Zimbabwe using GIS by Corbett and Carter (1996), spatial characterisation of summer rainfall over Zimbabwe by Unganai and Mason (2001a), spatio-temporal analysis of climate-inter-annual malaria incidence (Mabaso et al., 2006), and exploring local climate zones and land surface temperature interlinkages using remotely sensed data (Mushore et al., 2019). This reveals a knowledge gap (i.e. of limited use of geospatial tools in climate research) which could be worsened by limited availability of quality *in-situ* climatic data such as rainfall and temperature measurements. Furthermore, where such data are available, often it is incomplete due to poor distribution and investment in necessary infrastructure to observe important climatic phenomena. Other data access challenges relate to: (1) inaccessibility due to bureaucratic red-tapes and prohibitive costs for long-term climatic datasets charged by government agencies such as the Meteorological Department and (2) inconsistent and poor spatial coverage which often renders it of limited use in climate research in the country. This is also confirmed by Gumindoga et al. (2016), who noted that historic temperature and rainfall data for Zimbabwe are incomplete and often costly to purchase, and thus a limiting factor in climate research. In light of such limitations, researchers have exploited freely available remotely sensed climatic and other datasets to overcome these challenge, notwithstanding the inherent spatial and in some instances temporal resolution limitations of using these datasets at a local scale.

## 2.4 CLIMATE MODELLING STUDIES

### 2.4.1 A brief global and regional overview

Climate modelling science is a highly active field of research with rapid advancements in knowledge marked and driven by rapid developments in the tools and/ techniques (models) used in this domain. Two main types of models (Global Climate Models [GCMs] and Regional Climate Models [RCMs]) are used in climate modelling studies. GCMs are numerical tools/models representing physical processes in the atmosphere, ocean, cryosphere and land surface used for simulating the response of the global climate system to increasing greenhouse gas concentrations (IPCC, 2001). Examples of GCMs include the Hadley Centre Coupled Model, version 3 (HadCM3), the Commonwealth Scientific and Industrial Research Organisation Mark 3 (CSIRO Mk3) GCM (Gordon and O’Farrell, 1997, Flato et al., 2013), the Geophysical Fluid Dynamics Laboratory Climate Model version 2.5 (GFDL CM2.5) (Delworth et al., 2012) and the Model for

Interdisciplinary Research on Climate – Earth Systems Model (MIROC-ESM) (Watanabe et al., 2011) and the more recent Hadley Centre Global Environment Model 3 – Global Coupled version 3.1 (HadGEM3-GC3.1) (Williams et al., 2018). Other variable resolution GCMs such as the Conformal-Cubic Atmospheric Model (CCAM) of the CSIRO have also been developed for regional climate and weather research (Horowitz et al., 2015, Thevakaran et al., 2016) and have been applied at different scales globally. Over the years, the GCMs have been used to improve our understanding of how climate systems work, to forecast the drivers of climate change, improve estimates of climate sensitivity and to predict future climatic conditions and impacts (Stouffer, 2006, IPCC, 2013, Stocker et al., 2013, McCarroll, 2015). Advances in this domain have seen the progression from Atmosphere-only GCMS (AGCMs), to Coupled Atmosphere–Ocean models (AOGCM) and fully coupled earth system models (ESM) in an attempt to improve the statistical confidence in the GCM outputs. Thus, the emergence of AOGCMs has allowed for more reliable projections of climate at various spatial and temporal scales (Pitman et al., 2011, IPCC, 2013, Ashofteh et al., 2016). This has been realised in light of the well appreciated inherent uncertainties and weaknesses associated with the use of such models. For example, Motesharrei *et al.* (2016) argued that two-way feedbacks are missing from most climate models and other critical socio-economic variables such as inequality, consumption, and population are often inadequately-modelled, hence increasing uncertainty in outputs. Fowler *et al.* (2007) further emphasise that GCMs have relatively coarse resolutions, hence are unable to resolve significant sub-grid scale features such as land use and land cover (LULC) and topography, thus limiting their accuracy and application at a local scale. To this end, the IPCC and other climate scientists have progressed to implement and develop the Coupled Model Intercomparison Project (CMIP) with the latest being CMIP6 (Pascoe et al., 2020). In CMIP6, various ensembles of GCMs have been run collectively and results compared in an attempt to understand how the global climate will respond to future scenarios of increasing/decreasing anthropogenic radiative forcing relative to present-day climate conditions (Ashofteh et al., 2016, Roberts et al., 2019, Morim et al., 2020). For example, Andrews et al. (2020) recently ran simulations using the HadGEM3-GC3.1 for CMIP6, testing climatic responses to historical forcings such as solar irradiance, ozone concentrations, greenhouse gases, land-use changes, and aerosols, comparing results to observational data.

To resolve the shortcomings of GCMs, downscaling techniques (Bouwer et al., 2004, Hewitson et al., 2004, Hidalgo et al., 2008) have been used to develop finer resolution Regional Climatic Models with varying levels of accuracies at sub-grid scale with higher statistical validity and reduced biases compared to GCM simulation outputs. Examples of such RCMs include the Consortium for Small-Scale Modelling and Regional Climate Model (COSMO-CLM), Regional Climate Model version 4 (RegCM4), and the Providing Regional Climates for Impacts Studies (PRECIS) model. RCM data have been widely used in numerous impact studies as input in hydrological models because of their higher resolution (compared to GCMs). For example, they have been used to assess the variability of hydrological responses due to past, present and future climate change scenarios (Landman et al., 2006, Kalognomou et al., 2013b, Dosio et al., 2014, Moyo and Nangombe, 2015). Furthermore, to drive and coordinate active research in both dynamic and statistical regional climate downscaling (RCD) techniques of GCMs so as to provide higher-resolution climate information at regional level, the World Climate Research Programme (WCRP) has run the Coordinated Regional Climate Downscaling Experiment (CORDEX) (Gutowski et al., 2016). The CORDEX has, over the years, allowed for an objective assessment and intercomparison of various RCD techniques. This involves an evaluation of their performance, illustration of benefits and shortcomings of different approaches, thus providing a more solid scientific basis for impact assessments and other uses of downscaled climate simulations. To this end, high resolution regional climate simulations of the CORDEX CORE activity are now available covering all major inhabited areas of the world at a resolution of 25 km including Africa (Domain: Region 5).

Numerous climate modelling studies have been done both at global and regional scale in an effort to better understand the past, present and future climate dynamics in space and time. While significant progress has been realised in global climate modelling science (Arnell, 1999, Zachos et al., 2001, Kondrat′ev et al., 2003, Delworth, 2006, Randall et al., 2007b, Kamusoko and Aniya, 2009, Pitman et al., 2011, Micheli et al., 2012, Cannon et al., 2015, Andrews et al., 2020), there has been relatively less work published for Africa in this regard (Gumindoga et al., 2017), let alone at local (country) level. Some countries such as South Africa have been leading and have made considerable strides in climate modelling research and actively contributing to the IPCC working groups and the CORDEX-Africa, for example. GCMs such as the Canadian Climate Centre Model

(CCCM) and GFDL-3 have simulated changes of plus 2 to 4°C increases in mean surface air temperature across southern Africa under doubled atmospheric carbon dioxide scenarios showing over and underestimations when validated with observed data over local areas (Kuri et al., 2014). Other models that have been applied in Africa include the HadCM3, Parallel Climate Model (PCM) and the Coupled Global Climate Model (CGCM3) (Faramarzi et al., 2012). These show varying simulation outputs with limited local use considering their inherent uncertainties related to forcings and horizontal biases as discussed by Arora (2019).

Conversely, downscaled RCMs have demonstrated more competence in simulating local climatic conditions compared to GCMs (Hewitson et al., 2004, Meque and Abiodun, 2015, Shongwe et al., 2015, Archer et al., 2018, Abiodun et al., 2019), although contradictions and parameter over and underestimation of rainfall and temperature scenarios still persists when model outputs are compared (World Meteorological Organization, 1975, Refsgaard and Knudsen, 1996, IPCC, 2013). For example, RCMs have shown to successfully simulate future projection of droughts in southern Africa (Abiodun et al., 2019); predict seasonal and regional climatic scenarios (Archer et al., 2018); and project an annual-averaged temperature rise at about 1.5 times the global rate of temperature increase in the African subtropics during the 21st century (Engelbrecht et al., 2015). The general consensus, however, among climate scientists, is that projections of future climate change are restricted to assumptions of climate forcing, limited by shortcomings of the climate models used and inherently subject to internal variability when considering specific periods (Hewitson et al., 2004, Salathé et al., 2010, Henderson-Sellers and McGuffie, 2012, India and Bonillo, 2013). This justifies the need for sustained research in regional climate downscaling research as supported in the CORDEX framework. As a result, numerous studies have been undertaken in Africa and southern Africa under CORDEX, showing remarkable advancements with more accurate and region-relevant results (Kalognomou et al., 2013a, Kalognomou et al., 2013b, Dosio et al., 2014, Horowitz et al., 2015, Meque and Abiodun, 2015, Shongwe et al., 2015, Dosio and Panitz, 2016, Pinto et al., 2016a, Pinto et al., 2016b, Abiodun et al., 2017, Maúre et al., 2018). Details of the findings of these studies are outside the scope of this review.

### 2.4.2 Climate modelling studies in Zimbabwe

Despite the advances in climate modelling science globally and regionally as earlier alluded to, the scope of climate modelling research in Zimbabwe has been rather limited. Of the 107 prominent climate studies done in Zimbabwe (covered in this review), only 8% of these directly or indirectly involved climate modelling at some level (see Figure 2.2). The studies covered climate modelling in relation to aspects such as disease vector distribution (Kristensen et al., 2007, Gwitira et al., 2015, Lord et al., 2018), and climate impacts on hydrological systems (Love et al., 2010, Zhu and Ringler, 2012, Mahere et al., 2014), agricultural productivity (Patt and Gwata, 2002a), urban environments and natural ecosystems (Mahere et al., 2014, Sango and Nhamo, 2014, Mushore et al., 2019), and general prediction of future climatic conditions (Unganai, 1996). Unganai (2014) used two GCMs (the GFDL and the CCCM) to simulate future climate conditions for Zimbabwe using a doubled carbon dioxide concentration forcing and concluded that the models were inefficient in predicting the magnitude of precipitation change, for example. Similarly, Makadho (1996a) used the same two GCMs to assess potential impacts of climate change on maize production, while Matarira and Mwamuka (2018) used the Goddard Institute of Space Studies (GISS) model to assess forest vulnerability to climate change. Simulated maize yields decreased considerably under dryland conditions based on climate change scenarios largely due to shorter growing seasons driven by increased temperatures (ibid). Matarira et al. (1996) on the other hand, tested a combined crop model (CERES-Maize) with climate scenarios derived from two GCMs which showed that future low rainfall and high temperature will threaten agricultural production in Zimbabwe. In their stable malaria transmission study, Ebi et al. (2003) tested four GCMs (i.e. the CCCM, the United Kingdom Meteorological Office (UKMO) model, the Henderson-Sellers and the GISS model) to simulate and relate future climatic scenarios to malaria transmission. They concluded that changes in temperature and precipitation due to climate change could alter the spatial distribution of malaria in Zimbabwe, with previously unsuitable areas of dense human population becoming suitable for transmission.

From all these reviewed modelling studies, most used GCM simulations directly, which could have had negative implications on the accuracy of their findings due to the known inherent limitations of GCMs application at a local level. A few exceptions such as

Pedersen et al. (2014b) and Moyo and Nangombe (2015) attempted to use RCMs and/ applied downscaling techniques to generate more accurate climate simulations from GCMs for their studies. For example, Makuvaro (2005) used Statistical and Regional dynamic Downscaling of Extremes for European regions (STARDEX) to come up with downscaled local scenarios for his study. Overall, it is emerging that most of these studies have directly used downscaled GCMs and RCMs with limited regard of inherent limitations of these different models implying possible inaccuracies in some of the findings and conclusions of these studies. This is in light of the fact that most models are developed to be more region specific and transferring them to or applying them in other regions of the world will give inaccurate results by the inherent design of the model. Furthermore, considering the advances in revision and/or improvements on old climate models and the development of new, better and region specific models (e.g. under the CORDEX programme), it is apparent that there is a need to revisit and advance climate modelling science in Zimbabwe (Kalognomou et al., 2013b, Dosio et al., 2014). This means testing new, advanced, and properly downscaled RCMs and use of region specific GCM ensembles so as to update climate scientific knowledge in the country. This will also help in improve understanding of past, present and future climate trends or scenarios in the country. In this review, no known study was found that have comparatively assessed the more recent RCMs and GCMs competence in simulating local climate over Zimbabwe. Furthermore, no contextual optimization of RCMs over Zimbabwe has been done despite the fact that RCMs are known to have the highest skill in reproducing local climatic characteristics as revealed in research work covering southern Africa by Engelbrecht et al. (2019), Dosio (2017) and Abiodun et al. (2016). Such research advances and the ensuing results could help inform more contextual national climate adaptation and mitigation policy appraisal and response strategy development by the GoZ, as earlier discussed.

## 2.5 CLIMATE CHANGE / VARIABILITY IMPACT STUDIES

### 2.5.1 A general global overview

A number of climate scholars have explored the impacts of climate change and/or variability on various natural and human systems (IPCC, 2001, IPCC, 2007, Henderson-Sellers and McGuffie, 2012, Wanders and Wada, 2014, Estrada et al., 2017, Boone et al., 2018, Matsumoto, 2019, Shakhawat Hossain et al., 2020) and the results indicate heightened community vulnerabilities (Pielke, 2013, Ishimwe et al., 2014, Ngie et al., 2014, Stigter and Ofori, 2014, Shah et al., 2019, Fakhruddin et al., 2020) at global, regional and local scales. Amongst other noted impacts, most of the studies have shown that climate change has an overall negative impact on hydrological systems in the world (Knowles and Cayan, 2002, Vicuna and Dracup, 2007, LaFontaine et al., 2015). Arnell (2004) for example, noted reduced runoff in the Mediterranean, Central and Southern America, and southern Africa, with increased evaporation in some areas (Abutaleb et al., 2015, Muhire et al., 2015a). In southern Africa, climate change has also been linked to the El Niño–Southern Oscillation (ENSO) induced droughts (Allison et al., 2009, Christensen et al., 2013, Kalognomou et al., 2013b, Meque and Abiodun, 2015, Manatsa et al., 2017, Gore et al., 2020) with devastating effects on communities and the environment in general. Several studies have quantified the extent of impacts and their dynamics (in space and time) on water resources (Arnell, 1999, Arnell, 2004, Hanson and Dettinger, 2005, Gurdak et al., 2009, Maina et al., 2012), food security (Pielke, 2013, Reddy, 2014, Stigter and Ofori, 2014, Plagányi, 2019), ecosystems (National Research, 2002, Scholes et al., 2015, Tian et al., 2016, Boone et al., 2018, Powers and Jetz, 2019), energy (Kamusoko and Aniya, 2009, Yamba et al., 2011, Spalding-Fecher et al., 2016, De Cian and Sue Wing, 2019, Li et al., 2019b) and human health (Rogers et al., 2010, Pedersen et al., 2014b, Sande et al., 2016). All these studies have revealed that climate change is a very significant factor to consider in holistic planning for community resilience and adaption for sustainable development, and more importantly in African developing countries such as Zimbabwe. Considering the intricate coupling of human and natural systems, most of these studies have used diverse advanced methods in an attempt to understand climate change dynamics *vis-à-vis* all the earlier mentioned factors. Of note has been the widespread use of climate model simulations (from both GCMs and RCMs) in climate impact models to explore how natural and human systems may be affected by climate change (Arnell, 2004, IPCC, 2013). That is, climate simulations have been used in integrated climate change impact assessments, notwithstanding the limitations of under and overestimating some climate extreme impacts, as revealed by Schewe et al. (2019).

While these impacts are well acknowledged to be more devastating in vulnerable communities in developing countries due to their weak institutional arrangements and policies for resilience and adaptation (SADC, 2011), climate science research still lags behind in most of these countries (Letcher, 2009, von Storch and Navarra, 2013, Soussana et al., 2019). This has heightened future climate vulnerability due to limited scientific knowledge to guide pragmatic policy development and strategies for adaptation and resilience.

### 2.5.2 Climate change impact studies in Zimbabwe

In this review, 52 of the 107 (39%) climate studies done in Zimbabwe over the past 29 years were found to be climate impact studies, as earlier alluded to. Table 2.3 and Figure 2.3 show thematic summaries of findings in this regard. The emerging themes/ categories covered by these studies include climate agricultural impacts (Makadho, 1996a, Unganai and Murwira, 2010, Nyabako and Manzungu, 2012, Gwitira et al., 2014), socio-economic impacts (Mano and Nhemachena, 2007, Brown et al., 2012, Utete et al., 2019), ecological impacts (Torr and Hargrove, 1999, Gandiwa and Zisadza, 2010, Chapungu and Nhamo, 2016), hydrological impacts (Unganai, 1992, Ncube, 2010, Zhu and Ringler, 2012), energy impacts (Spalding-Fecher et al., 2016) and health impacts (Ebi et al., 2005, Pilossof, 2016). Agricultural, ecological and health impact studies were found to be the three top categories of impact studies, while energy impact studies were the least covered category over the past 29 years in Zimbabwe (Figure 2.4). The scope of coverage of these studies ranged from national through district, ward to catchment level. This basically revealed limited and, in some instances, outdated scientific knowledge in the least covered categories (i.e. socio-economic, energy and hydrological impacts of climate change). With limited research output informing climate impact on energy, it may imply that planning for energy security in the face of climate risks could be a major contributing factor to the persistent energy problems that the country has been grappling with over the years, climaxing with the recent (2019) near total shutdown of the country's main hydro-electricity power source (i.e. the Kariba South Power station) due to poor rains and the resultant low inflows into the Kariba reservoir.

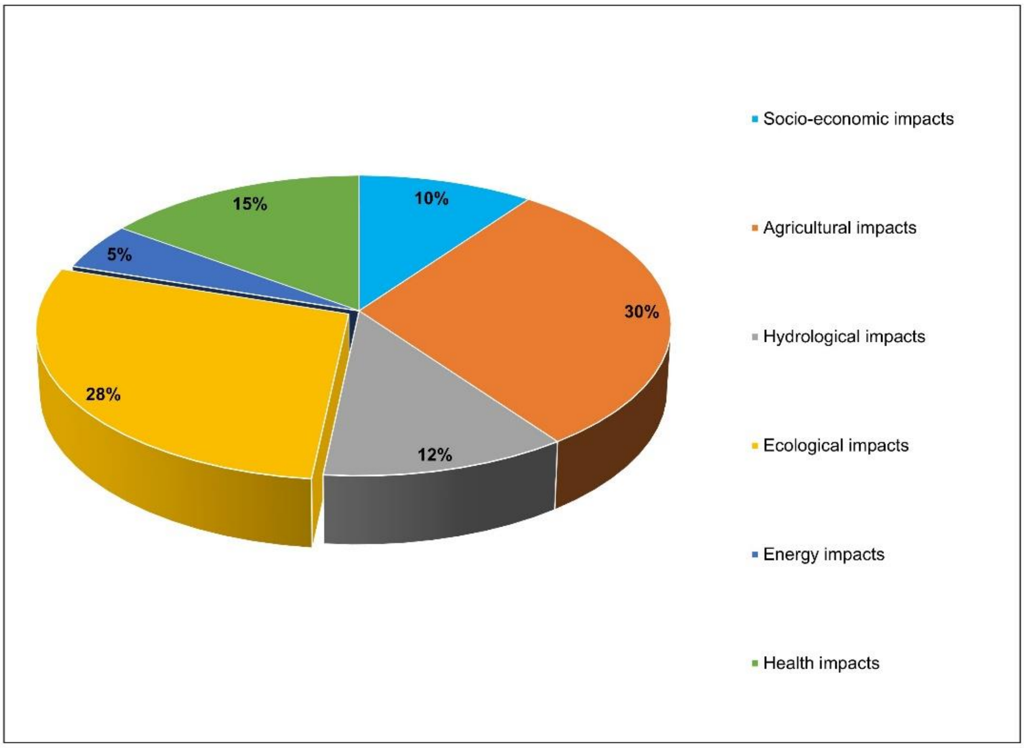

**Figure 2.4:** Chart showing proportions (%) of the various climate impact study themes covered in climate studies in Zimbabwe during the past 29 years. Ecological and agricultural impacts are the predominant themes covered by impact studies *(n= 52)*

**Table 2.3:** Summary table showing climate impact study categories and study examples done in Zimbabwe from 1990 to 2019 *(n = 52)*

| ***Study theme*** | ***Frequency*** | ***Examples of studies*** |
|---|---|---|
| ***Socio-economic impacts*** | 6 | *(Matarira and Mwamuka, 1996), (Dube et al., 2018), (Brown et al., 2012), (Manyeruke et al., 2013), (Utete et al., 2019)* |
| ***Agricultural impacts*** | 18 | *(Corbett and Carter, 1996), (Makadho, 1996b), (Gwimbi, 2009), (Matarira et al., 1995), (Masanganise et al., 2012), (Svotwa et al., 2007), (Patt and Gwata, 2002b), (Nyabako and Manzungu, 2012), (Mutekwa, 2009), (Zinyengere et al., 2011),*<br>*(Unganai, 2009)* |
| ***Hydrological impacts*** | 7 | *(Unganai, 1992), (Salewicz, 1995)*, (Davis and Hirji, 2014), (Love et al., 2010), (Chemura et al., 2016), (Mamombe, 2017)* |
| ***Ecological impacts*** | 17 | *(Nyanganyura, 1999), (Gwitira et al., 2014), (Marshall, 2012), (Booth et al., 1990), (Sango et al. 2014), (Pilossof, 2016)*, (Gandiwa and Zisadza, 2010), (Sango and Nhamo, 2014), (Magadza, 2011), (Pedersen et al., 2014a)*, (Chikodzl and Mutowo, 2014), (Chapungu and Nhamo, 2016), (Gwitira et al., 2015)**<br>*(Matawa et al., 2013)* |
| ***Energy impacts*** | 3 | *(Salewicz, 1995)*, (Spalding-Fecher et al., 2016), (Yamba et al., 2011)* |

| | | |
|---|---|---|
| ***Health impacts*** | 9 | *(Williams et al., 1994), (Ebi et al., 2005), (Gwitira et al., 2015)*, (Pilossof, 2016)*, (Pedersen et al., 2014a)*, (Torr and Hargrove, 1999), (Gunda et al., 2017), (Gunda et al. 2017), (Kristensen et al., 2007)* |

*NB: Eight (8) of the studies marked with an asterisk (*) fall within at least two categories considering their scope.*

Some of the emerging general conclusions from the reviewed impact studies are presented hereon. Climate-agricultural impact studies generally reveal that smallholder agricultural production is significantly constrained by high temperature and low rainfall in Zimbabwe (Mano and Nhemachena, 2007) and that climate change has compounded Zimbabwean peasant farmers' climate vulnerability to drought, and hence food insecurity and poverty (Tekleab et al., 2014). This has necessitated pragmatic adaptive management of agro-biodiversity to ensure equitable sharing of resources in the face of climate change and uncertainties as suggested by Masocha et al. (2017). Given that smallholder and subsistence farmers are highly vulnerable to climate change (Beniston, 2006), there is need for deliberate investment in climate adaptation strategies and clear policies on irrigation and early warning systems to bolster the farmers' climate resilience (Corbett and Carter, 1996, Gwitira et al., 2014) in line with the southern African Development Community (SADC) Climate Change Adaptation Strategy (SADC, 2011). Crop production has also been related to climatic conditions in some of these studies. For example, cotton production levels were noted to have declined as precipitation decreased and temperatures increased in Gokwe district of Zimbabwe (Gwimbi, 2009), while maize productivity has been projected to decrease in response to various global climate change scenarios (Nyabako and Manzungu, 2012, Manyani et al., 2017). The ENSO has been successfully linked to rainfall, drought and maize yield (Unganai and Kogan, 1998, Nyanganyura, 1999, Gwimbi, 2009, Manatsa and Mukwada, 2012, Nyabako and Manzungu, 2012, Chingombe et al., 2015) and livestock productivity (Senda et al., 2016). Within agro-ecology impacts, Mugandani et al. (2001) and Chingombe et al. (2015) agree that the main food production regions of Zimbabwe (regions 1 and 2) are likely to decrease in size due to climate change and variability, pointing to possible reduction in food production and food security, and hence the need to have commensurate mitigation measures to avert potential negative impacts.

As earlier presented, there are other emerging themes related to ecosystem impacts (Pedersen et al., 2014b). Matarira and Mwamuka (2018) in their modelling study projected a 17 to 18% land area shift from subtropical thorn woodland and subtropical dry forest to tropical very dry forest under a modelled climate scenario of reduced precipitation and an increase in ambient temperatures. Climate change/ variability has been shown to be a current and future threat to energy security in Zimbabwe (i.e. hydroelectric power potential will be reduced in all existing and proposed hydroelectric power schemes due to climate change and increasing water demand) (Salewicz, 1995, Watson et al., 1998, Beck and Bernauer, 2011, Yamba et al., 2011). The energy-climate link is already evident as earlier discussed in the recent Kariba power station situation. With regards to public health, literature reviewed in this study indicates negative impacts and/ trends of climate. For example,  results from a climate suitability for stable malaria transmission in Zimbabwe under different climate change scenarios by Ebi et al. (2003) suggest that changes in temperature and precipitation could alter the spatial distribution of malaria in Zimbabwe, with previously malaria unsuitable areas of dense human population such as Bulawayo becoming suitable for transmission. Gwitira et al. (2015) and Ebi et al. (2005) concluded that climatic factors such as temperature and annual precipitation are critical factors intricately linked to current and possibly future changes in the distribution of malaria in Zimbabwe. Other studies are indicating changes in abundance and distribution of tsetse flies, suggesting possible redistribution of African trypanosomiasis (sleeping sickness) incidence in Zimbabwe in future, due to climate change (Pilossof, 2016).

Table 2.4 presents some of the projected climate impacts by sector for the year 2080. Of note is that projections indicate worsening of negative impacts in almost all sectors under consideration. For example, runoff is projected to decrease significantly within major catchments such as the Save and the Mzingwane, with wide-ranging consequences for resident communities and in the face of high vulnerability and low resilience.

**Table 2.4:** Projected climate change impacts by sector in Zimbabwe

| | **Sector** | **Projected climate change impacts** |
|---|---|---|
| **1** | ***General*** | ▪ Predicted warming of around 2degrees Celsius by 2080.<br>▪ Present southwest-northeast-east rainfall gradient will become steeper. |
| **2** | ***Agriculture*** | ▪ General vulnerability of communal agriculture to climate change and variability.<br>▪ Generally, maize suitable areas will decrease by 2080, while cotton and sorghum suitable areas will increase by 2080.<br>▪ In the south western parts of the country, sorghum and maize will become increasingly vulnerable to climate change while cotton will become less vulnerable.<br>▪ In the north central and eastern parts of the country, maize, sorghum and cotton will become less vulnerable |
| **3** | ***Water*** | ▪ Overall, surface water resources are projected to be reduced significantly by 2080 irrespective of the scenario used.<br>▪ North eastern and the eastern parts of Zimbabwe are predicted to experience a surplus in surface water while the western and southern parts of Zimbabwe are projected to experience a drying up.<br>▪ Runoff will decrease significantly in the Mzingwane, Shashe, Nata, and Save catchments. |
| **4** | ***Health*** | ▪ The area under high to extremely high malaria hazard will tend to increase by 2080.<br>▪ High malaria hazard will be concentrated in the low lying parts of the country including the Zambezi valley, and the South-east lowveld.<br>▪ Expected minimum pressure on plant diversity for best and worst case scenarios is 42%. |
| **5** | ***Forestry and biodiversity*** | ▪ Net Primary Production (NPP) will decrease from the current average maximum of over 8 tonnes per hectare per year to just over 5 tonnes per hectare per year by 2080 translating to decreased rangeland carrying capacity for both livestock and wildlife. |
| **6** | ***Human settlement*** | ▪ Any reduction in available water will lead to increased water scarcity thus impacting on livelihoods. |
| **7** | ***Tourism*** | ▪ With decreasing rainfall and rising temperatures, significant declines in biodiversity are expected to occur in most parts of the country especially the western regions where most of the park estates are located.<br>▪ Lower resilience of ecosystems to other global environmental changes. |

*Adopted from Gwenzi et al. (2016) after Murwira et. al (nd)*

Some researchers in Zimbabwe such as Cobo et al. (2010) and Davis and Hirji (2014) corroborate conclusions by IPCC (2007b) and Kundzewicz et al. (1998) that observational records and climate projections provide evidence that freshwater resources are vulnerable to and will be strongly impacted by climate change in the future. Such impacts are likely to have wide-ranging consequences for human societies and ecosystems. Studies on climate impacts on water resources indicate negative trends such as reduction in water reservoir water levels, increased evaporation and surface and groundwater storage and hydro-electricity potential  which are directly related to climate impacts on rainfall and temperature (Fischer et al., 2005, Ncube, 2010, Unganai and Murwira, 2010, Dalu et al., 2012). Very few studies have focused on modelling the hydrological impacts of climate change and variability in Zimbabwe, indicating a gap in knowledge in this regard. These are covered more extensively under the hydrological modelling studies section of this review.  To note is that 11% of all the climate impact studies reviewed here, directly or indirectly employed climate modelling and/ climate impacts modelling techniques in their methodologies, notwithstanding the rapid advancements within this domain. This limited utilisation of these advanced climate modelling tools and techniques thus presents a need to advance research in this direction, so as to expand knowledge and close such apparent gaps in climate impact studies in Zimbabwe.

Relative to these developments in methodologies in climate impact studies, there has been an increase in the integration of indigenous knowledge systems in climate research in Zimbabwe over the past decade. These studies have opened a new frontier in climate research which is aimed at understanding aspects such as seasonal climate forecasts (Chagonda et al., 2013, Soropa et al., 2015, Mubaya et al., 2017b) and local climate adaptation practices and strategies (Jiri et al., 2015, Manyanhaire, 2015, Manyani et al., 2017, Mugambiwa, 2018). Developments in this regard indicate a drive to leverage and streamline existing local indigenous knowledge in the development of pragmatic, low-cost local climate interventions and mitigation strategies.

## 2.6 HYDROLOGICAL MODELLING

### 2.6.1 Hydrological modelling studies: A general overview

Hydrological models are representative simplifications of complicated hydrological processes using mathematical means to demonstrate the principal elements of processes, and their combination and function as a comprehensive hydrologic system (Xu, 2002). These hydrological models have been classified in various ways but Refsgaard and Knudsen (1996) grouped them into three broad categories, namely: (i) empirical black box models, (ii) lumped conceptual models, and (iii) distributed physically-based system.

Examples of these include the TANK model (Chen et al., 2005), Hydrologic Engineering Center's Hydraulic Modeling System (HEC-HMS) (Dotson, 2001, Oleyiblo and Li, 2010), TOPMODEL, Système Hydrologique Européen (SHE), Soil and Water Assessment Tool (SWAT) (G. Arnold et al., 2012, Ghoraba, 2015) and complex conceptual models such as MODified HYDROLOG (MODHYDROLOG) (Chiew et al., 1993). A review of the advantages and disadvantages of these models by Sivapalan et al (2013) and Jaiswal et al. (2020) revealed that distributed-physically based models have the advantage of accounting for spatial heterogeneities and provide detailed description of the hydrological processes in a catchment with limited demands of input data, hence their widespread use in numerous hydrological studies (Refsgaard, 1997, Dotson, 2001, Wooldridge et al., 2001, Uhlenbrook et al., 2004, Refsgaard et al., 2010, Gao et al., 2018). The same notion was confirmed by the World Meteorological Organization (1975) in their inter-comparison of conceptual hydrological models for operational hydrological forecasting. Furthermore, considering that these models use parameters which are directly related to the physical characteristics of river basins (e.g. topography, soil, LULC and geology) and account for spatial variability of meteorological conditions, they have been very useful in hydrological studies (Refsgaard and Knudsen, 1996). For example, they have been used in advancing the understanding of changes in hydrological processes such as surface run-off (Chiew et al., 1993, Karvonen et al., 1999, Chen et al., 2005, Gal et al., 2016) and groundwater storage (Finch, 1990, Gurdak et al., 2009) in space and time and simulating future hydrologic conditions.

## 2.7 GIS AND REMOTE SENSING IN HYDROLOGICAL MODELLING

As alluded to earlier on, over the years, GIS and RS techniques have become indispensable in most state-of-the-art hydrological models premising on the extensive spatio-temporal data capture and analysis capabilities of these technologies. Schultz (1988) presented three main applications of RS in hydrological modelling studies as: (i) model parameter estimation with the aid of multi/ hyper-spectral satellite data; (ii) computation of historic monthly runoff using satellite data as input; and (iii) real-time flood forecasting using radar rainfall measurements as input. In this regard, many researchers have used GIS and RS in hydrological modelling studies aimed at optimisation of catchment management in the Mediterranean regions (Makhamreh, 2011), water resources management in India (Bhavsar, 1984, Halvorsen and Ibsen, 2015), forest hydrology (Stewart and Finch, 1993, Thanapakpawin et al., 2007, Bhatasara and Nyamwanza, 2018), assessing water quality *vis-à-vis* human activities in Korea (Lim and Choi, 2015), monitoring small dams in semi-arid regions (Finch, 1997, Deus et al., 2013) and general parameterisation of hydrological models (Gangodagamage et al., 2001, Uhlenbrook et al., 2004, Nyoni et al., 2013, Evans, 2015). GIS and RS have been noted to have a major advantage of accurately sizing and characterising catchments in rainfall-runoff modelling over and above the fact that analysis can be performed much faster, especially when there are complex mixtures of land use classes and different soil types (Shadeed and Almasri, 2010). In Africa, numerous studies have also exploited the same tools and techniques to advance knowledge in this domain (Stewart and Finch, 1993, Helmschrot and Flügel, 2002, Shalaby and Tateishi, 2007, Zengeya et al., 2011, Sibanda and Murwira, 2012, du Plessis et al., 2015, Adam et al., 2017). This has been enhanced by improved and free access to valuable satellite earth observation data from various systems such as Meteorological satellites (Haggard, 1972) and Tropical Rainfall Measuring Mission (TRMM) (Abd Elbasit et al., 2017, Adam et al., 2017, Twumasi et al., 2017). All these studies indicate that globally, GIS and RS have become an almost indispensable part of hydrological modelling studies over the past decades.

To this end, in the face of considerable uncertainty in determining water availability/ security relative to climate and landuse-landcover changes which impact hydrologic conditions, it is critical for water resources managers and decision makers to have a better and simplified understanding of past, present and ideally future hydrological processes through sound water resources studies (which leverage GIS and Remote sensing technology) (Singh et al., 2019).

## 2.8 HYDROLOGICAL MODELLING STUDIES IN ZIMBABWE

Of the 107 studies reviewed in this study, 7% directly or indirectly involved hydrological modelling, indicating very limited hydrological modelling research in Zimbabwe over the period under review. Hydrological modelling studies in Zimbabwe date back to 1986 when Knudsen et al. (1986) tested the capability of the WATBAL model in simulating ungauged catchments using medium size dams in Zimbabwe. Another early study is by Vörösmarty and Moore (1991), who used a simple catchment-scale model to simulate seasonal variation in discharge in the Zambezi river and how it might respond to climate and land use change. Although developments have been slow in the past 29 years, advances made thus far have seen shifts from use of simple statistical models to empirical-black box models, lumped conceptual models and more recently to coupled distributed-physically-based hydrological models such as SWAT and HecHMS. For example, Love et al. (2001) used an empirical model (the Hydrologiska Byråns Vattenbalansavdelning (HBV) model) to simulate hydrological processes in the northern Limpopo basin (Mzingwane catchment), while the HEC-HMS model has been successfully used in simulating run-off in the gauged and ungauged upper Manyame sub-catchments of Zimbabwe (Gumindoga et al., 2015, Gumindoga et al., 2018). The same model has been applied by Gumindoga et al. (2016) in modelling the water balance of the Lower Middle Zambezi Basin, successfully estimating the total inflows into the Cahora Bassa Dam and recommending ways of managing artificial floods in this basin. Mazvimavi (2003) successfully demonstrated the application of two lumped conceptual models - i.e. the Thomas *abcd* model (Alley, 1984) and the Pitman model (Pitman, 1978) to estimate catchment descriptors such as flow characteristics in 52 ungauged sub-catchments in all the seven main catchments of Zimbabwe. Other models that have been used in Zimbabwe include the Surface Energy Balance System (SEBS) Water Balance Model, which determine actual evapotranspiration in the upper Manyame catchment (Rwasoka et al., 2011), and the TOPMODEL to simulate streamflow of upper Save River catchment (Gumindoga et al., 2011). The flownet computational and modelling method (Sibanda et al., 2009) has also been applied in groundwater recharge modelling within the Gwayi catchment. From these studies, it is apparent that the shift has been from lumped, empirical/ mathematical based models towards distributed physically-based models in hydrological studies in Zimbabwe over the past 29 years.

A review of the scope of coverage of these studies revealed that all seven water catchments in Zimbabwe (i.e. the Gwayi, Manyame, Mzingwane, Runde, Sanyati, Mazowe and the Save catchment) have been studied to varying degrees using various hydrological modelling techniques and tools. However, most of these studies have been done in the Zambezi basin catchments (i.e. the Mazowe and the Manyame catchments). Catchments in the north-eastern and south-western part of the country (i.e. the Gwayi and the Save catchments) have received very limited attention in terms hydrological modelling research over the years, while the Mzingwane catchment has had four prominent studies (Love et al., 2001, Love et al., 2005, Love et al., 2010, Makungo et al.,

2010) that directly applied modelling techniques over the past two decades. Furthermore, in as far as the integration of land use, land cover change, and climate modelling in hydrological modelling studies is concerned, it is noted that very few studies (approximately 15% of hydrological studies) to date have attempted to advance knowledge in this direction. In other words, utilisation of advanced, coupled distributed-physically based hydrological modelling techniques to expand the scope of understanding of the climate-landuse-hydrology nexus in Zimbabwe has been very limited, thus showing a huge knowledge gap in this regard. However, other non-modelling hydrological studies have been done in almost all catchments in the country, covering various themes such as reservoir capacity and sedimentation rate estimation (Finch, 1990, Sawunyama et al., 2006), groundwater yield estimation (Dalu et al., 2012), water quality assessment (Kibena et al., 2014), in-field and rainwater harvesting (Munamati and Nyagumbo, 2010, Nyamadzawo et al., 2013) and general catchment characterisation – water balance relationships (Love et al., 2001, Love et al., 2005).

Although there has been tremendous advances in integration/ streamlining of GIS and RS in hydrological modelling research globally over the past decades as earlier discussed (Kristensen et al., 2007, Adam et al., 2017, Singh et al., 2019), in Zimbabwe however, very few studies have applied these tools and techniques showing a need to expand knowledge in this area leveraging these techniques (Finch, 1990, Lorup et al., 1998, Dalu et al., 2012, Chikodzi, 2013, Gumindoga et al., 2015, Gumindoga et al., 2016, Masocha et al., 2017). This could be attributed to limited expertise and GIS and RS infrastructure/equipment to fully streamline the use of the techniques in hydrological modelling studies. This could also be exacerbated by the earlier highlighted challenges of limited accessibility and availability of good quality *in-situ* climatic /meteorological data, such as rainfall and temperature measurements in the country.

## 2.9 CONCLUSION

### 2.9.1 Climate change/ variability studies

Despite the developments in climate and hydrological research, and the already confirmed climate impacts on human livelihoods, economies and general well-being and water resources in Zimbabwe, the scope of understanding of the climate-landuse-hydrology interlink is still limited. Similarly, climatic studies in Zimbabwe covered in this review present varying, and in some instances contradictory, conclusions. However, most agree that the climate has been changing or varying considerably in space and time, with a temperature rise of less than about 0.1 °C and an approximately 10% decrease per decade for rainfall over the 1900 - 1993 period. Follow up studies in this regard basically indicate the similar temperature and rainfall trends, although magnitudes of change have been varying and, in some instances, contradictory owing to the different methodologies used in these studies. It was noted that the use of different methodologies in the analysis of data in these studies further compounds the problem of comparability of findings. For example, some studies used simple parametric inferential statistics to test for significance of climatic trends, while others used non-parametric techniques on the same. This basically shows the need for care in interpreting and/or comparing study findings in this regard. Furthermore, new and more robust climate trend analysis techniques have been developed over the years, which can be utilised to re-interrogate the available climate datasets with more scientific rigor to close knowledge gaps related to biases and inaccuracies of some of the past studies covered in this review.

We can conclude that climate change and variability impact studies and climate vulnerability, adaptation and mitigation studies are the two-predominant categories of climate studies in Zimbabwe, while climate modelling and governance study themes were the least covered. For climate impact studies, there has been greater bias towards agricultural and ecological impact themes with very limited coverage of energy and socio-economic climate impacts. Other themes that emerged included climate impacts on health and hydrological systems. Findings in this regard converged on this general conclusion asserted by the IPCC that Zimbabwe is a highly climate vulnerable country with limited resilience and poor adaptation policies and strategies in place to avert the inherent impacts of climate change and variability. Furthermore, considering that global and regional climate forecasts indicate worsening conditions, it is thus very important that climate science in Zimbabwe is updated to generate new and contextual scientific knowledge. This endeavour should leverage cutting edge, recently developed tools and techniques rather than rely on outdated conclusions from past studies to inform climate policy formulation and strategy development for the country.

Furthermore, in this review, it emerges that climate modelling research is still a largely grey area in Zimbabwe. Most past studies have used GCMs and only a few have used

RCMs with limited to no bias corrections. The implications of this are potential biases and errors and thus limited local applicability of some of their findings, considering also recent developments and cautions in application of these tools at a local scale. This therefore necessitates further expansion of knowledge on the same by leveraging on the potential presented by new and advanced southern Africa regions-specific GCMs and RCMs, such as the CCAM which have the ability to generate accurate climate perturbations at regional and local scale through advanced downscaling and bias correction techniques. New studies could expand knowledge by modelling impact scenarios in agriculture, biodiversity and hydrology, such as surface run-off which influences overall water availability and thus security in Zimbabwe. Advancing knowledge in this regard will be vital, especially for identifying, for example, the hydrologic consequences of changes in important climatic variables such as temperature, precipitation, and other landscape variables such as land use-land cover. This could contribute to holistic policy development and effective planning of current and future water management and security interventions. Furthermore, highly prohibitive costs of *in situ* current and historic climate and hydrological data imposed by governmental agencies such as the Zimbabwe National Water Authority (ZINWA) and the Meteorological Services Department are noted to be one of the potential serious bottlenecks impeding climate science research in the country. It is therefore important for the Government of Zimbabwe to address this by coming up with more pragmatic data-access policies that will make climate datasets more easily available and accessible to the Zimbabwean scientific community, so as to encourage more research. This will allow for unhindered fast progress or advancement of climate science research in Zimbabwe, exploiting also the available national supercomputing capabilities at the ZCHPC.

### 2.9.2 Hydrological modelling studies

Hydrological modelling is a relatively grey area of research in Zimbabwe with very few studies reviewed herein covering this research domain. Of the seven water catchments in Zimbabwe, the Manyame and the Mazowe catchments have received most attention as frontiers of hydrological modelling research in Zimbabwe, whilst the Gwayi, Runde, Save and Sanyati catchments have had least coverage. While some hydrological modelling research has been done on the Mzingwane catchment, the scientific knowledge is outdated (i.e. has been outpaced by advances in techniques and tools developed and used in this domain over the past two decades globally). With such knowledge gaps, *vis-à-vis* the already acknowledged highly vulnerable climate of Zimbabwe and the predicted worsening future climatic conditions in the country, it thus becomes very critical that deliberate efforts cascading from policy level, prioritise climate-hydrology modelling research in Zimbabwe. This is because all these aspects speak to present and future sustainable development in terms of water security and livelihoods.

Regarding the types of models, there is generally a need to test or apply new/ advanced coupled hydrological models to better understand interlinkages between climate-hydrology and landuse in Zimbabwe to update existing knowledge to be abreast with global and regional developments within this domain. In order to achieve this, approaches encompassing coupling of distributed hydrological models and properly downscaled GCMs/RCMs and climate simulate simulations as advocated for by various researchers should be considered. Such approaches could enhance understanding of local feedback mechanisms and interrelations between key natural-human systems influencing community livelihoods, which is a specialised area of research within this domain. Furthermore, we note a relatively new and important frontier of climate-hydrology research, which involves the integration of indigenous knowledge systems (IKS) in the context of climate adaptation and mitigation in Zimbabwe, but which has to be encouraged and streamlined within this domain.

Overall, it can be concluded that climate science and hydrological modelling research in Zimbabwe is lagging behind vis-à-vis global and regional developments within these domains and thus the need to adopt a more systematic and holistic approach exploiting among other tools and techniques, coupled systems-based approaches (integrating climate-landuse-hydrological modelling and GIS/RS) for better understanding of past, present and future climatic conditions and their hydrological impacts. This should be done without negating the need of developing new and/or fine-tuning the existing climate related and other relevant policy, legislative and institutional frameworks in Zimbabwe.

# CHAPTER 3: PAST AND FUTURE LAND USE LAND COVER CHANGES IN UMS

*Based on a published paper:*
*Title: Analysis of past and future multi-temporal land use and land cover changes in the semi-arid Upper-Mzingwane sub-catchment in the Matabeleland South Province of Zimbabwe* [2]

## Abstract

In this study, past spatio-temporal land use and land cover (LULC) change dynamics in the upper Mzingwane sub-catchment (UMS) located in the semi-arid Matabeleland south region of Zimbabwe using Landsat 5 Thematic Mapper (L5-TM) and Landsat 8 Operational Land Imager (L8-OLI) imagery for the periods of 1989, 2004, 2013 and 2018 are analysed. Future LULC scenarios for UMS are also modelled. Five LULC classes (water, bare land, dense woodland, shrubland and grassland) are distinguished using a hybrid approach entailing image classification in R-software using the Random Forest (RF) and Support Vector Machine (SVM) algorithms. Accuracy assessment and Kappa statistics revealed better performance of the SVM, hence its outputs were used in the change analysis (to quantify LULC transitions and trends statistically). We then utilised the TerrSet Land Change Modeller (LCM) (using the Markov Chain algorithm with Multi-Layer Perceptron) to model future LULC scenarios up to 2038 at 5-year intervals. Results revealed that the grass, shrub and woody vegetation are predominant land covers, covering 48.5%, 31.5% and 18.8% in 1989 and 54.4%, 28.8% and 15.8% respectively in 2018. Dense woodland cover was projected to experience the greatest net loss of 43.6% while shrubland, grassland, water and bareland increase by 10.7%, 4.5%, 26.9% and 15.1% respectively between 2023 and 2038. The study conclusion is that the UMS has since 1989, been losing and will continue to lose dense woodland cover into the future, possibly due to increased human activities such as small scale and illegal gold mining in the area. As such, immediate remedial action needs to be taken to reverse the observed and possible future negative LULC change trends, especially for woodland cover so as to avert likely adverse socio-economic, hydrological and ecological consequences within and beyond the UMS.

Keywords: GIS, land use, land cover, Mzingwane, Markov chain, Zimbabwe

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[2] *Paper published in International Journal of Remote Sensing ( DOI: https://doi.org/10.1080/01431161.2020.1731001 )*

## 3.1 INTRODUCTION

Changes in land use and land cover (LULC) have been well acknowledged as an important driver of environmental change at all spatial and temporal scales, with both direct and indirect implications on sustainable development, livelihood systems and perturbations of the earth's biogeochemical cycles (Turner et al., 1995, Lambin et al., 2001, Flato et al., 2013). Impacts of LULC change have been well documented in hydrological studies, revealing how changes in distinctive LULC types influence the hydrological conditions and consequently sustainable water resource management (Lorup et al., 1998, Niehoff et al., 2002, Thanapakpawin et al., 2007, Nie et al., 2011, Woldesenbet et al., 2016, Gumindoga et al., 2018). LULC changes have also been associated with climate systems change and variability (Verburg et al., 2011), ecosystem services disturbances (Maina et al., 2013, Mondal and Zhang, 2018), rapid population growth, urbanisation (Bagan and Yamagata, 2012, Ngie et al., 2013, Pan et al., 2017), other developmental activities (Foley et al., 2005, Yao et al., 2017), and agricultural expansion among other anthropogenic activities in both developed and developing countries.

With regards to the underlying causes of LULC change, Lambin et al. (2001) concluded that overall, LULC changes are driven by peoples' responses to economic opportunities, as mediated by institutional factors (which are either amplified or attenuated by global geopolitical and economic factors) over and above population growth and poverty. Factors such as soil suitability, slope steepness, proximity to main cities (Nahuelhual et al., 2012), conflicting property rights, land rent and overgrazing (Serneels and Lambin, 2001, Qasim et al., 2013) have also been noted as key proximate drivers of LULC change and consequently water availability particularly in water stressed semi-arid regions of Sub-Saharans Africa. In this regard, numerous studies have been undertaken since the 1990s to explore past and future LULC dynamics so as to increase understanding of associated impacts LULC changes and to provide updated LULC information using geospatial technologies. Examples of such studies include: mapping and modelling of LULC changes (Ayad, 2005, Shalaby and Tateishi, 2007), land use patterns analysis (Turner, 1990, Ramankutty and Foley, 1998, Li and Yeh, 2004), long-term landscape change analysis (McGarigal and Marks, 1995, Bender et al., 2005, Haase et al., 2007), assessing patterns and drivers of LULC changes in Eastern Ethiopia (Ali and Tesgaya,

2010) and quantification of LULC changes in Zimbabwe (Chikodzi, 2013, Kibena et al., 2014). Others have also attempted to model future LULC scenarios (Messina and Walsh, 2001, Wegehenkel, 2003, Wu et al., 2006, Tope-Ajayi et al., 2016) so as to guide decision making in ensuring sustainable land use development and water resources management. To model future LULC changes efficiently, various spatially explicit models have been applied with the purpose of evaluating future LULC scenarios (Mishra and Rai, 2016). Examples of such spatially explicit models include the Logistic Regression (LR) model, Artificial Neural Network (ANN) model, Cellular Automata (CA) model, the Markov chain (MC) model and the combined Cellular Automata _Markov Chain (CA_MC) model (Subedi et al., 2013, Ramezani and Jafari, 2014, Gidey et al., 2017a). In this study, the Land Change Modeller (LCM) in TerrSet software was used for its implementation simplicity and robustness as it employs the MC algorithm (known for its efficient land use change quantities prediction) leveraging the strengths of the Multi-Layer Perceptron (MLP) (Clark Labs, 2009, Clark Labs, 2015).

In this chapter, past and future LULC change dynamics in the upper Mzingwane Sub-catchment (UMS) are analysed. The catchment (located in the semi-arid region of Matabeleland South, Zimbabwe) is an important sub-catchment both nationally and regionally. The UMS generates approximately 9.3% of total run-off into the Limpopo River and also hosts all the five major portable water supply dams for Bulawayo (i.e. the Upper and Lower Ncema, Inyankuni, Mzingwane and the Insiza dams). Human activities (extensive small scale legal and illegal gold panning) (Ncube-Phiri et al., 2015) and deforestation related to the Government of Zimbabwe's fast track land-resettlement programme and communal farming activities (Moyo et al., 2006) in this area have over the past three decades led to visible yet unquantified LULC changes and related environmental problems such as siltation of rivers and water pollution (Nare et al., 2006). This implies that such changes within the sub-catchment's LULC structure will impact on water security and livelihoods in and beyond this sub-catchment in many ways, hence the need to explore and update knowledge on the LULC change dynamics in this area, notwithstanding work already done in this regard by Love et al. (2005). In this regard, a hybrid, longitudinal, multi-temporal approach was used to explore past LULC dynamics and model future LULC scenarios in the UMS. This knowledge will give quantified insights on transitions that have occurred and guide future land use development and catchment conservation planning for this highly strategic area.

## 3.2 METHODOLOGY

### 3.2.1 Study area description

The UMS is one of the four sub-catchments (i.e. Shashe, Lower Mzingwane and the Mwenezi) of the Mzingwane catchment, nested in the northern extreme of the Limpopo basin in southern Zimbabwe (Figure 3.1). The sub-catchment covers an area of 2138 km$^2$ and falls in Natural Region IV of Zimbabwe, receiving rainfall ranging from 450 mm to 650 mm per annum (Görgens and Boroto, 1997). This translates to a mean annual run-off of about 600 mm, thus contributing most of the run-off of the Mzingwane River flowing in a southerly direction towards and into the Limpopo River. This demonstrates the significance of this sub-catchment, not only nationally but regionally. The annual mean minimum and maximum temperatures are 5$^o$C and 30$^o$C respectively (Mazvimavi, 2010a), while evaporation ranges between 1800 mm to 2000 mm per annum, with an increasing north – south gradient. Elevation range is between 864 to 1560 m, with a mean of 1160 m in the UMS. Flora and fauna are typical of a dry savannah ecosystem with woodlands predominated by *Brachystegia spiciformis*, *Colophospermum mopane*, *Terminalia*, *Acacia species* and *Combretum species*, while thatch grass species (*Hyparrhenia filipendula* and *Heteropogon contortus*) are also common. Due to increased human activity in the study area, much of the typical savannah wildlife, including reptiles, birds of prey and mammals, have retreated into the nearby Matopos National Park to the west of the study area.

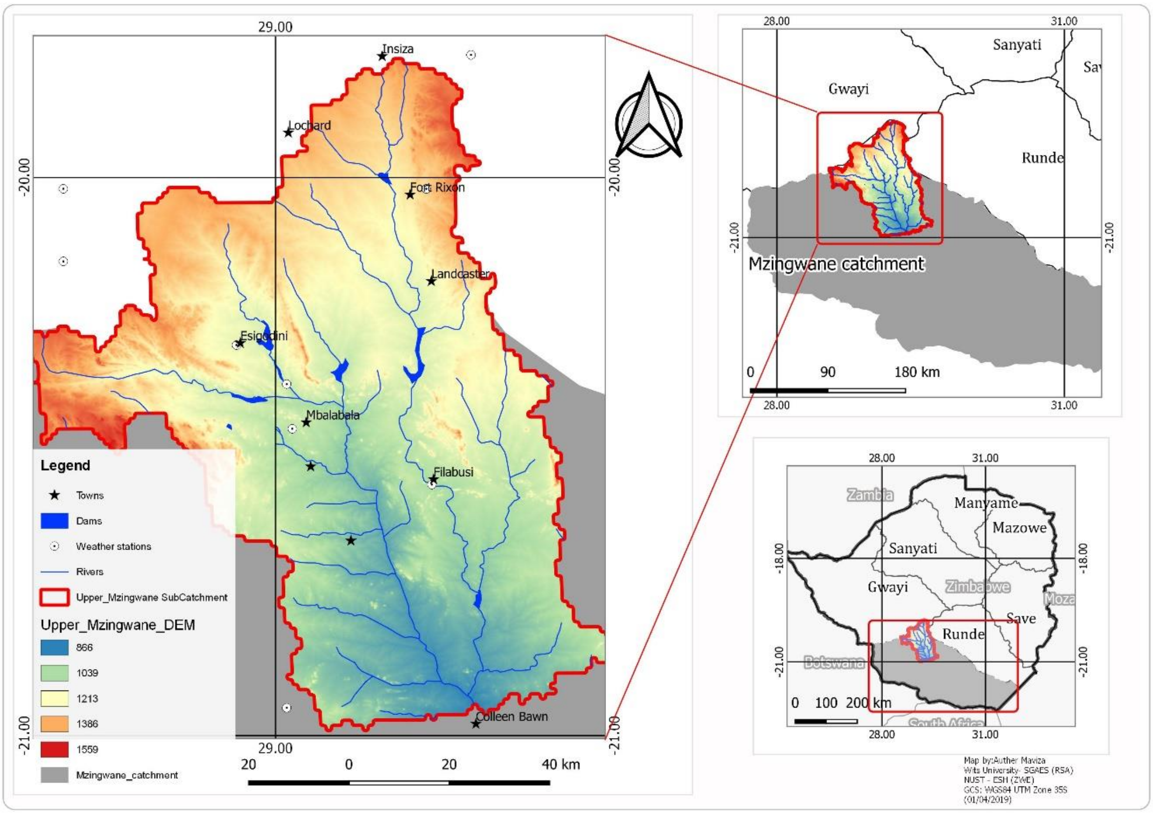

**Figure 3.1:** Study area map (Upper Mzingwane sub-catchment) showing its location within the Mzingwane catchment (the Northern Limpopo basin) of Zimbabwe

Straddling over three districts; namely Insiza (to the east), Umzingwane (on the north-western extent) and Gwanda (on the south-western section), the UMS has a diverse land use system. The system has an agro-ecological and socio-economic structure characterised by a mixture of commercial and subsistence agriculture, small-scale low cost drip irrigation farming, wildlife /game viewing, dam recreational activities, gold panning, private safari operations, fishing, communal and ranch-lands (Love et al., 2005). Gold panning (both legal and illegal) is supported by the Zimbabwean Craton greenstone belts and granitic terrain which most of the catchment is underlain by (Ashton et al., 2002). The soils are moderately coarse grained kaolinitic sands (from the granites and Limpopo gneisses), very shallow to moderately shallow clays and loams (derived from the greenstone belts); and very shallow sands, formed from the basalts (Love et al., 2005, Sawunyama et al., 2006). The socio-economic significance of the sub-catchment cannot be over emphasised in light of the aforementioned.

### 3.2.2 Data acquisition and pre-processing

#### *3.2.2.1 Selected Earth Observation datasets*

Satellite imagery for the months of April and May from Landsat 5 Thematic Mapper (L5-TM) for year 1989 and from Landsat 8 Operational Land Imager (L8-OLI) for years 2004, 2013 and 2018 were downloaded from the United States Land Processes Distributed Active Archive Centre (LP DAAC) using the Earth Explorer Website tool (USGS, 2015). Images were selected for the Path/Row (170 and 171/ 74 and 75) which covered the study area (Table 3.1 and Figure 3.2). Other criteria used for selection of the time periods was image quality, availability of scenes (Path/Row) to cover the study area within the desired time period, and less than 10% cloud cover. All imagery came with a 30 m spatial resolution and in projected coordinate system (i.e. Universal Transverse Mercator (UTM) Zone 35 South). A 6-bandset of all the selected imagery was used (excluding the thermal bands and Band 1 for L8-OLI).

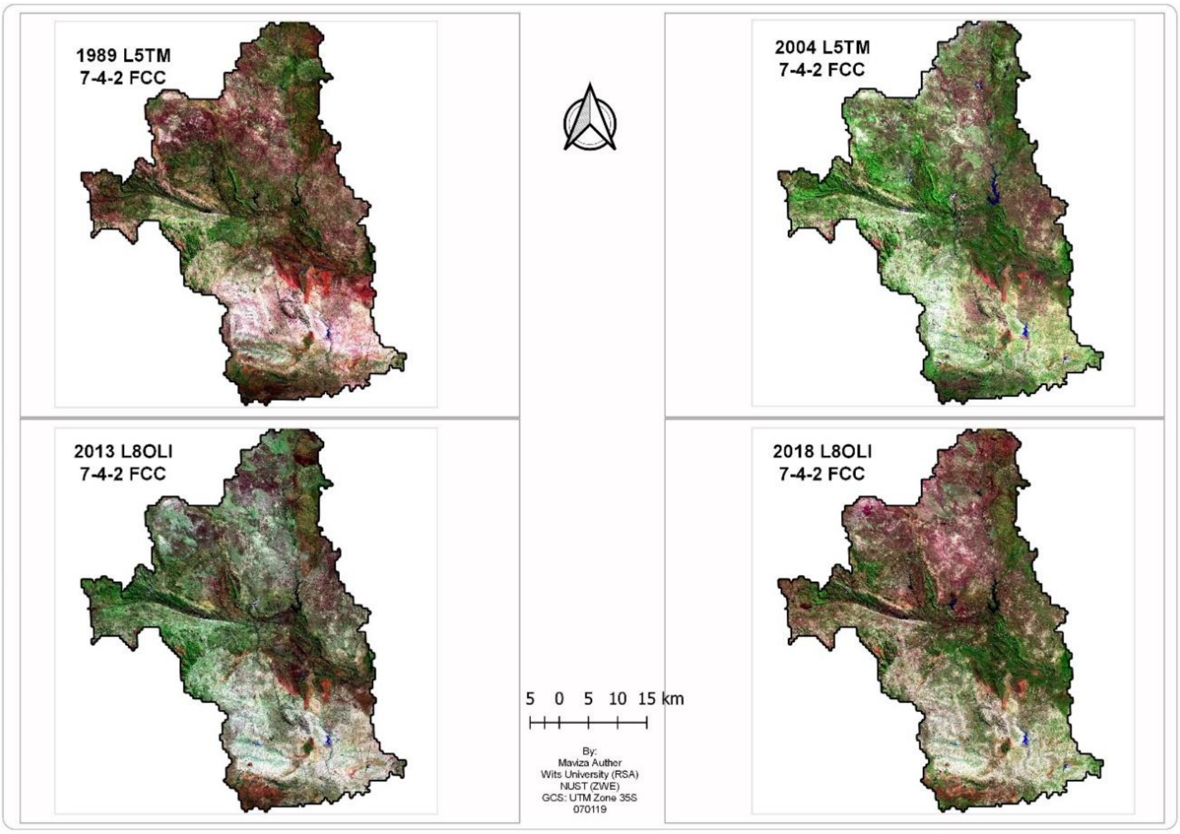

**Figure 3.2:** Landsat imagery (for years 1989, 2004, 2013 and 2018) used in the study shown in 7-4-2 False Colour Composites

**Table 3.1:** Summary of main metadata of the selected Landsat datasets used in the study. Main spectral bands (SWIR and VNIR) sub-set used in the LULC change analysis from 1989-2018. *(TM = Thematic Mapper, OLI = Operational land Imager, SWIR = Shortwave Infra-Red, VNIR = Visible Near Infra-Red)*

| Year | Scene ID | Platform - sensor | Acquisition date | Path/ Row | Spectral band number | Spatial resolution (m) |
|---|---|---|---|---|---|---|
| **1989** | LT51710741989162JSA01 | L5-TM | 11 June 1989 | 171/074 | 6 | 30 |
| | LT51700741989171JSA01 | L5-TM | 20 June 1989 | 170/074 | 6 | 30 |
| | LT51700751989171JSA01 | L5-TM | 20 June 1989 | 170/075 | 6 | 30 |
| **2004** | LT51700742004149JSA00 | L5-TM | 28 May 2004 | 170/074 | 6 | 30 |
| | LT51700752004165JSA00 | L5-TM | 13 June 2004 | 170/075 | 6 | 30 |
| | LT51710742004172JSA00 | L5-TM | 20 June 2004 | 171/074 | 6 | 30 |
| **2013** | LC81710742013164LGN02 | L8-OLI | 13 June 2013 | 171/074 | 6 | 30 |
| | LC81700742013173LGN01 | L8-OLI | 22 June 2013 | 170/074 | 6 | 30 |
| | LC81700752013173LGN01 | L8-OLI | 22 June 2013 | 170/075 | 6 | 30 |
| **2018** | LC81700742018171LGN00 | L8-OLI | 20 June 2018 | 170/074 | 6 | 30 |
| | LC81700752018171LGN00 | L8-OLI | 20 June 2018 | 170/075 | 6 | 30 |
| | LC81710742018178LGN00 | L8-OLI | 27 June 2018 | 171/074 | 6 | 30 |

#### *3.2.2.2 Image pre-processing*

Image pre-processing entailed edge trimming of the 1989 imagery scenes to remove bad edge lines, geometric rectification, radiometric calibration and atmospheric correction, and topographic correction. All these are a prerequisite for a combination of different time-step data in a LULC classification process (Wang and Yuhai, 1999, Lu and Weng, 2007, Gidey et al., 2017b, Maponga et al., 2018). Pre-processing was implemented using the image pre-processing modules in the Environment for Visualizing Images (ENVI) 5.4 software toolbox that is (radiometric calibration and Quick Atmospheric Correction (QUAC)) to get imagery with surface reflectance values. Radiometric calibration converted raw Digital Numbers (DN values) to Top-of-Atmosphere (TOA) reflectance, while the application of the QUAC algorithm (Bernstein et al., 2012) atmospherically corrected the images to move from TOA reflectance to Surface Reflectance measurements (Santer et al., 2007, Liu et al., 2015). The QUAC algorithm was selected for use in this study because of its significantly faster computational speed compared to the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) (Bernstein et al., 2005), and better competence in aerosol optical depth retrieval compared to Dark Object Subtraction (DOS) (Chavez, 1988). During the QUAC implementation, all the datasets were spatially subset by masking them using a boundary shapefile of the study area.

Considering that the study area hosts a mountainous terrain stretching from the north-westerly through the central to the eastern extent, hill shadow effect was noted to be prominent in these areas. To rectify this, topographic correction was implemented using the *'topocorr'* tool in R-software (R Core Team, 2018) after Gao and Zhang (2009). The tool was set to use the study area Digital Elevation Model (DEM) and the Cosine algorithm (selected for its robustness and relatively quick computational time) to reduce and or remove the topographic effects on the satellite imagery without significantly impacting on the data integrity compared to other methods such as Gamma Correction Method, Linear-Correlation Method and Histogram Matching (Sarabandi et al., 2004). All the path/row datasets were then mosaicked using the Seamless Mosaic tool and then co-registered to 2018 as the base image in ENVI 5.4. The output from this process were analysis-ready datasets for the years 1989, 2004, 2014 and 2018 which were exported to R-software in GEOTIFF format for classification.

#### *3.2.2.3 Selection of model training samples and classification system*

A hybrid spectral pattern recognition approach (Wang and He, 1990, Franklin and Wulder, 2002) utilising the pre-processed imagery, Google Earth imagery (for dates 31 December 1989, 31 December 2004 and 18 June 2013) and the Normalised Difference Vegetation Index (NDVI) was used in the visual comparison, identification, selection and labelling of training pixels/samples corresponding to the five LULC classes (Table 3.2). The training sample sizes were 236, 264, 259 and 222 for each of the time-steps (i.e. 1989, 2004, 2013 and 2018 respectively). The classification scheme was adapted from Lembani et al. (2018). NDVI has been widely used in identifying LULCs through NDVI value thresholding to correspond to certain LULCs (e.g. negative NDVI values indicate water), as done in numerous studies (Yunfeng et al., 2008, Bhandari et al., 2012, Gandhi et al., 2015, Herrero et al., 2016). This was done to improve the accuracy of selection of training samples for each of the study time steps.

**Table 3.2:** LULC classification scheme showing the 5 main LULC classes identified and used in the study and their description

| LULC Class | Class description |
|---|---|
| **Water** | Permanent and perennial open water reservoirs (e.g. dams, lakes and wetlands) |
| **Bareland** | Exposed soils, rock outcrops, paved surfaces and compacted land, roads, settlements and bare agricultural fields |
| **Dense woodland** | Woody forested areas and riparian woody vegetation |
| **Shrubland** | Small sparse woody vegetation cover |
| **Grassland** | Grass species mixed with herbaceous species with no persistent aboveground biomass. Areas also characterised by the co-existence of saplings, small shrubs and revegetating agricultural areas |

### 3.2.3 Image classification, interpretation, and analysis

#### *3.2.3.1 Image classification and analysis*

Image classification was done in R-software using the *superClass* package where two most prominent image classification models (the Random forest (RF) and the Support Vector Machines (SVM) classifier) were implemented in a semi-autonomous script with a ‘split sample’ of (70%-30%) for training-validation respectively. The 2 classifiers were implemented to compare their performance so as to select the best output results based on the overall accuracy and Kappa coefficients since RF is known to be easier to parameterise while SVM is less susceptible to topographic effects (Pal, 2005, Belgiu and Drăguţ, 2016).

#### *3.2.3.2 Accuracy assessment*

Overall, the SVM performed better than the RF, with overall accuracy (Kappa coefficients) ranging between 0.9846 and 0.7763 (0.9791 - 0.6633), while RF values ranged between 0.8982 and 0.8115 (0.8621 - 0.7366) (see Table 3.3). In all the study time-steps, the SVM outperformed the RF results except for year 2013.

**Table 3.3:** Summary of LULC classification models validation results presenting overall accuracy, 95% CI and the Kappa statistic for years 1989, 2004, 2013 and 2018. (RF = Random Forest, SVM = Support Vector Machine, OA = Overall Accuracy)

| **Year** | **Class model** | **OA 95% Confidence Interval (CI)** | **Model training/ Validation sample size (70%/30%)** | **Overall accuracy** | **Kappa coefficient (k)** |
|---|---|---|---|---|---|
| **1989** | RF | 0.8834 - 0.9117 | (167/69) | 0.8982 | 0.8621 |
| | SVM | 0.9778 - 0.9897 | (167/69) | 0.9846 | 0.9791 |
| **2004** | RF | 0.8117 - 0.8500 | (187/77) | 0.8115 | 0.7631 |
| | SVM | 0.8344 - 0.8706 | (187/77) | 0.8532 | 0.7932 |
| **2013** | RF | 0.8005 - 0.8451 | (183/76) | 0.8236 | 0.7366 |
| | SVM | 0.7515 - 0.7997 | (183/76) | 0.7763 | 0.6633 |
| **2018** | RF | 0.8564 - 0.8973 | (157/65) | 0.8779 | 0.7928 |
| | SVM | 0.9247 - 0.9545 | (157/65) | 0.9409 | 0.9007 |

### *3.2.3.3 LULC change detection*

The geometry (area) of the final LULC classification results were computed and these were used to quantify LULC transitions (net and percentage areal changes, class area gains and losses) (see Figure 4) for each time step in TerrSet using the Equations 1 and 2 as presented by Clark Labs (2015).

$$C = \frac{N}{D} \times 100 \qquad \text{Equation (1)}$$

$$A = \frac{N}{T} \times 100 \qquad \text{Equation (2)}$$

Where *C* = Percentage change (%) and *A* = Percentage area (%), *N* = Number of pixels changed for a LULC class, *T* = Total area of LULC map (in km$^2$) and *D* = Area of class in later LULC image (in km$^2$).

### *3.2.3.4 Future LULC change prediction (Markov Chain model)*

The MC process handles the temporal changes of LULC classes based on produced transition probability matrices, whereas the spatial changes are controlled by resultant transition potential maps from the same process (Clark Labs, 2009, Hua, 2017). The MC model has been successfully applied in many LULC studies over the years (Hastings, 1970, Al-sharif and Pradhan, 2014, Ramezani and Jafari, 2014, Sayemuzzaman and Jha, 2014, Gidey et al., 2017b) although others have used it together with CA to improve model performance (Arsanjani et al., 2011, Subedi et al., 2013, Gidey et al., 2017a).

### *Markov Chain model*

The MC model is a discrete-temporal stochastic process in which the probability distribution of the current state is conditionally independent of the path of past states. It is based on the first rule of Geography (Webster, 1990), namely that pixels close to each other are more likely to be similar to or become like those closer to them, than pixels farther away. MC is very powerful to determine the possibility of LULC change between two time periods as it efficiently handles the dynamic and stochastic nature of natural and socio-economic variables of LULC prediction (Mishra and Rai, 2016), although it cannot provide the spatial distribution of occurrences of LULC change. The MC first analyses a pair of historic LULC base maps (i.e. 2013 and 2018 in our study) and outputs LULC change maps showing categorical patterns of change between the maps of two time steps. Secondly, transition probability matrices (i.e. Table 3.4 in this study) are computed based on the projection dates (i.e. years 2023, 2028, 2033 and 2038 in our study) together with transition areas matrices (i.e. Table 3.5 in our study) and a set of conditional probability maps. The transition probability matrices provide the transformation rules, and demonstrate the probability of change of different LULC classes into other classes (e.g. dense woodland to shrubland), while the transition area matrices reflect the quantity of LULC change (i.e. amount of one LULC class changing to another LULC class) in the predicted future time-step.

**Table 3.4:** Transition probabilities matrix for periods 2018-2023, 2023-2028, 2028-2033 and 2033-2038

| Year | *Given* | *Water* | *Bareland* | *Dense woodland* | *Shrubland* | *Grassland* |
|---|---|---|---|---|---|---|
| | Probability to transition to * | | | | | |
| **2023** | *Water** | 0.9010 | 0.0851 | 0.0053 | 0.0033 | 0.0054 |
| | *Bareland** | 0.0459 | 0.5672 | 0.0344 | 0.1100 | 0.3500 |
| | *Dense woodland** | 0.0028 | 0.0050 | 0.7103 | 0.2570 | 0.0269 |
| | *Shrubland** | 0.0011 | 0.0010 | 0.1329 | 0.5885 | 0.3650 |
| | *Grassland** | 0.0023 | 0.0001 | 0.0065 | 0.1600 | 0.8459 |
| **2028** | *Water** | 0.4169 | 0.1086 | 0.1199 | 0.0909 | 0.2638 |
| | *Bareland** | 0.1891 | 0.3136 | 0.2105 | 0.1276 | 0.1591 |
| | *Dense woodland** | 0.0054 | 0.0263 | 0.5061 | 0.3298 | 0.1324 |
| | *Shrubland** | 0.0002 | 0.0042 | 0.2189 | 0.3600 | 0.4167 |
| | *Grassland** | 0.0001 | 0.0005 | 0.0553 | 0.2161 | 0.7280 |
| **2033** | *Water** | 0.7411 | 0.1401 | 0.0758 | 0.0244 | 0.0185 |
| | *Bareland** | 0.0781 | 0.1924 | 0.4456 | 0.2072 | 0.0766 |
| | *Dense woodland** | 0.0069 | 0.0049 | 0.4303 | 0.3542 | 0.2037 |
| | *Shrubland** | 0.0045 | 0.0024 | 0.1831 | 0.3503 | 0.4597 |
| | *Grassland** | 0.0060 | 0.0017 | 0.0542 | 0.2402 | 0.6980 |
| **2038** | *Water** | 0.6742 | 0.1429 | 0.1095 | 0.0439 | 0.0295 |
| | *Bareland** | 0.0809 | 0.1175 | 0.4112 | 0.2546 | 0.1359 |
| | *Dense woodland** | 0.0085 | 0.0051 | 0.3559 | 0.3487 | 0.2817 |
| | *Shrubland** | 0.0061 | 0.0029 | 0.1806 | 0.3199 | 0.4905 |
| | *Grassland** | 0.0075 | 0.0022 | 0.0756 | 0.2564 | 0.6583 |

**Table 3.5:** Transition area matrix for periods 2018-2023, 2023-2028, 2028-2033 and 2033-2038

| **Year** | ***Pixels in*** | ***Water*** | ***Bareland*** | ***Dense woodland*** | ***Shrubland*** | ***Grassland*** |
|---|---|---|---|---|---|---|
| | Expected to transition to * | | | | | |
| **2023** | Water* | 44884 | 4239 | 264 | 164 | 269 |
| | Bareland* | 1881 | 23247 | 1409 | 4508 | 14345 |
| | Dense woodland* | 3630 | 6482 | 920867 | 333187 | 34874 |
| | Shrubland* | 2602 | 2365 | 314316 | 1391835 | 863245 |
| | Grassland* | 10289 | 447 | 29078 | 715778 | 3784227 |
| **2028** | Water* | 30282 | 3689 | 0 | 0 | 0 |
| | Bareland* | 0 | 43644 | 0 | 0 | 8259 |
| | Dense woodland* | 0 | 34701 | 674893 | 435151 | 174694 |
| | Shrubland* | 0 | 0 | 510740 | 850222 | 972249 |
| | Grassland* | 0 | 2240 | 0 | 968238 | 3510029 |
| **2033** | Water* | 42818 | 6979 | 0 | 0 | 0 |
| | Bareland* | 0 | 37704 | 0 | 100 | 3137 |
| | Dense woodland* | 0 | 0 | 572062 | 458393 | 263626 |
| | Shrubland* | 0 | 0 | 432516 | 844014 | 1086174 |
| | Grassland* | 26746 | 7402 | 130 | 1074021 | 3363209 |
| **2038** | Water* | 48100 | 1423 | 0 | 0 | 294 |
| | Bareland* | 0 | 39876 | 0 | 0 | 1114 |
| | Dense woodland* | 0 | 0 | 1132863 | 90414 | 73041 |
| | Shrubland* | 0 | 0 | 0 | 2133044 | 232011 |
| | Grassland* | 6710 | 1968 | 0 | 229406 | 4235526 |

### *Markov Model validation*

Automated map comparison within the TerrSet VALIDATE module was utilised to estimate the Kappa Index of Agreement (KIA) (Memarian et al., 2012). The KIA gives unbiased summary statistics (i.e. $K_{\text{no}}$, $K_{\text{location}}$ and $K_{\text{standard}}$ values) on degree of similarities between actual image and simulated image (Hua, 2017, Palmate et al., 2017). In this study, the actual 2013 LULC map and the predicted 2013 LULC are shown in Figure 3.3. The $K_{\text{no}}$, $K_{\text{location}}$ and $K_{\text{standard}}$ values for this study were found to be satisfactory at 0.737, 0.712 and 0.709 respectively, indicating that the MC model simulation process can be executed for future periods, such as for the next twenty years (up to 2038) at 5 year time steps with the year 2018 as the reference base map.

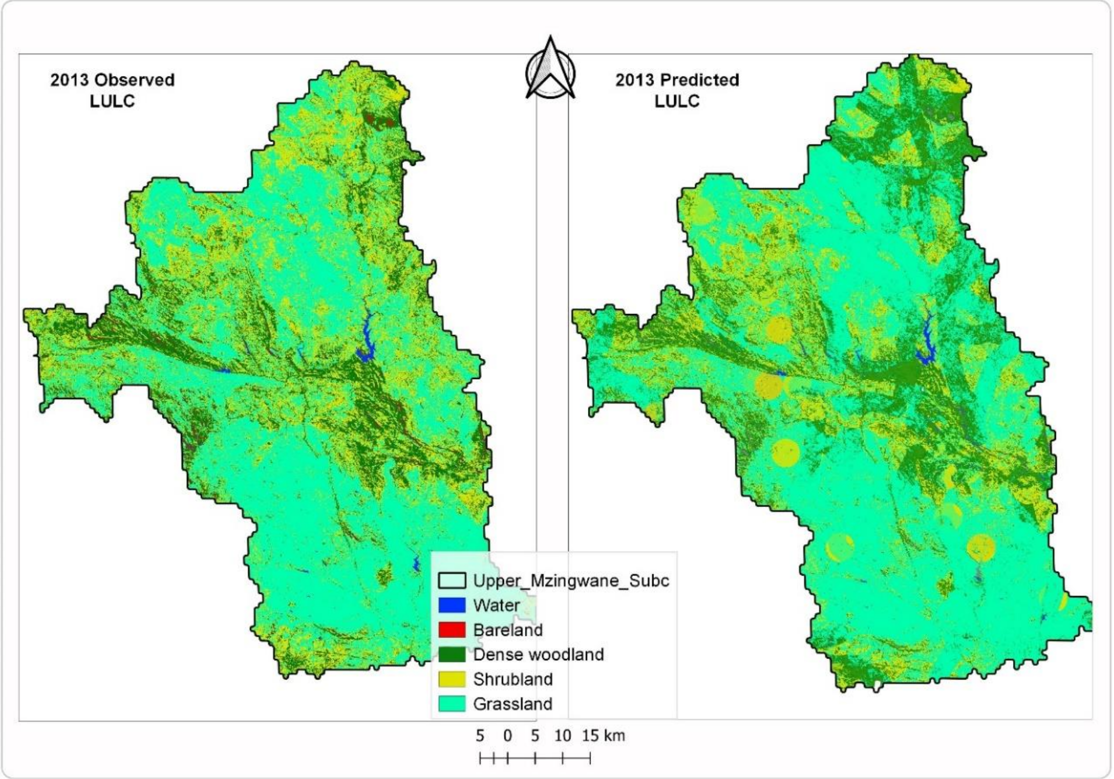

**Figure 3.3**: Comparison between actual and predicted LULC map for the year 2013 (used in the study for validation). The output shows marginal prediction errors mostly in the shrubland and dense woodland classes in the north-eastern and south western extents of the study area

*LCM transition potential parameterisation*

The LCM uses empirical modelling to establish relationships between driver variables (i.e. main roads, settlements, elevation (DEM) and slope raster datasets in our study). These were all evaluated within the LCM and determined to be good potential LULC change explanatory variables (all having scored Cramer's V values of association greater than 0.15) (Mitsuda and Ito, 2011, Akoglu, 2018) and thus were used in LULC prediction part of this study. Whilst the LCM supports logistic regression, modified K-Nearest Neighbour (KNN) and the MLP neural network for model development, the MLP was used due to its robustness in modelling several transitions at once, automatic parameter value generation ability and its requirement of less data for training and short model calibration time (Mishra and Rai, 2016). While the LCM allows for a maximum of nine transition potential sub-models to be set up in running the MLP, a single transition potential sub-model was used (set as general anthropogenic impact adapted from Mishra et al. (2014)) for all possible LULC transitions in this study. This was based on limited data availability (for other driver variables) and the assumption that all possible LULC transitions had the same underlying driver variables, such as transitions shared the same underlying driving determinants for prediction. The MLP neural network automatically used a 5073 cell sample size per class, run at 50% - 50% (training – validation), with 2 hidden neural network nodes and the stop criteria set to Root Mean Square Error (RMSE) of 0.01, over 10000 iterations and an accuracy rate of 100% while the rest of the parameters were left at default settings as recommended by Clark Labs (2015).

## 3.3 RESULTS AND DISCUSSION

### 3.3.1 Historical and existing spatio-temporal land use and land cover types, pattern, magnitude and trends from 1989 to 2018

The multi-spatial heterogeneity of the study area were successfully quantified on a multi-temporal scale, notwithstanding the accuracy limitations presented in Section 3.2.3 (Table 3.3). Results presented in Figure 3.4 and Figure 3.5 reveal that grass, shrub and woody vegetation are predominant land cover types representing aerial coverage of 48.5%, 31.5% and 18.8% in 1989 and 54.4%, 28.8% and 15.8% respectively in 2018 of the UMS.

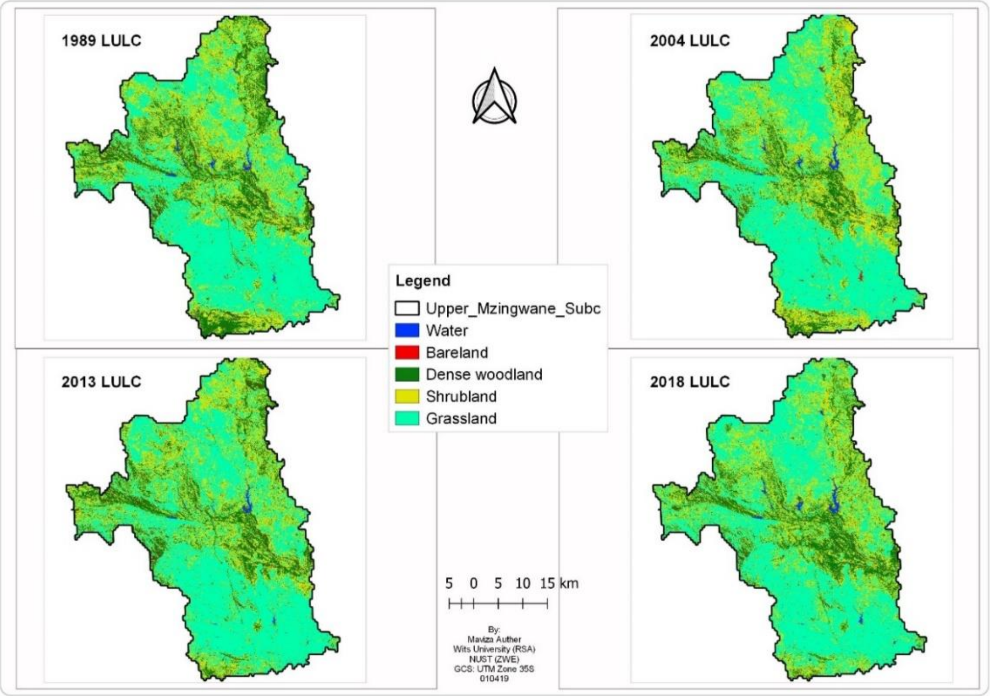

**Figure 3.4:** Final classified LULC maps for years 1989, 2004, 2013 and 2018 for UMS showing the variations in the five (5) main LULC classes (Water, Bareland, Dense woodland, Shrubland and Grassland)

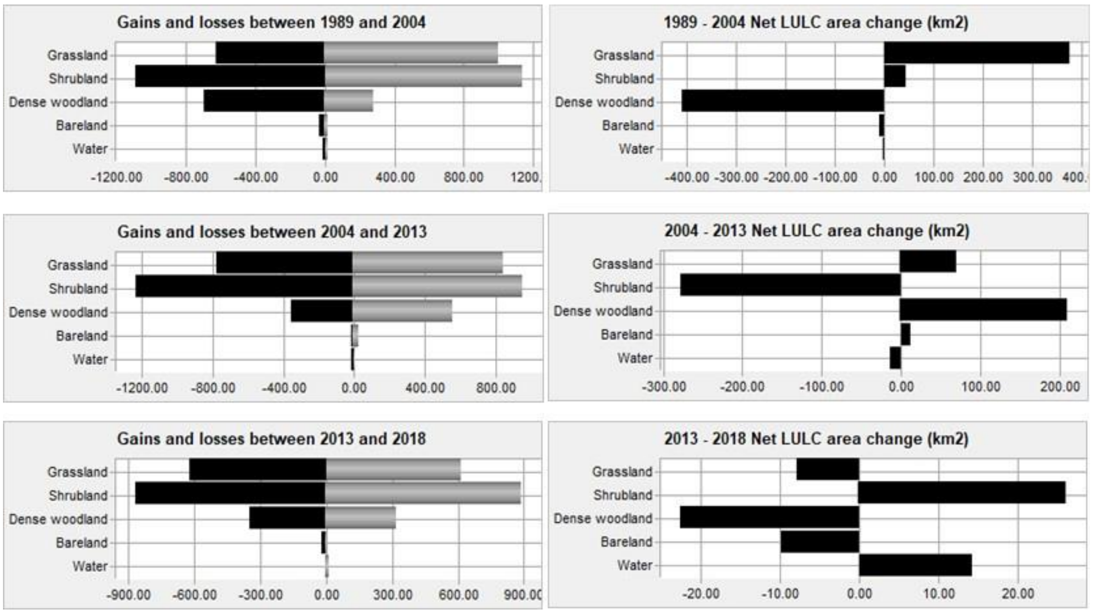

**Figure 3.5:** Areal gain and loss (in km$^2$) for each LULC from 1989 to 2004, 2004 to 2013 and 2013 to 2018. Net areal changes for each time step are also presented here. Overall, dense woodlands and grassland showed the greatest percentage net loss and gain between 1989 and 2018 respectively

This landscape is a typical savanna ecosystem characterised by dense indigenous hardwood tree species such as *Brachystegia*, *Terminalia* and *Acacia* (in the northern-central part of the study area), with grasses and sparse shrubs becoming more predominant as one moves to the southern extent of the study area. This is consistent with the ecosystem description by Love et al. (2005). The dense woodland vegetation cover is predominantly situated on a central mountainous rugged terrain stretching from the north-west to the south eastern extent of the study area. The north to south woodland to grassland ecological gradient along the northern Limpopo escarpment follows the north-south decreasing rainfall climatic gradient known to strongly influence vegetation phenology in tropical and semi-arid regions, such as in this study area (Peterson et al., 1998a, Mutanga et al., 2016).

Water and bare land are found to be the covering the least area, averaging 0.47% and 0.6% total land cover in 1989 and 2018 respectively. The study area boasts 273 dams comprising small dams, weirs and large dams (including the five main water supply dams for the city of Bulawayo (i.e. Inyankuni, Upper and Lower Ncema, Insiza and Mzingwane dams). Over 90% of these are small dams which are known to be highly vulnerable to climate change and or variability (Sawunyama et al., 2006, Davis and Hirji, 2014, Gidey et al., 2017b), hence their diminished persistence within the landscape is highly variable. In this regard, considering also the recurrent droughts (with at least two such events occurring within the study time period, namely 1992 and 2002) and the sporadic cyclones (accompanied by excessive and above average rains), most small dams were over the years adversely affected, with some completely drying up and or collapsing completely. This could explain the decrease in areal coverage of the water cover class in the study area over the study period. Furthermore, over the past decades, there has been increased sporadic human activities such as resettlement since the Government of Zimbabwe's 2000 fast-track land reform programme, coupled with illegal gold-mining activities within this catchment. These are known drivers of water body siltation (Ashton et al., 2002) and possible total collapse which could be the case for most small dams that were reported to have collapsed in the area. This could have also contributed to the reduced areal cover for the water class although the changes in bareland cover class do not reflect a complementary and commensurate change within the same period for the same reasons. While over 10 new small dams were constructed in the Upper Mzingwane catchment between 1994 and 2000 under the Give-A-Dam (GAD) programme (Love et al., 2005), no increase in the water land cover class was reflected in the study area, which could be attributed to the aforementioned reasons.

Considering the resettlement resulting from the fast track land reform programme and the increased small-scale and illegal gold mining activities that increased since 2000, the expectation was that results will reflect a proportionate increase in Bareland class areal cover. However, the reflected marginal decrease of 29.5% could be attributed either to possible failure of the SVM classification algorithm (like most classification algorithms) to detect subtle, subpixel LULC variations and changes (Pal, 2005, Gao and Zhang, 2009). This could also be explained by the fact that bareland in most semi-arid and tropical ecosystem can be easily and quickly colonised by grasses through natural succession processes (Herrero et al., 2016), hence its detection as grassland depending on pre-existing rainfall conditions in the area. Furthermore, also to consideration is that most large commercial farms which could have been detected as bareland (i.e. as open fields) in the study area collapsed after the 2000 fast-track resettlement programme, and hence were left fallow for most if not the entire study period. This allowed them to revegetate by natural succession to grassland and scrublands, which could explain also the overall areal increase in these two predominant land cover classes in the study area. Relative to this, shortcomings in functions of the Mzingwane water catchment and sub-catchment councils in protecting the entire Mzingwane catchment as presented by Love et al. (2005) could also be a factor allowing for unfettered deforestation and other anthropogenic activities (including logging of woody vegetation for firewood) in the catchment. This could also be a contributing factor explaining the 16.1% reduction in woodland cover in the study area between 1989 and 2018.

### 3.3.2 Predicted LULC scenarios for 2023 to 2038

The predicted LULC scenarios for the years 2023 to 2038 are presented in Figure 3.6 and the respective graphical (boxplot) descriptive statistics of LULC areal covers shown in Figure 3.7 illustrate the future spatio-temporal LULC dynamics in the UMS.

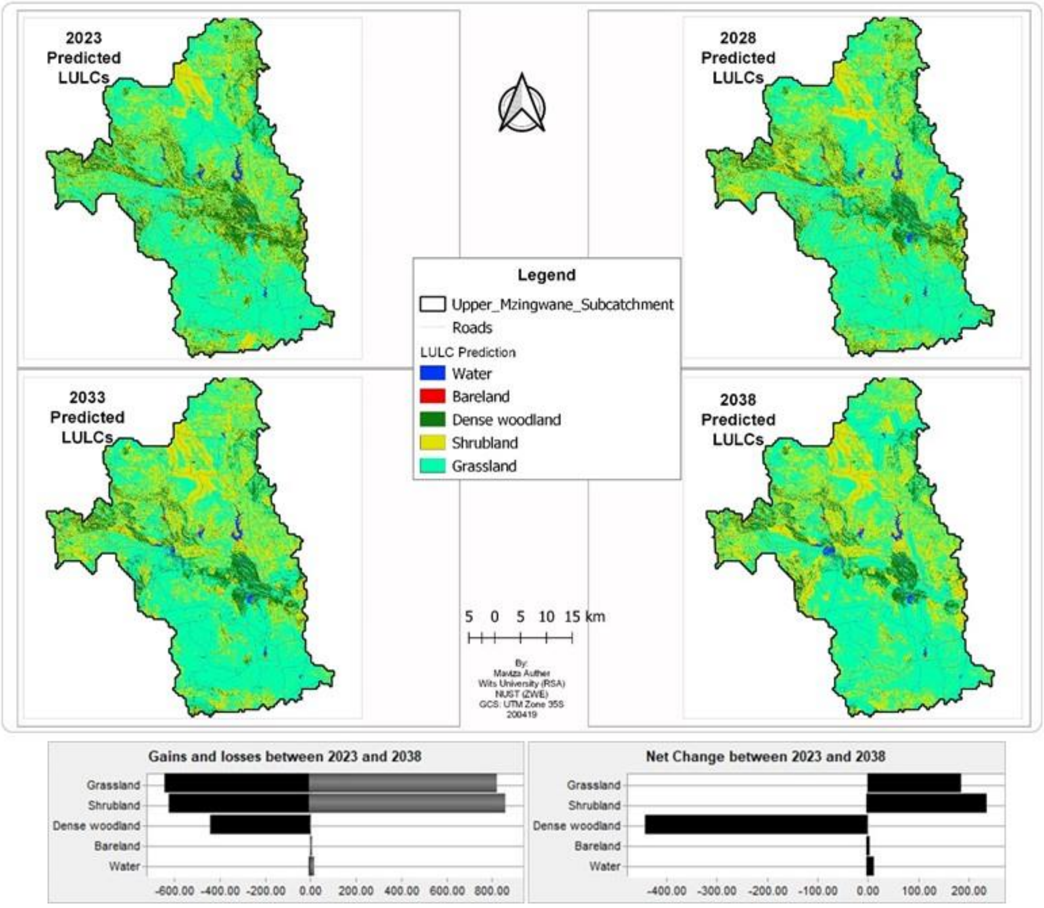

**Figure 3.6:** Predicted LULC maps for years 2023, 2028, 2033 and 2038 showing possible future LULC scenarios for UMS. Projected areal gains, losses and net changes are also presented showing a continued greatest loss in dense woodland of over 400 km$^2$ between 2023 and 2038.

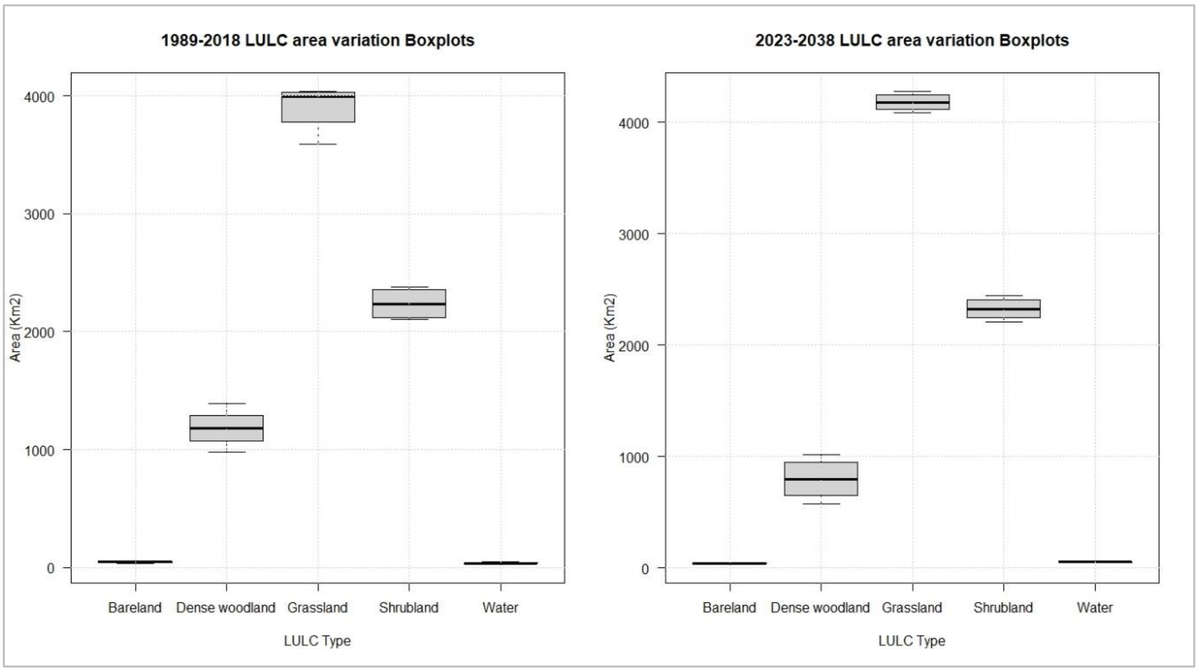

**Figure 3.7:** Box plots showing the variation in ranges in areal cover for all the LULCs from 1989 to 2018 and the prediction period (2023 to 2038)

Results reveal that dense woodland areal cover is projected to experience the greatest net loss of 441 km$^2$ (i.e. 43.57% decrease), while shrubland, grassland, water and bareland will increase by 237 km$^2$ (10.73%), 185 km$^2$ (4.5%), 14 km$^2$ (26.85%) and 6 km$^2$ (15.09%) respectively between 2023 and 2038. The extended LULC areal trends (from 1989 to 2038) are presented in Figure 3.8, using linear regression models. Strong, positive and statistically significant trends ($R^2 = 0.7982, 0.8538$; $p = 0.000339, 0.012059$) are found for grassland and water cover respectively, while a strong, negative and significant trend ($R^2 = 0.7968$, $p = 0.004491$) is found for dense woodland cover. Trends for shrubland and bareland are weak, positive and statistically insignificant ($R^2 = 0.0978, 0.1708$; $p = 0.12071, 0.981364$) respectively.

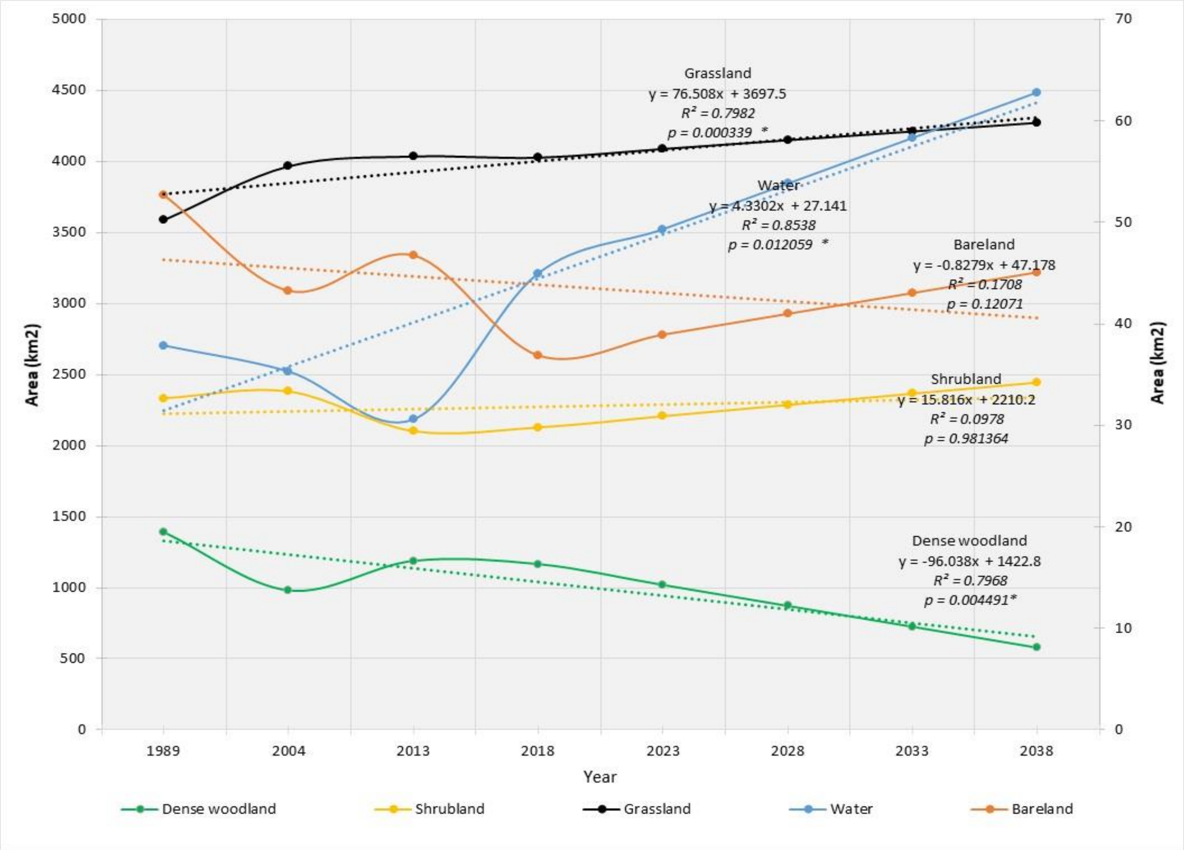

**Figure 3.8:** Graph showing actual (1989 to 2018) and the predicted (2023 to 2038) LULC areal coverage trends and their respective linear regression models over the study time period. $R^2$ and p-values quantifying the strength and significance of the trends are also shown. *p-values* marked with an asterisk (*) were found to be significant at $\alpha = 0.05$. (NB: Primary y-axis on the graph quantifies areal cover for dense woodland, grassland and shrubland whilst water and bareland LULCs are quantified on the secondary y-axis)

Spatial trends of change reveal that the highest dense woodland transitions are found to be from dense woodland to grassland and shrubland occurring within the northern-interior extent of the UMS, which hosts districts such as Esigodini and Filabusi, known for extensive illegal gold mining activities (Figure 3.9). Impetus for increased artisanal and illegal gold mining activities could be supported by known large gold-bearing greenstone deposits found in this area as described by Ashton et al. (2002). Coupled with this could be the continued deforestation from land clearance for new settlements and illegal logging all of which could be potential drivers of the predicted spatial trends (i.e. decrease in dense woodland cover). This also could be exacerbated by the poor environmental protection legislation enforcement by the Environmental Management Agency of Zimbabwe (EMA), which over the years had been known to be limited in terms of manpower and other key resources to fully execute their mandate in this regard.

Furthermore, the spatial trends of changes also reveal a higher vulnerability of the grassland cover along a general north - south gradient. Overall, the study model predicts the highest spatial trends of change to occur in the central part of the UMS, implying that this area is most susceptible to extensive LULC transition in future hence should a target for extensive and collective catchment conservation efforts by the UMS council and the EMA.

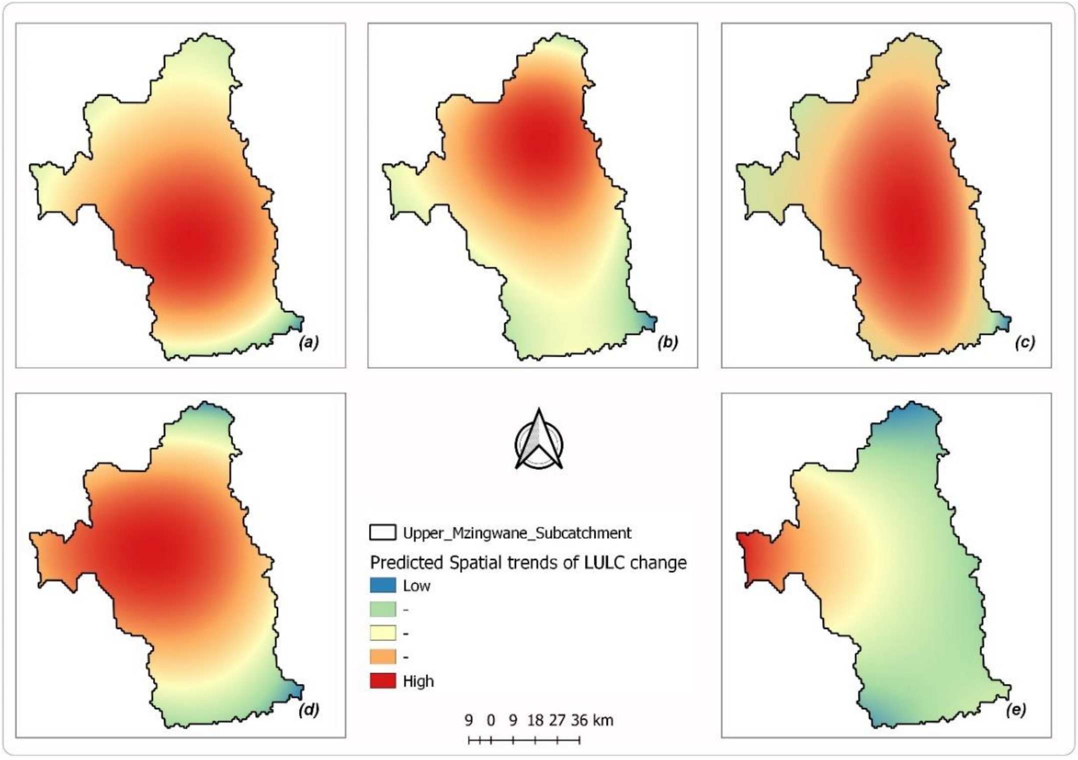

**Figure 3.9:** Maps showing overall future spatial trends of change: (a) Water to all LULCs, (b) Shrubland to all LULCs, (c) Grassland to all LULCs, (d) Dense woodland to all LULCs and (e) Bareland to all LULCs between 2023 and 2038. Red colour depicts areas predicted to have the highest spatial transition from one LULC to any other LULC while green colour shows areas with persistence of past LULC (i.e. limited to no change in LULC)

Another possible factor that could drive the predicted vegetation LULC transitions in the study area is climate variability, as it is known that vegetation growth and ultimate phenology (related to its surface reflectance properties) is dependent on temperature and rainfall patterns (Peterson et al., 1998a, Murwira and Skidmore, 2006, Gandhi et al., 2015, Muhire et al., 2015b). More rainfall and resultant increased inflows into major dams such as Inyankuni (to the north) and Silalabuhwa (to the south) over the projection period could also be a likely factor that could contribute to the 27.3% increase in water areal cover predicted in this study. Possible construction of new and or rehabilitation of old small dams (as it has been the plan for the GoZ) could also be contributing factor in this regard. This, however, may not necessarily imply an increase in water storage capacity considering the high dam siltation risk in the fragile, projected deforested UMS landscape. Bareland on the other hand could be driven by increased growth of the main settlements in the study area, such as Gwanda, Filabusi, Esigodini and Mbalambala.

Implications of these projected LULC changes, particularly reduced dense woodland cover, could range from adverse impacts on water security (Van Wyk, 1998) due to increased erosion and thus siltation  and reduction in water-holding capacity of the major water supply dams in the study area (Niehoff et al., 2002, Dalu et al., 2012). This may have ripple effects on community livelihoods (Stigter and Ofori, 2014, Chagumaira et al., 2016) within and beyond the study area, considering the sphere of influence and the socio-economic significance of some dams in the study area. For example, Inyankuni dam is a major portable water source and recreational lake for Bulawayo, supporting small-medium scale crop irrigation and is used for fishing. Furthermore, communities could be directly impacted when they lose ecosystem services from woodlands such as extraction of traditional medicines from these. The predicted LULC changes also indicate potential ecological consequences (Wiens, 1989, Chari et al., 2003) such as threats to depletion of ingenious woody and other plant species beyond their regeneration capacity, habitat fragmentation and the consequent loss of key faunal species. This could lead to the disruption and potential collapse of the ecosystem structure in the UMS and the Matopos National Park adjacent to and on the western extent the study area (which is the biggest wildlife conservancy in Matabeleland South region of Zimbabwe, with extensive eco-tourism value).

## 3.4 CONCLUSION

Considering the socio-economic, cultural and environmental significance of the UMS, it is imperative that its landscape structure is closely monitored in space and time. This will ensure rapid and accurate identification and quantification of any changes in LULC that may occur such that appropriate and proportionate strategic legislative, policy and other remedial interventions can be taken to protect this area. The study presents a practical and a satisfactorily accurate GIS and Remote sensing hybrid approach to achieve this, notwithstanding the inherent known limitations of application of these geospatial techniques in such studies. It can be concluded that the UMS has been a grass-shrubland predominated landscape with proportionate woody species typical of savannah ecosystems, although dense woodland experienced greatest net losses while grasslands and shrubs had net areal gains between 1989 and 2018. The same trend is predicted to continue into 2038, with more drastic net losses in woodland cover, with potential adverse societal, economic, water security and ecological impacts.

In this regard, it is recommended that a robust and proactive catchment protection/conservation programme (co-designed with communities to ensure their buy in) be set up to immediately respond to and possibly reverse the negative LULC change trends outlined in this study, with priority given to dense woodland cover conservation. Targeted and consistent reforestation efforts could help in this regard. Future land developmental plans for this sub-catchment could consider and be guided by the predicted LULCs from this study so as to minimise the negative impacts of such developments on the environment, water resources and community livelihoods overall. To improve LULC predictions in future studies in the UMS, it will be prudent to incorporate constraints and incentives together with other relevant socio-economic site and driver variables in the transition model parameterisation with the LCM or integrate Cellular Automata (i.e. use CA_Markov model).

# CHAPTER 4: Historical trends of precipitation extremes in the UMS

*Based on a manuscript under review:*
*Title: Twentieth century precipitation trends in the upper Mzingwane sub-catchment*
*(northern Limpopo basin), Zimbabwe* [3]

## Abstract

This study aims to establish precipitation trends in the upper Mzingwane sub-catchment (UMS) of Zimbabwe using core precipitation indices of the World Climate Research Programme (WCRP) Expert Team on Climate Change Detection and Indices (ETCCDI). The UMS is of strategic socio-economic significance in terms of its provision of water security and sustenance to livelihoods. Daily precipitation records were obtained for the period 1921-2000, covering the four stations: Bulawayo Goetz, Filabusi, Mbalabala and Matopos National Park. Data quality pre-analysis was undertaken and subsequently the RClimDex software used to compute climate indices to establish annual time series of extremely wet days, Consecutive Dry/Wet Days and annual total precipitation (PRCPTOT). The Mann-Kendall test (Sen's slope estimator) was applied to determine the significance (magnitude and direction) of each of the indices trends using R-software. Results indicate that most indices trends vary (±) but are not statistically significant across the UMS, with the exception of Matopos station (in the westernmost extent of UMS) which records significant increasing (declining) trends for most dryness (wetness) extreme indices, indicative of declining precipitation over the study period. We identify a general north to south-western declining precipitation gradient and possible periodicities of between 20 and 30 years for most precipitation extremes anomaly events during the past ~69 years over the UMS. Our findings not only provide a valuable baseline for future extended historical and future precipitation trend studies, but could also serve to inform decision making on mitigation and adaptation strategies given the socio-economic impacts that extreme events have in this region.

Keywords: Precipitation trends, climate indices, extremes, Mzingwane, Zimbabwe

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[3] *Manuscript submitted and under review with Springer, Theoretical and Applied Climatology journal*

## 4.1 INTRODUCTION

Weather or climate extremes refers to the occurrence of a weather or climate variable above or below a specific threshold value near the upper or lower ends of the range of its observed values (distribution) in a specific region (IPCC, 2012). These can be grouped into two broad categories; namely (i) those based on simple climate statistics and which occur annually (e.g. very heavy daily precipitation, monthly total precipitation) and (ii) those which are more complex event-driven extremes (e.g. droughts, floods) which do not necessarily occur every year. Since 1995, concerted global efforts have been made to collect, consolidate, quality control, and analyse data on and to increase scientific knowledge related to climate extreme events and trends. This has come against the backdrop of the Intergovernmental Panel on Climate Change (IPCC) second assessment conclusions that knowledge gaps existed in understanding changes in extreme climate events and that other key questions on the same could not be answered with any confidence (IPCC, 2001, IPCC, 2007, Nicholls and Alexander, 2007). The impetus to gain a deeper understanding of various climate extremes and trends has been increased over the years, heightened by the potential impacts posed by these extremes at varying levels of the biosphere as revealed in the IPCC 4th assessment report and other related scientific contributions (IPCC, 2007, Letcher, 2009, Henderson-Sellers and McGuffie, 2012, Giugni et al., 2015, Ramírez-Villegas and Thornton, 2015). More recently, studies such as that by Hoegh-Guldberg et al. (2018) have elaborated on the IPCC Special report on the impacts that a 1.5°C global warming scenario may have on natural and human systems, further outlining potential trajectories of climate extreme events and their likely impacts under different Shared Socio-economic Pathways (SSPs) (Hulme, 2016, IPCC, 2018, First, 2019).

To this end, the general consensus within the climate science community pertaining the changes in the frequency and or intensity of extreme climate events and the ensuing mostly negative impacts on nature and society (Easterling et al., 1997, Ren et al., 2013, Easterling et al., 2016, Dike et al., 2019) has demonstrated the need for sustained scientific enquiry in this domain. The scope of enquiry has looked at both the past (historical) and future events (modelled scenarios) of the same so as to inform effective interventions for impact mitigation and adaptation (Christensen et al., 2013, Stocker et al., 2013, Anderson et al., 2019). The need for such research has been more urgent in

Africa where data sources indicate that at times, extreme hydroclimatic variability (especially rainfall variability) are an intrinsic component of the natural environment with negative implications on water security (Nash et al., 2016). Furthermore, there has been reports of general warming and drying (i.e. decreasing annual precipitation) over large parts of the continent since the start of the twentieth century (Moss et al., 2010, Ramírez-Villegas and Thornton, 2015, Miller and Croft, 2018, Hannaford, 2020). However, despite such findings, at many sub-regional levels in sub-Saharan Africa, quantified knowledge of climate trends and moreso climate extremes is still in its infancy owing to a lack of longer-term data (Christensen et al., 2013, Stocker et al., 2013).

In West Africa, studies analysing daily (maximum and minimum) temperature and precipitation data over the period 1961 to 2000 revealed patterns consistent with warming for temperature extremes indices (such as extreme hot (95th percentile) days increased by 8.2 days/decade) (New et al., 2006). However, while most precipitation indices showed inconsistent or statistically insignificant trends across this region, Mouhamed et al. (2013) found a general decrease in annual total precipitation and maximum number of consecutive wet days though cumulative precipitation of extremely wet days showed positive trends in most parts of the region. These trends have been confirmed even in finer scale studies e.g. in Mali, where a decrease in consecutive wet day and extremely wet days, was found against an insignificant decrease in total annual precipitation between 1961 and 2014 (Touré-Halimatou et al., 2017). Future trends derived from the simulation datasets from the Coordinated Regional Climate Downscaling Experiment (CORDEX) indicate a likely increase in intensity and frequency of extreme precipitation events such as extreme wet (99th percentile) days over coastal cities such as Lagos (Abiodun et al., 2017) showing heightened vulnerability of such areas to climate extremes.

Analysis of observation data from Central Africa indicate a general decrease in cold extremes, an increase in warm extremes and a decrease in extremely wet (heavy precipitation) events over the last half century (Aguilar et al., 2009). Within the Central Equatorial African region, these extremes have manifested as long-term drying trends over the past decades negatively impacting on the forest photosynthetic capacity the Congo basin (Hua et al., 2016, Hua et al., 2018). Future projections indicate a non-significant decrease in total wet-day precipitation amount over the middle (2029–2058) and late twenty-first century (2069–2098) over this region, with total number of occurrence of precipitation events above the 95th percentile registering a decrease of 4–8 % during pre-monsoon months (Fotso-Nguemo et al., 2019).

Similar trends of increasing propensity in extreme temperature indices, and irregular rainfall patterns have been reported in East African countries such as Ethiopia, Kenya and Tanzania (Gebrechorkos et al., 2019) with increasing episodes of drought across the region (Gebremeskel-Haile et al., 2019). For example, and Berhane et al. (2020) found that the number of very wet and extremely wet days, and maximum 5 days precipitation showed significant negative trends while monthly maximum and minimum value of temperature, number of hot days and hot nights revealed positive trends throughout Western Tigray, Ethiopia between 1983 to 2016 signalling drying conditions. Mekasha et al. (2014) also found similar trends in temperature extremes but concluded that precipitation extreme trends showed high variability among 3 designated eco-environments in Ethiopia over a 42years (1967 - 2008). As for future trends, Shongwe et al. (2011) simulations revealed a generally wetter climate with more intense wet seasons and less severe droughts over East Africa notwithstanding the model uncertainties.

Over Southern Africa (SA), analysis of regionally averaged occurrence of climate extremes have revealed declining trends in total precipitation and increase in diurnal temperature range (DTR) coupled with rapid increases in maximum temperature extremes (New et al., 2006, Seneviratne et al., 2012). The decreases total precipitation have over the past second half of the twentieth century been found to be associated with increasing (though insignificant) trends in extreme precipitation days and in maximum annual 5-day and 1-day precipitation (Frich et al., 2002). Historical climate signals from dynamic downscaling of Last Glacial Maximum (LGM) climate over SA using a RCM have shown that there were significantly lower temperatures during the LGM compared to the present-day, with annual average temperatures 4 - 6 °C lower then along the eastern escarpment coupled with generally wetter conditions (Engelbrecht et al., 2019).

To better understand future climatic trends and extremes in SA, various Global Climate Models (GCMs) and RCMs have been used by e.g. (Engelbrecht et al., 2013, Kalognomou et al., 2013b, Meque and Abiodun, 2015, Shongwe et al., 2015, Dedekind et al., 2016, Archer et al., 2018, Maúre et al., 2018) generally revealing a general progression in dryness coupled with more variable precipitation trends over the region overall. For instance, future projections of the SA climate under 1.5 °C and 2 °C of global warming using CORDEX regional climate models by Maúre et al. (2018) reveal rainfall decreases of between 0.2 and 0.4 mm day$^{-1}$ over most of the central and western parts of the region. These decreases in precipitation are expected to be accompanied worsening extremes characterised by increases (decreases) in the number of consecutive dry (wet) days over the region (New et al., 2006, Shongwe et al., 2015, Archer et al., 2018).

Most of the aforementioned studies and others such as (Klein-Tank and Können, 2003, Kruger, 2006, Kruger and Nxumalo, 2017, Zarekarizi et al., 2018, Abbasnia and Toros, 2019) have advocated for and demonstrated utility of various climate indices such as the World Meteorological Organization–Commission for Climatology (WMO - CCL) and the Research Programme on Climate Variability and Predictability (CLIVAR) Expert Team for Climate Change Detection Monitoring and Indices (ETCCDI) climate indices (Peterson et al., 2001; Zhang et al., 2011) to explore trends in climate extremes over Africa and globally. However, despite this and all the earlier discussed advances in climate trends and extremes research in Africa and the sub-regions, countries such as Zimbabwe still lag behind in progress within this domain. This has been largely attributed to the paucity of reliable data (Gumindoga et al., 2017), absence of long multi-decadal scale datasets, large data gaps and the closure of meteorological recording stations (Peterson et al., 1998b) due to lack of finances and technical expertise.

As such, while historical climatic trends in Zimbabwe reveal that since 1950, the country has experienced more hot and fewer cold days (marked by daily minimum (maximum) temperatures rising by ~ 2.6°C ( 2°C)) over the last century coupled with mean annual precipitation decline of about 5% (Brown et al., 2012), very few studies have explored climate extremes trend. Such exceptions are Aguilar et al. (2009) who analysed precipitation highs over Zimbabwe albeit in very general sense revealing no significant increase in heavy precipitation between 1955-2006 while Love et al. (2010) and Sibanda et al. (2018) noted a decline in total precipitation, declines in number of rainy days and increases in dry spells over the entire Mzingwane catchment. The most comprehensive study possibly to date, based on 40 climate stations over Zimbabwe for the period 1892-2000 by Mazvimavi (2010b), found no significant changes in extreme precipitation trends. The study however was limited to using quantile regression to establish the presence of seasonal and annual rainfall trends for high (low) rainfall percentiles i.e. the

$70^{th}$, $80^{th}$ and $90^{th}$ ($10^{th}$, $20^{th}$ and $30^{th}$) percentiles without preprocessing for artificial change points and autocorrelation in the datasets. Furthermore, this and other like studies used monthly data to ascertain trends, hence finer-scale climate detail for establishing the behaviour of extreme events remain unaccounted for. Such details can be easily quantified though indices derived from daily data which allow for a more objective extraction of information concerning extremes which are known to adversely affect human and natural systems (Powell and Keim, 2015).

It is against this backdrop that the current study uses historical daily precipitation data to compute WMO - CCL/CLIVAR ETCCDI climate change indices for south-western Zimbabwe. To this end, we analyse trends of 10 ETCCDI extreme precipitation indices i.e. [Maximum 1-day precipitation amount (RX1day), Maximum 5-day precipitation amount (RX5day), Simple daily intensity index (SDII), Number of heavy precipitation days (R10), Number of very heavy precipitation days (R20), Consecutive dry days (CDD), Consecutive wet days (CWD), Very wet days (R95p), Extremely wet days (R99p) and Annual total wet-day precipitation (PRCPTOT) for the upper Mzingwane sub-catchment (UMS) in the northern Limpopo basin of Zimbabwe. The indices are measures to establish extreme precipitation events and trends over the period 1921-2000. This is the first such study for Zimbabwe to assess historical (> 50 years) extreme precipitation events and trends using such core indices at a sub-catchment scale. Such an analysis is of particular value to decision and policy makers as it gives a comprehensive understanding of trends in precipitation extremes and thus their likely current and possibly future impacts on water resources infrastructure and livelihoods. This can help inform current and future planning and identification of the types and range of climate resilience and adaptation options and opportunities to minimise climate extremes exposure risks.

## 4.2 MATERIALS AND METHODS

The methodology of Kruger (2006) was adapted, combined with the change detection test approach developed by Wang et al. (2010). A 5-step approach (summarised in Figure 4.1) was followed entailing (1) data collection (digitizing of selected daily precipitation records), (2) pre-processing (cleaning and conversion as explained in Section 2.2), (3) testing for artificial change points in the datasets, (4) further quality checking for errors (i.e. check for duplicates, inconsistent/ unrealistic records), and (5) computation of the indices (Table 4.1) and testing for significance of trends.

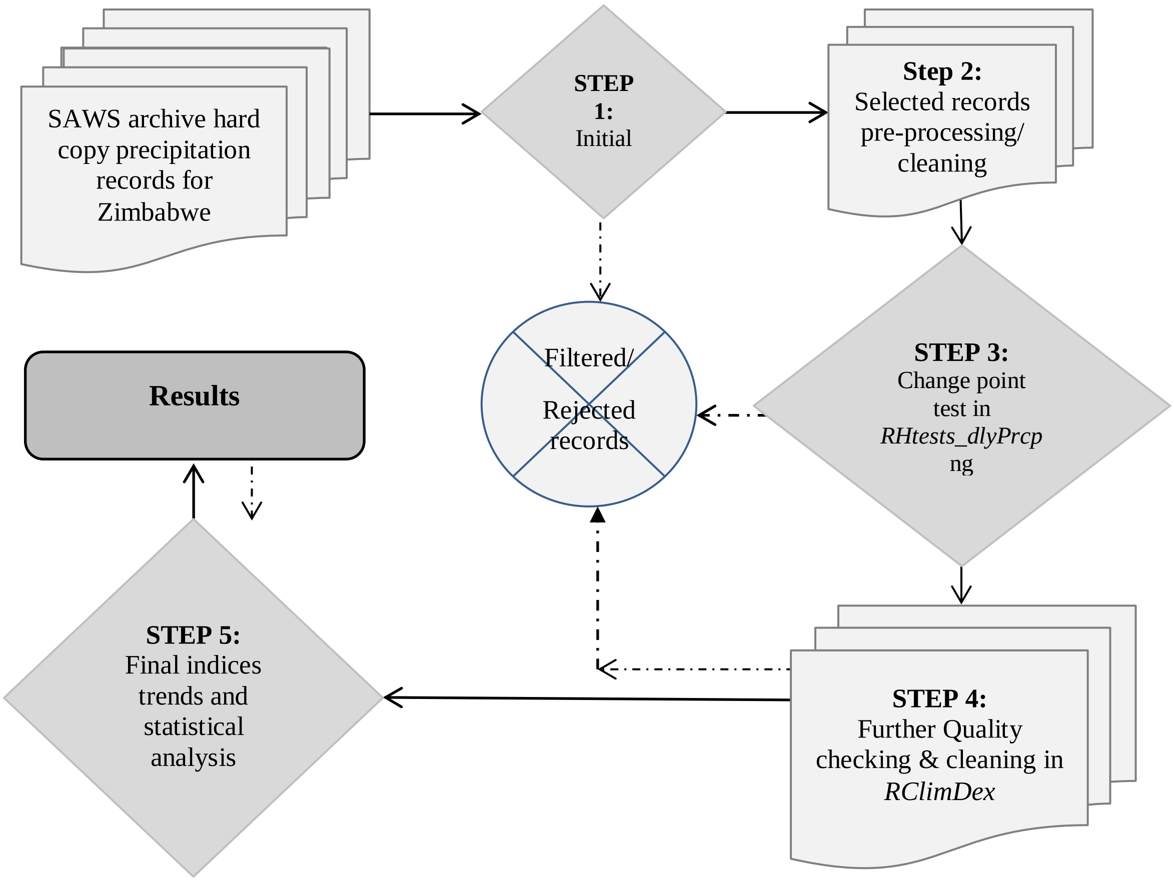


**Figure 4.1:** Methodological design of data handling

**Table 4.1**: Summary description of the ETCCDI precipitation indices computed in this study, including their units and computation algorithms. (*A wet day is defined when RR > or = to 1 mm and a dry day when RR < 1 mm)

| Index ID | Index name | Description | Algorithm | Algorithm description | Units |
|---|---|---|---|---|---|
| **RX1day** | Max 1-day precipitation amount | Monthly maximum 1-day precipitation | $RX1day_j = max(RR_{ij})$ | Where $RX1day_j$ = maximum 1-day values for period *j*, $RR_{ij}$ = daily precipitation amount on day *i* in period *j*. | mm |
| **RX5day** | Max 5-day precipitation amount | Monthly maximum consecutive 5-day precipitation | $RX5day_j = max(RR_{kj})$ | Where $RX5day_j$ = maximum 5-day values for period *j*, $RR_{kj}$ = daily precipitation amount for the 5-day interval ending on day *k* in period *j*. | mm |
| **SDII** | Simple daily intensity index | Annual total precipitation divided by the number of wet days (i.e. PRCP ≥ 1.0mm) in the year | $SDII_j = \frac{\sum_{w=1}^{W} RR_{wj}}{W}$ | Where $SDII_j$ = Simple daily intensity index, $RR_{wj}$ = daily precipitation amount on wet days, w(RR ≥ 1mm) in period *j*, W = number of wet days in *j*. | mm/day |
| **R10** | Number of heavy precipitation days | Annual count of days when PRCP ≥ 10mm | $RR_{ij} \geq 10mm$ | Where R10 = number of days where precipitation is ≥ 10mm, RR*ij* = daily precipitation amount on day *i* in period *j*. | days |
| **R20** | Number of very heavy precipitation days | Annual count of days when PRCP ≥ 20mm | $RR_{ij} \geq 20mm$ | Where R20 = number of days where precipitation is ≥ 20mm, RR*ij* = daily precipitation amount on day *i* in period *j*. | days |
| **CDD** | Consecutive dry days | Maximum number of consecutive days with RR < 1mm | $RR_{ij} < 1mm$ | Where CDD = number of consecutive days where precipitation is less than 1mm, RR*ij* = daily precipitation amount on day *i* in period *j*. | days |
| **CWD** | Consecutive wet days | Maximum number of consecutive days with RR ≥ 1mm | $RR_{ij} \geq 1mm$ | Where CWD = number of consecutive days where precipitation is ≥ 1mm, RR*ij* = daily precipitation amount on day *i* in period *j*. | days |
| **R95p** | Very wet days | Annual total PRCP when RR > 95th percentile | $R95p_j = \sum_{w=0}^{W} RR_{wj}$ (where $RR_{wj} > RR_{wn}95$) | Where $RR_{wj}$ = daily precipitation amount on wet days (w(RR ≥1mm)) in period *j*, $RR_{wn}95$ = the 95th percentile on wet days in the base period, W = number of wet days in the period, | mm |
| **R99p** | Extremely wet days | Annual total PRCP when RR > 99th percentile | $R99p_j = \sum_{w=0}^{W} RR_{wj}$ (where $RR_{wj} > RR_{wn}99$) | Where $RR_{wj}$ = daily precipitation amount on wet days (w(RR ≥1mm)) in period *j*, $RR_{wn}99$ = the 99th percentile on wet days in the base period, W = number of wet days in the period, | mm |
| **PRCPTOT** | Annual total wet-day precipitation | Annual total PRCP in wet days (RR >=1mm) | $PRCPTOT_j = \sum_{i=0}^{I} RR_{ij}$ | Where RR*ij* = daily precipitation amount on day *i* in period *j*, *I* = number of wet-days in *j*, | mm |

Adapted from Wang et al. (2010)

## 4.3 STUDY AREA

The UMS (Figure 4.2) is one of the four sub-catchments belonging to the Mzingwane catchment in the northern Limpopo basin, south-western Zimbabwe. The UMS covers 2138 km$^2$ in areal extent and is located in Natural Region IV of Zimbabwe, which receives ~450 - 650 mm of rainfall per annum (Görgens and Boroto, 1997). This translates to a mean annual run-off of about 600 mm, thus contributing most of the Mzingwane River's run-off. This river contributes almost 25% of the Limpopo River's flow volume before entering Mozambique and is thus of considerable hydrological importance to the region. Mean annual $T_{max}$ and $T_{min}$ are 26°C and 15°C respectively while potential evaporation ranges between 1800 mm to 2000 mm per annum (Love et al., 2005). The region varies in elevation from ~864 to 1560 metres. The ecosystem is typically semi-arid savannah with sparsely distributed woodlands species such as *Brachystegia spiciformis*, *Colophospermum mopane*, *Terminalia*, *Acacia*, *Combretum*, aloes, and grass species such as *Hyparrhenia filipendula* and *Heteropogon contortus* (Sawunyama et al., 2006).

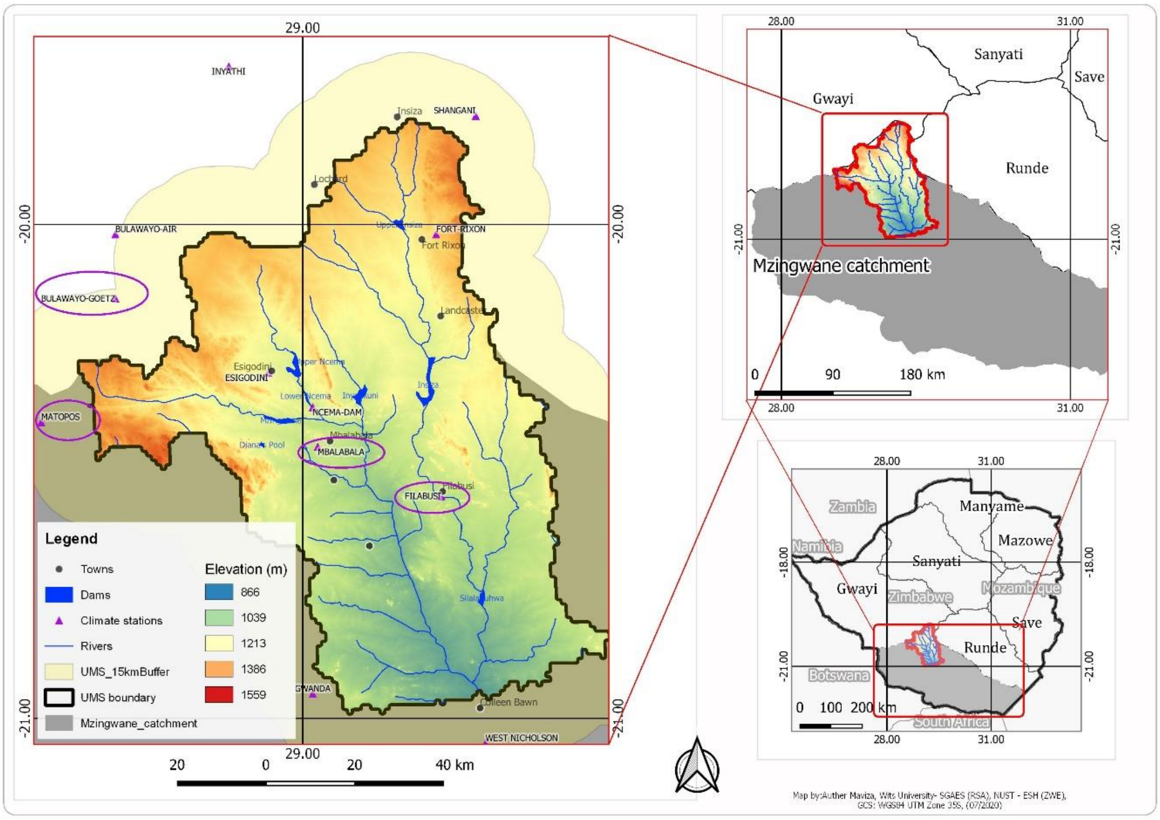


**Figure 4.2:** Location of the four selected climate stations used in this study (marked with purple ellipses) inside and within 15 km distance of the UMS

The UMS extends across three districts: Insiza (to the east), Umzingwane (north-western extent) and Gwanda (to the south-western end) (Figure 2), and hosts a population of over 50 000 people. It has a diverse agro-ecological and socio-economic structured land-use system characterised by a mixture of commercial and subsistence agriculture such as small-scale low cost drip irrigation farming, dam recreational activities and private safari operations (Love et al., 2005). Gold panning is feasible in the Zimbabwean Craton greenstone belts and granitic terrain underlying most of the catchment (Ashton et al., 2002). The soils consist of moderately coarse grained kaolinitic sands (from the granites and Limpopo gneisses), very shallow to moderately shallow clays and loams, and very shallow sands derived from locally weathered basalts (Love et al., 2005, Sawunyama et al., 2006).

## 4.4 DATA COLLECTION AND PRE-PROCESSING

Given limited access to daily precipitation data from the Meteorological Services Department of Zimbabwe (MSDZ), datasets utilised in this study were secured from the South African Weather Services (SAWS) library archives and digitised to soft copy format. Unfortunately, post 20th century data are only kept by the MSDZ, but are unaffordable. Criteria utilised in distilling the datasets were (1) spatial coverage (i.e., stations should be located in the UMS or at least within a 15 km radius from the UMS boundary), (2) have the longest time period possible and (3) retain a sufficient number of rainfall records/have minimum missing records. This process culminated in the selection of four stations: Bulawayo Goetz (BG), Matopos National Park (MNP), Mbalabala (Mb) and Filabusi (Fl) (Table 2), representing the north, east, central and western extents of the study area respectively. Pre-processing was undertaken following the specifications by Zhang and Yang (2004), where data were converted and structured using the RClimDex software.

**Table 4.2:** Details of climate stations in and around UMS used in this study

| | **Station name** | **Location** | | **Elevation** | **Period** | **Number of years** |
|---|---|---|---|---|---|---|
| | | x | y | | | |
| **1** | Bulawayo Goetz | -20.15 | 28.62 | 1340 | 1930 - 2001 | 72 |
| **2** | Mbalabala | -20.45 | 29.03 | 1100 | 1931 – 1994 | 64 |
| **3** | Filabusi | -20.55 | 29.28 | 1070 | 1921 - 1995 | 75 |
| **4** | Matopos National Park | -20.40 | 28.47 | 1338 | 1931 - 1998 | 68 |

Considering that precipitation data series usually contain artificial shifts that could be related to changes in observation instruments, station location and the environmental setting etc. (Wang et al., 2010), it is important to test for artificial change points/discontinuities in the data (Wang, 2003, Touré-Halimatou et al., 2017). Since we used the RClimDex software (which runs tests with an assumption that the data series have Gaussian errors) to compute indices, we first used the RHtests_dlyPrcp software package (Wang and Feng, 2015) for detection and automatic adjustment of artificial shifts in daily precipitation data.

### 4.4.1 Change point detection and data homogenisation

The default software parameterisation were used (e.g. setting the nominal level of confidence at which to conduct the test [*p.lev=0.95*]); the maximum number of years of data immediately before or after a change point to be used for estimating the Probability Distribution Function (PDF) (set to use the whole data set without segmentation); and the lower threshold of precipitation (*pthr=0.0*). The homogenisation procedure was divided into two primary steps: (i) detection of inhomogeneities (change points) and (ii) calculation and application of data adjustment parameters for each station, as described by Wang and Feng (2013). The process follows an iterative run of the *'StepSize'* function to help detect statistically insignificant change points and homogenise the dataset by applying the Box-Cox transformation technique (Osborne, 2010; Sakia, 1992) without the use of a separate reference dataset (i.e. to normalise the data). The Box-Cox transformation also lowers False Alarm Rates (FARs) and improves extreme trend detection power. FARs are a form of Type 1 statistical error showing a false positive (which in this study means a change point is determined to be statistically significant when it is not). Table 4.3 summaries results for this stage of the analysis, which presents the number of significant change points. Graphical test results for MNP, Ml and Fl are shown in Figure 4.3 A – F, Figure 4.4 A – F and Figure 4.5 A – C respectively. Given that no change points were identified for BG, data were used as is.

**Table 4.3:** Summary of change point detection within the data series for the stations: BG, Fl, Matopos NP and Mbalabala. Change points marked with an asterisk (*) are significant

| *Station* | *Change points Type* | *Change point dates* | *Test statistic ($PF_{max}$)* | *95% confidence interval (for $PF_{max}$ percentiles)* |
|---|---|---|---|---|
| **Bulawayo Goezt** | 0 | - | - | - |
| **Filabusi** | 1 | 19521212 | 15.1119 | (13.2744-15.9107) |
| | 1* | 19661105 | 15.9343 | (13.0708-15.6246) |
| | 1* | 19821011 | 40.7961 | (12.9841-15.5028) |
| | 1* | 19951023 | 21.4010 | (12.7305-15.1490) |
| **Matopos NP** | 1* | 19351123 | 18.4385 | (12.6158-15.3131) |
| **Mbalabala** | 1* | 19840315 | 71.6603 | (14.1142-17.0640) |
| | 1 | 19971007 | 13.3329 | (13.2458-15.8367) |

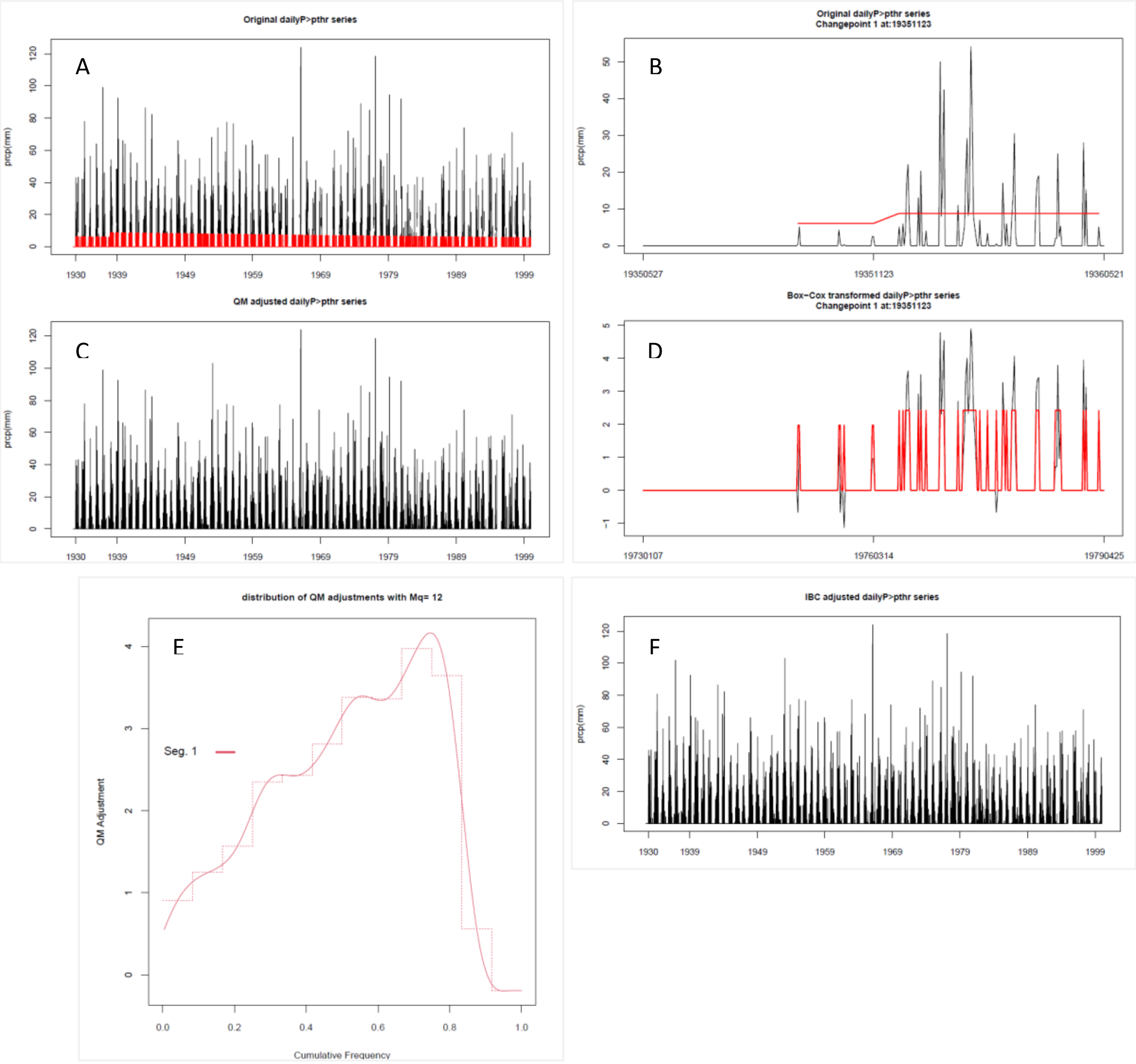


**Figure 4.3:** A) Graphical presentation of original data series; B) the detected change point 1 (i.e. red step-change); C) the Quantile-Matching (QM) adjusted distribution; D) Box-Cox transformed series for change point 1; E) the Cumulative distribution of the applied QM adjustments and F) the Inverse Box-Cox (IBC) adjusted series for Matopos NP

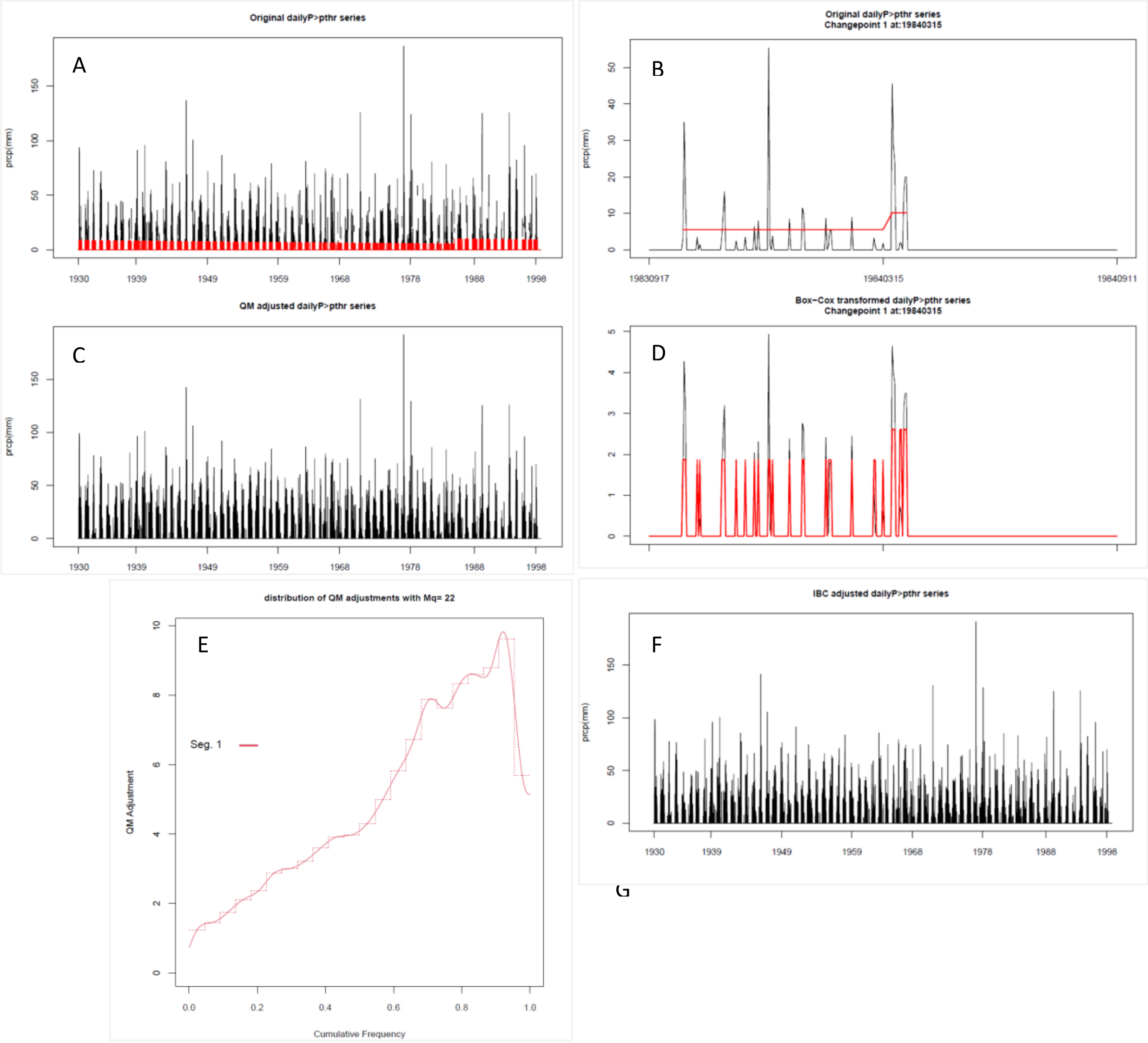


**Figure 4.4:** A) Graphical presentation of original data series; B) the detected change point 1 (red step-change); C) QM adjusted series: D) Box-Cox transformed series for change point 1; E) Cumulative distribution of QM adjustments; and F) IBC adjusted series for Mbalabala

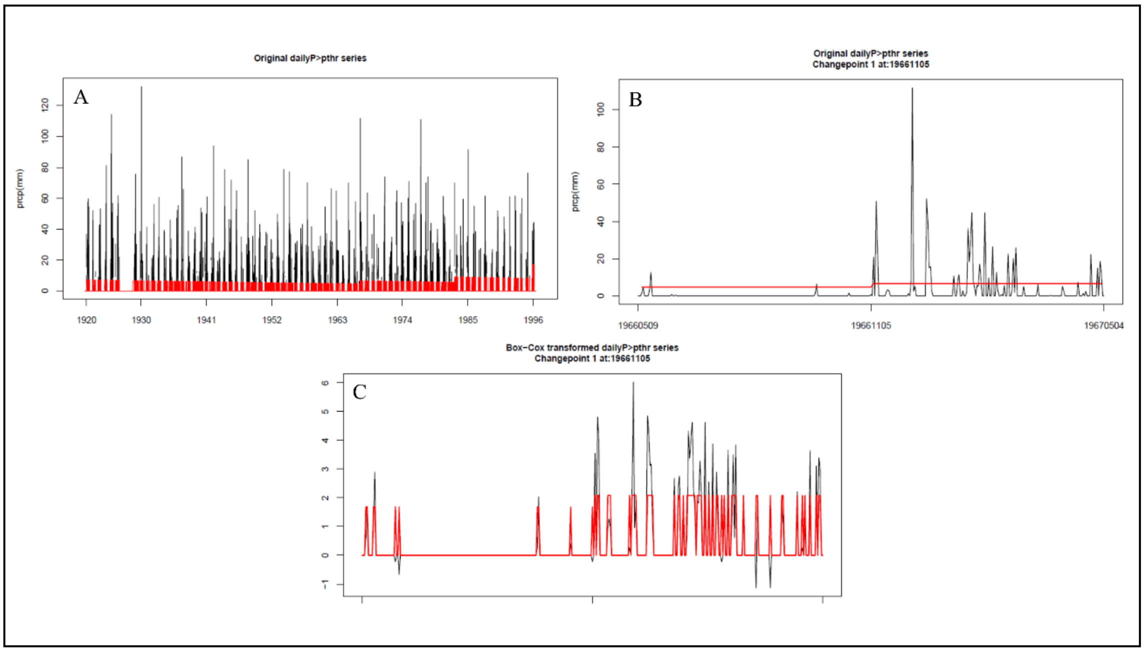


**Figure 4.5:** A) Graphical presentation of original data series; B) the detected change point 1 (red step-change) (for date 19661105); C) Box-Cox transformed series for change point 1 for Filabusi

## 4.5 DATA ANALYSIS

### 4.5.1 Computation of Indices

The RClimDex software used in this study only computes monthly indices if no more than three days of data are missing in a given month, while annual values are calculated if no more than 15 days are missing in a given year. Annual values are only calculated if data are available for all 12 months, while threshold indices are computed if at least 75% of data are present. The computed indices can be grouped into five broad categories: Absolute indices (RX1Day and RX5DAY); percentile-based indices (R95P and R99P); threshold indices (R10MM and R20MM); duration indices (CDD and CWD); and others (PRCPTOT and SDII). Algorithms for computation of the indices are presented in Table 4.1 and details for internal processes of the RClimDex software refer to Zhang and Yang (2004).

### 4.5.2 Trends and statistical analysis

In order to detect trends, statistical significance and the slopes of the index series, we employed the non-parametric Mann–Kendall (MK) trend test (Mann, 1945, Kendall, 1975) and the Sen's Slope Estimator (Sen, 1968) respectively. These have been widely used to evaluate significance of trends in numerous studies (Haylock et al., 2006; Mark

& Kudakwashe, 2010; Rahayu, 2013; Sousa et al., 2011). The null hypothesis tested in MK has no significant trend in the series and $H_0$ is rejected if the p-value is $\leq \alpha$ (0.05). The MK Statistics $S$, $(S)$ and standardised test statistics $Z$ are computed as follows:

$$\boldsymbol{S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(X_j - X_i)} \qquad (1)$$

$$\boldsymbol{sgn\ (X_j - X_i)} = \begin{cases} \mathbf{1}, & if\ (X_j - X_i) > 0 \\ \mathbf{0}, & if\ (X_j - X_i) = 0 \\ \mathbf{-1}, & if\ (X_j - X_i) < 0 \end{cases} \qquad (2)$$

$$\boldsymbol{V(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)\right]} \qquad (3)$$

$$\boldsymbol{Z} = \begin{cases} \dfrac{\boldsymbol{S-1}}{\sqrt{\boldsymbol{VAR(S)}}}, & if\ S > 0 \\ \mathbf{0}, & if\ S = 0 \\ \dfrac{\boldsymbol{S+1}}{\sqrt{\boldsymbol{VAR(S)}}}, & if\ S < 0 \end{cases} \qquad (4)$$

In all the equations (1, 2 and 3), $X_i$ and $X_j$ are time series observations in chronological order, $n$ = length of the time series, $tp$ = the number of ties for $p$th value, and $q$ = the number of tied values. Positive (negative) $Z$ values indicate an upward/increasing (downward/decreasing) trend in the time series.

The first step in the calculation of the Sen's estimator is to evaluate the values of $Q_i$, given N pairs of data:

$$\boldsymbol{Q_i = \frac{x_i - x_k}{j - k}} \qquad (5)$$

Where $x_i$ and $x_k$ represent data values at time $j$ and $k$ (with $j > k$), respectively.

If there is only one datum in each time period, then $N = n(n–1)/2$, where $n$ = number of time periods. For multiple observations in one or more time periods, then $N < n(n - 1)/2$, where $n$ = total number of observations.

The Sen's estimator is then computed as the median $Q_{med}$ of the N values of $Q_i$, ranked from the smallest to the largest. i.e.:

$$\boldsymbol{Q_{med}} = \begin{cases} \boldsymbol{T_{(N+1)/2}}, & N\ is\ odd \\ \\ \boldsymbol{\frac{1}{2}(T_{N/2} + T_{(N+2)/2})}, & N\ is\ even \end{cases} \qquad (6)$$

The $Q_{\text{med}}$ sign (value) reveals the behaviour (magnitude) of the trend - i.e. positive (negative) $Q_{med}$ value represents an increasing (decreasing) trend over time.

Prior to applying the MK test, we also tested for the presence of serial correlation in all the annual index series in R-software. An example of obtained results (Figure 4.6) showed insignificant serial and partial autocorrelation in the index series, hence then applying the MK analysis.

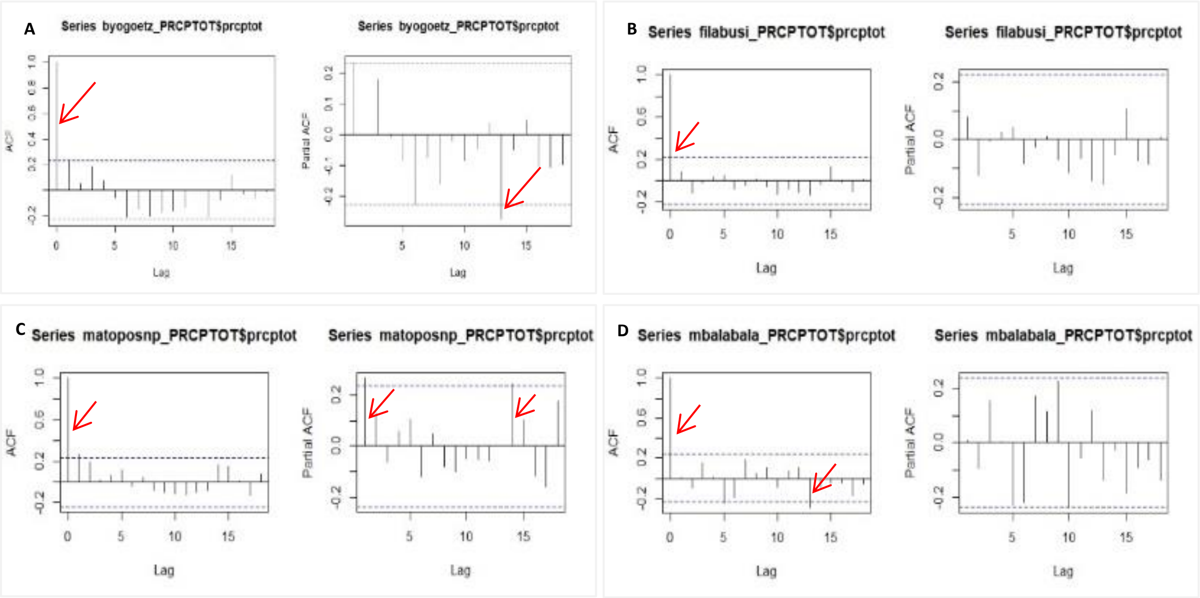


**Figure 4.6:** Serial autocorrelation (ACF) and Partial autocorrelation (PACF) test results for PRCPTOT for BG (A), Fl (B), MNP (C) and Mb (D). Most vertical spikes (marked by red arrows) on the plots fall within the horizontal bands (defined by the blue dotted lines) beyond which autocorrelation would be deemed significant. Similar results were found for all the other index series

## 4.6 RESULTS

### 4.6.1 Annual total precipitation trends (PRCPTOT)

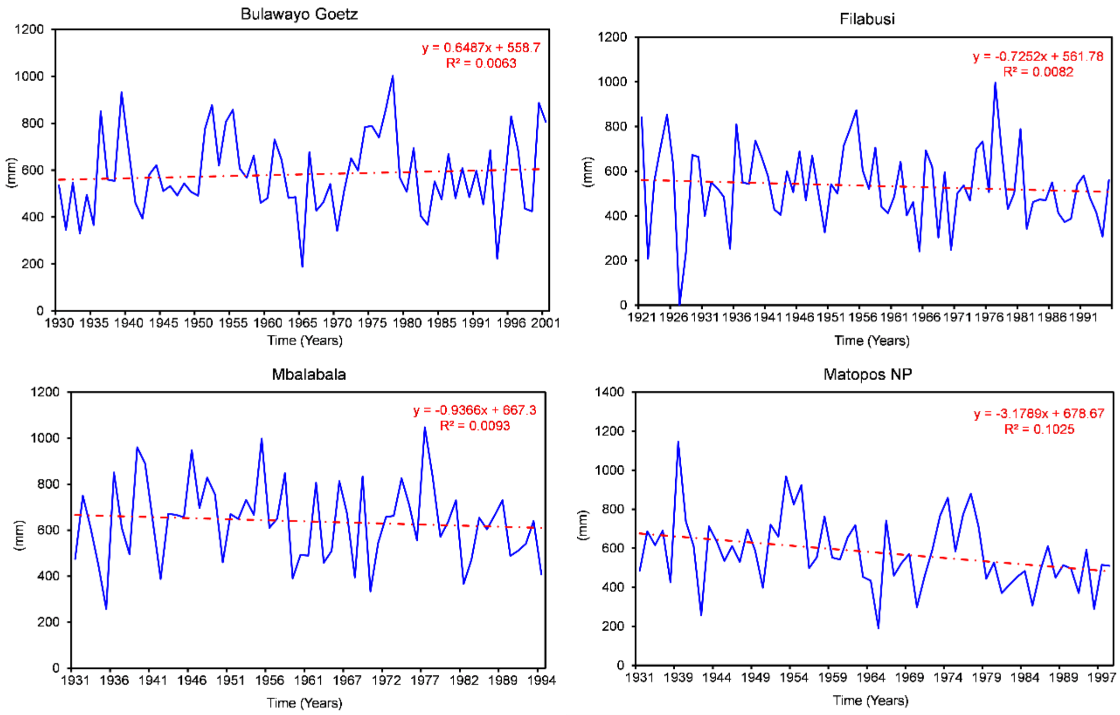


**Figure 4.7:** PRCPTOT series and trends for the four stations. Red dotted lines = linear trends

Figure 4.7 shows that all stations had declining trends in annual total precipitation over the past 69 years with the exception of Bulawayo Goetz which had a marginal insignificant increasing trend ($Q_{med}$ =-0.626, p = 0.568). Matopos station however was the only station recording a significant declining trend in annual total precipitation ($Q_{med}$ =-3.073, p = 0.011), indicating potential drying condition in the western part of the UMS. These results, for the first time, disaggregate and present in greater detail the general declining annual total precipitation trends reported by Love et al. (2001). Though other stations show statistically insignificant declining trends, the general patterns indicate potential adverse impacts on livelihoods especially rain-fed agricultural activities in the UMS. The smoothed 5year moving average trends for PRCPTOT anomalies (Figure 4.8) are indicative of possible near 30-year and 20-year periodicities for Bulawayo Goezt and Mbalabala stations respectively. Overall, mean PRCPTOT anomalies show a general negative trend of between -0.06mm and -6.36mm in the northern and western region of the UMS suggesting general drying over the study period.

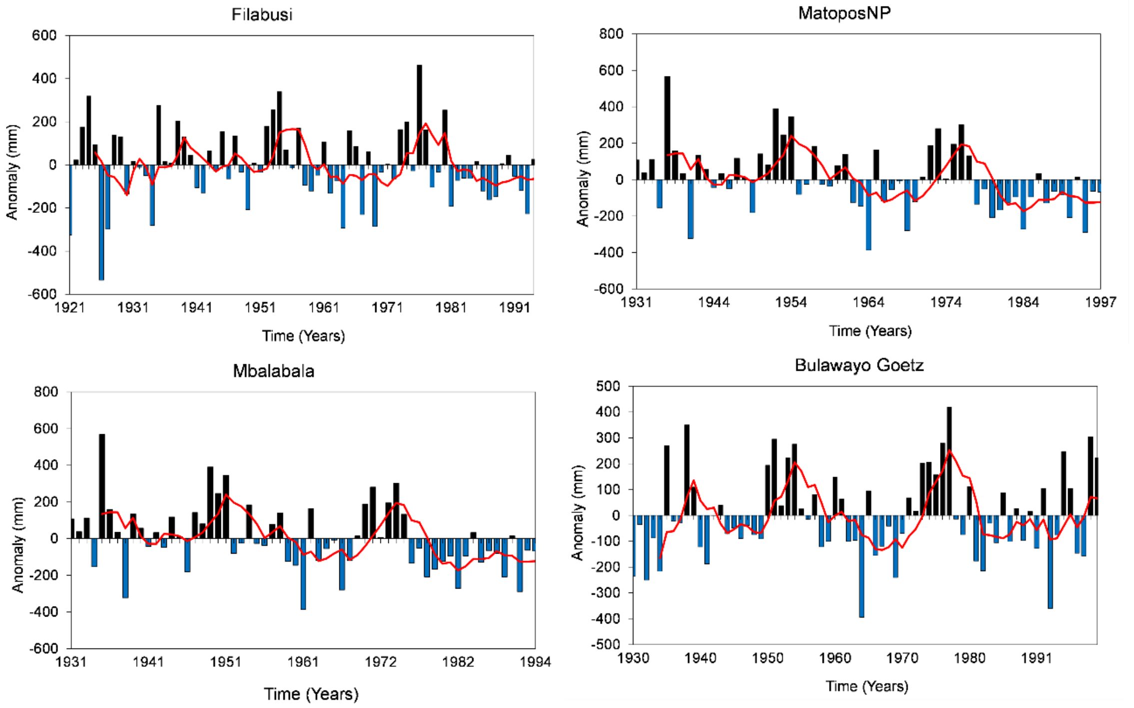


**Figure 4.8:** PRCPTOT trend anomalies for the four stations. Anomalies are relative to the series mean values for each station's full recording period. Red line = 5-years running means; black (blue) bars show anomalies above (below) the long term PRCPTOT mean

### 4.6.2 Absolute indices (RX1DAY and RX5DAY)

Trend line results for RX1DAY and RX5DAY are presented in Figure 4.9 and Figure 4.10 respectively, while the trend significance results are shown in Table 4.4 RX1Day trends for all but Matopos National Park station were positive and statistically insignificant. Overall, marginally increasing trends in all the UMS zones (mean = 0.2mm) were found, expect for the western extent which showed a declining trend (mean = -0.463mm) over the study period. Bulawayo Goetz and Filabusi (Mbalabala) stations had insignificant negative (positive) trends for RX5DAY with the exception of Matopos National Park station, which recorded a significant negative trend ($Q_{med}$ =-0.672, p = 0.018). Three of the stations exhibit declining RX5Day trends, (mean = -0.879mm/annum). The negative (significant) trends in the western extent of UMS suggest a decline in extreme events in the form of 5-day maximum precipitation. Overall, the smoothed 5-year moving average trends for both index anomalies (Figure 4.11 and 4.12) seem to reveal a near 20 to 30 year periodicity for Bulawayo Goetz while other stations show no distinct patterns in anomaly trends, though mean anomalies show negative values ranging between -0.399 and -1.112 (-0.482 and -0.99) for RX1DAY (RX5DAY) which are indicative of deteriorating precipitation conditions in the UMS.

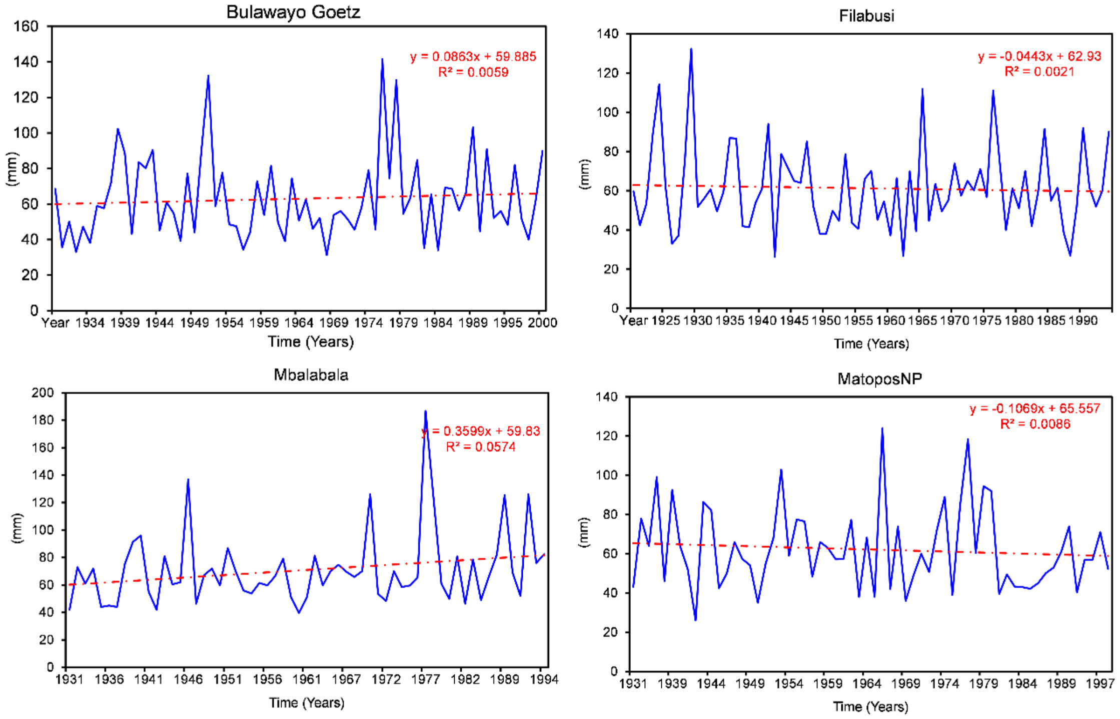


**Figure 4.9:** RX1DAY series trends for the four stations. The red dotted lines are linear trend lines illustrating weak and insignificant trends

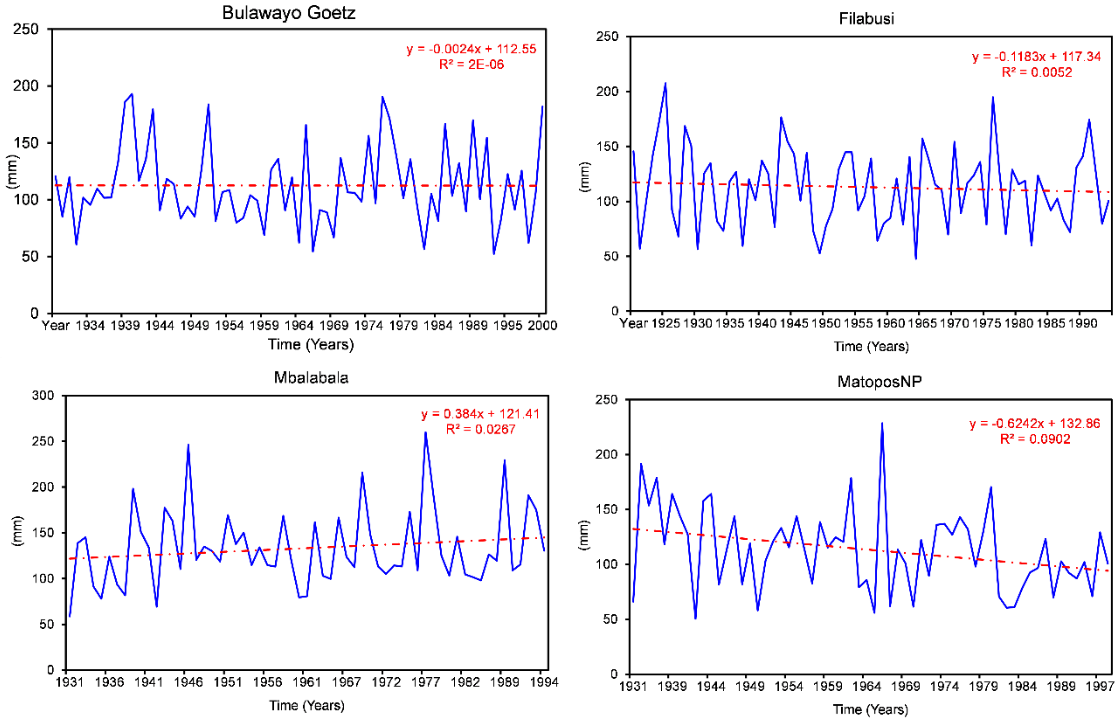


**Figure 4.10:** RX5DAY series trends for the four stations. The red dotted lines are linear trend lines illustrating weak and insignificant trends

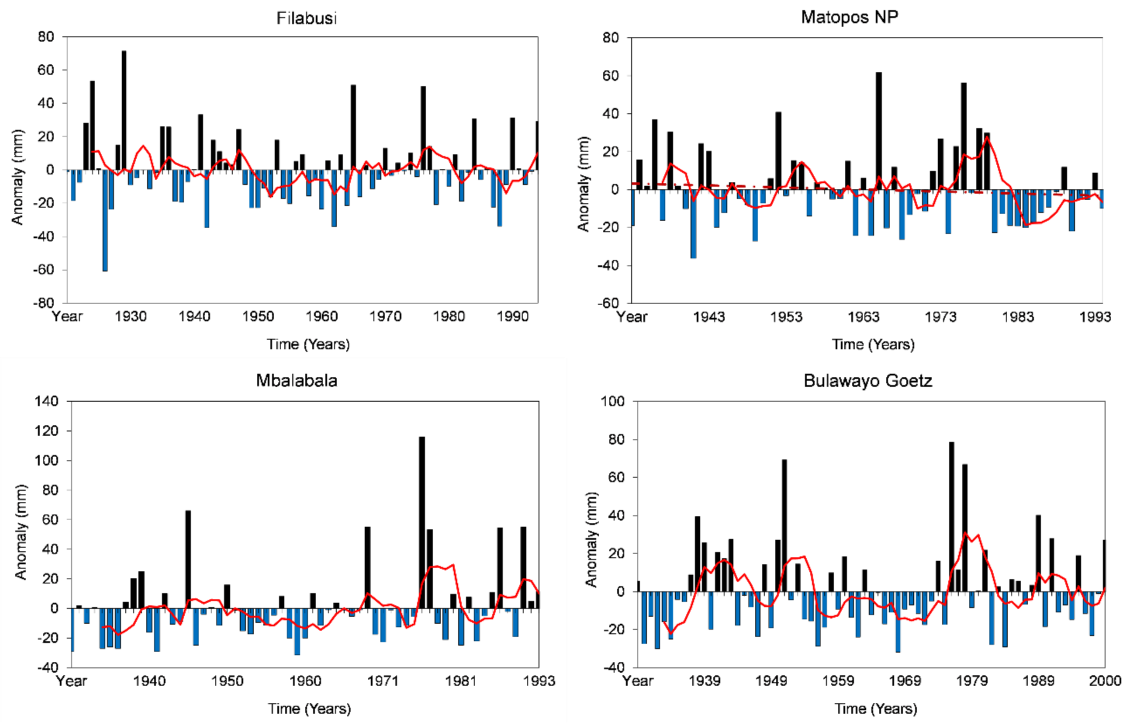


**Figure 4.11:** RX1DAY trend anomalies for the four stations. Anomalies are relative to the series mean values for each station's full recording period. Red line = 5-years running means; black (blue) bars show anomalies above (below) the mean

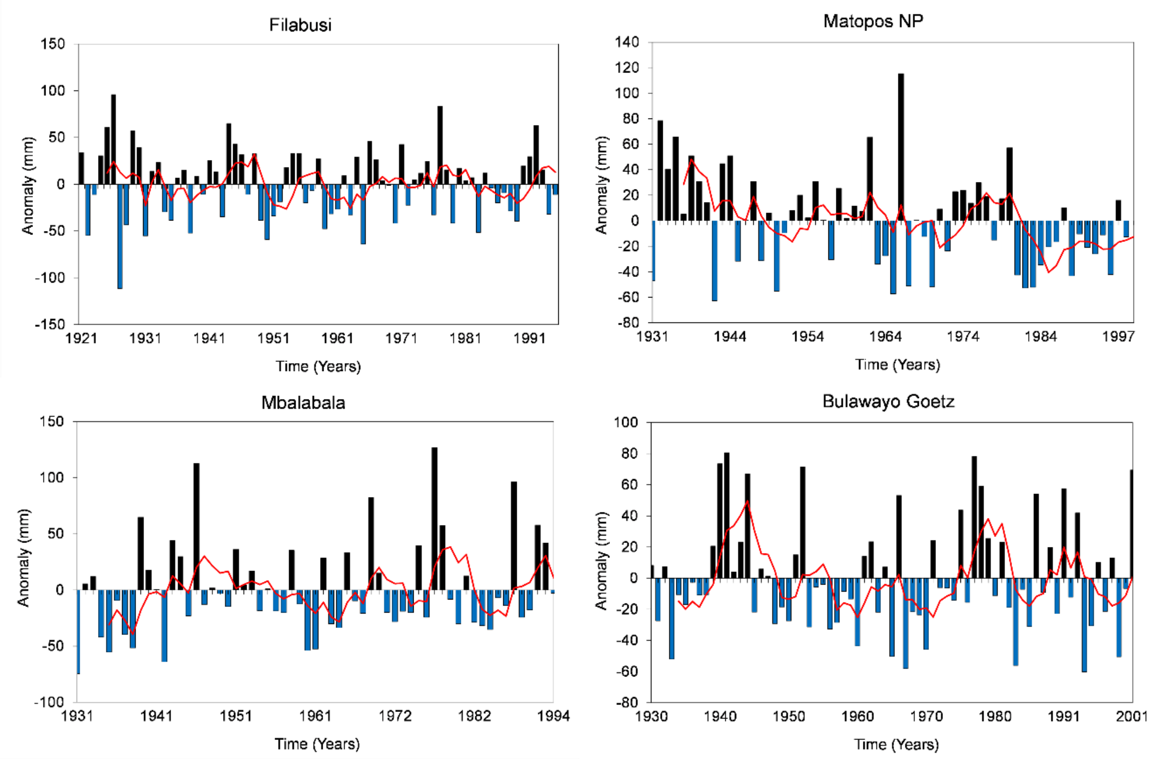


**Figure 4.12:** RX5DAY trend anomalies for the four stations. Anomalies are relative to the series mean values for each station's full recording period. Red line = 5-years running means; black (blue) bars show anomalies above (below) the mean

### 4.6.3 Percentile-based indices (R95p and R99p)

No significant trends were detected for historical very wet day (R95p) and extremely wet day (R99p) events over the study time period for three stations, with the exception of MNP which registered a significant declining trend ($Q_{med}$ = -1.41; p = 0.029) for R95p and an insignificant declining trend for R99p (see Table 4.4). These declining trends over MNP are consistent with the earlier discussed significant declining trend in total annual precipitation ($Q_{med}$ = -3.073, p = 0.011 over the western extent of the UMS marked by a drastic drop in R99p from 150 mm to about 50 mm between the 1970s and 1990s. Trends (anomalies) for R95p and R99p are shown in Figures 4.13 and 4.14 (Figure 4.15 and 4.16). Anomaly results show that all the stations have over the period under study experienced more years with annual total precipitation > 95th and > 99th percentile below the long term mean R95p and R99p.

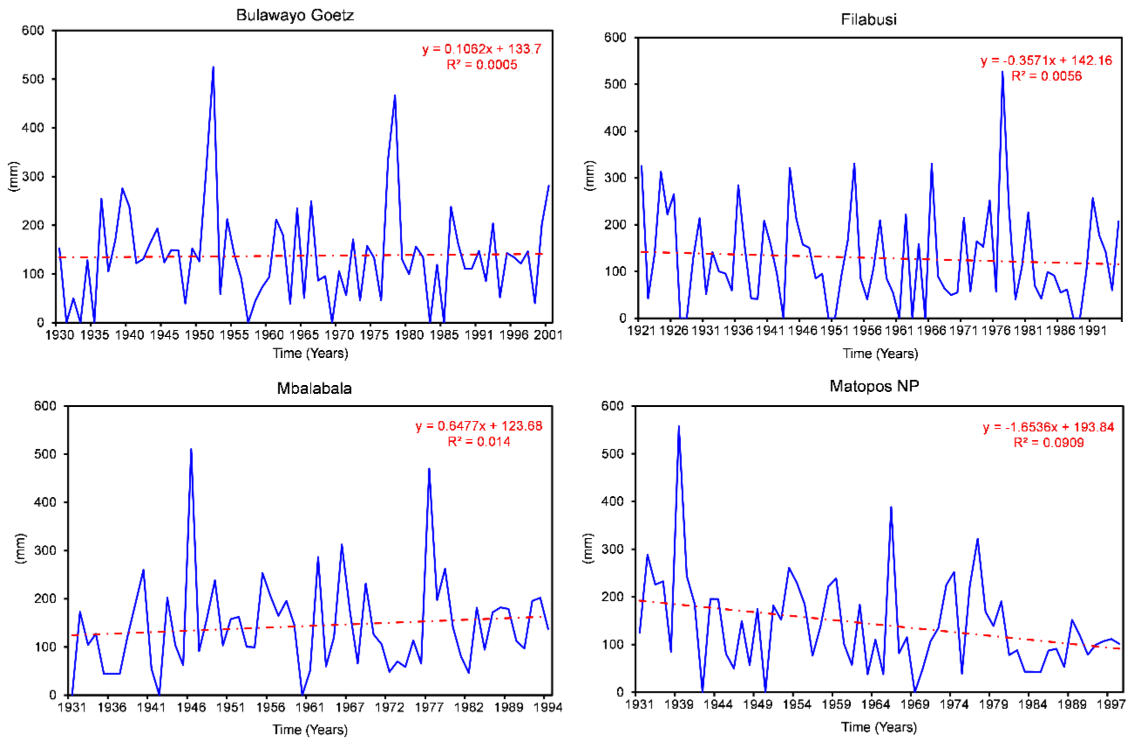


**Figure 4.13:** R95p series and trends for the four stations. All red dotted lines = insignificant linear trends with MNP only showing a significant declining trend

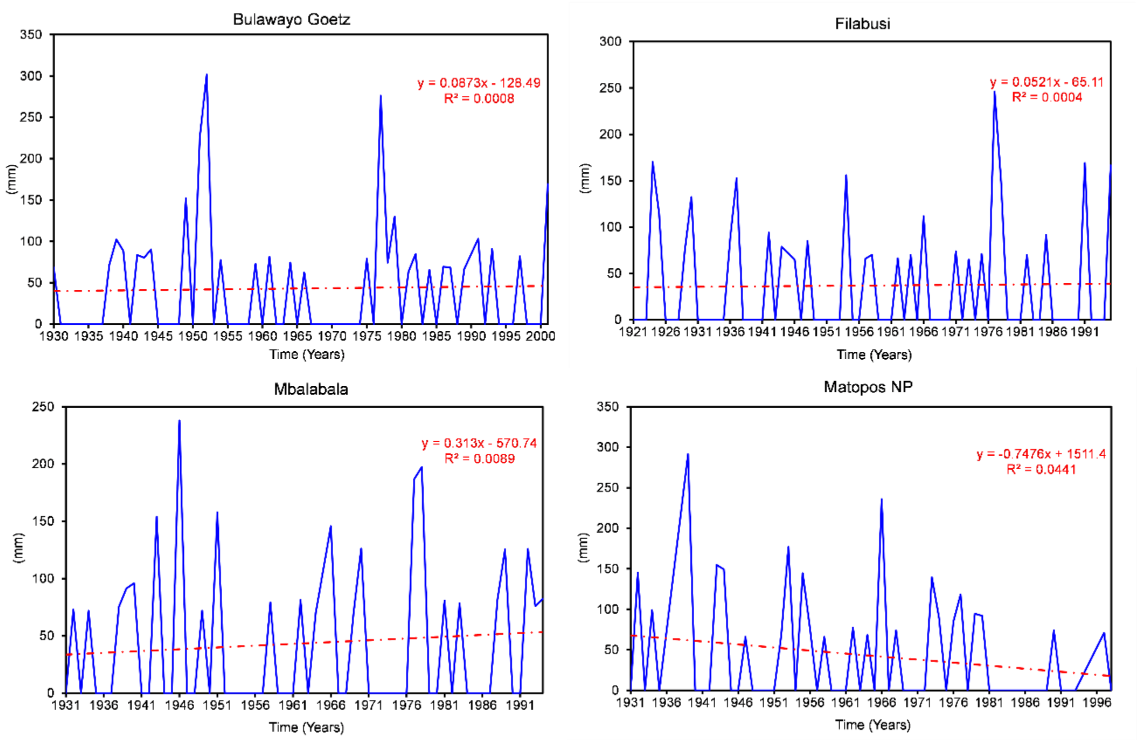


**Figure 4.14:** R99p series and trends for the four stations. All red dotted lines = marginally positive, insignificant linear trends for all stations with the exception of MNP having a declining trend over the study period

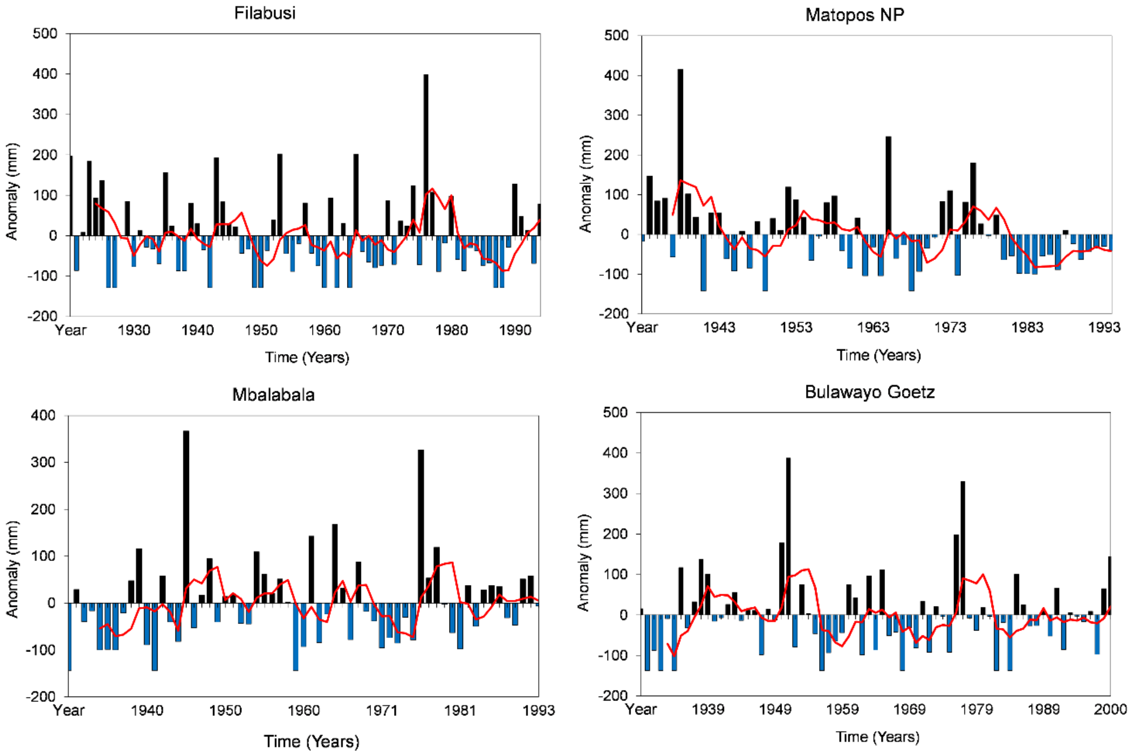


**Figure 4.15:** R95p anomalies and trends for the four stations. Red lines = 5-year running mean; black (blue) bars = anomalies above (below) the mean

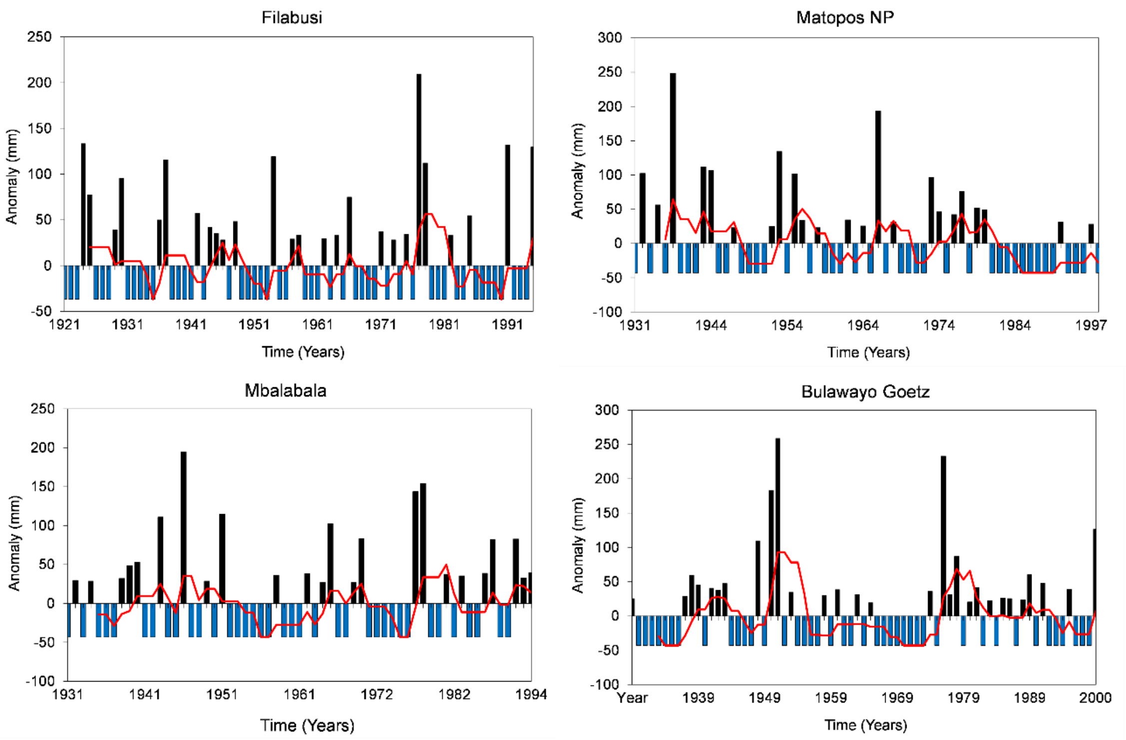


**Figure 4.16:** R99p anomalies and trends for the four stations. Red lines = 5-year running mean; black (blue) bars = anomalies above (below) the mean

### 4.6.4 Threshold and other indices (R10, R20 and SDII)

Results for heavy rainfall days above 10mm (R10) and 20mm (R20) per day (Figure 4.17 and Figure 4.18) reveal that three of the stations record declining but statistically insignificant trends (mean R10/R20 = 19/9 days respectively), while MNP records significant negative trends both indices i.e. R10 (R20) $Q_{med}$ = -0.093, p = 0.023 ($Q_{med}$ = -0.075, p = 0.003). The magnitude of these trends is notably very low (below 1%) at all stations (Table 4.4). These declining trends in R20 and R10 were matched with declining trends of PRCPTOT (as earlier indicated in Figure 4.7) at three of the stations, the exception being at BG which recorded an increasing, albeit insignificant trend ($Q_{med}$ = 0.626, p = 0.568). Over the same period, trends in the intensity of daily precipitation (depicted by the SDII) significantly increased (decreased) for Fl (MNP), $Q_{med}$ = -0.033, p = 0.033 ($Q_{med}$ = -0.035, p = 0.004), while the remaining two stations recorded marginally positive but insignificant trends (Figure 4.19). Anomaly trends for R10, R20 and SDII are presented in Figures 4.20, 4.21 and 4.22 respectively. MNP and BG show the greatest range in R10 (R20) anomalies of the between +15 and -13 days (+10 and -8 days) over the study period. Of note is the consistent correspondence between the mean negative anomalies for R10, R20 and SDII over the MNP from mid 1970s through the 1990s, indicative of possible deterioration in precipitation conditions over this area.

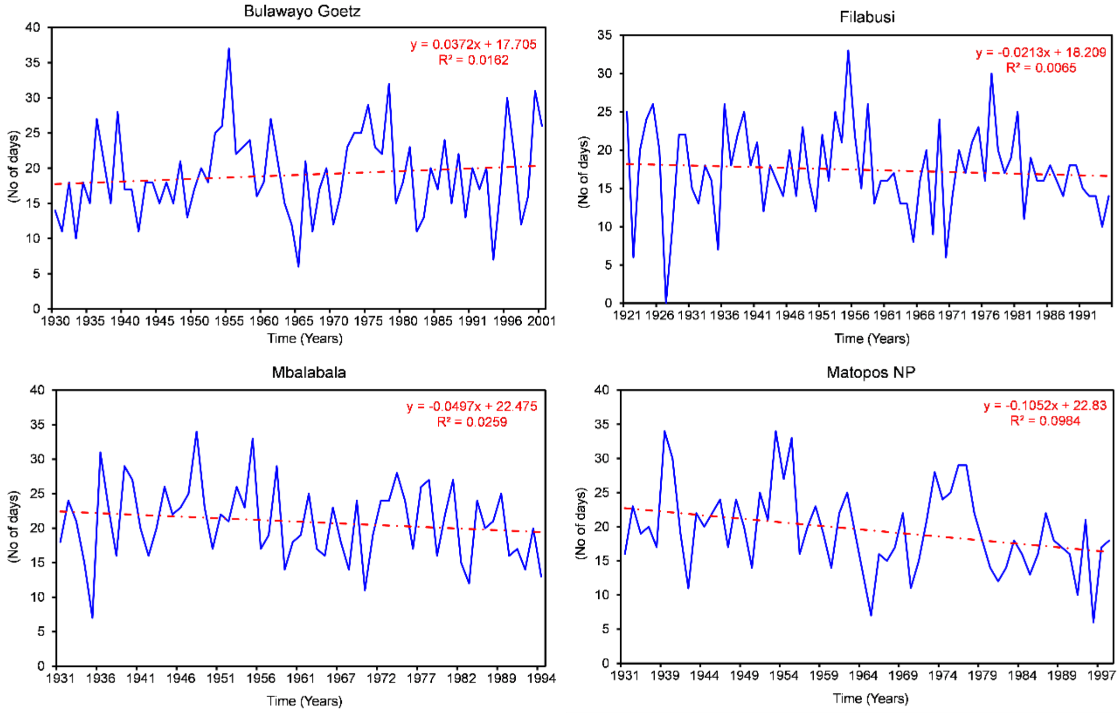


**Figure 4.17:** R10 series and trends for the four stations. Red dotted lines = linear trends. All stations show negative trends except Bulawayo Goetz

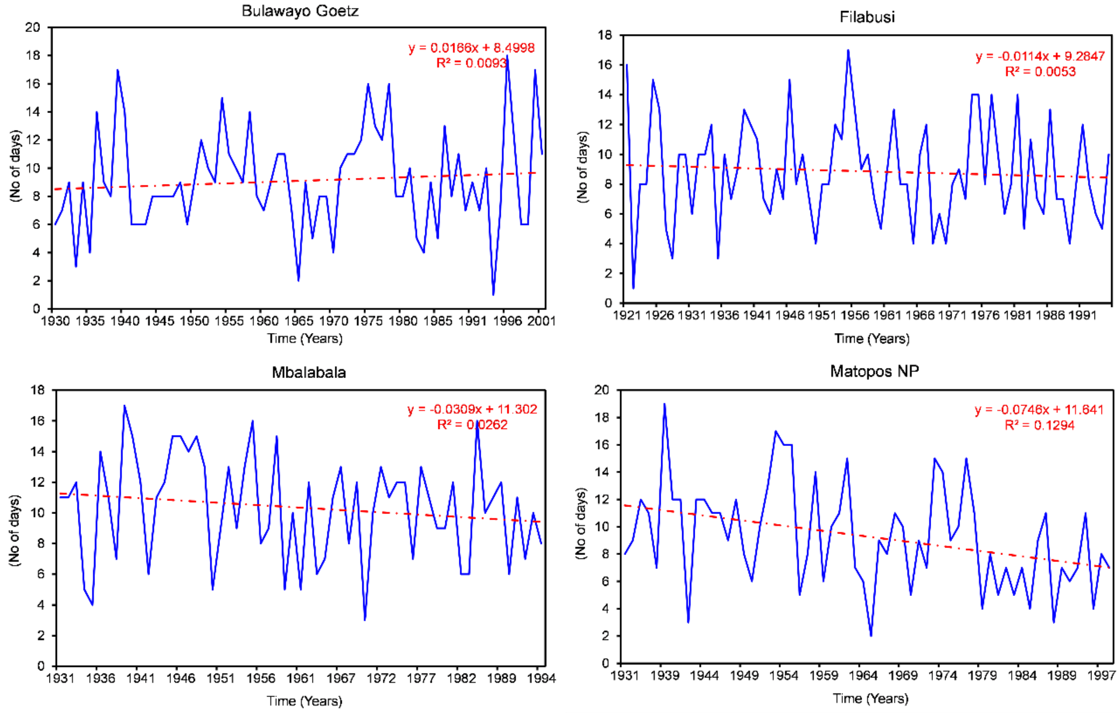


**Figure 4.18:** R20 series and trends for the four stations. Red dotted lines = linear trends

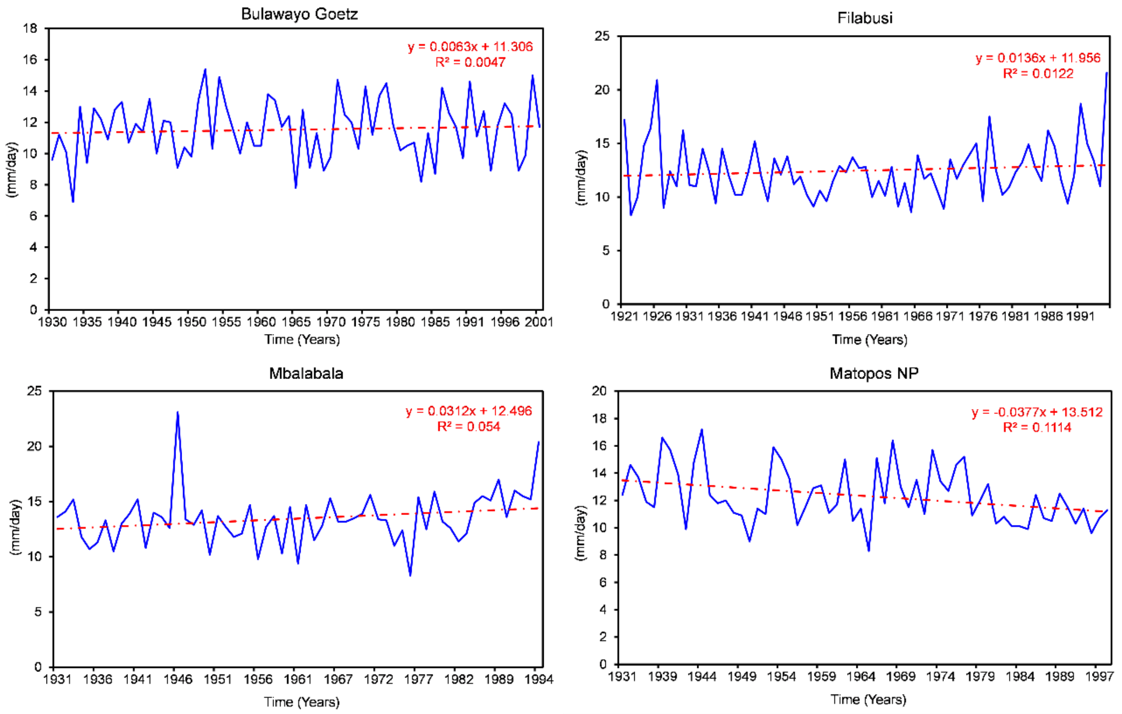


**Figure 4.19:** SDII series and trends for the four stations. Red dotted lines = linear trends

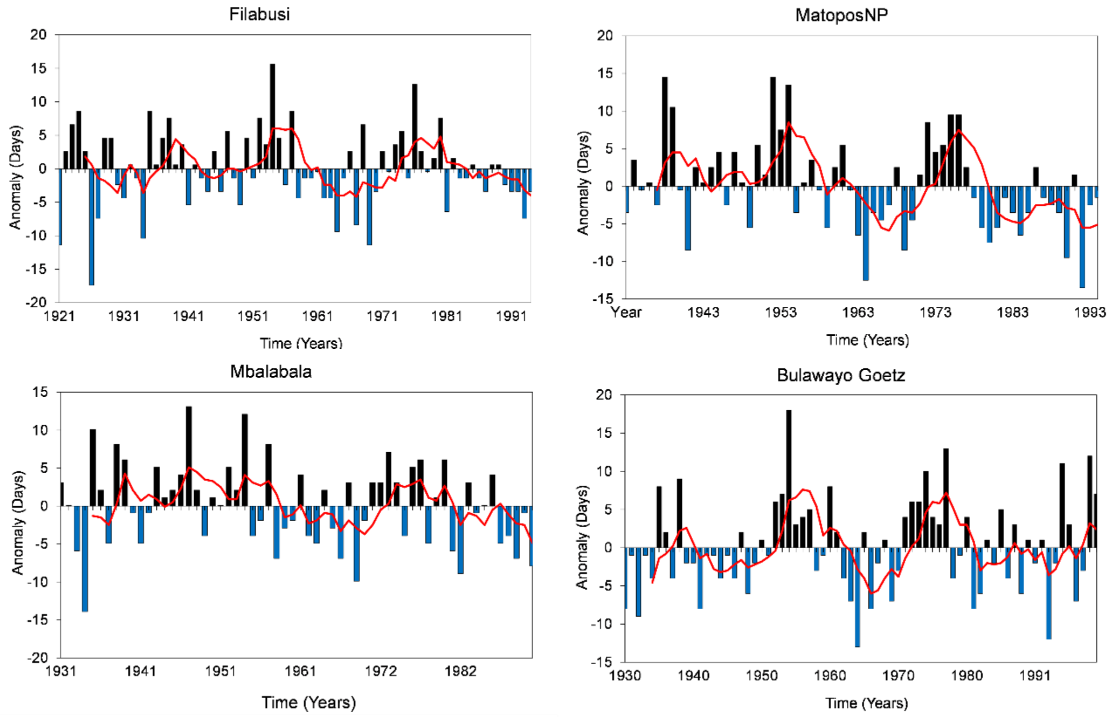


**Figure 4.20:** R10 anomalies and trends for the four stations. Red lines = 5-year running mean; black (blue) bars = anomalies above (below) the mean. Overall, negative anomalies generally show a greater mean amplitude than positive anomalies

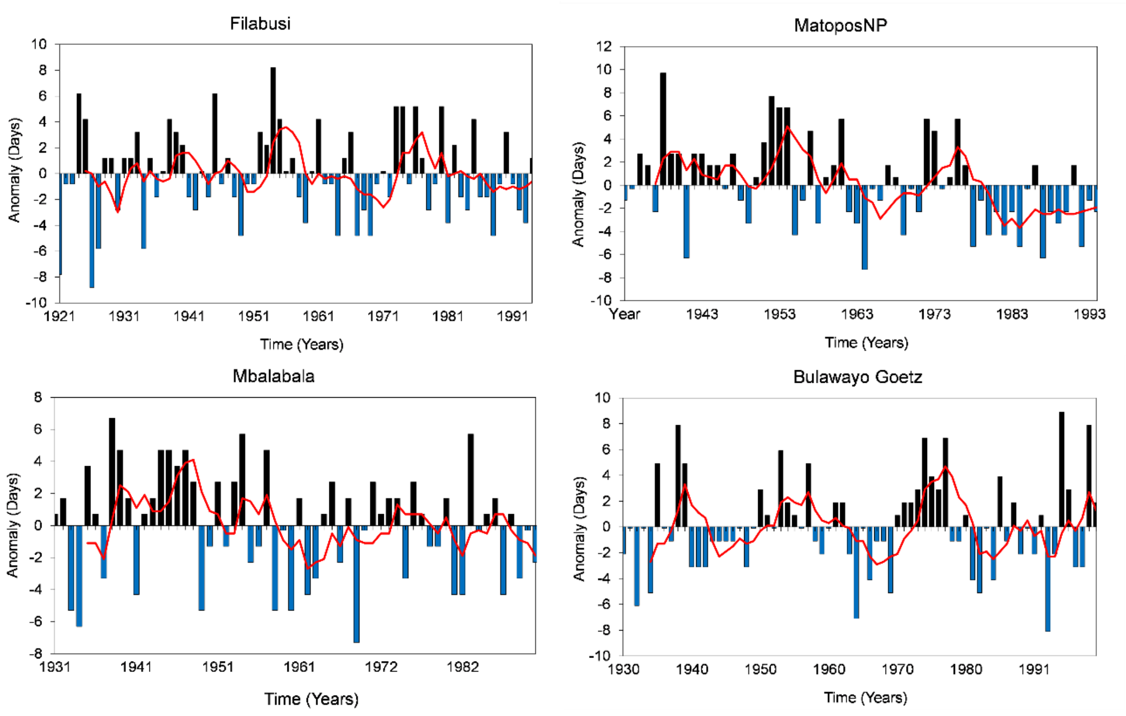


**Figure 4.21:** R20 anomalies and trends for the four stations. Red lines = 5-year running mean; black (blue) bars = anomalies above (below) the mean

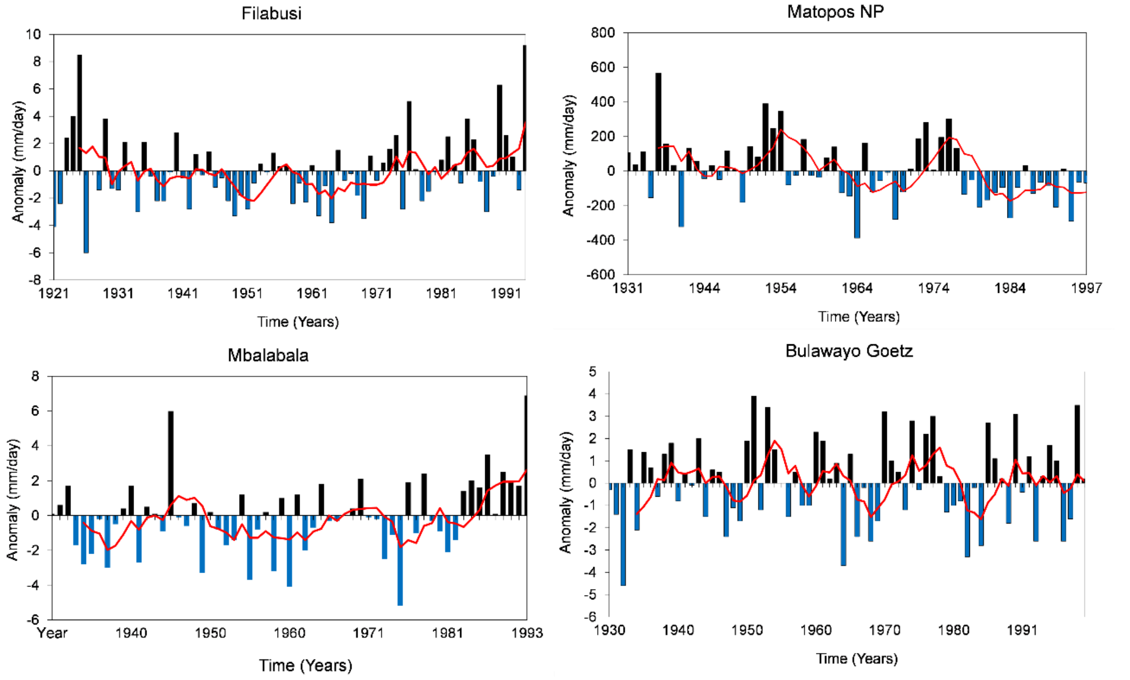


**Figure 4.22:** SDII anomalies and trends for the four stations. Red lines = 5-year running mean; black (blue) bars = anomalies above (below) the mean

### 4.6.5 Duration indices (CDD and CWD)

The indices CDD (CWD) are a measure of dry (wet) ‘spell duration’ in days. Results reveal $Q_{med}$ (p-values) ranging between -0.075 and -0.543 (0.099 and 0.857) for CDD, indicating insignificant decreasing trends (Figure 4.23) of consecutive dry days at three of the stations, with the exception of Fl which had an insignificant increasing trend ($Q_{med}$ = 0.286, p = 0.353). Similar insignificant, declining trends are recorded for CWD with the exception of Fl which had an insignificant increasing trend ($Q_{med}$ = 0.0001, p = 0.952) (Figure 4.24). Decreasing trends in CDD do not necessarily translate into an improvement in precipitation conditions considering the recorded negative trends in CWD over the most of stations in the UMS. With regards to anomalies, MNP shows negative CWD anomalies from 1984 up to 1997 (Figure 4.26) which is matched by an alternating trend above and below long term mean for CDD ranging between ~ +50 and – 70 days (Figure 4.25). For all other stations, anomaly trends do not show any distinct pattern though there is a marginal skew towards more negative anomalies in general.

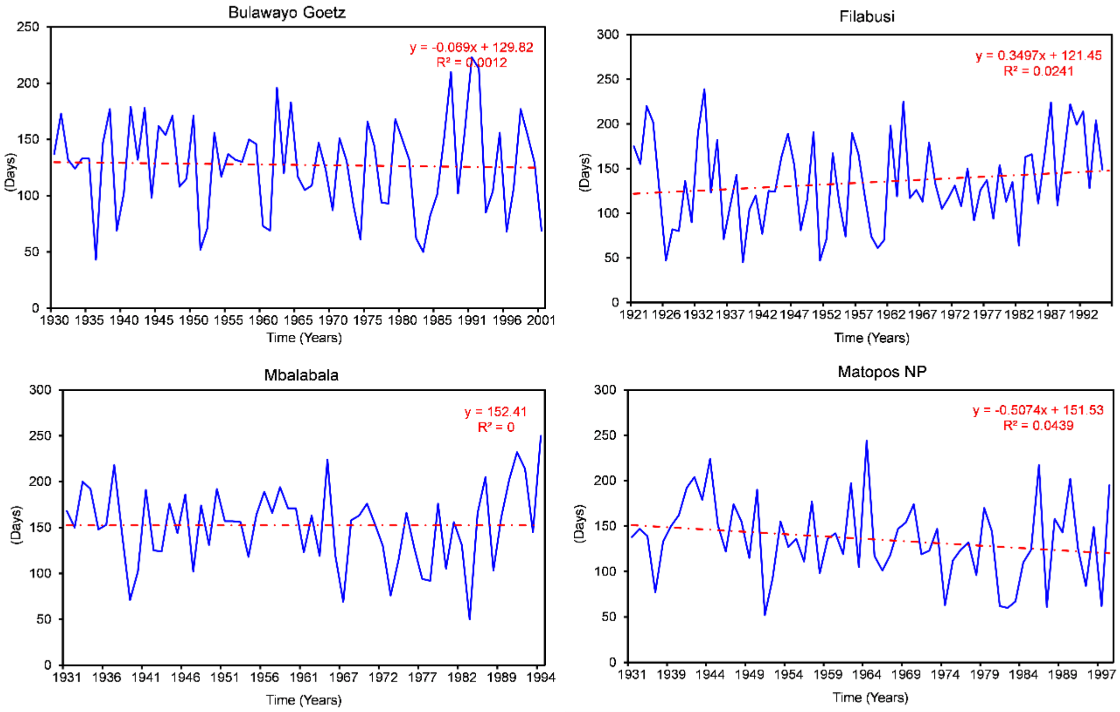


**Figure 4.23:** CDD series and trends for the four stations. Red dotted lines = linear trends

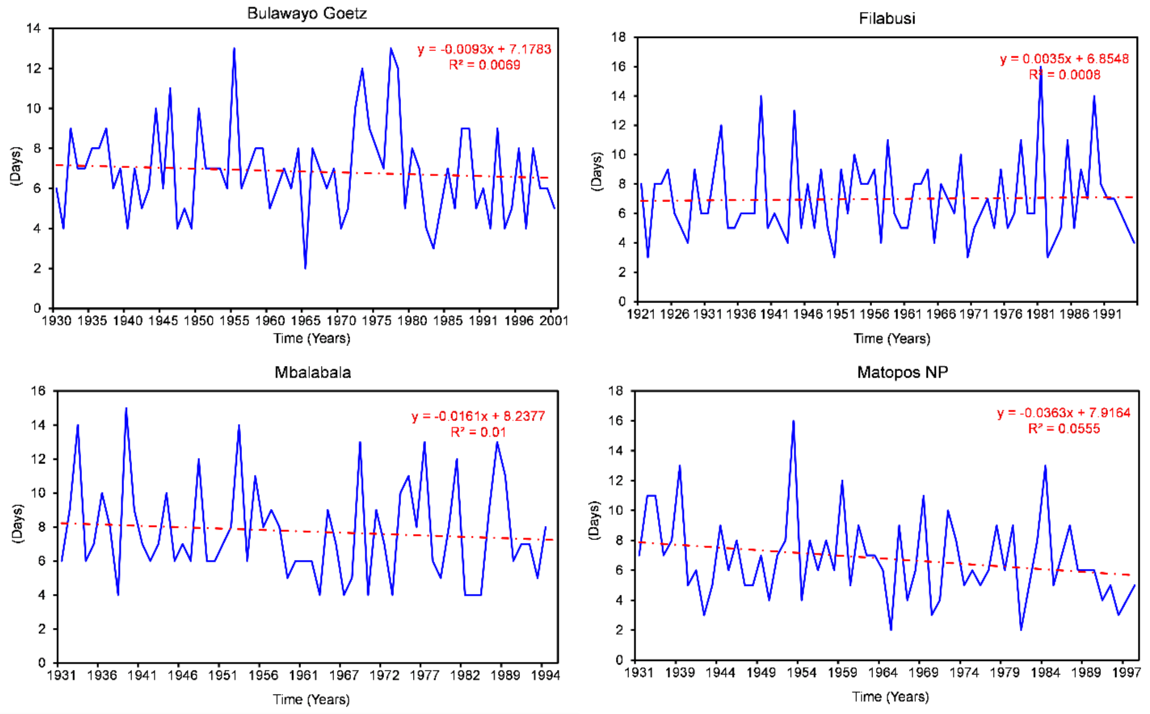


**Figure 4.24:** CWD series and trends for the four stations. Red dotted lines = negative linear trends with exception for Filabusi station which has a positive trend

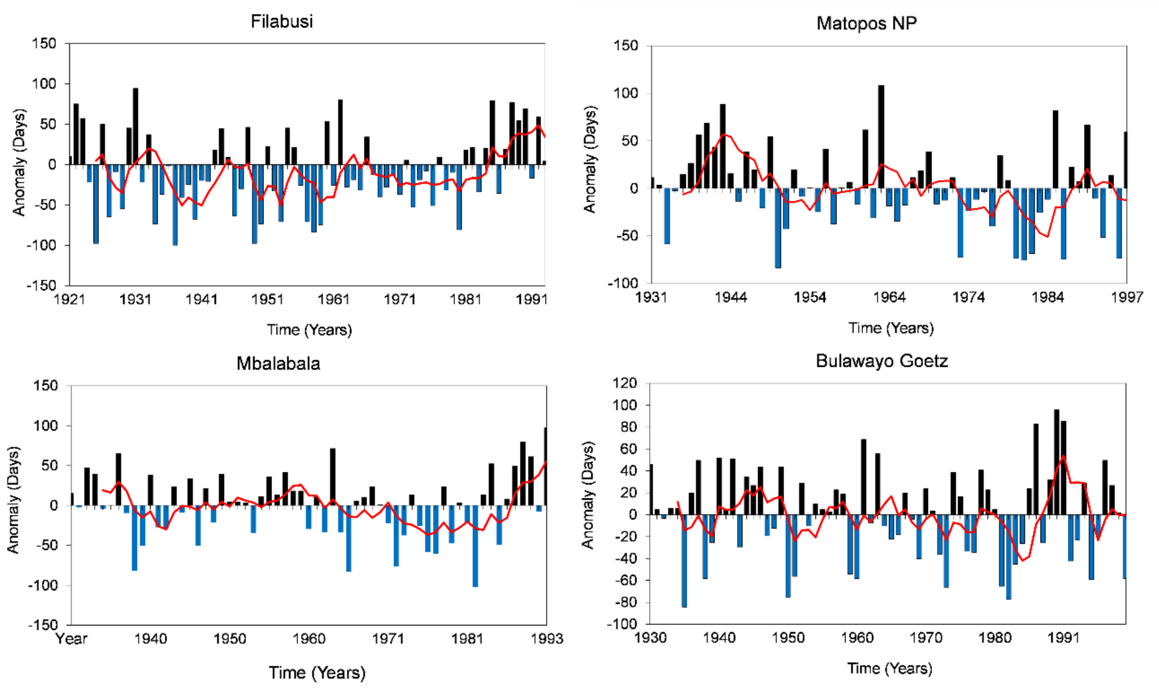


**Figure 4.25:** CDD anomalies and trends for the four stations. Red lines = 5-year running mean; black (blue) bars = anomalies above (below) the mean. Anomaly trends do not show any discernible cylicity for all the stations

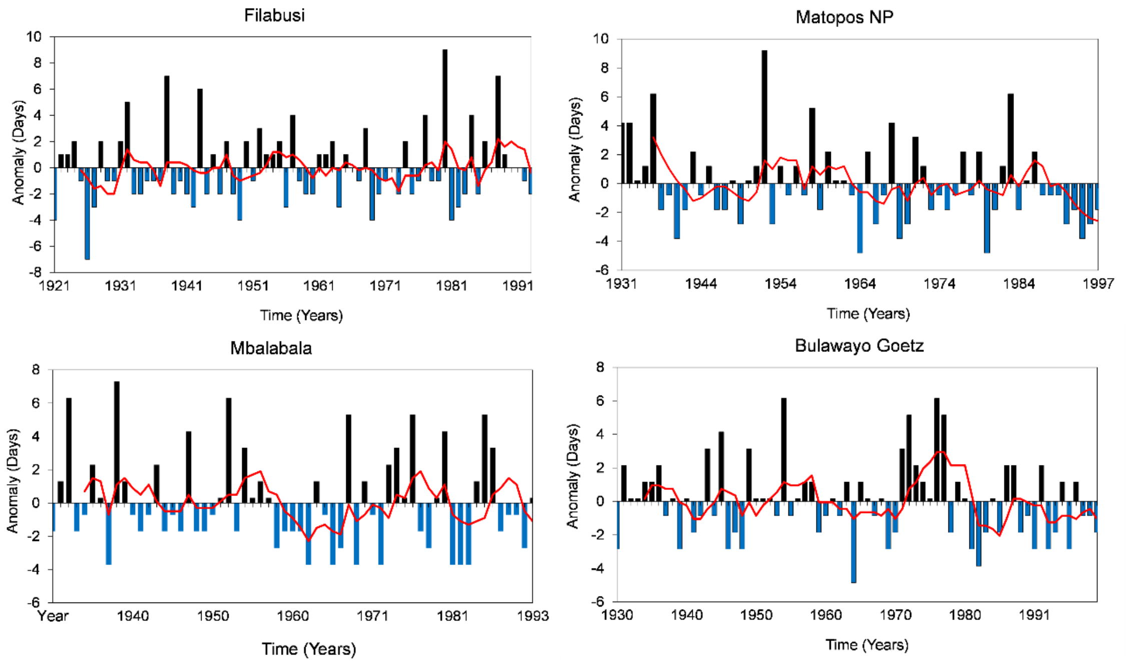


**Figure 4.26:** CWD anomalies and trends for the four stations. Red lines = 5-year running mean; black (blue) bars = anomalies above (below) the mean

**Table 4.4:** Statistical test results (Kendall’s tau (τ) Sen’s slope ($Q_{med}$) and MK p-values) for all index trends. Green (orange) shaded columns indicate upward (downward) trends of respective indices. Values in bold font indicate statistically significant trends (i.e. $p < 0.05$). MNP generally shows most (60%) statistically significant negative trends in extreme indices over the study period

| | | | Indices | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | RX1day | RX5day | SDII | R10 | R20 | CDD | CWD | R95p | R99p | PRCPTOT |
| Stations | Bulawayo Goetz | tau (τ) | 0.066 | -0.019 | 0.0279 | 0.099 | 0.081 | -0.054 | -0.071 | 0.0182 | 0.0334 | 0.0467 |
| | | $Q_{med}$ | 0.095 | -0.032 | 0.005 | 0.042 | 0.000 | -0.142 | 0.0002 | 0.069 | 0.0003 | 0.626 |
| | | p-value | 0.418 | 0.819 | 0.736 | 0.23 | 0.34 | 0.512 | 0.413 | 0.827 | 0.712 | 0.568 |
| | Filabusi | tau (τ) | 0.007 | -0.033 | 0.089 | -0.115 | -0.065 | 0.074 | 0.005 | -0.055 | -0.021 | -0.121 |
| | | $Q_{med}$ | 0.006 | -0.094 | 0.016 | -0.044 | 0.000 | 0.286 | 0.0001 | -0.194 | 0.0001 | -1.375 |
| | | p-value | 0.931 | 0.681 | 0.264 | 0.157 | 0.429 | 0.353 | 0.952 | 0.495 | 0.825 | 0.127 |
| | Mbalabala | tau (τ) | 0.14 | 0.059 | **0.188** | -0.114 | -0.126 | -0.017 | -0.079 | 0.119 | 0.089 | -0.074 |
| | | $Q_{med}$ | 0.23 | 0.227 | **0.033** | -0.057 | -0.035 | -0.075 | 0.0001 | 0.735 | 0.0001 | -0.892 |
| | | *p-value* | 0.114 | 0.509 | **0.033** | 0.203 | 0.167 | 0.857 | 0.393 | 0.177 | 0.361 | 0.401 |
| | Matopos NP | tau (τ) | -0.066 | **-0.206** | **-0.252** | **-0.202** | **-0.265** | -0.144 | -0.171 | **-0.191** | -0.119 | **-0.223** |
| | | $Q_{med}$ | -0.11 | **-0.672** | **-0.035** | **-0.093** | **-0.075** | -0.543 | -0.032 | **-1.41** | 0.0002 | **-3.073** |
| | | *p-value* | 0.451 | **0.018** | **0.004** | **0.023** | **0.003** | 0.099 | 0.061 | **0.029** | 0.219 | **0.011** |

## 4.7 DISCUSSION

With the acknowledged caveats, results from this study region depict a scenario of long-term drying over the 69 year period, most particularly so over the westernmost portion (represented by the MNP station). Such a drying trend is consistent with previous findings for other parts of southern Africa (e.g. Daron, 2014; Morioka et al., 2015; Scholes et al., 2015) and Zimbabwe in general (Brazier, 2015, Makuvaro et al., 2017, Nangombe et al., 2018). However, while there is generally decreasing total annual precipitation (mean = -0.54 mm/annum), this is accompanied by increased precipitation intensity (marked by increasing maximum 1-day precipitation amounts (RX1Day)) over most of the study region. While Love et al. (2006) found a general declining trend in annual total precipitation over the entire Mzingwane catchment from years 1931 to 2003, our findings provide a finer-scale detail on how this declining PRCPTOT trend manifests at a sub-regional (or sub-catchment) scale for the UMS over the period 1921-2000, including an analysis of extreme events and anomalies. Mean values for PRCPTOT anomalies ranging between -0.06 mm, -1.51 mm, and -1.74 mm for Mbalabala, Filabusi, Bulawayo Goezt and Matopos station also confirm the deteriorating precipitation condition in the UMS over the study period. A general visual analysis of the smoothed 5year moving average trends for PRCPTOT anomalies (Figure 9) shows a near 30 year and 20 year cyclicity in total precipitation anomaly trends for Bulawayo Goezt and Mbalabala stations respectively though further analysis using Fourier-based methods may need to be applied to more objectively confirm these indicative periodicities.

In addition, given the fact that trends in precipitation intensity over longer periods (revealed by RX5DAY trends) demonstrate a general declining trend, the northern and interior extents of the UMS indicate general increasing trends in the very wet precipitation index (R95p), while the westernmost extent records a significant declining trend. Coupled with this, R95p and R99p anomaly results show that over the period under study, UMS has generally experienced an increasing trend in annual total precipitation > 95th and > 99th percentile overall though a declining trend in the westernmost extent is noted for the same indices. There is hence an increasing drying trend over time from north to south-west extent in the UMS which is slightly different from the general north to south gradient reported by authors such as Masvopo (2012), Love et al. (2005) and Sibanda et al. (2018).

Declining trends in threshold indices (R10 and R20) indicate that there are fewer days with daily precipitation above 10mm (-19/days/decade) and 20 mm (-9days/decade) respectively. This may imply that increased precipitation intensities (RX1Day) are concentrated on extreme precipitation days (e.g. R95p) as also suggested in similar studies by Griffiths (2007) and Berhane et al. (2020). In this regard, it is also possible that time-averaged measures of precipitation which have often been used in past climate trend analysis studies in this region e.g. (Unganai and Mason, 2002, Klein-Tank and Können, 2003, Dike et al., 2019) may be inaccurate or could have failed to capture these subtle changes given that increases in precipitation intensity may compensate for decreases in frequency. Furthermore, a general analysis of total and mean precipitation (without considering extremes and anomalies) would have failed to reveal important shifts in trends and patterns of precipitation in the UMS and thus limit the scope of valuable new knowledge on extreme events generated in this study.

Results for CWD (wet spells) show a general negative trend in most part of the UMS, apart from Filabusi which has a very marginal increasing trend. The westernmost region (MNP) registered a decreasing trend (~2days/decade), hence complementing and elaborating further on the characteristics of the drying trend depicted by other earlier discussed indices such as the PRCPTOT for the same western sub-region. Further to this, declining trends in the consecutive number of dry days (dry spells) (CDD) were noted in all but the eastern sub-region (i.e. Filabusi with its marginally positive trend) (Table 4). This may be an indication that dry spells are more regularly becoming interrupted by precipitation events. The decline in dry spells does not necessarily imply commensurate favourable/ normal precipitation conditions as might be assumed. This could be attributed to the fact that CDD (and CWD) are very sensitive indices, such that even single day rainfall events are enough to terminate a CDD or CWD period as indicated by Hofstra and New (2009). This, however, does not diminish the utility of the CDD index as it has been widely used as a meaningful measure of unusually dry conditions and a potential proxy drought indicator (Griffiths, 2007).

While Love et al. (2010) assessed general annual total precipitation anomalies for the greater part of the Mzingwane catchment from 1931 to 2001, findings in this study present a new perspective pertaining anomaly trends on precipitation extremes, more specifically in the UMS. The 5-year moving average trends for PRCPTOT anomalies (Figure 9) indicate a possible near 20 year periodicity for Mbalabala station notwithstanding the earlier limitations in analysis in this regard while by Love et al. (2010) found a 17 to 20 year periodicity in annual precipitation.

The cycles align with recorded historical droughts in Zimbabwe and the correspondent El Nino Southern Oscillation (ENSO) events over the past decades (Manatsa et al., 2008). The El Niño years (i.e. 1982/83, 1986/87, 1987/88, 1991/92, 1994/95, 1997/98, 2002/03) were all drought years in Zimbabwe (Makarau and Jury, 1997, Phillips et al., 1998, Manatsa and Mukwada, 2012, Mamombe et al., 2017b). This shows the link between the ENSO and Zimbabwean climate anomalies in general. In these years, e.g. 1981, 1987 and 1991, results in this study reveal negative trends in mean PRCPTOT anomalies of between -0.06 mm and -6.36 mm in the northern and western sub-region of the UMS, suggesting general drying over the study period. This presents, for the first time, more direct evidence of a possible ENSO teleconnection at a sub-catchment level in Zimbabwe though further analysis may be required to more objectively substantiate this assertion. Further to this, a distinct pattern of negative anomaly trends for all indices is shown in the western portion (MNP) of the UMS from the early 1980s through 1997 confirming earlier discussed deteriorating precipitation conditions in this region over the decades. It is apparent that the ENSO events could be the main contributing factor to the observed drought conditions in the UMS as supported by Chamaillé-Jammes et al. (2007). This, therefore, shows the potential that the indices used here have in augmenting a deeper understanding of incidence and trends of extreme events such as drought years at sub-catchment level.

An understanding of these temporal changes in climatic extremes and their anomalies is important given the impacts that extreme events have on society and the natural environment (Abiodun et al., 2017, Farjad et al., 2019). For instance, trends for the RX1DAY and very wet days (R95p) are relevant for planning and projecting changes in demands on drainage and sewerage systems at different locations (Klein-Tank and Können, 2003), while the CDD can serve as a proxy for drought detection and thus allows for appropriate water resource planning and management. In this study, new information on climate extremes and trends could be useful in the design of new and/ upgrading of old water supply storage infrastructure such the Insiza, Mzingwane and Inyankuni dams located within the UMS so as to achieve targeted water security goals for the city of Bulawayo and the surrounding communities by the local and central government of Zimbabwe. Similarly, the Zimbabwe National Water Authority (ZINWA) could, for instance, leverage the R95p, R99p and CWD trends and anomalies periodicity findings of this study to guide decision making pertaining proper sizing and/ upgrading of flood control systems to cope with more short and intense precipitation events which have been associated with destructive, intermittent flash floods (Chingombe et al., 2015, Eccles et al., 2019). The findings can also be used for climate monitoring, targeting approaching extreme events which can inform proactive impact mitigation plans as highlighted by Davis and Hirji (2014).

## 4.8 CONCLUSION

Notwithstanding the limitations of access of up-to-date station precipitation data for our study area, we were able to successfully analyse and demonstrate the utility of climate extreme indices in understanding historical precipitation extremes in the UMS for the period 1921-2000. Most computed index values in this study showed varying though mostly negative, statistically insignificant precipitation extreme trends across the UMS. The exception is for the westernmost extent of the area, which showed significant negative precipitation extreme trends and anomalies indicative of drying over time. A general shift towards shorter very wet periods with more intense precipitation and a decrease in the number of dry spells is noted in the study area. For the first time in this sub-region, this study was able to show a possible ~ 20 to 30 year periodicity for annual total precipitation anomaly events with marginal variations across the UMS, notwithstanding the need for further objective analysis as earlier discussed. The negative anomaly trends appear to correspond with recorded historical extremely dry/ drought events (ENSO teleconnections) over Zimbabwe in general. This demonstrates the potential utility the extremes indices have in characterising the unique nature of each of these events as suggested by Mukherjee et al. (2018). Overall, a general north to south-western declining precipitation gradient across the UMS is identified contrary to the general north to south gradient identified in previous studies. Findings from this study could also serve as a baseline in follow-up studies aimed at extended historical analysis, modelling future trends in extreme precipitation conditions and the likely impacts in the UMS using alternative datasets such as CCAM and CHIRPS.

# CHAPTER 5: Modelling future climatic trends in the UMS

*Based on a manuscript in preparation*
*Title: Modelling climate trends in the upper Mzingwane sub-catchment (northern Limpopo basin), Zimbabwe using the Conformal Cubic Atmospheric Model (CCAM) data*

## 5.1 INTRODUCTION

Climate change is recognised as one of the major global factors shaping the environment and society (IPCC, 2007, 2018, Anderson et al., 2019, Hannaford, 2020). Its impacts on both natural and human systems are well documented, and include accelerated land degradation, aggravated rangeland desertification (Cui et al., 2017, Burrell et al., 2020, Huang et al., 2020), compromised food and water security (Vörösmarty et al., 2000, Krause, 2002, Farley et al., 2011, Kibena et al., 2014, Bodansky et al., 2020), and changing patterns in vector-borne and emerging infectious diseases (Patz et al., 1996, Tanser et al., 2003, Gage et al., 2008, Caminade et al., 2019). In light of these and other potential negative impacts, climate research has been a rigorous and continuously active area of scientific enquiry, which aims to improve our understanding of climate system dynamics at various spatial and temporal scales (i.e. from global to local). It is thus not surprising that since the mid-1990s, the World Climate Research Programme (WCRP) Working Group on Coupled Modelling (WGCM) have together with the IPCC been fostering international coordination and partnerships that have contributed to advancing scientific understanding of multi-scale climate and/or earth system dynamics. One notable initiative in this regard is the WCRP-supported Coupled Model Intercomparison Project (CMIP).

CMIP is the leading international project aimed at generating climate simulations made with various coupled ocean-cryosphere-atmosphere-land GCMs (Meehl et al., 2000, Meehl et al., 2005, Taylor et al., 2012). Now in its sixth phase, CMIP provides projections of future climate change until the end of the 21st century and beyond. The IPCC in the accompanying Assessment Report Six (AR6) focuses its analysis largely on the near-term ( 2021-2040), mid-term (2041-2060) and the long-term (2081-2100),thus allowing for a comprehensive assessment of future climate change trajectories and their likely impacts (Kattenberg, 1996, Riahi et al., 2011, Tebaldi et al., 2011, Gualdi et al., 2013). The CMIP6 GCMs have resolutions of 100 to 200 km in the horizontal, which is course to provide the spatial detail needed to assess aspects of climate change impacts. At a regional scale, the Coordinated Regional Climate Downscaling Experiment (CORDEX) has been valuable in providing region specific climate simulations through the downscaling of GCM projections by RCMs. These multi-model ensemble datasets (for future precipitation, temperature, humidity and other climate variables) have been made freely available at a resolution of about 50 km in the horizontal, and are thus successfully used in various global to regional climate science studies (Tabor and Williams, 2010, Gualdi et al., 2013, Sillmann et al., 2013, Gutowski et al., 2016, Fotso-Nguemo et al., 2018, Luo et al., 2020). Even more detailed regional projections have been obtained at subcontinental scales, for example 8 km resolution simulations over southern Africa (Engelbrecht et al., 2019).

The value of GCM and RCM simulations in understanding future climate scenarios has been well demonstrated, notwithstanding acknowledged shortcomings, which include structural uncertainties and related model biases over and above the uncertainties associated with different mitigation scenarios (Rodo and Comin, 2003, Torn and Harte, 2006, Tebaldi and Knutti, 2007, Tebaldi et al., 2011, Friedlingstein et al., 2014, Arora, 2019). Over southern Africa, utility of GCMs and downscaled RCMs has been demonstrated in numerous studies (Engelbrecht et al., 2013, Kalognomou et al., 2013b, Meque and Abiodun, 2015, Shongwe et al., 2015, Dedekind et al., 2016, Archer et al., 2018, Maúre et al., 2018). For instance, using CORDEX regional climate model projections, Maúre et al. (2018) found that rainfall decreases of between 0.2mm and 0.4 mm day$^{-1}$ over most of the central and western parts of the region under forcings of between 1.5°C and 2°C global warming accompanied by noted increasing in dryness over the region (New et al., 2006, Shongwe et al., 2015, Archer et al., 2018). In fact, regional modelling has consistently indicated, across AR4 and AR5 that the southern African region is likely to become generally drier under continued global warming (Christensen et al., 2007; Niang et al., 2014). Simulated regional climate scenarios have also indicated a general increase in rainfall characterised by more rain days with higher intensity rainfalls over the eastern part of southern Africa (Lumsden, 2009).

As discussed in Chapter 4, climate change simulations using different emission scenarios in the CMIP3, CMIP5 and CMIP6 multi-model ensembles have been successfully used in analysing changes in a wide variety of climate extremes at regional scales over the 21st century (Sillmann et al., 2013, Abiodun et al., 2016, Pinto et al., 2016a, Fotso-Nguemo et al., 2018). The assessment of changes in climatological averages and extremes provides the basis for the formulation of appropriate response strategies and adaptation policies. Southern Africa is in dire need of the development of actionable messages for adaptation. This stems from the region which is naturally dry and warm being projected to become generally drier and drastically warmer, with pronounced negative impacts on livelihoods being expected (Magadza, 2000, Moyo and Nangombe, 2015, Scholes et al., 2015, Hannaford, 2020). These factors resulted in the region being classified as a climate change hotspot in the IPCC Special Report on Global Warming of 1.5°C (Hoegh-Guldberg et al., 2018).

While numerous studies have analysed projections of future climate change over the larger southern African region towards informing climate-related decision making processes, very few such studies have been undertaken for Zimbabwe (Chapter 2). Only 8% of the 107 published climate studies on Zimbabwe over the past 29 years (as reviewed in the Chapter 2) are found to directly or indirectly involve climate modelling (Figure 2.2 and Table 2.2) (Maviza and Ahmed, 2021). Most of these studies, such as Unganai (2014) and Masanganise et al. (2013), either used GCM and RCM simulations directly without downscaling and/or bias correction, hence the possibility of inaccuracies in some of their conclusions. Some of the models used in these studies include GFDL-CM2.0, GISS-ModelE20, the United Kingdom Meteorological Office (UKMO) model, GISS, MPI-ECHAM5 and the CCCMA-CGCM3.1 (Kristensen et al., 2007, Masanganise et al., 2013, Chikobvu and Chifurira, 2015, Gwitira et al., 2015, Chemura et al., 2016, Lord et al., 2018). Furthermore, although several studies have successfully simulated future climatologies at a catchment level in the southern African region using RCMs such as CCAM (Adegoke et al., 2012, Horowitz et al., 2015, Evans et al., 2016), only one known study in Zimbabwe by Masimba et al. (2019) has attempted to simulate catchment-level climatologies (i.e. in upper Manyame sub-catchment of northern Zimbabwe). The study projected declining, statistically non-significant (increasing, statistically significant) trends in precipitation (maximum and minimum temperature) for the 2030s and 2060s using data from HadCM3 and CanESM2. None of these studies have applied bias-correction of the datasets to enable more accurate results in their analysis. This further reveals a knowledge gap with regards to simulation of catchment-level future climate scenarios using appropriately downscaled RCMs, so as to help guide more realistic climate impact mitigation and adaptation strategies and policy development.

In the context of this study, while several studies have assessed historical climate trends in the upper Mzingwane sub-catchment (UMS), no study to date has explored future climate scenarios using bias-corrected climate simulations in this highly economically strategic catchment area. This presents limitations and planning uncertainties due to unavailability of up-to-date scientific knowledge to guide decision making related to climate change mitigation and adaptation, hence the justification for this study. In this regard, this chapter aims at assess future climatic trends in the UMS through the use of bias-corrected CCAM simulation data.

## 5.2 MATERIALS AND METHODS

This study follows a four step methodology which include (1) Data acquisition and preprocessing, (2) Bias correction validation, (3) Grid data analysis (computation of multi-model future climatologies) and (4) Presentation of results (in the form of maps), discussion and conclusion. These mains steps are summarised in Figure 5.1.

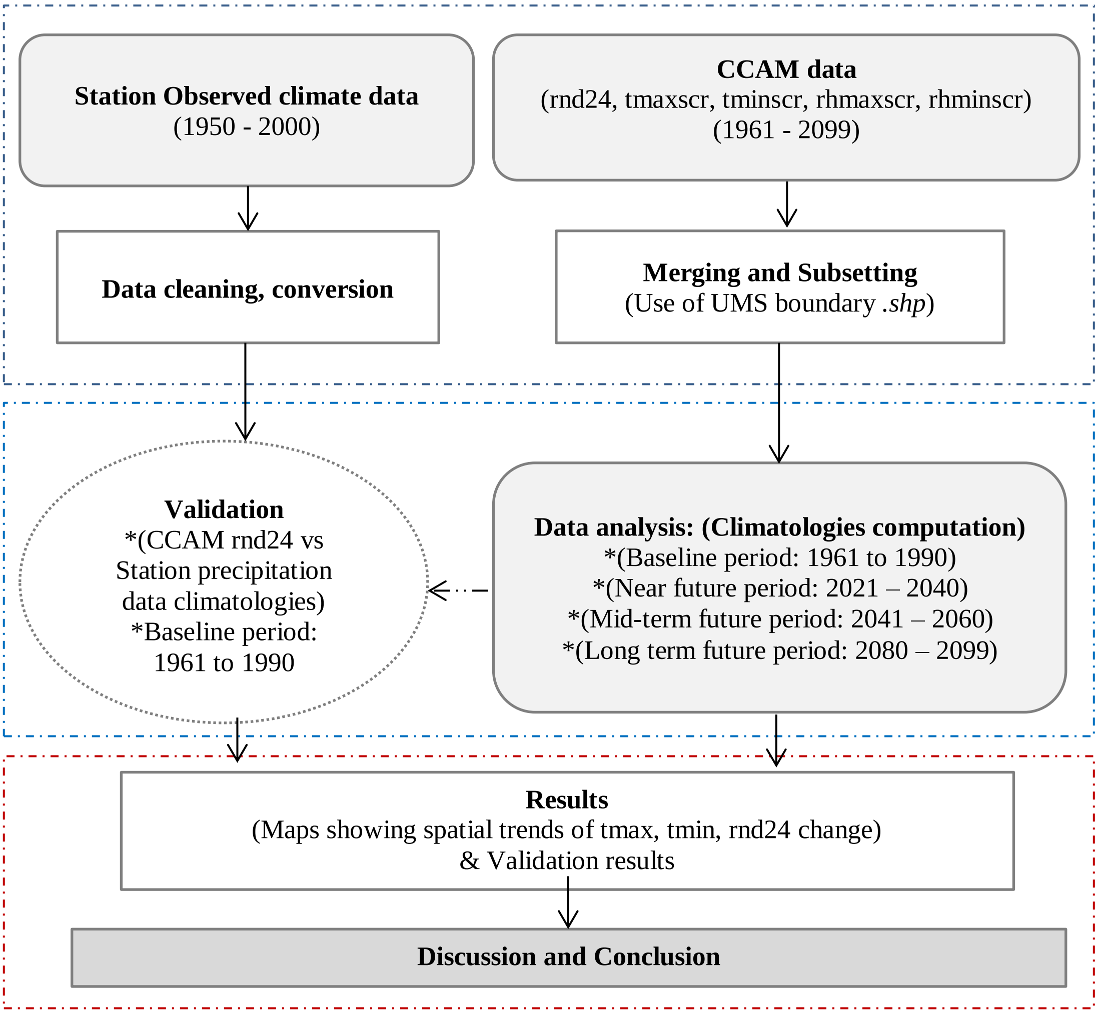


**Figure 5.1**: Main steps of the study methodology

### 5.2.1 Data acquisition and preprocessing

Bias corrected CCAM data, climate station observation and vector datasets (shapefiles) are used in this study. A metadata summary of the datasets is presented in Table 5.1.

**Table 5.1:** Summary of main metadata for datasets used in the study

| Dataset | Time period | Resolution | Projection | Format | Source |
|---|---|---|---|---|---|
| **CCAM data** | 01/1961 – 12/2099 | 0.1° × 0.1° (~ 8km × 8km) | WGS84 | NetCDF (.nc) | Wits University Global Change Institute |
| **Climate station data** | 1950 - 2000 | N/A | N/A | Comma Separated Values (.csv) | South African Weather Services and Other private databases |
| **Spatial vector data** | N/A | N/A | WGS84 | ESRI shapefile (.shp) | Zimbabwe Surveyor General |

#### *5.2.1.1 CCAM data*

CCAM data used in this study are downscaled simulations from 6 CGCMs (i.e. ACCESS1.0 (Bi et al., 2012), CCSM4 (Gent et al., 2011), CNRM-CM5 (Voldoire et al., 2013), GFDL-CM3 (Donner et al., 2011, Griffies et al., 2011), MPI-ESM LR (Giorgetta et al., 2013) and the NorESMI-M (Bentsen et al., 2012, Iversen et al., 2013)). The simulations have been produced from a double downscaling approach following Engelbrecht et al. (2011). Selection of the CCAM data is based on the fact that it is the best known and readily available high resolution southern Africa region-specific climate simulation dataset that can provide detail at the sub-catchment level, and secondly, the model has been shown to satisfactorily simulate present-day climate and future climate change over northern and southern Africa (Engelbrecht et al., 2011, Adegoke et al., 2012, Winsemius et al., 2014, Engelbrecht and Engelbrecht, 2016). As a variable-resolution regional model, CCAM has been shown to realistically simulate annual temperature and rainfall distributions, intra-annual cycles in rainfall, produce realistic observed daily climate statistics, and the occurrence (frequency) of extreme rainfall events over the southern African region (Engelbrecht et al., 2009, Martens et al., 2021). CCAM thus shows potential value through its use in the UMS under the *in situ* climate data paucity challenges in the study area. The climate parameters covered in the dataset are precipitation *(rnd24)*, maximum temperature *(tmaxscr)* and minimum temperature *(tminscr)*, wind speed *(u10)*, maximum relative humidity *(rhmaxscr)* and minimum relative humidity *(rhminscr)*, and covers the period 1961 to 2099.

#### *5.2.1.2 Station observation data*

Monthly observational data (precipitation) from seven climate stations (Table 5.2 and Figure 5.2) were used in the validation stage of the analysis, as explained in section 2.3 of this Chapter. The data were extracted from physical data archives from the South African Weather services library and digitised, cleaned and streamlined to cover a 50 year period (1950 – 2000) in .csv format using Microsoft Excel software.

**Table 5.2:** Climate stations used in this study

| **Station name** | **Coordinates** | | **Elevation (metres)** | **Period** |
|---|---|---|---|---|
| | Lat | Lon | | |
| **Bulawayo Goetz** | -20.15 | 28.62 | 1340 | 1950 - 2000 |
| **Filabusi** | -20.55 | 29.28 | 1070 | 1950 - 2000 |
| **Matopos National Park** | -20.40 | 28.47 | 1338 | 1950 - 2000 |
| **Fort Rixon** | -20.02 | 29.27 | 1290 | 1950 - 2000 |
| **Gwanda** | -20.95 | 29.02 | 990 | 1950 - 2000 |
| **Shangani** | -19.78 | 29.35 | 1370 | 1950 - 2000 |
| **Esigodini** | -20.30 | 28.93 | 1190 | 1950 - 2000 |

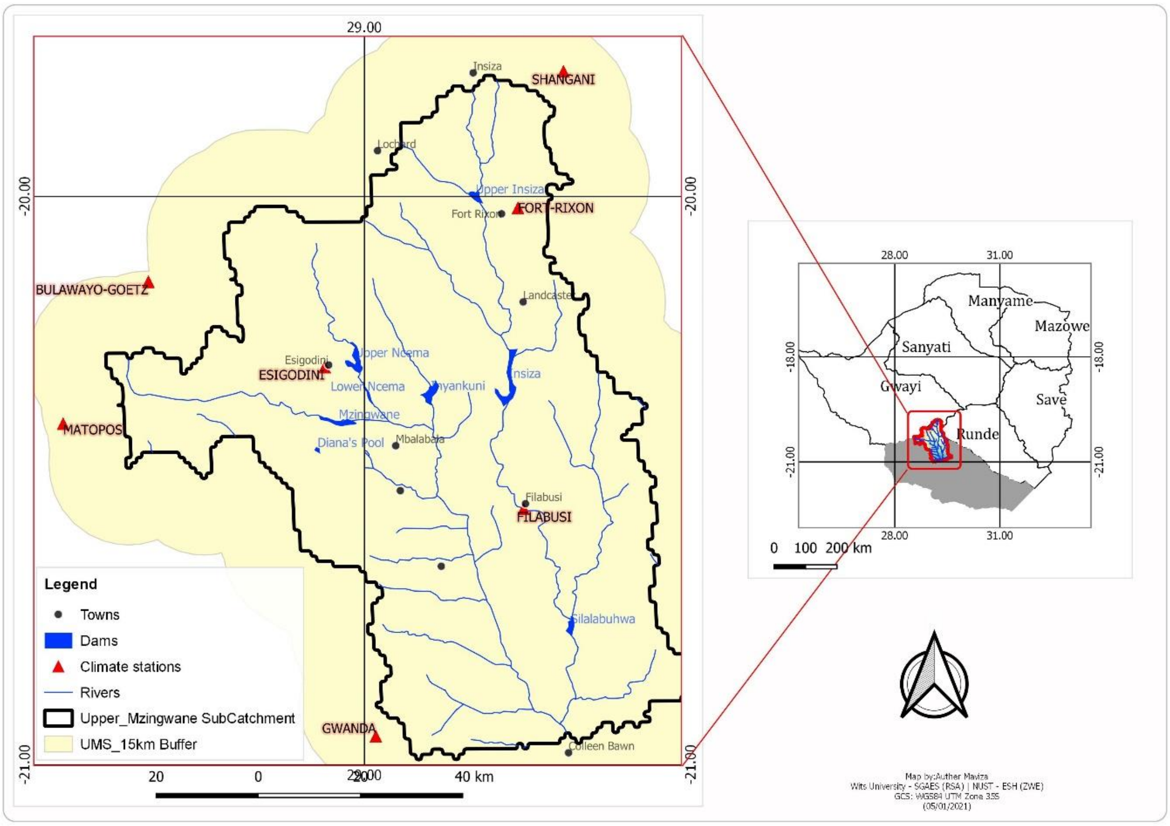


**Figure 5.2**: Map showing the location of seven climate stations (red triangles) used in this study

#### *5.2.1.3 Data preprocessing*

Data pre-processing entailed sub-setting of the CCAM data to the bounding box of the UMS boundary shapefile using the *'sellonlatbox'* algorithm in the Climate Data Operator (CDO) software. Furthermore, all datasets were reprojected into the same projection system (i.e. WGS84 to allow for easy overlaying). This was followed by checking completeness of the main variables for analysis in this study (i.e. precipitation, maximum temperature and minimum temperature) from all the CCAM ensemble members.

### 5.2.2 CCAM data bias correction methodology

Considering that CCAM data, like other climate simulation data have biases, it is important that bias correction be carried out to ensure that the modelled mean, variance, and/or higher moments of the distribution of climate variables are adjusted to more closely match the physical observations (Haerter et al., 2011, Teutschbein and Seibert, 2012, François et al., 2020). In this regard, the CCAM data used in this study came already pre-bias corrected using the methodology of Engelbrecht et al. (2015) for temperature and rainfall, and Engelbrecht and Engelbrecht (2016) for relative humidity. The methods essentially entail comparing the simulated and the corresponding monthly climatologies computed from the CRU TS4.04 data (National Center for Atmospheric Research Staff, 2019, Harris et al., 2020a, Harris et al., 2020b) for the baseline period (1961 - 1990) for each month of the year and for each of the CCAM 6 ensemble member simulations. The bias correction script written and compiled in Fortran implemented the linear scaling additive algorithm in the correction of temperature data and the linear scaling multiplicative algorithm to bias correct the precipitation data in a similar format described by Sippel et al. (2016). The algorithms build on conventional statistical bias correction schemes based on linear transfer functions of the form:

$$\boldsymbol{x_{cor} = a + bx} \qquad \text{[Equation 1]}$$

Where $\boldsymbol{x}$ and $\boldsymbol{x_{cor}}$ represent the simulated and corrected climatic variable, $\boldsymbol{a}$ and $\boldsymbol{b}$ are coefficients to be calibrated. The transfer function is applied additively (for temperature, i.e. $\boldsymbol{b} = 1$), such that:

$$\boldsymbol{a = \overline{T_{obs}} + \overline{T_{sim}}} \qquad \text{[Equation 2]}$$

Where $\boldsymbol{T_{obs}}$ and $\boldsymbol{T_{sim}}$ represent the means of simulated (CCAM data in this study) and observed (CRU data) monthly temperatures, respectively. To account for positivity constraints for precipitation, a multiplicative adjustment (correction factor) is applied such that:

$$\boldsymbol{a} = \frac{\overline{x_{obs}}}{\overline{x_{sim}}} \qquad \text{[Equation 3]}$$

A multiplicative (additive) correction factor is applied where the model simulation overestimates (underestimates) precipitation considering that model simulations are of higher resolution (at 8km × 8km) compared to the observations (CRU data in this case). A multiplicative factor is applied for regions where the model simulation overestimates precipitation, since the application of an additive factor could result in unrealistic “negative” precipitation values. A detailed description of this bias correction method is provided in Engelbrecht et al. (2015).

### 5.2.3 Data analysis

#### *5.2.3.1 Gridded data analysis (computation of multi-model future climatologies)*

Long-term and monthly mean climatologies were computed for all the CCAM data parameters for each of the baseline, near, mid-term and distant future periods (i.e. 1961 – 1990, 2021 – 2040, 2041 – 2060 and 2061 – 2099) respectively. For each of the six ensemble members, the difference between the baseline period and each of the future periods were also computed to determine projected (magnitude) future climate changes. Equation 4 shows the basic linear function form of the algorithm used for computing the magnitude of future climate change.

$$\boldsymbol{D_i} = \boldsymbol{a_i} - \boldsymbol{b_i} \qquad \text{[Equation 4]}$$

Where $\boldsymbol{a}$ and $\boldsymbol{b}$ represent a future time period and baseline period computed values for a specific climate parameter respectively, $\boldsymbol{D}$ represents the difference (magnitude of change) between baseline and future time periods while $\boldsymbol{i}$ = ensemble member.

Data were analysed using CDO tools and results visualised and mapped in grid format using GrADS software. All other further overlaying and refined mapping was executed using ArcGIS software.

### 5.2.4 Validation of CCAM model performance

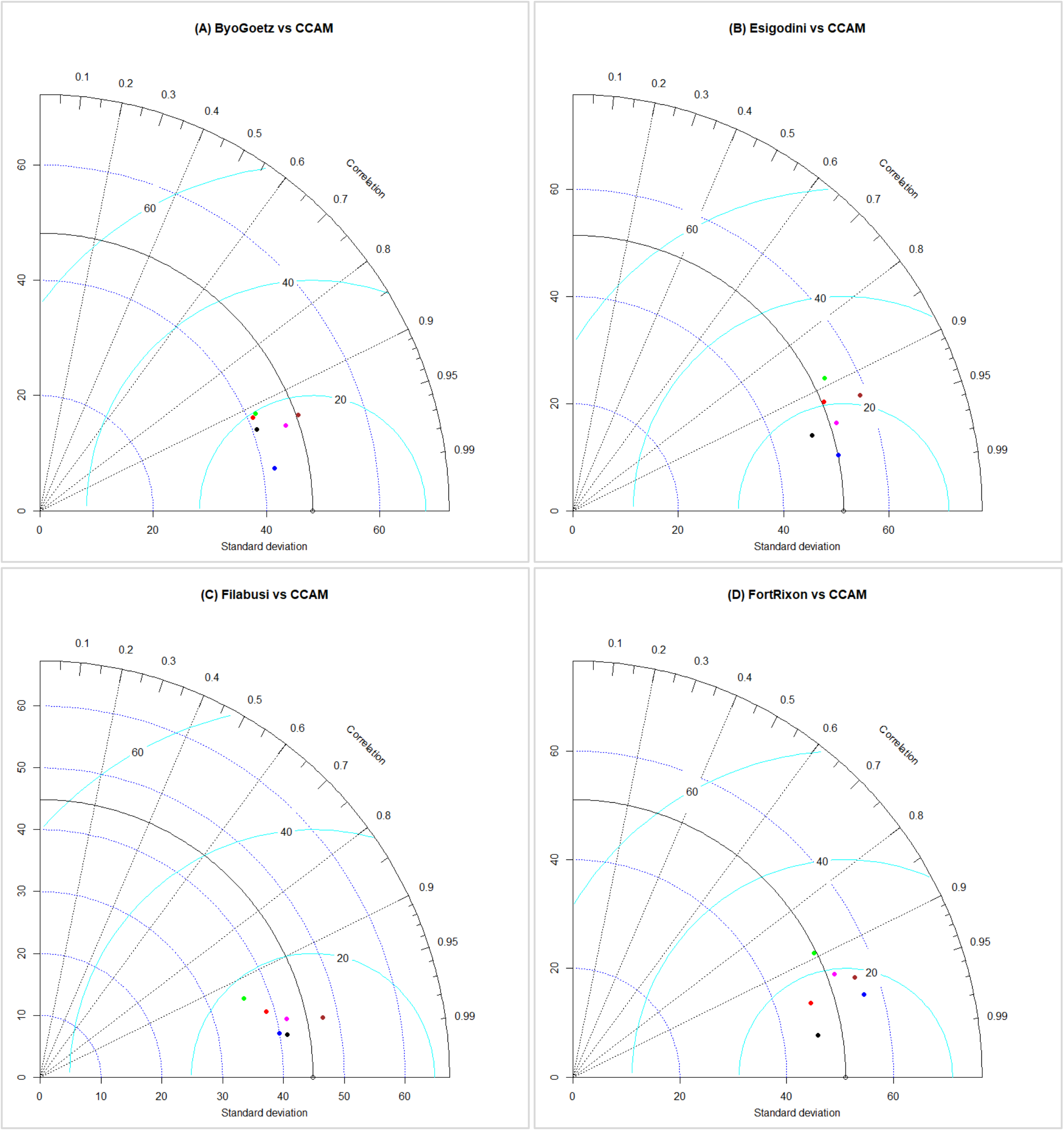
In this study, each model performance is tested by analysing how well each model simulates monthly total precipitation (rnd24) changes compared to the selected corresponding climate station locations (Table 5.2) for the baseline period (1961 – 1990). This is used as a measure of validation of the simulated climatologies in the study. Due to data paucity, validation is done for precipitation only. Validation is measured using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the Pearson's Correlation (r). Each of the model's performance measures (MAE, RMSE, and r) are compared and ranked to identify the top (worse) three scoring and thus performing models overall. Taylor's diagram (Figures 5.3 A – G) are used to present the validation results graphically i.e. to show the relationship between each ensemble member's RMSE, MAE and the r values while Table 5.3 shows values obtained for these measures.

MAE basically measures how far predicted values are away from observed values. Low (high) values of MAE indicated better (poor) performance and distributional agreement between the CCAM simulations and the station observed values, averaged across all quantiles. MAE is more robust to data with outliers hence a good measure of model performance. The RMSE on of the residuals (observed minus predicted) measures how close, on average, the predictions are to reality. In general, lower values of MAE, and RMSE imply higher accuracy of model while a higher values of 'r' are considered desirable as indicators of good model performance.

## 5.3 RESULTS AND DISCUSSION

### 5.3.1 Model validation

Taylor diagrams (Figures 5.3 A - H) illustrate how each of the ensemble members' performance compare to each of the seven station long-term average monthly precipitation for the baseline period (1961 – 1990). The diagrams show three performance metrics: i) standard deviation (SD) ii) correlation coefficient (r) and iii) RMSE between station observed and downscalings simulated long-term monthly average precipitation.



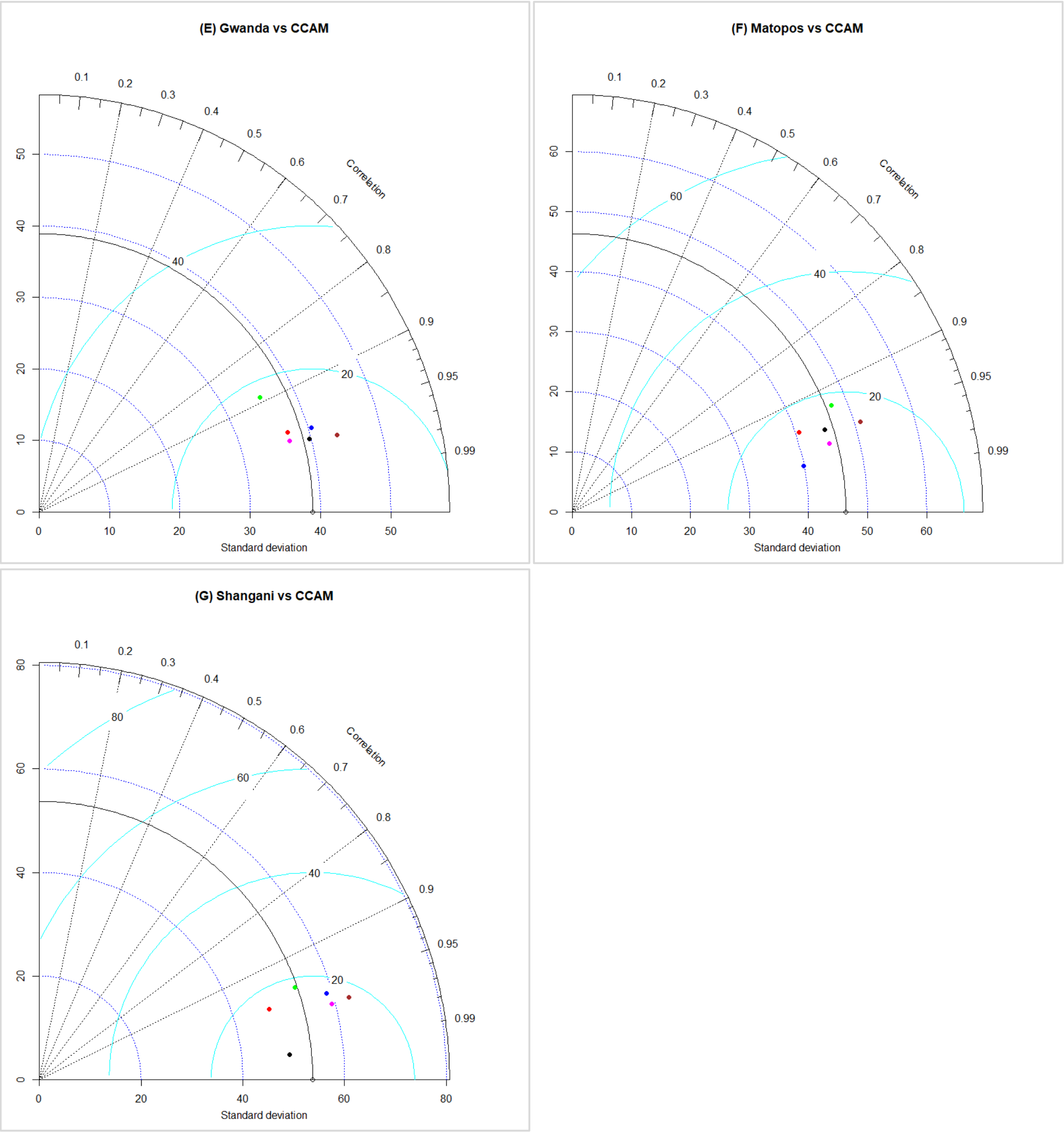


**Figure 5.3** Comparison of r, RMSE and SD for each ensemble member average monthly precipitation observations at Bulawayo Goetz, Esigodini, Filabusi, Fort Rixon, Gwanda, Matopos and Shangani (A, B, C, D, E, F and G) climate stations. Ensemble members are represented by dots on the Taylor diagrams: red = ACCESS1.0, green = CCSM4, blue = CNRM-CM5, magenta = GFDL-CM3, black = MPI and brown = NorESMI-M. The light blue contour lines represent RMSE values, dotted, dark blue lines = SD values while ‘r’ values are shown by dotted black lines increase downward along the quadrant arc

The Taylor Diagram indicates the baseline observed point where ‘r’ is 1 and RMSE is 0 (white dot on the x-axis). If the projected point is close to the observed station point, it means that they are similar in terms of SD, their ‘r’ is high, and their RMSE is close to zero. The solid black line that represents the SD of the observed time series. If dots are above (below) this line, it means that the model datasets have a higher (lower) variation that the station data. For example, the MPI model consistently shows variation higher than that of station observations in all stations while the CCSM4 and the ACCESS1.0 show an opposite trend (i.e. lowest ‘r’-values and higher RMSE). Relatively higher correlation (‘r’) as shown by the MPI and the CNRM-CM5 models shows a higher level of agreement between observed and projected data thus higher model accuracy.

Table 5.3 gives detailed values for each of these performance metrics (including MAE). The RMSE is considered a more robust measure of model performance compared to other parameters. The RMSE values range between 5.41 and 25.03, while the *r-values* range high between 0.8881 and 0.9952. Considering the three performance parameters, overall, the models can be ranked as follows, from highest to lowest performance: MPI > CNRM-CM5 > GFDL-CM3 >NorESMI-M> ACCESS1.0> CCSM4. The MPI and the CNRM-CM5 best model the average monthly precipitation in the UMS. These results give evidence of validity and hence more confidence when using simulations from these top performing models.

**Table 5.3:** RMSE, MAE and r values for all models at each station. Top three performing models are marked with an asterisk (*) and colour codes

| Validation | | Station | | | | | | | Rank Score |
|---|---|---|---|---|---|---|---|---|---|
| Measure | Model | ByoGoetz | Esigodini | Filabusi | FortRixon | Gwanda | MatoposNP | Shangani | |
| r | ACC85 | 0.9188 | 0.9195 | 0.9619 | 0.9562 | 0.9542 | 0.9455 | 0.9578 | 1 |
| | CCS85 | 0.9145 | 0.8881 | 0.9350 | 0.8926 | 0.8909 | 0.9270 | 0.9429 | 0 |
| | CNR85* | 0.9843 | 0.9794 | 0.9840 | 0.9630 | 0.9571 | 0.9815 | 0.9590 | 5 |
| | GFD85* | 0.9464 | 0.9500 | 0.9741 | 0.9323 | 0.9635 | 0.9678 | 0.9692 | 5 |
| | MPI85* | 0.9386 | 0.9549 | 0.9860 | 0.9862 | 0.9664 | 0.9524 | 0.9952 | 5 |
| | NOR85 | 0.9398 | 0.9301 | 0.9793 | 0.9447 | 0.9693 | 0.9559 | 0.9674 | 5 |
| MAE | ACC85 | 13.0440 | 12.3970 | 9.4164 | 9.9950 | 7.6584 | 11.4513 | 11.2639 | 1 |
| | CCS85 | 13.9053 | 14.5542 | 10.2328 | 12.1116 | 8.6695 | 12.5256 | 11.3380 | 0 |
| | CNR85* | 10.0484 | 7.5454 | 6.8688 | 10.1106 | 7.1339 | 8.5900 | 10.1617 | 7 |
| | GFD85* | 10.3918 | 10.0805 | 7.1038 | 10.1960 | 6.1421 | 7.5824 | 10.6923 | 6 |
| | MPI85* | 12.8328 | 9.8751 | 5.9693 | 5.8352 | 7.4025 | 11.0715 | 3.7371 | 6 |
| | NOR85 | 12.4794 | 18.3027 | 8.2676 | 15.4948 | 10.3795 | 11.6404 | 16.3835 | 1 |
| RMSE | ACC85 | 20.0644 | 19.9908 | 13.3550 | 14.7043 | 11.2315 | 16.0482 | 15.8382 | 2 |
| | CCS85 | 22.1043 | 25.0368 | 18.7999 | 23.7009 | 17.8100 | 18.8414 | 18.1431 | 0 |
| | CNR85* | 13.3331 | 10.5977 | 10.2148 | 16.5157 | 11.9141 | 12.5617 | 17.5598 | 5 |
| | GFD85* | 16.6288 | 16.4746 | 10.0742 | 18.9862 | 10.2167 | 12.1640 | 16.1487 | 6 |
| | MPI85* | 19.7225 | 15.3012 | 8.6483 | 9.2751 | 10.4629 | 15.1951 | 5.4130 | 6 |
| | NOR85 | 16.6333 | 24.7783 | 11.7897 | 21.1470 | 13.5305 | 16.1875 | 23.8769 | 1 |

*(Colour codes: Red = highest, Orange = high, Green = Average)*

The MPI ranked highest with a total rank score of 17 while the CCSM4 ranked lowest with a score of 0.

### 5.3.2 Baseline period (1961 – 1990) precipitation conditions

In this section, baseline climatologies are displayed for each model in Figure 5.4 A- F.

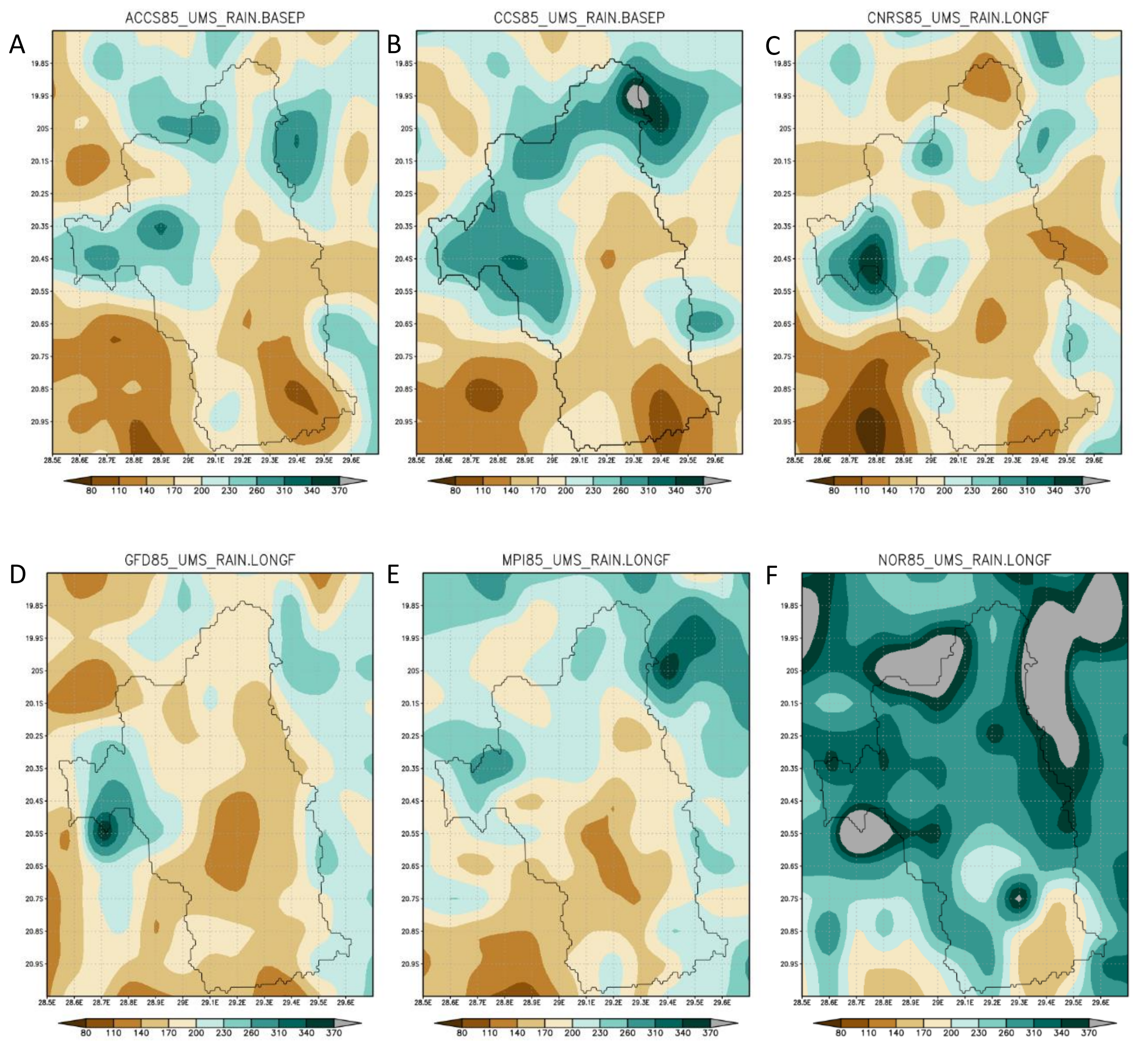


**Figure 5.4** Maps showing spatial patterns of baseline conditions of long term average of total precipitation for the 6 ensemble members (A, B, C, D, E, and F) (ACCESS1.0, CCSM4, CNRM-CM5, GFDL-CM3, MPI-ESM LR and NorESMI-M respectively). All models basically show similar spatial pattern i.e. a south to north gradient of low to high precipitation conditions between 1961 to 1990 (range 90mm to 550mm)

The downscalings are indicative of a marked spatial gradient in rainfall across the catchment. Rainfall increases from less than about 110 mm in the southern part of the domain to more than

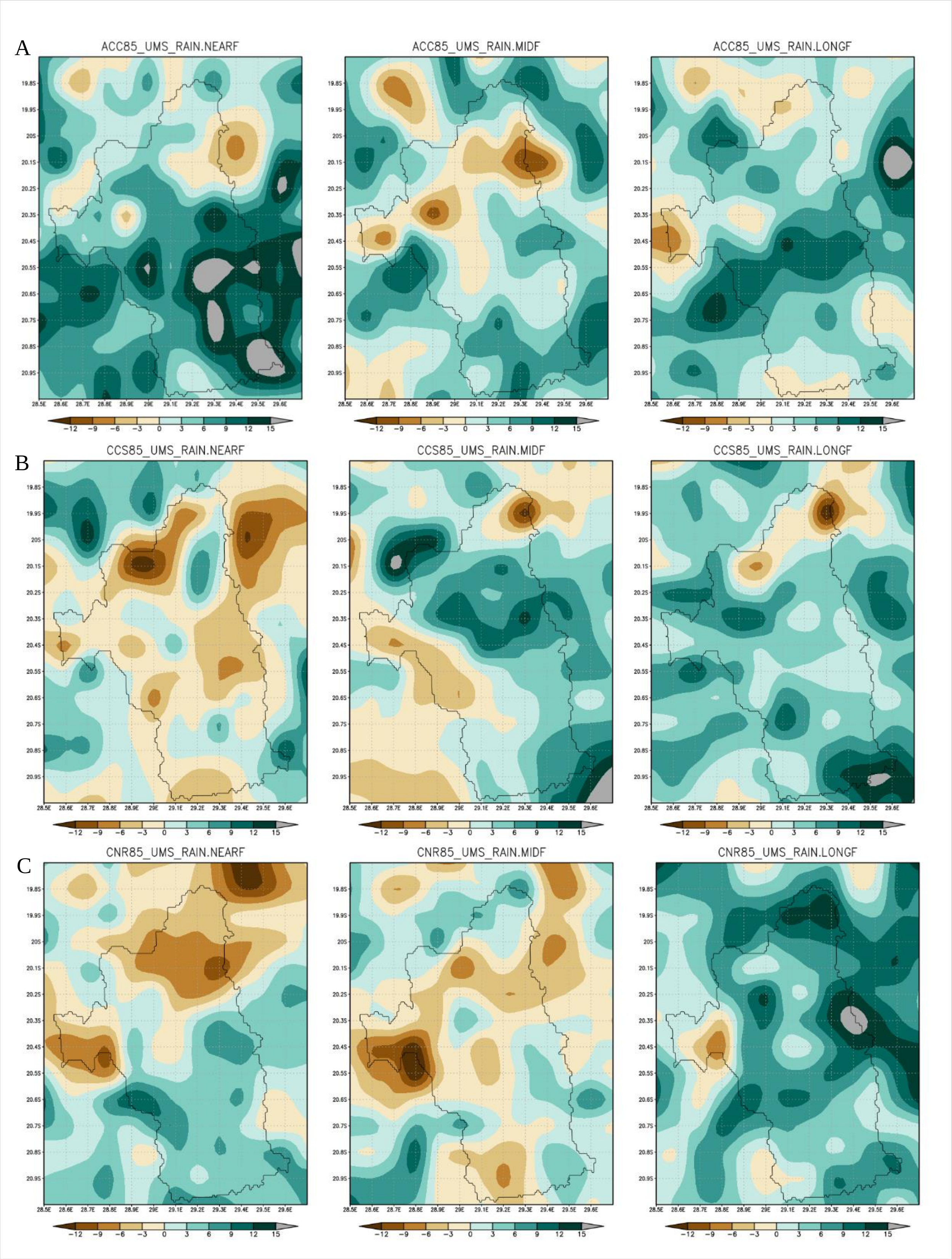
340 mm in the north. This pattern can be attributed to the local topography of thee area which generally is mountainous to north-eastern region and decreases southwards into the northern Limpopo escarpment. This place is characterised by low-rainfall (Love et al., 2005, Sibanda et al., 2020) and majority of the downscalings reflect this pattern with the exception of the NorESMI-M which shows higher rainfall deeper south of the domain.

### 5.3.3 Projected future precipitation changes in the UMS

The results (Figure 5.5 A, B, and C) show a general pattern of increasing in annual average of total annual precipitation from three of the models (i.e. the ACCESS1.0, CCSM4 and CNRM-CM5) while the other two (GFDL-CM3 and NorESMI-M) show declining trends with some variations in the magnitude of the anomaly signals over the three future periods.

#### *Near-term future precipitation climatology*

Models show an overall anomaly signal ranging from -15 mm to +18 mm change in annual total precipitation over the UMS. Considering the annual total precipitation in UMS ranges between 450 mm to 650 mm according to Love et al. (2005), this translates to changes in this range to minimum 435 mm and maximum 668 mm per annum in the future. The ACCESS1.0 model (Figure 5.5 A) shows a strongest positive signal (>15 mm) in the greater extent of the study area with the exception of the north-eastern region which shows a moderate, negative signal. This similar pattern is also observed in the CNRM-CM5 projections though the magnitude of change is lower by between 2 mm to 4 mm following a north-south increasing gradient as well. The GFDL-CM3 model on the contrary projects an opposite gradient of change i.e. positive anomalies in the northern region and a declining trend of up to 3mm of precipitation in the southernmost extent of UMS (see Figure 5.4 D). Such a trend could imply more precipitation potentially translating to stream flow thus increasing water levels in the 5 major supply dams for the City of Bulawayo. The CCSM4 and the NorESMI-M model on the other hand, project a distinct, predominantly negative precipitation signal over ~90% of the UMS though the latter shows a much stronger magnitude of change (of as low as -15 mm) especially in the south-eastern region covering the Filabusi area. Of note in the near-future projections is that all downscalings with the exception of the GFDL-CM3 show consistency in projecting a negative anomaly signal over the north-eastern extent of the UMS (an area stretching over Shangani and Insiza). This region host the greater part of the catchment area of the largest water supply dam in this area (the Lower Insiza dam) and the smaller Upper Insiza dam which means there is a possibly of reduced water inflows to these strategic reservoirs with negative impacts on water security and/ rain-fed agriculture in a round this region of the UMS.



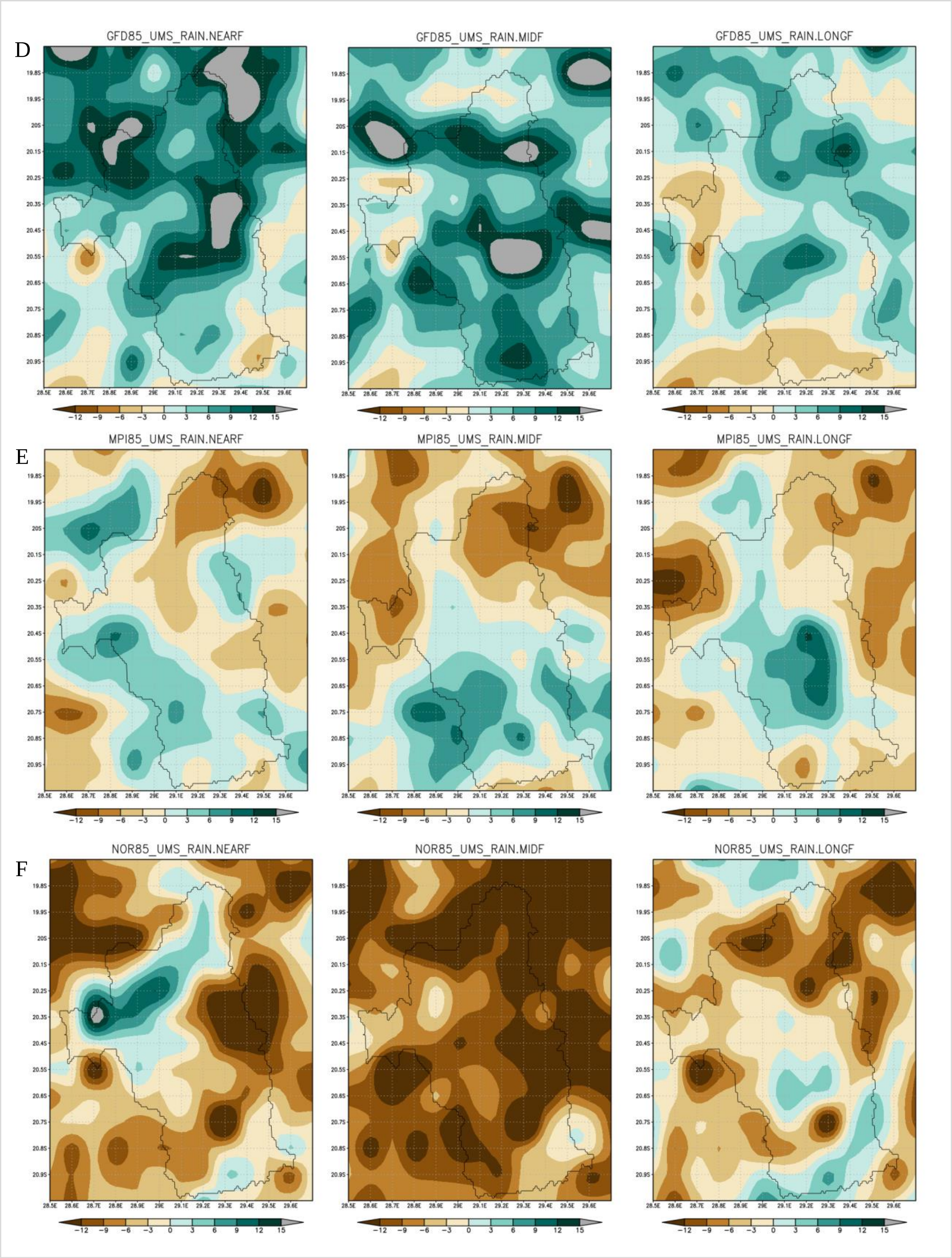


**Figure 5.5** Projected spatial patterns of change in long term average of total precipitation 6 ensemble members (A, B, C, D, E, and F) (ACCESS1.0, CCSM4, CNRM-CM5, GFDL-CM3, MPI-ESM LR and NorESMI-M respectively) over the UMS. The NorESMI shows greatest negative precipitation anomaly of > -12mm in the mid-term future

### *Mid-term future precipitation climatology*

In this future period, there are still differences in the magnitudes of the precipitation change in the six member CCAM simulations. Comparatively, while three of the ensemble members (ACCESS1.0, CCSM4 and GFDL-CM3) show a predominantly positive precipitation anomaly, the magnitude of change is clearly lower relative to the near future period. The positive anomalies range between +3 mm and +9 mm compared to +3 mm and +15 mm in the near-future period. Of these there models, the GFDL-CM3 shows the strongest magnitude of positive change especially in interior regions of the UMS covering Mzingwane dam, Inyankuni and Ncema dam sub-basin zones. On the contrary, the NorESMI-M model (Figure 5.5 F) distinctly and consistently shows an intensifying negative precipitation anomaly over the UMS (> 12 mm). The magnitude of this anomaly is most pronounced in the northern tip (Bulawayo area), eastern (Filabusi) region and the north-western (Matopos) sub-region of the UMS. Such anomalies could be influenced by mid-tropospheric troughs located 25°S over the east and west coasts of Africa near which have long been known to increase anti-cyclonic vorticity over south-eastern Zimbabwe in dry spells (Matarira and Jury, 1992). The wetter conditions on the other hand could an indication of a stronger influence of the known wet phases of the Dyer–Tyson cycle which favours the tropical systems landfall and their subsequent westward shift from the South-western India Ocean over southern Africa. These bring heavy rainfall over southern Zimbabwe (where the UMS is situated) (Malherbe et al., 2012). Shifts in the El Niño Southern Oscillation (ENSO) which are known to strongly influence rainfall variability over Zimbabwe (Makarau and Jury, 1997, Phillips et al., 1998, Unganai and Mason, 2001a, Meque and Abiodun, 2015). Overall, in this future period, the CCAM simulations show slightly better agreement in terms of a declining (increasing) intensity in the positive (negative) long tern average change in total precipitation over much of the UMS.

### *Long-term future precipitation climatology*

The downscaling projections show no clear consensus in long term average of total precipitation in this period over the UMS though a majority (four) of the ensemble members project a general increase in the positive anomaly strength. These members are the ACCESS1.0, CCSM4, CNRM-CM5, and the GFDL-CM3. They projection a positive trend especially in the interior (Mbalabala) and southern (towards Gwanda-West Nicholson) regions of the UMS. The CCSM4 and the CNRM-CM5 seem to be the only two models which consistently agree and project progressively improving precipitation conditions from the near-future to the mid-term right through the long term future period. The magnitude of change is between +3 mm and +12 mm especially in interior region. The NorESMI-M on the contrary projects negative anomalies in precipitation conditions relative to the mid-term future period. It is important to note that all downscalings (with the exception of the CCSM4) reveal a consistent and distinct negative anomaly in the north-western (Matopos) region and the north-eastern (Insiza, Fort Rixon) regions of the UMS. Though such long term projections are known to be fraught with large uncertainties concerning future changes in precipitation due to its stochastic nature (Evans et al., 2016) these findings give a glimpse of possible long term future precipitation scenarios in the UMS that can be valuable in understanding future changes outside the natural variability and thus guide planning and decision making.

Overall, while authors such as Archer et al. (2018) project that southern Africa is likely to become generally drier under low-mitigation climate change futures, the trends they present are broad and general and do not present the level of detail presented in this study. This study has managed to disaggregate the course/ general southern African regional projected precipitation signals revealed in studies such Fučkar et al. (2020) and Shongwe et al. (2015) to reveal fine, local scale variations of these. For example, the contrasting dry west and wet east pattern in the precipitation zonal gradients over southern Africa found by Bell et al. (2018) using the CORDEX projections are partly captured in some of the mid to long term projections by the CCSM4, the CNRM-CM5 and the GFDL-CM3 models at a finer scale in this study (see Figures 5.4 B, C and D). While there could be a number of atmospheric and surface related factors influencing the future projected precipitation climatologies presented here, it is already established in that some systems play a major role in the local climate covering the UMS. For example, some of the wet-dry patterns seen in this study are known to be influenced by pronounced annual cycle as well as high inter-annual variability influenced by the Hadley circulation (Diaz and Bradley, 2004, Karnauskas, 2014) and movement of the associated main tropical cloud and rain band/ the Intertropical Convergence Zone (ITCZ) (Nicholson, 2018). In this regard, the future global changes in Sea Surface Temperature (SSTs) and the extent and duration of excursion of the ITCZ into southern Zimbabwe are most like to be the driving forces shaping the future trend and patterns of precipitation revealed in this study. The study shows that ensemble members do not all have a total consensus on future precipitation conditions in the UMS though the indication is towards a general increasing trend in the long term average trends of total annual precipitation in the UMS. The disagreements in the projected future precipitation conditions are not uncommon in climate projection studies. These have been attributed to variations in ensemble member structure, scenarios and model configuration, initial conditions and differences and/ failure in handling local feedback mechanisms that have a bearing precipitation (Rodo and Comin, 2003, Torn and Harte, 2006, Friedlingstein et al., 2014). Other potential reasons for the variations in projections observed in this study relate downscaling uncertainty (which is known to be significant for variables primarily affected by local processes, such as summer convective precipitation) and Greenhouse gas (GHG) emission scenario uncertainty which tend to affect near-term and long-term projections differently as highlighted by Arora (2019). Notwithstanding all these limitations, the projections presented in this study show future precipitation scenarios in UMS at a higher resolution never presented before for the first time in the semi-arid northern Limpopo region using high resolution downscaled CCAM ensemble data.

### 5.3.4 Baseline maximum (tmax) and minimum (tmin) temperature climatologies

Baseline mean monthly tmax (tmin) are displayed for each downscaling in Figure 5.6 A - F (Figure 5.7 A-F). All models agree and show a distinct north to south gradient of increasing tmax ranging between 23°C and 29.5°C over the UMS though there are minor variations of approximately ±0.5°C. The NorESMI-M downscaling shows relatively lower tmax values of all ensemble members. With regards to tmin, similar patterns are observed whereby all downscalings show an increasing north to south gradient in tmin with variations of between ±0.2°C among the ensemble members. The central south-eastern part of the domain consistently shows relatively higher tmax (tmin) values slightly above 29.5°C (13.5°C).

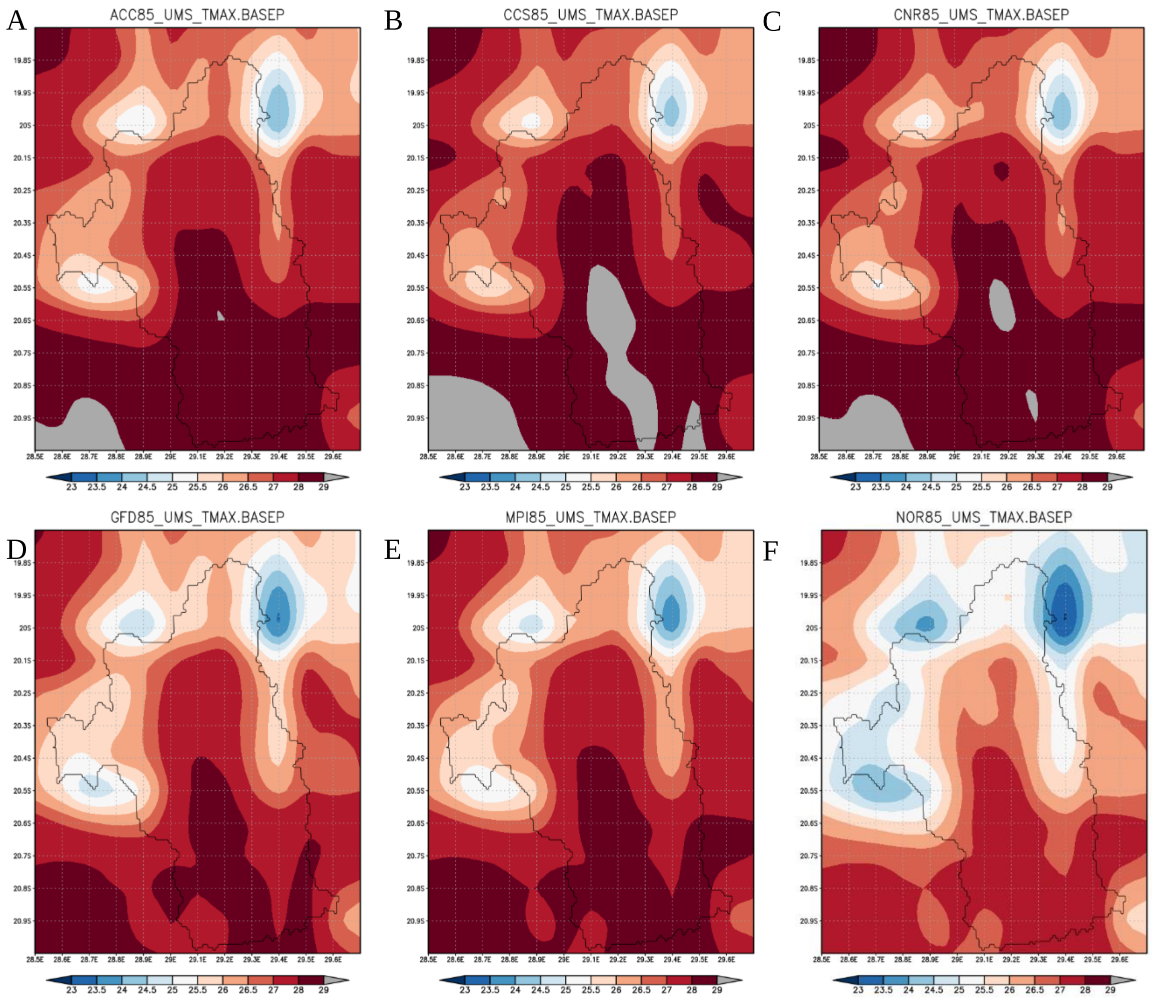


**Figure 5.6** Spatial patterns of baseline mean monthly maximum temperature (tmax) for the 6 ensemble members (A, B, C, D, E, and F) (ACCESS1.0, CCSM4, CNRM-CM5, GFDL-CM3, MPI-ESM LR and NorESMI-M respectively)

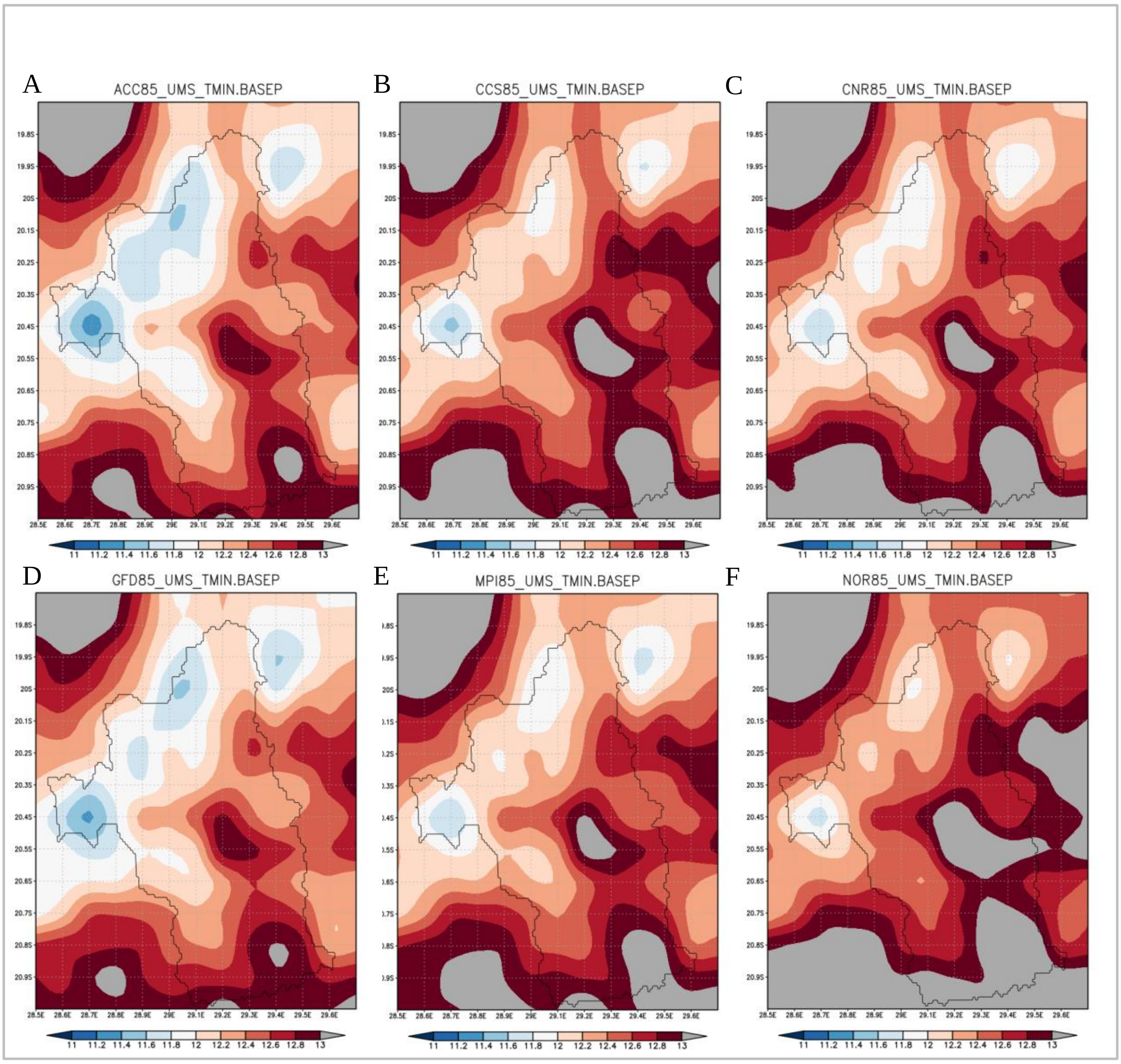
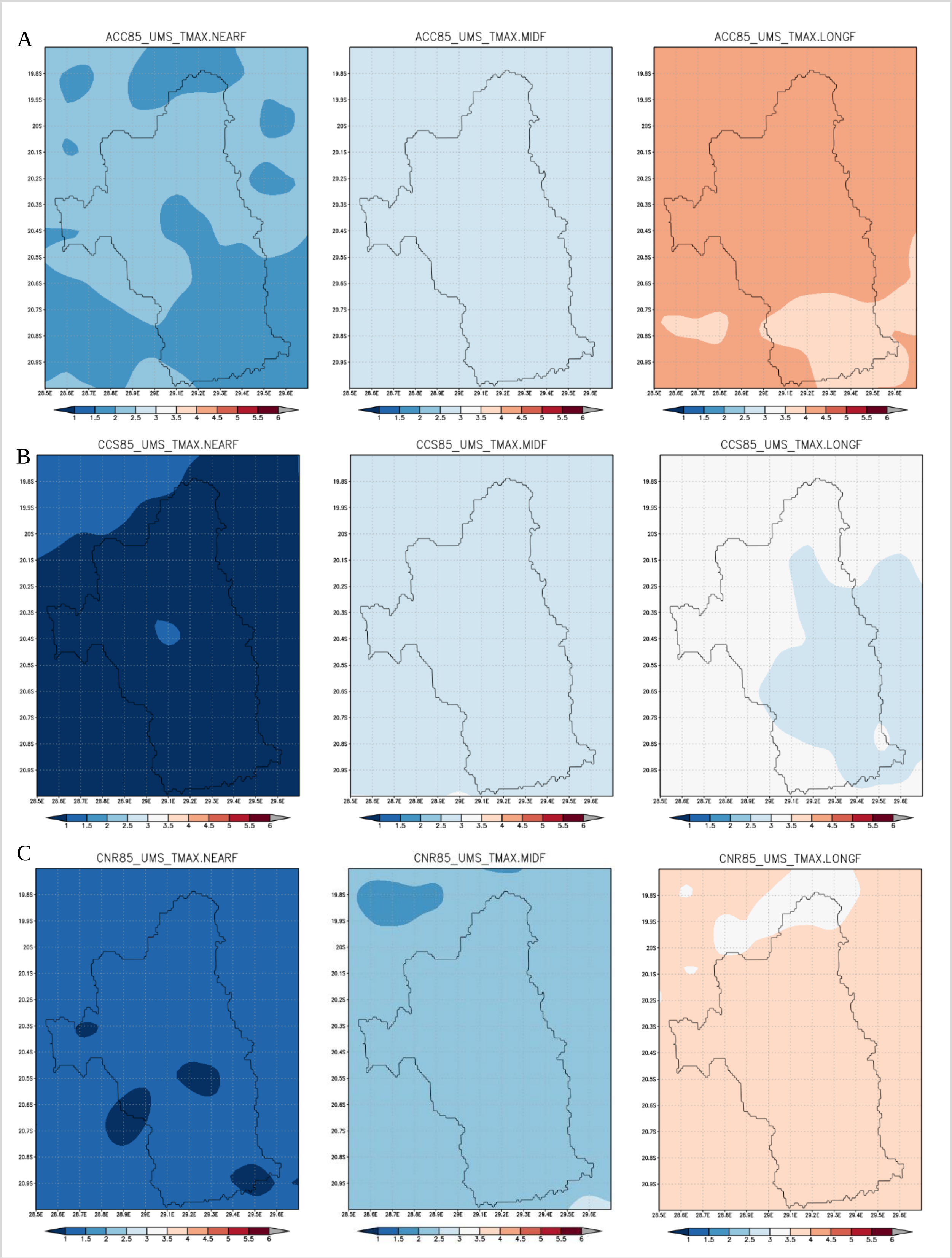


**Figure 5.7** Spatial patterns of baseline mean monthly minimum temperature (tmin) for the 6 ensemble members (A, B, C, D, E, and F) (ACCESS1.0, CCSM4, CNRM-CM5, GFDL-CM3, MPI-ESM LR and NorESMI-M respectively)

These baseline downscalings are consistent with observed tmax and tmin values of the region which are well documented in studies such as Sibanda et al. (2018) and (Love et al., 2005) though there is greater detail on changes tmax and tmin spatio-temporal patterns over the UMS.

### 5.3.5 Projected future temperature (tmax and tmin) changes in the UMS

Figure 5.8 (Figure 5.9) show general patterns of change of projected mean monthly maximum (minimum) temperature changes in the near, mid-term and long-term future periods for the six ensemble members relative to baseline 1961-1990 period.


A
ACC85_UMS_TMAX.NEARF
ACC85_UMS_TMAX.MIDF
ACC85_UMS_TMAX.LONGF
B
CCS85_UMS_TMAX.NEARF
CCS85_UMS_TMAX.MIDF
CCS85_UMS_TMAX.LONGF
C
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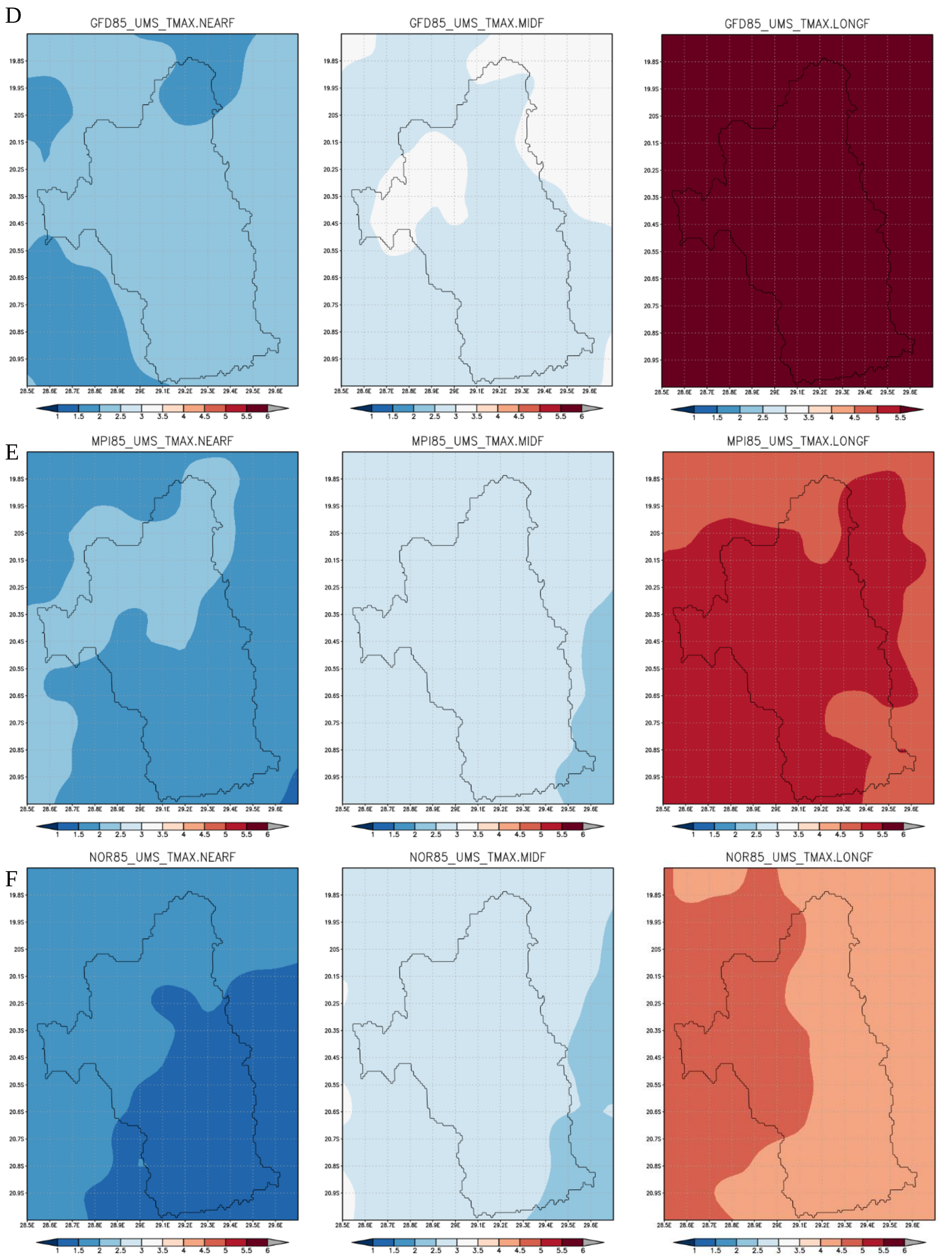
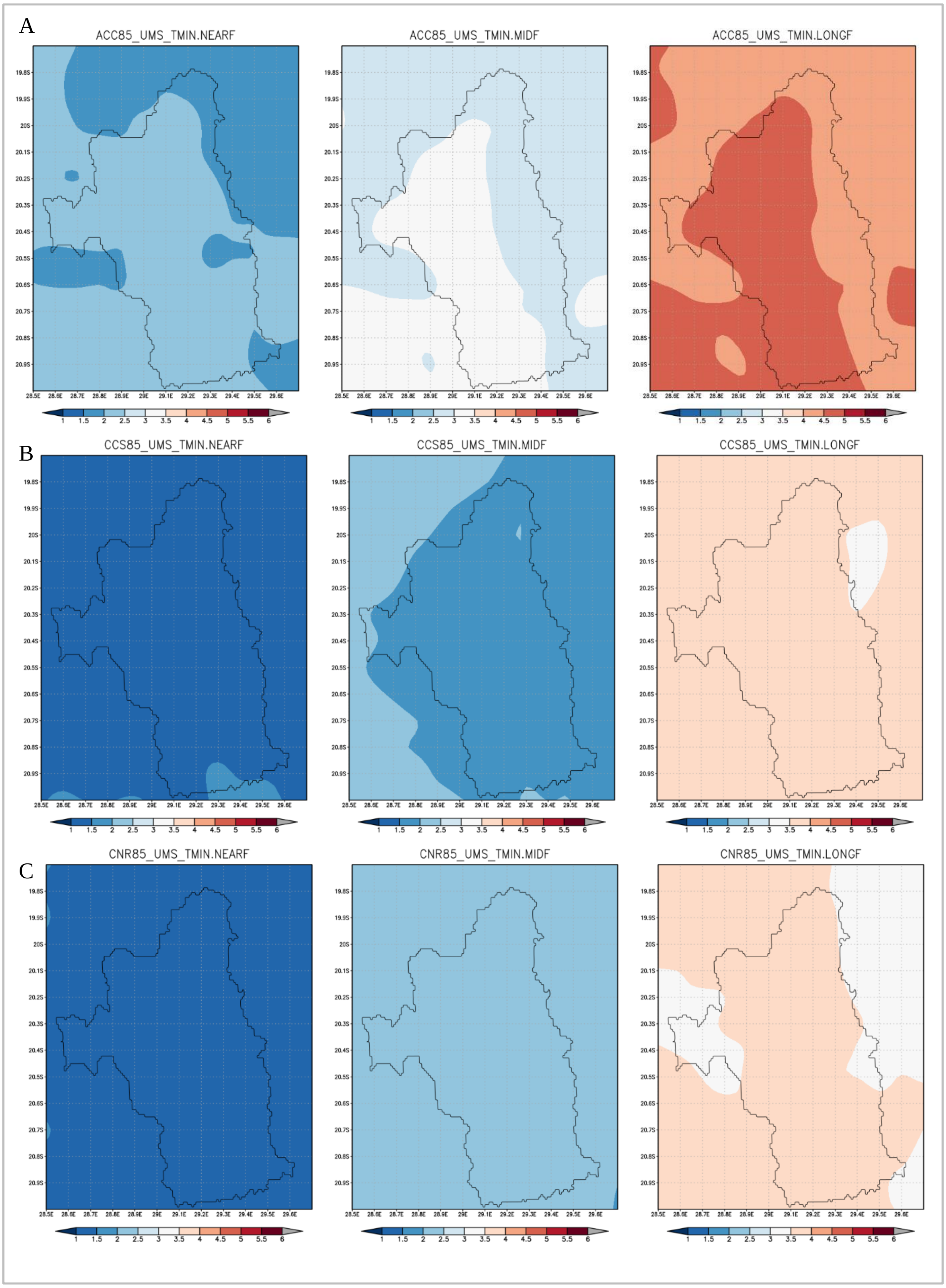


**Figure 5.8** Projected spatial patterns of future mean monthly maximum temperature anomalies from the 6 ensemble members over UMS. Generally, all models (A – F) project progressively increasing trends in mean maximum temperature changes over the entire UMS in all future time periods with a signal amplitude ranging between +1.1°C and +6.6°C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CCS85_UMS_TMIN.MIDF
CCS85_UMS_TMIN.LONGF
C
CNR85_UMS_TMIN.NEARF
CNR85_UMS_TMIN.MIDF
CNR85_UMS_TMIN.LONGF
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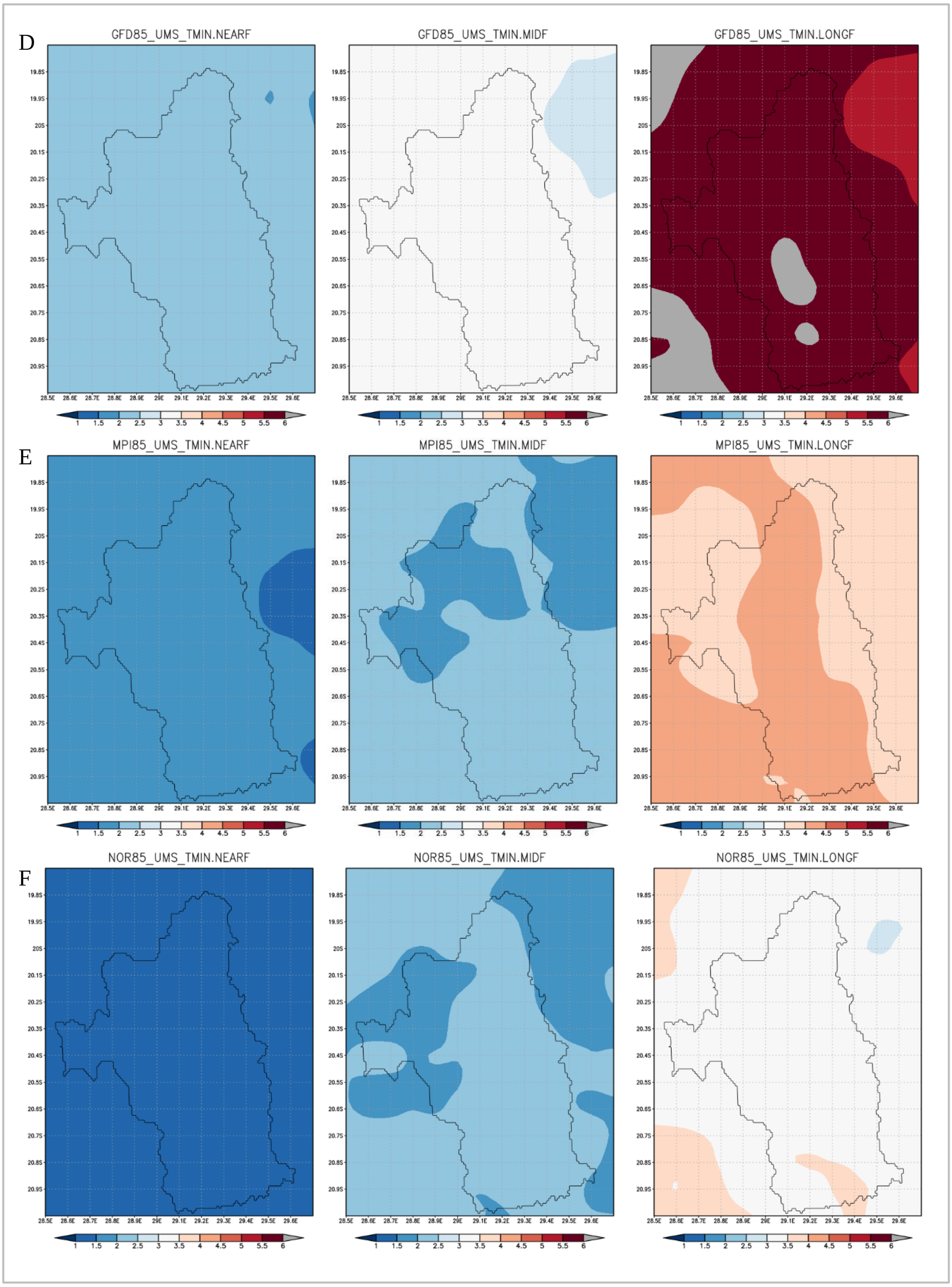


**Figure 5.9** Projected spatial patterns of future mean monthly minimum temperature (tmin) anomalies from the 6 models. All models project generally progressively increasing trends in mean minimum temperature changes over the entire UMS in all future time periods with amplitude of change ranging between +1.17℃ and +6.1℃

### *Near-term future temperature climatologies*

Near-term future tmax projections show a positive signal with an amplitude range of between +1.4°C and ~ +2.3°C for all ensemble members over the 20 year (2021 to 2040) period. This translated to an increase of between +0.7°C to +1.15°C decade$^{-1}$ in mean tmax. The GFDL-CM3 (Figure 5.6 D) model projects the strongest amplitude of change of up to +2.3°C in the interior-south eastern regions of the UMS while the CCSM4 model shows the weakest signal of up to ~ +1.1°C over the domain. All other models (CNRM-CM5, MPI and NorESMI-M) show a general consensus in the spatial pattern of change in mean tmax which shows an almost homogenous marginal increase in mean tmax of between +1.2°C and +2.3°C.

With regards to tmin, downscaled projections (Figure 5.8) also show increasing trends for all ensemble members though there are differences in the amplitudes of the signals. The ACCESS1.0 (NorESMI-M) models project the strongest (weakest) mean tmin change signals of between +1.9°C and 2.35°C (+1.15°C and +1.35°C) over the near future period. Of note in the findings is that all models (with the exception of the CCSM4) project a distinct, consistent high amplitude of positive change in the interior (Mzingwane – Mbalabala) region following a north – south pattern in the UMS.

### *Mid-term future temperature climatologies*

Results for mid-term (2041 – 2060) future show that models have distinct spatial patterns of change in future tmax projections though they reveal a clear consensus of an increasing amplitude range of ~ +45% compared to the near future period projected ranges. However, the MPI and the NorESMI-M downscalings (Figure 5.8 E and F) show a declining trend in the positive signal with amplitude ranging from +3°C to ~ 2.2°C following a north-western – south-eastern gradient.

Tmin projections in the mid-term show the highest amplitude of change from the GFDL-CM3 model (range +3.05°C to +3.3°C) followed by the ACCESS1.0 model (range ~ +2.8°C to 3.25°C). These two models also show similar spatial patterns of tmin change variation whereby the signal is strongest in the interior region of the UMS. This area is hosts communal and newly resettled farmers besides the illegal and small-scale artisanal gold mining activities as mentioned in the earlier Chapters of this thesis. On the other hand, the NorESMI-M model showed the lowest projected change with range between +1.9°C and +2.19°C.

### *Long-term future temperature climatologies*

All ensemble members project a continued warming in this time period with the upper (lower) range tmax value +6.6°C (3.0°C) in the UMS. The GFDL-CM3 model projection shows the highest amplitude of change while CCSM4 shows the lowest change. A unique, distinct strong positive pattern of change in tmax (characteristic of increased warming) is noted in all model projections for the entire western stretch of the UMS covering Matopos, parts of Esigodini and stretching all the way south towards Gwanda compared to the eastern region of the UMS.

As for tmin, all ensemble members also project similar increases in long term mean monthly tmin following the same, earlier described pattern tmax. The rank order of the model projections of tmin (from highest to lowest) in terms of amplitude of changes is as follows: GFDL-CM3 > ACCESS1.0 > MPI > CCSM4 > CNRM-CM5 > NorESMI-M. The amplitude of increase in tmin is also stretches along western region of the UMS but unlike the tmax signal, it appears to be more pronounced in the central region and then diffuse in an easterly direction across study area relative the patterns shown in the mid-term future.

Overall, the temperature (both tmax and tmin) patterns of warming of up to +6°C in the mid to long term future revealed in this study corroborate with other regional future temperature simulations over Southern Africa in studies such as (Sithole and Murewi, 2009, Daron, 2014, Meque and Abiodun, 2015, Scholes et al., 2015, Engelbrecht and Engelbrecht, 2016). In this study, results show for the first time how this climate change signal varies in space at a local scale in Zimbabwe. Such patterns of continued warming in/ rising temperature are most likely to result in potentially negative health impacts such as redistribution of disease vectors such as anopheles mosquitoes *(Anopheles gambiae)* and tsetse flies *(Glossina morsitans)* and hence disease endemicity (Patz and Olson, 2006, Gage et al., 2008, Caminade et al., 2019). There are possibilities of reduced plant species diversity (Gwitira et al., 2014) and drastic increases high impact climate events such as heat-wave days and high fire-danger days as well (Engelbrecht et al., 2015, Dosio, 2017). Furthermore, it is already well acknowledged in research and by the IPCC that any temperature increase of over 1.5°C to 2°C are most likely to have serious adverse impacts especially in less climate reliant and poorly adapted communities in semi-arid regions such as southern Africa (IPCC, 2018, Maúre et al., 2018, First, 2019). As such, since the project changes in this study frim the mid-term already indicate amplitudes of over 2°C, such conditions can also alter natural patterns of the hydrological system in the UMS e.g. evapotranspiration and hence water availability in this region. Water levels in the main water reservoirs for Bulawayo are also likely to be negatively impacted by increased evaporation since the projections point towards progressively rising temperatures overall. Soil moisture is also like to be negative impacted and thus agricultural productivity as pointed out by (Masikati et al., 2019). Furthermore, the ensuing fluctuations in diurnal temperature ranges as a result of the projected fluctuations in tmax and tmin will also lead to changes in crop suitability of the local climate thus rendering some crops no-viable in some parts of the UMS. This could bring about food security challenges in the future if cropping conditions for the main staple crop i.e. maize (*Zea mays*) is impacted in this way in this area.

## 5.4 CONCLUSION

Results of this study demonstrate for the first time the successful application of downscaled high resolution CCAM ensemble climate data in simulating future climatic (precipitation and temperature) conditions at a catchment level in the northern Limpopo basin. While the CCAM downscaled future precipitation projections show no clear consensus on the future precipitation conditions in the UMS, it is apparent that trends are more inclined towards increased precipitation trends especially in the northern regions compared to the southern regions. The amplitude of change is shown to be decreasing though overall the total levels are projected increase. This may indicate concentration or increase in frequency/ incidence of high rainfall or extremes events over shorter time periods in the future time periods. From the findings, it can concluded that a distinct decreasing total precipitation signal in the westernmost extent of the UMS which is around the Matopos National Park is also revealed in this study. It is worth noting that two models i.e. the MPI and the NorESMI-M seem to agree on a decreasing trend and intensifying magnitude of change in annual total precipitation change throughout all the future periods. In this regard, such contradictory findings introduce some measure of uncertainty on the future trajectories precipitation in the UMS beyond already presented predominant indicative increasing (decreasing) changes in the north (south) regions of the study area by the ensemble consensus. Furthermore, it be concluded that the MPI, CNRM-CM5 and the GFDL-CM3 are the top-three models with relatively high competence in simulation future long terms average monthly precipitation climatologies in the UMS while the CCSM4 and the ACCESS1.0 have the lowest performance. As such, any consensus in precipitation simulations among any two or all of these top-performing models can be considered an indication of a more likely future climate scenarios with greater certainty. Such scenarios can be used with some measure of confidence in planning for climate impact mitigation in the UMS.

With regards to temperature projections, it can be concluded that models show a progressively warming climate over the UMS from the near-future through to the long-term future which is consistent with the IPCC of between 4 to 6°C over the tropics during the 2st century. The magnitude of change is projected to range from ~ 1.1°C to just over 6°C for both maximum and minimum temperature. Such increases in temperature may drive and/ alter evapotranspiration dynamics and hence precipitation in the UMS. The models mid to long term future projections show a strong positive signal in the western stretch of the UMS following a decreasing gradient in a west to east direction. The consequences of a warming climate and projected wetter (drier) conditions could negatively impact on food production systems (especially irrigation and rain-fed agriculture), water security (especially for the city of Bulawayo) and vector-borne disease incidence and distribution in the future periods in the UMS. As such, the projected future climate scenarios revealed in this study can serve as a guide in the formulation and/ appraisal of policies, strategies and programmes aimed at enhancing climate impact mitigation, resilience, adaptation and adaptation in communities within and outside of the UMS whose livelihoods are dependent on the resources of the UMS.

It is recommended that simulation of precipitations presented in this study be used or incorporated into climate resilience, adaptation and impact mitigation plans and strategies for the UMS by the Zimbabwe Civil Protection Unit (CPU) and other humanitarian agencies operating in the area. This may entail using the precipitation and temperature projections as a general guide for mid to long-term strategy development to prepare communities for possible climate shocks related to the scenarios presented in this study. Furthermore, provincial and local (rural district council) authorities in jurisdictions of Esigodini, Filabusi, Gwanda and parts of Mberengwa could leverage thee findings to incorporate climate proofing community development strategies and plans. However, it is important that validation of the temperature projections presented in this study be carried out to ascertain each of the ensemble member competence if simulating the future tmax and tmin conditions in the UMS. Such steps may complement the validation efforts implemented in this study and thus help in the presentation of a more complete and validated picture of the future climate of the UMS. Thereon, holistic climate impact mitigation interventions can be planned for and implemented accordingly.

# CHAPTER 6: Modelling land use – land cover change and climate change impact on surface run-off in the UMS

*Based on a manuscript in preparation*
*Title: Modelling future impact of land use – land cover and climate change on surface hydrology in the upper Mzingwane sub-catchment (northern Limpopo basin), Zimbabwe using HecHMS and GeoHecHMS model*

## 6.1 INTRODUCTION

Water is indispensable for human existence and thus the management of water resources is one of the most pressing current global challenges (Chaplin, 2001, Molden, 2013, Staddon and Scott, 2018, Makarigakis and Jimenez-Cisneros, 2019). The rising need to feed the projected 2 to 4 billion more people by 2050, eliminate poverty, and reverse ecosystem degradation, are expected to globally exacerbate water scarcity and security (Cohen, 2003). These challenges are expected to be most pronounced in many semi-arid international/regional river basins with shared water resources, such as the Nile, and where water securitisation practices are set to be key in the evolution of future water conflicts (Ashton, 2003, Stetter et al., 2011, Zeitoun et al., 2020). With the likelihood of water conflicts set to increase as populations continue to grow, climate change and its manifest impacts are also projected to exacerbate water security challenges (Allan et al., 2013, Eekhout et al., 2018). This is especially true in most parts of Africa where community climate resilience, mitigation and adaption capacities are very low, coupled with high climate change vulnerability (Swain, 2004, Petersen-Perlman et al., 2017, Schilling et al., 2020).

Most climate model simulations from numerous studies indicate increases in incidence of extreme events such as droughts and floods, which will most likely negatively impact on rain-fed agriculture (and thus food security), river regime dynamics (and thus water and energy security) and general community livelihoods (Milly et al., 2005, Gualdi et al., 2013, Mpandeli et al., 2018a, Shah et al., 2019, Mtilatila et al., 2020). Essentially, climate change has taken centre stage to become an indirect driver of social instability (Mpandeli et al., 2018b). Furthermore, future climate impacts on river systems indicate negative trends. For example, future climate change scenarios are projected to result in an average 21.8% decrease in streamflow in Thailand (Shrestha et al., 2018) and increase in flood peak and volume in some parts of the world (Gao et al., 2020). Coupled with this, the Intergovernmental Panel on Climate

Change (IPCC) Special Report on Climate Change and Land (SRCCL), further revealed that accelerated anthropogenic land use – land cover (LULC) changes will most likely lead to extensive desertification and land degradation. This will not only impact on food security and ecosystems stability, but also significantly contribute to the alteration of hydrologic systems in many regions globally, thus worsening the water security situation (Milly et al., 2005, Sterling et al., 2013, IPCC, 2019, Huang et al., 2020).

Available scientific evidence indicates that climate change and LULC surface characteristics are two key factors influencing changes in surface hydrologic conditions such as streamflow/runoff (Ngigi et al., 2007, Wanders and Wada, 2014, Boongaling et al., 2018, Gao et al., 2018). For example, studies have shown that replacement of grassland by mesquite (small leguminous trees) leads to decreased baseflow/percolation and increased evapotranspiration, thus negatively impacting on water resources (Nie et al., 2011). In other semi-arid areas, strong correlations have been found between changes in bareland/impervious surfaces and runoff (Khare et al., 2015, Woldesenbet et al., 2016, Hu et al., 2020). Shrestha et al. (2018) projected that future LULC changes were likely to result in an average 5.8% increase in streamflow in Thailand, while Trang et al. (2017) projected an increase annual river discharge due to climate change and LULC changes in eastern Asia. Similar findings have been made by a host of African-based studies (Maina et al., 2012, Gal et al., 2016, Schütte and Schulze, 2017, Guzha et al., 2018, Op de Hipt et al., 2019). These and other examples have led to the general scientific consensus that LULC and climate change are key drivers of hydrological system dynamics, and hence water security, especially in semi-arid and other water stressed regions of the world.

All the foregoing demonstrate the need to strengthen sustainable land use practices, and increase the community climate adaptive capacity through robust comprehensive strategies and programmes. These in turn need to be backed by sound policies and well-informed accurate scientific knowledge (Lemos and Rood, 2010, Pokhrel et al., 2018). This means that reliable simulations of hydrological conditions are central to providing valuable information for river catchment and ecological systems management. It is against this backdrop that different types of hydrological models have been developed over the years and which have been continuously improved.

While some studies have focused on hydrological systems change over the long-term and at a macro-scale (Helmschrot and Flügel, 2002, Arnell, 2004, Flügel, 2017, Nasab and Chu, 2018, Singh. et al., 2020), others have explored the same over transient- to medium-term time periods at catchment and meso-scale levels (Becker et al., 2004, Uhlenbrook et al., 2004, Boongaling et al., 2018, Sibanda, 2018, Birhanu et al., 2019, Gabiri et al., 2020). In an attempt to understand future effects of climate change on catchment hydrology, interest has increasingly focussed on the integration of climate models/data in such studies (Bouwer et al., 2004, Maina et al., 2013, Arheimer et al., 2020). To achieve this, various hydrological modelling approaches have been used to understand the mechanisms and driving forces causing changes in hydrological processes, which in turn has helped to more accurately estimate available water resources within river basins around the world (Zhu and Ringler, 2012, Woldesenbet et al., 2016). As earlier discussed in Chapter 2 of this thesis, the models range from simple lumped and conceptual catchment models to the more complex distributed and physically based models such as the Hydrologic Engineering Center's Hydrologic Modelling System (HEC-HMS), Topographically-driven rainfall-runoff Model (TOPMODEL), and the Soil and Water Assessment Tool (SWAT). Such models have been widely used in numerous studies (Johnson et al., 2002, Oleyiblo and Li, 2010, Ghoraba, 2015, Gumindoga et al., 2015, de Moraes et al., 2018, Castro and Maidment, 2020). Further developments in the application of hydrological models have seen the emergence of state-of-the-art, new generation, distributed models integrating Geographic Information Systems (GIS), Earth observation data and climate model simulation datasets so as to better understand the climate-LULC-hydrology nexus (Sande et al., 2016, Pokhrel et al., 2018). Such models have enabled leverage of their flexibility and relatively higher competence in simulating different climatic and/ or physiographic scenarios and processes at various spatio-temporal scales, thus allowing for more accurate prediction of future impacts of climate and landscape changes on regional hydrology (Andersen, 2008).

While several studies have been carried out in semi-arid regions of southern Africa, using various advanced hydrological models driven by Regional Climate Model (RCM) simulation datasets and LULC change projections at varying spatial resolutions (Teutschbein and Seibert, 2010, Li et al., 2015, Yira et al., 2017, Tramblay et al., 2018, Natarajan and Radhakrishnan, 2019, Ahbari et al., 2020, Mami et al., 2021), few have focussed on Zimbabwe. The literature review (Chapter 2) of this thesis, outlined that of the 107 published, reviewed climate studies undertaken in Zimbabwe during the past 29 years, only 7% have explored climate-hydrology interlinkages, and very few have integrating GIS and remote sensing in their methodological approaches. Further, the review identified that knowledge in this regard was outdated and spatial coverage patchy or incomplete (in terms the seven water catchment areas of Zimbabwe).

It was noted that the Mzingwane catchment in general was among the least researched of the seven catchments in Zimbabwe. Furthermore, it was apparent that while several studies have assessed historical climate trends in the upper Mzingwane sub-catchment (UMS), no known study has explored the impact of future LULC changes and climate change on surface hydrology in this area. The unavailability of up-to-date scientific knowledge has not only presented limitations in planning but also challenges in development of pragmatic policy and decision making related to climate proofing water resources, thus ensuring robust impact mitigation and adaptation. It is against the afore-presented context that this study aims to project future hydrological conditions in the UMS in relation to future LULC scenarios (see Chapter 3 of this thesis) and future climate change simulations (see Chapter 5 of this thesis). In so doing, the aim is to identify likely future water security scenarios, which is important in the context of guiding appropriate policy and planning for the region.

## 6.2 HYDROLOGICAL MODELLING: A BRIEF OVERVIEW

Hydrological models are representative simplifications of complicated hydrological processes (Figure 6.1) using mathematical means to demonstrate the principal elements of the processes, their combination and function as a comprehensive hydrologic system (Xu, 2002).

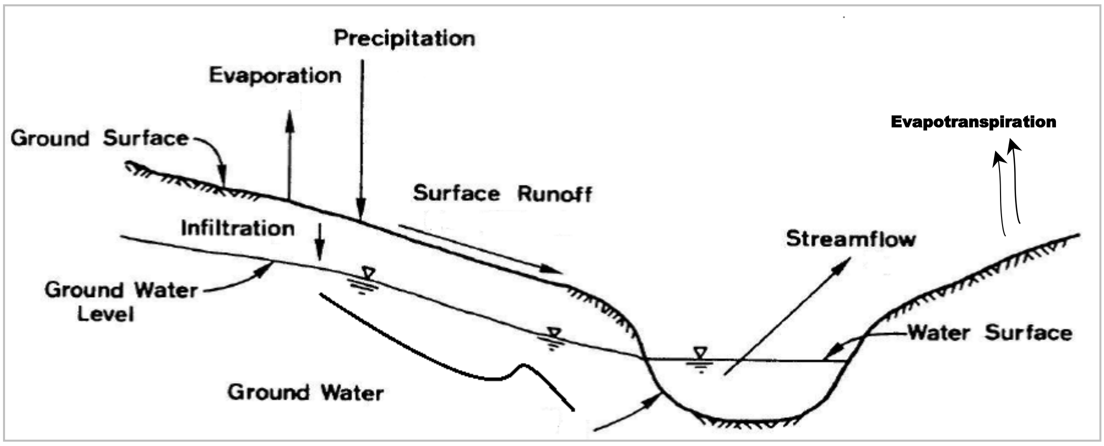


**Figure 6.1:** Conceptual representation of hydrological processes (e.g. precipitation, run-off, groundflow and streamflow) within a catchment area

*(Adapted from Xu (2002))*

These hydrological models have been classified in various ways but Refsgaard and Knudsen (1996) classified them into three broad categories; namely: (i) empirical black box models, (ii) lumped conceptual models, and (iii) distributed physically based system. Examples of these include the HEC-HMS (Oleyiblo and Li, 2010),TOPMODEL, Système Hydrologique Européen (SHE), SWAT (Ghoraba, 2015) and complex conceptual models such as MODHYDROLOG (Chiew et al., 1993) and the Genie Rural 4-parameter Journalier (GR4J) model (Perrin et al., 2003). A review of the strengths and weaknesses of these models revealed that distributed-physically based models have the advantage of accounting for spatial heterogeneities and provide detailed description of the hydrological processes in a catchment with limited demands of input data, hence their widespread use in hydrological studies (Sivapalan et al., 2013). The same notion has been confirmed by the World Meteorological Organisation (1975) in their inter-comparison of conceptual hydrological models for operational hydrological forecasting. Furthermore, considering that these models use parameters which are directly related to the physical characteristics of river basins (e.g. topography, soil, LULC and geology) and account for spatial variability of meteorological conditions (Refsgaard and Knudsen, 1996, Trang et al., 2017, Gao et al., 2018, Singh. et al., 2020), they have been very useful in advancing studies that focus on changes in catchment hydrological process. In the current study, the HEC-HMS is used together with the HEC-GeoHMS module in ArcGIS software.

### 6.1.2 HEC-HMS and HEC-GeoHMS description

#### *6.1.2.1 HEC-HMS*

The HEC-HMS was designed and is maintained by the United States Army Corps of Engineers (USACE). The software can simulate rainfall-runoff processes of catchment systems of varying scales (i.e. from small watersheds to large transboundary basins). It is described as a deterministic, semi-distributed, event-based/continuous, mathematically based model that uses other sub-models to characterise disparate elements of the runoff process, such as evaporation, percolation, surface runoff, and groundwater flow. The HEC-HMS takes into account the spatial distribution of catchment features by partitioning it into sub-basins with homogenous features such as LULC and soil type. These and other geospatial datasets can be organised in GIS software such as ArcGIS using HEC-GeoHMS and then directly imported into HEC-HMS (Baumann and Halaseh, 2011, Shukur, 2017).

The HEC-HMS model comprises of four modules: (1) Basin model, (2) Meteorological model, (3) Control specifications, and (4) the Input data component (e.g. time series, point and/ gridded data). The Basin model holds data on the physical properties of the model, such as basin areas, river reach connectivity or reservoir data. The meteorological model performs meteorological data analysis using parameters such as precipitation, evapotranspiration, and temperature, both in point and grid data format. Control specifications contain data on the timing of the model, such as incidence of events (e.g. storms) and the type of time interval to be adopted in the model. Finally, the input data component stores boundary and parameter conditions for basin and meteorological models.

The HEC-HMS employs certain methods which have to be selected for simulating stream discharge. These include the (1) Loss method, (2) Transform method and (3) the Routing method, which reflect the spatial and hydro-geomorphologic information necessary to execute the stream flow simulations in the model.

*Loss method*

This method allows choosing the process to be used to calculate rainfall losses absorbed by the ground. It computes the runoff volume by accounting for the losses that occur during a rainfall event as a result of infiltration and evapotranspiration. For each time interval in the modelling process, the loss method calculates the amount of water that translates into runoff in the river (i.e. effective rainfall). The Constant and Deficit (DC) method is used in this study for this purpose. The Deficit and Constant is a quasi-continuous model of precipitation loss where initial loss can recover after a prolonged period of no rainfall. It is preferred and suitable in this study considering that it can be used for continuous simulation, it is easy to implement and has been widely applied in similar semi-arid catchments in Zimbabwe (Dlamini et al., 2016, Gumindoga et al., 2016, Masimba et al., 2019). The parameters therefore used in the DC method include (i) the Maximum Deficit (which represents the total soil water storage depth), (ii) the Initial Deficit (which represents the empty storage depth at the beginning of the simulation) and (iii) Constant Rate (which can be viewed as the ultimate infiltration capacity of the soils measured in mm/hour). Each sub-basin requires an Initial Deficit (in mm) quantity, a Maximum Deficit (in mm), Constant rate (mm/hour) and Estimated sub-basin surface Imperviousness (%). Values used in this study are presented in Appendix 1.

*Transform method*

This method specifies how excess rainfall is to be converted into direct surface runoff. In this study, the SCS unit hydrograph method is used where values of lag-time are computed for each sub-basin using slope length and CN values. The formula (Equation 5) shows the implementation of the SCS method.

$$Q_p = C\,\frac{A}{T_p} \qquad \text{[Equation 5]}$$

Where $Q_p$ is peak discharge (m$^3$/s.cm), $A$ is the catchment area (km), $C$ is a conversion constant (2.08) and $T_p$ is time to unit hydrograph peak. $T_p$ is also related to the duration of the unit of excess precipitation as shown in Equation 6:

$$T_p = C\,\frac{t_r}{2} + t_{lag} \qquad \text{[Equation 6]}$$

Where $t_r$ is the excess precipitation duration, $t_{lag}$ is the basin lag (i.e. the difference between the centre of mass of rainfall excess and the peak of the unit hydrograph). $t_{lag}$ is thus determined by the following formula (Equation 7):

$$t_{lag} = 0.6\,t_c \qquad \text{[Equation 7]}$$

Where $t_c$ is computed as:

$$t_c = 60\left(\frac{11.9L^3}{H}\right)^{0.385} \qquad \text{[Equation 8]}$$

Where $L$ is the length of the longest watercourse, $H$ is the elevation difference between divide and outlet.

The computed $t_{lag}$ and $t_c$ values used in this study are presented in Appendix 1.

*Routing method*

Routing accounts for changes in the flow hydrograph as a flood wave progresses downstream. The Muskingum routing method (Yoon and Padmanabhan, 1993) is used in this study. The method employs travel time $K$ (assumed as CN lag time or the estimated interval between similar points on the inflow and outflow hydrographs used to a generate discharge hydrograph at downstream point in channel) and degree of storage values, Muskingum $X$ (is a constant coefficient with values from 0 to 0.5). However, in semi-arid regions such as UMS, this value can be higher. In this study, 0.55 was adopted as it is widely used and has been determined to be realistic in similar catchments in Zimbabwe (Dlamini et al., 2016, Gumindoga et al., 2016, Masimba et al., 2019).

While the HEC-HMS is considered competent in stream runoff discharge modelling, simplified representation of the rainfall-runoff process does not account for the storage and movement of water vertically within the soil layer (Bennett. and Peters., 2000).

#### *6.1.2.2 HEC-GeoHMS*

HEC-GeoHMS is a GIS extension that provides a set of procedures, tools, and utilities for the preparation/generation of GIS data for import into the HEC-HMS model (Fleming and Doan, 2013). As part of Environmental Systems Research Institute (ESRI)'s ArcGIS software and the Spatial Analyst extension, HEC-GeoHMS has several advantages over the simple HEC-HMS because it allows for visualisation of spatial information, documentation of watershed characteristics, spatial analysis, delineation of sub-basins and streams, construction of inputs to hydrologic models, and assists with report compilation. Using mainly a Digital Elevation Model (DEM) as the main input, the HEC-GeoHMS allows for seamless, easy and efficient creation of hydrologic inputs that can be used directly with the HEC-HMS software with limited computational power requirements. Although several studies have utilised the HEC-GeoHMS globally (Johnson et al., 2002, Al-Abed et al., 2005, Knebl et al., 2005, Ali et al., 2011, Wang et al., 2019, Ramly et al., 2020), and despite its apparent strengths over other similar models, HEC-GeoHMS has not been used in any known hydrological modelling study in the entire Matabeleland region of Zimbabwe (which includes the Mzingwane catchment), hence the motivation to use it for the first time in this study area.

## 6.2 METHODS AND DATA

The main steps in the methodology employed in this study entail: (1) data preprocessing, (2) DEM processing using ArcHydro tools (i.e. terrain preprocessing tools to delineate the UMS basin, sub-basin, and stream network), (3) extraction of the hydrologic parameters of the UMS river basin from the terrain preprocessed data using the HEC-GeoHMS and (3) simulation of streamflow runoff from the hydrologic parameters using in HEC-HMS version 4.6.1. Statistical trend analysis and comparisons are made for the different CCAM ensemble member forced hydrographs for the three future time periods (presented in Chapter 5 of this thesis). A basic overview of the main steps of the methodology are shown in Figure 6.2, while Figure 6.3 shows the UMS sub-basins, gauging stations and river system.

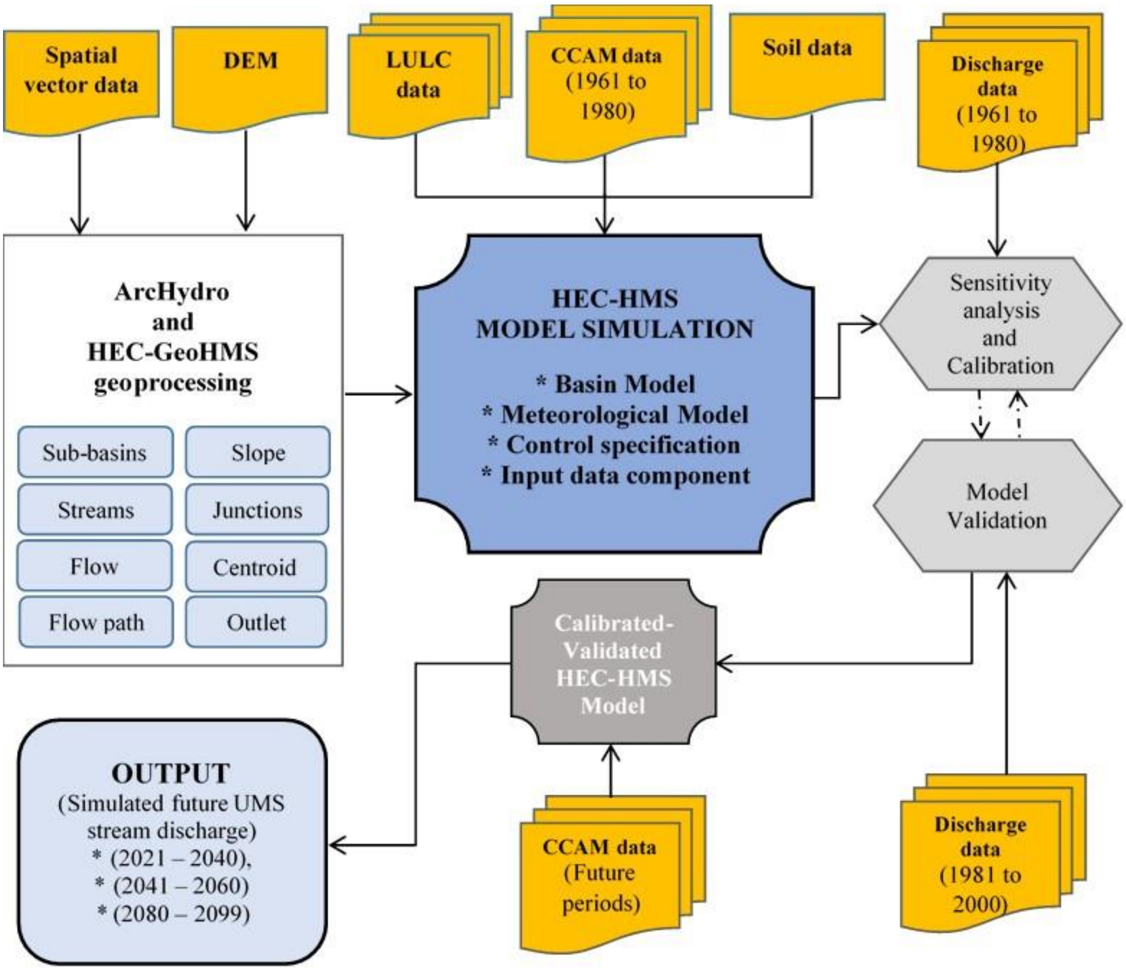
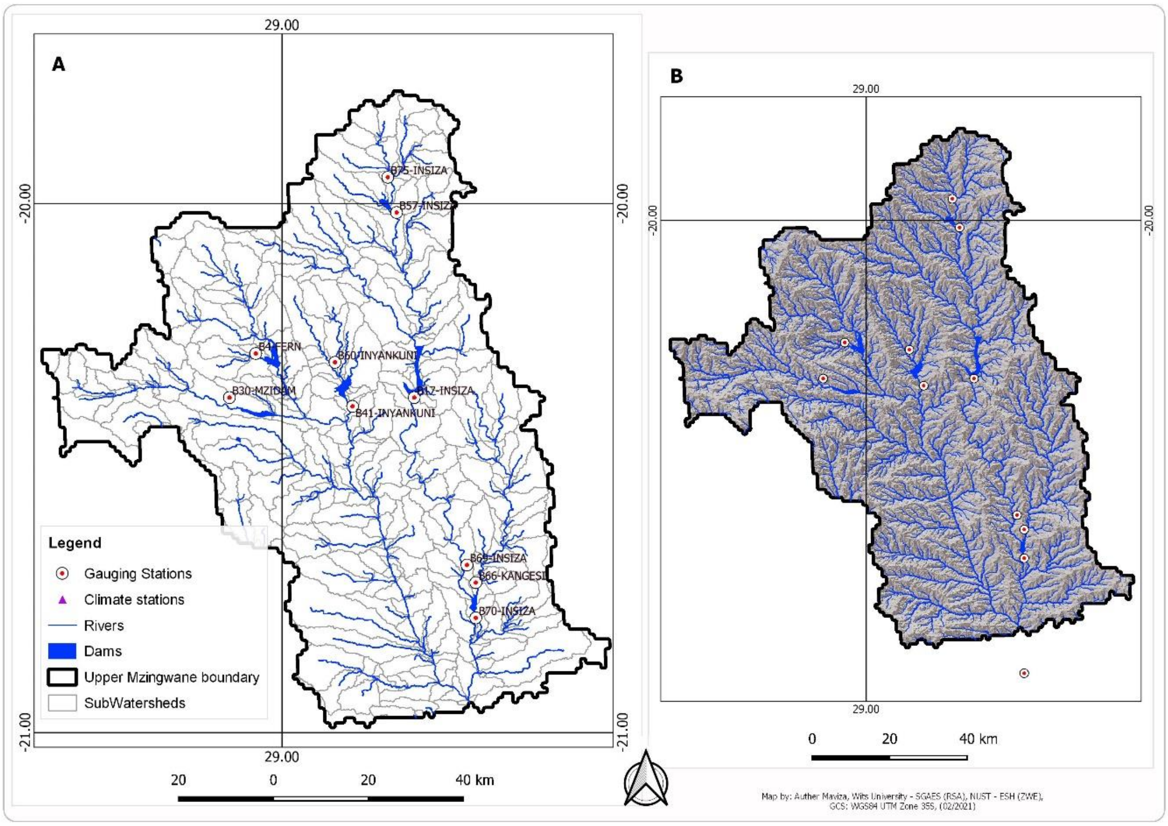


**Figure 6.2:** Hydrological modelling flow diagram showing the main steps in the model implementation

*(Adapted from Ghoraba (2015))*



Map by: Auther Maviza, Wits University - SGAES (RSA), NUST - ESH (ZWE),
GCS: WGS84 UTM Zone 35S, (02/2021)

**Figure 6.3**: Upper Mzingwane subcatchment with: (A) gauging stations and sub-watersheds, (B) drainage direction raster with detailed rivers and streams extracted from the area DEM

### 6.2.1 Data preprocessing

Descriptive summaries of the datasets used in this study are presented in Tables 6.1 and 6.2.

**Table 6.1:** Summary of datasets used

| Dataset | Time period | Resolution | Projection | Format | Source |
|---|---|---|---|---|---|
| **CCAM data** | 01/1961 – 12/2099 | 0.1° × 0.1° (8km × 8km) | WGS84 | Unformatted binary (.dat) | Wits University Global Change Institute |
| **Gauging station data** | 1950 - 2000 | Daily | N/A | Comma Separated Values (.csv) | Zimbabwe National Water Authority (ZINWA) (Gauging stations: B11, B30, B40, B60, B61, B74 and B75) |
| **Spatial vector data** | N/A | N/A | WGS84 | ESRI shapefile (.shp) | Zimbabwe Surveyor General |
| **Topographic data (DEM)** | N/A | 30m × 30m | WGS84 | GeoTiff (.tif) | NASA (http://www.gdem.aster.ersdac.or.jp/ ) |

| | | | | | |
|---|---|---|---|---|---|
| **Soils data** | N/A | 0.05° × 0.05° (5km × 5km) | WGS84 | NetCDF (.nc) | NASA Regridded Harmonized World Soil Database v1.2 (Wieder, 2014) |
| **LULC data** | 1979 – 2018; 2038 | (30km × 30km) | WGS84 | Geotiff (.tif) | Historical and Future LULC maps from Chapter 3 (Maviza and Ahmed, 2020) |
| **Potential Evapotranspiration data** | 1979 – 2018; 2038 | (1km × 1km) | WGS84 | Geotiff (.tif) | Global Potential Evapotranspiration (ET0) Climate Database v2 (Antonio and Robert, 2019) |

#### *6.2.1.1 CCAM data*

CCAM data used in this study are downscaled and bias corrected simulations from 6 CGCMs i.e. ACCESS1.0 (Bi et al., 2012), CCSM4 (Gent et al., 2011), CNRM-CM5 (Voldoire et al., 2013), GFDL-CM3 (Donner et al., 2011, Griffies et al., 2011), MPI-ESM LR (Giorgetta et al., 2013) and the NorESMI-M (Bentsen et al., 2012, Iversen et al., 2013). The climate parameters covered in the dataset are precipitation, maximum temperature and minimum temperature, wind speed, maximum relative humidity and minimum relative humidity; these cover the period 1961-2099. Details about this dataset can be found in Chapter 5. Precipitation and temperature data are used in the meteorological model of the HEC-HMS.

#### *6.2.1.2 Gauging station data*

Daily mean discharge data (in cubic metres / second (m$^3$/s) from nine discharge stations (Table 6.2 and Figure 6.3) were acquired from ZINWA, preprocessed by combining and converting it to .csv format using MS Excel software. This was to enable preparation for incorporation into the HEC-HMS software and further statistical analysis of stream flow trends. Missing values were appropriately coded (with an arbitrary value of -999). The data cleaning process also entailed streamlining the discharge data to cover corresponding time periods with the climatological data.

**Table 6.2:** Summary description of gauging station data used in this study

| **Station name** | **Coordinates** | | **Catchment area ($km^2$)** | **Elevation** (metres) | **Period** |
|---|---|---|---|---|---|
| | Lon | Lat | | | |
| ***B4-Fern*** | 28.9500 | -20.2833 | 82.87 | 1156 | 1954-2008 |
| ***B17-Insiza*** | 29.2500 | -20.3667 | 1870.00 | 1140 | 1963-1973 |
| ***B30-Mzidam*** | 28.9000 | -20.3667 | 448.00 | 1178 | 1958-2016 |
| ***B41-Inyankuni*** | 29.1333 | -20.3833 | 365.00 | 1145 | 1961-2016 |
| ***B57-Insiza*** | 29.2167 | -20.0167 | 570.00 | 1241 | 1966-2016 |
| ***B60-Inyankuni*** | 29.1000 | -20.3000 | 194.00 | 1131 | 1965-2016 |
| ***B66-Kangesi*** | 29.3667 | -20.7167 | 673.00 | 998 | 1966-2016 |
| ***B69-Insiza*** | 29.3500 | -20.6833 | 2260.00 | 1019 | 1966-2016 |
| ***B75-Insiza*** | 29.2000 | -19.9500 | 401.00 | 1258 | 1968-2016 |
| ***B70-Insiza*** | 29.3667 | -20.7833 | 3030.00 | 957 | 1982-2016 |

*(Source data: Data and Research Division, Zimbabwe National Water Authority)*

The UMS was first partitioned into nine sub-basins using the ArcHydro basin discretisation tools and the climate data series (1981–2015) divided into sub-intervals 1985-1995 and 1995-2005 in preparation for the calibration and validation processes respectively. Data preprocessing also entailed conversion of the CCAM data into HEC-HMS usable format (.csv) using Climate Data Operator (CDO) software. Furthermore, all gridded datasets (including LULC data) were reprojected into the WGS84 coordinate system and resampled to the CCAM spatial resolution for correct data alignment during overlay processes. Only four of the nine gauging stations (i.e. B30, B41, B66 and B75) were selected and used in the model calibration because they comprise the headwaters of the UMS which makes model calibration process easier and they had the most complete datasets compared to other gauging stations. The hydrographs showing the stream discharge for the four stations are presented in Figure 6.4 (A – D). Hydrographs for the rest of the gauging stations are presented in Appendix 2.

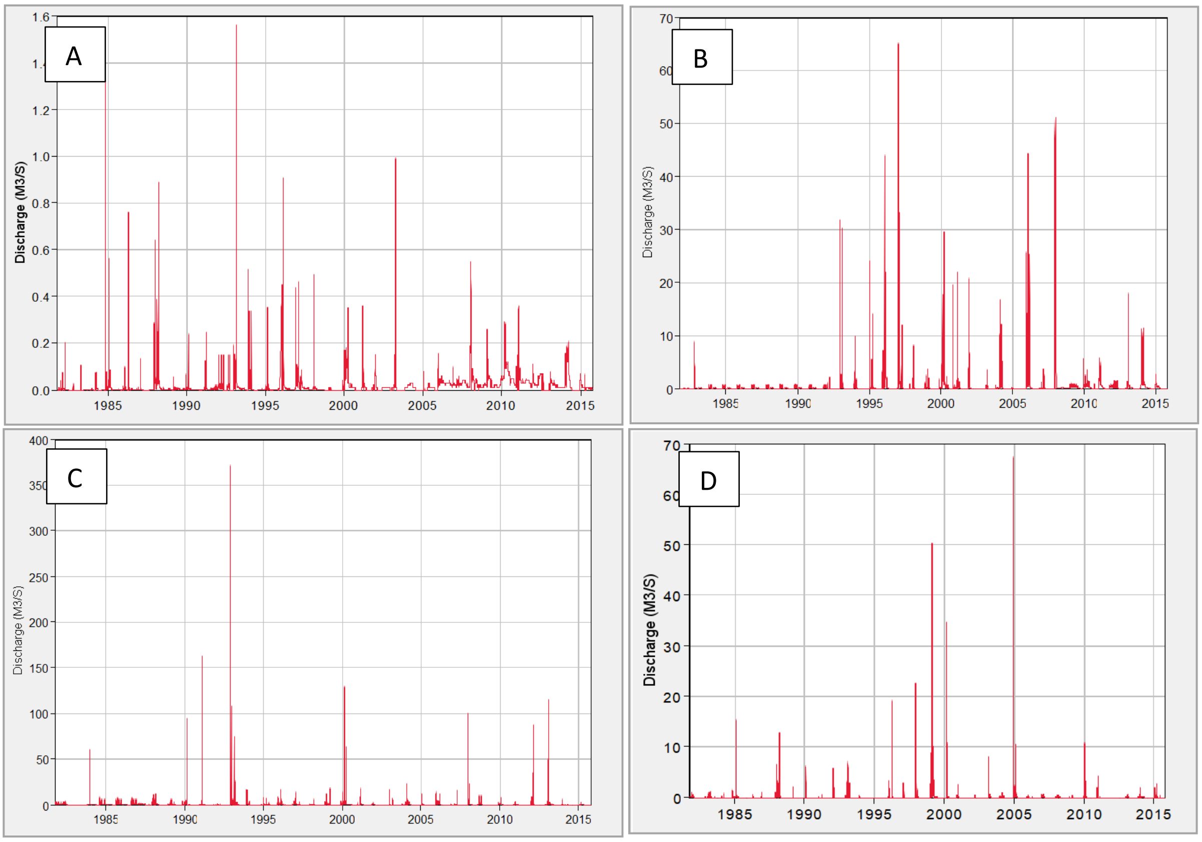


**Figure 6.4:** Observed Stream discharge for the four gauging stations (A = B41, B = B66, C = B30 and D = B75) used in the validation process. Highest discharge is noted from B30 which is along the Umzingwane River

#### *6.2.1.3 Soil data*

Soil data was acquired from the Harmonised World Soil Database version 2 and subset to the UMS. Figure 6.5 A and B shows the main soil characteristics used in the determination of the key basin parameters i.e. water retention time and subcatchment maximum deficit and the Muskingum (X) constants. These factors (shown in Appendix 1) are key in determining the water routing within each catchment and thus stream flow.

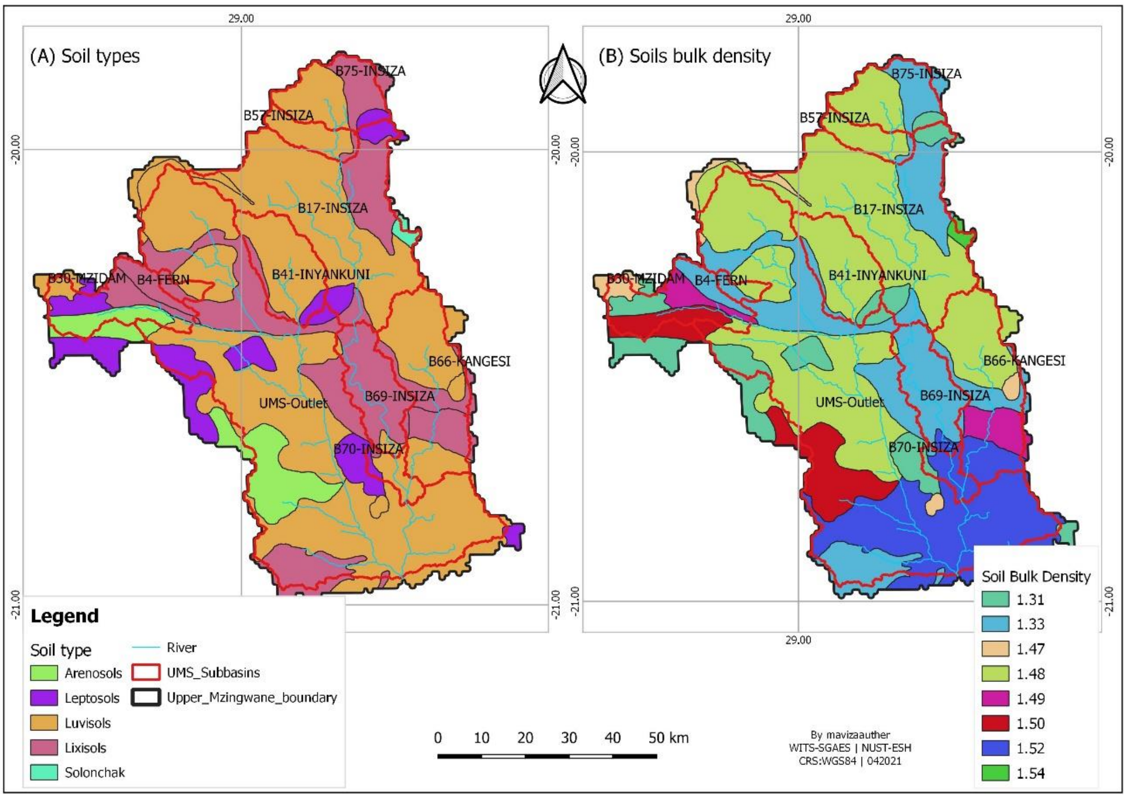


**Figure 6.5:** UMS soil types and soli bulk density maps. On overlay, each sub-basin has a unique combination of soil type (A) and bulk density (B) which were used in estimating the model parameters such as catchment maximum water retention. The UMS is predominated by luvisols and lixisols which are known to have relatively high infiltration rates

### *Potential Evapotranspiration (PET) data*

The Global Reference Evapotranspiration (Global-ET0) Version 2 dataset provides high-resolution (1km) global PET estimates in grid format. The Global-ET-0) provides PET estimates using the Penman Monteith Evapotranspiration equation relating evapotranspiration processes and rainfall deficit for potential vegetative growth (Sumner and Jacobs, 2005). The monthly Global-ET0 PET product is used in this study. Grid PET values are extracted in ArcGIS 10.6 using the Climate station coordinates and converted into csv format in preparation for entry into the HecHMS model. Appendix 5 shows the PET rate values (mm/month) used in this study.

### 6.2.3 Data analysis

#### *6.2.3.1 Hydrological analysis*

CCAM daily gridded precipitation data are used and monthly averaged evapotranspiration computed and added to the meteorological sub-model of the HEC-HMS model. Required parameters for the model are interception storage, surface storage, infiltration rate, soil storage, tension zone storage and soil zone percolation rate. These are estimated using historical and future LULC data (from Chapter 3) and soil data (Figure 6.5) following the approach by Gumindoga et al. (2015). From the LULC maps and the hydrologic soil groups, the run-off Curve Number (CN) map of the UMS is computed using the earlier presented formula (Equations 2).

Figure 6.2 summarises the steps that were followed in 'forcing' the HEC-HMS model in this study. A catchment-based approach which identifies representative hydrological areas after Arnell (1999) is adopted. A 30metre resolution Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global DEM Version 2 covering the UMS was processed using catchment delineation, terrain pre-processing, basin processing and geo-analysis ArcHydro tools in the HEC-GeoHMS. The outputs were then ingested as spatial inputs into the HMS together with part of the historic/baseline period (i.e. 1961-1980 period) CCAM climatic and discharge data for the initial run. The model was calibrated and validated using the split-sample procedure, as described by Refsgaard (1997), where part of the historical observed discharge data were used for calibration and the remainder used for validation. This same approach has been successfully used in previous studies such as those by Yue and Pilon (2004) and Ouédraogo et al. (2018).

#### *6.2.3.2 UMS HecHMS model structure*

Figure 6.6 shows the UMS models structure used in this study. The model compromise of nine subbasins (listed in Table 2) and ten stream junctions which are sub-basin outlets (the 10th being the overall catchment outlet where final catchment discharge is measured), nine stream reaches (connecting all the junctions and channelling stream discharge from each sub-basin along the catchment drainage network) and the 5 UMS water reservoirs (dams).

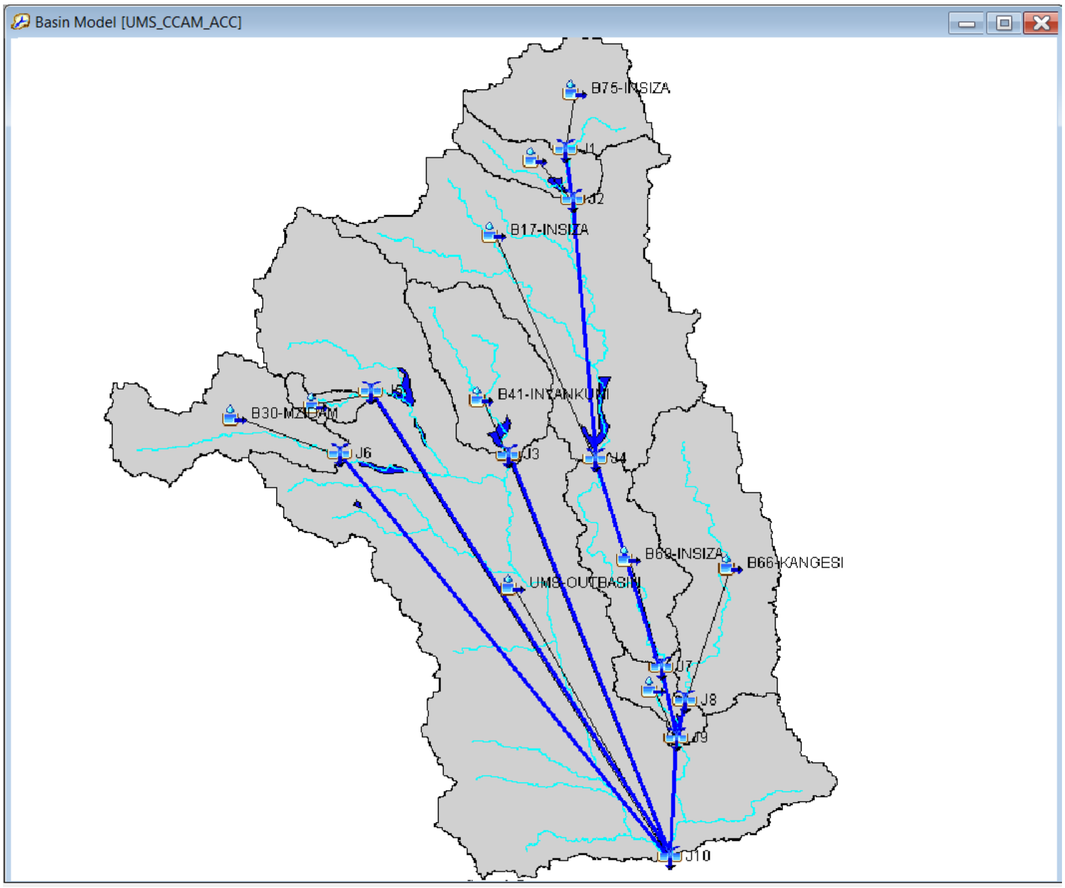
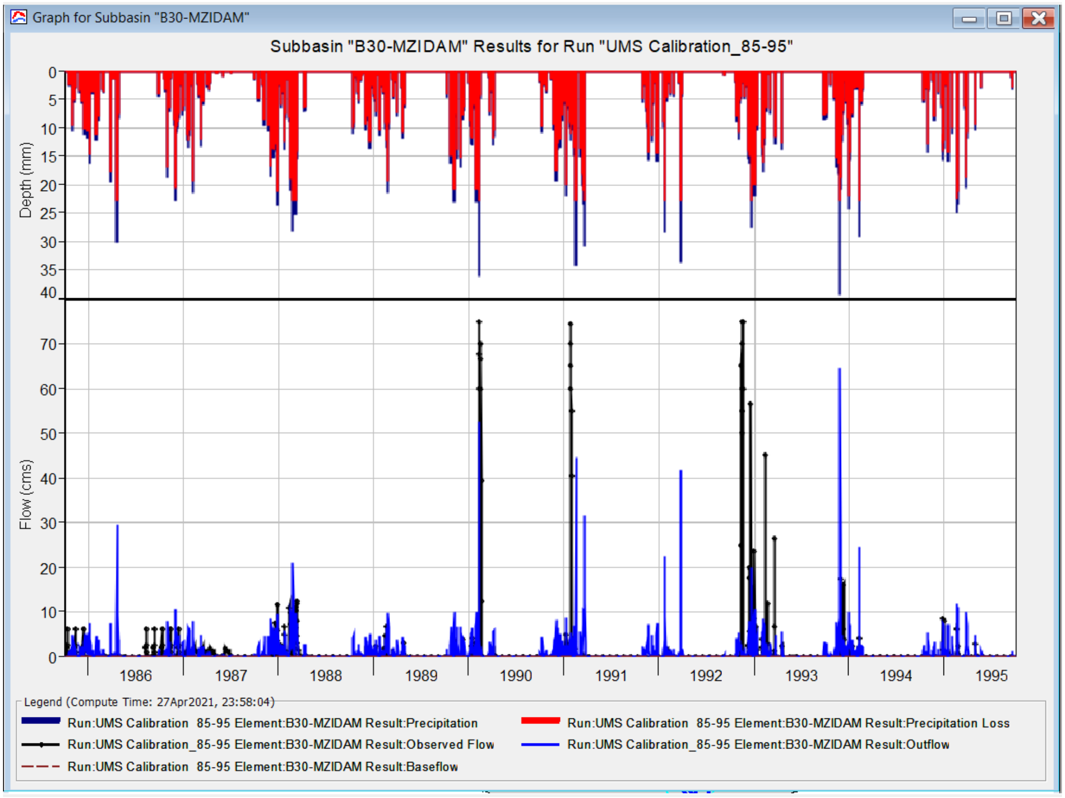
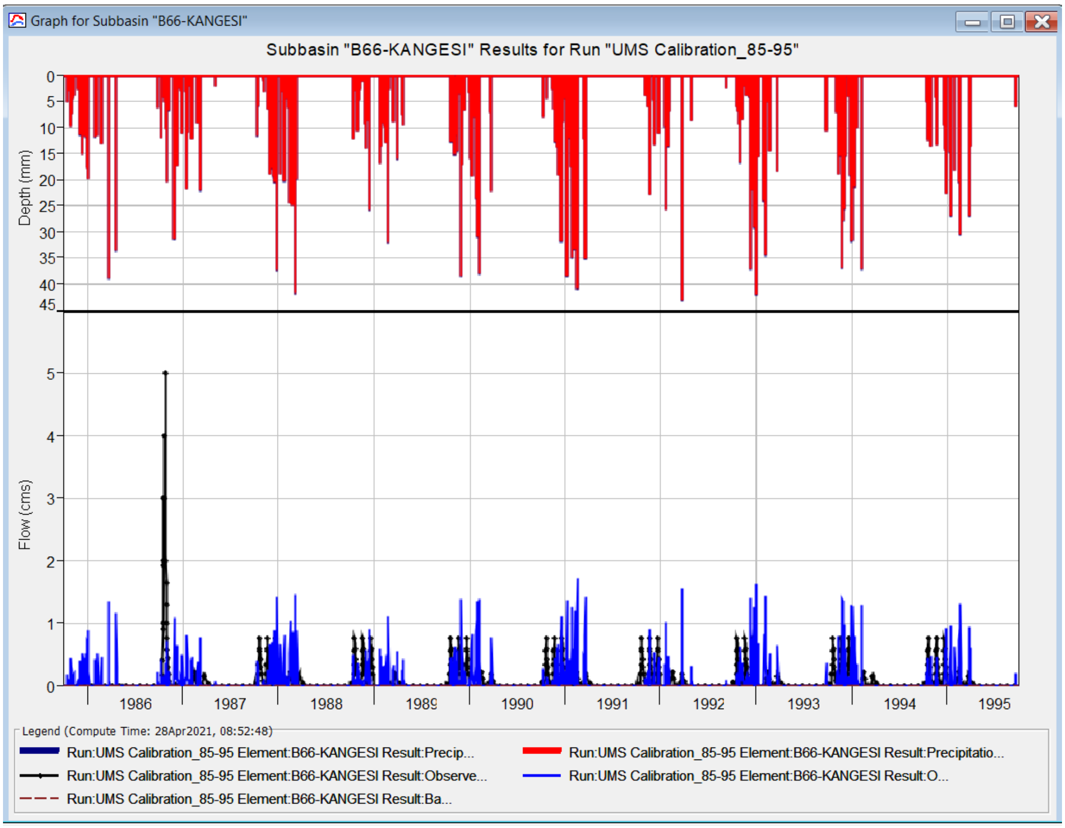


**Figure 6.6:** UMS HecHMS model structure showing the basin shape and components. Dark blue line = reach, Cyan = streams

### *6.2.3.3 Model calibration*

Discharge data from the gauging stations B30, B41, B66 and B75 were used in the model calibration stage for the historic/baseline period (1985 - 1995). Precipitation time-series data of the from the corresponding time period were entered into the model as well under the HecHMS Meteorologic Model module. After all the aforementioned data was entered and the model run parameters confirmed and model run was compiled and run in HecHMS and results obtained. Loss and transformation parameters values were manually changed (by creating new run parameters) until a good fit was achieved between the simulated and observed stream discharge. In order to improve the model performance, the parameter optimisation function in the model was used to determine the calibration optimal parameter values. The goodness of fit was determined by the visual closeness between the observed and the simulated unit hydrographs and computed statistics values. Figure 6.7 (A-D) shows the observed and simulated hydrographs for the four calibration stations. The comparison shows a good fit between observed and simulated discharge as depicted by the correspondence between observed and simulated peak discharges in response to peak precipitation events. The calibration performance parameters are presented in Table 6.4.





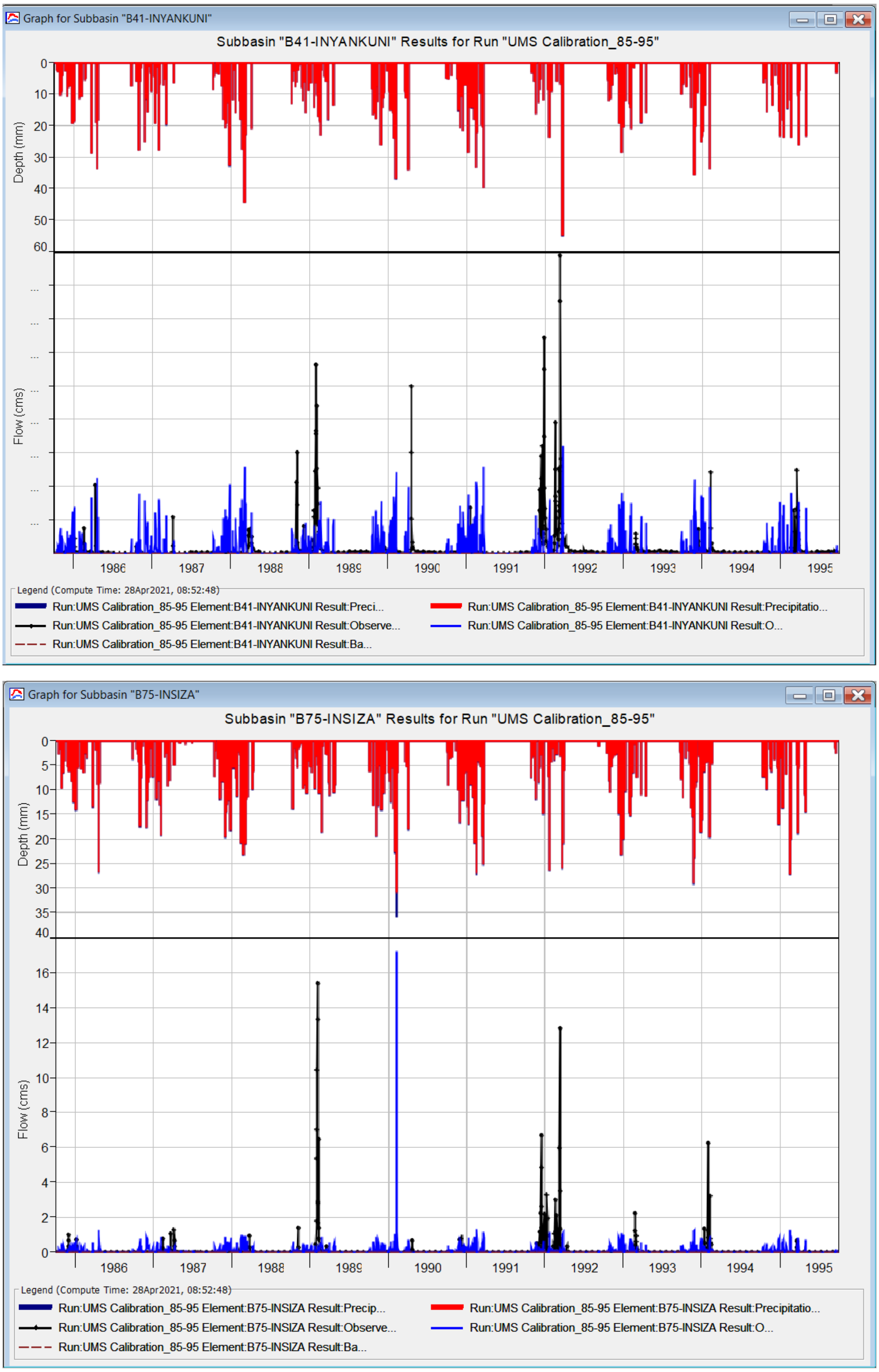


**Figure 6.7:** Gauging stations B30 (A), B66 (B), B41 (C), and B75 (D) observed and simulated daily stream discharge for the calibration period. *Red = Observed precipitation, Blue = Simulated stream discharge, Black = Observed stream discharge*

### 6.2.4 Model validation (performance analysis)

Owing to the complexity of prevailing physical and dynamic climatic conditions in different landscapes, the application of hydrological models need proper parameterisation, calibration, validation and sensitivity analysis (Wegehenkel and Kersebaum, 2005). This helps to quantify the capabilities and limitations of these models in simulating certain conditions, and hence their value. Refsgaard (1997) suggested that model validation is a critical process to demonstrate how well a given site-specific model is capable of making accurate simulations for periods outside its calibration period. A model is said to be validated if its accuracy and predictive capability in the validation period have been proven to lie within certain acceptable limits or errors (Wegehenkel and Kersebaum, 2005, Liu et al., 2018). In this study, discharge data for the period 1995 - 2005 is used for model validation to match the 10year calibration period as recommended by Wang et al. (2016). The model efficiency/performance in simulating stream run-off at the UMS outlet was assessed using the Root Mean Square Error (RMSE), Percentage bias (Mean Absolute Error (MAE) as a percentage) and a comparison of simulated and observed peak discharge and run-off volume at gauging stations B30, B41, B66 and B75. These statistical measures of model efficiency are robust and together have been successfully used to quantitatively describe the predictive accuracy of hydrological models in numerous studies (Love et al., 2001, Gumindoga et al., 2011, Abushandi and Merkel, 2013, Gumindoga et al., 2015, Gumindoga et al., 2018, Singh. et al., 2020). RMSE and PB are expressed as shown in Equations 9 and 10. Validation performance results in Tables 6.5. Overall, the model performance was satisfactory and hence used in the future period stream discharge simulations.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \qquad \text{[Equation 9]}$$

$$Percentage\ Bias\ (PB) = \frac{\sum_{i=1}^{n}(O_i - P_i)}{n} \times 100 \qquad \text{[Equation 10]}$$

Where O = observed values; P = predicted values; n = number of observations

After validation, the HMS was ‘forced’ using data from all the other CCAM future periods, i.e. the near future (2021 – 2040), mid-term future (2041 – 2060) and long-term future (2080 – 2099) to simulate future stream discharge scenarios. For each of the future periods, LULC was held constant for the year 2018. To test the impact of LULC change on stream discharge, LULC was varied using the projected 2038 LULC scenario and the stream discharge simulation for outlet run again. Results of future simulations for each time period and ensemble member are presented in Figures 6.9, 6.10 and Table 6.6.

## 6.3 RESULTS AND DISCUSSION

### 6.3.1: Model performance

Model validation results for the calibration and validation periods are presented in Tables 6.3 and 6.4 respectively. Figure 6.8 (A and B) shows the validation discharge graphs for gauges B75 and B30 respectively.

**Tables 6.3:** Model performance results (calibration period)

| **Parameter** | | **Station** | | | | |
|---|---|---|---|---|---|---|
| | | B30 | B66 | B75 | B41 | Mean |
| **Peak Discharge m3s$^{-1}$** | Observed | 75 | 5.0 | 15.4 | 0.9 | 24.08 |
| | Simulated | 64.7 | 5.0 | 17.3 | 0.3 | 21.83 |
| **Runoff volume (mm)** | Observed | 515.33 | 29.12 | 48.03 | 6.9 | 149.85 |
| | Simulated | 512.60 | 30.56 | 50.86 | 7.53 | 150.39 |
| **Percent bias (%)** | | 0.53 | 4.93 | 5.89 | 9.1 | 5.11 |
| **RMSE** | | 1 | 1.4 | 1.2 | 1.2 | 1.2 |

**Tables 6.4:** Model performance results (validation period)

| **Parameter** | | **Station** | | | | |
|---|---|---|---|---|---|---|
| | | B30 | B66 | B75 | B41 | Mean |
| **Peak Discharge m3s$^{-1}$** | Observed | 75.0 | 5.0 | 15.4 | 0.9 | 24.08 |
| | Simulated | 100.5 | 3.6 | 13.9 | 0.56 | 29.64 |
| **Runoff volume (mm)** | Observed | 515.33 | 29.12 | 48.03 | 6.9 | 149.85 |
| | Simulated | 568.33 | 31.18 | 61.19 | 8.57 | 167.32 |
| **Percent bias (%)** | | 10.28 | 7.07 | 12.39 | 14.17 | 1.98 |
| **RMSE** | | 1.1 | 1.4 | 1.2 | 1.3 | 1.25 |

The model performance values presented both in the calibration and validation periods indicate satisfactorily good performance of the model though the model shows better output in the former than the later period. In the calibration phase, the model shows marginal underestimation of the simulated peak discharge by a mean factor of 2.25 m$^3$s$^{-1}$ compared to an overestimation of 5.56 m$^3$s$^{-1}$ in the validation phase. However, the model over estimates total run-off volume in both the calibration and validation stages by mean factors of 0.54 m$^3$s$^{-1}$ and 17.47 m$^3$s$^{-1}$ respectively. This shows a 31.4% decline is model performance from the calibration to the validation period. This could be attributed to changes in the model run periods i.e. from the 1985-1995 calibration period to the 1995-2005 validation period. It is known that the

HecHMS model bases its final model performance assessment on the variation in and correspondence between peak precipitation events and discharge dynamics (Fleming and Doan, 2013). As such, the apparent differences in precipitation events and the corresponding discharge changes between the calibration period and the validation period could be a contributing factor as reported in numerous studies (Ramly and Tahir, 2016, Wang et al., 2016, Nasab and Chu, 2018, Wang et al., 2019). Furthermore while the basin model parameters are held constant between the two periods, it is well acknowledged that any disturbances or changes that may occur within any basins, alter the surface conditions and thus tend to alter the stream hydrology of an area. This could be the case as well in this instance seeing the validation period falls within the period when the Government of Zimbabwe was fast-tracking the land redistribution and resettlement programme where there could have been landscape changes.

The RMSE (PB) values in both periods range between 1 and 1.4 (0.54 and 14.17) which are well within the performance levels often considered as satisfactorily good in most similar studies (Gumindoga et al., 2015, Masimba et al., 2019). The model generally captures the pattern of magnitude of stream discharge shown by the gauge observations e.g. highest (lowest) discharge simulated and observed in station B30 (B41).

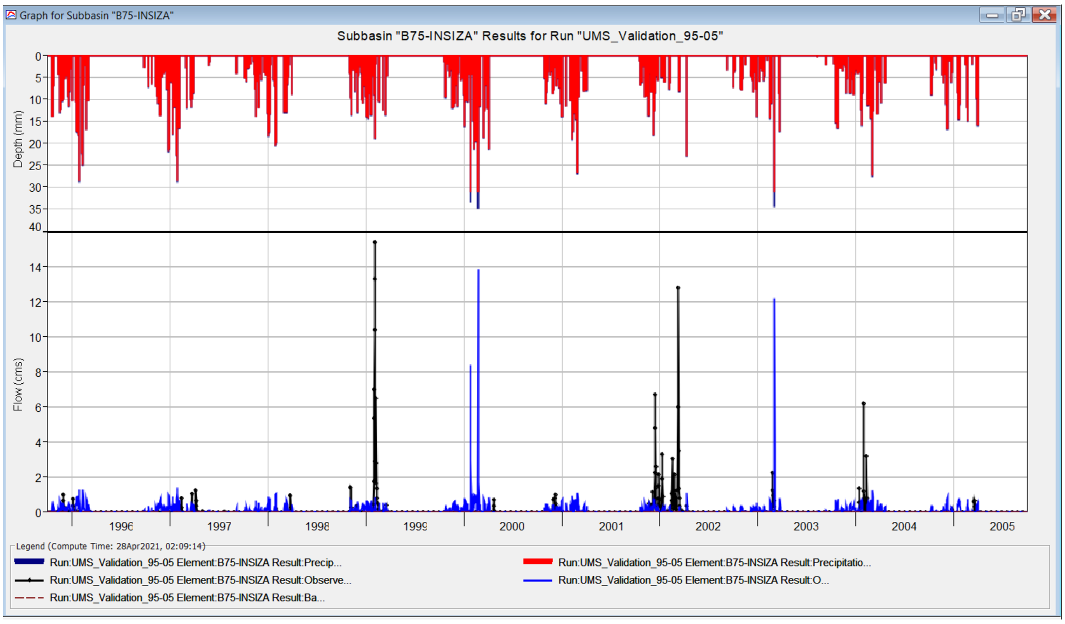


**Figure 6.8A:** Gauging stations B75 observed and simulated daily stream discharge for the validation period. *Red = Observed precipitation, Blue = Simulated stream discharge, Black = Observed stream discharge*

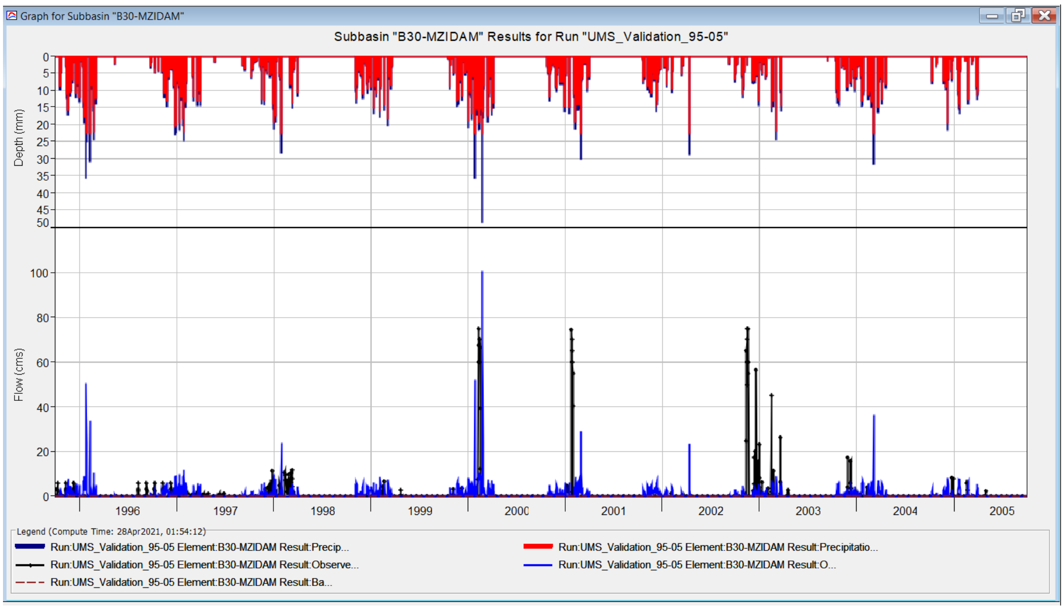


**Figure 6.8B:** Gauging stations B30 observed and simulated daily stream discharge for the validation period. *Red = Observed precipitation, Blue = Simulated stream discharge, Black = Observed stream discharge*

### 6.3.2 Projected stream runoff trends in UMS

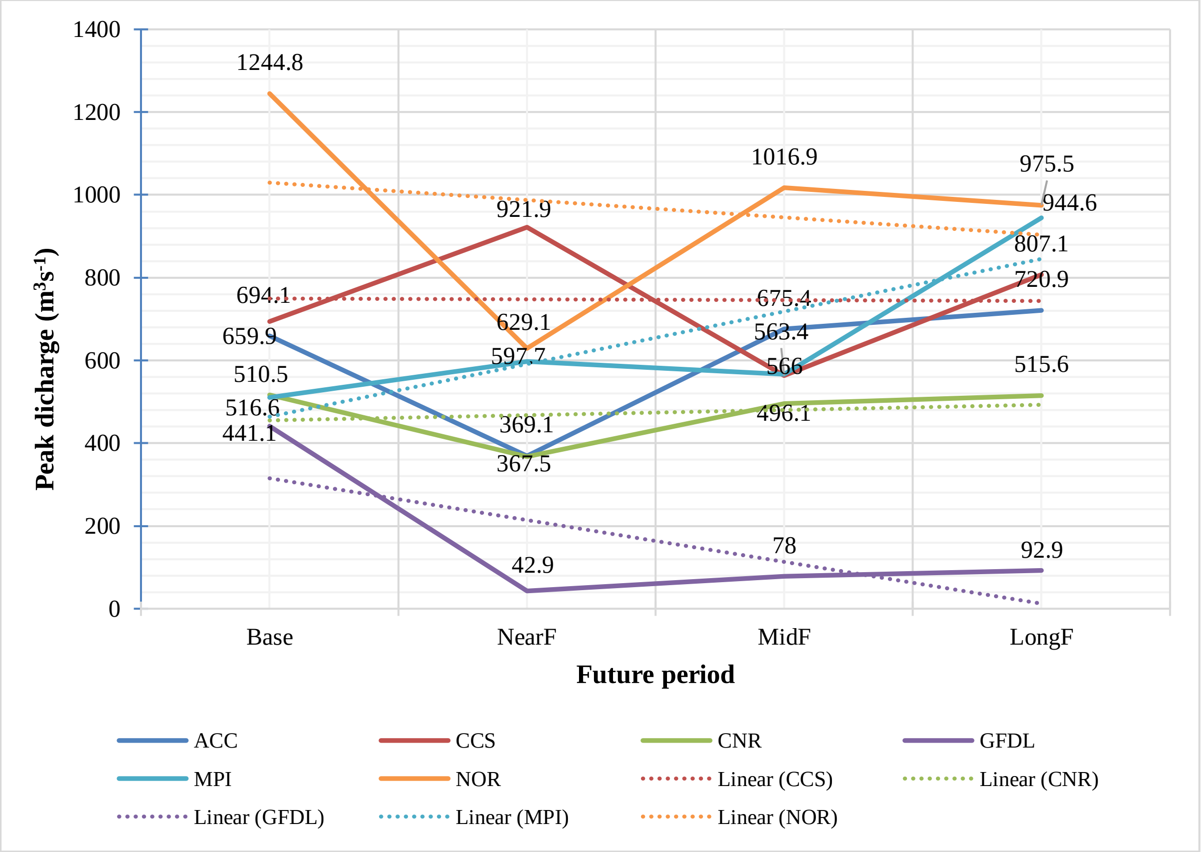


**Figure 6.9:** Simulated peak stream discharge at UMS outlet for near-future (NearF), mid-term future (MidF) and long-term-future (LongF) for each ensemble member. Trend lines are also presented.

Results show that the NorESMI and the GFDL-CM3 model project declining trends in peak stream discharge though the former simulates the highest peak discharge in the baseline period (1996 – 2015). Overall, the simulated peak discharges ranges between 1244.8 $m^3s^{-1}$ and 42.9 $m^3s^{-1}$ though most (4) of the downscalings simulate a mean increase in peak discharge of ~620 $m^3s^{-1}$ i.e. ~7.83 $m^3s^{-1}yr^{-1}$ over the entire future period. Such increases in discharge can be attributed to the projected increases in precipitation over the UMS as revealed in Chapter 5 of this thesis. Increases in precipitation rates are known to be highly correlated to peak discharges in small catchments (Ogden and Dawdy, 2003) and as such it highly likely that the projected increases in the UMS could be related to the same projections. Another key factor that is also likely to influence the peak discharges in the future is deforestation. Surface runoff is known to increase were there are high forest cover losses and increased cultivation (Guzha et al., 2018) and as such, considering the already established dense forest cover losses of up ~ 13% between 1989 and 2018 in the UMS (see Chapter 3), such disturbances, coupled with increases in impervious surfaces related to land clearing for potential infrastructure and settlement development could contribute to the simulated peak discharge increases. This possibility is also supported by Kalantari et al. (2014) who concluded that a 30% catchment area deforestation translated to a 60% increase in peak discharge and a 10% increase in total runoff in small catchments. Notwithstanding inherent limitations of computation of peak discharges using model simplifications and ignoring key hydraulic and hydrological variable dynamics (Wu et al., 2010), such peak discharge projections are valuable in flood risk analysis thus could assist in flooding prevention and early warning systems in the UMS. Furthermore, the model also projects dates when peak discharges are expected to occur (see Table 6.5) which provides useful guidance on fore-planning to avert impacts of potential flooding due to high peak discharges on those days. For example 07 January 2069 and 02March 2092 are projected to be peak discharge days. As such, the Civil Protection Unit of Zimbabwe can use this information to send out flood risk alerts to the 'at-risk' communities in the low-lying areas especially in the southern part of the UMS thereby mitigate against high impacts of floods.

**Table 6.5:** Summary table of simulated peak discharge and date of peak discharge

| Model | Period | Peak Discharge ($m3s^{-1}$) | Date of Peak | Volume (mm) |
|---|---|---|---|---|
| NOR | Base | 1244.8 | 05Apr2015, 00:00 | 604.41 |
| | NearF | 629.1 | 12Mar2035, 00:00 | 662.03 |
| | MidF | 1016.9 | 10Mar2045, 00:00 | 691.57 |
| | LongF | 975.5 | 21Jan2082, 00:00 | 1208.07 |
| ACC | Base | 659.9 | 06Dec2010, 00:00 | 514.56 |
| | NearF | 369.1 | 05Feb2025, 00:00 | 389.35 |
| | MidF | 675.4 | 29Oct2050, 00:00 | 555.9 |
| | LongF | 720.9 | 07Jan2069, 00:00 | 1231.25 |
| CCS | Base | 694.1 | 10Jan2015, 00:00 | 585.27 |
| | NearF | 921.9 | 05Jan2025, 00:00 | 555.13 |
| | MidF | 563.4 | 31Jan2050, 00:00 | 440.31 |
| | LongF | 807.1 | 11Nov2087, 00:00 | 1327.57 |
| CNR | Base | 516.6 | 10Feb1998, 00:00 | 522.42 |
| | NearF | 367.5 | 16Feb2032, 00:00 | 447 |
| | MidF | 496.1 | 17Nov2058, 00:00 | 453.73 |
| | LongF | 515.6 | 31Jan2097, 00:00 | 1069.76 |
| GFD | Base | 441.1 | 13Jan2002, 00:00 | 583.25 |
| | NearF | 42.9 | 26Dec2034, 00:00 | 274.39 |
| | MidF | 78 | 28Nov2043, 00:00 | 331.24 |
| | LongF | 92.9 | 31Jan2080, 00:00 | 501.31 |
| MPI | Base | 510.5 | 12Jan2007, 00:00 | 498.81 |
| | NearF | 597.7 | 12Jan2025, 00:00 | 516.99 |
| | MidF | 566 | 16Jan2054, 00:00 | 536.6 |
| | LongF | 944.6 | 02Mar2092, 00:00 | 1063.9 |

Figure 6.10 shows the stream runoff volumes associated with the earlier discussed peak discharges.

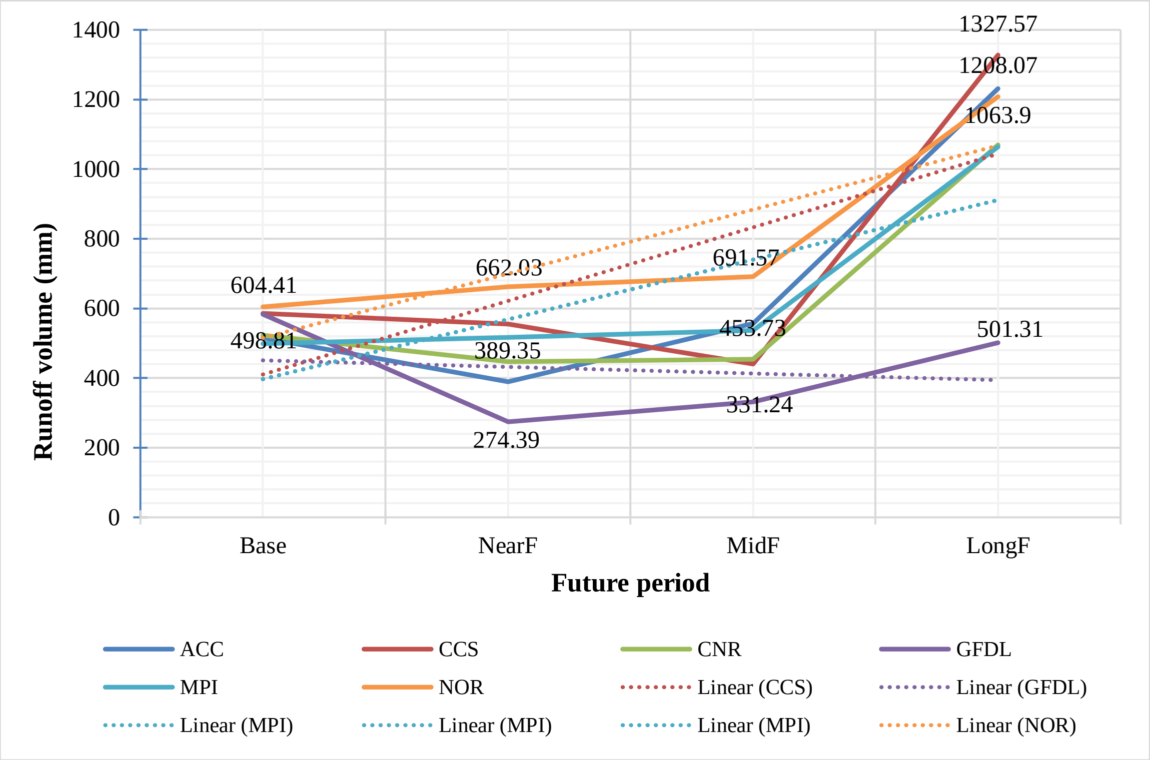


**Figure 6.10:** Simulated total stream run-off volume (mm) at UMS outlet for near-future (NearF), mid-term future (MidF) and long-term-future (LongF) for each ensemble member. Trend lines are also presented

For the first time in this catchment, simulations are successfully made showing future hydrological conditions beyond the general historical discharge and stream run-off perspectives presented by Love et al. (2005). There is a general ensemble member consensus of an almost doubling of run-off volume by the long term future which is contrary to GCM driven stream discharge projections of declining discharge trends over the entire Mzingwane catchment reported by Love et al. (2006). All models project increases in stream run-off volumes over the future periods with the exception of the GFDL-CM3 model which projects a declining trend. The simulated run-off seems to increase gradually from each successive future period following the patterns of increase in precipitation revealed in Chapter 5. In addition to the earlier discussed reasons for high peak discharges, increases in imperious surfaces due to settlement development are known to increase stream run-off as precipitation routing to the streams is increased as infiltration decreases as suggested by Du et al. (2015). Other reasons for the observations could be similar to those explained in the peak discharge section. It is important to note that increase in stream discharge tends to have negative impacts of the aquatic ecosystem of UMS as the high hydraulic loads can potentially erode the banks, and bring ore silt into the river systems. This scenario over time could lead to total siltation and collapse of the aquatic ecosystems and reduce the recharge potential of the extensive network of alluvial aquifers (Moyce et al., 2006) within the UMS thus posing a threat to community water security (especially during the dry seasons when water sources run dry).

### 6.3.3 Landuse – Landcover change impact on stream discharge

**Table 6.6**: Summary of results on impacts of LULC change on stream run-off

| Time-step | Peak Discharge ($m3s^{-1}$) | Date of Peak | Volume (mm) | % Volume change |
|---|---|---|---|---|
| Baseline (2018) | 917.6 | 06Dec2010, 00:00 | 470.34 | |
| 2028 | 749.2 | 12Jan2025, 00:00 | 295.01 | -37.28 |
| 2038 | 642.2 | 16Feb2036, 00:00 | 565.87 | 20.31 |

Results indicate a decrease in stream discharge volume of 37.28% in relation to the projected 2028 LULC changes of ~ 230 $km^2$ loss in dense woodland, and increases of ~ 120 $km^2$, 60 $km^2$, 30$km^2$ and 20$km^2$ in grassland, shrubland, bareland and water respectively. In the projected 2038 time-step, where 441 $km^2$ (i.e. 43.57%) of dense forest is projected to be lost while shrubland, grassland, water and bareland increase by 237 $km^2$ (10.73%), 185 $km^2$ (4.5%), 14 $km^2$ (26.85%) and 6 $km^2$ (15.09%) respectively, stream discharge volume is projected to increase 20.3% in the UMS outlet. The projected increase in stream discharge is consistent with most studies in semi-arid and other regions globally which show that forest cover loss increases annual stream discharges and peak flows. For example, Guzha et al. (2018) concluded that a 16 ± 5.5% increase in stream discharge and a mean of 10 ± 2.8% increase in peak discharge were linked to deforestation in Kenya. Similarly, Coe et al. (2011) observed a 25% increase in the Araguaia River (in east-central Brazil) between the 1970s and 1990s largely to due to extensive deforestation. As such, the observed increases could be related to the projected forest cover losses in the UMS. However, other authors such as De Kok and Hoekstra (2008) argue that stream volume and peak discharge modelling has numerous uncertainties related to model design and the stochastic nature of precipitation which is key in determining these parameters more that than landscape configuration. In this regard, the findings in this study present two contrasting, plausible scenarios future stream discharge scenarios in relation to future LULCs which need to be explored further to ascertain if indeed there is an impact of LULC on surface run-off in the UMS.

## 6.4 CONCLUSION

Findings show that future projections are likely to alter the stream discharge characteristics in the UMS. All ensemble members with the exception of the GFDL-CM3 project an increase in peak and total stream run-off discharge. The magnitude of change varies depending of the precipitation levels/ forcings by the respective ensemble members. It is apparent that the higher the precipitation levels a downscaling has, the hydrological model responds by a higher magnitude of change in stream discharge. These projected changes have utility and implications on flood hazard analysis in the UMS and thus consequential to strategy development and flood impact mitigation planning by the government agencies such as the Civil Protection Unit (CPU). While literature indicates that deforestation results in increased stream volume and peak discharge, findings in this study present two contrasting outcomes despite the fact of both scenarios indicating deforestation in the UMS. This may imply that there are other factors such as soil type, porosity and permeability and temperature condition that could be influencing these discharge but were not factored into or parametrised in the model.

# CHAPTER 7: SYNTHESIS, CONCLUSIONS AND RECOMMENDATIONS

Climate change and/ variability are key drivers of global change and will continue to occupy centre stage in the global development agenda. In this regard, climate science research has been, and will continue to be, key in generating new and better knowledge to answer many questions related to climate, such as historical trends, future trends and the likely impacts on both natural and socio-economic systems globally and at local scales. With the IPCC categorisation of Zimbabwe as a highly climate vulnerable country, with limited resilience and poor adaptation policies and strategies to avert the inherent impacts of climate change and variability, advancing scientific knowledge on the subject of climate is therefore most important. This study sought to add new knowledge the climate discourse by assessing the local scale impacts of land use and land cover changes and climate change on surface hydrological conditions in the semi-arid Upper Mzingwane sub-catchment in the northern Limpopo basin of Zimbabwe. The impetus to carry out this study was informed by a dearth of up-to-date scientific knowledge on climate change and its likely impacts on surface hydrological conditions in this well acknowledged, strategically important catchment in the Matabeleland South region of Zimbabwe.

First, an in-depth literature review on progress in climate and hydrological research undertaken in Zimbabwe over the past twenty-nine years is presented in Chapter 2. Findings from this Chapter set the stage for this research by exploring what scientific research has been done, presenting a critique and finally exposing the contextual knowledge gaps to be addressed, not only in this current PhD study, but also for more general purposes. Following a systematic review approach, findings revealed that that climate and hydrological scientific knowledge is not only outdated (lagging-behind) compared to other countries in the region, such as South Africa, but is also skewed in topic-coverage. It was noted that climate change and variability impact studies, and climate vulnerability, adaptation and mitigation studies, are the two-predominant categories of climate studies in Zimbabwe, while climate modelling and governance study themes were the least covered. For climate impact studies, there has been bias in favour of agricultural and ecological impact themes with very limited coverage of energy and socio-economic climate impacts. Furthermore, it has been apparent from the findings that while there has been extensive progress in the continuous development of new climate research tools and techniques, such as GCMs and RCMs, these have not been not well tested/ applied in Zimbabwe. It was also noted that climate research has progressed to incorporate new research themes such as integration of IKS, interlinkages between climate systems, their driving factors and impacts were poorly researched in Zimbabwe. The same pattern was noted also regarding hydrological modelling studies, which show very limited scope in terms of coverage and use of more recent advanced modelling tools. It also emerged that the Mzingwane catchment was among the most under-researched catchments in Zimbabwe, alongside the Gwayi and Save catchments.

In light of the identified knowledge gaps in Chapter 2, Chapter 3 of this study explores how the UMS landscape had evolved over time and projected future land use and land cover scenarios therein. Using advanced GIS and RS tools and techniques, historical LULC changes from 1989 to 2018, as also future (2025 up to 2038) LULC scenarios, are presented. Results show that the UMS has been a grass-shrubland predominated landscape with proportionate woody species typical of savannah ecosystems, although dense woodland experienced greatest net losses while grasslands and shrubs had net areal gains between 1989 and 2018. The same trend was predicted to continue into 2038, with more drastic net losses in woodland cover, with potential adverse societal, economic, water security and ecological impacts. These findings present key new knowledge that is valuable to guide decision making and interventions not only to reverse the degradation trends but also put in place plans to avert future negative scenarios.

In Chapter 4, this research explored historical climatic conditions in the UMS using historical observation data for the period 1921-2000. The focus was to test the utility of climate extreme indices for the first time in this region. However, due to data access limitations, only precipitation conditions were explored using daily observation data from four climate stations. Most of the computed index values show varying though mostly negative, statistically insignificant precipitation extreme trends across the UMS. The exception was for the westernmost extent of the area (covering Matopos National Park and Mzingwane dam sub-catchment). This area shows significant negative precipitation extreme trends and anomalies indicative of drying over the study period. A general shift towards shorter very wet periods with more intense precipitation and a decrease in the number of dry spells was noted in the study area. In general, the conclusion in this regard was that precipitation conditions have been deteriorating in the UMS. These findings, coupled with the negative trends in historical LULC scenarios revealed in Chapter 3, present a picture of convergence and possible compounding of negative impacts of communities and their livelihood in the UMS. It is also worth noting that although this part of the study was a success, the challenges experienced in trying to access adequate (necessary) observation data from government agencies for this part of the study, attest that data access is one of the main challenges and limitations to climate science research in Zimbabwe. From exploring historical climate conditions, future climate projections for the UMS were explored in Chapter 5.

Future climate projections (of precipitation, maximum and minimum temperature) were analysed using the high resolution CCAM data for three future climate periods i.e. near future (2020 – 2040), mid-term future (2021 – 2060) and long-term future (2061 – 2099). For the first time in the northern Limpopo basin, the utility of the CCAM data comparing future climatologies from six ensemble members was applied successfully. The ensemble members show no clear consensus in the future projected precipitation conditions in the UMS, although it is apparent that trends are more inclined towards increasing trends especially in the northern extent compared to the southern extent of the UMS. The precipitation range of change is projected to be decreasing from between +3mm and +9mm in the near future, to +3mm and +15mm in mid-term future and between +3mm and +12mm in the long-term future especially in interior region of the UMS. This is despite the indications of overall increases in total precipitation levels. With regards to model competence in projecting the average monthly precipitation in the UMS, the following ranking (from the best to the worst) is noted: MPI > CNRM-CM5 > GFDL-CM3 >NorESMI-M> ACCESS1.0> CCSM4. The MPI and the CNRM-CM5 best simulated the historical precipitation conditions in the UMS, and as such, its future simulations can be used with a relatively higher level of confidence compared to other model simulations. It is also worth highlighting that projections of precipitation increase may not necessarily translate into positive impacts on communities as they might be related to increases in frequency of extreme events, as revealed from historical trends. This could point to possibilities of flooding vis-à-vis the projected vulnerable/ degraded landscape projected in Chapter 3.

Projections of both maximum and minimum temperature conditions in all future periods show increasing trends of magnitudes of ~ +1.1°C to just over +6°C in the UMS. This suggests continuous warming in this region which coupled with possible increase (decreasing) trends in precipitation over the northern (southern) UMS could results in various impacts on community livelihoods, changes in disease vector distribution (and thus disease endemicity) and water security. Furthermore, heat waves are most likely to be frequent with potentially serious human health implications. As such, it becomes important that health promotion and interventions plans, strategies and programmes take into consideration these simulations. However, there still remains a need to validate these temperature projections as was done with the precipitation projections. This will improve confidence in the utility of these projections.

Chapter 6 brings together the LULC findings in Chapter 3 and the future climate projections presented in Chapter 5 to force a physical semi-distributed hydrological model (the HecHMS) to show future stream run-off conditions in the UMS. In this Chapter, the climate-LULC-hydrology nexus is fully explored and the overarching aim of the thesis addressed. The background literature from Chapter 2 coupled with the historical perspectives of extreme precipitation conditions (from Chapter 4) provide a basis for discussion of the results found in Chapter 6. Hydrological modelling results herein revealed that the NorESMI and the GFDL-CM3 model project declining trends in peak stream discharge though the former simulates the highest peak discharge in the baseline period (1996 – 2015). Overall, the simulated peak discharges ranges between 1244.8 $m^3s^{-1}$ and 42.9 $m^3s^{-1}$ though most (4) of the downscalings simulate a mean increase in peak discharge of ~620 $m^3s^{-1}$ i.e. ~7.83 $m^3s^{-1}yr^{-1}$ over the entire future period. Such increases in discharge can be attributed to the projected increases in precipitation over the UMS as revealed in Chapter 5 of this thesis. With regards to the impact of land use landcover changes on stream run-off, the model presents two contrasting results: one indicating declining levels of stream run-off and peak discharge in year 2028 and a marginal increase in 2038. However, considering that the HecHMS model used in this this study for hydrological simulation did not account for sub-basin flows, it is possible that the stream discharges and peak flows could be lower that depicted here. This is also considered against the fact that basins in the semi-arid Matabeleland of Zimbabwe have considerable subterranean flows within the alluvial sands deposited within river systems.

Overall, this study manages for the first time to test the applicability of high resolution downscaled CCAM data in simulating local future climatologies with good levels of accuracy. Furthermore, the forcing of a hydrological model to simulate future stream discharge is achieved as well demonstrating that indeed climate change and to some extent LULC change does have an impact on surface run-off in the UMS. The findings thus provide not only a template methodology to test or explore the climate-LULC-hydrology nexus but also valuable, new scientific information that can be used to guide appraisal of climate, water and catchment conversation in the UMS. It is recommended that the temperature climatologies revealed in this study be subjected to validation with observation data so as to ensure the validity of the simulations. Furthermore, considering that confirmatory conclusions of this study that climate change and/ variability will most likely alter the future surface hydrology (stream run-off) in the UMS, this will most likely make water availability more unpredictable coupled with increased frequency and intensity of extreme climate related hazards such as floods and droughts. The climate hazards will not only result in extensive property damages and losses but also environmental degradation, among others impacts, which will impose constraints to the poor rural communities within the UMS and the surrounding localities which are highly dependent on rainfall variability for subsistence. In addition, it thus imperative that the leadership in the Bulawayo City Council extends its scope and active participation in the management of the UMS together with the UMS Council. This is necessitated by the fact that over the years the Bulawayo city authorities have been keen on supply side of water resource management through water shedding in dry seasons of low water level in the dams with limited participation the UMS conservation planning, strategy development and implementation. Such improved participation will ensure that water security interests of the city are well considered in the UMS management process and/ plans.

As such, though results from this study project increases in rainfall in the mid-to-distant future, these will be coupled with significant temperature increases throughout the 21st century which will impose constrains in water security not only for the local communities but the city of Bulawayo (whose main water sources as hosted in the UMS). This is pertinent considering the projected continued deforestation i.e. land degradation in the UMS shown in this study. The combination of factors i.e. increased deforestation, increased rainfall indicate potentially increased surface and river run-off which will lead to increased top-soil erosion (negatively impacting on subsistence farming yields and thus food security to some extent). Similarly, prolonged and uncontrolled erosion will consequently exacerbate the already well acknowledged river and dam siltation problem in the UMS.

Considering that the potential/future water-land-water nexus challenges exposed in this study are multifaceted in nature, it is prudent that synergistic and holistic forward planning and cooperation between the central and local government, relevant/ key government agencies (such as CPU and EMA), humanitarian agencies and the private sector is fostered to achieve optimal water resources management and development solutions for the UMS. To deal with these complex and interlinked climate-landuse-water challenges, it will prudent for the GoZ to effectively coordinate and improve the way they manage strategic catchments such as the UMS and its water resources and its associated ecosystem services. This can be achieved by strengthening Integrated Water Resources Management Systems (IWRMS) through investing in institutional strengthening, climate and water information management, and enhancing (natural and man-made) water infrastructure development. It will be prudent for efforts to be couple with institutional tools such as legal and regulatory frameworks aimed at strengthening water catchment and water resources protection and/ conservation. Robust information systems buttressed by sound scientific evidence and modern technologies (such as geospatial technology with modelling) are needed to effectively and/ proactively plan for early warning and hydro-meteorological forecasting, resource monitoring, and quick decision making under evident climate change/ variability and uncertainty in general. Overall, these initiates will enhance water security but also help mitigate against climate shocks in vulnerable communities within and beyond the UMS.

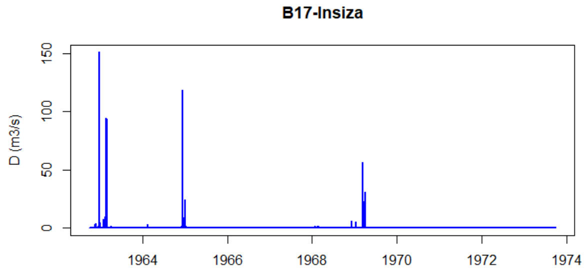
# APPENDICES

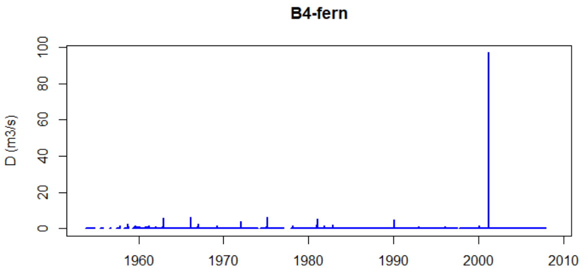
## APPENDIX 1: UMS HecHMS model parameters

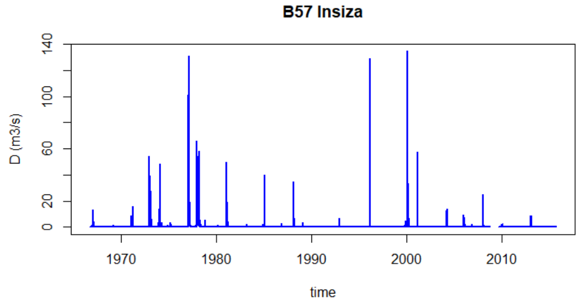
| cln | Basin name | Perimeter | CatchmentArea | ZinwaCatchArea (Km2) | CatchmentArea (km2) | TotalUpstreamArea | TotalUpstreamArea (km2) | TotalDrainageLength | LongestFlowPathLength(m) | Outlet Elevation(m) | Outlet Elevation(feet) | Divide Elevation(m) | Divide Elevation(feet) | Length in (mi) | Time of concentration (min) *tc* | Time lag (min) *tlag* | Distance between reaches(m) | Muskingum (K) hrs | Muskingum (X) | Initial Deficit (mm) | Maximum Deficit (mm) | Constant Rate (mm/hr) | % impervious | Reach |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | B4-FERNSPRUIT | 46666.9 | 50367728 | 82.87 | 50.37 | 50367728 | 50.37 | 38160.2 | 19151.7 | 1157 | 3795.93 | 1414 | 4639.11 | 11.87 | 202.73 | 121.64 |  |  | 0.55 | 80 | 130 | 6.75 | 2 |  |
| 2 | B75-INSIZA | 101247.04 | 332284911 | 401 | 332.28 | 332284911 | 332.28 | 254155 | 27143.15 | 1258 | 4127.30 | 1448 | 4750.66 | 16.83 | 340.68 | 204.41 |  |  | 0.55 | 85 | 150 | 6.75 | 4 |  |
| 3 | B30-UMZINGWANE | 142775.07 | 372612977 | 448 | 372.61 | 372612977 | 372.61 | 271939.5 | 49697.75 | 1114 | 3654.86 | 1474 | 4835.96 | 30.81 | 535.66 | 321.39 |  |  | 0.5 | 100 | 170 | 5.75 | 3 |  |
| 4 | B41-INYANKUNI | 107796.82 | 360945322 | 365 | 360.95 | 360945322 | 360.95 | 272770.4 | 40278.02 | 1062 | 3484.25 | 1352 | 4435.70 | 24.97 | 456.69 | 274.02 |  |  | 0.55 | 85 | 150 | 6.75 | 2 |  |
| 5 | B57-INSIZA | 76133.29 | 142082761.5 | 570 | 142.08 | 474367672.5 | 474.37 | 102231.2 | 27841.81 | 1225 | 4019.03 | 1382 | 4534.12 | 17.26 | 377.57 | 226.54 | 9704.673 | 2.1935 | 0.55 | 90 | 150 | 6.25 | 2 | R1 |
| 6 | B66-KANGESI | 170855.15 | 660734474 | 673 | 660.73 | 660734474 | 660.73 | 447166 | 66303.95 | 989 | 3244.75 | 1243 | 4078.08 | 41.11 | 854.70 | 512.82 |  |  | 0.55 | 85 | 140 | 5.75 | 2 |  |
| 7 | B17-INSIZA | 267037.17 | 1214966924 | 1870 | 1214.97 | 1689334597 | 1689.33 | 905174.5 | 80426.62 | 1110 | 3641.73 | 1403 | 4603.02 | 49.86 | 1011.09 | 606.65 | 43686.627 | 9.1535 | 0.55 | 85 | 150 | 6.75 | 2 | R2 |
| 8 | B69-INSIZA | 120021.84 | 320912940 | 2260 | 320.91 | 2010247537 | 2010.25 | 223564.9 | 52047.17 | 999 | 3277.56 | 1110 | 3641.73 | 32.27 | 888.76 | 533.26 | 44217.822 | 12.5844 | 0.55 | 70 | 130 | 6.85 | 3 | R6 |

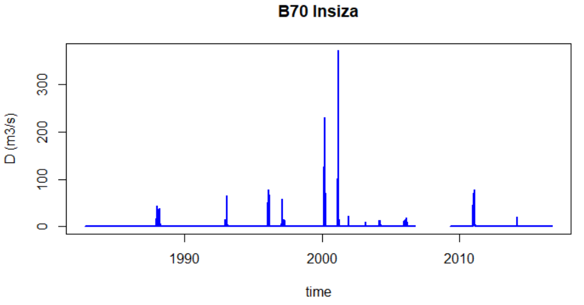
| | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 9 | B70-INSIZA | 74336.34 | 95427564.33 | 3030 | 95.43 | 2766409575 | 2766.41 | 64533.4 | 21734.84 | 962 | 3156.17 | 1076 | 3530.18 | 13.48 | 320.85 | 192.51 | 13244.21 | 3.2585 | 0.55 | 90 | 170 | 6.25 | 2 | R7 |
| 10 | UMS-Outlet | 535837.67 | 3146824460 | | 3146.82 | 6697160062 | 6697.16 | 2331768.4 | 145414.59 | 867 | 2844.49 | 1397 | 4583.33 | 90.16 | 1595.00 | 957.00 | 6639.125 | 1.633448585 | 0.55 | 95 | 150 | 6.25 | 4 | R9 |
| | | | | | | | | | | | | | | | | | 71010.541 | 12.98140215 | 0.55 | 95 | 150 | 6.25 | 4 | R3 |
| | | | | | | | | | | | | | | | | | 92540.617 | 16.91730478 | 0.55 | 95 | 150 | 6.25 | 4 | R5 |
| | | | | | | | | | | | | | | | | | 93021.459 | 17.00520727 | 0.55 | 95 | 150 | 6.25 | 4 | R4 |
| | | | | | | | | | | | | | | | | | 6639.125 | 1.633448585 | 0.55 | 95 | 150 | 6.25 | 4 | R8 |

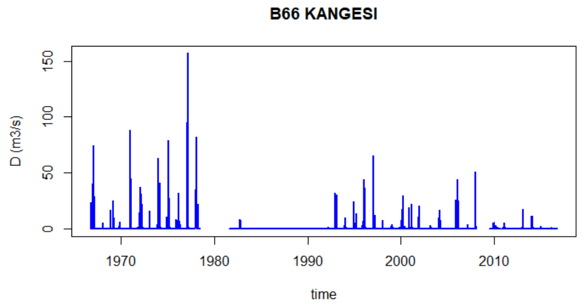
# APPENDIX 2: UMS daily stream discharge at each gauging station

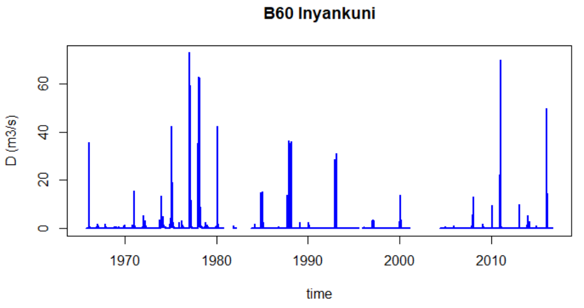


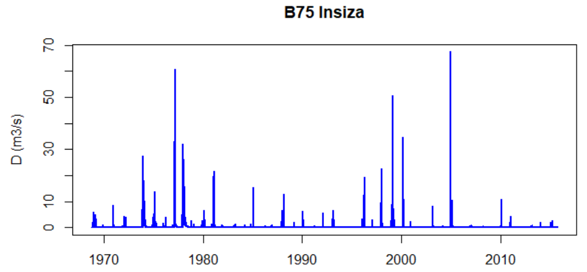


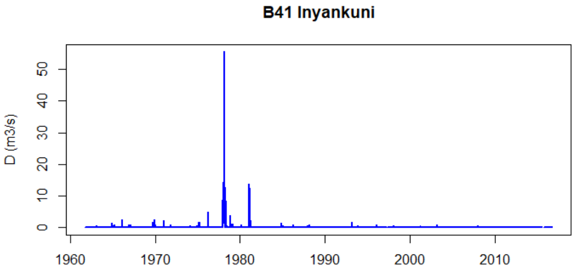


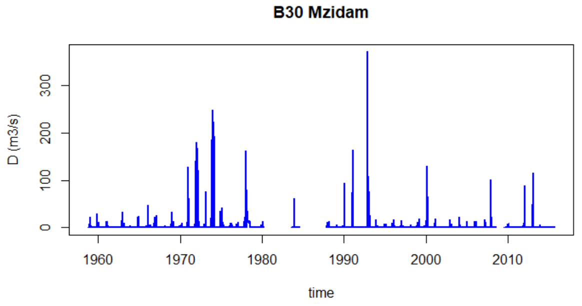


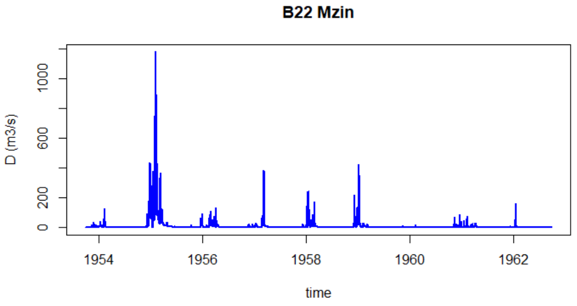












## APPENDIX 3: HMS Consistency Checking Log

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HMS Consistency Checking Log

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Project: UpperMz_HecHMS
    •   File Creation Date: 19/4/2021
    •   File Creation Time: 12:38:35

Checking uniqueness of names.
    •   Checking River HydroID uniqueness:
    •   End of checking River HydroID uniqueness - all IDs are unique.
Checking River Name uniqueness:
    •   End of checking River Name uniqueness - all Names are unique.
Checking Drainage Area HydroID uniqueness:
    •   End of checking Drainage Area HydroID uniqueness - all IDs are unique.
Checking Drainage Area Name uniqueness:
    •   End of checking Drainage Area Name uniqueness - all Names are unique.
Checking VIP Name uniqueness:
    •   End of checking VIP Name uniqueness - all Names are unique.
End of checking uniqueness of names.

Checking river containment...
    •   End of checking river containment.

Checking centroid...
    •   End of checking centroid.

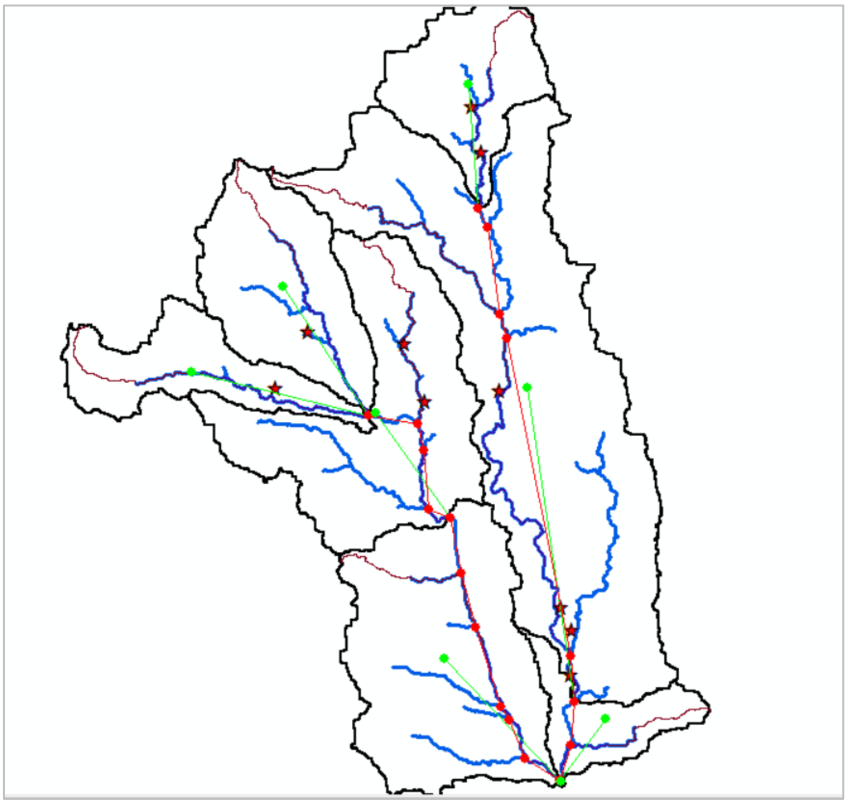
Checking river's connectivity
    •   End of checking river's connectivity.

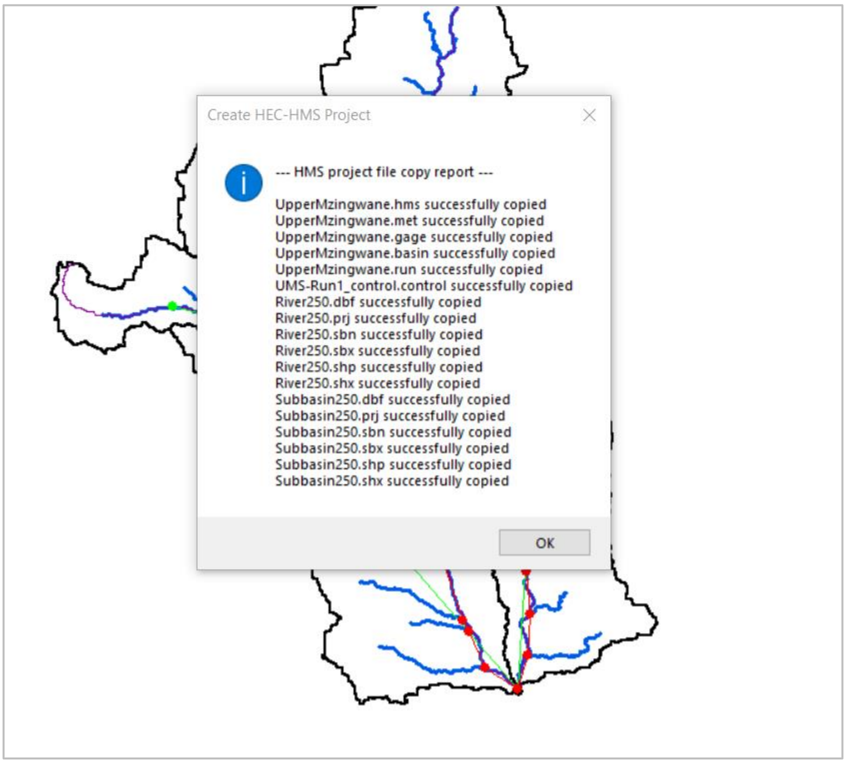
Checking project points [VIP points]...
    •   Checking VIP Point: Outlet1 x=744918.3232, y=7682256.0834
    •   End of checking point: name=Outlet1 oid=1 - No PROBLEM found.
End of checking project points [VIP points].

Checking Finished: 12:38:35

CHECKING SUMMARY
****************
    •   Unique names         - no problems.
    •   River containment    - no problems.
    •   Center containment   - no problems.
    •   River connectivity   - no problems.
    •   VIP relevance        - no problems.
```

## APPENDIX 4: HecHMS Project create report, River longest flow path and reaches





--- HMS project file copy report ---

UpperMzingwane.hms successfully copied
UpperMzingwane.met successfully copied
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UpperMzingwane.basin successfully copied
UpperMzingwane.run successfully copied
UMS-Run1_control.control successfully copied
River250.dbf successfully copied
River250.prj successfully copied
River250.sbn successfully copied
River250.sbx successfully copied
River250.shp successfully copied
River250.shx successfully copied
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Subbasin250.sbn successfully copied
Subbasin250.sbx successfully copied
Subbasin250.shp successfully copied
Subbasin250.shx successfully copied

## APPENDIX 5: PET rate values (mm/month) used in this study

| Station | ByoGoetz | Filabusi | MatoposNP | Mbalabala |
|---|---|---|---|---|
| Jan | 184 | 191 | 186 | 189 |
| Feb | 159 | 164 | 160 | 162 |
| March | 177 | 172 | 171 | 174 |
| April | 159 | 152 | 159 | 155 |
| May | 152 | 137 | 145 | 142 |
| June | 135 | 120 | 124 | 124 |
| July | 148 | 128 | 134 | 130 |
| August | 180 | 166 | 171 | 166 |
| September | 217 | 201 | 209 | 200 |
| October | 230 | 225 | 234 | 230 |
| November | 196 | 201 | 198 | 197 |
| December | 180 | 185 | 182 | 182 |

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