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FACULTY OF SCIENCE, ENGINEERING AND AGRICULTURE

DEPARTMENT OF EARTH SCIENCES

Modelling impacts of climate change on hydrology of Latonyanda River Quaternary Catchment, Limpopo Province, South Africa

By

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A dissertation submitted to the Department of Earth Sciences, Faculty of Science, Engineering and Agriculture, University of Venda in fulfilment of a Masters of Earth Sciences Degree in Hydrology and Water Resources (MESHWR)

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DECLARATION

I, Shudufhadzo Godlive Mukwevho declare that, this dissertation titled “Modelling impacts of climate change on hydrology of Latonyanda River Quaternary Catchment, Limpopo Province, South Africa” submitted to Department of Earth Sciences, Faculty of Science Engineering and Agriculture, University of Venda in fulfilment of a Masters of Earth Sciences in Hydrology and Water Resources (MESHWR) has not been submitted in any institution of higher learning, and that it contains my own work and all references used are acknowledged accordingly.

Signature…… …   Date…29/06/2023…

DEDICATION

I dedicate this work to the Lord Almighty for always making it possible, and my son Oritonda Immortal Lebepe.

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ABSTRACT

The study assessed the impacts of climate change on hydrology of Latonyanda River Quaternary Catchment (LRQC). The Soil and Water Assessment Tool (SWAT) model played a huge role in climate change impact analysis because it helped in improving the understanding of climate change impacts on hydrology as well as in determining mitigation measures. Arc-GIS 10.7 model with a compatible version of Arc-SWAT interface was used to model the impact of climate change on hydrology of LRQC. The SWAT model set up for calibration and validation was done using historic data. The SWAT Output viewer was used to view model performance results. Model performance was assessed based on scatter plots, graphical fits and performance measures which include Nash Sutcliffe Efficiency (NSE), percent bias (PBIAS), and coefficient of determination (R^2). Climate change projections from Conformal Cubic Atmospheric Model (CCAM) were used to forecast the impact of climate change on hydrology. The historical, near future and far future periods are 34 (1981-2014), 30 (2023-2052) and 30 (2053-2082) years, respectively. To determine trends on annual average flows and statistical significance for historical, near and far future, regression analysis was used. Regression analysis showed that significance levels of the p-value for historical, near, and far future annual flow trends is 0.010, 0.034 and 0.030, respectively. The model performance was good and acceptable with NSE, PBIAS, and R^2 for both calibration and validation as 0.67 and 0.68, -9.3 and -13.4%, and 0.70 and 0.69, respectively. The findings of the current study show that streamflow amount is decreasing over time with annual average totals of 4.849, 2.340 and 2.051 m^3/s for the historical near, and far future respectively. The results will aid in raising awareness to the community and municipality governing around LRQC. This study recommends venturing into smart development technologies to minimise the impact caused by climate change. Further climate change related studies should be conducted as there is a gap in ungauged catchments. The expansion of the current study to include land use impacts on hydrology is recommended.

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LIST OF ABBREVIATIONS

ACRU	Agricultural Catchment Research Unit
AGRR	Agricultural Land-row crops
ANION-EXCL	Void space
ARC-ISCW	Agricultural Research Council Institute of Soil, Climate, and Water
ASABE	American Society of Agricultural and Biological Engineers
AWC	Available water capacity
C	Organic carbon content
CCAM	Conformal Cubic Atmospheric Model
CMIP3	Coupled Model Inter-comparison Project Phase 3
CMIP5	Coupled Model Inter-comparison Project Phase 5
CORDEX	Coordinated Downscaling Experiment
d	Index of agreement
DEM	Digital elevation model
GCMs	Global Climate Models
HBV	Hydrologiska Byrans Vattenavdelning
HRUs	Hydrologic Response Units
HSPF	Hydrological Simulation Program-FORTRAN
IPCC	Intergovernmental Panel on Climate Change
Ks	Saturated hydraulic conductivity
LRC	Luvuvhu River Catchment
LRQC	Latonyanda River Quaternary Catchment
LULC	Land use/land cover
NSE	Nash Sutcliffe efficiency
OWBE	Overall water balance error
PBIAS	Percent bias
pc_i	Rainfall within the catchment
PCPD	Average number of days of precipitation in month
PCPMM	Average or mean total monthly precipitation
PCPSKW	Skew coefficient for daily precipitation in month
PCPSTD	Standard deviation for daily precipitation in month

PMs	Performance measures
ppm	Parts-per-million
PR_W1	Probability of a wet day following a dry day
PR_W2	Probability of a wet day following a wet day
R^2	Coefficient of determination
rc_i	Runoff within the catchment
RCPs	Representative Concentration Pathways
RMSE	Root mean square error
RSR	Standard deviation of measured data
SSP	Socioeconomic pathway
SSP3	Regional Rivalry
SSP5	Fossil-fueled Development
SWAT	Soil and water assessment tools
SWRN	Arid Range
TEX	Soil texture
TOPMODEL	TOPography based hydrological model
WEAP	Water Evaluation and Planning

LIST OF SYMBOLS

%	Percentage
∞	Infinity
i	Station number
N	Number of pairs of items
α	Alpha

LIST OF APPENDICES

CHAPTER ONE: INTRODUCTION

1.1 Background

Human based practices are the reason for increased greenhouse gases that raise the Earth's temperatures (Burke *et al*., 2005; Xu *et al*., 2013). Globally, greenhouse emissions from gases such as methane (CH_4), nitrous oxide (N_2O), and carbon dioxide (CO_2) have resulted into increased temperature rate, because they absorb the earths energy rapidly in the atmosphere which affect the ecosystem (Pandey *et al*., 2016; Xie *et* al., 2008). The conclusion made by the atmospheric scientists is that global warming is occurring, and the earth's temperature is assumed to continue rising (Li *et al*., 2020a).The assessments of the Intergovernmental Panel on Climate Change (IPCC) have highlighted that the earths climatic conditions are changing due to increased emission of greenhouse gases into the atmosphere (Kusangaya *et al*., 2014; Solomon, 2007). Climatic variability and change have been reported to have major impact on the precipitation pattern and other climate variables. The status of regional and local water accessibility addresses the impact of climate change in an area (Poulin *et al*., 2011, McCarthy *et al*., 2001).

Anthropogenic activities such as deforestation and fossil fuel burning are the most contributing factors to emission of greenhouse gases that are continuing to increase the earth's temperature which in-turn lead to climate change (Trenberth, 2018). The emission of greenhouses gases is increasing with increase in global economy and population resulting in the heat being trapped by CH_4, N_2O, and CO_2 in the atmosphere. When these gases become thicker, they form a blanket which makes the planet warmer (Reddy and Reddy, 2015). The changing climate is also resulting in extreme and unpredictable hydrologic events such as droughts followed by strong rainfalls which influence flooding (Trenberth, 2011).

The CO_2 gas emission has concentrated the atmosphere at unique rates for the last 800,000 years. The level of generating CO_2 has been recorded as 278 parts per million (ppm) during the establishment of the observation. Since the year 2016 the record for CO_2, has increased to above 400 ppm. This shows that there has been a continuous global increase of CO_2 gas emissions as detected by the Mauna Loa Carbon Dioxide Observatory (Johnson *et al*., 2017).

The hydrological cycle is mostly impacted through changes of its own component such as the precipitation and evaporation rates. The precipitation changes give rise to floods and droughts whose occurrence and changes affect the hydrological cycle and the environment at large. Such changes result in some parts of the world experiencing major decrease in precipitation amount, or major changes during the wet and dry seasons (Allan *et al*., 2020). The changes associated with global temperature and precipitation that are occurring continuously have major consequences on water resources including streamflow amount. Streamflow predictions is necessary when the focus of a study is to understand the impact of climate change and land use/land cover (LULC) on hydrologic response of an area (Obiero *et al*., 2019). The LULC has been intentionally changed so that it meets the demand of natural resources such as water, food, fuel and fiber in most parts of the world. The hydrological responses have been adversely impacted by these changes and so are available water resources. This is because the hydrological responses of a catchment depend on changes in LULC (Warburton *et al*., 2012).

Mekonnen and Hoekstra (2016) estimated that by 2025, about 4 billion people will be living in an environment experiencing water stress with the potential to be imposed by climate change. African continent particularly the southern African region has been known to be mostly vulnerable to climate change because of its low adaptive capacity and vulnerability predicted (Badjeck *et al*., 2010). A study by (Hassan and Nhemachena, 2008) showed that climate change mostly impacts hydrology, which lead to changes in streamflow and regional water resources. The regional water resources are significantly impacted by the increase in global hydrological cycle impacts that has resulted from climate change. Floods and droughts occurrences will be influenced by the impact of precipitation distribution and intensity which in-turn will directly affect the runoff rate. (Mukheibir, 2005). The Luvuvhu River Catchment (LRC) is characterised by rainfall variability of a high magnitude of extremely dry and wet conditions (Mazibuko *et al*., 2021).

1.2 Problem statement

Climate change is one of the major causes of droughts and floods in South Africa, limiting the availability of surface water (streamflow). The agricultural sector is the most affected sector by droughts and floods than other sectors (domestic and industrial) due to its primary dependency on precipitation for crop development and production (Douglas *et al*., 2000). Floods have negatively impacted development and infrastructure due to the damage caused both to property and life on the LRC in South Africa (Singo *et al*., 2012).

Luvuvhu River and its tributaries in the upstream of the catchment are the main recharge sources of Nandoni Dam which is used for municipal water supply and small-scale farming. The climate change in Luvuvhu River Catchment which is the mother catchment of 14 quaternary catchments including the Latonyanda River Quaternary Catchment (LRQC) is a problem since it leads to droughts and floods which influences water supply problems in Vhembe district municipality.

The LRQC contribute flows to Luvuvhu River downstream of Albasini Dam. These flows are essential for maintaining the river ecology and sustaining the water needs of residence living at downstream of the catchment and support agricultural activities occurring within the catchment (Odiyo *et al*., 2012). South African economy primarily depend on agricultural production. Therefore, small scale farming in LRQC is also likely to be highly affected by climate change impacts. Rainfall is unevenly distributed all over the country, with the eastern part of the country experiencing humid subtropical conditions with the yearly rainfall average of 1 000mm. The western part of the country experienced dry conditions with a yearly rainfall average of 100mm. South Africa receives an average yearly rainfall of 450mm, which is lower than 860mm of the world's average, thus, the overall rainfall distribution is not enough to support agricultural practices all over the country (Benhin, 2006). Limpopo Province is agriculture driven and accountable for the production of about 60% of fruits, cotton, vegetables, wheat and maize in South Africa (Turpie and Visser, 2013). The impact of climate change will give rise to economic constraints since agricultural sector is the first to be negatively impacted by climate change (Tibesigwa *et al*., 2015). Limpopo Province was identified by International Food Policy Research Institute as the most vulnerable province in the agricultural sector to climate change because of the high proportion of small-scale farming which is a problem that cannot be easily mitigated.

The impact of climate change in agriculture extends into livelihoods problems in Limpopo Province which are likely to increase with climate change. Food security in Limpopo Province is negatively impacted by drought like any other sectors (domestic, water, and industrial) resulting in food shortage (Tibesigwa *et al*., 2015). The most impacted areas are rural, where agriculture is their source of food in the province. Such areas have less chances of surviving climate change impact and adaptation measures designed for the changing conditions. Resilience strategy global health challenges outlined that the impact of climate change in human health is mostly prone to children and elders and associated with causing diarrhoea, respiratory disease, asthma, and malaria. In this regard, most of households in Limpopo Province including those in the study area use their income for health care which is a huge problem to the poor. Since LRQC forms part of the LRC it is also affected by the impact of climate change similarly as the main catchment.

1.3 Motivation

Climate change has resulted to floods which have caused damage to infrastructure and impacted negatively on fauna and flora in LRC (Singo *et al*., 2012). The LRQC forms part of the Luvuvhu River system which is one of the major water sources in Vhembe District Municipality. Assessing impacts of climate change using a model that can integrate both land-use/land cover and climate change is very important to improve on understanding their impacts on hydrology of LRQC as well as in determining mitigation measures. An integrated model will also assist on improving the reliability of the research findings.

The Agricultural Catchment Research Unit (ACRU) model identified reduced rainfall over Limpopo Province in the long-term. These rainfall estimates remain within present day variability, with other models suggesting that there may be future increases which shows uncertainty in model projections (Tshiala *et al*., 2011). This indicates that more research needs to be done in the area to at least find common climate change projections. The uncertainty emerges out of that the region experiences more changes in precipitation which will lead to the increase in evaporation rates, indicating that they will be drought in the future regardless of the presence of heavy rainfall.

Warburton *et al*. (2012) studied the challenges associated with modelling hydrological responses to impacts and interactions of land use and climate change in LRQC using ACRU model. The study did not cover future climate change projections and their impacts on water resources availability. This study indicated that climate change impacts on the hydrology of LRQC will be modelled focusing on the future climate change projections rather than focusing on challenges that occur in modelling hydrological response. The limitation of ACRU model is that it is designed to cover small scale sub-catchments (a maximum of 30 km^2 per sub-catchment) (Jewitt and Garratt, 2004). Nkuna and Odiyo (2016) studied the relationship between temperature and rainfall variability in LRC and hence did not cover aspects of climate change. Obiero *et al*. (2019) conducted a study in LRQC based on hydrologic response modelling, using Soil and water assessment tools (SWAT) model but did not cover the aspect of climate change impact on hydrology of LRQC which grant enough reason to study the impact of climate change on hydrology of LRQC. Odiyo *et al*. (2012) also estimated river flows contribution to Luvuvhu River located downstream of Albasini Dam. Therefore, there is a gap in studies that focused on impacts of climate change on hydrology in LRQC. Findings of this study will assist in catchment management and deriving measures that should be undertaken for climate change adaptation. It will further help in obtaining information that will be used for climate change preparedness or mitigation. The study will also help in projecting future climate change so that it becomes easy to mitigate or adapt to the projected climatic conditions.

1.4 Objectives

1.4.1 Main objective

- To model the impact of climate change on hydrology of the LRQC.

1.4.2 Specific objectives

- To identify the historical and future climate change scenarios for LRQC.
- To assess the efficiency of the selected model in predicting historic and future streamflow.
- To project the impact of future climate change scenarios on hydrology of LRQC using a hydrologic model.

1.5 Research questions

- What are historic and future climate change scenarios in LRQC?
- What is the efficiency of the selected model in predicting streamflow of LRQC?
- What is the impact of climate change on hydrology of LRQC?

1.6 Study area

The LRQC is located within the LRC, with latitudes and longitudes 22°59′12″S and 23°05′56″S and 30°09′58″E and 30°21′58″E respectively (Figure 1.1). It has a catchment area of approximately 129.34 km^2. Latonyanda River is a tributary of Luvuvhu River with Livhungwa River being its major tributary. Latonyanda River joins the Luvuvhu River at the upper reaches which is the downstream of Albasini dam. The point of Interest in the LRQC for streamflow is the outlet of quaternary catchment of A91D which is located downstream of the catchment.

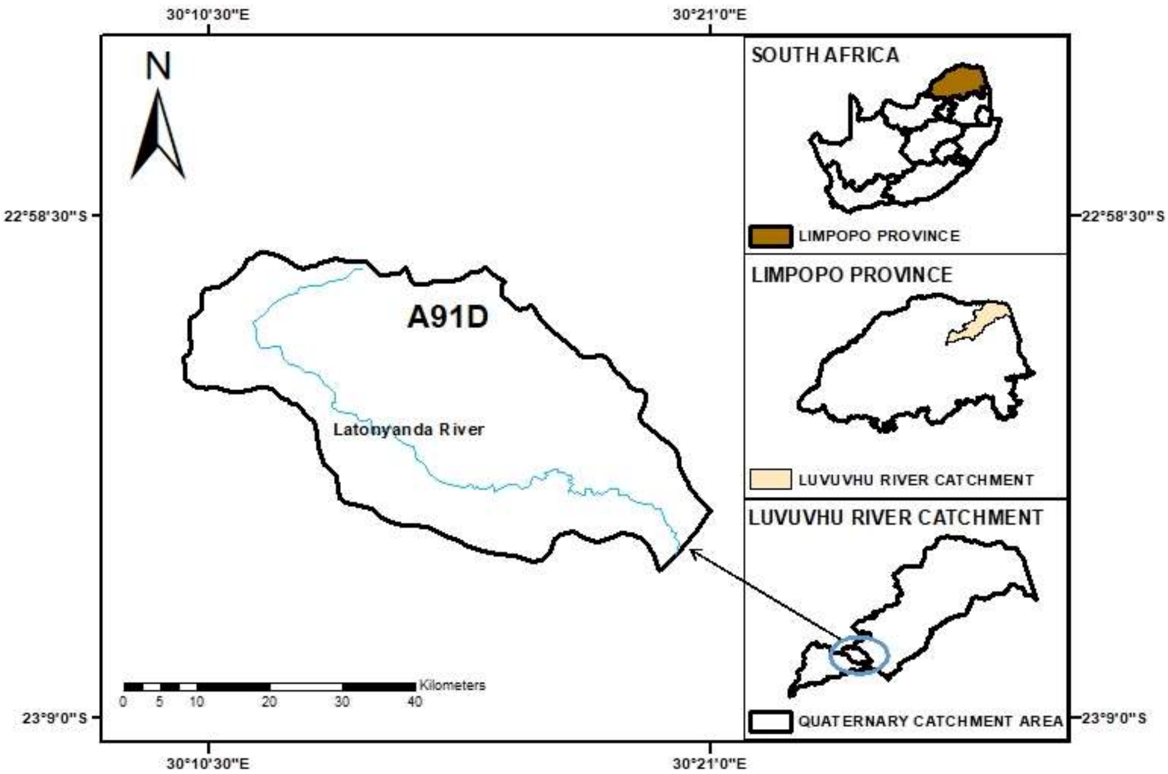

Figure 1.1: Study area map

1.6.1 Land cover/ Land-use

Land use activities around LRC, include commercial forestry estate, protected game reserve, human settlements subsistence agriculture, and cultivated lands (Therivel *et al*., 2013). Forestry plantation is practised in the upstream of the Luvuvhu and Latonyanda Rivers extending to the Albasini Dam. The southern part of LRC is covered by unusual tree plants of eucalyptus and pines (Odiyo *et al.,* 2015). Many small-scale irrigation schemes are found within the LRC, most of which exploit streamflow and do not have authority to abstract water from the catchment (Jewitt and

Garratt, 2004). The LRQC is mostly characterised by sandy clay loam soil. The catchment is characterised by forestry and agriculture in the upstream, and rural settlements in the downstream (Odiyo *et al*., 2012). The study area is characterised by thicket bushland, forest plantations, cultivated commercial dry lands and cultivated temporary semi-commercial dry land (Obiero *et al*., 2019).

1.6.2 Hydrology and Water use

The Latonyanda River is one of the major tributaries, rising in the Soutpansberg Mountains, other major rivers include, Mutshindudi, Mutale and the Sterkstroom. Jewitt and Garratt (2004) estimated that dams regulate 55 million m^3 of the 395 million m^3 Mean Annual Rainfall in the catchment. Thohoyandou, Makhado and Malamulele townships depend on the catchment for their water supply. In the LRQC, the rainfall pattern is mainly seasonal (October-March). Temperature ranges from 2 to 34 °C with the mean annual value of 18 °C and an average annual rainfall and evaporation of 1287mm and 1200-1600mm, respectively (Obiero *et al*., 2019).

CHAPTER TWO: LITERATURE REVIEW

2.1 Preamble

This chapter consist of literature on impacts of climate change in a global perspective and use of models for assessing the impact of climate change on hydrology is reviewed. Analysis on impact of climate change, previous studies, data quality control, model sensitivity, uncertainty and model performance are also reviewed.

2.2 Impact of climate change on hydrology

Studies such as (Li *et al*., 2020b; Zhuan *et al*., 2018; Hansen *et al*., 2012) have indicated that human induced climate change is already occurring and has impacted on resources such as water. Observations that were identified by the scientists have shown that the mean annual temperature of the Earth has escalated by a range of 0.3-0.6 °C since the 19th century with the possibility of increasing further by 1-3.5°C over the next 10 decades (Bruce *et al*., 1996; Li *et al*., 2020a). Climate change has been represented by changes in precipitation pattern which has been influenced by increased temperature which at the end is going to impact the hydrological cycle, changing the timing and production of streamflow (Barranco *et al*., 2014; Demaria *et al*., 2016). Changes in precipitation patterns due to continuous increase in temperature can also have an impact on sediment yield. The buildup of sediments in the catchment may decrease water availability and an increase in soil moisture decline caused by increased evapotranspiration (Azari *et al*., 2016). According to the IPCC report, increased temperature and rainfall variability will lead significantly to water-related risks such as floods and droughts, especially in developing countries like India which is now facing severe climate change effects on water and agriculture (Watanabe *et al*., 2018). The impact of climate change is mostly felt in rural areas because of their vulnerability, it even gets complicated to analyse because of the scale which requires more detailed climatic information for the analysis to be successful.

Temperature changes in South Africa, have occurred 1.5 times the observed global temperature average of 0.65 °C over the past 5 decades with the frequency of extreme rainfall events increased (Ziervogel *et al*., 2014; Nangombe *et al.,* 2019). Limpopo Province is predicted to face a potential increase in temperature by about 2°C by 2035, 1-2°C between 2040 and 2060, and 3-6°C between 2080 and 2100. Temperature increases is projected to increase water demand, leading to an extreme effect on regional water resources (New *et al.,* 2002; Deveopment, 2016).

Climate change affects hydrological cycles in a local and global perspective, in most cases it changes the amount of water and the rate of streamflow, which makes it difficult to manage existing water infrastructure and bring risks of water shortages and floods (Zhu and Ringler, 2012; Mukheibir, 2005). The direct impact of climate change is mostly felt by water and agricultural sectors because of their direct dependence on climate variables and contact (Praveen and Sharma, 2019).

The impact of climate change in South Africa is negatively impacting water resources, health, food security, infrastructure, biodiversity and the ecosystem services in general (Zwane, 2019). Putting into consideration, the increased level of South Africa's poverty and inequality which results in critical drawback for national development. Climate change mitigation has been a subject of interest in South Africa for a number of years because of its annual emissions per person which are higher as opposed to the other countries on in African and globally (Bhorat *et al*., 2016).

2.3 Climate change projections

Global Climate Models (GCMs) are very useful in terms of providing information on climate change under different greenhouse gases emission scenarios (Chou *et al*., 2020). Since GCMs are designed to work in higher resolution for global representation of information, they are not ideal to use for capturing local features such as topography, watershed, and coastlines because of the grid sizes. It is therefore necessary to introduce the Regional Climate Models since they play an important role in downscaling the global climate simulations to precise resolutions. Representative Concentration Pathways (RCPs) are used as inputs in climate and atmospheric modelling because they have the source of information on all radiative forcing components (Wayne, 2014). Van Vuuren *et al*. (2011) presented four RCPs namely: RCP 8.5, RCP 6, RCP 4.5 and RCP 2.6 that have been recently used across the scientific forcing target level for the period of up to 2100. The RCPs were individually developed using different models and tools. RCP 8.5 was developed based the Model for Energy Supply Systems and their General Environmental impact model and the Integrated Assessment Framework by the International Institute for Applied Systems Analysis, Austria. This type of scenario represents increased emission of greenhouse gases overtime which lead to high level of greenhouse gas concentration (Hayhoe *et al*., 2010), the most important aspects of this parameter is that it is used as an input to the Coupled Model Inter-comparison Project Phase 5 (CMIP5).

The Access and Inclusion Model undertaken by the research team at the National Institute for Environmental Studies in Japan developed RCP 6 (Fujino *et al*., 2006), which represent the stabilisation of the total radiative forcing immediately after 2100 with no sign of emission exceedance. The RCP 4.5 scenario predicts climate under the belief that the present level of carbon dioxide emissions is controlled, the radiative forcing increases will result in a linear until about the year 2060, afterwards the increase will occur slowly down until the end of the century where it becomes steady. The Integrated Model to Assess the Global Environment modelling team in Netherlands Environmental Assessment Agency also developed RCP 2.6. This scenario represents very low greenhouse gas concentration levels which show increase and decrease. The above is due to radiative forcing level first reaches a value of around 3.1 W/m^2 by mid-century and returns to 2.6 W/m^2 by 2100. In order to achieve such levels, the emission of greenhouse gas are decreased with time (Van Vuuren *et al*., 2007). The low-emission scenario (RCP 2.6) will have an increase of over 1 °C of average temperature with an extreme scenario (RCP 8.5) increasing over 4 °C (Knutti and Sedláček, 2 013). The availability and quality of long-term record and trend analysis is important for the successful use of data (Banzon *et al*., 2016). The information related to how the climate has been changing is obtained using historical trend and it can further be used for climate models verification to improve model performance (Eyring, 2019).

IPCC reports shows different climate model simulation experiments. This report outlines the use of the third Coupled Model Intercomparison Project (CMIP3) and the CMIP5 (Vicente-Serrano *et al*., 2022). The Fourth Assessment Report gave more details on the third phase of. The simulations of the fifth phase (CMIP5) were carried out in 2011 (Taylor *et al.,* 2012) then later followed by the sixth phase (CMIP6) (Touzé-Peiffer *et al*., 2020). The scenarios that are associated to the Shared Socioeconomic Pathway (SSP) thoroughly illustrate the frequency of uncertainty that will occur to the economy due to climate change impacts.

The IPCC's Sixth Assessment Report is based on the SSPs. The highest-growth SSP scenario was found to be the Fossil-fueled Development (SSP5) which has projected an increasing growth and extreme inter-country income convergence. The slowest-growth scenario is the Regional Rivalry (SSP3) which has projected less world Gross Domestic Products per capita in 2100 (Burgess *et al*., 2022). The two scenarios have posed a difference in simulating climate change which has resulted in an extra 1°C of global warming by 2100 (SSP5) if no climate adaptation measure is undertaken (Tebaldi *et al.,* 2021).

The Coordinated Downscaling Experiment (CORDEX) is a framework technique that is used to produce simulations of regional climate projections for all areas globally (Giorgi and Gutowski, 2016). The Conformal Cubic Atmospheric Model (CCAM) have been used to simulate existing climate and future climate change with a practice of more than a decade in South Africa. Strategies such as the precipitation analysis and runoff over a period of time, the use of projection of future trends in global population, economic and development of technology to produce climate scenarios together with GCMs and the downscaling of temperature and precipitation to a regional or local scale have been established to evaluate climate change impact on hydrology (McGregor, 2015).

Downscaling is specifically designed to acquire detailed temporal and spatial information from GCMs (Ekström *et al*., 2016). Rainfall-runoff models give runoff projection using climate scenarios for middle and long-term water planning (Banzon *et al*., 2016). The accuracy and reliability of GCMs outputs are affected by uncertainty when downscaling to a catchment level. Therefore, calibration of rainfall-runoff models and runoff produced are based on substantial errors (McGregor, 2015) such as amplified runoff changes in response to small precipitation changes and spatial-temporal scale mismatches (Kundzewicz and Gerten, 2015).

Assessing the impacts of climate change in the water sector involves the use of analytical models to evaluate water availability in a quantitative manner and allocation in relation to present and changed climatic conditions (Matondo *et al*., 2004). The GCMs were established to simulate and project the present and future climatic change, respectively (Carter and Kohn, 1994). When researching on the impacts of global climate change the focus is mainly on societal feedback to the local and regional impacts of large-scale changes (Xu, 1999). Below are GCMs limitations that are considered to be very important:

- The accuracy of GCMs decreases when spatial and temporal scales are slightly increasing, while the need of impact studies equally increase with higher resolution.
- Free tropospheric variables GCMs accuracy decreases to surface variables, with the water balance calculations having direct practice on variables at the earth's surface.
- GCMs accuracy decreases from climate driven variables such as wind, evapotranspiration, temperature, humidity and air pressure to precipitation, soil moisture and runoff, while the subsequent variables are importance in hydrologic systems.

The advantages associated with GCMs include:

- GCMs helps with dynamic downscaling approaches to produce high-resolution meteorological inputs needed for input in hydrological models.
- They use statistical downscaling method for local scale surface variables simulation from free tropospheric variables.
- Macroscale hydrological modeling methods for simulating streamflow in large river basins and for correcting perceived weaknesses in the representation of hydrological processes in GCMs.

2.4 Projected historical and future climate change scenarios

Based on the regions, seasons, and drought metrics, there is tangible evidence that climate change will increase drought risk and severity. Understanding the concept of past climate variability and change can assist in predicting the future impact. In the past and recent years, the semi-arid regions have experienced extreme changes which have been predicted to recur in the near future (Chadwick *et al*., 2016).

For accurate prediction in model projections, model performance is not the only considered factor. The considered factors of interest may include those that have controlled their variability in the past, and the once that will control their trends in the future with also the concept of human based activities accounted (Biasutti, 2019). Focusing on the mechanisms of rainfall changes at different scales, assessing models on their ability to duplicate those mechanisms, and assessing climate projections on the probability that the same mechanisms will be precise in the future is essential (Hall *et al*., 2019).

In Australia, there has been an increase interest in spatial attributes on previous changes in mean and extreme rainfall events. Since Australia is ranked as the second driest continent on Earth, the water resource managers and policy makers strongly depend on studies that are done which make it essential to conduct reliable projections around rainfall trends and variability in future (Dey *et al*., 2019).

In Sub-Saharan Africa, climate change impacts will be felt in different ways due to natural and human induced impacts. The climate change scenarios for the Sub-Saharan region will result in a warming trend that will mostly be felt in the inland subtropics with extreme heat events occurring frequently, increasing aridity, and rainfall patterns changes (Conway, 2009). The regions will have different impacts based on the location. The Southern Africa region will have a decline and East Africa will have an increase in rainfall (Serdeczny *et al*., 2017). West part of Africa is said to be exposed to climate change due to high climatic variability, high dependence on rain-fed agriculture, and limited economic and institutional capacity to account for climate variability and change. Therefore, studying the impact of climate change in West Africa is crucial (Sultan and Gaetani, 2016). Impact of climate change predictions on water use and agriculture in South Africa should be reliable because South Africa is a water-scarce country. Therefore, reliable projections will assist in planning for adaptation strategies (Jones *et al*., 2015).

The Limpopo Province is prone to climate change and global warming, this was noted in observations and climate change models. The maximum temperatures escalated by more than 2°C for the past 20 years. Evaluation of the projected future climate change impacts on water related sectors in the Limpopo River Basin with focusing on South Africa can assist in planning for the future to avoid water shortages. The simulated streamflow from the CORDEX model projections were assessed at three different time intervals such statistical metrics focusing on trends in projected streamflow, the Standardized Streamflow Index (SSI), the proportion of dry and wet years and drought monitoring indicators are used to assess the impacts of future climate on water-based sectors in the Limpopo River Basin (Botai *et al*., 2020). This indicates that Limpopo province is prone to drought hence it is important to simulate streamflow and project the future impact for drought/flood preparedness.

Climate change projection models are the new adopted methods used to predict how climate change is going to impact water resources in the future (Odiyo *et al*., 2020). Engelbrecht *et al*. (2011) showed that the performance of most of the climate change models are criticised because they are not verifiable due to the fact that projections are made for longer period which jeopardise the accuracy (the longer the projection period the lesser the model accuracy). Climate scenarios are essential for providing detailed simulations which are needed for regional climate change impact studies in small catchments such as LRC (Odiyo *et al*., 2020).

The increase in extreme events (such as floods and droughts) in LRC is affecting rainfall trends. The temperature trends are also furnished with increased magnitude of heatwaves mostly in drought seasons of the catchment. High temperatures have adverse impact on evaporation rate that are increasing at a fast pace which results in open water and soils been compromised (Nkuna and Odiyo, 2016). Odiyo *et al*. (2020) show that the increase in temperature is predicted for the far future with the range from 1.5°C to 2.5°C under RCP 4.5.

2.5 Hydrological models used for analysis of climate change impacts

Hydrological models give users an opportunity to operate the model parameters in an understandable manner which helps in identifying and solving differences between variables when it arises (Sokolowski and Banks, 2011). Sorooshian *et al*. (2008) stated that the best model gives results that represent reality and are not meant to be always correct, with the minimal utilisation of model parameters and model complexity. Spatial and temporal variations of hydrological models are suggested by users based on the interest of a study and they are classified based on the hierarchy of the physical based processes and the spatial characteristics of the catchment (Pechlivanidis *et al.,* 2011). Since modelling of streamflow enables prediction of streamflow hydrographs, prediction on climate change impacts and land use on catchment hydrologic response, it is of very high significance (Obiero *et al*., 2019).

2.5.1 Soil and water assessment tool (SWAT) model

The SWAT model is used to analyse and predict the sediment circulation, water, and agriculture production that requires the use of chemicals in basins having the absence of hydrological stations (Kim *et al*., 2008). It is a comprehensive, semi-distributed (the catchment is easily divided into sub-catchments characterised of even roles) watershed model (Arnold *et al*., 2012) which requires a little exact calibration to attain quality hydrologic estimation, but in instances were results are not satisfactory, manual calibration can be done to adjust the output in an acceptable standard (Brouziyne *et al*., 2017). The expansion of the SWAT model is a continuous time process which is used for the replacement of the Simulator for Water Resources in Rural Basins model (Kim *et al*., 2008). The procedure of SWAT model set-up and running for climate change impacts projection includes setting up a Digital Elevation Model (DEM), defining the soil, slope and LULC of a catchment, followed by weather generation. The model performs long term simulations, and it divides the whole catchment into sub-catchments which are further broken down into hydrologic response units (HRUs), vegetation, land use, and soil characteristics (Mauser and Bach, 2009). The inputs required by the SWAT model includes hydrological and meteorological data which are used by the model to describe nutrients circulation, sediment circulation, water, and vegetation growth. After the successful initial run with good model results, climate projection scenarios can be used to project future streamflow to allow climate change impact projection. The SWAT model has been applied globally for analysis of climatic conditions (Brouziyne *et al*., 2017). The following water balance equation is used (Neitsch *et al*., 2002). The Assumption states that the dimensions of the catchment remain stationary which is the limitation of the model.

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day-Q_{surf}-E_{a-w_{seep}-Q_{gw}}}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.1)}$$

Where:

SW_t = Humidity of the soil, SW_0= Base humidity, R_{day}= Volume of rainfall in mm

Q_{surf}= Surface run-off, *Wseep*= Seepage of water from soil to underlying layers

E_a= Evapotranspiration, Q_{gw}= Ground water runoff, t = Time in days

2.5.2 Water Evaluation and Planning (WEAP) model

The function of the WEAP model is to combine the conclusion and support of the model which allows the description of the water system in each designated water unit (Rosenzweig *et al*., 2004). The model is also used as an integral part to support water development aimed at balancing the water supply attained in occurrence of the physical processes of the water-shed scale, multiple water demands and environmental entries, which are considered by spatially and temporally variable in allocation priorities and water supply preferences (Sieber and Purkey, 2007). The future climate change is assessed by comparing a number of WEAP outputs between the future scenarios and the current conditions. This will only occur when future conditions differ from the current land-use, water consumption and, vegetation types, in addition to climate change (Rosenzweig *et al*., 2004). The model also calculates (algorithms calculations) the water balance in the system on an interval of a month. Water is allocated to meet in-stream and water demand requirements.

2.5.3 TOPography based hydrological model (TOPMODEL)

The TOPography based hydrological model (TOPMODEL) is used to obtain the derivation of topographic index distributions from DEM data to calculate the depth to water table based on Geographical Information System and TuaDEM tools. The TOPMODEL is a physically based, rainfall-runoff model. The streamflow and subsurface-saturation state of the catchment are simulated by using a topographic wetness index computed from values of surface-elevation, represented by the saturation shortage (Nystrom and Burns, 2011). The model can be used in different ways such as single or multiple sub-catchments utilising the elevation grid data for the catchment area. It is very effective in modelling catchments with shallow soil and moderate topography, this model further aids in estimation of hydrological response in the basins (Devia *et al*., 2015). They are main factors that are considered such as catchment topography and soil transmissivity to generate storage shortage or water table depth at any location. The storage shortage value occur as the function of topographic index (a/tanβ) (Devia *et al*., 2015). Climate change impacts modelling using the TOPMODEL is conducted by focusing on the analysis of the contour maps which is done manually, this is accepted because the index is focused on the topography of the basin and gives calculations for only the values of the representative indices. (Quinn *et al*., 1995).

2.5.4 Hydrologiska Byrans Vattenavdelning (HBV) model

The HBV model is utilised in river basin analysis for the prediction of runoff, this is performed by using the application of temperature and precipitation measurements. The HBV model is categorised as a semi-distributed conceptual model (Bergström, 1976). The procedure involves dividing the catchment into smaller sub-units (sub-catchments) which are later categorised into diverse elevation and vegetation zones. The model is operated using daily and monthly rainfall data, evaporation, and air temperature. The accumulation of snow is computed using air temperature data (Devia *et al*., 2015). The following general water balance equation is used.

$$P - E - Q = \frac{d}{dt}[SP + SM + UZ + LZ + lakes] \qquad (2.2)$$

Where:

P= Precipitation, *E*= Evaporation, *Q*= Runoff, *SP*= Snowpack, *SM*= Soil moisture

UZ and *LZ*= Upper and lower ground water zone, *Lakes*= Volume of the lake.

2.5.5 Agricultural catchment research unit (ACRU) Model

The ACRU model is a physical-based, agrohydrological model which uses daily observed data (Warburton *et al*., 2010). The ACRU model was implemented and advanced in the early 1970s to be used for the purpose of reservoir yield simulation, crop yield modelling, and design hydrology (Smithers *et al*., 2001). The model set-up and running requires input parameters such as daily rainfall, air temperature, and reference evaporation (Smithers *et al*., 2013). The major processes of the hydrological cycle such as the water level in streams, peak runoff, and the hydrograph are simulated using the ACRU model (Kienzle *et al*., 2012). The hydrographs having changes in peak discharges are simulated and developed using historical rainfall data (Smithers and Chetty, 2005).

The other uses of this model include modelling by using exceedance probability plots and risk analysis (Kienzle *et al*., 2012). The design of the ACRU model makes it very sensitive to changes that occur due to climate, land cover/use and soil, which in-turn influence accurate results when utilised for analysing changes in future climate estimations (Jewitt and Garratt, 2004). The use of this model for climate change impacts and flood estimation has been gaining more attention overtime. The model may be also applied as a point or lumped catchment model. In-instances where there are complications within the physical-based process, the model can be used as a distributed model (Smithers *et al*., 2013). The process entails dividing the catchment into sub-catchments each having an area of less than 30 km^2 (Smithers and Chetty, 2005). The ACRU model requires an expert to successfully run the model which is a disadvantage (Thavhana *et al*., 2018)

2.5.6 Hydrological Simulation Program-FORTRAN (HSPF) model

The HSPF is a hydrological model which is used for continuous simulation of watershed focusing on simulating nonpoint-source runoff and pollutant loadings for a watershed and performs flow and water quality routing in reaches, well-mixed lakes and impoundments (Yuan *et al*., 2020). Duda *et al*. (2012) showed the detailed information and guidance that can be utilised to assist in understanding the scope of the proposed American Society of Agricultural and Biological Engineers (ASABE) activities for model calibration and validation using the HSPF model. Model calibration and validation are very important and critical steps that all hydrological models must undergo to ensure quality results. Table 2.1 show the summary of hydrologic models.

Table 2.1: Summary of hydrologic models (Baloch, 2009; Thavhana *et al*., 2018; Ibrahim *et al*., 2022)

Hydrologic models	Category	Purpose	Operating procedure
SWAT model	Semi-distributed model	The SWAT model is used to analyse and predict the sediment circulation, water, and agriculture production that requires the use of chemicals in basins having the absence of hydrologic stations.	The procedure includes setting up a DEM, defining the soil, slope and LULC of a catchment, followed by weather generation.
WEAP model	Semi-distributed model	The WEAP model is used as an integral part to support water development aimed at balancing the water supply with demand.	The model integrates climate change scenarios and hydrologic process along factors such as economic, population growth, and policies on historic and future water availability and demand in the catchment with the use of the water balance principle.
TOPMODEL	Semi-distributed model	The model is used to obtain the derivation of topographic index distributions from DEM data to calculate the depth to the water table based on Geographical Information System and TuaDEM tools.	The topographic wetness index simulates the streamflow and subsurface-saturation state of the catchment by computing from values of surface-elevation, represented by the saturation shortage.
HBV model	Semi-distributed model	The HBV model is used in river basin analysis for the prediction of runoff.	The procedure is to apply the measurement of temperature and precipitation. The catchment is divided into sub-catchments which are later categorised into diverse elevation and vegetation zones.
ACRU model	Distributed model	The purpose of the ACRU model is to account for reservoir yield simulation, crop yield modelling, and design hydrology.	The procedure includes dividing the catchment into sub-catchments each having an area of less than 30 km^2.
HSPF model	Lumped model	The HSPF model is used for continuous simulation of watershed focusing on simulating nonpoint-source runoff and pollutant loadings for a watershed and performs flow and water quality routing in reaches, well-mixed lakes and impoundments.	The procedure is to identify the data requirements for the modeling systems, identify the quality attributes of the available or required data, analysing the effect of using such a dataset on the acceptability of model results based on model performance, and a model applicability pathway is determined under strict data conditions.

2.6 Previous studies on hydrological modelling and impacts of climate change on hydrology

Mulla and Mondal (2021) conducted uncertainty analysis of dominating hydrological parameters in diverse hydrometeorological micro-watersheds in Krishna basin of Southern India. This study simulated streamflow using the Algorithm SUFI-2 of SWAT-CUP models in two different hydro-meteorological watersheds of Marol, and Talikot in Krishna basin of Southern India, where the unregulated flow exit. The results show that the R^2 and NSE values for calibration are 0.87 and 0.84, respectively, and 0.65 and 0.58 for validation, respectively for the Moral Watershed. For the Talikot watershed, values for R^2 and NSE are 0.90 and 0.52; and 0.83 and 0.74, respectively for both calibration and validation.

Edokpayi *et al*. (2020) reviewed the influence of global climate change on water resources in South Africa focusing on an adaptive management approach. Climate change scenarios in South Africa and their impact on water resources, water security, and authority, were presented. The study showed increase and decrease in water levels in South Africa which were caused by climate change-imposed events such as floods and droughts. The study recommended that the use of smart water technology adaptive measures should be implemented to ensure that adaptation to the changing climatic condition and appropriate legal and regulatory water resources framework of management to reduce water insecurity is achieved.

Thavhana *et al.* (2018) conducted the SWAT model uncertainty analysis, calibration, and validation for simulating runoff in LRC. The QSWAT which is an advancement of SWAT model, was used as an interface with QGIS. The model ran for a period of 33-year (1983–2015). The sequential uncertainty fitting (SUFI-2) algorithm was used to obtain the sensitivity analysis, calibration and validation through the SWAT interface for calibration and uncertainty process. Model results before iteration indicated an over-estimation of low flows with regression slope of< 0.7. The SUFI-2 algorithm identified the model behavior with calibration results presenting an R^2 of 0.63, NSE of 0.66, RSR of 0.56 and a positive PBIAS of 16.3 while validation results show an R^2 of 0.52, NSE of 0.48, RSR of 0.72 and PBIAS of 19.90. In conclusion, it was indicated that calibration of the SWAT model showed acceptable results with fair validation results, meaning the model can be used successfully for water resources analysis and not for hydrological extremes analysis in the LRC.

Bajracharya *et al*. (2018) assessed climate change impacts on the hydrological regime of the Kaligandaki Basin. The SWAT model was used to obtain the impact of climate change and future projection in this study based on RCP 4.5 and 8.5 of ensemble downscaled CMIP5 GCM. Based on the modelling results on prediction of climate change impact, there will be an increase in the annual average temperature of over 4 °C, and an increase in the annual average precipitation of over 26% by the year 2199 under RCP 8.5 scenario. The modeling results further projected that there will be significant variations in the basin's water balance and hydrological regime with 50% increase in discharge expected at the outlet of the basin.

Shrestha *et al*. (2016) showed that an increase in annual average discharge in both the Melamchi and Indrawati Rivers show that the changes in discharge are non-linear. The projections on discharge show that the Melamchi River will have a decrease during the period of March–July and increase during August–February. The Indrawati River will have a decrease during November–April and increase during May–October. The findings of the study will be useful in preparing an adaptation plan to account for the negative impacts caused, while at the same time taking into consideration the positive impacts of climate change on the river basin.

Zhu and Ringler (2012) analysed the impacts of climate change on water availability and use in the Limpopo River Basin of Southern Africa. The aim of the study was to estimate the extend of how climate change impacts will affect irrigation water supply in the Limpopo River Basin within Botswana, Mozambique, South Africa and Zimbabwe. An approach of using an integrated model consisting of a semi-distributed global hydrological model and the Water Simulation Module of the International Model used for analysis of policies for Agricultural Commodities and Trade was adopted. The model result discovered that the water resources of the Limpopo River Basin are already affected regardless of the current climatic conditions. The study further indicated that if the current climatic conditions prevail the water infrastructure and management interventions will be adopted to improve the situation by 2050 since water supply availability was projected to worsen considerably by 2050.

Odiyo *et al*. (2012) conducted a study on rainfall–runoff modelling aimed at estimating water flow that is contributed to Luvuvhu River downstream of Albasini Dam by Latonyanda River. Catchment delineation was done on the upper LRQC, at streamflow gauging station number A9H027. The Mike 11 NAM rainfall–runoff model was used for simulation with 4 years selected as calibration period and 2 years as model validation period. Model performance was based on R^2, RMSE, overall water balance error (OWBE) PBIAS. The flows that Latonyanda River contribute to Luvuvhu River were obtained from removing irrigation abstractions and runoff amount from the simulated runoff. The value for R^2, RMSE, OWBE and PBIAS for calibration and validation were 0.86 and 0.73, 0.21 and 0.2, 2.1 and 1.3, and 4.1 and 3.4, respectively. The findings of the study show that the model results for runoff simulation in the LRQC is interrelated to the areal rainfall indicating that the results are well established. The amount of flow estimated from unmeasured data makes it possible to plan and manage the water requirements demand at the downstream of the river.

Moriasi *et al*. (2012) and other model developers and expert users of mostly used hydrologic and water quality models from all over the world were recruited to write scientific articles based on model calibration and validation procedures to develop guidelines for that subject (model calibration and validation). A total of 25 hydrologic and water quality models were selected, this study produced 22 research articles that have detailed information on calibration and validation. The models were scaled from the field to watershed scales for simulating hydrology, pesticides at temporal scales varying from hourly to yearly, nutrients, bacteria, and sediment. A respective Individual article offer model experts with complete model customised guideline on calibration, validation, and utility. Cooperatively, the articles are characterised of a framework with detailed material that will aid in the advancement of a planned set of ASABE model calibration and validation guidelines.

Schulze and Perks (2000) have undertaken a study in South Africa, using the modified ACRU model to determine climate change impact on water resources at the smallest hydrological unit. Factors such as soils, slope, land use activities, and influenced changes in infiltration and soil water redistribution are considered during runoff generation process. Climate change also impacts groundwater resources which is widely used as a source of water supply for various use in South Africa. The rapid use of groundwater resources requires that it becomes recharged more often and faster to meet the demand. The recharge index was measured using the ACRU model to determine climate change impact in different regions of South Africa.

Xu (1999) used GCMs to obtain the simulation of the current climatic condition and predict future climatic change. This study found that the GCMs were unable to represent local sub-grid-scale features and dynamics, but they have previously represented continental and hemispheric spatial scales with a large percentage of global system complexity. This study further outlines the existing gap and the methodologies such as Dynamic downscaling, Statistical downscaling, Macroscale hydrological modeling and Hypothetical scenarios for narrowing the gap between GCMs' ability and the need of hydrological modelers. The challenges for future studies of the hydrological impacts of climate change are also identified.

2.7 Data quality control

Data analysis is complemented by data completeness and quality (Sattari *et al*., 2017). Data quality is impacted by methodologies used for data collection in the field, with human factors being the main considered aspect. The appropriate data collection approach result into good data quality (Chao *et al*., 2015). During data measurements, different errors such as random and systematic errors could be created in the observational recording of the data. Therefore, data quality control is useful and necessary in determining the reliability and eliminating such errors (Wilby *et al*., 2017; Sun *et al*., 2018).

2.7.1 Factors to be considered when checking data quality

- **Measurement errors**

The data collection agencies such as Agricultural Research Council and Department of Water and Sanitation having either automated or manual gauges are responsible for measuring the water level. In cases where the water level is reduced, the reading is not well calculated. The shift on the gauge is reproduced on the time series graph as change in the trend (Alsdorf *et al*., 2007; Maidment *et al*., 2015). The changes that occur in discharge and water level trend have been considered as noticeable errors for some selected stations and need to be attended to in consultation with the data collecting institutions. Trend changes can be influenced by other factors such as construction of structures that can change the flow rate or depth of rivers (Sethi *et al*., 2015). In this case, these types of errors should be cautiously accommodated.

- **Missing Data**

The frequency of time series data is based on ordinary time intervals such as annually, monthly, and daily. The data gaps that are attained due to an obstruction or malfunction of an equipment, the gap should be patched for quality results (Sattari *et al*., 2017). Therefore, the national water resource database has encouraged that the period of missing data should be addressed in the future by the use of proper methodology such as the arithmetic averaging, the multiple linear regression, and the non-linear partial least squares algorithm method(Alam *et al.,* 2014).

2.7.2 Use of double mass analysis for data quality control

Hydrological data corrections are determined by the use of the double mass analysis with the ability to interpret variations in data collection process. This method further detects possible variations in hydrological data series and trends. This is done by examining the ratio of accumulated values of the series to be analysed *(*Branisavljević *et al*., 2009). The occurrence of data fluctuations may be due to a number of factors such as changes in instrumentation, or changes in gauge location and nearby conditions, and also changes in observation procedures, (Sethi *et al*., 2015). The results of the analysis report are represented in a series called the doubles mass curve. The double mass curve shows a straight line for best fit of the test series. A gap in the test-series will create a break, and a trend will result into a curved line.

In case the series contains missing data, a specified minimum number of elements over a period of time (daily, monthly and annually) should be available to define the period as a non-missing data (Simolo *et al.,* 2010; Tawn *et al*., 2020).

Procedure

If Y_i, (i =1, N) is the test series and X_i, (i =1, N) the base series. The following equations is used for the ratio of two series:

$$rc_{i}=\frac{\sum_{j-1}^{i} Yj}{\sum_{j-1}^{i} Xj} \quad \ldots\ldots (2.3)$$

$$pc_{i}=\frac{\sum_{j-1}^{i} Yj}{\sum_{j-1}^{i} Yj}-\frac{\sum_{j-1}^{N} Xj}{\sum_{j-1}^{i} Xj} \quad \ldots\ldots (2.4)$$

Where:

X_j, Y_j= The base and the test series, ΣX_j, Y_j=Sum of the base and the test series

N= Number of pairs of items, i= Station number, rc_i= Runoff within the catchment

pc_i =Rainfall within the catchment

2.8 Model calibration and validation

In hydrological modelling calibration and validation processes are very important and are implemented to analyse model sensitivity and performance. The analysis is focused mostly on sensitive parameters in a catchment (Mutenyo *et al*., 2013). The model parameter influences how the catchment respond. The huge number of model parameters the more the influence on catchment processes (Gyamfi *et al*., 2016). This factor shows the importance of undertaking sensitivity analysis. The t-test and p-value measures are used to classify relative sensitivity of individual parameters and stipulate the importance of a trend. SWAT-Cup Premium and SWAT output viewer tools are used for SWAT model result viewing and analysis (Thavhana *et al*., 2018). SWAT-Cup Premium is also used for model parameterisation and allows interaction of parameters to improve model performance and multi-objective calibration which have an advantage of choosing 11 functions to process all at once. The program also allows sensitivity, and uncertainty analysis, with the ability to statistically analyse the t-test and p-value which are used in the model to rank different parameters that are reflected to have more influence on streamflow. Programmes such as SWAT Precipitation Input Preprocessor (pcpSTAT) is used to calculate statistical parameters of daily precipitation data used by the weather generator on SWAT model (Amin and Nuru, 2020).Table 2.2 show parameters that can be calculated easily even by the use of Microsoft Excel, except for PR_W1 and PR_W2 which requires a lot of time to process.(Gurara *et al*., 2020)

Table 2.2: Statistical Parameters of precipitation used in SWAT model (Liersch, 2003)

PCPMM(mon)	Average or mean total monthly precipitation
PCPSTD(mon)	Standard deviation for daily precipitation in month
PCPSKW(mon)	Skew coefficient for daily precipitation in month
PR_W1(mon)	Probability of a wet day following a dry day
PR_W2(mon)	Probability of a wet day following a wet day
PCPD(mon)	Average number of days of precipitation in month

2.9 Model performance measures

The model performance measures (PMs) and performance evaluation criteria are important in examining both the calibration and validation of models (Pachepsky *et al*., 2016). Evaluation of hydrologic model behavior and performance is mainly influenced and presented through comparisons of simulated and observed variables. In a normal case, comparisons are done on simulated and measured streamflow at the catchment outlet (Krause *et al*., 2005). Model PMs recommended by Moriasi *et al*. (2015) include coefficient of determination (R^2), percent bias (PBIAS), root mean square error (RMSE; alongside the ratio of RMSE and standard deviation of measured data, RSR), Nash Sutcliffe efficiency (NSE), index of agreement (*d*), and several graphical performance measures (PMs). The model calibration and validation performance are driven by direct and derived graphical PMs (Moriasi *et al*., 2015). There are different types of hydrological models such as Deterministic and conceptual models. The distributed model is one of the categories in deterministic model. In this category the approaches such as comparison of simulated and observed measurements for the output of validation can be integrated into the evaluation procedure for overall modelling performance (Krause *et al*., 2005).

The R^2 estimates both the predicted series and the combined dispersion together with single dispersion of the observed data. The range of R^2 is between 0-1, value of 0 mean no correlation at all and 1 mean the dispersion of the prediction is equal to that of the observation (Krause *et al*., 2005). NSE is a standardized statistic which is used to analyse the relative magnitude of the noise compared to the measured data (Nash and Sutcliffe, 1970). NSE is a quantitative measure which is beneficial for the development of performance evaluation criteria and it is utilised to regulate how the trends are simulated by the model (stream flow, sediments, nutrients, pesticides and temporal scales) (Moriasi *et al*., 2015). Furthermore, it can be used to incorporate measurement uncertainty (Harmel and Smith, 2007; Harmel *et al*., 2010). The equations for R^2 and NSE are outlined below:

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \acute{Ó})(P_i - \acute{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \acute{Ó})^2 (\sqrt{\sum_{i=1}^{n}(P_i - \acute{P})^2}}} \right]^2 \text{ ....(2.5)}$$

$$NSE = 1 - \frac{\sum_{I=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \acute{Ó})^2} \text{ ....(2.6)}$$

The PBIAS is used to measure the average inclination of the simulated data for it to be diverse to that of the observed data. In instances where the model overpredicts and underpredicts streamflow, PBIAS gives a false reading of model performance. The reading of PBIAS will be close to 0 regardless of the poor model simulation (Shamsudin and Hashim, 2002). The simulation of the average magnitude of streamflow can be obtained by the use of PBIAS. The equation for PBIAS is outlined below:

$$PBIAS = \frac{\sum_{i=1}^{n} O_i - P_i}{\sum_{i=1}^{n} O_i} \times 100 \text{ .... (2.7)}$$

The *d* was developed by Willmott as a standardised measure of model prediction, it represents the ratio between the mean square error and the potential error (Willmott, 1984). The *d* is used to find additive and proportional variations in the mean and variance of observed and simulated data. The problem occurs when there is an overly sensitive to extreme amounts owing to the squared differences (Legates and McCabe Jr, 1999). The values of *d* ranges between 0 to 1. The *d* can be used instead of R^2 to identify that model predictions are free from errors (Legates and McCabe Jr, 1999).Table 2.3 illustrate the summary of model evaluation criteria.

Table 2.3: Model evaluation criteria for recommended statistical performance measures (Ritter and Munoz-Carpena, 2013)

Performance measure	Performance rating
NSE	>0.75 Very Good >0.65 Good >0.50 Satisfactory <0.50 Unsatisfactory
PBIAS (%)	±25 % Acceptable
R^2	>0.8 Very Good >0.7 Good >0.50 Satisfactory <0.50 Unsatisfactory

CHAPTER THREE: METHODOLOGY

3.1 Preamble

This chapter describes data acquired for assessing the impact of climate change and future projections on hydrology of LRQC. Furthermore, field survey and data analysis methods are also described.

3.2 Field survey

Field survey was conducted to allow understanding of the physical features of the catchment area. Field survey is an approach that is used to understand the characteristics of an area, land cover/land use activities taking place, and beliefs of the people by visiting the area. Visited sites include the hydro-meteorological gauging stations, bridges and dams located in the upstream, midstream, and downstream of the catchment. The survey helped in identifying the presence of hydro-meteorology measuring devices and their functionality. The field survey also helped in finding challenges such as restricted access to the study area due to remoteness or reroute of the road that might be due to changes in LULC, flood or any other kind of natural events.

3.3 Selection of Hydrological Model

To determine the impact of climate change on hydrology of LRQC, SWAT model with Arc-SWAT interface was selected. The model is designed to estimate surface runoff, baseflow, soil moisture change, and evapotranspiration for each HRU. The SWAT model was selected because of its input variables such as information on weather, soil properties, land management practices, vegetation, and topography that occur at the catchment area. These variables are of interest in the current study because they assisted in obtaining accurate results. The selection of the model was also influenced by its requirements such as minimal exact calibration to attain quality hydrologic estimation, but in instances where results are not satisfactory, manual calibration is done to adjust the output to an acceptable standard.

3.4 Data collection

3.4.1 Meteorological data

Meteorological data including daily temperature for station 0723485 (Levubu) and rainfall for stations 0723363 (Klein Australie) and 0766480 (Entabeni (Bos) were obtained from the South African Weather Service (SAWS). The observed data over the period 1981-2014 was complete which made it suitable to input on a SWAT model since one of its requirements is that the availability of input data for the selected period must be continuous (Obiero *et al*., 2019). Station data were used to understand the rainfall patterns and climate change response of LRQC. The rainfall stations 0766480 and 0723363 were chosen due to its data quality and availability and used together as individual stations to obtain good simulation results. Table 3.1 showed the details of rainfall and temperature with historic data used to set-up the SWAT model.

Table 3.1: Meteorological stations used for model set-up in LRQC

Station number	Station name	Data source	Data period	Data type	Sub-basin	Latitude	Longitude	Elevation
0766480	Entabeni (Bos)	SAWS	1981-2014	Rainfall	A91D	-23.000	30.270	1070
0723363	Klein Australie	SAWS	1981-2014	Rainfall	A91D	-23.050	30.22	780
0723485	Levubu	SAWS	1981-2014	Temperature	A91D	-23.094	30.286	706

Figure 3.1 shows the distribution of monitoring stations across the catchment area. Figures 3.2 and 3.3 shows daily rainfall data for stations 0766480 and 0723363, respectively, used in the study. Appendix A1 shows monthly average rainfall in each station. Figure 3.4 indicates the daily temperature data for station 0723485, with monthly average outlined in Appendix A2.

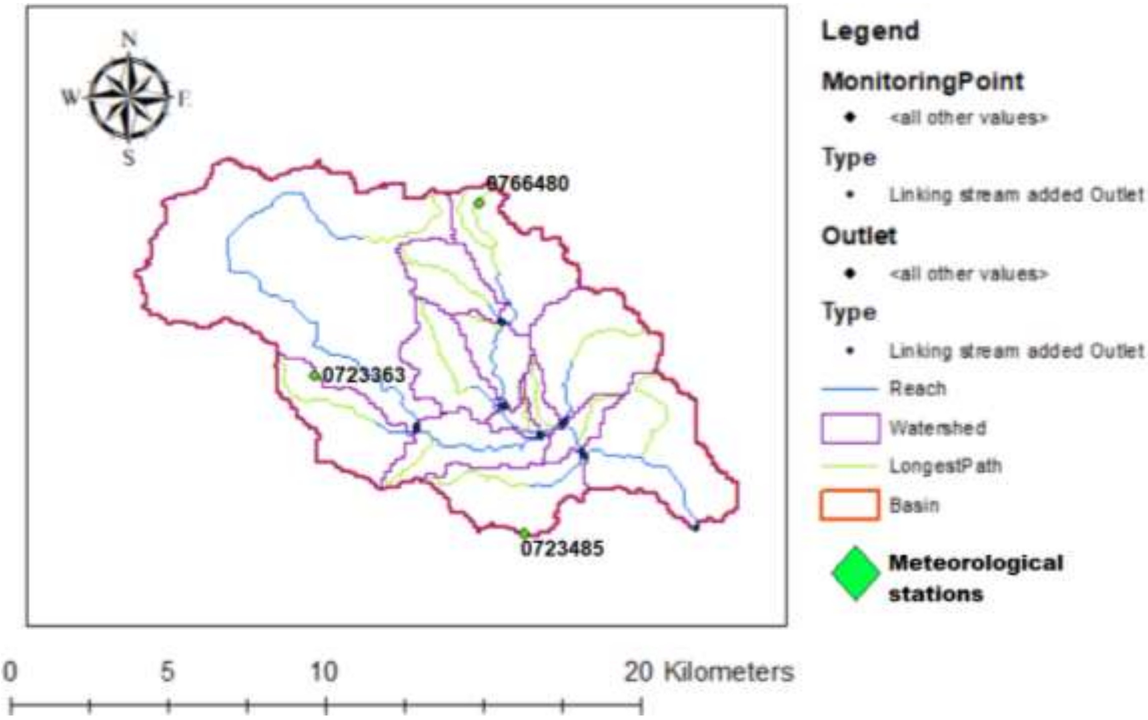

Figure 3.1: Meteorological stations used in LRQC

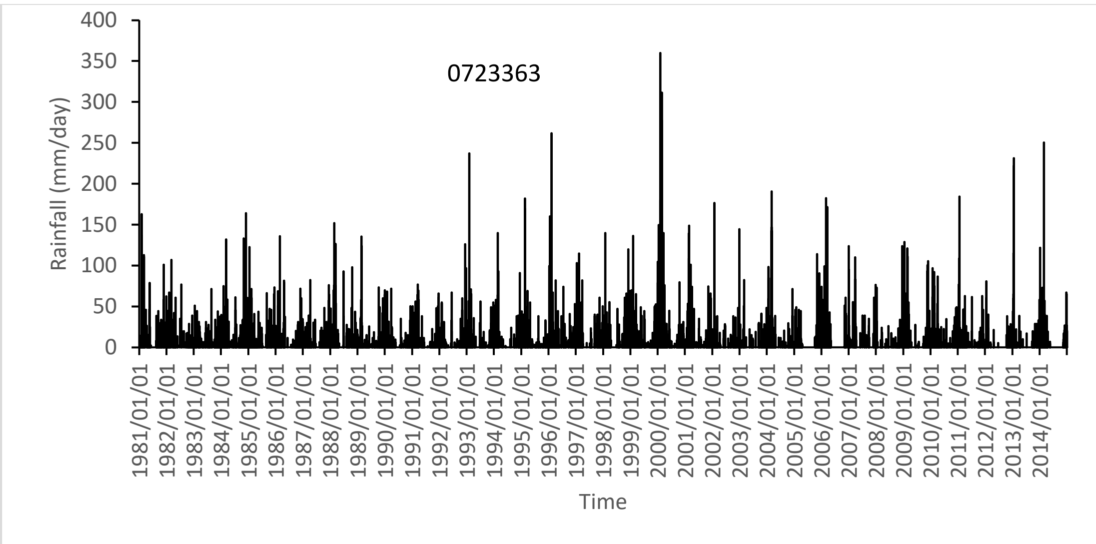

Figure 3.2: Rainfall variation for station 0723363

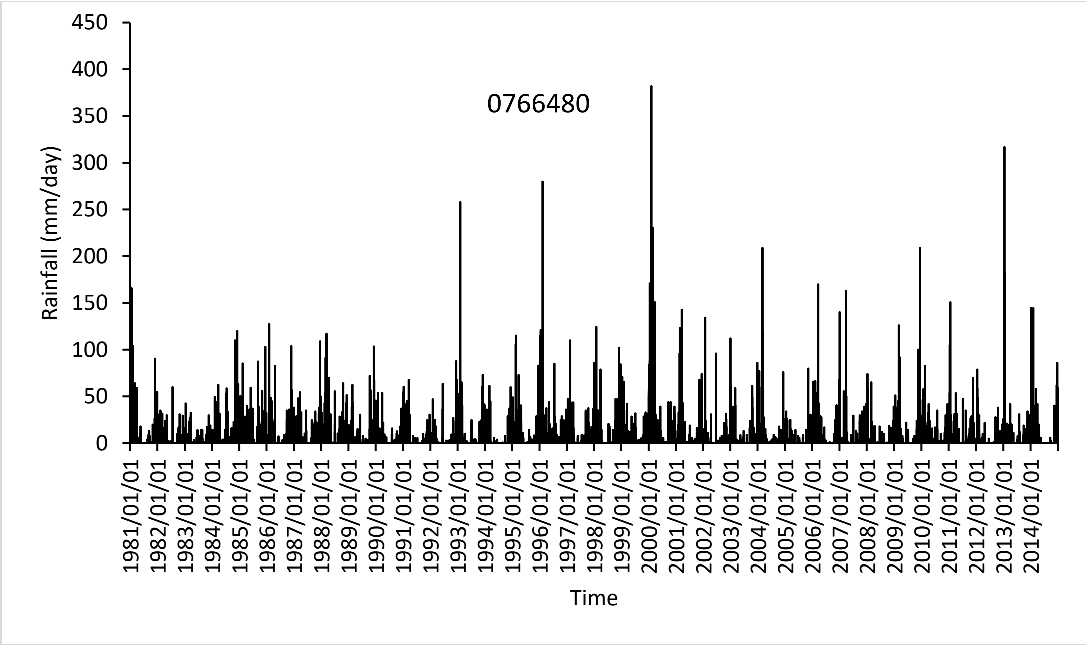

Figure 3.3: Rainfall variation for station 0766480

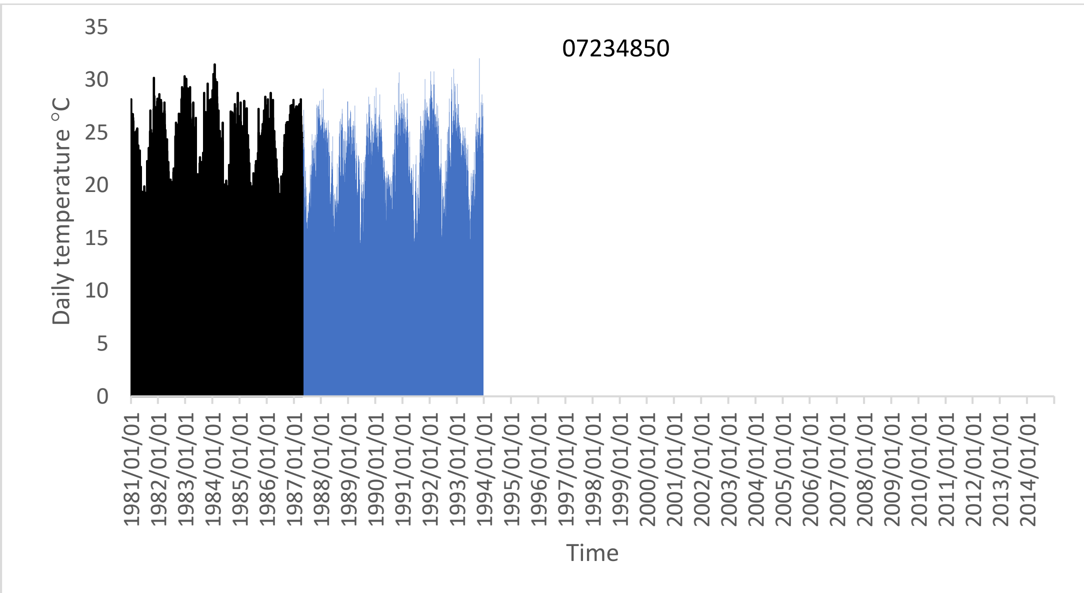

Figure 3.4: Temperature behavior in station 0723485

3.4.2 Streamflow data

Streamflow data for 29 years (1981-2009) for the LRQC outlet was selected from the historical data obtained at Water Resources of South Africa, 2012 study (WR2012). The station used to acquire observed stream flow data contains data record from 1920-2009, hence the desired data period was selected based on data completeness and availability. The historical streamflow data were also used in calibration and validation of the hydrological model which was used to simulate flows for near and far future periods. The simulation of streamflow data helped in determining missing data from the selected station in the catchment since periods with gaps were excluded during model calibration and validation.

3.4.3 Soil data

Soil data including soil mapping units and soil properties were obtained from Agricultural Research Council Institute of Soil, Climate, and Water (ARC-ISCW). The study used pedotransfer functions to predict soil hydraulic parameters from measured soil properties. The properties include pH, soil bulk density, particle size distribution, porosity, organic matter content, cation exchange capacity, calcium carbonate content, aggregates content, and mean particle diameter. This was explored to obtain soil hydraulic properties from basic data on texture where detailed data is not available**.** Figure 3.5 show the data-set which was extracted from the available LRC soil maps data-set to create the actual soils map for this study.

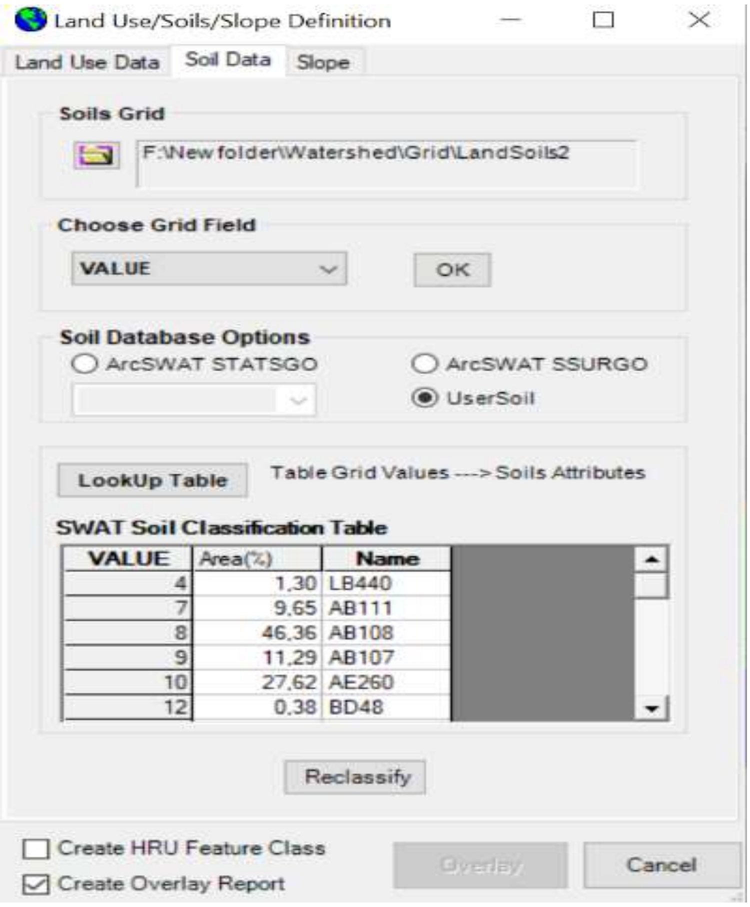

Figure 3.5: Soils definition

3.4.4 Slope

The DEM file was converted to polygon so that areas that are covered by slopes are identified and classified. The slope was created in each sub-basin by choosing number of slope classes and set them manually. The selected classes were set as the input raster and reclassified. The raster data was then converted to a polygon feature class from the elevation data. The slope catergory include, single and multiple slope. Therefore, slope was then calculated and the most dominant slope type is identified. Slope was used to identify the nature of the area in terms of gentle or steep, in this study 5 classes (%) were selected with a range of 0-10, 10-20, 20-30, 30-50, and 50-99.99 (Figure 3.6). The multiple slopes which influence the ability of the model to preserve the spatial variability of the topography were selected. Figure 3.6 show data classification which is used as input to define the topography of LRQC.

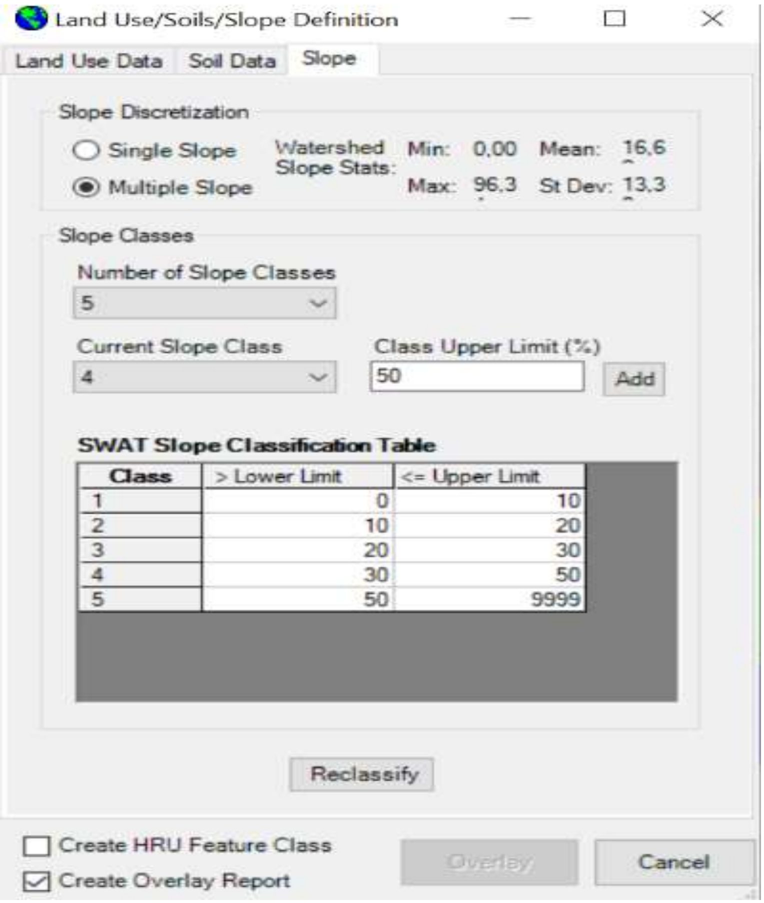

Figure 3.6: Slope classification

3.4.5 Land-use/ Land-cover data

Land use / Land cover (LULC) data was obtained from processed satellite images covering the study area. Aerial photographs were acquired from National Geospatial Information Centre in Cape Town and Pretoria to be used in supervised classification of land use data processed from satellite images. The LULC for the study area was extracted from these satellite images. Field survey was undertaken to understand the characteristics of the catchment area such that the simulated LULC is successfully compared with observed LULC. Figure 3.7 show classification of LULC data-set in the catchment within SWAT model.

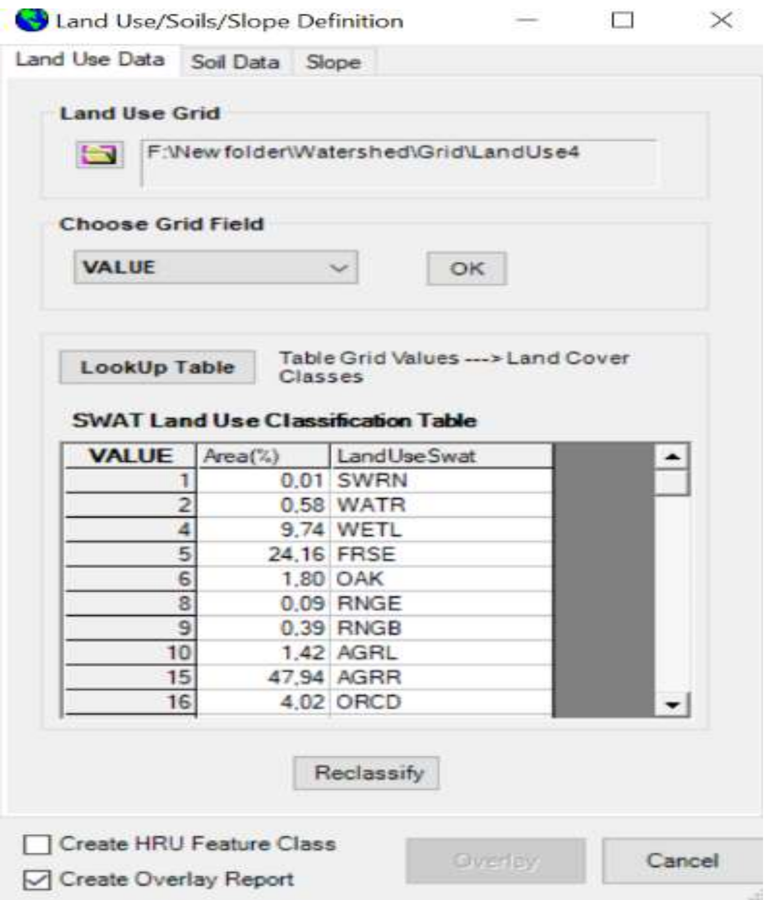

Figure 3.7: LULC definition

3.4.6 The DEM and watershed delineation

The DEM was set to be the main input parameter required by the model to define the topography of the catchment area and enable the process of watershed delineation. A watershed is an upslope area that contributes to water flow. For this study, the watershed was delineated by running the raster data that is used to identify the flow direction, flow accumulation and drainage area in Arc-SWAT. The topographical maps were obtained at an appropriate scale (100 pixels/inch or 40 pixels/cm). The Shuttle Radar Topography Mission DEMs were used in this study. To ensure that there are no challenges in the accuracy of the model, collected ground truth data was used, the accuracy of the ground truth data was based on the Global Positioning System readings. The data was collected by driving a vehicle carrying Global Positioning System receivers along radar-identifiable roads. This helped in producing a set of data representing a non-uniform sampling of the latitude, longitude and height. The reason of choosing Shuttle Radar Topography Mission DEM is because it has a high resolution of approximately 5m and it is meant to be very accurate (Rodriguez *et al*., 2005).

3.5 Data quality management

Different types of data are affected by various factors including human and systematic errors. For this study meteorology and hydrologic stations were assessed on their functionality and the data was checked for missing gaps. Therefore, the selection of station 0723485 (temperature station), 0723363, 0766480 (rainfall stations) and A91D (catchment outlet data for streamflow) were based on data completeness and quality. Stations with more than 10% missing data were not included in the study as part of data quality control. A DEM with high resolution of approximately 5 m and high accuracy (Rodriguez *et al*., 2005) was also used to define topography and watershed delineation.

3.6 Data analysis and set-up

3.6.1 Hydrological modelling of climate change impact

The SWAT model was used in this study to model the impact of Climate change on Hydrology of LQRC. Due to its data requirements, the arrangement and formatting of raw rainfall, temperature, and streamflow data for compatibility in Arc-SWAT and SWAT output viewer was done using Microsoft Excel. For data processing, extensions such as pivot tables and pcpSTAT for precipitation data manipulation were also used.

To determine trends on annual average flows and statistical significance for historical, near and far future, regression analysis was undertaken using the data Analysis tool in Microsoft Excel. The measure of significance of a trend was based on significance level (α) of 0.05. therefore, for a trend to be considered statistically significant, the computed p-value should be less than $\alpha<0.05$. If the computed p-value was found to be greater than 0.05 it was not statistically significant. The t-test give the measure of sensitivity of a parameter and the p-value give the significance of sensitivity of a parameter (Gyamfi *et al*., 2016). Microsoft excel also conducts linear regression based on t-test and p-value using the data analysis tool that has been proven to be effective (McCullough and Heiser, 2008).

3.6.2 Model set-up

The procedure for model set-up was influenced by Sohel (2012) in which model set-up was integrated using Arc-SWAT interface. The DEM, soils and land use in a grid format were imported into SWAT model to obtain a combination of exceptional results of land use, soil and slope. When undergoing the simulation process, catchment delineation was established as the first procedure. To eliminate minor classes of land uses and slopes, multiple HRUs, soil and slope thresholds were set. Weather station meteorological data were also imported into the model as recommended in the SWAT user manual. Time series of projected climate scenarios were used as input parameters of the hydrological model to simulate impact of future climatic changes on hydrology of LRQC. For compatibility, Arc-Map 10.7 with an extension of Arc-swat 10.7 in Arc-GIS was used. The historical meteorological data that was used to run the model ranged from 1981-2014 (34 years), with 3 years (1981-1983) selected to serve as warm up period so that before the model start to generate the actual outputs initial conditions are eliminated. The period of 1984-2014 (31 years) was then selected as simulation period. Comparison between observed and simulated flow was done from 1984-2009 (26 years) because the observed streamflow data was available until 2009. Figure 3.8 show how the methodology was structured to set-up the model for climate change on hydrology of LRQC.

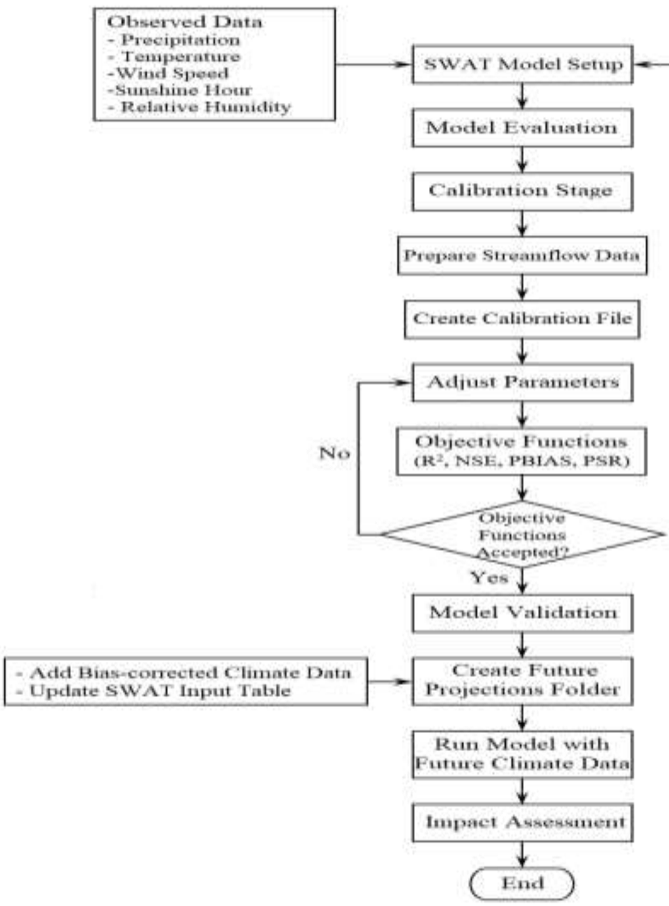

Figure 3.8: Methodology framework for model set-up (Oo *et al*., 2020)

3.6.3 Model calibration, validation, and performance evaluation

The processes of calibration were done manually with the help of SWAT-Output viewer tool. Calibration was done using historical observed streamflow data in a monthly timestep. Catchment historical streamflow data for the entire catchment (A91D) was used in the study to compare the model performance by evaluating the results of model predictions. The data obtained at the outlet of A91D was used amongst others station data, such as A9H007 and A9H027 because of its location, data quality and availability. Evaluation of model performance for both calibration and validation runs were done based on performance measures described in section 2.7. In this study SWAT-Output viewer was used to compute model performance measures such as NSE, PBIAS and R^2.

Calibration of the model was conducted from 1991-2003 (13 years) and validation from 2004-2009 (6 years). These periods were selected because of good model performance with simulated and observed hydrograph corresponding to each other, which is good for the presentation of model calibration and validation. Graphical fits and scatter plots of observed and simulated streamflow were also used in evaluating model performance.

3.6.4 Streamflow simulation

Global and regional climate models are the main tools that are used for projection of future climate change, at both international and national level. The Coordinated Downscaling Experiment (CORDEX) and the Conformal Cubic Atmospheric Model (CCAM) have also been used for simulation of future rainfall in the Luvuvhu River Catchment up to the year of 2100 (Odiyo *et al*., 2020). The SWAT2012 database includes extensions such as SWAT Executables, Arc-SWAT interface, and SWAT-CUP Premium/SWAT-output viewer which were used to set-up, view, and analyse the outputs of SWAT model. The model used daily timestep data for variables such as rainfall and temperature to simulate streamflow. The SWAT model weather generator tool can assist infilling missing data for the entire period of simulation. Weather generators were initially developed to help solve the problem of data gaps by producing artificial data so that the minimum amount of data required is equalled (Thavhana *et al*., 2018). This type of method uses deterministic mathematical models which are called stochastic weather generators. Stochastic models use a set of historical observed climatic data to statistically simulate similar artificial weather data to that of observed data. Catchment response to climate change, LULC and soil is used to understand how these changes can affect future projection of streamflow. Table 3.2 show how the model was built and trained to simulate streamflow of LRQC.

Table 3.2: Model set-up details

Simulation Length (yrs)	34
Warm up (yrs)	3
HRUs	131
Sub-basins	13
Output Timestep	Monthly
Precip method	Measured
Watershed area km^2	129.34 km^2

3.7. Climate change impact projections

To model the impact of climate change on hydrology of LRQC, projected rainfall and temperature from CCAM meteorological stations p230302 and t230302 were used as input into a SWAT model. The CCAM data consisted of rainfall and temperature data. The CCAM utilise the compatible set of physical parameterizations by computing the hydrostatic equations that are complex to solve, using a semi-implicit/semi-Lagrangian methodology. The period of 2023-2052 (30 years) and 2053-2082 (30 years) were used for projecting climate change impact in the near and the far future, respectively. The climate scenarios were conducted using model GFD85 with data period ranging from 1961-2099. The selection of the near future and far future projection periods was based on the minimum data period required for analysis, which is 30 years, because within this return period the extremes of hydrologic events are well established as noted by Zahmatkesh *et al*. (2015). Table 3.3 show details of the data used for near and far future climate scenarios.

Table 3.3: Future climate projection station

Simulation period (yrs)	Station no:	Data source	Data type	Co-ordinates	Elevation	Output Timestep	Precip method
2023-2052	p230302 t230302	SAWS	Climate Scenarios	-23.00, 30.20 -23.00, 30.20	1011.420	Daily	Simulated
2053-2082	p230302 t230302	SAWS	Climate Scenarios	-23.00, 30.20 -23.00, 30.20	1011.420	Daily	Simulated

The projected meteorological data for rainfall station p230302 and temperature station t230302, were used as input parameters into a readily calibrated SWAT model to simulate future streamflow based on the projected climate scenarios that are in place. Figure 3.9 shows location of stations used for projection of rainfall and temperature into the future.

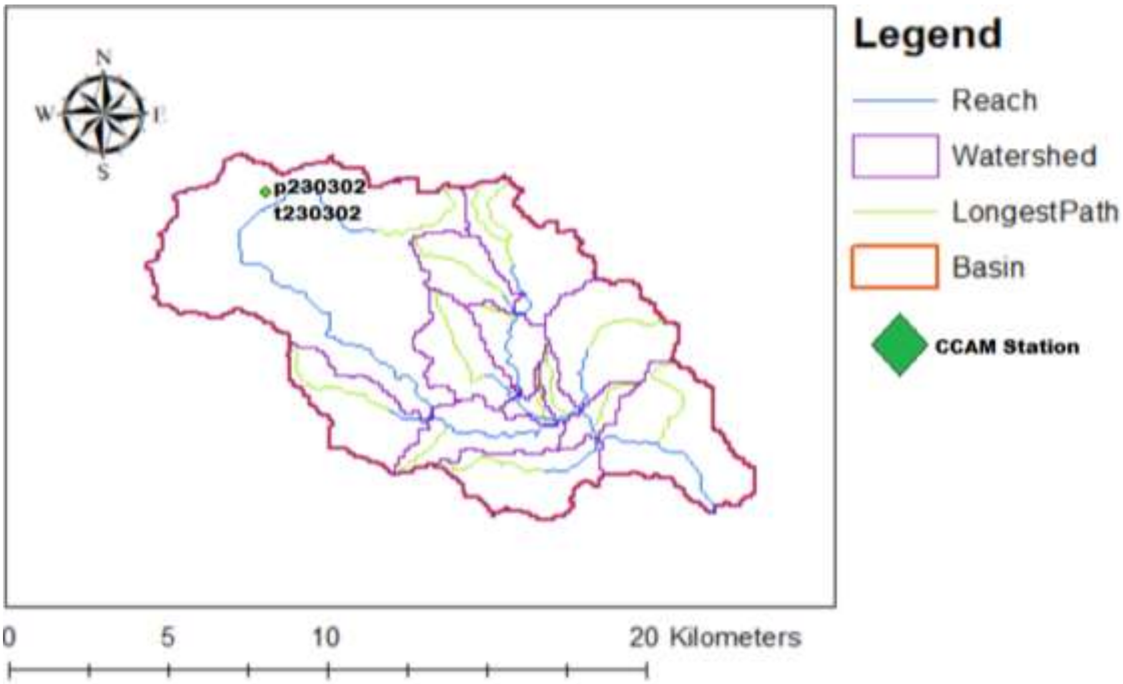

Figure 3.9: CCAMs station used for climate change projections in LRQC

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 Preamble

This chapter contains presentations and discussions of the modelling results including modelling impact of climate change on hydrology of LRQC. It further contains field survey observations which will help in quantify the model results.

4.2 Field survey observations

During field survey, the upstream, midstream, and downstream of the catchment were visited to understand the hydrological characteristics and to have knowledge of the land use activities in the study area. Figures 4.1 a and b show the LULC on the upper reach of the catchment. The most dominant LULC is agricultural land-row crops (AGRR) with the least area covered by Water. The upper reach is located just above the Albasini Dam. The middle reach of the LRQC is mostly characterised by the wetland with the least land covered by oak as shown in Figure 4.1c. Lastly, the lower reach of the catchment is located around the Tshakhuma area. The most dominant LULC is forest evergreen and residential medium/ low density area with the least dominant area covered by the arid range (SWRN) as shown in Figures 4.1d and e.


Figure 4.1a: Macadamia trees
Figure 4.1b: Banana trees
Figure 4.1c: Wetland and Oak trees
Figure 4.1d: Forest evergreen
Figure 4.1e: Residential area

Figure 4.1: LULC in all reaches of the study area

4.3 Delineated catchment, LULC, soils, slope and HRUs

The DEM in Figure 4.2 indicates the river reach, longest path, watershed and the drainage basins which are factors that help in indicating how the elevation, slope and aspects are estimated, identify drainage networks, watershed and terrain stability. The DEM also helped in soil mapping which is the function of elevation. The highest and the lowest elevation values of 1509 m and 597 m, respectively, indicating the topography distribution of the catchment area. The elevation value of 1509 m in the DEM of LRQC indicates the area of high slope which is known of being slidy with less vegetation cover. This type of an elevation has proven effects on streamflow of the catchment area with significant higher rainfall influenced by the topography. Such an area is very useful to consider when planning for a part of residential development and road construction since the rate of water transmission is high due to slidy terrain and if not taken into account may lead to runoff which may cause serious damage to property and infrastructure.

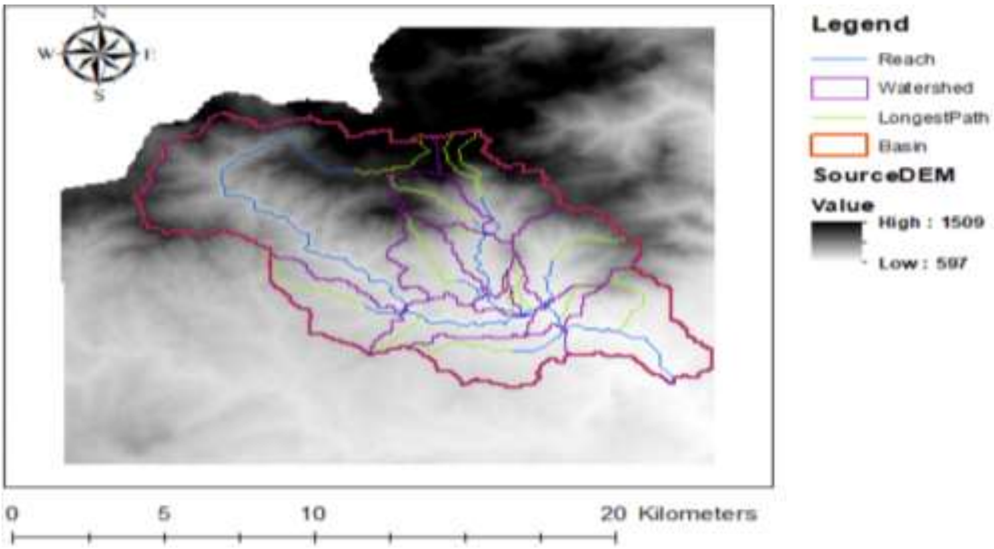

Figure 4.2: DEM of LRQC

In LRQC, the most dominant slope class is from 0-10 % and the least is 50-99.99 % with the coverage of 42.42 and 2.31 %, respectively. This means the area is covered mostly by moderately gentle slope. During rainfall, the water that moves down the slope removes soil at a relatively slower rate which can cause gullies to form over-time, leading to soil erosion due to the nature of the most dominant slope type in the catchment area.

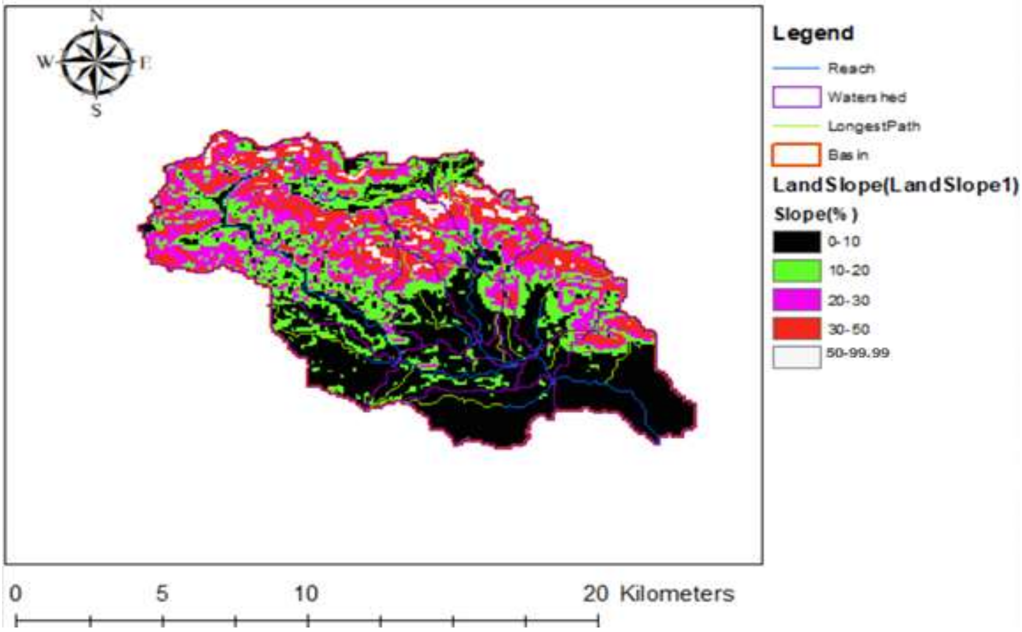

Figure 4.3: Slope of LRQC

The spatial distribution of the LULC of the catchment is based on 12 classes. The LRQC is divided into 13 Sub-basin with the most area covered by Agricultural Land-row crops (AGRR) and less with southern arid range (SWRN) with a coverage of 47.94 and 0.01 %. Since AGRR is the most dominant type of land cover in LRQC, it may influence infiltration and also act as an implementation tool to control runoff better than in a bare land which may results in no or minimised flood events in the area.

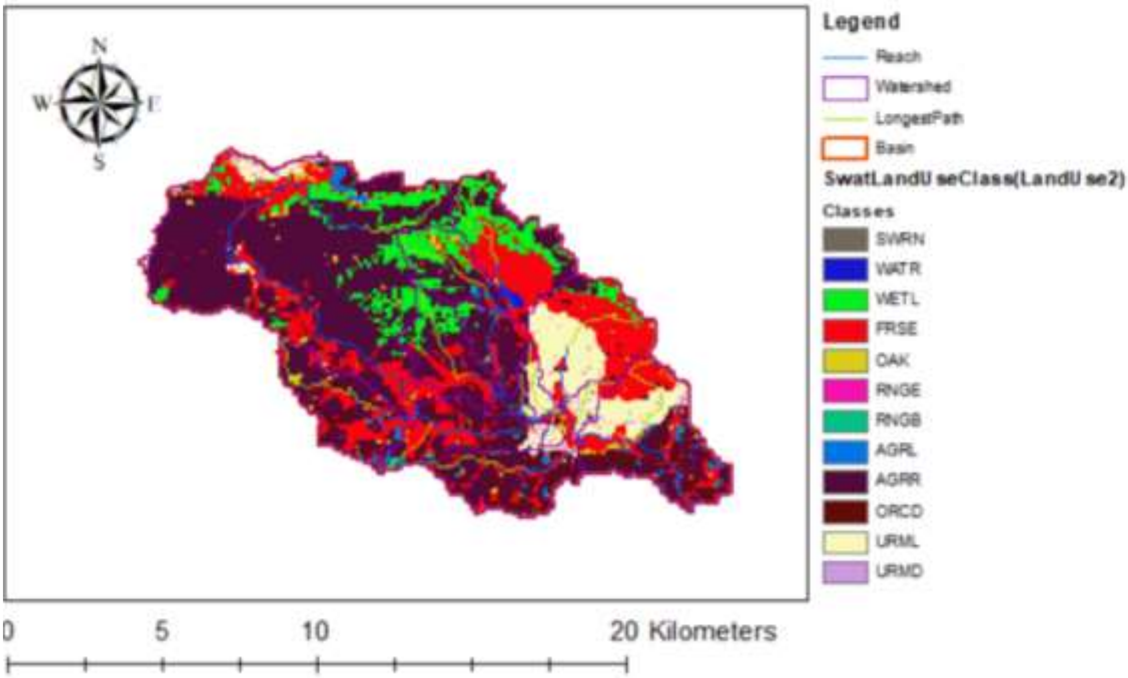

Figure 4.4: LULC of LRQC

Table 4.1 shows estimated soil properties for LRQC. Soil data set of LRQC is generated using the available land type maps since the data for this area is unavailable. The LRQC has 15 land type soils. The soil texture ranges from sand, clay and loam.

Table: 4.1 Estimated soil properties for the land types in LRQC, adopted from (Obiero *et al*. 2019)

Land type	Approx. Texture					Soil properties					
	Depth (mm)	Ave. % clay (given)	% silt	% sand	TEX	Bulk density	K_s (mm/h)	AWC (cm/cm)	ROCK %	OM %	C
Ib304	389	15.0	83.0	2.0	S-L	1.59	1.88	0.22	5	0.0	0.0
Ab109	1004	34	21	45	S-C-L	1.54	2.38	0.12	3.7	0.1	0.058
Ab108	1016	33	22	45	S-C-L	1.55	2.63	0.11	3.0	0.1	0.058
Ab173	807	36	19	45	S-C	1.53	1.86	0.12	0.0	0.1	0.058
Ib440	389	15.0	83.0	2.0	S-L	1.59	1.88	0.22	5.0	0.0	0.0
Ab111	887	33	22	45	S-C-L	1.55	2.67	0.12	13	0.1	0.058
Ab179	1058	25	30	45	L	1.59	6.01	0.12	11	0.1	0.058
Fa331	738	20	2	78	S-L	1.64	5.83	0.06	1.7	0.0	0.0
Ae260	981	30	25	45	S-C-L	1.57	3.64	0.12	0.1	0.0	0.0
Bd48	580	14	3	83	S-L	1.63	39.12	0.05	0.9	0.0	0.0
Ab107	763	32	23	45	S-C-L	1.56	2.98	0.12	1.7	0.1	0.058
Bb128	518	15	2	83	S-L	1.63	35.72	0.05	0.0	0.1	0.058
Ca91	568	18	30	52	S-L	1.62	13.31	0.11	0.0	0.1	0.058
Fa306	183	15.0	83	2.0	S-L	1.59	1.88	0.22	0.0	0.0	0.0
Fa308	443	17.0	3	80	S-L	1.64	27.66	0.06	0.0	0.0	0.0

The soil data required by the model is divided into two categories namely, physical and the chemical properties. In this study, the variables of the soils input files included the soil name, soil hydrologic group which is consist of four classes (A, B, C, D). This type of variables help in defining the infiltration rate of the soil, depth of the soil profile, void space which the model automatically set its input value as 0.5 unless a new value is introduced, soil texture (TEX) with sand, clay, and loam categories, depth from soil surface to bottom layer which has the same value as the, bulk density, available water capacity (AWC), organic carbon content (C), saturated hydrologic conductivity (K_S) , clay, sand, silt and rock in (%). Figure 4.5 shows that the most dominant soil type in the catchment is AB108, followed by AE260 with BD48 being the less dominant. The land types AB108, AE260 and BD48 cover an area of 46.02, 26.58 and 0.23%, respectively. The soil properties also show that the soil hydrologic group that is more dominant is B which will lead to influences of a moderate rate of infiltration resulting to moderate rate of water transmission which will influence moderately low runoff potential in an event of rainfall.

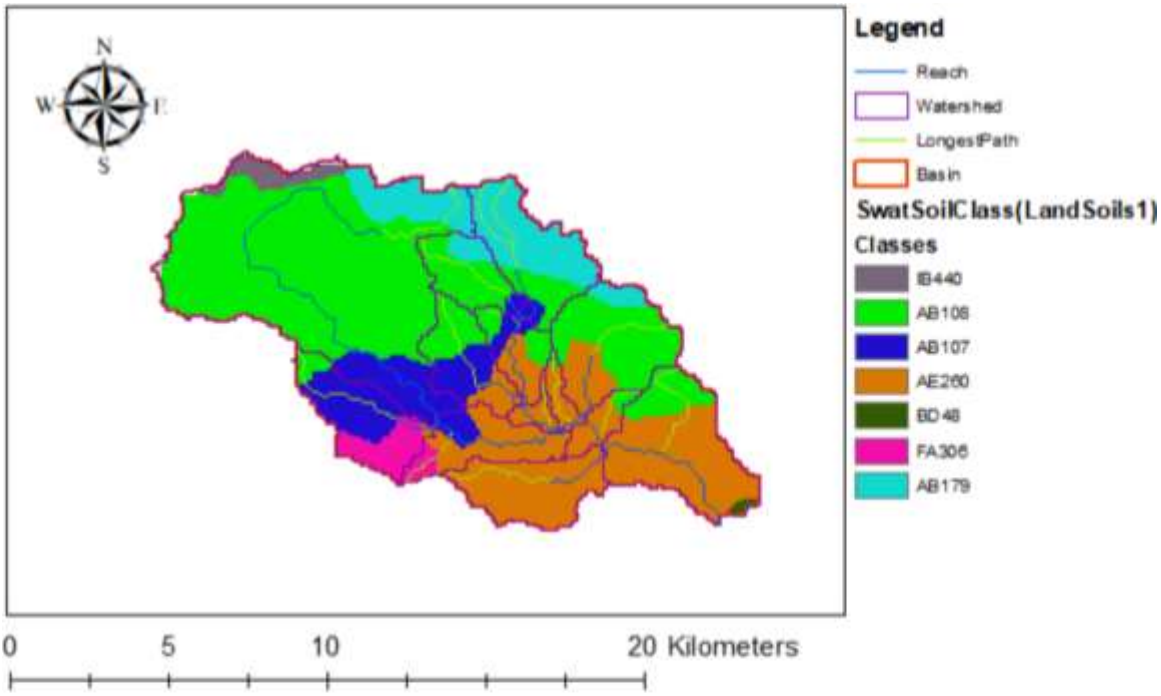

Figure 4.5: Soils of the study area

The data set for soil, LULC and slope are combined to generate the HRUs. The threshold selected for the optional parameters is 10% for all the set-up (LULC, soils and slope) which is successful in removing smaller sub-basins when processed by the model to avoid many HRUs produced. Since the sub-basin in the study area are 13, the entire catchment produced 131 HRUs. Figure 4.6 shows HRUs created for the study area.

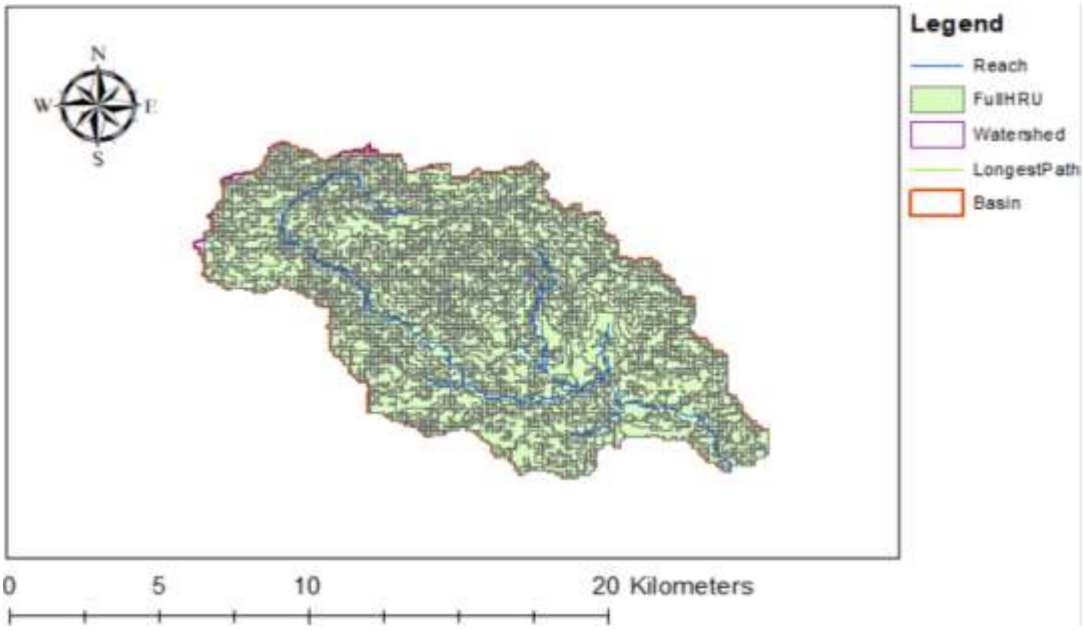

Figure 4.6: HRUs created in LRQC

Table 4.2 shows the distribution of slope, soils and LULC in LRQC. The acronym of land use chatracteristics in the catcment was also described to best explain LULC in the catchment area.The slope classes together with soil types found in the catchment area as discussed above are also detailed in Table 4.2. The figure also show the entire catcment area covered by the mentioned variables (129.34 km^2), this shows that the methodology was well designed and impemented to give accurate results that best decribe the study area. Table 4.2 generally aided with confirming the accuracy of model set-up based on literature and the methodology employed specifically for this study.

Table 4.2: Soils, slope and LULC report from SWAT

Detailed LANDUSE/SOIL/SLOPE distribution SWAT model class Date: 10/28/2021 12:00:00 AM Time: 07:52:12.7252951

		Area [ha]	Area[acres]	%Wat.Area
Watershed		12933.4958	31959.3147	
Number of Subbasins: 13				
LANDUSE:				
	Southwestern US (Arid) Range --> SWRN	0.7960	1.9670	0.01
	Water --> WATR	74.8245	184.8951	0.58
	Wetlands-Mixed --> WETL	1259.2805	3111.7452	9.74
	Forest-Evergreen --> FRSE	3124.3212	7720.3539	24.16
	Oak --> OAK	233.2296	576.3220	1.80
	Range-Grasses --> RNGE	11.9401	29.5045	0.09
	Range-Brush --> RNGB	50.1483	123.9191	0.39
	Agricultural Land-Generic --> AGRL	183.0812	452.4029	1.42
	Agricultural Land-Row Crops --> AGRR	6200.0861	15320.7227	47.94
	Orchard --> ORCD	519.7915	1284.4309	4.02
	Residential-Med/Low Density --> URML	1151.8198	2846.2044	8.91
	Residential-Medium Density --> URMD	124.1768	306.8472	0.96
SOILS:				
	AB107	1434.4017	3544.4784	11.09
	AB108	5951.7324	14707.0283	46.02
	AB179	1449.5258	3581.8508	11.21
	AE260	3437.1513	8493.3728	26.58
	BD48	30.2482	74.7448	0.23
	FA306	390.0426	963.8149	3.02
	IB440	240.3936	594.0247	1.86
SLOPE:				
	0-10	5486.8652	13558.3183	42.42
	10-20	3011.2884	7441.0443	23.28
	20-30	2341.8479	5786.8232	18.11
	30-50	1794.9922	4435.5154	13.88
	50-9999	298.5020	737.6134	2.31

4.4 Model calibration and validation

The SWAT model was set up to simulate model-based results. A total number of 13 sub-basins and 131 HRUs were generated. Streamflow simulation was done on sub-basin 13 since the catchment outlet is located at the sub-basin. Simulated streamflow from sub-basin 13 was compared with the observed monthly flow from the outlet of catchment A91D (Appendix B1). To compare the relationship between observed and simulated data is very much important because it shows how the model has perform. Studies such as Mengistu (2019) outlined that application of hydrological models is challenged by data scarcity which affects model set-up, making it difficult for the model to perform in an acceptable manner.

This study focused on measuring model performance based on NSE, PBIAS (%), and R^2. The process of calibrating and validating the SWAT model was followed as detailed in SWAT input/output documentation (Arnold *et al*., 2012). Feyereisen *et al*. (2007) also encouraged the procedure through the methodology undertaken.

Figures 4.7 and 4.8 indicate the graphical fits for calibration and validation runs, respectively. Flow patterns for both observed and simulated flows for calibration run were relatively similar even though the peak flows in February 1996, February and March 2000 were underpredicted by the model. The low flows also showed that there is a good relationship in the pattern of flows for both observed and simulated flow since they were mostly well simulated. The model validation runs (Figure 4.7) shows that the flow patterns were similar even though the peak flow were slightly underpredicted by the model in March 2006 and January 2008. The flows were overpredicted on a (March 2009) and b (November 2009) (Figure 4.8). A study by Makungo *et al*. (2010) explained that during high flow periods the hydrological phenomena are too complex for rainfall-runoff models to predict accurately. This explains why some peak flows were not well estimated by SWAT model. Obiero *et al*. (2019) show that variations in the model processes to determine flow that was used in flow observation has resulted into the model overpredicting the peaks flows and underpredict low flows.

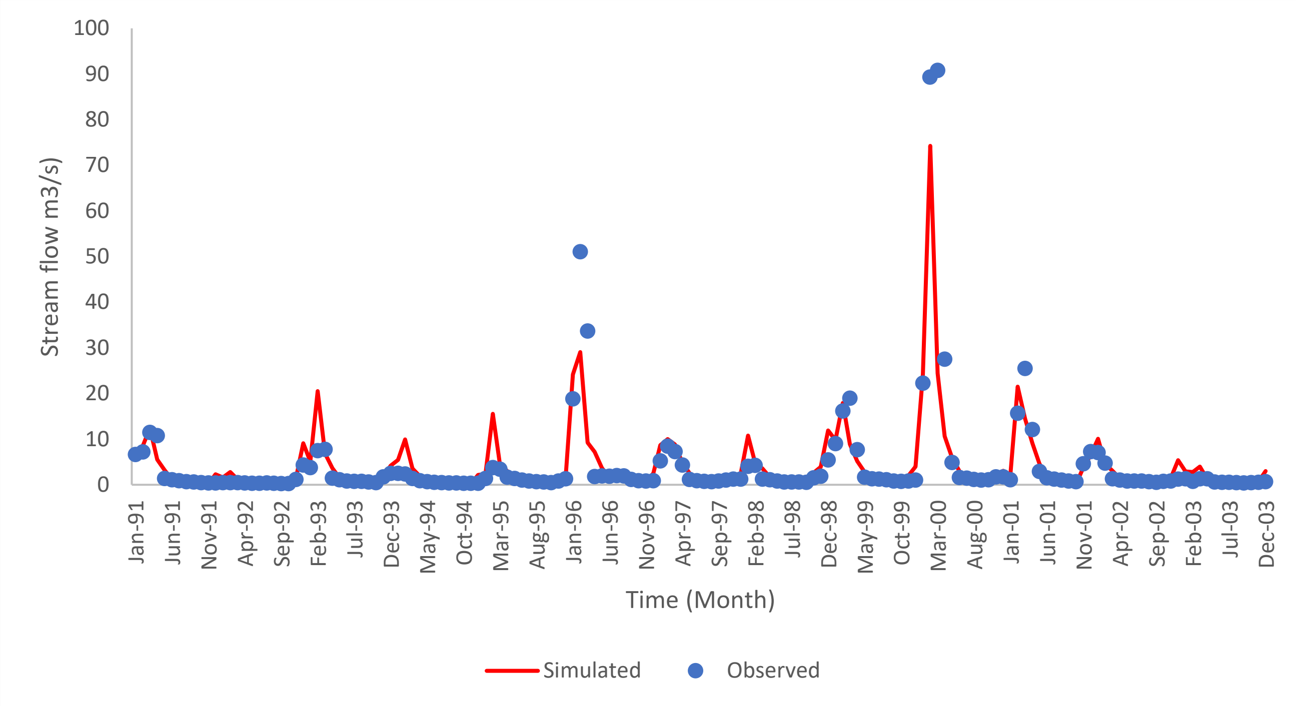

Figure 4.7: Observed and simulated monthly flow for calibration run

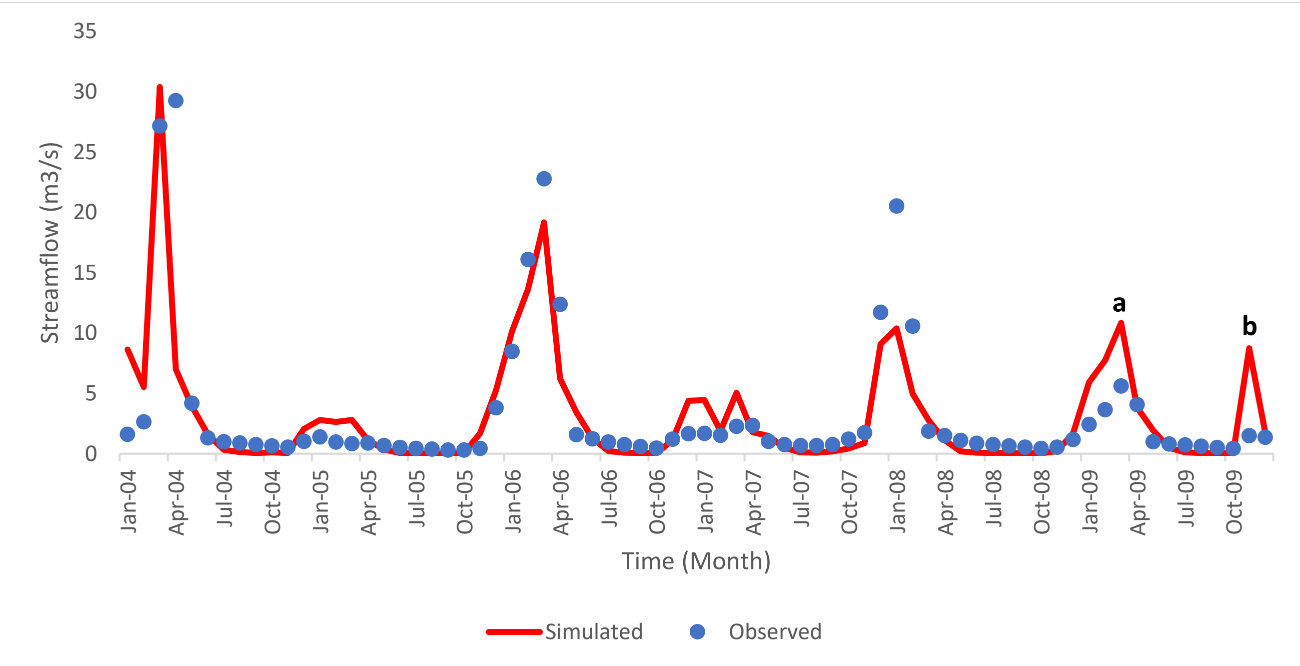

Figure 4.8: Observed and simulated monthly flow for validation run

The model performance for both calibration and validation run based on NSE, PBIAS, and R^2 are 0.67 and 0.68, -9.3 and -13.4 %, and 0.70 and 0.69, respectively (Table 4.3). Based on comparison, all the performance measures and performance criteria in Table 2.2, the model performance is good and acceptable. Good and acceptance model performance is influenced by successful selection of a model that serves the objectives of the study and also a balance in model input data.

Table 4.3: Model performance statistics

Calibration		Validation	Performance Rating
NSE	0.67	0.68	Good
PBIAS	-9.3%	-13.4%	Acceptable
R^2	0.70	0.69	Good
Period	1991-2003	2004-2009	

A study by Odiyo *et al.* (2012) which was done in LRQC indicated that observed and simulated flow showed similar flow pattern and measures of performances for calibration run fell within acceptable ranges. The value of R^2 and PBIAS for calibration were 0.86 and 4.1, respectively showing that the simulated flow for LRQC correlated well with the areal rainfall. In the current study the model achieved a relatively similar hydrograph to that of the observed. The consistency of model performance across the catchment area is reliable and the model can show that it can be used for modelling climate change impact on hydrology of LRQC.

The Figures 4.9 and 4.10 show the scatter plot for model calibration and validation runs. The comparisons of observed and simulated streamflow for calibration and validation runs shows a linear relationship with R^2 values of 0.7 and 0.69 respectively. This also shows that the model will provide accurate results when used for assessing the impacts of climate change on hydrology of LRQC. The scatter plots also indicated that the model has both overestimated and underestimated observed streamflow. The value points which are above and below the trend lines show overestimation and underestimation of observed streamflow (Makungo and Odiyo, 2019). The period which was selected to serve as calibration and validation in this study shows how responsive a model can be used in making accurate predictions in a given period. Limiting the calibration and validation period also limit uncertainty in model performance, this in-turn also limit the sensitivity of the model to certain parameters (Montanari and Di Baldassarre, 2013). The selection of the period helped in maintaining efficient model performance in both calibration and validation, hence, the model performance is acceptable.

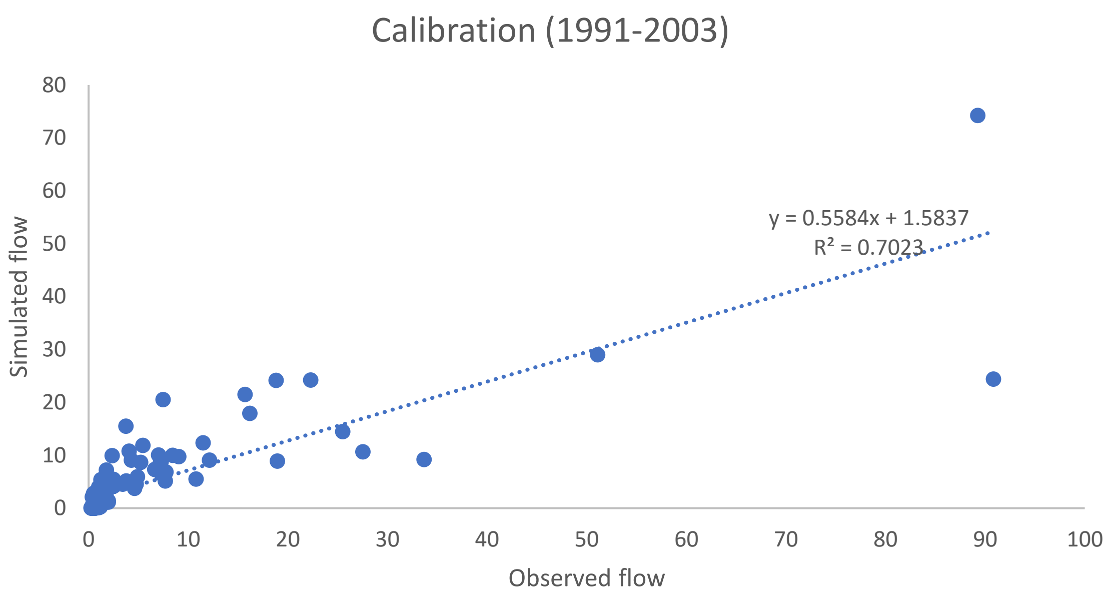

Figure 4.9: Scatter plot of observed and simulated monthly flow for calibration

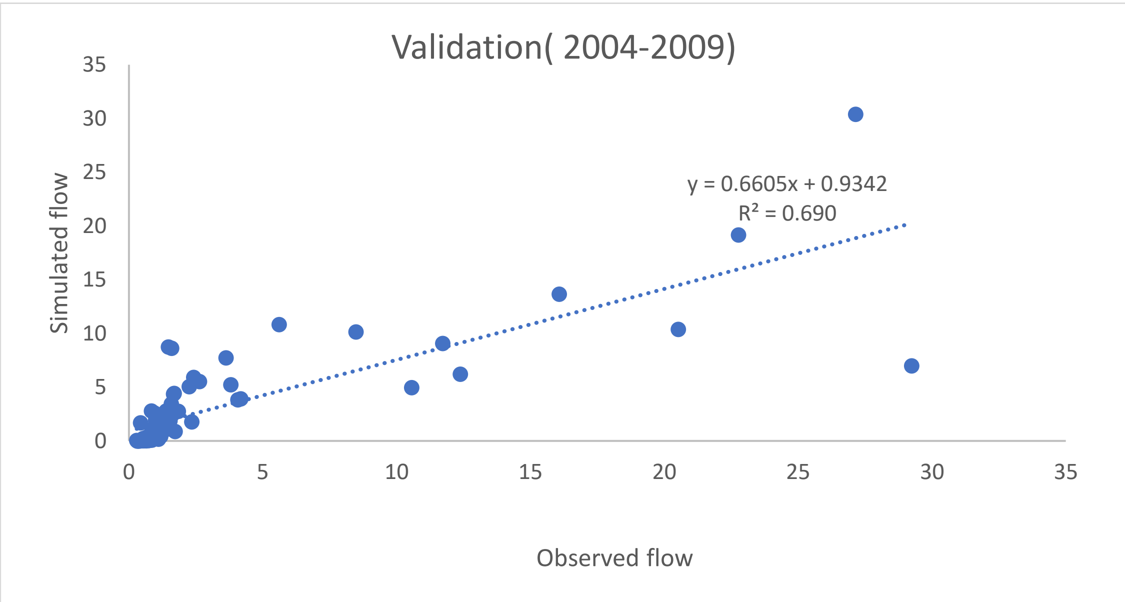

Figure 4.10: Scatter plot of observed and simulated monthly flow for validation

4.5 Impact of climate change on hydrology of LQRC

The projected monthly average rainfall and temperature in the historical, near and far future in Figure 4.11 shows how rainfall varied with time. The projected rainfall for June, July and December in far future will be more than that of the historical and near future. The months of February, March, April and October in the historical period indicate high rainfall than that of the near and far future. The rest of the remaining months (January, May, August, September, and November) show increased rainfall in the near future. Appendix C1 shows the monthly average rainfall. Figure 4.12 and Appendix C2 shows consistent increase in temperature in the far future as compared to the near future and historical. The results indicate variations in rainfall amount that will be received in the near and far future. Increase in rainfall event will lead to floods while decrease will result to droughts. Mathivha *et al*. (2021) show that extreme events (floods and droughts) are increasing over time in the LRC. Mazibuko *et al*. (2021) and Odiyo *et al*. (2020) indicated highly unreliable rainfall and prevalence of drought and floods in the LRC where the study area is located. A study by Mpandeli (2014) found that rainfall amount is more than the potential evapotranspiration in months between December-March. Since Makhado and Thohoyandou areas are located in micro-climatic conditions, the areas are affected by high climatic variability and change in rainfall and temperature. Kom *et al*. (2020) further indicate that the period from November to March has the highest average monthly rainfall every year In the Vhembe District, with the highest record of approximately 190 mm in February. In winter season, less than 20 mm of monthly average rainfall is received in the Vhembe District, with 8 mm of average rainfall dropped in August 2003.

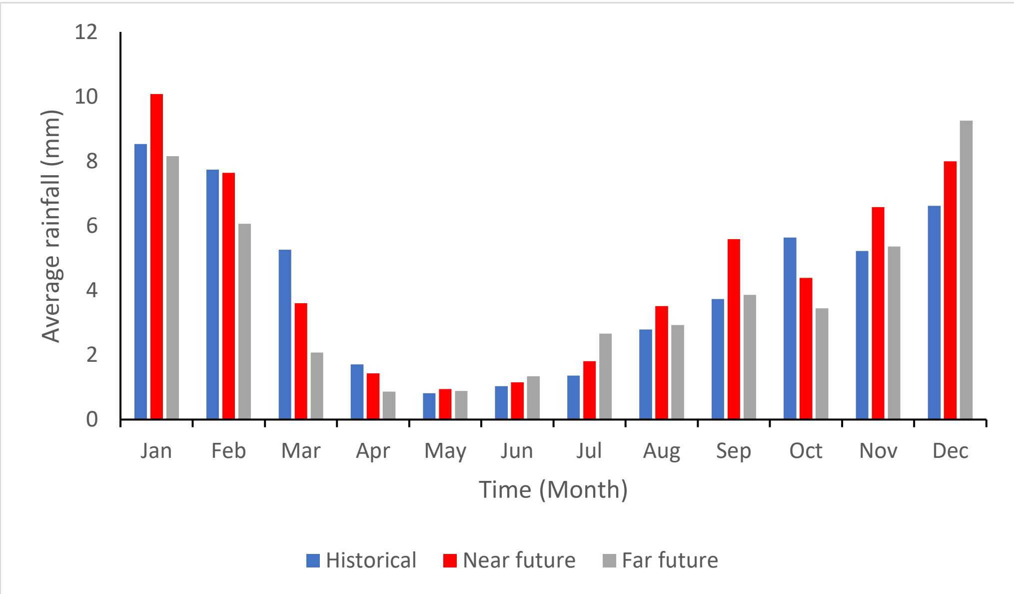

Figure 4.11: CCAM projection for future rainfall in LRQC

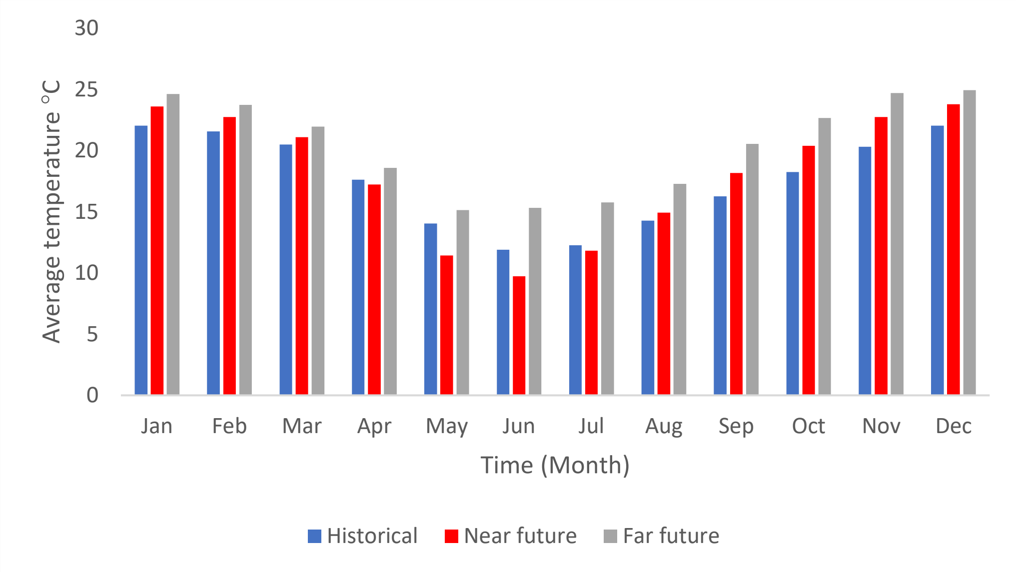

Figure 4.12: CCAM projection for future temperature in LRQC

Figure 4.13 shows the changes in streamflow in LRQC over time. The factors such as precipitation, temperature and amount of water evaporating from the stream and vegetation are essential in understanding changes in streamflow. Figures 4.11 and 4.12 show that in future it is likely that rainfall is going to decrease while temperature will increase. Changes in projected temperature and rainfall have been predicted to have also led into a decrease in average streamflow amount because evapotranspiration will be increased due to high temperature. Figure 4.13 show that in the near and far future there will be continuous decrease of streamflow when compared to historic values. The continuous reduction in streamflow will result in frequent droughts in the study area. The flows in the dry season (April-September) indicate that streamflow will be low as this season is characterised by low or no rainfall and in wet seasons (October-March) streamflow will peak. The reduced flow will negatively impact the community especially those that are located at the downstream of the catchment because of insufficient amount of water required to maintain the domestic, agricultural, and economic activities. The streamflow values for August and September in the far future show that there will be no water flowing in the catchment. This clearly shows how climate change is literally going to affect the hydrology of LRQC and LRC as a whole.

In general, the present study shows that streamflow amount is decreasing over time with annual averages of 4.849, 2.409 and 2.051 m^3/s for the historical near, and far future, respectively (Appendix D1). A study conducted in LRC by Masupha and

Moeletsi (2018) showed that the mild-moderate droughts in the earliest period of the near future (2020/21–2036/37) are expected to change in the far future period (2055/56–2089/90). Mukwada *et al*. (2021) showed that changes in rainfall trend that have occurred in LRC have negatively impacted vegetation health in areas with shallow-rooted plants.

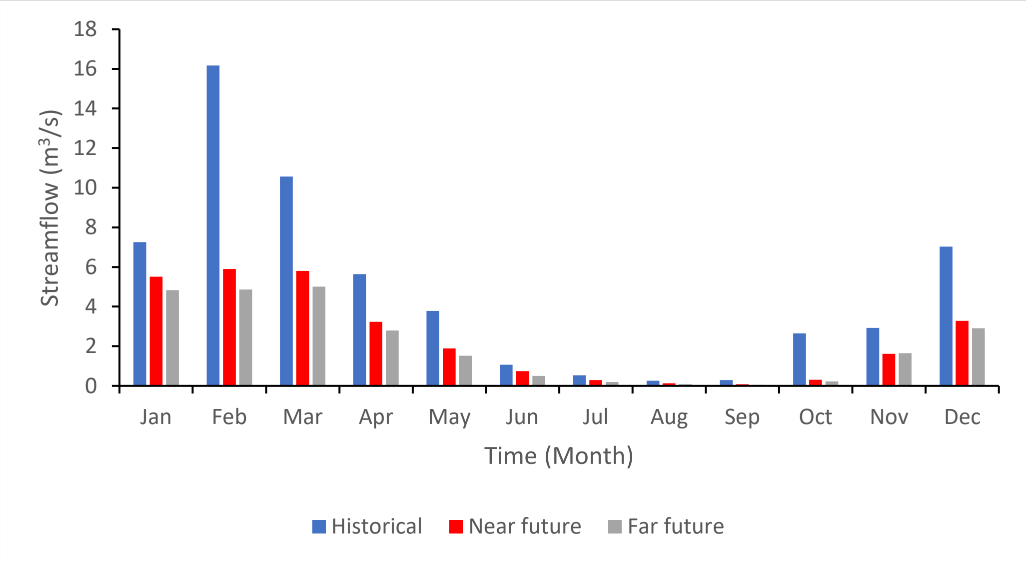

Figure 4.13: Projected monthly streamflow

The trends for annual average streamflow were determined for the historical, near and far future periods. The regression analysis statistics for the historical, near and far future periods are presented in Appendices E1, E2 and E3, respectively. Figure 4.14 indicates decreasing trend for annual average flows for historical year with the p-value of 0.010. Figures 4.15 and 4.16 (near and far future) show a linear increase in trend with p-value of 0.034 and 0.030, respectively. The p-values for historic, near and far future were less than the significance level (α) of 0.05 indicating that the trend for average flows for that periods is statistically significant. The significance may be influenced by climate change impact on streamflow that is occurring every year and the data period. In this study the model achieved a relatively balanced hydrograph, the consistency of model performance across the catchment area is reliable and efficient in modelling climate change impact on hydrology of LRQC.

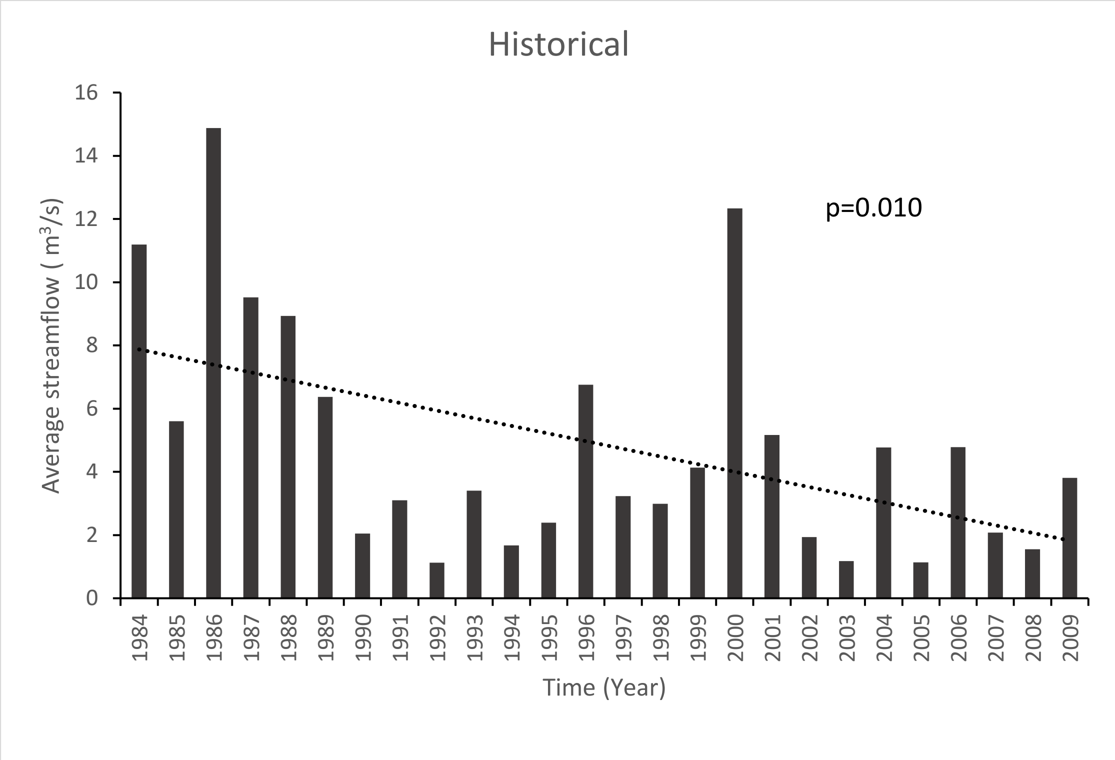

Figure 4.14: Annual average flow for historical years

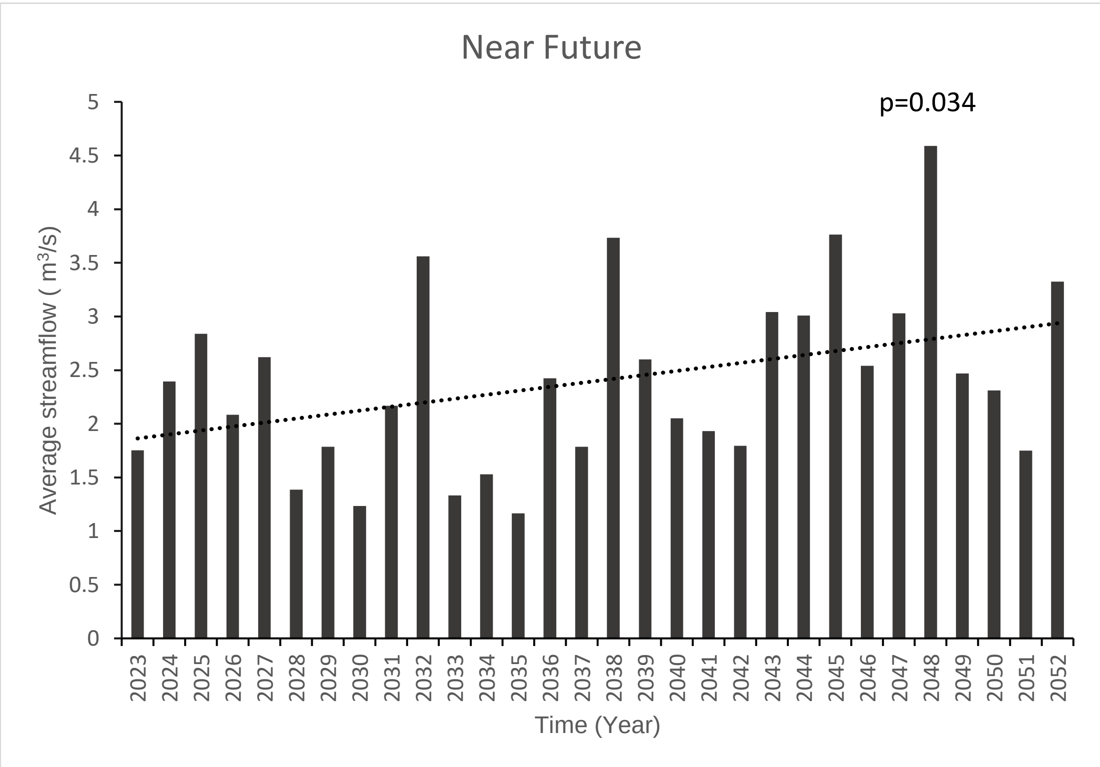

Figure 4.15: Annual average flow for near future period

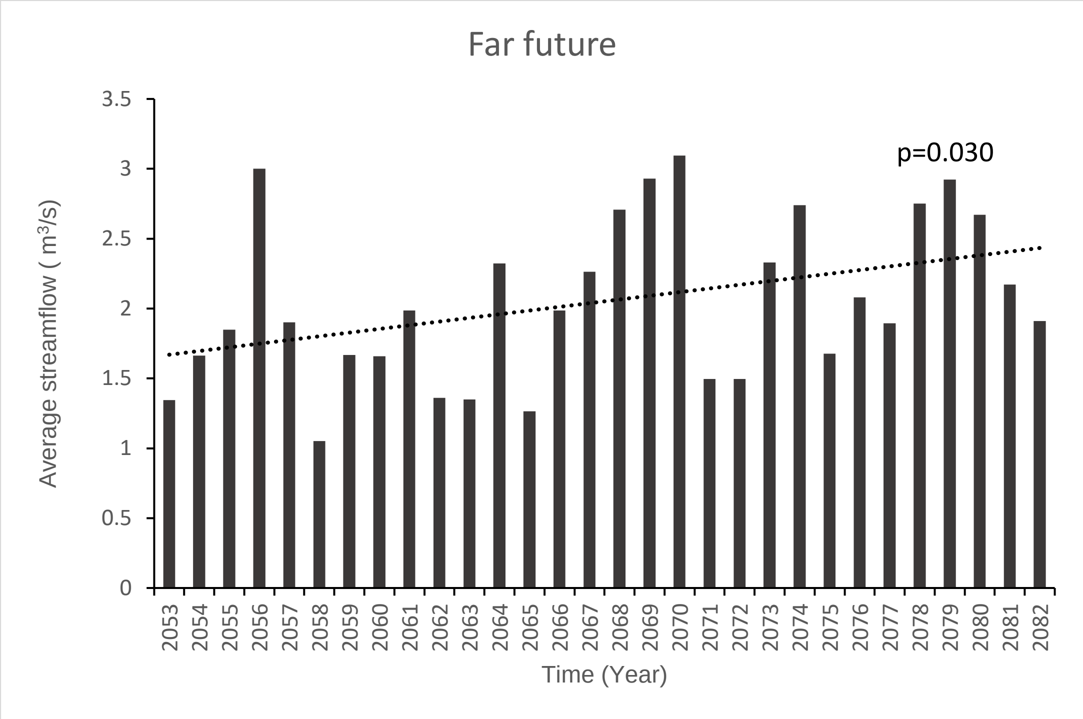

Figure 4.16: Annual average flow for far future period

Odiyo *et al*. (2020) reported contrasting trends for projected streamflow which were not statistically significant in the LRC. Contrasting and non-statistically significant trends have been associated with the inherit climate variability in semi-arid areas such as South Africa. In this study it is also likely that uncertainties associated with model structure, climate projections and input data for hydrological modelling may have had an influence on the trends and their statistical significance.

Makungo and Mashinye (2022) noted that although trends within the LRC and other areas in South Africa are mostly not statistically significant it is crucial to plan and come up with measures to adapt to extreme events. This is due to that extreme hydrological events (floods and droughts) have caused devastating impacts livelihoods of communities within these area. These areas are also vulnerable to climate change impacts due to high levels of poverty and lack of knowledge on adaptation.

CHAPTER FIVE: CONCLUSIONS AND RECCOMENDATIONS

5.1 Conclusions

The study was conducted to model the impacts of climate change on hydrology of LRQC located within the LRC, Limpopo, South Africa. The main objective of this study was accomplished by identifying and assessing the efficiency of a model in predicting historical and future climate change, identify future climate change scenarios and project the impact of future climate change on hydrology of LRQC. The SWAT model was selected to be an efficient model and set-up to run the simulation from 1981-2014. Model calibration and validation were done for the period of 13 years (1991-2003) and 6 years (2004-2009) respectively. Streamflow simulation was compared with observed streamflow using SWAT Output viewer tool. The results of model performance were also viewed using this tool.

The computed measures of performance (NSE, PBIAS, and R^2) for both calibration and validation runs were 0.67 and 0.68, -9.3 and -13.4 %, and 0.70 and 0.69, respectively. The values for each model performance showed good and acceptable results. The model calibration and validation results for both observed and simulated data followed the same pattern of flow with a slight underprediction of low flows and overprediction of peak flows by the model. The scatter plots also quantify that the model results are accurate and acceptable which shows that SWAT model is an efficient model in determining climate change impact on hydrology of LRQC and also good in predicting historic and future streamflow.

From the climate change scenarios in place, it was evident that the hydrology of LRQC is going to be negatively impacted by changes caused by high temperature and reduced rainfall amount in some of the months. This in turn will affect the streamflow which negatively impact the community (small scale famers and residents especially at downstream of the catchment), riparian vegetation and aquatic life at large. The p-values obtained were 0.010, 0.034 and 0.030 for historical, near, and far future, respectively. The findings of this study indicate that streamflow amount is decreasing over time with the annual average totals of streamflow in each period (historical, near and far future) as 4.849 m^3/s, 2.409 m^3/s and 2.051 m^3/s, respectively.

To determine the impact of climate change on streamflow, statistical significance using regression analysis was done. The annual average flows were obtained based on the p-factor.

5.2 Recommendations

Modelling climate change impact on hydrology of LRQC was successfully undertaken, hence the hydrological response of the near and far future climatic conditions of LRQC is readily understood. This is going to help in planning, managing, developing and implementation of adaptation strategies that will reduce or prevent the continuous impact of climate change on hydrology of LRQC. The establishment of adaptation strategies will assist the communities in adjusting to current resilient plans so that the impact of climate change on hydrology and livelihoods is reduced or avoided.

This recommendation will assist the decision makers to be knowledgeable about the water resources status both in gauged and ungauged catchments. Further climate change related studies should be conducted as there is a gap in ungauged catchments. The expansion of the current study to include land use impacts on hydrology is recommended.

The other recommendation is to venture into smart development technologies to minimise the impact of climate change on hydrology with the use of fourth industrial revolution. This can be done by developing both short-term and long-term strategies that are environmentally friendly, affordable, and user friendly. To deal with the main factor that influences climate change, the emission of greenhouse gases should be monitored because if greenhouse gases are managed in an efficient manner the practice of developing adaptation strategies to the changing climatic condition can be minimised. The less the release of greenhouse gases to the atmosphere the less the global climate warms which will lead to change in the climate pattern and if maintained it can decrease the influence of climate change to droughts and floods which was predicted to occur into the future. In conclusion, this study recommends that prevention is better than remediation, therefore the major causes (Human based activities) that are resulting to climate change should be prevented.

Knowledge dissemination through community awareness campaigns and other information sharing platforms is recommended so that the research findings are easily accessible to communities and decision makers.

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APPENDICES

Appendix A: Historical meteorological input data

Appendix A1: Monthly average rainfall data for 2 stations

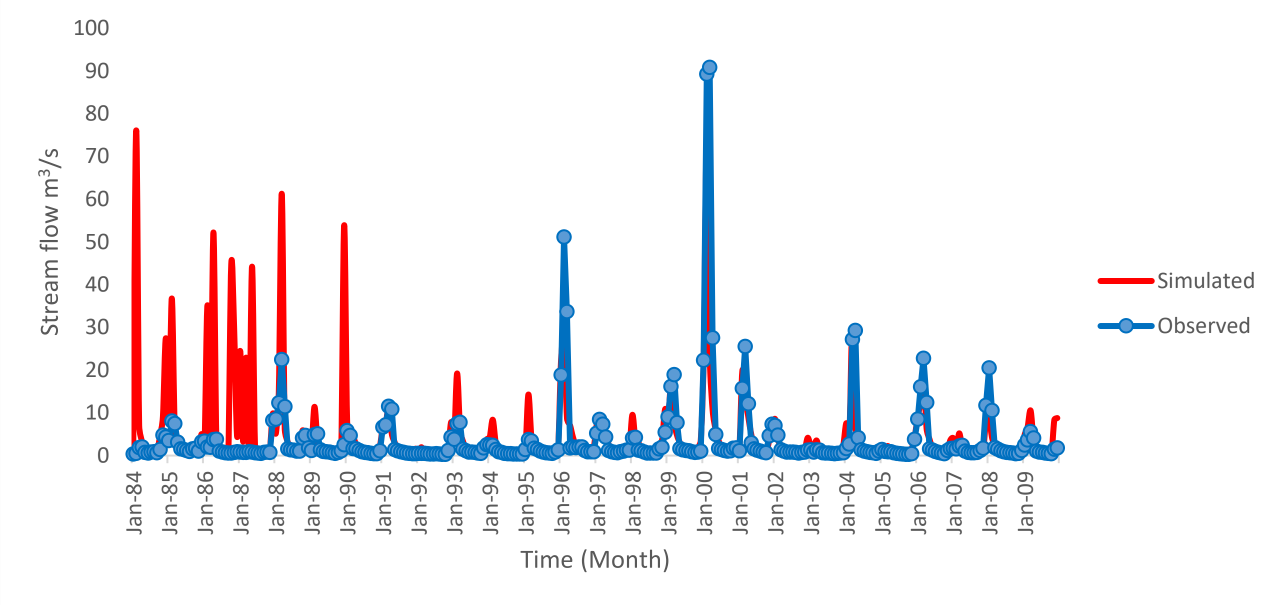
Month	0766480	0723363
Jan	9.822	11.282
Feb	11.636	13.038
Mar	7.154	8.117
Apr	2.942	3.985
May	1.103	3.514
Jun	1.132	1.851
Jul	1.224	0.892
Aug	0.961	0.492
Sep	1.446	1.1308
Oct	3.043	9.116
Nov	4.960	6.120
Dec	6.810	9.528
Annual average	**4.317**	**5.727**

Appendix A2: Historical monthly average temperature

Month	0723485
Jan	24.063
Feb	23.482
Mar	22.806
Apr	20.729
May	18.121
Jun	15.697
Jul	15.627
Aug	17.387
Sep	19.807
Oct	21.075
Nov	22.556
Dec	22.589
Annual Average	**20.311**

Appendix B: Model simulation

Appendix B1: Comparison of simulated and observed streamflow for the entire period of simulation



Appendix C: Future climate change scenarios

Appendix C1: Monthly average rainfall

Month	Near future	Far future
Jan	9.760	9.659
Feb	7.530	8.792
Mar	3.678	4.057
Apr	1.402	1.471
May	0.953	0.765
Jun	1.178	0.960
Jul	1.788	1.648
Aug	3.445	2.997
Sep	5.699	3.1511
Oct	4.190	4.193
Nov	6.599	3.515
Dec	7.994	6.42
Annual average	**4.504**	**3.951**

Appendix C2: Monthly average temperature

Month	Near future	Far future
Jan	23.533	25.635
Feb	22.668	25.331
Mar	21.028	24.196
Apr	17.853	21.957
May	14.526	18.537
Jun	13.320	16.083
Jul	14.640	16.246
Aug	16.333	17.292
Sep	18.490	19.424
Oct	20.824	22.241
Nov	22.708	24.097
Dec	23.694	25.784
Annual average	**19.119**	**21.384**

Appendix D: Streamflow data

Appendix D1: Streamflow comparison for historical, near and far future

Month	Historical	Near future	Far future
Jan	7.254	5.511	4.830
Feb	16.176	5.890	4.872
Mar	10.572	5.806	5.012
Apr	5.645	3.240	2.791
May	3.778	1.899	1.518
Jun	1.064	0.751	0.499
Jul	0.538	0.288	0.192
Aug	0.261	0.133	0.081
Sep	0.288	0.082	0.050
Oct	2.659	0.309	0.222
Nov	2.928	1.615	1.643
Dec	7.025	3.276	2.909
Annual average	**4.849**	**2.409**	**2.051**

Appendix E: Regression analysis summary output

Appendix E1: Summary output for historical period

Regression Statistics								
Multiple R	0.49665657							
R Square	0.246667749							
Adjusted R Squ	0.215278905							
Standard Error	6.77541025							
Observations	26							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	1	360.7515827	360.7515827	7.858452844	0.009853508			
Residual	24	1101.748417	45.90618406					
Total	25	1462.5						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2001.444672	2.208369225	906.2998387	6.23986E-56	1996.886822	2006.003	1996.886822	2006.002523
Historical	-1.01974922	0.363768305	-2.803293214	0.009853508	-1.7705301	-0.26897	-1.7705301	-0.268968339

Appendix E2: Summary output for near future period

Regression Statistics								
Multiple R	0.388455							
R Square	0.150898							
Adjusted R Square	0.120573							
Standard Error	8.255642							
Observations	30							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	1	339.1424	339.1424	4.976	0.033891217			
Residual	28	1908.358	68.15563					
Total	29	2247.5						
	Coefficients	andard Err	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2027.711	4.640067	437.0003	3.16E-55	2018.205993	2037.215485	2018.205993	2037.215485
Near Future	4.078871	1.82852	2.230695	0.033891	0.333317106	7.824425158	0.333317106	7.824425158

Appendix E3: Summary output for far future period

Regression Statistics	
Multiple R	0.396607399
R Square	0.157297429
Adjusted R Square	0.127200908
Standard Error	8.224471388
Observations	30

ANOVA

	df	SS	MS	F	Significance F
Regression	1	353.5259708	353.5259708	5.226432	0.030015934
Residual	28	1893.974029	67.64192961		
Total	29	2247.5			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	2055.247766	5.565737029	369.2678536	3.53E-53	2043.846871	2066.648662	2043.846871	2066.648662
Far future	5.972451114	2.612461722	2.286139185	0.030016	0.621065864	11.32383636	0.621065864	11.32383636