Watershed Delineation and Runoff Estimation using GIS and HEC-HMS Model in the Gwayi Catchment, Zimbabwe

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MSc Research Report

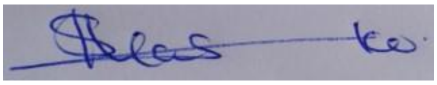
Submitted in partial fulfilment of the requirements for the degree of **Master of Science in Geographic Information Systems and Remote Sensing** in the School of Geography, Archaeology and Environmental Studies, Faculty of Science, University of the Witwatersrand, Johannesburg, South Africa

2024

DECLARATION

I, **Sambulisiwe Maseko**, Student Number: 2515589, declare that this report is my own work. It is being submitted in partial fulfilment of the degree of Master of Science in Geographic Information Systems and Remote Sensing to the University of the Witwatersrand, Johannesburg, South Africa. It has not been submitted before for any degree or examination to any other University**.**

Student signature **Date**



11 September 2024

ABSTRACT

Climate change poses significant challenges to hydrological systems by causing erratic rainfall patterns and increased flooding. Understanding hydrological cycle patterns and changes are essential for effective watershed management. Hydrological modelling is widely applied globally to estimate hydrological behaviour. However, its application has been limited in the data-scarce Gwayi catchment in Zimbabwe. The aim of this study was to utilize the Hydrologic Engineering Centre Hydrologic Modelling System (HEC-HMS) model to delineate watersheds and predict the surface runoff at the sub-basin level in the Gwayi catchment. The HEC-HMS model was calibrated and validated over a period of five years in five sub-basins from 2017-2021 based on the completeness of the data. The model efficiency was evaluated using the Nash Sutcliffe Efficiency (NSE). During the calibration period, the NSE values ranged from 0.19 to 0.44, and during the validation period, they ranged from they ranged from -2.7 to 0.22. The trial-and-error method was used in calibration. The model predicted a total runoff volume of 102.19mm for the specified period. The analysis highlights the significant influence of land use, soil, and slope parameters on surface runoff generation because they were the most sensitive during calibration. Findings indicated that surface storage data is an important input in HEC-HMS to evaluate the model's potential to accurately estimate discharge. This is because reservoirs play a critical role in regulating river flow and water levels and therefore have a substantial effect on the timing and magnitude of flows. The study findings contribute to the body of knowledge in hydrological modelling in the Gwayi and similar environment. It is recommended that further research be conducted at smaller scales, less than 5000km² to reduce model complexity and enhance precision.

Keywords; HEC-HMS, GIS, Remote Sensing, Modelling, Run-off simulation, Gwayi catchment, Zimbabwe

DEDICATION

Dear Sambulisiwe Maseko, I am super proud of you!

ACKNOWLEDGEMENTS

Dear God, thank you!

As I complete my postgraduate studies at the University of the Witwatersrand, I need to pause and reflect on how far I have come and express my gratitude to those who have been a key part of the journey. After having felt like my mental health is compromised on numerous occasions, I am excited to have finally arrived and at the same time acknowledge that it is time to pursue other goals. At this point, it feels like everything that I have ever dreamt of becoming is possible in the future because I see it as an opportunity. I can never thank my family and friends enough for the support. My time at Wits, the best!

To my family, thank you. I count it a blessing to know I have people who have my back no matter what. To my Gatsheni who always lets me know she is praying for me, you hold a special place in my heart. My parents are the most beautiful souls ever, I am blessed. My sister Nkazimulo and my brother-in-law Dube, I appreciate your presence in my life! My sister's advice and encouragement has kept me grounded, thank you. I have friends who have stuck closer than brothers. Thando, Mhambi and others who are still and are no longer alongside, the sacrifices made for my sake will forever be cherished.

Dr Iqra Atif, thank you for the mentorship and encouragement throughout the course of this research. Thank you for sharing opportunities that have led to both my personal and professional growth. Thank you for setting up the High Computational Geo-Facility which came in handy especially on periods when I did not have a reliable working computer with the required software. As a first-time user, the HEC-HMS model gave me a hard time, multiple times! Thank you for your patience and taking the time to render some advice and set up regular meetings where I was able to give updates on the research progress.

My colleagues at Dabane Trust Water Workshops have also been quite supportive. I would like to express my sincere gratitude, specifically to the Natural Resources Management (NRM) team for the patience throughout my studies, it cannot go unnoticed.

If this phase of my life has taught me anything, it is that there is joy in the journey, one just has to pay attention.

Sambulisiwe Maseko

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LIST OF ACRONYMS

ATHYS	A Telier Hydrologique Spatialisé
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CN GRID	Curve Number Grid
CN	Curve Number
DEM	Digital Elevation Model
DSMW	Digital Soil Map of the World
FAO	Food and Agriculture Organization
GIS	Geographic Information Systems
GW	Ground water
HBV	Hydrologiska Byrans Vattenbalansavdelning
HEC-HMS	Hydrologic Engineering Center - Hydrologic Modelling System
HSG	Hydrologic Soil Group
IPCC	Intergovernmental Panel on Climate Change
LULC	Land Use and Land Cover
NetCDF	Network Common Data Form
NSE	Nash Sutcliffe Efficiency
PBIAS	Percent Bias
QGIS	Quantum Geographic Information System
RMSE	Root Mean Square Error
SCS CN	Soil Conservation Service Curve Number
SMA	Soil Moisture Accounting
TOPMODEL	TOPography based hydrological MODEL
UH	Unit Hydrograph
USACE	United States Army Corps of Engineers
UTM	Universal Transverse Mercator
ZINWA	Zimbabwe National Water Authority

CHAPTER 1: INTRODUCTION

1.1. BACKGROUND

The hydrological cycle is affected by climate change and this threatens the whole planet (Mutekwa, 2009). This has a direct impact on the availability of water, surface runoff and river discharge. According to Willems, (2012), globally, some areas experience floods whilst some experience drought. Precipitation frequency and intensity are also among the affected because of climate change (Gebre, 2015). Love et al., (2010) observed that in many parts of the world, the demand for water often surpasses its availability because of low rainfall and high rates of evapotranspiration. Consequently, surface runoff is influenced by watershed-specific characteristics such as topography and land use. Zimbabwe experiences climate change through hotter and drier conditions in some parts and wetter and cooler in others (Mugandani et al., 2012). According to Samu & Kentel, (2018), on a yearly basis, floods, as a result of climate change, claim people's lives in Zimbabwe. Some mitigation measures are structural constituting the construction of surface water storage facilities such as dams. In turn, Love, Uhlenbrook, Twomlow, et al., (2010) highlights climate change as contributing to a decrease in rainfall in Zimbabwe. This has a negative impact on discharge because of interception. As a result, this greatly impacts availability of water resources and ultimately threatening livelihoods.

According to Daide et al., (2021), effective catchment management is rooted in understanding hydrological cycle patterns. This includes appreciating the catchment inputs and outputs affecting the water balance (Gebre, 2015). Changes in the hydrological components present challenges in managing water resources (Love, Uhlenbrook, Twomlow, et al., 2010). The analysis of trends regarding the availability of water resources provides insight into management and allocation putting into consideration the different users in the region. Therefore, to achieve various water and environmental management initiatives, all the important components need to be studied (e.g., precipitation, soil water and streamflow).

According to Panigrahi et al., (2014), hydrological modelling is used to estimate the hydrological responses of basins as a result of precipitation. Several models exist for estimating run-off and these take the forms of either fully distributed (e.g., TOPMODEL), lumped (e.g., ATHYS) and semi-distributed (e.g., HEC-HMS) (Fathy et al., 2015). Fully distributed models integrate spatial distribution data and require huge amounts of input data, lumped models evaluate the response of the basin at outlet and assume uniformity in rainfall, soil types, vegetation and land use whilst semi-distributed models vary in space and subdivide the watersheds (Gebre, 2015). Semi-distributed models are therefore a compromise between fully distributed and lumped models.

The HEC-HMS model, according to Panigrahi et al., (2014), is a semi-distributed model aimed at estimating runoff in different watersheds. Gumindoga et al., (2016) noted that the HEC-HMS model investigates variations in space across watersheds. Ismael et al., (2017) attributed the popularity of the HEC-HMS model to long and short-term capabilities in estimating runoff events, simplicity in operation and use of common methods. A wide use of the HEC–HMS model by researchers to estimate surface runoff in different watersheds has been noted (Gebre, 2015; Ismael et al., 2017). According to Dzirekwa et al., (2023), the HEC HMS model is designed for applicability in different geographic areas and to solve an array of problems. Halwatura & Najim, (2013) highlighted that sparse data presents a major challenge in quantifying and understanding the generation of runoff and the accumulation at the outlet. Unit hydrographs present opportunities for the estimation of flood hydrographs and peaks.

1.2. RATIONALE

This study uses Gwayi catchment as a case study, the catchment is home to rivers, dams which are a source of water for domestic, livestock and commercial uses. Little attention has been given on the Gwayi catchment regarding hydrological modelling research. Therefore, water resources management initiatives will benefit from the study of runoff trends and the relationship between rainfall and runoff.

1.3. RESEARCH PROBLEM STATEMENT

Despite the use of hydrological models globally, hydrological modelling has not been fully explored in Zimbabwe (Maviza & Ahmed, 2021). Of the 107 climate studies reviewed by Maviza & Ahmed, (2021), only seven percent focused on hydrological modelling, with the Gwayi catchment receiving the least attention. The majority of notable hydrological studies have been concentrated in the Mzingwane, Manyame and Mazowe catchments. In contrast, only two studies have been conducted in the Gwayi catchment: Mazvimavi et al., (2003) evaluated the applicability of runoff models in areas lacking data, while Sibanda et al., (2009) employed the Flownet method to assess recharge.

Climate change threatens poverty reduction and sustainable development in Zimbabwe (Moyo et al., 2017). As climatic conditions are predicted to worsen in the country, Maviza & Ahmed, (2021), accurately estimating runoff due to rainfall is crucial for appropriate watershed management (Rajbanshi, 2016). Research results will shed light on the rainfall runoff relationships and the applicability of the HEC-HMS model in the Gwayi catchment.

1.4. SIGNIFICANCE AND NOVELTY

In the prime of climate change, understanding the hydrological processes of watersheds is key in ensuring effective catchment planning and management (Gebre, 2015). Surface runoff estimation contributes positively to flood control initiatives and water resources planning and allocation. As the Gwayi catchment ultimately feeds into the largest Lake in the world by volume, Kariba, which is a source of hydro-electric power in the country, knowledge on the runoff is key to make decisions on both water and electricity allocation. Limited research focusing on hydrology has been carried out in the Gwayi catchment (Maviza & Ahmed, 2021). Whilst other research has been done in other Zimbabwean catchments, there has been no documented research on runoff estimation using the HEC-HMS model in the Gwayi catchment. The research builds upon the work carried out by (Dzirekwa et al., 2023; Gumindoga et al., 2016; Masimba et al., 2022; Ndemere et al., 2024; Nharo et al., 2019) in similar Zimbabwean contexts. It assesses the applicability of the HEC-HMS model to simulate surface runoff in a catchment the size of Gwayi. The research introduces a potential for informed decisions on water and environmental conservation by policy makers and environmental management bodies in an area with sparse observed data.

1.5. AIM AND OBJECTIVES

1.5.1. AIM

The main goal of this research was to delineate watersheds and estimate runoff of Gwayi Catchment using GIS and the HEC-HMS hydrological model

1.5.2 OBJECTIVES

i. To develop input parameters using GIS based HEC-HMS model
ii. To assess the feasibility of calibrating and validating the HEC-HMS model with sparse data
iii. To simulate the stream flow using the HEC_HMS Model

1.6. RESEARCH QUESTIONS

i. Which parameter is most sensitive for model calibration?
ii. Is it feasible to calibrate and validate model with sparse data?
iii. Is it possible to derive model input parameters using remote sensing satellite data?
iv. How well does the HEC-HMS model simulate stream flow response?

1.7. STRUCTURE OF THE RESEARCH

The research report comprises 5 Chapters. The study is introduced in Chapter 1 where the hydrological modelling background is highlighted globally and locally. The rationale, research problem statement and objectives are presented. Literature review on climate change, water resources and hydrological processes are covered in Chapter 2. The chapter also assesses the integration of geospatial technologies with hydrological modelling. Materials and methods consisting of data collection and analysis procedures as well as adopted methods to attain objectives are discussed in Chapter 3. Results and discussions are presented in Chapter 4 whilst the conclusions and recommendations emanating from the study are presented in Chapter 5.

CHAPTER 2: LITERATURE REVIEW

2.1. WATER RESOURCES MANAGEMENT

According to Savenije and Van der Zaag (2008), there are limited freshwater resources which need to be divided to meet different societal needs. There is need to acknowledge that overexploitation is real when it comes to water resources, therefore, instead of a generic approach, localised planning to cater for social and ecological constraints is required. Integrated water resources management (IWRM) has become popular encompassing planning and protection with the focus being on sustainability (Savenije and Van der Zaag, 2008). Owing to the finite nature of water, to ensure sustainable utilization, management is key and to successfully manage resources, knowledge on the watershed characteristics and responses is required. To effectively plan and manage the available water resources, understanding the hydrologic and meteorologic phenomena is key (Dzirekwa et al., 2023).

According to Government of Zimbabwe (GoZ), (2002), for managing water resources, Zimbabwe is divided into 7 catchments namely Gwayi, Mazowe, Sanyati, Manyame, Save, Runde and Mzingwane. The annual surface water produced in Zimbabwe is said to be 11.26 million km^3 (GoZ, 2002) and the flow of rivers varies in the Gwayi catchment based on the frequency and intensity of rainfall. According to GoZ, (2002), high rainfall variability and its unpredictable nature threatens water resources management in a surface water dependent economy.

2.2. WATER RESOURCES MANAGEMENT MODELS

To better understand hydrological processes and the availability of water resources, hydrological models have been utilised worldwide for various river basins. (Gebre, 2015). In the age of climate change, hydrological models become an integral part to assess and forecast the availability of water in watersheds. This is to enable the formulation of appropriate adaptation strategies. Three main categories are used to classify hydrological models and these are distributed, semi-distributed and lumped (Panigrahi et al., 2014). For lumped models, there is no spatial variation, and the watershed hydrological response is only estimated at the outlet with no accountability for micro-catchments. Distributed models account for spatial variation and the resolution is user defined, with semi-distributed models introducing a balance between lumped and distributed models in terms of complexity in runoff estimation (Fathy et al., 2015).

2.2.1. ALLOCATION MODELS

According to Vichete et al., (2023), when water allocation is appropriate and effective, it results in a reduction in conflict and sustainability is promoted. Water allocation models refer to those models that calculate water that is actually and lawfully available. They also represent different components in a river network, and these include reservoirs, abstraction and diversions among others. The different types of water users are incorporated in the model such as industrial, agriculture and municipal. The parameters can be calculated, or user defined.

Vichete et al., (2023) noted that allocation models present challenges in calibration to produce realistic responses. The challenge is in the correct representation of changes because of use of resources and the linkages with outputs. As a result, this requires incorporating yield data and water use by farming. Hishinuma et al., (2014) highlighted that the lack of experience and knowledge in utilizing the models presents challenges in creating effective water management systems. To understand and interpret the different interactions, several tests and checks are crucial in the verification of the presence of relationships. This is done to ensure model reliability.

Additionally, the unavailability of ground-based hydrological data is said to be the greatest challenge faced by catchment managers and hydrologists (Hishinuma et al., 2014). As a result, calibration procedures are not performed satisfactorily. In semi-arid mountainous regions, data scarcity becomes a major issue because of the more pronounced spatio-temporal variations of hydro-meteorological parameters. The lack of integration of ecosystem services and functions as well as contribution of new technologies has also been stated as a challenge in water allocation modelling (Ortiz-partida et al., 2023). The basic relationship between groundwater and surface water is also considered a limitation. Ortiz-partida et al., (2023) noted that groundwater is normally considered an alternative in the absence of surface water. However, there is a need to bridge this gap by incorporating groundwater to optimize and maintain for future use to avoid over drafting of available water resources. Moreover, Ortiz-partida et al., (2023) noted a divide between modelers and stakeholders as a challenge. Coordination with vulnerable stakeholders in decision making can enhance climate change adaptation and mitigation. This is because unequal distribution undermines sharing of existing water resources efficiently.

2.2.2. SIMULATION MODELS

Unlike allocation models, simulation models make use of mathematical functions and simultaneously available variable records to produce a record for a hydrological variable for a specified period of time (KlemeŠ, 1986). With these types of models, prediction is possible given the availability of predictors records from independent simulations. Hydrologic simulation models are divided broadly into two main categories which are stochastic and deterministic. According to Fanta & Feyissa, (2021), stochastic models introduce randomness in the output whilst deterministic models produce single outcomes. Deterministic models are further classified into lumped, distributed and semi distributed models. Semi-distributed models partition basins into smaller ones (Gebre, 2015).

According to Hishinuma et al., (2014), the use of hydrological simulation models effectively is seriously affected by data scarcity, limiting the potential for water resource development design. As a result, in poorly gauged basins, there should be careful consideration in the use of hydrological models. Data uncertainties must be thoroughly assessed, for example, testing precipitation data reliability through the application of a water balance equation. Additionally, in developing countries, the scarcity of high-resolution ground data creates difficulties in modelling and projecting the impacts of climate change on single watersheds. This combined with a lack of understanding of climate spatio-temporal variations results in challenges in forecasting the location and timing of significant economic and ecological impacts of changes in river flow. Limited data normally results in short calibration periods (Seibert & Meerveld, 2016). This reduces model robustness and increases uncertainty. Using longer periods for calibration and shorter periods for validation is recommended for more reliable results and uncertainty estimates. Nearby catchments may be used as a reference to compare model simulations with the assumption of initial similarity in the functioning of the catchments (Seibert & Meerveld, 2016).

Sezen & Sraj, (2024) highlighted the complexity of hydrological simulation modelling in heterogeneous catchments comprising diverse topographic, climatic and geological conditions. Poor performance has been noted in simulating baseflow. According to Sezen & Sraj, (2024), employing diverse modelling approaches may provide solutions related to numerous factors affecting the performance of hydrological simulation models such as characteristics of catchments, inputs and model structures utilized. Moreover, according to Kempen et al., (2021), quantifying the structural uncertainty of simulation models is challenging because of the time and effort it takes to set up and run various model structures.

2.3. SURFACE RUNOFF MODELLING

The examination and comparison of runoff and rainfall datasets at various positions in a watershed can be used to extract information on the availability of water resources and analyse present and past trends for future forecasting (Love, Uhlenbrook, Twomlow, et al., 2010). The analysis of long-term variations in temperature, rainfall and discharge can be used to assess threats and explain changes to water resources.

Modelling water resources is common and enables the forecasting of hydrologic response to watershed practices (Panigrahi et al., 2014). Various researchers have used different models in modelling surface runoff in different watersheds with different successes. These include for example Panigrahi et al., (2014) who applied the HEC-HMS model in India, Brirhet & Benaabidate, (2016) who compared the ATHYS and HEC-HMS model in Morocco and Muhammed, (2012) who used the TOP-MODEL in Ethiopia. According to Mabande & Rientjes, (2012), the HEC-HMS model has been widely used and preferred especially in developing countries where customization of already existing models is cheaper compared to model development. Gumindoga et al., (2016) proved that the HEC-HMS model can be utilised in Zimbabwe. There is still a gap in terms of the HEC-HMS model application in the Gwayi catchment as highlighted by Maviza & Ahmed, (2021).

According to Halwatura & Najim, (2013), sparse data presents a challenge in hydrological studies to understand and predict surface runoff. This is attributed to the time-consuming nature of the process and that several iterations must be carried out to draw conclusions. Hydrological models present a good alternative and opportunities for the estimation of flood hydrographs and peaks (Fanta & Feyissa, 2021). To estimate how watersheds respond to precipitation, hydrological models are commonly used, and model selection is dependent on project goals. The HEC-HMS model has been mentioned by various scholars to be capable of estimating surface runoff in different environments. This ranges from small, simple and manageable watersheds to complex ones (Hernández-Romero et al., 2022). Its ability to also generate continuous unit hydrographs provides key capabilities in accounting for changes over time.

Sensitivity analysis is necessary in modelling studies to identify key parameters and calibration accuracy level requirements (Al-Mukhtar & Al-Yaseen, 2019). According to the US Army Corps of Engineers Hydrologic Engineering Center, (2000), observed hydro-meteorological data is used in calibration to obtain parameters yielding the best fit of the computed results to the observed runoff. Figure 1 shows the calibration procedure in a graphical format.

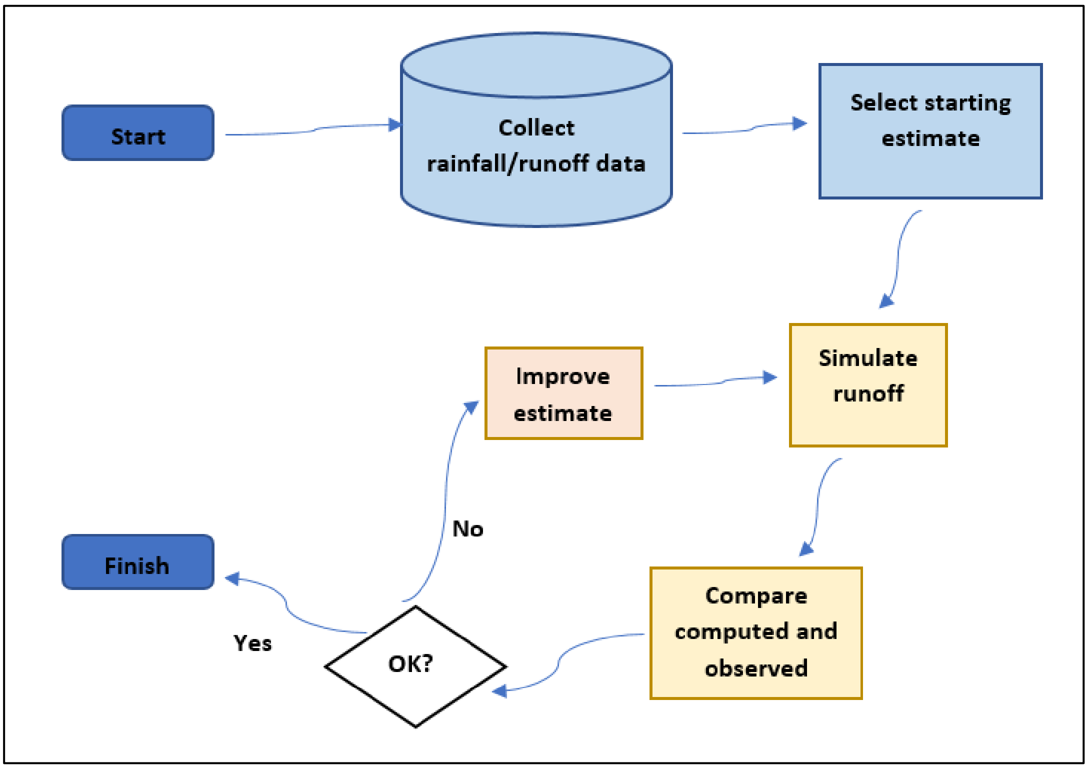

Figure 1. Schematic of calibration procedure (US Army Corps of Engineers Hydrologic Engineering Center, 2000)

2.3.1. SURFACE RUNOFF

According to Gajbhiye, (2015), surface runoff causes soil erosion and areas downstream of watersheds are mostly affected. Rajbanshi, (2016) highlighted that to appropriately manage watersheds, detailed knowledge of the watershed resources is required and accurately estimating surface runoff is a must.

2.3.2. FACTORS AFFECTING SURFACE RUN-OFF

Following precipitation events, soil type, land use and slope are some of the factors that influence surface runoff in watersheds Rajbanshi, (2016). According to the US Army Corps of Engineers Hydrologic Engineering Center, (2000), the generation of runoff is greatly influenced by infiltration rate and the time taken to reach saturation excess. Therefore, the differences in soil moisture conditions, rainfall, terrain, soil properties as well as land use and landcover contribute to the variability in the generation of runoff. Large errors are introduced when any one of these conditions are not accurately represented (Rajbanshi, 2016). To reasonably represent real world conditions, properly modelling runoff is therefore crucial.

2.3.3. GIS AND HYDROLOGICAL MODELLING

The use of GIS and Remote Sensing in hydrology has mushroomed to address various issues (Khatami & Khazaei, 2014). This is mainly because the different hydrological processes do not only vary temporally but spatially as well. GIS tends to bridge this gap through the provision of data with a spatial component resulting in specification of variables that tend to vary spatially, for example, slope.

GIS and Remote sensing results in a greater coverage of reality and for more complex models allows for monitoring of different locations varying spatially to inform management strategies. Remote Sensing also plays a role in data provision in data scarce regions. According to Ndemere et al., (2024), precipitation is an important component of the hydrological cycle. Due to the failure of rain gauges to accurately represent precipitation spatially, estimates from satellites have become a good alternative. These estimates also account for the gaps normally found in the observed and when the data is not available (Ndemere et al., 2024).

The application of GIS and remote sensing to hydrological studies in Zimbabwe have been conducted by different scholars (Dzirekwa et al., 2023; Gumindoga et al., 2017; Masimba et al., 2022; Ndemere et al., 2024; Nharo et al., 2019). This has enabled the representation of boundary conditions spatially through discretization (grid by grid cell computation) instead of treating the watershed as a lumped unit.

2.4. SUMMARY

This Chapter highlighted issues around water resources management and the different types of water resources management models that can be utilised to understand different watersheds. Surface runoff, the factors affecting surface runoff as well as surface runoff modelling were studied both globally and locally. Finally, the link between Geographic Information Systems (GIS) and hydrological modelling was discussed. The findings from the review of literature revealed several gaps. High rainfall variability and its unpredictable nature threatens water resources management. Data scarcity creates difficulties in modelling and projecting the impacts of climate change on single watersheds. Future research directions are aimed at utilizing nearby catchments as references to compare model simulations with the assumption of initial similarity in the functioning of the catchments. Calibration to produce realistic responses is a major issue in hydrological modelling. This coupled with a lack of experience and knowledge undermines effective water resources management. In water allocation modelling, coordination with vulnerable stakeholders in decision making can enhance climate change adaptation and mitigation. This is because unequal distribution undermines sharing of existing water resources efficiently.

CHAPTER 3: MATERIALS AND METHODS

3.1. STUDY AREA DESCRIPTION

The Gwayi Catchment covers a total area of 43331km². The area is located North-West of Zimbabwe between -20.125º & -17.125º South of Latitude and 25.375º & 29.125º East of Longitude. Summer temperatures peak around 38ºC in October and November, with a gradual fall to 2.5ºC during the winter months of June and July until they begin rising again in September. The highest rainfall is received during the months of December to February with a mean monthly rainfall ranging from 120-180mm. The only source of runoff is rainfall; therefore, its temporal and spatial variations significantly influence runoff patterns within Zimbabwe. The area comprises Miombo woodlands with Kalahari sands and Karoo sequence. Evaporation ranges from 1850mm - 2200mm/yr. Annual runoff varies from 5-44mm depending on the rainfall, soil type and slope. Figure 2 shows the location of Gwayi Catchment in Zimbabwe.

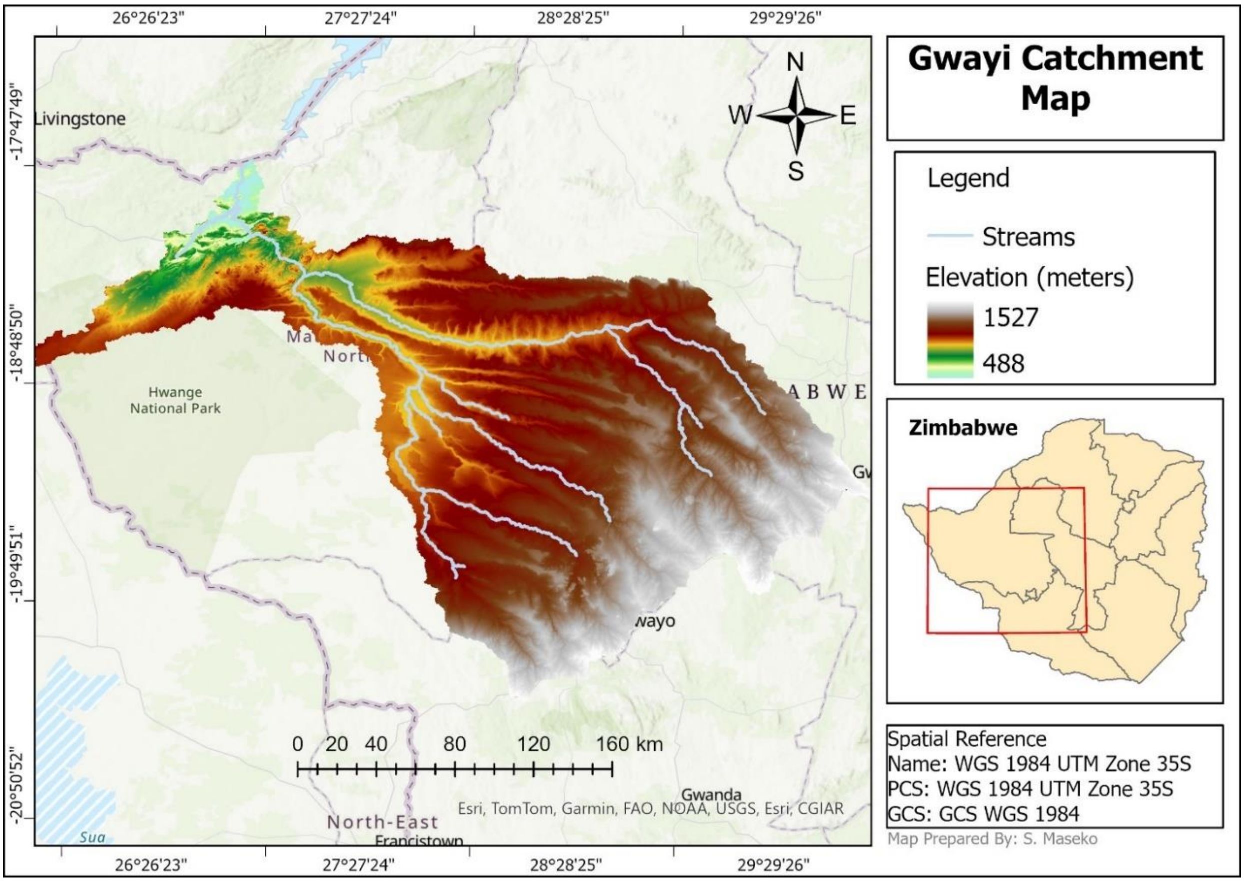

Figure 2. Location of Gwayi Catchment in Zimbabwe

3.2. HYDRO-METEOROLOGICAL DATA

Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) with a 0.05 degrees resolution at a daily time step was utilised in this study. This is because it has been shown to be one of the datasets closely related to ground conditions (Matingo et al., 2018). In addition, compared to other precipitation datasets, CHIRPS data has a higher resolution as some of the commonly used datasets such as Climate Prediction Center morphing technique (CMORPH), Tropical Rainfall Measuring Mission (TRMM), Precipitation Estimation from Remote Sensed Information Using Artificial Neural Networks (PERSIANN), Integrated Multi-satellite Retrievals for GPM (IMERG) range from 0.1 to 0.5 degrees. The CHIRPS dataset has records from 1981-present and consists of both monthly and daily records.

According to Hernández-Romero et al., (2022), CHIRPS produces time series precipitation through combining land observations and satellite data. Satellites provide good alternatives when observed data is not available because of their temporal and spatial power (Hernández-Romero et al., 2022). The study used daily data for the period of October 2016 to September 2021. Gridded precipitation data was used for precipitation input into the model which was downloaded as a NetCDF and converted to a Data Storage System (DSS) file recognized by the HEC-HMS model. The CHIRPS data was then linked to the meteorological model. According to (Ndemere et al., 2024), satellite products such CHIRPS data can be used to represent precipitation patterns in Zimbabwe. However, because this dataset tends to overestimate ground conditions, bias correction is required to improve the accuracy.

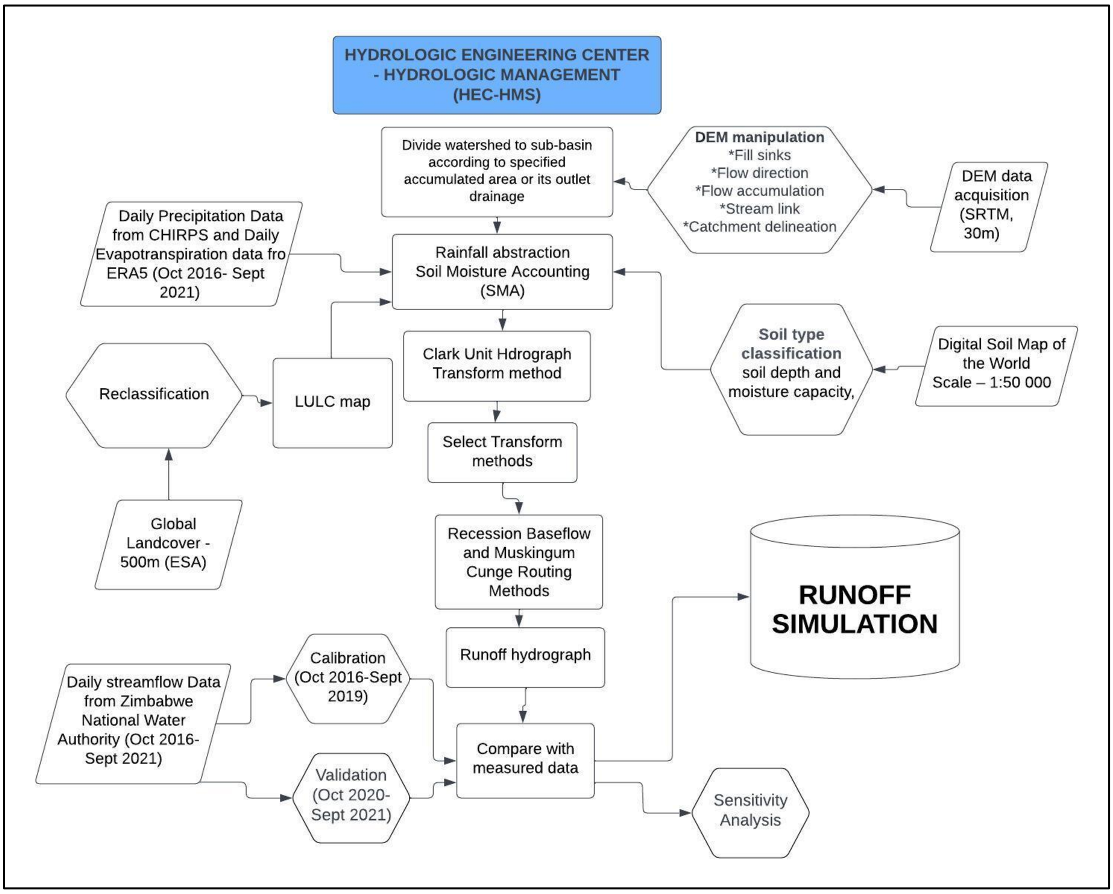

Figure 3. Methodological Flow Chart

Four gauging stations; A36, A38, A39 and A68 were used for daily discharge data for the above period, (Table 1) and added in the model as time-series data. The Zimbabwe National Water Authority provided this data. The main reason for the selection of the above period was because of the completeness in observed data for that period and because some of the stations have been closed. The time series gauges parameters and time window was specified. This automatically created a table to which the values were manually entered. To achieve this, the streamflow data was reorganized in Excel from annual records into a continuous dataset to match the format required by HEC-HMS. The values were then pasted in the model. For streamflow, time series data represented as discharge gauges was added and linked with the corresponding sub-basins and junctions to enable flow simulation. As evapotranspiration is key in accounting for losses in continuous modelling, this was specified for the meteorologic model using the ERA5 dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) (Kassem et al., 2023).

Table 1. Gauging stations utilised in the study

Station Name	River	Station Name	Start	End
A36	Shangani	Gwayi confluence	Oct 2016	Oct 2021
A38	Gwayi	Dahlia control sect	Oct 2016	Oct 2021
A39[1]	Bubi	Lupane G/w	Oct 2016	Oct 2021
A68	Gwayi	D/S Mbembesi confluence	Oct 2016	Oct 2021

3.3. HEC HMS MODEL AND ITS STRUCTURE

The HEC HMS model can be used in lumped/semi-distributed models and for both event and continuous simulation. Model results are normally used in studying the availability of water and forecasting flow together with other software (Gumindoga et al., 2016). The HEC HMS model has a number of loss, transform, baseflow as well as routing methods (Halwatura & Najim, 2013). Some of the models are ideal for event simulations, for example, the SCS curve number method whereas some are ideal for continuous simulation, for example, the Soil Moisture Accounting Loss method.

Continuous simulation was carried out by calculating loss rate (Soil Moisture Accounting), flow transformation (Clark Unit Hydrograph), a meteorologic model (precipitation), baseflow (Recession) and reach routing (Muskingum Cunge). Remote sensing was utilised to acquire datasets used in watershed delineation, transformation, and loss accounting. These were digital elevation model

[1] Located immediately downstream of Lupane Dam

(DEM), precipitation data (CHIRPS), and land use and land cover. Detailed explanations of these datasets can be found in Sections 3.2, 3.3.1, and 3.3.2.

3.3.1. WATERSHED DELINEATION

The Shuttle Radar Topography Mission (SRTM) sensor with a 30m spatial resolution was used to derive the basin model of the Gwayi catchment comprising of sub-basins, reaches and junctions. Hydrological processing capabilities of HEC HMS enabled the division of the watershed into 5 subbasins representing the Gwayi catchment's main tributaries and mainly because of the location of gauging stations that would be converted into computation points. Merging of sub-basins was done to simplify the calibration process and to represent ground conditions in terms of the official Gwayi sub-catchments. The model automatically produced the junctions for the different sub-basins. Gebre, (2015) highlighted that the sub-division of the watershed contributes to improved model performance as computations are distributed and not lumped. The GIS capabilities of the HEC-HMS 4.10 software were utilized to preprocess the DEM of the Gwayi catchment. The steps followed in watershed delineation included preprocessing sinks and drainage, identifying streams and break points as well as delineating and merging elements. Preprocessing sinks to artificially remove depressions that disrupt river networks was carried out. Pre-processing the drainage allowed for identification of streams and ultimately the delineation of the Gwayi catchment and sub-basins based on elevation and the direction of flow of water. The river length and slope, basin slope and centroids were determined and were key in parameter estimation such as the time of concentration. The basin and meteorologic model as well as control specifications were developed inside the HEC-HMS model.

3.3.2. LAND USE/COVER AND SOILS DATA

The Land use and Land cover map of the Gwayi catchment was derived from the 300m resolution Global Landcover product by the European Space Agency whereas soil properties were acquired from the FAO soils database - Digital Soil Map of the World (DSMW) with a scale of 1:50 000. ArcGIS Pro and QGIS were used to manipulate and visualise the maps. Land use data was used to estimate percent impervious and maximum storage. The percentage impervious values were estimated as a function of the built-up ratio per sub-basin. The interception values for the sub-basins ranged between general vegetation, grasses, and deciduous trees (Table 2).

3.3.3. CANOPY METHOD

According to the HEC-HMS manual (US Army Corps of Engineers Hydrologic Engineering Center, 2000), this method is used to show and represent plants presence. This is required for continuous simulation because precipitation reaching the ground surface is reduced by interception by plants and this water is removed from plants through evaporation. This process combined with the extraction of water from the soil by plants is usually called evapotranspiration. The Simple Canopy method was selected for this research with the initial storage set to zero and maximum storage values estimated from literature based on the landcover (Table 2). Since the Gwayi catchment falls under grasses and deciduous trees as well as general vegetation, the initial values were estimated using the values in Table 2 and changed during the calibration phase. Whilst these values provided initial estimates, the use of single values only account for the dominant land use and landcover types do not capture the spatial variances within the sub-basins.

Table 2. Interception depths for the Canopy method, Zinke (1967)

Canopy description	Storage (in)	Storage (mm)
General Vegetation	0.05	1.27
Grasses and Deciduous trees	0.08	2.03
Coniferous trees	0.1	2.54

3.3.4. SURFACE METHOD

Water reaching the soil can infiltrate into the soil, form pools or flow over the land. The water captured in pools is called depression storage. Over time, the water on the surface will either runoff, infiltrate or evaporate. In the HEC-HMS model, runoff will only begin when precipitation exceeds infiltration capacity and depression storage is filled. In this study, the simple surface method was selected as it is the most used. Parameter values were selected based on the physical conditions of the area (Table 3). The sub-basins were identified to fall under most areas with pervious surface and have gentle to moderate slopes, whilst sub-basin 4 fell under steep slopes. Like the canopy method, the values were generalized based on mean values for slope and percentage of impervious surfaces. However, gradual changes to physical conditions such as slope are usually experienced and therefore mean values were used to estimate sub-basin initial estimates. This does not eliminate errors introduced because of failure to account for spatial differences.

Table 3. Surface depression depths for the surface method, Bennet (1998)

Surface Description	Storage (in)	Storage (mm)
Steep, smooth slopes	0.04	1.01
Most areas with impervious surface	0.125-0.250	3.175-6.35
Most areas with pervious surface	0.25-0.50	6.35-12.7
Flat agricultural land	2.0	50.8

3.3.5. LOSS METHOD

Initially, the study employed the Deficit and Constant Loss method to account for runoff volume. This included estimating initial loss, constant loss, maximum deficit and percent impervious. The initial loss was estimated to be the ground conditions at the beginning of the simulation, constant loss as the hydraulic conductivity of the soil, maximum deficit as soil storage and percent impervious as the ratio of the built-up area in a sub-basin.

After several calibration attempts without producing an acceptable model fit, the Soil Moisture Accounting Loss method was used. The method was selected because it accounts for continuous simulation and was combined with the simple canopy and surface method for soil water extraction as a result of evapotranspiration (US Army Corps of Engineers Hydrologic Engineering Center, 2023). The parameters required for this method are percent impervious, infiltration rate, soil percolation rate, tension storage, soil storage, GW layer 1 and 2 storage depth and coefficient. Parameters such as canopy, surface, soil, and tension zone storage, percent impervious, infiltration, soil percolation and groundwater layer 1 percolation rate were estimated from land use and soil whereas groundwater layers 1 and 2 storage depth as well as groundwater 1 and 2 coefficient were a result of the analysis of recession of streamflow.

The maximum infiltration and percolation rate, soil and tension zone storage values were estimated from the soil characteristics such as saturated hydraulic conductivity, porosity, and field capacity. The values for saturated hydraulic conductivity were estimated from literature using soil texture data derived from the Digital Soil Map of the World (Table 4). For example, the maximum infiltration rate was considered as a weighted average for saturated hydraulic conductivity. The component percentage (for example sandy loam) and the saturated hydraulic conductivity was used to achieve this.

Table 4. Saturated Hydraulic Conductivity and soil textures (Rawls et al., 1983)

Texture	Saturated Hydraulic conductivity (in/hr)
Clay	0.01
Clay Loam	0.04
Loam	0.1
Loamy Sand	1.2
Sand	4.6
Sandy Clay	0.02
Sandy Clay Loam	0.06
Sandy Loam	0.4
Silt Loam	0.3
Silty Clay	0.02
Silty Clay Loam	0.04

3.3.6. TRANSFORM METHOD

The Clark unit hydrograph was used, which is a synthetic method making use of the time area curve in developing a hydrograph because of precipitation. The method was selected because it produces reasonable input and is ideal for continuous simulation (US Army Corps of Engineers Hydrologic Engineering Center, 2023). The standard method was selected in this study. The method has two main inputs which are time of concentration (Tc) as shown by Equation 1 and storage coefficient (R) as shown by Equation 2 and 3. Time of concentration specifies the time taken by water from the furthest point in a subbasin to the outlet. Whilst the storage coefficient puts into consideration the storage effects. These parameters were calculated using the following equations:

Time of concentration (Tc):

$$T_c = 2.2\left[\frac{L\ x\ Lca}{\sqrt{S_{10-85}}}\right]^{0.3} \qquad \text{Equation 1}$$

Tc = Time of Concentration (hr)

L = Longest Flow path (mi)

Lca = Centroidal Longest Flow path (mi)

S_{10-85} = 10-85 Stream Slope (ft/mi)

Storage Coefficient (R):

$$\frac{R}{T_c+R} = Constant \qquad \text{Equation 2}$$

R = Storage Coefficient (hr): Tc = Time of Concentration (hr): 0.5 = Constant

Therefore,

$$\frac{R}{T_c + R} = 0.5$$

Equation 3

$$R = 0.5T_c + 0.5R$$

$$R - 0.5R = 0.5T_c$$

$$R = T_c$$

3.3.7. BASEFLOW METHOD

The Recession baseflow method designed for both event and continuous simulation was used (US Army Corps of Engineers Hydrologic Engineering Center, 2023). The initial discharge, which was determined from streamflow was specified and the recession constant, which highlights the rate of recession by baseflow after rainfall events. Initial values of recession constant and ratio to peak were adopted from the values recommended on the HEC-HMS user manual and were changed during the calibration process. The recession constant normally ranges from 0.7 to 1, with an initial estimate of

0.9 adopted and changed during calibration (US Army Corps of Engineers Hydrologic Engineering Center, 2023). The ratio to peak is a value detailing where baseflow recession starts. The initial estimate was adopted to be 0.2 and changed during the calibration process. The changes in these values mainly contribute to the recession and attenuation of the hydrograph.

3.3.8. ROUTING METHOD

The Muskingum Cunge method was used in this study as it takes into consideration the hydraulic properties of the catchment. It is based on mass conservation and recalculates parameters based on the properties of the channels with the assumption that the surface is not level (US Army Corps of Engineers Hydrologic Engineering Center, 2023). The method involves specifying the reach length, slope, Manning's n Roughness coefficient as well as space time and index methods. For the purposes of this study, the channel was assumed to be a trapezoid and the index method as celerity. The depth and width were calculated from the digital elevation model (DEM). The changes in these values mainly contribute to the attenuation and timing of the hydrograph within reaches.

3.4. CALIBRATION AND VALIDATION

Calibration involves the adjustment of parameters, with the main goal being to match output with observed data (US Army Corps of Engineers Hydrologic Engineering Center, 2000). To initiate the calibration process, goals were first set. Goodness of fit was the main goal as the research aimed to identify how well the HEC-HMS model simulates surface runoff in the Gwayi catchment. Statistical metrics were used to evaluate the model, and these were Nash Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), Percent Bias (PBIAS) and coefficient of determination (R^2). These were selected because they are the most commonly used statistical evaluations in hydrological modelling (Halwatura & Najim, 2013). The magnitude, volume and timing were also monitored during the calibration phase to identify the impact of changes in different parameter values. The model was calibrated (October 2016 – September 2019) and validated (October 2019 – September 2021) both manually and making use of the optimization techniques in the HEC-HMS model at a daily and 15-minute time steps. The calibration process started from upstream to downstream sub-basins. Efforts were made to fit simulated flow with observed flow by varying parameters whilst working within acceptable ranges relating to known physical conditions.

Following the calculation of the required parameters, daily streamflow data from October 2016 to September 2019 for four gauging stations was added to time series data and evapotranspiration data was added to the meteorological model. The calibration process started with automatic parameter optimization. An optimization-run was created from "Optimization Trial Manager" in HEC-HMS and calibration parameters were added to find the optimized values. The model was run and baseflow output examined marking the beginning of manual calibration. Some of the initial calibration values were determined from automatic calibration, for example, groundwater (GW) percolation rate. Each step of calibration resulted in fixing the canopy and surface methods, with storage coefficient and time of concentration changed while manually calibrating the model. To match observed discharge, loss parameters such as maximum infiltration, tension, and soil storage as well as percent impervious were adjusted. These were identified to be the most sensitive. Validation began following the achievement of the 'best' possible model calibration based on available inputs. Validation was performed using streamflow data from October 2019 to September 2021. The final calibration model parameters are presented in Table 8.

Statistical evaluation was conducted to examine time series agreement and the differences between observed and simulated values. Root Mean Square Error (RMSE), Percent Bias (PBIAS), Nash Sutcliffe Efficiency (NSE) and Coefficient of Determination (R^2) are commonly used statistical evaluations (Halwatura & Najim, 2013). The Bias statistic shows whether the model tends to over or underestimate observed data, with zero being an ideal value. Table 5 was used to assess the goodness of fit of HEC HMS model in the Gwayi catchment.

Table 5. Metrics Reference, (Moriasi et al., 2007)

Performance Ratings for Evaluation Metrics for a daily and weekly time step				
Performance Rating	**R^2**	**NSE**	**RSR**	**PBIAS**
Very Good	$0.65<R2\leq1.00$	$0.65<NSE\leq1.00$	$0.00<RSR\leq0.60$	$PBIAS<\pm15$
Good	$0.55<R2\leq0.65$	$0.55<NSE\leq0.65$	$0.60<RSR\leq0.70$	$\pm15\leq PBIAS<\pm20$
Satisfactory	$0.40<R2\leq0.55$	$0.40<NSE\leq0.55$	$0.70<RSR\leq0.80$	$\pm20\leq PBIAS<\pm30$
Unsatisfactory	$R2\leq0.40$	$NSE\leq0.40$	$RSR>0.80$	$PBIAS\geq\pm30$

CHAPTER 4: RESULTS AND DISCUSSION

4.1. RESULTS

The chapter presents findings of the research from model input parameters to calibration and validation parameters as well as surface runoff simulation results. In this chapter, watershed delineation, land use and soil properties, meteorologic input parameters as well as model results are presented.

4.1.1 BASIN MODEL PARAMETERS

The inputs into the basin model were derived using GIS and these were elevation, slope, land use and land cover, soil types and hydrologic soil groups. The results are given in detail below.

i. WATERSHED DELINEATION

The Gwayi catchment covers a total area of 43331km² and the areas for the sub-basins representing the catchment's main tributaries are shown in Table 8. The Gwayi river and its tributaries form a dendritic drainage pattern and flow in a Northwestern direction. Rivers draining into the Gwayi are mostly from Matabeleland North, Bulawayo and Midlands Provinces. The elevation of Gwayi ranges from 511m to 1510m (Figure 4), with the slope generally gently sloping (3-4%) in the Southeastern part of the catchment to sloping (8%) in the North-Western part towards the outlet (Figure 5).

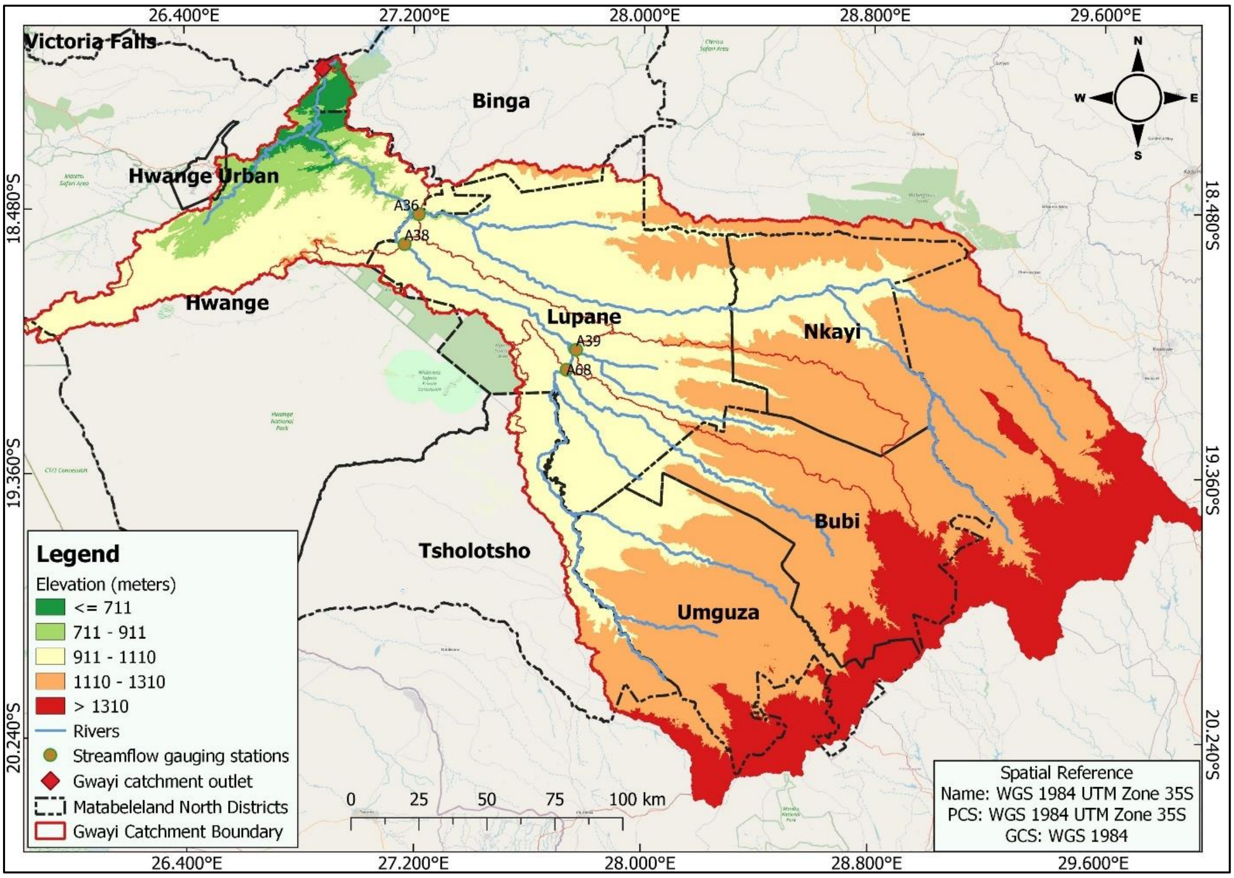

Figure 4. Gwayi catchment boundary and elevation

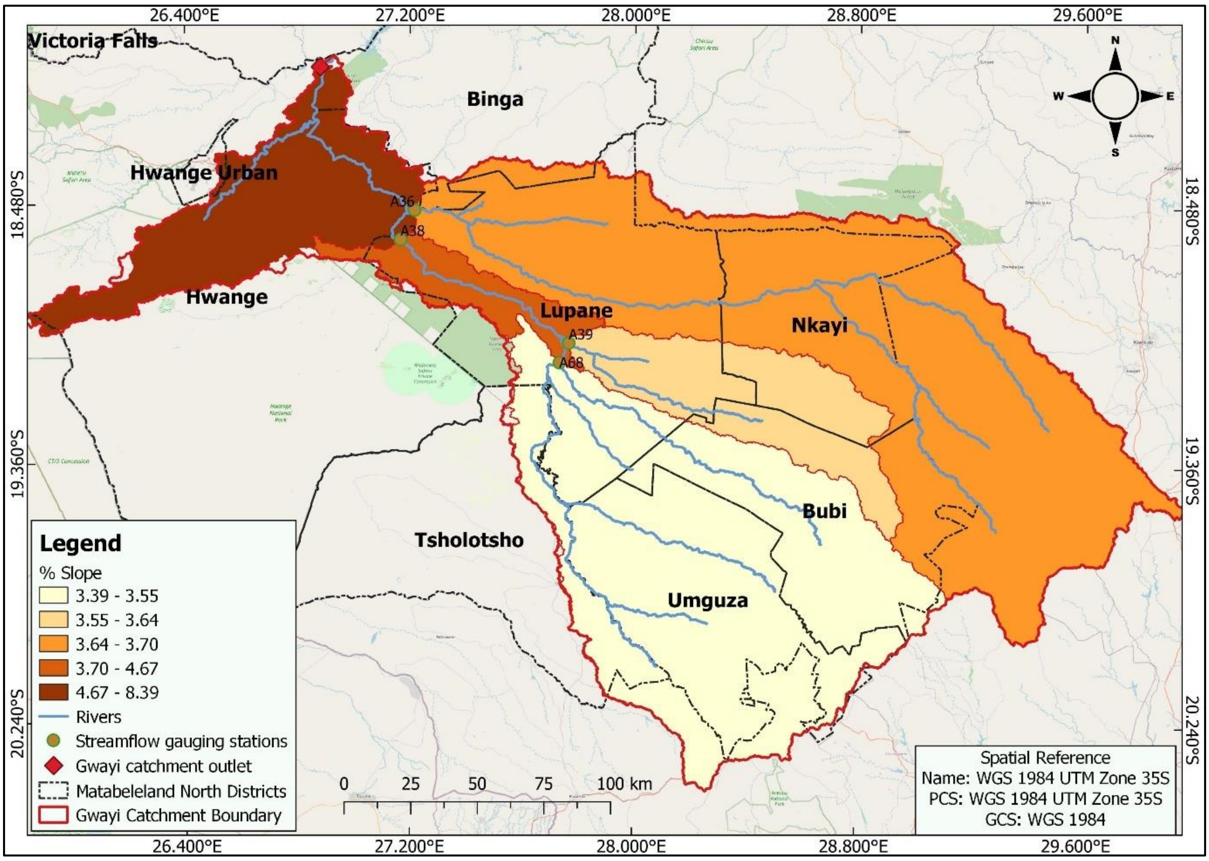

Figure 5. The slope variation in Gwayi catchment

ii. LAND USE/COVER

The catchment consists of six main land cover types including dense woodland (33%), open woodland (28%), agriculture or cultivation (24%), grassland (14%) as well as built-up and waterbodies (1%), (Figure 6). Dense woodland, open woodland and cultivation form the greater part of the Gwayi catchment. This has an impact on the surface runoff generated in the area taking into consideration the predominant soil type. The classes were then reclassified to mimic the Soil Conservation Service (SCS) land uses as shown by Table 6.

Table 6. Reclassification of land uses

Initial Classification		**Reclassification**	
Class Name	**Class Number**	**Class Name**	**Class Number**
Water Bodies	1	Water	1
Agriculture	2	Row crops/fallow	2
Dense Woodland	3	Woods	3
Open Woodland	4	Herbaceous	4
Grassland	5	Pasture, Grassland or Range	5
Built-Up	6	Impervious Areas	6

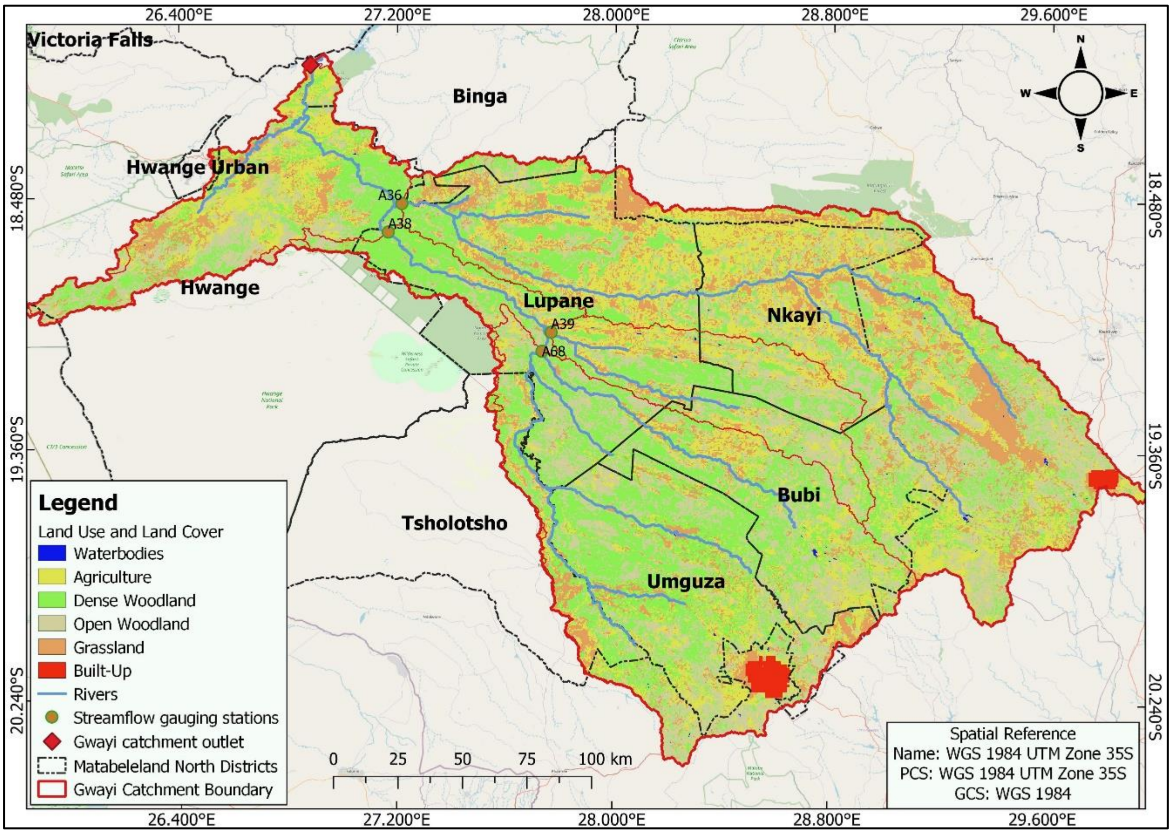

Figure 6. Land use and Land cover classification of Gwayi catchment

iii. SOIL PROPERTIES

The Digital Soil Map of the World by the Food and Agriculture Organization (FAO) was used to derive the soil properties required. The Gwayi catchment mainly comprises sandy loam (67.85%), sandy clay loam (18.18%) and clay soils (13.9%) as shown in Figure 7. Soil texture is required to determine the hydrologic soil group of an area used to determine other parameters such as the infiltration and percolation rate as well as soil and tension zone storage for the SMA loss method. However, the data from the DSMW comprised soil names and unique identifiers. To determine the soil texture and the hydrologic soil group, the SWAT 2012 data was used. The area falls under hydrologic soil groups C and D as shown in Figure 8 and Table 7. These have moderate to high potential of runoff with transmission of water restricted. This also results in pronounced sediment transportation.

Table 7. Soil classification of Gwayi catchment

Soil Name	Hydrologic Soil Group	Area (%)
Sandy Loam	C	68
Sandy Clay Loam	C & D	18
Clay	C & D	14

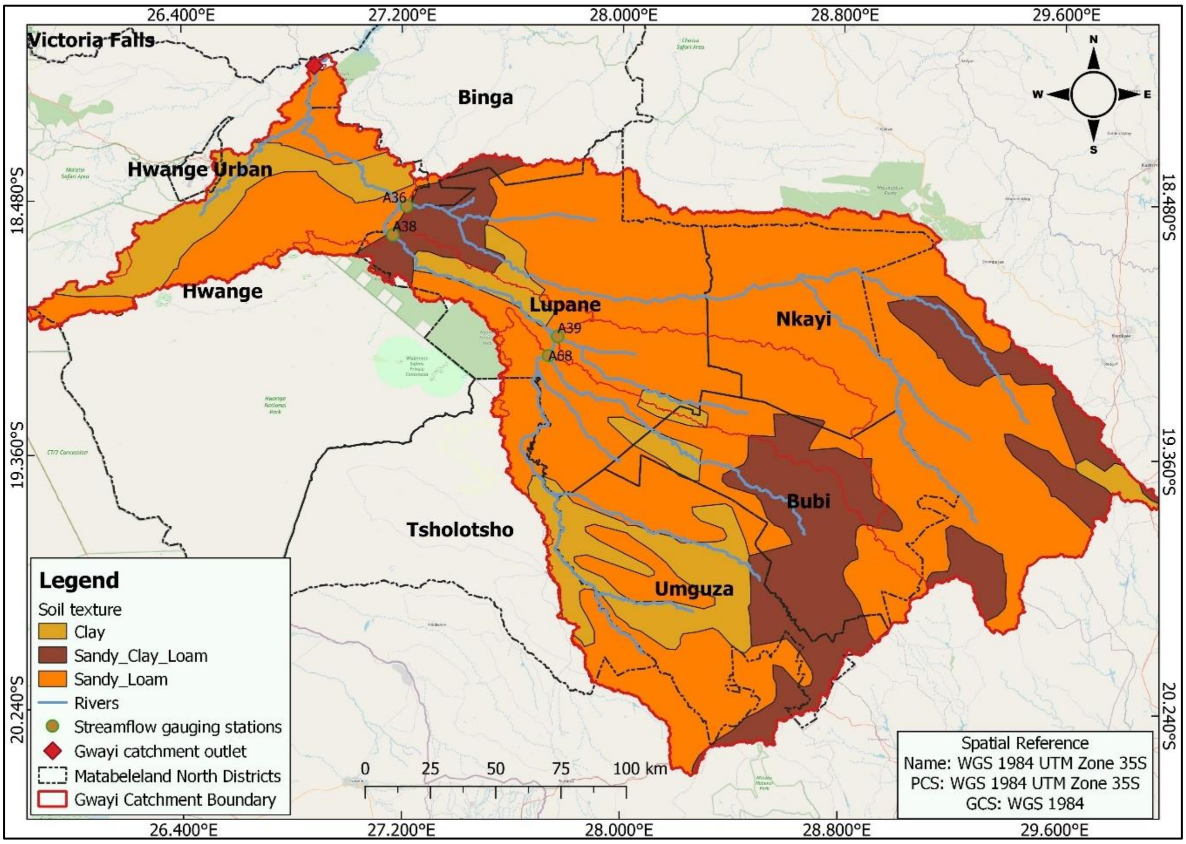

Figure 7. Soil texture classes in the Gwayi catchment

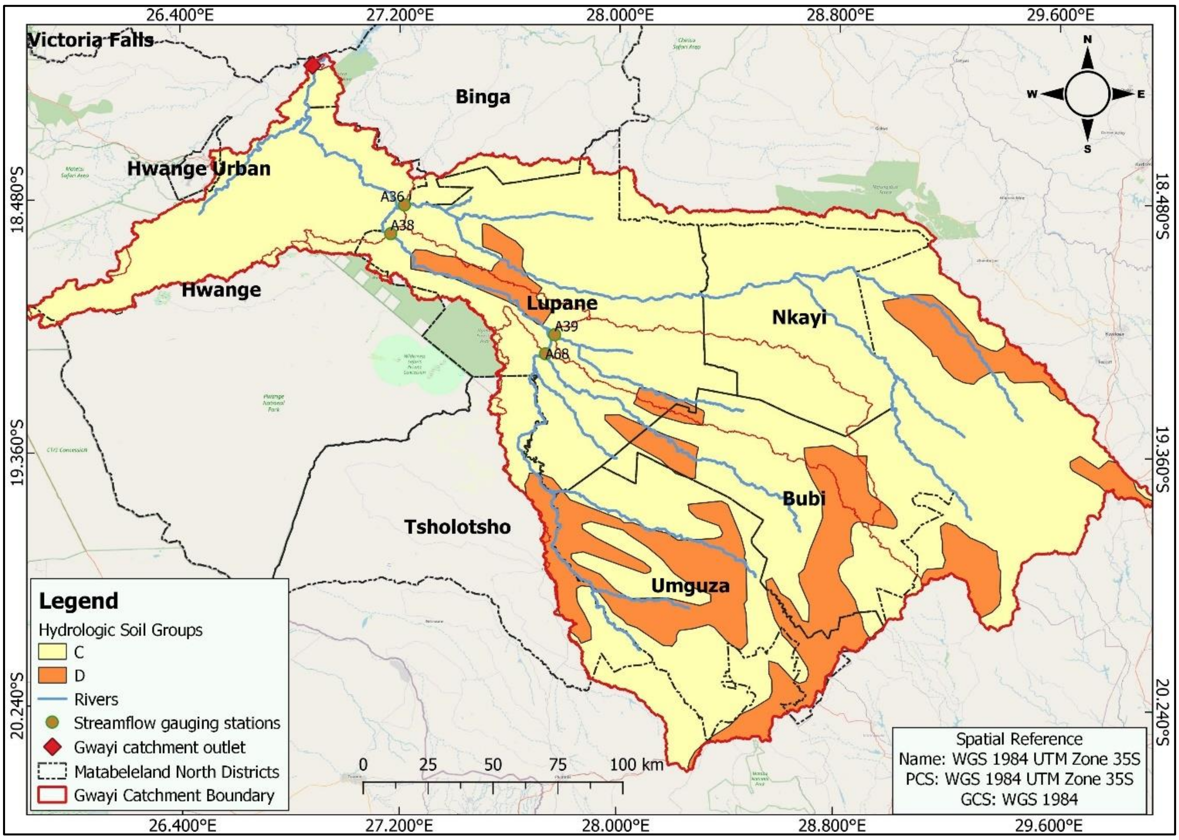

Figure 8. Hydrologic Soil Groups in the Gwayi catchment

4.1.2. METEOROLOGIC MODEL PARAMETERS

The results in Figure 9 indicate that precipitation in the Gwayi catchment is received from October to April. In the 2017/2018 season, the peak was above 30mm in February whereas in the 2018/2019 season, the peak was below 25mm in the same month. Observed flow shows a decreasing trend from the year 2017 to 2019 (Figure 9). The peak of over 700m³/s is shown in the 2017/2018 season whilst in the 2018/2019 season, the peak is in March towards the end of the rainy season. The presence of precipitation is expected to result in surface runoff generation. However, Figure 9 shows that this is not the case for Gwayi catchment. This can be attributed to factors such as infiltration and interception because of soil conditions and land use, evapotranspiration and presence of water storage systems such as dams which may be contributing to the lag in surface runoff recorded at a gauging station. These factors contribute to minimum runoff observed as the amount of water available to flow over the surface is reduced. This is because water either seeps into the ground or is intercepted by existing vegetation.

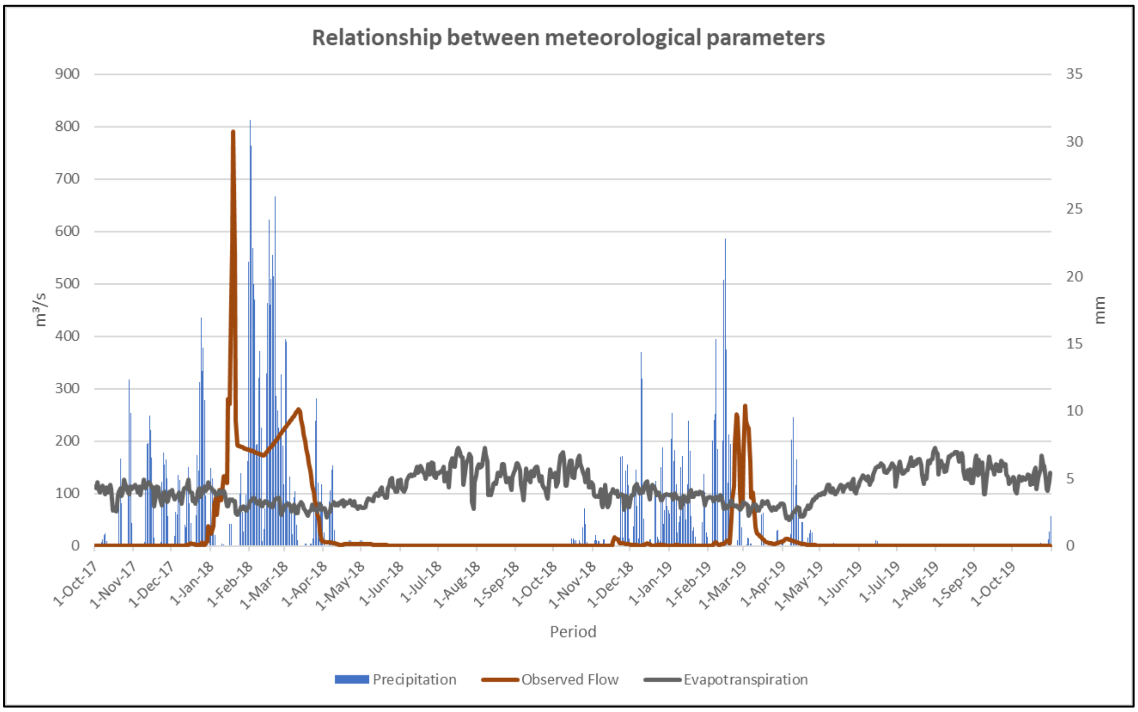

Figure 9. Graph showing the relationship between precipitation, observed flow (gauging station A36) and evapotranspiration

4.1.3. MODEL CALIBRATION AND VALIDATION

Figure 10 shows the schematic of the reaches, sub basins and junctions in HEC-HMS. Table 7 summarizes the catchment characteristics and parameters. Sub-basin 1, with Shangani as the main river has the largest area with 17988km² whereas subbasin 3 has the smallest area with 1507.7km². The time of concentration of water is higher in sub-basin 1 (120hrs) which was expected as it has the largest area. However, sub-basin 3 and sub-basin 4 values show different results (Table 8). Sub-basin 3 has a higher time of concentration (30hrs) with an area of 1507.7km² and a slope of 4% whilst sub-basin 4 has a lower time of concentration (21.04hrs) with an area of 4971.4km² and a slope of 8%. The variance is attributed to the differences in slope. The calibration and validation metrics are shown in Table 9.

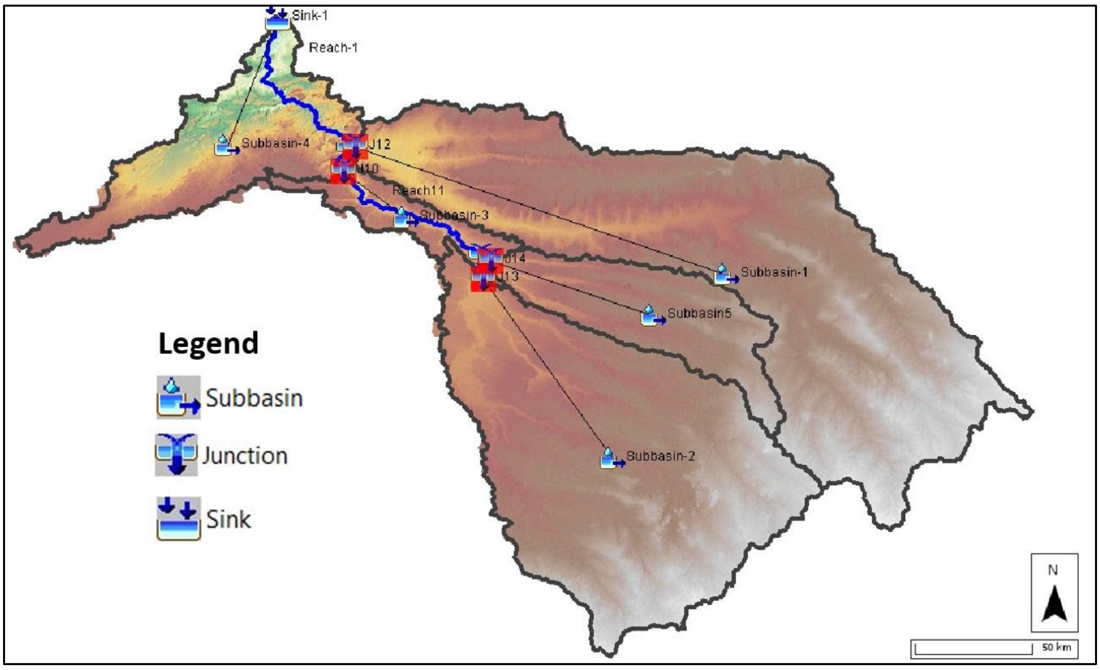

Figure 10. HEC-HMS schematic of sub-basins, junctions, reaches and sinks

Table 8. Gwayi catchment characteristics and input parameters

	Sub-basin				
Parameter	**1**	**2**	**3**	**4**	**5**
Gauge Name	A36	A68	A38	n/a	A39
Area (km2)	17988	14606	1507.7	4971.4	3912.1
Canopy Initial Storage	0	0	0	0	0
Canopy Maximum Storage	1	1	1	2.03	1
Crop Coefficient	0.9	0.9	0.9	0.4	0.9
Soil (%)	87	80	80	90	85
GW 1 (%)	50	80	80	80	80
GW 2 (%)	50	20	20	20	20
Maximum Infiltration (mm/hr)	50	100	50	100	50
% Impervious	20	10	10	6	10
Soil storage (mm)	50	160	100	185	150
Tension storage (mm)	40	150	80	168	140
Soil Percolation (mm/hr)	50	165	100	165	150
GW 1 Storage (mm)	100	702	200	702	702
GW 1 Percolation (mm/hr)	100	137	50	137	137
GW 1 Coefficient (hr)	5228	5228	5228	5228	5228
GW 2 Storage (mm)	393	393	393	393	393
GW 2 Percolation (mm/hr)	204.61	204.61	204.61	204.61	204.61
GW 2 Coefficient (hr)	3441	3441	3441	3441	3441
Time of Concentration (hr)	120	80	30	21.04	55
Storage Coefficient	120	30	30	21.04	70

Initial Discharge	5	10	0	0	1
Recession Constant	0.9	0.73	0.9	0.9	0.9
Ratio to Peak	0.2	0.2	0.2	0.2	0.2

The model had 5 sub-catchments which were developed, and 4 sub-basins had observed streamflow data. The graphs below show observed (red) and simulated (blue) trends for surface runoff in 2 sub-basins. Table 9 shows the metrics for performance evaluation for calibration and validation phases. Model calibration and validation results revealed both satisfactory and unsatisfactory results based on Table 5 for statistical metrics (Moriasi et al., 2007). Figures 13, 16, 19 and 22 show model results of the relationship between precipitation depth with observed and simulated flow. In most cases, when precipitation events were experienced, the model recorded flow showing a significant relationship between precipitation and simulated flow. However, this was not the case with observed flow as lags would be experienced in most cases. This is attributed to existing surface storage conditions in the Gwayi catchment.

Table 9. Metrics results for performance evaluation

CALIBRATION				
Computation Point	**Root Mean Square Error (RMSE)**	**Nash Sutcliffe Efficiency (NSE)**	**Percent Bias (PBIAS)**	**Coefficient of Determination (R^2)**
Junction 13	0.8	0.44	-8.04	0.46
Junction 14	0.9	0.19	24.47	0.34
Junction 10	0.9	0.21	8.88	0.39
Junction 12	0.9	0.27	5.13	0.40
VALIDATION				
Junction 13	1.6	-1.61	42.58	0.02
Junction 14	1.7	-1.75	121.98	0.03
Junction 10	0.9	0.22	-16.28	0.46
Junction 12	1.9	-2.73	52.29	0.12

i. JUNCTION 13 – SUB-BASIN 2

Figure 11 and 12 show calibration and validation results for sub-basin 2 respectively. In Figure 11, the highest discharge peak was recorded in March 2017 (over 300m³/s) with a decline in 2018 and 2019. Calibration results for Sub-Basin 2 indicate over simulation of flow, for example 2018-2019. Surface runoff is also recorded earlier for simulated flow (February) as compared to observed flow (March). For the period 2016-2017, the model successfully represented observed flow in terms of the shape of the hydrograph (Figure 11). However, the magnitude was successfully represented in a few cases, with over simulation and under simulation in some instances. During calibration, the following metrics were observed: RMSE: 0.8, NSE: 0.44, Percent Bias: -8.04 and R^2: 0.46. The RMSE, NSE and R^2 are rated as satisfactory whilst the Percent Bias was rated as very good from performance metrics proposed by (Moriasi et al., 2007).

Figure 12 shows that simulated flow was recorded later in January 2020 whilst observed flow was recorded in December 2019. The attenuation of the hydrograph is also not successfully represented in the 2020/2021 season as evidenced by the differences between simulated and observed flow graphs. During validation, the following metrics were observed: RMSE: 1.6, NSE: -1.61, Percent Bias: 42.58 and R^2: 0.02. The metrics were rated as unsatisfactory from performance metrics proposed by (Moriasi et al., 2007). The model was not able to reproduce observed values with a different dataset based on statistical metrics. However, the simulated volume and peak discharge values were close to the observed.

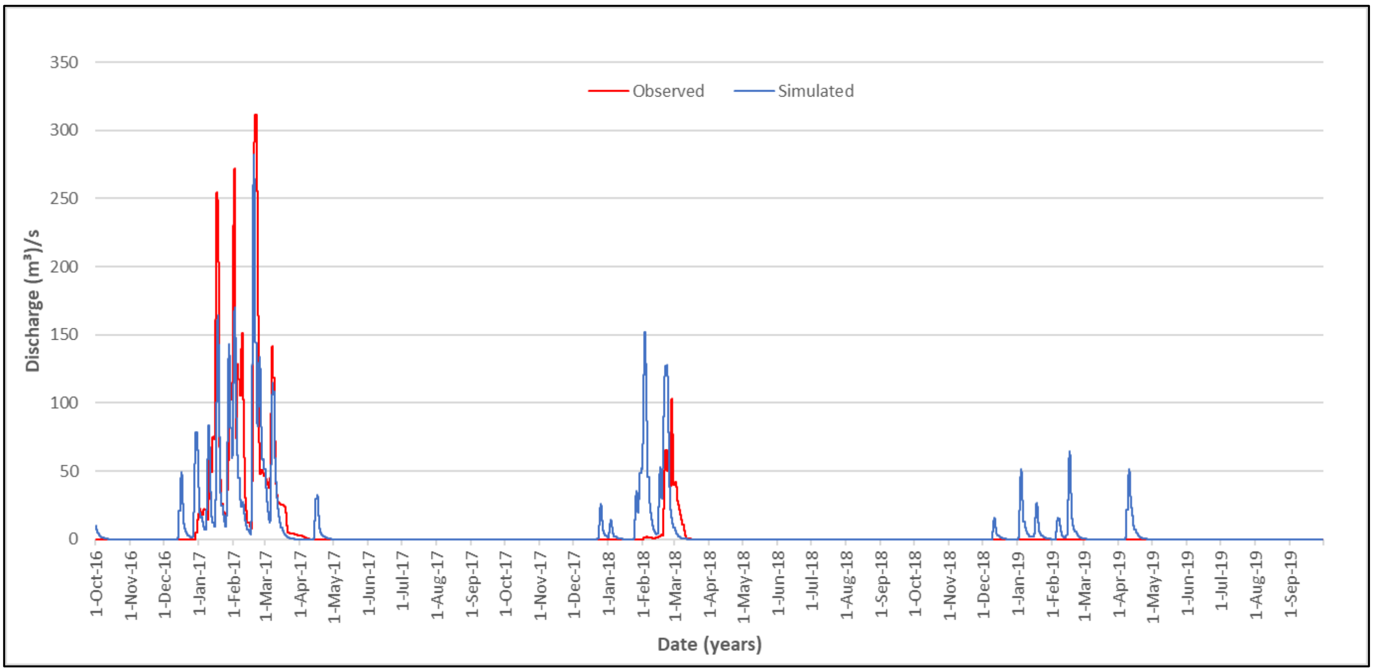

Figure 11. Calibration results for Junction 13 (Sub-basin 2)

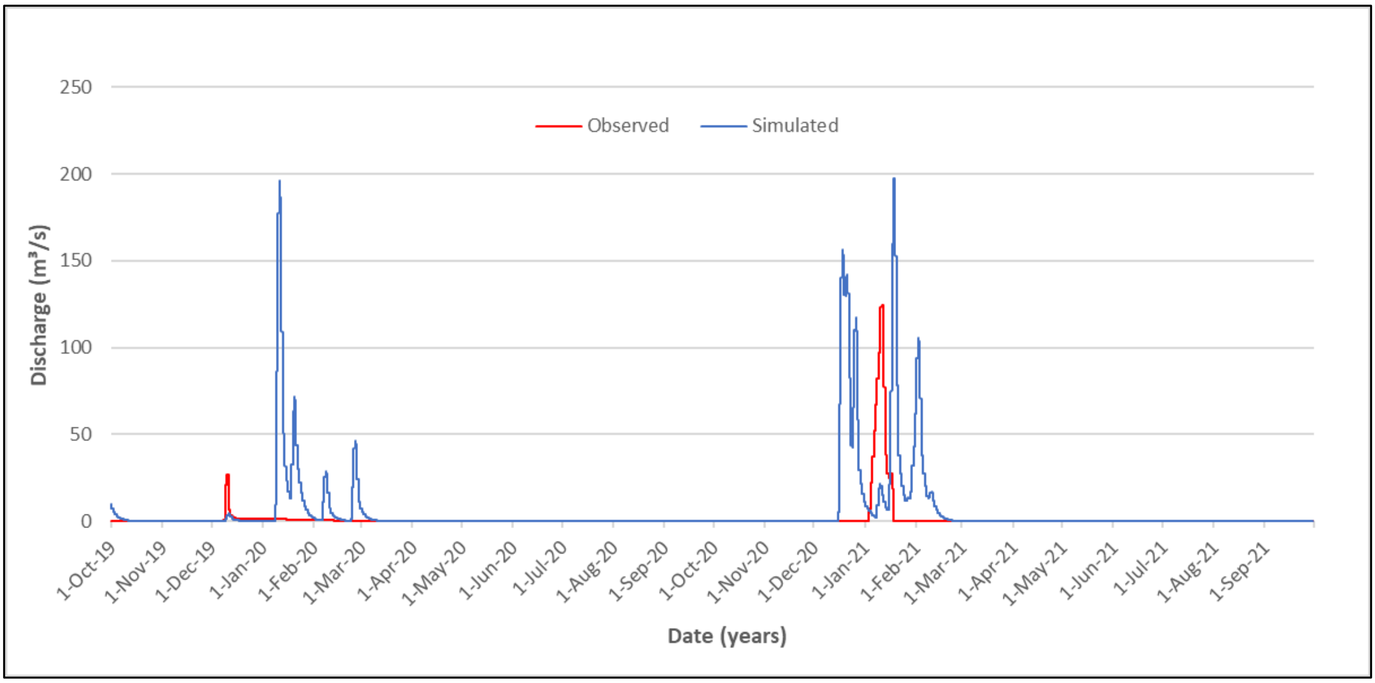

Figure 12. Validation results for Junction 13 (Sub-basin 2)

Figure 13 shows the relationship between simulated and observed discharge with precipitation at Sub-basin 2. During the 2016/2017 season, a peak in precipitation was recorded in February whilst both simulated and observed discharge recorded peaks in March. This was expected as the rainfall received was converted to surface runoff. The 2017/2018 season shows a lag in observed discharge whilst simulated discharge is recorded earlier. Zero discharge was recorded as observed flow whilst simulated values were relatively low (below $50m^3/s$) in the 2018/2019 season. Whilst the season recorded low values compared to others, zero values were not expected. This is suspected to be because of surface storage facilities such as dams.

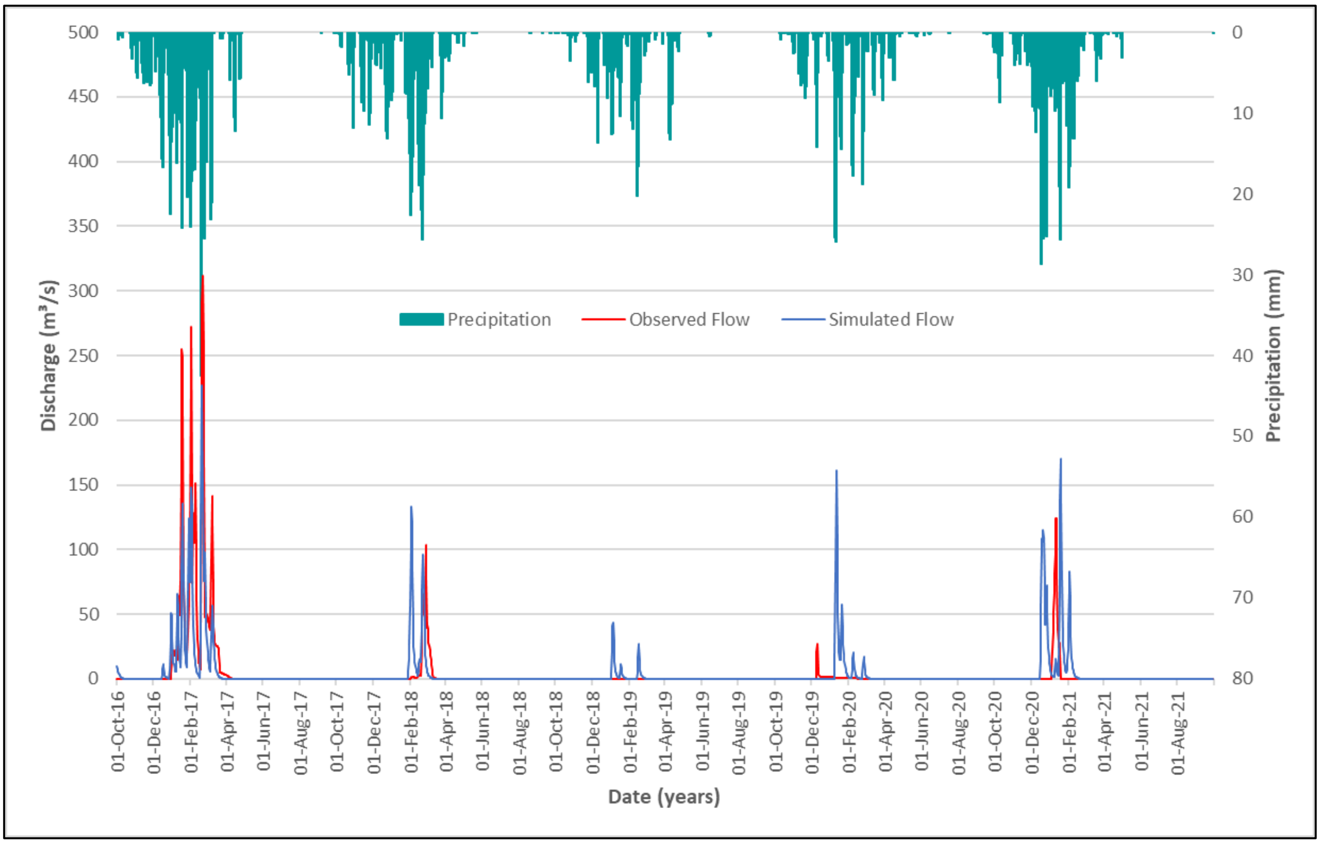

Figure 13. Comparison of observed and simulated discharge at Sub-basin 2 with precipitation for the period 2016-2021

ii. JUNCTION 14 – SUB-BASIN 5

Over simulation of observed flow was recorded for the period 2018-2020 with under estimation of the peak in 2017 (Figure 14 and 15). During calibration, the following metrics were observed. RMSE: 0.9, NSE: 0.19, Percent Bias: 24.47 and R^2: 0.34. The RMSE, NSE and R^2 were rated as unsatisfactory whilst the Percent Bias was rated as satisfactory from performance metrics proposed by (Moriasi et al., 2007). During validation, the following metrics were observed: RMSE: 1.7, NSE: -1.75, Percent Bias: 121.98 and R^2: 0.03. The metrics were rated as unsatisfactory from performance metrics proposed by (Moriasi et al., 2007). The model was not able to reproduce observed values with a different dataset based on statistical metrics. However, the simulated volume and peak discharge values were close to the observed.

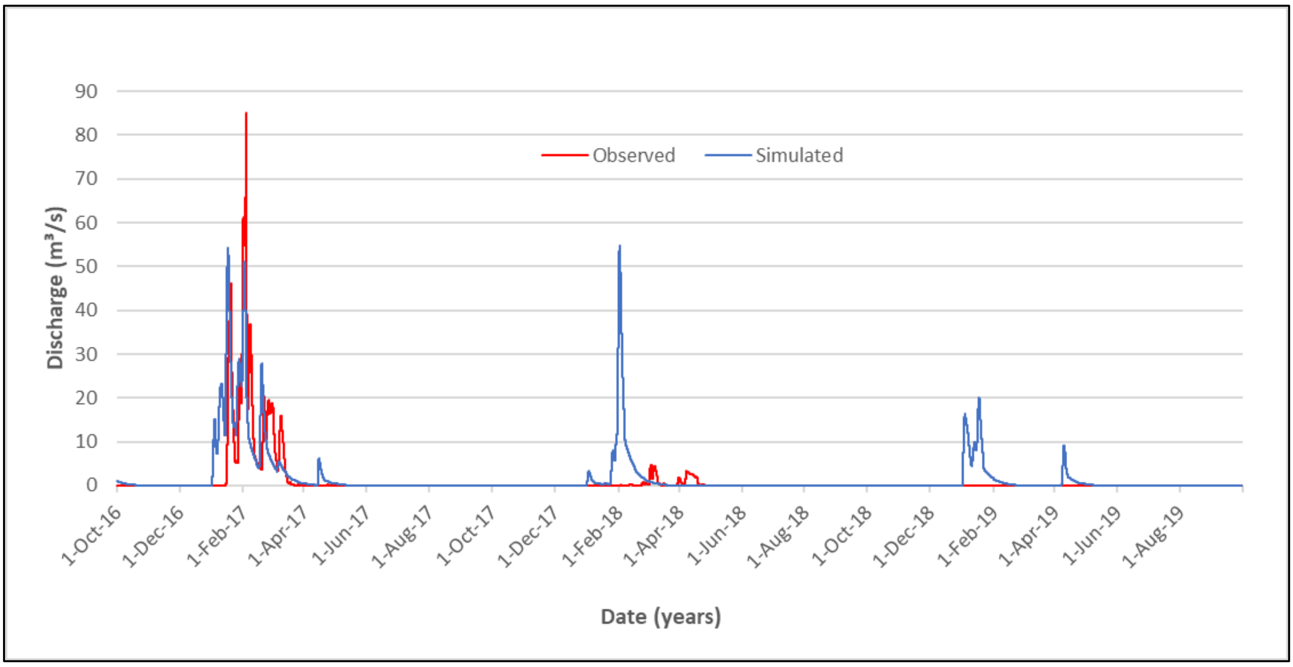

Figure 14. Calibration results for Junction 14 (Sub-basin 5)

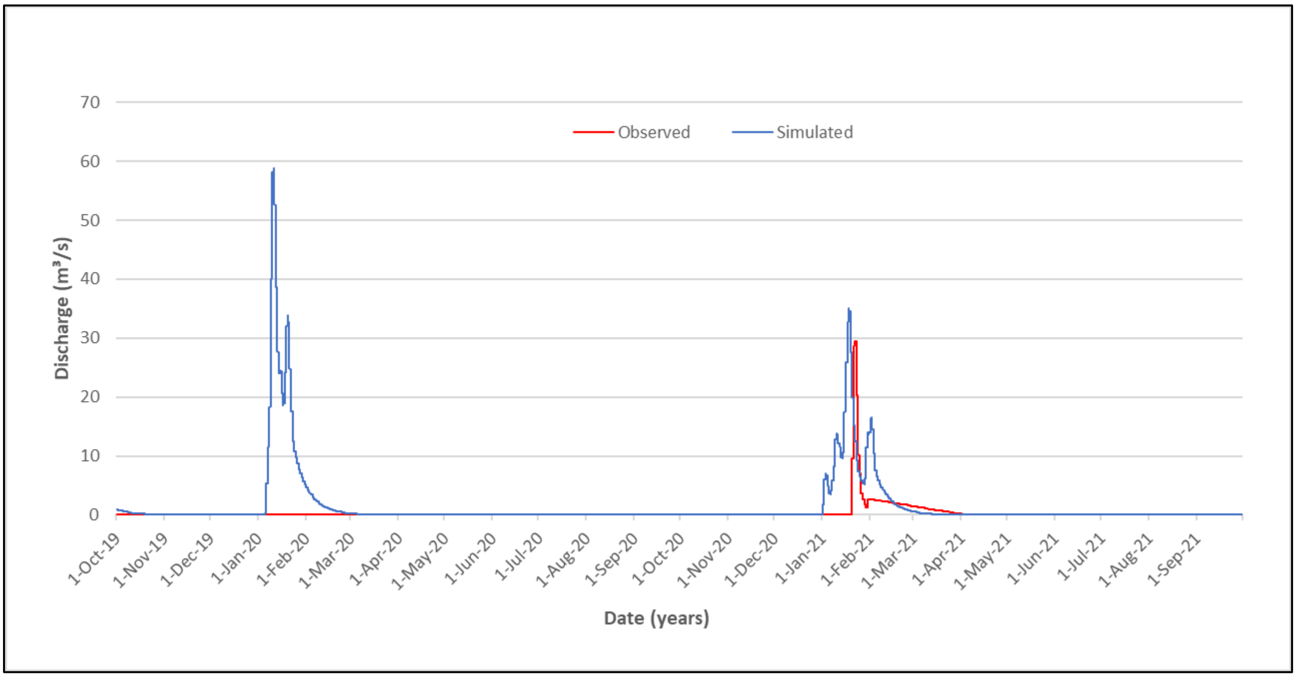

Figure 15. Validation results for Junction 14 (Sub-basin 5)

Figure 16 shows the relationship between simulated and observed discharge with precipitation at Sub-basin 5. During the 2016/2017 season, a peak in precipitation was recorded in March whilst both simulated and observed discharge recorded peaks in February. This was not expected and may be a result of an accumulation of previous rainfall events. The decline in discharge even after a peak in precipitation could be explained by a decrease in the volume of discharge at the time with a high probability of low intensity and frequency of precipitation. The 2017/2018 season shows a lag in observed discharge whilst simulated discharge is recorded earlier and with higher values. Zero discharge was recorded as observed flow whilst simulated values were relatively low (below 20m³/s) in the 2018/2019 and 2019/2020 seasons. Whilst the season recorded low values compared to others, zero values were not expected. However, the gauging station (A39) is downstream of Lupane dam possibly serving as an explanation for zero values recorded.

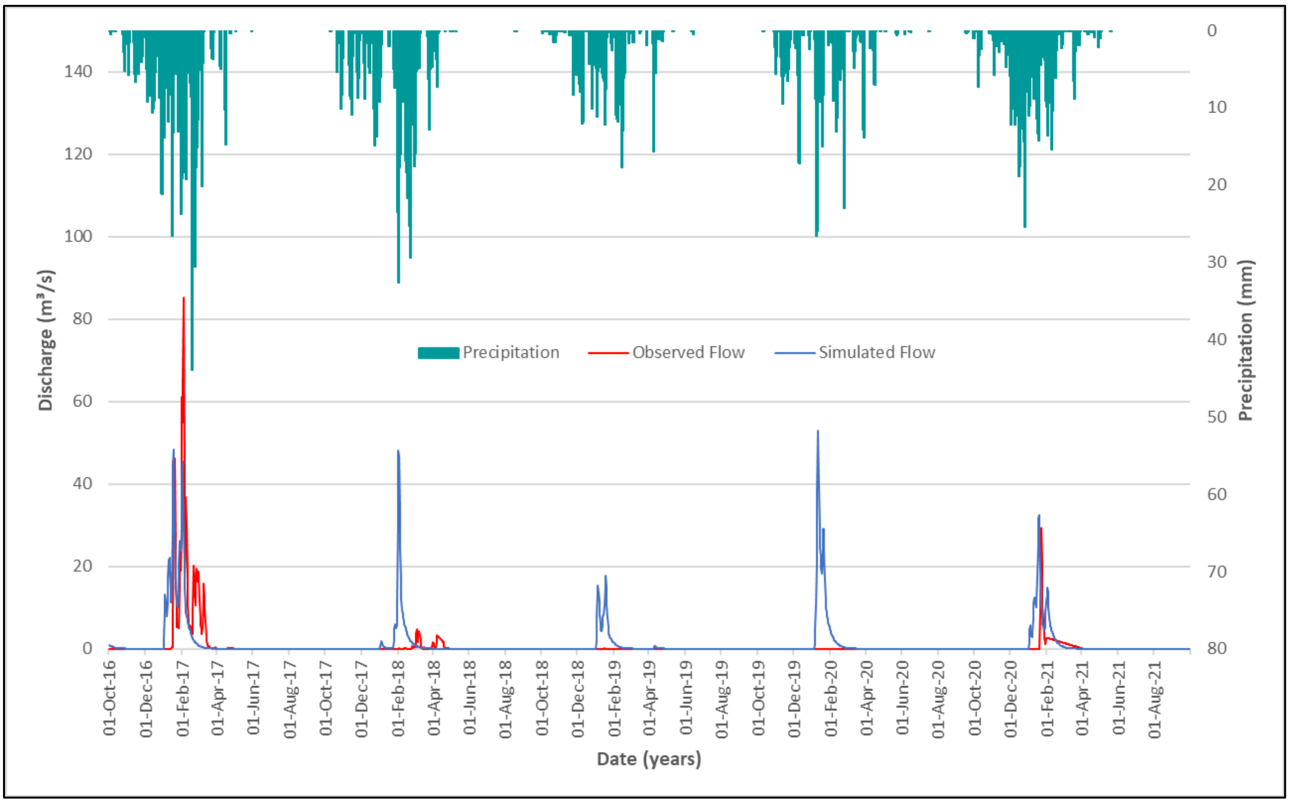

Figure 16. Comparison of observed and simulated discharge at Sub-basin 5 with precipitation for the period 2016-2021

iii. JUNCTION 10 - SUB-BASIN 3

Over simulation of observed flow was recorded for the period 2018-2020 (Figure 17 and 18). During calibration, the following metrics were observed: RMSE: 0.9, NSE: 0.21, Percent Bias: 8.88 and R^2: 0.39. The RMSE, NSE and R^2 are rated as unsatisfactory whilst the Percent Bias was rated as very good from performance metrics proposed by (Moriasi et al., 2007). During validation, the following metrics were observed: RMSE: 0.9, NSE: 0.22, Percent Bias: -16.28 and R^2: 0.46. NSE was low but was the highest among all sub-basins. PBIAS and R^2 were satisfactory whilst RMSE was rated as unsatisfactory from performance metrics proposed by (Moriasi et al., 2007). In this sub-basin, the applicability of the HEC-HMS model was evidenced by a positive NSE value compared to negative values in other sub-basins. However, the simulated volume and peak discharge values were close to the observed.

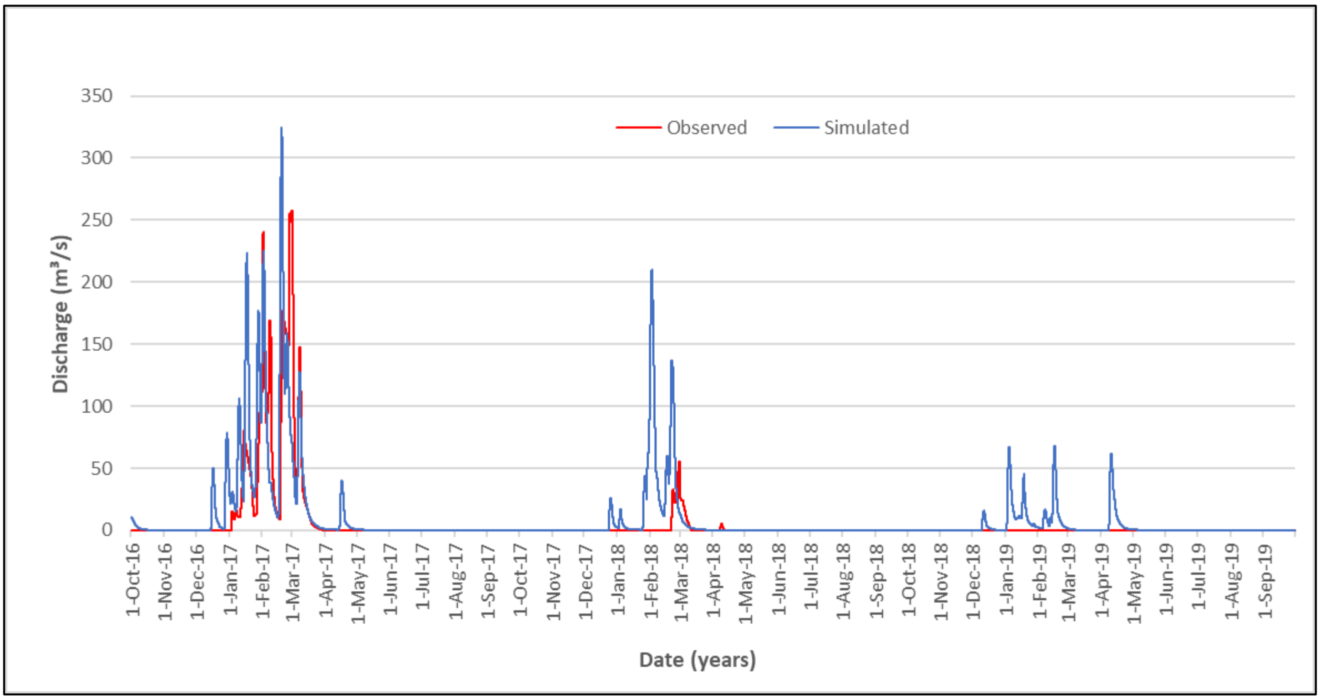

Figure 17. Calibration results for Junction 10 (Sub-basin 3)

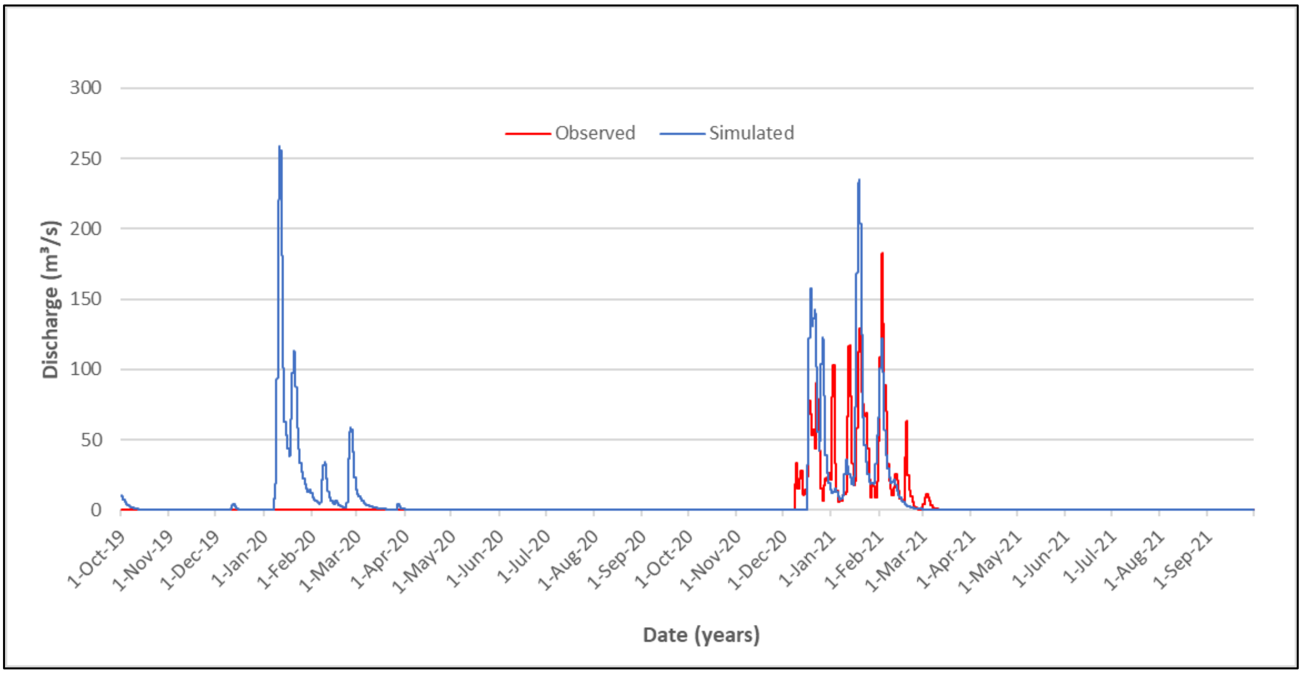

Figure 18. Validation results for Junction 10 (Sub-basin 3)

Figure 19 shows the relationship between simulated and observed discharge with precipitation at Sub-basin 3. During the 2016/2017 season, a peak in precipitation was recorded in February whilst both simulated and observed discharge recorded peaks in March, with simulated peaks recorded earlier. This was expected as the rainfall received was converted to surface runoff. This is like sub-basin 2. The 2017/2018 season shows a lag in observed discharge whilst simulated discharge is recorded earlier. Zero discharge was recorded as observed flow whilst simulated values as high as 200m³/s were recorded in the 2018/2019 season. Whilst the season recorded low values compared to others, zero values were not expected. This is suspected to be because of surface storage facilities such as dams.

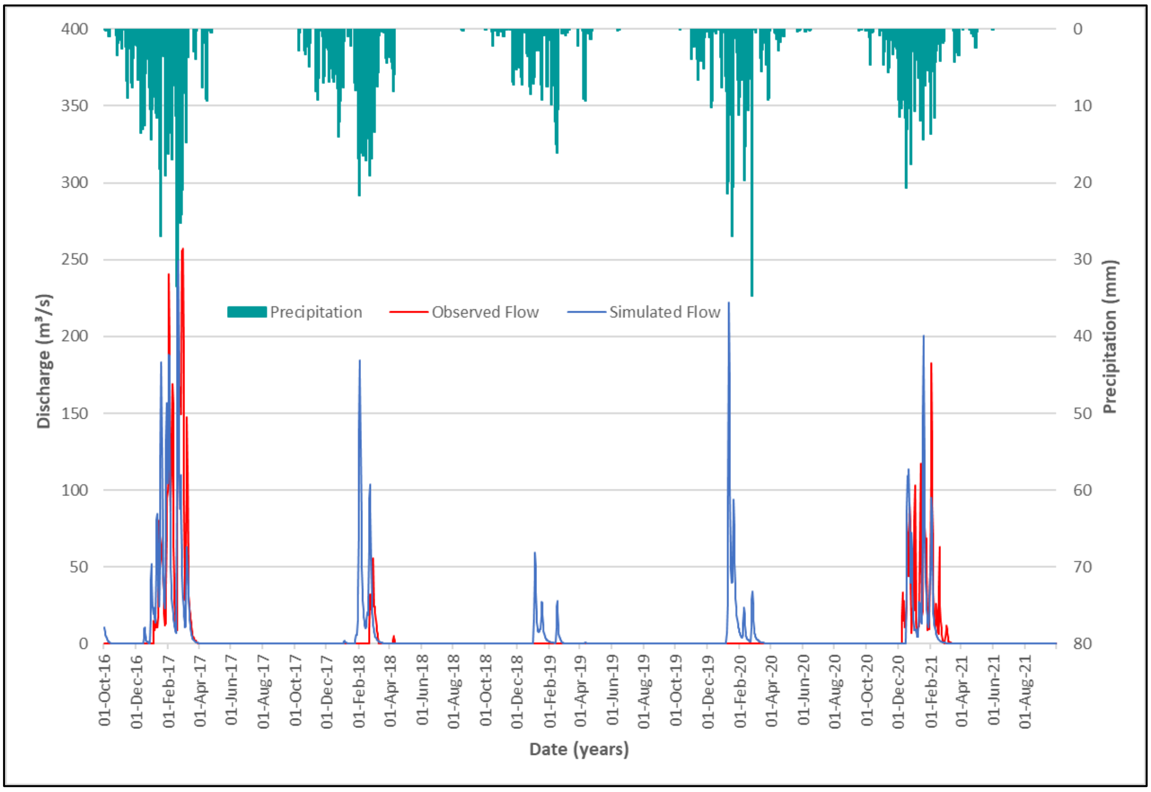

Figure 19. Comparison of observed and simulated discharge at Sub-basin 3 with precipitation for the period 2016-2021

iv. JUNCTION 12 - SUB-BASIN 1

Over simulation of observed flow was recorded for the period 2018-2020 (Figure 20 and 21). During calibration, the following metrics were observed: RMSE: 0.9, NSE: 0.27, Percent Bias: 5.13 and R^2 - 0.40. The RMSE and NSE are rated as unsatisfactory whilst the R^2 and Percent Bias were rated as satisfactory and very good respectively from performance metrics proposed by (Moriasi et al., 2007). During validation, the following metrics were observed: RMSE: 1.9, NSE: -2.73, Percent Bias: 52.29 and R^2: 0.12. The metrics were rated as unsatisfactory from performance metrics proposed by (Moriasi et al., 2007). The model was not able to reproduce observed values with a different dataset based on statistical metrics. However, the simulated volume and peak discharge values were close to the observed.

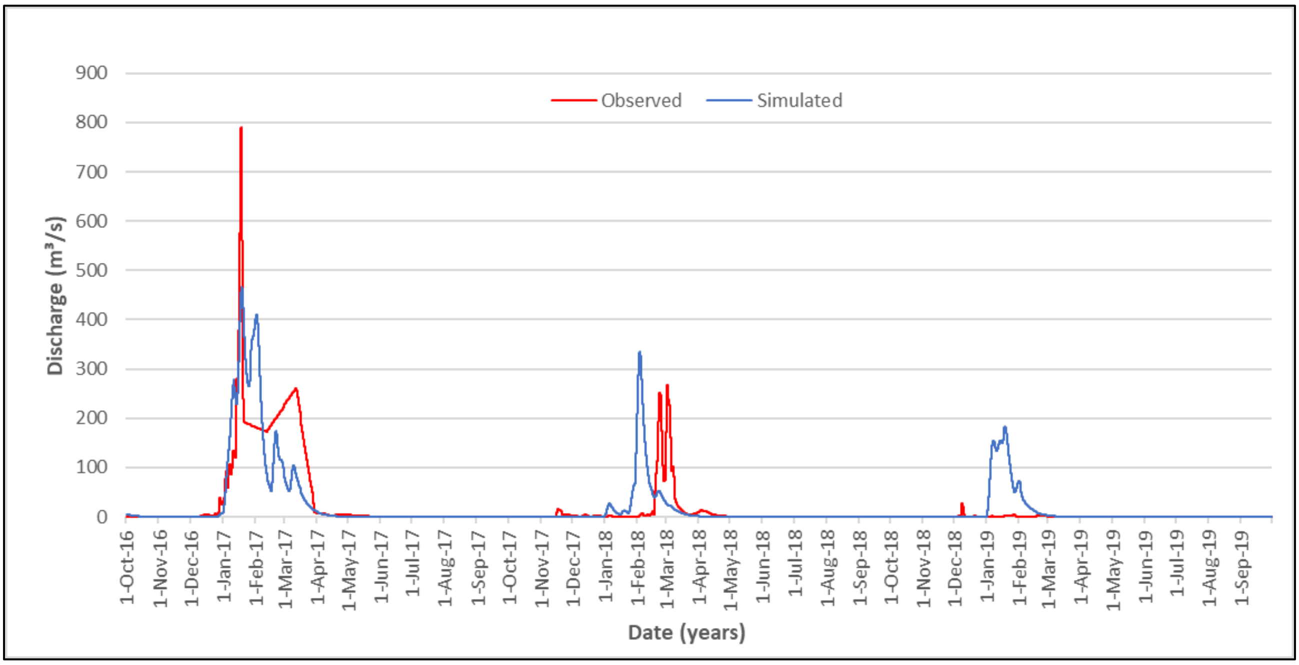

Figure 20. Calibration results for Junction 12 (Sub-basin 1)

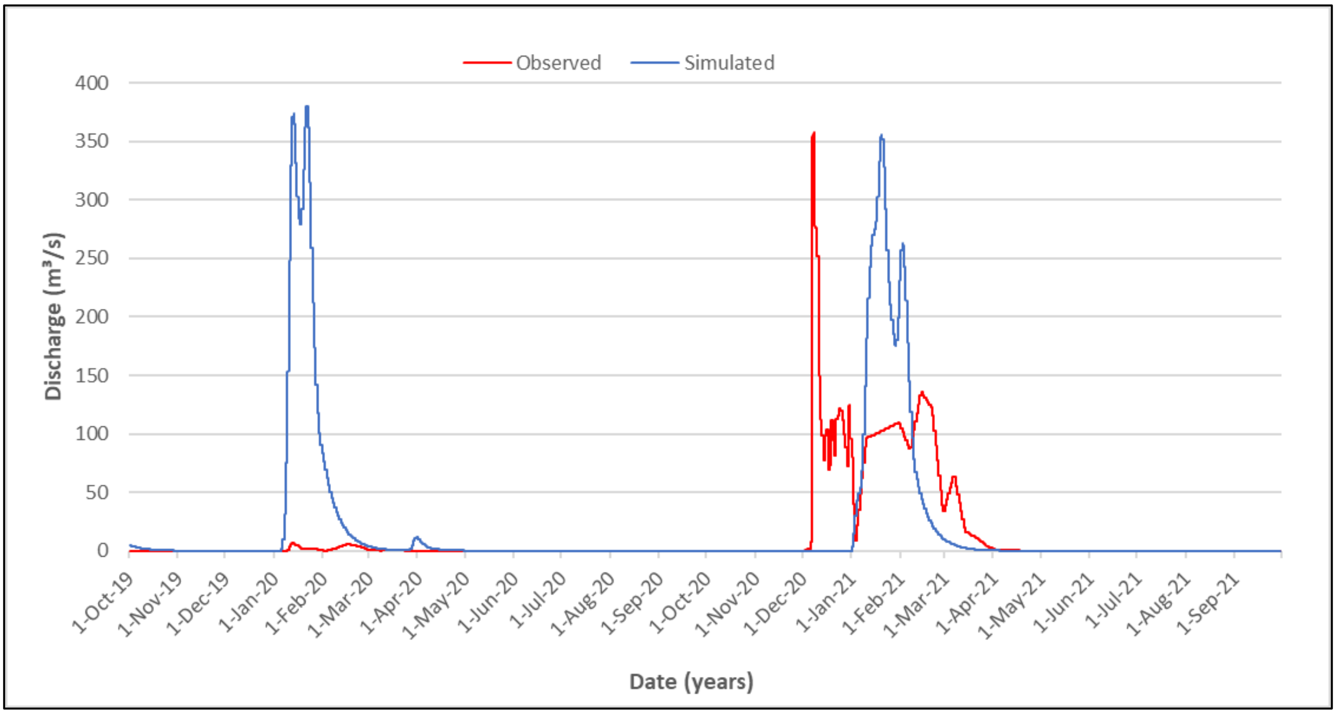

Figure 21. Validation results for Junction 12 (Sub-basin 1)

Figure 22 shows the relationship between simulated and observed discharge with precipitation at Sub-basin 1. During the 2016/2017 season, a peak in precipitation was recorded in March whilst both simulated and observed discharge recorded peaks in January. This was not expected and may be a result of an accumulation of previous rainfall events. The sharp increase and sharp decrease in discharge may be a result of high intensity rainfall experienced within a short period of time. In addition, sub-basin 1 is the largest with several tributaries. Therefore, accumulation of water from different directions may have resulted in the sudden changes. The 2017/2018 season shows a lag in observed discharge whilst simulated discharge is recorded earlier and with higher values. Low discharge was recorded as observed flow (below 50m³/s) whilst simulated values as high as 350m³/s were recorded in the 2018/2019 season. The low observed values are suspected to be because of surface storage facilities such as dams.

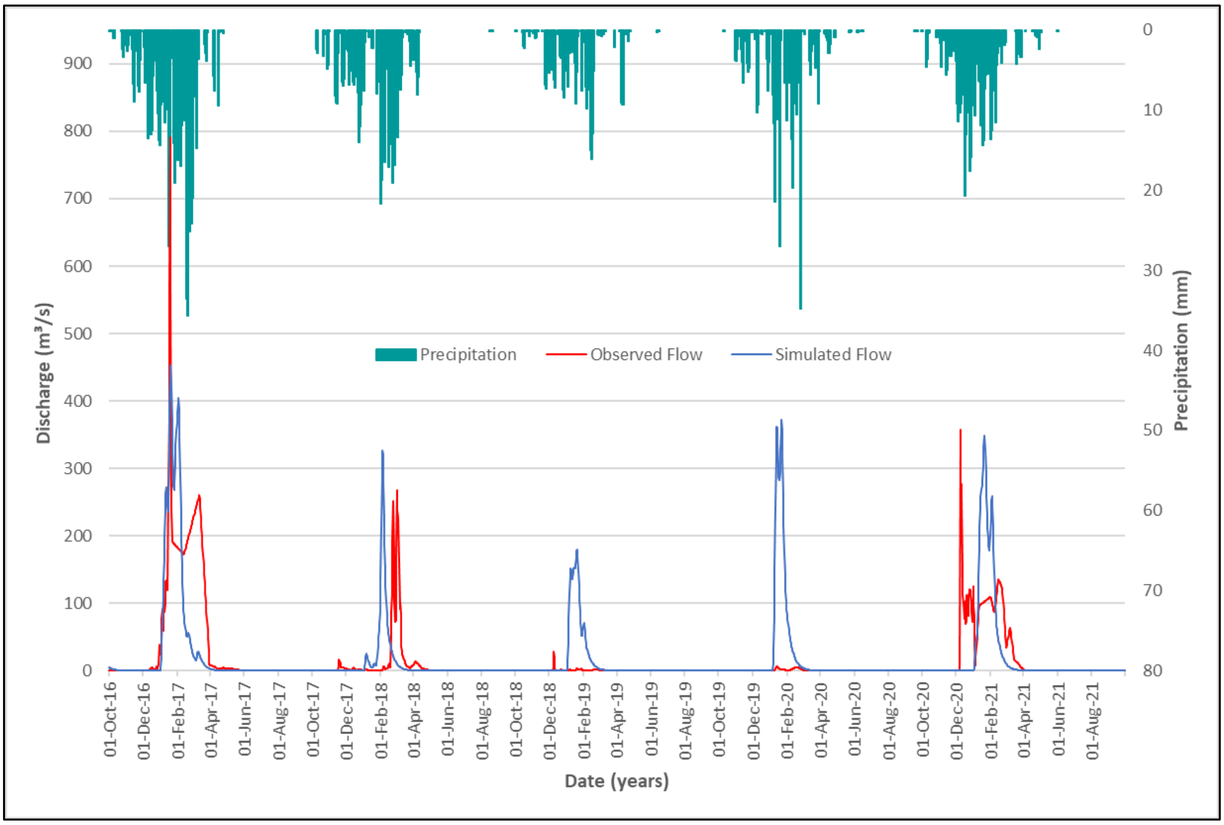

Figure 22. Comparison of observed and simulated discharge at Sub-basin 1 with precipitation for the period 2016-2021

4.1.4. STATISTICAL EVALUATION

To assess the performance of the model, statistical metrics such as the Nash-Sutcliffe efficiency (NSE), Root Mean Square Error (RMSE), Percent Bias (PBIAS) and coefficient of determination (R^2) were used. For the NSE, the optimal value is 1. Table 8 shows that the calibration values range from 0.19 to 0.44 for NSE, -8.04 to 24.47 for PBIAS, 0.8 to 0.9 for RMSE and 0.34 to 0.46 for R^2.

The study findings in terms of peak discharge and volume are presented in Table 10. Generally, the model under simulated peak discharge, except in Junction 10 where there was over simulation. Junction 13 had the lowest difference in peak discharge values between the simulated and observed flow (29m³/s). This Junction also recorded statistical values in the satisfactory range as shown in Table 9. For volume, simulated values tended to be higher compared to observed. Junctions 13 and 12 had the lowest differences of 5mm and 7.4mm respectively. The differences in metrics across different sub-basins highlight the importance of spatial variations in the Gwayi catchment in terms of hydrology and physical characteristics.

Table 10. Peak discharge and volume values during the calibration phase

Computation Point	**Peak Discharge (m^3/s)**		**Volume (mm)**	
	Simulated	Observed	Simulated	Observed
Junction 13	282.6	311.6	46.01	41.16
Junction 14	54.8	85.1	40.70	24.94
Junction 10	324.3	257.2	44.79	26.41
Junction 12	466.9	790.5	108.39	100.99

4.2. DISCUSSION

4.2.1. WATERSHED DELINEATION

The study results indicate that the Gwayi catchment covers a total area of 43331km², with rivers forming a dendritic drainage pattern in a Northwestern direction. The findings show that there is no relationship between the watershed and administrative boundaries (Kauffman, 2002). This is shown in Figure 4 where the Gwayi catchment boundary is not related to the Matabeleland North provincial boundary. This is because the delineation of the Gwayi catchment was based on the elevation and the direction of flow of water and not the administrative zones. The results are not consistent with previous studies in the catchment by (Gwate et al., 2022; Thebe, 2012) who highlighted a total catchment area of 94 858km². From these studies, the Gwayi catchment is like the Matabeleland North boundary. This has led to the understanding that what is formally known as the Gwayi catchment is based on administrative and not watershed boundaries.

4.2.2. LANDUSE/COVER, SOIL PROPERTIES AND SURFACE RUNOFF

Study findings show that the Gwayi catchment comprises dense woodland (33%), open woodland (28%), agriculture or cultivation (24%), grassland (14%) as well as built-up and waterbodies (1%). The soils found in the area are sandy loam (67.85%), sandy clay loam (18.18%) and clay soils (13.9%). The findings show that woodlands, cultivation, and grassland form the greater part of the land use/cover of the Gwayi catchment, with sandy loam found to be the dominant soil type. This means that during the rainy season, some of the water is intercepted by trees and some infiltrates as sandy loam soils tend to quickly drain water (Kuok et al., 2023). The influence of land use/cover is validated by (Gumindoga et al., 2016) where the percentage of impervious land, derived as a function of land use/cover, has a direct effect on the surface runoff generated.

4.2.3. USE OF REMOTE SENSING TO DERIVE MODEL INPUTS

The results emanating from this study agree with several studies conducted at local and regional scales. The results indicate that it is possible to derive model input parameters from remote sensing satellite data. This is because parameters such as slope, flow path, landcover and soil properties, precipitation and evapotranspiration were derived from satellite products. Findings from Ndemere et al., (2024) study indicated that satellite precipitation products can be used in hydrological modelling and are best used when supporting specific hydrological applications. In this study, the CHIRPS dataset was used as the primary input. Whilst overestimation has been flagged as the main challenge with CHIRPS data Ndemere et al., (2024), for this purpose, it enabled the establishment of rainfall runoff relationships given the absence of observed data. The main limitation was the absence of observed data for bias correction. Dzirekwa et al., (2023) highlighted that the potential of CHIRPS data is limited by the existence of clouds. Therefore, its applicability is dependent on the goals of the research.

In line with the above, in data sparse regions such as the Gwayi catchment, remote sensing satellite data account for gaps which are a result of spatial variances (Gumindoga et al., 2016). This is because rain gauges are normally sparsely distributed. According to Gebre, (2015), for large study areas (above 5000km^2), gridded models are the best choice compared to lumped models as they account for the spatial heterogeneity of the landscape through the use of grids. Erratic rainfall patterns indicating a decreasing trend are shown in Figure 9. This is validated by Dzirekwa et al., (2023). It is therefore possible to set up the model and derive input parameters (Hernández-Romero et al., 2022). For calibration and validation, however, observed data is required to draw conclusions on the model's potential to simulate runoff in ungauged basins.

Remote Sensing satellite data was utilised to derive land use and land cover parameters. This was for the purposes of determining percentage impervious and estimating canopy storage. On the other hand, the SRTM DEM was used to extract the catchment's physical characteristics. The area, slope, reach length enabled the calculation of time of concentration as well as storage coefficients and hydraulic properties of the channel. Gwate et al., (2022) validated the applicability of remote sensing satellite data to derive input parameters for hydrological modelling. This is because the remotely sensed data utilised in the study produced a good model fit, with the evapotranspiration data recording a Root Mean Square Error (RMSE) within 5% of evapotranspiration derived from the shortened water balance. The rainfall data RMSE was 16% of the observed annual mean.

4.2.4. RUNOFF SIMULATION USING THE HEC HMS MODEL

In this study, at Junction 13 in sub-basin 2, the HEC-HMS model produced a runoff volume of 46.01mm and a peak discharge of 282.6m^3/s whilst observed data had recorded 41.16mm and 311.6m^3/s respectively. It is evident that the model was able to compute values close to the observed in terms of peak discharge and volume. This aligns with the Zimbabwe National Water Authority figures highlighting an annual range of 5 to 44mm per year in the Gwayi catchment. Statistical metrics indicate that the HEC-HMS model satisfactorily reproduced observed flow at Junction 13 in sub-basin 2, with an NSE of 0.44 and RMSE of 0.8 during the calibration phase. During the validation phase, an NSE of -2.33 and RMSE of 1.8 was recorded. Junction 10 showed a change in the Nash coefficient in the positive direction (from 0.21 during calibration to 0.22 during validation). These results highlight the importance of calibration at sub-basin level as the different physical and hydro-meteorological characteristics contribute to surface runoff generation. According to (Moriasi et al., 2007), values below zero indicate that the performance of the model is unsatisfactory. Since the calibrated parameters were used to validate the model, further analysis of the model is required to assess the ability of the model to produce a good fit with a different set of data. When analysing the hydrographs, the main finding was that the HEC-HMS model captured the attenuation and did not capture peak discharge. In some cases, the model recorded surface runoff earlier whereas a lag was also noted in some instances. Moreover, in most cases, the model overestimated streamflow, with underestimation in a few cases. These challenges have been previously cited (Nharo et al., 2019).

Study results indicated mostly over simulation in comparison with observed values. Reviewing literature revealed that studies such as Gumindoga et al., (2016) incorporated reservoirs when using the HEC HMS model in Upper Manyame catchment in Zimbabwe. The Gwayi catchment has 4 major dams (Exchange, Lupane, Lower and Upper Mguza). However, in the model, this data was absent. The presence of reservoirs contributes to the amount of surface runoff recorded at the different gauging stations. Streamflow observations at gauging stations downstream following storm events are therefore delayed. As these reservoirs play a critical role in regulating river flow and water levels, they have a substantial effect on the timing and magnitude of flows. Therefore, the absence of this data led to discrepancies between observed and modelled hydrological responses, affecting the model's ability to predict conditions accurately under different scenarios.

The results from the study indicate that the relationship between precipitation and discharge in the Gwayi catchment varies both in space and time. In sub-basins 2 and 3, during the 2016/2017 season, peaks in precipitation were recorded earlier than discharge as expected as the rainfall received was converted to surface runoff. This was confirmed by Love et al., (2010) where a linear relationship between rainfall and discharge was highlighted. However, zero discharge was recorded as observed flow whilst simulated values were between 50m^3/s and 200m^3/s in the 2018/2019 season. This is suspected to be because of surface storage facilities such as dams. On the other hand, sub-basins 1 and 5 showed significantly different results. Both simulated and observed discharge peaks were recorded earlier than precipitation peak, suspected to be because of previous rainfall events. The presence of a dam upstream of the gauging station in sub-basin 5 provided an explanation for zero values recorded as observed discharge. In sub-basin 1, the sharp increase and decrease in discharge is potentially a result of high intensity rainfall and the presence of a number of different feeder streams. Love, Uhlenbrook, Corzo-Perez, et al., (2010) validated the contribution of different factors to surface runoff generation.

4.2.5. CALIBRATION AND VALIDATION OF MODEL

The study results indicate that sparse data presents challenges in calibrating and validating the model. This is because of the time-consuming nature of the process and that several iterations must be carried out to draw conclusions. This was confirmed by (Gumindoga et al., 2016). Statistical metrics were used for assessing the performance of the model in representing ground conditions. The lowest and highest statistical metrics were (NSE: 0.18 and 0.44; RMSE: 0.8 and 0.9; PBIAS: -8.04 and 24.47; R^2: 0.34 and 0.46). Masimba et al., (2022) presented unsatisfactory results for one of the sub-basins studied. The poor performance was attributed to missing data. In this case, the poor performance of the model for some sub-basins is attributed to the variations in features between and within the sub-basins. These variations were not accounted for as the dominant characteristic was used to estimate input parameters per sub-basin.

In line with the above, previous scholars have also studied smaller catchments (less than 3000km²), (Dzirekwa et al., 2023; Gumindoga et al., 2016; Nharo et al., 2019) which were further subdivided into smaller sub-basins. It is suspected that the size of the Gwayi catchment (43331km²) and the sub-basins posed challenges as larger catchments have more complex hydrological processes including varying soil types, land use and topography which can affect runoff generation and flow paths. NSE and PBIAS results for metrics during the validation phase were mostly negative. The lowest and highest statistical metrics were (NSE: -2.33 and -0.16; RMSE: 1.1 and 1.8; PBIAS: -78.43 and 67.83; R^2: 0.02 and 0.46). This is an indication of difficulty in calibrating and validating the model with sparse data.

Due to the absence of observed rainfall data, CHIRPS data was used. According to Ndemere et al., (2024), the dataset tends to overestimate observed rainfall. As observed meteorological data was absent, the precipitation data was not bias corrected. This is suspected to be the reason for higher runoff volumes in computed values as compared to observed. The focus of the research was not on a single flood but how the model represents peaks and descents over a 5-year period. As a result, CHIRPS data was used without bias correction putting into consideration the potential for overestimation.

4.2.6. SENSITIVITY ANALYSIS AND MODEL PERFOMANCE

When calibrating the model, the losses and transform functions were found to be the most sensitive based on iterations. A study by Daide et al., (2021) revealed similar findings. In HEC HMS, loss values play an integral role as they determine the volume of surface runoff generated. Hydro-meteorological and physical parameters are the influencing factors. Whilst calibrating, the parameter values of loss and transform methods were changed whilst other values remained constant and the monitoring of statistical graphs and tables was done to identify the changes and effects (Nharo et al., 2019). An increase in the transform function such as lag time resulted in a decrease in hydrograph peak resulting in similarities between observed and simulated flow. The study findings indicated that the area and slope of sub-basins plays an important role in transforming rainfall. This is in the sense that larger sub-basins have a higher time of concentration compared to smaller ones. For example, sub-basin 1 has a higher time of concentration compared to sub-basin 3. Thus, accurately computing these parameters is critical. This revealed the importance of ensuring the high quality of land use and land cover as well as soil data. It is therefore recommended that further research make use of datasets with a higher spatial resolution.

Visually, results showed that the HEC-HMS model is capable of simulating surface runoff in the Gwayi catchment as validated by different scholars (Dzirekwa et al., 2023; Fanta & Feyissa, 2021; Gumindoga et al., 2016; Nharo et al., 2019). This is because the attenuation and values for volumes were close to each other (Table 10). Poor performance is however revealed in capturing peak discharge. The differences between calibration and validation metrics are an indication that further analysis and modelling is required before the adoption of the model in the Gwayi catchment. The findings provide a basis for future hydrological modelling studies in the Gwayi catchment.

4.3. SUMMARY

The study found that it is possible to derive model input parameters from remote sensing satellite data. This shows that remotely sensed data is a good alternative and can be utilized in data sparse and data scarce regions. However, to ensure quality of the dataset, accuracy assessments and bias correction are recommended. In terms of model calibration and validation, the loss and transform parameters estimated from the sub-basin physical properties for example flow path, slope, land cover and soil information were found to be the most sensitive. These findings indicate that valid and complete data is crucial to ensure model robustness in future studies. It is also possible to calibrate the HEC HMS model with sparse data though it is complex and requires time. However, data scarcity presents new challenges because of missing data which is required as inputs. Based on the visual and statistical results, streamflow response estimation can be done using the HEC HMS model in the Gwayi catchment and similar catchments, however, adequate inputs fully representing ground conditions are critical as they contribute to the performance of the model. The study could not account for the contribution because of surface water resources. Therefore, future studies in the Gwayi catchment should focus on smaller catchments and account incorporate surface water resources data.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1. CONCLUSIONS

GIS and Remote Sensing satellite data together with the HEC HMS model can be used to develop model input parameters. In this study, to develop basin and meteorologic input parameters such as the land use/cover, DEM, precipitation and evapotranspiration data, satellite imagery was used. This led to the calculation of parameters such as soil storage, canopy storage, maximum infiltration and slope among others. This would not have been possible to use traditional methods of collecting data within the research time frame. The combination of GIS and Remote Sensing as well as the HEC HMS model allowed for watershed delineation, land use/cover mapping, derivation of soil properties and ultimately the simulation of surface runoff in the Gwayi catchment. The use of models such as HEC HMS for simulating surface runoff therefore becomes a good alternative especially in areas with sparse data such as the Gwayi catchment. However, errors are always present thereby highlighting the importance of high-quality inputs.

The study concludes that sparse and scarce data presents a major challenge in calibrating the HEC HMS model. When calibrating the model, observed data is required for comparisons with the model results. As a result, the absence or scarcity of this data results in calibration being done at a larger scale, thereby contributing to the complexity of the model. Data availability greatly contributes to model performance. The study also concludes that the availability of reservoirs data is crucial in catchments such as the Gwayi where surface storage structures such as dams are present. In this study, for example, the unavailability of reservoirs data contributed negatively to model performance leading to unsatisfactory values for some of the performance evaluation metrics. As a result, calibration becomes complex to balance model simplicity and accurate runoff estimation.

The study concludes that the loss and transform parameters are the most sensitive when it comes to model calibration and special attention should be given to these parameters. These take into consideration the physical conditions and parameters of the sub-basins to abstract rainfall and produce hydrographs. For example, halving the time of concentration significantly increases the Nash-Sutcliffe Efficiency and decreases the Root Mean Square Error whilst the opposite is true when the time of concentration is doubled. Therefore, during the calibration phase, a great deal of attention should focus on tuning the loss and transform methods to produce a good fit.

The relationship between precipitation and discharge is both linear and nonlinear in the Gwayi catchment. Several factors including sub-basin physical and hydrological characteristics contribute to the surface runoff generated. As a result, it is not always the case that high rainfall results in high discharge. The intensity and frequency of rainfall greatly contributes to the volume of discharge with surface storage facilities such as dams also contributing to the surface runoff recorded at gauging stations located downstream. The size of a sub-basin also plays a role in surface runoff generation. This is because whilst water may be lost as it travels across the sub-basin, high intensity rainfall events may result in a peak in discharge because of recharge from feeder streams.

The HEC-HMS model can simulate surface runoff in the Gwayi catchment in Zimbabwe. The conclusion is based on visual analysis of hydrographs for both simulated and observed flow. Model results for peak discharge and volume also showed the close relationship between simulated and observed flow. The statistical metrics such as NSE, R^2, PBIAS and RMSE gave a picture of the model performance. Satisfactory performance for all the statistical metrics used was recorded at Junction 13 in sub-basin 2 during the calibration phase. Negative statistical metrics for validation results presented an indication of inadequacy in terms of model performance.

In conclusion, in the age of climate change, understanding how a catchment responds to changes in the hydrometeorological parameters is critical. Extreme events resulting in either floods or drought result in environmental and socio-economic challenges for different communities in Zimbabwe. This study will serve as the basis for future research initiatives aimed at understanding the hydrological interactions in the Gwayi catchment or similar catchments. Ultimately, seeing the dependence on natural resources in the Gwayi catchment, negative changes in surface runoff have an impact on economic activities such as fishing and agriculture. Responsible authorities can benefit from such studies as this contributes to the body of knowledge in hydrological modelling. It is against this background to conclude that if pursued, such studies will contribute to sustainable development goals 1, 2, 9 and 13. These include no poverty, zero hunger, climate action and industry, innovation and infrastructure directly and indirectly.

5.2. RECOMMENDATIONS

Taking into consideration the highlighted conclusions, this study recommends the following.

i. For further research in the Gwayi catchment or similar catchments, the study recommends working with smaller manageable catchments (less than $5000km^2$) when conducting hydrological modelling because larger catchments tend to introduce complexities and discrepancies between simulated and observed runoff. For example, the Gwayi catchment can be studied utilising the existing sub-basins.
ii. In line with the above recommendation, fully incorporating the different factors affecting surface runoff such as dams which act as storage facilities should be considered to accurately represent ground conditions and produce a good fit between observed and simulated runoff.

Further research to also investigate forecasting to enable informed decision making and accurate planning.

iii. Catchment management initiatives aimed at constructing weir dams to address issues around water scarcity for both livestock and household use reinforced by environmental conservation works to reduce siltation.

iv. An online database of observed hydro-meteorological data to allow ease of access of data to fully understand the different catchment characteristics is recommended.

REFERENCES

Al-Mukhtar, M., & Al-Yaseen, F. (2019). Modeling water quality parameters using data-driven models, a case study Abu-Ziriq marsh in south of Iraq. *Hydrology*, *6*(1), 1–17. https://doi.org/10.3390/hydrology6010021

Brirhet, H., & Benaabidate, L. (2016). Comparison Of Two Hydrological Models (Lumped And Distributed) Over A Pilot Area Of The Issen Watershed In The Souss Basin, Morocco. *European Scientific Journal, ESJ*, *12*(18), 347. https://doi.org/10.19044/esj.2016.v12n18p347

Daide, F., Afgane, R., Lahrach, A., Chaouni, A., Msaddek, M., & Elhasnaoui, I. (2021). *Application of the HEC-HMS hydrological model in the Beht watershed (Morocco). 05003*.

Dzirekwa, S., Gumindoga, W., Makurira, H., Mhizha, A., & Rwasoka, D. T. (2023). Prediction of climate change impacts on availability of surface water resources in the semi-arid Tugwi Mukosi catchment of Zimbabwe. *Scientific African*, *20*. https://doi.org/10.1016/j.sciaf.2023.e01691

Fanta, S. S., & Feyissa, T. A. (2021). Performance evaluation of HEC-HMS model for continuous runoff simulation of Gilgel Gibe watershed, Southwest Ethiopia. *Journal of Water and Land Development*, *50*, 85–97. https://doi.org/10.24425/jwld.2021.138185

Fathy, I., Negm, A. M., El-fiky, M., Nassar, M., & Al-, E. (2015). *RUNOFF HYDROGRAPH MODELING FOR ARID REGIONS (CASE STUDY : WADI SUDR – SINAI) Lumped Hydrologic Models Semi-Distributed Hydrologic Models Distributed Hydrologic Models*. *5*(1), 58–68.

Gajbhiye, S. (2015). Estimation of Surface Runoff Using Remote Sensing and Geographical Information System. *International Journal of U- and e-Service, Science and Technology*, *8*(4), 113–122. https://doi.org/10.14257/ijunesst.2015.8.4.12

Gebre, S. L. (2015). Application of the HEC-HMS Model for Runoff Simulation of Upper Blue Nile River Basin. *Journal of Waste Water Treatment & Analysis*, *06*(02). https://doi.org/10.4172/2157-7587.1000199

GoZ. (2002). Water Resource Management , Supply and Sanitation. *Zimbabwe Report*, 1–50.

Gumindoga, W., Makurira, H., Phiri, M., & Nhapi, I. (2016). Estimating runoff from ungauged catchments for reservoir water balance in the lower middle Zambezi basin. *Water SA*, *42*(4), 641–649. https://doi.org/10.4314/wsa.v42i4.15

Gumindoga, W., Rwasoka, D. T., Nhapi, I., & Dube, T. (2017). Ungauged runoff simulation in Upper Manyame Catchment, Zimbabwe: Application of the HEC-HMS model. *Physics and Chemistry of the Earth*, *100*, 371–382. https://doi.org/10.1016/j.pce.2016.05.002

Gwate, O., Dube, H., Sibanda, M., Dube, T., & Nyikadzino, B. (2022). Understanding the influence of land cover change and landscape pattern change on evapotranspiration variations in Gwayi catchment of Zimbabwe landscape pattern change on evapotranspiration. *Geocarto International*, *0*(0), 1–17. https://doi.org/10.1080/10106049.2022.2032386

Halwatura, D., & Najim, M. M. M. (2013). Application of the HEC-HMS model for runoff simulation in a tropical catchment. *Environmental Modelling and Software*, *46*, 155–162. https://doi.org/10.1016/j.envsoft.2013.03.006

Hernández-Romero, P., Patiño-Gómez, C., Corona-Vásquez, B., & Martínez-Austria, P. F. (2022). Rainfall/runoff hydrological modeling using satellite precipitation information. *Water Practice and Technology*, *17*(5), 1082–1098. https://doi.org/10.2166/wpt.2022.048

Hishinuma, S., Takeuchi, K., Magome, J., Hishinuma, S., Takeuchi, K., & Magome, J. (2014). Challenges of hydrological analysis for water resource development in semi-arid mountainous regions : case study in Iran Challenges of hydrological analysis for water resource development in semi-arid mountainous regions : case study in Iran. *Hydrological Sciences Journal – Journal Des Sciences Hydrologiques*, *59*(9), 1718–1737. https://doi.org/10.1080/02626667.2013.853879

Ismael, O., Joseph, S., & Patrick, K. H. (2017). Hec-Hms Model for Runoff Simulation in Ruiru Reservoir Watershed. *American Journal of Engineering Research (AJER)*, *6*(4), 1–7.

Kassem, Y., Gökçekuş, H., & Alijl, N. (2023). Gridded Precipitation Datasets and Gauge Precipitation Products for Driving Hydrological Models in the Dead Sea Region, Jordan. *Sustainability (Switzerland)*, *15*(15), 1–29. https://doi.org/10.3390/su151511965

Kauffman, G. J. (2002). What if... the United States of America were based on watersheds? *Water Policy*, *4*(1), 57–68. https://doi.org/10.1016/S1366-7017(02)00019-3

Kempen, G. Van, Wiel, K. Van Der, & Melsen, L. A. (2021). *The impact of hydrological model structure on the simulation of extreme runoff events*. 961–976.

Khatami, S., & Khazaei, B. (2014). Benefits of GIS Application in Hydrological Modeling: A Brief Summary. *Vatten: Tidskrift För Vattenvård /Journal of Water Management and Research*, *70(1)*, 41–49.

KlemeŠ, V. (1986). Operational testing of hydrological simulation models. *Hydrological Sciences Journal*, *31*(1), 13–24. https://doi.org/10.1080/02626668609491024

Kuok, K. K., Chiu, P. C., Rahman, M. R., Said, K. A. bin M., & Chin, M. Y. (2023). Evaluation of total infiltration and storage capacities for different soil types in Sarawak using SWMM. *Discover Water*, *3*(1). https://doi.org/10.1007/s43832-023-00042-0

Love, D., Uhlenbrook, S., Corzo-Perez, G., Twomlow, S., & van der Zaag, P. (2010). Relations précipitation-interception-évaporation-écoulement dans un bassin versant semi-aride (nord du Limpopo, Zimbabwe). *Hydrological Sciences Journal*, *55*(5), 687–703. https://doi.org/10.1080/02626667.2010.494010

Love, D., Uhlenbrook, S., Twomlow, S., & van Der Zaag, P. (2010). Changing hydroclimatic and discharge patterns in the northern Limpopo Basin, Zimbabwe. *Water SA*, *36*(3), 335–350.

Mabande, P. K., & Rientjes, T. (2012). Applicationg of a satellite based rainfall - runoff model for large scale flood simulation : a case study of Cuvelai basin in Namibia. *Dept. of Water Resources*, *MSc*, 1–85.

Masimba, O., Gumindoga, W., Mhizha, A., & Rwasoka, D. T. (2022). Impacts of climate change on streamflow and reservoir inflows in the Upper Manyame sub-catchment of Zimbabwe. *Water SA*, *48*(4), 359–368. https://doi.org/10.17159/wsa/2022.v48.i4.3920

Matingo, T., Gumindoga, W., & Makurira, H. (2018). Evaluation of sub daily satellite rainfall estimates through flash flood modelling in the Lower Middle Zambezi Basin. *Proceedings of the International Association of Hydrological Sciences*, *378*, 59–65. https://doi.org/10.5194/piahs-378-59-2018

Maviza, A., & Ahmed, F. (2021). Climate change/variability and hydrological modelling studies in Zimbabwe: a review of progress and knowledge gaps. *SN Applied Sciences*, *3*(5), 1–28. https://doi.org/10.1007/s42452-021-04512-9

Mazvimavi, D., Stein, A., Meijerink, A. M. J., & Savenije, H. H. G. (2003). Estimation of flow characteristics of ungauged catchments : a case study in Zimbabwe. In *Wageningen University PhD thesis and inernational Research Centre; Summaries in Dutch and EnglishITC Dissertation*. http://www.itc.nl/library/Papers_2003/phd_theses/mazvimavi.pdf

Moriasi, D. N., Arnold, J. G., Liew, M. W. Van, Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). *M e g s q a w s*. *50*(3), 885–900.

Moyo, M., Dorward, P., & Craufurd, P. (2017). Characterizing Long Term Rainfall Data for Estimating Climate Risk in Semi-arid Zimbabwe. *Climate Change Management*, 661–675. https://doi.org/10.1007/978-3-319-49520-0_41

Mugandani, R., Wuta, N., Makarau, A., & Chipindu, B. (2012). *Re-classification of agro-ecological regions of Zimbabwe in conformity with climate variability and change _ Mugandani _ African Crop Science Journal*. *20*(January), 361–369.

Muhammed, A. H. (2012). Satellite Based Evapotranspiration Estimation and Runoff Simulation : a Topmodel Application To the Gilgel Abay Catchment , Ethiopia. *Thesis*, 1–85.

Mutekwa, V. T. (2009). Climate change impacts and adaptation in the agricultural sector: the case of smallholder farmers in Zimbabwe. *Journal of Sustainable Development in Africa*, *11*(2), 237–256. http://0-search.ebscohost.com.catalog.library.colostate.edu/login.aspx?direct=true&AuthType=cookie,ip,url,cpid&custid=s4640792&db=lah&AN=20103307506&site=ehost-live%5Cnhttp://www.jsd-africa.com/Jsda/V11N02_Fal2009/PDF/Climate ChangeImpactsAdaptation.pdf

Ndemere, K., Gumindoga, W., Makurira, H., & Rwasoka, D. T. (2024). Performance evaluation of multiple satellite rainfall products in mountainous catchments of Zimbabwe. *Scientific African*, e02120. https://doi.org/10.1016/j.sciaf.2024.e02120

Nharo, T., Makurira, H., & Gumindoga, W. (2019). Mapping floods in the middle Zambezi Basin using earth observation and hydrological modeling techniques. *Physics and Chemistry of the Earth*, *114*(June), 1–9. https://doi.org/10.1016/j.pce.2019.06.002

Ortiz-partida, J. P., Fernandez-bou, A. S., & Maskey, M. (2023). *Hydro-Economic Modeling of Water Resources Management Challenges : Current Applications and Future Directions*. *9*(1). https://doi.org/10.1142/S2382624X23400039

Panigrahi, B., Choudhari, K., & Chandra Paul, J. (2014). Watershed planning using interactive multi objective linear programming approach: A case study Academic excellence View project Simulation of rainfall-runoff process using HEC-HMS model for Balijore Nala watershed, Odisha, India. *International Journal of Geomatics and Geosciences*, *5*(2). https://www.researchgate.net/publication/327606890

Rajbanshi, J. (2016). Estimation of Runoff Depth and Volume Using NRCS-CN Method in Konar Catchment (Jharkhand, India). *Journal of Civil & Environmental Engineering*, *6*(4), 4–9. https://doi.org/10.4172/2165-784x.1000236

Rawls, W. J., Brakensiek, D. L., & Miller, N. (1983). Green-ampt Infiltration Parameters from Soils Data. *Journal of Hydraulic Engineering*, *109*(1), 62–70. https://doi.org/10.1061/(asce)0733-9429(1983)109:1(62)

Samu, R., & Kentel, A. S. (2018). International Journal of Disaster Risk Reduction An analysis of the fl ood management and mitigation measures in Zimbabwe for a sustainable future. *International Journal of Disaster Risk Reduction*, *31*(July), 691–697. https://doi.org/10.1016/j.ijdrr.2018.07.013

Seibert, J., & Meerveld, I. Van. (2016). *Hydrological change modeling : Challenges and opportunities*. https://doi.org/10.1002/hyp.10999

Sezen, C., & Sraj, M. (2024). *Science of the Total Environment Improving the simulations of the hydrological model in the karst catchment by integrating the conceptual model with machine learning models*. *926*(March). https://doi.org/10.1016/j.scitotenv.2024.171684

Sibanda, T., Nonner, J. C., & Uhlenbrook, S. (2009). Comparison of groundwater recharge estimation methods for the semi-arid Nyamandhlovu area, Zimbabwe. *Hydrogeology Journal*, *17*(6), 1427–

1441. https://doi.org/10.1007/s10040-009-0445-z

Thebe, T. A. (2012). The value of wastewater in a water-stressed sub-catchment of Zimbabwe. *Soil and Water Engineering. International Conference of Agricultural Engineering - CIGR-AgEng 2012: Agriculture and Engineering for a Healthier Life, Valencia, Spain, 8-12 July 2012, 1998*(October), C–0761. http://cigr.ageng2012.org/images/fotosg/tabla_137_C0761.pdf

US Army Corps of Engineers Hydrologic Engineering Center. (2000). Hydrologic Modeling System Technical Reference Manual. *Hydrologic Modeling System HEC-HMS Technical Reference Manual, March*.

US Army Corps of Engineers Hydrologic Engineering Center. (2023). Hydrologic Modeling System HEC-HMS User ' s Manual. *Hydrologic Modeling System HEC-HMS User's Manual*.

Vichete, W. D., Méllo Júnior, A. V., & Soares, G. A. dos S. (2023). A Water Allocation Model for Multiple Uses Based on a Proposed Hydro-Economic Method. *Water (Switzerland)*, *15*(6). https://doi.org/10.3390/w15061170

Willems, P. (2012). Impacts of Climate Change on Rainfall Extremes and Urban Drainage Systems. In *Water Intelligence Online* (Vol. 11). https://doi.org/10.2166/9781780401263