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Modelling River Discharge Response to Precipitation Variability (1969–2015) Using HEC-HMS in the Gucha-Migori Basin

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Abstract
The purpose of this article is to determine the response of river discharge to precipitation variability in the Gucha-Migori River Basin, where recurrent flood events persist despite the limited application of non-structural mitigation measures. Understanding the rainfall–runoff relationship is essential for improving flood risk management and decision-making. The study employed the Hydrologic Engineering Centre–Hydrologic Modelling System (HEC-HMS) to simulate river discharge using precipitation data for the period 1969–2015. The model's performance was evaluated through R^2 and Nash–Sutcliffe efficiency during calibration and validation. A correlation analysis was also done to determine how seasonal rainfall relates to river discharge. The results show that the HEC-HMS model achieved moderate performance, with R^2 and Nash values of 0.52 and 0.36 during calibration, and 0.42 and 0.31 during validation, respectively. The findings further indicate a statistically significant positive relationship between seasonal precipitation and river discharge at the 0.05 significance level, confirming that precipitation variability strongly influences discharge patterns in the basin. The study concludes that precipitation variability is a key driver of river discharge and that HEC-HMS is a suitable tool for simulating rainfall–runoff processes. It is recommended that hydrological modelling be integrated into flood risk assessment and early warning systems to enhance preparedness and support sustainable water resource management in the basin. The findings provide a basis for improving flood response planning and reducing vulnerability to flood hazards.

Key words: Climate variability impact, HEC-HMS model, hydrologic modelling, precipitation variability, river discharge.

INTRODUCTION

In the Gucha-Migori River Basin, floods are the most frequent and severe natural disasters, happening almost annually and resulting in considerable socio-economic and environmental disruption. Despite the application of structural mitigation measures such as dykes and dams, the increasing frequency and severity of flood events indicate that these approaches alone are insufficient to effectively manage flood risks. Previous studies (Adero, 2017; Gaya, 2020; Ogembo, 2018) show that flood magnitude, occurrence, and associated damages have progressively increased over recent decades, underscoring the need to better understand the hydrological processes driving these events. In particular, a limited understanding of how precipitation variability influences river discharge presents a critical gap in flood risk management within the basin.

Climate change and expanding socio-economic activities continue to alter hydrological regimes globally, affecting watershed responses and increasing uncertainty in water availability (Archer et al., 2010; Wambua et al., 2017). In Kenya, these changes are associated with ecosystem degradation, variability in water inputs, and shifts in watershed storage, which collectively intensify extreme hydrological events such as floods (Juma et al., 2021; Opere, 2013). Flooding is primarily driven by intense and prolonged rainfall that exceeds the soil's infiltration capacity or the flow capacity of rivers and streams, resulting in increased surface runoff (Thavhana, 2018). This runoff may occur as Hortonian overland flow, when rainfall intensity exceeds the soil's infiltration capacity, or as saturation overland flow, when the soil becomes fully saturated due to subsurface processes (Singo et al., 2012; Warburton et al., 2010). The generated runoff contributes to increased river discharge, which determines the magnitude and occurrence of flooding events.

In the Gucha-Migori River Basin, heavy rainfall in upstream areas generates substantial surface runoff that flows into the Gucha and Migori river systems, increasing river discharge and contributing to downstream flooding (Adero, 2017). As runoff moves through the catchment, it also transports sediments that accumulate within river channels, further influencing flow dynamics. Floodplain areas within the basin are additionally affected by runoff from surrounding hills, which disrupts agricultural activities and livelihoods (Ogembo, 2018). These dynamics emphasise the need to understand how precipitation variability influences changes in river discharge within the basin.

Hydrologic modelling provides a practical approach for analysing the relationship between precipitation and river discharge by representing hydrological processes through mathematical simulations. The Hydrologic Engineering Centre–Hydrologic Modelling System (HEC-HMS) is widely applied for simulating rainfall–runoff processes, including precipitation, infiltration, surface runoff, and channel flow, using relatively moderate data requirements (Bhuiyan et al., 2017; Gyawali & Watkins, 2013). In this context, river discharge refers to the volume of water flowing through a river channel at a given time, while precipitation variability describes fluctuations in rainfall patterns over time. An understanding of the interaction between these variables is key to examining hydrological responses within a river basin.

This study, therefore, focuses on determining the response of river discharge to precipitation variability in the Gucha-Migori River Basin using the HEC-HMS model for the period 1969 to 2015. By simulating rainfall–runoff processes and evaluating model performance, the study seeks to provide insights into how variations in precipitation influence discharge patterns. The findings are expected to support improved understanding of basin hydrology and contribute to informed water resource management within the study area.

LITERATURE REVIEW

Response of Flood Events to Precipitation Variability

Changes in climate and land-use systems alter the hydrologic regime of a basin by changing precipitation partitioning, which brings about extreme variations of subsurface flows, groundwater flows, and surface runoff (Amisi et al., 2020). Such changes bring different responses of runoff, which may then contribute to flooding events because precipitation variability and changes in the Land-use system occur at different spatial and temporal scales. Besides, the impact of changes in precipitation and LULC might compensate for or strengthen each other. On the other hand, some researchers like Renner et al. (2014) explain that they both might occur in parallel.

Mwetu (2019) provided an example by assessing how land cover changes and climate variability shape the discharge regime of the Njoro River Catchment in

Kenya. Results showed a negative trend of annual discharge that corresponded to increased deforestation, open fields, bare land, and grassland. Further analysis pointed out that human activity, mainly deforestation, accounted for 75 per cent of the reduction of discharge, while precipitation variability accounted for 25 per cent of the reduction of discharge. This implies that land-use changes were largely responsible for runoff, which in turn would then potentially contribute to flooding events.

Although there have been several studies conducted on the surface runoff response to changes in LULC, the evidence from some studies is still contradictory. For example, other researchers elaborate that an increase in the annual discharge is caused by a reduction of forest cover (Farley et al., 2005; Hayhoe et al., 2011). On the other hand, studies like Githui et al. (2009) and Kundu (2007) postulate that land-use changes from forest to mixed rural built-up lands and subsistence agriculture cause the increase of runoff but deteriorate subsurface as well as groundwater flows.

However, the aforementioned responses of surface water circular are based on the fact that LULC influences soil physical properties, available water content, infiltration capacity, and saturated hydraulic conductivity. This would mean that the changes in the land-use system might significantly influence flood magnitude, time, and spatial variation.

For example, Olang and Fürst's (2011) analyses on the effect of LULC on flood peak discharges and runoff volumes in Nyando River Basin, Kenya, using HEC-HMS successfully outlined the hydrologic consequences of the imminent land cover changes. The model results also showed that increased upstream deforestation led to at least a 10% rise in runoff, flood peak discharges, and flood volumes across the basin. Such findings are consistent with many studies, like Brody et al. (2014) and Hussein et al. (2020). Conversely, Kabeja et al. (2020) evaluated the impact of reforestation-induced LULC on flood peak discharge using HEC-HMS. Their results pointed out that the reforestation resulted in a decrease in flood peak discharge ranging from 14-16 per cent.

Although changes in LULC influence runoff and flood magnitudes, the main dominant factor in the basin affecting the spatial and temporal distribution of flood routing processes is precipitation variability (Davenport et al., 2021). For instance, Tabari (2020) quantified the response of flood intensities to changes in extreme precipitation and found that extreme storm events intensified flood volumes with the seasonal cycle of water availability. Similarly, Chegwidden et al. (2020) and Gandini et al. (2020) have also reported a stronger relationship between precipitation and flood events. Also, for the runoff analysis, Ogembo (2018) carried out hydrologic modelling and climate change studies on the River Kuja Basin using HEC-HEC-GeoHMS and reported that both Runoff and precipitation showed a downward trend analysis.

The analysis by Ogembo (2018) revealed a significant decline in runoff in drier months compared to wetter months and concluded that there will be a high risk of flash floods in the future, but consequently very low discharges during dry seasons. A similar response has also been reported by Amisi et al. (2020), Mango et al. (2011) and Mwangi et al. (2016). It implies that direct runoff is a result of the spikes caused by a rainstorm, which then contributes to peak flow, hence river or flash floods.

Therefore, it can be inferred that precipitation variability influences the variation in spatial redistribution, time, frequency, and magnitude of floods. Therefore, it is imperative to note that the response of flood routing events to precipitation variability is complex, uncertain, and varies spatio-temporally, and hence may only be simulated in most cases by hydrologic models (Devia et al., 2015; Mwangi et al., 2016).

Hydrologic Modelling

Hydrologic modelling is the characterisation of real hydrologic features and systems by the use of computer simulations, mathematical analogues, and small-scale physical models (Devia et al., 2015). Hydrologic models can broadly be classified into stochastic and deterministic models. In stochastic models, inherent randomness allows the same parameters and initial conditions to yield multiple possible outcomes, whereas deterministic models produce a single outcome entirely determined by those parameters and initial conditions (Farmer & Vogel, 2016).

Marhaento et al. (2016) elucidate that hydrologic models are vital to the optimisation and operation of water resources, and this explains why many statistical, empirical, and conceptual discharge prediction models have been developed for decision support in water management. However, statistical techniques, such as linear regression-based approaches, are constrained, simplistic, and have limited capacity to handle non-linear relationships (Amisi et al., 2020).

Conceptual hydrologic models are usually considered the best alternative because they take into account hydrologic processes through mathematical formulations (Devia et al., 2015). The laws of conservation of mass, momentum, and energy guide the development of conceptual hydrologic models, since most physical modelling involves the storage of water, the spatial and temporal distribution of flows, and their occurrence. These laws can be expressed by the concept of continuity and momentum Equations (2.1 and 2.2). The equations are applied in modelling under the assumption that the flow is unidirectional, the fluid is incompressible, vertical accelerations are negligible and hydrostatic pressure prevails.

$$\frac{\partial A}{\partial t} + \frac{\partial (vA)}{\partial x} - q = 0 \quad (2.1)$$

$$\frac{\partial Q}{\partial t} + \frac{\partial (vQ)}{\partial x} + gA\left(\frac{\partial y}{\partial x} - s_0 + s_f\right) = 0 \quad (2.2)$$

where q is the lateral inflow (m3), Q is the discharge in the channel (m3/s), A is the area of flow in the channel (m2), n is Manning's coefficient for the channel, is the bed slope (m/m), and is the friction slope of the channel (m/m).

Many researchers and organisations affirm the importance of conceptual hydrologic models such as SWAT, HRDROTEL, HEC-HMS, WATFLOOD, MIKE11/SHE, SPHY, WEAP, and TOPMODEL in the vital role they play in integrated water resources management solutions. Out of all the conceptual models, HEC-HMS has been demonstrated to be the most preferred model for flood routing processes simulation (Fleming, 2004; Oleyiblo & Li, 2010). HEC-HMS has been widely used because it is more physically based than lumped models and less demanding of input data than fully distributed models (Bhuiyan et al., 2017; Gyawali & Watkins, 2013; Thu et al., 2019). Besides, it explains why the HEC-HMS model has been applied successfully in many River basins in Kenya, which include Nyando (Olang & Fürst, 2011), Ruiru (Ismael et al., 2017), Kuja (Ogembo, 2018), Mkurumudzi (Ouédraogo et al., 2018), and Umba (Tesfamariam et al., 2021).

Hydrologic Engineering Centre - Hydrologic Modelling System (HEC-HMS)

The Hydrologic Engineering Centre (HEC-HMS) is a model developed by the US Army Corps of Engineers of the Hydrologic Engineering Centre (HEC), which contains an integrated tool for simulating hydrologic variables of dendritic river basin systems. It is a physically-based, semi-distributed, event-scale hydrologic model used to represent hydrological processes (Chu & Steinman, 2009). As further illustrated by Fleming (2004), the construction of the HEC-HMS model for simulation involves dividing an entire river basin into homogeneous sub-basins based on the defined drainage area threshold. The mass flux and energy balances within the hydrologic cycle are then modelled using mathematical equations.

The HEC-HMS model requires spatial data (digital elevation model, LULC, and Soil maps), meteorological, and hydrologic datasets (Ouédraogo et al., 2018). The spatial data is prepared and processed from HEC-GeoHMS and imported to the HEC-HMS model to simulate flow, stage, and timing for the river basin.

Therefore, the HEC-HMS model has three major components, namely, control specification, meteorological model, and basin model (Ramly & Tahir, 2016). The meteorological model consists of the precipitation and evaporation datasets, the control specification contains calculation intervals for the run, while the basin model contains elements of the sub-basin, the connectivity, and the runoff parameter. The HEC-HMS model consists of the following components for the simulation of the runoff response to precipitation (Gebre, 2015; Ogembo, 2018). The precipitation specification option describes the historical data at a given location.

The second component is the loss models that approximate the runoff magnitudes given precipitation datasets and river basin characteristics. Other components include direct runoff models that account for overland flow, energy losses, and storage, and the hydrologic routing models, which account for energy flux and storage during the period water flows through the stream channels. Some of the additional models are those for naturally occurring confluences and bifurcations, and models of water control measures. The

HEC-HMS model contains eight elements, which include the diversions, reservoir, sink, source, junction, reach, and sub-basins (Ogembo, 2018; Ramly & Tahir, 2016).

Every sub-basin has corresponding precipitation; thus, the outflow for the element is computed through the subtraction of the precipitation losses. Surface runoff is then calculated, and the base flow is added. The reach element conveys the river discharge to the basin model, and the inflow into the reach is obtained from the upstream elements. Translation and attenuation should be accounted for, then the outflow from the reach is calculated. Figure 1 shows an overview of the rainfall-runoff process simulation in HEC-HMS.

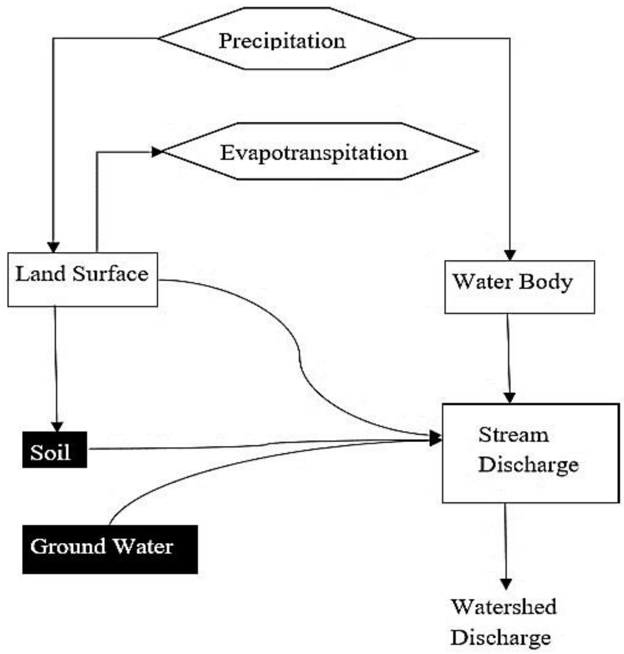

Figure 1: Schematic Diagram of the Rainfall-Runoff Process in HEC-HMS
Source: Ogembo (2018)

All the inflow into the junction must be summed up to obtain the outflow, and the source element introduces inflow into the basin model. However, the outflow of the source element may be defined by the user, so the sink element represents the basin outlet. The reservoir element models the hydrograph detention and attenuation as a result of the detention pond. Computation of the outflow from the reservoir can be achieved by applying any of the routing approaches in HEC-HMS (Fleming, 2004; Ogembo, 2018).

The diversion element models the discharge leaving the main channel, and its inflow can be obtained from many upstream channels. It should be noted that the computation of the diverted flow can be done using the user's input. The non-diverted and diverted can be connected to other hydrologic elements located downstream of the diversion elements.

Hydrologic Engineering Centre -Geospatial Hydrologic Modelling Extension

HEC-GeoHMS is an extension for ArcGIS released by the US Army Corps of Engineers, Hydrologic Engineering Centre (HEC) (Fleming, 2004; Tesfamariam et al., 2021). It is a toolkit of geospatial hydrology, which allows operators to process and create basin parameters based on the topographic data for hydrologic modelling (USACE, 2010). In addition, HEC-GeoHMS processes geospatial data and creates its input files in ArcGIS for HEC-HMS. Figure 2, adapted from USACE (2013), shows the relationship between GIS, HEC-GeoHMS, and HEC-HMS.

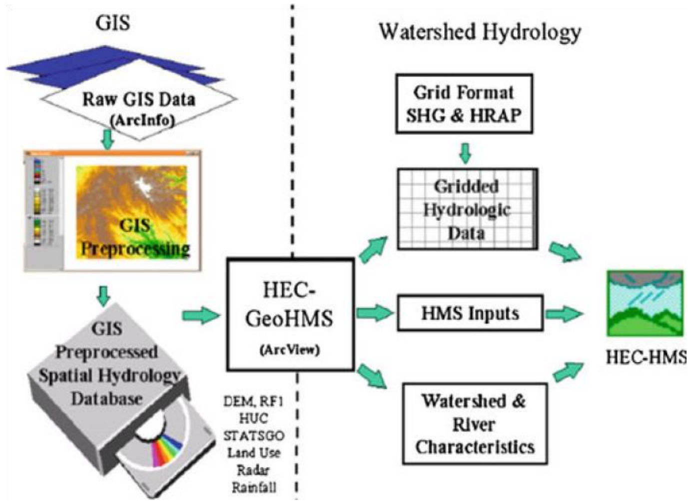

Figure 2: Overview of HEC-GeoHMS Program
Source: USACE (2010)

HEC-GeoHMS is applied to derive a river network of the basin from the digital elevation data. To obtain a digital elevation model to demarcate various components of the catchment, some of the major steps undertaken include filling sinks, flow direction derivation, demarcation of basin and sub-basin, calculation of flow accumulation, and stream network definition (USACE, 2013). HEC-GeoHMS creates the drainage network by analysing the digital terrain data and transforming the drainage paths and basin boundaries into a hydrologic data structure.

HEC-HMS Model Calibration and Validation

The successful application of hydrologic models, including HEC-HMS, depends on how well calibration and validation are achieved. Calibration is the process of minimising the model output uncertainties before running simulations by adjusting parameters to best capture the local conditions (Kamali et al., 2013). However, validation is the running of the model with calibrated parameters in an independent data set so that the applicability of the model can be assessed through statistical tests. For the HEC-HMS model, manual calibration is performed by visual inspection and trial-and-error procedures. (Kamali et al., 2013). Some studies, such as Dariane et al. (2016), point out that manual calibration can be tedious, time-consuming, and may require experience and experimental information. Auto-calibration is based on systematic techniques to find the best parameter values based on pre-defined objective functions, thus, more likely to produce better results (Dariane et al., 2016; Kamali et al., 2013).

Some of the widely applied auto-calibration techniques for the HEC-HMS model entail Sequential Uncertainty Fitting 2 (SUFI-2), Genetic Algorithm (GA), Nelder-Mead (NM), Univariate-Gradient (UG), Melody Search Algorithm (MeS), and Self-Adaptive Global Harmony Search (SGHS). Several studies have highlighted various aspects and challenges inherent in the aforementioned auto-calibration approaches, such as parameterisation, non-uniqueness of parameter values, and data quantity and quality. Also, the type and the number of objective functions and their characteristics (indifference to parameter values, non-convexity, and multi-modality) (Kamali et al., 2013), and the performance of the optimisation algorithms. The methodology for addressing uncertainty, sensitivity, calibration, and validation has been detailed. Specific techniques used, parameters tested, and evaluation criteria are explained to ensure robustness and reliability of the model.

For instance, studies by Kamali et al. (2013) preferred the use of a multi-objective Particle Swarm Optimisation (PSO) algorithm for automatic calibration of HEC-HMS. According to Dariane et al. (2016), the Genetic Algorithm is preferred to Nelder-Mead and Univariate-Gradient when using a snowmelt module in a continuous model for the enhancement of efficiency. Several studies have shown that the SUFI-2 algorithm is an efficient and widely used method for hydrological model calibration and uncertainty analysis, as it accounts for multiple sources of uncertainty and iteratively optimises parameter ranges to improve model performance (Abbaspour et al., 2007; Arnold et al., 2012).

Hydrologic Model Performance Assessment

A variety of statistical measures have been applied to assess HEC-HMS hydrologic predictions, with the Coefficient of Determination (R^2) and the Nash–Sutcliffe efficiency (Nash) being the most commonly used for model calibration and validation. The R-squared measures how the observed versus simulated regression line approaches an ideal match. R^2 values range from zero to one, with a value closest to zero indicating no correlation, while a value closest to one indicates relatively perfect linear covariation between the two datasets. It implies that a correlation measurement reveals the high accuracy of the model when the value is approaching one. Nash Sutcliffe model efficiency ranges from -1∞ to 1 and measures how well the observed and simulated data match the 1:1 line (Moriasi et al., 2007). The values of Nash closer to zero or equal to 0 indicate that the mean of the observed data is a better predictor than the model, and the values closer to one or 1 imply a perfect fit between the observed and simulated. Considering various time steps of modelling, the performance evaluation of the hydrologic model under the defined values of Nash and R^2 can be rated as per the recommendations by Moriasi et al. (2007). Practical recommendations for future research and water resource management have been provided. These include specific areas for further investigation and actionable advice for policymakers to improve flood management and mitigation strategies.

Table 1:General Performance Ratings for Recommended Statistics

Nash	R^2	**Rating**
75.0% Nash ≤ 100%	75.0 % < R^2 ≤ 100 %	Very good
60.0 % < Nash ≤ 75.0%	60.0% <R^2 ≤ 75.0 %	Good
36.0 % <Nash ≤ 60.0 %	50.0% <R^2 ≤ 6 0.0 %	Satisfactory
0.0 % <Nash ≤ 36.0 %	25.0 % < R^2 ≤ 50.0 %	Poor
Nash ≤ 0.0%	R^2 ≤ 25.0 %	Inappropriate

This study discusses the use of the HEC-HMS model for flood simulation (Ikhwali et al., 2022; Ismael et al., 2017). While HEC-HMS is a widely used tool, the review does not sufficiently critique its limitations, such as its performance in different geographic settings or its dependency on high-quality input data, which may not always be available. For example, the HEC-HMS model, though superior in its physical basis compared to other lumped models, relies heavily on detailed and accurate input data, including digital elevation models (DEM), land use/land cover (LULC), and soil maps. In regions where such data is scarce or outdated, the model's accuracy can be significantly compromised.

However, the application of the HEC-HMS model in different hydrological and climatic contexts has revealed varying degrees of effectiveness. Studies have shown that the model's calibration and validation processes are essential to ensure reliable simulation results (Dariane et al., 2016). However, manual calibration, often employed in these studies, is not only labour-intensive but also subjective, leading to potential inconsistencies in the results. Auto-calibration methods, while more systematic, may still fall short in capturing the unique hydrological characteristics of diverse river basins.

Despite these challenges, HEC-HMS remains a popular choice for flood modelling due to its balance between physical representation and data requirements. Its integration with GIS through the HEC-GeoHMS extension further enhances its utility by allowing for detailed spatial analysis and visualisation. However, further studies need to be done to address the need for continuous updates and improvements in input data and the calibration process to maintain the model's accuracy and applicability across different settings.

METHODOLOGY

This study adopted a quantitative, observational research design to assess the response of river discharge to precipitation variability in the Gucha-Migori River Basin, Kenya. The basin spans five counties and includes the R. Gucha and R. Migori rivers, with elevations ranging from 2000 m to 3000 m above sea level. Spatial and hydrological data were collected, including Digital Elevation Model (SRTM-DEM, 30 m resolution), FAO soil data, and Landsat 1 MSS imagery for land use/land cover classification. Meteorological data comprised daily precipitation and temperature records from 1969 to 2015, while hydrologic data included river discharge and water level measurements at three gauging stations. Fieldwork involved GPS mapping of streams, land-use types, and ground-truthing of satellite imagery.

Hydrologic modelling was conducted using the HEC-HMS platform, incorporating geospatial, meteorological, and hydrologic datasets. Key steps included DEM processing to delineate sub-basins and flow networks, soil and land-cover classification to determine Curve Numbers, and simulation of runoff, base flow, and channel flow. The model was calibrated and validated using split-sample river discharge records and assessed via the Coefficient of Determination (R^2) and Nash-Sutcliffe efficiency. Sensitivity analyses were performed on critical parameters, and regression analysis correlated seasonal precipitation anomalies with simulated discharge to quantify the hydrological response. All analyses were conducted using ArcMap, HEC-GeoHMS, HEC-HMS, and MATLAB 2019. Ethical considerations included the use of publicly available secondary data and proper acknowledgement of data sources.

FINDINGS AND DISCUSSION

Modelling Response of River Discharge to Precipitation Variability

Precipitation Variability

The precipitation annual anomalies over the Gucha-Migori River Basin for January, February, and March (JFM) are presented in Figure 3.

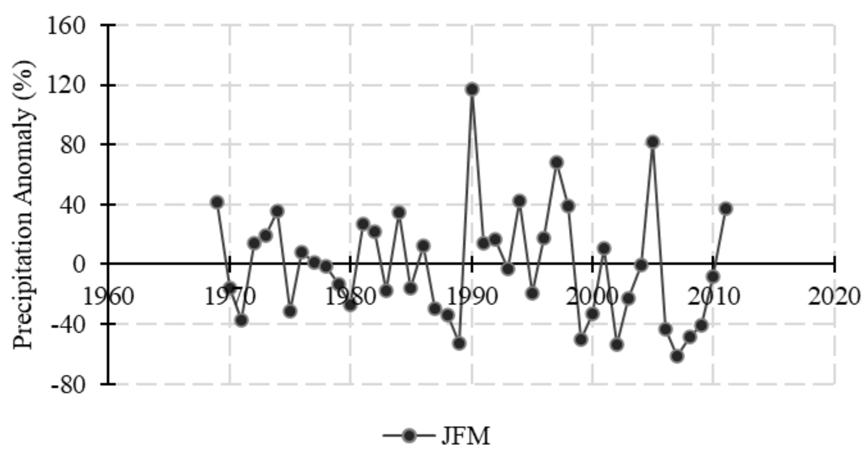

Figure 3: Precipitation Anomaly for the Months of January, February, and March

From the results of the average JFM precipitation datasets, the anomalies for the 43 years varied between -61.21 (2007) and 117.15 per cent (1990) of the long-term average. Values beyond -35 and + 35 per cent anomalies threshold were considered as extremely dry and wet climatic conditions, respectively. These anomaly ratings were based on the findings of IPCC (2007). However, the precipitation anomalies above 40 per cent indicated periods associated with river discharges that cause flooding events. Practical recommendations for future research and water resource management have been provided. These include specific areas for further investigation and actionable advice for policymakers to improve flood management and mitigation strategies. Daily mean precipitation for January, February, and March ranged from 8.23 to 1.47 mm for the period between 1969 and 2015. Out of all the annually recorded precipitation events, 11.63 per cent (events of above +40 anomalies) represented extremely wet climatic conditions. Eight independent flood events occurred in January (1973 and 2007), February (2007 and 2010), and four events in March (1969 and 1985) for the period between 1969 and 2015.

The precipitation annual anomalies over the Gucha-Migori River Basin for the months of April, May, and June (AMJ) are shown in Figure 4.

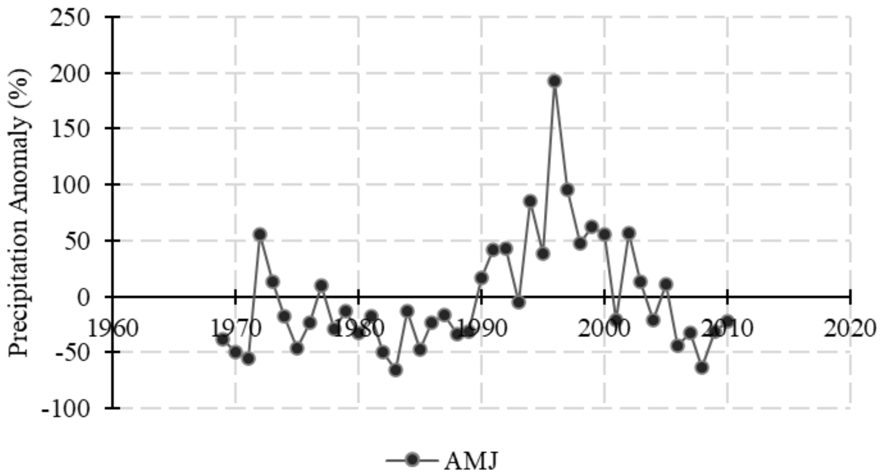

Figure 4: Precipitation Anomaly for the Months of April, May, and June

Based on the mean daily precipitation data of the period 1969- 2015 for April, May, and June, the anomalies ranged between -65.97 (1983) and 192.89 per cent (1996) of the long-term average. The year 1983 had the lowest (1.15 mm) recorded mean daily precipitation for the three months, while 1986 had the highest (9.9 mm). Out of all the annually recorded precipitation events, 23.81 per cent (events of above +40 anomalies) represented extremely wet climatic conditions. Independent flood events experienced in April include 1(1971), 2(1974), 1(1977), 2(1969), 2(1979), 1(1981), 1(1982), 1(1985), 1(1990), 1(2004), 1(2006), 1 (2011), and 4 (2013) in the study area.

In the case of May, the number of independent flood events recorded includes one, three, five, and two occurring in the years 1977, 2012, and 2013, respectively, while only 2 in June 1982. Precipitation trends in any of the periods, anomalies, and temporal variation for the months (April, May, and June) showed the manifestation of variability. The variability would affect the spatial as well as temporal response of inflow, storage, and outflow in a catchment, hence changes in quantity and dynamics of stream flow (Kundu, 2007)

The precipitation annual anomalies over the Gucha-Migori River Basin for July, August, and September (JAS) are presented in Figure 5.

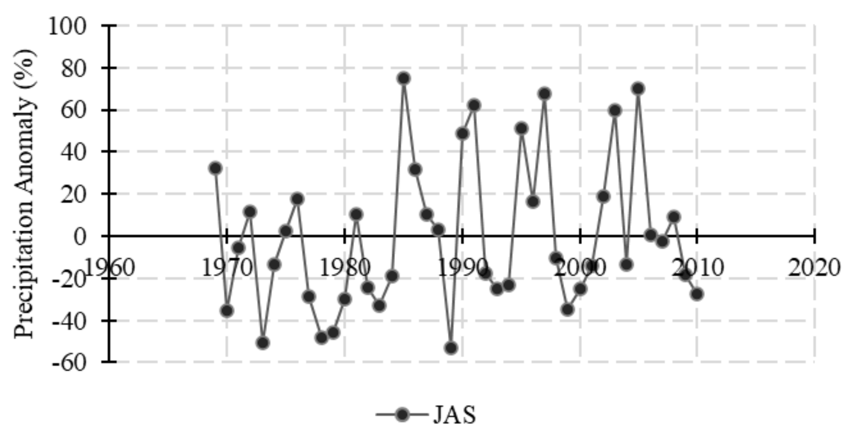

Figure 5: Precipitation Anomaly for the Months of July, August, and September

As indicated in Figure 5, the mean daily precipitation data of the period 1969- 2013 for July, August, and September, the anomalies ranged between -53.11 (1989) and +75 per cent (1985) of the long-term average. The year 1989 had the lowest (1.51 mm) mean daily precipitation for the three months, while 1985 had the highest (5.64 mm). Out of all the annually recorded precipitation events, 16.28 per cent (events of above +40 anomalies) represented wet climatic conditions. There were no independent flood events in July, August, and September for the period 1969 to 2015.

The precipitation anomalies for October, November, and December (OND) are shown in Figure 6.

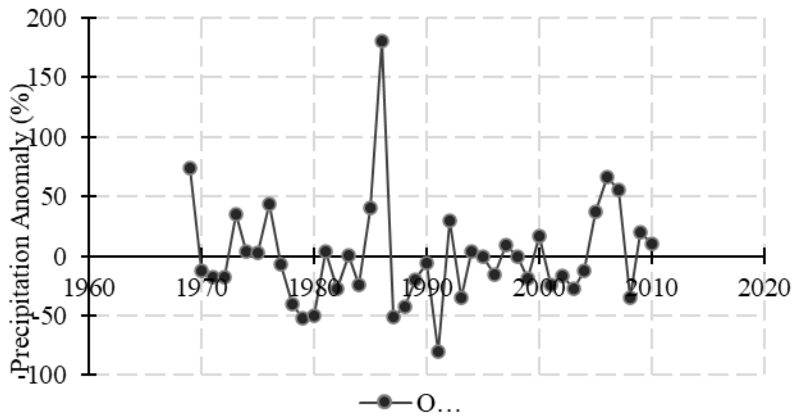

Figure 6: Precipitation Anomaly for the Months of October, November, and December

As revealed in Figure 6 of the mean daily OND precipitation datasets, the anomalies for the 43 years ranged from -80.20 (1991) to 179.87 per cent (1986) of the long-term average. Daily mean precipitation for October, November, and December varied from 8.34 to 0.59 mm. Out of all the yearly-recorded precipitation events, 11.63 per cent (events of above +40 anomalies) represented wet climatic conditions. There was no record of independent flood events in October and November. Nevertheless, six events (3 in 1982 and another 3 in 2011) occurred in December for the period between 1969 and 2015.

The monthly and seasonal precipitation variability at the Gucha-Migori River Basin could be attributed to changes in the Hadley circulation that imply a twice-a-year relocation of the Intertropical Convergence Zone (ITCZ). Dry seasons and months in equatorial East Africa, particularly in January and February, are associated with the dominance of northeasterly trade winds originating from the Arabian Peninsula and surrounding continental regions, combined with the seasonal migration of the Intertropical Convergence Zone (ITCZ), which suppresses convection and reduces rainfall (Nicholson, 2017; Camberlin & Okoola, 2003). The characteristics exhibited by the monthly and seasonal precipitation variability from one year to another (as illustrated in Figures 3, 4, 5, and 6) were sufficient evidence of unreliable changing weather patterns, hence the manifestation of extreme hydrologic events. It implies that some months would experience extreme (flooding) or reduced (drought) runoff, subsurface flow, recharge, and return flow, thus river discharge variation. Each figure in the Results and Discussion chapter is accompanied by a detailed explanation, describing what the figure shows, interpreting the data, and explaining its relevance to the study. Figures are well-labelled and referenced in the text.

Calibration and Validation of the HEC-HMS Model

Parametrisation, calibration, and validation for the river discharge simulation were done at sub-basin 1 (Figure 7 and Figure 9). The calibration range and fitted HEC-HMS model parameter values are presented in 1.

Table 2: Initial Parameters from HEC-GeoHMS Used in the HEC-HMS Model

Parameter Name	Range	Initial Value	Optimized Value
Land Use Curve Number	35.00~95.00	67.10	78.00
Lag Time SCS	0.02~1000.00	318.60	636.04
Muskingum X-value	0.17~0.50	0.20	0.19
Muskingum K-value	26.77~36.77	27.00	29.31
Basin Reach	1.00~14.00	1.00	2.00
SCS CN – CN ~ Scale Factor	0.01~100	1.00	0.01

Simulations were accomplished using the same values, but the output hydrograph was not a relatively perfect match to that of the observed river discharges (Figures 7 and 9). Besides, the parameters' ranges (Table 2) represent model output, which is an envelope of relatively fair solutions from a lumped process expressed by a certain level of prediction uncertainty. Thus, the disparity could be attributed to uncertainties associated with merging the sub-basins and using the average parameters in the simulation process. The methodology for addressing uncertainty, sensitivity, calibration, and validation has been detailed. Specific techniques used, parameters tested, and evaluation criteria are explained to ensure robustness and reliability of the model. Each figure in the Results and Discussion chapter is accompanied by a detailed explanation, describing what the figure shows, interpreting the data, and explaining its relevance to the study. Figures are well-labelled and referenced in the text.

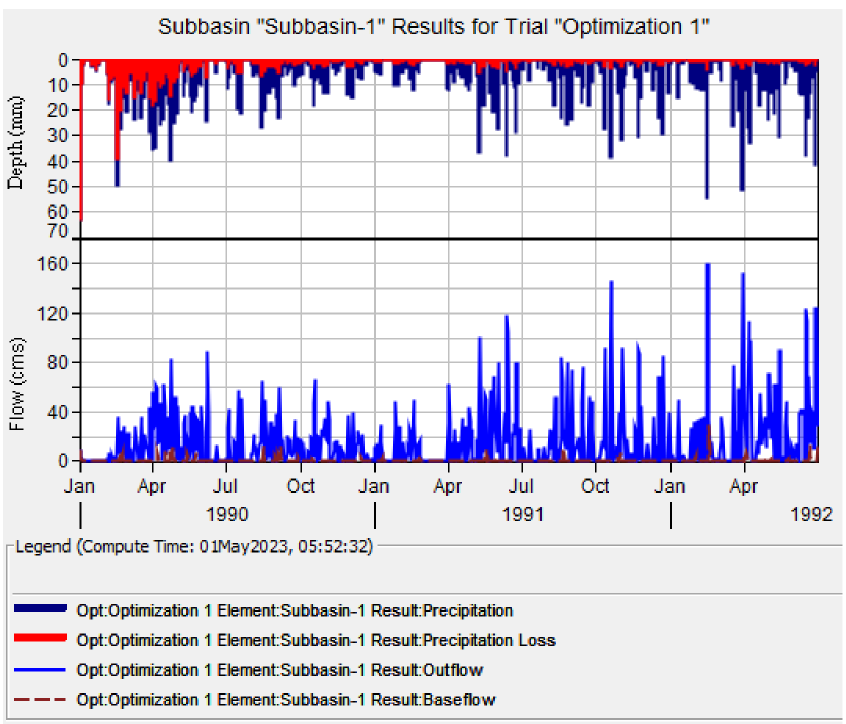

Figure 7: Calibration Optimisation Simulation Element

For the calibration (Figure 8), the optimisation trials of the parameterisation process yielded discharge outputs that were not acceptable performance according to the recommendations by Moriasi et al. (2007) and Van Liew et al. (2003). As indicated in Figure 8, the R^2 and NSE values for calibration of daily river discharge at sub-basin 1 were 0.52 and 0.36, respectively. From the hydrographs, the observed values exceeded the simulated values by 9.5 per cent. This is a margin considered reasonable for analysing the hydrologic modelling of the basin and not for forecasting purposes (Bajirao et al., 2021; Doherty & Johnston, 2003; Ogembo, 2018). Practical recommendations for future research and water resource management have been provided. These include specific areas for further investigation and actionable advice for policymakers to improve flood management and mitigation strategies.

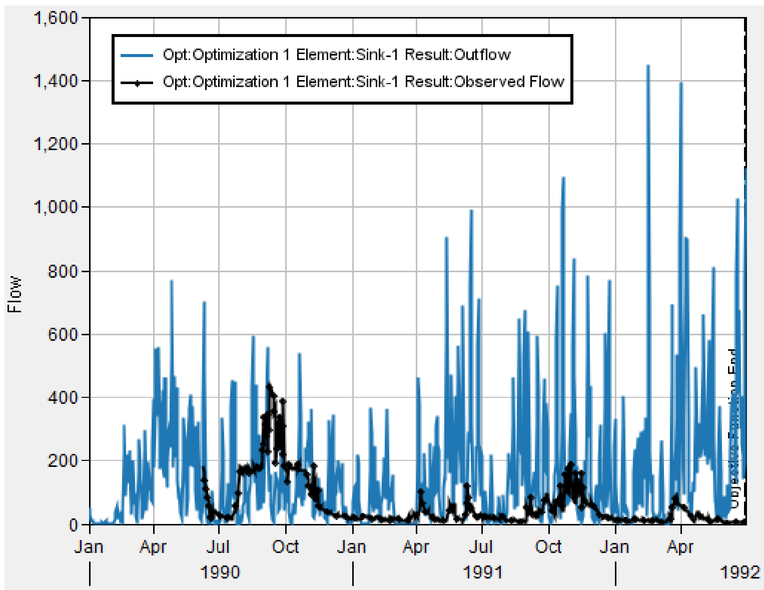

Figure 8: Calibration of HEC-HMS using Observed River Discharge Data at 1KB05

Figure 9 shows the validation trial simulations for the Gucha-Migori River Basin.

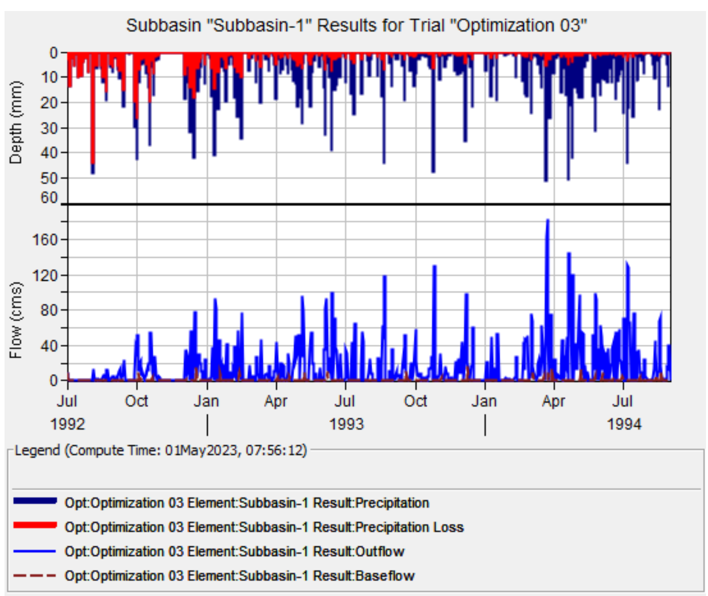

Figure 9: Validation Optimisation Simulation Element

Simulations were accomplished using the optimised values, but the output hydrograph for the validation was not the perfect match to that of the observed river discharges (Figure 9). As given in Figure 10, R^2 and NSE values for validation of daily river discharge were 0.42 and 0.31, respectively.

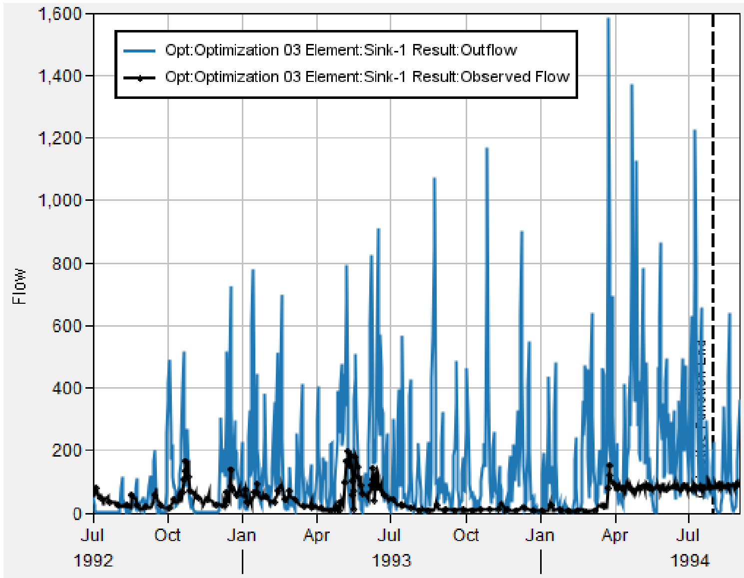

Figure 10: Validation of HEC-HMS using Observed River Discharge Data at 1KB05

The reduction in the coefficient of determination value from 0.52 to 0.42 could have been a result of errors in the rainfall and streamflow data due to several missing data points. Another factor that could have led to this reduction may be due to the merging of 49 sub-basins to simplify the simulation process. The most likely factor for such a variation may be associated with the fact that the precipitation data did not represent the spatial variability of the entire basin. Besides, in the research carried out by Yassin et al. (2015) in Pakistan, the validation results linked to a single meteorological station were also less than the calibration results, with an NSE value of 0.44. They further recommended the use of many weather station datasets to meet international standards and improve the modelling accuracy.

These results (Figures 8 and 10) are close to those attained by Hashmi (2005) when studying rainfall–runoff modelling from the Kaha hill torrent watershed in Pakistan, where a difference of 8.2 per cent was considered acceptable. Since the difference in the observed and simulated did not exceed 10 per cent, these results were within the permissible limits for inference of the correlation between the precipitation and river discharge datasets. However, as had been expected, the HEC-HMS model underestimated most of the peak flows and low flows. Other studies carried out in the same river basin with corresponding HEC-HMS performance include Ogembo (2018).

Correlation between River Discharge and Precipitation Variability

As presented in Figure 11, the relationship between river discharge and precipitation was evaluated using a two-tailed Pearson correlation coefficient.

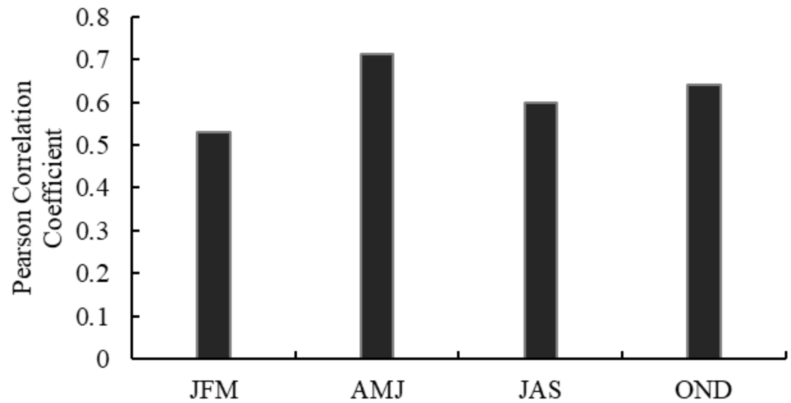

Figure 11: Pearson Correlation Coefficient Between Precipitation and River Discharge

Based on Figure 11, the correlation coefficients between daily-averaged precipitation for JFM, AMJ, JAS, and OND and the corresponding river discharges were significant at the 0.05 level. Out of all the precipitation and simulated river discharge datasets in all the months, the strongest relationship (r = 0.714) was found in wetter months (April, May, and June) while the weaker correlation (r = 0.529) was realised in dry months (January, February, and March).In practice, it is often necessary to solve problems involving variables, which by experience are known to have an inherent relationship (Su et al., 2012; Weisberg, 2005). Thus, it can be concluded with 95 per cent confidence that the precipitation data is a key and useful variable for modelling spatial and temporal river discharge variability in the Gucha-Migori River Basin.

Figure 12 represents standardised hydrometric indices for the season from January to March. The season is characterised by 18 positive and 25 negative indices. From the correlation analysis of the JFM, precipitation values could only account for 28 per cent of the river discharge variance; hence, the total number of negative (wet conditions) and positive (dry conditions) indices out of the total number of the standardised hydrometric indices.

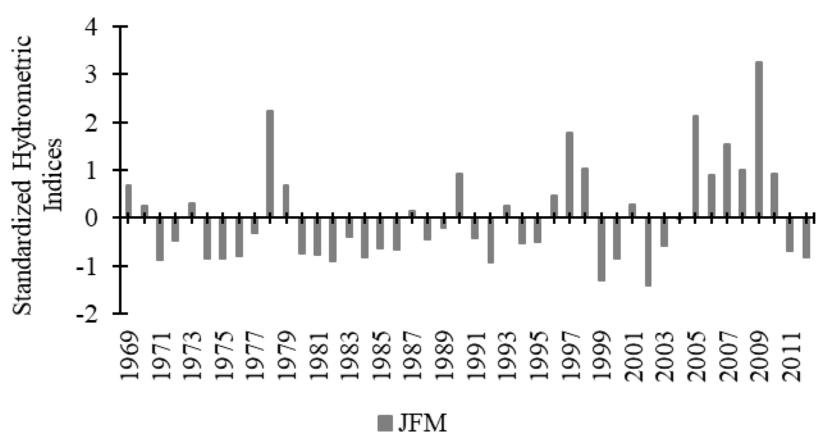

Figure 12: Standardised Hydrometric Indices for January, February, and March

Figure 13 shows river discharge variability for the period (1969 – 2012) for the season from April to June. A total of 22 years had positive indices, while 20 had negative indices. However, precipitation data could only explain 51 per cent of the variability in the hydrometric patterns of the simulated river discharge data for the aforementioned season.

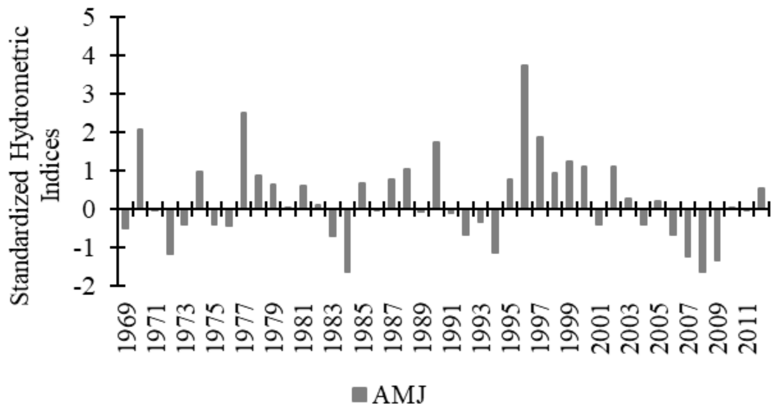

Figure 13: Standardised Hydrometric Indices for April, May, and June

As indicated in Figure 14, 23 years had positive indices while 21 had negative indices for river discharge variability for the period (1969 – 2012) for the season from July to September. Nevertheless, the precipitation dataset could only account for 36 per cent of the variance of the simulated values and variability of the hydrometric patterns of the simulated river discharge data.

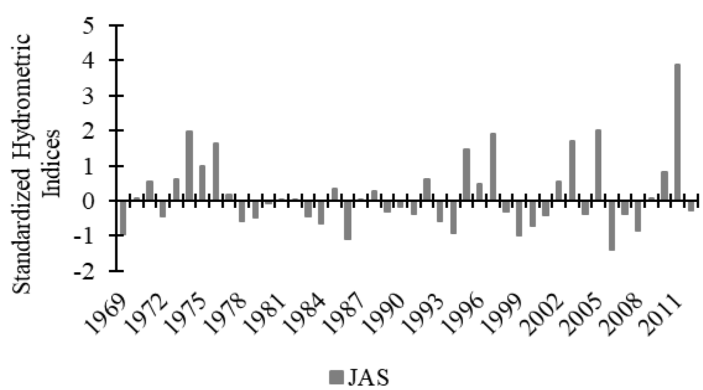

Figure 14: Standardised Hydrometric Indices for July, August, and September

Figure 15 represents river discharge variability for the period (1969 – 2012) for the season from October to December. A total of 12 years had positive indices, while 30 had negative indices.

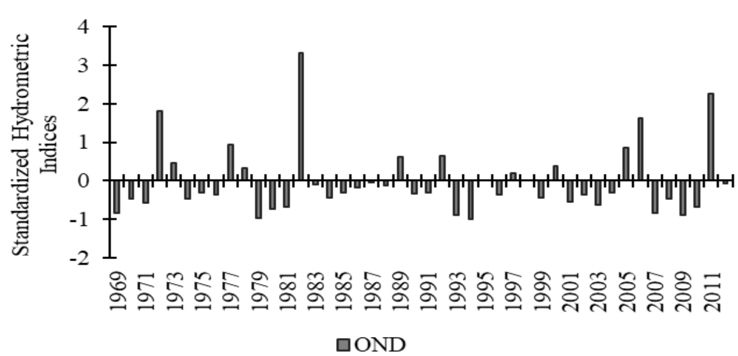

Figure 15: Standardised Hydrometric Indices for October, November, and December

Nonetheless, precipitation values could only explain 41 per cent of the variability in the hydrometric patterns of the simulated river discharge datasets. Some of the related studies with corresponding analyses on discharge hydrometric indices entail Gao et al. (2011) and Jahangir and Yarahmadi (2020). In the aforementioned studies, the +0.5 and -0.5 hydrometric indices represented extreme wet and dry climatic conditions, respectively. It implies that for the case of the Gucha-Migori River Basin, flood occurrences were simulated by the HEC-HMS model in 12, 18, 13, and 8 years for the seasons JFM, AMJ, JAS, and OND, respectively. There was sufficient evidence of the close relationship between precipitation variability and simulated river discharge temporal variations.

CONCLUSION AND RECOMMENDATIONS

Conclusion: The HEC-HMS model demonstrated moderate performance in simulating daily river discharge, with R^2 values of 0.52 during calibration and 0.42 during validation, and NSE values of 0.36 and 0.31, respectively. The significant positive correlation between daily precipitation and river discharge across different seasonal periods (JFM, AMJ, JAS, OND) indicates that precipitation is a critical driver of river discharge variability in the basin. These results highlight the need for further refinement of the model to improve predictive accuracy.

Recommendations: The HEC-HMS model should be employed with reliable data from multiple meteorological stations to better understand the spatial-temporal effects of precipitation variability on river discharge. This approach may help reduce errors and uncertainties during the modelling set-up, parameterisation, calibration, and validation processes.

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