

Rainfall-Runoff Hydrological Modeling Using Observed and Remotely Sensed Rainfall Data for Sustainable Watershed Management over Modjo Catchment, Central Ethiopia: Insights from HEC-HMS Model

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Article

Rainfall-Runoff Hydrological Modeling Using Observed and Remotely Sensed Rainfall Data for Sustainable Watershed Management over Modjo Catchment, Central Ethiopia: Insights from HEC-HMS Model

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Abstract: The primary obstacle in making accurate runoff predictions in the catchment is the unavailability of precise rainfall measurement data. The objective of this study is to apply the HEC-HMS to estimate runoff using observed and satellite precipitation products over the Modjo catchment and measure and compare the performance of each simulation. The study considered two commonly used gridded precipitation products: CHIRPS. In the HEC-HMS model setup, the study used the SCS Curve Number, SCS Unit Hydrograph, and the Muskingum method for Loss, transform, and routing model, respectively. Hydro-meteorological data, collected daily, were compiled and prepared for the process of model calibration (spanning 2010-2019) and validation (2020-2023). Results showed that NSE, R^2 , and PBIAS values become 0.842, 0.85, and -2.99 for observed rainfall products and 0.711, 0.72, and +5.6 for CHIRPS rainfall products during calibration and 0.751, 0.78, and -3.112 for observed rainfall products and 0.622, 0.64, and +7.99 for CHIRPS rainfall products during validation. The estimated peak flood discharge simulated with observed, and CHIRPS data was 288.9 m³/s, and 369.2 m³/s, then compared with the observed stream flow of 248.1 m³/s. The model results have revealed that global precipitation products have showcased a promising and observed precipitation an effective performance in simulating runoff over the Modjo catchment and are recommended for further investigation to improve the accuracy.

Keywords: flood; HEC-HMS; hydrological modeling; Modjo; rainfall; and runoff

Highlights

- Precipitation is the major data required for hydrological simulations, and satellite precipitation products have become more common to fill the gap of precipitation discontinuity.
- CHIRPS are currently commonly used gridded satellite precipitation products used worldwide.
- The present study compares the performance of observed and CHIRPS products for runoff generation.
- The results revealed that the satellite precipitation products demonstrated good and satisfactory results.

1. Introduction

Global water resources are facing escalating threats due to rising demand driven by rapid urban development, population increase, and the impacts of climate change. Climate change effects, including modified rainfall patterns, higher temperatures, and severe weather occurrences, significantly influence water resources (Gebre, 2015). Hydrological and associated water-evaluation simulations have been extensively utilized to tackle a wide range of water resource issues around the world (Akoko et al., 2021). Precisely forecasting daily streamflow within the basin is essential for reducing flood damage and facilitating early alerts (Iamampai et al., 2024). Hydrological models are vital for enhancing the comprehension of hydrological processes, managing and analyzing water resources, ensuring their sustainable use, and supporting informed decision-making and planning. To tackle the issue of insufficient observed data at the local level for water resource planning and

utilization within the river basin, the hydrologic simulation approach has become extensively employed in recent years (Marahatta et al., 2021). Rainfall-runoff hydrological models for catchments are essential in hydrological research (Chakravarti et al., 2015). Hydrological models can enhance the understanding of the functions of various components within the hydrological cycle for each catchment, while also providing a foundation for modeling additional hydrological processes (Flores et al., 2021). Hydrological models are extensively utilized for the comprehensive evaluation and management of water resources within catchments (Ruan et al., 2017). Grasping the intricate connections between rainfall and runoff processes is crucial for accurately forecasting surface runoff (Fereidoon et al., 2019). Modeling surface runoff is employed to analyze catchment yields and their responses, assess water availability, track changes over time, and make predictions (Knights, 2017). Runoff modeling is used to gain insights into watershed productivity and responses, as well as to anticipate water availability, monitor changes over time, and predict extreme events (Jehanzaib et al., 2022). The administration and planning of water resources, such as irrigation management, river basin engineering, reservoir operations, and navigation, greatly depend on runoff modeling (Ranjan & Singh, 2022). Rainfall-runoff models are commonly employed to evaluate climate risks by forecasting alterations in streamflow and other hydrological processes resulting from expected human-induced climate change (Watson et al., 2022). However, modeling the runoff process poses a significant hydrological challenge due to its inherent randomness and complex spatial and temporal dynamics (Shekar et al., 2023), and is affected by precipitation characteristics, catchment shape, and size, soil types, land use and topography are the main factors affecting runoff from a catchment (Ranjan & Singh, 2022).

The existing modeling techniques are typically classified into one of three categories: (i) Empirical models, (ii) Conceptual models, and (iii) Physically-based models (Sidle, 2021). Empirical models are developed exclusively through the analysis of existing data, which is why they are often referred to as data-driven models. In contrast, physically-based models offer a more accurate representation of real-world phenomena by mathematically modeling these processes (Nath et al., 2020). Physical hydrological models, which are created to replicate the movement and storage of water within a watershed, are classified according to their spatial representation. Lumped models consider the entire basin as a single entity, averaging parameters and overlooking spatial variability (Okiria et al., 2022). Semi-distributed models segment the basin into smaller sub-basins, providing a degree of spatial differentiation while simplifying the interactions between these areas (Fathy et al., 2015). In contrast, distributed models utilize a fine grid to represent every point within the basin, effectively capturing complex spatial heterogeneity and delivering the most detailed and realistic simulations (Pelletier & Andréassian, 2022). The selection of these models is influenced by various factors, including the objectives of the study, the complexity of the basin, the availability of data, and the computational resources at hand. Lumped models are appropriate for rapid assessments, semi-distributed models are suitable for basins of moderate complexity, while distributed models are best for in-depth investigations.

The advancement of computer technology and programming has enabled academics, industries, and researchers to develop a variety of software tools for modeling watershed processes (Chathuranika et al., 2022). Among many other available computer models used for simulating rainfall-runoff processes, the Soil and Water Assessment Tool (Arnold et al., 2012), the Hydrologic Engineering Centre-Hydrologic Modelling System (Cazanescu et al., 2012), Artificial Neural Network (Dawson & Wilby, 1998) are frequently used by hydrological modelers around the world. The Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS) is a software program designed for hydrologic modeling, created by the US Army Corps of Engineers. It features an integrated tool for simulating the hydrologic processes of dendritic watershed systems (Hamdan et al., 2021). The HEC-HMS model is commonly utilized in numerous hydrological studies due to its ease of use, low data requirements, and ability to implement standard methodologies (Janicka & Kanclerz, 2023). The HEC-HMS model is lump-based (Chathuranika et al., 2022). Incorporation of a GIS workspace into HEC-HMS simplifies the modeling process and greatly enhances user experience

with the software. While numerous models have been created for watershed hydrology, the limited access to temporal and spatial data has been a major obstacle to their implementation, particularly in developing countries. (Kangsabanik & Murmu, 2017).

The modeling of catchment runoff and its precision are greatly affected by the availability and quality of rainfall data in the catchment area. Creating rainfall-runoff models in areas with limited data poses a considerable challenge, as it is often hard to acquire dependable precipitation information across the catchment. Most precipitation datasets are derived from weather stations; however, these gauge-based products encounter various issues, such as uneven station distribution and a lack of long-term, continuous observations, especially in developing regions where data scarcity and gaps are prevalent (Hu et al., 2024). In Ethiopia, the uneven distribution of rainfall gauging stations, marked by low data quality and considerable data gaps, undermines the overall reliability of rainfall information (Aniley et al., 2023; Chinasho et al., 2021; Gashaw et al., 2023; Gebere et al., 2015). In these situations, employing remotely sensed rainfall products can be an effective way to address the data shortfall. Remote sensing information can act as alternatives to conventional ground gauges in regions lacking sufficient rainfall and soil moisture data (Iamampai et al., 2024). These products, obtained from satellite observations, provide a useful alternative, particularly in developing nations where ground-based precipitation networks are scarce. Gridded precipitation data derived from gauge stations has been extensively studied and utilized to create hydrological models (Ruan et al., 2017).

The aim of this study is to assess the performance and variability of observed versus remotely sensed precipitation products in terms of their effectiveness for generating runoff. The research employed the widely utilized HEC-HMS hydrologic models to simulate and compare the streamflow generation capabilities within the Modjo River catchment in the Awash River basin, located in central Ethiopia. The study focused on the most commonly used global remote sensing precipitation datasets, specifically the Climate Hazards Infrared Precipitation with Station (CHIRPS), which has a spatial resolution of 0.05 degrees. CHIRPS was selected for this investigation due to its thorough validation across Africa, which has shown its ability to effectively capture rainfall variability and trends in comparison to ground observations (Dagne et al., 2024). The model was calibrated between 2010 and 2019 (for 10 years) and validated from 2019 to 2023 (for 4 years) at the same discharge station. The hydrologic model statistical performances for both models were examined using the Coefficient of Determination (R^2), Percentage of bias (PBIAS), and the Nash Sutcliffe Efficiency (NSE). These parameters were used to determine the streamflow computational capabilities.

2. Materials and Methods

2.1. Study Area Description

The research was conducted in the Modjo catchment of the Awash River basin, situated in the Oromia Regional State of Ethiopia. Its precise location spans Latitudes: 8°40' to 9°4'N and Longitudes: 38°45' to 39°13'E, as illustrated in Figure 1. The area covers roughly 1,420 square kilometers. The catchment features rolling topography, extensive and deep valleys formed by small streams, and narrow flatlands in the southern region, which have been affected by inadequate land-use practices, soil erosion, and deposition processes (Besha et al., 2022). The catchment consists of three primary soil types: eutric cambisol, eutric nitosol, and pellic vertisol. Elevations within the catchment range from 1,764 to 3,091 meters. The slope of the catchment is expressed as a percentage, varying from 0% to 200.48%. It receives an average annual rainfall of 427 mm, with values ranging from 387 mm to a peak of 511 mm. The average minimum and maximum monthly temperatures in the area fluctuate between 9.96 °C and 18.76 °C, and 26.8 °C to 35.70 °C, respectively. The highest temperatures occur in May, while the lowest are recorded in December. The main rainy season spans from June to September. The catchment is mainly characterized by lumped watershed features, predominantly covered by agricultural land, and is classified as Hydrological Soil Group C. Its geographical location, approximately 70 km east of Addis Ababa, enhances its importance in the context of regional

hydrology. In the study area, the catchment and its tributaries consistently supply water to the Modjo River (M. G. Alemu et al., 2022). The Modjo River acts as a tributary to the Awash River in central Ethiopia. The catchment area is located near Modjo town (see Figure 2), providing vital data for hydrological studies and assessments. This river is significant for the local ecosystem and water resources, and it connects with other tributaries.

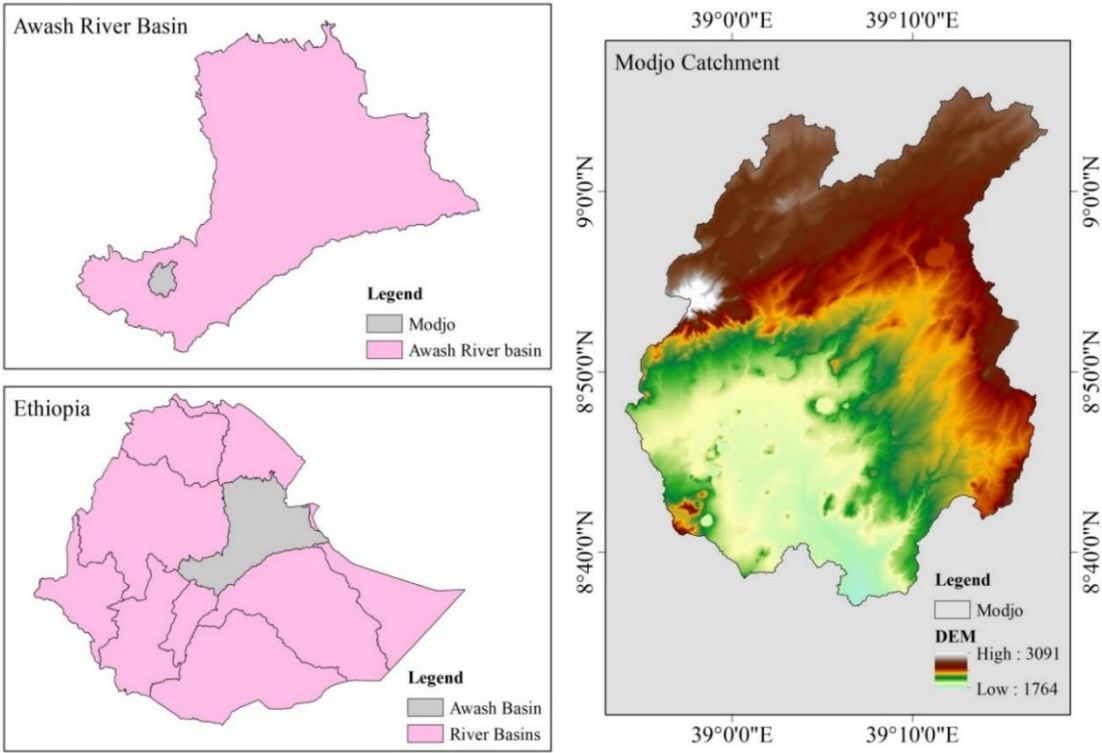


Figure 1. Study Area.



Figure 2. Modjo River at the Modjo River gauging station (near Modjo town).

2.2. Data Sets

HEC-HMS rainfall-runoff modeling necessitates data on land use and land cover (LULC) to assess infiltration and runoff rates, rainfall data to characterize events and their intensity, streamflow data for model calibration and validation, a Digital Elevation Model (DEM) to outline the basin and flow paths, and soil data to evaluate infiltration and runoff characteristics. The streamflow data collected was measured at the outlet of the Modjo catchment, situated near Modjo town. The recorded rainfall was sourced from three gauging stations within the Modjo catchment: Chefe Donsa, Ejere, and Modjo meteorological stations. In addition to the observed data, satellite precipitation products, specifically CHIRPS, were obtained. A summary of the data utilized is presented in the Table 1 and Figure 3.

Table 1. Summary of data used.

Data type	Source	Spatial resolution	Purpose	Temporal resolution	Date of acquisition
DEM	USGS	30m × 30m	Terrain processing	-	01/08/2024
Soil map	FAO		CN generation	-	01/08/2024
LULC	Esri	10m × 10m	CN generation	2023	01/08/2024
Observed rainfall	NMAE	Point data	Model simulation	2009 – 2023	14/07/2024
CHIRPS	UCSB/CHG	0.05°	Model simulation	“	02/08/2024
Observed streamflow	MoWE	Point data	Validation and calibration	“	21/07/2024

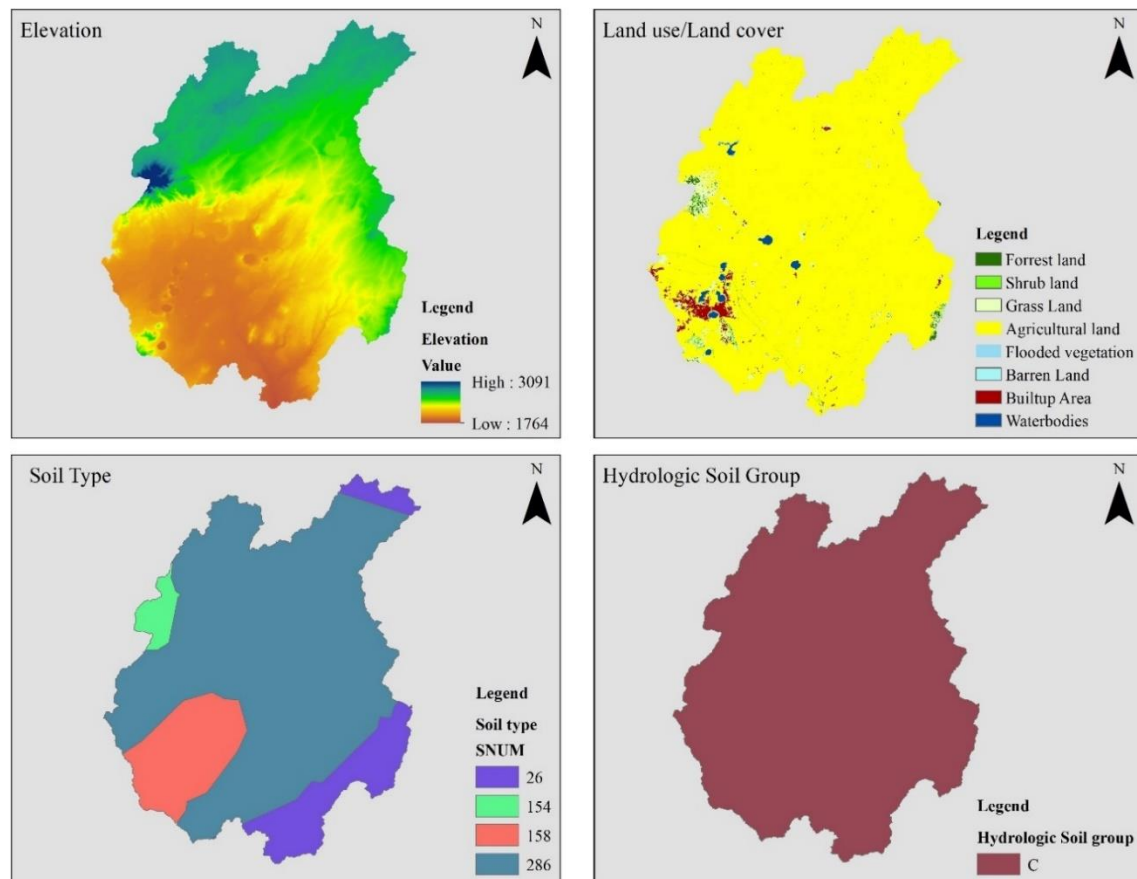


Figure 3. Data used.

The CHIRPS rainfall products, from 2009 to 2023, were extracted using the Google Earth Engine cloud API using the `ee.ImageCollection` algorithm and a filter command (`ee.Filter.calendarRange`) to cover the study period from 2009 to 2023. Prior to their integration into the model processing, CHIRPS rainfall data were adjusted for bias, a crucial step for achieving improved outcomes.

2.3. HEC-HMS Model Construction

All modifications were performed using HEC-HMS version 4.11, which includes five key components for developing the hydraulic model: terrain preprocessing, basin models, meteorological models, control specifications, and time-series data. The methods employed in this study are summarized in the figure below (Figure 4).

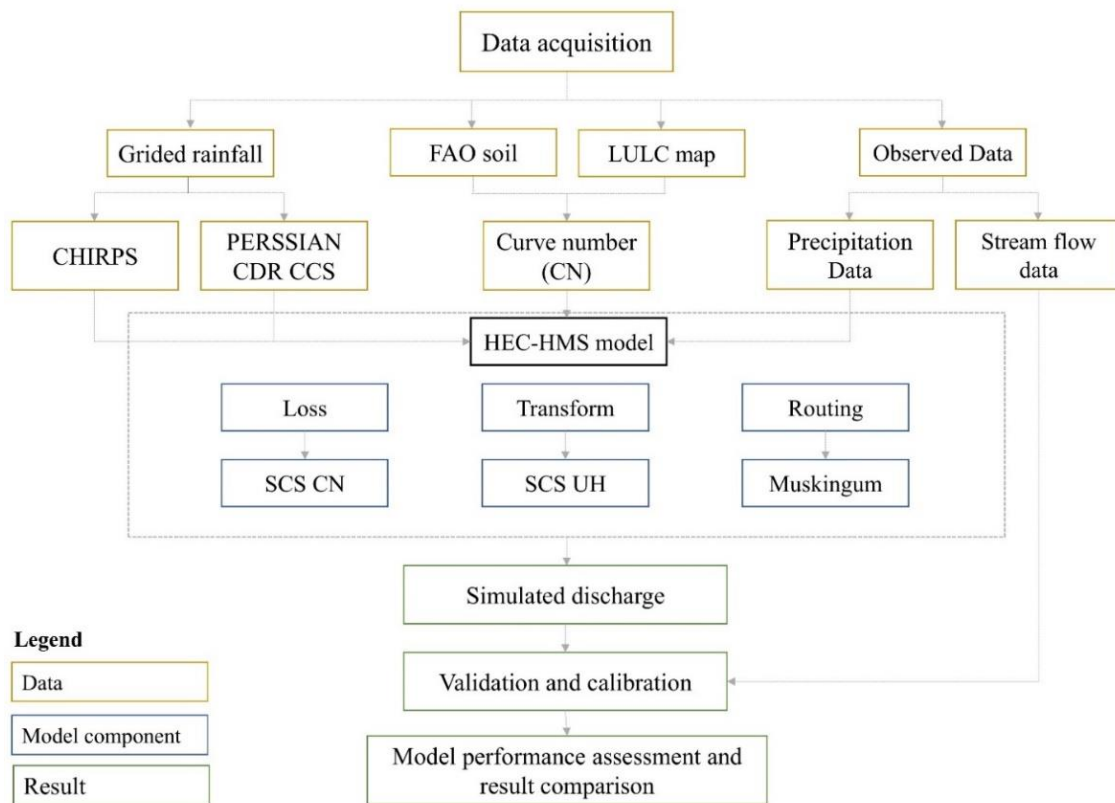


Figure 4. Methodology flowchart.

2.3.1. Loss Model

The loss method in HEC-HMS is a vital component for simulating the rainfall-runoff interactions within a watershed. It focuses on quantifying the volume of rainfall that is absorbed through infiltration and various processes prior to contributing to surface runoff (Hamdan et al., 2021). The loss method applied in this study is the Soil Conservation Service (SCS) Curve Number technique. This approach aims to estimate direct surface runoff resulting from rainfall by establishing an empirical connection between precipitation and various land conditions, including soil type and land use (Derdour et al., 2018). The curve number (CN) values rise linearly with the potential for runoff and decrease inversely in relation to the infiltration coefficient (Horablaga et al., 2024). The net rainfall was estimated as follows Eq. (1) (Yu & Zhang, 2023):

$$Pe = \frac{(P - Ia)^2}{P - Ia + S} \quad (1)$$

Where Pe is effective rainfall; P is rainfall; Ia is an initial abstraction, assumed to be 20 percent of S ; S is potential maximum retention after runoff begins, which can be estimated by Eq. (2) (Yu & Zhang, 2023)(Fanta & Feyissa, 2021):

$$S = \frac{25400 - 254CN}{CN} \quad (2)$$

Where CN is the runoff curve number.

2.3.2. Transform Model

In HEC-HMS, the transform model is an essential element that converts surplus rainfall into runoff. For this study, the Soil Conservation Service Unit Hydrograph model was chosen to calculate runoff. This approach necessitates estimating the lag time (TL), which is defined as the duration from

the centroid of the excess rainfall to the centroid of the direct runoff (Horablaga et al., 2024; Jabbar et al., 2021). The sole input parameter for this method is lag time (Tlag), which is influenced by the time of concentration (TC). Both lag time (TL) and time of concentration (TC) are parameters that dictate the speed at which a watershed reacts to rainfall across its area (Guduru et al., 2023). Time of Concentration is defined as the time required for a drop of water to travel from the most hydrologically remote point in a watershed to the point of collection. The lag time was computed using Eq. (3) (Jabbar et al., 2021).

$$T_{Lag} = 0.6 \times Tc \quad (3)$$

The time of concentration can be estimated based on basin characteristics including topography and the length of the reach by Kirpich's formula Eq. (4) (Kirpich, 1940).

$$Tc = 0.0078 \times \left(\frac{L^{0.07}}{S^{0.385}} \right) \quad (4)$$

Where L is the reach length in feet, and S is the slope.

2.3.3. Routing Model

HEC-HMS offers several routing techniques to model the flow of water through river segments, and in this study, the Muskingum method was employed. The Muskingum method is a widely used hydrologic routing approach in HEC-HMS that simulates the propagation of flood waves through a river segment by accounting for both storage and flow relationships over time (Baláz et al., 2011). This model requires two input parameters: the travel time of the flood wave (k) through a specific routing segment and the factor for attenuating the flood wave (Tangam et al., 2024). Eq. (5) was adopted in the present study as the Muskingum equation (Maharathi, 2021).

$$S = k[XI + (1 - X)Q] \quad (5)$$

Where K is Flood wave traveling time ($0 \leq K \leq 150$), X is a weighting factor, I is inflow, Q is outflow, and S is storage.

2.3.4. Calibration and Validation

Model calibration and validation are critical processes in hydrological modeling that ensure the reliability and accuracy of simulations. Proper calibration and validation play a crucial role in enhancing water resource management and decision-making, especially in light of climate change and various environmental challenges. Model Calibration in HEC-HMS involves adjusting model parameters to ensure that the simulated runoff closely matches observed streamflow data. This process typically uses historical hydrological data to fine-tune parameters such as curve numbers, loss rates, and routing coefficients. Model Validation follows calibration and involves testing the model's predictive capability using a different dataset that was not used during the calibration phase. Model validation involves evaluating the model's ability to replicate observed data that was not utilized during the calibration phase, ensuring this is done with an acceptable level of accuracy. This step is crucial to confirm that the model can accurately simulate runoff under various conditions. The present study utilizes approximately 75% of the available data for calibration, covering the period from 2010 to 2019, while the remaining data was reserved for validation, spanning from 2020 to 2023. This approach ensures that the model is effectively tuned to historical data before being tested against a separate dataset to evaluate its predictive accuracy.

2.4. Model Simulation Evaluation

Assessing the effectiveness of hydrological models such as HEC-HMS is vital for confirming their dependability in simulating runoff and other hydrological elements. In this study, various statistical methods were utilized to evaluate how accurately the model simulations reflect observed data, which is crucial for efficient water resource management and planning. The techniques were applied to both simulations: one using actual rainfall data and the other utilizing CHIRPS rainfall data. This research considered the evaluation of the model's performance through metrics such as Nash-Sutcliffe Efficiency (NSE), Percentage of Bias (PBIAS), and the coefficient of determination (R^2), which are widely recognized indicators in hydrological modeling.

2.4.1. Nash-Sutcliffe Efficiency (NSE)

Nash-Sutcliffe Efficiency (NSE) is a statistical indicator utilized to assess the forecasting capability of models by comparing the values that are observed with those that are simulated (McCuen et al., 2006). It is especially significant in hydrology for evaluating how effectively a model can mirror real-world data. NSE assesses the relative disparity between the extent of residual data variance ("noise") and the variance of the measured data ("information") (USACE, 1998). NSE was computed using Eq. (6) (Arciniega-Esparza et al., 2022; Guduru & Mohammed, 2024)

$$NSE = 1 - \frac{\sum (Q_{ob(t)} - Q_{sim(t)})^2}{\sum (Q_{ob(t)} - Q_{ob})^2} \tag{6}$$

2.4.2. Coefficient of Determination (R^2)

R^2 describes the degree of collinearity between simulated and observed data (USACE, 1998). The value of R^2 was computed using Eq. (7) (Muleta & Marcell, 2023).

$$R^2 = \frac{\sum (Q_{ob(t)} - \bar{Q}_{obs}) \sum (Q_{sim(t)} - \bar{Q}_{sim(t)})}{\sum (Q_{ob(t)} - \bar{Q}_{obs})^2 \sum (Q_{sim(t)} - \bar{Q}_{sim(t)})^2} \tag{7}$$

Where Q_{obs} is simulated stream flow at a time t , and Q_{sim} is simulated flow at time t .

The following table (Table 2) the range of NSE and R^2 and their satisfactory classes.

Table 2. NSE and R^2 acceptability range.

Measurements	Very good	Good	Satisfactory	Unsatisfactory
NSE	0.75–1	0.65–0.75	0.50–0.65	<0.50
R^2	0.75–1	0.65–0.75	0.50–0.65	<0.50

2.4.3. Percentage of Bias (PBIAS)

The Percentage of Bias (PBIAS) is a statistical measure employed in HEC-HMS to evaluate the precision of model simulations compared to actual observed data (Faty et al., 2023). It quantifies the average tendency of the simulated values to either surpass or fall below the true observed values (Kumar et al., 2024). The following equation was used to calculate PBIAS in this study (Goodarzi et al., 2024).

$$PBIAS = \frac{\sum_{i=1}^n (Q_{o,i} - Q_{s,i})}{\sum_{i=1}^n (Q_{o,i})} \times 100 \tag{8}$$

The following table (Table 3) the range of PBIAS and their satisfactory classes.

Table 3. General Performance evaluations for suggested statistics related to PBIAS (JHS et al., 2019).

PBIAS	value<±10	±10≤value<±15	±15≤value<±25	value≥±25
Performance	Very good	Good	Satisfactory	Unsatisfactory
Rating				

2.5. Limitations of the Study

Recognizing the limitations and shortcomings of research is essential in any study. In this particular research, several notable limitations have been identified. First, there is a significant issue with observed data discontinuity. Effective runoff simulation models rely on accurate observed data for simulation, calibration, and validation, which includes actual precipitation and stream flow data. Unfortunately, our analysis reveals substantial discontinuities in the data, potentially affecting the reliability and applicability of the findings. Additionally, another limitation is that the study concentrates on a single-gridded global precipitation product. This focus restricts the exploration and comparison of multiple datasets, which could provide a more comprehensive understanding of the results.

3. Results and Discussions

3.1. Model Setup Results

The HEC-HMS software was utilized to convert precipitation data into direct runoff, taking into account the terrain and surface characteristics of the area being modeled. The basin model is a vital component of the HEC-HMS system, enabling an accurate representation of the rainfall-runoff interactions throughout the entire watershed. Calibration of the model occurred over a decade, from 2010 to 2019, with validation spanning four years, from 2020 to 2023, including an initial year at the same discharge monitoring station. To develop the catchment basin model, a thorough delineation process was performed, leading to the identification of ten unique sub-basins and fourteen flow paths, leveraging the GIS functionalities embedded in HEC-HMS. For the evaluation of these sub-basins and flow paths (see Figure 5), three distinct modeling strategies were considered: the Loss Model, the Transform Model, and the Routing Model. Each of these modeling frameworks requires specific types of input data to operate efficiently, underscoring the necessity of customized data needs for each model component. This comprehensive strategy guarantees a robust simulation of hydrological processes within the watershed.

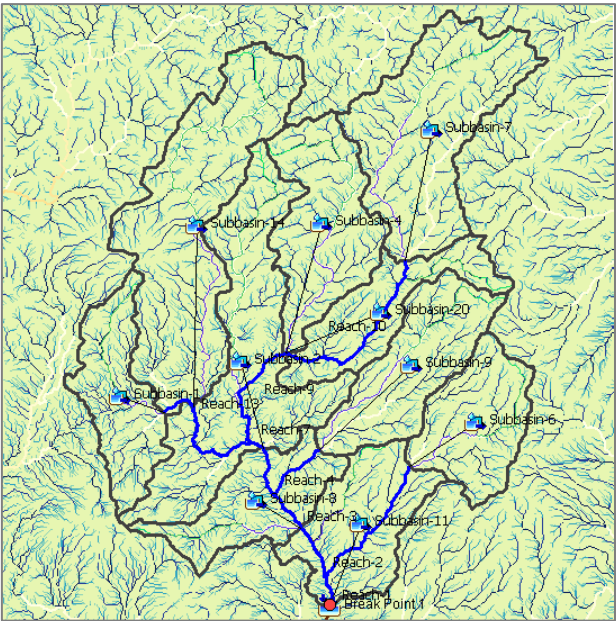


Figure 5. HEC-HMS model set-up for simulation.

3.2. Sensitivity Analysis

Identifying the most sensitive variables in the Modjo catchment is the initial step in calibrating and validating the HEC-HMS model. Sensitivity analysis was a key component of the model, helping to pinpoint the most sensitive parameters. This assessment was performed through the NSE index by modifying the values of different model parameters. Furthermore, the sensitivity analysis method is employed to assess the influence of hydrologic parameters on the runoff hydrograph for the specific catchment. Therefore, the sensitivity analysis included parameters such as the curve number, Muskingum K, Muskingum X, initial abstraction, lag time, and recession constant. Based on the analysis, it was noticed that the main parameter which affect runoff quantities were the recession constant and curve number (Figure 6). The parameter lag time and Initial abstraction were the third and fourth control effects on NSE, respectively. The remaining parameters were not showed significant changes on value of NSE. The same kind of observation was also highlighted in a study by (G. T. Alemu et al., 2023).

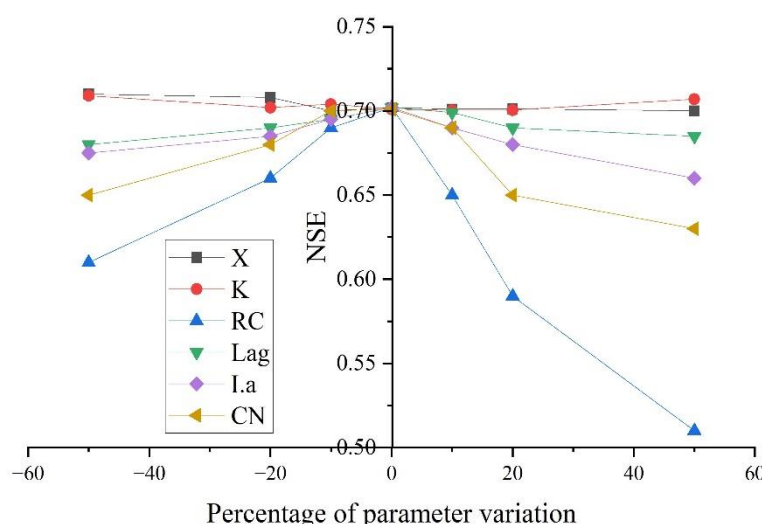


Figure 6. Sensitivity analysis plot for HEC-HMS parameters.

3.3. Model Simulation with Observed Rainfall Data

The statistical parameters applied to evaluate the modelling process demonstrated a strong alignment between the observed and simulated discharge values for the Modjo catchment. The analysis of daily rainfall-runoff simulations over the Modjo catchment using HEC-HMS reveals critical insights into model performance during both the calibration phase (2010-2019) and the validation phase (2020-2023). During calibration, the Nash-Sutcliffe Efficiency (NSE) of 0.842 indicates a strong correlation between observed and simulated runoff, suggesting that the model effectively captures the hydrological dynamics of the catchment. This high NSE value, approaching 1, signifies reliable predictions, while the Percent Bias (PBIAS) of -2.89 reflects a slight underestimation of runoff, remaining within acceptable limits and indicating minimal bias. Additionally, the Coefficient of Determination (R^2) of 0.85 implies that 85% of the variance in observed runoff can be explained by the model, reinforcing its credibility. However, during the validation phase, the NSE decreases to 0.751, indicating a decline in predictive capability and raising concerns about the model's adaptability to new data. The PBIAS shifts to -3.112, suggesting a transition towards overestimation of runoff, which may reflect changes in rainfall patterns or other hydrological factors inadequately captured during calibration. Furthermore, the R^2 value drops to 0.780, indicating that the model explains only 78% of the variance in observed runoff during validation, highlighting potential deficiencies in capturing hydrological processes under varying

conditions. Collectively, these findings underscore the necessity for ongoing refinement and validation of the HEC-HMS model to enhance its predictive accuracy and reliability in simulating runoff within the Modjo catchment. The hydrological modeling results revealed a close correspondence between the simulated and observed hydrographs, as shown in Figure 7.

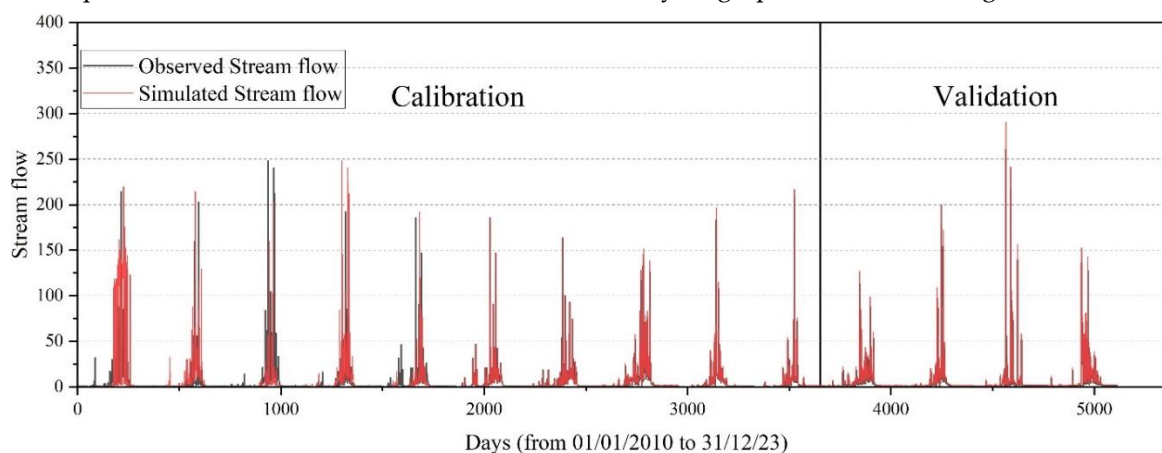


Figure 7. Simulated and observed hydrographs in calibration and validation period based on a daily basis using observed precipitation data.

3.4. Model Simulation with CHIRPS Rainfall Data

The statistical metrics used to assess the model's performance highlighted a strong correlation between observed and simulated discharge values for the Modjo catchment. The evaluation of daily rainfall-runoff simulations using CHIRPS precipitation data over the Modjo catchment through HEC-HMS reveals important quantitative insights during both the calibration phase (2010-2019) and the validation phase (2020-2023). During calibration, the Nash-Sutcliffe Efficiency (NSE) of 0.711 indicates a moderate correlation between observed and simulated runoff, suggesting that while the model captures some hydrological dynamics, there is room for improvement in its predictive accuracy. The Percent Bias (PBIAS) of +5.6 indicates a slight overestimation of runoff, which, although within a tolerable range, suggests that the model may not fully account for certain hydrological processes. The Coefficient of Determination (R^2) of 0.72 implies that the model can explain 72% of the variance in observed runoff, reinforcing its utility but also highlighting limitations in capturing the full complexity of the catchment's hydrology. In the validation phase, the NSE decreases to 0.622, indicating a further decline in predictive capability and raising concerns about the model's generalizability to new data. The PBIAS increases to +7.98, suggesting a growing tendency to overestimate runoff, which may reflect changes in rainfall patterns or other hydrological factors that were not adequately represented during calibration. Additionally, the R^2 value drops to 0.64, indicating that only 64% of the variance in observed runoff is explained by the model during validation, pointing to significant deficiencies in accurately simulating runoff under varying conditions. Collectively, these findings underscore the need for ongoing refinement and validation of the HEC-HMS model to enhance its predictive accuracy and reliability in simulating runoff within the Modjo catchment. The hydrological modeling results revealed a close correspondence between the simulated and observed hydrographs, as shown in Figure 8. This figure compares the time series of discharge values, both simulated and observed, at the catchment outlet during the calibration period (2010-2019) and the validation period (2020-2023).

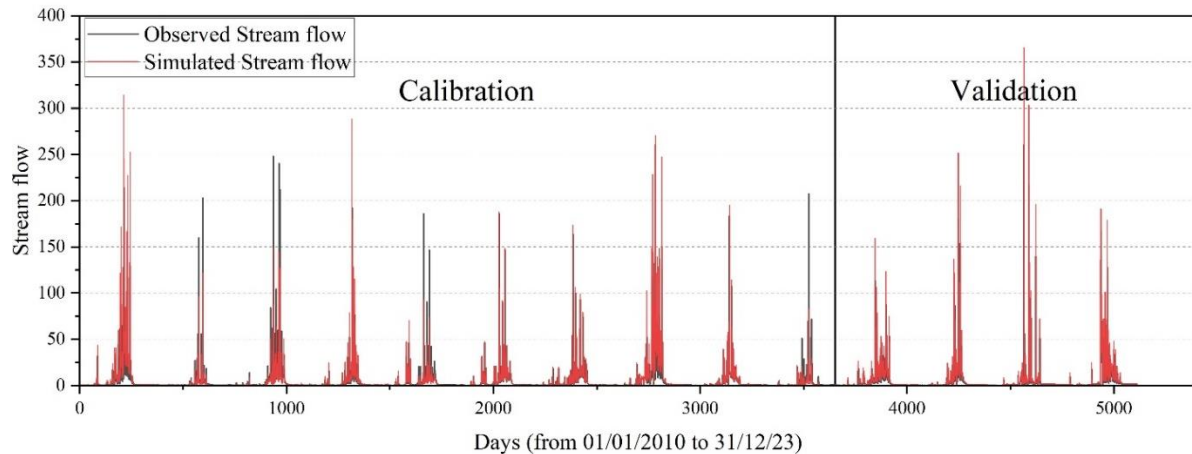


Figure 8. Simulated and observed hydrographs in calibration and validation period based on a daily basis using CHIRPS rainfall data.

The estimated peak flood discharge during both calibration and validation phases was 288.9 m^3/s for observed precipitation data and 369.2 m^3/s for CHIRPS data. In comparison, the observed stream flow was 248.1 m^3/s . This indicates that while the CHIRPS data significantly overestimated peak discharge, the observed precipitation data provided a closer approximation to the actual stream flow measurements. Graphical techniques, like comparing observed and simulated hydrographs, provide a way to visually evaluate the performance of a model. This approach highlights trends, discrepancies, and how closely the model outputs match actual data. A visual review of the monthly cumulative of simulated hydrographs in Figure 9 indicates that both simulations using observed rainfall data and CHIRPS rainfall data align closely with the observed hydrographs. The subsequent plot of monthly streamflow distribution during the calibration and validation periods offers additional visual insight for comparing the simulations with the observations. The pattern and form of the hydrograph appear to be similar.

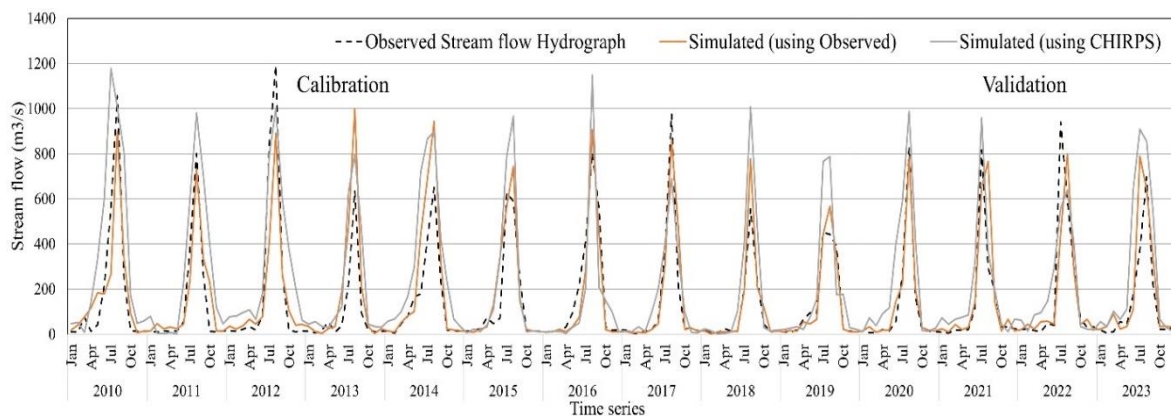


Figure 8. Monthly cumulative simulated and observed hydrographs in calibration and validation period.

The comparison of simulated and observed values for the entire watershed reveals that, while the model generally captured the trends and magnitudes of hydrological responses, discrepancies in specific areas suggest the need for further calibration and refinement of input parameters to improve accuracy. The correlation coefficients for simulations using observed data are 0.92 during the calibration phase and 0.88 during the validation phase. In contrast, the correlation coefficients for simulations based on satellite data are 0.85 for the calibration period and 0.80 for the validation period (Figure 10). The correlation between model simulations using observed rainfall data and CHIRPS rainfall data indicates that simulations based on observed precipitation datasets perform better than

those based on CHIRPS data. However, the differences in correlation are relatively small, suggesting that both datasets provide similar levels of accuracy in the simulations. This implies that while observed data may yield slightly superior results, CHIRPS data still offers a viable alternative for hydrological modeling. The following Taylor diagram plot illustrates the correlation coefficient between the observed data and the simulations, providing a visual representation of the model's performance concerning both datasets. This diagram helps to further understand the relationship between the observed and simulated rainfall, highlighting the strengths and weaknesses of each dataset.

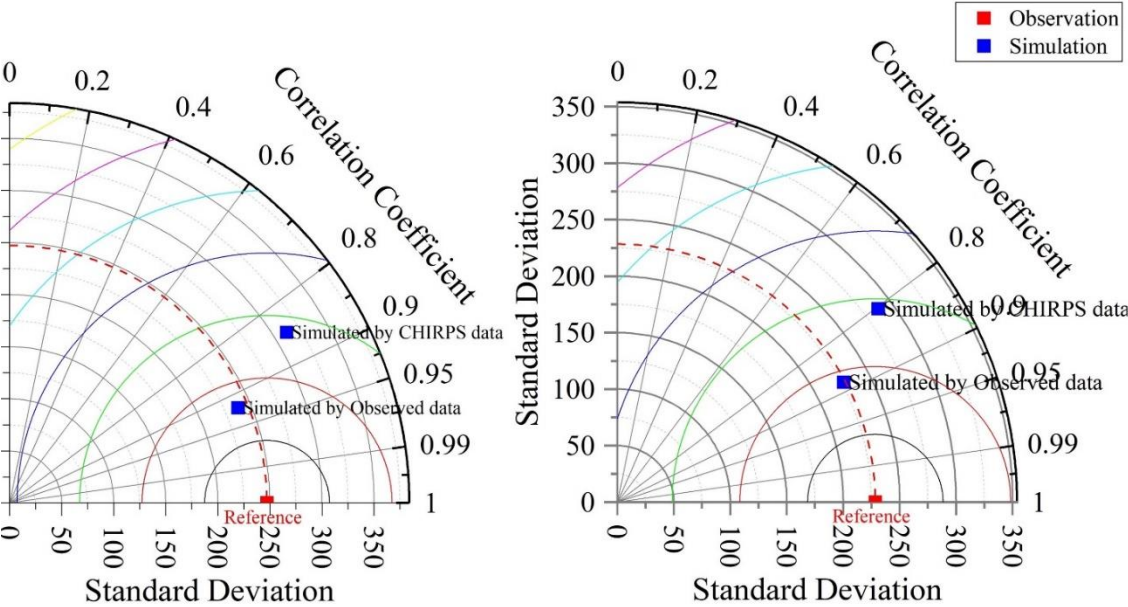


Figure 9. Tylor diagram for simulated and observed stream flow.

3.5. Comparison of Model Simulation by Observed and Satellite Precipitation Products

When comparing the results of rainfall-runoff simulations using CHIRPS precipitation data with those using observed precipitation over the Modjo catchment, several key differences emerge in terms of model performance metrics during both calibration and validation phases. For the CHIRPS data, the calibration phase yields an NSE of 0.711, indicating a moderate correlation between observed and simulated runoff, while the PBIAS of +5.6 suggests a slight overestimation of runoff. The R^2 value of 0.72 indicates that 72% of the variance in observed runoff is explained by the model, reflecting a reasonable fit but highlighting limitations in capturing the full hydrological dynamics. In contrast, the observed precipitation simulations demonstrate a higher NSE of 0.842 during calibration, suggesting a stronger correlation and more effective representation of hydrological processes. The PBIAS for observed data is -2.89, indicating a slight underestimation of runoff, which is generally more favorable than the overestimation seen with CHIRPS data. The R^2 value of 0.85 for observed precipitation further reinforces its credibility, as it explains 85% of the variance in observed runoff, showcasing a more robust model performance. During the validation phase, both datasets show a decline in model performance, but the observed precipitation maintains a higher NSE of 0.751 compared to the CHIRPS value of 0.622, indicating better predictive capability. The PBIAS for CHIRPS increases to +7.98, reflecting a growing tendency to overestimate runoff, while the observed data's PBIAS remains more stable at -3.112. Additionally, the R^2 for CHIRPS drops to 0.64, suggesting that only 64% of the variance in observed runoff is explained, which is significantly lower than the observed data's R^2 of 0.780. Overall, while both datasets exhibit challenges in validation, the observed precipitation simulations demonstrate superior performance metrics, highlighting the importance of accurate rainfall input data in hydrological modeling. All the values of the statistical metrics is shown in Table 4.

Table 4. Performance measurement matrices for all simulation.

Data type	Simulation	Performance measurement metrics		
		NSE	PBIAS	R ²
Observed	Calibration	0.842	-2.89	0.85
	Validation	0.751	-3.112	0.78
CHIRPS	Calibration	0.711	+5.6	0.72
	Validation	0.622	+7.98	0.64

3.6. Comparison with Other Studies

Ensuring the accuracy of flood risk mapping data is crucial since it facilitates policy formulation. It encourages integrated management techniques, enhances engagement with stakeholders, and makes the most use of available resources. This study confirmed its outcomes by comparing it with similar studies conducted in the country and globally. The study compares its findings based on NSE and R² values with those from other studies that primarily use satellite precipitation products to simulate runoff. A study by (Belayneh et al., 2020) reported a NSE of nearly 0.68 and a coefficient of determination (R²) of 0.77 for calibration, while for validation, the NSE dropped to 0.51 and R² to 0.7. A study by (Benkirane et al., 2023) performed an event-based analysis to simulate floods using satellite precipitation products from GPM data, reporting NSE values ranging from 60% to 90% for calibration and 50% to 80% for validation across different analyses. These results align well with the findings of the present study. Similar to the present study, findings by (Anh et al., 2022) reported promising results for CHIRPS rainfall products, with NSE and R² values greater than 80% and a lower PBIAS of 0.45. This demonstrates a significant decrease from calibration to validation, which is consistent with the findings of the present study. The study (Rafiee et al., 2024) who found that using Global Precipitation Measurement (GPM) remote sensing data is reliable for modeling key hydrological parameters, aligning with the findings of the present study. Similar investigations across different studies have revealed that global precipitation datasets demonstrate a promising level of accuracy, albeit with lower values compared to observed precipitation in catchment rainfall-runoff simulations (Adam et al., 2017; Belayneh et al., 2020; Hernández-Romero et al., 2022). This suggests that while these datasets can be effective, there may still be discrepancies when compared to ground-truth measurements.

3.7. Implication of the Findings

Studies have shown that while HEC-HMS can yield satisfactory simulations of hydrological processes, discrepancies between simulated and observed runoff can occur, emphasizing the need for continuous validation and calibration of models with diverse precipitation sources to improve forecasting accuracy and water resource management. This improvement underscores the critical role that accurate precipitation data plays in hydrological modeling, especially in areas where ground-based measurements are limited. By integrating satellite-derived precipitation, HEC-HMS can better simulate the hydrological response of watersheds, leading to more reliable flood predictions and improved water resource management strategies. This approach not only enhances the accuracy of runoff simulations but also facilitates the application of hydrological models in diverse geographical contexts where traditional data sources may be insufficient. The effective results of HEC-HMS rainfall-runoff modeling using both observed and satellite precipitation products highlight the importance of accurate precipitation data in hydrological simulations. In regions where traditional precipitation measurements are sparse, such as many developing countries, satellite data can provide critical insights into spatial and temporal precipitation patterns, enhancing the reliability of runoff predictions.

4. Conclusions and Key Recommendations

The study specifically aimed to compare the effectiveness of observed precipitation data against satellite-derived products in simulating runoff, thereby providing insights into their applicability for sustainable water management in the region. The study selects CHIRPS, a widely utilized global precipitation dataset, for the simulations. Sensitivity analysis revealed that the primary parameters affecting runoff quantities are the recession constant and the curve number. The comparison of rainfall-runoff simulations using CHIRPS and observed precipitation data revealed significant differences in model performance metrics. During calibration, CHIRPS achieved a Nash-Sutcliffe Efficiency (NSE) of 0.711, a Percent Bias (PBIAS) of +5.6, and an R^2 of 0.72, indicating moderate correlation and slight overestimation of runoff. In contrast, observed precipitation simulations yielded a higher NSE of 0.842, a more favorable PBIAS of -2.89, and an R^2 of 0.85, demonstrating superior predictive capability. During validation, CHIRPS' performance declined, with an NSE of 0.622 and a PBIAS of +7.98, while observed precipitation maintained a higher NSE of 0.751 and a stable PBIAS of -3.112. The R^2 for CHIRPS dropped to 0.64, compared to 0.780 for observed data, further highlighting the observed precipitation's effectiveness in accurately capturing runoff dynamics. The estimated peak flood discharge during both calibration and validation phases was 288.9 m³/s for observed precipitation data and 369.2 m³/s for CHIRPS data. These comparative results underscore the importance of integrating both data sources for improved hydrological modeling, particularly in regions where ground-based data may be limited. The insights gained from this study are crucial for informing water resource management strategies in the Modjo catchment, especially in the face of climate variability and increasing water demand. By demonstrating the strengths and limitations of different precipitation products, this research contributes to the broader understanding of hydrological modeling in Central Ethiopia, paving the way for more effective and sustainable water management practices. Future research should focus on enhancing the accuracy of satellite precipitation estimates and exploring advanced modeling techniques to further improve runoff predictions, ultimately supporting the sustainable management of water resources in the region.

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