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Hydrological modeling using HEC-HMS model, case of Tikur Wuha River Basin, Rift Valley River Basin, Ethiopia

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ABSTRACT

Modeling rainfall-runoff is widely recognized as one of the most complex types of hydrological modeling, primarily because it involves the integration of a diverse array of watershed characteristics. Due to its ability to emulate the hydrological behavior of a watershed, the modeling of rainfall-runoff plays a crucial role in predicting the runoff generated at the watershed's outlet. The present study aimed to simulate runoff by utilizing HEC—HMS in the Tikur Wuha River watershed situated in the Rift Valley Basin of Ethiopia. To achieve this goal, tools such as HEC-GeoHMS and ArcGIS were employed to establish the necessary input parameters for HEC—HMS. Various methods were implemented at different stages of the modeling process, including SCS-CN for estimating precipitation loss, SCS-UH for transforming excess rainfall, Muskingum for flood routing, and the monthly constant method for modeling base flow. The process of calibration and validation entailed the use of daily observed flow data from the periods (1990 to 2009) and (2010 to 2015) correspondingly. Nash Sutcliff Efficiency (NSE) and coefficient of determination (R^2) were employed as metrics to evaluate the model's performance. The findings showed that the model exhibited high performance in both calibration and validation stages, producing values of (NSE = 0.83, R^2 = 0.91) and (NSE = 0.84, R^2 = 0.86) respectively. Furthermore, the Percent Bias (PBIAS) values in calibration and validation remained within acceptable ranges, registering at 2.69 % and 4.67 % respectively. After the calibration and validation of the model, the estimated peak flood discharge simulated by the model (206.3m^3/s) was compared with the observed stream flow (197.1m^3/s), indicating a significant similarity between the model's output and the observed data. Consequently, it can be inferred that the model exhibits a high capability in replicating hydrological parameters effectively for the Tikur Wuha watershed and other watersheds sharing similar hydrological characteristics.

1. Introduction

Hydrological modeling involves the analysis of how the hydrology of a watershed responds to diverse physical characteristics of the basin. It has been employed in numerous river basins globally to enhance understanding of the availability of water resources (Sintayehu, 2015). Currently, the use of hydrological models plays a vital role in assessing the water availability in river basins and devising effective approaches to manage environmental changes. Estimating the volumes of runoff and peak floods can be facilitated by employing a modeling framework and a comprehensive understanding of the factors that initiate runoff (Zhang et al., 2010). The simulation of Stream flow data from rainfall events has been advanced over numerous decades (Todini, 2007; Obasi et al., 2020; Gholami and Sahour, 2021). Hydrological modeling is frequently employed method to assess the hydrological reaction of a basin to precipitation. The model assists in the management of watershed practices by considering the hydrological response associated with the projected peak flood, to combine data for enhancing comprehension and execution of these practices (Kadam, 2010). Rainfall-runoff modeling is crucial hydrological modeling that is commonly utilized to examine the relationship between rainfall and runoff, considering factors unique to the watershed (Salwa and Wardah, 2015). Moreover, it plays a vital role in various activities such as flood simulations, monitoring water levels, and forecasting floods (Wang and Liu, 2023). Furthermore, it provides valuable insights for effective planning and management of water resources. Additionally, it is important for catchments with limited data, as it provides accurate predictions. Hence, adequate knowledge of hydrological modeling is very important to predict runoff produced from

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watersheds.

Despite the data scarcity, different researchers conducted rainfall-runoff modeling in various river basins. For instance, Sardoii et al. (2012) simulated the rainfall-runoff process in the Amirkabir watershed. Kimhuy *et al.* (2016) developed rainfall-runoff modeling to assess stream flow and water resource accessibility in the Stung Sangker watershed of the Mekong' Tonle Sap Lake basin in Cambodia. Bitew et al. (2019) created a precipitation spillover model for stream simulation in the Lake Tana Basin for the case of Gilgel Abay catchment, Upper Blue Nile Basin, Ethiopia.

Although numerous options of rainfall-runoff models are available, selecting an appropriate model is crucial for effective watershed planning and management.

Currently, numerous models are available for hydrological modeling. The choice of model is contingent upon the specific characteristics of the basin as well as the intended purpose of the hydrological forecasting within that particular basin (Ocio et al., 2019). This research utilized a semi-distributed hydrologic model, the Hydrologic Engineering Center-Hydrologic Modelling System (HEC—HMS), to study the rainfall-runoff process in the Tkur Wuha River watershed. The Hydrologic Engineering Center's Hydrologic Modeling System (HEC—HMS) model was created by the US Army Corps of Engineers (Chu and Steinman, 2009) and is suitable for various hydrological simulations. Hydrologic Engineering Center (HEC—HMS) is a hydrologic modeling that contains an integrated tool for modeling hydrologic processes of dendritic watershed systems (Chu and Steinman, 2009). Moreover, it has been widely used in many hydrological studies due to its simplicity and capability (Halwatura and Najim, 2013; Jayanti, 2020; Sahu et al., 2023). Furthermore, HEC—HMS is a comprehensive tool that encompasses all hydrologic processes of dendritic watershed systems. The widespread adoption of HEC—HMS in hydrology is attributed to its capacity to simulate runoff in various event durations, ease of use, and utilization of standard methods (Oleyiblo *et al.*, 2010).

The Geospatial Hydrologic Modeling Extension (HEC-GeoHMS) is a public-domain software package for use with Geographical Information Systems (GIS), GeoHMS ArcView, and Spatial Analysis to develop several hydrological modeling inputs. Upon examination of the data from the Digital Elevation Model (DEM), HEC-GeoHMS converts the drainage routes and watershed limits into a hydrological data framework that illustrates the watershed's reaction to precipitation (Hoogestraat, 2011). Several researchers employed the HEC—HMS model to depict flow through simulated rainfall-runoff processes. The study by Tahmasbinejad et al. (2012), HEC—HMS and GIS were effectively utilized to replicate the rainfall-runoff process in the Karun River basin in Iran. Similarly, Sampath et al. (2015) carried out runoff simulation in the Tropical Region of Deduru Oya River Basin in Sri Lanka using the HEC—HMS model, demonstrating its effectiveness in simulating runoff. Abdessamed et al. (2018) formulated a rainfall-runoff model in a semi-arid region of the Ain Sefra watershed in Algeria by implementing an HEC—HMS model. Zelelew and Melesse (2018) emphasized the location-specific nature of model simulation results, where different combinations of model components responded variably. Tassew et al. (2019) performed a rainfall-runoff simulation with HEC—HMS for the Lake Tana Basin of the Gilgel Abay catchment in the upper Blue Nile basin in Ethiopia, using six extreme daily time-series events. The findings suggested the model's suitability for hydrological simulations. Saeedrashed et al. (2020) utilized computational hydrological and hydraulic modeling systems that integrate GIS with the modeling systems to predict floodplains for the Greater Zab River using HEC—HMS. Wana et al. (2020) applied HEC—HMS for rainfall-runoff modeling in the Awash Bello sub-catchment, concluding its efficient predictive capabilities. Furthermore, Hamdan et al. (2021) conducted Rainfall-Runoff Modeling with the HEC—HMS Model for the Al-Adhaim River Catchment, Northern Iraq, affirming its suitability for hydrological simulation. The Tikur Wuha River watershed is situated in the southern part of the Rift Valley River basin.

The fluctuation in stream flow within the Tikur Wuha river basin varies seasonally, leading to flooding issues for surrounding agricultural areas, particularly between June and September (Mekin et al., 2020). It is challenging to estimate flood depth without using hydrological models. To address these issues, the development and application of rainfall-runoff modeling is crucial. Therefore, this study aims to establish rainfall-runoff modeling specifically for this area. The outcomes of this research are significant for the region as the model was meticulously prepared, incorporating various elements such as DEM maps, Isohyetal maps, land use/land cover data, soil types, curve numbers, rainfall information, and simulated discharge values. Additionally, the characteristics of the Tikur Wuha river watershed were delineated using HEC-Geo HMS and transferred to HEC—HMS. The calibrated hydrological parameters will be used for upcoming hydrological investigations in this watershed and others alike, helping in the efficient management of water resources.

2. Materials and methods

2.1. Description of study area

The Tikur Wuha river basin is situated within the geographical coordinates of 6°46′ to 7°10′ N and 78°32′ 23′' to 78°39′ 23′' E in the southern Rift Valley basin of Ethiopia. It encompasses an area of 623 km^2 at the gauging station with elevations ranging from 1645 m to 2986 m above mean sea level (Fig. 1). Originating from the Cheleleka Wetlands, the Tikur Wuha River is the primary watercourse that flows into Lake Awasa (Mekin et al., 2020). The predominant soils and land use in the watershed are Chromic Luvisols and Cultivated land respectively, as illustrated in Table 1. The watershed displays significant topographic diversity, with the most prevalent slope classes being 8–15 % and 15–30 %, which together cover approximately 54 % of the total area. The slope class of 3–8 % encompasses 21.6 %, while slopes exceeding 30 % constitute 19 %, primarily found in the Northern, Eastern, and South Eastern escarpments of the sub-watershed area. The remaining 5 % of the total area is categorized under the 0–3 % slope class according to the FAO slope classification for soil and water conservation (FAO, 2006). In terms of climate, the watershed experiences a semi-humid climate, with average annual rainfall ranging from 210 mm to 250 mm based on data from 1990 to 2017, with over 80 % of precipitation occurring during the summer season (June to August).

2.2. Data set, and sources

This study used various datasets including daily precipitation, stream flow, soil types, Land use/cover (LULC), and Digital Elevation Model (DEM) 12.5 × 12.5 m data. The precipitation data was collected from four meteorological stations (Hawasa, Hasayita, Tula, and Waterersa) available in the study area spanning from 1990 to 2017 sourced from the Ethiopian Meteorological Agency, and stream flow data from 1990 to 2015 at the gauging station (indicated on Fig.1) from the Ethiopian Hydrological Agency. Similarly, the Soil and DEM data were acquired from the Ethiopian Ministry of Water Resource, Irrigation, and Electricity, whereas the LULC data was obtained from the Ethiopian Mapping Agency. The accuracy of the gathered original meteorological and hydrological data has a notable impact on the accuracy of the data used in the model and, by extension, the model's simulations. Initially, the daily rainfall and stream flow data underwent visual inspection for quality assurance (Kim et al., 2023). Subsequently, missing data points were filled in and a thorough evaluation was conducted using the normal ratio and double mass curve analysis techniques (Gao et al., 2017). Data consistency was assessed using the double mass curve method, and additional data quality tests like the homogeneity test were carried out using Excel Stat statistical software. The land use/land cover (LULC) and soil data of the Tikur Wuha river watershed were extracted from the LULC and soil map of the Rift Valley basin. Furthermore, given

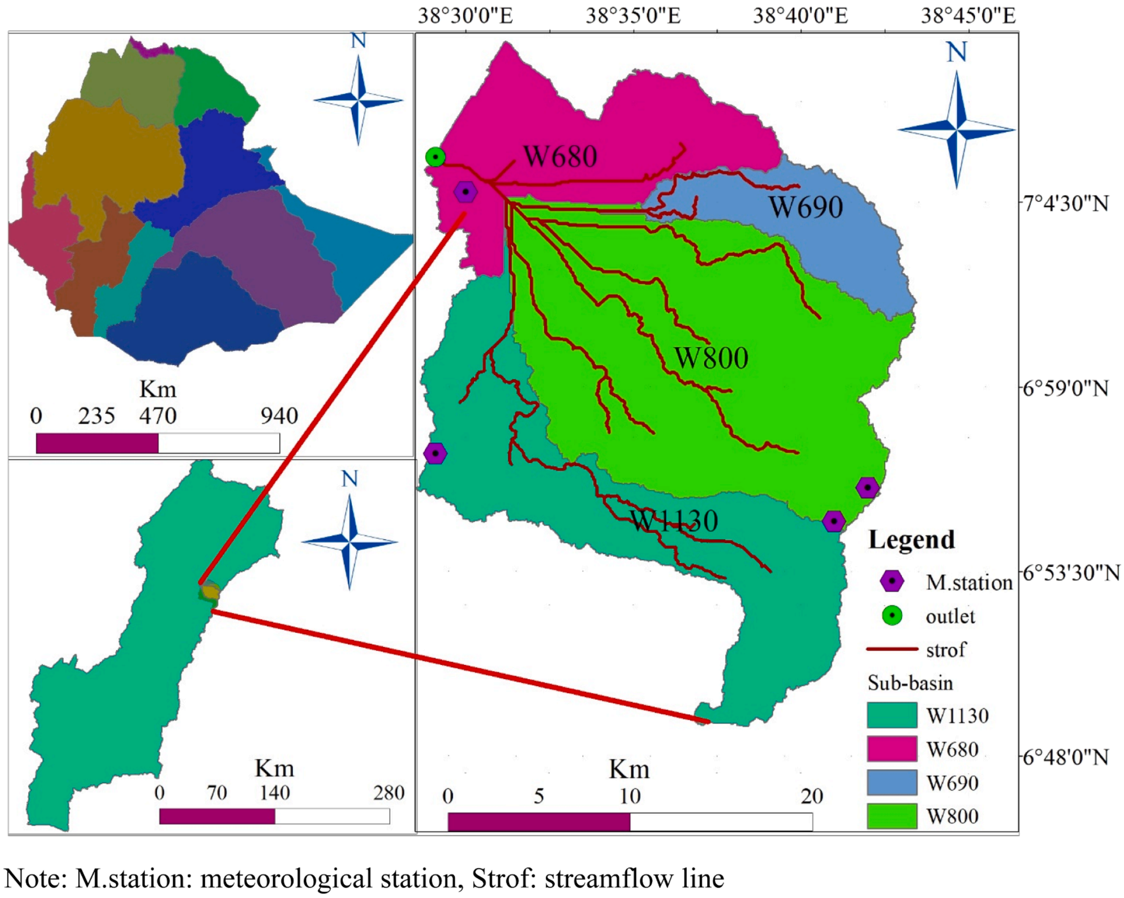

Fig. 1. Location of Tikur Wuha River Watershed.
Note: M.station: meteorological station, Strof: streamflow line.

Table 1
Spatial areal coverage and percentage of LULC and soil type of study area.

No	LULC	Area (km^2)	Area (%)	Soil type	Area (km^2)	Area (%)
1	Bush Land	83.86	12.9	Chromic Luvisols	258.01	40
2	Cultivated land	224.9	34.85	Haplic Luvisols	245.56	38
3	Forest land	332.13	51.5	Eutric Cambisol	30.4	4.7
4	Residential area	1.173	0.18	Vitric Andosols	29.08	4.4
5	wetland	2.1	0.36	Vitric Luvisol	78.7	12.2
6	Water body	0.132	0.025	Leptosol	3.66	0.56
	total	645.36	100	total	645.36	100

the variability in precipitation levels across different locations, accurately estimating the average precipitation for the basin is crucial rather than relying solely on single-point rainfall data. Hence, the Isohyetal method was selected for calculating average precipitation due to its ability to provide the most precise estimation (Subramanya, 2008). Accordingly, the average areal precipitation data was computed for each station (W1130, W680, W690, and W800) as shown in Fig.2. Subsequently, the hydrological and meteorological data in the form of spatial and time series were organized in a way that was appropriate for the application of the HEC—HMS hydrological model in the context of rainfall-runoff modeling.

Table 2

2.3. Methods

2.3.1. Software used

ArcGIS, HEC-GeoHMS, and HEC—HMS were the software employed in this work. ArcGIS was used to prepare curve numbers grid by merging soil and land use data, which was subsequently utilized as an input in HEC-GeoHMS to produce curve numbers. The ArcGIS HEC-GeoHMS extension toolkit was also used for watershed delineation and the creation of parameters such as curve numbers, basin model files, gage model files, and met model file (precipitation data) to construct a model in HEC—HMS. HEC-GeoHMS acts as an intermediary between ArcGIS and HEC—HMS, facilitating the smooth transfer of data from ArcGIS to HEC—HMS. HEC—HMS requires watershed background shape files for precise watershed configuration.

2.3.2. HEC—HMS model

The Hydrologic Engineering Centre-Hydrological Modeling System (HEC—HMS), is a highly adaptable and effective hydrological model used to analyze the rainfall-runoff process within a watershed. This model has been widely embraced in numerous hydrological investigations due to its capacity to replicate runoff occurrences in both short-term and long-term scenarios, as well as its user-friendly interface (Najim, 2013). It is specifically created to mimic the precipitation-runoff mechanisms of complex watershed systems (Scharffenberger, and Fleming, 2016). The HEC—HMS model can be employed to simulate various scenarios such as single storm events lasting from hours to days, or extended periods of stream flow (daily, monthly, and seasonal) (Fleming, and Doan, 2013). The setup of the HEC—HMS model comprises four key components: basin model, meteorological model, control specifications, and input data (time series, paired data, and gridded

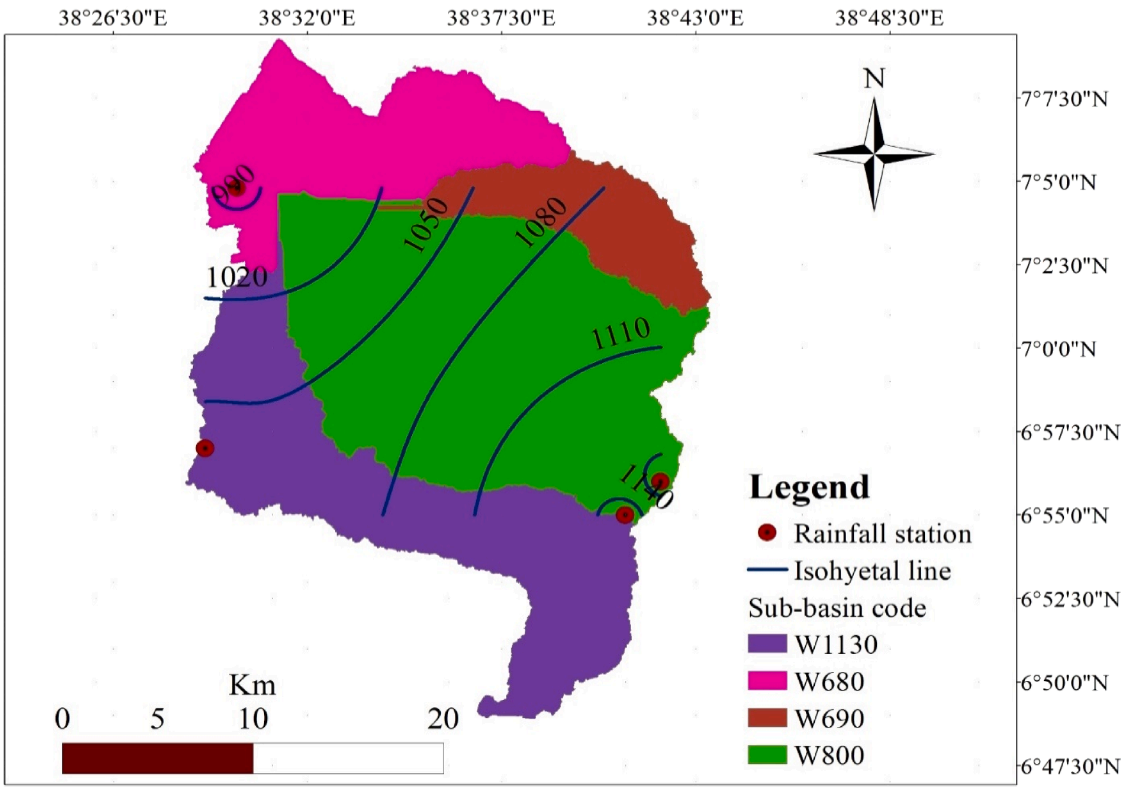

Fig. 2. Isohyetal map study area.

Table 2
Average precipitation computed by Isohyetal method for this study area.

No	Isohyetal range (mm)	Average (mm)	Area sq.Km	Average rainfall (mm)
1	<990	985	32	49
2	990–1020	1005	69	107.45
3	1020–1050	1035	104	167
4	1050–1080	1065	134	221
5	1080–1110	1095	207	352
6	1110–1140	1125	83	145
7	>1140	1155	16.36	29.3
			$\sum A =$ 645.36	$\sum A_{ve} = 1071$

data). There are multiple techniques available within the model to simulate processes like infiltration losses, direct runoff estimation, channel routing, base flow modeling, and meteorological modeling. The selection of the appropriate model component depends on factors such as data availability, modeling objectives, and global standards. For the present study, methods such as Soil Conservation Service Curve Number (SCS-CN), Soil Conservation Service Unit Hydrograph (SCS-UH), Muskingum and Gage weights methods, and constant monthly base flow were chosen to calculate runoff volume, transform excess precipitation to surface runoff, manage channel routing, and simulate the overall process, respectively. Additionally, the watershed was subdivided into four sub-basins to enhance the model's performance. The SCS-CN methods employed by the Soil Conservation Service (SCS) uses the Curve Number method for calculating runoff and is applied to ascertain the overall volume of infiltration that occurs during a rain event (Lee et al., 2023). Curve Number (CN) is an index developed by the Soil Conservation Service (SCS) to estimate rainfall loss into soil and the subsequent surface runoff, which is essential for the modeling of rainfall-runoff in hydrological simulations (Jayanti, 2020). It is commonly employed for the estimation of surface runoff in hydrology (Im et al., 2020). The values of the Curve Number for a specific watershed is determined upon various factors such as land use, soil composition, and Antecedent Soil Moisture (AMC), with values ranging from 30 soils with high infiltration rates) to 100 (water bodies) (Scharffenberg, Fleming, 2016). The SCS CN model is represented by Eq. (1) (Uwizeyimana et al., 2019).

$$Q = \frac{(P - I_a)^2}{(P - I_a) + S} \tag{1}$$

Where: Q = runoff value (mm); P = precipitation (mm); Ia = initial abstraction (mm); S = potential maximum retention is given by Eq. (2): The potential maximum retention (S) is a function of Curve Number (CN) and is inversely proportion to CN. The potential maximum retention is given by Eq. (2):

$$S = \frac{25400}{CN} - 254 \tag{2}$$

2.4. Model calibration and validation

Calibration of a model involves the meticulous adjustment of specific parameter values within the model to ensure that the simulated outcomes align closely with the actual observations. The effectiveness of a hydrologic model is contingent upon the accuracy of its calibration process, as highlighted by Vaze *et al.* (2011) in their research. Following the initial simulation of a model using certain parameters, the subsequent step involved the calibration of the model against observed streamflow data. This calibration process entailed the fine-tuning of parameters such as the curve number, lag time, and initial abstraction values until a satisfactory alignment between the simulated and observed results was achieved. Both automated and manual methods were employed to complete this calibration process, reflecting the complexity and precision required in model calibration procedures. To carry out the calibration, 18 years of daily observed streamflow data spanning from 1990 to 2010 were utilized, ensuring a robust and comprehensive evaluation of the model's performance. The iterative nature of model calibration underscores the significance of this process in enhancing the reliability and accuracy of hydrologic models for various applications in water resource management and environmental studies. Through the systematic adjustment of parameters based on observed data, model calibration serves as a critical step in validating the predictive capabilities of hydrologic models and improving their overall performance in simulating real-world scenarios. The utilization of extensive observed data over a prolonged period further enhances the robustness and credibility of the calibration outcomes, leading to more informed decision-making in water-related projects and policy development. Model validation involves confirming the model's predictive ability for timeframes beyond the calibration period while keeping the input parameters unchanged from the calibration process (Vaze et al., 2011). This process guarantees the effectiveness of the calibrated parameters when applied to a separate dataset. The validation of the model was carried out by analyzing daily streamflow data from 5 years (2011 to 2015).

2.4.1. Model performance evaluation

The assessment of the HEC—HMS model's performance included analyzing the accuracy of the observed and simulated stream flow. A statistical error test was utilized to assess the quality and dependability of the simulated values produced by the HEC—HMS model. In this study, the evaluation of the model's effectiveness considered the Nash-Sutcliffe Efficiency (NSE) and coefficient of determination ($\mathbf{R^2}$) as widely used metrics in hydrological modeling.

A. **Nash-Sutcliffe Efficiency (NSE)**

The Nash-Sutcliffe Efficiency (NSE) is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance (Moriasi et al., 2007). Mathematically, it is calculated as Eq. (3).

$$NSE = 1 - \frac{\sum \left(Q_{ob(t)} - Q_{sim(t)}\right)^2}{\sum \left(Q_{ob(t)} - \overline{Q}_{ob}\right)^2} \tag{3}$$

Where, NSE: Nash and Sutcliffe Efficiency, Qob: observed value at the i^{th} time interval, Q_{sim}: simulated value at the i^{th} time interval, $\overline{Q}_{ob}$: mean of the observed discharges

A. **Coefficient of determination ($\mathbf{R^2}$)**

The Coefficient of determination (R^2) is another commonly utilized statistical measure that signifies the level of co-linearity existing between the simulated and observed data. It reflects the accuracy of a model, with a range from zero to one. A value of one indicates flawless prediction, while a value of zero indicates inadequate prediction (Moriasi et al., 2007). Its mathematical calculation is performed using Eq. (4).

$$R^2 = \frac{\sum \left(Q_{obs(t)} - \overline{Q}_{obs}\right) \sum \left(Q_{sim(t)} - \overline{Q}_{sim(t)}\right)^2}{\sum \left(\left(Q_{obs(t)} - \overline{Q}_{obs}\right)^2 \sum \left(Q_{sim(t)} - \overline{Q}_{sim(t)}\right)^2\right.} \tag{4}$$

Where, R^2 = coefficient of determination, Q_{obs} = observed value at the i^{th} time interval, $Q_{sim(t)}$= simulated value at the i^{th} time interval, $\overline{Q}_{obs}$= mean of observed discharges, $\overline{Q}_{sim(t)}$ = Mean of simulated discharges value at i^{th} time interval.

2.5. Flood prediction

Comprehensive flood frequency analysis is critical, as it serves as a critical tool for elucidating the intricate characteristics and potential severity of both present and forthcoming flood events, thereby equipping researchers and policymakers with invaluable insights necessary for effective disaster management and mitigation strategies (Keast & Ellison, 2013;Strupczewski et al., 2017). In this study, the quantity of the flood was determined utilizing the HEC—HMS model in conjunction with the statistical approach known as the Gumbel distribution method, which is widely recognized for its efficacy in extreme value analysis and has been extensively utilized in hydrological studies to predict the probability of occurrence of rare flood events with a high degree of reliability and precision (Farooq et al., 2018; Parchure and Gedam, 2019; El Mehdi Saidi et al., 2020). To comprehensively assess the frequency of flooding events various return periods (2, 10, 25, 50, and 100 years) were considered. This rainfall depths data corresponding to these return periods, was calculated using Intensity-Duration-Frequency (IDF) curve. The IDF results for different storm durations and average recurrence intervals (ARI) of the region are detailed in Table 3. The greatest rainfall depth was observed over a 24-hour period, and these values were employed in the model simulations.

Following model calibration and validation, flood frequency analysis was carried out for return periods. For this analysis, the depth of rainfall recorded over a 24-hour period was employed as the critical input parameter for the HEC—HMS, while simultaneously, the maximum annual rainfall data pertinent to the geographic study area was used in the Gumbel method to examine and quantify the magnitude of potential flood events.

This dual approach not only facilitates a robust evaluation of flood frequency but also enhances predictive accuracy regarding the anticipated severity of flooding scenarios within the designated area of study, ultimately contributing valuable insights for effective flood management and mitigation strategies.

3. Results and discussion

3.1. Hydrologic parameters

As deliberated in the section on methodologies, crucial watershed attributes such as Curve number, basin lag time, watershed area, basin slope, potential maximum retention (S), and the initial abstraction from the watershed were established. The spatial variation of the CN value within the study area was determined. The study area exhibited a range of CN values, with a minimum of 30 for forested areas and a maximum of 100 for water bodies. However, for rainfall-runoff simulation, each sub-basin necessitates a singular CN value. Consequently, HEC-GeoHMS had already calculated the weighted CN values for each sub-basin. The minimum and maximum weighted curve number values were identified as 74.15 and 72.13, respectively. These extremities were observed in sub-basins W690 and W680, respectively. The Curve Number value directly influences runoff generation. Sub-basins with lower CN values result in minimal runoff and higher infiltration rates. Conversely, sub-basins with higher CN values exhibit greater runoff potential. Hence, sub-basins W690 and W680 generate high and low runoff, respectively. The spatial distribution of CN is illustrated in Fig.3. Similarly, the minimum and maximum initial abstractions were recorded as 17.71 mm in W690 and 19.68 mm in W680 sub-basin. This discrepancy signifies the variance in runoff values between W680 and W690. The steepest

Table 3
Design storm of rainfall intensity for Tikur Wuha river watershed.

Rainfall intensity duration(hr.)	Rainfall depth(mm) versus return period (yrs.)			
	10	25	50	100
1	43.2	50.22	55.125	60.03
2	51.78	59.60	65.42	71.25
3	56.125	64.6	70.9	77.23
6	62.73	72.2	79.25	86.31
12	68.7	79.07	86.8	94.53
24	74.45	85.70	94.07	102.45

Source: (ERA, 2013).

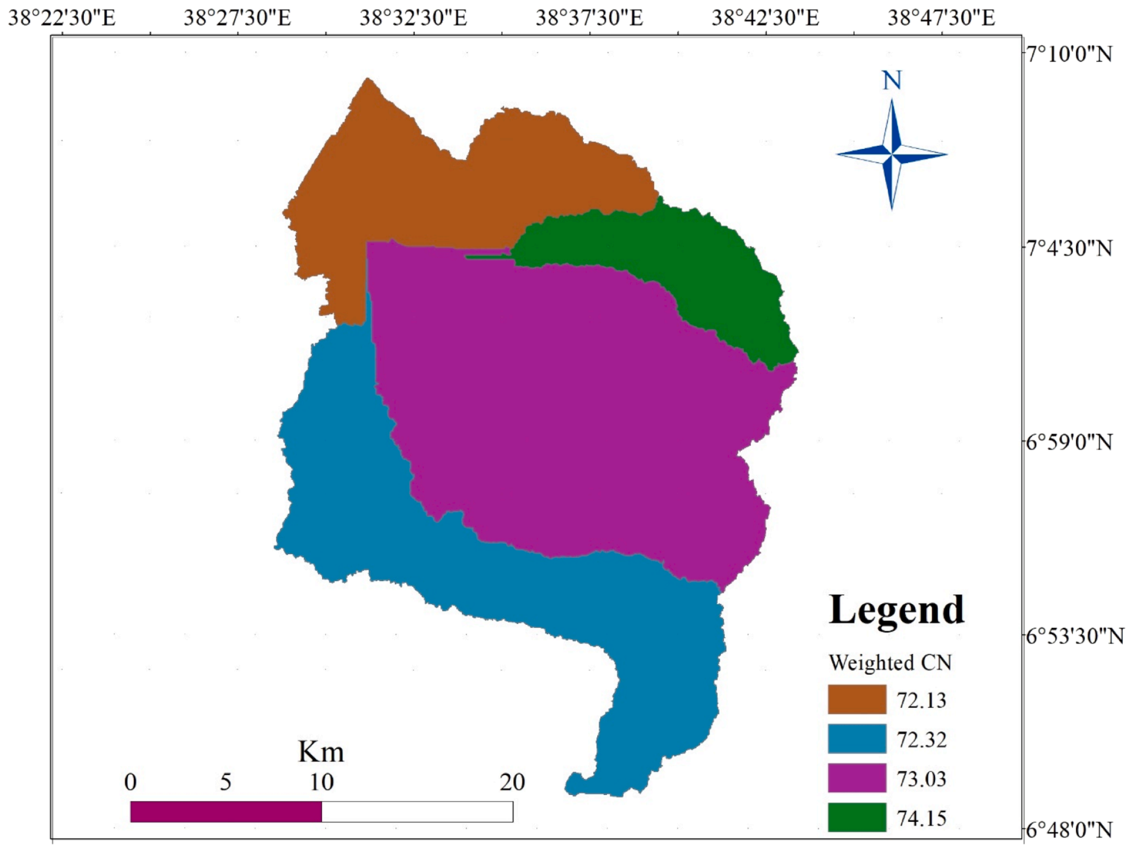

Fig. 3. Mean Curve Number map of the Meki River watershed.

basin slope, measuring 44.93 %, was observed in sub-basin W800. This indicates that W800 is the steepest sub-basin among all. The basin lag time ranged between 20.72 and 36.32 min for the study area. A lower basin lag time implies quicker surface runoff reaching the outlet point. The detailed watershed characteristics are presented in Table 4.

3.2. Model simulation result

The maximum daily flow rate at the watershed outlet has been calculated to be 286.8m^3/s, as indicated by the findings. This particular value carries significant implications for the overall hydrological processes within the watershed. Furthermore, a comprehensive breakdown of the daily estimated flow rates for each sub-basin and river can be found in the detailed information provided in Table 5, enhancing the understanding of the flow dynamics within the watershed. The analysis highlights the W690 sub-basin as contributing the most significant volume compared to other sub-basins. On the contrary, the W800 sub-basin is identified as the least significant in terms of the amount of runoff it generates. This information underscores the variations in hydrological contributions from different areas within the watershed. Additionally, the noticeable increase in water depth as the river advances towards the outlet location signifies a shift in the hydrological characteristics along the river network, potentially influencing downstream water flow and quality.

Table 4
Watershed parameters generated by HEC-GeoHMS for Tikur Wuha River watershed.

Sub-basin Code	Area km^2	Slope %	$I_a(mm)$	S (mm)	CN^*	Lag time (min)
W680	112.87	26.3	19.68	98	72.13	27.11
W690	58.2	43.94	17.71	88.5	74.15	20.72
W800	281.05	44.93	18.76	93.8	73.03	26.45
W1130	179.42	39.68	19.44	97.2	72.32	36.32

Table 5
Simulated results at each sub-basin and river reaches.

Sub-basin	Daily peak discharge (m^3/s)	River channel	Routed flood (m^3/s)	River channel	Routed flood (m^3/s)
W680	152.5	R480	33.9	R400	226.0
W690	153.6	R470	34.0	R430	226.6
W800	31.8	R500	33.8	R350	258.5
W1130	64.9	R540	33.7	R240	258.8
Outlet	286.8	R330	156.6	R420	278.1
		R320	157.8	R410	278.7

3.3. Model calibration and validation

3.3.1. Model calibration

The calibration of the HEC—HMS model involved the adjustment of model parameters to ensure a close match between simulated and observed flow data within an acceptable range of deviation. This process aimed to enhance the agreement between the two datasets by refining the model's representation of the hydrological processes. Notably, the time to peak of both simulated and observed events coincided, further validating the model's performance. Through iterative adjustments during the calibration process, the peak stream flow values were refined to 286.8 m^3/s for simulated data and 208.6 m^3/s for observed data, indicating a significant improvement in model accuracy. To achieve this calibration, various watershed parameters such as lag time, curve number, initial abstraction, flood wave traveling time (Muskingum-k), and weighted coefficient of discharge (Muskingum-x) were carefully selected. The sensitivity analysis revealed that all these parameters played crucial roles in optimizing the HEC—HMS model, with particular emphasis on curve number and lag time. Detailed results presented in Table 6 showcased the initial and optimized values of these parameters along with their corresponding objective function sensitivity values. For instance, the range of initially computed values for Muskingum-k spanned from 1:23 to 3:00 h, which were subsequently adjusted to 1:18 and 2:77 h post-calibration.

Furthermore, the calibration process involved computing and adjusting the Muskingum-k values for each reach, as outlined in the comprehensive Table 6. This meticulous approach ensured that the model accurately captured the flow dynamics at different sections of the watershed. Similarly, the determination of Muskingum-x values for each reach was achieved through a methodical trial and error process, ultimately resulting in optimized values of 0.24. These detailed adjustments and optimizations underscore the thoroughness and rigor applied to the calibration of the HEC—HMS model, leading to a more reliable representation of the hydrological system.

Fig. 5 illustrates the comparison between the simulated and observed flow hydrographs of the Tikur Wuha River watershed at the outlet following the calibration period. The agreement between the low flow and peak flow of both the simulated and observed hydrographs was notably strong, displaying a consistent pattern throughout the calibration period. Additionally, the scatter plot depicting the relationship between the measured and simulated stream flow for the same calibration period reveals a correlation coefficient (R^2) of 0.91, signifying a robust correlation between the simulated data and the actual observed stream data as depicted in Fig.4.

3.3.2. Model validation

All statistical error tests were observed to fall within an acceptable range (0.75–1) throughout the validation process, specifically during the calibration period, indicating that the predicted calibration outcome has been duly confirmed. The graphical representation in Fig.6 illustrates a close alignment between the low flows and peak flow of both the simulated and observed streamflow hydrographs, demonstrating a consistent pattern during the validation phase. This empirical evidence strongly suggests that the HEC—HMS model exhibits a high level of performance in replicating stream flow data within the designated study area. Hence, it can be inferred that the model holds promise for accurately representing the hydrological processes in the region.

The scatter plot of measured and simulated flow during the validation period shows a fair linear correlation between the simulated and observed data during the calibration period Fig. 7. The shape and scatter of the simulated and observed stream flow hydrograph at the outlet of the watershed during the validation period show a similar pattern as the model calibration period.

Table 6
HEC—HMS optimized parameters of Tikur Wuha watershed.

Element	Parameter	Unit	Initial value	Optimized value	Objective function sensitivity
W680	Lag time	HR	75.95	77.23	−0.37
	Curve Number		65.7	56.21	−0.17
W690	Lag time	HR	53.6	54.3	−0.46
	Initial abstraction	MM	22.3	22.45	−0.23
W800	Initial abstraction	MM	10.3	15.15	0.00
W1130	Initial abstraction	MM	8.7	9.13	0.00
	Curve Number		85.4	84.34	−0.32
R480	Muskingum-k	HR	3.00	2.77	0.00
	Muskingum-x		0.25	0.24	0.00
R330	Muskingum-k	HR	2:00	1.88	0.00
R320	Muskingum-k	HR	1:89	1.78	0.00
	Muskingum-x		0.25	0.24	0.00
R400	Muskingum-k	HR	1:75	1.65	0.00
R350	Muskingum-k	HR	1:23	1.18	−0.01

3.4. Model performance evaluation

The performance of the model was evaluated using Nash-Sutcliffe Efficiency (NSE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2). Moriasi et al. (2007) studied model evaluation guidelines for systematic quantification of accuracy in Watershed simulations and stated that the model to be very good, the value of NSE and R^2 should be between 0.75 and 1.0, whereas, the value of RMSE should be 0 to 0.5. Similarly, Schaefli and Gupta (2007), Kashid (2010), and Vaze (2011) stated that, if the value of NSE and R^2 during calibration and validation are between 0.75 and 1 the model performance rating is classified as a very good model. For the current research, the NSE and R^2 values exceeded 0.75 in both the calibration and validation periods, while RMSE values were 0.5 and 0.4 during calibration and validation, respectively. The results from calibration and validation phases demonstrated a robust correlation between the modeled and observed streamflow data. Consequently, the HEC—HMS model achieved a high performance rating based on these statistical metrics. The model's ability to predict accurately during calibration and validation stages suggests its efficacy in efficiently simulating daily streamflow from rainfall data in the study area. Therefore, the model's performance was deemed satisfactory and deemed suitable for predicting peak floods under various management scenarios in the future. Additionally, the simulated streamflow data effectively represented the observed streamflow data in the study area.

Table 7

3.5. Flood prediction

3.5.1. Flood prediction by HEC-HMS

Flood frequency analysis was carried out for return periods of 2, 10, 25, 50, and 100 years utilizing the HEC—HMS model within the Tikur Wuha River watershed. The analysis took into account a 24-hour rainfall depth, resulting in peak floods of varying magnitudes. The investigation revealed that the range of peak flood levels at the outlet of the Tikur Wuha River watershed spanned from 133.2 m3/s to 346.19 m3/s. This disparity signifies that the lowest peak flood within the Tikur Wuha River watershed occurred during a 2-year return period with a 24-hour storm duration, while the highest flood was observed for the 100-year return period under similar storm conditions. Assuming a constant basin lag time across all return periods (2, 10, 25, 50, and 100 years), the study successfully predicted the peak discharge and shape of the hydrograph for each scenario. These predictions were visually observed in Table 8, providing a comprehensive overview of the hydrological dynamics in the Tikur Wuha River watershed.

3.5.2. Comparison of HEC-HMS and gumbel distribution result

The distribution that exhibited the highest level of suitability to the stream flow data provided was found to be the Gumbel distribution through rigorous statistical analysis. The anticipated maximum flow rate derived from the application of this specific probability distribution function has been delineated and presented thoroughly within Table 9, offering valuable insights into the potential peak flow scenarios in the context of the studied data set. This statistical modeling approach not only aids in understanding the underlying patterns and trends within the stream flow data but also facilitates the projection of peak flow values with a certain degree of confidence, thereby enhancing the predictive capabilities of the analysis.

The outcome derived from the Gumbel method was observed to exhibit a high degree of proximity to the simulated outcome generated by HEC—HMS model as illustrated in Fig.8. Nevertheless, it was noted that the maximum flood level forecasted by the HEC—HMS model

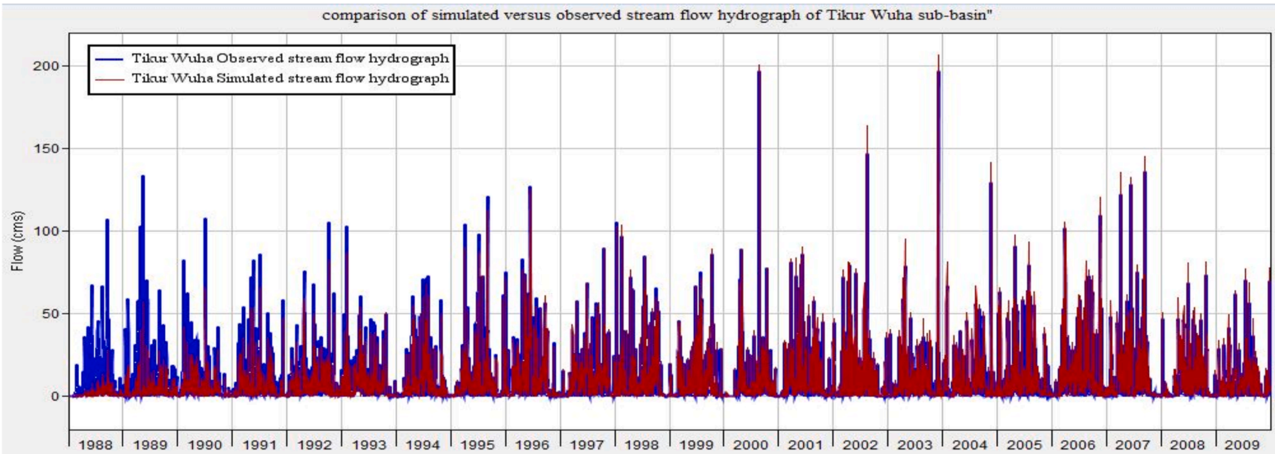

Fig. 4. Simulated and observed flow hydrographs after calibration.

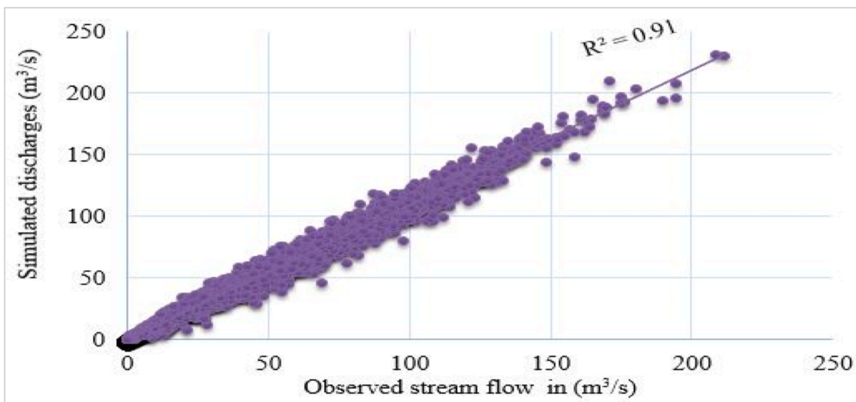

Fig. 5. Scatter plot of observed and simulated flow after calibration.

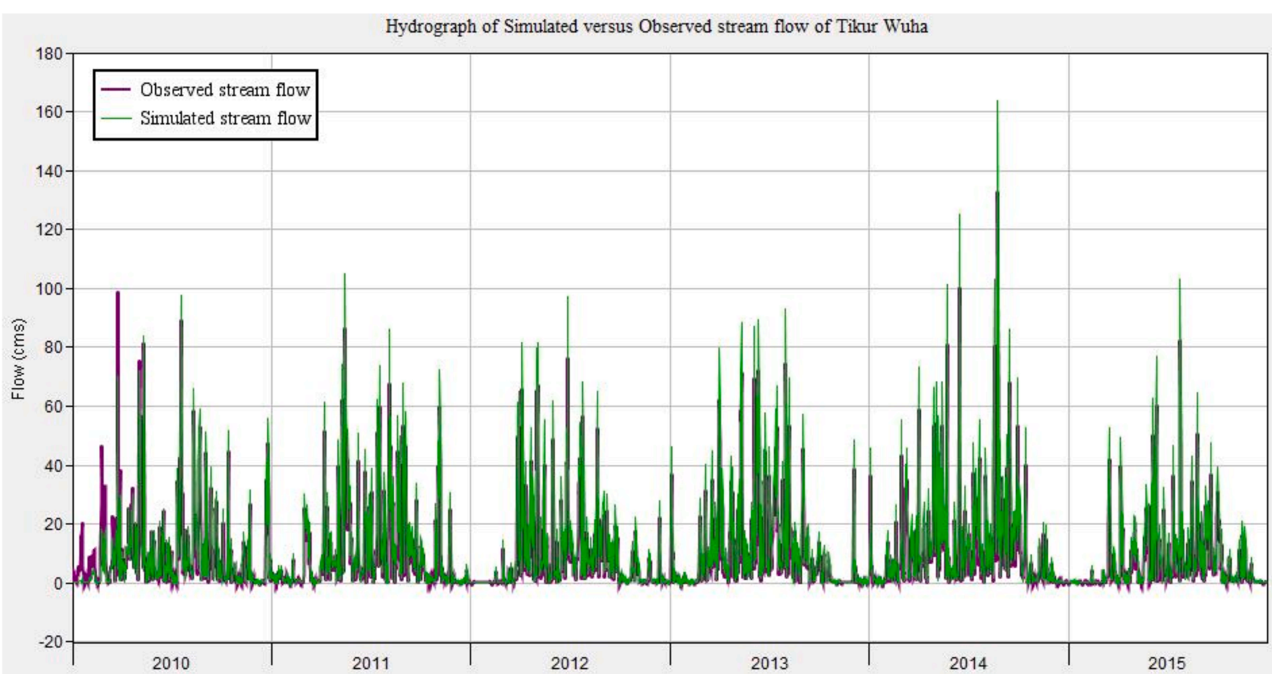

Fig. 6. Simulated and observed stream flow hydrographs after validation.

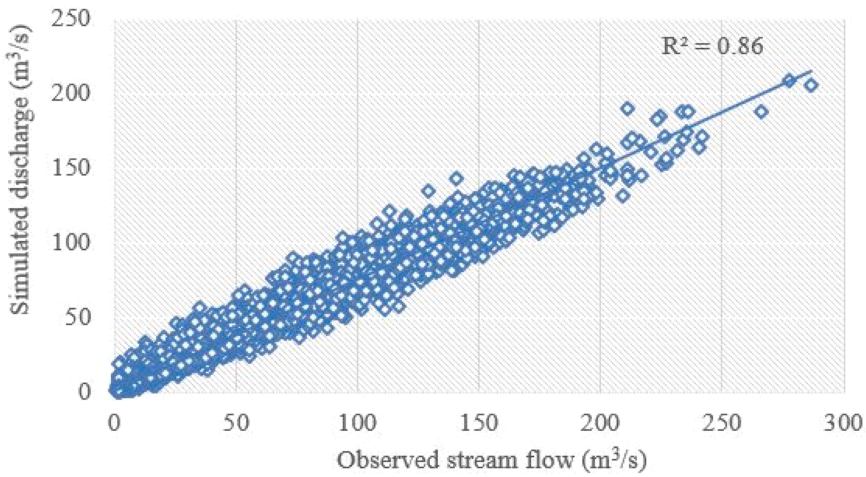

Fig. 7. Scatter plot of observed and simulated flow after validation.

Table 7
Summary of model performance evaluation.

Performance rating	After		Allowable range	Remark
	Calibration	Validation		
Nash-Sutcliffe Efficiency (NE)	0.83	0.80	0.75–1.0	accepted
Coefficient of determination (R^2)	0.91	0.86		accepted

Table 8
Simulated peak flood of different return period by HE-HMS.

Return period (year)	24 hour storm (mm)	peak flood (m^3/s) by HEC—HMS
2	47.54	133.2
10	67.66	178.1
25	77.92	239.7
50	85.62	313.2
100	93.34	346.19

Table 9
Peak discharge found from flood frequency analysis.

No.	Return period (year)	Peak flood (m^3/s)	
		Simulated HEC—HMS	Computed Gumbel
1	2	133.2	126.7
2	10	178.1	167.8
3	25	239.7	223.5
4	50	313.2	287.9
5	100	346.19	331.87

surpassed the maximum flood level calculated through the Gumbel method. This observation serves to imply that the simulated peak discharge values produced by the HEC—HMS model hold potential for further application in the realms of flood mapping and the implementation of strategies aimed at mitigating the impact of floods.

4. Conclusion

Rainfall-runoff modeling holds significant importance in the realm of hydrology as it plays a crucial role in simulating the intricate response patterns of watersheds to varying intensities of rainfall events, ultimately leading to the generation of flow hydrographs. These hydrographs are widely utilized in the realm of flood forecasting and the strategic planning of water resources management. The utilization of the HEC—HMS model in the current research endeavor facilitated the modeling of stream flow within the Tikur Wuha watershed, showcasing the efficacy and reliability of this computational tool. Various essential datasets including hydro-meteorological information, soil characteristics, land use/land cover data, and Digital Elevation Model (DEM) data were meticulously incorporated into the framework of this research to ensure a comprehensive and robust analysis. The integration of advanced software tools such as ArcGIS and HEC-GeoHMS enabled the creation of basin models, alongside the determination of crucial input parameters like Curve Number, lag time, and initial abstractions, which are pivotal in accurately representing the hydrological processes within the watershed. Moreover, the excluded value was computed using both simple and standard ratio techniques, while areal precipitation was assessed through Isohyetal methods. Additionally, the missed stream flow value was estimated using linear regression methods. The research employed techniques such as the Soil Conservation Service Curve Number, Soil Conservation Service Unit Hydrograph, constant base flow, and Muskingum method to evaluate different aspects of the hydrological cycle, encompassing rainfall loss, runoff, base flow modeling, and channel routing. The model was subjected to calibration and validation processes using 18 years (1987–2004) and 6 years (2005–2010) of daily observed streamflow data, respectively. The study site displays curve numbers ranging from 30 to 100. Key factors influencing output include lag time, curve number, initial abstraction, flood travel time (Muskingum-k), and discharge weighting factor (Muskingum-x). The model's efficacy was assessed using the Root Mean Squared Error, Nash-Sutcliffe Efficiency (NSE), and Coefficient of Determination (R^2), achieving values of 0.5, 0.832, and 0.91 respectively during calibration, and 0.4, 0.804, and 0.86 during validation. These findings demonstrate the robust performance of the model, indicating that the HEC—HMS model is well-suited for simulating streamflow data based on rainfall data within the study area. Based on the results of the goodness of fit analysis carried out using the easy fit software, the Gumbel method emerged as the most appropriate probability distribution function for fitting the observed stream flow time series data, ranking first in both the Kolmogorov-Smirnov and chi-squared tests. Subsequent modifications to the model configuration led to the performance of flood frequency analysis for various return periods, ranging from 2 to 100 years, utilizing rainfall data from a 24-hour storm in the Tikur Wuha river watershed obtained from ERA, 2013. Consequently, the projected maximum flood discharge estimated using HEC—HMS and the Gumbel method for return periods of 2, 10, 25, 50, and 100 years were found to be 133.2, 178.1, 239.7, 313.2, and 346.19 m3/s, and 126.7, 167.8, 233.5, 287.9, and 331.87 m3/s respectively. The peak flood anticipated by the HEC—HMS model surpasses that predicted by the Gumbel distribution.

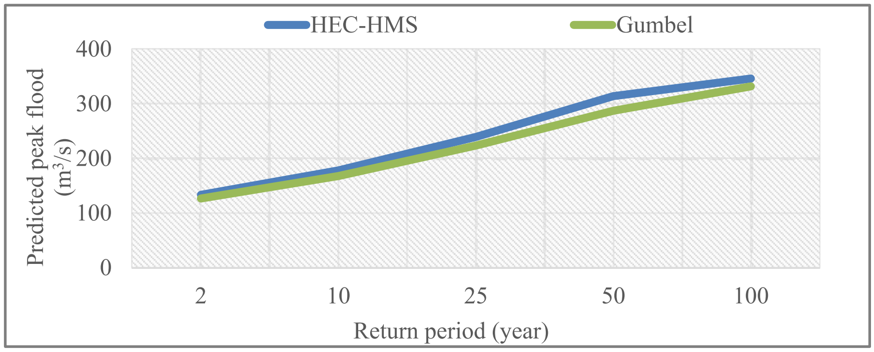

Fig. 8. Graphical Comparison of HEC—HMS result with the Gumbel method.

In general, study verified the practical applicability of the proposed model in conjunction with the quantification of flood events across the study area, thereby establishing its potential utility as a base input for subsequent researchers who aim to delineate the areal extent of flooding as well as the identification of areas that are particularly susceptible to flooding and implementing suitable strategies to mitigate its effects in the specified research area within the watershed.

CRediT authorship contribution statement

Jerjera Ulu Guduru: Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Conceptualization. **Ayatullah Shis Mohammed:** Writing – original draft, Visualization.

Declaration of competing interest

The author declared no conflict of interest.

Data availability

Data will be made available on request.

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