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Rainfall-runoff modeling using HEC-HMS model for Meki river watershed, rift valley basin, Ethiopia

Jerjera Ulu Guduru [a,*], Nura Boru Jilo [a], Zeinu Ahmed Rabba [b], Wana Geyisa Namara [c]

[a] , Department of Hydraulic and Water Resources Engineering, Haramaya Institute of Technology, Haramaya University, Dire Dawa, P.O. Box 138, Ethiopia
[b] Faculty of Civil and Environmental Engineering, Jimma Institute of Technology, Jimma University, Ethiopia
[c] Department of Hydraulic and Water Resources Engineering, Jimma Institute of Technology, Jimma University, Ethiopia

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ABSTRACT

Detail understanding of rainfall-runoff processes is tremendously important for a watershed with variable streamflow generation. The streamflow of the Meki River fluctuates seasonally causing flooding on surrounding agricultural land. This study adopted Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS) to model the streamflow and predict flood in the Meki watershed, Rift valley basin. The model was calibrated with observed streamflow data from (1987–2004) whereas the consecutive year's data (2005–2010) was used for model validation. The evaluation criteria namely: Nash Sutcliff Efficiency and coefficient of determination were preferred to evaluate the model performance. The finding relieved that, the model can perform very well (NSE = 0.83, R^2 = 0.91) during Calibration, and (NSE = 0.804, R^2 = 0.89) at validation period. Moreover, the predicted floods at 2, 10, 25, 50, and 100 years were 133.2, 178.1, 239.7, 313.2, and 346.19 m^3/s, respectively in the watershed. The novelty of this study lies in evaluating the model results using both statistical parameters (NSE and R^2) and the Generalized Extreme Value method). The finding of this study is vital to developing flood mapping and designing flood mitigation measures in the study area. Further, the developed models can be applied to other hydrology with similar hydrological conditions.

1. Introduction

Adequate knowledge of runoff within a watershed is vital to planning and designing water resources and related projects (Zelelew and Melesse, 2018). The actual estimation of runoff volume and peaks are also important for planning different interventions in integrated watershed management and flood protection projects (Romali et al., 2018). However, detailed hydrological studies are challenged due to the scarcity of data and complexity of hydrological systems. The runoff simulation model is one of the hydrological models that can drive the watershed rainfall response and forecast flood for water resources management (Teng et al., 2017). So, flood simulation is simplified through employing model and understanding factors triggering runoff (Tassew et al., 2019). However, different models need several input parameters that are not easily obtained (Anh, 2018; France and Rumpe, 2004). In case, it is necessary to select a model with a simple structure, minimum input data, and accurate prediction (Beven, 2012). The HEC-HMS model is one of the hydrological models that need little input data and provide a reliable result (Ramesh, 2017). It is widely used due to its ability to simulate floods in short and long-term events as well as very simple to use (Sok and Oeurng, 2016).

Several previous studies indicated the ability of the HEC-HMS model in flood simulation. Regarding this, Zelelew and Melesse (2018) stated that the results of the model simulation were location-specific. Bitew *et al.* (2019) used HEC-HMS Model to predict flood in the Lake Tana Basin in the Case of Gilgel Abay watershed, Ethiopia. From his finding, the model can simulate flood. Hirpessa and Hailu (2019) conducted an assessment of failure on drainage structures along the Ethiopian national railway line of Sebeta-Mieso (a case study of Akaki river crossing drainage structure) and they concluded that HEC-HMS modeled design discharge appropriately.

The flood produced will depend on various factors (Morita, 2014). These are intensity and duration of rainfall, soil types, Antecedent Moisture Condition (AMC), Topography (slope of the watershed) and Land ng Use Land Cover (LULC) are the main factors (Subramanya, 2008). Intense rainfall generates floods beyond the river channel capacity (Archer and Fowler, 2018). The rainfall pattern varies from season to season especially in Ethiopia, a prolonged heavy rainfall occurs in

* Corresponding author. Rainfall-Runoff modeling for Meki River Watershed, Rift Valley Basin, Ethiopia.
E-mail address: jerjeraulu@gmail.com (J.U. Guduru).

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the summer season (Jun to September) (Wagesho and Yohannes, 2016; Abegaz and Mekoya, 2020; Alhamshry et al., 2020; Harka et al., 2021). Intense rainfall in highland areas during the rainy season cause inundation of agricultural land close to river courses (Getahun and Gebre, 2015). Meki watershed is one of the Rift valley sub-basin which is frequently inundated due to prolonged rainfall with high intensity that occurs in the summer season (Ademe et al., 2020; Goshime et al., 2021; Tadiwos et al., 2020). Therefore, mitigating the impact of floods is extremely important to manage flood risk. Flood controlling measures are of two types (structural and non-structural) (PATEL and DHOLAKIA, 2010; Kim et al., 2019). Structural measures are concerned with physical control of flood (constructing hydraulic structure) which is uneconomical and time taking whereas non-structural measures are done through planning, providing detailed information regarding flood generated at different reoccurrence intervals with high accuracy (PATEL and DHOLAKIA, 2010; Minea and Zaharia, 2011; Yuniartanti et al., 2019). Flood frequency analysis is one of the non-structural measures that can help to predicted floods at different reoccurrence intervals (Archer, 1988). Consequently, flood frequency analysis is extremely important to take appropriate action to flood risk and prevention measures. Therefore, this study intended to; a) simulate streamflow by using HEC-HMS model, b) predict flood frequency analysis using both HEC-HMS and statically probability distribution function, and c) Compare the results of HEC-HMS with probability distribution functions and identify the best fit probability distribution methods to observed streamflow data for the Meki River watershed. The novelty of this study lies in evaluating model results using both statistical parameters (NSE and R^2) and statistical distribution function (the Gumbel Extreme Value) method.

2. Materials and methods

2.1. Description of the study area

The watershed is located in the rift valley basin, Ethiopia. Its river originated from Gurage Mountains and ends at Lake Ziway. Geographically, the study area is bounded within the limits of 70 59′ 32” to 80 27′ 23” N latitude and 380 14’ 48” to 380 49” 35” E longitude and covers a total area of about 2240 Km^2. The watershed lies within altitudes ranging from 1631m near Ziway Lake to 3614m along the Western Highlands (Guraghe Mountains) above mean sea level. The upstream of the watershed is steep and mountainous while the downstream is flat with a broad valley (Legesse et al., 2010; Yifru et al., 2021). Its main river originated from the mountains area and travels 100 km to reach Lake Ziway (Fig. 1). Fig. 1 indicates features (i.e topography, hydro-metereological stations, drainage line and geographical location) of the study area. The overall methodological flowchart of this study is presented in Fig. 2.

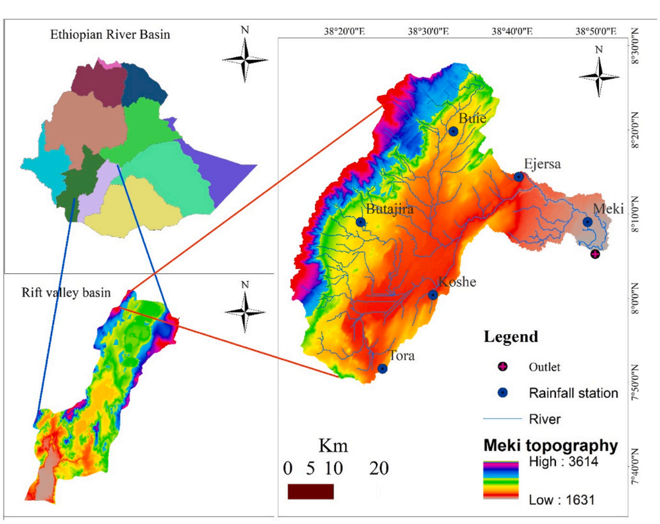

Fig. 1. Location of the study area.

The most common LULC of the study area are forest, woodland, grassland, cropland, marshland, bare land, shrubland, and water body. Among these, the cropland is the most dominant one in the study area. Forests area covered the mountainous part of the watershed while the flat and lower elevation areas are covered with cultivated land. The dominant soils in the study area are Calcaric fluvisols, Chromic Cambisol, Eutric Cambisol, Eutric Vertisol, and Haplic Luvisol. The study area obtained rainfall with high intensity during the summer season which extends from June to September. The recorded mean monthly rainfall all over the watershed ranges from 25 mm to 210 mm.

2.2. Datasets and sources

The vital input data for simulating the rainfall-runoff process are classified into hydrological (rainfall), meteorological (streamflow), and physiographic (land use/cover, soil type, and digital elevation model. In this study, rainfall, streamflow, soil, Land Use Land Cover (LULC), and digital elevation model 30*30m resolution data were used. The digital elevation model and Soil data were obtained from the Ministry of Water Resource, Irrigation, and Electricity, Ethiopia. The LULC data was collected from the Mapping Agency of Ethiopia. In the same way, rainfall data (1987–2017) of six stations in the study area was obtained from the Ethiopian Meteorological Service Agency (Table 1). Table 2 indicated that the areal rainfall computed by Isohyetal method.

The input data namely digital elevation model, LULC, percent impervious area, and soil were mainly required to set up the HEC-HMS model. In calibrating and validating the model, hydrological models need a series of observed runoff data (Joo et al., 2014; Tassew et al., 2019; Onyutha, 2019; Koch et al., 2020; Melišová et al., 2020). For this purpose, long term (1987–2010) daily runoff data at the outlet of the study area and nearby station (Awash River at Hombole and Gedamso River) to fill in missed data were taken from the Ethiopian Hydrological Agency. Rainfall data was collected for two purposes: computing areal rainfall over the watershed (Fig. 3) and developing a hydrological model setup. In the watershed, the rainfall pattern was spatially varied, and the Isohyetal method is recommended for such a situation (Subramanya, 2008). Hence, the Isohyetal method was used to compute the average rainfall over the watershed. Further, the missed rainfall data was filled by the normal ratio method while the missed runoff data were filled using a linear regression method.

2.3. HEC-GeoHMS model

HEC-GeoHMS extension in ArcGIS was used to delineate the boundary of the study area by considering the outlet point of the Meki watershed. Further, HEC-GeoHMS generates six sub-watersheds, sixteen routing reaches, and necessary hydrologic parameters. To increase the model performance, a series of stream segments and sub-watershed generated in the HEC-GeoHMS model were merged into six sub-watersheds. Additionally, it creates the Background map files, basin model files, meteorological model files, and a grid cell parameter which is later exported into HEC-HMS.

2.4. HEC-HMS model

HEC-HMS model is very popular and widely applied in several hydrological studies due to its ability to simulate short and long events runoff, ease to operate (Sok and Oeurng, 2016; Tassew et al., 2019; Daide et al., 2021). Several model components namely basin model, metrological model, control specification, and input data are available (Fleming and Brauer, 2016). The precipitation and streamflow data were used as input for the meteorological model. In this study, the meteorological model methods such as Frequency Storm and Gage

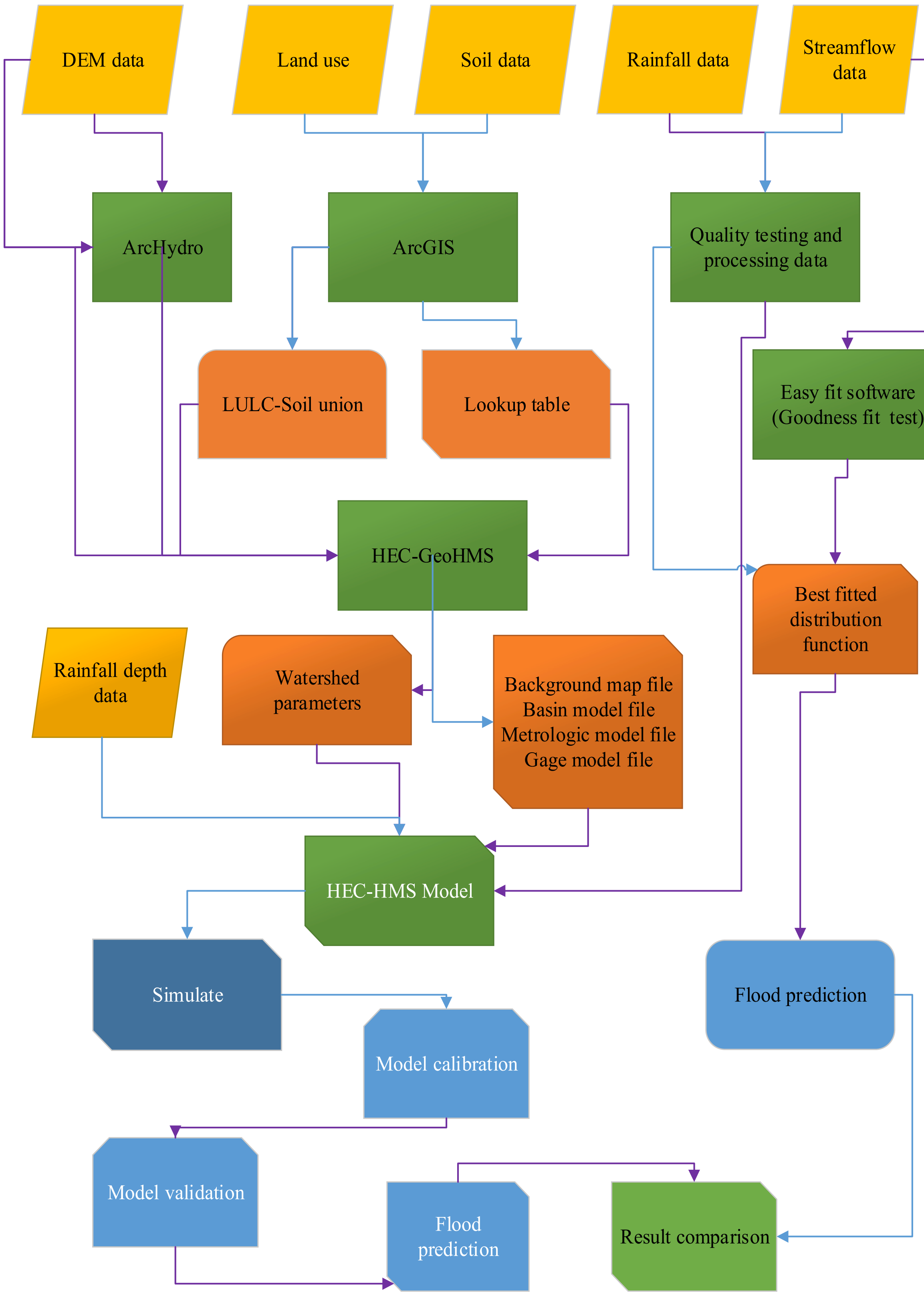

Fig. 2. Overall framework of methodology.

Table 1
Average annual rainfall of selected stations in Meki river watershed.

Station	Lat (Decimal degree)	Long (Decimal degree)	Altitude (m)	Mean Annual Rainfall (mm)
Buie	8.33	38.55	2020	1013
Butajira	8.15	38.37	2000	1060
Ejersa	8.24	38.68	1797	871
Koshe	8.06	38.51	1878	800
Meki	8.15	38.82	1662	754
Tora	7.86	38.41	2001	834

Table 2
Areal mean annual precipitation computed by Isohyetal method.

Isohyetal (mm)	Average (mm)	Area (km^2)	Areal rainfall (mm)
<800	775	150	53.5
800–850	825	350	128.85
850–900	875	415	162.04
900–950	925	290	119.70
950–1000	975	674	293.24
1000–1050	1025	327	149.56
>1050	1050	34	15.93

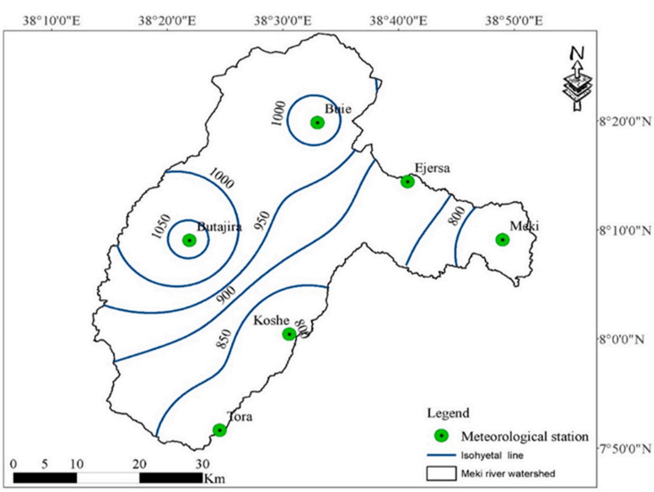

Fig. 3. Meki watershed Isohyetal map.

weights were used. The simulation period is controlled by the control specifications component. Accordingly, the control specification for this simulation was from (Jan 01, 1987–Dec 31, 2017) with an hourly time step. It contains components that compute runoff, direct runoff, and base flow. The SCS-CN, SCS-UH, monthly constant base flow, and Muskingum methods were used. These methods were selected based on the applicability and availability of data (Kamali and Mousavi, 2014; Jin et al., 2015).

i) Loss Model

The loss models normally calculate the runoff volume by computing the volume of water lost and reducing it from the rainfall. Although the HEC-HMS model has various options for loss modeling, for this study, the Soil Conservation Service-Curve Number loss method was selected due to its versatility, widely applicable in estimating runoff, requires few input data, and provide reliable results (Askar, 2013; Lal et al., 2017; Soulis, 2021; Uwizeyimana et al., 2019). The Soil Conservation Service Curve Number is estimated using Equation (1)

$$P_e = \frac{(P - 0.2S)^2}{(P + 0.8S)} \tag{1}$$

where, Pe is the excess rainfall (mm), P is the precipitation, S is the potential maximum retention after r through studies of many small agricultural watersheds. The potential maximum retention (S) is a function of Curve Number (CN) and is inversely proportional to CN. The potential maximum retention is given by equation (2).

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

For watersheds with different soil types, weighted CN is necessary and computed by equation(3).

$$CNw = \frac{\sum (Ai^*CNi)}{At} \tag{3}$$

where, Ai is a sab-basin area, At is the watershed area, CN is the weighted sub-basin Curve number. The Curve Number (CN) was already generated by HEC-GeoHMS and embedded into the basin model file thus the software automatically assigned the curve number value for each sub-basin.

ii) Transform Model

The models transform the excess precipitation into a direct runoff. In this study, the Soil Conservation Service Unit Hydrograph model was selected to compute runoff. The input parameter for this method is only lag time (Tag) which in turn depends on time of concentration (T_C). Lag time (TL) and time of concentration (TC) are two parameters that determine how quickly a watershed responds to rainfall over its watershed (Sultan et al., 2022). Several formulas have been already developed to compute time of concentration based on watershed characteristics. Thus, in watersheds largely dominated by channel flow than overland flow, it is appropriate to estimate time of concentration using Williams, 1922, Kirpich (1940), Johnstone and Cross (1949), Harka et al. (2021), Simas and Hawkins (2002), empirical equation. Fang et al. (2008) studied Time of concentration estimated using watershed parameters determined by automated and manual methods applied all the above methods to estimate time of concentrations. They noted that the Kirpich and Haktanir–Sezen methods are more accurate than other methods. However, Kirpich and Haktanir–Sezen methods are effective for small watersheds and do not consider the velocity of flow. Moreover, numerous studies (McCuen et al., 1984; Sharifi and Hosseini, 2011; Seyam and Othman, 2014; Ayalew et al., 2015) stated that all methods of estimating Tc provide significant errors. However, the Natural Resources Conservation Service (NRCS,1986) velocity method is the most popular and accurate method in determining Tc for both rural and urban catchments (McCuen et al., 1984; Fang et al., 2008; Sharifi and Hosseini, 2011; Perdikaris et al., 2018). Due to the NRCS velocity method relies on a solid hydraulic basis to compute flow velocity (Fang et al., 2008) and evidencing a close agreement between the mean Tc computed by this method and from rainfall and hydrograph data (McCuen et al., 1984); more reliable than purely empirical equations (Fang et al., 2008). In NRCS method, Tc is the sum of the travel times of flow segments Eqn. (5). Later on the initial Tc value computed by NRCS velocity method was optimized in the model calibration. Beside this, NRCS (1986) developed formula that relates, time to lag and time of concentration as shown in equation (4). Mathematically, the equation of NRCS (1986) Velocity Method were shown by eqns. (5) and (6).

$$T_L = 0.6^*T_C \tag{4}$$

$$T_c = T_{sheet} + T_{shallow} + T_{channel} \tag{5}$$

$$T_c = \frac{0.0018^*L_{sheet}^{0.6}{}^*n^{0.6}}{i^{0.4}{}^*S_w^{0.3}} + \frac{L_{shallow}}{3.6C\sqrt{S_w}} + \frac{0.0018^*L_c{}^*n^{0.75}}{i^{0.25}{}^*A^{0.125}{}^*S_c^{0.375}} \tag{6}$$

Where T_L is the lag time (hour), Tc is a time of concentration (hour) computed by equation (5), Where: Lc, = main channel length (km), Lsheet = length of sheet flow (km), Lshallow = length of shallow concentrated flow (km), A = area in km^2, and Sc = main channel slope and Sw = average basin slope, n = Manning's roughness coefficient and C = constant equal to 4.918 for unpaved and 6.196 for paved areas. L_C is the longest flow path (m), and S_C is the average slope longest flow path.

iii) Flood routing

Dispute various flood routing components are available in the HEC-HMS model, the Muskingum method was employed for this study due to its simplicity and require few input data (Baláž et al., 2011; Lee et al., 2018). It is a simple approximate method used to calculate the outflow hydrograph at the outlet point (O'Sullivan et al., 2012). It needs two input parameters such as flood travel time (K) of the flood wave through routing reach, and the attenuation flood wave (X). These parameters are usually derived through calibration using measured discharge data (Birkhead and James, 2002). Subramanya (2008) stated that the Muskingum method was computed through Equation (7).

$$S = k[xI + (1 - x)Q] \tag{7}$$

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

2.5. Calibration and validation of the model

The model is calibrated to adjust parameters to match the simulated with the observed values (Moriasi et al., 2007). The model calibration was done by adjusting parameters like lag time, curve number, initial abstraction, flood wave traveling time (Muskingum-k), and weighting coefficient of discharge (Muskingum-x) until the simulated result was well-matched with the observed one. The process was completed automatically and manually by adjusting the parameters. Further, the model is validated to check that the model parameters work outside the flow conditions used in calibration (Moriasi et al., 2007). In this study, ¾ (75%) of events was used for calibrating model and the remaining ¼ (25%) of events was used to validate the model. Thus, 18 years (1987–2004) events were used for model calibration and the remaining 6-year (2005–2010) events was used for validating model.

Lastly, statistical evaluation techniques such as the Nash-Sutcliffe Efficiency (NSE), and coefficient of determination (R^2) were applied to evaluate the performance of the model. Different researchers range the model performance. Regarding this, Moriasi et al. (2007) stated that the NSE and R^2 value ranges from 0.75 to 1.0 the model is categorized as very good. Moreover, several researchers (Schaefi and Gupta, 2007 and Vaze et al., 2011) stated that a very good model has the value of NSE and R^2 greater than 0.75 both at calibration and validation period.

2.6. Peak flood prediction

Conducting flood frequency analysis is essential to understand the nature and magnitude of current and future floods corresponding to a given return period. Moreover, reviewing frequency analysis is vital to identify most suitable model that could anticipate extreme events of flood. However, it is challenging to determine rainfall and flood return periods. Different researchers have suggestions on taking the rainfall and flood return period. Viglione et al. (2009) stated that for a single storm duration, and storm durations vary, the rainfall and flood return period is always equal, irrespective of the shape of the unit hydrograph. Moreover, for rainfall-induced extremes over the small watershed, the rainfall and flood return period is almost equal (Dickinson et al., 1992). Due to peak floods being induced by rainfall than snowmelt over a small watershed, this study assumed the same return period for rainfall and flood.

Despite considerable methods being available, the HEC-HMS model (using design storm) and statistics probability distribution (using observed streamflow data) were used in this study. The design storm data was derived using the Intensity Duration Frequency curve (IDF) developed by the Ethiopian Roads Authority (ERA). Flood frequency analysis was carried out for 2, 10, 25, 50, and 100 years return periods.

The best fit probability distribution was determined by applying Easy-Fit software. Easy Fit is a well-known statistical data analysis and simulation tools that enable to choose the most appropriate Probability distribution (Ahmad et al., 2016). In regard with this, several researchers (Kamal et al., 2017; Sarauskiene and Kriauciuniene, 2011; Singo et al., 2012) used easy fit software to analyze flood frequency.

In this case, the choice of an appropriate flood distribution model was based on approaches of goodness-of-fit (GOF) tests (Kolmogorov Smirnov, Anderson Darling, and Chi-Squared) (Ghasemi and Zahediasl, 2012). The goodness of fit tests provides several distribution types. Overall, for selecting the best-fit distribution a ranking system was done, with rank 1 being the best, 2 the second best and the last relieves the worst probability distribution. Anderson Darling test is the most preferable test for selecting the best fit Probability distribution model (Alam et al., 2018). According to Subramanya (2008), the Gumbel's method is shown in Table 3.

3. Results

3.1. Watershed parameters

Table 4 shows different watershed parameters considered in model calibration and validation. For instance, the CN value was spatially varied (30 for the area covered with forest and the maximum value of 100 for the area covered with water bodies). The overall weighted curve number range between 65.7 and 85.4. The spatial distribution of weighted CN values was shown in (Table 4). Similarly, the initial abstraction was varied from 8.7 mm in W1200 to 26 mm in the W770 sub-basin. Moreover, the steepest basin slope of watershed is 78.1% found in the W940.

3.2. Model simulation result

The details for each sub-basin are given in Table 5. As shown in Table 5, the sub watershed W7700, W1100 and Outlet point have high discharge values because water depth increases as the river reach approach the outlet point. Moreover, the routed flood result indicated that as the river reach approach to outlet point water depth increases. Hence discharge increased from river reach (R480 to R420) (Table 5). These relieved that for design purpose peak flood at outlet point is very important (Table 5). Moreover,the parameter and optimized value were indicated by Tables 6 and 7.

3.3. Calibration and validation

The simulated and observed hydrograph for the calibration and validation period exhibits almost similar shapes and trends (Fig. 4&5). However, the simulated flow was slightly overestimated. The scatter

Table 3
Gumbel's distribution method formula (Subramanya, 2008).

distribution	Formula		
Gumbel	$X_T = \overline{X} + K_T\sigma$ $\overline{X} = \frac{\sum_{i=1}^{N} X_i}{N}$	$K_T = -\frac{\sqrt{6}}{\pi}\{0.5772 + \ln[\ln(\frac{T}{T-1})]\}$	$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \overline{X})^2}{N-1}}$

Note: Where X_T is peak flood, σ is the standard deviation, K_T is the frequency factor, $\overline{X}$ is the mean value of the events, Xi is the ith event magnitude, and N is the number of events.

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

Sub-basin	Area (Km^2)	Lag Time (hr.)	Basin Slope (%)	CN	(S) (mm)	Ia (mm)
W770	681	75.8	16.8	65.7	132.8	26
W1100	629.2	54.3	22.8	69.5	111.5	22.3
W1320	200	37.72	11.6	83	51.5	10.3
W1200	297.6	23	36.2	85.4	43.5	8.7
W990	349.8	35.742	26.8	77.2	75	15
W940	82.4	12.8	78.1	78.29	70	14

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

Sub-basin	peak discharge (m^3/s)	River channel	Routed flood (m^3/s)	River channel	Routed flood (m^3/s)
W7700	156.5	R480	33.9	R400	226.0
W1100	157.6	R470	34.0	R430	226.6
W1320	33.8	R500	33.8	R350	258.5
W1200	69.9	R540	33.7	R240	258.8
W990	103.4	R570	33.6	R150	259.2
W940	28.8	R600	33.4	R220	260.0
Outlet	296.2	R330	156.6	R420	278.1

Table 6
HEC-HMS optimized watershed parameters of the study area.

Sub-basin	Parameter	Unit	Initial	Optimized	Objective function
W7700	Lag time	hr.	75.95	77.23	−0.37
	CN		65.7	56.21	−0.17
W1100	Lag time	hr.	53.6	54.3	−0.46
	Ia	mm	22.3	22.45	−0.23
W1320	Ia	mm	10.3	15.15	0.00
W1200	Ia	mm	8.7	9.13	0.00
	CN		85.4	84.34	−0.32

Table 7
Optimized Muskingum parameters for each reach.

Reach	Muskingum(X) value		Muskingum(K) (hr)		Objective function
	Initial	Optimized	Initial	Optimized	
R480	0.25	0.24	3.00	2.77	0.00
R330	0.273	0.264	2:00	1.88	0.00
R320	0.25	0.24	1.89	1.78	0.00
R400	0.23	0.25	1:75	1.65	0.00
R350	0.19	0.21	1:23	1.18	−0.01

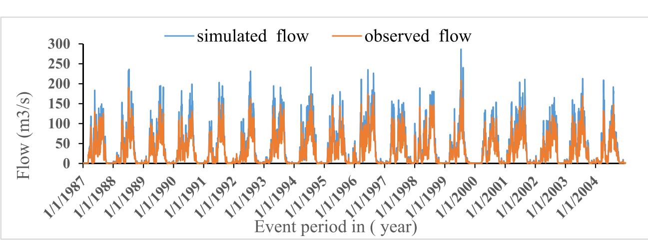

Fig. 4. Simulated and observed streamflow hydrographs after calibration.

plot of the measured and simulated flow during the calibration and validation period were with a correlation coefficient (R^2) of 0.91 and 0.89. This shows that this strong correlation between the simulated and observed stream data (Fig. 6).

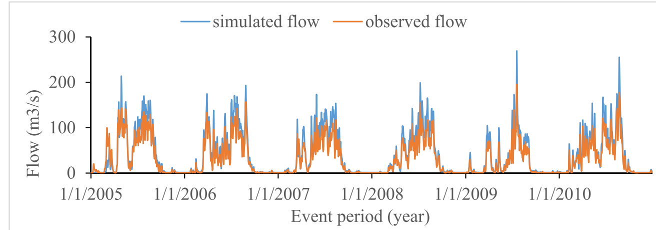

Fig. 5. Simulated and observed stream flow hydrographs after validation.

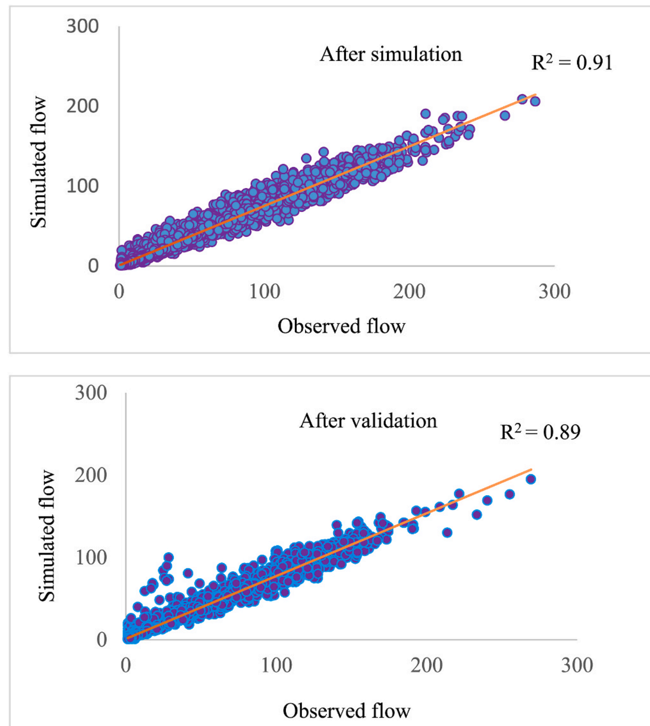

Fig. 6. The Scatter plot of observed and simulated flow after calibration and validation.

Table 8
Statistical distribution best-fit analysis result by Easy Fit5.6

Distribution Function	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
	Statistics	Rank	Statistics	rank	Statistics	rank
Gumbel	0.07292	1	0.218559	1	0.03889	1
Log Pearson 3	0.0752	2	0.21288	1	0.12325	2
Log Normal	0.07558	3	0.22103	3	0.36018	3
Normal	0.15793	4	1.0482	4	1.6624	4

3.4. Model performance evaluation

In this study, the value of the statistical evaluation criteria during calibration and validation period were, NSE = 0.832, R^2 = 0.91 and, NSE = 0.803, R^2 = 0.89 respectively. This indicates that the applied statistical error tests were found within an acceptable range. several researchers (Moriasi et al., 2007; Schaefi and Gupta, 2007; Vaze et al., 2011) very well model, have the NSE, and R^2 value above 0.75.

3.5. Selection of best fit probability distribution

Table 8 relieved the ranks of (Gumbel, log Pearson, lognormal, and normal) statistical distribution functions in GOF test. As shown from this

Table 9
The predicted flood of the study area.

No.	Return period (year)	Peak flood (m^3/s)	
		HEC-HMS	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

table, the Gumbel distribution ranks first in all GOF tests, Log Pearson 3 the second best fit and Normal distribution ranks the last. This mean the Gumbel method was the best-fit to observed data while normal distribution was not good for this data. Hence, Gumbel method was selected to predict flood at various return periods.

3.6. Peak flood prediction

The predicted flood over different return periods were shown in Table 9. The minimum flood predicted by HEC-HMS is 133.2 and 346.19 m^3/s whereas the minimum and maximum flood computed by the Gumbel method is 126.7 and 331.87 m^3/s. This shows that for the same return period, the predicted flood by HEC-HMS is greater than Gumbel method. Taking the same basin lag time interval for 2, 10-, 25-, 50-, and 100-year return periods, the peak discharge and shape of the hydrograph were predicted (Fig. 7). In both methods the larger value occurred at 100-year return period. Overall, this study is similar with Kebebew and Awass (2022) and Acharya and Joshi (2020). Fig. 8 relieved that result obtained by HEC-HMS is slightly greater than the Gumbel method.

4. Discussion

Several physical parameters were taken into account in this study. Tassew et al. (2019) stated that the Curve number represents the impact of both soil type and LULC upon the watershed response toward hydrological parameters. The curve Number value can greatly influence runoff generation (Lal et al., 2017). The CN value of this study area was spatially varied, with 30 for the area covered with forest and a maximum value of 100 for the area covered with waterbodies. The curve number value is directly proportional to runoff generation (Lal et al., 2017). Therefore, the lower value of CN indicates a low runoff coefficient, whereas a high value shows a high runoff coefficient (Ranjan and Singh, 2022). However, during rainfall-runoff processing, each sub-basin requires a weighted curve number value. Hence, the weighted CN values were extracted by HEC-GeoHMS for each sub-basin (Fleming and Brauer, 2016). The basin lag time of the study area was varied from 12.8 to 75.8 h. This means that for low basin lag time value, the flood reach outlet points slowly and the corresponding peak discharge is also low. The lower the basin lag time, the quicker surface runoff reaches the outlet point (Yu et al., 2000). Moreover, the basin slope can also bring significant change on quantity of runoff (Garg et al., 2013; Jourgholami et al., 2021). Thus, the steeper the basin, the faster runoff reaches the outlet point. Despite several watershed parameters considered, the curve number and lag time parameters were found to be the most influential parameters. The model slightly systematically overestimated streamflow even though it followed the same pattern as the observed one. This is may be due to some water is supplied for irrigation purpose and imprecise measurement of streamflow data by data collector. In line with this, several researchers (Oleyiblo and Li, 2010; Sardoii et al., 2012; Asadi and Boustani, 2013; Sok and Oeurng, 2016; Ramesh, 2017; Romali et al., 2018; Tassew et al., 2019; Gunathilake et al., 2019; Suprayogi et al., 2021; Hamdan et al., 2021) obtained almost similar results. The HEC-HMS is designed to simulate the rainfall-runoff process of watershed systems and has an optimization feature that can be used to match the simulated streamflow with the observed flow (Thu et al., 2019; Hamdan et al., 2021). Model calibration and validation require the examination of the accuracy of results to ensure valid representation of hydrological processes in the watershed. Modelers have used different performance methods for basin calibration and validation in the literature. The statistical performance evaluation criteria refer to model performance qualitative ratings with the corresponding threshold for model performance measures (Moriasi et al., 2015). The statistical model performance evaluation result showed, the model can be well applied for the study area. According to the range mentioned in Akoglu (2018), the mean correlation coefficient obtained in this study can be considered as strong (>0.8). Furthermore, this finding relieved that the model can simulate streamflow in the Meki watershed. Estimation of the design flood for a desired return period is of prime importance for the safe design of hydraulic structures such as dams, spillways, bridges, culverts, urban drainage systems, and flood plain zoning. Frequency analysis enables estimation of the probability of occurrence of a certain hydrological event of practical importance by fitting a probability distribution to one that is empirically obtained from recorded annual maximum discharge data (Desalegn and Mulu, 2021; Vivekanandan, 2012; Saghafian et al., 2014). It is used to predict design floods for sites along a river. According to Saghafian et al. (2014), probability distribution functions fitted to maximum flood series are commonly applied to determine flood discharges of different probabilities. Despite choosing the best-fitted probability distribution function is often controversial, Gumbel method was appropriately fit to observed data based on GOF tests. The flood frequency analysis shows that peak floods will increase with increasing reoccurrence intervals. Keeping basin lag time constant, the variation in peak and shape of the hydrograph obtained occurred due to the variation in return period and magnitude of maximum probable precipitation. The result obtained by the Gumbel's method was very close to simulated value (Table 9). However, to appropriately manage flood risk, the maximum probable flood is extremely important, so HEC-HMS result is recommended in designing flood control measurement.

In conclusion, the finding of this study can help to develop appropriate watershed management strategies and combat flood risks in the different parts of the watershed.

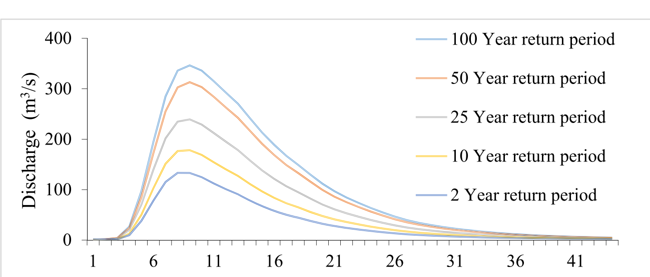

Fig. 7. Hydrograph of different return period.

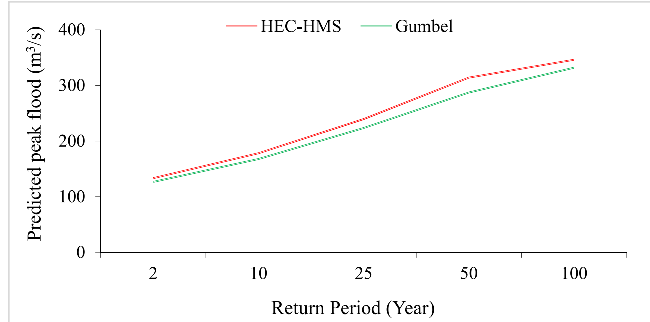

Fig. 8. Graphical Comparison of HEC-HMS result with Gumbel method.

5. Conclusion

In this study, the rainfall-runoff process was conducted using HEC-HMS. The correlation between simulation and observation was very good, but the total peak of discharge for this study was slightly overestimated. Peak flood for different return period were conducted using hec-hms and Gumbel methods. It was noticed the curve number, initial abstraction, lag time, flood traveling time (Muskingum-k), and discharge weighting factor (Muskingum-x) were the main parameters that affect runoff generation. The Nash-Sutcliffe Efficiency (NSE) and Coefficient of Determination (R^2) were used to assess the performance of the model. The result indicated HEC-HMS model is well suited for flood simulation from rainfall data of the study area. Further, this finding can offer detailed information regarding peak floods in the watershed. Thus, it is useful to plan, design, and manage flood risk in the watershed. Moreover, it helps further investigation of hydrological modeling of adjacent catchments with a similar hydrological setting. The limitation of this finding was it assumed the same return period for rainfall and observed streamflow data in analyzing flood frequency.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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