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# Extenuating the parameters using HEC-HMS hydrological model for ungauged catchment in the central Omo-Gibe Basin of Ethiopia

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**Abstract:** Characteristics of ungauged catchments can be studied from the hydrological model parameters of gauged catchments. In this research, discharge prediction was carried out in ungauged catchments using HEC-HMS in the central Omo-Gibe basin. Linear regression, spatial proximity, area ratio, and sub-basin mean were amalgamated for regionalization. The regional model parameters of the gauged catchment and physical characteristics of ungauged catchments were collated together to develop the equations to predict discharge from ungauged catchments. From the sensitivity analysis, crop coefficient (*CC*), storage coefficient (*R*), constant rate (*CR*), and time of concentration (*TC*) are found to be more sensitive than others. The model efficiency was evaluated using Nash–Sutcliffe Efficiency ($N_{SE}$) which was greater than 0.75, varying between −10% and +10% and the coefficient of determination ($R^2$) was approximated to be 0.8 during the calibration and validation period. The model parameters in ungauged catchments were determined using the regional model (linear regression), sub-basin mean, area ratio, and spatial proximity methods, and the discharge was simulated using the HEC-HMS model. Linear regression was used in the prediction where p-value ≤ 0.1, determination coefficient ($R^2$) = 0.91 for crop coefficient (*CC*) and 0.99 for maximum deficit (*MD*). Constant rate (*CR*), maximum storage (*MS*), initial storage (*IS*), storage coefficient (*R*), and time of concentration (*TC*) were obtained. The result is that an average of 30 $m^3/s$ and 15 $m^3/s$ as the maximum monthly simulated flow for ungauged sub-catchments, i.e. Denchiya and Mansa of the main river basin.

**Keywords:** HEC-HMS; Regionalization; Stream flow simulation; Ungauged catchments; Omo-Gibe sub-basin

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## Introduction

Water resources management is a challenge in the absence of adequate hydrological data. Most of the Ethiopian river watersheds are ungauged and poorly monitored in some cases. There are a total of 560 gauged stations, 454 of which are operational for both lakes and rivers (Arsenault et al. 2019; Swain and Patra, 2019; Nega and Seleshi, 2021). Continuous stream flow prediction under the above circumstances is difficult to do for the purpose of hydrology study and watershed management under the above circumstances (Samuel and Couli baly, 2011; Shoaib et al. 2013; Donnelly et al. 2016). In most cases, hydrometric stations are either not available in ungauged basins or they have become defunct. Estimations and predictions of hydrological parameters and responses at ungauged places are difficult either due to the required variables are not sampled at the required resolution or it has been recorded during a specific period of time (Pinheiro and Naghettini, 2013; Li et al. 2015; Barbarossa et al. 2017; Zamoum and Gamane, 2019). Besides, proper design of infrastructure and water supervision are associated with human beings, biodiversity, and conventional natural resources, which often need detailed exploration of hydrological variables at ungauged sites. The risks of severe hydrological calamities like floods and droughts are steadily increasing with changing land cover, climate, and population growth (Haile-

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georgis et al. 2015; Javeed and Apoorva, 2015; Mosavi et al. 2021). Since most of the catchment is ungauged, the regionalization procedure may help the planner, designer, and water resources managers to predict the flow from the catchment with existing physical characteristics.

The reliable prediction of continuous stream flow in ungauged catchments and its parameter estimation have remained a challenge, although significant insights have been gained in recent years (Hailegeorgis et al. 2015; Teutschbein et al. 2018). The establishment of the Prediction in Ungauged Basins (PUB) initiated by the International Association of Hydrological Sciences (IAHS) shows that there is still much to be done in this area (Siva palan et al. 2003; Wagener et al. 2004). It is usually assumed that the model parameters represent some inherent and time-invariant properties of the catchment under study. Early attempts at modelling ungauged catchments simply used the parameter values derived from neighboring catchments where stream flow data were available, i.e. a geographical proximity approach (Teutschbein et al. 2018; Rajendran et al. 2020; Tesfalem et al. 2021). However, this seems to be insufficient since even nearby catchments can be quite different in their hydrological behavior (Shoaib et al. 2013; Pool et al. 2017; Rajendran et al. 2020). Others propose to estimate parameters from, soil properties such as porosity, field capacity and wilting point (for model storage capacity parameters); percentage of forest cover (evapotranspiration parameters); or hydraulic conductivities and channel densities (time constants) (Roy and Mistri, 2013). The basic methodology calibrates a specific model structure to as many gauged catchments as possible and derives statistical (regression) relationships between local model parameters and catchment characteristics. These statistical relationships, or regional models as mentioned here, and the measurable properties of the ungauged catchment can be used to estimate the (local) model parameters. This procedure is usually referred to as regionalization or spatial generalization (Sivapalan et al. 2003; Abebe et al. 2010).

This paper proposes both theoretical and applied issues related to the regionalization of continuous lumped and parsimonious (parameter efficient) conceptual for rainfall runoff models. The principle of parameter regionalization is discussed and current problems and future directions of improvement are identified and evaluated using eleven catchments located in central parts of Omo Gibe Basin, Ethiopia. The objective is not to derive a reliable and robust regional model equation, which is unlikely with the small number of catchments used, but to investigate model parameter issues through regionalization and lumped conceptual rainfall runoff models.

## 1 Study area

Omo-Gibe river basin is one of the major river basins in Ethiopia and is located in the southern part of the country. The geographical location of the basin lies between 6°25′N and 8°20′N latitude and 35°30′E and 37°35′E longitude enclosing an area of 15 610 km$^2$. It is surrounded by a river basin in the southern boundary that flows into Lake Turkana of Kenya (Fig. 1).

Lack of rainfall and flow data has long been a matter of concern for hydrological modeling. To compensate the missing data of climate, average values have been used, and the regression method was adopted to generate flow data (Oudin et al. 2008; Wale et al. 2009; Sellami et al. 2014).

## 2 Methods

The Hydrological Modeling System (HEC-HMS), a comprehensive hydrologic modeling tool was used to simulate the precipitation-runoff processes of the watershed. The main reason for selecting this tool is that it is physically based, spatially distributed and available in the public domain (IHMS, 2006). For this particular study, deficit constant loss method, Clark unit hydrograph, and constant monthly base flow technique in HEC-HMS were used to simulate runoff for each sub-basin.

Sensitivity analysis of the model parameters was manually followed by estimating the values of selected objective functions (Zhang and Chiew, 2009; Bao et al. 2012; Donnelly et al. 2016). The value of each parameter is plotted against the selective objective function and the parameters are considered the most sensitive when the objective function shows a steep slope with respect to the parameter values in the ranges from 60% to 20%, while the parameters with less steep slope or nearly flat were considered less sensitive.

### 2.1 Data collection

In the study area, seven gauging stations were in working conditions out of the fourteen available stations. Hydrological data were collected from the Ministry of Water, Irrigation, and Electricity (*MoWIE*, Government of Ethiopia), and meteorolo-

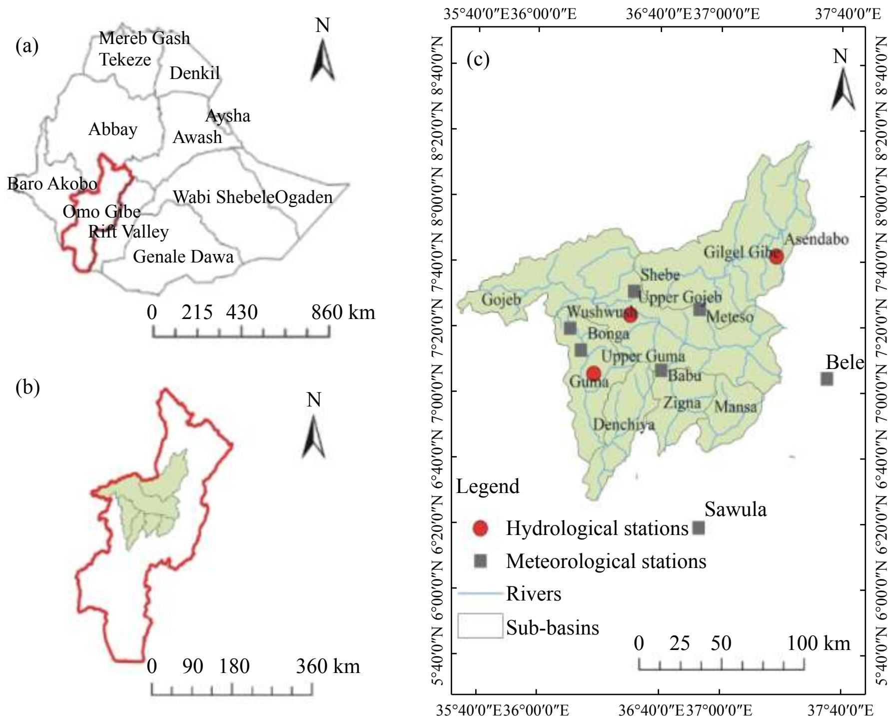


**Fig. 1** Study Area a) Major river basins in Ethiopia, b) Omo-Gibe River Basin and selected sub-watersheds c) Selected sub-watersheds and rivers

gical data were obtained from the National Metrological Agency (*NMA*, Government of Ethiopia) for the studied period.

## 2.2 Data analysis

After the raw data were collected, the missing data in stream flow and meteorological data were filled and consistency, homogeneity of data record was checked using double mass curve and non-dimensional parameterization techniques, respectively (**Table 1**).

**2.2.1 Selection of representative physical catchment characteristics**

HEC-GeoHMS tools that work with Arc-GIS 10.2.2 were used to process high resolution 12.5 m × 12.5 m *DEM* (Digital elevation model). The selection of the physical catchment characteristics (PCCs) was based on the well-recorded data in the catchments including climate, geography, physiographic, soil type, land use and land cover and geology (Mazvimavi, 2003). However, before the selection of physical catchment characteristics for regionalization, evaluation were carried out to avoid inter-dependency or inter-correlation between different physical catchment characteristics. Thirty-two PCCs were selected from each of three gauged and seven ungauged catchments.

**2.2.2 Model calibration**

From HEC-HMS Model results there are three sub-catchments to calibrate hydrographs. The scatter plotting depicts a perfect calibration from 1992 till the end of 2013 before the start of validation. The validation starts from early 2014 till 2020.

**2.2.3 Model performance**

**Root mean squared error (RMSE):** *RMSE* is the square root of the mean of the square of all errors. The *RMSE* value less than 10% is rationally acceptable. The performance is equated by the formula (Equation 1).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{sim}-Q_{obs})^2} \qquad (1)$$

Where: *RMSE* = Root mean squared error between the predicted and observed flow calculated in %;

**Table 1** Summary of hydrologically gauged stations

| No | River | Station/site | Area (km$^2$) | Latitude/Degree | Longitude/Degree |
|---|---|---|---|---|---|
| **1** | Upper Gojeb | Near Shebe | 3 577 | 7.4 | 36.5 |
| **2** | Gilgel Gibe | Near Asendabo | 2 966 | 7.7 | 37.3 |
| **3** | Upper Guma | Near Andra | 231.2 | 7.1 | 36.3 |

$Qsim$ = simulated flow;
$Qobs$ = observed flow;
$i$ = the time step, and $n$ is the total amount of time steps used throughout the standardization.

**Nash–Sutcliffe Efficiency ($E_{NS}$):** $E_{NS}$ is used to evaluate the whole arrangement or profile of the simulated and observed hydrograph. $E_{NS}$ indicates the model's effectiveness by linking the goodness of fit of the simulated data to the variance of the measured data (Equation 2).

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(q_{oi}-q_{si})^2}{\sum_{i=1}^{n}(q_{oi}-\bar{q}_o)^2} \tag{2}$$

Where: $q_{si}$ = the simulated value;
$q_{oi}$ = *the observed value;*
$\bar{q}_o$ = *the average observed flow;*
$E_{NS}$ values range from 1.0 (best) to - ∞.

**Coefficient of determination ($R^2$):** The $R^2$ value indicates the strength of the relationship between the observed and simulated values. The $R^2$ coefficient and NSE simulation efficiency measure how well trends in the measured data are reproduced by the simulated results over a specified time period and for a specified time step. $R^2$ value ranging from 0.75 to 1.0 indicating very good model performance and 0.5 to 0.75 refers to good performance between observed and simulated stream flow (Equation 3).

$$\frac{\left[\sum_{i=1}^{n}(qsi-qsavg)(qobs-qoavg)\right]^2}{\sum_{i=1}^{n}(qsi-qsavg)^2(qobs-qoavg)^2} \tag{3}$$

#### 2.2.4 Regionalization

Simulation of stream flow at a point of interest requires transfer of various hydrologic information including model parameters, hydrologic indices, and stream flow values from gauged to ungauged catchments. This procedure is commonly referred as regionalization, which is a method of shifting data from a similar watershed to the catchment of interest (Samuel and Coulibaly, 2011). Discharge prediction needs a model parameter optimization for gauged catchments by fitting observed and simulated stream flow (Merz and Bloschl, 2004; Blöschl, 2005; Sawicz et al. 2011). For instance, it is crucial to practice regionalization in such watersheds to transfer data from adequate records to inadequate ones. Spatial proximity had to be used for the watersheds, which may not have comparable gauged catchments. Therefore, the methods of regionalization using similarity of catchment characteristics (regional model) were applied to estimate flow for ungauged catchments (Solomon, 2001; Sivapalan et al. 2003; Goswami et al. 2005; Bao et al. 2012; Hailegeorgis et al. 2015; Ibrahim, 2015; Javeed and Apoorva, 2015; Tamalew and Kemal, 2016).

## 3 Result and discussion

### 3.1 Sensitivity analysis of model parameters

For the Upper Gojeb sub-basin, in terms of NSE, the model response is most sensitive to crop coefficient ($CC$) and storage coefficient ($R$). The remaining parameters, such as initial deficit ($ID$), maximum deficit ($MD$), constant rate ($CR$), initial storage ($IS$), maximum storage ($MS$), time of concentration ($TC$), and Muskingum constants ($K$ and $X$) do not affect the Nash Sutcliffe efficiency ($E_{NS}$) (Fig. 2). In the case of coefficient of determination ($R^2$), storage coefficient ($R$) is the most sensitive parameter. The parameter crop coefficients ($CC$) slightly deflect, so the following sensitive parameter is crop coefficient ($CC$). When considering an objective function of root mean squared error (RMSE), crop coefficient becomes the most sensitive parameter. Also, constant rate ($CR$) is more sensitive than the remaining parameters. The other model parameters are less sensitive.

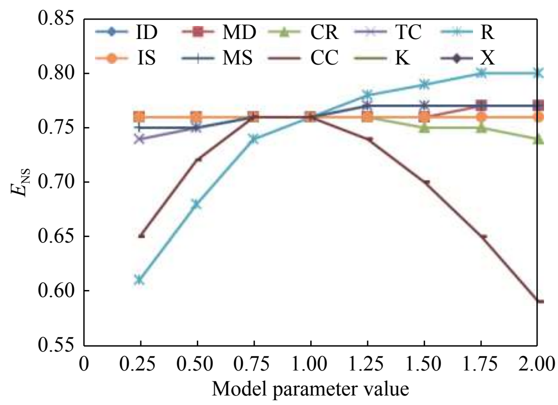


**Fig. 2** Sensitivity analysis using $E_{NS}$ of Upper Gojeb Sub-catchment

### 3.2 HEC-HMS model calibration results

Model calibration results show that the model performance of Upper Gojeb, Upper Guma, and Gilgel Gibe is sufficient to evaluate criteria like $E_{NS}$, where $R^2$ exceeds 0.6 and $RMSE$ lying between 0 and +5%, indicating that the model performs reasonably for the calibrated period of 1992 to 2013.

## 3.3 Model validation

The results of stream flow estimations indicate that the HEC-HMS model is a good predictor of stream flow in the central part of the Omo-Gibe basin. As discussed earlier, the model parameters range, results of the optimized model, and validation model parameters of gauged catchments that satisfy the objective functions for calibration also have reasonable performance for validation tests from 2014-2020. The hydrograph for calibration and validation periods is shown in Fig. 3.

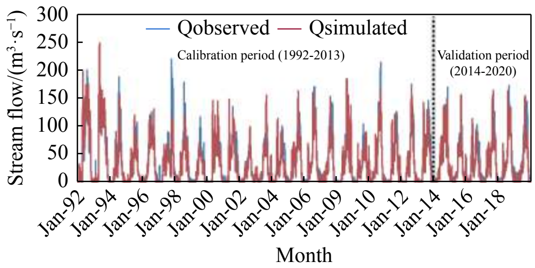


**Fig. 3** Calibration and Validation of the hydrograph

## 3.4 Results of regionalization

### 3.4.1 Catchment selection criteria for regionalization

Based on the calibration results (Upper Gojeb, Upper Guma, Gilgel Gibe), catchments were selected for regionalization since objective functions $E_{NS}$ values were greater than 0.75 and *RMSE* between 0 and +5%. Therefore, these catchments model parameters were used for regionalization.

### 3.4.2 Model parameters and catchment characteristics

The relationship between HEC-HMS model parameters (*MPs*) and physical catchment characteristics (*PCCs*) allows us to realize and possibly forecast how an alteration in the physical properties of watersheds impacts on its hydrological behaviors. Optimized *MPs* and *PCCs* of gauged catchments were used to regulate the relationships. As the correlation coefficient relies on critical values of −0.90 to 0.90, the corresponding correlation is statistically significant (Table 2). The simple linear regression indicated that the significant relationship of *MPs* and *PCCs* is 93 out of 283 relations.

### 3.4.3 Multiple linear regressions

In this study, the use of linear PCCs gave better relations. Linear regressions were applied to create a regional model using optimized PCCs and MPs for gauged catchments in Microsoft Excel. Depending on the $R^2$ (≥0.85) and significance or p-value (≤ 0.10 for 95% confidence interval), PCCs were selected to establish regression equations.

### 3.4.4 Determining MPs and evaluating stream flow at ungauged catchments

To determine model parameters for ungauged catchments, three gauged catchments (Upper Gojeb, Upper Guma, and Gilgel Gibe) and five ungauged catchments (Mansa, Zigna, Denchiya, Lower Guma, Lower Gojeb) were selected in the middle Omo-Gibe basin. To determine *MPs* of those ungauged catchments the following four methods were used by the regionalization model method (Table 2).

### 3.4.5 Simulation of stream flow at ungauged catchments

Model parameters estimated from ungauged catchments were simulated by the HEC-HMS model. The total period ranges from 1990 to 2020, whereas the warm-up period started from 1992. The result of daily stream flow was converted to monthly average simulated flow for selected Lower Guma sub-catchments which are ungauged represented by four various regionalization methods, namely Linear Regression (*LR*), Sub-basin Mean (*SM*), Spatial Proximity (*SP*), and Area Ratio (*AR*) method.

### 3.4.6 Similarity of catchment characteristics between gauged and ungauged catchments by spatial proximity

The similarity of catchment characteristics between gauged and ungauged catchments of middle Omo-Gibe sub-basin are discussed below.

Table 3 shows the result of geographic and physiographic catchment characteristics by using 12.5 m × 12.5 m *DEM*. The correlation ($R^2$) of ungauged Mansa is 0.92, 0.82, and 0.83 with gauged catchments of Upper Guma, Upper Gojeb,

**Table 2** Model parameters estimated for ungauged catchments using regional model

| Ungauged catchments | TC | R | IS | MS | ID | MD | CR | K | X | CC |
|---|---|---|---|---|---|---|---|---|---|---|
| Mansa | 27 | 25 | 17 | 11 | 0.47 | 2.7 | 0.42 | 1.6 | 0.18 | 0.58 |
| Zigna | 25 | 26 | 18 | 11 | 0.39 | 2.6 | 0.24 | 0.6 | 0.18 | 0.67 |
| Denchiya | 26 | 26 | 18 | 11 | 0.46 | 2.6 | 0.25 | 0.6 | 0.18 | 0.82 |
| Lower Guma | 30 | 26 | 18 | 11 | 0.39 | 2.6 | 0.17 | 0.5 | 0.19 | 0.83 |
| Lower Gojeb | 52 | 29 | 23 | 9 | 0.47 | 2.8 | 0.35 | 1.6 | 0.23 | 0.84 |

and Gilgel Gibe, respectively. As the correlation result indicates, the ungauged Mansa catchment obtained MPs from the Upper Guma catchment. Similarly, the correlation of other catchments was shown in Table 3.

The correlation ($R^2$) result in Land use and land cover shows that ungauged Lower Gojeb has 0.58, 0.08, 0.58, and 0.67 with gauged catchments of Upper Guma, Upper Gojeb, Gilgel Gibe respectively. As the result shows Gilgel Gibe and Lower Gojeb catchments have high similarities in land use land cover *PCCs* (Table 3).

The correlation ($R^2$) of ungauged Zigna in soil *PCCs* is 0.92, 0.98, and 0.42 with gauged catchments of Upper Guma, Upper Gojeb, and Gilgel Gibe, respectively. Similarly, the correlation of other catchment characteristics such as soil catchment characteristics and climate catchment characteristics, Land Cover catchment characteristics, and geographic and physiographic catchment characteristics with gauged and ungauged catchment are shown in (Table 4). Fig. 4 shows the transfer of *MPs* from gauged catchments to ungauged catchments by area ratio method and Fig. 5 shows the model parameter transfer by spatial proximity method.

Fig. 6 shows that runoff simulated by sub-basin mean and linear regression method has a high volume compared to the other two methods. This implies that the area ration method is less reliable because it only considers the size of the catchment area between gauged and ungauged catchments. In the case of the remaining catchment, i.e. Zigna and Denchiya, runoff simulated by spatial proximity has a high volume compared to other methods. However, runoff estimated by linear regressions is fitted with the observed flow properly. Therefore, this method is the best compared to other methods for the central Omo-Gibe basin.

Time of concentration is positively correlated with mean elevation and negatively correlated with natural forest, while maximum deficit positively correlates with the area and negatively correlates with dystric nitosols. On the other hand, crop coefficient positively correlates with longest flow path and reversely relates with basin shape. The relationship to other characteristics is shown in Table 5.

## 4 Conclusions

Based on the applied methodology and results, it is concluded that characteristics of ungauged catchments can be studied from the results from the hydrological model parameters of gauged catchments. The three selected gauged stations have been simulated, which have a reasonable performance with $E_{NS}$ greater than 0.75 and *RMSE* in between 0 and +5%. According to the sensitivity analysis, model parameters of *CC*, *R, CR,* and *TC* are more sensitive while *ID*, *MD, IS, K*, and *X* are relatively less sensitive in the central part of the

**Table 3** Geographic and physiographic catchment characteristics correlation ($R^2$) and Land Cover catchment characteristics correlation ($R^2$)

| Ungauged Catchments | Geographic and physiographic catchment characteristics correlation ($R^2$) | | | Land Cover catchment characteristics correlation ($R^2$) | | |
|---|---|---|---|---|---|---|
| | Gauged catchments | | | Gauged catchments | | |
| | Upper Guma | Upper Gojeb | Gilgel Gibe | Upper Guma | Upper Gojeb | Gilgel Gibe |
| Mansa | 0.92 | 0.82 | 0.83 | 0.52 | 0.06 | 0.62 |
| Zigna | 0.90 | 0.85 | 0.85 | 0.03 | 0.06 | 0.03 |
| Denchiya | 0.87 | 0.84 | 0.83 | 0.01 | 0.08 | 0.01 |
| Lower Guma | 0.90 | 0.84 | 0.84 | 0.77 | 0.05 | 0.88 |
| Lower Gojeb | 0.56 | 0.96 | 0.92 | 0.58 | 0.08 | 0.67 |

**Table 4** Correlation of Soil catchment characteristics ($R^2$) and Climate catchment characteristics ($R^2$)

| Ungauged Catchments | Correlation of Soil catchment characteristics ($R^2$) | | | Climate catchment characteristics ($R^2$) | | |
|---|---|---|---|---|---|---|
| | Gauged catchments | | | Gauged catchments | | |
| | Upper Guma | Upper Gojeb | Gilgel Gibe | Upper Guma | Upper Gojeb | Gilgel Gibe |
| Mansa | 0.35 | 0.37 | 0.11 | 1 | 1 | 1 |
| Zigna | 0.92 | 0.98 | 0.42 | 1 | 1 | 1 |
| Denchiya | 0.48 | 0.53 | 0.14 | 1 | 1 | 1 |
| Lower Guma | 0.93 | 0.98 | 0.41 | 1 | 1 | 1 |
| Lower Gojeb | 0.45 | 0.48 | 0.15 | 1 | 1 | 1 |

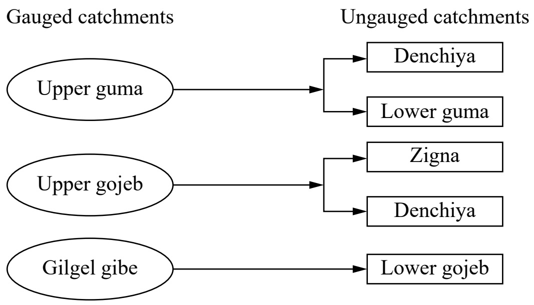


**Fig. 4** Model parameter transfer by spatial proximity method

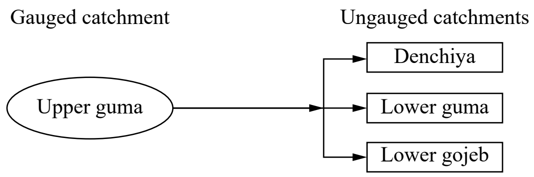


**Fig. 5** Model parameter transfer by area ratio method

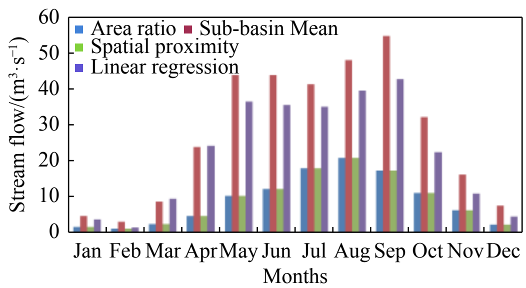


**Fig. 6** Comparsion of average monthly simulated flow for selected sub-catchment of Lower Guma by using four regionalization method

Omo-Gibe sub-basin. The $R^2$ and overall significance of the linear regression equations are acceptable. The comparisons of the regionalization methods indicate that the stream flow estimation at ungauged catchments by regional model, spatial proximity, sub-basin mean, and area ratio method can

**Table 5** Correlation values between model parameters (MPs) and physical catchment characteristics (PCCs) for gauged catchments

| PCCs | *TC* | *R* | *IS* | *MS* | *ID* | *MD* | *CR* | *K* | *X* | *CC* |
|---|---|---|---|---|---|---|---|---|---|---|
| Avarge slope | −0.64 | −0.76 | −0.44 | −0.44 | −0.98 | −0.83 | −0.99 | −0.02 | −0.77 | −0.24 |
| Longest flow path | −0.64 | −0.51 | 0.96 | −0.96 | −0.04 | 0.69 | 0.34 | 0.99 | −0.50 | −0.91 |
| Mean elevation | 0.99 | 0.97 | −0.50 | 0.50 | 0.72 | 0.00 | 0.41 | −0.82 | 0.96 | 0.94 |
| Minimum elevation | 0.89 | 0.95 | 0.05 | −0.05 | 0.98 | 0.55 | 0.84 | −0.38 | 0.96 | 0.60 |
| Maximum elevation | 0.57 | 0.44 | −0.98 | 0.98 | −0.04 | −0.75 | −0.42 | −0.97 | 0.43 | 0.88 |
| Sum stream length | −0.40 | −0.25 | 1.00 | −1.00 | 0.4 | 0.87 | 0.59 | 0.90 | −0.24 | −0.76 |
| Area | −0.43 | −0.29 | 1.00 | −1.00 | 0.21 | 0.85 | 0.56 | 0.92 | −0.27 | −0.79 |
| Perimeter | −0.21 | −0.06 | 0.98 | −0.98 | 0.43 | 0.95 | 0.74 | 0.80 | −0.04 | −0.62 |
| HI | – | – | – | – | – | – | – | – | – | – |
| DD | 0.44 | 0.29 | −1.00 | 1.00 | −0.20 | −0.84 | 0.55 | −0.92 | 0.28 | 0.79 |
| CI | 0.73 | 0.61 | −0.92 | 0.92 | 0.16 | −0.60 | −0.23 | −1.00 | 0.60 | 0.96 |
| EL | −0.99 | −1.00 | 0.26 | −0.26 | −0.87 | −0.26 | −0.63 | 0.65 | −1.00 | −0.82 |
| Basin shape | 0.30 | 0.15 | −0.99 | 0.99 | −0.34 | −0.91 | −0.67 | −0.85 | 0.13 | 0.69 |
| Dystric nitosols | −0.70 | −0.80 | −0.37 | 0.37 | −0.99 | −0.79 | −0.97 | 0.06 | −0.81 | −0.31 |
| Dystric fluvisols | 1.00 | 1.00 | −0.32 | 0.32 | 0.84 | 0.20 | 0.58 | −0.69 | 1.00 | 0.86 |
| Orthic acrisols | 0.32 | 0.47 | 0.74 | −0.74 | 0.83 | 0.98 | 0.98 | 0.38 | 0.48 | −0.13 |
| Dystric gleysols | 0.09 | −0.07 | −0.95 | 0.95 | −0.54 | −0.98 | −0.81 | −0.71 | −0.08 | 0.52 |
| Leptosols | −0.99 | −0.96 | 0.50 | 0.50 | −0.72 | 0.00 | −0.41 | −0.41 | −0.96 | −0.94 |
| Cambisols | −0.99 | −0.96 | 0.50 | −0.50 | −0.72 | 0.00 | −0.41 | −0.41 | −0.96 | −0.94 |
| Chromic vertisols | 0.58 | 0.70 | 0.51 | −0.51 | 0.96 | 0.87 | 1.00 | 0.10 | 0.71 | 0.16 |
| Eutric cambisol | −0.99 | −0.96 | 0.50 | −0.50 | −0.72 | 0.00 | −0.41 | −0.41 | −0.96 | −0.94 |
| Eutric nitosols | −0.16 | 0.00 | 0.97 | −0.97 | 0.48 | 0.96 | 0.77 | 0.77 | 0.01 | −0.58 |
| Orthic solonchaks | −0.99 | −0.96 | 0.50 | −0.50 | −0.72 | 0.00 | −0.41 | 0.82 | −0.96 | −0.94 |
| Gypsic yermosola | −0.99 | −0.96 | 0.50 | −0.50 | −0.72 | 0.00 | −0.41 | 0.82 | −0.96 | −0.94 |
| Eutric fluvisols | 0.59 | 0.71 | 0.50 | −0.50 | 0.96 | 0.87 | 0.99 | 0.08 | 0.72 | 0.18 |
| Cultivation | 0.99 | 1.00 | −0.29 | 0.29 | 0.86 | 0.23 | 0.60 | −0.67 | 1.00 | 0.84 |
| Natural forest | −0.98 | −1.00 | 0.22 | −0.22 | −0.90 | −0.30 | −0.66 | 0.61 | −1.00 | −0.71 |
| Shurb land | – | – | – | – | – | – | – | – | – | – |
| Grass land | −0.79 | −0.68 | 0.88 | −0.88 | −0.24 | 0.53 | 0.14 | 1.00 | −0.67 | −0.98 |
| Wood land | – | – | – | – | – | – | – | – | – | – |
| SAAR | −0.18 | −0.33 | −0.83 | 0.83 | −0.74 | −1.00 | −0.94 | −0.51 | −0.34 | 0.28 |
| MP dry | −0.44 | −0.57 | −0.65 | 0.65 | −0.90 | −0.94 | −1.00 | −0.26 | −0.59 | 0.00 |
| MP wet | −0.20 | −0.35 | −0.82 | 0.82 | −0.76 | −1.00 | −0.95 | −0.49 | −0.36 | 0.25 |
| PET | 0.38 | 0.23 | −1.00 | 1.00 | −0.27 | −0.88 | −0.61 | −0.89 | 0.21 | 0.75 |

**Note:** CI-Circularity index, DD-Drainage density, EL-Elongation Ratio, HI-Hypsometric integral, PET-Potential Evapotranspiration, SAAR-Standard Annual Average Rainfall.

have high or low runoff volume in the study area. Regional model (linear regression method) is regarded to be the best compared to the other models. Generally, in the middle Omo-Gibe basin, the HEC-HMS model is found to have a satisfactory result for estimating daily stream flow at ungauged catchments.

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## References

Abebe NA, Ogden FL, Pradhan, NR. 2010. Sensitivity and uncertainty analysis of the conceptual HBV rainfall–runoff model: Implications for parameter estimation. Journal of Hydrology, 389: 301-310.

Arsenault R, Breton-Dufour M, Poulin A, et al. 2019. Streamflow prediction in ungauged basins: analysis of regionalization methods in a hydrologically heterogeneous region of Mexico. Hydrological Sciences Journal, 64(11): 1297-1311.

Bao Z, Zhang J, Liu J, et al. 2012. Comparison of regionalization approaches based on regression and similarity for predictions in Ungauged catchments under multiple hydro-climatic conditions. Journal of Hydrology, 466-467: 37-46

Barbarossa V, Huijbregts MAJ, Hendriks AJ, et al. 2017. Developing and testing a global-scale regression model to quantify mean annual stream-flow. Journal of Hydrology, 544: 479-487.

Blöschl, G. 2005. Rainfall runoff modeling of ungauged catchments In M. L. Anderson, ed. Encyclopedia of hydrological sciences UK: John Wiley & Sons: 2061– 2080.

Donnelly C, Andersson JCM, Arheimer B. 2016. Using flow signatures and catchment similarities to evaluate the E-HYPE multi-basin model across Europe. Hydrological Sciences Journal, 61(2): 255-273.

Goswami M, Connor KM, Bhattarai KP, et al. 2005. Assessing the performance of eight real-time updating models and procedure for the Brosna River. Hydrology and the Earth System Sciences, 9(4): 394-411.

Hailegeorgis TT, Abdella YS, Alfredsen, K, et al. 2015. Evaluation of regionalization methods for hourly continuous streamflow simulation using distributed models in Boreal Catchments. Journal of Hydrologic Engineering, 1-20: 04015028.

Ibrahim B, Wisser D, Barry B, et al. 2015. Hydrological predictions for small ungauged watersheds in the Sudanian zone of the Volta basin in West Africa. Journal of Hydrology: Regional Studies, 4: 386-397.

IHMS. 2006. Integrated Hydrological Modeling System Manual. Version 5.1.

Javeed Y, Apoorva KV. 2015. Flow regionalization under limited data availability application of IHACRES in the Western Ghats. Aquatic Proceeding 4: (LCWRCOE) 2015: 933-941.

Li H, Zhang Y, Zhou X. 2015. Predicting surface runoff from Catchment to Large Region. Advances in Meteorology: 1-13.

Mazvimavi D. 2003. Estimation of flow characteristics of ungauged catchments: Case study in Zimbabwe. Wageningen Universiteit: 1-176.

Merz R, Bloschl G. 2004. Regionalization of catchment model parameters. Journal of Hydrology, 287(1-4): 95-123.

Mosavi A, Golshan M, Choubin B. 2021. Fuzzy clustering and distributed model for streamflow estimation in ungauged watersheds. Scientific Reports, 11: 8243.

Nega H, Seleshi Y. 2021. Regionalization of mean annual flow for ungauged catchments in case of Abbay River Basin, Ethiopia. Modeling Earth Systems and Environment, 7: 341-350.

Oudin L, Andre´assian V, Perrin C, et al. 2008. Spatial proximity, physical similarity, regression and Ungauged catchments: A comparison of regionalization approaches based on 913 French catchments. Water Resources Research, 44: W03413.

Pinheiro VB, Naghettini M. 2013. Calibration of the parameters of a rainfall-runoff model in Ungauged basins using synthetic flow duration curves as estimated by regional analysis. Journal of Hydrologic Engineering, 18: 1617-1626.

Pool S, Viviroli D, Seibert J. 2017. Prediction of hydrographs and flow-duration curves in almost ungauged catchments: Which runoff measurements are most informative for model calibration? Journal of Hydrology, 554: 613-622.

Rajendran M, Gunawarden ERN, Dayawansa NDK. 2020. Runoff prediction in an ungauged catchment of Upper Deduru Oya Basin, Sri Lanka: A comparison of HEC-HMS and WEAP models. International Journal of Progressive Sciences and Technologies (IJPSAT), 18(2): 121-129.

Roy S, Mistri B. 2013. Estimation of peak flood discharge for an Ungauged River: A case study of the Kunur River, West Bengal, Geography Journal, 214140: 11.

Samuel J, Coulibaly P, Metcalfe RA. 2011. Metcalfe estimation of continuous stream flow in ontario ungauged basins: Comparison of regionalization methods. Journal of Hydrologic Engineering, 16(5): 447-459.

Sawicz K, Wagener Sivapalan TM, Troch PA, et al. 2011. Catchment classification: Empirical analysis of hydrologic similarity based on catchment function in the eastern USA. Hydrology Earth Systems Sciences, 15(9): 2895-2911.

Sellami H, Jeunesse IL, Benabdallah S, et al. 2014. Uncertainty analysis in model parameters regionalization: A case study involving the SWAT model in Mediterranean catchments (Southern France). Hydrology and Earth System Sciences, 18: 2393-2413.

Shoaib SA, Bardossy A, Wagener T, et al. 2013. A different light in predicting Ungauged Basins: Regionalization approach based on Eastern USA Catchments. Journal of Civil Engineering and Architecture, 7 (3) (64): 364-378.

Sivapalan M, Takeuchi K, Franks SW, et al. 2003. IAHS decade on predictions in ungauged basins (PUB), 2003-2012: Shaping an exciting future for the hydrological sciences. Hydrologocal Sciences Journal, 48(6): 857-880.

Solomon SM. 2001. Climate change 2007-The physical science basis: Working group1 contribution to the fourth assessment report of the IPCC: (vol. 4). Cambridge University Press.

Swain JB, Patra KC. 2019. Impact of catchment classification on streamflow regionalization in ungauged catchments. SN Applied Sciences 1: 456.

Tamalew C, Kemal A. 2016. Estimation of discharge for ungauged catchments using rainfall-runo model in Didessa Subbasin: The case of Blue Nile River. International Journal of Innovations in Engineering Research and Technology, 3(9): 62-72.

Tesfalem A, Yan L, Sirak T, et al. 2021. Quantifying the regional water balance of the Ethiopian Rift Valley Lake basin using an uncertainty estimation framework. Hydrology and Earth Science System:1-25.

Teutschbein C, Grabs T, Hjalmar L, et al. 2018. Simulating streamflow in ungauged basins under a changing climate: The importance of landscape characteristics. Journal of Hydrology, 561: 160-178.

Wagener T, Wheater HS, Gupta HV. 2004. Rainfall-runoff modelling in gauged and ungauged catchments. London, Imperial College Press: 300.

Wale A, Rientjes THM, Gieske ASM, et al. 2009. Ungauged catchment contributions to Lake Tana's water balance. Hydrological Processes, 23(6): 3682-3692.

Zamoum S, Souag-Gamane, D. 2019. Monthly streamflow estimation in ungauged catchments of northern Algeria using regionalization of conceptual model parameters. Arabian Journal of Geosciences, 342: 12 (11).

Zhang Y, Chiew FHS. 2009. Relative merits of different methods for runoff predictions in ungauged catchments. Water Resources Research, 45(7).