Rainfall-Runoff Simulation And Modeling Using HEC-HMS Model

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Abstract:
River discharge prediction is a critical subject in water resource engineering concerns. The HEC-HMS model has been successfully used in discharge forecasting problems. In this research HEC-HMS model was applied for forecast daily discharge for M.H. Halli gauge Station which lies in Karnataka state region in India. In order to calibration and validation of the models, the recorded daily rainfall, temperature and discharge which available for fifteen years (2003–2017) was divided into two sets. The model's performance was evaluated by using the root means square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). The current study's findings supported the proposed methodology's applicability for precise discharge modeling.

Keyword: Forecasting; HEC-HMS Model; Hydrologic Model.

1. Introduction

Rainfall-runoff modeling is one of the most important hydrological processes, especially large- scaled processes (Chang, 2009; Gajbhiye et al. 2015). Also, nonlinearity and multidimensionality render the modeling of the transformation of rainfall into runoff very complex (Ishtiaq et al.,

2010; Meshram et al. 2017). Hydrological models have an extensive classification but in general, these models have been divided into three groups, which are the empirical or data-driven models, conceptual or gray box models, and physically-based or white box models (Willems, 2000). Empirical or data-driven models do not explicitly use laws and processes, instead they merely relate the input conversion functions to output one (Leavesley et al., 2002). The second group consists of conceptual models which are not formed based on all the physical processes but on understanding the behavior of system model's designer. The third group, which includes the theoretical models (physically-based models), try to provide all the existing processes in the required hydrology system through inserting physical senses (Moore et al., 1988).

It has been reported by many researchers that hydrological models are mainly depending on the input data, hydrological parameter and structure of the model (Meresa et al. 2016; Meresa et al. 2017; Meresa and Gatachew 2018; Meshram et al. 2019a,b). Particularly, studies on river modeling in ungauged catchment using the climate and physiographic characteristics are possible only if detailed information about topography, land use, soil, vegetation, and climate are depends on available data (Gunter Bloschl 2005; Wale et al. 2009; Adib et al. 2010; He et al. 2011; Meshram et al. 2022a,b). Runoff response estimation from ungauged river catchments is currently a topical issue in hydrology and water resources management (Gunter Bloschl 2005; Wale et al. 2009; Adib et al. 2010; He et al. 2011; Meshram et al. 2022c,d) and in developing countries for hydraulic infrastructure construction.

Nowadays, there are several studies performed the rainfall and runoff process simulation using empirical, data driven, hydrological model and statistical models comparisons. Meresa and Gatachew (2018) compared three conceptual hydrological models for climate change impact study, and found that accuracy of the modeled flow is mainly depends on the model structure and number of model parameters. Yaghoubi and Massah (2014) compared three models of HBV, IHACRES and HEC-HMS in Azam Harat river catchment in Iran. Among these models HVB model performed better in proved resinable river flow in mean and variability whereas HEC- HMS exhibited worst performance in root mean square value. Asati and Rathore (2012) developed an autoregressive model, ANN and MLR for a complex catchment behavior which is non-linear relationship between rainfall and runoff, which is compared without incorporating the nature of process. Dastorani et al. (2009) compared artificial neural network with various data driven models for rebuilding the observed flow data and they concluded the ANN were dominant in comparison to other models (the normal ratio and correlation methods). Moreover, in recent decades, the development of artificial intelligence techniques, such as Artificial Neural Networks (ANN), Support Vector Machine (SVM) and more, have provided a significant evolution in the predictors of hydrological phenomena (Yang et al., 2009; Kisi et al., 2009; Kocabasa et al., 2009;Kisi and Cigizoglu, 2007; Meshram et al. 2021a,b). Mathematically, the SVM is used for both classification and regression algorithms, which are formulated through the principles of statistical learning theory by Vapnik (1995). Due to the wide capability of the SWAT and SVM model regarding water and soil research studies, many studies have been performed all over the world by these models separately (Shepherd et al., 1999; Spruill et al., 2000; Saleh and Du, 2004; Birhanu et al., 2007; Gassman et al., 2007).

In general, it seems HEC-HMS is the most widely applied to predict discharge in river catchments. Due to the reason that there are no previous studies in M.H. Halli station that are focused on discharge forecasting. This research work provides innovative research approach and robust solutions in discharge estimation. The few available meteorological data often present significant gaps. This makes the research work very innovative and original in terms of study area, methodology and framework approach.

Generally, river discharge models are designed to gain a better understanding of the hydrologic characteristics of a catchment and to generate a synthetic hydrologic data for river flow facility design like flood protection, water resources planning, mitigation of contamination, or for flood early warning and forecasting. Specifically, the objective of this study is therefore to estimate discharge through the hydrological model.

2. Material and Methodology

2.1 Study area and data set

The Hemavati River which is a major tributary of the Cauvery River, originates from theWestern Ghats at an elevation of about 1219 m amsl near the Ballalarayanadurga village in the Chikmagalur District of the Karnataka state, India. It passes from Hassan District and joined its chief tributary, the Yagachi River at Hemavati dam and then into Mysore district before joining the Cauvery River near Krishnarajasagara. It is approximately 245 km long and has a drainage area of about 5,410 km². In this study the study area for hydrological simulation has been taken upto its gauging site located at M.H Halli. Geographically the study area has the extent oflatitude from 12°37’8” N to 13°23’24” N and longitude from 75°29’23” E to 76°10’2” E. The study area falls under humid climatic conditions with an average annual rainfall of 1530 mm (Shekar and Hemalata, 2021) and the average annual maximum temperature of 29.35°C and min temperature of 18.68°C. The soil type found to be loamy, clay and clay skeletal textures with deep in depth and well drainage class and the elevation profile falls between 733m to 1778m amsl.

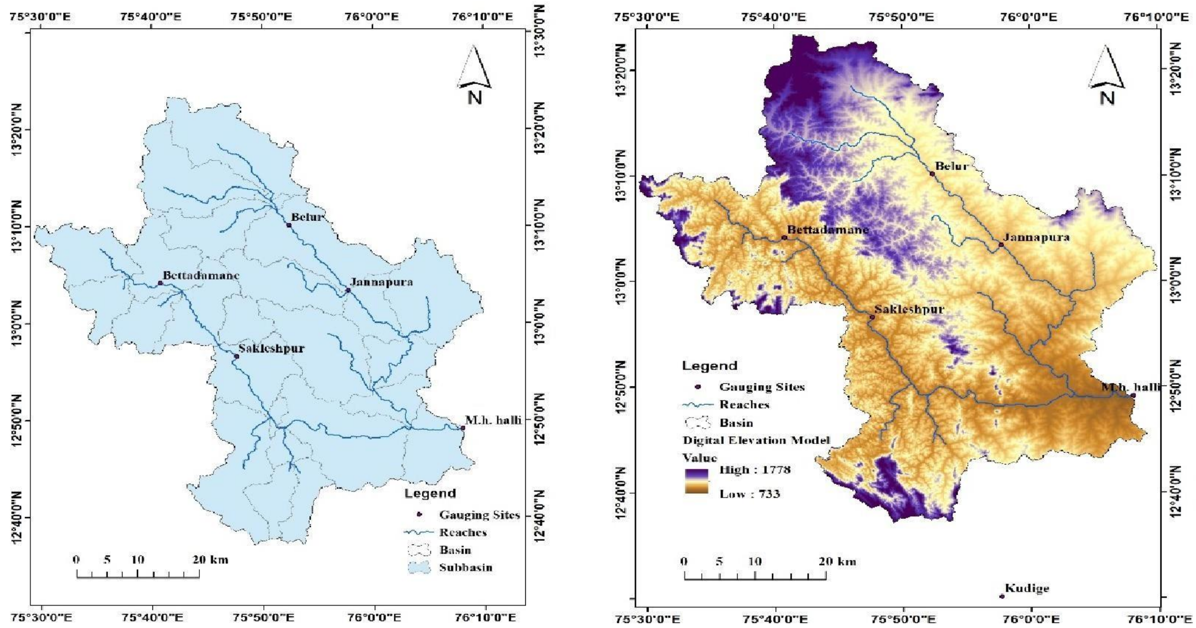

Fig. 1: Location map and Digital Elevation Model of the Study area

For the period 2003 to 2017, discharge (m^3/s), rainfall (mm) and temperature (^0C) data in daily scale from the M.H. Halli station were used. First eight year of the data for discharge, rainfall and temperature were used for model development/calibration, while the remainingseven year was used to test and evaluate the model's performance. The time series of the whole data that was applied for M.H. Halli station is shown in Figure 2. The statistical parameters for the results are listed in Table 1.

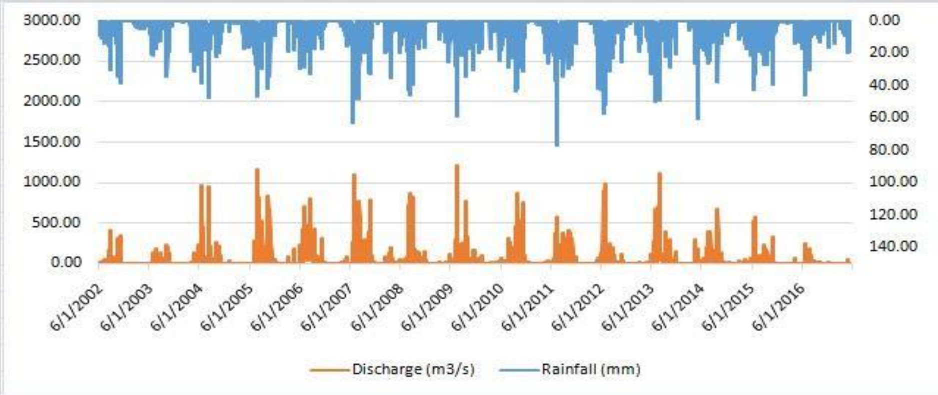

Figure 2: Time series of observed data (rainfall, temperature and discharge) used fortraining and testing stages

Table 1: Statistics of the data

Dataset	Datatype	Data no.	Mean	STD	CV	Max	Min
Calibration (2003-2010)	Rainfall (mm)	1346	6.12	8.34	1.36	62.415	0.000
	Discharge (Cumec)		95.13	167.47	1.76	1203.000	0.023
	Temperature (^{0}C)		23.23	1.01	0.05	27.733	19.920
Validation (2010-2017)	Rainfall (mm)	1198	6.33	8.67	1.37	76.940	0.000
	Discharge (Cumec)		68.53	123.19	1.80	1102.000	0.040
	Temperature (^{0}C)		23.47	1.14	0.09	29.135	19.804

2.2 Model descriptions

In this study, an HEC-HMS model was applied to simulate discharge in the M.H. Halli Station. ***HEC-HMS Model:*** HEC-HMS is a hydrologic model package developed by the United State Army Corps of Engineers-Hydrologic Engineering Centre (HEC). It is a semi-physically basedand conceptual semi-distributed model designed to simulate continuous and event based rainfall- runoff processes in a wide spatial scale range, from large river basin flood hydrology to smallurban and natural catchment runoff. The software package includes runoff transform, losses, channel routing, base flow, canopy, surface, rainfall-runoff simulation and parameter estimation. HEC-HMS hydrological model uses different packages to represent each component of the riverrunoff process, including models that compute runoff volume, models of base flow, and models of direct runoff. Each model run combines a meteorological model, basin model and control specifications with run options to obtain results (Choudhari et al. 2014).

The basin model, which describes the different elements of the hydrologic system. It consists of different methods like infiltration loss and transforms method. The infiltration methodis used to compute runoff volume and estimates losses resulting from infiltration and evapotranspiration during rainfall event. In this study the soil moisture accounting method has been used as the loss method which simulates the water movement and its storage on plants, soil surface, and soil profile and groundwater layers. The transform method is used to transform the excess precipitation at the watershed into a hydrograph at the outlet. In this study the transformation of precipitation into surface runoff was accomplished by SCS unit hydrograph. The Soil Conservation Service (SCS) unit hydrograph method defines a curvilinear unit hydrograph by first setting the percentage of the unit runoff that occurs before the peak flow (NRCS, 2007). A triangular unit hydrograph can then be fit to the curvilinear unit hydrograph so that the total time base of the unit hydrograph can be calculated. The SCS unit hydrograph method requires only one parameter for each sub-basin: lag time between rainfall and runoff in the sub-basin. The program computes Tc (time of concentration) and Qp (peak flow) to rescale the SCS-CN dimensionless unit hydrograph. This is then used to compute the direct runoff hydrograph for the sub-basin.

Model Results Evaluation: There are many criteria selected to evaluate the prediction performance based on hydrological forecasting guidelines; according to these criteria, the best model for forecasting was chosen. In this research three statistical criteria are used, coefficient ofdetermination (R^2), mean absolute error (MAE) and root mean square error (RMSE). The formulation can be expressed as follows:

$$R^2 = \left(\frac{1}{n} \times \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{(\sigma_x)(\sigma_y)}\right)^2 \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \quad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \quad (4)$$

Where m is the number of data, 7 and are observed and estimated values, and σ7 and σ arethe standard deviation of the observed and estimated data. It should be mentioned that low value (closer to zero) for the *RMSE*, while for R^2, a high value (closer to the unity) signify that there is a good agreement between observed and modeled estimation data.

3. Results and Discussion

This study has used daily discharge, rainfall and temperature data from the M.H. Halli station in India. As stated earlier, two models, i.e., HEC-HMS model has been developed for dischargeforecasting. A general view of the study is given Figure 3.

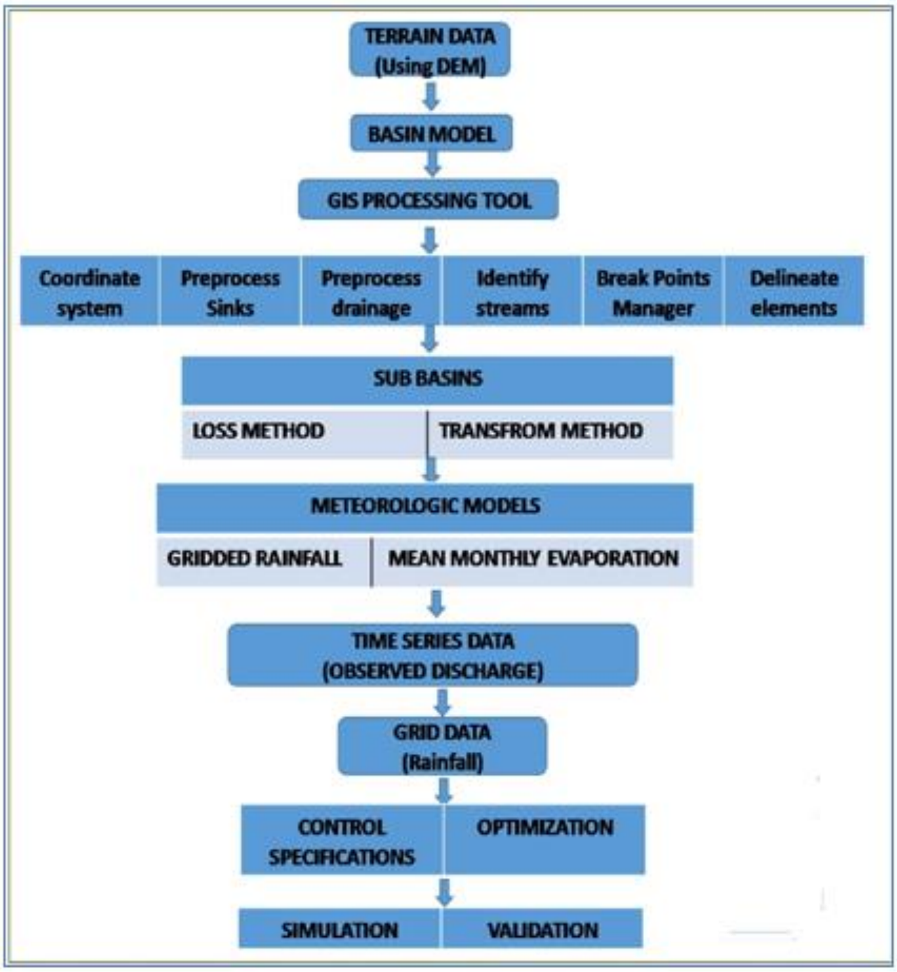

Figure 3. Flowchart of the modeling procedure

3.1 *Statistical Analysis of Data*

Initially, daily discharge, rainfall and temperature data were divided into two parts i.e. calibration/training and validation/testing. Among entire data, 8 years data were selected for calibration and the remaining 7 years data were selected for testing the developed models. The statistical parameters for calibration/training and validation/testing of discharge, rainfall and temperature datasets were calculated as shown in Table 1.

The coefficient of variance (CV) values for the rainfall, discharge and temperature testing/validation datasets were higher than those for the training/calibration, but, the mean and standard deviation values for discharge testing datasets were less than those for the training (Table 1). Furthermore, the maximum value of the discharge variable is higher during thetraining dataset. The maximum values for the rainfall and temperature testing dataset were higherthan those for the training.

3.2 Discharge prediction with HEC-HMS hydrological model

The HEC-HMS hydrological model has been calibrated manually and automatically to optimize to obtain the best possible option fit. Initial deficit constant loss, Snyder unit hydrograph transform, and recession base flow method used. The calibration and validation performance of the HEC-HMS 3.5 is carried out by comparing of the daily simulated discharge with the observed discharge at the M.H. Halli station. To assess the performance of the model predictability of representing the hydrological simulation of the reality of the basin. Four basic statistical hydrological model performance check used. The R^2 (relation coefficient), MAE(mean absolute error) and RMSE (root mean square error).

3.2.1. Model Calibration

The model for MH Halli station is calibrated using 2003 to 2010 daily rainfall, temperature and discharge data. Manual and automatic calibration techniques are applied to estimate values of parameters. The sub basins are assumed to be homogenous and the model parameters areassigned according to the type of soil and land use pattern within sub-basin. The optimal values of the model parameters are obtained using the criterion of maximizing the efficiency by comparing the observed and simulated flows. The accuracy of the model is verified by qualitative and quantitative analysis.

The simulated and observed discharge time series (Figure 4) and scatter plot at calibration period 2003 to 2010 is shown in Figure 5. It is seen that the daily hydrograph of the simulated discharge caught the observed discharge during calibration period (2003-2010). However, the peak value of the simulated discharge is under predicted in the model as compared to the observed discharge of the outlet station. From the statistical analysis (Table 2) the coefficient of determination (R^2) has calculate as 0.854. Which shows the developed hydrological model for the MH Halli station is well performing for calibration period. Manual and automatic method was applied for the optimization of model parameter during calibrationand validation period.

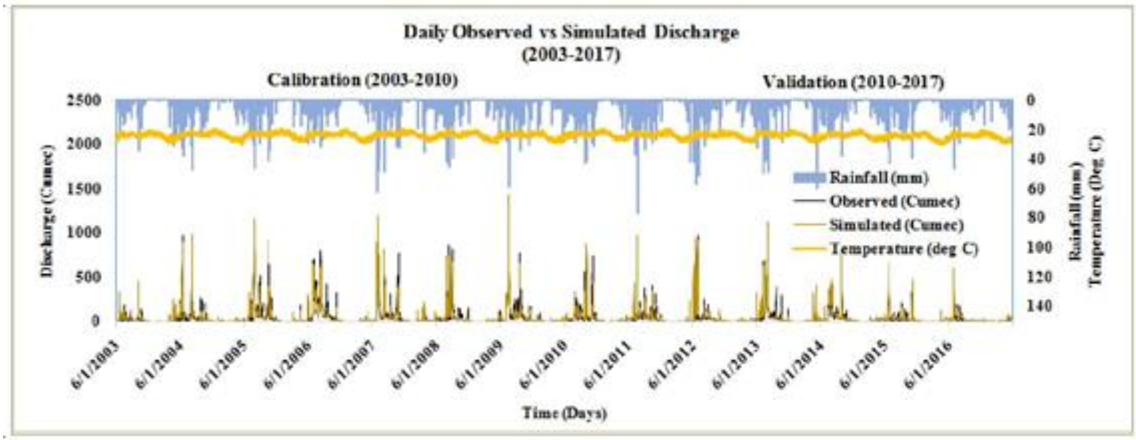

Figure 4: HEC-HMS model performances in terms of comparison of observed and simulated discharge

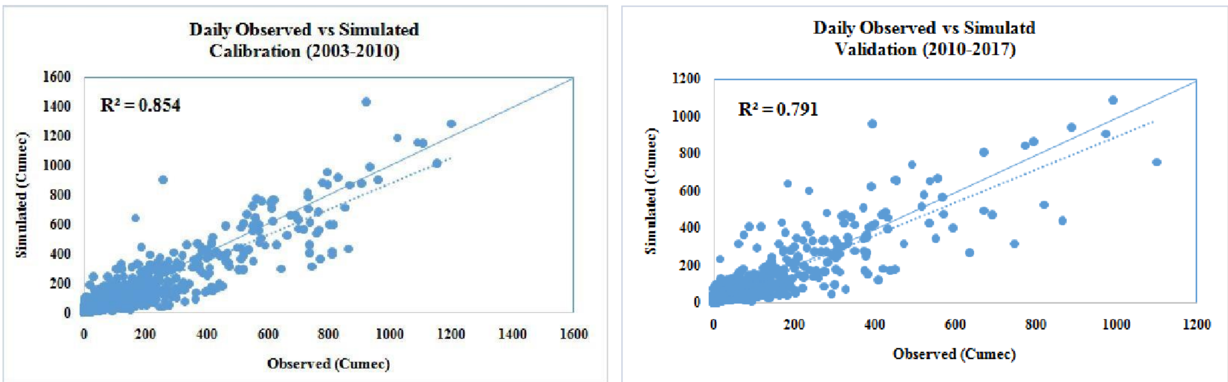

Figure 5: HEC-HMS model scatter plot between observed vs simulated discharge during calibration and validation stage

Table 2. Comparison of HEC-HMS and Random forest models in terms of R^2, RMSE, and MAE

Models	Calibration			Validation		
	R^2	RMSE	MAE	R^2	RMSE	MAE
HEC-HMS	0.854	49.59	22.03	0.791	41.64	16.85

3.2.2 Model Validation

The validated result of the HEC-HMS model for MH Halli station can be seen in the Figure 4-5. Based on the calibrated parameters and values the model is validated from (2010 – 2017), and the performance a little bit improved. The daily hydrograph well simulated with observeddischarge flow. From the statistical analysis (Table 2) the coefficient of determination (R^2) has calculate as 0.791. Which shows the developed hydrological model for the MH Halli station is well performing for calibration period. However as like calibration period, there is also under prediction in the peak flow.

4 Conclusions

Hydrological studies are important and necessary for water and environmental resources management. Demands from society on the predictive capabilities of such study and analysis of hydrological parameters are becoming higher and higher, leading to the need of enhancing existing research theories and even on developing new theories. The study has been conducted inthe MH. Halli station of Hemvati River, Karnataka state, India, which is an important river basin in India from Hydropower, perspective.

The HEC-HMS hydrological simulation catchment model has been calibrated (2003 – 2010) and validated (2010 – 2017) at the MH Halli station. The coefficient of determination (R^2),RMSE and MAE of model performance criterion are used to evaluate the model applicability. The HEC-HMS model was found to provide better prediction results. The HEC-HMS model provided the highest R^2 and the lowest MAE and RMSE in testing data sets. Where the calculated value of R^2 has found 0.854 for calibration period and 0.791 for validation period. Which shows the model has well simulated the daily discharge flow, however there is a slight under and over prediction of the high flows; this is the common draw backs of hydrological models. The results obtained are satisfactory and acceptable. Thus, HEC-HMS model are recommended as an alternative model to the other model in predicting runoff.

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Conflict of Interest: All Authors declare that they have no conflict of interest.

Ethical Approval: This article does not contain any studies with human participants or animalsperformed by any of the authors.

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