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Comparison Of The Performance Of HEC-HMS And RF Models In Rainfall Runoff Simulation

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Abstract: *River discharge prediction is a critical subject in water resource engineering concerns. The HEC-HMS model and random forest (RF) models have been successfully used in discharge forecasting problems. In this research HEC-HMS model and RF were 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 output of the HEC-HMS model was compared with the recorded data of the discharge, the residual time series values, which resulted from the comparison, was solved by using the RF approach. The root means square error (RMSE), mean absolute error (MAE), and coefficient of determination (R2) for M.H. Halli station using HEC-HMS model were found to be more efficient than RF model in forecasting the daily discharge. The current study's findings supported the proposed methodology's applicability for precise discharge modeling.*
Keyword: *Forecasting; HEC-HMS Model; RF Model.*

INTRODUCTION

Rainfall-runoff modeling is one of the most important hydrological processes, especially large-scaled processes (Chang, 2009). Also, nonlinearity and multidimensionality render the modeling of the transformation of rainfall into runoff very complex (Ishtiaq et al., 2010). 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). 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). 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) 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). 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).
These advantages and increased computing power of computers have propelled the research and use of data driven models for discharge prediction. These methods are particularly useful in rivers basin for predicting floods, and drought sequence, where scarce data records and resource limitations hinder the use of physical based models. The data driven models used for prediction and classification are Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), Fussy rule-based system and Model Trees (MT), Long Short-Term Memory (LSTM), Extreme Learning Machines (ELM) and so on (Bafitlhile and Li, 2019; Adnan et al., 2021). For limited discharge data set available, Support Vector Machine (SVM) method based on machine learning techniques perform better or as par as artificial neural network models (Gizaw and Gan, 2016; Liong and Sivapragasam, 2002). In classification and regression problems, SVM is widely used, developed by Vapnik and chervonenk (Cortes and Vapnik, 1995). SVM theoretically reduces the expected error of a learning model, and minimizes the problem of over fitting. The details of SVM are well described in the literature and can be found elsewhere (Cortes and Vapnik, 1995; Tongal and Booij, 2018; Wang et al., 2006; Yu et al., 2017; Yoon et al., 2011). Similarly, random forest (RF) method is another machine learning, decision tree-based method requiring less user defined parameters than SVM and often performing better in flood forecasting than the latter (Yu et al., 2017; Zhou et al., 2019). RF was used in flood hazard prediction in Dongxiang River (Sadler et al., 2018) and for drought prediction in Australia (Deo and Şahin, 2015). More details about RF can be found in many published literatures (Breiman, 2001).
In general, it seems HEC-HMS and RF are the most widely applied to predict discharge in river catchments. That is why in this research work, the comparison was done using these two hydrological and data driven model. 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 (i) estimate discharge through the hydrological and data driven models and (ii) compare hydrological and data driven models for discharge prediction (HEC-HMS and RF)

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 the Western 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 of latitude 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.

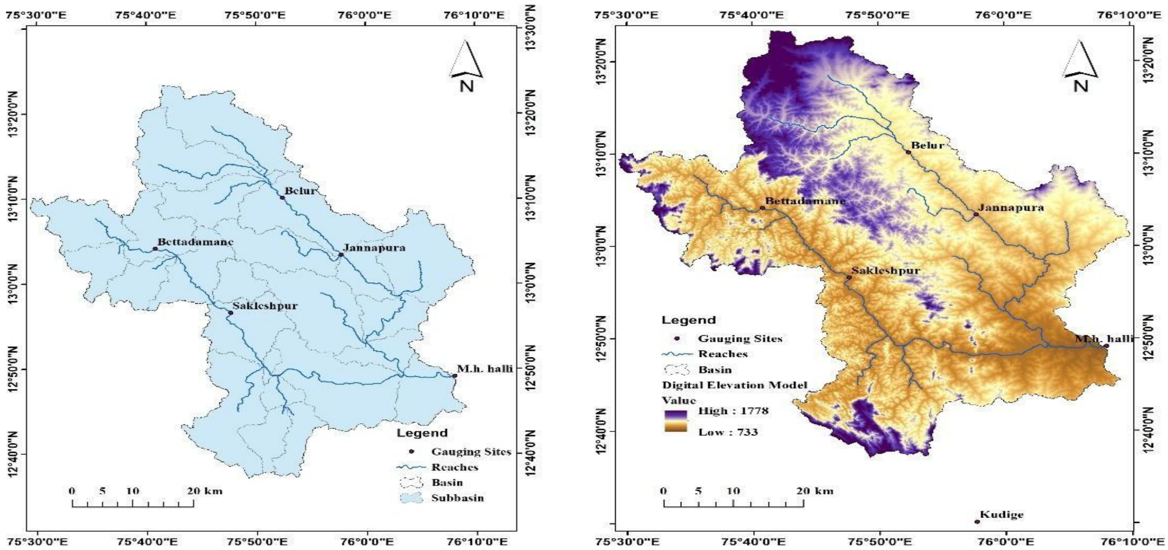

Fig. 1: Location map and Digital Elevation Model of the Study area

For the period 2003 to 2017, discharge (m3/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 remaining seven 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.

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 (0C)		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 (0C)		23.47	1.14	0.09	29.135	19.804

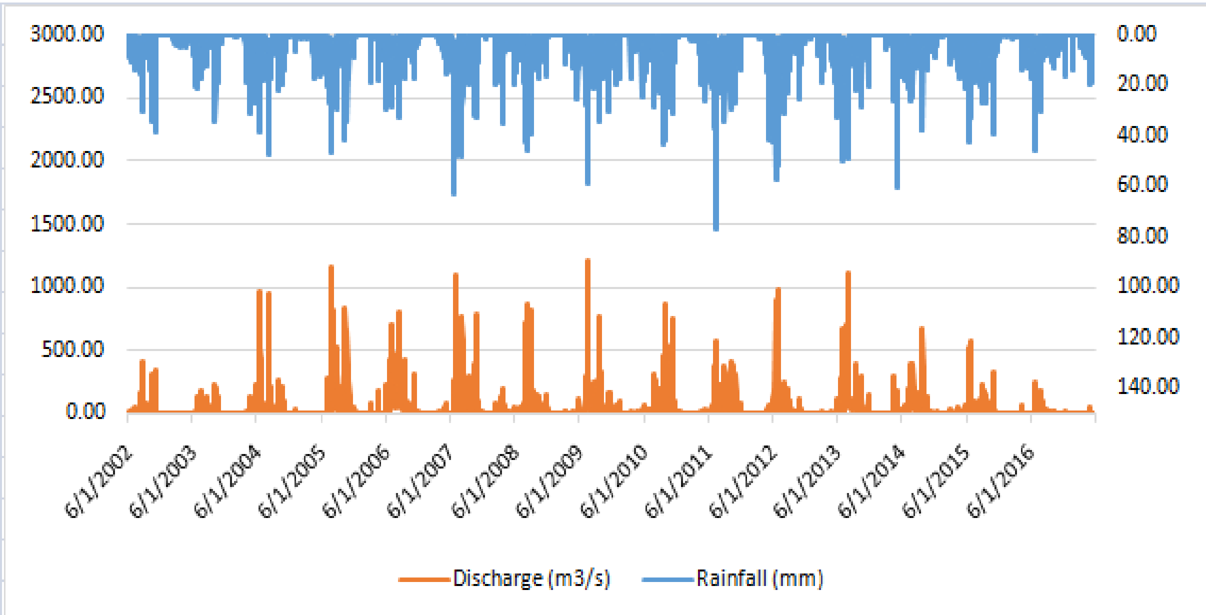

Figure 2: Time series of observed data (rainfall, temperature and discharge) used for training and testing stages

2.2 Model descriptions

In this study, an HEC-HMS and RF model were applied to simulate discharge in the M.H. Halli Station.

2.2.1 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 based and 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 small urban 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 river runoff 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 method is 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.

2.2.2 Data driven model (Random Forest)

RF was first developed by Breiman (2001), who used a decision tree classifier to generate the model (Breiman and Cutler, 2004). A method for regression and classification called RF is a grouping of different learning algorithms that can be used in conjunction. The random forest methodology relies on the creation of a forest of random trees, which are produced by randomly dispersing the information at each decision tree node. In an effort to create a more accurate model, RF uses an ensemble approach to aggregate the resilience of many trees (Goeschel, 2016).

Several studies (Rudianskait et al. 2015; Yaseen and colleagues 2019 a,b) have examined the use of RF in engineering and proved its feasibility for prediction methodologies. The "out-of-bag" data that is not picked for the bootstrapping procedure is referred to as "out-of-the-bag" data. The huge number of trees in the RF technique ensures that over-fitting does not occur, and random variables of the suitable type are chosen to ensure precise categorization. The number of trees, the minimum gain, and the maximum tree depth are all characteristics that must be optimized in RF.

For each bootstrap sample of b = 1, 2, 3, . . ., B, an RF model is fitted to calculate the output of $\hat{f}_{rf}^{B}(x)$ in input x (Hastie et al., 2009).The following formula computes the output of the RF model by the creation of a random forest tree Tb on bootstrapped data:

$$\hat{f}_{rf}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x). \quad (1)$$

The fundamental disadvantage of the RF model is that it is a hyper-parameter method.

2.2.3 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 of determination (R2), mean absolute error (MAE) and root mean square error (RMSE). The formulation can be expressed as follows:

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

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

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

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Where n is the number of data, x and y are observed and estimated values, and σx and σy are the standard deviation of the observed and estimated data. It should be mentioned that low value (closer to zero) for the RMSE, while for R2, 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 and RF model have been developed for discharge forecasting. A general view of the study is given Figure 3.

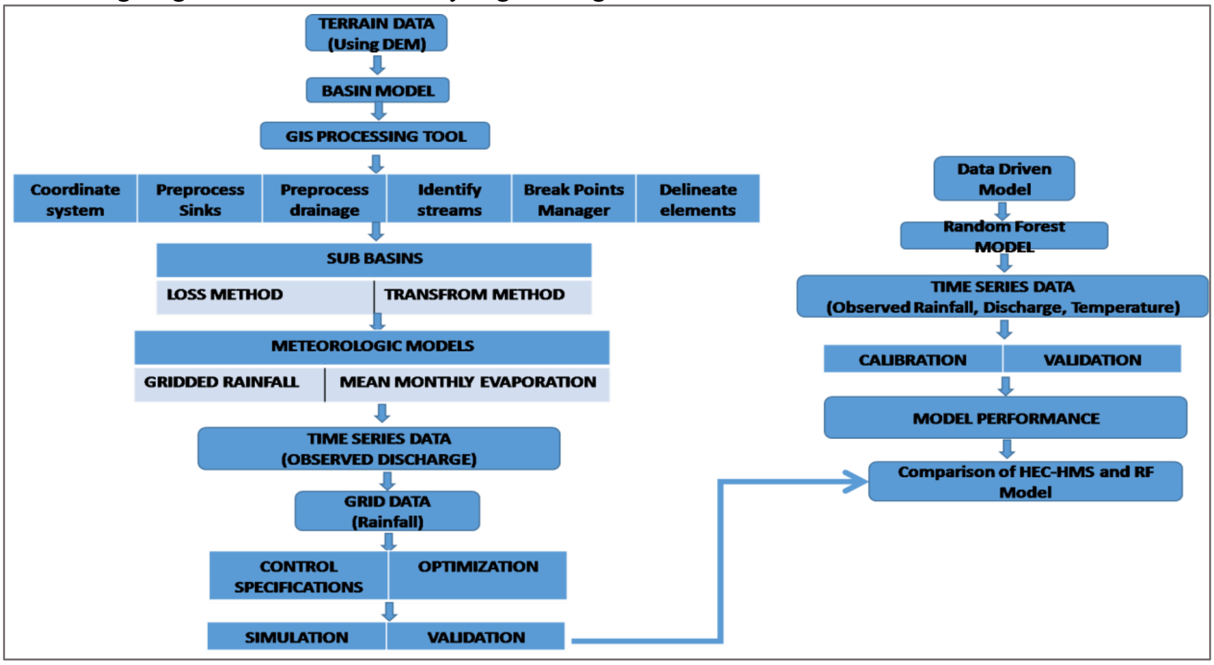


Figure 3. Flowchart of the modeling procedure

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 the training dataset. The maximum values for the rainfall and temperature testing dataset were higher than 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 R2 (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 are assigned 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.

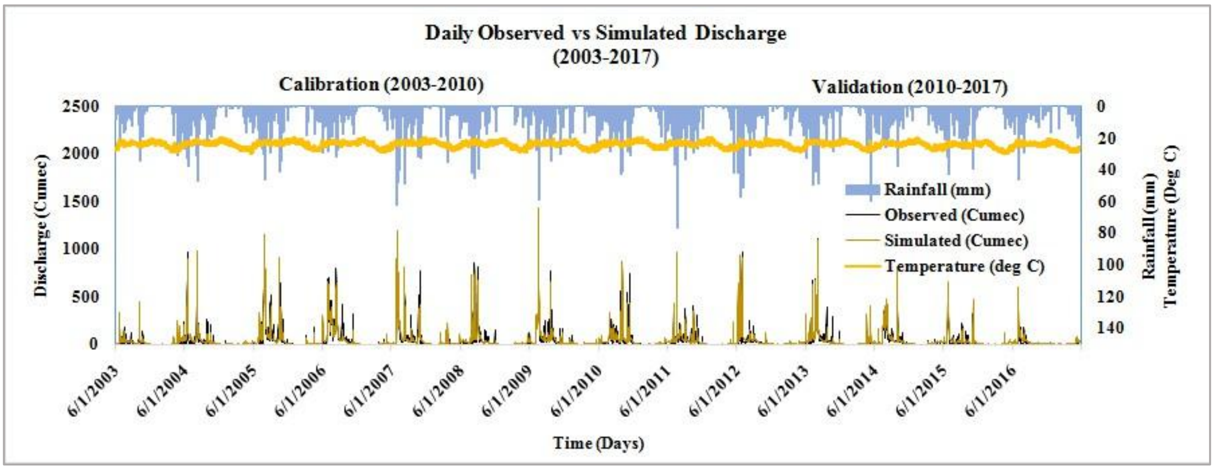


Figure 4: HEC-HMS model performances in terms of comparison of observed and simulated discharge

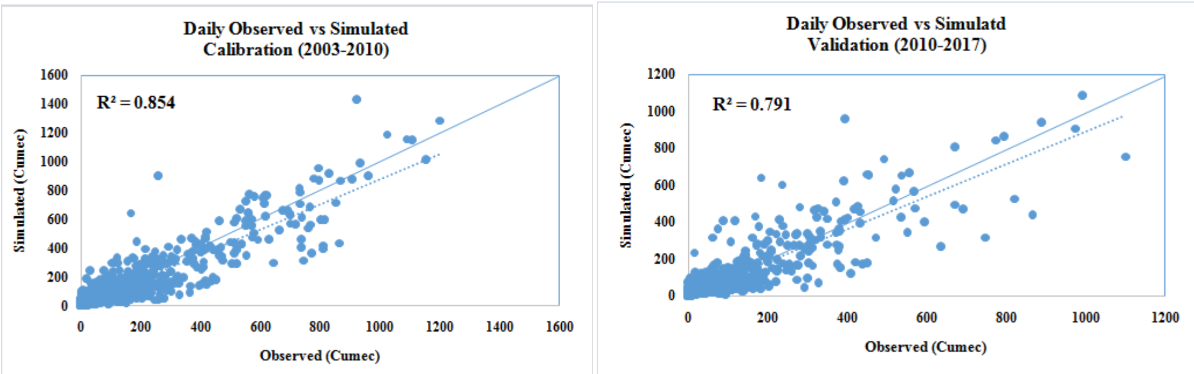


Figure 5: HEC-HMS model scatter plot between observed vs simulated discharge during calibration and validation stage

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 (R2) 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 calibration and validation period.

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 observed discharge flow. From the statistical analysis (Table 2) the coefficient of determination (R2) 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.

3.3 Discharge prediction with RF model

Table 2 appears the RF prediction performance using the best predictive variables based on the R2, RMSE, and MAE for the calibration. Figure 6-7 delineates the performance of the RF models. As shown in Table 2, the range of R2 for the predicting discharge in all scenarios was highly correlated (R2= 0.974 - 0.994) in training phase. According to the R2 values, the RF model from the second scenario produced the best performance during training (0.994), followed by the first scenario. R2 is susceptible to outliers and should not be used entirely for evaluating generated models because it is optimized for differences between the mean and variance of measured and expected quantities (Legates and McCabe 1999; Shiri and Kisi 2012). As a result, alternative error measurement indices were employed to assess the performance of the model. Based on RMSE and MAE, the RF (2nd scenario) was superior to the other types. The training phase rather than the testing phase yields superior results for the effectiveness of RF (2nd scenario). For instance, the MAE and RMSE indices during the training stage were 0.166 and 12.61, respectively. Each tree in RF regression trees is created separately on a bootstrap sample. As a result, they are only weakly connected. The risk of over fitting the training data set was reduced as a result. Furthermore, it was discovered that the RF algorithm could nearly formulate the data trend, that the model could accurately give the rainfall prediction, and that the predicted and observed values were nearly identical.

Table 2. Comparison of HEC-HMS and Random forest models in terms of R2, RMSE, and MAE

Models	Calibration			Validation		
	R2	RMSE	MAE	R2	RMSE	MAE
HEC-HMS	0.854	49.59	22.03	0.791	41.64	16.85
Data Driven model						
Rain, Temp, Discharge (1st scenario)	0.974	29.02	0.418	0.189	88.12	25.29
Rain, Temp, D-1, D-2 (2nd scenario)	0.994	12.61	0.166	0.325	87.85	25.15

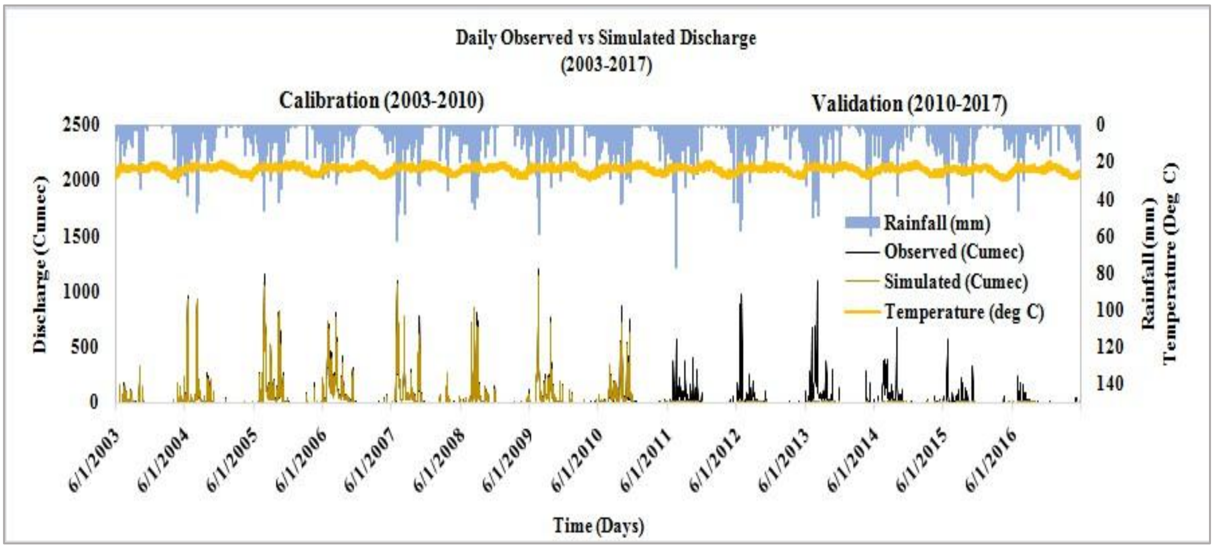
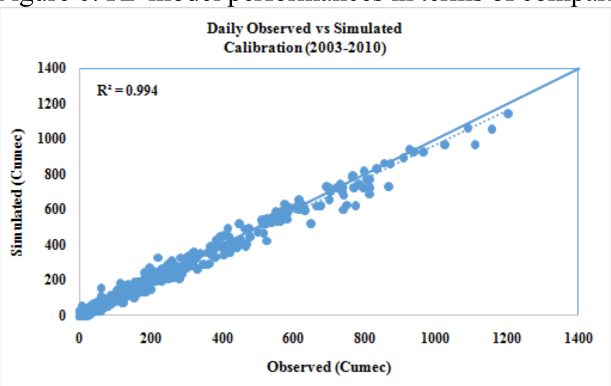


Figure 6: RF model performances in terms of comparison of observed and simulated discharge



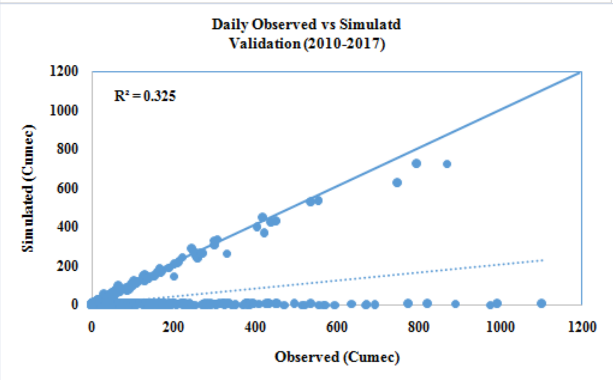


Figure 7: RF model scatter plot between observed vs simulated discharge during calibration and validation stage

3.4 Comparison of Prediction Models

We investigated the ability of the HEC-HMS model for runoff prediction and compared with RF model. The accuracies of the HEC-HMS and RF models were compared using R2, MAE and RMSE. Table 2 presents the training and testing results of the MH Halli station. In Table 2, it is shown that HEC-HMS model acquired the best R2, MAE and RMSE in the training and testing stages. Figure 8 delineate the comparison of HEC-HMS and RF model. The HEC-HMS model considerably improved the accuracy with respect to RF model in the testing stage. Results indicated that the HEC-HMS model might provide an alternative to the RF models for predicting runoff.

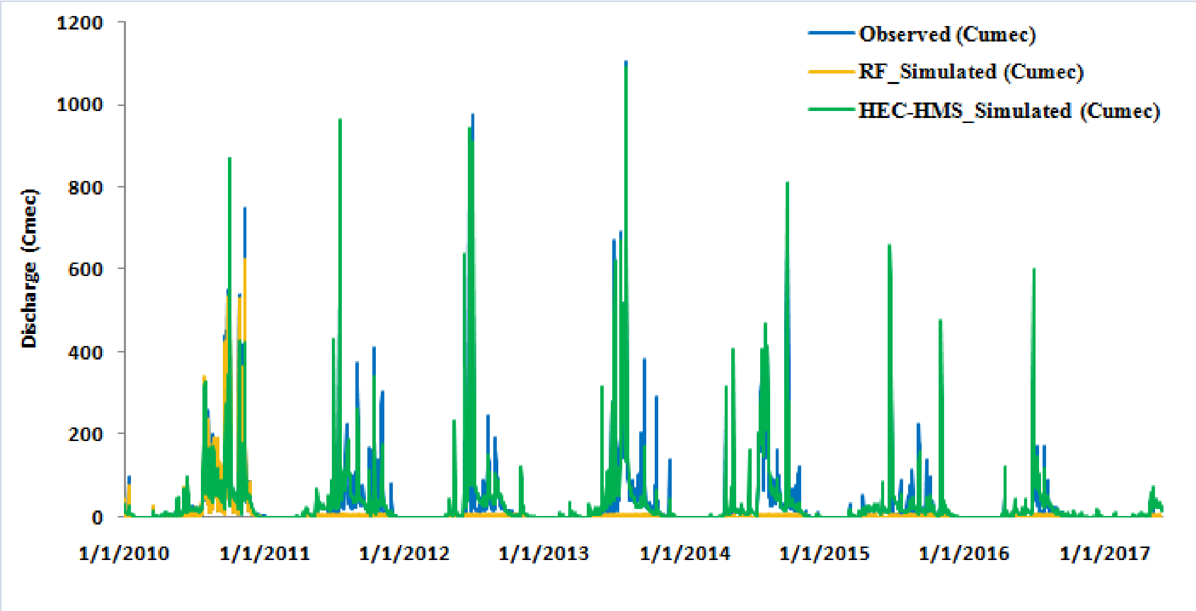


Figure 8: Comparison of HEC-HMS and RF model

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 in the 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 (R2), 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 than RF model. The HEC-HMS model provided the highest R2 and the lowest MAE and RMSE in testing data sets. Where the calculated value of R2 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 RF model in predicting runoff.

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