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Assessment of Streamflow Variability with Upgraded HydroClimatic Conceptual Streamflow Model

Mayank Suman[1] · **Rajib Maity**[2]

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Abstract

HydroClimatic Conceptual Streamflow (HCCS) model is a conceptual model for prediction and future assessment of daily streamflow using climate inputs and time-varying watershed characteristics. However, without denying its useful salient features in a changing climate, applicability of the HCCS model is limited to the basins without any major man-made river structure(s), such as reservoirs. Considering this, the originally proposed HCCS model is upgraded (hereinafter 'upgraded HCCS model') to accommodate the human-intervened release from such structures within the basin, if any, and to include routing component through the river channels without using rigorous information from the river channels. The upgraded HCCS model is expected to be useful to assess (i) the effect on the streamflow at downstream due to upstream dam release, and (ii) the long-term modification required in the reservoir/dam operation under a changing climate for ensuring water-availability in downstream. The upgraded HCCS model is applied to three river basins for assessing the future streamflow characteristics. Two of these basins have one each and the third basin has two major man-made river structures within them. Hadley Centre Coupled Model, version 3 (HadCM3) simulated climate variables till 2035 are used as inputs for demonstration. The model predicts an increase in streamflow in future. In general, the upgraded HCCS model can be applied to any tropical river basin having major man-made river structure(s) for daily streamflow prediction as well as assessment of future streamflow variation considering the changing climate and watershed characteristics.

Keywords HydroClimatic conceptual streamflow (HCCS) model · Streamflow · Climate change impact · Water availability

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✉ Rajib Maity
rajib@civil.iitkgp.ac.in; rajibmaity@gmail.com

[1] School of Water Resources, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal 721302, India

[2] Department of Civil Engineering, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal 721302, India

1 Introduction

The ever increasing water demand and adverse impact of climate change on available water resources demand a proper assessment of streamflow to ensure water securities for drinking, irrigation, industries and energy. Many hydrological models are developed to capture the basin-scale streamflow variability. Such models can be broadly divided into three major categories: Physically based models, Conceptual models and Artificial Intelligence (AI) based models. Physically based models, such as Soil and Water Assessment Tool (SWAT) (Grizzetti et al. 2003; Neitsch et al. 2011) and Community Land Model (CLM) (Lawrence et al. 2011) attempt to simulate different hydrological processes and, thus, heavily depend on the enormous spatially distributed data from the basin. Still, the predictions from the physically based models often suffer due to over-parameterization, and non-availability of required comprehensive data sets (Piotrowski and Napiorkowski 2012). The AI based models, such as artificial neural network (Nagesh Kumar et al. 2007; Isik et al. 2013; Shiau and Hsu 2016; Abdollahi et al. 2017), genetic programming (Maity and Kashid 2010; Mehr et al. 2014; Abdollahi et al. 2017), least square support vector machines (Maity et al. 2010; Kisi 2016; Kalteh 2016) and others, consider a black-box approach by modeling the streamflow using different inputs to basin like precipitation, air temperature, relative humidity, wind speed etc. The performance of the AI based models may often be better than that of the physically based models (Wang et al. 2009). However, both of these modeling approaches are computationally demanding due to their complexity. In contrast, the conceptual models conceptualize different hydrological processes in a watershed. Some of the conceptual models are National Weather Service River Forecast System (NWSRFS) (Anderson 1973), Integrated Runoff Model – Bultot (Bultot and Dupriez 1976), MODified HYDROLOG (MODHYDROLOG) (Porter and McMahon 1976), Hydrologic Simulation Program- FORTRAN (HSPF) model (Crawford and Linsley 1966; Bicknell et al. 1996; Stern et al. 2016). These models, instead of modeling exact representation of hydrological processes in the watershed, assume the watershed as a system, which after considering the inputs like precipitation, air temperature etc. produces response in the form of streamflow, evaporation, groundwater recharge etc. However, the conceptual models do not require a large amount of data as compared to physically based models.

Understanding the impact of changing climate on the streamflow and other hydrological variables is challenging but essential for a sustainable progress in the water sector. The models, which can simulate such impacts, will be of immense importance in this context. However, most of the existing approaches inherently assume stationarity in hydro-climatic factors/ conditions, which may not be a valid assumption under a changing climate. Moreover, if the gradual changes in climate and watershed characteristics are not simultaneously accounted for, the consistency (decadal to climatic scale) in the model performance may be affected. Some models like HydroClimatic Conceptual Streamflow (HCCS) model (Bhagwat and Maity 2014) can account for the effect of climate change and basin characteristics simultaneously by varying its parameters. The HCCS model is a conceptual model, which takes into consideration the time-varying property of the watershed along with daily climatic inputs like rainfall, air temperature etc. while predicting daily streamflows. Additionally, it also provides average estimate of daily groundwater recharge component and evapotranspiration component over the entire basin. Conceptually, the HCCS model assumes that the major hydrological components such as evapotranspiration, groundwater recharge are related to water available near surface strata at any time, also known as System Wetness Condition, denoted as $V(t)$. Maximum value of the System Wetness Condition (V_{max}) is also assumed to vary with time (though slower than

$V(t)$) to account for effect of climate change and watershed characteristics. The consideration of the time-varying watershed characteristics renders the HCCS model usable for assessment of future streamflow variation under changing climate. However, the originally proposed HCCS model had a limitation that the basin should not have any major man-made river structure. However, most of river basins are being developed, hence, the assumption of not having a major man-made river structure limits the application of the HCCS model in many cases. Moreover, with streamflow being regulated across river network, amount of water available in the downstream section of river becomes an important question for the city planners/policy makers. Existing HCCS is inadequate in providing these information and helping the planning process.

The objective of this study is to upgrade the existing HCCS model for predicting streamflow in a basin having major man-made river structure apart from considering the climate change effect. Improvements in HCCS model include (i) provision of flood routing module using Muskingum method (Chow et al. 1988) with consideration to transmission or conveyance loss (Costelloe et al. 2003) for routing flood from upstream major man-made river structure, and (ii) improved non-linear optimization technique 'Sequential Quadratic Programming (SQP)' (Boggs and Tolle 2000; Nocedal and Wright 2006) for optimization of model parameters. These improvements have enhanced the model applicability and reduced the computational requirement. Rest of paper is organized as follows: Section 2 provides a brief overview of HCCS methodology and its improvement. Details of study area and data are provided in section 3. In section 4, results and discussion are provided followed by the summary and conclusions in section 5.

2 Methodology

The HCCS model, proposed by Bhagwat and Maity (2014), is a conceptual model, which is able to predict the daily streamflow variation and to give an estimate of the spatially averaged evapotranspiration loss and groundwater recharge from the entire catchment. The model is also suitable for simulating the future streamflow variation using projected future climate data over tropical basins. A brief overview of conceptualization assumed in HCCS is provided in the section 1 of the supplementary document and the details can be referred from Bhagwat and Maity (2014).

In HCCS model, four parameters namely B, b, k and V_{max} are used to characterize the basin. Parameter B is a function of V_{max} and maximum streamflow (S_{max}) over watershed. The inverse of parameter b is the measure of degree of nonlinearity between ratio of streamflow and maximum streamflow and ratio of $V(t)$ and V_{max}. Parameter V_{max} represents maximum system wetness condition. The System Wetness Condition ($V(t)$) is the amount of water that is stored in the near-surface strata of the watershed as depression storage, soil water retention, reservoir storage, etc. at a given instance of time. Hence, V_{max} indicates the maximum surface water holding capacity of the watershed at a particular time and has dimension of length (unit m or mm). Parameter k is a unit-less, indicating the net contribution of catchment to groundwater recharge. These parameters depend on the catchment characteristics, e.g. urbanization, deforestation, topography etc., which influence the system response and may also be interrelated. Thus, the model parameters are estimated simultaneously during model calibration by minimizing the sum of square error (SSE) between observed and predicted streamflow (eq. S6 in the

supplementary document). The set of the parameter values that yield minimum sum of square error are used as estimated parameters.

2.1 Improvements in the Upgraded HCCS Model

Two major improvements in the HCCS model implemented in this study are i) provision for separating the sub-basin keeping major man-made river structure at either upstream or downstream of sub-basin and routing module for intervened sub-basin (sub-basin that has major structure at the upstream end) ii) provision of a new nonlinear optimization technique namely Sequential Quadratic Programming (SQP) (Boggs and Tolle 2000) for optimizing the model parameters.

The upgraded HCCS model requires the basin to be divided into a number of sub-basins. The separation of these sub-basins is done in such a way that the major man-made river structures, if any, in the basin should fall on either upstream or downstream end of the sub-basins. For delineating the first virgin sub-basin (most upstream sub-basin till the first major man-made river structure), flow direction is calculated and the area contributing streamflow to the sub-basin outlet is considered as the part of the sub-basin. For the subsequent sub-basins in the downstream, the same procedure is followed and the area from all upstream sub-basins is removed. In this way, different sub-basins are demarcated. Henceforth, the sub-basin(s) having the major man-made river structure at its upstream end is(are) termed as intervened sub-basin. The streamflow at the downstream end of these intervened basins are conceptually separated into two sources – routed Streamflow contribution due to Upstream Inflow (SUI) and Streamflow contribution due to Lateral Inflow within the sub-basin (SLI). The HCCS model was originally designed to model SLI part only. For the most upstream sub-basin, i.e., sub-basin till first major man-made river structure, the HCCS model is applied without any streamflow separation since the entire streamflow originates from runoff within the sub-basin. For the estimation of the SLI component in the intervened sub-basin, the SUI component is first calculated by routing the inflow at the upstream end to the downstream end using the Muskingum method with proper consideration of conveyance loss. Adapting from the Muskingum method (Chow et al. 1988), the routing equation can be expressed as

$$Q_2 = C_0 I_2 + C_1 I_1 + C_2 Q_1 \tag{1}$$

where, C_0, C_1 and C_2 are the Muskingum coefficient having a sum of unity. Q and I represent the outflow at sub-basin downstream end and inflow at sub-basin upstream point respectively. Subscript *1* and *2* denote the beginning and end of time interval. However, the above formulation of the Muskingum equation ignores any losses in the routing that may occur in a natural stream (Costelloe et al. 2003). If l shows the percentage loss during conveyance (also known as conveyance loss), the equation can be modified as:

$$Q_2 = (C_0 I_2 + C_1 I_1 + C_2 Q_1)(1 - l/100) \tag{2}$$

The conveyance loss can be estimated by analysis of high temporal resolution streamflow data or from field experiments. Further details about the methodology used for estimating Muskingum coefficients and conveyance loss is provided in section 3 of the supplementary document.

Next, the SLI is calculated by subtracting SUI component from the observed streamflow at the outlet of intervened sub-basin. The SLI component of streamflow is then used to calibrate the upgraded HCCS model. These changes in the HCCS model ensured that the model can

take care of the release from the major man-made river structure at the upstream end of intervened sub-basin.

Bhagwat and Maity (2014) used grid search optimization algorithm for parameter estimation. The resolution of grid or spacing of grid vertices were user adjustable. The grid search algorithm evaluates the optimization criteria at the intersection of the grid. Depending on the grid resolution, the optimum solution may not always yield exactly optimized value. On the other hand, if the resolution increases (thus, the number of grid points), the computation increases exponentially with the number of decision variables. Hence, the used algorithm is computationally intensive and still may fail to provide most optimized result. The upgraded HCCS model is based on nonlinear optimization namely Sequential Quadratic Programming (SQP) (Boggs and Tolle 2000). The SQP is an iterative algorithm for solving constrained nonlinear optimization problem (NLP) and it tries to formulate quadratic programming sub-problem at each iteration step to estimate the solution. The SQP converges very fast unlike grid search optimization, resulting in better optimization with less processing time. Mathematical details of the SQP algorithm are provided in section 2 of the supplementary document. It should be further noted that in the upgraded HCCS model only three parameters (b, k and V_{max}) are user configurable. The parameter B is estimated by using eq. S2b provided in the supplementary document.

In a nutshell, for the application of the upgraded HCCS methodology, basin needs to be divided into a number of sub-basins in such a way that the major man-made river structure(s), if any, falls (fall) on the either upstream or downstream end of a sub-basin. Depending on the nature of upstream inflow to the sub-basin, the routing module is used in the intervened sub-basins. The streamflow contributed by runoff in a sub-basin is modelled by using inputs like daily streamflow, rainfall (after Thiessen Polygon averaging), maximum air temperature, minimum air temperature, average air temperature and solar declination at sub-basin outlet. Parameters of the upgraded HCCS model (B, b, k and V_{max}) are estimated during the model calibration period. With the estimated parameters, the model is applied to estimate the runoff from the respective sub-basin in testing/future period. The model performance for calibration and testing periods can be investigated through different performance measures, such as, degree of agreement (D_r), correlation coefficient (CC), Nash-Sutcliffe efficiency (NSE) and root mean square error (RMSE). The details of these performance measures are discussed in section 4 of the supplementary document.

3 Study Area and Data Used

3.1 Study Area

One river basin from the Deccan plateau and two from the Chota Nagpur plateau in India are chosen for studying the efficacy of upgraded HCCS model – i) Bhadra river basin till Holehonnur gaging station (henceforth Basin-A) ii) Barakar river basin till Manot reservoir (henceforth Basin-B) iii) Damodar river basin till Panchet reservoir (henceforth Basin-C). Barakar River is tributary of Damodar River and they meet at the downstream of Panchet and Maithon. These basins along with major man-made river structure are shown in Fig. 1. Basin-A and Basin-B has one major dam/reservoir (Bhadra and Tilaiya reservoir respectively) within it, whereas the Basin-C has two major dams/reservoirs (Tenughat and Konar) within it. Due to division at the dam site, the first two basins have two sub-basins and Basin-C has three sub-

basins. Hence, in these basins there are four virgin sub-basins (sub-basin-I in both Basins A and B, sub-basin-I and II in Basin-C) and three intervened sub-basins (sub-basin-II in both Basins A and B, sub-basin-III in Basin-C) as shown in Fig. 1. The details of these sub-basins are tabulated in Table 1. The Basin-A is predominately forested. However, Basin-B and C are highly developed; having high industrial and agricultural demand.

3.2 Data

3.2.1 Data Required for Calibration and Testing

Historical records of daily rainfall, streamflow, air temperature and solar declination are required for calibration and testing of HCCS model. Daily gridded (0.25° latitude × 0.25° longitude) rainfall data is obtained from India Meteorological Department (Pai et al. 2014). Daily gridded (1° latitude × 1° longitude) maximum, minimum and average temperature data are obtained from India Meteorological Department (Srivastava et al. 2009). The solar declination for different sub-basins are calculated as per Bhagwat and Maity (2014). Daily streamflow at Holehonnur gauging station is obtained from Water Resources Information System, India (WRIS 2015). The Bhadra reservoir daily discharge and inflow data is obtained from Karnataka Neeravari Nigam Limited for period of June 1, 2005 – May 31, 2012. Similarly, the daily inflow and dam discharge for different dam/reservoir in Basin-B and Basin-C are obtained from Damodar Valley Corporation for June, 1980 – May, 2014. Based on data availability, June 2005 – May 2011 and June 2011 – May 2012 are selected as calibration and testing period respectively for Basin-A. Similarly, the calibration and testing periods for Basin-B and C are June 1980 – May 2000 and June 2000 – May 2013 respectively.

3.2.2 Future Climate Data

Projected climate data for future period are obtained from the data archive of Intergovernmental Panel on Climate Change, Fifth Assessment Report (AR5) (IPCC 2013). The General Circulation Model (GCM) output ensemble of the Hadley Centre Coupled

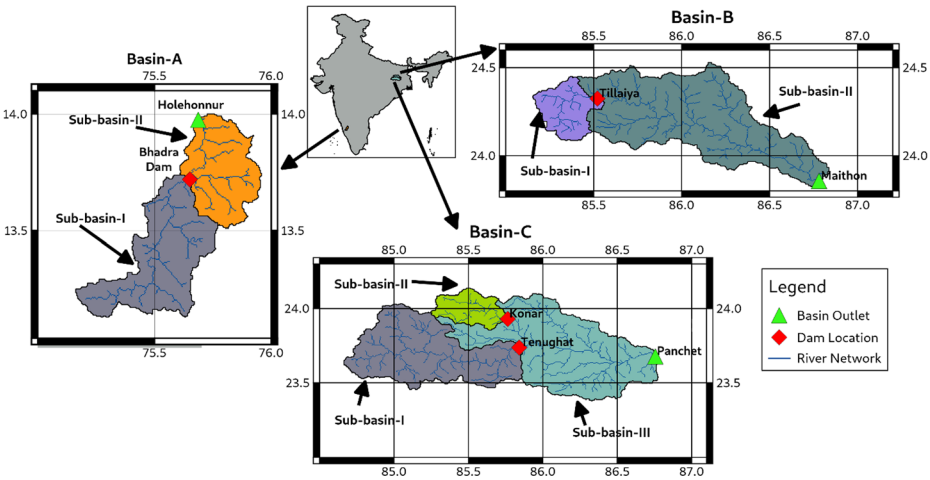


Fig. 1 Location of the study basins and their sub-basins

Table 1 Details of different sub-basins and HCCS parameters

Basin ID	Sub-basin ID	Sub-basin Type	Area (km^2)	Ground elevation at outlet (m)	HCCS model parameter			
					B	b	k	V_{max} (mm)
A	I	Virgin	1968.0	612	17.896	0.900	0.250	1000
	II	Intervened	1608.0	567	17.456	0.668	0.250	287
B	I	Virgin	1087.8	355	11.663	0.925	0.250	716
	II	Intervened	5851.8	147	12.238	0.690	0.250	256
C	I	Virgin	4972.7	222	10.101	0.709	0.250	263
	II	Virgin	1073.5	398	7.842	1.000	0.250	502
	III	Intervened	6342.2	97	12.161	0.736	0.250	231

Model version 3 (HadCM3) for the emission scenario Representative Concentration Pathways 4.5 (RCP4.5) is used for future projection of streamflow in the sub-basin. RCP4.5 correspond to the climate change scenario in which there will be increase in radiative forcing of 4.5 W/m^2 on average by 2100. This climate change scenario is considered moderate and suggested by different studies (Moss et al. 2008; van Vuuren et al. 2011). Data for all available ten simulations of the GCM, namely R1 to R10 (10 different realizations) are procured. The predictor variables include daily precipitation, daily average air temperature, daily maximum air temperature and daily minimum air temperature. These variables are obtained for the period 2006 to 2035 and have a spatial resolution of 2.5° latitude × 3.5° longitude.

4 Results and Discussion

The spatially averaged rainfall over the sub-basins (Fig. 1) are calculated using Thiessen polygon method. For virgin sub-basins, SUI is zero and inflow to respective downstream end represents SLI. However, the SUI components at outlet of the intervened sub-basins (sub-basin-II in Basins A and B and sub-basin-III in Basin-C) are calculated by using Muskingum flood routing method (eq. 2) as detailed in section 3 in supplementary document. Using the Muskingum coefficient and conveyance loss tabulated in Table S1 in the supplementary document, SLI is obtained by subtracting SUI from observed streamflow at these sub-basin outlets. It should be noted that higher conveyance loss is observed in intervened sub-basin of comparatively more industrialized basins (Basin-B and C), probably due to high industrial and agricultural water demand.

The upgraded HCCS model is calibrated for the sub-basins to predict the SLI at sub-basin outlet using the spatially averaged sub-basin rainfall, maximum air temperature, minimum air temperature, average air temperature and solar declination at sub-basin outlet for model calibration period. Four parameters of upgraded HCCS model, i.e., B, b, k and V_{max} are estimated during model calibration by minimizing the sum of square error (SSE) between observed and modelled streamflow. The calibrated values of B, b, k and V_{max} are shown in Table 1. High value of V_{max} for virgin sub-basins indicates that maximum water holding capacity thus depression storage, soil moisture retention etc. in these sub-basins is higher. Hence, it also matches with the fact that these sub-basins have reservoir within their boundaries. Same values of k suggest similar groundwater

abstraction in these basins as these basin are part of the Deccan plateau and are having hilly terrain. The value of the parameter *b* revels that relationship between the system wetness condition and streamflow is comparatively less non-linear for the virgin sub-basins compared to intervened sub-basin. Further, the Basin-A has more water holding capacity than other developed basins as evident by the high values of parameter *B*. The model is further tested using the calibrated parameters and its performance statistics is tabulated in Table 2. The predicted daily streamflow (summation of predicted SLI and routed SUI) and observed daily streamflow in sub-basin II in Basin-A are shown in Fig. 2. From the figure, the potential of the upgraded HCCS model in capturing dynamics of daily streamflow can be observed. The performance measures are satisfactory and comparable during both calibration and testing period. High values of CC, Dr. and NSE are the indication of the efficiency of model. As mentioned before, the groundwater recharge and evapotranspiration components can also be estimated as other outputs of the model. However, it should be noted that these estimates are spatially averaged magnitudes over the respective sub-basins. Daily variation of groundwater recharge and evapotranspiration component for sub-basins of Basin-A are presented in figs. S1 and S2 respectively in the supplementary document. The magnitude of losses (both groundwater and evaporation) are found higher in virgin sub-basin as compared to intervened sub-basin in the same basin. In case of Basin-A, the losses in sub-basin I increase in monsoon season and decrease in sub-sequent months. The increase in evapotranspiration during monsoon months may be caused due to geographical location of sub-basins as they are situated in the leeward side of western ghat range. The characteristics for estimated groundwater recharge and evapotranspiration component during testing period is found to be similar to that of during calibration period for all the sub-basins. For the assessment of seasonal variability, monthly cumulative estimates of groundwater recharge and evapotranspiration component for sub-basin II in Basin-A during calibration and testing period are shown in Fig. 3. Though, these estimates cannot be compared with the observed values due to non-availability of data, seasonality in groundwater recharge component and evapotranspiration component values is visible in monthly scale plots and matches with the climatology of Indian sub-continent. Figure 3b also shows an increasing trend in evapotranspiration for sub-basin II in Basin-A. Similar figures for intervened sub-basin in other basins are provided in supplementary document (Fig. S3 and S4).

Table 2 Model performance during calibration and testing period for different study basins

Basin ID	Sub-basin ID	Performance Metrics							
		Calibration Period				Testing Period			
		CC	Dr	NSE	RMSE (m^3/s)	CC	Dr	NSE	RMSE (m^3/s)
A	I	0.901	0.868	0.805	83.987	0.914	0.864	0.794	65.384
	II	0.891	0.821	0.793	49.526	0.886	0.816	0.782	42.400
B	I	0.740	0.738	0.423	27.534	0.735	0.715	0.401	23.159
	II	0.837	0.799	0.583	141.438	0.785	0.713	0.515	158.784
C	I	0.819	0.791	0.585	116.946	0.801	0.795	0.565	125.933
	II	0.650	0.706	0.227	33.998	0.707	0.653	0.283	26.491
	III	0.909	0.868	0.809	135.754	0.878	0.841	0.760	141.679

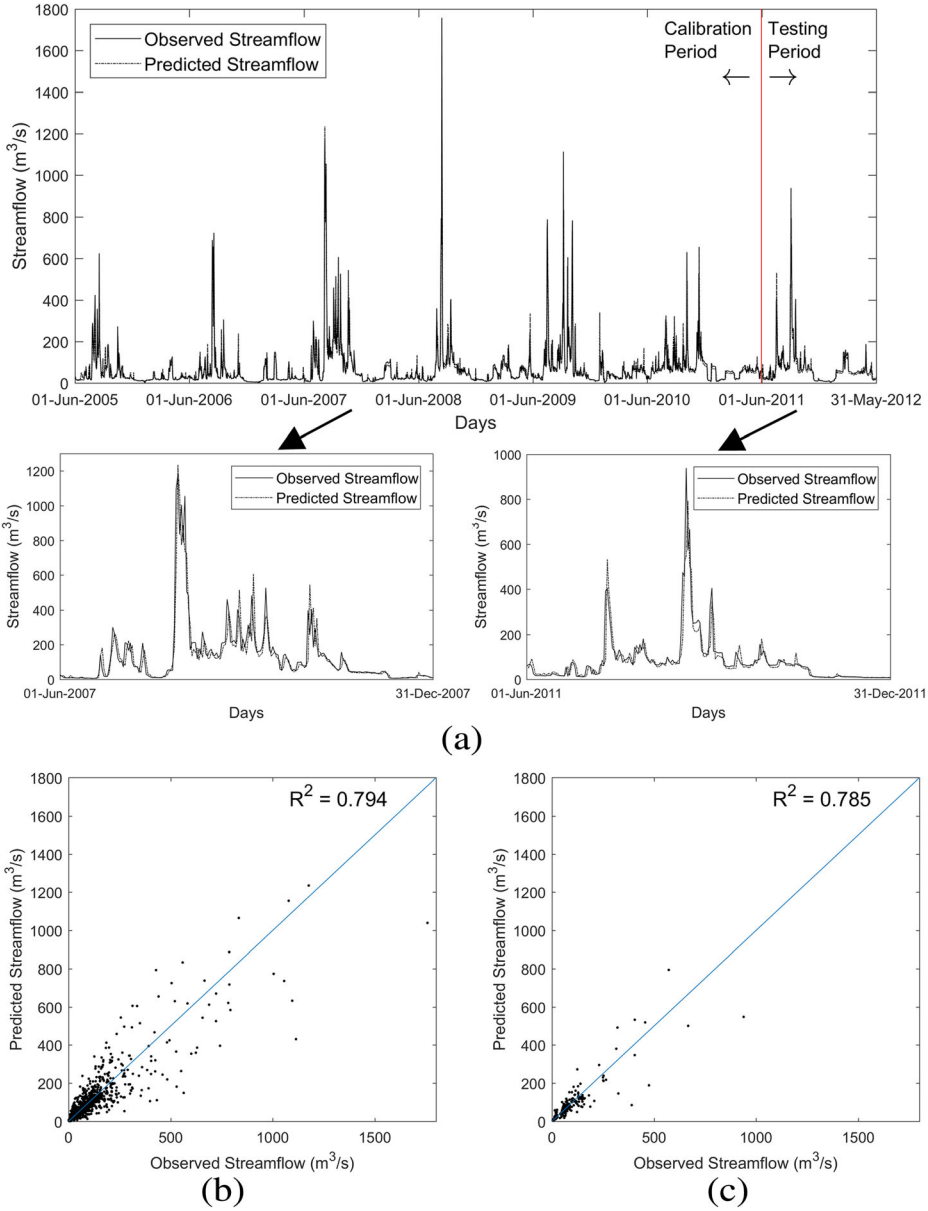
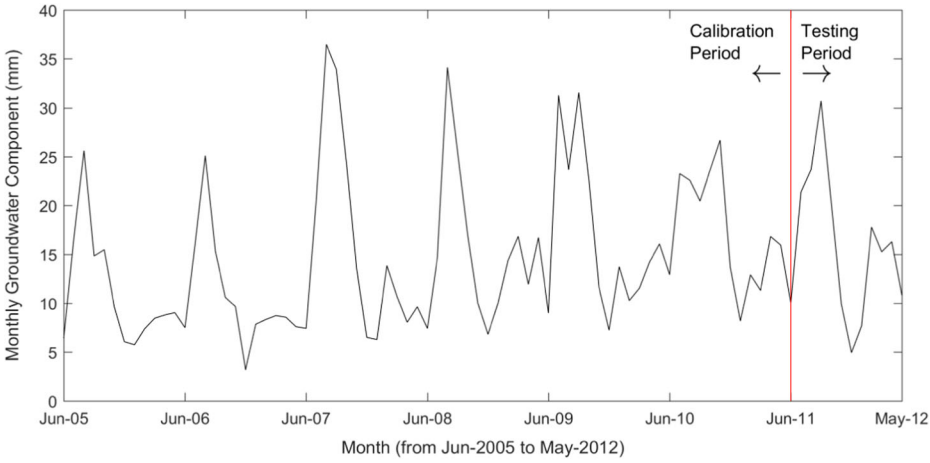


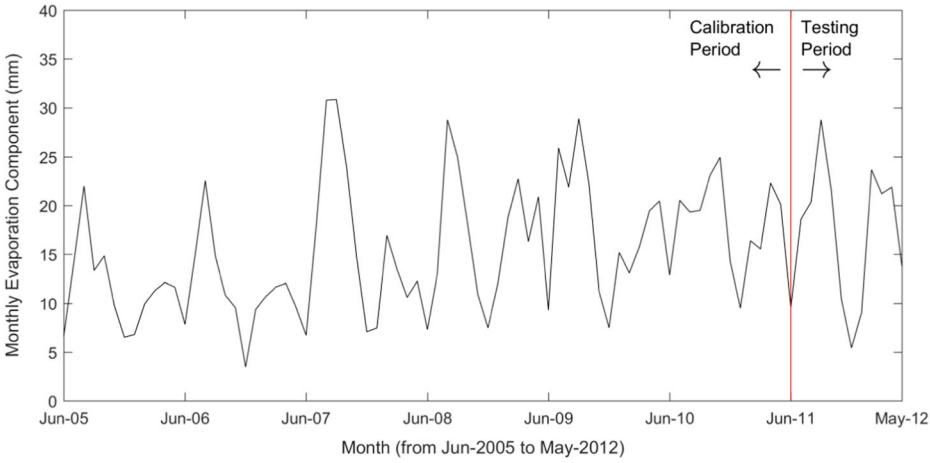
Fig. 2 Model performance for sub-basin II in Bhadra Basin (Basin-A). **a** Observed and predicted daily streamflow series with two zoomed portions and scatter plot between observed and predicted streamflow in the same sub-basin for **b** Calibration period and **c** Testing period

4.1 Relationship between *S(t)* and *V(t)*

In HCCS, a non-linear relationship between the runoff (per unit area of the watershed; S) and the system wetness condition (*V*) is assumed (Bhagwat and Maity 2014). The system wetness condition of current time is expected to affect the one-step-ahead streamflow (eq. S5 in the



(a)



(b)

Fig. 3 Monthly variation of **a** Groundwater recharge and **b** Evapotranspiration for sub-basin II in Bhadra Basin (Basin-A)

supplementary document). In an intervened sub-basin, the HCCS is used for predicting SLI component of streamflow only. Hence, for checking the validity of 'non-linear relationship between streamflow and system wetness condition' assumption in the upgraded HCCS model, the model generated *V(t)* and observed SLI streamflow values *S(t + 1)* are analyzed. This analysis is only required for intervened sub-basin as Bhagwat and Maity (2014) already established it for a basin having no major man-made river structure. Scatter plot between future step $S(t+1)$ and model generated *V(t)* is presented in Fig. 4 for all intervened sub-basins. For Basin-C, the best fit non-linear curves are showing a coefficient of determination of 0.92 and 0.89 between $S(t+1)$ and model generated $V(t)$ during model calibration and testing periods respectively. However, with the assumption of linear relationship between system wetness condition and streamflow, the coefficient of determination are found to be 0.70 and 0.67 respectively for model calibration and testing period in the same sub-basin. This shows

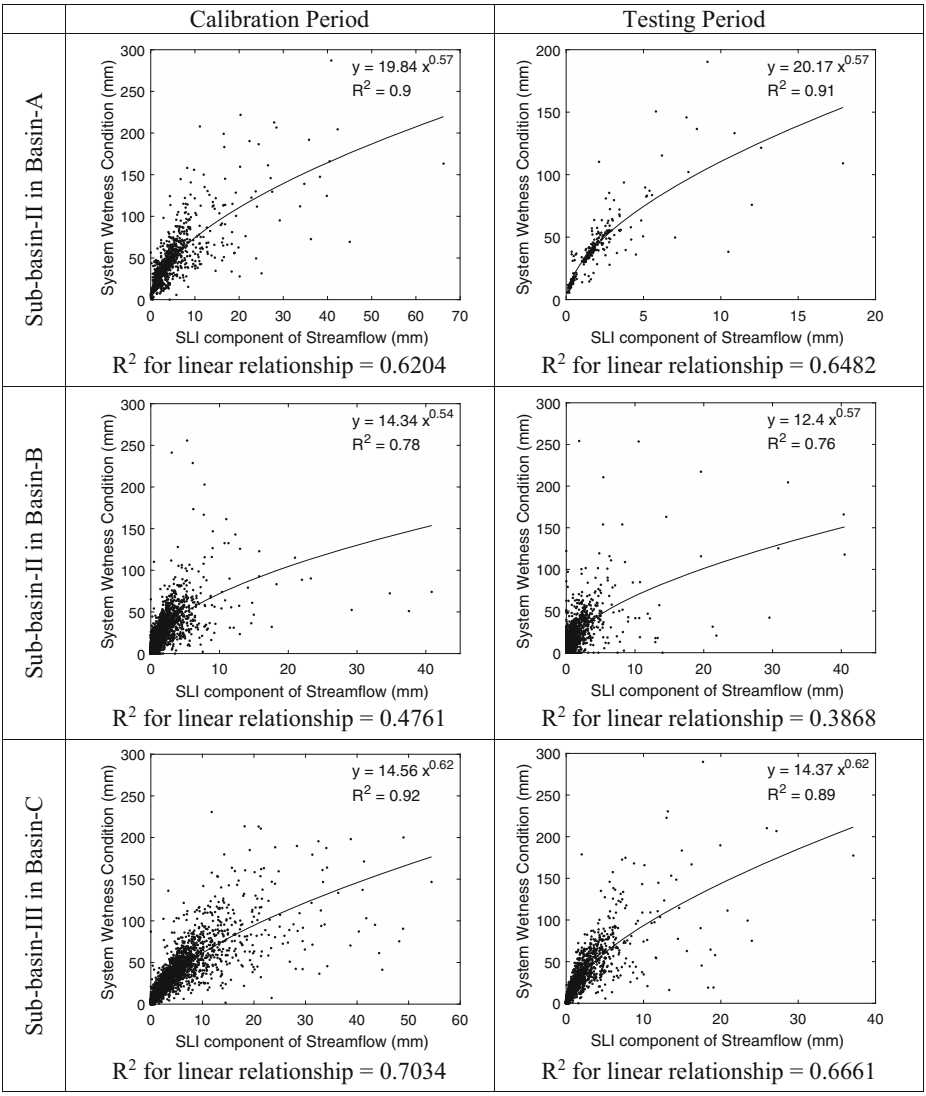


Fig. 4 Relationship between $S(t+1)$ and modeled $V(t)$ for intervened sub-basin in different basins during calibration and testing period

that the assumption of non-linearity between streamflow and system wetness condition is more appropriate. The equations for the best-fit non-linear curves are shown in the respective plots. The coefficient and the powers in the equations of the best-fit curves are the actually an approximation for parameters B and b. By comparing them with the estimated values, it is noticed that the estimated parameters and these values are fairly close to each other.

4.2 Assessment of Future Streamflow

Daily assessment of future streamflow is carried out for all the sub-basins, however, for some of the analysis (mostly to study the seasonality), daily results are converted to monthly as study

of monthly variation is more meaningful than daily variation of streamflow in future periods. Parameters like B, b, k and V_{max} are likely to change in future, however, without any knowledge of their trend in possible change, these parameters are considered constant in this study, as observed in the last calibration period. Using input variables estimate from ten simulations (R1 to R10) of HadCM3 (RCP4.5 ensemble), ten realizations of forecasted streamflow are obtained for the study sub-basins.

It should be noted that the forecasted values for any intervened sub-basin is SLI component of streamflow. Routed dam release from the upstream (SUI) is required to be added to the forecasted SLI to get forecasted streamflow for these sub-basins. By using the information of past dam release, two different cases are framed for approximating the future dam release. In the first case, the average daily dam release in the future is assumed same as average daily dam discharge in calibration period. In the second case, the average daily dam release in calibration period is multiplied by corresponding ratio between monthly average inflow to reservoir in upstream virgin sub-basin during calibration period and last decade of future period (2026–2035). Hence, the second case assumes that the percentage change in daily dam release is same as percentage change in average monthly inflow to reservoir in upstream virgin sub-basin for corresponding month. This is logical because the release pattern must change as per the change in reservoir inflow to make reservoir operation sustainable in the future. Computed SLI component is added to the routed SUI components by using either dam release to obtain the streamflow at the downstream end of intervened sub-basin.

The ensemble mean for ten sets of forecasted streamflow (using the first dam release scenario) along with its upper and lower quartile (75% and 25% percentiles respectively) for different intervened sub-basins is shown in fig. S5-S7 in supplementary document. By comparing the figs. S5 and 2, it is inferred that the streamflow is going to decrease in future period as compared to calibration and testing period for sub-basin-II in Basin-A. The comparison between forecasted monthly mean streamflow and calibration period monthly mean streamflow for same sub-basin (Fig. S8 in supplementary document) suggests that the forecasted mean streamflow in the river is less as compared to calibration period for most of months except June–August. For other intervened sub-basins, the mean streamflow is expected to increase for the most part of year except July–September, resulting in higher instances of increased streamflow (and flash flood) in river.

To study the effect of climate change on different basins (if any), the ensemble mean, ensemble maximum and ensemble minimum for last decade forecasted (2026–2035) monthly streamflow (using the first dam release scenario) are compared with observed monthly streamflow (2005–2012) (as shown in Fig. 5 for sub-basin II in Basin-A and fig. S9 and S10 in supplementary document for sub-basin-II in Basin-B and sub-basin-III in Basin-C respectively). In case of Basin-A, mean streamflow is expected to decrease in most of the months. Ensemble minimum streamflow is also low in future and dependent upon the dam release at the upstream end. However, high streamflow may become more frequent in five months, i.e., June to October. Overall, the frequency of high streamflow events during these months may increase and drought condition during other months may intensify in future. These changes in characteristics of streamflow may lead to shortage of water. Hence, the observed streamflow at the Holehonnur station is expected to decrease and for some of the months the river will not be able to fulfil the water requirements of the community living within or downstream of the Bhadra Reservoir. However, for Basin-B and C, the streamflow at the outlet is expected to increase in most of the months in year leading to increase in flood events as shown in fig. S9 and S10 in the supplementary document. These applications demonstrate usefulness of the upgraded HCCS model for estimating the daily variation of streamflow and assessment of water availability in a river basin under climate change, which may help city planners/policy makers.

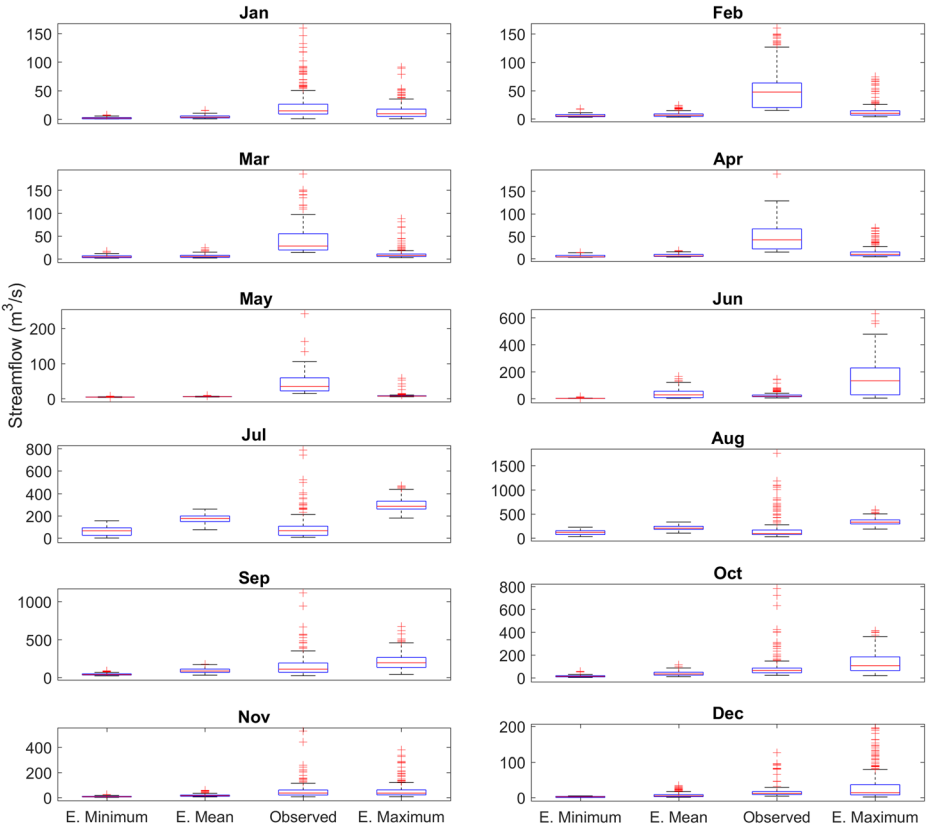


Fig. 5 Comparision of ensemble minimum, maximum and mean with observed streamflow for sub-basin II in Bhadra Basin (Basin-A) from all ten HadCM3 simulations (R1 to R10) for period 2026–2035 with the observed value of streamflow during 2005–2012. E. stands for Ensemble

5 Summary and Conclusion

In this study, existing HCCS model is upgraded to accommodate the effect of major man-made river structure(s) within the river basin. The two major improvements in the HCCS model are the provision of the routing module and the use of sequential quadratic programming (SQP) for model parameter estimation. For the upgrade HCCS, the study basin need to be separated into number of sub-basins depending upon the location of the major man-made river structures. Taking three river basins as study basins, the upgraded HCCS model was validated over them. Following conclusions can be drawn from the study:

a) Upgraded HCCS model is found to produce satisfactory performance when applied over three study basins. The comparable performances during calibration and testing periods indicate that model is not getting over fitted for calibration period and it can be used for future predictions.
b) Application of Sequential Quadratic Programming (SQP) instead of grid search optimization technique for optimizing parameters during model calibration have improved the

model reliability as the SQP is expected to converge to global minima and its behavior is not governed by the resolution of grids. Use of the SQP has also improved the model runtime during calibration for most of the study basins.

c) In addition, upgraded HCCS model is also provides spatially averaged estimates of groundwater recharge and evapotranspiration components. Though these estimates cannot be compared with the observed values (due to non-availability of data), seasonality in these estimates is visible which matches with the regional hydro-climatology. Moreover, this information can help in better water resource management.

d) The loss due to evapotranspiration and infiltration are found to be high in sub-basin I in Basin-A during monsoon season which reduces in sub-sequent months. These losses are increasing and are required to be checked as streamflow contribution of the Bhadra reservoir for downstream areas is expected to further decrease in future. For sub-basin II in Basin-A, the evapotranspiration loss is showing increasing trend.

e) The streamflow for Basin-A at the Holehonnur gaging station is expected to decrease for most of the months in the future period (2026–2035). However, high streamflow events may become frequent during monsoon months, i.e., July to September. In general, high flow events may become more frequent in wet month and drought condition may prevail in dry months. Moreover, there may be increased stress on river for water requirements in future and streamflow will not be enough for fulfilling the requirements, if upstream characteristics do not change.

f) For Basin-B and C, the streamflow characteristics at the outlet is going to change as compared to the past (1980–2005). Interestingly, higher than normal streamflow is expected throughout the year excluding peak monsoon months (July–September), leading to higher than normal streamflow in non-monsoon months. This information can be used to design new reservoir operation scheme to manage the water availability throughout the year.

It is worthy to note that the upgraded HCCS model has a limitation in calculating groundwater and evaporation component for the intervened sub-basin as it only considers runoff from the basin for calculation. However, this limitation can be easily overcome if information regarding nature of conveyance loss is available for the stream. Further, as a future scope of the study, the upgraded HCCS model can be used in tandem with weather forecasting services to serve as real time streamflow forecast system for different section of river even in cases when the flow is being intervened by a number of major man-made river structure(s).

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Compliance with Ethical Standards

Conflict of Interest Authors declare that there is no conflict of interest.

Research Involving Human Participants and/or Animals The authors declare that the research does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent The authors declare that the 'Informed Consent' is not applicable in the research since it does not contain any studies with human participants or animals performed by any of the authors.

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