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Development of a method to identify change in the pattern of extreme streamflow events in future climate: Application on the Bhadra reservoir inflow in India

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A R T I C L E I N F O

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A B S T R A C T

Study region: Bhadra basin (1968 km^2), located in peninsular India, is considered for demonstration.
Study focus: A general framework to assess the impact of climate change on the pattern of daily extreme streamflow events is proposed. Whereas, the impact is confirmed in the recent literature for most of the hydrologic variables at monthly/seasonal time scale, assessment and quantification at finer time scale, e.g. daily, is challenging. Complexity increases for the derived hydrologic variables, such as soil moisture and streamflow as compared to primary hydrologic variables, such as precipitation. The proposed general framework is demonstrated with the daily inflow to the Bhadra reservoir. Different statistical limits of extremes are defined and change in daily extreme pattern (number and magnitude) in the future (2006–2035) is assessed with respect to the baseline period (1971–2000).
New hydrological insights for the region: Demonstration of the proposed methodology with the inflow to Bhadra reservoir reveals that the daily extreme events are expected to increase in number with the increase in the threshold of the extreme. For a particular threshold, the average magnitude of the extreme events in the future is found to be higher as compared to the baseline period. However, for monthly totals the case is not the same – it remains almost similar. The methodology, being general in nature, can be applied to other locations in order to assess the future change in streamflow and other derived variables.

1. Introduction

Climate change is expected to have a substantial impact on the available water resources almost everywhere across the world. However, its impact may vary spatio-temporally depending on the topographical and climatological features of the basin (Arnell, 1999; Maity and Kashid, 2011; Maity et al., 2013; Pichuka and Maity, 2016; Rashid et al., 2016; Ashofteh et al.,

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2016a). Change in spatio-temporal pattern of primary hydrologic variables, such as rainfall, causes the variation in the other derived hydrologic variables, such as evapotranspiration, streamflow, soil moisture, ground water table etc. (Arnell, 1999; Dore, 2005; Das and Maity, 2015; Haddeland et al., 2014; Mcmichael et al., 2006; Taylor et al., 2013). However, it is difficult to generalize the extent of impact on any hydrologic variable across different locations. The complexity is even more for the derived hydrologic variables than the primary hydrologic variables. It is identified from the studies that the temperature variations are accompanied by changes in precipitation and runoff (Kabiri et al., 2015; Labat et al., 2004; Probst and Tardy, 1989). This phenomenon, after going through complex basin-hydrologic processes, leads to variation in streamflow and ground water recharge. At small temporal scale (e.g. daily), hydrological systems are expected to experience not only the changes in the average availability of water, but also changes in the extreme events (Grillakis et al., 2016; Jiang et al., 2007; Modrick and Georgakakos, 2015; Piras et al., 2016). Hence, a general framework to assess and quantify the change in daily extreme events of secondary hydrologic variables owing to climate change is utmost important, which is the focus of this study.

A plethora of studies have been carried out around the world to assess the impact of climate change on hydrological variables (Burn, 1994; Menzel and Burger, 2002; Zuo and Xu, 2015; Ashofteh et al., 2016b). For instance, Lindström and Bergström (2004) investigated the time series of runoff volumes, annual and seasonal flood peaks in Sweden. Ashofteh et al. (2013a) has investigated and confirmed the climate change impact on monthly inflow volume of the reservoir in an East Azerbaijan river basin. Tofiq and Guven (2014) attempted to predict the peak monthly discharge from statistical downscaling approach. Mishra and Singh (2010) and Mishra et al. (2011) has investigated the changes in extreme precipitation in Texas. Novotny and Stefan (2007) studied about streamflow records in five main river basins in Minnesota, USA. Aich et al. (2014) used Soil and Water Integrated Model (SWIM) to investigate the future streamflow over African river basins due to climate change. Ashofteh et al. (2013b) assessed the monthly streamflow simulations during the 21st century by using the GCM outputs and also examined the streamflow transition probabilities at each month. Liang et al. (2015) quantified the impacts of climate change on streamflow in China's Loess Plateau using a Budyko hydrological model. Jiang et al. (2014) carried out streamflow simulations at monthly and annual scales and found that the relationship between streamflow and precipitation is positive, whereas the same between streamflow and temperature is negative in the Luanhe basin of North China. Devkota and Gyawali (2015) assessed the hydrological regime of the Koshi River in Nepal and concluded that the average water availability is not much affected by the climate change. However, temporal flow variations will increase in the future. Islam et al. (2012) found that the rise of temperature results in the decreasing annual streamflow over the Brahmani river basin in India. Wang et al. (2012) explored the monthly streamflow variations under climate change conditions and concluded that the future monthly streamflow and hydrological extremes are expected to increase in the Shiyang river basin. Vicente-Guillén et al. (2012) developed a model based on the physical characteristics of the basin to predict monthly streamflow in the context of changing climate for the ungauged watersheds in Spain.

Most of the previous studies deal with the assessment of the climate change impact at monthly, seasonal and annual scales (Ashofteh et al., 2013a,b; Bennett et al., 2016; Dehghani et al., 2015; Huang et al., 2014; Jiang et al., 2007; Lindström and Bergström, 2004; Mishra and Singh, 2010; Mishra et al., 2011; Tofiq and Guven, 2014; Wang et al., 2012; Xie et al., 2015; Zamani et al., 2016; Zhang et al., 2015). Analyses at daily scale are few and mostly focus on the modeling of mean values rather than extremes (Bhagwat and Maity, 2014; Elias et al., 2015; Kopytkovskiy et al., 2015; Mantua et al., 2010; Maurer et al., 2010). However, assessment and quantification of climate change impact on the daily extremes might be more useful from management point of view. For instance, daily extreme streamflow may lead to flash floods in a basin and difficult to manage even with the existing reservoirs if such extreme events are not considered in its design. In some cases, extreme events may also cause the failure of capacity of the reservoir and it may lead to failure of the dam. Thus, it becomes vital to assess the changes in such daily extremes.

Keeping this in mind, the objective of this study is to develop a general framework to assess and quantify the change in daily extreme events of secondary hydrologic variables owing to climate change. First, a Rainfall-Runoff (RR) model is calibrated and validated using historical daily observed precipitation and inflow data. Next, the developed RR model is applied during future period using downscaled GCM data as input and to check the performance using the 'kept-aside' observed data from the considered 'future period'. Finally, different statistical thresholds of extremes are defined in order to assess the change in number and magnitude of the daily extreme pattern in future with respect to present.

The Hydrologic Engineering Center-Hydrologic Modelling Software (HEC-HMS) is used as RR model and Statistical Downscaling Model (SDSM) version 5.2 is used as downscaling tool. However, changing HEC-HMS and SDSM to some of its equivalent tools does not alter the overall approach to assess the impact of climate change on extreme events except the individual capability of the used tools. In this paper, HEC-HMS and SDSM are used for demonstration after calibration and validation with reasonable accuracy.

Two issues are important to mention here. Since the day-to-day variation in streamflow may not be much meaningful in far future (say after 30 years), the general framework is necessary to assess and quantify the change in the pattern of daily extreme (number and magnitude). Secondly, the far future is good for water management but quality of GCM simulation and reliability of emission scenarios in far future is uncertain. Assessment on daily streamflow variation next 20 years can be useful in many applications, such as flood management and watershed management in near future. However, developed approach should be general enough to be applicable for far future as well.

2. Materials and methods

2.1. General circulation models (GCMs) and downscaling

GCMs are process-based models that simulate the climate system (Crane and Hewitson, 1992; Hewitson and Crane, 1996; Phillips, 1956; Wilby and Wigley, 1997; Xue et al., 1996). The output from Hadley Centre Coupled Model, Version-3 (HadCM3) is used in this study. It is a coupled atmosphere-ocean general circulation model developed at the Hadley centre (Devon, United Kingdom). However, the accuracy of GCMs is restricted due to the course scale (~200–300 km) and their outputs cannot be used directly to the hydrological models, which are generally used for much smaller scales. Therefore, downscaling of GCM projections to obtain the estimates of future climate is crucial for studies related to assessment of climate change impact on water resources. Statistical Downscaling Model (SDSM, version 5.2) is employed to downscale the daily precipitation data. The large-scale atmospheric variables are downloaded from the Coupled Model Intercomparison Project phase-5 (CMIP-5) data portal. As before, the model is first calibrated by using 25 years (1971–1995) of observed daily precipitation data and validated with 10 years (1996–2005) of daily precipitation data. The causal variables are selected through the *Screen Variables* window of SDSM 5.2 from the results of seasonal correlation analysis, partial correlation analysis and scatter plots. The separate analyses are performed at the daily and monthly scale for identifying the best causal variables. Consequently, the correlation between the causals and target variable are obtained from the *Screen Variables* window. The causals which possess good correlation with the precipitation (target) are selected in this step (Pichuka and Maity, 2016). The surface specific humidity, mean sea level pressure, precipitation flux, zonal and meridional velocities at 500 hpa pressure levels and geopotential height at 850 hpa pressure levels are found to possess good correlation with the observed precipitation (target variable) in the study area (explained later). The major steps to run the SDSM are quality control, screening of causal variables and weather generation and scenario generation. Details of these steps can be found in Wilby et al. (2002) and Wilby and Dawson (2013).

2.2. HEC-HMS

The HEC-HMS, developed by the US Army Corps of Engineers-Hydrologic Engineering Center (HEC), is used in this study to simulate the daily inflow.

2.2.1. Setting up the model

The inflow values are simulated by setting up several input and control variables. The transform method is used to compute direct runoff from excess precipitation. In this study, the Snyder's unit hydrograph (synthetic unit hydrograph) model is used to transform the flows (Snyder, 1938). The linear reservoir base flow method is chosen for modeling the base flow. This method requires initial base flow, groundwater storage coefficient and the number of ground water reservoirs as inputs.

2.2.2. Model calibration, validation and testing

The split sample procedure is followed in the model testing. In total 43 years (1971–2013) of observed daily streamflow data is available for setting up the model. The first 25 years (1971–1995) of observed streamflow data are used for calibrating the hydrological model and the next 10 years (1995–2005) of data are used as validation period. The remaining 8 years (2006–2013) of data are kept aside and used later for checking the performance of the model as a representative of a future period. The characteristics of the river basin i.e. land use, properties of soil etc., are assumed constant throughout the simulation period. The parameter in Snyder's unit hydrograph transform method and linear reservoir base flow method are taken into consideration in the simulation.

Model parameters are selected during calibration period through a systematic search for the optimized parameters. The model parameters are selected by Univariate-Gradient Algorithm in which successive corrections to the parameter estimate are implemented by Newton's method. In brief, initial estimate of the parameters are used to run the model and successive corrections are applied depending on the model performance reflected by the selected objective function. Thus, it is an iterative procedure that can be briefly explained as follows. If m^k is the parameter estimate at iteration k, the new estimate m^{k+1} is expressed as –

$$m^{k+1} = m^k + \Delta m^k \tag{1}$$

where Δm^k is the correction to the parameter at iteration k. This correction is obtained by approximating the objective function (f) through Taylor series expansion and equating the derivative of the objective function to zero. Following this, after simplification, it reduces to

$$\Delta m^k = -\frac{\frac{df\left(x^k\right)}{dx}}{\frac{d^2 f\left(x^k\right)}{dx^2}} \tag{2}$$

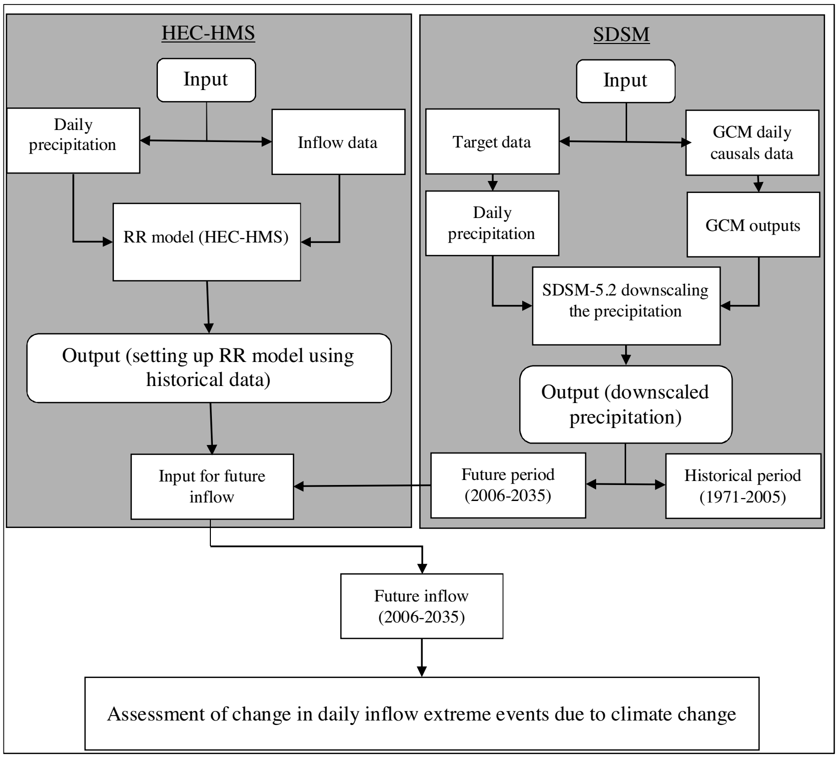

Fig. 1. Flow chart representing the general methodology to assess daily inflow extreme events.

This procedure is repeated till the model performance is satisfactory which is reflected by no further improvement in the objective function. The peak weighted root mean square error is chosen as the objective function. It is same as root mean square error except the errors are weighted by the magnitude of the ordinates. For a set of model parameters, one parameter is considered at a time keeping all others constant and it is repeated for each parameter one after another. Further details on the model parameters calibration can be found in Feldman (2000).

Once the model is calibrated and validated, it is then used to predict the future inflow during the future period (2006–2035). The observed inflow data, which was kept aside (2006–2013), is used here to check/verify how good the developed model is in simulating the future inflow values. The performance is checked by means of various statistical parameters.

2.3. Methodological approach

The general methodological outline is as follows – (i) a Rainfall-Runoff (RR) model (this study uses Hydrologic Engineering Center-Hydrologic Modelling Software, HEC-HMS) is calibrated (1971–1995) and validated (1996–2005) using continuous historical daily observed precipitation and inflow data, (ii) confidence is gained to use the developed model in the future period by using projected downscaled precipitation (this study uses Statistical Downscaling Model version 5.2, SDSM-5.2) by using General Circulation Model (GCM, this study uses Hadley centre Coupled Model, version-3, HadCM3) outputs over the historical period (1971–2005) and tested during 2006–2013, (iii) assuring a satisfactory performance in inflow simulation is achieved using downscaled GCM precipitation as input with respect to observed precipitation as input to RR model, the developed RR model is applied during future period (2006–2035), (iv) for the future period, the performance is tested using the 'kept-aside' observed data during 2006–2013, (v) different statistical limits of extremes are defined and change in daily extreme pattern (number and magnitude) in the future (2006–2035) is assessed with respect to the baseline period (1971–2000).

The overall methodological flow chart is shown in Fig. 1. Simulation of daily inflow is carried out continuously and a daily time series of simulated inflow values are obtained. Next, the extreme values are picked out from the observed and simulated inflow series. In this study, three sets of thresholds are considered by means of various statistical Upper Limits (ULs). To select these thresholds for extremes, observed inflow series during the baseline period (1971–2000) is fitted to a suitable probability distribution and the values corresponding to the 90th quantile (90% UL), 95th quantile (95% UL) and 99th (99% UL) are computed.

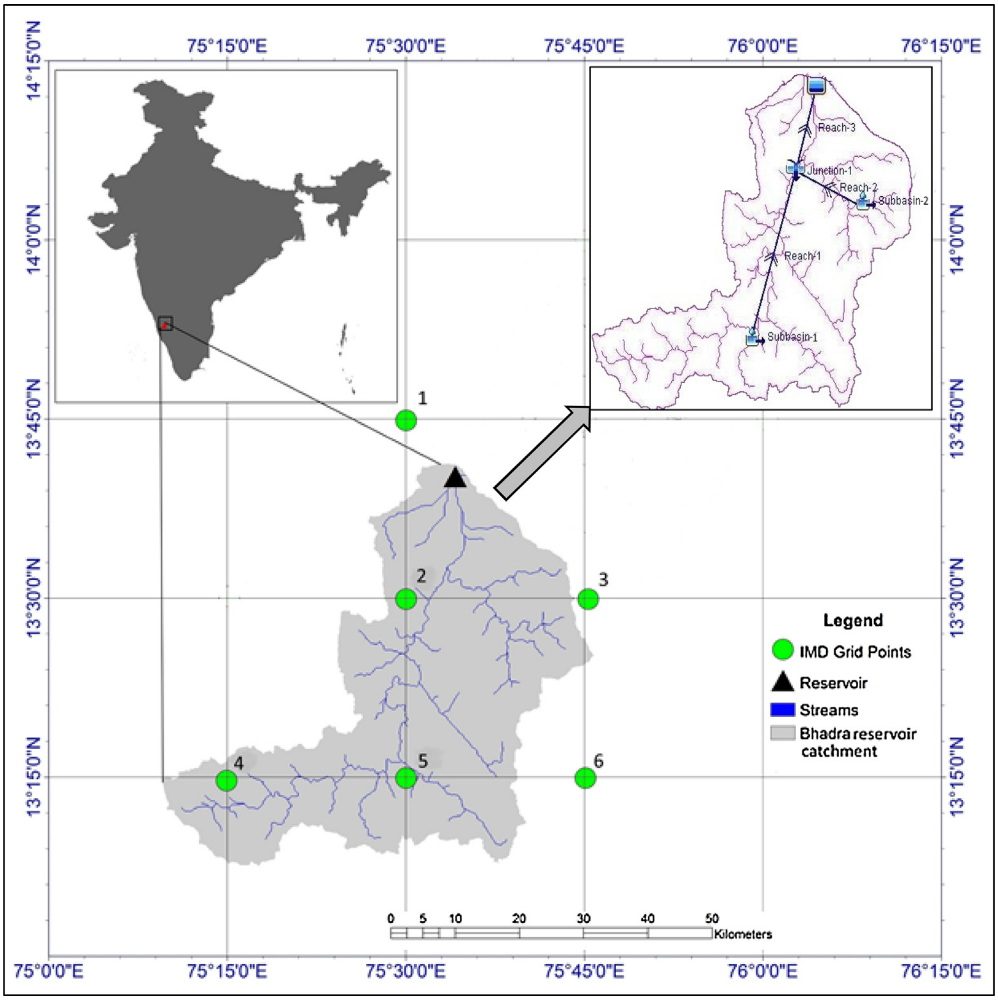

Fig. 2. Study area map showing the location of Bhadra reservoir (triangle) and locations considered for downscaling the precipitation (circles).

Then the daily inflow events beyond these thresholds are counted for each of the thresholds during baseline as well as future periods. Thereafter, the mean of those extreme values is also computed for different thresholds. The following possibilities are explored –

(i) How does the number of daily extreme events change in future? Is this change uniform for different thresholds?
(ii) How does the magnitude of the mean of extreme events change in the future for different thresholds?

If the number of extreme events and the magnitude of their mean both are more in the future (baseline) period, it represents the more (less) occurrence of extreme events with greater (lesser) magnitude and/or frequency.

3. Study area and data

The Bhadra river basin map is shown in Fig. 2. The river originates at Gangamoola in Varaha Parvatha in the Western Ghats range of Karnataka, India. The geographical location of the Bhadra basin lies between latitudes of 13.124° N–13.750° N and longitudes of 75.157° E–75.750° E. The elevation of the Bhadra basin is about 1198 m and contains an average slope of 6% with the catchment area of 1968 km^2. The Bhadra basin receives an average rainfall of 2320 mm mostly during the monsoon months (June through November). The south-west monsoon contributes 90% of the total rainfall, whereas the remaining 10% rainfall occurs from the north-east monsoon. The area of the reservoir is 117 km^2 at full reservoir level and storage capacity is 1784×10^6 m^3. The annual mean evapotranspiration is estimated as 1678 mm based on 25 years of observed data.

Table 1
Statistical measure of association between observed vs SDSM downscaled daily and monthly precipitation.

Period	Location No.	Daily scale				Monthly scale			
		r	*ubRMSE (mm)*	*NSE*	D_r	*r*	*ubRMSE (mm)*	*NSE*	D_r
during calibration period (1971–1995)	1	0.75	6.16	0.4	0.74	0.88	66.31	0.67	0.77
	2	0.77	5.24	0.29	0.76	0.91	40.82	0.75	0.77
	3	0.76	4.04	0.39	0.76	0.87	30.13	0.67	0.75
	4	0.81	16.37	0.28	0.75	0.87	87.55	0.81	0.81
	5	0.82	15.23	0.28	0.75	0.88	68.87	0.76	0.79
	6	0.76	5.73	0.35	0.75	0.82	41.8	0.59	0.74
during validation period (1996–2005)	1	0.76	6.83	0.26	0.74	0.89	60.78	0.73	0.78
	2	0.8	6.48	0.38	0.76	0.84	47.35	0.62	0.76
	3	0.81	6.25	0.28	0.76	0.9	34.83	0.73	0.77
	4	0.74	14.9	0.39	0.74	0.87	83.28	0.77	0.8
	5	0.8	13.51	0.43	0.76	0.87	58.93	0.82	0.79
	6	0.79	6.09	0.27	0.75	0.84	45.35	0.65	0.77
during testing period (2006–2013)	1	0.8	12.87	0.27	0.77	0.9	99.86	0.82	0.84
	2	0.76	5.61	0.31	0.76	0.84	42.28	0.55	0.71
	3	0.77	5.82	0.27	0.75	0.78	39.92	0.44	0.69
	4	0.79	17.6	0.25	0.74	0.9	73.43	0.81	0.83
	5	0.73	10.55	0.3	0.73	0.91	81.13	0.75	0.77
	6	0.8	6.22	0.18	0.75	0.87	36.57	0.65	0.74

3.1. Data description

Daily precipitation data for a grid size of $0.25^\circ \times 0.25^\circ$ is obtained from India Meteorological Department (IMD), Pune, for the period of 1971–2013. This data is converted into effective precipitation data using the Thiessen polygon method to cover the entire study area. The daily inflow data (1971–2013) into the Bhadra reservoir is used as observed inflow and it is obtained from Karnataka Niravari Nigam Limited (KNNL) divisional office located at Bhadra dam site. The basin characteristics such as land use, properties of soil, etc., are assumed to be constant throughout the model simulation and estimates of various soil parameters are obtained from available literature of the study area (STRIVER Report, 2006). In this report, the approximate ranges of hydrological properties of the soil such as saturated hydraulic conductivity, maximum moisture deficit, percentages of impervious space, basin lag, crop coefficient and dryness coefficient are given. The exact estimate of each of these values for each sub-basin is obtained during the model calibration. The Bhadra reservoir inflow and outflow data are obtained from the Water Resources Department, Karnataka. Evapotranspiration data for Chikkmagalur district (mean monthly) is obtained from India water portal website (http://www.indiawaterportal.org/met_data/).

The daily large scale atmospheric variables (causal) data are obtained from the HadCM3 GCM outputs during the historical period (1971–2005). The Representative Concentration Pathway-4.5 (RCP-4.5) daily causal data are considered during the future period (2006–2035) as the RCP-4.5 is only data which is available for HadCM3 GCM. The other RCP data (RCP-2.6, RCP-6.0 and RCP-8.5) are under construction. The daily causal data are downloaded from the CMIP-5 web portal (http://www.ipcc-data.org/sim/gcm_monthly/AR5/Reference-Archive.html).

4. Results and discussion

4.1. Downscaling of precipitation by using SDSM

4.1.1. Analysis during calibration period (1971–1995)

The daily precipitation is downscaled by using the HadCM3 GCM outputs from a spatial resolution of 2.5° (latitude) by 3.75° (longitude) to 0.25° by 0.25° grid size at all the selected locations of the Bhadra basin (shown in Fig. 2). The model is first calibrated against the observed daily precipitation data obtained from the IMD. The analysis is carried out at two temporal scales i.e. daily scale and monthly scale. The performance of the SDSM is evaluated for various statistical measures, i.e. the correlation coefficient (r), the unbiased Root Mean Square Error (*ubRMSE*), the Nash-Sutcliffe Efficiency (*NSE*) and the Degree of agreement (D_r). The performance of SDSM during the calibration period (1971–1995) is shown in Table 1. The r value varies from 0.75 (location 1) to 0.82 (location 5). The corresponding D_r values are 0.74 and 0.75 respectively. The *ubRMSE* value is obtained as 6.16 mm and 15.23 mm at the corresponding locations. The *NSE* values range between 0.28 (location 4) and 0.40 (location 1). The values of these performance metrics indicate the satisfactory performance at daily scale with a variation in performance from one location to another. The comparison between the model performances using observed and SDSM downscaled daily and monthly precipitation during calibration period (1971–1995) is presented in Table 1. Inevitably, the statistical measures at monthly scale are better than that at daily scale. The minimum r value is observed as 0.82 (location 6) whereas the maximum value found to be 0.91 (location 2). The corresponding *NSE* (D_r) values are noted as 0.59 (0.74) and 0.75 (0.77) respectively at these locations.

Table 2
Statistical measure of association between observed inflow and simulated inflow.

Period	Statistical metrics	Observed precipitation as input		Downscaled GCM precipitation as input	
		Daily	Monthly	Daily	Monthly
during calibration period (1971–1995)	r	0.79	0.85	0.76	0.83
	$ubRMSE$ ($\times 10^6$ m^3)	13.55	172.58	13.87	215.38
	NSE	0.38	0.67	0.36	0.65
	D_r	0.65	0.78	0.63	0.75
during validation period (1996–2005)	r	0.85	0.92	0.8	0.85
	$ubRMSE$ ($\times 10^6$ m^3)	8.52	152.83	11.79	155.2
	NSE	0.44	0.67	0.38	0.64
	D_r	0.7	0.78	0.67	0.76
during testing period (2006–2013)	r	0.84	0.9	0.85	0.89
	$ubRMSE$ ($\times 10^6$ m^3)	13.26	163.32	13.98	169.46
	NSE	0.51	0.72	0.41	0.68
	D_r	0.74	0.79	0.67	0.79

4.1.2. Analysis during validation period (1996–2005)

The calibrated SDSM is then validated for a period of 10 years (1996–2005). The daily and monthly precipitation data during the validation period are downscaled. The same causal variables which are screened out during the calibration period are used for the validation period. The relationship between causal and target variables is assumed to be static (same as calibration period) during the validation period. The statistical measures obtained from the observed and downscaled precipitation are presented in Table 1. It is noticed that location 3 has a maximum value of r (0.81) whereas the minimum r value is found at location 4 (0.74). The performance at daily scale is satisfactory as the maximum and minimum NSE values are between 0.43 (location 5) and 0.26 (location 1). The D_r values at corresponding locations are 0.75 and 0.74 respectively and indicate a satisfactory performance. The results at monthly scale are even better than the performance at daily scale.

4.1.3. Downscaling during future period (2006–2035) and analysis during testing period (2006–2013)

The data for the predictor variables during the historical period is considered up to the 2005 (available up to this year only) and the future data (i.e. RCP-4.5) is considered from 2006 onwards. This data is downloaded from the CMIP5 data portal. The developed SDSM is further utilized to obtain the downscaled daily future precipitation during the future period (2006–2035). Subsequently, the performance of the model is tested during the future period by comparing the output with the observed daily data during 2006–2013 which was kept aside. The data period is named as 'testing period' which consists of 8 years (2006–2013) of "future" data. The statistical measures are obtained at daily and monthly scales and are shown in Table 1. The statistical performance metrics such as r, NSE, $ubRMSE$ and D_r at daily scale vary between 0.73–0.80, 0.18–0.31, 5.61–17.60, and 0.73–0.77 respectively. These results are considered satisfactory. The downscaled precipitation data are used as input to HEC-HMS during the entire future period to obtain the inflow values for the future time period. The monthly performance is better as expected. Overall, these results indicate a satisfactory performance of the SDSM to downscale the daily and monthly precipitations over the study basin and the downscaled precipitation may satisfactorily be used for further analysis.

4.2. Simulation of inflows through hydrological model (HEC-HMS) to the Bhadra reservoir

The basin is divided into two sub-basins (sub-basin-1 and sub-basin-2) depending upon the river network in the basin. The locations of these sub-basins are shown in Fig. 2. Each sub-basin is connected through reaches which are routed using Muskingum routing method and reach-3 carries the inflow to the reservoir.

4.2.1. Model performance during calibration and validation

Firstly, inflows are simulated by using the observed precipitation as input to HEC-HMS. A comparison between observed and simulated inflows (using observed precipitation) at daily scale and at monthly scale is carried out. Next, the downscaled precipitation values are used to simulate inflow values during the calibration period.

The statistical performance metrics during the calibration period are presented in Table 2. These values indicate that the simulated inflows using observed precipitation are slightly better corresponding to observed inflow as compared to downscaled precipitation as input at daily scale. Relatively similar results ensure the good correspondence between observed precipitation and downscaled precipitation. The statistical measures at monthly scale (for both cases of precipitation inputs) are also shown in Table 2. These values indicate a good correspondence between observed and simulated inflow.

Once the model is calibrated, it is validated by using the observed inflow and the set of calibrated parameters obtained during the calibration period. As stated before, 10 years (1996–2005) of data is considered for validating the model. The procedure is similar to that of the calibration period. Next, the simulated inflows are obtained by using downscaled precipitation as input. The statistical performance measures between observed and simulated inflows using observed and downscaled precipitation as input at daily and monthly scales during the validation period are presented in Table 2. The performance is satisfactory and comparatively similar to the calibration period. Thus, the downscaled precipitation can be satisfactorily

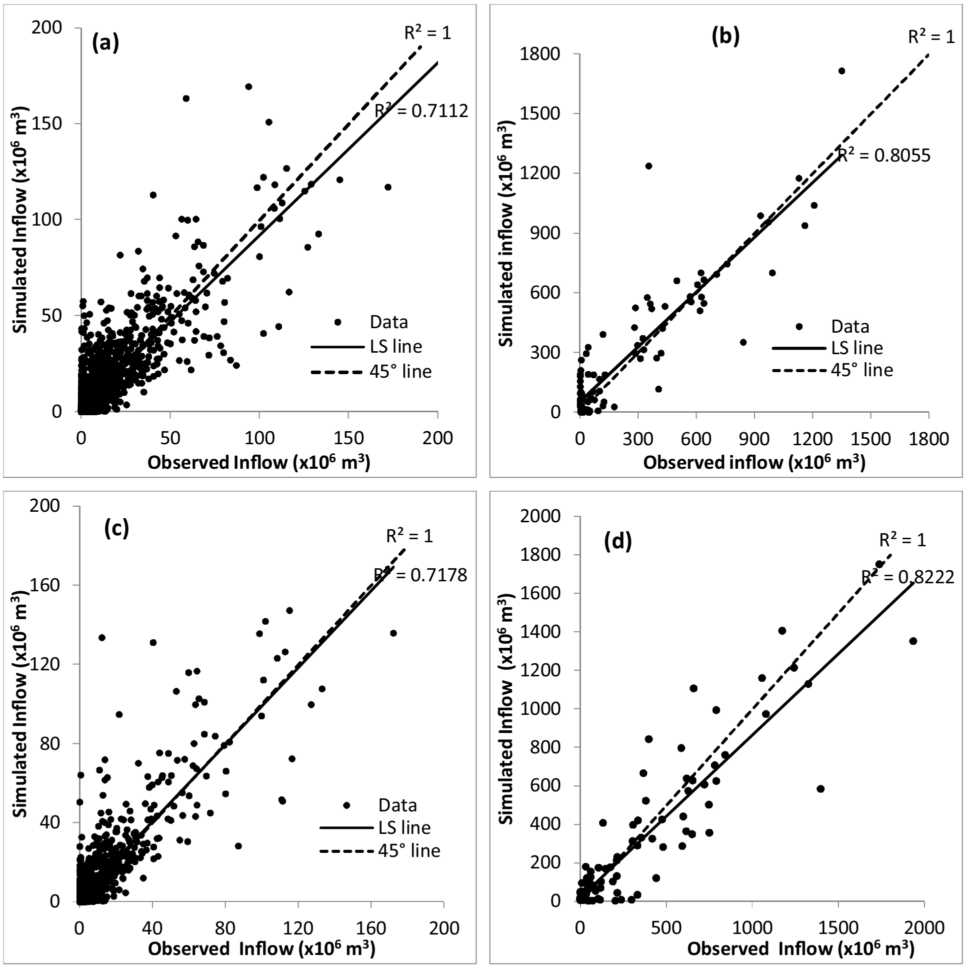

Fig. 3. Scatter plot between observed and simulated inflow during testing period using observed precipitation as input to HEC-HMS (a) daily scale (b) monthly scale and using SDSM downscaled precipitation as input to HEC-HMS (c) daily scale (d) monthly scale.

used for computing the inflows for the study basin. Therefore, in the future period, where the daily precipitation is not available, the downscaled precipitation is a reliable input to the developed model.

4.2.2. Simulation of daily inflow during testing period (2006–2013)

The precipitation during the future 30 years (2006–2035) period is downscaled by the SDSM using the developed parameter during the calibration period. The downscaled precipitation is then used as input to the developed HEC-HMS model for simulating the future inflows to the Bhadra reservoir. The first 8 years of the future period (i.e. 2006–2013) is used as testing period as it ensures more confidence on the predictability of the model.

The obtained results are compared with the corresponding observed inflow data which remains unused yet for cross-checking the model performance. The scatterplot shown in Fig. 3 represents the performance of HEC-HMS during testing period with observed precipitation as input. The *panel a* of Fig. 3 shows that the inflow events are simulated well at daily scale. The correspondence at monthly scale is presented in *panel b* of Fig. 3, which indicates that the simulated inflow values match with the observed monthly inflows with r^2 value of 0.81. It is also noteworthy that the model is slightly overestimating during low inflow events and underestimating in case of high inflow events.

This performance may be considered as the maximum achievable performance given the capability of the developed model. However, the goal is to analyze how well this performance matches with the performance when downscaled precipitation is used to assess the model performs without the observed precipitation and the reliability of downscaled precipitation for simulating the daily inflows for the study basin. Thus, the same procedure has been followed to simulate the daily and monthly inflows by providing downscaled precipitation as input. Results are shown in Table 2 and the scatterplots between observed and simulated inflow at daily and monthly scales are shown in *panel c* and *panel d* of Fig. 3, respectively. The results are almost similar to the output using observed precipitation as input (Table 2). It indicates the reliability of downscaled daily precipitation for simulations of inflow for future time period.

Table 3
Number of extreme events in baseline period (1971–2000) and future period (2006–2035) with respect to various Upper Limits (ULs).

Value of UL	Number of extreme events		Mean values ($\times 10^6$ m^3)	
	Baseline period	Future period	Baseline period	Future period
90% UL	174	163	82.45	109.31
95% UL	28	64	123.19	159.48
99% UL	0	1	0	298.57

4.2.3. Future simulation of inflows

Once the model is successfully calibrated, validated and verified with observed/downscaled data, the next step is to use the developed model for estimating the future climate scenarios (RCP 4.5). In the previous sections, some part of the future data (2006–2013) was already used as testing period. The downscaled future precipitation is used as input in the HEC-HMS for computing the daily inflows. The simulated future inflows are then compared with the observed inflow during baseline period (1971–2000). It is noticed that the extreme events are going to increase both in frequency and magnitude, depending on the threshold in the future period (2006–2035). Simulated daily inflows are also converted into monthly inflows. The magnitude of future monthly inflow values seem to be comparatively same as in case of baseline. Quantification of such changes are elaborated in the next section.

4.2.4. Assessment of future daily extreme inflows

The extreme events are identified considering various thresholds as defined in section-2.3. Log-normal distribution is found to best fit the data and selected for the computation of the thresholds for extremes. The results are presented in Table 3. The number of extreme events corresponding to 90% UL (59.53×10^6 m^3) as threshold is more during the baseline period (174) than during future period (163). However, the mean of these extreme events are higher in future period (109.31×10^6 m^3) as compared to the baseline period (82.45×10^6 m^3). It indicates, though the number of extreme events is less in the future, the magnitudes of such events are higher or more extreme in the future as compared to the baseline period. However, as the threshold of extreme events is increased, the number of extreme values is also found to be more. For instance, the numbers of extreme events are 64 and 1 considering the threshold as 95% UL (102.81×10^6 m^3) and 99% UL (286.52×10^6 m^3) respectively in future as compared to 28 and 0 during the baseline period. The mean values of such extreme events are very high during the future period i.e. 159.48×10^6 m^3 (95% UL) and 298.57×10^6 m^3 (99% UL) compared to the baseline period 123.19×10^6 m^3 (95% UL) and 0×10^6 m^3 (99% UL). It indicates that more severe extreme events (higher side) are expected in future. The low inflow events may also increase in future. It can be observed by comparing the mean inflow values of baseline period and future period. The 30 years of daily mean inflow value obtained during the future period (7.07×10^6 m^3) is far lower than the mean inflow value obtained during the baseline period (8.72×10^6 m^3).

It is worth mentioning that basin characteristics are assumed to be same as that in the current situation. However, in reality, if the societal development leads to an increase in impervious characteristics of the basin, more severe extremes are expected. Secondly, proposed methodology is general in nature to be applicable to other basins and for other derived hydrologic variables. However, it is a data driven approach and a satisfactory model calibration/validation is essential for a reliable assessment for the future change.

5. Conclusions

Development of a general approach to assess the change in derived hydrological variables in future climate was in the focus of this study. The proposed approach helps to assess the impact of climate change on any derived hydrologic variable in a future climate scenario. The developed approach is demonstrated in case of daily inflow to the Bhadra reservoir in India. The change in the pattern of daily extreme inflows to the Bhadra reservoir is assessed. Simulated inflow values are obtained from the calibrated and validated HEC-HMS model using downscaled precipitation as input. SDSM (version 5.2) is used as the downscaling model. The large scale predictor variables (causal) are considered from the HadCM3 GCM. The surface specific humidity, mean sea level pressure, precipitation flux, zonal and meridional velocities at 500 hpa pressure levels and geopotential height at 850 hpa pressure levels have been used as the most significant predictors of the precipitation in the study area. Considering the case of the study basin, the major conclusions drawn from the present study are as follows –

1. The daily and monthly time scales are the two temporal scales considered for the impact assessments at the Bhadra basin. The HEC-HMS model shows reasonably good performance while simulating the daily inflows with monthly totals. Monthly totals match with a better accuracy, as expected.
2. At daily scale, the simulated inflows obtained by considering the downscaled precipitation as input to HEC-HMS correspond satisfactorily to the simulated inflows while using the observed precipitation as input. This indicates the suitability of that the downscaled precipitation from the GCM outputs for simulation of daily inflows.
3. The proposed approach indicates a more frequent occurrence of extreme events (high inflow and low inflow) in the study basin in future time period. Moreover, with the increase in the threshold value, the number of daily extreme high inflow events is expected to increase during the future period (2006–2035) as compared to the baseline period (1971–2000).

However, in all the cases, the magnitudes of the extremes are found to be very high as compared to the baseline period (1971–2000).

4. It is also noticed from the results that there will be more number of days with low inflows to the Bhadra reservoir in future time period. Assessment at monthly scale reveals that there is not much deviation in monthly total inflow volume during the future period. The results are expected to be helpful for reservoir planning and management and effective flood protection measures. The policy makers can make better policies/decisions when they are aware about the change in inflow pattern in the reservoir.

As the methodology is general, it can be applied to other locations in order to assess the change in future for streamflow. Also, as mentioned before, the methodology can also be applied to far future (till the end of the century) with a caution of reliability of emission scenarios in far future based on which GCM products are available. Future scope of the applicability of the developed approach includes its application to other derived variables, such as soil moisture. The use of HEC-HMS and SDSM is a flexible choice and may be changed to similar tools. It does not change the overall approach provided such tools are satisfactorily calibrated before making any assessment on the impact of climate change on extreme events.

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