

Performance evaluation and hydrological trend detection of a reservoir under climate change condition

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Abstract Water is the key of development and stability of any region. Under climate change condition, water systems are less reliable and more vulnerable. In this study, performance of Saline reservoir in Odisha, India has been evaluated under the climate change condition. The study mainly focused on the trend analysis for identified the temporal changes in precipitation and inflow time series using Mann–Kendall test, quantification of inflows to reservoir using ARNO model and performance evaluation of reservoir using WEAP model under climate change condition. In the results, it has been observed that there is no significant trend for annual, seasonal and for any monthly rainfall. Variation in precipitation shows that rainy days are decreasing whereas number of intense rainy days (>100 mm) are increasing. A significant rising trend with test statistic value of +3.18 is observed for daily inflow series at 95 % confidence level. Evaluation of inflow to reservoir, ARNO model shows that the change in simulated flow is directly proportional to the change in rainfall. In order to 25 % Change, decrease or increase in rainfall amount resulted in equal amount of decrease or increase in the inflow. Performance evaluation of reservoir using WEAP model shows that if inflows reduced by 20 % there would be a decrease in supply reliability and it would not be possible to increase supplies. Reducing live storage by 10 % influence supply delivered in May and June, but again has little impact on the rest of the year.

Keywords Climate change · Trend analysis · Mann–Kendall · ARNO model · WEAP model

Introduction

There are many heat trapping green house gases (GHGs) increasing in last few decades and human intervention has been proved as well. Climate is changing in term of rising global mean temperature, rise level of sea and variability in precipitation (Camici et al. 2014; IPCC 2014). Under climate change conditions, many water systems are projected to be less reliable and more vulnerable in meeting user demands, exacerbating existing competition for water resources. At the global scale, water demand will grow in the next decades due to population growth, and substantial changes in irrigation water demand as a result of climate change. In general, negative effects of climate change on water resource systems will complicate changing economic activity, water quality, increasing population, land use change and urbanization (Buytaert et al. 2009; Franczyk and Chang 2009; Poulin et al. 2011). A reduction of available water resources is expected in regions where runoff is projected to decrease; conversely, where rainfall increases are expected, increased water supply is projected (Mondal et al. 2014). However, the benefit of this might be reduced by negative effects of higher variability of precipitation and seasonal runoff in water supply, food risks, and water quality. Identification of temporal changes in hydrological regimes of river basins is an important topic in contemporary hydrology because of the potential impacts of climate change on river basin. For this purpose, generally parametric and nonparametric techniques have been employed; the latter have been widely used mainly because of a fewer number of assumptions involved in their

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implementation (Mishra et al. 2009; Shadmani et al. 2012; Khaliq et al. 2009). In any sign investigation study, mostly it is vital to estimate hydrological trends at local scales, i.e. point estimates. Precipitation is one of the most important meteorological variables which can impact the occurrence of drought or floods. Analysis of precipitation and drought data offers important information which can be applied to improve water management strategies, to protect the environment, to plan agricultural production or in general to impact on economic development of a certain region. In recent years, a plethora of scientists have compared and analyzed the precipitation trends in the worldwide (Gemmer et al. 2004; Partal and Kahya 2006; Tabari et al. 2012). In Europe, Brunnetti et al. (2001) analyzed trends in daily intensity of precipitation during the period 1951–1996 and detected the significant positive trend in northern Italy. Tolika and Maheras (2005) studied the wet periods for the entire Greek region. They showed that the longest wet periods are observed in Western Greece and in Crete, while stations in the Central and South Aegean area had the shortest wet periods. In Bulgaria, Koleva and Alexandrov (2008) analysed the long-term variations in precipitation and concluded that the last century can be divided into several wet and dry periods with duration of 10–15 years. Niedźwiedź et al. (2009) discussed the patterns of monthly and annual precipitation variability at seven weather stations in east central Europe during the period 1851–2007. They also identified the dry period in the 1980s and the first half of the 1990s. Ruiz Sinoga et al. (2011) observed the temporal variability of precipitation in southern Spain to detect trends and cycles and noted the general decreasing trend in seasonal precipitation. For the Indian region, There are many study have been carried out to estimate the trend and future projection of hydro climatic parameters (Goyal 2014; Machiwal and Jha 2009; Ranjan 2014). Jain et al. (2013) investigated the trend of rainfall and temperature. In the results, author find that there is decreasing trend of rainfall whereas increasing trend in temperature. Long term trend analysis of precipitation for central India (Madhya Pradesh) has been carried out by Duhan and Pandey (2013). Arora et al. (2005) has been performed the trend analysis of temperature considering the 125 station distributed over whole India. The impact climate change on water resources has received much attention globally especially last decade. Rainfall, the main driver of hydrological process, has been varying in the parts of the world. In this context, estimating hydrological response under a changing climate is a need for better water resources management. Conceptual runoff models are frequently used to predict the effects of a potential change in global climate on hydrology (e.g., Nĕmec and Schaake 1982; Gleick 1987; Parkin et al. 1996; Viney and Sivapalan 1996; Panagoulia and Dimou 1997; Gellens and Roulin 1998, Xu

1999a). A review of these modeling approaches can be found in Xu (1999b). The Sacramento rainfall-runoff model has been used in experiments with 60 year daily series to appraise the runoff changes due to climatic warming (Buchtele 1993). The impacts of climate change on runoff and soil moisture in 28 catchments of Australia were simulated using a hydrological daily rainfall-runoff model (Chiew and McMahon 1994). Bronstert (2006) reported rainfall-runoff models are frequently used as a tool to assess the impacts of climate and land-use changes on the runoff generating processes. Whyte et al. (2011) used lumped conceptual model SIMHYD and claims that a 1 % change in rainfall leads to a 2–3 % change in runoff in the Murray-Darling Basin. In the current study, the Mann–Kendall (MK) test is used for identifying temporal changes in observed rainfall and inflows records for Salia basin in Odisha state. ARNO model has been developed for inflow modeling and different scenarios are developed to assess the impact of climate change.

Study area and data collection

The total length of the Salia river is about 48 km. A dam has been constructed in the catchment area which is about 245 km² connecting two hills on both sides and serves as a medium irrigation project. Salia dam is located across river Salia near village Panasadihi (85°-04'-35"East, 19°-47'-54"North) in Banpur Block of Khordha district in the state of Odisha (Fig. 1). The project belongs to East and South Eastern Coastal Plane agro climatic Zone. It is irrigating 8445 ha of land in Kharif and 2751 ha in Rabi season through a canal network. Observed rainfall and inflows data for 42 years (1970–2011) have been collected and other hydrometeorological data also collected for analysis.

Methodology

Mann–Kendall test

To identify trend in the climatic variables with reference to climate change, the Mann–Kendall test has been employed by a number of researchers with temperature, precipitation and streamflow data series (Burn 1994; Douglas et al. 2002; Yue and Hashino 2003; Burn et al. 2004; Lindström and Bergström 2004). This commonly used non-parametric test was applied in this study to determine monotonic trends in different variables. Before applying the Mann–Kendall test, the data series were tested for serial correlation. If the lag-1 auto-correlation (r_1) was found to be non-significant at 95 % confidence level, then the Mann–Kendall test was applied to the original data

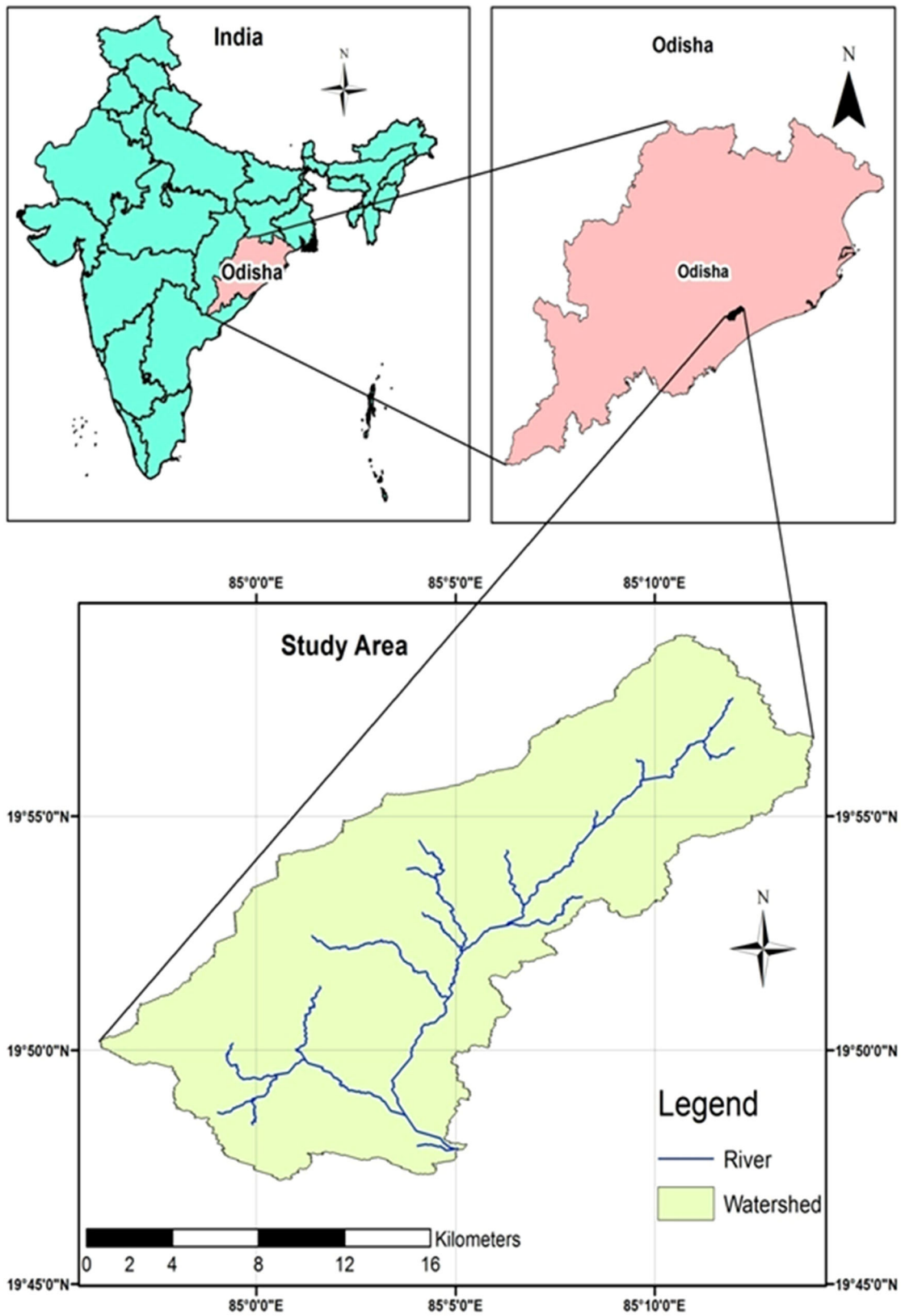


Fig. 1 Study area

series (x_1, x_2, \dots, x_n) , otherwise the Mann–Kendall test was applied to “pre-whitened” series obtained as $(x_2 - r_1 x_1, x_3 - r_1 x_2, \dots, x_n - r_1 x_{n-1})$ (Von Storch and Navarra 1995). The Mann–Kendall statistic (S) is defined as (Salas et al. 2005):

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^N \text{sgn}(x_j - x_i) \tag{1}$$

$$\text{sgn}(x_j - x_i) = \begin{cases} 1 & \text{if } (x_j - x_i) > 1 \\ 0 & \text{if } (x_j - x_i) = 1 \\ -1 & \text{if } (x_j - x_i) < 1 \end{cases} \tag{2}$$

and N is the number of data points.

$$\text{var}(S) = \frac{N(N-1)(2N+5) - \sum_{k=1}^n t_k(t_k-1)(2t_k+5)}{18} \tag{3}$$

where n is the number of tied (zero difference between compared values) groups, and t_k is the number of data points in the k th tied group. The standard normal deviate (Z statistic) is then computed as (Hirsch et al. 1993):

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{var}(S)}} & \text{if } S < 0 \end{cases} \tag{4}$$

If $Z > +1.96$ or $Z < -1.96$, the null hypothesis (H_0) is rejected at 95 % significance level.

ARNO model development

The ARNO model is a semi-distributed conceptual rainfall-runoff model which is now in widespread use both in land-surface-atmosphere process research and as an operational flood forecasting tool on several catchments in different parts of the world. The model mainly involves the concepts of spatial probability distribution of soil moisture capacity and of dynamically varying saturated contributing areas. Details on ARNO model is reported and developed by Todini (1996). In the present study an attempt has been made to set-up the model for the Salia river Sub-basin in Odisha. For the calibration, a 29 year period (1972–2000) was used where daily data of precipitation, potential evaporation, temperature, and catchment runoff are available. In the calibration procedure, several model parameters have to be adjusted using trial and error to obtain optimum values. These optimum values are considered as the representative coefficient to determine the runoff within the catchment area. In the present analysis, the calibration was carried out in two steps, viz, initially the model was calibrated using the in-built auto-calibration facility to obtain a set of model parameters. After obtaining the set of

model parameters, then a trial and error method was applied to optimize each of the model parameters varying within their physically permissible range. To find out the optimal model developed in estimating stream flow, different statistical indices are introduced. The indices employed are the Nash–Sutcliffe coefficient of correlation (R^2), root-mean-square error (RMSE) between the observed and forecasted values and the coefficient of efficiency (Nash and Sutcliffe 1970). The definitions of different statistical indices are presented below:

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$$

$$d = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (|S_i - \bar{O}| + |O_i - \bar{O}|)^2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (O_i - S_i)^2}{n}}$$

$$R^2 = \left(\frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (P_i - \bar{P})^2}} \right)^2$$

where O_i and P_i respectively are the observed and computed values at time t , and \bar{O} and \bar{P} are the mean of the observed and computed values corresponding to n patterns.

Result and discussions

Trend analysis

Observed daily rainfall data for 42 years (1970–2011) have been collected and used for sign test. A plot showing annual rainfall is presented Fig. 2. Monthly maximum

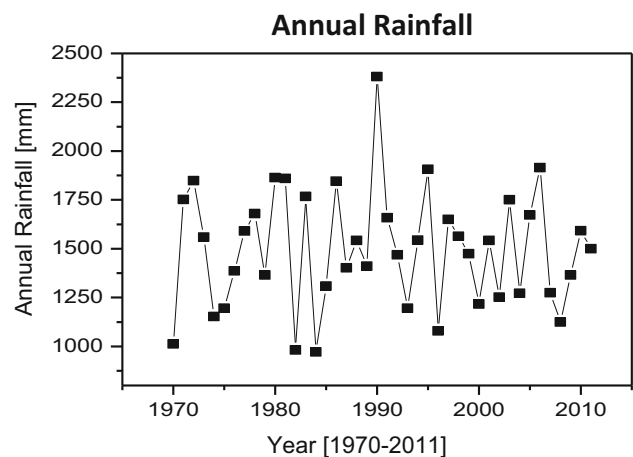


Fig. 2 Plot showing annual rainfall from 1970 to 2011

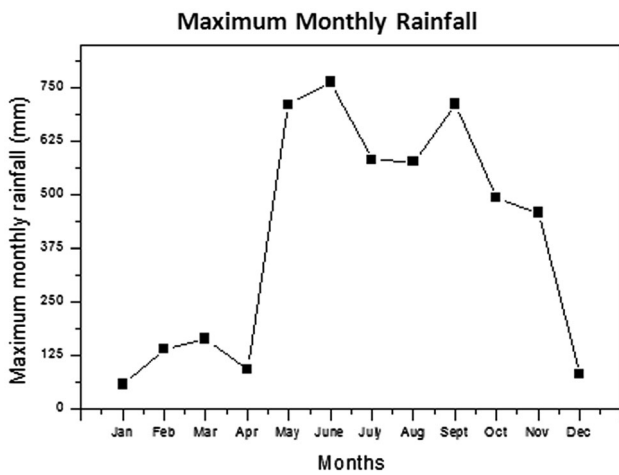


Fig. 3 Plot showing maximum monthly rainfall

rainfall observed during the study period is also presented in Fig. 3. From Fig. 3 it is observed that monsoon period receives highest monthly rainfall. The non-parametric Mann–Kendall (MK) statistical test has been widely used to assess the significance of trends in hydro-meteorological time series due to its robustness against non-normally distributed, censored and missing data as well as its comparable power to parametric competitors (Serrano et al. 1999; Yue et al. 2002). Experiment is conducted for significant level of α at 0.05 and 0.01 for MK Test. If the p-value of a test is less than α , the test rejects the null hypothesis. If the p-value is greater than α , there is insufficient evidence to reject the null hypothesis. The p-value of a test is the probability, under the null hypothesis, of obtaining a value of the test statistic as extreme or more extreme than the value computed from the sample. In the analysis Mann–Kendall’s test result for precipitation showed no trend with significant level of α at 0.05 and 0.01 for rainfall data. Further trend analysis has been carried using monthly, seasonal and annual rainfall data. There is no statistically significant trend is observed in monthly rainfall data. It is worth mentioning that there is evidence of a statistically significant increasing trend in southwest monsoon (June to September) rainfall using MK test.

In order to check the variation of rainfall event, number of rainy days are calculated and presented in the Fig. 4. From the Fig. 4, it is observed that number of rainy days decreasing over the years. Red line in Figs. 4 and 5 shows the rate of change for the mean values of the rainy days. Number of events having more than 100 mm/day (intensity of rainfall) of rainfall are estimated and presented in the Fig. 5. In this analysis an attempt has been made to detect trend in the rainfall data. Though consistent trend was not found in the rainfall data, it was found that number of rainy days is decreasing and intensity of rainy days is increasing. Detection of

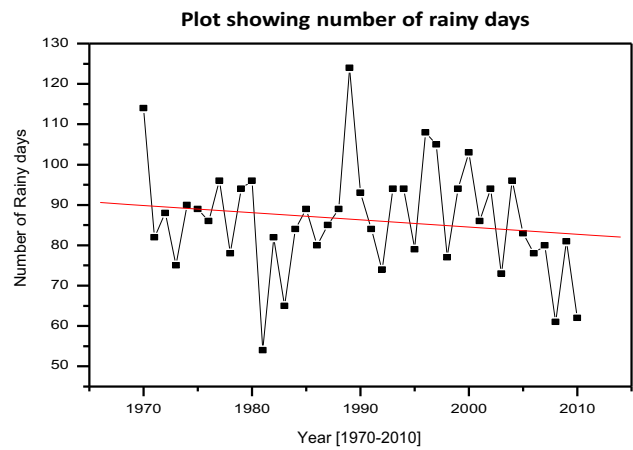


Fig. 4 Plot showing number of rainy days

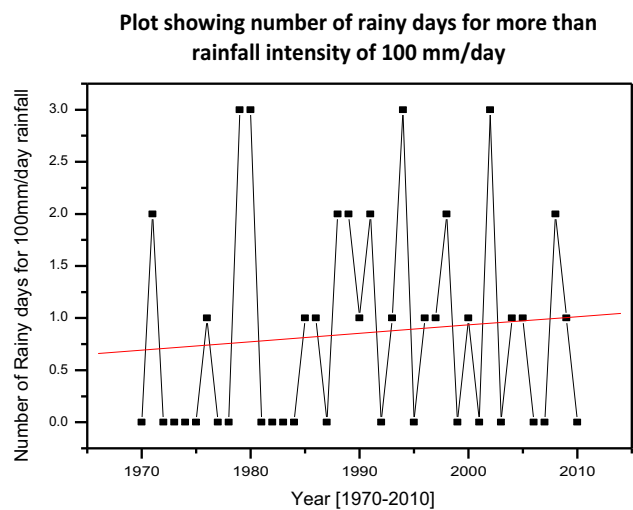


Fig. 5 Plot showing number of rainy days having intensity more than 100 mm/day

changes in river discharge is the most important and (at the same time) the most complicated step within water resources prediction. Statistical analysis of periodicity or wet and dry cycles depends on the availability of long-term data series. Similarly, the series consisting of the daily inflows to Salia reservoir was considered for the trend analysis using Mann-Kendal test. Before applying the Mann–Kendall test, the data series were tested for serial correlation. If the lag-1 auto-correlation (r_1) was found to be non-significant at 95 % confidence level, then the Mann–Kendall test was applied to the original data series (x_1, x_2, \dots, x_n), otherwise the Mann–Kendall test was applied to the pre-whitened series obtained as described. It was found that serial correlation exit in the inflows series. Therefore pre-whitened series was obtained as described above. A significant rising trend with the test statistic value of +3.18 is observed for daily inflow series at 95 % confidence level.

Table 1 Optimized model parameters

Sl no.	Optimized model parameters	Calibration
1	Initial storage capacity of the basin, mm	20
2	Maximum storage capacity of the basin, mm	350
3	Shape factor	0.001
4	Drainage threshold value	118
5	Maximum drainage mm/hr	4.1
6	Maximum drainage fraction corresponding to the threshold value mm/hr	0.9
7	Drainage exponent	6.4
8	Deep percolation threshold value	5
9	Percolation coefficient	0.15
10	Maximum base flow	2.35
11	Moisture content threshold for baseflow	1

ARNO model result

As stated earlier, the ARNO model was used to simulate the inflows into Salia reservoir. As a first step, the model was calibrated using the observed inflow for a period of 29 years (1972–2000) and validated the model for a period of 12 years (2001–2012). The reliability of the model was evaluated based on the Nash and Sutcliffe (1970), Index of agreement (d-index) and RMSE. There were several related studies available for model performance evaluation such as by Aitken (1973) and Fleming (1975). The procedure by Nash and Sutcliffe (1970) had been widely used for the detection of systematic errors with respect to long term simulation. In the calibration procedure, several model parameters have to be adjusted using trial and error to obtain optimum values. These optimum values are considered as the representative coefficient to determine the runoff within the catchment area. In the present analysis, the set of model parameters were obtained through a trial and error method to optimize each of the model parameters varying within their physically permissible range. The model parameters so obtained are presented in Table 1.

The values of performance indices in estimating river flow are evaluated and presented in the Table 2 for the calibration as well as the validation period. A plot comparing the observed and simulated flow during the calibration period is presented in Fig. 6.

It is observed from the Fig. 6 that the peak flows are simulated with their timing accurately. The flows are predicted with an efficiency of 0.698 during the calibration and 0.586 during validation. The RMSE obtained for calibration is quite higher than that of the validation indicating the more accurate prediction of flows.

From the Table 1, it is noted that, the value obtained for maximum storage capacity of the basin is 350 mm. The value of maximum storage capacity obtained by applying the ARNO for various basins under different climatic regimes vary between 275 and 350 mm. This is quite a

Table 2 Statistical indicators for ARNO model for simulating flows

Sl no.	Statistical indicators	Calibration	Validation
1	NSE	0.698	0.586
2	D-index	0.806	0.846
3	R ²	0.706	0.726
4	RMSE	7.880	3.795

representative values as the depth of the soil in the basin which varies between 1 and 2 m and has a good potential for the moisture storage. Also the result is in line with the earlier reported maximum soil moisture values (Venkatesh 1998; Venkatesh and Jain 2000) through the application of various rainfall-runoff models. The other parameter “shape parameter” is responsible for the generation of the flow in the basin. In the present analysis the value obtained is 0.001. As reported by Todini 1996; Franchini et al. 1996; Venkatesh 1991, lower the value of shape parameters, more is the runoff generated over the basin. The higher values of maximum storage and the lower values of the shape parameter will result in a higher base flow and drainage than that of the quite flow. This is quite true, as this catchment is characterized by higher percentage of forest (70 %) land. This is further supported by the higher threshold value for drainage and base flow. This aspect is further supported by the well-defined and relatively shallow recession curve response in simulated hydrographs of the basin during the calibration period. The similar phenomenon is seen even in the validation period also, confirming the representativeness of the runoff generation processes in the basin.

The validation was carried out using the calibrated parameters. The efficiency of the model in the validation period was found to be 0.58. Figure 7 presents the scatter plots of observed and computed flows during validation period. Further, the observed and simulated data were used to fit the Least Square Regression (LSR) line. The fitted LSR

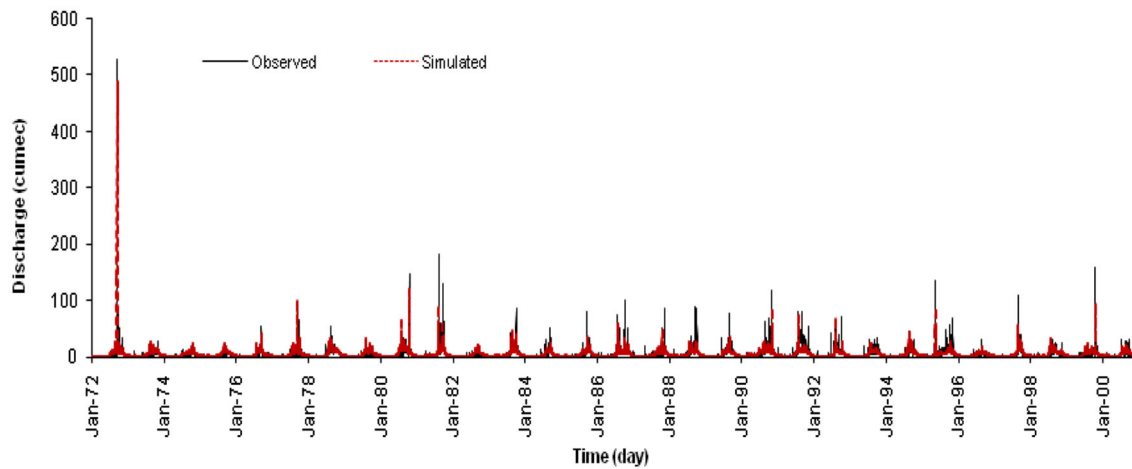


Fig. 6 Observed and simulated flow during the calibration period

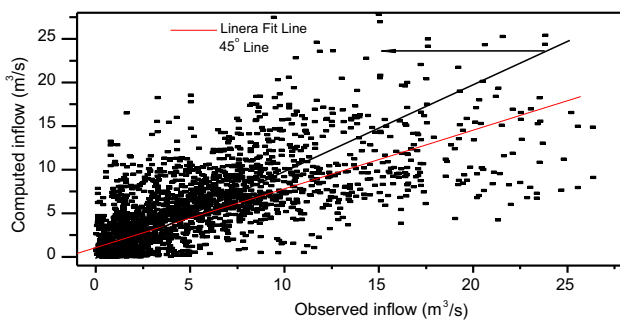


Fig. 7 Scatter plot of observed and simulated flow during validation period

line would coincide with the 45° line if the computed flow is equal to that of the observed flow. The difference between the regression line and the 45° line is simply the measure of reliability of prediction. A comparison of the orientation of the regression line and the 45° line gives a visual representation of the relative accuracy of estimation. As the accuracy decreases, the regression line tends more toward the

horizontal. A perfect horizontal line indicates no skill associated with the model estimation. The plot obtained in this analysis gives an indication that the model does not deviate so much in the lower range, whereas the higher flow are simulated much lower than that of the observed.

Sensitivity analysis

The present analysis which is aimed at analysing the effect of climate change on the reservoir inflows. However, we intended to simulate the effect of climate change especially with respect to change in the rainfall patter. In view of this, we adopted a procedure wherein the observed rainfall for the calibration period of 29 years (1972–2000) are changed by the some know percentage, i.e., starting from ±5 to ±25 % at an interval of ±5 %. The results obtained are tabulated in Table 3.

It is clear from table above, the simulated volume of inflow vary as the rainfall amount vary. The simulated flow increase/decrease is directly proportional to the change in

Table 3 Total simulated runoff and relative error

Sl no.	Items	Simulated runoff (Cumecs)	Relative difference (%)
1	Calibration	49,981.28	−0.347
2	Validation	15,213.40	−2.600
3	5 % increase	52,325.40	+4.689
4	10 % increase	54,646.89	+9.334
5	15 % increase	56,959.86	+13.962
6	20 % increase	60,147.96	+20.340
7	25 % increase	62,681.46	+25.409
8	5 % decrease	47,621.51	−4.721
9	10 % decrease	45,224.06	−9.518
10	15 % decrease	42,790.53	−14.386
11	20 % decrease	40,158.70	−19.652
12	25 % decrease	37,499.45	−24.973

the rainfall decrease/increase. However, these changes are observed due to rainfall changes only. As reported by the other researcher elsewhere (Ojha et al. 2009), the changes in the discharge/inflow is not only depends on the rainfall but also due to the changes in the evaporation. Further it is observed that, a change of 25 % decrease or increase in rainfall amount resulted in equal amount of decrease or increase in the inflow. This pattern of decrease or increase in rainfall does not influence on the processes such as maximum soil moisture storage, drainage and base flow. The one reason could be the presence of forest coverage in the catchment (more than 70 % of the catchment is under forest). The forest coverage may not allow the maximum soil moisture to undergo significant change due to the changes in the rainfall amount. Secondly, there are no significant changes in the maximum rainfall amount which are responsible for producing higher flows.

IWRM tools

After identification of climate change and reservoir performance evaluation, there are some adaptation and coping strategies have been proposed which is based on Integrated water resources management tools. IWRM tools are the key for water sector and water-related developments and measures. However, the potential impacts of climate change and associated increasing climate variability need to be sufficiently incorporated into IWRM plans. It should form the encompassing paradigm for coping with natural climate variability and the prerequisite for adapting to the consequences of global warming and associated climate change under conditions of uncertainty. Adaptation is a process by which individuals, communities and countries seek to cope with the consequences of climate change, including climate variability. It should lead to harmonization with countries' more pressing development priorities such as poverty alleviation, food security and disaster management. Management of land and water resources presents the major input in addressing all development priorities; therefore, IWRM planning processes must incorporate a dimension on climate change adaptation.

Conclusions

The aim of this chapter is to perform a trend analysis for precipitation and inflows time series for Salia river basin. Initially, monthly, seasonal and annual precipitation trends behaviour have been studied in Salia basin between 1970 and 2011. In order to achieve this, daily, monthly and annual precipitation data were analysed using the Mann–Kendall test. In the analysis Mann–Kendall's test result for

precipitation showed no trend with significant level of α at 0.05 and 0.01 for all data set. Variation of precipitations shows that number of rainy days is decreasing and number of intense rainy days (more than 100 mm) is increasing. As a result flash floods and dry spells are creating havoc in Salia command. To detect trend in inflows series similar test is conducted. It was found that serial correlation exist in the inflows series. Therefore pre-whitened series was obtained as described above. A significant rising trend with the test statistic value of +3.18 is observed for daily inflow series at 95 % confidence level.

In order to assess the impact of climate change ARNO model was used to simulate the inflows into Salia reservoir calibrating the observed inflow for a period of 29 years (1972–2000) and validating the model for a period of 12 years (2001–2012). It is observed that the peak flows are simulated with their timing accurately and the flows are predicted with an efficiency of 0.698 during the calibration and 0.586 during validation period. It is also observed that the relative percentage of simulated volume is lower in the calibration period (−0.347). The calibrated model was used for predicting the flows by varying the observed rainfall between ± 5 and ± 25 . A change of 25 % decrease or increase in rainfall amount resulted in equal amount of decrease or increase in the inflow. The simulations indicate that the simulated flows vary with respect to the variation in the rainfall due to the presence of forest coverage in the catchment (more than 70 % of the catchment is under forest).

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