

# Estimation of the climate change impact on a catchment water balance using an ensemble of GCMs

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## Abstract

This work evaluates the impact of climate change on the water balance of a catchment in India. Rainfall and hydro-meteorological variables for current (20C3M scenario, 1981-2000) and two future time periods: mid of the 21<sup>st</sup> century (2046-2065) and end of the century (2081-2100) are simulated using Modified Markov Model-Kernel Density Estimation (MMM-KDE) and k-nearest neighbor downscaling models. Climate projections from an ensemble of 5 GCMs (MPI-ECHAM5, BCCR-BCM2.0, CSIRO-mk3.5, IPSL-CM4, and MRI-CGCM2) are used in this study. Hydrologic simulations for the current as well as future climate scenarios are carried out using Soil and Water Assessment Tool (SWAT) integrated with ArcGIS (ArcSWAT v.2009). The results show marginal reduction in runoff ratio, annual streamflow and groundwater recharge towards the end of the century. Increased temperature and evapotranspiration projects an increase in the irrigation demand towards the end of the century. Rainfall projections for the future shows marginal increase in the annual average rainfall. Short and moderate wet spells are projected to decrease, whereas short and moderate dry spells are projected to increase in the future. Projected reduction in streamflow and groundwater recharge along with the increase in irrigation demand is likely to aggravate the water stress in the region under the future scenario.

**Key words:** ArcSWAT; GCM; Climate change; MMM-KDE downscaling model

## 1. Introduction

Global climate change and its impact on hydrologic processes have been widely discussed in the recent past. With increase in temperature, climate change is accelerating the global hydrologic cycle (Huntington, 2006; Oki and Kanae, 2006). Climate change is projected to cause changes in precipitation pattern, variation in the frequency and distribution of floods and droughts, and increase in evapotranspiration rate over different regions in the world (Frederick and Major, 1997; Ficklin *et al.*, 2012). Under the changing climate scenario, changes in streamflows have been found to be largely linked with the variations in precipitation. However for some locations, especially for moisture limited regions, small increase in temperature and the associated increase in evapotranspiration can cause larger variations in streamflows (McCabe and Wolock, 2011). In a study by Sankarasubramanian and Vogel (2003), storage processes within the catchment have been identified as the major factor that defines the non-linearity between the streamflow and precipitation. For moisture limited arid regions, actual evapotranspiration is limited due to the limited moisture availability. For such regions, any increase in precipitation causes a proportional increase in actual evapotranspiration, causing changes in the runoff to be less dramatic. On the other hand in humid regions, where moisture availability is not limited, any increase in precipitation may not result in proportional increase in evapotranspiration. In other words, changes in evapotranspiration rate with respect to changes in rainfall are less prominent. Therefore, any changes in rainfall are likely to cause larger changes in streamflow (Sankarasubramanian and Vogel, 2003). Basin level hydrologic analyses are therefore essential to assess the sensitivity of the basin to climate change scenarios, and to develop appropriate water resources management policies and climate change adaptation strategies.

Global Climate Models (GCMs) are the primary tools that provide future projections of climate variables in the changing environment. GCMs are complex mathematical models capable of simulating the behavior of the Earth's atmosphere, ocean and land surface in three dimensions (McGuffie and Henderson-Sellers, 1997). However, they remain relatively coarse in resolution, and are unable to resolve significant sub-grid scale features often necessary in any hydrologic study (Allen and Ingram, 2002; Fowler *et al.*, 2007). Therefore, studies

dealing with the climate change impact assessment at catchment scale require downscaling of GCM projections to an appropriate scale to represent the catchment heterogeneity (Silberstein *et al.*, 2012). Various statistical (Anandhi *et al.*, 2008; Mehrotra and Sharma, 2010) and dynamic downscaling methods (Misra *et al.*, 2003; Dominguez *et al.*, 2012) have been adopted in the past to downscale large scale atmospheric variables from the GCMs to a regional scale or to a finer scale representative of a catchment.

Downscaled climate simulations are often used as an input to hydrologic models to simulate the hydrologic responses and to assess the impact of climate change on water resources (Chang and Jung, 2010; Vaze and Teng, 2011; Ruelland *et al.*, 2012). In such studies the hydrologic models are first calibrated using historic data, and then run using future scenarios to translate the climate change signals into corresponding changes in the hydrologic responses. When GCM data are used, large amount of uncertainty is inherent in the analyses. For instance, climate change projections are based on the Green House Gas (GHG) emission scenarios under different conditions of economic and technological development, as well as the balance between global and local growth. There are many emission scenarios mentioned in the Special Report on the Emission Scenario-SRES (IPCC, SRES, 2000). Besides that, there are many GCMs available, giving different projections of the climate variables for the same future GHG emission scenario. From the previous studies (Wilby and Harris, 2006; Chen *et al.*, 2011), choice of a single GCM has been consistently identified as the major contributor to the overall uncertainty in such analyses. Uncertainties arising from GHG emission scenario and the hydrologic model structure have been identified to be the least significant (Wilby and Harris, 2006; Minville *et al.*, 2008; Chen *et al.*, 2011; Woldemeskel *et al.*, 2012). Due to the large uncertainty introduced by the GCMs, climate change impacts estimated from the use of a single GCM need to be interpreted cautiously. Hence, multi-model ensemble climate simulations have been used in many of the recent studies (Tebaldi and Knutti, 2007; Knutti *et al.*, 2010; Jung *et al.*, 2012; Zhang and Huang, 2013). Multi-model mean has been found to be giving better simulation of the climate variables compared to the individual models (Gleckler *et al.*, 2008; Knutti *et al.*, 2010; Zhang and Huang, 2013).

In light of these facts, in this study, the hydrologic impact of climate change on Malaprabha catchment in India is evaluated using climate projections from an ensemble of 5 GCMs. Rainfall and meteorological variables are downscaled from large scale atmospheric variables simulated by the GCMs. A conceptual, yet spatially distributed hydrologic model SWAT is used to derive the hydrologic simulation using inputs from each GCM. In this study, SWAT integrated with ArcGIS graphical user interface (ArcSWAT. V. 2009) is adopted. A weighted ensemble average approach is used to estimate the average hydrologic responses of the catchment under future scenarios and to evaluate the hydrologic impact of climate change in the catchment.

The World Climate Research Programme's Coupled Model Intercomparison Project phase 3 (CMIP3) and CMIP5 datasets each contain output from a large number of GCMs. Both datasets use different scenarios describing the amount of greenhouse gas in the atmosphere in the future. CMIP3 uses scenarios from the Intergovernmental Panel on Climate Change's (IPCC) Special Report on Emissions Scenarios (SRES) whereas CMIP5 uses Representative Concentration Pathways recommended in the IPCC Fifth Assessment Report (IPCC, 2013). In this study, GCMs included in the CMIP3 project and IPCC SRES emission scenario are used to obtain the climate projection for the 20th century as well as the future scenarios. The IPCC notes that, for both large-scale climate patterns and the magnitudes of climate change, there is overall consistency between the projections based on CMIP3 and CMIP5 (IPCC 2013). Results of a few recent studies show that both CMIP3 and CMIP5 models well simulate the large scale atmospheric variables used in this study for the statistical downscaling of rainfall (Mueller and Seneviratne, 2014; Woldemeskel et al., 2016). In addition, based on the studies conducted using CMIP3 and CMIP5 models, Shashikant et al. (2014) concluded that the Indian Summer Monsoon Rainfall simulations from both models do not differ significantly. Hence the current study helps to understand the sensitivity of the catchment to the projected climate scenarios, even though an additional analysis using CMIP5 models and appropriate RCPs would further strengthen the findings of the study.

## **2. Study area and input data**

### **2.1 Study area**

Malaprabha River originates from the Western Ghats in the Belgaum District in North Karnataka, India. The area drained by Malaprabha River and its tributaries up to Malaprabha dam is selected as the present study area. The catchment area is 2564 sq.km with elevation ranging from 1024 m to 430 m. Location map of the Malaprabha catchment is shown in Fig.1, based on the Survey of India maps (<http://www.surveyofindia.gov.in/>).

Climatology of the catchment varies from tropical humid in the upper catchment to semi arid in the lower catchment. Annual average rainfall in the catchment exhibits large spatial variation ranging from 3000 mm in the upper region to less than 500 mm in the lower region. Annual average rainfall, averaged over the catchment is 1051 mm, much of which is received during the south-west monsoon period from June-September (Anandhi *et al.*, 2008). Mean monthly maximum and minimum temperatures in the catchment vary from 25 to 34°C and 17 to 21°C, respectively (Anandhi *et al.*, 2009). Malaprabha reservoir is the major source of irrigation water for the 218191 hectares (Anandhi *et al.*, 2009) of agricultural area in the arid regions in north Karnataka, and is also the major source of drinking water for about one million people in Hubli and Dharwad cities. Malaprabha catchment is a hydrologically sensitive area such that any change in water yield in the catchment is likely to effect vast areas that are dependent on the reservoir for irrigation and drinking water. In addition, due to extensive groundwater extraction to meet the irrigation demand, groundwater table in a large part of the catchment has been drastically depleted (CGWB, 2007; Reshmidevi and Nagesh Kumar, 2012). Scientific studies are therefore essential to analyse the hydrologic responses of this water scarce catchment under the projected climate change scenario to facilitate the planning of appropriate mitigation measures.

### **2.2 Data used**

Digital elevation model (DEM), digital soil map and land use/ land cover (LU/LC) map are used to represent the catchment heterogeneity for the hydrologic analysis. DEM of

Malaprabha catchment at 30 m spatial resolution is obtained from Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) Global DEM (GDEM) data set released by the Japan's Ministry of Economy, Trade and Industry (METI) and NASA. Multi season Landsat-7 ETM+ imageries are used to extract LU/LC map of the catchment. In this study, a combination of visual and digital image interpretation technique is used to extract the LU/LC map from the satellite imagery (Reshmidevi and Nagesh Kumar, 2012). Seven main LU/LC classes viz., water, agricultural land, barren/ fallow land, rocky area, forest, urban settlement and grass land are extracted in the first step. Appropriate bands that show unique band ratio are identified for each land cover class. A combination of visual interpretation and unsupervised classification using band ratio (Lillesand *et al.*, 2004) is used to identify the seven major land cover classes. The second level classification, i.e., classification of the crop types is achieved using multi-temporal satellite images (Dutta *et al.*, 1998) representing different cropping seasons. Depending upon the presence or absence of crop in each image, different crop types are classified. Field information and the district statistical information about the crop production are used to substantiate the classification.

Soil map of the area is obtained from the National Bureau of Soil Survey and Land Use Planning, Nagpur, India. Monthly inflow into the Malaprabha reservoir for the period 1973-2000 is obtained from the Water Resources Development Organization, Bangalore, India and is used as the observed streamflow data to calibrate the hydrologic model.

Rainfall and meteorological variables viz., maximum and minimum temperatures and relative humidity at daily time steps are used for hydrologic simulation. In order to incorporate the large spatial heterogeneity, rainfall data from 9 stations are used in this study. Locations of the stations for which the downscaled rainfall and meteorological data are available are shown in Fig.1. Daily rainfall data at these 9 stations in the catchment are available for the period 1971-2000, whereas observed meteorological data are available only for a short period 1993-2000. Mass curve analysis of the rainfall data was performed, from which the period 1993-2000 was found to be insufficient to represent the entire study period 1971-2000. Therefore, rainfall and meteorological variables are downscaled from the National Center for Environmental Prediction (NCEP) reanalysis data for the period 1971-2000. In addition, for historic and

future time periods, rainfall and hydro-meteorological variables are downscaled from multiple GCMs. Modified Markov Model-Kernel Density Estimation (MMM-KDE) model (Mehrotra and Sharma 2010) is used to downscale rainfall from large scale atmospheric variables to the multiple raingauge stations shown in Fig.1. Also, the k-nearest neighbor resampling method is used to downscale the meteorological variables to the single location shown in Fig.1. The MMM-KDE model and the k-nearest neighbor resampling methods are explained in the next section.

Based on the easy availability of daily data of the atmospheric variables from the World Climate Research Programme's Coupled Model Intercomparison Project phase 3 (CMIP3), 5 GCMs are considered in this study. These are (i) BCCR-BCM2.0 developed by the Bjerknes Centre for Climate Research (BCCR), University of Bergen, Norway, (ii) MRI-CGCM2 developed by the Meteorological Research Institute (MRI), Japan, (iii) CSIRO-mk3.5 developed by the Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia, (iv) MPI-ECHAM5 developed by the Max Planck Institute for Meteorology (MPI), Germany, and (v) IPSL-CM4 developed by the Institute Pierre Simon Laplace (IPSL), France. The 20<sup>th</sup> century climate experiment (20C3M) for the period 1981-2000 is selected to represent the historic scenario. Hydrologic impact of climate change is also studied for two 20 year future time periods: 2046-2065 (referred hereafter as mid of the century) to represent the mid 21<sup>st</sup> century, and 2081-2100 (referred hereafter as end of the century) to represent the end of 21<sup>st</sup> century. For each time period, required atmospheric variables at GCM grid nodes over the catchment are extracted from a single continuous (transient) run corresponding to SRES A2 emission scenario. The A2 scenario, which is at the higher end of the SRES emission scenarios (but not the highest), is selected in this study as it would be more informative from impact and adaptation point of view compared to the lower end scenario. Hydrologic model SWAT is used to simulate the catchment hydrologic responses for historic and two future time periods under the A2 scenario. Please note that during the time of this study, runs from the Coupled Model Intercomparison Project phase 5 (CMIP5) were not available. Nevertheless, many studies have raised concerns about whether CMIP5 models are capturing the historic monsoon trends accurately (Kitoh *et al.*, 2013; Ogata *et al.*, 2014; Sooraj *et al.*, 2014; Saha *et al.*, 2014) and whether the monsoon projections are reliable in these models (Sabeerali *et al.*,

2014). Recent study by Shashikant *et al.*, (2014) shows that biases in the statistically downscaled Indian Summer Monsoon Rainfall (ISMR) data do not differ significantly for CMIP3 and CMIP5 data sets. In this study, future estimates of runoff and rainfall are derived using smooth varying atmospheric variables which are considered to be equally well estimated by majority of GCMs used in both CMIP3 and CMIP5 projects (Mueller and Seneviratne, 2014; Woldemeskel *et al.*, 2016). Hence the current study is restricted only to the CMIP3 data.

### **3. Methodology and model description**

#### **3.1 Statistical downscaling of rainfall and meteorological variables**

The variable convergence score (Johnson and Sharma, 2009) is used to identify the GCM atmospheric variables for use in downscaling daily rainfall. These variables include mean sea level pressure (MSLP), north-south (N-S) gradient of MSLP, temperature depressions (TD) at 850 hPa, 700 hPa, 500 hPa, N-S gradient of TD at 850 hPa, U and V components of the wind velocities at 850 hPa, Equivalent potential temperature (EPT) at 850 hPa, N-S gradient of the geopotential height (GPH) at 700 hPa, specific humidity (SPH) at 500 hPa, N-S gradient of SPH at 500 hPa and E-W gradient of SPH at 850 hPa (Mehrotra *et al.*, 2013). The selected GCM atmospheric variables for 20C3M (1981-2000) and future time periods (2046-65 and 2081-2100) are then bias-corrected by adopting a nested bias correction procedure (Johnson and Sharma, 2012). The nested bias correction (NBC) method offers an improvement over the quantile mapping method by incorporating the persistence of rainfall through lag-1 autocorrelation. Also, corrections are nested from finer to coarser time scales, by which the GCM outputs are corrected for biases in mean, standard deviation and Lag-1 auto-correlation at daily, monthly, seasonal and annual time scales simultaneously. Any biases in the GCM atmospheric fields are thus removed before their use for downscaling, while the mean shift from current to future climate is preserved. Previous studies have demonstrated successful use of NBC for bias correction of atmospheric variables in reproducing the observed low frequency variability in the rainfall simulations (Johnson and Sharma, 2011; Sharma *et al.*, 2012, Ojha *et al.*, 2013).

Modified Markov Model-Kernel Density Estimation (MMM-KDE) modelling framework (Mehrotra and Sharma, 2010) is used to downscale rainfall at multiple sites in the catchment. The model operates in two steps: in the first step the Modified Markov Model (MMM) is used to identify wet and dry days, and in the second step intensity of rainfall during wet days is estimated using the Kernel Density Estimation (KDE) approach. A wet day is defined as a day with rainfall greater than or equal to 0.3 mm.

Markov model is a stochastic model that predicts a state variable at any point of time as a function of the variable in the previous time step. In MMM, to include the influence of changing climate, the simple Markov model is modified by including atmospheric predictors as conditioning variables. Thus in MMM, probability of occurrence of a wet or dry day consists of two terms, first term showing the transition probability of rainfall similar to a simple Markov model and the second term showing the effect of inclusion of a predictor set consisting of the atmospheric variables of interest. The KDE approach simulates the intensity of rainfall during each time step (which is identified as a wet day by the MMM) based on the rainfall intensity of previous time step and selected atmospheric variables. Conditional nonparametric multivariate probability density of rainfall amount  $R_t$  for day  $t$  for each site may be defined as follows (Mehrotra *et al.*, 2013).

$$f(R_t|\mathbf{X}_t) = \sum_{i=1}^N \frac{1}{(2\pi\lambda^2 S')^{1/2}} w_i \exp\left(-\frac{(R_t - b_i)^2}{2\lambda^2 S'}\right) \quad (1)$$

where,  $\lambda$  is the kernel bandwidth and  $X_t$  is the vector representing the climate variables influencing the rainfall.  $S'$  is the measure of spread of the conditional density, and  $b_i$  is the conditional mean, both expressed in terms of covariance between  $R$  and  $X$ .  $w_i$  is the weight associated with each kernel.

Since rainfall at multiple stations are considered in this study, spatial dependence over these point locations at each time step is incorporated by using uniform random variates that are independent in time, but exhibit a strong dependence across the multiple point locations considered. More details on the MMM-KDE model structure are available in Mehrotra and

Sharma (2010) and Mehrotra *et al.* (2013). MMM-KDE model produces multiple realizations of the downscaled variables. In this study, 20 such realizations generated for 20C3M and the future scenarios are considered and the average hydrologic responses are estimated for each scenario. Daily values of maximum and minimum temperature, and relative humidity are downscaled from the large scale atmospheric variables using the *k*-nearest neighbor resampling.

### **3.2 ArcSWAT**

ArcSWAT is the Soil and Water Assessment Tool (SWAT), with a powerful user interface integrated with the ArcGIS platform (Winchell *et al.*, 2007). SWAT is a conceptual model capable of simulating the catchment hydrologic processes at a continuous time scale (Arnold *et al.*, 1998). Capability of SWAT to simulate basin level hydrologic characteristics for varying land use and climate conditions makes it a widely adopted tool for climate change studies related to hydrology (Wang *et al.*, 2008; Bae *et al.*, 2011; Ficklin *et al.*, 2012). Geographical Information System (GIS) interface of ArcSWAT allows the users to provide spatially referenced data. Using the topographical information, ArcSWAT divides the catchment into sub-basins. Each sub basin is further divided into homogeneous Hydrological Response Units (HRUs) using the spatially distributed soil, land use/ land cover and slope information. Each HRU is vertically divided into different control volumes like surface layer, root zone, shallow aquifer and deep aquifer.

Different approaches and approximations are used to partition the precipitation into various hydrologic components in these control volumes. A part of the precipitation is available as surface runoff and the remaining portion infiltrates into the soil layer. Partitioning of rainfall into surface runoff and infiltration is achieved using the Soil Conservation Services Curve Number (SCS-CN) method (SCS, 1972) embedded in ArcSWAT. Large number of studies conducted over a wide range of catchments have shown that SWAT gives reasonably good simulation of the surface runoff processes (Steenhuis *et al.*, 1995; Ponce and Hawkins, 1996; Mishra and Singh, 2004; Reshmidevi *et al.*, 2008). Runoff from each HRU is further routed through channels to the watershed outlet using the variable storage method (Williams, 1969).

A part of infiltrated water leaves the soil layer as lateral flow, which is estimated using a kinematic flow equation involving saturated hydraulic conductivity of the soil layer, slope, drainable porosity and drainable volume of water present in the layer. Another fraction of water that reaches the soil layer percolates further and joins the groundwater storage, which is called groundwater recharge. Groundwater recharge is computed as a function of drainable volume of water present in the soil layer. This groundwater recharge may be further divided into shallow aquifer recharge and deep aquifer recharge (Reshmidevi and Nagesh Kumar, 2012). Shallow aquifer storage contributes to the groundwater flow and adds to the streamflow within the watershed, whereas groundwater flow from the deep aquifer is assumed to meet the stream only outside the catchment.

In this study, Hargreaves method (Hargreaves and Samani, 1985) available in the ArcSWAT interface is used for estimating potential evapotranspiration (PET). ArcSWAT provides options to define various agricultural operations for each crop at the HRU level. Irrigation requirement for the crops is defined according to the plant water stress condition (Reshmidevi and Nagesh Kumar, 2012). Digital elevation model of the catchment, spatial variation in soil and LU/LC are the primary spatially referenced data used in ArcSWAT. Rainfall and meteorological data viz., maximum and minimum temperature, and relative humidity at daily time step are also used as input to the model. Details of ArcSWAT components can be found in literature (Arnold *et al.*, 1998).

### **3.3 ArcSWAT calibration and validation**

ArcSWAT (v.2009) is applied at daily time scale over the study area. The catchment is first divided into 12 sub-basins and each sub-basin is further divided into HRUs using the LU/LC, soil and slope information. Irrigated areas in the catchment are identified and the irrigation application is defined when plant water stress exceeds a threshold of 0.95. Daily values of rainfall at 9 stations and hydro-meteorological variables at the single location shown in Fig.1, are downscaled from the reanalysis data and are used for model calibration and validation. Simulated discharge is compared with the observed monthly streamflow data. The period 1971-2000 is selected in this study, out of which the first two years are used as the warm-up

period for the model and the period 1973-2000 is used for model calibration and validation. Multiple realizations of the downscaled rainfall and climate variables produced by MMM-KDE approach are used in the hydrologic modelling. In order to derive stable values of model parameters during calibration, concatenated data set is formed using multiple realizations. From the ensemble of 20 realizations first 9 realizations are used for calibration and the remaining 11 realizations are used for model validation. Each realization being of 28 years (excluding the warm-up period) total length of the calibration run is thus 252 years.

Model sensitivity analysis is performed using Latin Hypercube (LH) and One-factor-At-a-Time (OAT) methods included in the ArcSWAT (Van Griensven, 2005) and the sensitive parameters are manually calibrated. Capability of the model to accurately produce flow-duration curve (FDC) for the annual and monsoon (June-September) streamflows is considered as the evaluation criteria during calibration. Using monthly streamflow simulations from the model, annual and monsoon streamflows are calculated for each realization and the average FDCs for the annual and monsoon periods are generated. Deviation of the simulated FDC from the observed FDC is measured using mean absolute relative error (MARE) as given in Eq.2.

$$MARE = \frac{1}{N} \sum_{i=1}^N \left| \frac{(Q_{obs} - Q_{sim})}{Q_{sim}} \right| \quad (2)$$

where,  $N$  is the number of points considered from the FDC,  $Q_{obs}$  and  $Q_{sim}$  are the corresponding flow values from the observed FDC and the simulated FDC, respectively.

### **3.4 Multi-model ensemble projection under the future scenario**

Ensemble of simulations from the hydrologic model, obtained by using rainfall and meteorological data from the 5 GCMs is used to evaluate the hydrologic impact of climate change in the catchment by comparing hydrologic responses in the future time periods with that obtained under 20C3M scenario. When the temporal periods do not overlap, FDCs are commonly used for comparing the flow regimes in the hydrologic analyses (Sugawara 1979; Yu and Yang, 2000; Westerberg *et al.*, 2011). Since the temporal periods of the 20C3M and

the future scenarios do not overlap, FDCs of annual and monsoon flows are used here for the comparison.

A weighted ensemble average approach is used to derive ensemble average streamflow simulation from the 5 GCMs. ArcSWAT is run using the downscaled rainfall and meteorological data from each GCM, and FDCs for the annual and monsoon flows are generated. Simulated FDCs for 20C3M scenario are then compared against FDCs of the observed streamflow data for the same period. Deviation of the simulated FDCs from the observed FDC, expressed in terms of MARE is used as the evaluation criterion. For each hydrologic simulation (using input from different GCMs), MARE of the annual and monsoon FDCs are estimated and the mean of these two values is used to derive the weight for each simulation using Eq.3.

$$weight = \frac{\left( \frac{1}{meanMARE} \right)}{\sum_{m=1}^5 \left( \frac{1}{meanMARE} \right)} \quad (3)$$

where,  $m$  is the model index. Using this set of weights, weighted FDCs of the annual and monsoon flows are generated for the 20C3M scenario and are used as the reference FDCs to quantify the future changes in the streamflow.

GCMs simulating the historic scenario satisfactorily are expected to be capable of simulating the future scenarios reasonably well (Reichler and Kim, 2008; Errasti *et al.*, 2010). Therefore, the weights derived for the hydrologic simulations under 20C3M scenario are adopted for the future time periods as well. Hydrologic responses of the catchment under the future time periods (mid of the century and end of the century), are simulated by using the downscaled rainfall and meteorological variables from each GCM, and the FDCs of both annual and monsoon flows are generated. Further, using the set of weights derived from the 20C3M scenario, weighted average FDCs for the future scenarios are generated. Future projections are compared with 20C3M simulations to quantify the streamflow variation under future scenarios. A flowchart of the methodology is shown in Fig 2.

Hydrologic simulations from the 5 GCMs are aggregated to find variations in other water budget components viz., potential evapotranspiration (PET), actual evapotranspiration (ET), irrigation demand and groundwater recharge in the future time periods.

### 3.5 Test for statistical significance

Statistical significance of projected changes in the mean annual and monsoon streamflows is evaluated using non-parametric, rank-based, Mann-Whitney test (Wilcoxon, 1945; Mann and Whitney, 1947). Mann-Whitney test is commonly used to identify statistical significance of the difference in mean or median of hydrological time series (Lettenmaier, 1976; Xu *et al.*, 2003; Caloiero *et al.*, 2011). The test is based on the null hypothesis that medians of the two series compared are the same, and the alternate hypothesis that they differ significantly from one another. When two series of size  $n_1$  and  $n_2$  are compared, the standardized test statistic is represented as follows (Chen *et al.*, 2006).

$$Z_c = \frac{R_1 - [n_1(n_1 + n_2 + 1)/2]}{\sqrt{n_1 n_2 (n_1 + n_2 + 1)/12}} \quad (4)$$

where,  $R_1$  is the rank sum of the values in series-1. The ranks are assigned by combining all the values in series 1 and 2, and arranging them in the ascending order. For a large sample size the null hypothesis is rejected, in other words a difference between the medians is established, at a significance level  $\alpha$  when the probability of occurrence of  $Z_c$  obtained from the standardized normal distribution table is greater than or equal to  $1-\alpha/2$ .

In this study, the weighted average annual and monsoon streamflow series of the future time periods are compared against the 20C3M scenario and the test statistic is derived. This test statistic is used to find the corresponding  $\alpha$ , which indicates the statistical significance of difference in the medians of the two streamflow series compared.

## 4. Results and discussion

### 4.1 ArcSWAT calibration and validation

DEM, soil map, and LU/LC map of the Malaprabha catchment are used as spatially referenced input to ArcSWAT to simulate the catchment hydrological processes. The model is run at daily time scale using downscaled rainfall and hydro-meteorological data from the reanalysis data set. Streamflow simulations at daily time scale are aggregated to monthly scale, and are compared with the observed data. Table 1 shows the MARE values for annual and monsoon flows. MARE is found to be less than 0.1 for both calibration and validation phases. Further, monthly streamflow data series is generated taking average of 20 realizations (used for calibration and validation), and the same is compared with the observed monthly streamflow data in Fig. 3. Simulated monthly streamflow series matches well with the observed data, albeit slight underestimation of the peak flow values. Nash-Sutcliffe Efficiency (NSE) coefficient is found to be 0.82, which is considered to be excellent according to the general performance rating for monthly streamflow recommended by Moriasi *et al.* (2007). Since, a simple averaged monthly flow is used as the benchmark model in NSE, higher values of NSE may be due to the high seasonality of the monthly data. Therefore, as recommended by Schaefli and Gupta (2007), an additional index NSEB is also used in this study to evaluate the model performance. Long-term average streamflow for each month is used as the benchmark model to calculate NSEB. During the calibration period NSEB is obtained as 0.74 for the monthly streamflow simulations. Higher values of NSE and NSEB indicate better performance of the current hydrologic model compared to the selected benchmark models.

The calibrated hydrologic model is used to simulate hydrological responses under 20C3M scenario. Simulated FDCs of annual and monsoon flows obtained using the downscaled rainfall and meteorological data from the 5 GCMs are compared with the FDCs of the observed data in Fig.4. Table 2 shows the MARE of the annual and monsoon flows for the 5 GCMs and the corresponding weights. Using the set of weights, weighted average FDC for the 20C3M scenario is derived, which is also plotted in Fig.4. The weighted average annual FDC matches well with the observed data with the exception of some underestimation of

moderate and low monsoon flows. This may be mainly due to the small differences between the observed and the downscaled rainfall data in terms of annual wet days and the amount of rainfall per wet day (Mehrotra *et al.*, 2013). Since bias corrected GCM outputs are used in the downscaling, such variations may be due to systemic errors from the downscaling model and therefore, may persist for the future scenarios as well. Hence to quantify the future changes in the streamflow, hydrologic responses in the future time periods are compared with the weighted ensemble average streamflow for the 20C3M scenario.

#### **4.2 Hydrologic responses in the future**

Fig. 5 presents the weighted ensemble average FDCs of the annual and monsoon flows for the 20C3M, mid of the century and end of the century scenarios, from which some interesting observations can be drawn. Moderate (corresponding to 40-60% exceedance probability) and high (corresponding to 10% exceedance probability) streamflows at both annual and monsoon timescales show nominal increases for the mid of the century scenario, whereas low flows (corresponding to 90% exceedance probability) show some reduction in the future (Figs. 5a and 5b). Streamflow projections for the end of the century show an overall reduction in monsoon flows as seen from Fig. 5b. This may be attributed to the changes in the rainfall pattern projected towards the end of the century and an increase in the evaporation demand. Study conducted by Mehrotra *et al.* (2013) shows a plausible reduction in the number of short (2-4 days duration) and moderate (5-7 days duration) wet spells, whereas an increase in the rainfall amounts from short, moderate and long (more than 7 days duration) wet spells over the study area by the mid of the century. On the other hand, short (2-9 days duration) and moderate (10-18 days duration) dry spells are projected to increase under the future scenarios (Mehrotra *et al.*, 2013). Projected increase in the dry spells is likely to cause a reduction in the annual and monsoon low flows.

Using the weighted ensemble simulation, mean annual and monsoon flows are calculated for mid of the century and end of the century scenarios. In addition, annual and monsoon streamflow values corresponding to 10%, 90% and 95% exceedance probability are also estimated from the FDCs, which are given in Table 3. Since streamflow values with less than

10% exceedance probability indicate peak flows, years corresponding to the peak flows are called wet years. On the other hand, 90% and 95% dependable flows indicate lower annual flows, and the years in which annual average flow corresponds to 90% or 95% dependable flows are considered as the low flow years or dry years. The results show an increase in the average annual and monsoon flows in the mid of the century scenario. The study also shows an increase in peak flows as indicated by the increase in the annual and monsoon streamflow values corresponding to 10% exceedance probability. Accordingly, in the mid of the century more number of years are projected to have annual streamflow in excess of the current peak flow corresponding to 10% exceedance probability. In other words, more number of wet years are projected under the mid of the century scenario. Further, a reduction in the 90% and 95% dependable flows indicate an increase in the number of dry years. In other words, frequencies of both wet and dry years are projected to increase towards the mid of the century. Some of the previous studies analyzing the historic rainfall in the 20<sup>th</sup> century have also reported an increase in the wet and dry years in the changing climate conditions (Changnon, 1987; Sousa *et al.*, 2009).

Streamflow simulations for the end of the century scenario show some reduction in mean annual and monsoon flows corresponding to 10% exceedance probability, whereas no significant changes in the lower flows (90% and 95% dependability). This implies that frequency of wet years is likely to decrease towards the end of the century. These changes, however, are insignificant as indicated by the Mann-Whitney test. The test statistics and significance levels of the percentage changes in the mean annual and monsoon flows are presented in Table 4.

Although, the projected changes in mean annual and monsoon flows are not significant, the intra-annual variation of flows needs to be analysed. Box-whisker plots of the weighted ensemble average monthly flows for the 20C3M and the two future scenarios are shown in Fig. 6. These plots show some variations in the monthly flows during the monsoon period. Median and the 75 percentile flows are projected to increase in June while some reduction is noted during July and August under the future scenario. Close to 25% reduction in the streamflow is observed in July towards the end of the century. Being the peak sowing period

for the Kharif crops in India, any drop in the water availability in July in the future scenario may have adverse impact on the agriculture.

### **4.3 Climate change impact on water budget components**

Monthly hydrologic simulations of the catchment under the 20C3M and future scenarios are used to analyse the changes in other catchment water budget components as well. Variations in ET, irrigation demand and groundwater recharge are estimated under the projected climate conditions. Fig.7 shows the variations in streamflow and irrigation demand with the changes in rainfall and temperature. In general, an increase in rainfall causes an increase in streamflow. Rainfall projections from various GCMs vary from -10.9% to 8.4% with respect to the 20C3M scenario, whereas the streamflow projections vary from -20.6% to 9.0% towards the end of the 21st century (Fig. 7a). Likewise, the irrigation demand is projected to increase by 3.2% to 15.7% across various GCMs by the end of the 21st century (Fig. 7b). From Fig. 7a and 7b it can be observed that changes in the streamflow and irrigation demand are largely related to the variation in rainfall and the GCM. Nevertheless, small deviations may be observed, which may be attributed to the changes in  $T_{max}$  and  $T_{min}$  as shown in Fig. 7c to 7f. For example, using BCCR-BCM2.0 larger increases in irrigation demand towards the end of the century is projected, which may be attributed to the highest increase in  $T_{max}$  as shown in Fig 7.d. Likewise, results from CSIRO-mk3.5 project significant reduction in streamflow and increase in irrigation demand, which may be attributed to the combined effect of large increases in  $T_{max}$  and  $T_{min}$ , and significant reduction in rainfall.

Fig. 8 shows the catchment water budget components for the 20C3M scenario at the annual time scale as well as for the monsoon period. Evapotranspiration is the major abstraction from the rainfall amounting close to 70% annually and close to 45% during the monsoon period. Irrigation supplements the crop water demand to a large extent. Ground water recharge is the amount of water that reaches the shallow aquifer. A part of it appears as groundwater flow and contributes to the streamflow at the watershed outlet.

Percentage changes in the water budget components projected under the future scenario with respect to 20C3M scenario at the annual time scale are shown in Fig. 9 a. Weighted ensemble

average simulations show marginal increases in annual average rainfall under the future scenarios (2.2% towards the mid of the century and 1.6% towards the end of the century). Though the changes in the annual average rainfall are nominal, the variations in the rainfall pattern in terms of number and durations of wet and dry spells are of major concern.  $T_{\max}$  is projected to increase by 0.51 °C and 0.84 °C (1.8% and 2.9%) towards the mid of the century and end of the century, respectively. Similarly,  $T_{\min}$  is projected to increase by 0.29 °C and 0.46 °C (1.5% and 2.4%) towards the mid of the century and end of the century, respectively. With changes in temperature and rainfall pattern, evapotranspiration rates are projected to increase by 2.3% and 4.1%, respectively for the mid of the century and end of the century scenarios. Runoff ratio (ratio of average annual runoff to average annual rainfall) of the catchment is found to be 0.4184, 0.4178 and 0.4083 for 20C3M, mid of the century and end of the century scenarios, respectively. The 2.5 % reduction in the runoff ratio shows 1.2% reduction in the annual average streamflow towards the end of the century. In addition, groundwater recharge rates are also projected to decline (by 7.3%) towards the end of the century.

The projected variations in the water budget component may be attributed to the increase in the temperature as well as the changes in the rainfall pattern in the catchment under the future scenarios. The upper catchment is under tropical humid zone, whereas the lower catchment is under semi-arid agro-climatic zone with limited moisture availability. Increase in precipitation and temperature therefore results in increase in evapotranspiration from the catchment and consequently increase in the irrigation demand. Projected increases in the short and moderate rainfall events are likely to cause more infiltration into the soil layer. Thus, a relatively less fraction of rainfall would appear as streamflow at watershed outlet. On the other hand, projected increases in the short and moderate dry spells results in more soil moisture extraction to meet the increased evapotranspiration rates, thereby reducing the groundwater recharge.

Monsoon rainfall being the source of water for the catchment, projected changes in the water budget components during the monsoon season is also studied (Fig. 9 b). During the monsoon period the rainfall is projected to decline by 1.4 % towards the end of the century. Reduction

in the rainfall together with the increase in the temperature is projected to result in 18.5% increase in the irrigation demand during the monsoon period. In addition, streamflow is also projected to decline under the future scenarios. The analysis shows that percentage changes in the water budget components are more during the monsoon period. This may be attributed to the changes in the rainfall distribution in the form of reduction in the short and moderate wet spells and increase in the dry spells. The projected increase in irrigation demand when combined with the likely reduction in the recharge would aggravate the water scarcity problems of the area, which is already identified as a groundwater overexploited region.

## **5. Summary and conclusions**

This study explores the impacts of climate change on the hydrology and water budget components of the Malaprabha catchment for two future periods (mid of the 21<sup>st</sup> century, 2046 - 2065, and end of the century, 2081-2100). In order to address the uncertainty issues that arise from the use of a single GCM, an ensemble of 5 GCMs (MPI-ECHAM5, BCCR-BCM2.0, CSIRO-mk3.5, IPSL-CM4, and MRI-CGCM2) is used in this study. Large scale climate variables simulated by the GCMs are first bias corrected using the NBC approach, and are used to downscale rainfall and meteorological variables at the catchment level using MMM-KDE model. Rainfall and meteorological variables downscaled from each of the 5 GCMs are used as input to a conceptual hydrological model and the corresponding hydrological components for current and future climate scenarios are simulated. Hydrologic simulations using inputs from various GCMs are evaluated for their ability to simulate the hydrologic responses for the 20C3M scenario, and the weights are assigned accordingly. Weighted ensemble average outputs are used to analyze the changes in hydrologic components under the future scenarios. Not many studies have attempted similar kind of work for Indian catchments. The limited data availability and the large scale heterogeneity in the catchment characteristics often hinders such studies. Standing within the constraints of data availability, the study is an efforts to analyse the hydrologic sensitivity of the catchment under the projected climate change scenarios. This would be a stepping stone to understand the climate change vulnerability of the catchment.

The results show only marginal changes in annual average rainfall in the catchment under the future scenarios. Corresponding changes in the hydrologic components are also found to be statistically insignificant both for the annual and monsoon periods. Even though the changes in the streamflow and irrigation demand are strongly related to the variation in rainfall, they are not directly proportional to each other. Such deviations may be attributed to the GCMs used, as well as the changes in rainfall pattern and atmospheric temperature. With 0.84°C and 0.46°C increases in the daily maximum and minimum temperatures towards the end of the century, evapotranspiration rate is projected to increase by 4.1%, irrigation demand is projected to increase by 18.5% and groundwater recharge is projected to decline by 7.3%. Streamflow projections for the end of the century scenario show nominal reduction in the average annual and monsoon flows. Changes in rainfall and temperatures are projected to reduce the runoff ratio by 2.5% by the end of the century. Projected increase in the evapotranspiration and irrigation demand, associated with the decrease in the groundwater recharge and streamflow is an indication of possible aggravation of the water stress in the catchment in future.

Hydrological analyses to investigate the impact of climate change on the catchment water balance are affected by the uncertainty in the climate projections, as well as the uncertainty in the hydrological model itself. In order to reduce the uncertainty in the climate projection, in the present study an ensemble of GCMs included in the CMIP 3 data sets are used to derive the climate projections. On the other hand, uncertainty in the hydrological model still persists. Even though the streamflow simulations are validated with respect to the observed data, lack of sufficient observed data for the catchment restricts the validation of the other water budget components. The use of an ensemble of hydrological models may help to address this issue to some extent. Nevertheless, as reported in literature (Wolock and McCabe, 1999; Arnell and Liv, 2001), the study help to indicate the sensitivity of the hydrologic systems to the climate change. Further analysis using CMIP5 models and representative concentration pathways might help to further understand the impact of climate change projections over the region.

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Fig. 4. Simulated Flow-Duration Curves of the annual and monsoon flows for the 20C3M scenario

Fig. 5. Weighted ensemble average projections of the annual and monsoon streamflows for the 20C3M, mid of the century and end of the century scenarios

Fig. 6. Comparison of the weighted average monthly flows for the 20C3M scenario and the future time periods. In the box plot, upper and lower hinges represent the 75 and 25 percentiles, respectively. The whiskers show the other data points except the outliers. The line within the box shows the median

Fig. 7. Relationship between the projected changes in streamflow and irrigation demand with projected changes in the climate from the 5 GCMs

Fig.8 Water budget components in the Malaprabha catchment for the 20C3M scenario

Fig. 9. Percentage changes in the future water budget components with respect to the 20C3M scenario

Table 1. Performance evaluation index of ArcSWAT in calibration and validation phases

MARE		
Phase	Annual	Monsoon
Calibration	0.094	0.072
Validation	0.070	0.084

Table 2. MARE values of the GCMs for the 20C3M scenario and the corresponding weights

	MRI- CGCM2	BCCR- BCM2.0	CSIRO- mk3.5	IPSL- CM4	MPI- ECHAM5
Annual MARE	0.039	0.081	0.095	0.063	0.068
Monsoon MARE	0.066	0.064	0.109	0.132	0.058
Weight	0.28	0.20	0.14	0.15	0.23

Table 3. Annual and monsoon flow statistics simulated using the 5 GCMs for the 20C3M scenario and the future time periods for the A2 scenario

		Flow statistics (M.cu.m)*							
GCM	Scenario	Annual				Monsoon			
		1	2	3	4	5	6	7	8
MRI- CGCM2	20C3M	1028.5	1427.2	673.1	630.1	796.6	1143.9	480.4	425.8
	<i>Mid of the century</i>	<i>1038.1</i>	<i>1441.8</i>	<i>668.3</i>	<i>605.8</i>	<i>793.1</i>	<i>1156.3</i>	<i>467.0</i>	<i>404.8</i>
	<b>End of the century</b>	<b>1064.3</b>	<b>1459.1</b>	<b>736.7</b>	<b>685.1</b>	<b>768.5</b>	<b>1096.9</b>	<b>494.9</b>	<b>444.6</b>
BCCR- BCM2.0	20C3M	1050.9	1492.1	616.3	551.4	825.5	1233.9	446.0	381.2
	<i>Mid of the century</i>	<i>1145.0</i>	<i>1809.5</i>	<i>508.2</i>	<i>432.8</i>	<i>871.4</i>	<i>1434.5</i>	<i>307.9</i>	<i>246.5</i>
	<b>End of the century</b>	<b>1145.5</b>	<b>1560.6</b>	<b>759.3</b>	<b>703.6</b>	<b>924.1</b>	<b>1313.4</b>	<b>574.8</b>	<b>522.6</b>
CSIRO- mk3.5	20C3M	1002.2	1490.0	534.7	445.8	786.0	1239.9	379.8	305.9
	<i>Mid of the century</i>	<i>991.1</i>	<i>1449.0</i>	<i>533.7</i>	<i>457.5</i>	<i>791.8</i>	<i>1203.5</i>	<i>383.4</i>	<i>314.6</i>
	<b>End of the century</b>	<b>795.3</b>	<b>1251.7</b>	<b>373.2</b>	<b>332.2</b>	<b>610.8</b>	<b>1031.4</b>	<b>242.3</b>	<b>205.4</b>
IPSL- CM4	20C3M	964.0	1363.5	584.2	509.6	744.4	1098.0	412.8	346.6
	<i>Mid of the century</i>	<i>994.5</i>	<i>1438.7</i>	<i>582.2</i>	<i>535.1</i>	<i>777.6</i>	<i>1170.2</i>	<i>388.4</i>	<i>334.4</i>
	<b>End of the century</b>	<b>986.4</b>	<b>1389.2</b>	<b>593.6</b>	<b>537.5</b>	<b>731.7</b>	<b>1097.3</b>	<b>401.0</b>	<b>343.8</b>
MPI- ECHAM5	20C3M	1057.3	1517.8	643.8	598.0	838.2	1242.2	461.4	414.3
	<i>Mid of the century</i>	<i>1087.0</i>	<i>1574.9</i>	<i>657.4</i>	<i>553.9</i>	<i>864.3</i>	<i>1292.1</i>	<i>489.3</i>	<i>401.9</i>
	<b>End of the century</b>	<b>987.7</b>	<b>1392.0</b>	<b>587.9</b>	<b>546.7</b>	<b>749.7</b>	<b>1110.8</b>	<b>394.9</b>	<b>350.9</b>
Weighted average	20C3M	1026.3	1460.5	622.1	562.8	802.7	1191.4	444.8	385.4
	<i>Mid of the century</i>	<i>1057.6</i>	<i>1546.6</i>	<i>601.8</i>	<i>527.6</i>	<i>822.7</i>	<i>1252.1</i>	<i>416.7</i>	<i>349.2</i>
	<b>End of the century</b>	<b>1013.0</b>	<b>1424.0</b>	<b>633.9</b>	<b>584.7</b>	<b>767.4</b>	<b>1134.2</b>	<b>437.9</b>	<b>389.6</b>

\* 1)Average annual flow 2) Annual streamflow corresponding to 10% exceedance probability  
3) 90% dependable annual flow 4)95% dependable annual flow 5) Average monsoon flow  
6) Monsoon streamflow corresponding to 10% exceedance probability 7) 90% dependable  
monsoon flow 8)95% dependable monsoon flow

Table 4. Mann-Whitney test statistics for the percentage change in the mean annual and monsoon flows in the future

	Mid of the century		End of the century	
	Annual flow	Monsoon flow	Annual flow	Monsoon flow
Test statistic	0.19	0.10	0.10	0.10
Significance level ( $\alpha$ )	0.849	0.92	0.92	0.92

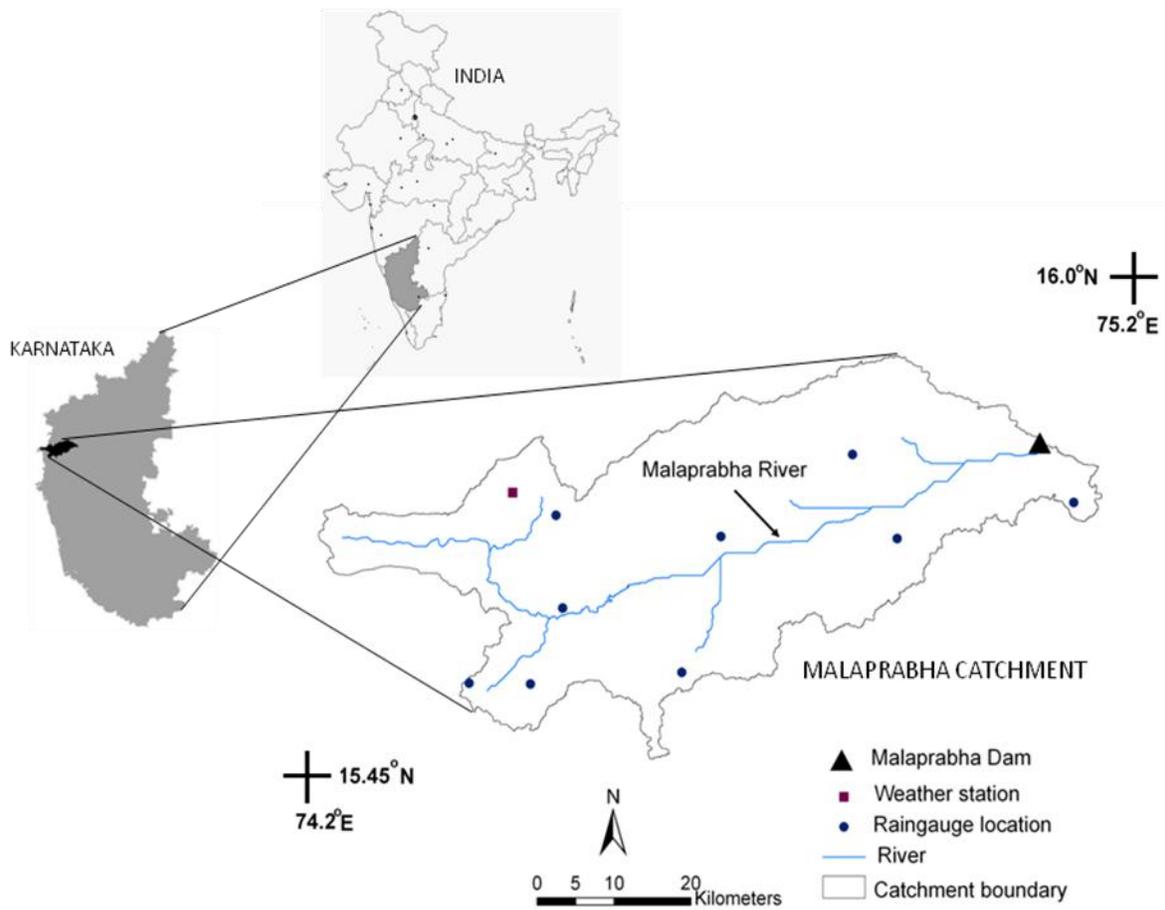


Fig. 1. Location map of the Malaprabha catchment

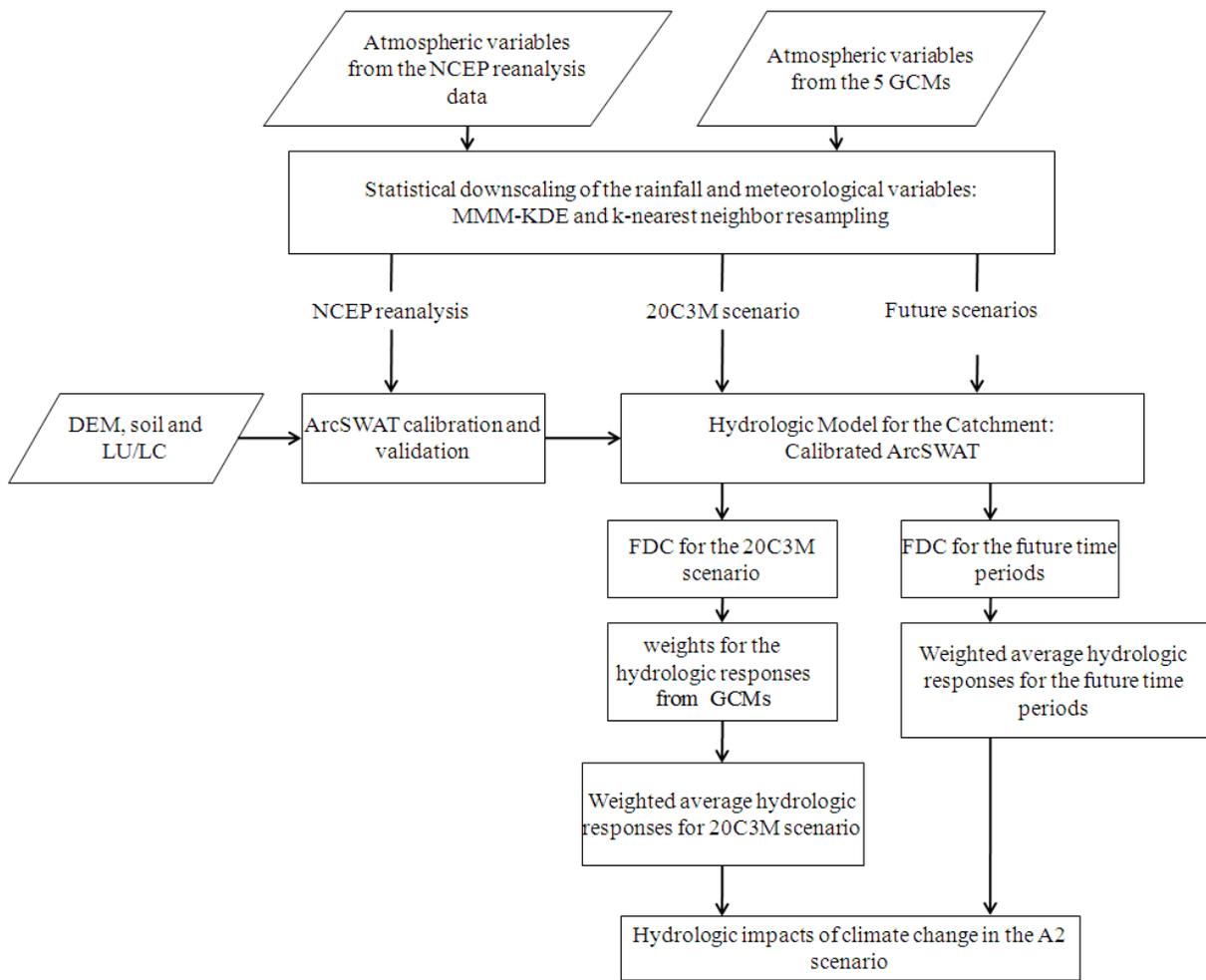


Fig.2 Schematic representation of the methodology

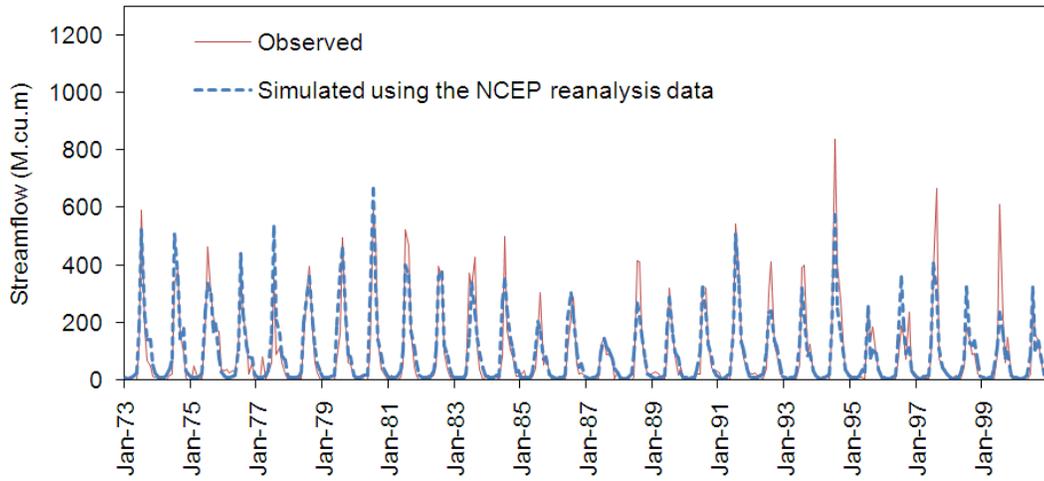


Fig. 3. Comparison of the monthly streamflow hydrograph simulated using the rainfall and meteorological variables downscaled from the NCEP reanalysis data with the observed data

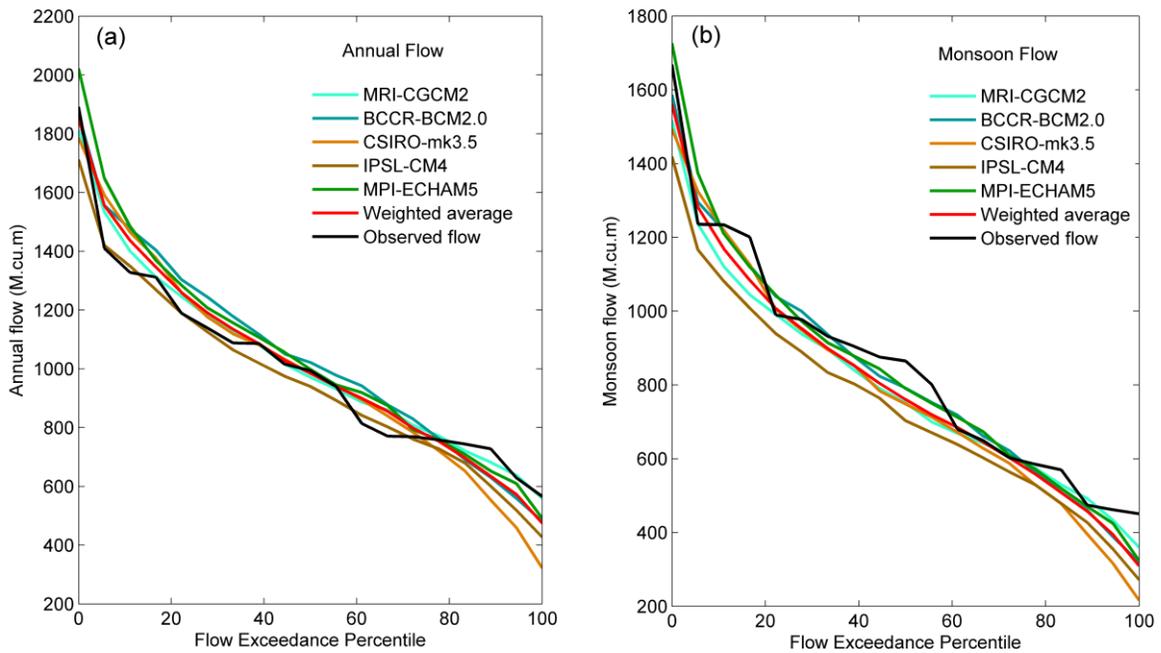


Fig. 4. Simulated Flow-Duration Curves of the annual and monsoon flows for the 20C3M scenario

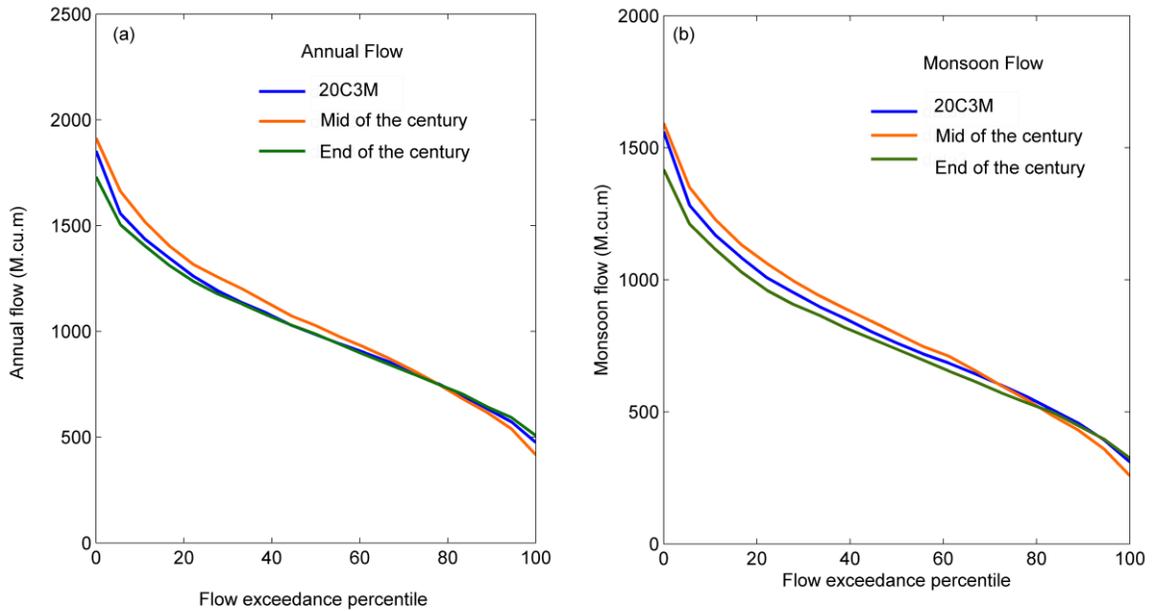


Fig. 5 Weighted ensemble average projections of the annual and monsoon streamflows for the 20C3M, mid of the century and end of the century scenarios

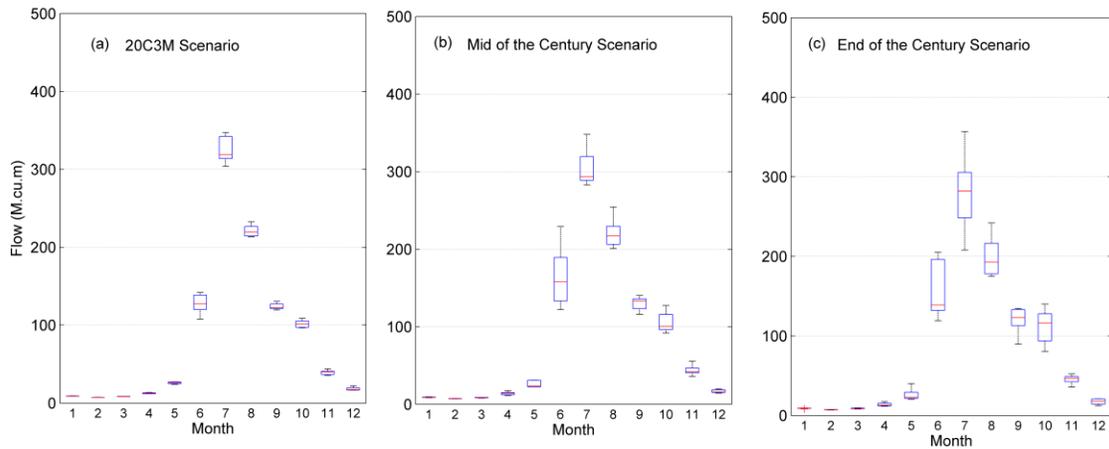


Fig. 6 Comparison of the weighted average monthly flows for the 20C3M scenario and the future time periods. In the box plot, upper and lower hinges represent the 75 and 25 percentiles, respectively. The whiskers show the other data points except the outliers. The line within the box shows the median

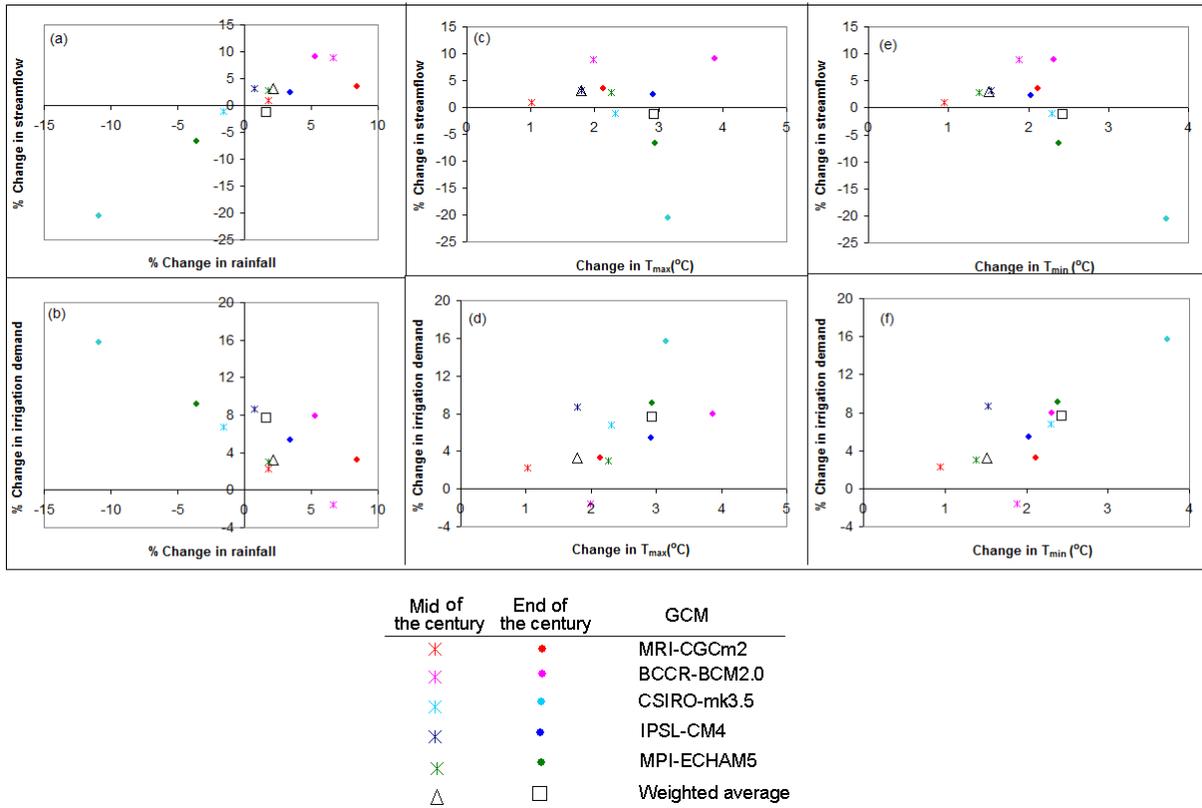


Fig. 7 Relationship between the projected changes in streamflow and irrigation demand with projected changes in the climate from the 5 GCMs

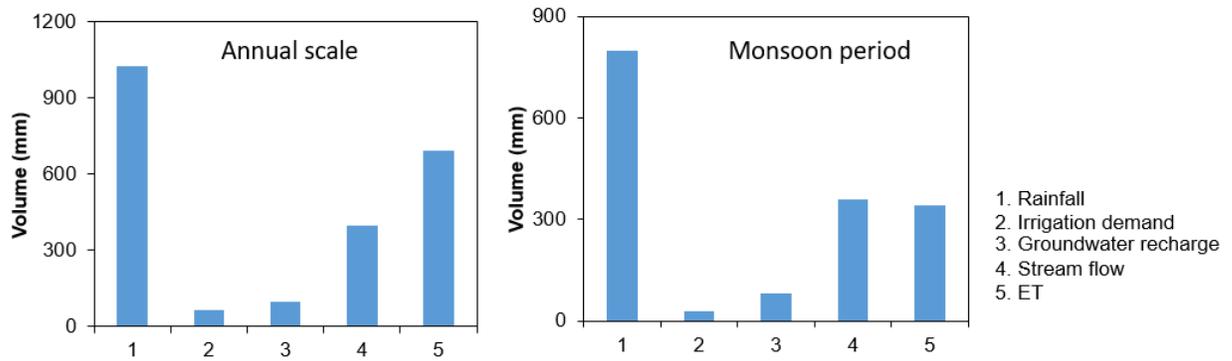


Fig.8 Water budget components in the Malaprabha catchment for the 20C3M scenario

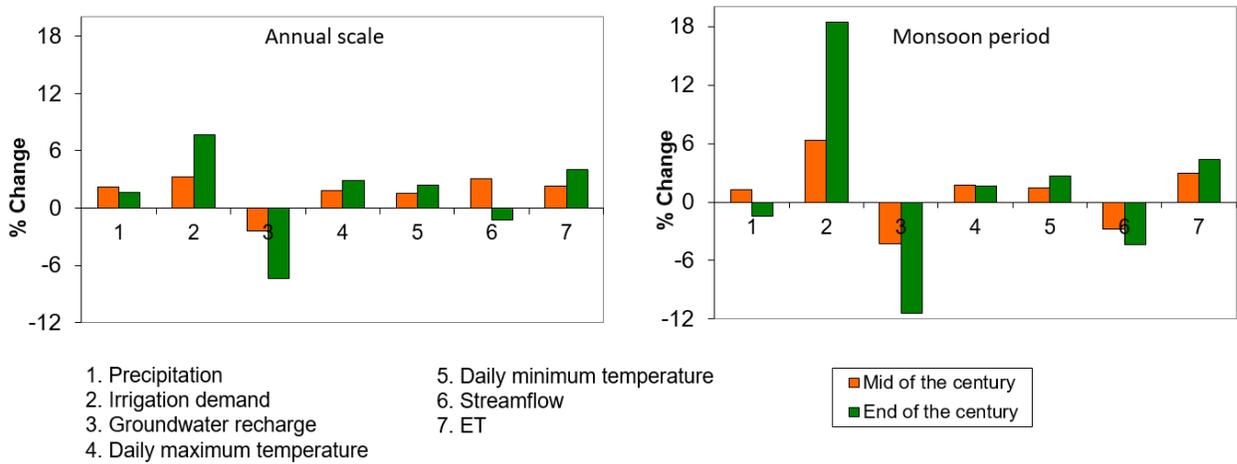


Fig. 9 Percentage changes in the future water budget components with respect to the 20C3M scenario