



Impacts of Climate Change on Regional Water Resources

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Abstract | Water is the most important medium through which climate change influences human life. Rising temperatures together with regional changes in precipitation patterns are some of the impacts of climate change that have implications on water availability, frequency and intensity of floods and droughts, soil moisture, water quality, water supply and water demands for irrigation and hydropower generation. In this article we provide an introduction to the emerging field of hydrologic impacts of climate change with a focus on water availability, water quality and irrigation demands. Climate change estimates on regional or local spatial scales are burdened with a considerable amount of uncertainty, stemming from various sources such as climate models, downscaling and hydrological models used in the impact assessments and uncertainty in the downscaling relationships. The present article summarizes the recent advances on uncertainty modeling and regional impacts of climate change for the Mahanadi and Tunga-Bhadra Rivers in India.

Keywords: *Climate Change, Statistical Downscaling, GCM, Uncertainties.*

1 Introduction

Global climate change has serious implications for water resources and regional development due to inextricable link between **climate** and water resources.¹ **Climate change** refers to systematic change in the long-term statistics of climate variables such as temperature, humidity, atmospheric pressure and wind of a given region.

Climate change is the variation in the mean and variability of global climate over time scales ranging from decades to millions of years for a particular region. Climatic change can be caused by internal forces such as volcanic eruptions, ice sheet changes, CO₂ increases and deforestation, and/or external forces such as variations in solar radiation or, more recently, by human activities. Climate change describes changes in the global temperature over time (i.e., increase in global temperature or global warming) and its consequences on other climatic variables, such as pressure, humidity, wind etc. One of the major causes of global warming is the emission of **greenhouse gases** due to **anthropogenic activities**.¹ The

increase in global surface temperature in the past century is about $0.74 \pm 0.18^\circ\text{C}$, from 1906–2005. According to the Intergovernmental Panel on Climate Change² the observed increase in temperature since the middle of the 20th century was caused by increasing concentrations of greenhouse gases resulting from human activity such as fossil fuel burning and deforestation.

The General Circulation Models (GCMs) are the climate models that provide simulations of the global climate system. These are computer-driven models designed to represent the physical processes in the atmosphere, ocean, cryosphere and land surface. They describe the climate using a three dimensional grid over the globe typically having a horizontal resolution of between 250 and 600 km, 10 to 20 vertical layers in the atmosphere and sometimes as many as 30 layers in the oceans.² The GCMs are numerical models that analyze the atmosphere on an hourly basis in all three-dimensions based on the law of conservation of energy, mass, momentum and of water vapor and ideal gas law. The GCMs are the most credible

Climate: Climate is usually defined as the average weather or as the statistical description in terms of mean and variability of meteorological variables such as temperature, humidity, atmospheric pressure, wind and rainfall in a given region over long periods of time ranging from months to thousands or millions of years.

Climate change: Any systematic change in the long-term statistics of climate elements (such as temperature, pressure, or winds) sustained over several decades or longer.

Greenhouse gases: Gases in the atmosphere that absorb and emit radiation within the thermal infrared range, e.g., water vapor, carbon dioxide, ozone, methane, nitrous oxide, and chlorofluorocarbons. These gases are fairly transparent to the short wavelengths of solar radiation but efficient at absorbing the longer wavelengths of the infrared radiation emitted by the earth and atmosphere and thus increase the global temperature.

Anthropogenic activities: Human activities as a result of which climate change occurs.¹

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General circulation models:

Atmospheric time-dependent numerical models. The governing equations include the conservation laws of physics expressed in finite-difference form, or finite-element form or spectral form. Model circulation is computed by time integration of these equations starting with an initial condition.

Evapotranspiration:

Evapotranspiration refers to the process by which water is simultaneously lost through evaporation from the soil and transpiration from the plants.

Climate change impact assessment:

Studies that attempt to evaluate or predict the impact of climate change on physical and ecological systems, human health, and socioeconomic sectors (Source: American Meteorological Society).

Predictor and predictand:

In the statistical downscaling methodology, the regional hydrologic variable to be predicted is called predictand and the climatic variables used as input to model the predictand are called predictors.

Base flow: Base flow is the initial flow of the stream before the rain comes. It is the delayed flow that reaches a stream essentially as ground water flow.

tools designed to simulate time series of climate variables globally, accounting for the greenhouse gases in the atmosphere. The GCMs project the global average temperature increase as more than 4°C, with respect to the temperature during 1980–99.² The projections of climate variables provided by the GCMs are used to predict projections of other regional variables, such as precipitation and **evapotranspiration** in the **climate change impact assessment** studies. GCMs operate at a coarse spatial resolution of 2.5° latitude X 2.5° longitude, and are generally used for weather forecasting, understanding climate, and projecting climate change. Predictability of the GCMs decreases from climate variables (e.g., temperature, wind, humidity and air pressure) to hydrologic variables (e.g., precipitation, runoff, soil moisture, and evapotranspiration) which are also simulated by the GCMs. Such limitations of the GCMs restrict the direct use of their output in water resources impact assessment studies.

In this context, there is a need to convert the GCM outputs into hydrologic variables (e.g., precipitation and streamflow) at regional scale to study the climate change impacts on surface water resources system. Modeling of hydrologic variables at a finer scale based on the coarser scale GCM outputs is an important step in hydrological impact assessment studies and is known as downscaling. Statistical downscaling techniques are generally applied to obtain the projections

of hydro-meteorological variables (e.g., rainfall, streamflow, air temperature, relative humidity, wind speed) at a finer scale based on coarser scale climatic variables (e.g., mean sea level pressure, wind speed) simulated by a GCM. It involves downscaling the projections of climatic variables, generally referred as **predictors**, (e.g., temperature, humidity, mean sea level pressure etc.) to hydrologic variables, generally referred as **predictands**, (e.g., precipitation and streamflow), at regional scale. Development of procedures and methodologies to downscale regional hydrologic variables in water resources impact assessment has been an important area of research in the past decade.^{3–6} One of the major current interests among the water resources research community is the development of a suitable modeling framework to quantify the water resources management impacts due to climate change (based on GCM outputs) using appropriate downscaling methodologies.

Figure 1 shows a typical water resources system, where the reservoir serves the purpose of hydropower generation, irrigation, industrial and municipal water supply, and flood control. The surface water system is hydrologically complemented by the ground water through **base flow**. There may be effluent dischargers, including industries and municipalities that use assimilative capacity of the river to discharge wastes according to the regulations and standards of the pollution control boards. The storm runoff which

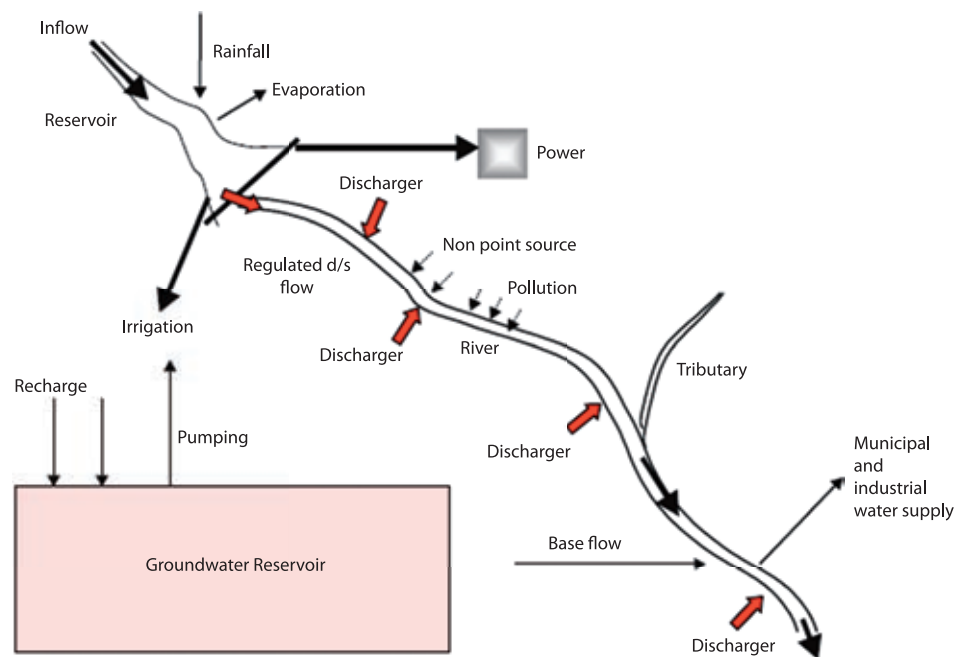


Figure 1: A regional water resources system with components impacted by climate change. Source: Mujumdar,¹⁶ Copyright by Infrastructure Development Finance Company (IDFC) (reproduced with permission).

may gather pollutants (e.g., pesticides and fertilizers used in the agricultural practices) acts as non-point source of pollution to the river. The downstream water quality of the river is governed by the release from the reservoir, the intermediate withdrawals and the effluent discharges. Increased evaporation, resulting from higher temperatures, together with regional changes in precipitation characteristics (e.g., total amount, variability, and frequency of extremes), has the potential to affect the runoff, frequency and intensity of floods and droughts, soil moisture, water quality, water supplies and water demands for irrigation and hydropower generation as shown in Figure 1. It is prudent to examine the anticipated impacts of climate change on these different components, individually or combinedly, at regional scales, with a view to develop optimal policies to minimize the climate change induced risk in water resources systems. Hydrologic impact assessment studies on water resources management and deriving operating policies by combining statistical downscaling models and climate scenarios is currently a vital area of research.^{7,8}

Several authors carried out extensive studies in the field of the hydrologic impacts of climate change on Indian river basins.^{9–12} The impact of climate change on the water resources of Indian river systems is carried out by Gosain et al.⁹ using the HadRM2 daily weather data with a distributed hydrological model namely SWAT (Soil and Water Assessment Tool). The results of the study reveal that under green house gas scenario, severity of droughts and intensity of floods in various parts of the country may get deteriorated. River basins of Cauvery, Ganga, Narmada and Krishna may experience seasonal or regular water-stressed conditions. River basins of Godavari, Brahmani and Mahanadi may not have water shortages but are predicted to face severe flood conditions. Salvi et al.¹² used a statistical downscaling methodology based on classification and regression tree, and kernel regression to develop the projections all-India monsoon rainfall at a resolution of 0.5° in latitude/longitude. The results of this study reveal a possible increase in rainfall for the western coastline and northeastern India and a decrease in northern India, western India, and on the south-eastern coastline.

The hydrological impact assessment studies of climate change based on downscaling of GCM outputs are subjected to various uncertainties including the choice of GCM, **greenhouse gas emission scenario**, downscaling methods and hydrological models used for impact assessment. GCM uncertainty is due to the inadequate information about

the underlying geophysical processes of climate change, variability in the internal parameterizations of each GCM.¹³ Further, GCMs may simulate quite different responses to the same forcing, simply because of the way certain processes and feedbacks are modeled.² The downscaled projections with a single climate model under a particular scenario represents a single trajectory among a number of realizations derived using various scenarios with climate models. Such single trajectory alone may not represent the future climate change scenario and will not be useful in the impact assessment studies. This leads to significant dissimilarity between the projections derived with multiple climate models. Use of multiple climate models and emission scenarios leads to multiple ensembles and may not be useful in decision making in water resources planning and management. Climate change projections may also vary with the downscaling methodology leading to uncertainty due to multiple downscaling methods. Such uncertainties of future climate can be the most important barriers for climate change adaptation. Therefore, there is a need to develop methodologies for addressing uncertainty in the future climate in terms of GCM and scenarios, and downscaling methodologies in the regional water resources modeling. In this context, climate model uncertainty is increasingly being addressed by assigning weights to GCMs to derive a weighted mean projections,^{14,15} which can be useful to study the policy implications.

The present research article explores some of the recent studies carried out in the field of climate change impact assessment on water availability, water quality and irrigation demands and the integrated impact assessment models in the context of uncertainty quantification using the results from case studies namely, Mahanadi and Tunga-Bhadra River basins in India.

2 Climate Change Impacts on Water Availability

The investigations of regional and global climatic changes and variabilities and their impacts on water availability have received considerable attention in recent years. The impact of global climate change on water availability needs to be assessed at river basin scales.

In the study of Ghosh and Mujumdar,⁵ the decrease in the monthly peak flow of Mahanadi river is observed. The future monsoon streamflow projections are obtained using a relevance vector machine (RVM) with fuzzy clustering from GCM projections of large scale climatological data of surface air temperature at 2 m, mean sea level pressure, geopotential height at a pressure level of

Greenhouse gas emission:

Greenhouse gas emissions are the resultant of very complex dynamic systems, determined by driving forces such as demographic development, socio-economic development, and technological change.

Scenario: "A scenario is a coherent, internally consistent and plausible description of a possible future state of the planet"²

500 hecta Pascal (hPa) and surface specific humidity. The GCM considered for the projection of future streamflows is that of Center for Climate System Research/National Institute for Environmental Studies (CCSR/NIES), Japan, with B2 scenario.

Figure 2 shows the box plots for the monsoon streamflow for the current periods and for the future scenarios of 2020s, 2050s, and 2080s down-scaled using GCM outputs. The box plot represents the median (red horizontal line in the box plot), upper and lower quartiles and the outliers. The upper and the lower edge give 75 percentile and 25 percentile of the data set respectively. The results of their study reveal that although there is no significant change in median (red horizontal line in the box plot) of the monsoon flow, the occurrence of high flows will reduce significantly due to high surface warming, and therefore there is a decreasing trend in the monthly peak flow. This may be due to the insensitivity of climate variables towards low flows because of significant

ground water component, and therefore only the effect on high flow is reflected. Such a decrease in water availability may cause a critical situation for Hirakud reservoir in meeting the projected water demands.

Figure 3 shows the flow duration curves for monsoon streamflows for current and for future scenarios for 2045–2065 and 2075–2095 periods for the Mahanadi river in East-Central India, for the range of GCM-scenario combinations.¹⁷ The Flow duration curves are often used to characterize the river discharge, which relates flow magnitude to the percentage of time that it is equaled or exceeded in the record. The flow duration curves are generally used to describe the river discharge by specifying the flow that may be exceeded at a given level of probability. The conditional random field (CRF)-downscaling model is used with fourth Assessment Report (AR4) projections. This informative means of streamflows will be used in the hydrologic design of dams, bridges, culverts

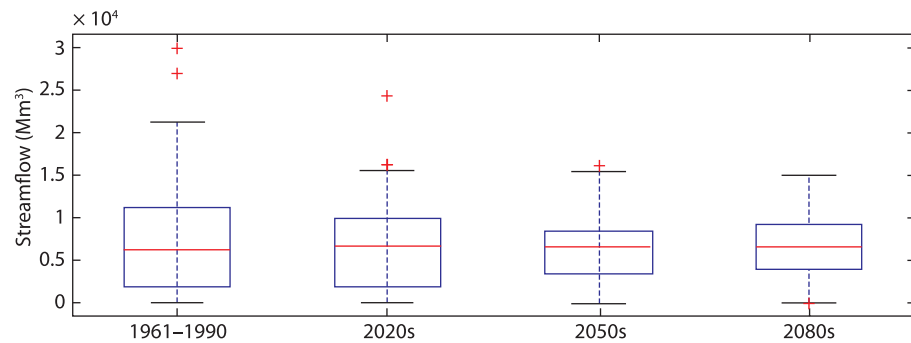


Figure 2: Monsoon streamflow projections of Mahanadi River at Hirakud.
Source: Ghosh and Mujumdar.⁵

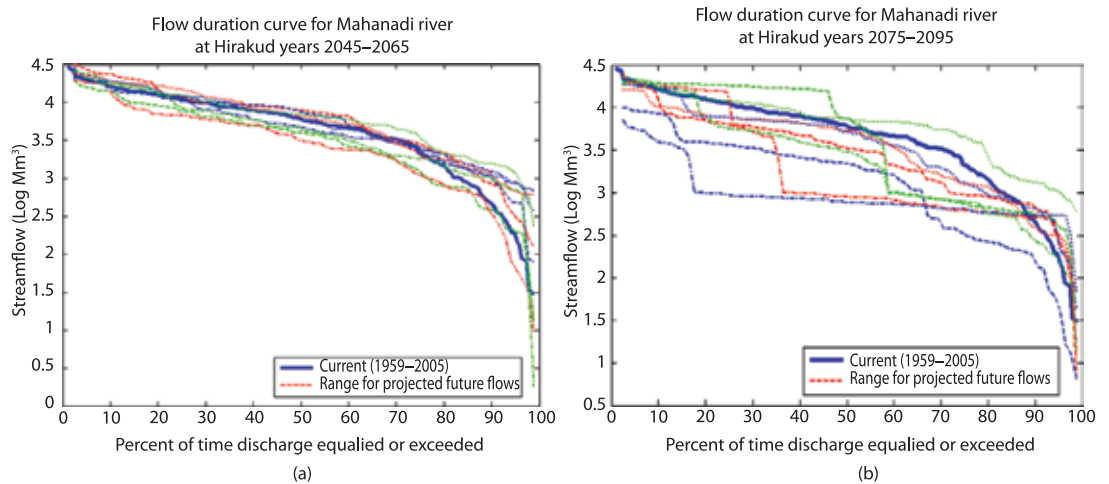


Figure 3: Range of projected future flow duration curve for Mahanadi river for two time slices, 2040–65 and 2075–95.
Source: Raje and Mujumdar.¹⁷

and stormwater drainage network etc. In Figure 3 the dark blue curve represents the flow duration curve for the case of the historical data. The other curves show projected flow duration curves under climate change scenarios.

There is a decrease in the mid level flows (flows that are exceeded 20–70 percent of the time) for most future scenarios, which govern the performance of the water users. High flows are predicted to increase for most scenarios for 2040–65, whereas low flows show a slight increase for 2040–65 (flows that are exceeded 80 percent of the time) but a smaller range of low flows increase for 2075–95 (above 90 percent flows only). It is important to use such projected streamflow information to develop reservoir operating policies. Raju and Mujumdar¹⁷ used the flow duration curves as shown in Figure 3 to derive reservoir operating policies for Hirakud reservoir to best maintain the reliability of hydropower generation at the current level, considering trade-offs between hydropower, irrigation, and flood control. In their study, the climate change impact on reservoir performance is studied for the ‘business-as-usual’ case and with optimal operating policies. Climate change impacts on monthly power generation and four performance criteria (reliability, resiliency, vulnerability, and deficit ratio) are studied with the standard operating policy (SOP). The optimal operation has shown a decrease in hydropower and increase in vulnerability for the future. The climate change will have a significant impact on the reservoir performances showing decrease in reliability and increase in vulnerability for future scenarios. The results of their study reveal that by marginally sacrificing reliability with respect to irrigation and flood control, hydropower reliability and generation can be increased for future scenarios. The possible decrease in inflow to the Hirakud reservoir suggests revising the reservoir rules accounting for climate change. To overcome situations of water deficiencies, policy makers have to pay significant attention towards the reallocation of available water resources to improve overall benefits of the reservoir under climate change. Summarily, the climate change is likely to affect the reservoir performance significantly, changes in the reservoir operation for the future scenarios is unable to restore the past performance levels.

The general procedure involved in the quantification of hydrologic impact assessment studies on water availability, based on GCM outputs, is the first to downscale the hydrological variables such as precipitation, temperature at regional scale. Next, the climate change projections are input into a hydrologic model to simulate future

scenarios to represent the future streamflow variability compared to the historical flows. Finally, such assessments can be used to formulate long-term planning and infrastructural decisions. In the study of Meenu et al.,¹⁸ the possible future climate change impacts on the hydrology of the catchment area of the Tunga-Bhadra river is evaluated. Their study used SDSM (Statistical Down-Scaling Model) 4.2 to downscale the maximum and minimum temperature and daily mean areal precipitation in the four sub-basins of the study area. The downscaled temperature and precipitation projections obtained from SDSM are input to a HEC-HMS (Hydrologic Engineering Center’s Hydrologic Modeling System version 3.4) to derive the future streamflows at the outlet of the basin. The streamflow is predicted to increase by 46% in 2080s in accordance to increase in precipitation projections by 28% with HadCM3 (Hadley Climate Model 3), A2 scenario for Tunga-Bhadra river catchment area.

3 Climate Change Impacts on River Water Quality

The climate and fresh water systems are closely related and the water quality will be influenced by various climatic factors, including air temperature, precipitation and occurrence of extreme events.¹⁹ The river water quality is influenced because of changes in river water temperature due to changes in climatic variables (e.g., air temperature, humidity, solar radiation, wind speed). Pronounced increase in river water temperature drives the rates of biological and chemical processes, affecting the reaction kinetics. An increase in river water temperature decreases the oxygen holding capacity, causing a decrease in **Dissolved Oxygen** (DO) concentration, which directly affects the self-purification capacity of the river system. Another dominant factor affecting the river water quality is streamflow, which defines the pollutant transport and dilution of nutrients and pollutant loads. Future expected risk of **Low Water Quality** (LWQ) has to be quantified by considering the climate induced changes in river water temperature and streamflow in river water quality management as discussed in Rehana and Mujumdar.²⁰ The large-scale GCM climate projections are downscaled to predict the future hydro-meteorological variables at regional scale of interest. A multivariable downscaling methodology based on principal component analysis and Canonical Correlation Analysis (CCA) is used to downscale the hydro-climatic variable (inflow, rainfall, maximum and minimum temperatures, relative humidity, and wind speed) projections. The CCA downscaling methodology

Dissolved oxygen: It refers to the concentration of oxygen gas absorbed by water from atmosphere. Sufficient DO is essential to growth and reproduction of aerobic aquatic life.

Low water quality: The situation when the DO level is less than a specified value it is considered as Low Water Quality (LWQ) event and is represented as a failure of the river system.

is adopted to relate the surface-based observations and atmospheric variables to obtain a simultaneous projection of hydro-meteorological variables. The projected hydro-meteorological variables are used in the water quality simulation model to examine the impact on the river water quality. The river water temperature is modeled by using an analytical temperature model^{21,22} that includes the downscaled hydro-meteorological variables. Even though the river water temperature depends on many factors including human modifications such as waste water inputs or by ground water inflows, the ambient climate variables affected by climate change will also play a significant role. The river water temperature is projected to increase under Model for Interdisciplinary Research on Climate (MIROC) 3.2 medium resolution (Center for Climate System Research, Japan) GCM with A1B scenario with increasing trends of temperature variables and minor changes of wind speed and relative humidity along the Tunga-Bhadra river basin. The projections of streamflow and water temperature are used in the prediction of water quality threshold exceedance of DO and then to quantify the likelihood of the risk of the low water quality. The occurrence of LWQ for a specified threshold, conditioned on future projections of streamflow and temperature is considered as projected risk of LWQ or climate induced risk.

A significant decreasing trend is observed for streamflow at various locations along Tunga-Bhadra river basin. For example, Figure 4 shows the box plots of observed and predicted streamflow from GCM for Shimoga along Tunga river. Figure 4(a) gives the validation of the GCM predicted data with the observed data in training the downscaling model and Figure 4(b) shows the future projections with the GCM. The horizontal line in the middle of the box represents the median. The star denotes the mean value of the period under consideration while the line

connecting the stars depicts the mean trend of Streamflow projected by GCM. The projected decrease in streamflow and increase in river water temperature is causing a significant impairment of water quality with decrease in DO levels. Figure 5 shows the observed and future simulated DO levels for 30-year time slices (2010–2040, 2040–2070 and 2070–2100) at checkpoints 1 and 10 along the river stretch (for details of the case study and the methodology see Rehana and Mujumdar).²⁰ These check points refer to the locations along the river stretch under consideration at which the river water quality is estimated for current and for future scenario.

The remaining check points along Tunga-Bhadra river are also showing significant decrease in DO levels. For example, at checkpoint 5 where the current DO level is at 6.80 mg/L it may go down to 5.60 mg/L in 2080s, even though this checkpoint is not immediately downstream of a discharge. This is due to the reduced dilution capacity and low water velocities derived from the reduced streamflows and also due to the changes in reaction rates derived from the increase in water

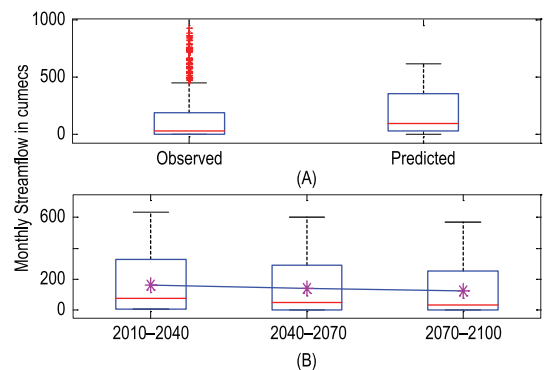


Figure 4: Streamflow projections at Shimoga along Tunga River.
Source: Rehana and Mujumdar.²⁰

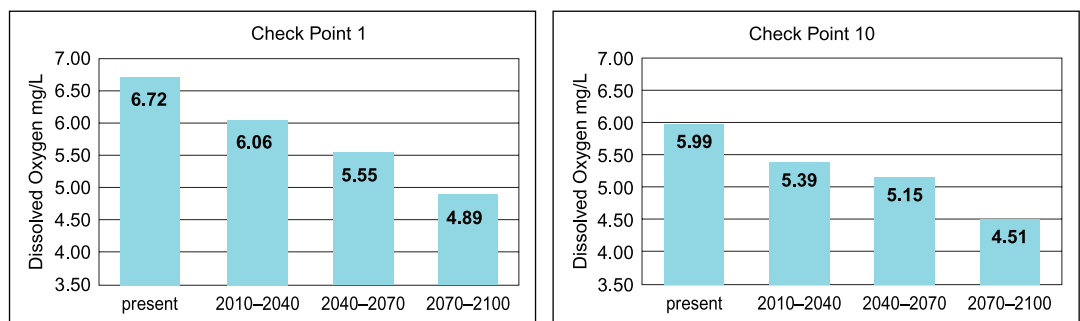


Figure 5: Present and future estimates of DO levels at various checkpoints along Tunga-Bhadra river.
Source: Rehana and Mujumdar.²⁰

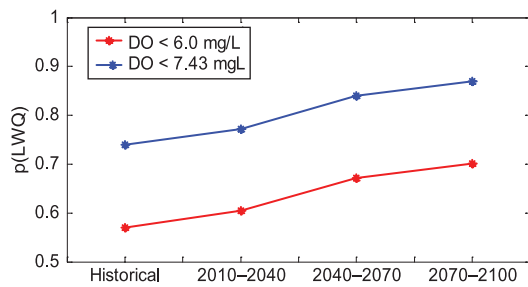


Figure 6: Likelihood of low water quality for varying DO thresholds.

Source: Rehana and Mujumdar.²⁰

temperature. Such reduction in DO levels under climate change are also observed for the same case study with hypothetical scenarios of streamflow and temperatures in the study of Rehana and Mujumdar.²³ Further, historical data analysis has shown a significant decrease in streamflows over the last few years in Tunga-Bhadra river, along with an increase in the temperature in the region. The river water quality at a location is primarily affected by the upstream activities in terms of pollutant discharge, streamflow and air and water temperatures. In the unaltered conditions of effluent loadings, the DO levels will be changed significantly due to changes in streamflow and water temperatures.

Figure 6 shows the likelihood of low water quality by varying the thresholds. The threshold of 6.0 mg/L represents the lower bound and 7.43 mg/L represents the upper bound of the future likelihood of risk levels. Both the bounds of risk of occurrence of LWQ are predicted to increase in the future. The quantified bounds of future risk levels can be included in the water quality management model to obtain the optimal treatment levels. The results reveal that even to maintain the current standards, the dischargers need to increase the treatment levels under climate change scenarios. Further, the current river water quality standards have to be improved significantly to achieve better river water quality levels in the future scenario. Efforts have to be made to ensure a healthy river environment by adopting new treatment systems, minimum environmental flows at various locations of the river system and revision of standards of pollution control agencies.

4 Climate Change Impacts on Irrigation Water Demands

Agriculture is one of the most important sectors that will be affected directly in terms of change in crop water demands due to global climate change. The rising levels of atmospheric carbon dioxide

(CO₂) lead to changes in temperature, and precipitation patterns and affect the evapotranspiration demand, and thus affecting water availability and crop production.²⁴ The crop factors which influence the irrigation water requirement include the type of crop, cropping pattern, crop season, growth stage of the crops, soil type and topography, and the climatic factors are precipitation, temperature, humidity, wind velocity, intensity of sunlight. Due to changes in climatic factors, even with no change in cropping pattern, irrigation demands can be expected to change. The climatic factors such as temperature, humidity, wind velocity, intensity of sunlight etc. combinedly influence the crop water requirements in terms of evaporative demand. Water requirement of a crop is the quantity of water required to meet the evapotranspiration needs including the amount of water required for land preparation, transplanting, leaching, and other losses. The irrigation water requirement is about supplement releases to be made in addition to the natural rainfall to meet crop water requirements to avoid water deficits. Therefore, the agricultural or irrigation water demand is expected to be affected in the near future in the face of likely changes in both the rainfall and the evaporative demand due to climate change. Assessment studies focusing on the impacts of climate change on irrigation demands using GCM outputs are becoming more accepted in recent years.²⁴⁻²⁸ In the study of Rehana and Mujumdar,²⁹ the expected changes in irrigation demands of the crops under future scenarios are examined by integrating a climate change projection model, irrigation demand model and an evapotranspiration model. The future projections of rainfall and other meteorological variables are downscaled using canonical correlation analysis with MIROC 3.2 medium resolution GCM with A1B scenario for Bhadra command area. The large-scale climate variables considered in the downscaling of meteorological variables include surface air temperature at 2 m, Mean Sea Level Pressure (MSLP), geopotential height at 500 mb, surface U-wind, surface V-wind, specific humidity at 2 m, surface relative humidity, surface latent heat flux, sensible heat flux, surface short wave radiation flux and surface long wave radiation flux are selected. These selected predictors containing large scale climate information will be useful in the development of quantitative relationships with local meteorological variables (e.g., rainfall, maximum and minimum temperatures, relative humidity and wind speed). The monthly rainfall is projected to increase over Bhadra command area, Karnataka, India. The Bhadra reservoir is located on Bhadra River, a tributary of

Tunga-Bhadra River, India. Nine IMD (India Meteorological Department) locations encompassing the entire command area are selected to evaluate the irrigation water demands. The total irrigated area of each crop in the command area is distributed equally among the selected downscaling locations consisting of all the crops. The predicted rainfall increase is defined by the consideration of large-scale climatic variables (mean sea level pressure, air temperature, geopotential height, wind speed and humidity) as predictors. Such projected increase in rainfall is also observed for the same case study of Bhadra command area in a hydrologic impact assessment study of Meenu et al.¹⁸ Figure 7(a) shows the observed and the simulated results obtained with NCEP and GCM data during training the downscaling model. Figure 7(b) shows the future projections with the green box plots for the period of 2020 to 2044, the blue box plots for the period of 2045 to 2069 and the red box plots for the period of 2070 to 2095.

The projected increase of maximum and minimum temperatures and relative humidity is predicted to increase the reference evapotranspiration. The evapotranspiration projections are modeled using Penman-Monteith evapotranspiration model accounting for the projected changes in temperature, relative humidity, solar radiation and wind speed. The monthly reference evapotranspiration computed from Penman-Monteith evapotranspiration model is adjusted with crop coefficients for each crop to compute the potential evapotranspiration which, in turn, can be used to compute the irrigation water demand of the crop. An irrigation demand model is used

with the projected rainfall and evapotranspiration to predict the crop water demands of paddy, sugarcane, permanent garden and semi dry crops over Bhadra command area.

Figure 8 shows the annual irrigation water requirements of paddy, sugarcane, permanent garden and semidry crops for nine locations encompassing the Bhadra command area. Due to the cropping pattern and the command area, the irrigation water demand of paddy and sugarcane are higher compared to those of permanent garden and semi dry crops. The maximum annual paddy demand is predicted to occur at Location 8 with current demand as 14.00 Mm³ and for the future time slices of 2020–44 as 26.97 Mm³, for 2045–69 as 27.35 Mm³ and for 2070–95 as 27.8 Mm³. Even though the projected irrigation water demands are higher compared to the observed ones, the relative difference between the future demands are small, due to the projected increase in rainfall. Such irrigation demand assessment study will give an overall idea about the changes in demands for each particular crop at each location over the command area and also in decision making for better management of irrigation systems. Such projected irrigation water demand assessment will be useful in examining different cropping patterns in the command area keeping in view the increased crop water demands. The projected crop water requirement assessment will serve as a guideline for the decision makers to accommodate sufficient water in those months when rainfall alone would not be sufficient to fulfill the crop water requirements.

The actual evaporation rate depends on the water availability. For example, reduction in soil

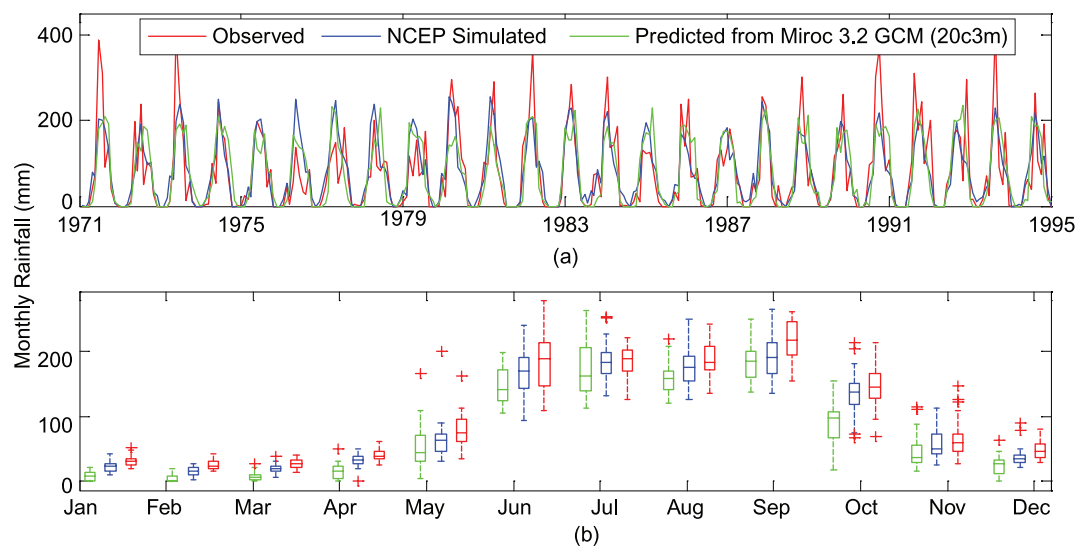


Figure 7: Rainfall projections over Bhadra Command Area.
Source: Rehana and Mujumdar.²⁹

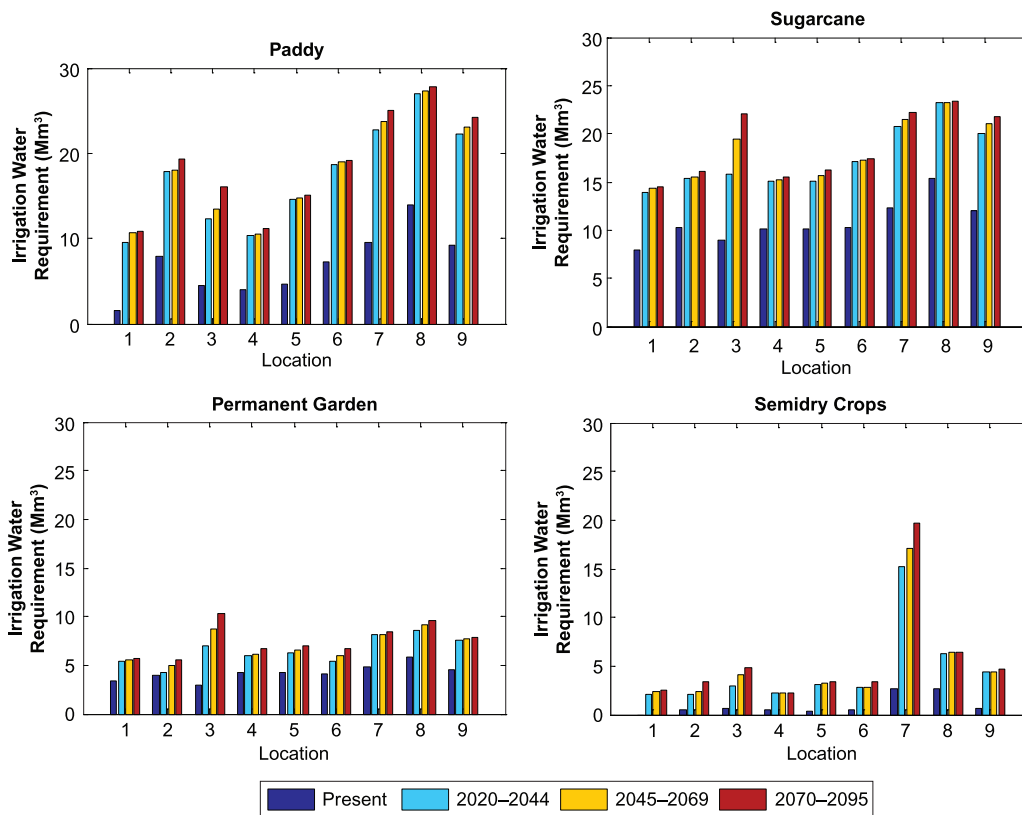


Figure 8: Projected annual irrigation water requirements for Bhadra command area.

Source: Rehana and Mujumdar.²⁹

moisture could lead to reduction in the evaporation for a command area despite an increase in evaporative demand. In general, the amount of water stored in the soil is another important factor for agriculture in addition to the rainfall and evaporation. Therefore, projected irrigation demand quantification should include not only the effect of climate change on soil moisture, but also the soil characteristics. Soil moisture contents simulated by GCMs should be included in irrigation demand quantification.

5 Uncertainty Modeling for Future Climate Projections

Climate change impact assessment models developed based on GCM output are subjected to a range of uncertainties due to incomplete knowledge, inadequate information and understanding about the geophysical processes of global change. This leads to significant dissimilarity between the projections derived with multiple GCMs. In addition, choice of the GCM is identified as the largest source of uncertainty for hydrological impacts.³⁰ It is relevant to assess the effectiveness of the GCMs and also to judge which of the scenarios represent the present situation best under climate change forcing. During

last decade, research on climate model uncertainty in climate change impact assessment studies has advanced on several fronts. A methodology has been developed by Mujumdar and Ghosh³¹ to model GCM and scenario uncertainty using possibility theory. Possibility values are assigned to GCMs and scenarios depending on the model performance in simulating signals of climate forcing in the recent past (1991–2005). The objective of the study is to derive possibilistic mean cumulative distribution function (CDF) for the future scenarios based on the possibilistic weights. The possibilistic model is demonstrated with the monsoon streamflow of Mahanadi at Hirakud dam with surface air temperature at 2 m, mean sea level pressure, geopotential height at a pressure level of 500 hPa, and surface specific humidity as climate variables. These predictor variables are selected as climate variables to model the projections of streamflow by following (i) the predictors selected should be reliably simulated by GCMs (ii) readily available from the archives of the GCM outputs, and (iii) strongly correlated with the surface variables of interest. Three GCMs Centre for Climate System Research/National Institute for Environmental Studies (CCSR/NIES), Hadley Climate Model 3 (HadCM3) and Coupled Global Climate Model 2

(CGCM2) with two scenarios, A2 and B2, are used in the GCM and scenario uncertainty modeling. Figure 9 shows the CDFs of the future streamflow derived with different GCMs and scenarios. The derived CDFs for all the GCM and scenario combinations represent the uncertainty bandwidth for the current periods (1990–2005) and for future time periods of 2020s, 2050s and 2080s. For the observed period of 1990–2005 the uncertainty bandwidth is high with probabilities in the range 0.2–0.5 and become smaller at lower or higher probabilities. Such results reveal the existence of higher disagreement between the simulations of GCMs for medium flow in the observed period. From Figure 9, there is a significant dissimilarity among the projections of GCMs and scenarios leading to climate model uncertainty in the hydrologic impact assessment studies. To model the resulting uncertainty, possibilities are assigned to GCMs and scenarios based on their performance in predicting the streamflow during recent past (1991–2005) for deriving the possibilistic mean CDF the future scenarios. The mean cumulative distribution function of streamflow projections are derived with possibilities assigned to

GCMs and scenarios for periods 1961–1990, 2020s, 2050s and 2080s. Table 1 presents the streamflow quantiles derived from the upper bound and the lower bound CDF and the difference between them corresponding to the CDF values of 0.25, 0.5, 0.75, 0.9, and 0.95, for future periods of 2020s, 2050s, and 2080s. The difference between the lower and the upper bounds of streamflow quantiles for a given CDF value is assumed to represent the uncertainty associated with the assessment of hydrologic impacts of climate change. The results reveal that for a given CDF value the amount of uncertainty increases with time, due to different climate sensitivity among the models. Such uncertainty analyse point out that the use of single GCM and single scenario, may mislead the climate change impact assessment studies. This suggests the use of multimodel ensembles in the hydrologic impact assessment studies.

In a study of Ghosh and Mujumdar³² the GCM uncertainty is modeled using imprecise probability to address the uncertainty caused by partial ignorance to represent the missing outputs of GCM in IPCC data distribution centre. The underlying uncertainty is modeled with reliability

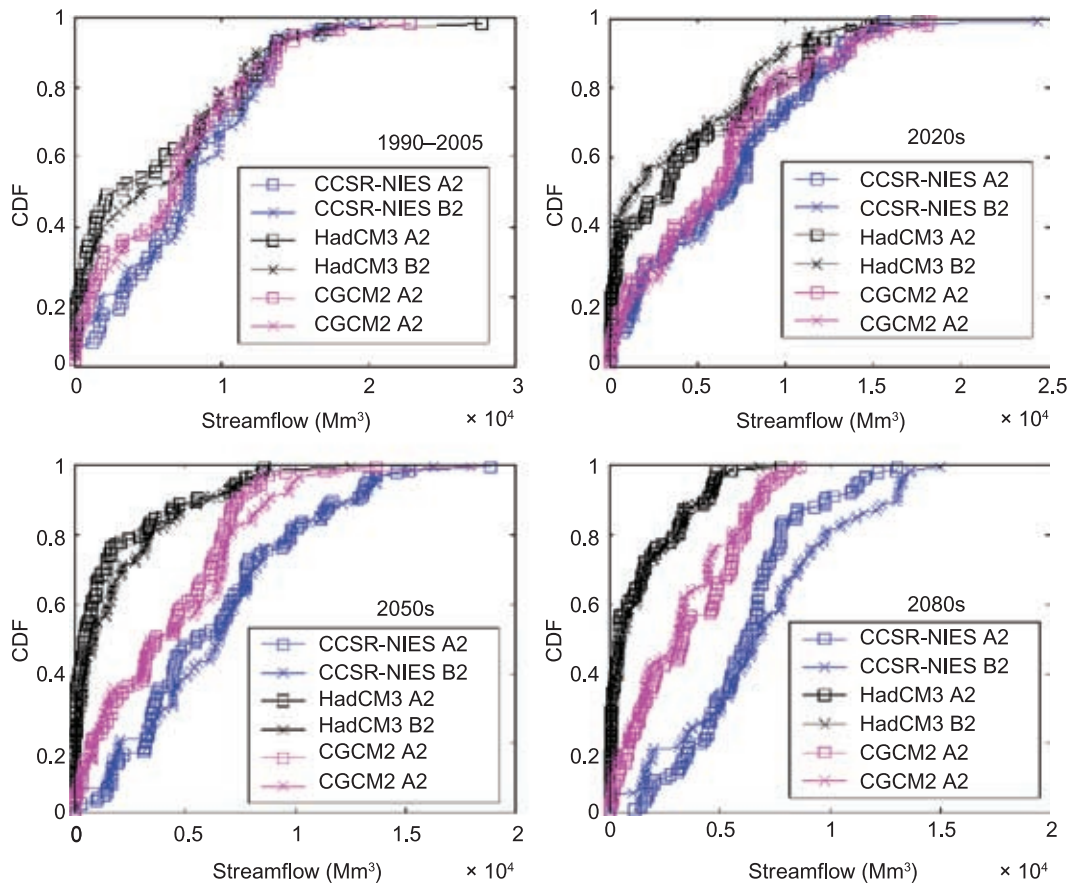


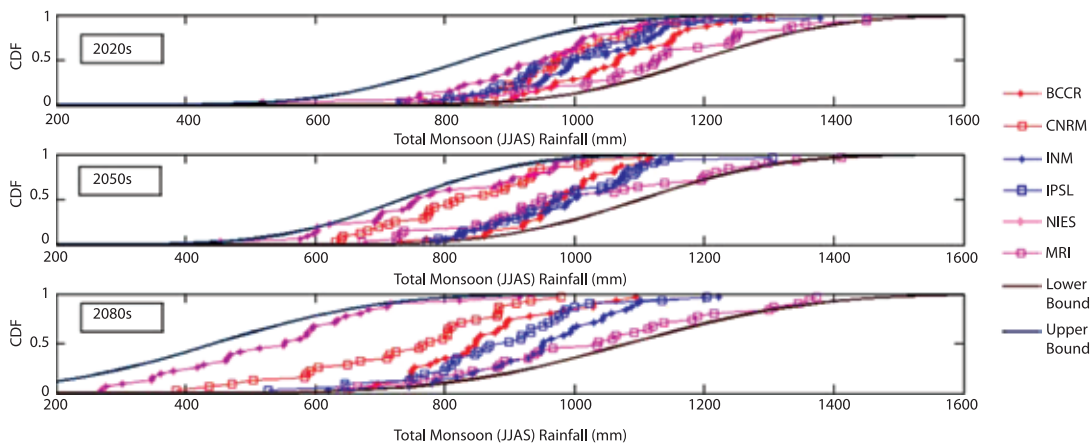
Figure 9: Predicted Streamflow with different GCMs and scenarios.

Source: Mujumdar and Ghosh.³¹

Table 1: Uncertainty in streamflow projections.

CDF value	Quantile [Streamflow, (Mm ³)]								
	2020s			2050s			2080s		
	UB CDF	LB CDF	Difference	UB CDF	LB CDF	Difference	UB CDF	LB CDF	Difference
0.25	131	2732	2601	63	3524	3461	76	4508	4433
0.50	1381	6807	5426	393	6576	6183	491	6690	6199
0.75	7329	10144	2815	1639	8623	6984	1638	9120	7482
0.90	9811	13412	3601	5584	13009	7425	3375	13070	9695
0.95	11313	15482	4169	7395	13667	6272	4675	13263	8586

Source: Mujumdar and Ghosh.³¹

**Figure 10:** Imprecise CDF for A1B scenario.

Source: Ghosh and Mujumdar.³²

ensemble averaging by assigning weights to each GCM based on the model performance and model convergence. The model performance is evaluated by determining the deviation of CDF of GCM-simulated downscaled rainfall for 20C3M with respect to the CDF derived with observed rainfall. The model convergence is evaluated based on the deviation of CDFs derived with individual GCMs for future with respect to weighted mean CDF, which is derived with the weighted projections of multiple GCMs. The imprecise probability modeling approach results in imprecise CDFs for monsoon rainfall for the Orissa meteorological subdivision. Principal component analysis and linear regression are used to downscale the subdivisional monsoon rainfall. The CDFs generated with multiple GCMs result in a band of CDFs, which contain the CDFs generated with all the available GCMs, to an extent that accounts for the uncertainty resulting from the missing GCM output. Figure 10 shows the imprecise CDF for the monsoon rainfall over Orissa meteorological subdivision for various GCMs with A1B scenario. The dark black lines show the bounds of CDFs

representing the uncertainty in the climate change projections. The lower bound of the uncertainty envelope does not show any significant change with time, whereas decrease in the value, at which the upper bound CDF reaches 1, can be observed. The imprecise probability enables the water resources planners to consider both the possible cases, “no change” in rainfall and decrease in rainfall corresponding to lower and upper envelope of CDF respectively. The results reveal that there will be a reduction in monsoon rainfall in future if there is any hydrologic change at all. The imprecise CDFs of monsoon rainfall can be used to compute the imprecise risk for meeting water demands in terms of upper and lower bounds.

The statistical downscaling methodologies are burdened with a basic assumption that the relationship between the climate variables and the regional hydrologic variables is unchanged between present and future climates. Generally, the relationship derived between climate variables and regional hydrologic variables is assumed to be constant over time and it holds true in a changed climate. However, the assumption of the changes

in natural variability patterns is questionable. The future changes in downscaling relationship can be incorporated by separately examining the relationships for duration of each natural cluster and projecting the effect of changes in frequencies of these clusters. Addressing stationarity in the downscaling relationship has become an active research area in recent years.^{33,34} Raje and Mujumdar³⁵ developed an uncertainty modeling approach where, in addition to GCM and scenario uncertainty, the uncertainty in the nature of the downscaling relationship is investigated by linking downscaling with patterns of natural variability of climate variables. The downscaling methodology is linked with the frequency changes of natural variability. This facilitates examination of the likely changes in future in the downscaling relationship to provide robust estimates of uncertainty. The future projections of natural cluster frequencies are derived using the GCM-projected monthly geopotential height at 500 hPa. Figure 11 shows the spatial pattern of geopotential height corresponding to cluster 1, which corresponds to a temperature difference between the Central Indian Ocean and the West and East Indian Ocean. Overall, spatial pattern of all clusters has shown that the Indian Ocean appears to have a large impact on climate variability. The GCMs used in the uncertainty analysis are CGCM2 (Meteorological Research Institute, Ibaraki, Japan), MIROC3.2 medium resolution (Center for Climate System Research, Chiba, Japan), and GISS model E20/Russell (NASA

Goddard Institute for Space Studies, Greenbelt, MD, USA) with three scenarios (A2, A1B, B1).

Figure 12 shows the range of monsoon 4 monthly standardized streamflow index (SSFI-4) classifications for current and for future scenarios. The Figure 12(a) shows the predicted SSFI-4 classifications for the observed period of 1960–2000 across three GCMs and Figure 12(b) for across three GCMs and five clusters. Figure 12(c) is across three GCMs and three scenarios, unclustered, for years 2045–2065, showing uncertainty envelope capturing GCM, scenario and downscaling uncertainty. In Figure 12(d) the increased bounds of the uncertainty envelope capturing GCM, scenario, and downscaling uncertainty as well as downscaling relationship uncertainty. All clusters, scenario, and GCM combinations, clearly shows the increased uncertainty owing to nonstationarity in the downscaling relationship captured in the uncertainty envelope. The results reveal that assumption of a stationary relationship will either over-predict or under-predict the downscaled projections and associated uncertainty. The GCM simulation of natural variability can be applied to constrain regional predictions. The results of the study show that climate change will have significant impacts with increasing probability of extremes, severe and moderate drought in Orissa, India, and with a decreasing probability of normal to wet conditions due to a decrease in monsoon streamflow in the Mahanadi River.

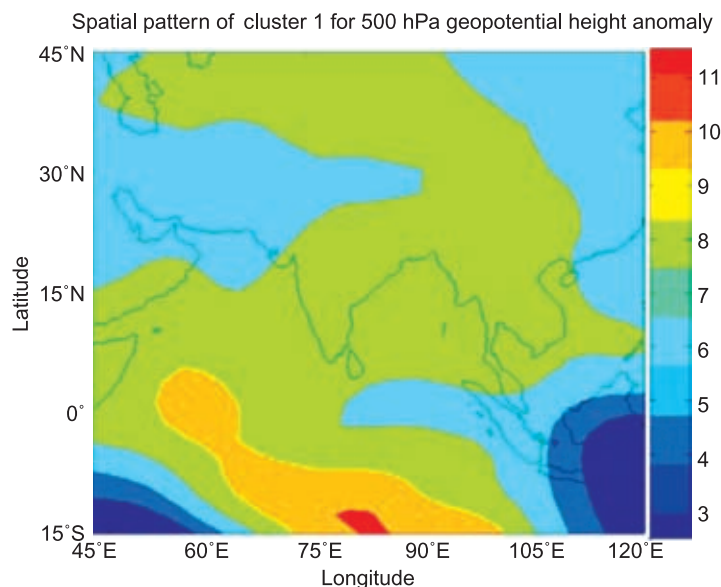


Figure 11: Spatial pattern of geopotential height anomaly for cluster 1 used to identify the modes of natural variability.

Source: Raje and Mujumdar.³⁵

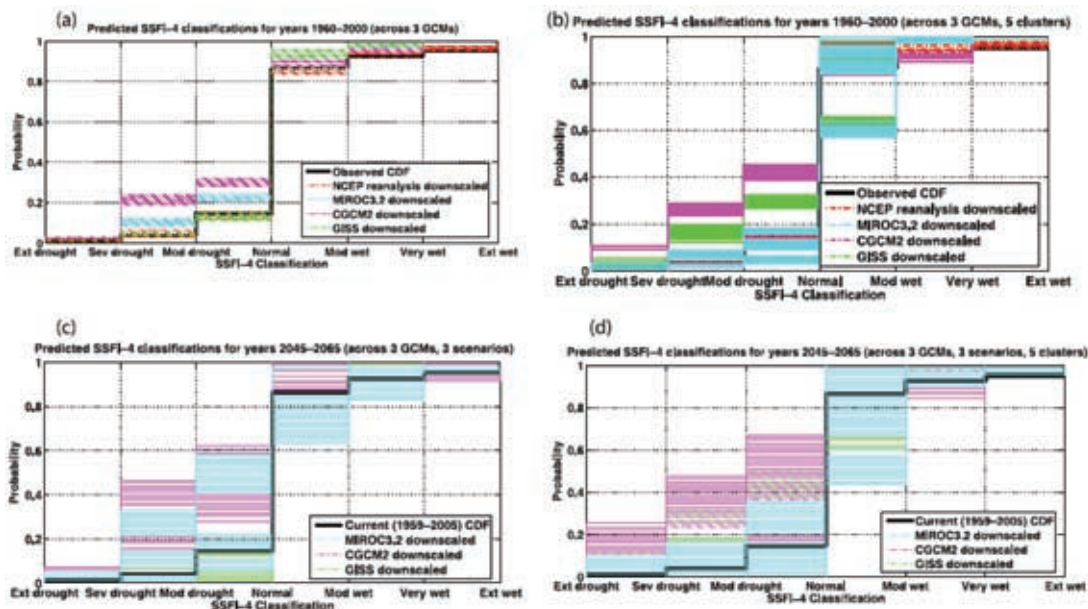


Figure 12: Range of monsoon 4 monthly standardized streamflow index (SSFI-4) classifications for current and future years for extreme (Ext), moderate (Mod), and severe (Sev).

Source: Raje and Mujumdar.³⁵

6 Conclusions

Global warming is affecting in all aspects of water resource management including water availability, water quality and irrigation demands. Significant advancements have happened on several fronts of the climate change impact assessment studies in the recent years. The present study reveals that global climate change may severely impact the regional water resources systems with decrease in water availability, river water quality impairments, increase in the water demands and finally water scarcity in the future scenarios. Climate change impact on various components of a water resources system such as water flow amounts of rivers and the resulting effect on water quality and irrigation demands have to be addressed in an integrated framework. Uncertainties in the future climate change projections act as important barriers for adaptation to climate change. The policy makers must use projections provided by climate models in assessing the regional impacts to consider the uncertainties, while planning the long-term water resources management policies. Climate change analysts should focus on the impacts, costs, and benefits of mitigation strategies. The current research on hydrologic impacts of climate change is mainly focusing on quantification of projected changes in water supply and demands based on the future scenarios of various hydro-climatic variables. However, the regional changes in water demands may be due to demographic profiles and

land use patterns, and impact assessment studies should give appropriate attention towards demands in forecasting improvements along with the climate change mitigation approaches.

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