## CHAPTER 13

## UNCERTAINTY IN HYDROLOGIC IMPACT ASSESSMENT

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### 13.0. Introduction

Changes in the frequency, magnitude, spatial extent and duration of extreme hydroclimate are one of the most significant consequences of climate change (e.g. Jones, 1999; Seneviratneet al., 2012). Therefore, knowledge of severity, spatial and temporal variability, duration, and frequency of occurrence of extreme hydrological events (i.e. floods or droughts) is important information for an effective planning and design of water resources infrastructure and distribution of water resources to overcome the detrimental impacts of extreme hydroclimate. To project the impacts of changing hydroclimate on the hydrology of Indian sub-continent, it is necessary to analyse the projected future climate at a regional scale. However, this involves three major concerns: (a) general circulation models or global climate models (GCMs) are coarser than the scale of the local phenomenon influencing the regional climate, (b) GCM simulations are primarily the projections of the mean climatic conditions limiting the direct use of these simulations in the study of extreme hydrological events, and (c) the uncertainty introduced into the GCM simulations at several stages of its development and run. Therefore, the issues pertaining to the spatial resolution, extreme climate simulation and model uncertainty needs to be addressed prior to conducting any regional scale impact studies. This chapter discusses various sources of uncertainties in GCM simulations and methods to quantify and/or reduce these uncertainties.

The accuracy of global scale GCMs can be well understood by exploring the physical processes and laws associated with them. A confidence in the projections from GCMs comes from the correct representation of physical laws associated with the climatic processes (e.g. law of conservation of mass, energy and momentum) and better understanding of the current regime of climate, i.e., variability in temperature, precipitation etc. The ability to simulate historical and future climate using a GCM will depend on how relevant the selected models are to the study area of interest (Daniels et al., 2012). Intergovernmental Panel on Climate Change (IPCC) has generated multiple versions of GCMs, from after 1998, with large number of variables associated with certain factors including the changing rate of greenhouse gas (GHG) concentrations, $CO_2$ concentration levels in the atmosphere, land-use changes, aerosols concentration and ocean warming (Pachauri et al., 2014), most of them have been successfully utilized in various climate change studies (e.g. Ghosh and Mujumdar, 2008; Goyal and Ojha, 2012;Apurv et al., 2015; Singh et al., 2017; Tiwari et al., 2018). However, the projected outcome from each GCM differed considerably and the amount of uncertainty varied with each model run, despite the similar types of application (Pachauri et al., 2014). For example, majority of the GCMs depicted a significant increase in the global averaged near surface temperature over the last few decades, likely associated to the accelerated anthropogenic emissions of GHG, and the future projections indicated further increase however, the magnitude of this change/increase varied from one model to another, for the same period and same region (Chaturvedi et al., 2012; Pachauri et al., 2014; Tiwari et al., 2018), Figure 13.1a.

## 13.1. Sources of Uncertainty

Although several GCMs, approved by the IPCC exist to simulate climate of the 21st century, intermodal uncertainties are one of the major issues in these simulations. No simulation from one GCM is same as any other simulation from a different GCM, despite using the same emission scenario or representative concentration pathway (RCP), leading to an intermodal uncertainty. Intermodal uncertainty is primarily because of the uncertainties accumulated in each model from various sources at several stages of its development and run. Uncertainty in the climate projections is initially introduced at the stage of model building with the model physics and the numerical structure (method of solving differential equations) used, at the stage of its run with the assumed future emissions of GHGs chosen to force the model, and finally at the downscaling stage with the method or technique adopted (Evans et al., 2012). These three major sources of uncertainty, i.e. uncertainty from GCMs, uncertainty from future emission scenario and uncertainty from downscaling technique, together limit the confidence of the future climate projections from any GCM.

### 13.1.1. Uncertainty from GCMs

Uncertainty from GCMs is primarily due to the misrepresentation of the climate processes (model physics) or erroneous model structuring (interrelationships) or failure in representing the interannual or decadal variability (Mishra et al., 2014; Tiwari et al., 2014; Xueet al., 2014; Joseph et al., 2018).However, the major source of uncertainty in any climate model is the representation of complex interactions among the subsystems (atmosphere, hydrosphere, lithosphere, etc.) of the global climate system(Berliner, 2003). Although the underlying physical, chemical and biological processes of the earth's system is well understood, numerically representing such processes in a model is cumbersome leading to parametrization of several processes occurring at a spatial scale much smaller than the scale used in the GCM building. In several recent studies, it has been shown that the projected changes in climate from various GCMs differed in magnitude and frequency (IPCC2014). To characterize uncertainty between various GCMs, the Coupled Model Intercomparison Project (CMIP) was initiated by the World Climate Research Programme (WRCP) in 1995 to coordinate experiments by different groups of modellers. Several studies compared the earlier versions (e.g. CMIP2/CMIP3) of GCM projected climate with that of the latest versions (CMIP4/CMIP5) and the results indicated substantial differences (e.g. Onyutha et al., 2016; Sharma et al., 2018). Despite the improvements in model building over the years, the magnitude of uncertainties has not changed significantly (IPCC 2014). Although uncertainty from GCM is inevitable, it can be quantified and addressed to produce a plausible future projection (Mishra et al., 2014; Joseph et al., 2018). For instance, since the ability of any model in perfectly simulating the regional climatic processes is limited, the projections from several GCMs are assembled to produce a mean ensemble or median ensemble representing the most probable future climate (Chaturvedi et al., 2012; Mishra et al., 2014; Trzaska and Schnarr, 2014; Joseph et al., 2018), Figure 13.1.

Uncertainty is also associated with the type of parameterization adopted to represent a specific process in model building (Dickinson, 2012). Furthermore, the method of numerical solution used in solving the non-linear differential equations of the complex earth climate systems is the other source of uncertainty. Several numerical techniques exist to solve these differential equations, and the accuracy of each technique varies depending on the type of problem and the computational costs. Thus, in spite of better understanding and representation of the physical processes controlling the climate, the numerical method induces uncertainty into the solution of the fundamental differential equations

(Harvey, 2012). The other and important source of uncertainty arise from the initial conditions provided to run the model, which can simulate one possible future climate among many others that have the same probability of occurrence. By slightly varying the initial conditions and running the model again, several other possible scenarios can be developed. If averaged over several decades, all these scenarios produce a very similar mean climate statistic, but the individual scenarios help us to better understand and evaluate the possible extreme events (Alexander & Telbadi, 2012). The amount of uncertainty associated with each of these sources is unknown, but the cumulative impact from various GCMs can be quantified by the amount of spread in the projected climate from these GCMs (e.g. Rupa & Mujumdar, 2019).

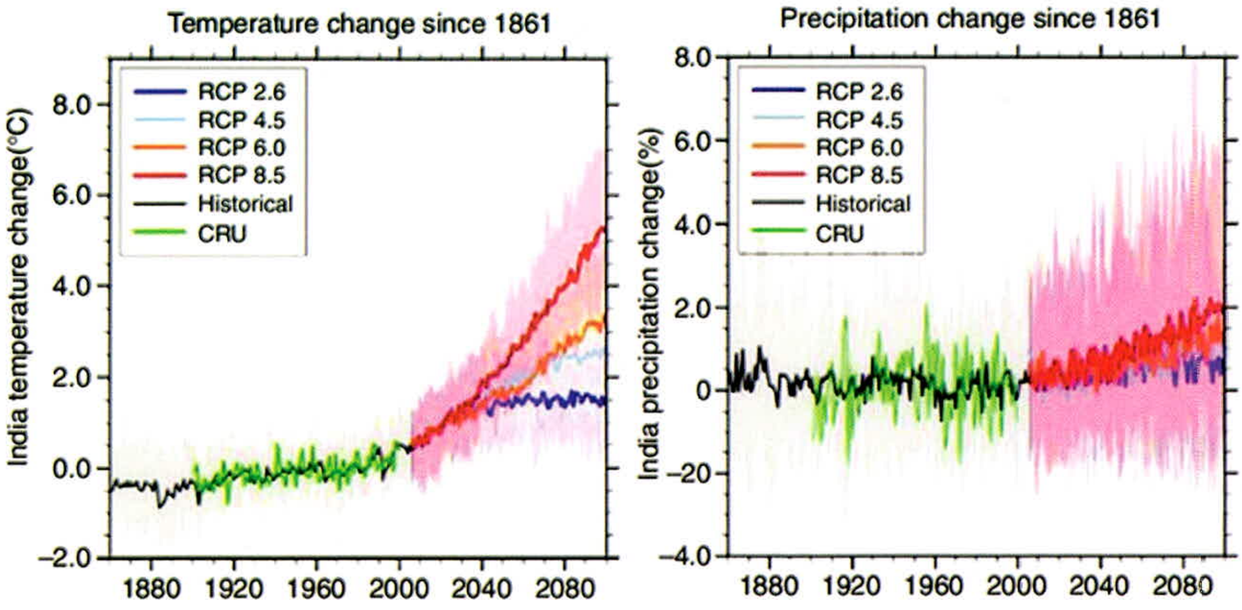


***Figure 13.1**. CMIP5 model-based time series of temperature and precipitation anomalies (historical and projections) from 1861 to 2099 relative to the 1961-90 baseline for the RCP scenarios. Shaded area represents the range of changes projected by the 18 models for each year. The model ensemble averages for each RCP are shown with thick lines. The observed temperature and precipitation trend from CRU is shown by green line and the solid black line refers to model ensemble values for historical simulations. (Source: Chaturvedi et al., 2012)*

### 13.1.2. Uncertainty from Future Emission Scenario

The second major source of uncertainty in GCM simulations is the knowledge of future environment policies or the magnitude of GHG emissions. Prediction of future GHG emissions is a complicated assignment, and is dependent on several factors including population growth, technological advancements, economic growth, sources of energy and their usage. In general, the GHG emissions are substantially influenced by the future climate policy decisions and human activities. The projections of GHG emissions for use in GCMs are earlier presented as emission scenarios (Nakecenovic et al., 2000), and currently as RCPs (Moss et al., 2008) by the IPCC. "RCPs are referred to as pathways in order to emphasize that their primary purpose is to provide time dependent projections of atmospheric GHG concentrations. They are representative in that they are one of the several different scenarios that have similar radiative forcing and emission characteristics" (Moss et al., 2008). Given all the uncertainties involved, several RCPs have been created to cover a range of plausible emission scenarios based on the radiative forcing, currently four RCPs, viz. RCP8.5, RCP6.0, RCP4.5, and RCP2.6, are being used (Moss et al., 2008).The optimistic GHG emission scenario aims to likely keep global warming at less than 2°C above pre-industrial temperatures (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and the worst case scenario with very high GHG emissions (RCP8.5).For example, the worst cases scenario or the high GHG emissions pathway (RCP8.5) is based on the assumption that by 2100, the radiative forcing is as large as 8.5 W/m$^2$ and might increase further. These four emission scenarios produce a range of changes in future precipitation and temperature. For instance, the projections of global surface temperature indicate that the major source of uncertainty arise from the range of GCM simulations based on various GHG concentrations or RCPs, i.e. RCP scenario spread (Hawkins and Sutton, 2009; 2011; Kitmanet al., 2013), Figure 13.2.

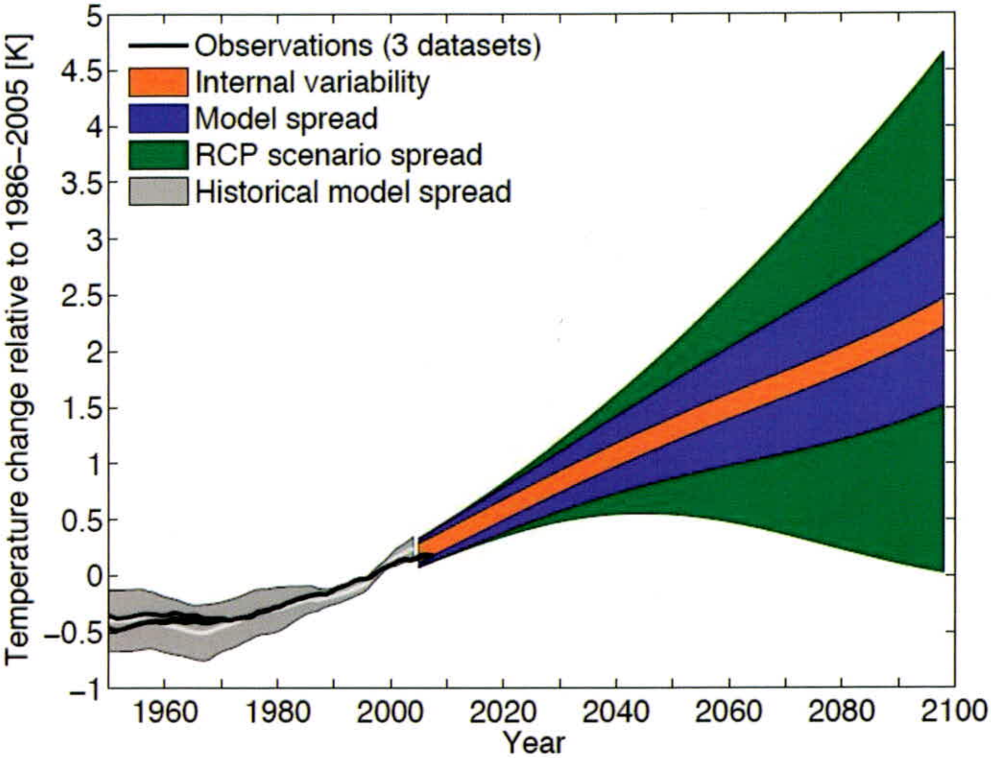


***Figure 13.2.*** *Projections of global mean surface air temperature together with the quantification of uncertainty arising from internal variability, model spread and RCP scenario spread (Source: Kitmanet al., 2013).*

### 13.1.3. Uncertainty from Downscaling Technique

GCM outputs are currently inadequate for producing reliable and consistent hydrological forecasts, in response to the projected climate change, at spatial scales relevant for decision-making. Therefore, to assess the impacts of climate change at regional scale, downscaling techniques are adopted to spatially scale down GCM simulations. The assumptions made in downscaling technique, dynamical or statistical, further introduces uncertainty in the projections of regional hydroclimate. Dynamical downscaling involves the same set of uncertainties as mentioned for the GCM uncertainty in addition to the uncertainty from the stationarity assumption, i.e. the parameterisations of physical processes represented in GCMs or regional climate models (RCMs) remain valid in the future. The method of downscaling initially inherits the uncertainty associated with the GCM and emissions scenarios, and the uncertainty is further increased from the assumptions made in downscaling technique (Chen et al., 2011; Teng et al., 2015; Sharma et al., 2018). Therefore, evaluating trade-offs in error associated with GCM and emission scenario and that induced by the assumptions made in downscaling technique is vital. With the same GCM, different downscaling techniques produce different projections. For example, Chen et al., (2011) evaluated six different techniques to downscale the projected climate from the same GCM and found that the simulated streamflow does not agree with each other, despite using the same hydrological model, Figure 13.3.

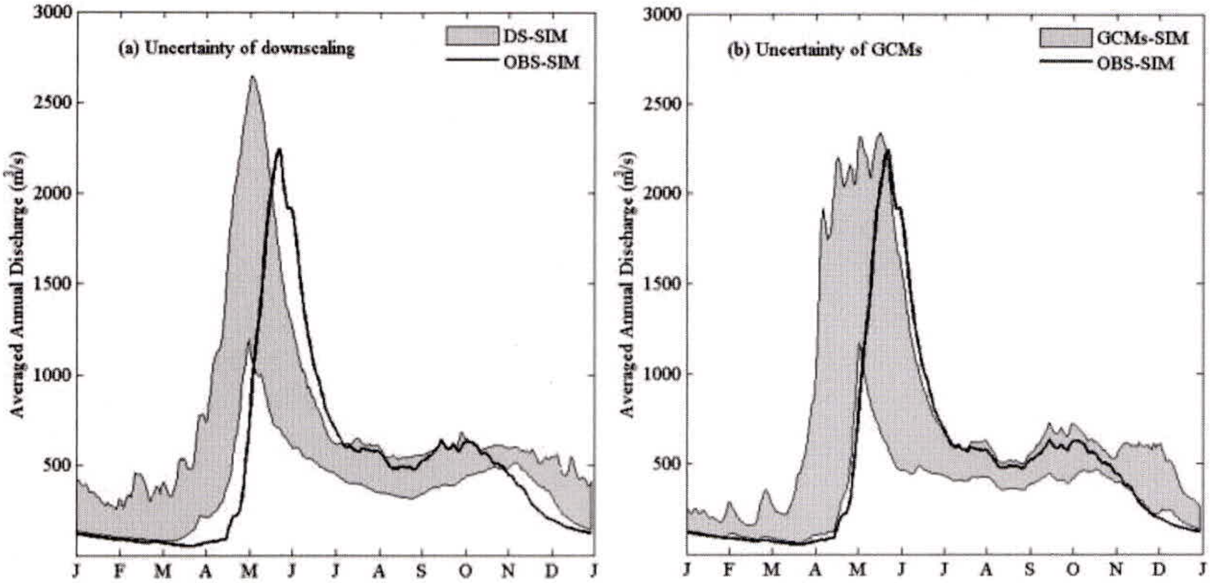


***Figure 13.3****. Uncertainty envelopes of simulated discharge with (a) 6 downscaling techniques and (b) 28 GCMs and emission scenarios using the change factor downscaling method for the future period (2070-2099). The discharge simulated with observed climate data for the reference period (1970 – 1999) is also plotted for comparison. (Source: Chen et al., 2011).*

Many studies have acknowledged the relevance of the dynamically downscaled higher resolution RCMs and they replaced GCMs in majority of the climate change impact assessment studies (e.g. Miao et al., 2016; Sanjay et al., 2017). Regional scale (~ 20 – 50 km resolution) climate phenomenon are comparatively well represented in dynamically downscaled RCMs and are considered more relevant in producing reliable estimates of regional climate. However, a few studies challenge their ability in predicting point-scale climate information, i.e. precipitation or temperature at a meteorological or weather station (e.g. Miao et al., 2016; Tao et al., 2018). In addition, few studies have found that RCMs overestimated the frequency of precipitation, while they underestimated the heavy precipitation (e.g. Singh et al., 2017). Furthermore, several studies have highlighted the spatial and temporal variability in the performance of RCMs (e.g. Leander and Buishand, 2007; Karmalkar et al., 2018). For example, in a recent study, Sanjay et al. (2017) found large uncertainty associated with dynamic downscaling in the projected changes of seasonal temperature and precipitation over the hilly sub-regions within the Hindu Kush Himalayan region by the end of the 21$^{st}$ century.

Several methods of statistical downscaling exist and the uncertainties associated with each method differs. Major sources of uncertainties in statistical downscaling are the stationarity assumption, i.e. historical statistical relationship remains the same in future, and the assumption that a climate variable will follow a specific distribution which may not be true all the time. For example, the properties of a statistical distribution changes with the size of sample used in the distribution fitting. In addition, the empirical relationships between predictors (e.g. large-scale climatic variables) and predict (e.g. regional precipitation) are influenced by the warming climate. In addition, inconsistencies between the variables representing physical processes, and the inherent uncertainties of each statistical downscaling technique add to the uncertainty in the simulated climate. The statistical downscaling methods do not account for the interactions between the physical processes that define climate, thus producing physically unrealistic climate variables. Quantifying these uncertainties is quite cumbersome, those associated with the assumption of stationary climate in particular (Rupa & Mujumdar, 2019). The future climatic conditions can significantly vary from that of the historically recorded conditions, which were used to calibrate the model.

Despite several studies involving the use of both statistical and dynamical downscaling techniques, no single downscaling technique was found to consistently out-perform other methods (e.g. Haylocket al., 2006; Landman et al., 2009; Gutmannet al., 2012; Roux et al., 2018). Several studies indicate that the method of model output statistics (MOS), bias correction techniques in particular, produced better results when applied to the simulations from the dynamically downscaled models, i.e. reduced uncertainty to some extent (e.g. Landman et al., 2009). Overall, both dynamic and statistical downscaling technique are capable of capturing the spatio-temporal variability in hydroclimatic conditions, but the uncertainties transferred from the GCM simulations, sometimes limit their reliability. Sharma et al. (2018) found that the statistically downscaled hydrological projections captured the observed spatio-temporal variability in hydroclimatic conditions more efficiently than the dynamically downscaled projections. They observed that the uncertainty in the statistically downscaled projections was much smaller than the inter-GCM uncertainty. However, the limitations of the stationarity assumption made in statistical downscaling should be well understood, i.e. the implications of the deviations from basic assumptions should be quantified (Rupa & Mujumdar, 2019).

### 13.1.4. Uncertainty from Hydrological Models

In addition to the uncertainties associated with the GCM simulations, uncertainty is induced in the projected hydrological responses, such as streamflow projections, associated with the assumptions made in the hydrological model building. The well calibrated hydrological model producing acceptable results for an observed baseline period may not work adequately in projecting hydrological response to a changing climate. Similarly, different hydrological models may respond very differently when forced with the same climate change scenario. Uncertainties in hydrological projections are due to a range of factors, including the reliability and availability of data used to calibrate models, limited understanding of regional hydrologic processes and the omission of other influential dynamics, such as modal and quantitative changes in water and land use (Lacombe et al., 2018). Therefore, a separate quantification of uncertainties is required for GCM downscaling approaches and those associated with the hydrological modeling, respectively. For example, Jana et al. (2018) demonstrated that the method of potential evapotranspiration (PET) estimation used in the hydrological model induced uncertainty in the streamflow projections, i.e. PET estimation methods created a significant spread of projected streamflow for certain months. In addition, the spatial scale of a hydrological model plays a vital role in its efficiency, for example, the global scale hydrological model employs a large grid size and several local hydroclimatic processes are parameterised, leading to less accurate regional hydrologic projections (Thomson et al., 2013). In Indian context, some of the major sources of uncertainties in hydrological projections arise from representation of various regional hydrological processes with limited understanding, viz., processes involved in extreme weather events, or processes regulating snowmelt and glacial melt, and interactions between groundwater and surface water (Lacombe, 2018). In addition, limited observation networks and data availability present further difficulties in validating models and estimates of water balances (Mathisonet al. 2015). However, a majority of the studies from recent past emphasize that the uncertainties associated with the hydrological models are relatively smaller than those associated with the GCMs, emission scenarios and the method of downscaling (e.g. Sharma et al., 2018; Smitha et al., 2018; Tiwari et al., 2018).

## 13.2. Climate Uncertainty and Bias Correction

To address adaptive management practices and policies for planned adaptation to changing climate, it is vital to quantify the above-mentioned uncertainties. Producing several estimates of future climate helps in sampling various aspects of future climate (Alexander and Tebaldi, 2012). One method of producing GCM ensemble is to run the model several times by slightly modifying the initial conditions. Thus produced ensemble helps in understanding the uncertainty associated with the internal climate variability, and is the dominant way of producing weather forecasts using numerical weather prediction (NWP) models. Although this ensemble helps in understanding the uncertainty in internal variability over shorter time periods, when averaged over decadal timescale it fails to capture uncertainty when compared to the other methods of ensemble creation. The other method of creating an ensemble, called perturbed-physics ensemble is to run the model several times by slightly modifying the parameters of the physical processes. Meticulous selection of sensitive parameters influencing the climate helps in reducing the required number of simulations. When averaged over longer timescales (e.g. decades), ensembles of perturbed-physics capture larger range of uncertainties compared to those of perturbed-initial condition.

The other method of creating GCM ensemble is either to choose simulations from several GCMs and/or several runs from the same model, regarded as a multimodel ensemble. A multimodel ensemble samples the uncertainties from several GCMs or several simulations from the same GCM. Such ensemble also helps in sampling the uncertainties from different parameterisations of physical processes, and various numerical solution techniques. World climate research programme (WCRP) established coupled model intercomparison projects (CMIP) including CMIP3 (Meehlet al., 2007) and CMIP5 (Taylor et al., 2012)to create and evaluate multimodel ensembles. Similarly, the uncertainties in RCMs can be mapped or evaluated by creating multimodel ensemble of RCMs, platforms such as NARCCAP (Mearns et al., 2009), and CORDEX (Varikodenet al., 2018) aid the creation and assessment of multimodel RCMs. Likewise, an ensemble of statistical downscaling techniques to sample the uncertainty associated with the statistical downscaling is beneficial (e.g. Gutiérrez et al., 2018; Hertiget al., 2018).

In evaluating the GCM simulated climate with the observed climate, the general consensus is that the multi-model ensemble performs better than any individual model (e.g. Pierce et al., 2009). However, the critical steps in creating an ensemble is first the picking of GCMs and second the weightage to be given to individual models. In creating an ensemble, the GCMs are chosen based on the range of projected changes in climate and on the skill of the model in simulating past climate (e.g. Lutz et al., 2016). The skill of the model to simulate historical climate is dependent on various factors including the physics, initial conditions, etc. and not all the models perform the same. Thus the models are given a weight based on their performance, the poorly performing models are given the least or zero weight. For example, Gillett (2015) demonstrate that the weighted ensemble performed better than the unweighted ensemble. One approach for deciding weightage for each model is the Reliability Ensemble Averaging (REA) method (Giorgi and Mearns, 2002; Sengupta and Rajeevan, 2013). The two criteria used in the REA method are (a) comparison of the models' performance in representing observed climate (bias) and (b) comparison of the models' projected changes to that of the multi-model mean projected change (model convergence criteria). To quantify the uncertainty and the reliability associated with the GCM projections of Indian summer monsoon climate, Sengupta and Rajeevan (2013) created an ensemble of ten CMIP5 GCMs based on the REA approach. They observed that REA method reduced the uncertainty in the ensemble climate and recommend this method for determining forecasts of Indian monsoon. Although multimodel ensembles are created to handle uncertainty, ensemble mean provides a quantitative estimate of one of the most likely future climates. The other approach to account for uncertainty is to project future regional climate as probabilistic predictions based on the weighted frequency distributions. In this method, ensemble probability density function (PDF) is produced based on the weighted performance of each model in depicting probability density functions of observed daily data (Déqué and Somot, 2010).

Bias correction (BC) approach has emerged as a standard procedure to minimise uncertainties in GCM/RCM based outputs, which adjusts (corrects) the modeled output with reference to the observed datasets in the post-processing step (Josef et al., 2018). To improve the reliability of GCM and RCM outputs, bias correction is used in the climate change studies, where bias is defined as the time independent component of the error. Model bias is defined by the systematic climate model error detected during the validation of model simulations with the unbiased climate observations (Teutschbein and Seibert, 2013). It is generally accepted that the GCM/RCM bias arises from misrepresentation of atmospheric physics (i.e. parameterization) in the model (Karmalkar, 2018). The fundamental step of identifying the bias between the model simulated and observed climate forms the foundation for correcting both historic and future simulations of climate from any GCM/RCM (Mehrotra and Sharma, 2015). For successful application of any bias correction method, it is vital that the observed correlations between various hydroclimatological processes are well represented in the bias corrected series. The flow chart of bias correction approach is shown in Figure 13.4. A few more relevant and frequently used and also globally accepted bias correction methods are discussed in the following sections.

### 13.2.1. Method of Linear Scaling (LS)

The LS bias correction method attempts to perfectly match the corrected values of the GCM/RCM simulated monthly mean climate to that of the historically observed climate (for more details, please refer Fang et al., 2015). In this method, the precipitation and temperature values are corrected at monthly timescale and the corrections are based on the differences between the observed and GCM/RCM simulated data. Precipitation values are corrected using a multiplicative factor and temperature is corrected using an additive term. Chen et al. (2013) adopted this method to correct the downscaled data for hydrologic impact studies over several watersheds of North America. Despite its simplistic approach and wide acceptance in hydrologic impact studies (e.g. Fang et al., 2015), several studies have highlighted the disadvantages of this method (e.g. Chen et al., 2013). For example, this method does not account for the changes in distribution and frequency of the meteorological variable.

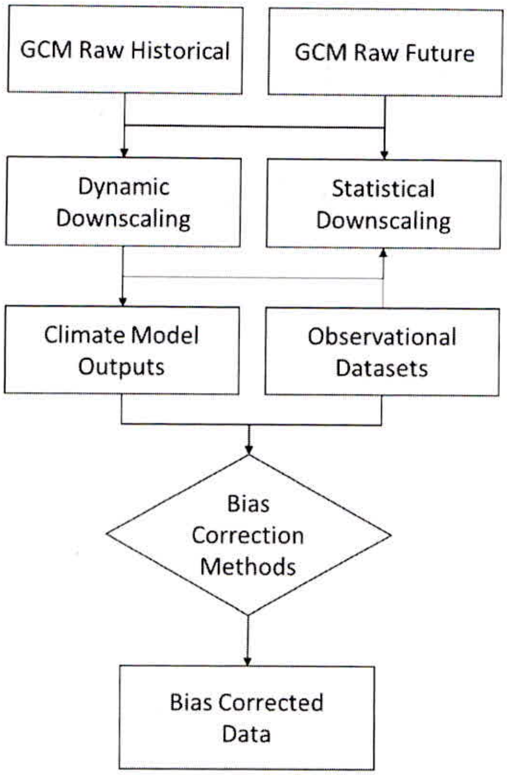


***Figure 13.4:*** *Flow chart showing the general bias correction approach.*

### 13.2.2. Local Intensity Scaling (LIS) Method

The LIS method corrects intensities and frequencies of wet-day and can successfully improve the biased datasets with too many drizzle (very small amount of precipitation) days (for more details, please refer Schmidli et al., 2006). This method is carried out in two steps: (1) a wet-day threshold for a month is determined from the raw precipitation data to ensure that the threshold exceedance matches the wet-day frequency of the observed data and (2) a scaling factor is applied to ensure that the mean of the corrected precipitation is equal to that of the observed precipitation (Fang et al., 2015). LIS utilizes a spatially variable scaling factor to correct the modelled precipitation at point scale of the observation. Themeßl et al. (2012) performed statistical downscaling and used LIS bias correction method to minimize the gaps between RCMs output and observed precipitation data. They found out that the LIS performed very well in precipitation corrections except in a few instances at higher quantiles, where the precipitation is underestimated. A similar observation was made by Fang et al. (2015), who found that LIS method was able to correctly estimate mean, median and wet-day probability but slightly underestimated the standard deviation and higher quantiles (e.g. 99$^{th}$ percentile). The biggest disadvantage of this method is that it does not make adjustments on the temporal structure of the meteorological variables (Teutschbein and Seibert, 2012).

### 13.2.3. Power Transformation (PT) Method

The PT method utilizes an exponential form to correct the standard deviation of meteorological series, although it has a limitation in correcting the wet-day probability. To overcome this limitation, the LIS method is employed to correct precipitation prior to applying the PT method (for more details, please refer Fang et al. (2015). This method was often found useful in the correction of mean, median, wet-day probability, wet day intensity, and it also performed well at high order quantiles (e.g. Teutschbein and Seibert, 2012; Fang et al., 2015). Several studies indicated that this method performed well in capturing coefficient of variation (CV) and mean (e.g. Leander and Buishand, 2007; Terinket al., 2010).

### 13.2.4. Delta Change (DC) Method

DC method has been used widely to correct the statistically downscaled GCM and RCM outputs with reference to the observed datasets (Rasmussen et al., 2012; Teutschbein and Seibert, 2013; Sarret al., 2015). In this method, precipitation is corrected using a multiplicative factor and the temperature is corrected using an additive term. Comparing the RCM simulated climate with the observed data, Teutschbein and Seibert (2013; 2012) concluded that this is a robust method in correcting mean climate with reference to the observed data. In contrast, Rasmussen et al., 2012 found this method to be less applicable in the correction of standard deviation, wet-day frequencies, and their intensities.

### 13.2.5. Quantile-based Mapping (QM) Method

The QM based method is a non-parametric bias correction method and can be applied to all meteorological variables without any assumption on their distribution. This approach begins with the empirical transformation and has been successfully applied in the bias correction of GCM/RCM based simulated hydroclimatic variables such as precipitation (e.g. Sun et al., 2011; Wilckeet al., 2013; Fang et al., 2015). This method was found to be efficient in correcting the bias in mean, standard deviation and frequency, including the quantiles (Sun et al., 2011; Fang et al., 2015). This method can be applied in two ways; (1) quantile mapping based on empirical distribution and (2) quantile mapping based on a gamma distribution (Chen et al., 2013). This method is widely used because of its simplistic approach, nonparametric configuration, and its applicability to other hydroclimatic variables (Themeßlet al., 2012). Although several studies conclude that this method gave better results, it is conditional and depends on the spatio-temporal scales of the observed and simulated datasets (e.g. Themeßlet al., 2012; Chen et al., 2013; Fang et al., 2015).

## 13.3. Concluding Remarks

This chapter includes a significant discussion on the uncertainty associated with the GCM projected climate and the downscaling techniques. Several studies are reviewed and the applicability of high and course resolution data in different parts of the world are addressed. Various complexities associated with the minimisation of uncertainty are explored and several techniques available to adequately address these complexities are discussed. However, the complete removal of uncertainty is nearly impossible by a single deterministic approach and therefore creation of multi-model ensembles should be preferred (Ehret et al., 2012). Future projections from an ensemble of several models (GCM or RCM) are useful in identifying a most likely projection of a future climate and the amount of uncertainty surrounding it. However, building a useful ensemble is the biggest challenge and utmost care should be taken in adequately sampling the uncertainties associated with the projections of future climate and identifying the 'most likely' future climate. Future policy decisions are critical in increasing the uncertainty in GCMs and these decisions could move the future GHG concentrations from higher to lower radiative forcing in the future. Therefore, the decision makers should be aware of the differences in the impacts of high to low representative concentration pathway in the future, which requires a creation of ensemble for each emission scenario separately. Adequate sampling of uncertainty plays a vital role in the creation of such ensembles. The bias correction methods discussed in this chapter would be useful for all regions around the world. Overall, it should be noted that the uncertainty associated with future climate is largely irreducible both in spatial and temporal scales that are relevant to water resources projects (Lacombe et al., 2018). And GCMs are less capable of predicting variables that are most important for water resources projects, such as local hydrologic extremes (floods and drought). In addition to the uncertainties associated with the GCM and downscaling methods, the assumptions or parameterizations made in hydrological models also induce uncertainty in the hydrological projections. However, the discussions in this chapter are primarily focused on the uncertainty induced from the climate models, because several studies have highlighted that uncertainties associated with hydrological models are relatively smaller when compared to those associated with GCM and emission scenarios (e.g. Sharma et al., 2018; Smithaet al., 2018;Tiwari et al., 2018).

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