CHAPTER 2

DOWNSCALING OF CLIMATE DATA

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2.0 Role of Climate Models in Hydrological Studies

Weather conditions can be explained over a certain area in a certain time-span. In a natural hydrological cycle, water continuously interchanges between oceans and atmosphere through multiple processes such as precipitation, evaporation and percolation in various spatial and temporal scales. Climate change is a complex issue involving interactions between ocean, atmosphere, and land (Jiang et al., 2007). However, under the influence of anthropogenic climate change, this continuum is changing due to changes in energy and mass balance of the associated processes (Bhuvandas et al., 2014). The accurate computation of complex hydrological processes has been critical in the present and 21st century due to the acceleration of climate change conditions. At smaller scales, hydro-climatological processes are more dynamic which may further increase uncertainty in the present and 21st century simulations and projections, especially when climate is changing. A comprehensive review of hydrological trends under changing climate conditions is widely available that showed a significant variability in the global hydro-climatology from 1951 to 2100 (Karmalkar, 2018; Sharma et al., 2018; Gupta and Jain, 2018; Mishra et al., 2014). In India, the severity of climate change has been increased and it highlighted in various hydro-climatological studies (Sharma et al., 2018; Gupta and Jain, 2018; Mishra et al., 2014). The use of advanced hydrological models including numerical weather predictors (Sun et al., 2016), numerical methods for hydrological analysis (Tiwari et al., 2014), statistical and artificial intelligence approaches (Goyal and Ojha, 2012) coupled with General Circulation Models (GCMs) and Regional Climate Models (RCMs) provide a great asset in simulating and projecting the long-term hydro-climatological changes (Seiler et al., 2018; Sun et al., 2016; Tiwari et al., 2014; Mishra et al., 2014; Vu et al., 2015); however, they are significantly varied at global, regional and smaller scales.

GCMs are basically numerical coupled models that represent various earth systems, including the oceans, atmosphere, land surface and sea-ice. Therefore, the applicability of GCMs variables in simulating and projecting impacts of climate change depends on various factors, including topography, climatology, weather pattern and geography of the region (Sun et al., 2016). GCMs are considered to be the most comprehensive models for investigating the physical and dynamic processes of the earth's surface-atmosphere system and they provide plausible patterns of global climate change (Andrews et al., 2012). Studies utilizing GCMs conclude that the large-scale assessment of hydro-climatological changes can be done and GCMs have been found able to capture the large-scale changes in various climate scenarios (Karmalkar, 2018; Singh et al., 2017; Andrews et al., 2012). However, the small-scale studies utilizing coarser resolution GCMs are less predictive and erroneous (Karmalkar, 2018). Since 2013, the accuracy of GCMs has been improved (Andrews et al., 2012). The development of the last Couple Model Inter-Comparison Phase Five (CMIP5) based GCMs and Regional Climate Models (RCMs) along with low to extreme high Representative Concentration Pathway (RCP 2.6 to 8.5) scenarios have improved the accuracy of climatic projections and forecasted scenarios (Gupta and Jain, 2018; Seiler et al., 2018; Vu et al., 2016; Sarr et al., 2015). The large scale GCMs are re-gridded at a much finer scale through the dynamic downscaling and the resultant product is called the RCM, which supposed to be enhanced the accuracy of climate projections at the regional as well as smaller scale (Fenta Mekonnen and Disse, 2018). The main purpose was to generate finer resolution RCM, minimizing uncertainties in climate projections (Karmalkar, 2018; Singh et al., 2017). The scope of GCM versus RCMs has been analyzed in numerous climate change studies and it has been seen that RCMs performed superior than GCMs (Gupta and Jain, 2018; Seiler et al., 2018; Karmalkar, 2018; Singh et al., 2017).

A large number of hydrological and hydrodynamic models have been developed and performed in various applications such as flood routing, flood forecasting, water balance analysis, water quality modeling, hydro-climatological projections and extreme event analysis (Singh et al., 2017; Sun et al., 2016; Apurv et al., 2015). In case of projecting long-term hydrological variables, the coarse resolution GCMs cannot be directly coupled to hydrological models, because of the complexities involved in the coarse resolution GCMs and the simplification of the hydrological cycle. However, the downscaled GCM variables can be utilized as inputs to the hydrological and hydrodynamic models. Different downscaling methods have been developed to enhance the applicability of GCMs, which are able to highlight smaller scale climatic variations. (Singh et al., 2017; Sun et al., 2016; Humphrey et al., 2016). While coupling GCMs and hydrological models, the undergone processes should be properly understood. Because, each model has their own limit in terms of data-inputs, model structure, governing equations, capability to handle time-space variations, ability to generate scenarios at the desired time steps, calibration strategies to control model uncertainties and forecasting (Singh et al., 2017; Humphrey et al., 2016; Tiwari et al., 2014).

The scope of downscaled GCM and RCM variables and their coupling with hydrological/ hydrodynamic models have been evaluated worldwide (Tiwari et al., 2018; Singh et al., 2017; Jiang et al., 2007). For example, the deterministic hydrology models such as SWAT, VIC, MODFLOW etc. are easy to couple with GCMs and RCMs for the real time forecasting and projection of hydro-climatological variables (Singh et al., 2017; Rasmussen et al., 2012). A physically-based distributed-parameter models have been found complex in nature, because they require large amount of data-inputs; however, they have been successfully applied to provide satisfactory results for a wide range of climate change applications utilizing RCMs and GCMs (Sun et al., 2016; Jiang et al., 2007). The downscaled GCMs/RCMs with reference to observational datasets and their couplings with advanced modeling tools are flexible in recognizing and selecting the most suitable method and also to evaluate the applicability of GCMs/RCMs at any specific region (Karmalkar, 2018; Singh and Goyal, 2016; Goyal and Ojha, 2012).

2.1 General Circulation Models (GCMs)

Various types of climate models have been developed to investigate the Land, Ocean and Atmospheric (L-O-A) interactions across the World. GCMs represent various physical processes which are related to atmosphere, ocean, cryosphere and land surface. GCMs have been frequently used for modeling and analyzing the atmospheric variability and climatic diversity and changes related to the Earth's environment (Azmat et al., 2018; Tiwari et al., 2018; Mishra et al., 2014; Andrews et al., 2012). GCMs portray the climate using a three-dimensional grid over the globe (Figure 2.1), typically having a horizontal resolution between 250 and 600 km, vertical layers (10 to 20) in the atmosphere and around 30 layers in the oceans (Carter et al., 2007). GCMs resolutions are thus quite coarse relative to the scale of exposure units in most impact assessments. GCMs known properties must be averaged over the large scale in a technique known as 'parameterization'. This is one scene of uncertainty in GCMs based simulations of future climate.

Intergovernmental Panel on Climate Change (IPCC) Data Distribution Center (DDC) generated different GCM versions and their simulations involving various agencies around the World. Numbers of atmosphere-ocean-geophysical variables have been produced at different spatio-temporal scales (*https://cmip.llnl.gov/cmip5/data_portal.html*).

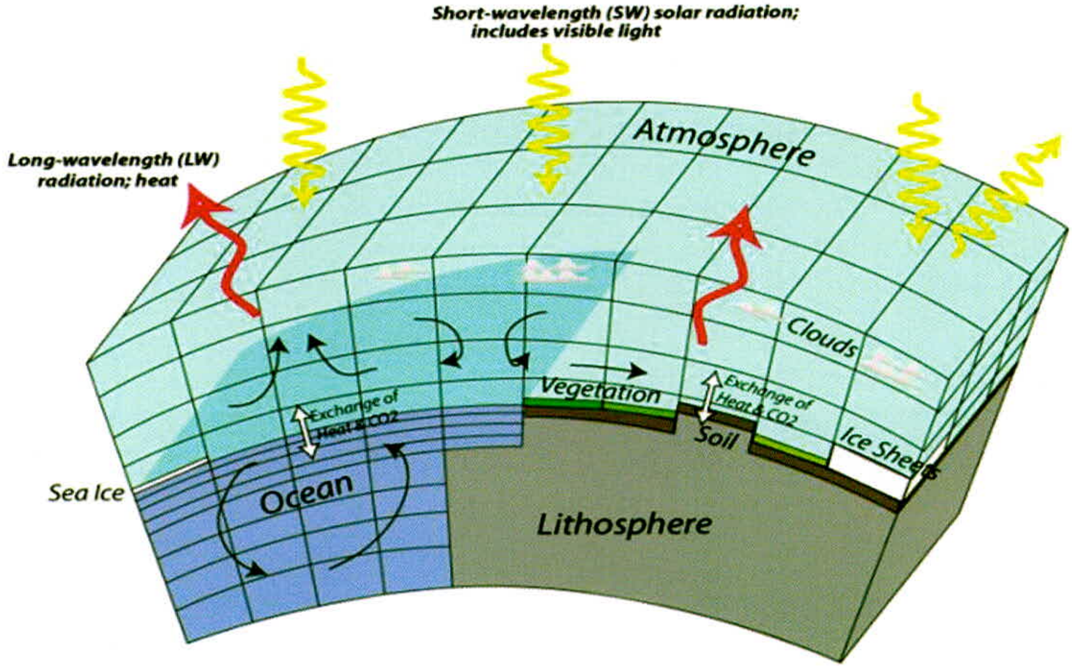

Figure 2.1: *Complex structure of a GCM grid and associated processes (Source: http://www.climate.be/textbook/chapter3)*

There are GCMs that model just the atmosphere (AGCMs), just the oceans (OGCMs) and those that include both (AOGCMs). GCMs characteristically include representations of surface hydrology, sea-ice, cloudiness, atmospheric radiation, convection and other pertinent processes (Azmat et al., 2018; Andrews et al., 2012). GCMs have coarse resolutions and therefore they cannot directly utilize for the analysis of smaller scale climate variations. Different versions of GCMs such as CMIP2 (Goyal and Ojha, 2012; Ghosh and Mujumdar, 2008), CMIP3 (Ghosh and Mujumdar, 2008), CMIP4 (Singh et al., 2017) and CMIP5 (Tiwari et al., 2018; Azamat et al., 2018; Gupta and Jain, 2018; Andrews et al., 2012) have been widely used to analyze atmospheric, terrestrial and climatic variations across the world, but many climatic observations based on GCMs are found reliable, mostly at the global scale (Gupta and Jain, 2018; Xue et al., 2014).

Hydrological models are generally complex in nature and mostly govern by the small-scale parameterizations. Therefore, the coupling of GCMs with complex hydrological tools may produce erroneous results while analyzing the impact of climate change in various hydro-climatological applications, especially at smaller and regional (Tiwari et al., 2018; Mishra et al., 2014; Xue et al., 2014). The global scale variables cannot directly couple with the local scale variables (Xue et al., 2014). The resolution of the climate model's dataset has a strong influence on the outputs of regional and small-scale processes. Thus, climate change studies performed utilizing coarser resolution GCMs sometimes may be failing in providing an accurate information (Xue et al., 2014; Mishra et al., 2014). Furthermore, GCMs are usually dependable at temporal scales of monthly means and longer.

Sometimes, the accuracy of projected and forecasting a climatic variable is a big challenge and we want to know how weather forecasts are so accurate? How climatic predictions have made over days and weeks? How cyclones or hurricanes have forecasted? GCMs and some large-scale climate indices (e.g. EL-Nino, ENSO, SOI etc.) are significantly involved in weather forecasting and they are extremely detailed grid-based simulations of weather that use atmospheric physics to predict events over hours, days and even further into the future. Therefore, GCMs can be utilized to predict or project climate changes in a long term like seasonal, annual, intra-annual and intra-decadal time series durations. GCMs may become more and more accurate as the physics of the atmosphere has become better understood. In a basic sense, the process of GCMs can be thought of in a few straightforward steps. In summary, GCMs provide quantitative estimates of future climate change that are valid in the global and continental scale and over long periods. GCM models are in a continuing state of development and evolution, so in the future, they will be more complex and realistic. The characteristics of GCM have been shown in Table 2.1.

Table 2.1: General features of GCM.

Contrasts	GCM
Goal	to predict climate
Spatial coverage	global
Temporal range	Years (1850-2300)
Spatial resolution	usually coarse (>100 km^2 to 500 km^2 grid)
Relevance of initial conditions	low
Relevance of clouds, radiation	high
Relevance of surface (land, ice, ocean)	high
Relevance of ocean dynamics	high
Relevance of model stability	high
Time dimension	ignored
Physics	equations of motion (plus radiative transfer equations and water conservation equations)
Method	Finite difference expression of continuous equations, or spectral representation; run prognostically
Output	state variables and motion of the atmosphere in 3 dimensions
Maximum time step	controlled by spatial resolution (CFL condition)

2.1.1 Model Scenarios

The IPCC has developed a whole set of scenarios that demonstrate the possible carbon emissions history for the next 100 years. The carbon emission is used as a key variable in driving climate modeling for each scenario (Taylor et al., 2012). Each scenario has been produced based on a group of assumptions about economic growth, population growth, and adoptions we might make regarding steps to minimize carbon emissions. A number of emission scenarios have been generated and their details are provided in the IPCC assessment reports (IPCC 2014, 2007). In this chapter, a few latest scenarios have been discussed. The projections corresponded to CMIP3 and CMIP5 have been utilized frequently and World-wide (Taylor et al., 2012). IPCC emission scenarios such as SRESA2, SRESA1B and SRESB1 generated under the CMIP3 assessment (2007). SRES A2 leads to a continuation of increased annual carbon emissions that follows the recent history. SRES A1B scenario envisions an integrated world characterized by rapid economic growth, a population growth and the rapid development of alternative energy sources that facilitate increased economic growth, while limiting and ultimately reducing carbon emissions. A SRES A1B scenario also assumes that there will be faster development and sharing of technologies which help us reduce our energy consumption. SRES B1 illustrates an even more integrated, more ecologically friendly world, but one in which there is still steady and strong economic growth. As in scenario SRES A1B, the population in this scenario peaks at 9 billion in 2050 and then declines. Each IPCC emission scenario shows emissions of carbon to the atmosphere (mainly from fossil fuel burning) (Gt C/yr; a GT is a billion tons!), so this is an annual rate. This highlights a flow into the atmosphere. Approximately, half of the carbon emitted will remain in the atmosphere and lead to a stronger greenhouse effect, which will, in turn, increase global temperature and change the climate in a variety of ways.

Under CMIP5 and earlier phases of IPCC model development, a few GCMs which have been frequently used in many climate change studies worldwide presented in Table 2.2. These GCMs have been developed by various agencies from the world. Under CMIP5 projection scenarios (2013), four representative concentration pathways (RCPs) were produced and defined by their total radiative forcing (RF) (cumulative measure of human emissions of GHGs from all sources expressed in Watts per square meter) pathway and level by 2100. The RCPs were chosen to represent a broad range of climate outcomes. The four RCPs used a common set of historical emissions data to initialize the integrated assessment models. The RCPs descriptions have been provided in Table 2.3.

Table 2.2: CMIP5 GCMs, their model components, resolution and sources (Source: IPCC 2014).

GCM	Model	Resolution (Lat × Lon)	Source
BCC-CSM and BCC-CSM 1.1 (m)	Atmospheric component, Ocean component, Land component, and Sea ice component are fully coupled. Information between the atmosphere and the ocean is exchanged once per simulated day. The exchange of atmospheric carbon with the land biosphere is	64 × 128 160 × 320	Beijing Climate Center, China Meteorological Administration, China

	calculated at each model time step (20 min).		
BNU-ESM	An earth system model is based on several widely evaluated climate model components and is used to study mechanisms of ocean-atmosphere interactions, natural climate variability, and carbon-climate feedbacks at interannual to interdecadal timescales	64 × 128	Beijing Normal University, China
CanESM2	It is the fourth-generation atmosphere-ocean general circulation model. Horizontal coordinates are spherical with grid spacing ~ 1.41 degrees in longitude and 0.94 degrees in latitude	64 × 128	National Center for Atmospheri c Research (NCAR), United States
CCSM4	The Community Climate System Model (CCSM) is a coupled climate model for simulating the earth's climate system, composed of four separate models simultaneously simulating the earth's atmosphere, ocean, land surface, sea ice, and one central coupler component	192 × 288	National Center for Atmospheri c Research (NCAR), United States
CNRM-CM5	CNRM-CM5 is an Earth system model designed to run climate simulations. It consists of several existing models designed independently and coupled through the OASIS software	128 × 256	CERFACS (Centre National de Recherches Meteorolog iques, France)
CSIRO-Mk 3.6.0	Australian Commonwealth Scientific and Industrial Research Organisation	96 × 192	

FGOALS-g 2	Flexible Global Ocean-Atmosphere-Land System (FGOALS) model includes four individual components (an atmosphere component, an ocean component, a land component, and a sea-ice component) that are driven by a flux coupler module	108 × 128	GFDL& Institute of Atmospheric Physics (LASG-IAP), Chinese Academy of Sciences, Beijing, China
FIO-ESM	Earth system model, which is named as the First Institute of Oceanography-Earth System Model (FIO-ESM), is composed of a coupled physical climate model and a coupled carbon cycle model.	64 × 128	The First Institute of Oceanography, SOA, China
GFDL CM3	GFDL has constructed NOAA's first Earth system models (ESMs). The atmospheric component of the ESMs includes physical features such as aerosols (both natural and anthropogenic), cloud physics, and precipitation. The land component includes precipitation, evaporation, streams, lakes, rivers, runoff, and a terrestrial ecology component to simulate dynamic reservoirs of carbon and other tracers. The oceanic component includes features such as free surface to capture wave processes; water fluxes, or flow; currents; sea-ice dynamics; iceberg transport of freshwater	90 × 144	Geophysical Fluid Dynamics Laboratory, United States
HadGEM2-ES	HadGEM2-ES is Earth system model that was used by the Met Office Hadley Centre for the CMIP5 centennial simulations. Earth system components included are the terrestrial and ocean carbon	145 × 192	Met Office Hadley Center, Unites Kingdom

	cycle and tropospheric chemistry. Ocean biology and carbonate chemistry are represented by diat-HadOCC, which includes limitation of plankton growth by macro- and micronutrients and also simulates emissions of DMS to the atmosphere		
MPI-ESM-LR and MPI-ESMR	MPI-ESM (MPG) is a comprehensive Earth system model and are coupled through the exchange of energy, momentum, water, and important trace gases such as carbon dioxide. The model is developed by the MPI for Meteorology (MPI-M) and based on its predecessors.	96 × 192	Max Planck Institute for Meteorolog y (MPI-M), Germany

Table 2.3: RCPs and their description (Source: IPCC 2014).

RCP	Description	Emission Level
RCP8.5	Rising radiative forcing pathway leading to 8.5 W/m2 in 2100.	Extreme emission scenario
RCP6.0	Stabilization without overshoot pathway to 6 W/m2 at stabilization after 2100	High emission scenario
RCP4.5	Stabilization without overshoot pathway to 4.5 W/m2 at stabilization after 2100	Moderate emission scenario
RCP2.6	Peak in radiative forcing at ~ 3 W/m2 before 2100 and decline	Mitigation/low emission scenario

2.2 Regional Climate Models (RCMs)

It is concluded that coarser resolution GCMs are not suitable for the local scale or regional scale studies, for example: to analyze the impact of climate change in a particular river basin or may be at district level requires more precise information than GCMs currently provide. GCMs determine a very large-scale effect of changing global climate system. The climatic parameters computed by the GCM can be effectively utilized as inputs to RCM for example: temperature and wind. Numerous RCMs have been developed, applied, inter-compared, and demonstrating important downscaling skills, but also model deficiencies are still yet to be resolved. RCM is a numerical climate prediction model forced by specified lateral and ocean conditions from a GCM or observation-based dataset (reanalysis) that simulates atmospheric and land surface processes, while accounting for high-resolution topographic data, land-sea contrasts, surface characteristics, and other components of the Earth-system. RCMs are initialized with the initial conditions and driven along its lateral-atmospheric-boundaries and lower-surface boundaries with time-variable conditions. Therefore, RCMs utilize to downscale global reanalysis or GCM runs to simulate climate variability with regional refinements.

RCMs enhances the spatial resolution as compared to GCMs, because RCMs have been produced at finer mesoscale grids (grids belong to 10 km^2 – 50 km^2) (Singh et al., 2017; McCarthy et al., 2012; Van Meijgaard et al., 2008; Mailhot et al., 2007). The spatial resolution-based comparison between GCMs and RCMs has shown in Figure 2.2. RCMs can then resolve the local impacts by giving the small-scale information about orography (land height), land use, weather and climate information at a resolution of 50 km^2 or 25 km^2 (Karmalkar 2018; McCarthy et al., 2012) while GCMs may fail to do this. RCMs can be applied over a given area or limited area driven by GCMs can provide information at much smaller scales, which are capable to support more detailed impact and adaptation assessment studies (Bhuvandas et al., 2014). Studies have shown that RCMs are able to analyze the effect of climate change and geophysical environment better than GCMs (Karmalkar 2018; Singh et al., 2017). However, it should be noted that solutions from the RCM may be inconsistent with those from the global model, which could be problematic in some applications.

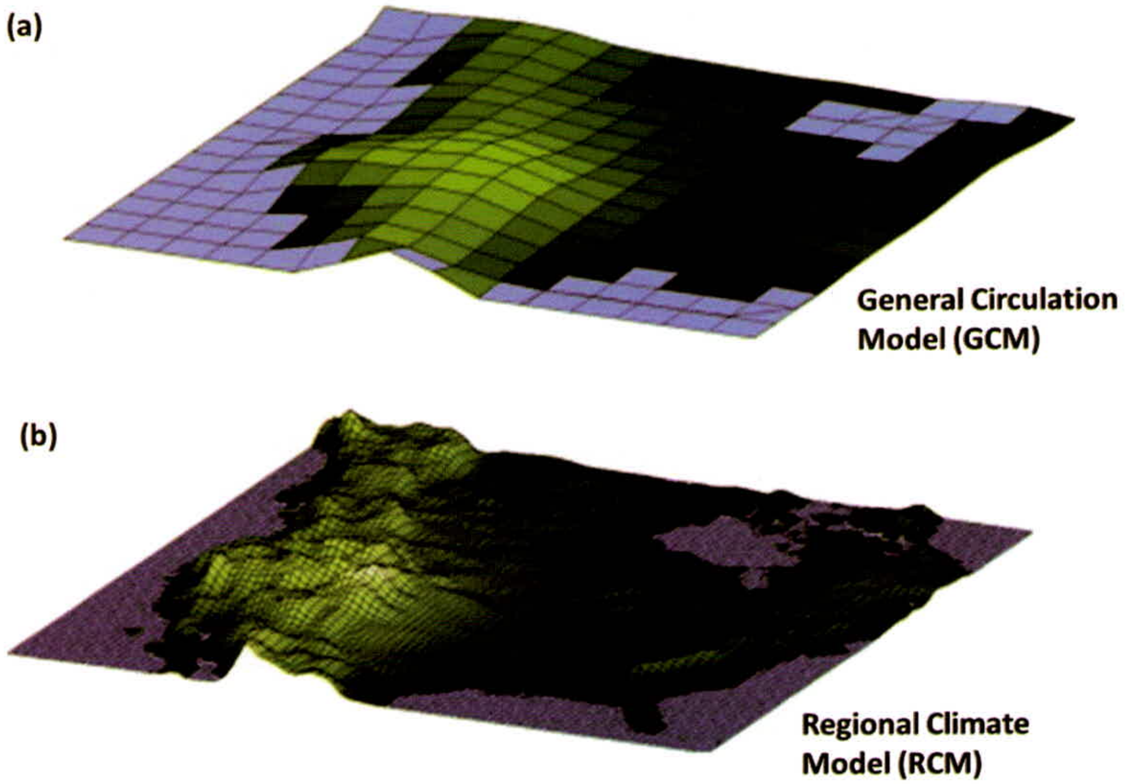

Figure 2.2: *Comparison in spatial resolution between GCM versus RCM (Source: Lee Hannah, in Climate Change Biology (Second Edition), 2015).*

RCMs which are commonly used in different climate change studies around the World include the U.S. Regional Climate Model Version 3 (RegCM3) (Pal et al., 2007); Canadian Regional Climate Model (CRCM) (Mailhot et al., 2007); UK Met Office Hadley Centre's Regional Climate Model Version 3 (HadRM3) (McCarthy et al., 2012); German Regional Climate Model (REMO) (Jacob and Podzun, 1997); Dutch Regional Atmospheric Climate Model (RACMO) (Van Meijgaard, 2008); and German HIRHAM, which combines the dynamics of the High-Resolution Limited Area Model (HIRLAM) (Tuomi et al., 1999) and European Centre-Hamburg (ECHAM) models (Tibaldi et al., 1997) generated under different IPCC CMIP assessments. CORDEX is a World Climate Research Programme (WCRP) framework has been developed to evaluate the RCMs performance through a set of experiments aiming to produce regional climate projections (Singh et al., 2017). CORDEX-East Asia is the branch of the CORDEX initiative produces RCM ensembles based on the dynamical downscaling methods forced by multi-model GCMs. One distinct advantage of RCM application is its higher spatial (or horizontal) resolution, which makes the RCM capable to handle more realistically certain and critically important climate processes (Karmalkar, 2018).

2.3 Downscaling

GCMs are capable in predicting large-scale heterogeneity, climate variability and changes. Therefore, GCMs have been successfully applied in various large-scale studies. However, due to their coarser scale resolutions, GCMs are less capable to explore small-scale changes. Several landscape features such as water bodies, mountains, water-balance in the basin and sub catchment scale, land-cover analysis and climate change impact at a local scale can be better explored utilize RCMs, because they produce at much finer scales than GCMs. However, sometimes RCM fails to incorporate very small scale and location-based heterogeneities and changes (Karmalkar 2018). To address the small-scale heterogeneities, which may be crucial for hydro-climatological studies and other applications, different downscaling methods have been developed (Moalafhi et al., 2017; Ghosh and Mujumdar, 2008). Downscaling depends on the hypothesis that local climate is a composition of large-scale atmospheric features (e.g. Hemisphere, continental, global and regional) and local conditions (e.g. land surface properties and topography).

The derivation of fine-scale climatic information is based on the hypothesis that the local climate is conditioned by relations between local features and large-scale atmospheric characteristics (Moalafhi et al., 2017; Mishra et al., 2014). Climate studies performed on a smaller scale utilizing a similar hypothesis-based approach concluded that it is possible to model local and large-scale interactions and established a relationship between present-day local climate and atmospheric conditions through multiple downscaling processes (Seiler et al., 2018). The downscaling processes enhance the information to the coarser GCM output so more realistic data can produce at a finer scale, capturing sub-grid scale differences (Mishra et al., 2014).

Downscaling of the large scale GCMs variables can be performed in both spatial and temporal aspects with reference to local scale variables. According to Trzaska and Schnarr (2014), "Downscaling is a process that converts a large-scale information (e.g. coarse resolution grid like 500×500 km^2) to finer scale information (e.g. 50 ×50 km^2)". Downscaling can be utilized to convert coarser spatial resolution GCMs to any desired local grid cell (suppose 20 km^2, a higher resolution grid cell) or even at a specific point location (Figure 2.3) (Shukla and Lettenmaier, 2013). Similarly, temporal downscaling can be referred to convert from coarser scale temporal GCM output (e.g. monthly precipitation) to finer scale GCM output (e.g. daily precipitation) (Xue et al., 2014).

In climate modeling, there are two main categories of downscaling distinguished: (i) statistical/ empirical downscaling (Wilby et al., 2014) and (ii) dynamical downscaling (Xue et al., 2014; Mishra et al., 2014; Shukla and Lettenmaier, 2013) (Figure 2.3). The dynamical downscaling method has several numerical advantages over statistical modeling, while dynamical downscaling has found computationally intensive and requires a large amount of datasets and high level of manpower to interpret/produce results (Trzaska and Schnarr, 2014). Each downscaling method contains uncertainties and has their own limitations. No official guidance is available on downscaling or downscaling methods that best meet the user's need. Therefore, the research community is still developing the downscaling methods.

2.3.1 Statistical Downscaling

Statistical downscaling methods have been developed to interpolate large-scale atmospheric predictor variable (e.g. average of precipitation and temperature, circulation characteristics such as mean sea level pressure, radiation, wind circulations etc.) to point scale or at gauge scale (e.g. rainfall, runoff, etc.) (Singh and Goyal, 2017; Singh and Goyal, 2016; Ghosh and Mujumdar, 2008; Wilby et al., 1998). From this point of view, the regional or local climate information is generated by first determining a statistical model which narrates large-scale climate variables called "predictors" to regional and a local variable called "predictand". Once a relationship has been established between predictand and predictor, the model can be setup in historical time duration and simulated scenarios can be generated along with the regression coefficients (e.g. parameters of the regression equation). After calibration and validation, the future climate scenarios can be predicted and forecasted under the presence of 21st century GCM variables and regression parameters.

Statistical downscaling has been successfully applied in various climatic simulations and projection studies where sufficient observed datasets (or predictands) are available to derive the statistical relationships (Singh and Goyal, 2016; Ghosh and Mujumdar, 2008). Statistical downscaling has been widely used in hydro-climatological studies around the world (Singh and Goyal, 2016; Wilby et al., 1998). A graphical user interface (GUI) based Statistical Downscaling Model (SDSM) developed by Wilby et al. (2004) has been successfully applied in various rainfall and temperature projection-based studies (Seiler et al., 2018; Singh et al., 2017). Wilby et al. (2004) used a weather generator based multiple linear regression method to build a relationship between large scale GCM outputs (predictors) and small scale/point scale observed variables (predictands) to forecast long term rainfall scenarios. Recently, an integrated "dynamic-statistical" approach has been presented to enhance the computations at a smaller scale in both temporal and spatial domains (Walton et al., 2015; Sun et al., 2015).

Sun et al. (2015) presented a hybrid downscaling approach which has been found more capable to capture spatial variations in warming even at smaller scales. Several studies utilized a "categorical approach" in statistical downscaling, which includes some classification and clustering based statistical techniques to relate GCM data to different groups as per large scale circulation patterns and data attributes (Bhuvandas et al., 2014; Zorita and Von Storch, 1999). Among multiple downscaling methods, SDSM based statistical downscaling approach has been considered to be the most suitable for downscaling of large scale GCM outputs at a point or gauge scale, especially to forecast climatological variables. (Xue et al., 2014; Bhuvandas et al., 2014). In case of statistical downscaling, the demand of available data is high and this could be a weakness of this method, but on the other hand the computational cost of statistical downscaling is comparatively low. The simplest approach of statistical downscaling cab be described by several sequential procedures as shown in Figure 2.4.

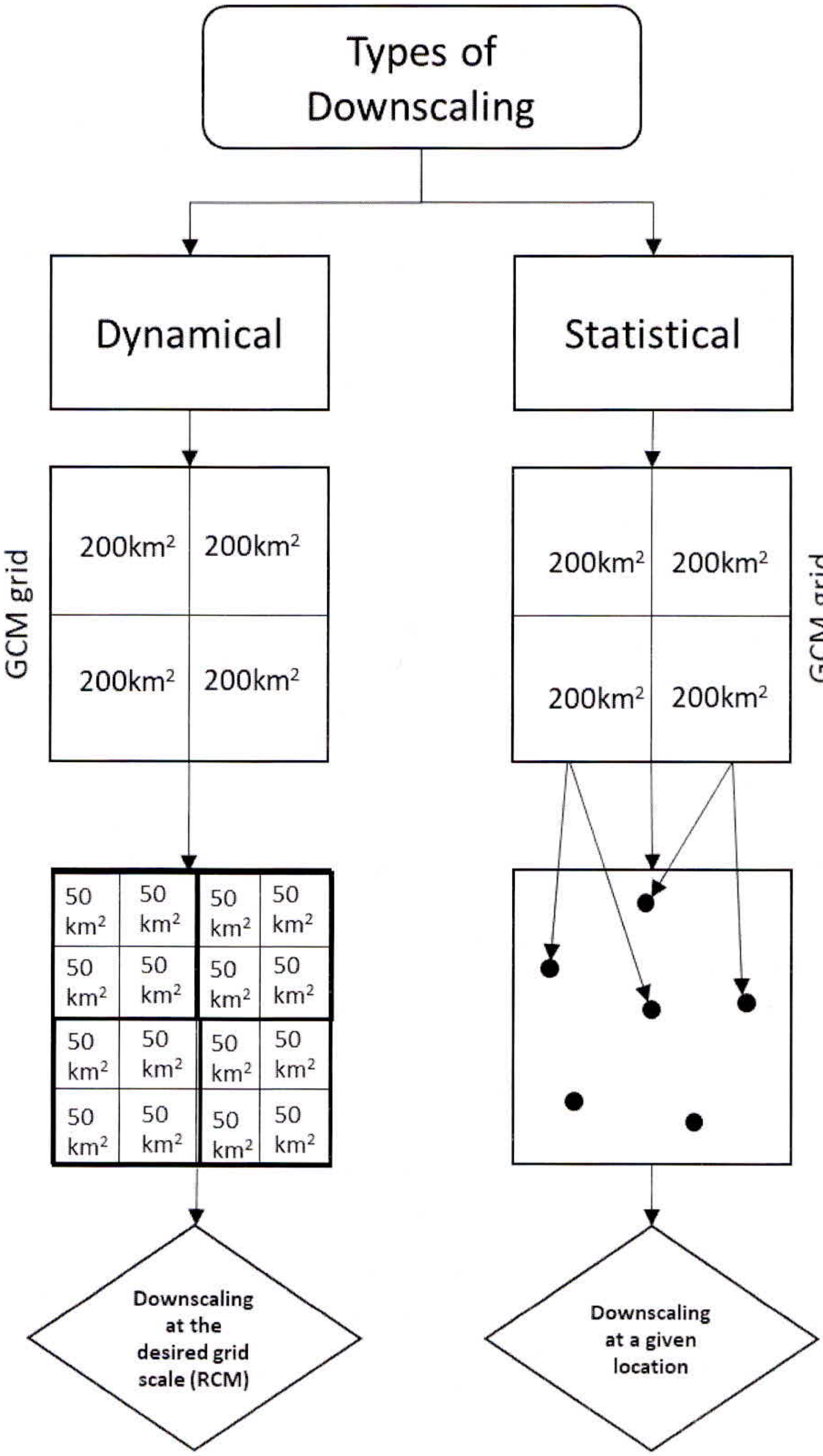

Figure 2.3: *Schematic representation of Dynamic and Statistical Downscaling.*

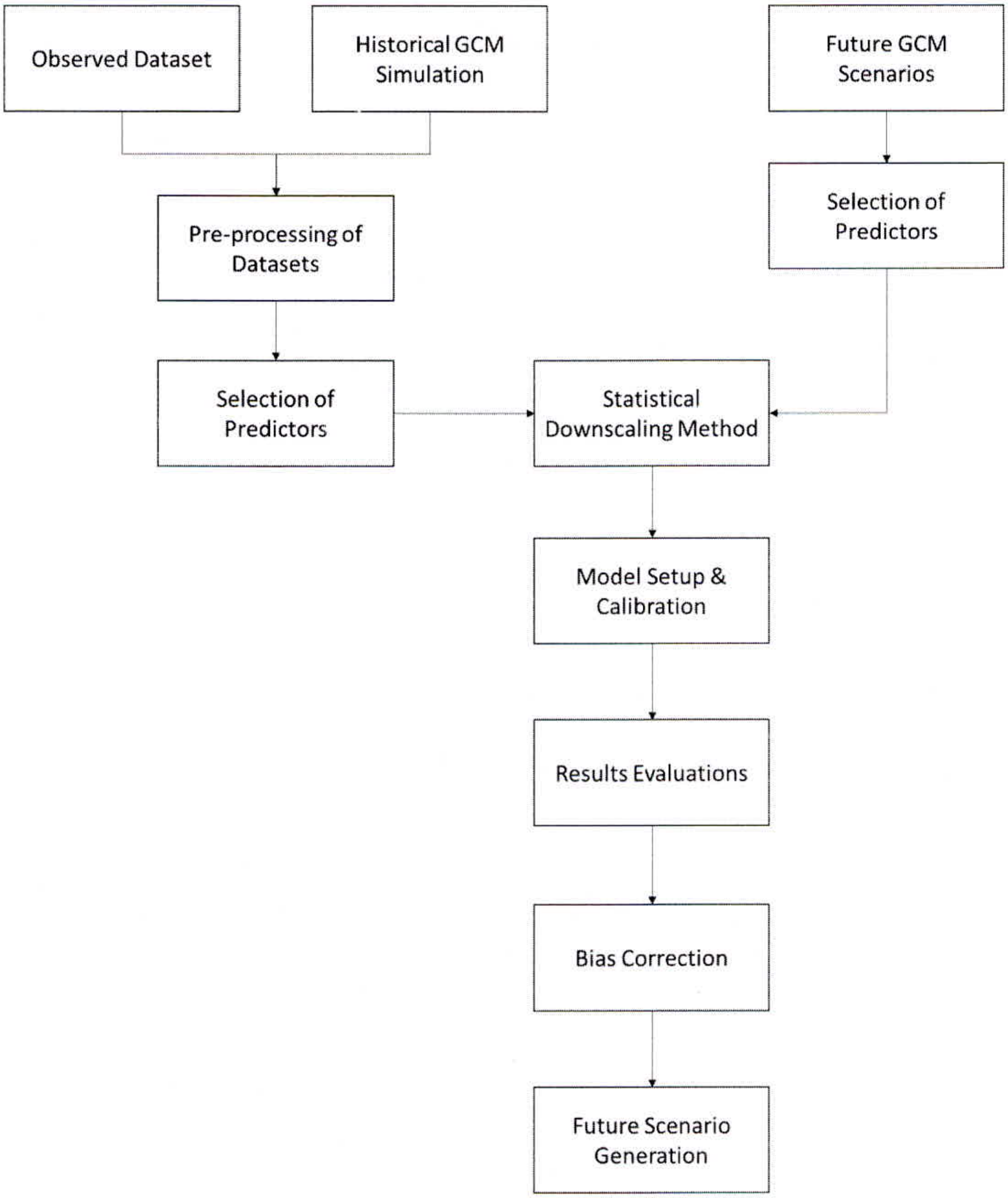

Figure 2.4: *Schematic flow chart of performing statistical downscaling and climate model scenario generation.*

Selection of GCM

In many climate change impact studies, the authors have faced problems while utilizing the full number of GCM simulations that are available; and thus, often only subsets are used. Each model may produce different outputs because of differences in model structure and model processes. The GCM related uncertainties have been explored utilizing a large number of GCMs and the level of uncertainty in each model has been quantified (Sharma et al., 2018; Joseph et al., 2018; Mishra et al., 2014). Many studies utilized multiple GCMs so that they cover different sources and levels of uncertainties. However, in case of limited computing resources, it is difficult to process all GCMs and quantifying various sources of uncertainties; thus, only part of the known uncertainty is considered (Sharma et al., 2018). Several climate change studies applied a cluster analysis method to select a subset of full numbers of climate simulations, which are the best representatives for the given area (Joseph et al., 2018; Xue et al., 2014).

By reducing the number of GCMs, the information available related to uncertainty in the projections and ensembles may also be reduced (Wilcke and Bärring, 2016). However, the selection of GCMs is not straightforward; and therefore, various methods have been suggested and tested in different studies which can be utilized such as the range of projected changes in the means (Lutz et al., 2016), based on climate extremes (Ruane and McDermid, 2017; Lutz et al., 2016), based on skill tests and cluster analysis (Lee and Kim, 2017; Lutz et al., 2016). Semenov and Stratonovich (2015) developed 'climate sensitivity indices' to select GCMs based upon mean precipitation and temperature changes. After that, Ruane and McDermid (2017) utilized a representative temperature and precipitation GCM sub-setting procedure and identified five individual GCMs that are able to capture a profile of the full number of GCM ensembles. In sub-setting/selecting GCMs, the aim should be that each GCM represents major type of change and is linked with probabilistic information correlated to the broader ensemble (Lee and Kim, 2017).

Selection of predictors

Statistical downscaling methods produce empirical/statistical links between the large-scale and local-scale variables. Statistical downscaling is not only useful in numerical weather prediction and synoptic climatology, but it also provides a local-scale information, which is very useful in climate change impact assessment studies (Singh and Goyal, 2016; Ghosh and Mujumdar, 2008). The SDSM downscaling tool implies on the empirical relationships between the local-scale predictands and large-scale predictor(s) (Willby et al., 2014). Because of the linear concepts of statistical downscaling, the selection of predictors (e.g. GCM variables) can be made while performing correlation and partial correlation analysis between predictands (e.g. observed variables like precipitation and temperature) and predictors, and the predictor weights can be estimated via ordinary least-square method (Willby et al., 2014). Each GCM model contains numbers of predictor variables and thus some of them can be dropped if they do not represent the property of local variables (Singh and Goyal, 2017). In statistical downscaling, the non-significant predictors may be dropped, if they do not show any significance (Singh and Goyal, 2017). A simple correlation analysis may be performed for the selection of most suitable predictors (Trzaska and Schnarr, 2018; Singh and Goyal, 2016).

To select the first and most suitable large-scale variable is relatively easy, though the judgment of the second, third, fourth and so on is much more subjective (Willby et al., 2014). Thus, several standard statistical evaluation methods can be performed for screening large scale variables corresponding to each local scale variable (Willby et al., 2014). In statistical downscaling, a correlation matrix can be prepared between large-scale predictors and local-scale predictand to find out suitable predictors. Then predictors having high correlation coefficients (a threshold can be used like >=0.7) can be taken and arranged in descending order (Singh and Goyal, 2016; Willby et al., 2014). Then among the selected predictors based on high correlation coefficients, the negative correlated predictors can be dropped from the analysis and only positive correlated predictors can be utilized as shown by Singh and Goyal (2016) and Wilby et al. (2014). The first ranked predictor, having the highest correlation coefficient among others, can be selected and will be defined as the first suitable super predictor (FSSP) (Willby et al., 2014). After this the absolute correlation (R) between predictor and predictand, and the correlation coefficient between individual predictors can also be calculated (Willby et al., 2014). Then the other highly correlated predictors (for precipitation it is 0.5 and above, and for temperature, it is 0.7 and above in this case) will be taken out in order to remove any multi-co-linearity (Singh and Goyal, 2016). The correlation coefficient up to 0.7 between two predictors is acceptable (Singh and Goyal, 2016; Wilby et al., 2014).

In case of the selection of the second, third and so on, a percentage reduction in a partial correlation (PRP) with respect to absolute correlation can be calculated for each predictor (Singh and Goyal, 2016). The PRP is the percentage reduction in partial correlation with respect to the correlation coefficient. The predictor which has a minimum PRP in partial correlation (Willby et al., 2014) can be selected as the second most suitable predictor (Singh and Goyal., 2016; Willby et al., 2014). This predictor has almost no or a very insignificant multi-co-linearity with the FSSP. The third, fourth and following predictors could be obtained by repeating the same procedure (Willby et al., 2014). A similar methodology for the selection of suitable predictors has been applied by various researchers across the world for the statistical downscaling of precipitation, temperature and other hydro-meteorological variables (Willby et al., 2014).

Calibration and validation

After selection of predictors, the regression model can be set up between predictors and predictands by selecting a homogenous time duration as per the availability of observed and simulated climate data (Willby et al., 2014). The regression model should be prepared by selecting best and suitable predictors only rather than all predictands, because multi-colinearity can affect trends and it must be avoided among predictors (Singh and Goyal, 2016). Many studies performed calibration/validation on a monthly and a daily time scale and both time steps gave satisfactory results (Sharma et al., 2018; Salvi et al., 2016). For the evaluation of calibration and validation results, the statistical evaluation methods such as coefficient of determination (R2), changes in mean, standard deviation and root mean square error (RMSE) have been successfully performed (Singh and Goyal, 2016). The explained variance and standard error methods also utilized to evaluate the performance of statistical regression methods (Salvi et al., 2016), in which the observed data are plotted against the regression model based simulated dataset. In most of the studies, it has been suggested that for regression modeling, a minimum 30 years' time series datasets are required (Willby et al., 2014).

Bias correction

In statistical downscaling, GCMs based simulations produced a significant amount of bias (or uncertainties) when they downscale at a point scale (or, finer scale), because coarser resolutions GCMs fail to explain small scale variations (Singh and Goyal, 2016). At present, GCMs simulations generally produce a significant amount of bias in hydro-climatological projections and forecasting scenarios. To reduce the bias in GCMs, various bias correction (BC) methods have been developed and their applicability in error reduction has been tested in many climate studies (Ghosh and Mujumdar, 2008). BC methods correct the simulated outputs in the presence of observational datasets in a post-processing step (Willby et al., 2014). The detail description of the bias correction methodology and its significance have been presented in the next chapter. After bias correction, a bias factor or mean bias can be derived (Singh and Goyal, 2016). The future scenarios generated by GCMs may further correct by applying the bias factor (Willby et al., 2014).

Scenario generation

In statistical downscaling, once the regression model has been successfully calibrated and validated based on a historical dataset (or training dataset), the optimized regression coefficients (or parameters of the regression equation) can be utilized for the 21st century scenarios generation (Willby et al., 2014). In statistical downscaling, a conditional sub-model can be utilized for the projection of maximum and minimum temperature without any transformation (Willby et al., 2014) and an unconditional sub-model may be applied in case of stochastic variable (e.g. precipitation) with fourth root transformations (Singh and Goyal, 2016).

2.3.2 Dynamic Downscaling

Dynamic downscaling is generally related to the use of RCM developed from mesoscale (e.g. 10 km^2 to 50 km^2 grids) atmospheric models, similar to GCM based principles. However, RCMs have higher spatial resolution than GCM (Xue et al., 2014; Wang et al., 2014). RCMs represent mesoscale atmospheric information which has been found suitable to produce more realistic and accurate climate information on a regional scale (e.g. 25-50 km^2 grid scale) (Xue et al., 2014). The distinct choice of domain size controls the disagreement between the RCMs and their driving GCMs. Dynamical downscaling enhances the approach of regional climate modeling and delivers better predictors for supplementary statistical downscaling to higher-resolution output (Guyennon et al., 2013).

The use of RCMs in climate modeling has been increased (Karmalkar, 2018; Singh et al., 2017), thus it is important to understand whether and under what conditions the dynamic downscaling is really capable of improving climate simulations/predictions. Few studies have compared the applicability of RCMs against GCMs has been compared mainly to test that whether RCMs are really capable to provide more precise climate information at different scales or not (Singh et al., 2017; Xue et al., 2014)? Although, RCMs may provide feedbacks to their driving GCMs. Most of the dynamic downscaling approaches have presented based on a one-way nesting approach and have no feedback from the RCM to the driving GCM (Xue et al., 2014). The RCM based dynamic downscaling will ultimately be evaluated by its capability to produce realistic simulations/predictions on the smallest scale (Xue et al., 2014). Several studies demonstrated that factors such as lower boundary conditions, domain size, physical processes and horizontal resolution have strong influence on the dynamic downscaling (Xue et al., 2014). Many studies utilized RCMs for projecting long term climate scenarios and concluded that RCMs performed superior than GCMs. The capability of RCM depends not only on the RCM's resolution, but also on the RCM's parameterization (Wang et al., 2014). These days, the RCM based projections of the future climate and many other applications such as producing high resolution data for hydrological assessments have increased as seen in many studies (Shukla and Lettenmaier, 2013).

A comparative assessment has been done between statistical and dynamic downscaling methods to highlight their various features is shown in Table 2.4:

Table 2.4: Comparison between statistical and dynamical downscaling.

	Statistical Downscaling	Dynamical Downscaling
Features	Any scale/down to gauge level/point level information Daily time series information Monthly time series information Scenarios for extreme events (only applicable to some methods)	Provides 20-50 km^2 grid call information Daily time series information Monthly time series information Scenarios for extreme events Historical scenarios Future scenarios

	Historical scenarios (only applicable to some methods) Future scenarios (only applicable to some methods)	
Advantages	Easy computation and efficient for many emissions scenarios and GCMs Methods range from simple to complex for purpose basis Same method can be applicable to all areas/regions/globe and for multiple GCMs Relies on observed climate dataset/variables Tools are freely available Requires medium/low computations resources Requires observational dataset In the absence of sufficient amount of observational data, it may produce large uncertainty in the outputs Assumption is that the existing relationship between large scale GCM and local scale processes will remain constant in the future	Based on physical mechanism and consistent Resolved based on surface processes and complex atmospheric processes occurring at sub-GCM grid scale Accuracy is more and realistic at regional scale 20-50kms grid scales RCMs products are available for uncertainty analysis Requires high computations resources and expertise Requires high amount of datasets Results are dependent as per RCM/GCM, different RCM may give different outputs Affected by bias as per the deriving GCM

2.3.3 Advanced Downscaling Methods

ANN based methods

Artificial neural networks (ANNs) are a pattern recognition tool which have been utilized to reproduce empirical, possible non-linear relationships between a set of 'input' variables and some corresponding 'output' variables (Dorji et al., 2017; Goyal and Ojha, 2012). ANNs works based on the physiology of the brain, through a series of 'nodes' which pass information between one another in a similar way to cells in the brain (Goyal and Ojha, 2012). For a full description of ANN theory, kindly see Bishop (2000) or Picton (2000) published studies. In climate dynamics, a relationship has been established between the GCM and RCM output parameter fields, specifically temperature and rainfall. This was done by representing properties of the GCM and RCM fields to an ANN, and 'training' it to be able to replicate the relationship between the two (Dorji et al., 2017). Similar to statistical downscaling, a linear and non-linear regression method has been employed in the ANN based downscaling approaches. In the ANN based downscaling, a relationship can be built between large-scale and small-scale variables (through input layers) and some weights are generated in their hidden layers to generate the prediction samples (Dorji et al., 2017) (through output layers).

Many studies utilized Multilayer Perceptron (MLP) neural network for the downscaling of various hydro-climatological variables (Dorji et al., 2017; Humphrey et al., 2016). MLP method is widely used to establish the nonlinear relationship between predictor and predictands (Dorji et al., 2017). The neural network improves the performance function between the predicted and observed values. There is a slight difference in statistical downscaling and MLP neural network-based downscaling, because statistical methods are mostly based on the data distribution while MLP makes no assumption (Humphrey et al., 2016). The complexity involved in MLP can be adjusted by increasing or decreasing the number of hidden layer nodes, which determine the number of free parameters in the model (Humphrey et al., 2016). Several studies utilized Bayesian ANN statistical forecasting model for the downscaling of GCMs and RCMs (Humphrey et al., 2016). Overall, ANNs based downscaling models are found more flexible and stable than ordinary statistical downscaling models. ANNs based methods have found better in capturing complex and nonlinear input-output relationships from data without any restrictive assumptions (Vu et al., 2015).

Weather generators (WGs)

Weather Generators (WGs) have significant ability to downscale weather variables and therefore, WGs are widely used in climate change studies, especially the short-term forecasting of meteorological variables. WGs are relatively easy to run and their outcomes are easy to post-process and interpret. Numerous WGs currently being used, including Weather Generator, WGEN (Chen et al., 2015); Climate Generator, CLIMGEN (Mehan et al., 2017); USCLIMATE; Stochastic Weather Generators, WeaGETS; and the Long Ashton Research Station Weather Generator, LARS-WG (Mehan et al., 2017). Dubrovsky et al. (2017) utilized a new gridded multivariate parametric stochastic WG modelled by Markov chain and Gamma distribution for forecasting precipitation in Europe. Dubrovsky et al. (2017) showed significant spatial and temporal variations in forecasted precipitation and the climate change scenarios are derived from the selected RCM simulations (CORDEX database). International Research Institute for Climate and Society (IRI) produced a stochastic weather generator which works based on the generalized linear modeling (GLM) (Kim et al., 2016). The GLM based stochastic WG has been applied mostly to forecast rainfalls and different studies, observation show that weather generator is able to generate the probability distributions of seasonally aggregated rainfalls and minimum and maximum temperature (Kim et al., 2016). Numerous WGs based studies performed in India revealed that WGs are able to forecast short-term and long-term meteorological scenarios (e.g. temperature and precipitation) (Sharma et al., 2018).

Other advanced statistical and machine learning methods

Very few studies utilized an advance downscaling method such as quantile-based regression method for the downscaling of GCM variables (e.g. daily minimum-maximum temperatures and daily precipitation) (Hassanzadeh et al., 2013). Quantile based downscaling successfully improved the projection of temperature and precipitation extremes. Quantile regression methods have been found able to capture the high and low order extreme events in the downscaled projected scenarios; while in other statistical methods, they are underestimated (Hassanzadeh et al., 2013). Rather than using a conventional statistical downscaling method, the data-driven techniques such as genetic programming is also successfully applied in several hydro-climatological studies to get the more robust computational outcomes (Fowler et al. 2007). The GP coupled with the quantile-based regression could be a useful tool to forecast and simulate more robust outcomes of climatic scenario (Hassanzadeh et al., 2013).

Zhai et al. (2018) presented an advanced stepwise clustered downscaling (SCD) approach utilizing multiple RCPs to downscale minimum and maximum temperature in Ottawa and the results of the study made satisfactory observations than previous downscaling methods. In SCD method, the outputs of GCMs and RCPs are used as inputs to the SCD and then downscaled scenarios are generated (Zhai et al., 2018). Azamat et al. (2018) compared two downscaling methods such as statistical downscaling model (SDSM) and smooth support vector machine (SSVM) and the results showed that SSVM performed better in forecasting precipitation scenarios than SDSM; however, SSVM takes a lot of efforts to optimize the best parameters to get better simulations. Advanced downscaling approaches based on machine learning methods such as random forest (RF) (He et al., 2016), support vector machine (SVM) (Ghosh and Mujumdar, 2008), least square support vector machine (LSSVM) (Campozano et al., 2016.), wavelet-least square support vector machine (WLSSVM) (Nourani et al., 2019) and wavelet-artificial neural network (WANN) (Assesm et al., 2017) have significantly utilized in the downscaling of temperature, precipitation and other hydro-meteorological variables and also highlighted their merits-demerits in simulations. Studies performed by Dorji et al. (2017) and Humphrey et al. (2016) compared the advance downscaling techniques to ordinary least-squares regression (OLR) method and their results showed that OLR regression is performed equally to simplest statistical downscaling method (Dorji et al., 2017; Humphrey et al., 2016).

2.3.4 Validation of Downscaling Methods

In climate downscaling, uncertainties related to GCM data, uncertainties associated with downscaling methods and model related uncertainties have been explored across the World (Sharma et al., 2018; Tiwari et al., 2018; Humphrey et al., 2016). The reliability of multi-model GCMs and downscaling methodology has been tested in both historical and 21st century. As per the progressive development of GCMs and RCMs under different IPCC assessments, each model and their ensembles have been widely used to assess short-term and long-term climate changes (Gupta and Jain, 2018; Sharma et al., 2018; Tiwari et al., 2018; Smitha et al., 2018; Singh et al., 2017; Pal et al., 2007). Scientific literatures collected based on the past studies contains a variety of studies regarding the development of downscaling methods to evaluate the potential effects of climate change relevant to Earth-Ocean-Atmospheric processes (Ali and Mishra, 2018). Statistical downscaling works based on the principle of empirical relationships (linear or may be non-liner) between large-scale atmospheric-ocean and local climate characteristics and therefore, statistical downscaling approaches have been easily applied in different heterogenous groups such as linear methods, weather classifications and weather generators (Tiwari et al., 2018; Onyutha et al., 2016; Sunyer et al., 2015). Statistical downscaling methods have found computationally efficient and inexpensive than dynamic downscaling that requires modeling of physical processes (Latombe et al., 2018). The statistical downscaling has been successfully applied for the projection and simulation of precipitation, minimum-maximum temperatures, solar radiation, humidity, soil moisture, streamflow, snowfall, snowmelt and groundwater flows, because the performance of statistical downscaling techniques relies on the selection of regional/local scale parameters (Latombe et al., 2018; Tiwari et al., 2018; Onyutha et al., 2016; Sunyer et al., 2015).

Statistical downscaling methods work on the relationship established between predictors and predictand. However, in case of linear methods, normal distribution of the predictor is required (Singh and Goyal, 2017; Ghosh and Mujumdar, 2008). Latombe et al. (2018) applied statistical downscaling model (SDSM) utilizing GCMs to analyze the climate variability at the time of Last Glacier Maximum (LGM) over western Europe utilizing GCMs and results revealed that the SDSM performed well in paleoclimate reconstruction at local sites. Salvi et al. (2016) established an empirical relationship between coarse resolution climate variables and high-resolution climate variables performed downscaling successfully under nonstationary climate conditions. Studies also utilized linear genetic programming (LGP) based statistical downscaling to project various hydro-climatological variables such as discharge, precipitation under multi-model GCMs and results showed that LPG is able to highlight the 21st century changes (Sachindra and Perera, 2018, 2016; Tofiq and Guven, 2014). A study conducted by Sunyer et al. (2015) utilized eight different statistical downscaling methods in the assessment of climate change and the relevance of 8 methods to extreme precipitation has been signified in Europe.

To avoid uncertainties in large scale coarser resolution GCMs, Fenta Mekonnen and Disse (2018) applied the statistical downscaling method over GCMs to analyse the future climate change impact on Upper Blue Nile River basin and then applied few bias correction methods to minimize uncertainty in outcomes. SDSM based analysis using CanESM2 CMIP5 GCMs are able to produce more accurate average rainfall predictions than raw GCMs (Fenta Mekonnen and Disse, 2018). Azmat et al. (2018) utilized multiple GCMs and compared the statistical downscaling with Smooth Support Vector Machine (SSVM) (one of the data mining methods) for the improvement of climate projections and concluded that SSVM performed superior than other methods. However, both approaches were able to simulate precipitation and temperature with a certain amount of uncertainties. Humphrey et al. (2016) presented a hybrid statistical ANN based forecasting model to project the monthly streamflow. The results of this study showed that the statistical ANN based approach was more suitable than dynamicaa dynamical forecasting modelt al. (2015) applied two different statistical downscaling methods: (i) delta change method for the computation of mean precipitation and different return period precipitation events and (ii) quantile-quantile (Q-Q) transformation for downscale monthly distribution of precipitations utilizing RCMs. Results showed a significant amount of uncertainty existed in both methods, because their results lead to a very different prediction of the direction and magnitude of change (Sarr et al. 2015). Goswami et al. (2018) presented a coupled framework employing statistical downscaling and copulas for projecting precipitation extremes over eastern Himalayas and calculated that copulas based 21st Century projections are more relevant to real scenario than projections were downscaled using simple statistical methods.

Xue et al. (2014) explored the controlling factors that have strong influence on dynamic downscaling ability in intra-seasonal simulations and future projection. Meresa et al. (2016) utilized multiple GCMs and RCMs for the projection of droughts in Polish catchments and observed a significant diversity in the climate projections of GCMs and RCMs over the region. A study conducted by Vu et al. (2015) utilized RCMs and dynamic downscaling to project future hydro-meteorological drought scenarios and their results have been found sensitive in the analysis. Seiler et al. (2018) applied dynamic downscaling products to minimize bias in the simulation of explosive extratropical cyclones. The CanESM2 GCMs integrated with the CanRCM4 and this reduces the frequency bias up to -22%. Moalafhi et al. (2017) used dynamic downscaling for reconstructing hydro-climatological data in southern Africa. Sun et al. (2016) linked ecohydrological model with (Weather Research and Forecasting Model) WRF utilizing dynamically downscaled RCMs dataset to project water yield and ecosystem productivity across the whole United States. A large spatial variability in the hydrological and ecosystem productivity responses has been highlighted, because different uncertainty assumed in the simulated outcomes. Karmalkar (2018) utilized NA-CORDEX and NARCCAP ensembles to explore uncertainties in regional climate change projections. It is found that NA-CORDEX GCMs poorly responded during winter over half of the United states and the Great Plains in the summer.

2.4 Applicability of Downscaling Methods and GCMs in Indian Context

2.4.1 Downscaling Methods Suitability in India

India has a very diverse hydro-climatology at a regional scale (Tiwari et al., 2017; Singh and Goyal, 2016). In this section, capabilities of statistical and dynamical downscaling have been evaluated in Indian hydro-meteorological conditions at both larger and smaller scales. Different downscaling approaches have found capable for the downscaling of various hydro-climatological variables and the downscaled products have been successfully utilized in various climate change studies across India (Goswami et al., 2017; Tiwari et al., 2017; Tiwari et al., 2014; Singh and Goyal, 2016; Ghosh and Mujumdar, 2008). Tiwari et al. (2018) utilized dynamic and statistical downscaling methods to predict winter precipitation in Northern India and the results indicated that the downscaled observations generated from statistical methods performed better than dynamical downscaling. However, both downscaling methods such as statistical and dynamic gave reliable predictions than directly involved GCM based predictions (Tiwari et al. 2018).

Goyal and Ojha (2012) developed a downscaling model utilizing the Multiple Linear Regression (MLR) and ANN for the projection of minimum and maximum temperature to a lake-basin scale. The ANN based downscaling results have given more accurate observations than MLR method, illustrating that ANN based observations contain less bias than MLR based observations. Sharma et al. (2018) applied statistical and dynamic downscaling methods to assess the uncertainty in the projections of hydro-climatic variables over India are utilizing GCMs and their results clearly highlighted that statistical downscaling-based observations are able to capture spatio-temporal variability in hydro-climatological variables, whereas the dynamic downscaling projections were poorly performed. Joseph et al. (2018) used dynamically downscaled RCMs and statistically downscaled GCMs outputs for comparing climate model uncertainty and hydrological parameter uncertainty in the Ganga River basin and the results showed significant amount of uncertainties in the future projections, especially in case of dynamically downscaled RCMs. However, uncertainties also exhibited a seasonal dependency in a climate model.

Despite various applications of downscaling in simulation and projections of climate variables, several studies assessed the direct applicability of GCMs and RCMs at regional and smaller scales utilizing advanced bias correction methods (Gupta and Jain, 2018; Smitha et al., 2018; Apurv et al., 2015). However, their direct applicability is still uncertain under regional and small-scale climate change assessment. Gupta and Jain (2018) utilized dynamically downscaled RCMs across India to investigate the musical impact of climate change on droughts and their results showed an increase in evapotranspiration due to the projected rise in temperature in most parts of India and causing droughts, but this study did not quantify uncertainties in their projections.

In this chapter, the applicability of dynamic and statistical downscaling methods has been discussed. Both downscaling methods have performed well in different climate change forecasting and assessment studies around the World. However, each method has shown its limitations and advantages as per the desired area of interest. Several advance downscaling methods such as ANN based approaches, Artificial Intelligence methods, including SVM and Random Forest (RF) etc. and Weather Generators (WGs) have been presented to explore their applicability in various climate studies across the World and India too. Given the diversity of developed downscaling methods, it is best to first evaluate the needs, relevant techniques, and limitations of the results of each method as per the desired goal and area of interest.

In the assessment of climate change and its impacts at regional, sub-regional scales and location based, a comprehensive appraisal of the information needs and the relevance of existing information should be carried out first. If the need for an original downscaling of the projections is confirmed, the method should be selected based on the information needs and also, importantly, on available resources (data, computing resources, expertise, and time-frames). Therefore, a decision tree (Figure 2.5) has been formulated to help the researchers and the scientists in determining an appropriate downscaling method.

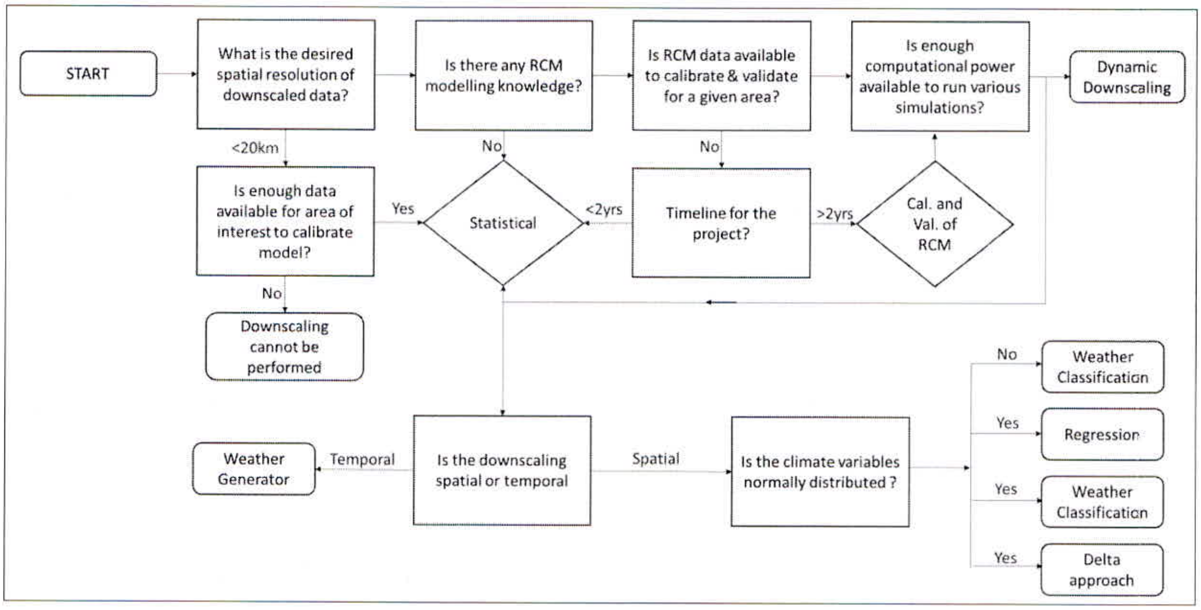

Figure 2.5: *Decision tree showing for different downscaling methods.*

2.4.2 GCMs Suitability in India

In India, very few studies have been completed to evaluate the GCMs applicability and to find out best GCMs for India (Ali and Mishra, 2018; Singh et al., 2017; Raju and Kumar, 2014). Several studies highlighted that no suitable GCMs are available in India region that may produce accurate predictions; for example, precipitation and temperature scenarios (Tiwari et al., 2014). Ali and Mishra (2018) compared the applicability of GCMs in terms of bias content and results show that five GCMs (e.g. MIROC5, MIROC-ESM IPSL-199, CM5A-MR, ACCESS1-0, and CNRM-CM5BEST-GCMs) show relatively lesser bias in P95 (median bias 1-15%) as compared to others. In another study done by Balvanshi and Tiwari (2018), the applicability of multi-model CMP5 GCMs has been tested over Madhya Pradesh Central India and GCMs such as CanESM2, CGCM3, GFDL2.0, HadCM3 and MIROC3.2 were found suitable for the analysis.

Mishra et al. (2014) tested the reliability of RCMs and GCMs over precipitation extremes in India and resulted that the mean ensemble of CORDEX-RCMs exhibited somewhat superior observations; however, the whole RCMs failed to expressively outperform GCMs. Singh et al. (2017) compared the applicability of CORDEX-RCMs (e.g. RegCM4) and CMIP5 GCMs (GFDL-CM3, GFDL-ESM2M, GFDL-CM2P1 etc.) for analyzing the hydro-meteorological changes at smaller scales over Sikkim Himalayas and the results showed that RCMs performed well only in case of temperature projections under stationary conditions; while in case of precipitation, GCMs and RCMs did not account much variability and represented similar amount of uncertainty in their outputs.

Table 2.5: Best GCMs recommended for climate change studies in India.

GCM	Resolution (Lat ×Lon)	Simulation Period	Origin	No. of Simulation Runs
BCC-CSM and BCC-CSM 1.1 (m)	64 × 128 160 × 320	1850-2099	China	3
CanESM2	64 × 128	1850-2100	Canada	1
CCSM4	192 × 288	1850-2099	USA	6
CNRM-CM5	128 × 256	1850-2100	France	10
GFDL CM3	90 × 144	1850-2100	USA	1
HadGEM2-ES	145 × 192	1850-2100	UK	4
IPSL-CM5A-LR	95 × 96	1850-2100	France	2

Smitha et al. (2018) used raw RCMs and GCMs (e.g. CNRM-CM5.0, GFDL-CM3.0) and applied bias correction methods such as local intensity scaling, power transformation and distributed mapping to correct precipitation over six different watersheds based on different climatic conditions; also concluded that bias corrected RCM has the largest influence on the accuracy of daily rainfalls. Apurv et al. (2015) utilized raw CMIP5 GCMs (e.g. GOALS-g2, BCC-CSM1-1, IPSL-CM5A, CanCM4 and MRI-CGCM3) and then applied bias corrections to analyze decadal floods over the Brahmaputra basin and resulted significant flood frequency observations under regional scale varying climate conditions. Raju and Kumar (2014) ranked the applicability of GCMs as per Indian climatic conditions and their assessment showed that GFDL2.0, INGV-ECHAM4, UKMO-HADCM3, MIROC3, BCCRBCCM2.0 and GFDL2.1 are most suitable GCMs identified. Based on the detail literature, the best GCMs that may be applicable to India have been presented in Table 2.5.

2.5 Concluding Remarks

This chapter describes the significance of different downscaling methods in hydro-climatological studies. The application of GCMs and RCMs under different downscaling methods are evaluated. Based on the literature used in this chapter, it is concluded that raw GCMs are less applicable to capturing small- and large-scale climate information. Whereas, statistical and dynamic downscaled GCMs and RCMs outputs are capable to capture larger scale and regional-scale climatic variations across the world. This chapter comprehensively addresses few important topics of climate modeling such are GCMs projection capacity, selection of downscaling method, their limitations, applicability of GCMs and RCMs under different climate conditions etc. Dynamically downscaled RCMs have shown strong influence on the small scale and regional scale hydro-climatological changes. It has been seen that RCMs have much capability to explore regional scale climatic variations because of its finer resolution, but are computationally expensive as it involves complex physics of atmospheric processes.

Due to less resources and high parameter demands in their processing, dynamic downscaling is not widely performed. Statistical downscaling approaches together with bias correction methods are helpful in the transformation of large-scale variables to local-scale variables. The statistical downscaling is well performed to overcome the special issue to get large-scale information at the finer scale. The scope of statistical downscaling of GCMs is capable to improve the skill of the prediction at local-scale. It is also clear that only GCMs or RCMs cannot give a proper estimation of hydro-climatological variables at different scales, because GCMs are mainly developed to predict the average general circulation pattern of the atmosphere-ocean-earth. Therefore, the coupling of downscaled GCMs and with hydrological models along with other physical, topographical and local meteorological parameters is necessary to produce reliable simulations and predictions of hydro-climatological variables. In this context, GCM derived climate perturbations can be utilized as model input in hydrological models. Although, RCMs have better spatial resolutions and able to capture the regional scale assessment, but their applicability is also limited and sometimes they also found less predictable in the case of point scale observation. The selection of downscaling method and GCMs/RCMs should be based on the scale and area specific, so appropriate RCMs and GCMs can be preferred that may enhance the prediction capability of the model. A comprehensive model validation procedure must be accounted to the selected and formulated models before they are utilized to simulate future climate change impacts.

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