

# Review of Downscaling Methods in Climate Change and Their Role in Hydrological Studies

Nishi Bhuvandas, P. V. Timbadiya, P. L. Patel, P. D. Porey

**Abstract**—Recent perceived climate variability raises concerns with unprecedented hydrological phenomena and extremes. Distribution and circulation of the waters of the Earth become increasingly difficult to determine because of additional uncertainty related to anthropogenic emissions. The world wide observed changes in the large-scale hydrological cycle have been related to an increase in the observed temperature over several decades. Although the effect of change in climate on hydrology provides a general picture of possible hydrological global change, new tools and frameworks for modelling hydrological series with nonstationary characteristics at finer scales, are required for assessing climate change impacts. Of the downscaling techniques, dynamic downscaling is usually based on the use of Regional Climate Models (RCMs), which generate finer resolution output based on atmospheric physics over a region using General Circulation Model (GCM) fields as boundary conditions. However, RCMs are not expected to capture the observed spatial precipitation extremes at a fine cell scale or at a basin scale. Statistical downscaling derives a statistical or empirical relationship between the variables simulated by the GCMs, called predictors, and station-scale hydrologic variables, called predictands. The main focus of the paper is on the need for using statistical downscaling techniques for projection of local hydrometeorological variables under climate change scenarios. The projections can be then served as a means of input source to various hydrologic models to obtain streamflow, evapotranspiration, soil moisture and other hydrological variables of interest.

**Keywords**—Climate Change, Downscaling, GCM, RCM.

## I. INTRODUCTION

DESPITE notable development, GCMs do not provide perfect simulations of reality and cannot provide the details on very small spatial scales due to incomplete scientific understanding and limitations of available observations [2], [3]. For bridging the gap between the scale of GCMs and required resolution for practical applications, downscaling provides climate change information at a suitable spatial and temporal scale from the GCM data. Statistical and dynamical downscaling are two broad main types. To study the impact of climate change on water resources the spatio-temporal changes in components of hydrological cycle like streamflow and precipitation is significant. To derive on GCM simulated information at local scale many downscaling techniques have

been adopted throughout the globe [4]. The dynamical downscaling is mainly covered by Regional Climate Models (RCMs). The RCMs utilize large scale and lateral boundary conditions from GCMs to produce higher resolution outputs that demands high computation time. Dynamical downscaling does not provide information at the point or station scale. For temperature projections, the uncertainty introduced by the RCM is less than that from the emissions scenario, but for precipitation projections, scenario uncertainty is larger than RCM uncertainty. Statistical downscaling are preferred in hydrologic impact assessment since they prove competent to observed data while being computationally inexpensive, provide prompt results, and their realm of application can be easily transferred from one region to another.

## II. CLIMATE AND HYDROLOGY

Climate is defined as the general weather conditions over a certain time-span and a certain area. Climate change refers only to the anthropogenic changes over comparable time periods [77]. However, in IPCC usage, climate change consists of both natural variability and human-induced change, despite the fact that most of the observed increase in global average temperature since the mid-20<sup>th</sup> century is likely related to anthropogenic activity [3]. In a broad sense, climate change is defined as a statistically significant variation in mean or variability persisting for an extended period [3]. In the hydrological cycle, water moves continually between oceans and the atmosphere through different processes such as precipitation, percolation and evaporation over various temporal and spatial scales. Under natural conditions, climate variations are already considered to be one of the major causes of hydrological change and have crucial social and economic implications for water resources and flood risk [5], [6]. As anthropogenic climate change affects the energy and mass balance of the fundamental hydrological processes, the water cycle is expected to be intensified [7] and hydrological patterns are very likely to be different under different climate scenarios [1]. Although there are distinctions between natural variability and anthropogenic climate abnormality, both human activity and natural climate influence are intertwined with current climate events and the changes in climate are expected to affect the balance of water distribution and living organisms on the earth [3].

### A. Observed Trends

Comprehensive reviews of hydrological trends are widely available. For example, Zhang et al. [8] detected human influence on precipitation trends. Milly et al. [9] identified

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global patterns of trends in streamflow and water availability. In the UK, Wilby et al. [10] surveyed historical hydrological trends related climate change and flood risk. The traditional stationarity assumptions in hydrology are challenged by climate change [9]. Past experience will not be very likely to provide a good guide to future conditions under a changing climate [1]. Therefore, understanding observed and projected change in hydrological processes is essential to future water resources management [11]-[13], flood risk management [14] as well as ecosystems [15]. In hydrology, different hydrological processes are related to each other and are under the rule of conservation of mass. Therefore, the trends of one hydrological process are likely to be related to that of other processes. Precipitation, evaporation, change in storage and runoff are the most fundamental processes in the water balance equation. Quantifying their time variant characteristics under the driving of climate change is foremost in current hydrological studies.

### 1. Streamflow

At a global scale, total continental streamflow data have been reconstituted using the discharge fluctuations calculated by combining the variations of the various incomplete continent gauge records [16], [17]. With small secular trends, large interannual variations which may be related to global circulations are observed in continental and global freshwater discharge [17]-[19]. Although some studies suggest that there are detected trends in global streamflows [20], the directions of streamflow trends are still equivocal [21]. At a regional scale, the historical trends in the numerous runoff records have been identified in numerous studies [22], [23] by different statistical tests. A consistent projection across most climate change scenarios as per for increases in annual mean streamflow in high latitudes and southeast Asia, and decreases in central Asia [24]. At a river basin scale Mondal and Mujumdar [25] suggests larger impacts of human induced change in climate on streamflow as compared to precipitation. The uncertainties in projections of future streamflow under climate change can also be quantified using a statistical framework [26].

### 2. Precipitation

The characteristics and trend of gridded precipitation have been analysed in many studies such as those of the Global Historical Climatology Network (GHCN) [27] and the Climatic Research Unit (CRU) [28]. From the gridded precipitation databases, the IPCC fourth report [3] summarised that over the 20th century, the precipitation generally increased from 30°N to 85°N but decreased between 10°N and 30°N, and there were no significantly strong trends over the Southern Hemisphere. As per IPCC 2007 the summer precipitation is likely to increase in northern Asia, East and South Asia. An increase in the frequency of intense precipitation events is likely to occur in parts of South and East Asia. Projections reveal a significant increase in mean monsoon precipitation of 8% and a possible extension of the monsoon period. An increase in precipitable water of 12–16%

is projected over major parts of India. A maximum increase of about 20–24% is found over the Arabian Peninsula, adjoining regions of Pakistan, northwest India and Nepal [29]. Extreme events are reported to be increased in a warming environment in India [30]. Also as per the relationship between Indian Ocean sea surface temperature and extreme rainfall events, an increase in the risk of major floods is expected over central India [31]. The analysis [32] of 17 GCMs shows an increasing trend in the frequency of wet events mostly in northern and coastal regions of India. Also basin level majority of Indian rivers show increase in precipitation [33].

### B. General Circulation Models

The historical variations and the observed trends as discussed above can only provide weak evidence or prediction support. Scenarios of potential changes in global climate are needed for decision support modelling [6]. For investigating hydrological impacts of climate change, global climate models or general circulation models (GCMs) are the main tool [6]. Over the last few decades, GCMs have been developed to emulate the present climate system and to project future climate scenarios. In the latest developments, the IPCC GCMs include complex energy and mass balance equations and even interactive chemical or biochemical components [3].

From the IPCC multi-model ensembles, the GCM climate projections show that precipitation is generally expected to increase in the tropical regions and at high latitudes but decrease in the subtropics [3]. The variations of projected precipitation depend on changes in large scale circulation and water vapour loading across regions, and they are substantially seasonal [1]. In spite of being able to capture large-scale circulation patterns and also model smoothly varying fields such as surface pressure, GCMs often fail to reproduce non smooth fields such as precipitation [34]. In addition to the above, the spatial scale on which GCMs predicts the variable at a coarser scale (e.g., 3.75° x 3.75°) for coupled global circulation model (CGCM2), for hydrological modeling purposes [35]. As the upcoming report of IPCC AR5 the most recommended GCM is the Coupled Model Comparison Project Phase 5 (CMIP5), a new generation of General Circulation Models (GCMs) has become available to the scientific community [36]. In comparison to the former model generation, these Earth System Models (ESMs) incorporate additional components describing the atmosphere's interaction with land-use and vegetation, as well as explicitly taking into account atmospheric chemistry, aerosols and the carbon cycle [37]. The uncertainty due to the missing GCM output is found from cumulative distribution functions [38] and the concept of imprecise probability can also be validated.

The new model generation is driven by newly derived atmospheric composition forcings the historical forcing for present climate conditions and the Representative Concentration Pathways (RCPs) [39] for future scenarios. The dataset resulting from these global simulations will be the mainstay of future climate change studies and is the baseline of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (AR5). Moreover this data set is the

starting point of different regional downscaling initiatives on the generation of regional climate change scenarios, which are being coordinated worldwide for the first time within the framework of the Coordinated Regional Climate Downscaling Experiment (CORDEX) [40]. These initiatives use both dynamical and statistical downscaling approaches to provide high resolution information over a specific region of interest at the spatial scale required for many climate change impact studies. Regional changes in the hydrological cycle are far more uncertain in GCM simulations. Downscaling is therefore necessary to model regional-scale climatic/hydrologic variables such as evapotranspiration, precipitation, soil moisture, etc. at a smaller scale, based on the large-scale GCM outputs.

### C. Downscaling

Downscaling is used for bridging the gap between the scale of GCMs and required resolution for practical applications at regional scale. It is a method that derives local- to regional-scale (10 to 100 km) information from larger-scale models or data analyses. Two main methods are distinguished: dynamical downscaling and empirical/statistical downscaling. The dynamical method uses the output of regional climate models, global models with variable spatial resolution, or high-resolution global models. There are certain distinct steps [41] that are generally adopted in downscaling techniques of which can be selected as per application of the problem. The empirical/statistical methods develop statistical relationships that link the large-scale atmospheric variables with local/regional climate variables. In all cases, the quality of the downscaled product depends on the quality of the driving model [24].

#### 1. Dynamical Downscaling

Dynamical downscaling is usually based on the use of regional climate models (RCMs), which generate finer resolution output based on atmospheric physics over a region using GCM fields as boundary conditions [42], [43]. The physical consistency between GCMs and RCMs is controlled by the agreement of their large-scale circulations [44]. The individual choice of domain size controls the divergence between the RCMs and their driving GCMs [40].

As a consequence of the higher spatial resolution output, RCMs provide a better description of topographic phenomena such as orographic effects [45]. Moreover, the finer dynamical processes in RCMs produce more realistic mesoscale circulation patterns [46]. However, RCMs are not expected to capture the observed spatial precipitation extremes at a fine cell scale [47]. Many studies [48] have found that the skill improvement of RCM depends not only on the RCM resolution but also on the region and the season. Although RCMs may give feedback to their driving GCMs, many dynamic downscaling approaches are based on a one-way nesting approach and have no feedback from the RCM to the driving GCM [49].

The main problem with RCMs is that significant biases in the simulation of mean precipitation on large scales can be

inherited from the driving GCM [50]. Also the boundary conditions are derived from a specific GCM; use of different GCMs will result in different projections [51]. Frei et al. [52] noted that inter-model differences are related to model biases. Moreover, Christensen et al. [53] suggest that GCM biases may not be linear and biases may not be cancelled out by simply taking differences between the control and future scenarios, which many studies have adopted [54]. Imperfect modelling and numerical stability are also plaguing RCMs [55], [49]. Despite their rapid development, RCMs are still ridden with problems related to parameterisation schemes due to the fact that physical processes are modelled at a scale on which they cannot be explicitly resolved [49]. The RCM precipitation outputs are still found to be sensitive to the numerical scheme and parameters [56]-[58]. The discrepancies between areal average values and site-specific data are expected to remain a problem [59].

#### 2. Statistical Downscaling

Based on particular statistical relationships between the coarse GCMs and fine observed data, statistical downscaling is a straightforward means of obtaining high resolution climate projections [60]. Statistical downscaling may be used whenever impacts models require small-scale data, provide suitable observed data are available to derive the statistical relationships and covers all kind of locations. The output obtained is generally small scale information on future climate or climate change (maps, data, etc.), the key input being appropriate observed data to calibrate and validate the statistical model(s) and GCM data for future climate to drive the model(s) [61]. Reviews of downscaling methods are widely available [62], [49]. Taking the relationship with RCMs into consideration, [49] divided statistical downscaling approaches into perfect prognosis (PP), model output statistics (MOS) and weather generators. In PP, the statistical downscaling relationships are established by observations.

In MOS, gridded RCM simulations and observations are used together to develop downscaling relationship. Using PP, MOS or both of them, weather generators are hybrid downscaling methods. With respect to types of statistical methods, downscaling can be categorical, continuous-valued or hybrid [47], [63]. In categorical downscaling, classifications and clustering are the common statistical techniques to relate data to different groups according to large-scale circulation patterns and data attributes [64]. For continuous-valued downscaling, regression relationships are widely used to map large scale predictors onto local-scale predictands [65]. When the GCM simulated variables are large in number, nonparametric stepwise predictor identification analysis may be performed based on partial mutual information [66]. In hybrid downscaling, different statistical approaches are combined [67] and they are sometimes referred to as weather generators, based on algorithms of conceptual processes [68], [69]. Based on the approach to model the daily precipitation occurrence, the spell length approach [70] is also used which is a type of weather generator, where instead of simulating rainfall occurrences day by day, the models operate

by fitting probability distribution to observed relative frequencies of wet and dry spell lengths. Statistical Downscaling Model (SDSM) was developed by Wilby et al. [67] and has been widely used since then till date [71]. Even though SDSM is an instant tool for statistical downscaling, its skills to reproduce the extreme precipitation were very limited. This was partly due to the high randomness and nonlinearity dominated in extreme precipitation process and because of the generally low predictability of daily precipitation amounts at local scales by regional forcing factors. Kannan and Ghosh [72], [73] developed Support Vector Machine-Probabilistic Global Search Algorithm coupled approach for statistical downscaling the rainfall from GCM output. They demonstrated its successful application in downscaling of the rainfall of Assam and Meghalaya of north eastern India using several GCMs. Kannan and Ghosh [74] proposed an algorithm that initially simulates the rainfall state of the entire river basin and then projects multisite rainfall amounts using a nonparametric kernel regression estimator. The study revealed considerable changes in rainfall intensity and dry and well spell lengths at different locations in their study area in India. Salvi et al. [75] most recently developed the methodology of statistical downscaling of multi site rainfall projections in India for climate change impact assessment using GCM developed by CCCMA and successfully demonstrated that it can also consider orographic effect on daily precipitation. The model effectively captured individual station means, the spatial patterns of the standard deviations, and the cross correlation between station rainfalls. It also reveals spatially non-uniform changes in rainfall, with a possible increase for the western coastline and northeastern India (rainfall surplus areas); and a decrease in northern India, western India (rainfall deficit areas), and on the southeastern coastline, highlighting the need for a detailed hydrologic study that includes future projections regarding water availability. Geostatistical approach [76] has recently been developed that has an added feature of its application in remote sensing. Although statistical downscaling can be a computationally efficient alternative to dynamic downscaling, the validity of statistical downscaling is based on an assumption that the empirical relationship identified for the current climate will hold for future climate scenarios [60].

### III. CONCLUDING REMARKS

The present literature on significance of downscaling in hydrological studies and parameters are abounding. In order to arrive at definitive answers for future prediction of the hydrological variables at local level it is mandatory to opt for downscaling. Few area to be focused upon are GCMs prediction capacity, selection of downscaling technique, its limitations, hydrological modelling and handling with uncertainties.

Dynamic downscaling leads to the development of finer scale physics based models known as Regional Climate Models (RCMs) that take input from GCMs simulations as initial and boundary conditions, incorporate the sub-grid features, and produce very high resolution results. The

uncertainty in hydrologic impacts is largely due to the driving. Using various RCMs, dynamic downscaling has been attempted successfully for rainfall projections. Regional climate models have the advantage of very fine resolution but are computationally expensive. Due to significant computational power demand dynamical downscaling is not widely performed. Also bias correction is yet another major problem in dynamical downscaling. Reduction of uncertainty relies upon the improvement in GCMs and downscaling techniques. Uncertainty measures can provide an estimate of confidence limits on model results and would be of value in the application of these results in risk and policy analyses. Various statistical downscaling methods is examined in this study which relies on data driven approaches that involve deriving empirical relationships that transform the large-scale features of GCM simulated climate variables (predictors) into regional-scale variables (predictand) such as rainfall. Statistical downscaling methods are computationally inexpensive and are useful if sufficient historical data is available for generating probability distribution functions and establishing statistical relationships.

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