DYNAMICAL DOWNSCALING

Introduction:

The impact of climate change is far-flung than it actually appears. It coaxes even the smallest of the natural ecosystems, environment and economy. Projecting the future climate, especially regional climate is thus extremely important in crafting the socio-economic policies of the particular country, state or region (Xu et al., 2019). The General Circulation Models (GCMs) helps to interpret and foresee the climate variability and changes, including the forecasting of the hydrologic extremes (Chen et al., 2018). However, the GCM operates on a coarse resolution and it is important to convert this to a regional/local climate process resolution and for this we depend on different downscaling methods, categorized as Statistical downscaling, Dynamical downscaling, and Hybrid Dynamical-Statistical downscaling methods, which are already listed and discussed in the previous sections. The GCMs also fails to capture the regional aspects such as local orography, land-sea contrast, small scale features such a convective cells, etc. and predominates large scale condition alone. This makes it difficult for GCMs to predict climate change and variability at regional/local scale. The high computations for an extended period of time make it difficult for the simulations to take place. This disadvantage of GCMs can be overcome by the use of a GCM with regional refinements also called as Regional Climate Model (RCM). These models also require high resolution computing facility, but less than that compared to the GCM itself. RCMs are thus employed for comparatively smaller regions with considerably higher resolution to simulate regional climate change and variability. The simulations in the RCMs are outputs from GCMs, and thus controlled by GCM data using several mathematical equations. This approach of using a GCM tied with a computationally lower model is known as Dynamical Downscaling (Feser et al., 2011).

Statistical downscaling methods primary works by establishing a statistical relationship between GCM outputs and local climate variables, which does not change with time (Meenu et al., 2013). These methods unfortunately fail to capture the interactions not recorded in the past observations and are also inappropriate to use in areas where the interaction between the large scale climate variables and local observations are equivocal or insignificant (Xu et al., 2019). Quite contrary to this, dynamical downscaling methods uses a Regional Climate Model (RCM), integrated with a GCM, providing initial and lateral boundary conditions for the RCM, which in turn generates regional climate data related to the climate change projections gaining higher resolution at smaller scales (Bao et al., 2015; Xu et al., 2019).

Role of RCMs in Dynamical Downscaling:

RCMs models are developed based on physical principles of fluid mechanics (Gooré Bi et al., 2017; Xu et al., 2019). Initially developed for mesoscale forcings, RCMs found their way into dynamical downscaling in the late 1980s (Xue et al., 2014). RCMs when applied to an area of the globe, gives a detailed account of the climate information for better resolution offers better representation of physical operations at finer scales (10 to 50 kms), as they can take into account the topography (mountains, hills), land-sea distribution (coastal lines), land-surface interactions (clouds), and land water discontinuities (lakes and streams) (Bao et al., 2015; Gooré Bi et al., 2017).

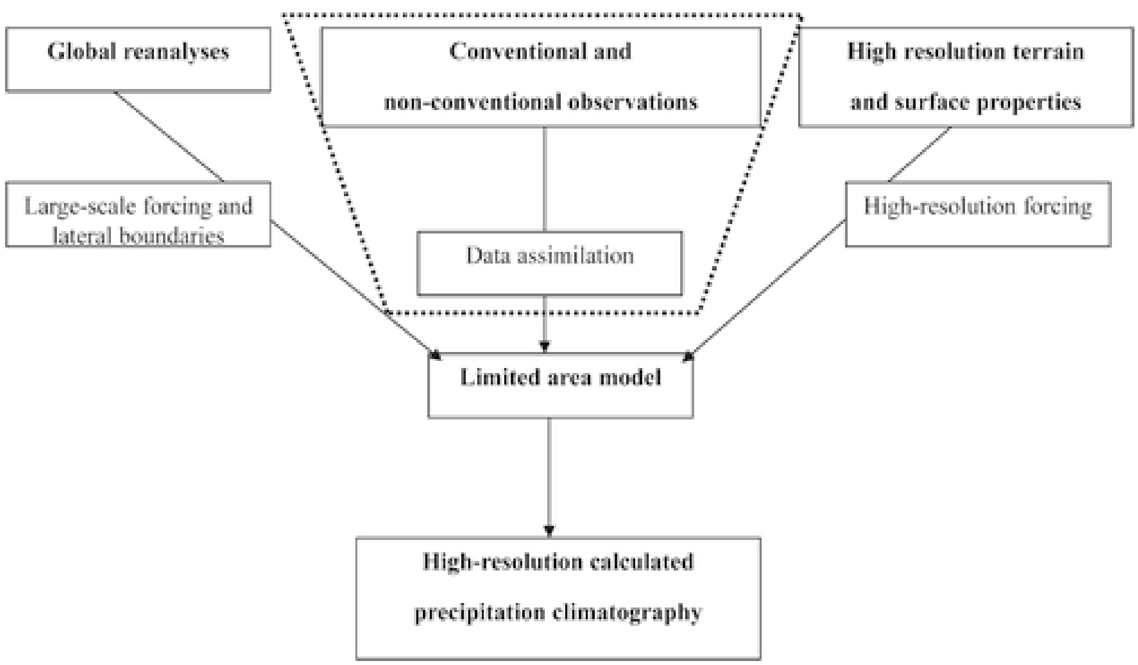

Figure 1: Flowchart of Dynamical downscaling method. Dotted lines indicates assimilation of the observation data (Rostkier-Edelstein et al., 2014).

The RCMs originated from meso-scale atmospheric models, initially used for reproducing past climate scenarios are now used for future climate projection generating high resolution data for hydrological assessments. Such applications provides us with lateral atmospheric boundary conditions (LBC), initial surface conditions and even surface boundary conditions like the sea surface temperature (SST) and sea ice from the analysis of observed data, Atmospheric GCMs (AGCMs), coupled Atmospheric-Ocean GCMs (AOGCMs), or reanalysis data sets (eg: NCEP-NCAR global reanalysis). Given the wide applications in dynamical downscaling, it is important to understand RCMs and how they improve the efficiency of dynamical downscaling in projecting the climate or adding more climate data at various scales, rather than just imposing the LBCs obtained from GCMs. Hypothetically, RCMs should simulate the coarse characteristics of the GCM outputs and reanalyses data that are used in the RCM and add more data at finer scales. However it is evident that there are wide gaps between our understanding of the use of coarse scale data and include data at finer scales, and to use this for many applications. Some of the studies hint that the RCMs are applied beyond their real downscaling ability.

Even though the terminology of Regional Climate models implies modeling and the definition given for RCM in American Meteorological Society states the same, most RCMs were not performing any climate predictions at regional levels. On the other hand, GCMs are only used for climate predictions. It is important to understand that the climate prediction is different from climate downscaling, such that the term downscaling indicates climate statistics, on the basis of the average of the climate system over a period of a month or more. Temporally RCMs operates at various scales, from intra-seasonal to seasonal. RCM has a huge advantage that its higher resolution makes it possible to manage critically important climate processes such as clouds and land surface processes sensibly, particularly as RCMs can allow clouds into their resolution to eliminate the huge parameterization issues. Detailed analysis proves that improved information over mountains and coastal regions will enable RCM to reproduce mesoscale processes and high resolution climate characteristics. However, there is no guarantee on how long RCM will persist, as GCMs with higher resolutions are achievable because of the ever-growing computational power. The life of RCM will depend on the efficiency it has in the dynamical downscaling. The simulations in RCM are highly affected by the factors such as domain size and location, both horizontal and vertical resolution, the quality of the large scale forcing data and physical processes involved (Xu et al., 2019).

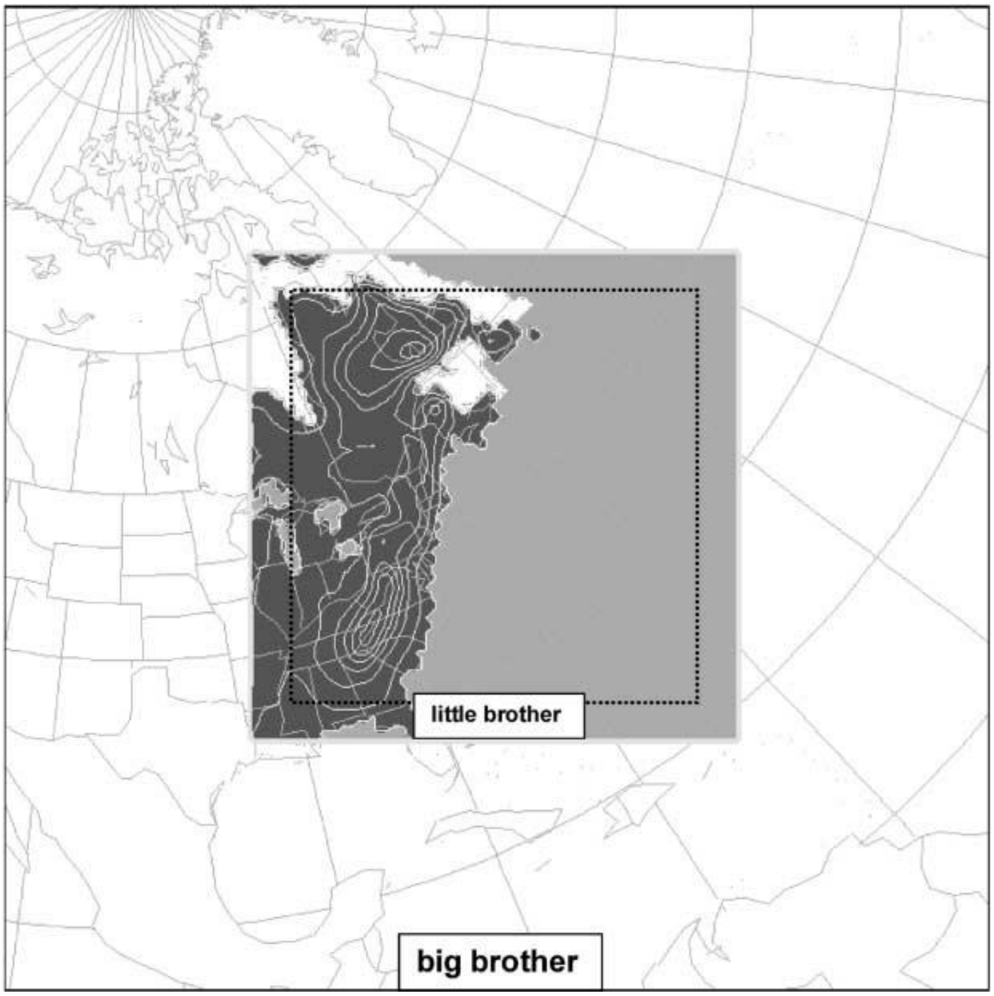

Figure 2: the geographical domain that represents the large area and the RCM nesting zone. The dotted lines indicate the nesting zone in which topography, sea ice (white area) and open water (grey area) is shown (Denis et al., 2002).

One of the major problems in dynamical downscaling is the unavailability of data available for validation for the small scale features. The global reanalyses does not have small scale features and thus low resolution global reanalyses cannot be used as climate references. To overcome this particular problem, a nested approach was developed by Denis et al., 2002, where in a large domain was used to generate a set of high resolution data, through which a low resolution data was obtained by filtering high frequency information. This approach was named as the 'Big Brother experiment'. The filtered, low resolution data was then used to run a nested RCM with same operations and physical processes over a small domain. The ability of the RCM in reproducing the filtered fine resolution characteristics, serves as the bench mark to evaluate the performance of the RCM in dynamical downscaling. Even though this experiment eliminates the problem with having only high resolution validation data, one major concern is that the nested RCM does not exemplify the real world processes, as it only generates features in the model with the same operations and physical processes. An RCM to be efficient in dynamical downscaling needs to provide realistic simulations/predictions (Xue et al., 2014).

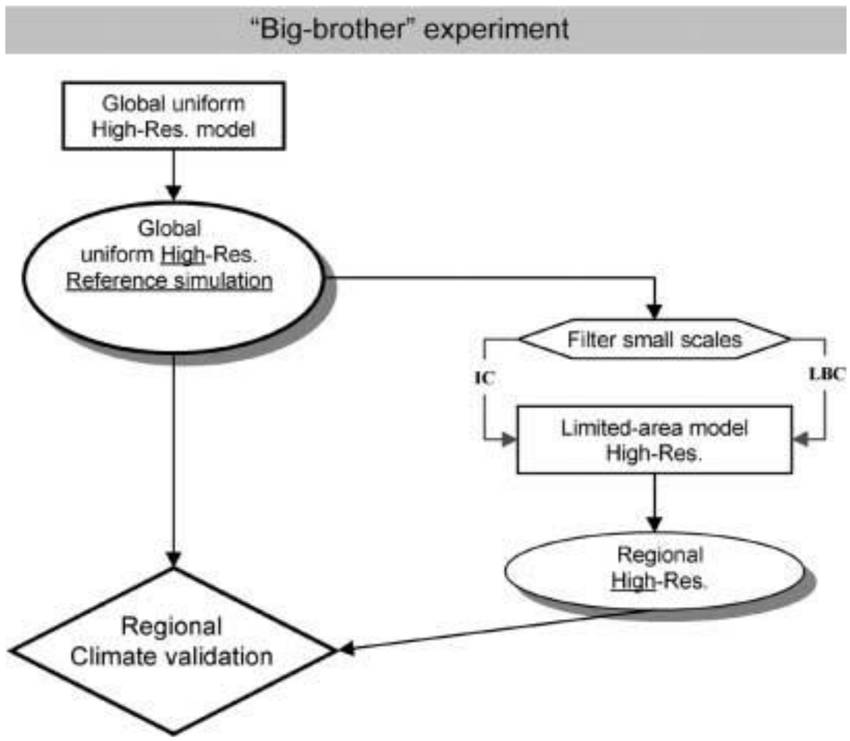

Figure 3: Flow chart of the Big brother experiment. The rectangular shape indicates models and the oval shape indicates their data sets. The diamond shape depicts the validation of the regional scale features against that of GCM data sets. The IC and LBC are spatially filtered such that smaller scales are removed (Denis et al., 2002).

The traditional dynamical downscaling (TDD):

The traditional dynamical downscaling is the method developed by Dickinson, 1989, where he used an RCM to check the high resolution climate. The RCM was embedded with a GCM and only covered a small region on earth's surface. The RCM was run by the GCM outputs as initial and lateral boundary conditions. This method is the oldest and now called as the traditional downscaling method. TDD has its applications in various fields from meteorology, hydrology, and atmospheric chemistry to air quality. Regardless of its wide usage, climate models are restrained by the systematic biases that deteriorate the quality in projecting the climate in dynamical downscaling and create high levels of uncertainties. TDD method, however, cannot curb this problem and it marks one of the limitations of the method (Xu et al., 2019). Despite its various shortcomings TDD method has been widely used for climate simulation projects the Regional Climate Model Inter-comparison Project for Asia (RMIP), Ensembles-Based Predictions of Climate Changes and Their Impacts (ENSEMBLES), North American Regional Climate Change Assessment Program (NARCCAP), and Coordinated Regional Downscaling Experiment (CORDEX), along with various combinations of GCMs and RCMs, called as ensemble simulation. Almost all GCMs are affected by the systematic biases and they are carried to the RCMs through the lateral boundary conditions in TDD thus degrading the downscaled simulations. Various studies shows that systematic biases effect the accuracy of the estimation of values of the variables such as precipitation, temperature, moisture content, etc., by either underestimating or overestimating them as compared to other dynamical downscaling methods (Xu & Yang, 2012).

Pseudo global warming (PGW) method:

The climate change has led to the increase in the concentration of greenhouse gases all over the globe. To project the response of climate to the increased GHG concentrations, pseudo global warming method was developed. In this method, lateral boundary conditions (LBCs) of RCM are developed by adding the projected change in GCM to the reanalysis data.

$$BC_F = RA_H + \overline{GCM}_F - \overline{GCM}_H$$

Where, BC_F: constructed RCM LBC at 6 hour intervals for the future

RA_H: 6-hourly reanalysis data over historical periods

'$\overline{\quad}$': represents the climatological mean

Subscripts H, F: indicates historical and future periods respectively

$\overline{GCM}_F - \overline{GCM}_H$: mean climate change between the future and historical periods computed with monthly data.

The lateral boundary conditions thus computed have a base climate that is obtained from reanalysis data and are free from GCM biases on dynamical downscaling. The single GCM data of the equation can be replaced by a multi-GCM ensemble for the purpose of uncertainty reduction, those usually single GCMs induces on RCMs. This helps in improved simulations of the future climate. Apart from climate predictions, PGW methods are useful in identification and attribution studies. To identify external forcings, internal climate variabilities are considered as noise. The levels of changes brought out by the external forcings are weak as compared to that of internal forcings thus it is difficult to differentiate their effects. The external forcing signal can be identified by conducting two dynamical downscaling simulations with LBCs framed using PGW method. The simulations of two dynamical downscaling carries similar internal climate variability transferred through LBCs to the RCMs. Internal variability is then eliminated by finding out the difference between the two dynamical downscaling, which keeps the external forcing signals. The constraints of the PGW method are intrinsic to the framing of the LBCs (Xu et al., 2019).

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