Training Course

Climate Change and its Impact on Water Resources

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LECTURE – 3 & 4

DOWNSCALING METHODS IN CLIMATE CHANGE STUDIES

By

SHARAD K. JAIN
VIJAY KUMAR

Organised by

National Institute of Hydrology
Roorkee- 247 667
&
Indian Institute of Technology
Roorkee -247 667

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In climate change studies, the temporal scales could vary from a very short time interval of 5 minutes (for urban water cycle) to a yearly time scale (for annual water balance computation). The spatial resolutions could be from a few square kilometers (for urban and rural watersheds) to several thousand square kilometers (for large river basins). General Circulation Models (GCMs) have been recognized to be able to represent reasonably well the main features of the global distribution of basic climate parameters, but these models so far could not reproduce well details of regional climate conditions at temporal and spatial scales of relevance to hydrological studies. In other words, outputs from GCMs are usually at resolution that is too coarse (generally greater than 2.0° for both latitude and longitude, and greater than 200km for middle latitudes) for many climate change impact studies. Hence, there is a great need to develop tools for downscaling GCM predictions of climate change to regional and local or station scales. In recent years, different downscaling methods have been proposed in a number of studies around the world. Of particular importance for the management of water resources systems are those procedures dealing with the linkage of the large-scale climate variability to the historical observations of the surface parameters of interest (e.g., precipitation and temperature). If this linkage could be established, then the projected change of climate conditions given by a GCM could be used to predict the resulting change of the selected surface parameters for hydrological impact studies. The required linkage can be developed using a wide range of downscaling methods.

These notes briefly explain the fundamentals of downscaling methods. Detailed treatment of the statistical method is available in Wilby et al. (2004).

1. Introduction

Coupled Atmospheric Oceanic GCMs (AOGCMs) are the modeling tools traditionally used for generating projections of climatic changes due to anthropogenic forcing. However, due to limited computational resources, the horizontal resolution of present day coupled AOGCMs is still of the order of a few hundred km. At this resolution, the effects of local and regional physiographic detail, like land-sea distribution, topography and land-sea on regional climate is not fully captured. Therefore, a number of techniques have been developed to enhance the regional information provided by coupled AOGCMs The basic objective of these regionalization techniques is to enhance the regional information provided by coupled AOGCMs by combining consistently large-scale climatic information with effects of small scale physiographic detail. In this contribution we review the state of the art of empirical downscaling.

1.1 Categories of Downscaling Procedures

Two broad categories of these downscaling procedures currently exist: dynamical downscaling (DD) techniques, involving the extraction of regional scale information from large-scale GCM data based on the modeling of regional climate dynamical processes, and statistical (or empirical) downscaling (SD) procedures that rely on the empirical relationships between observed (or analyzed) large-scale atmospheric variables and observed (or analyzed) surface environment parameters. Some recent comparisons of DD and SD techniques for climate impact have indicated that neither technique is consistently better than the other. In particular, based on the assessment of the climate change impacts on the hydrologic regimes of a number of selected basins in the United States, it was found that these two methods could reproduce some general features of the basin climatology, but both displayed systematic biases with respect to observations as well. Furthermore, a main finding from this study was that the assessment results were dependent on the specific climatology of the basin under consideration. Hence, it is necessary to test different, but physically plausible, downscaling methods in order to find the most suitable approach for a particular region of interest. However, it has been widely recognized that SD methods offer several practical advantages over DD procedures, especially in terms of flexible adaptation to specific study purposes, and inexpensive computing resource requirements. Several SD techniques have been developed to establish relationships between local weather variables and the large-scale GCMs' results. Among these techniques, the SD method based on the Statistical Downscaling Model (SDSM) and the stochastic weather generator LARS-WG are widely used for constructing climate change scenarios for daily precipitations and temperature extremes at individual sites using GCM grid point information. This lecture presents an overview of SD methods.

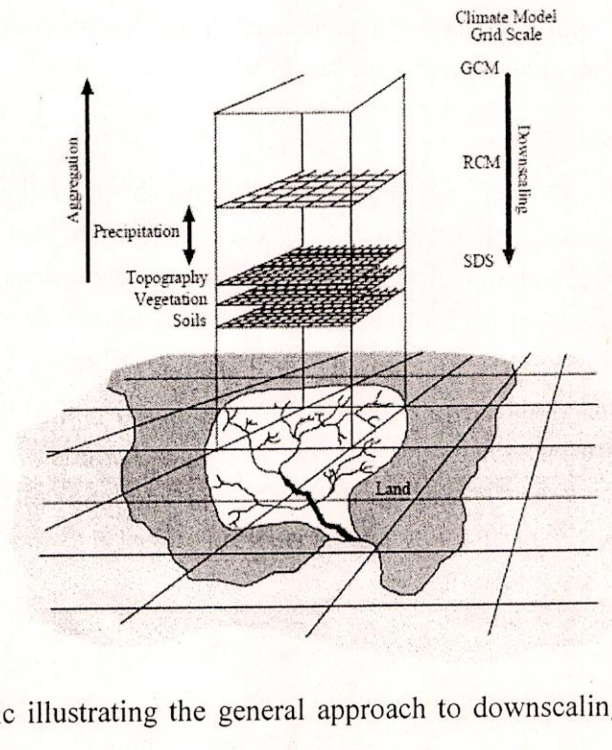

Fig. 1 A schematic illustrating the general approach to downscaling (Wilby & Dawson 2007).

2. Principles of Downscaling

"Downscaling" is based on the view that regional climate is conditioned by climate on larger, for instance continental or even planetary, scales. Information is cascaded "down" from larger to smaller scales. The regional climate is the result of interplay of the overall atmospheric, or oceanic, circulation and of regional specifics, such as topography, land-sea distribution and land-use. As such, empirical/statistical downscaling seeks to derive the local scale information from the larger scale through inference from the cross-scale relationships, using a random or deterministic function f such that:

$$\textit{local climate response} = f\,(\textit{external, larger scale forcing}) \qquad (1)$$

The concept of "downscaling" does not imply that the regional climate would be determined by the large-scale state; for similar large-scale states, the associated regional states may vary substantially. Instead, the regional climate is seen as a random process conditioned upon a driving large-scale climate regime. Of course, one could challenge this view since the small scales undoubtedly have an effect on the large scales as well, and that a proper regionalization should describe the mutual influence of large scales on small scales and vice versa. However, the effect of small scales on large scales is not limited to specific region, but all regions exert this influence. That is, one would have to model all regions, resulting in a global model of increased resolution everywhere. This strategy is pursued in high-resolution time slice simulations, but the computational load makes it inaccessible in most applications. Also, the effect of sub-grid scale influences on the large scales resolved in AOGCMs is taken care of in a summary, statistical manner by parameterizations.

Downscaling is not really a new approach, even though it is used in a new context, namely specifying expected regional and local climate variations and change. Similar techniques were used in the past decades for deriving finer-scale (local) weather information from numerical weather prediction models - called Perfect Prog - and for classifying weather regimes.

The conceptual approach lends itself to (relative) computational simplicity, and is thus attractive in situations where the resources for dynamical models are not available, or where a dynamical model does not explicitly model the predictand of interest. As a result a plethora of downscaling applications have been developed, and while there is methodological similarity, the permutations are diverse to the point of making inter-comparison of the climate change results from separate studies difficult, if not impossible.

The confidence that may be placed in downscaled climate change information is foremost dependent on the validity of the large-scale fields from the GCM. Since different variables have different characteristic spatial scales, some variables are considered more realistically simulated by GCMs than others. For instance, derived variables (not fundamental to the GCM physics, but derived from the physics) such as precipitation are usually not considered as robust information at the regional and grid scale. Conversely, tropospheric quantities like temperature or geopotential height are intrinsic parameters of the GCM physics and are more skillfully represented by GCMs. However, there is no consensus in the community about what level of spatial aggregation (in terms of number of grid cells) is required for the GCM to be considered skillful.

Formally, the concept of regional climate being conditioned by the large-scale state may be written as

$$R = F(L) \tag{2}$$

Here, R represents the predictand (a set of regional climate variables), L is the predictor (a set of large-scale variables), and F a stochastic and/or deterministic function conditioned by L. In general, F is unknown and is modeled dynamically (i.e., through regional climate models) or empirically from observational (or modeled) data sets. In some cases R and L are the same variables but on different spatial scales. Note that the formulation $R=F(L)$ implies that the variation of the regional or local variable may be displayed in a phase space spanned by L.

2.1 Assumptions in Downscaling

When using downscaling for assessing regional climate change, three implicit assumptions are made:

(1) The predictors are variables of relevance and are realistically modeled by the AOGCM.

(2) The transfer function is valid also under altered climatic conditions. This is an assumption that in principle cannot be proven in advance. The observational record should cover a wide range of variations in the past; ideally, all expected future realizations of the predictors should be contained in the observational record.

(3) The predictors employed fully represent the climate change signal.

In the following, an overview of statistical and dynamic downscaling is provided.

3.0 OVERVIEW OF STATISTICAL DOWNSCALING METHODS

Statistical (or empirical) downscaling (SD) methodologies can be classified into three categories according to the computational techniques used: weather typing approaches; regression methods; and stochastic weather generators. In general, these SD methods require three common assumptions (i) the surface local-scale parameters are a function of synoptic forcing; (ii) the GCM used for deriving downscaled relationships is valid at the scale considered; and (iii) the derived relationships remain valid under changing climate conditions.

3.1 Weather typing

The weather typing procedures consist of classifying atmospheric circulation pattern into limited number of classes; simulating weather types using stochastic models; establishing the link of rainfall occurrence to weather type using conditional probabilities; and simulating the rainfall process (or other hydrometeorological processes) using weather types. The interesting features of these methods are the consideration of the linkages between climate on the large scale and weather at the local scale, and the possibility of generating long sequences of daily precipitation at a site based on limited historical data sets. However, weather classification schemes are somewhat subjective. In particular, the main limitation of such procedures is that precipitation changes produced by changes in the frequency of weather patterns could be inconsistent with the changes produced by the host GCM.

The synoptic downscaling approach empirically defines weather classes related to local and regional climate variations. These weather classes may be defined synoptically or fitted specifically for downscaling purposes by constructing indices of airflow. The mean, or frequency distributions of local or regional climate are then derived by weighting the local climate states with the relative frequencies of the weather classes. Climate change is then estimated by determining the change of the frequency of weather classes.

In the "statistical-dynamical" approach, meso-scale atmospheric models are utilized for simulating a series of typical weather states. The advantage over the former technique is that in this way spatially distributed local climates are specified. Feasibility of this technique has been demonstrated by a series of studies on climate and climate change in the Alps.

The analog method was introduced into the downscaling context in 1990s. Conceptually similar, but mathematically more demanding are techniques which partition the large-scale state phase space, for instance with Classification Tree Analysis, and use a randomized design for picking regional distributions. Analog approaches return the right level of variance and correct spatial correlation structures.

3.2 Weather Generators

Weather generators are statistical models of observed sequences of weather variables. They can also be regarded as complex random number generators, the outputs of which resemble daily weather data at a particular location (Wilks and Wilby, 1999). There are two fundamental types of daily weather generators, based on the approach to modeling daily precipitation occurrence: the Markov chain approach and the spell-length approach. In the Markov chain approach, a random process is constructed which determines a day at a station as rainy or dry, conditional upon the state of the previous day, following given probabilities. If a day is determined as rainy then the amount is drawn from a probability distribution.

As defined by IPCC, a stochastic weather generator (WG) produces synthetic time series of weather data of unlimited length for a location based on the statistical characteristics of observed weather at that location. Models for generating stochastic weather data are conventionally developed in two steps. The first step is to model daily precipitation and the second step is to model the remaining variables of interest, such as daily maximum and minimum temperature, solar radiation, humidity and wind speed conditional on precipitation occurrence. Different model parameters are usually required for each month, to reflect seasonal variations both in the values of the variables themselves and in their cross-correlations.

The stochastic weather generators have been used extensively in the planning, design, and management of water resources systems. The stochastic weather generator methods are based mainly on the stochastic weather generator models such as WGEN and LARS-WG. These models typically involve the modelling of the daily rainfall occurrences, the description of the distribution of rainfall amount on a wet day, and the conditioning of other weather variables (temperature, radiation, etc.) on the wet/dry status of the day. The climate change scenarios are then stochastically generated based on the linkage between the stochastic model parameters with the corresponding variable changes in the GCM. In general, both generators have a similar structure in which observed data at a given site are used to estimate the parameters of the probability distributions of the daily climate variables (minimum and maximum temperatures, precipitation, and solar radiation). In addition, both models analyze dry and wet days separately and thus include a mechanism for selecting the precipitation status of each day. The generators differ mainly in the choice of the probability distributions used. WGEN uses standard distributions (e.g., two-parameter Gamma), whereas LARS-WG employs semi-empirical distributions. One advantage of using a standard distribution is that it will have a smoothing effect on the empirical frequency of the observed data and will only require the estimation of a few parameters. However, such distribution may not provide a very good fit to the observed data. A semi-empirical distribution, with a larger number of parameters, is more flexible and could accurately describe any shape of empirical frequency distribution. The performance of the WGEN and LARS-WG has been tested using data from a range of diverse climates. The LARS-WG generator was found to be able to describe the observed weather characteristics more accurately than the WGEN. In general, the principal advantage of the stochastic weather generator procedures is that they are able to reproduce many observed statistical characteristics of daily weather variables at a particular site. In addition, the stochastic weather generators could generate a large number of different climate scenarios for risk assessment studies. However, the main disadvantage of these procedures is related to the arbitrary manner of determining the model parameters for future climate conditions.

For statistical downscaling, parameters of the weather generator are conditioned upon a large-scale state, or relationships can be developed between large-scale parameters sets of the weather generators and local scale parameters. Conditioning on large-scale states alleviates one of the chronic flaws of many weather generators, which is the underestimation of inter-annual variations of the weather variables, and which, to a degree, induces spatial correlation.

3.3 Transfer functions

The regression-based downscaling methods mainly rely on the empirical statistical relationships between large-scale predictors and local-scale parameters. Different approaches in this empirical downscaling category can be identified according to the choice of the mathematical function for describing the predictor-predictand relationship, the computational technique used, or the selection of the predictor variables considered. In general, the main advantage of the regression downscaling procedures is that these methods are simple and computationally less demanding as compared to other downscaling methods. However, the application of regression-based procedures is limited to the locations where good predictor-predictand relationships could be found. Furthermore, similar to weather typing methods, the regression-based techniques assume validity of the estimated model parameters under future climate conditions.

The more common approaches found in the literature are regression-like techniques or piecewise interpolations using a linear or nonlinear formulation. The simplest approach is to build multiple regression models relating free atmosphere grid point values to surface variables. Other regression models use field of spatially distributed variables to specify local temperatures or principal components of regional geopotential height fields.

Canonical Correlation Analysis (CCA) has found wide application. A variant of CCA is redundancy analysis, which is theoretically attractive as it maximizes the predictands variance; however, in practical terms it seems similar to CCA. Also Singular Value Decomposition has been used, which is another variant of CCA. Oceanic climate and climate impact variables have also been dealt with: salinity in the German Bight; and salinity and oxygen in the Baltic sea level; and a number of ecological variables such as abundance of species. In addition, statistics of extreme events, expressed as percentiles within a month or season, have been modeled.

An alternative to linear regression is to use piecewise linear or nonlinear interpolation; geostatistics offers elegant "kriging" tools to this end. The potential of this approach has been demonstrated in many studies, e.g., relating local precipitation to large-scale pressure distributions. Another approach is to use cubic splines. An emerging non-linear approach is based on artificial neural networks (ANN), which are generally more powerful than other techniques, although the interpretation of the dynamical character of the relationships is less easy.

3.4 Temporal Variance

Transfer function approaches and some of the weather typing approaches suffer to varying degrees from an under-prediction of temporal climate variability, since only part of the regional and local temporal variability of a climate variable is related to large scale climate variations, while another part is generated regionally. Two approaches for bringing the downscaled climate variables to the right level of variability are in use: inflation and randomization. In the inflation approach the variation is increased by the multiplication of a suitable factor; a more sophisticated approach, named "expanded downscaling", was developed by Bürger (1996). It is a variant of CCA that ensures the right level of variability. In the randomization approach the unrepresented variability is added as unconditional noise; that is, in the simplest case, the "missing" variance is added in the form of white noise.

3.5 Validation

The validation of downscaling techniques is essential but difficult. It requires demonstrating the robustness of the downscaling under future climates, and that the predictors used represent the climate change signal. Both assumptions are not possible to rigorously test, as no empirical knowledge is available so far. The analysis of historical developments as well as simulations with GCMs can provide support for these assumptions.

The classical validation approach is to specify the downscaling technique from a segment of available observational evidence and then assess the performance of the empirical model by comparing its predictions with independent observed values. This approach is particularly valuable when the observational record is long and documents significant changes in the course of time. An example is the analysis of absolute pressure tendencies in the North Atlantic in which a regression model was fitted relating spatial air pressure patterns to pressure tendency statistics. Using data from the most recent decades, the study successfully reproduced the considerably stormier times earlier this century. Similarly Wilks (1999) developed a downscaling function on dry years and found it functioning well in wet years. However, the success of a statistical downscaling technique for representing present day conditions does not imply legitimacy for changed climate conditions.

An alternative approach is to use a series of comparisons between models and transfer functions. In the former study, it was first demonstrated that the GCM incorporated the empirical link; in the latter, a regional climate model was used. From these findings it was concluded that the dynamical models would correctly "know" about the empirical downscaling link; then the climatic change, associated with a doubling of carbon dioxide, was estimated through the empirical link and compared with the result of the dynamical model. In both cases, the dynamical response was found to be consistent with the empirical link, indicating the validity of the empirical approach and its legitimate approach in downscaling other global climate change information.

3.6 Comparison of downscaling methodologies

There is a paucity of systematic studies that use common data sets applied to different procedures over the same geographic region. A number of articles discussing different empirical and dynamical downscaling approaches have presented summaries of the relative merits and shortcomings of different procedures. These intercomparisons vary widely with respect to predictors, predictands and measures of skill.

A comprehensive study was reported by Wilby et al. (1998) who compared empirical transfer functions, weather generators, and circulation classification schemes over the same geographical region using climate change simulations and observational data. The study considered a demanding task to downscale daily precipitation for six locations over North America, spanning arid, moist tropical, maritime, mid-latitude, and continental climate regimes. A suite of 14 measures of skill was used, strongly emphasizing daily statistics. These included such measures as wet spell length, dry spell length, 95th percentile values, wet-wet day probabilities, and several measures of standard deviation. Downscaling procedures in the study included two different weather generators, two variants of an ANN-based technique, and two stochastic/circulation classification schemes based on vorticity classes.

The results prove to be illuminating, but require careful evaluation as they are more indicative of the relative merits and shortcoming of the different procedures, rather than a recommendation of one procedure over another. In the validation phase of the study the downscaling results were compared against the observational data, and indicated that the weather generator techniques were superior to the stochastic/circulation classification procedures, which in turn were superior to the ANNs. However, the superiority of the weather generator when validated against the observed data is misleading as the weather generators are constrained to match the original data perfectly. Similarly, the improved performance of the circulation classification techniques with regard to the ANNs is largely a reflection of the measures of skill used and indicates the tendency of ANNs to over-predict the frequency of trace rainfall days. In contrast, when the inter-annual attributes of monthly totals are examined the performance ranking of the techniques is approximately reversed with the weather generators performing especially poorly.

The results indicate strength of weather generators to capture the wet-day occurrence and the amount distributions in the data, but less success at capturing the inter-annual variability (the low frequency component). The important question with this procedure is thus how to perturb the weather generator parameters under future climate conditions. At the other end of the spectrum the ANN procedures performed well at capturing the low frequency characteristics of the data, and showed less ability at representing the range of magnitudes of daily events. The stochastic/circulation typing schemes, being somewhat a combination of the principles underlying weather generators and ANNs, appear to be a better all-round performer.

In application to GCM simulations of future climate, the procedures showed some consistency with the ANN indicating the largest changes in precipitation. However, assessing the relative significance of the changes is non-trivial, and at this level of inter-comparison the results of the climate change application are perhaps more useful in a diagnostic capacity of the GCM which appeared to show differences in the strength of the precipitation-circulation relationship. Studies have demonstrated that a suitably designed analog technique reproduces storm interarrival terms well.

An additional factor not yet fully evaluated in any comparative study is that of the temporal evolution of daily events. In this respect the manner in which daily events develop may be critical in some areas of impacts analysis, for example hydrological modeling. While a downscaling procedure may correctly represent, for example, the number of rain days, the temporal sequencing of these may be as important.

A final point to note with regard to different techniques is that of the relative merits of non-linear and linear approaches. Note that the relationships with precipitation on daily time scales are often non-linear. Some authors have applied multivariate adaptive regression splines (MARS) to approximate non-linearity in the relationships between large-scale circulation and monthly mean precipitation. However, the application of MARS to large volume daily data may be more problematic.

It thus appears that downscaling of the short-term climate variance benefits from the use of more flexible models, as long as enough empirical evidence is available for avoiding overfitting. In particular, downscaling of daily precipitation benefits appreciably from the ability to better capture convective events, while for longer time scales the advantage of higher flexibility is getting less.

Most of the comparative studies mentioned above come to the conclusion that techniques differ in their success of specifying regional climate, and the relative merits and shortcomings emerge differently in different studies. This is not surprising, as there is considerable flexibility in setting up a downscaling procedure, and the suitability of a technique and the adaptation to the problem at hand varies.

3.7 Predictors in statistical/empirical downscaling

The list of predictands in the literature is very broad and comprise direct climate variables (e.g.: precipitation, temperature, salinity, snow pack), monthly or yearly statistics of climate variables (distributions in wind speeds, wave heights, water levels, frequency of thunderstorm statistics), as well as impacted variables (e.g.: frequency of land slides).

However, outside of passing references in many studies to the effect that a range of predictors were evaluated, there is little systematic work that has explicitly evaluated the relevant skill of different atmospheric predictors. The one commonality between most studies is the use of some indicator of the large-scale circulation.

The choice of the predictor variables is of utmost importance. For example, the downscaled scenario of future change in precipitation may alter significantly depending on whether or not humidity is included as a predictor. The implication here is that while a predictor may or may not appear as the most significant when developing the downscaling function under present climates, the changes in that predictor under a future climate may be critical to determine change. A similar issue exists with respect to downscaling temperature. Studies show that changes of local temperature may not be driven by circulation changes alone, but may be dominated by changes in the radiative properties of the atmosphere. This is a particular vulnerability of any downscaling procedure in light of the propensity to use circulation predictors alone that do not necessarily reflect changed radiative properties of the atmosphere.

A possible solution is to incorporate the large-scale temperature field from the GCM as a surrogate indicator of the changed radiative properties of the atmosphere. Another solution is to use several large-scale predictors, such as gridded temperature and circulation fields. After the availability of homogeneous re-analyses, the number of candidate predictor fields has been greatly enhanced; earlier, the empirical evidence about the variability of regional/local predictands and large-scale predictors was very limited and many studies choose either gridded near surface temperature or air pressure, or both. These "new" data sets will allow significant improvements in accuracy of empirical downscaling techniques.

4.0 Dynamic Downscaling

Dynamic downscaling techniques consist on using the outputs of a global climate model as lateral boundary conditions for more sophisticated models of a limited geographic area and with a higher resolution in space. Dynamical downscaling uses regional climate models (RCMs) to simulate finer-scale physical processes consistent with the large scale weather evolution prescribed from a GCM. In dynamical downscaling, a regional climate model (RCM) uses GCM output as initial and lateral boundary conditions over a region of interest. A RCM is a downscaling tool that adds fine scale (high resolution) information to the large-scale projections of a global general circulation model (GCM). Fig. 2 gives a generalized diagram of a GCM.

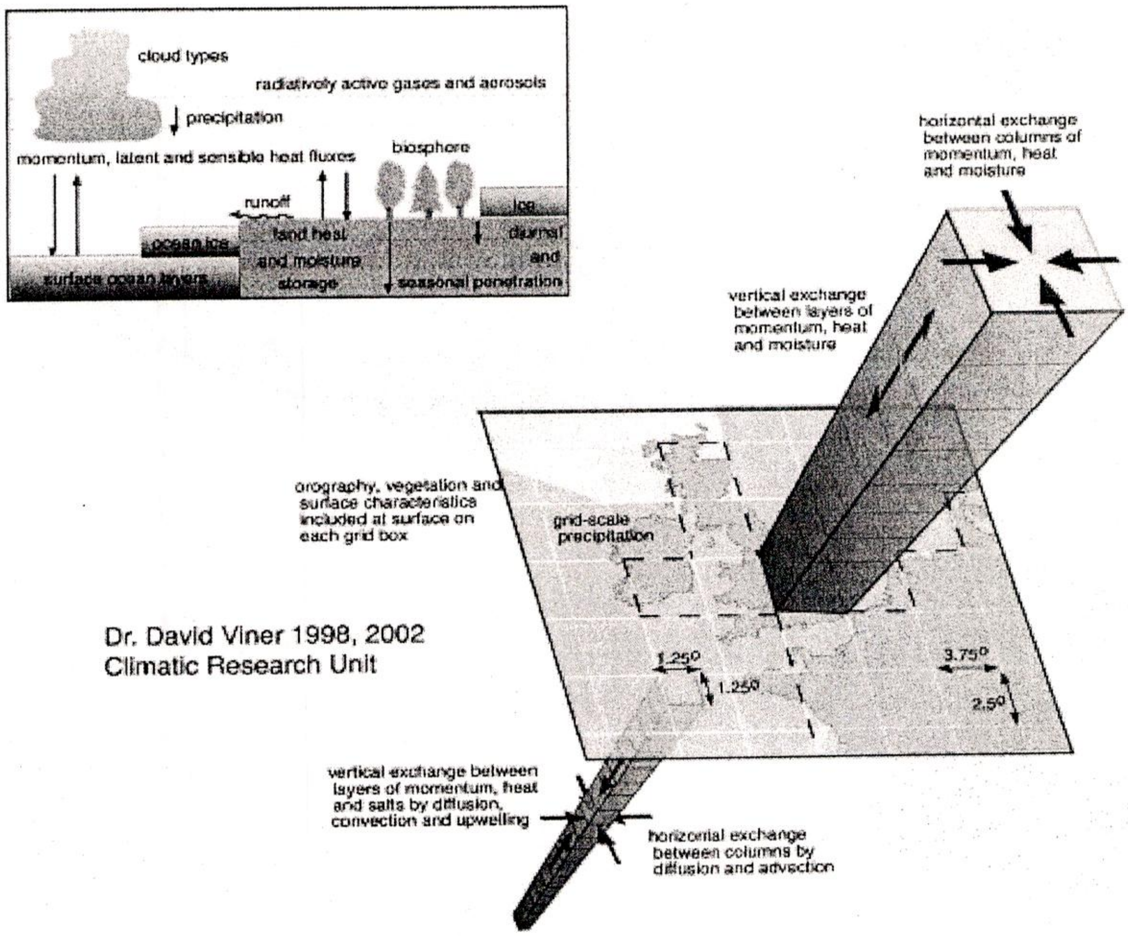

Fig. 2: A conceptual diagram of a GCM (Source: IPCC).

According to IPCC, GCMs representing physical processes in the atmosphere, ocean, cryosphere and land surface, are the most advanced tools currently available for simulating the response of the global climate system to increasing GHG concentrations. While simpler models have also been used to provide globally- or regionally-averaged estimates of the climate response, only GCMs, possibly in conjunction with nested regional models, have the potential to provide geographically and physically consistent estimates of regional climate change which are required in impact analysis.

GCMs depict the climate using a three dimensional grid over the globe, typically having a horizontal resolution of between 250 and 600 km, 10 to 20 vertical layers in the atmosphere and sometimes as many as 30 layers in the oceans. Their resolution is thus quite coarse relative to the scale of exposure units in most impact assessments. Moreover, many physical processes, such as those related to clouds, also occur at smaller scales and cannot be properly modelled. Instead, their known properties must be averaged over the larger scale in a technique known as parameterization. This is one source of uncertainty in GCM-based simulations of future climate. Others relate to the simulation of various feedback mechanisms in models concerning, for example, water vapour and warming, clouds and radiation, ocean circulation and ice and snow albedo. For this reason, GCMs may simulate quite different responses to the same forcing, simply because of the way certain processes and feedbacks are modelled.

GCMs can provide predictions of changes in climate down to scales of a few hundred kilometres or so at best. Currently the resolution of the atmospheric part of a typical GCM is about 250 km in the horizontal with 20 levels in the vertical. The resolution of a typical ocean model is 125 km to 250 km, with, again, 20 levels from the sea surface to the ocean floor. Hence GCMs make projections at a relatively coarse resolution and cannot represent the fine-scale detail that characterizes the climate in many regions of the world, especially in regions with complex orography or heterogeneous land surface cover or coastlines. As a result, "GCMs cannot access the spatial scales that are required for climate impact and adaptation studies" (WMO, 2002). Historically, GCMs have been the primary source of information for constructing climate scenarios and will always provide the basis of comprehensive assessments of climate change at all scales from local to global. GCMs predictions may be adequate where the terrain is reasonably flat and uniform, and away from coasts. However, in areas where coasts and mountains have a significant effect on weather (and this will be true for most parts of the world), scenarios based on global models will fail to capture the local detail needed for impacts assessments at a national and regional level. Also, at such coarse resolutions, extreme events such as cyclones or heavy rainfall are either not captured or their intensity is unrealistically low. The best method for adding this detail to global predictions is to use a regional climate model (RCM). GCMs are typically run with horizontal scales of 300km; regional models can resolve features down to 50km or less. This makes for a more accurate representation of many surface features, such as complex mountain topographies and coastlines. It also allows small islands and peninsulas to be represented realistically, whereas in a global model their size (relative to the model gridbox) would mean their climate would be that of the surrounding ocean. RCMs are full climate models, and as such are physically based. They represent most if not all of the processes, interactions and feedbacks between climate system components represented in GCMs. They produce a comprehensive set of output data over the model domain.

A regional climate model (RCM) has a high resolution (typically 50 km) and covers a limited area of the globe (typically 5,000 km x 5,000 km). It is a comprehensive physical model, usually of the atmosphere and land surface, containing representations of the important processes in the climate system (e.g. clouds, radiation, rainfall, soil hydrology) as are found in a GCM. A RCM does not generally include an ocean component; this would increase complexity and need more computing power; in any case, most applications for impacts' assessments require only land surface or atmospheric data. Given that RCMs are limited area models they need to be driven at their boundaries by time-dependent large scale fields (e.g., wind, temperature, water vapour and surface pressure).

These fields are provided either by analyses of observations or by GCM integrations in a buffer area that is not considered when analysing the results of the RCM. RCM predictions of ideally 30 years (e.g. the period 2071-2100) are needed to provide robust climate statistics, e.g. distributions of daily rainfall or intra-seasonal variability.

There are many different RCMs currently available, for various regions, developed at different modeling centers around the world. The different RCMs produce different high resolution scenarios for a given boundary forcing, due to differences in model formulation, but also due to small-scale internal variability generated by the RCM. There has been considerable international effort recently to quantify uncertainty in regional climate change through the inter-comparison of multiple RCMs. The typical grid size of RCM simulations to date has been 25 km or 50 km. However, recently RCM simulations with grid scales below 20 km have become available for Europe and RCMs with grid sizes of 5km or less are being developed at several modeling centers. For example a 5 km RCM has been developed over Japan.

In the following, a widely referred GCM is described first, followed by description of a RCM.

4.1 HadCM3

HadCM3 (*Hadley Centre Coupled Model, version 3*) is a coupled atmosphere-ocean general circulation model (AOGCM) developed at the Hadley Centre in the United Kingdom. It was one of the major models used by the IPCC. HadCM3 does not need flux adjustment (additional "artificial" heat and freshwater fluxes at the ocean surface) to produce a good simulation. The higher ocean resolution of HadCM3 is a major factor in this; other factors include a good match between the atmospheric and oceanic components; and an improved ocean mixing scheme. HadCM3 is composed of two components: the atmospheric model HadAM3 and the ocean model (which includes a sea ice model). The atmospheric component of the model has 19 levels with a horizontal resolution of 2.5 degrees of latitude by 3.75 degrees of longitude, which produces a global grid of 96 x 73 grid cells. This is equivalent to a surface resolution of about 417 km x 278 km at the Equator, reducing to 295 km x 278 km at 45 degrees of latitude. The atmosphere component of the model also optionally allows the transport, oxidation and removal by physical deposition and rain out of anthropogenic sulphur emissions to be included interactively. This permits the direct and indirect forcing effects of sulphate aerosols to be modelled given scenarios for sulphur emissions and oxidants. The oceanic component of the model has 20 levels with a horizontal resolution of 1.25 x 1.25 degrees. At this resolution it is possible to represent important details in oceanic current structures.

4.2 HadRM3

The third generation Hadley Centre RCM (HadRM3) is based on the latest GCM, HadCM3. It has a horizontal resolution of 50 km with 19 levels in the atmosphere (from the surface to 30 km in the stratosphere) and four levels in the soil. In addition to a comprehensive representation of the physical processes in the atmosphere and land-surface, it also includes the sulphur cycle. This enables it to estimate the concentration of sulphate aerosol particles produced from SO_2 emissions. These have a cooling effect as they scatter back sunlight and also produce brighter clouds by allowing smaller water droplets to form. The IPCC SRES emission scenarios show substantial changes in SO_2 emissions in the future, so it is important that the RCM can calculate their effect.

Developing, setting up and using a regional model over a specific area of the globe requires a considerable amount of effort from an experienced climate modeller. In addition, RCMs (like GCMs) are usually run on large computing installations. Both these factors effectively exclude many developing countries from producing climate change predictions and scenarios. The Hadley Centre has configured its third-generation Hadley Centre RCM to PRECIS so that it is easy to set up and can be run over any area of the globe on a relatively inexpensive fast PC.

4.3 PRECIS

PRECIS (*Providing Regional Climates for Impacts Studies)* is a regional modelling system that can be run over any area of the globe on a relatively inexpensive, fast PC to provide regional climate information for impacts studies. The PRECIS climate model is an atmospheric and land surface model of limited area and high resolution which is locatable over any part of the globe. Dynamical flow, the atmospheric sulphur cycle, clouds and precipitation, radiative processes, the land surface and the deep soil are all described. The model requires prescribed surface and lateral boundary conditions. Surface boundary conditions are only required over water, where the model needs time series of surface temperatures (sea-surface temperatures, SSTs) and ice extents. If this information is taken directly from a coupled GCM then its coarse resolution means that there could be quite large regional errors in the data, and for coastal points and inland seas they may have to be interpolated or extrapolated which could lead to even larger errors locally. An alternative is to use observed values (at higher resolution) for the GCM and RCM simulations of present-day climate and then obtain values for the future by adding on changes in the SSTs and sea-ice extent and thickness from a coupled GCM. The Hadley Centre has used the second of the above approaches. Observed SSTs and sea-ice (on a 1° grid) are used with an atmosphere-only GCM for the present-day simulation (which then provides lateral boundary conditions for the RCM present-day simulation). Lateral boundary conditions provide dynamical atmospheric information at the latitudinal and longitudinal edges of the model domain. There is no prescribed constraint at the upper boundary of the model. The lateral boundary conditions comprise the standard atmospheric variables of surface pressure, horizontal wind components and measures of atmospheric temperature and humidity. Also, as certain configurations of the PRECIS RCM contain a full representation of the sulphur cycle, a set of boundary conditions (including sulphur dioxide, sulphate aerosols and associated chemical species) are also required for this. These lateral boundary conditions are updated every six hours; surface boundary conditions are updated every day.

Application of the PRECIS is essentially a three-stage process comprising:

1) running the PRECIS RCM over the area of interest to provide simulations of a recent climate period (e.g. 1961-90), and comparing these with observations, to validate the model;
2) running the PRECIS RCM to provide climate change projections for the region of interest; the regional model is supplied with GCM fields from the Hadley Centre, although the system is being developed to use fields from other climate models; and
3) deriving relevant climate information from these projections guided by an understanding of the needs of the impacts models and an assessment of the climate models' performance and projections.

4.4 Advantages of RCMs

RCMs simulate current climate more realistically: Where terrain is flat for thousands of kilometres and away from coasts, the coarse resolution of a GCM may not matter. However, most land areas have mountains, coastlines etc. on scales of a hundred kilometres or less, and RCMs can take account of the effects of much smaller scale terrain than GCMs.

RCMs predict climate change with more detail: The finer spatial scale will also be apparent, of course, in predictions. When warming from increased greenhouse gases changes patterns of wind flow over a region then the way mountains and other local features interact with this will also change. This will affect the amount of rainfall and the location of windward rainy areas and downwind rain shadow areas. For many mountains and even mountain ranges, such changes will not be seen in the global model, but the finer resolution of the RCM will resolve them.

RCMs represent smaller islands: The coarse resolution of a GCM means than many islands are just not represented and hence their climate is predicted to change in exactly the same way as surrounding oceans. However, the land surface has a much lower thermal inertia than the oceans so will warm faster. If it has any significant hills or mountains, these will have a substantial influence on rainfall patterns. In an RCM, many more islands are resolved, and the changes predicted can be very different to those over the nearby ocean.

RCMs are much better at simulating and predicting changes to extremes of weather: Changes in extremes of weather, for example heavy rainfall events, are likely to have more of an impact than changes in annual or seasonal means. RCMs are much better than GCMs at simulating extremes.

4.5 Limitations of RCMs

In common with other techniques, regional climate models do not yet provide all the solutions for generating climate change scenarios. There will be errors in their representation of the climate system and their resolution will not be sufficient for some applications. Predictions from an RCM are dependent on the realism of the global model driving it; any errors in the GCM predictions will be carried through to the RCM predictions. This limitation is shared by all techniques for generating realistic climate scenarios.

5.0 Comparison of dynamical and empirical downscaling methods

Few formal comparative studies of different regionalization techniques have been carried out. To date, published work mostly focused on the comparison between regional climate model and statistical downscaling techniques.

Kidson and Thompson (1998) used the RAMS dynamical model to downscale reanalysis data (ECMWF) over New Zealand to a grid resolution of 50 km. The statistical downscaling used a screening regression technique to predict local minimum and maximum daily temperature, and daily precipitation. The regression technique limits each regression equation to 5 predictors (selected from EOFs of 1000 hPa and 500 hPa geopotential height fields, local scalar wind speed and anomalies of geostrophic wind speed at 500 hPa and 1000 hPa, anomalous 1000 hPa–500 hPa thickness and relative vorticity, and terms of vorticity advection). The results indicated little difference in skill between the two techniques, and Kidson and Thompson suggest that, subject to the assumption of statistical relationships remaining viable under a future climate, the computational requirements do not favour the use of the dynamical model, although it is noted that the dynamical model performed better with convective components of the precipitation.

Murphy (1999a,b) found similar levels of skill for present day climate for the dynamical and statistical methods, in line with the Kidson and Thompson (1998) study. The statistical method was nominally better for summertime estimates of temperature, while the dynamical model gave better estimates of wintertime precipitation. However, unlike the validation study which compared the downscaling against observational data, the climate change situation showed larger differences between the statistical and dynamical techniques. The study concludes that the differences in the temperature downscaling do not derive from a breakdown of the statistical relationships, as might be suspected, but are perhaps related to different predictor/predictand relationships in the GCM. In contrast, the downscaled precipitation differences may stem from the exclusion of specific humidity in the regression equation, as moisture was a weak predictor of the natural variability. This point would seem to confirm the humidity issue raised above.

Mearns et al. (1999) also compared regional model simulations and statistical downscaling, in this case using the RegCM2 regional model, and a semi-empirical technique whereby stochastic procedures are conditioned on weather types classified from circulation fields (700hPa geopotential heights). While Mearns et al. suggest that the semi-empirical approach incorporates more physical meaning into the relationships, this approach does impose the assumption that the circulation patterns are robust into a future climate in addition to the normal assumption that the cross-scale relationships are stationary in time. For both the techniques the driving fields are from the CSIRO GCM to downscale daily temperature and precipitation over central-northern USA (Nebraska). As with the preceding studies, the validation under present climate conditions indicated similar skill levels for the dynamical and statistical approaches, with some advantage by the statistical technique.

Also in line with the Murphy (1999a,b) study, larger differences were noted when climate change scenarios were produced. Notably for temperature, the statistical technique produced an amplified seasonal cycle compared to both the RegCM2 and CSIRO data, although similar changes in daily temperature variances were found in both RegCM2 and the statistical technique (with the statistical approach producing mostly decreases). The spatial patterns of change showed greater variability with RegCMs2 compared to the statistical technique. Mearns et al. suggest that some of the result differences are due to the climate change simulation exceeding the range of data used to develop the statistical model, while the decreases in variance are likely a true reflections of changes in the circulation controls.

Overall, the comparative studies indicate that under the present climate both the dynamical and empirical techniques have similar skill. The question arise as to which is "more correct" under future climates. While the dynamical model should clearly provide a better physical basis for change, it is still unclear whether different regional models generate similar downscaled changes, and whether the computational cost relative to statistical/empirical techniques is merited.

5.1 Uncertainty in Downscaling

There are several levels of uncertainty in the generation of regional climate change information. The first level is associated with emission scenarios. The second level of uncertainty is related to the simulation of the transient climate response by coupled AOGCMs for a given emission scenario. This uncertainty is important both, when coupled AOGCM information is used for impact work without the intermediate step of a regionalization tool, and when AOGCM fields are used to drive a regionalization technique. The final level of uncertainty occurs when the coupled AOGCM data are processed through a regionalization method. Overall, the natural variability of the climate system adds a further level of uncertainty in the evaluation of a climate change simulation.

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