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A REVIEW OF DOWNSCALING METHODS FOR CLIMATE CHANGE PROJECTIONS

SEPTEMBER 2014

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ARCC

African and Latin American Resilience to Climate Change Project

This report was prepared by Sylwia Trzaska[1] and Emilie Schnarr[1] through a subcontract to Tetra Tech ARD.

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This publication was produced for the United States Agency for International Development by Tetra Tech ARD, through a Task Order under the Prosperity, Livelihoods, and Conserving Ecosystems (PLACE) Indefinite Quantity Contract Core Task Order (USAID Contract No. AID-EPP-I-00-06-00008, Order Number AID-OAA-TO-11-00064).

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A REVIEW OF DOWNSCALING METHODS FOR CLIMATE CHANGE PROJECTIONS

AFRICAN AND LATIN AMERICAN RESILIENCE TO CLIMATE CHANGE (ARCC)

SEPTEMBER 2014

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ACRONYMS AND ABBREVIATIONS

AMMA	African Monsoon Multidisciplinary Analyses
ANN	Artificial Neural Network
ARCC	African and Latin American Resilience to Climate Change
BCSD	Bias-Corrected Spatial Disaggregation
CCA	Canonical Correlation Analysis
CCAFS	CGIAR Program on Climate Change, Agriculture and Food Security
CF	Change Factor
CGIAR	Consultative Group on International Agricultural Research
CIAT	International Center for Tropical Agriculture
CLARIS	Climate Change Assessment and Impact Studies
CMIP3	Coupled Model Intercomparison Project Phase 3
CORDEX	Coordinated Regional Climate Downscaling Experiment
CRCM	Canadian Regional Climate Model
ECHAM	European Centre – Hamburg
ENSEMBLES	ENSEMBLE-Based Predictions of Climate Change and their Impacts
ENSO	El Niño-Southern Oscillation
GCM	General Circulation Model
HadRM3	U.K. Met Office Hadley Centre's Regional Climate Model Version 3
HIRHAM	German model which combines the dynamics of the HIRLAM and ECHAM models
HIRLAM	High Resolution Limited Area Model
IPCC	Intergovernmental Panel on Climate Change
LARS-WG	Long Ashton Research Station Weather Generator
LGP	Length of Growing Period
NARCCAP	North American Regional Climate Change Assessment Program
NHMM	Nonhomogeneous Hidden Markov Model
NOAA	National Oceanic and Atmospheric Administration
PRUDENCE	Prediction of Regional Scenarios and Uncertainties for Defining European Climate Change Risks and Effects

RACMO	Dutch Regional Atmospheric Climate Model
RCM	Regional Climate Model
RegCM3	U.S. Regional Climate Model Version 3
REMO	German Regional Climate Model
STARDEX	Statistical and Regional Dynamical Downscaling of Extremes for European Regions
SOM	Self-Organizing Map
SVD	Singular Value Decomposition
UNFCCC	United Nations Framework Convention on Climate Change
USAID	U.S. Agency for International Development
WAM	West African Monsoon

GLOSSARY

Algorithm: Computational step-by-step, problem-solving procedure.

Bias correction: Adjustment of modeled values to reflect the observed distribution and statistics.

Change factor (CF): Ratio between values of current climate and future GCM simulations.

Climatology: Long-term average of a given variable, often over time periods of 20 to 30 years. For example, a monthly climatology consists of a mean value for each month computed over 30 years, and a daily climatology consists of a mean value for each day.

Coastal breeze: Wind in coastal areas driven by differences in the rate of cooling/warming of land and water.

Convective precipitation: Intense precipitation of short duration that characterizes most of the rainfall in the tropics.

Direct and indirect effect of aerosols: Atmospheric aerosols are solid and liquid particles suspended in air that influence the amount of solar radiation that reaches the surface of the Earth. Aerosols can cool the surface of the Earth via reflection of solar radiation. This is termed the *direct effect*. The effect of aerosols on the radiative properties of Earth's cloud cover is referred to as the *indirect effect*.

Downscaling: Derivation of local to regional-scale (10-100 kilometers) information from larger scale modeled or observed data. There are two main approaches: dynamical downscaling and statistical downscaling.

Emissions Scenario: Estimates of future greenhouse gas emissions released into the atmosphere. Such estimates are based on possible projections of economic and population growth and technological development, as well as physical processes within the climate system.

Feedback (climate): An interaction within the climate system in which the result of an initial process triggers changes in a second process that in turn influences the initial one. A positive feedback intensifies the original process and a negative one reduces it.

Frequency distribution: An arrangement of statistical data that shows the frequency of the occurrence of different values.

General Circulation Model (GCM): A global, three-dimensional computer model of the climate system that can be used to simulate human-induced climate change. GCMs represent the effects of such factors as reflective and absorptive properties of atmospheric water vapor, greenhouse gas concentrations, clouds, annual and daily solar heating, ocean temperatures, and ice boundaries.

Grid cell: A rectangular area that represents a portion of the Earth's surface.

Interannual variability: Year-to year change in the mean state of the climate that is caused by a variety of factors and interactions within the climate system. One important example of interannual variability is the quasi-periodic change of atmospheric and oceanic circulation patterns in the Tropical Pacific region, collectively known as El Niño-Southern Oscillation (ENSO).

Interpolation: The process of estimating unknown data values that lie between known values. Various interpolation techniques exist. One of the simplest is linear interpolation, which assumes a constant rate of change between two points. Unknown values anywhere between these two points can then be assigned.

Land-sea contrast: Difference in pressure and other atmospheric characteristics that arises between the land and ocean, caused by the difference in the rate of cooling/warming of their respective surfaces.

Large-scale climate information: Atmospheric characteristics (e.g., temperature, precipitation, relative humidity) spanning several hundred to several thousand kilometers.

Lateral boundaries: Information about the air masses, obtained from GCM output or observations, used by RCMs to derive fine-scale information.

Markovian process: When values of the future depend solely on the present state of the system and not the past.

Predictand: The variable that is to be predicted. In downscaling, the predictand is the local climate variable of interest.

Predictor: A variable that can be used to predict the value of another variable. In downscaling, the predictor is the large-scale climate variable.

Regional Climate Model (RCM): High-resolution (typically 50 kilometers) computer model that represents local features. It is constructed for limited areas, run for periods of ~20 years, and driven by large-scale data.

Spatial downscaling: Refers to the methods used to derive climate information at finer spatial resolution from coarser spatial resolution GCM output. The fundamental basis of spatial downscaling is the assumption that significant relationships exist between local and large-scale climate.

Spatial resolution: In climate, spatial resolution refers to the size of a grid cell in which 10-80 kilometers and 200-500 kilometers are considered to be "fine" and "coarse," respectively.

Stationarity: Primary assumption of statistical downscaling; as the climate changes, the statistical relationships do not. It assumes that the statistical distribution associated with each climate variable will not change, that the same large-scale predictors will be identified as important, and that the same statistical relationships between predictors and predictands exist.

Stochastic: Describes a process or simulation in which there is some indeterminacy. Even if the starting point is known, there are several directions in which the process can evolve, each with a distinct probability.

Synoptic: Refers to large-scale atmospheric characteristics spanning several hundred to several thousand kilometers.

Systematic bias: The difference between the observed data and modeled results that occurs due model imperfections.

Temporal downscaling: Refers to the derivation of fine scale temporal data from coarser-scale temporal information (e.g., daily data from monthly or seasonal information). Its main application is in impact studies when impact models require daily or even more frequent information.

Temporal resolution: The time scale at which a measurement is taken or a value is represented. Daily and monthly resolutions denote one value per day and one value per month, respectively.

Time-series: A set of observations, results, or other data obtained over a period of time at regular intervals. A time-series usually displays values as function of time, i.e., time is on the horizontal axis.

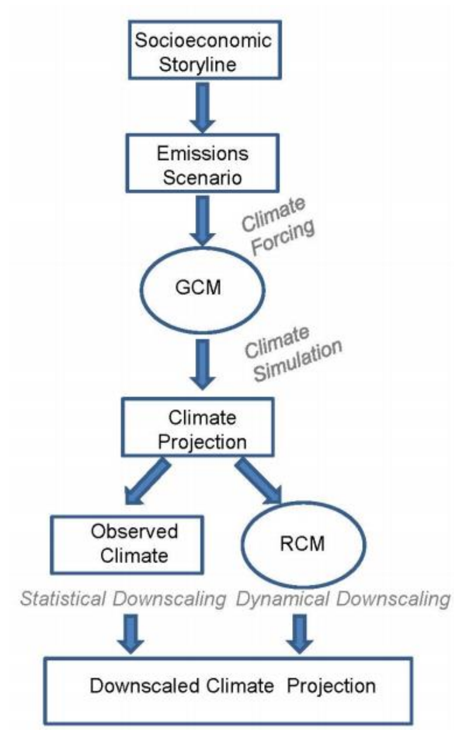
Uncertainty: An expression of the degree to which a value (e.g., the future state of the climate system) is unknown. Uncertainty can result from lack of information or from disagreement about what is known or even knowable. Uncertainty can be represented by quantitative measures (a range of values calculated by various models), or by qualitative statements, reflecting the judgment of a team of experts.

EXECUTIVE SUMMARY

To respond to the needs of decision makers to plan for climate change, a variety of reports, tools, and datasets provide projected climate impacts at spatial and temporal scales much finer than those at which the projections are made. It is important to recognize the variety of assumptions behind the techniques used to derive such information and the limitations they impose on the results. The main tools used to project climate are General Circulation Model (GCMs), which are computer models that mathematically represent various physical processes of the global climate system. These processes are generally well known but often cannot be fully represented in the models due to limitations on computing resources and input data. Thus, GCM results should only be considered at global or continental scales for climatic conditions averaged at monthly, seasonal, annual, and longer time scales.

Any information that is presented at spatial scales finer than 100 kilometers x 100 kilometers and temporal scales finer than monthly values has undergone a process called **downscaling**. While it produces climatic information at scales finer than the initial projections, this process involves additional information, data, and assumptions, leading to further uncertainties and limitations of the results, a consequence that is often not made explicit to end-users. International organizations or national governments currently provide no official guidance that assists researchers, practitioners, and decision makers in determining climate projection parameters, downscaling methods, and data sources that best meet their needs. Since the research community is still developing downscaling methods, users often need to read highly technical and specialized explanations in order to understand and adequately apply the results for impact studies, planning, or decision-making.

FIGURE 1. ILLUSTRATION OF THE COMPONENTS INVOLVED IN DEVELOPING GLOBAL AND REGIONAL CLIMATE PROJECTIONS



Source: Daniels et al., 2012

The following are important considerations and recommendations to keep in mind when designing and interpreting fine-scale information on climate change and its impacts.

- Downscaling relies on the assumption that local climate is a combination of large-scale climatic/atmospheric features (global, hemispheric, continental, regional) and local conditions (topography, water bodies, land surface properties). Representation of the latter is generally beyond the capacity of current GCMs.

- Deriving climate projections at local scales is a multistep process, as illustrated in Figure 1. At each step, assumptions and approximations are made. Uncertainties are inherent in projections of changes in climate and their impacts. They arise from different sources and need to be kept in mind, whether explicitly quantified or not.

- Downscaling can be applied spatially and temporally. Oftentimes, several downscaling methods are combined to obtain climate change information at desired spatial and temporal scales.
- There are two principal ways to combine the information on local conditions with large-scale climate projections:
  - Dynamical: by explicitly including additional data and physical processes in models similar to GCMs but at a much higher resolution and covering only select portions of the globe[1]. This method has numerous advantages but is computationally intensive and requires large volumes of data as well as a high level of expertise to implement and interpret results, often beyond the capacities of institutions in developing countries.
  - Statistical: by establishing statistical relationships between large-scale climate features that GCMs and local climate characteristics provide. In contrast to the dynamical method, the statistical methods are easy to implement and interpret. They require minimal computing resources but rely heavily on historical climate observations and the assumption that currently observed relationships will carry into the future. However, high quality historical records often are not available in developing countries.

In most cases, a sequence of different methods is needed to obtain results at the desired resolution; however, the analysis of select reports presenting changes in climate and/or their impacts has shown the following points:

- Information on downscaling and the limitations of the results are often not appropriately highlighted, leading the user to believe that the results are "true" and valid at the resolution presented. Extensive reading of technical documentation is often needed to uncover all the steps and assumptions that led to the final results.
- Uncertainties inherent in projections and additionally arising from applied downscaling are often not presented, quantified, nor discussed, leading the user to interpret the numerical results at face value.
- Validation of downscaled results (on historical data) is often omitted; comparing downscaled results to high-resolution observed information would highlight systematic biases and the limitations of results.

The above deficiencies most frequently result from simple oversight by the authors of the report or their efforts to make it easy to use. However, they are important, and an expert user may be able to detect them and estimate the limitations of the results.

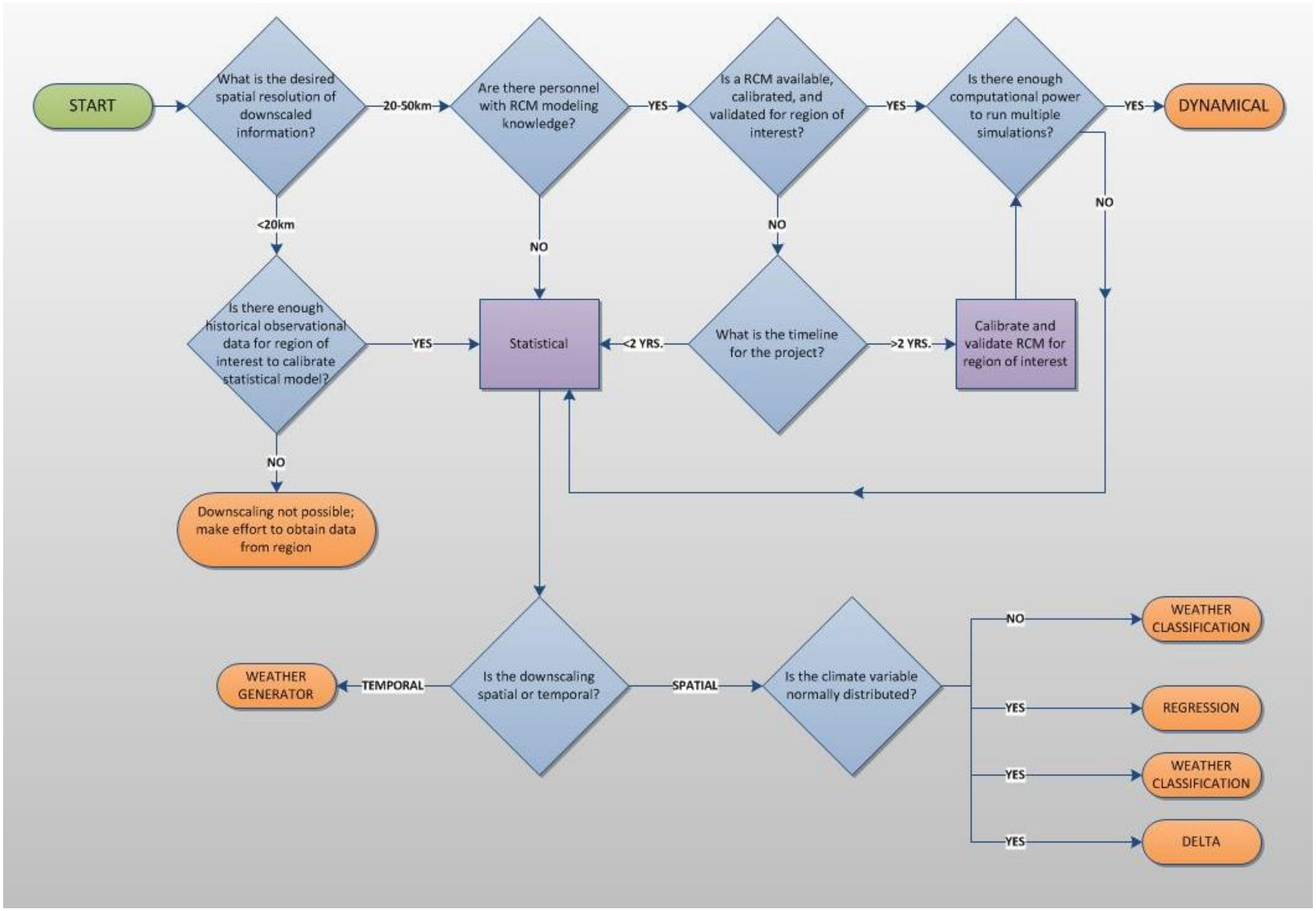
The overall diversity of the approaches and methods in existing reports and publications reflects the diversity of the goals and resources of each assessment. Thus, there is no single best downscaling approach, and downscaling methods will depend on the desired spatial and temporal resolution of outputs and the climate characteristics of the highest impact of interest. In light of current approaches and practices reviewed in this report, it is possible to make the recommendations that follow.

[1] Since the main constraint on resolution is the available computing resource, increasing the resolution requires reducing the area covered; therefore, Regional Climate Models (RCMs) usually cover portions of the globe.

RECOMMENDATIONS

- Given the diversity of developed approaches, it is best to partner with a climate scientist or downscaling expert who can help to evaluate the needs, relevant techniques, and limitations of the results, as detailed below.
- When designing assessments of climate change and its impacts at sub-regional scales, a thorough evaluation 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 approach should be selected based on the information needs and also, importantly, on available resources (data, computing resources, expertise, and time-frames). The decision tree (Figure 2) has been designed to guide the sponsors and the scientists in determining an appropriate downscaling method. The questions are important considerations that should be answered carefully. It is important to note that this decision tree is not customized to a particular assessment or project, and thus some questions that are essential to a particular case may be missing.
- When using/interpreting existing results/reports, the coarse resolution of the initial projections and the scales at which they are valid need to be kept in mind. Any results presenting fine-scale spatial details or using high temporal resolution data have undergone a manipulation (usually a sequence of manipulations) of the original projections, whether this process is described or not. It is only through an evaluation of the employed downscaling procedure that the validity of the results at a fine resolution and the value added over initial coarse projections can be assessed. Results that look detailed may actually not be robust; in general, a rigorous downscaling process requires including additional information, and a simple interpolation from coarse- to fine-scale may not lead to reliable results. Therefore, it is important to understand (and research if not directly available) at least the broad aspects of the applied downscaling.
- Since uncertainty is inherent to the projections, an estimate of it — quantitative or at least qualitative — should always be included and carried through the downscaling process. Such an estimate should at least include different potential future climate states and ideally should also estimate the influence of the downscaling procedure on the final results.

FIGURE 2. WHICH DOWNSCALING TECHNIQUE IS MOST APPROPRIATE FOR THE PRESENT STUDY?



1.0 INTRODUCTION

Decision makers are increasingly demanding climate information at the national to local scale in order to address the risk posed by projected climate changes and their anticipated impacts. Readily available climate change projections are provided at global and continental spatial scales for the end of the 21st century (Intergovernmental Panel on Climate Change [IPCC], 2007). These projections, however, do not fit the needs of sub-national adaptation planning that requires regional and/or local projections of likely conditions five to 10 years from now. Moreover, decision makers are interested in understanding the impacts of climate change on specific sectors, e.g., agricultural production, food security, disease prevalence, and population vulnerability.

In response to this demand, numerous impact and vulnerability assessments produced at different scales, from global to local, provide climate change impact results at spatial scales much finer than those at which projections are initially made. To produce such results, combinations of methods and indicators are often used, each with its own assumptions, advantages, and disadvantages. In reports, these essential factors may not be adequately communicated to the reader, thus leaving him/her without the ability to understand potential discrepancies between different reports. Often, global or continental-scale information is directly used to produce local-scale impact maps, which is not appropriate since this large-scale information does not account for differences at the local scale.

In order to derive climate projections at scales that decision makers desire, a process termed **downscaling** has been developed. Downscaling consists of a variety of methods, each with their own merits and limitations. International organizations or national governments currently provide no official guidance that assists researchers, practitioners, and decision makers in determining climate projection parameters, downscaling methods, and data sources that best meet their needs.

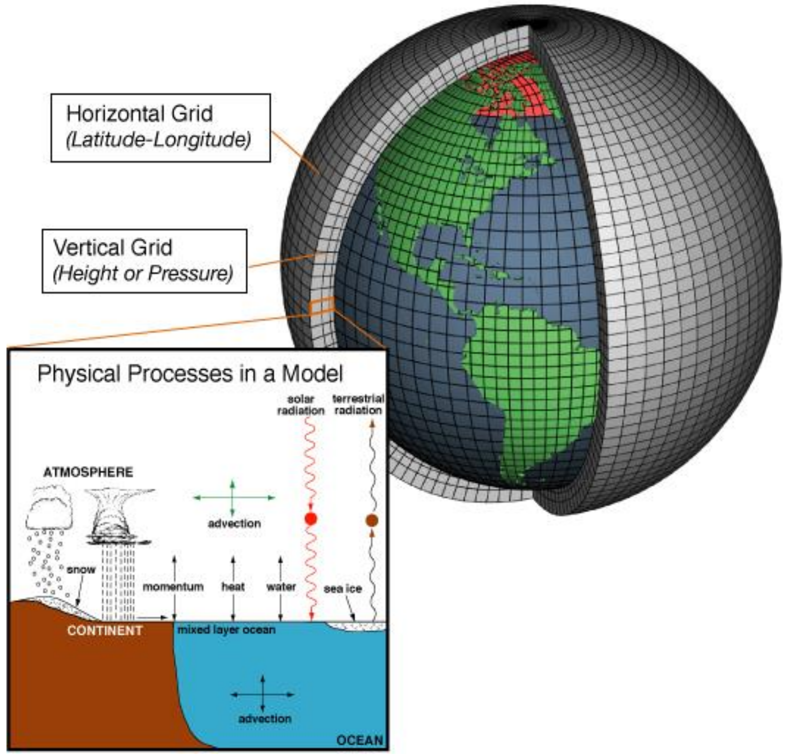
The goal of the present paper is to provide non-climate specialists with the ability to understand various downscaling methods and to interpret climate change downscaling studies and results. The remainder of this introductory section describes how global climate change projections are produced and downscaled. Section 2.0 provides details about the two primary downscaling approaches: dynamical and statistical. Section 3.0 offers an analysis of examples of reports that use downscaling to produce climate change impact maps. Short summaries of the main points/key takeaways are presented at the end of each of these sections. General conclusions and recommendations are provided in Section 4.0. Annexes A, B, and C describe in greater detail statistical downscaling methods, regional climate change assessment projects, and downscaling tools and software, respectively.

1.1 GENERAL CIRCULATION MODELS

General or global circulation models (GCMs) simulate the Earth's climate via mathematical equations that describe atmospheric, oceanic, and biotic processes, interactions, and feedbacks. They are the primary tools that provide reasonably accurate global-, hemispheric-, and continental-scale climate information and are used to understand present climate and future climate scenarios under increased greenhouse gas concentrations.

A GCM is composed of many grid cells that represent horizontal and vertical areas on the Earth's surface (Figure 3). In each of the cells, GCMs compute the following: water vapor and cloud atmospheric interactions, direct and indirect effects of aerosols on radiation and precipitation, changes in snow cover and sea ice, the storage of heat in soils and oceans, surfaces fluxes of heat and moisture, and large-scale transport of heat and water by the atmosphere and oceans (Wilby et al., 2009).

FIGURE 3. CONCEPTUAL STRUCTURE OF A GCM



Source: National Oceanic and Atmospheric Administration (NOAA), 2012

The spatial resolution of GCMs is generally quite coarse, with a grid size of about 100–500 kilometers. Each modeled grid cell is homogenous, (i.e., within the cell there is one value for a given variable). Moreover, they are usually dependable at temporal scales of monthly means and longer. In summary, GCMs provide quantitative estimates of future climate change that are valid at the global and continental scale and over long periods.

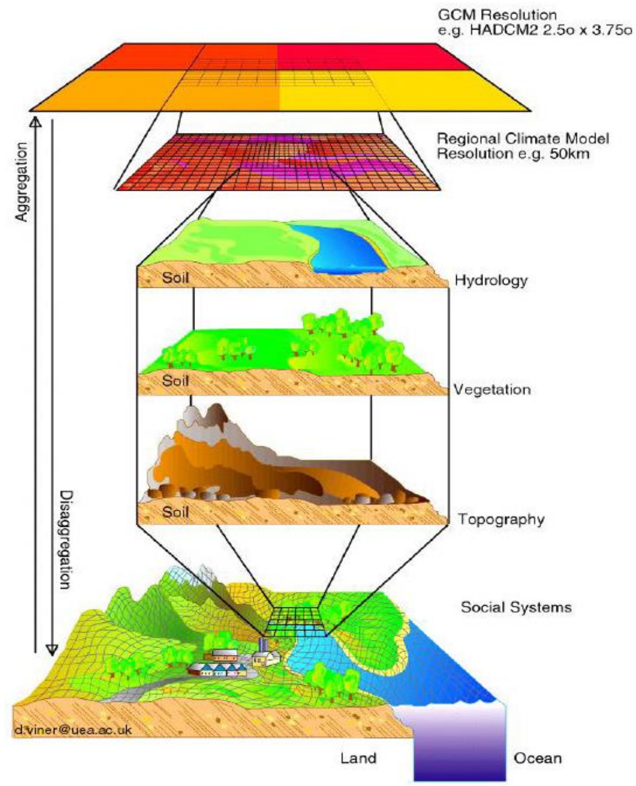
1.2 DOWNSCALING

Although GCMs are valuable predictive tools, they cannot account for fine-scale heterogeneity of climate variability and change due to their coarse resolution. Numerous landscape features such as mountains, water bodies, infrastructure, land-cover characteristics, and components of the climate system such as convective clouds and coastal breezes, have scales that are much finer than 100–500 kilometers. Such heterogeneities are important for decision makers who require information on potential impacts on crop production, hydrology, species distribution, etc. at scales of 10–50 kilometers.

Various methods have been developed to bridge the gap between what GCMs can deliver and what society/businesses/stakeholders require for decision making. The derivation of fine-scale climate information is based on the assumption that the local climate is conditioned by interactions between large-scale atmospheric characteristics (circulation, temperature, moisture, etc.) and local features (water bodies, mountain ranges, land surface properties, etc.). It is possible to model these interactions and establish relationships between present-day local climate and atmospheric conditions through the downscaling process. It is important to understand that the downscaling process adds information to the coarse GCM output so that information is more realistic at a finer scale, capturing sub-grid scale contrasts and inhomogeneities. Figure 4 (next page) presents a visual representation of the concept of downscaling.

Downscaling can be performed on spatial and temporal aspects of climate projections. Spatial downscaling refers to the methods used to derive finer-resolution spatial climate information from coarser-resolution GCM output, e.g., 500 kilometers grid cell GCM output to a 20 kilometers resolution, or even a specific location. Temporal downscaling refers to the derivation of fine-scale temporal information from coarser-scale temporal GCM output (e.g., daily rainfall sequences from monthly or seasonal rainfall amounts). Both approaches detailed below can be used to downscale monthly GCM output to localized daily information.

FIGURE 4. THE CONCEPT OF SPATIAL DOWNSCALING



Many of the processes that control local climate, e.g., topography, vegetation, and hydrology, are not included in coarse-resolution GCMs. The development of statistical relationships between the local and large scales may include some of these processes implicitly.
Source: Viner, 2012

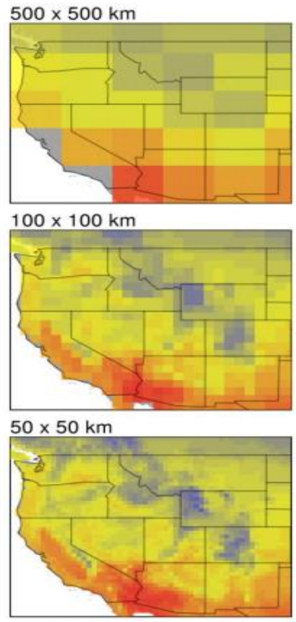
Dynamical downscaling relies on the use of a regional climate model (RCM), similar to a GCM in its principles but with high resolution. RCMs take the large-scale atmospheric information supplied by GCM output at the lateral boundaries and incorporate more complex topography, the land-sea contrast, surface heterogeneities, and detailed descriptions of physical processes in order to generate realistic climate information at a spatial resolution of approximately 20–50 kilometers (Figure 5).

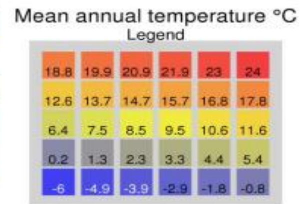
Since the RCM is nested in a GCM, the overall quality of dynamically downscaled RCM output is tied to the accuracy of the large-scale forcing of the GCM and its biases (Seaby et al., 2013). Despite recovering important regional-scale features that are underestimated in coarse-resolution GCMs, RCM outputs are still subject to systematic errors and therefore often require a bias correction as well as further downscaling to a higher resolution.

Statistical downscaling involves the establishment of empirical relationships between historical and/or current large-scale atmospheric and local climate variables. Once a relationship has been determined and validated, future atmospheric variables that GCMs project are used to predict future local climate variables. Statistical downscaling can produce site-specific climate projections, which RCMs cannot provide since they are computationally limited to a 20–50 kilometers spatial resolution. However, this approach relies on the critical assumption that the relationship between present large-scale circulation and local climate remains valid under different forcing conditions of possible future climates (Zorita and von Storch, 1999). It is unknown whether present-day statistical relationships between large- and regional-scale variables will be upheld in the future climate system.

Oftentimes, dynamical and statistical approaches are used in conjunction. *Dynamical-statistical downscaling* involves the use of an RCM to downscale GCM output before statistical equations are used to further downscale RCM output to a finer resolution. Dynamical downscaling improves specific aspects of regional climate modeling and provides better predictors for further statistical downscaling to higher-resolution output (Guyennon et al., 2013). *Statistical-dynamical downscaling* is a somewhat more complex approach but is less computationally demanding in comparison to dynamical downscaling. This method statistically pre-filters GCM outputs into a few characteristic states that are further used in RCM simulations (Fuentes and Heimann, 2000).

FIGURE 5. MEAN ANNUAL TEMPERATURE (1961–1990)





Presented at 500 kilometer typical GCM grid cell; 50 kilometer typical RCM grid cell; and 1 meter, which requires statistical downscaling. Source: Daniels et al., 2012

1.3 UNCERTAINTY

Confidence in global-scale GCM projections is based on well-understood physical processes and laws, the ability of GCMs to accurately simulate past climate, and the agreement in results across models (Daniels et al., 2012). Multiple model comparisons unanimously project warming of globally averaged near-surface temperature over the next two decades in response to increased greenhouse gas emissions. However, the magnitude of this increase varies from one model to another. Additionally, in certain regions, different models project opposite changes in rainfall amount, which highlights the uncertainty of future climate change projections even when sophisticated state-of-the art GCM tools are used.

There are four main sources of uncertainty in climate projections:

1. Uncertainty in future levels of anthropogenic emissions and natural forcings (e.g., volcanic eruptions);
2. Uncertainty linked to imperfect model representation of climate processes;
3. Imperfect knowledge of current climate conditions that serve as a starting point for projections; and
4. Difficulty in representing interannual and decadal variability in long-term projections.

Efforts are made to quantify these uncertainties. The future evolution of greenhouse gas emissions is highly uncertain due to socio-economic, demographic, and technological evolution. Alternative greenhouse gas emissions scenarios are used to drive GCMs in order to obtain a range of possible future outcomes. Additionally, models require initial conditions[2] to begin the forecast, and these are also not known with high accuracy. Therefore, projections are performed starting from slightly modified initial conditions to obtain a series of simulations, termed an "ensemble." Finally, models cannot perfectly simulate all climate processes; therefore, simulations from multiple models are produced, and a

[2] Current state of the atmosphere.

multi-model ensemble mean (or median)[3] is thought to be the most probable future climate trajectory. The spread among the individual simulations in a multi-model ensemble are an estimate of uncertainty due to sources 2 and 3 in the preceding list.

It is important to communicate uncertainty in climate change projections and provide the following messages:

- Uncertainty does not mean that future projections are unknown or false.
- Uncertainty can be quantified.
- Decisions can be made in the face of uncertainty. For example, decisions are routinely made in the context of military operations and financial investments when uncertainty is greater than that of climate projections.

Figure 6 illustrates uncertainty in GCM simulation of historical global temperature change (IPCC, 2007). The black line represents observed temperature anomalies, and each yellow line is a simulation produced by an individual GCM with the red line being the multi-model ensemble mean. The spread between the simulations illustrates uncertainty. Note that although the individual GCM simulations provide different results, there is consensus and general agreement between the models.

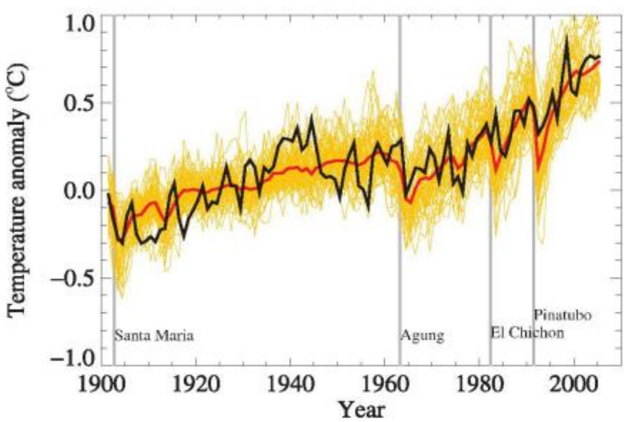


FIGURE 6. GLOBAL MEAN TEMPERATURE ANOMALIES (RELATIVE TO THE 1901–1950 MEAN)

Observations (black), simulations by 14 different GCMs (yellow) driven by natural and anthropogenic emissions, and the mean (red).
Source: IPCC, 2007

Uncertainty is compounded with downscaling due to assumptions that are inherent in models. With each modeling stage, uncertainties are naturally added because more assumptions are made. Although downscaling can provide decision makers with the ability to visualize relevant, fine-resolution climate features, a tradeoff is that uncertainty and error are difficult to quantify. Thus, evaluating tradeoffs in error created by the downscaling process versus uncertainties in GCM outputs is important. Often, practical information can be derived from GCMs alone (e.g., magnitude of temperature increase), which may be sufficient to identify potential impacts and a range of possible management options.

3 Different GCMs simulate certain climate processes accurately and others erroneously. Thus, a variety of GCMs are run, and the mean of this ensemble is determined to be the “best estimate” projection.

1.4 KEY TAKEAWAYS

The main tools used to project the impacts of future emissions on climate — GCMs — provide information at scales that are too coarse for impact assessment and planning for most decision makers. Numerous techniques have been developed to provide climate change information at scales more relevant to decision makers based on the assumption that local climate is a combination of large-scale atmospheric characteristics and local-scale features. However, this information is still contaminated with uncertainties inherent in the prediction process, and users must account for these uncertainties in the application of the information.

2.0 DOWNSCALING APPROACHES

2.1 DYNAMICAL DOWNSCALING

2.1.1 General Theory

Dynamical downscaling refers to the use of an RCM driven by a GCM to simulate regional climate. An RCM is similar to a GCM but has higher resolution and additional regional information, which enables it to better represent local landscape and possibly local atmospheric processes. The global model simulates the response of the global circulation to changes in atmospheric composition through a large number of processes, but some of them need to be approximated due to the coarse resolution of the models. On the other hand, at the resolution of 25–50 km for portions of the globe, the RCM is able to capture some of those smaller-scale processes more realistically. Atmospheric fields (e.g., surface pressure, wind, temperature, and humidity) simulated by a GCM are fed into the vertical and horizontal boundaries of the RCM. Locally specific data and physics-based equations are then used to process this information and obtain regional climate outputs. The primary advantage of RCMs is their ability to model atmospheric processes and land cover changes explicitly.

2.1.2 Assumptions and Caveats

Although there has been great advancement during the past decade in the technical ability of RCMs to simulate regional climate, significant challenges and concerns still exist. Since smaller grid cells, more surface information, and often more processes are included in an RCM, the number of computations might be as large, if not larger, than in a GCM that covers the entire globe[4]. Thus, RCMs are computationally demanding and may require as much processing time as a GCM to compute projections (Wilby et al., 2009). They also require a substantial amount of input, e.g., surface properties and high-frequency GCM information. In addition, complex calibration procedures are often needed to make realistic simulations.

Just like GCMs, RCMs have difficulty accurately simulating convective precipitation, which is a major concern for tropical regions. Most RCMs also do not accurately simulate extreme precipitation — a systematic bias that can worsen as the resolution is increased. Statistical bias corrections often need to be performed to better match the model output to the observations (Brown et al., 2008). In some cases, fine adjustments to the convective schemes can improve the realism of simulated rainfall, but these adjustments require substantial expertise and reduce geographic portability — that is, they create

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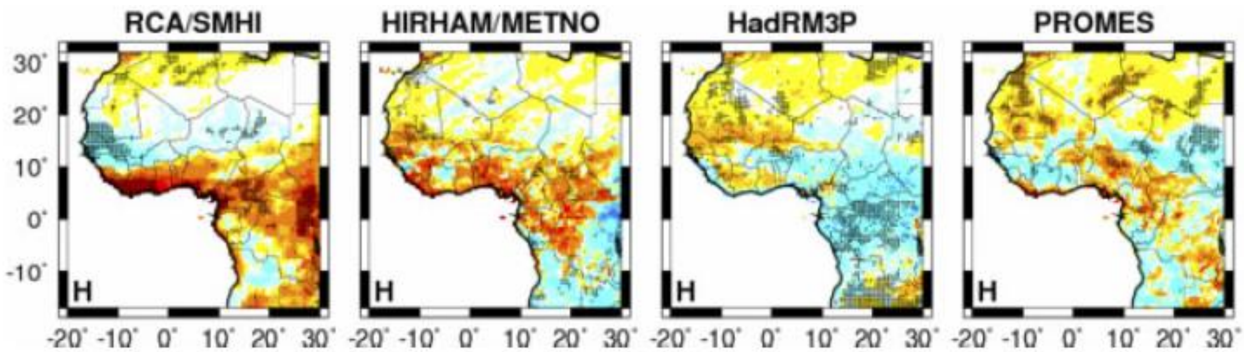
[4] Once all the input data — including GCM data — are ready, and depending on the complexity of the model and the computer used, it can take about 24 hours to simulate one year of atmospheric conditions. It usually takes several months to obtain a single simulation of 50 years of climate with a GCM or an RCM.

a version of the model that is well adjusted to a particular region but that may perform poorly elsewhere.

The quality of RCM results also depends on the driving GCM information. For example, if the GCM misplaces storm tracks, there will be errors in the RCM's precipitation climatology (Wilby et al., 2009). Additionally, different RCMs contain distinct dynamical schemes and physical parameters, which means that RCMs driven by the same GCM can produce different results (Figure 7).

FIGURE 7. PROJECTED CHANGES IN ANNUAL PRECIPITATION DURING THE 2001–2050 PERIOD



Maps depict four individual RCMs driven by one GCM and one emission scenario. Notice the differences in results. Source: Paeth et al., 2011

Finally, the grid-box size of an RCM is typically greater than 10 kilometers, which is still too coarse for hydrological and agricultural impact studies that require more local- or station-scale climate information (Benestad, 2009). To obtain higher resolution results, statistical methods are used in lieu of RCMs, or RCM output is further downscaled via statistical means.

In all circumstances, a validation of a model's performance over the historical period relative to simulated variables of interest, (e.g., temperature and/or rainfall) should be performed; RCM outputs should not be taken at face value.

2.1.3 Regional Climate Models and Application

RCMs are developed by research institutions that have sufficient computational capacity and technical expertise. Various RCMs differ in their numerical, physical, and technical aspects. The most commonly used RCMs in climate change downscaling studies include the U.S. Regional Climate Model Version 3 (RegCM3); Canadian Regional Climate Model (CRCM); UK Met Office Hadley Centre's Regional Climate Model Version 3 (HadRM3); German Regional Climate Model (REMO); Dutch Regional Atmospheric Climate Model (RACMO); and German HIRHAM, which combines the dynamics of the High Resolution Limited Area Model (HIRLAM) and European Centre-Hamburg (ECHAM) models.

Although the above models have been developed primarily over North America and Europe, they can be adapted to any region of the globe by incorporating appropriate information on terrain, land-cover, hydrology, and so on; hence, several RCM can be used over a given region. However, downscaled results can differ depending on which RCM(s) is used. It is important to recognize that a single RCM will most likely not provide 'accurate' results; therefore, researchers, practitioners, and decision makers should utilize the results with caution, keeping in mind dynamical downscaling assumptions and caveats.

Most intensive downscaling studies and projects utilize various RCMs to produce a multi-model ensemble and further validate results against observations.

A variety of climate change assessment projects have been established to provide high-resolution climate change scenarios for specific regions. They are usually multi-country, multi-institutional, large-scale projects. They are an important source of regional projections as well as of additional information about RCMs, methods, and even characteristics of current regional climate. Table 1 provides a quick summary about the projects, and more detailed information about each project can be found in Annex B.

TABLE 1. PROJECT NAME AND DATE, REGION OF INTEREST, PURPOSE, AND DOWNSCALING APPROACH USED FOR VARIOUS REGIONAL CLIMATE CHANGE ASSESSMENT PROJECTS

Project	Region	Purpose	Method
PRUDENCE (Prediction of Regional Scenarios and Uncertainties for Defining European Climate Change Risks and Effects) (2001–2004)	Europe	• Provide high-resolution climate change scenarios for 21st-century Europe.	Eight RCMs
ENSEMBLES (ENSEMBLE-Based Predictions of Climate Change and their Impacts) (2004–2009)	Europe	• Develop an ensemble prediction system to construct integrated scenarios of future climate change for quantitative risk assessment.	RCM ensemble
CLARIS (Climate Change Assessment and Impact Studies) (2008–present)	South America	• Predict climate changes and their socio-economic impacts.	Five RCMs
NARCCAP (North American Regional Climate Change Assessment Program) (2006–present)	North America	• Provide climate change scenario information for the United States, Canada, and Mexico. • Explore the separate and combined uncertainties in regional climate simulations that result from the use of different GCMs and RCMs.	Six RCMs

Project	Region	Purpose	Method
CORDEX (Coordinated Regional Climate Downscaling Experiment) (2009–present)	Africa	• Promote international downscaling coordination. • Facilitate easier analysis by scientists and end-user communities at the local level of regional climate changes.	Ten RCMs
AMMA (African Monsoon Multidisciplinary Analyses) (2009–present)	West Africa	• Improve understanding and ability to predict the West African Monsoon (WAM). • Relate variability of the WAM to various sectors. • Integrate multidisciplinary research with prediction and decision making.	Multi-RCM comparison
STARDEX (Statistical and Regional Dynamical Downscaling of Extremes for European Regions) (2002–2005)	Europe	• Identify robust downscaling methods to produce future scenarios of extremes for the end of the 21st century.	Dynamical and statistical

2.2 STATISTICAL DOWNSCALING

2.2.1 General Theory

Statistical downscaling involves the establishment of empirical relationships between historical large-scale atmospheric and local climate characteristics. Once a relationship has been determined and validated, future large-scale atmospheric conditions projected by GCMs are used to predict future local climate characteristics. In other words, large-scale GCM outputs are used as predictors[5] to obtain local variables or predictands. Statistical downscaling encompasses a heterogeneous group of methods that vary in sophistication and applicability (see Table 2 and Annex A).

Statistical downscaling methods are computationally inexpensive in comparison to RCMs that require complex modeling of physical processes. Thus, they are a viable and sometimes advantageous alternative for institutions that do not have the computational capacity and technical expertise required for dynamical downscaling. Unlike RCMs, which produce downscaled projections at a spatial scale of 20–50 kilometers, statistical methods can provide station-scale climate information.

[5] A variable that can be used to predict the value of another variable. In downscaling, the predictor is the large-scale climate variable.

2.2.2 Assumptions and Caveats

Although statistical downscaling is efficient, computationally inexpensive, and consists of a diverse group of methods, it contains the following inherent assumptions:

1. The statistical relationship between the predictor and predictand does not change over time.

2. The predictor carries the climate change signal.

3. There is a strong relationship between the predictor and predictand.

4. GCMs accurately simulate the predictor.

The first point is known as the stationarity assumption and postulates that the statistical relationship between the predictor and predictand remains stable into the future. Whether relationships based on present associations will be upheld under future climate conditions is unknown. The second is the assumption that the large-scale variable represents the climate system and captures any change that may occur in the future. Assumption three implies that the strength of the relationship should be initially evaluated to determine its validity. Assumption four relates to the ability of a GCM to simulate climate variables observed in the past as well as their future evolution. Predictor validations are usually performed prior to a given GCM's use in downscaling schemes.

2.2.3 Main Categories

Statistical downscaling consists of a heterogeneous group of methods that vary in sophistication and applicability. They are all relatively simple to implement but require a sufficient amount of high-quality observational data.

Methods can be classified into three main categories:

1. **Linear methods:** Establish linear relationships (i.e., some type of proportionality), between predictor(s) and predictand. Linear methods are very straightforward and widely used, and they can be applied to a single predictor-predictand pair or spatial fields of predictors-predictands. The greatest constraint is the requirement of a normal distribution of the predictor and the predictand values, which means that it cannot be used to predict the distribution of daily rainfall because it is typically non-normal (frequent small amounts of rainfall and a few heavy events generally make the distribution not symmetrical). These methods are primarily used for spatial downscaling.

2. **Weather classifications:** The local variable is predicted based on large-scale atmospheric "states." The states can be identifiable synoptic weather patterns or hidden, complex systems. The future atmospheric state, simulated by a GCM, is matched with its most similar historical atmospheric state. The selected historic atmospheric state then corresponds to a value or a class of values of the local variable, which are then replicated under the future atmospheric state. These methods are particularly well suited for downscaling non-normal distributions, such as daily rainfall. However, a large amount of observational daily data (e.g., 30 years of daily data for the region of interest) is required in order to evaluate all possible weather conditions. In addition, these methods are more computationally demanding in comparison to linear ones, due to the large amount of daily data analyzed and generated.

3. **Weather generators:** These statistical methods are typically used in temporal downscaling. For example, they are used to generate daily sequences of weather variables (e.g., precipitation, maximum and minimum temperature, humidity, etc.) that correspond to monthly or annual averages or amounts. Temporal downscaling is necessary for some impact models that require local spatial

data at a daily resolution, which GCMs cannot reliably provide. Weather generators produce sequences of daily values, but since different weather sequences may be associated with a given set of, for example, monthly values, multiple sequences commonly are generated to be further used in impact models. Weather generators are data-intensive, require long sequences of daily data, and are sensitive to missing or erroneous data in the calibration set (Wilby et al., 2009). In addition, only some weather generators have the ability to account for the coherency among variables when multiple variables are predicted, e.g., to generate a daily sequence of insolation that matches the generated daily sequence of rainy and dry days.

Table 2 identifies various statistical downscaling methods under the "linear," "weather classification," and "weather generator" categories, along with particular variable requirements, advantages, and disadvantages. Annex A describes each category and method in greater detail.

TABLE 2. STATISTICAL DOWNSCALING CATEGORY, METHOD, PREDICTOR AND PREDICTAND VARIABLES, ADVANTAGES, AND DISADVANTAGES

<table>
<tr><th colspan="2">Category & Method</th><th>Predictor & Predictand</th><th>Advantages</th><th>Disadvantages</th></tr>
<tr><td rowspan="3">Linear Methods
spatial</td><td>Delta method</td><td>Same type of variable (e.g., both monthly temperature, both monthly precipitation)</td><td rowspan="3">• Relatively straight-forward to apply
• Employs full range of available predictor variables</td><td rowspan="3">• Requires normality of data (e.g., monthly temperature, monthly precipitation, long-term average temperature)
• Cannot be applied to non-normal distributions (e.g., daily rainfall)
• Not suitable for extreme events</td></tr>
<tr><td>Simple and multiple linear regression</td><td rowspan="2">Variables can be of the same type or different (e.g., both monthly temperature or one monthly wind and the other monthly precipitation)</td></tr>
<tr><td>CCA& SVD</td></tr>
<tr><td rowspan="4">Weather Classification
Spatial and temporal</td><td>Analog method</td><td rowspan="4">Variables can be of the same type or different (e.g., both monthly temperature, one large-scale atmospheric pressure field and the other daily rainfall)</td><td rowspan="4">• Yields physically interpret-able linkages to surface climate
• Versatile, i.e., can be applied to both normally and non-</td><td rowspan="4">• Requires additional step of weather type classification
• Requires large amount of data and some computational resources
• Incapable of predicting new values that are outside the range of the historical data</td></tr>
<tr><td>Cluster analysis</td></tr>
<tr><td>ANN</td></tr>
<tr><td>SOM</td></tr>
</table>

			normally distributed data	
Weather Generator *Spatial and temporal*	*LARS-WG* *MarkSim GCM*	Same type of variable, different temporal scales (e.g., predictor is monthly precipitation and predictand is daily precipitation)	• Able to simulate length of wet and dry spells • Produces large number of series, which is valuable for uncertainty analysis • Production of novel scenarios	• Data-intensive • Sensitive to missing or erroneous data in the calibration set • Only some weathers generators can check for the coherency between multiple variables (e.g., high insolation should not be predicted on a rainy day) • Requires generation of multiple time-series and statistical post-processing of results
	NHMM	Variables can be of the same type or different (e.g., both monthly temperature, one large-scale atmospheric pressure and the other daily rainfall)		

Additional information about each method is included in Annex A.

2.3 SUMMARY OF DOWNSCALING APPROACHES

Table 3 attempts to summarize and compare different aspects of the dynamical and statistical downscaling approaches.

TABLE 3. ADVANTAGES, DISADVANTAGES, OUTPUTS, REQUIREMENTS, AND APPLICATIONS OF DYNAMICAL AND STATISTICAL DOWNSCALING

	Dynamical downscaling	Statistical downscaling
Provides	• 20–50 km grid cell information • Information at sites with no observational data • Daily time-series • Monthly time-series • Scenarios for extreme events	• Any scale, down to station-level information • Daily time-series (only some methods) • Monthly time-series • Scenarios for extreme events (only some methods) • Scenarios for any consistently observed variable

	Dynamical downscaling	Statistical downscaling
Requires	• High computational resources and expertise • High volume of data inputs • Reliable GCM simulations	• Medium/low computational resources • Medium/low volume of data inputs • Sufficient amount of good quality observational data • Reliable GCM simulations
Advantages	• Based on consistent, physical mechanism • Resolves atmospheric and surface processes occurring at sub-GCM grid scale • Not constrained by historical record so that novel scenarios can be simulated • Experiments involving an ensemble of RCMs are becoming available for uncertainty analysis	• Computationally inexpensive and efficient, which allows for many different emissions scenarios and GCM pairings • Methods range from simple to elaborate and are flexible enough to tailor for specific purposes • The same method can be applied across regions or the entire globe, which facilitates comparisons across different case studies • Relies on the observed climate as a basis for driving future projections • Can provide point-scale climatic variables for GCM-scale output • Tools are freely available and easy to implement and interpret; some methods can capture extreme events
Disadvantages	• Computationally intensive • Due to computational demands, RCMs are typically driven by only one or two GMC/emission scenario simulations • Limited number of RCMs available and no model results for many parts of the globe • May require further downscaling and bias correction of RCM outputs • Results depend on RCM assumptions; different RCMs will give different results • Affected by bias of driving GCM	• High quality observed data may be unavailable for many areas or variables • Assumes that relationships between large and local-scale processes will remain the same in the future (stationarity assumptions) • The simplest methods may only provide projections at a monthly resolution

	Dynamical downscaling	Statistical downscaling
Applications	• Country or regional level (e.g., European Union) assessments with significant government support and resources • Future planning by government agencies across multiple sectors • Impact studies that involve various geographic areas	• Weather generators in widespread use for crop-yield, water, and other natural resource modeling and management • Delta or change factor method can be applied for most adaptation activities

Sources: STARDEX, 2005; Fowler et al., 2007; Wilby et al., 2009; and Daniels et al., 2012

2.4 KEY TAKEAWAYS

- Choosing an appropriate downscaling method depends on the desired spatial and temporal resolution of the climate information, as well as resource and time constraints. A thorough investigation of these factors is required, and assistance from experts is recommended.
- In general, statistical methods are most appropriate if time and financial resources are a constraint.
- Large climate institutions and regional assessment projects primarily use RCMs to investigate climate over larger areas.

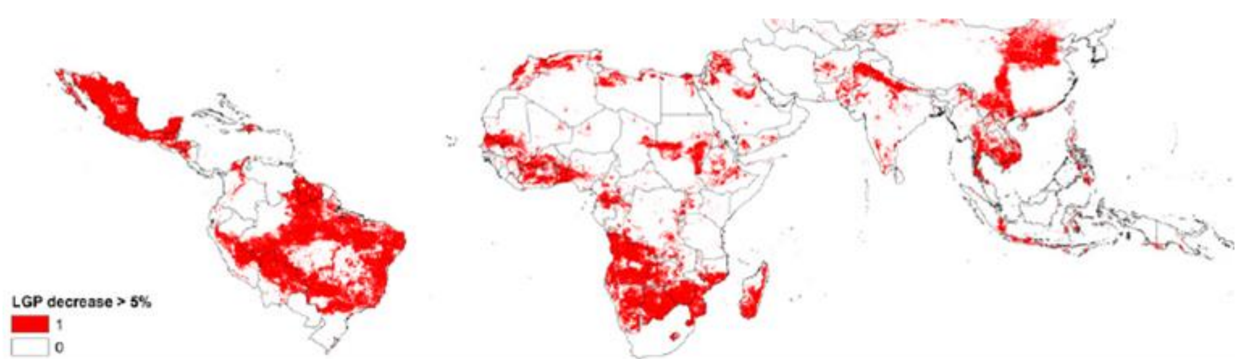
3.0 ANALYSIS OF DOWNSCALING PROCEDURES IN REPORTS

Various institutions commonly produce reports that identify regions of climate change and their impacts via high-resolution maps. Downscaling methods are used to create these maps, and it is important to understand the methodology to assess the validity of the results. Reports should clearly describe how the downscaling procedure was performed as well as caveats and limitations. Without this explanation, a knowledgeable downscaling reader must research how the maps were produced, and a reader with limited downscaling knowledge can be misled into thinking that the results are robust and that they can be taken at face value.

3.1 CCAFS REPORT NO. 5: MAPPING HOTSPOTS OF CLIMATE CHANGE AND FOOD INSECURITY IN THE GLOBAL TROPICS

This study was conducted by the Consultative Group on International Agricultural Research (CGIAR) Program on Climate Change, Agriculture and Food Security (CCAFS) to identify areas in the tropics that are food insecure and vulnerable to the impacts of future climate change. A range of indicators was used to map "hotspot" locations where climate change impacts are projected to become increasingly severe by 2050. The type of climate change hotspots was defined by thresholds. An example of such a threshold is shown in Figure 8, in which a detailed map displays areas that are projected to experience more than a 5-percent reduction in length of growing period (LGP). The LGP is defined by the average number of growing days per year that exceed a specific temperature and evapotranspiration value and begins when a certain number of these days have occurred in a row (Ericksen et al., 2011).

FIGURE 8. AREAS THAT WILL EXPERIENCE MORE THAN A 5-PERCENT REDUCTION IN LGP



Source: Ericksen et al., 2011

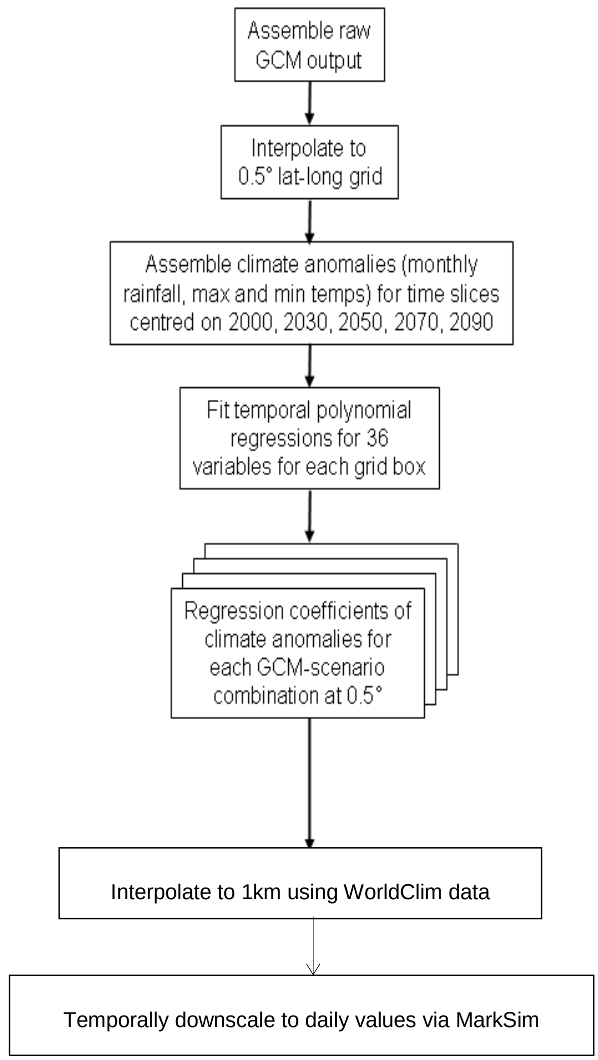
In order to produce a map that accurately shows this information, climate output from a variety of models, downscaled to a daily resolution, is required. In the report, it is stated that the hotspot indicators were derived from the mean outputs of four climate models, that there are many uncertainties associated with these indicators, and that different climate models give different results (Ericksen et al., 2011). This explanation is vague (e.g., downscaling is not explicitly mentioned), and further reading of another report (Jones et al., 2009), which is cited in CCAFS Report No. 5, was required.

Only in Jones et al. (2009) are the downscaling steps from raw GCM output to daily, high spatial resolution information described with enough detail. This procedure is summarized in Figure 9 and appears to be rather complex and use multiple methods.

It is not absolutely necessary for the reader to understand all downscaling details; however, she or he should get an idea of the various data and procedures that are used to create high-resolution climate information maps. Those multiple steps were not adequately described in the report.

On the positive side, uncertainties are provided in the appendix of the report and represented as probabilities. However, no further discussion of the impact of those uncertainties on the results is provided.

FIGURE 9. DOWNSCALING PROCEDURE

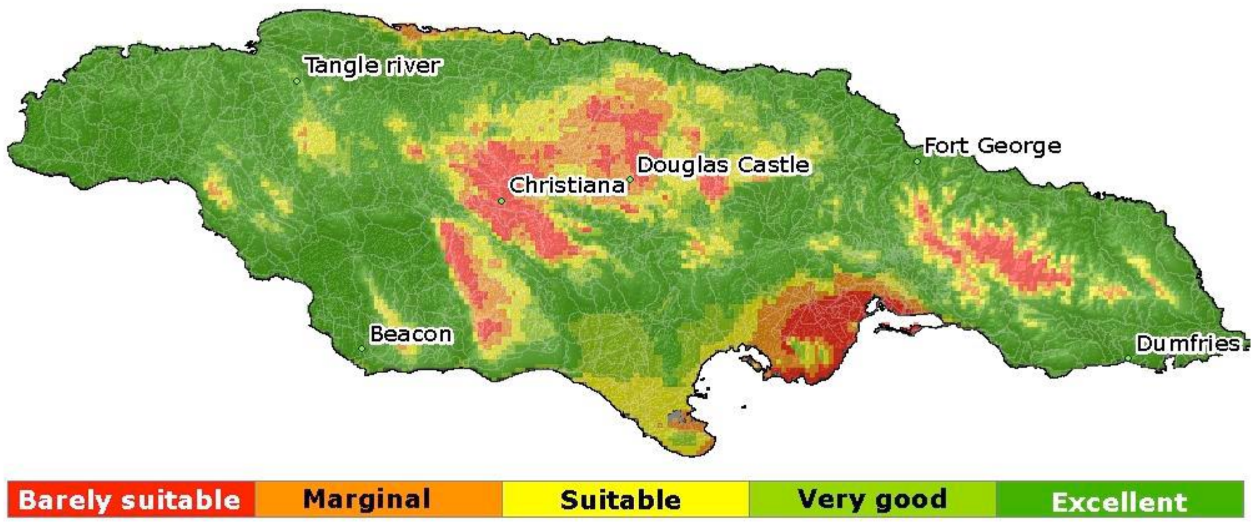


Source: Based on Jones et al., 2009

3.2 CASE STUDY: JAMAICA — IMPACT OF CLIMATE CHANGE ON JAMAICAN HOTEL INDUSTRY SUPPLY CHAINS AND ON FARMER'S LIVELIHOODS

The International Center for Tropical Agriculture (CIAT) and Oxfam produced this document to assess the impacts of climate change on farmer livelihoods and supply chains for 2030 and 2050. High resolution maps of crop suitability under future climate change conditions were produced. Figure 10 is an example of a suitability map for banana production.

FIGURE 10. PROJECTED BANANA SUITABILITY IN JAMAICA



Source: Eitzinger et al., 2011

In order to more fully describe how this map was created, unlike in the previous report, a methodology document is provided (Läderach et al., 2011).

The overall downscaling procedure described in Läderach et al. (2011) is summarized below:

1. Past monthly climatology from WorldClim at a 1 kilometer resolution was obtained.
2. Large-scale (150–300 kilometers) monthly outputs from 19 GCMs were obtained for the historical period and future time periods (2010–2039 and 2040–2069).
3. The delta method was used to derive downscaled climate projections for 2030 and 2050, i.e., the ratio between future and current GCM-simulated climate was computed, and this ratio was multiplied by the local-scale WorldClim data.
4. A crop suitability model was run using the downscaled climate projections in order to obtain an overall crop suitability rating.

This map is very detailed and provides high-resolution information of future crop conditions, which should be interpreted carefully and cautiously by the reader. An important component in this downscaling procedure, which is not described or displayed, would be to assess the range of climate projections from the various GCMs. GCMs do not produce the exact same results, and it is critical to show these differences to understand uncertainties.

In this study, WorldClim data is used because of its high resolution; however, it contains some limitations, which should be articulated in the report. WorldClim data are interpolated, which involves estimating unknown data value from known ones. This process can be inaccurate in regions where the landscape and elevation vary from one data point to the next. The use of actual station data would be preferable, but such data is sparse in the region analyzed in the document.

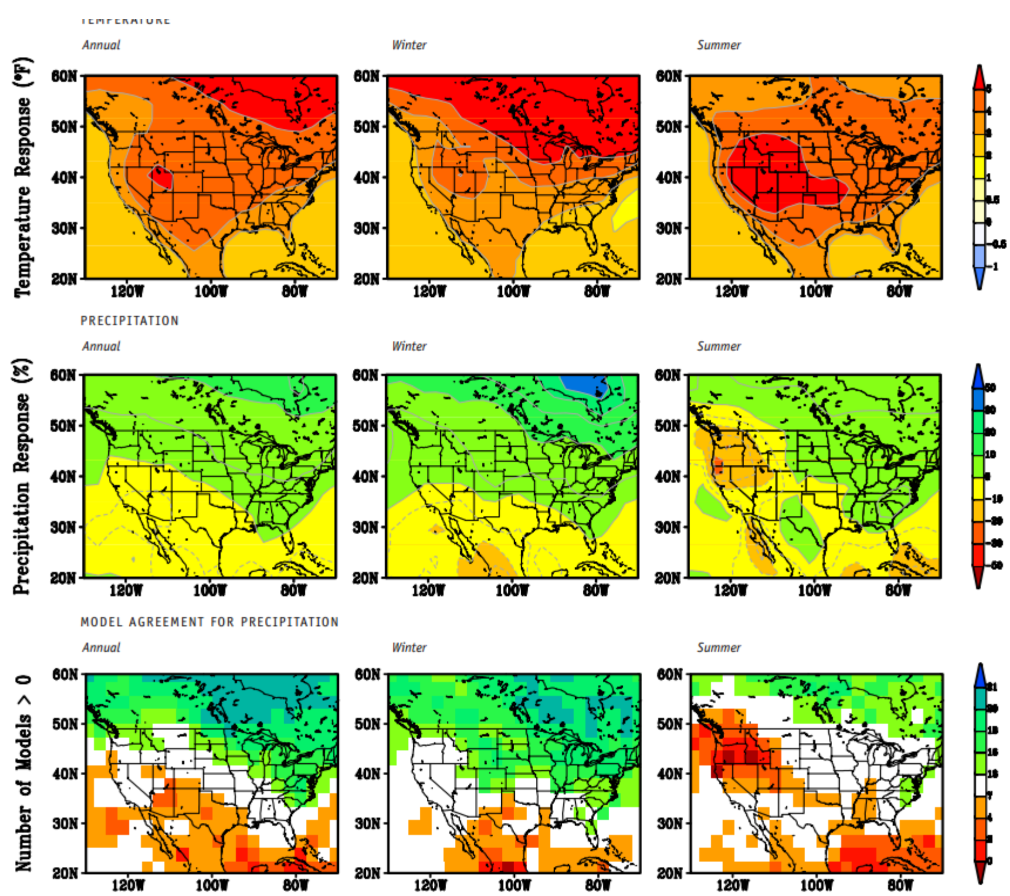
Finally, a validation of the results is not provided. Crop suitability modeled under current conditions should be compared to observed crop distribution to assess bias introduced by using the crop model.

3.3 WESTERN WATER ASSESSMENT: CLIMATE CHANGE IN COLORADO

The report, "Climate Change in Colorado," by the Western Water Assessment for the Colorado Water Conservation Board synthesizes climate change science that focuses on observed trends; modeling; and projections of temperature, precipitation, snowmelt, and runoff. This study summarizes specific findings from peer-reviewed regional studies and presents new graphics derived from existing datasets. It is a comprehensive and thorough document that describes the steps, data, and downscaling methods used to produce the images.

Climate projections for North America are clearly identified in the report and illustrated in Figure 11. The mean and range of temperature change and percent change in precipitation are provided. It is stated in the report that climate model projections are based on the Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset, which consists of 112 model runs from 16 GCMs using various emissions scenarios. Temperature and precipitation changes over North America are projected for 2050, and changes are shown relative to the 1950–1999 baseline average. The top row is the multi-model average temperature change for the annual mean (left), winter (center), and summer (right). The second row shows the percent change in total precipitation. Also, there is stronger agreement among the models for precipitation changes in the north compared to the south, as shown in the third row.

FIGURE 11. CLIMATE PROJECTIONS FOR NORTH AMERICA

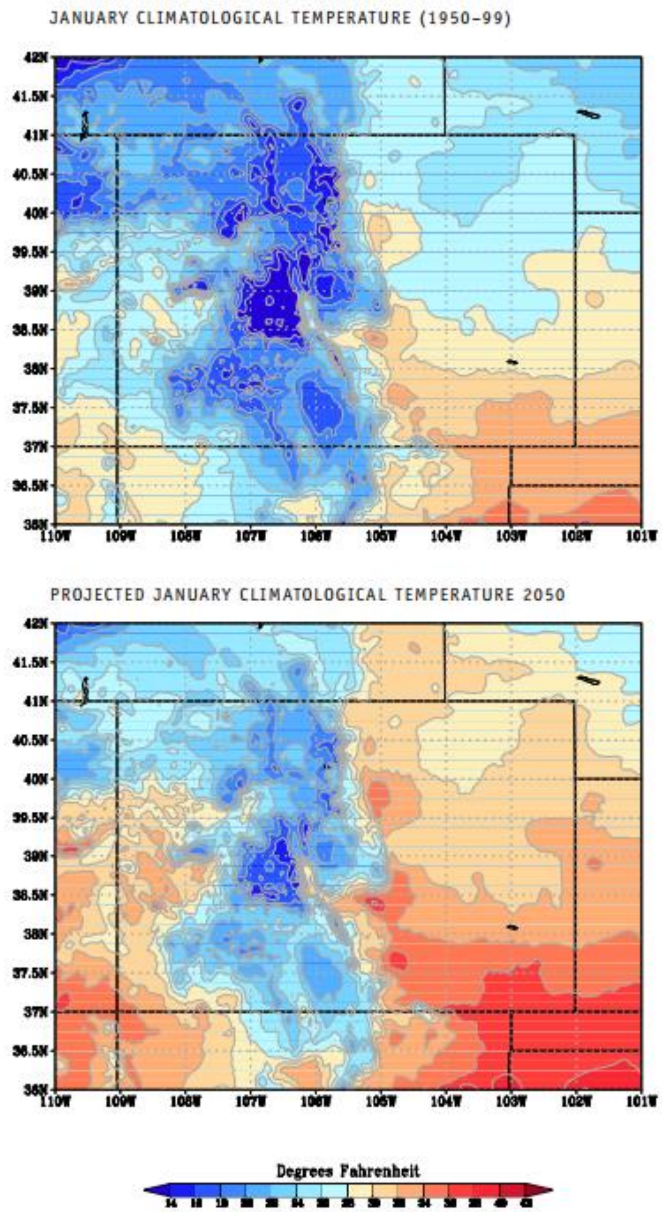


Top row: multi-model average temp. change for annual mean (left), winter (center), and summer (right). Second row: percent change in total precipitation. Third row: model agreement for precipitation. Source: Ray et al., 2008

The procedure for generating these maps is robust, because projections are made via many GCMs driven by various emissions scenarios. Additionally, the degree of agreement among models is demonstrated, which identifies regions where there is more confidence in projections. Since downscaling was not performed, conclusions about climate changes were not made for areas less than ~100–500 kilometers (the resolution of a GCM).

The maps on Figure 12 show much higher spatial resolution information, in which observed average daily temperature in January in Colorado for the 1950–1999 period and projections for 2050 are represented in the top and bottom images, respectively. Observed climatological averages are taken from PRISM, a sophisticated climate mapping system for the entire United States which incorporates point data, a digital elevation model, and expert knowledge of complex climate systems to produce estimates of climate factors, e.g., temperature, precipitation, etc. Monthly climatologies, i.e., average monthly values over 1981–2010, are available at an 800 m resolution. Values for each month for every year are available at a 4km resolution. It is important to make the distinction that PRISM is not a predictive tool. It is a mapping system that produces historical climate information. Projections were downscaled and calculated via the delta method, in which the GCM multi-model average temperature change was added to the observed climatology.

FIGURE 12. OBSERVED AVERAGE DAILY TEMPERATURE IN JANUARY IN COLORADO FOR 1950–1999 (TOP) AND PROJECTIONS FOR 2050 DOWNSCALED VIA THE DELTA METHOD (BOTTOM)



Source: Ray et al., 2008

This report also describes caveats and uncertainty inherent in these images. Although PRISM is a legitimate dataset and the delta method is a commonly used downscaling method the authors state that "temperature climatology does not capture year-to-year or day-to-day variations and neither do the climate projections." It is further specified that until higher-resolution dynamical downscaling is performed, and projected local land use and potential ecosystem changes are considered, it will be difficult to determine these local variations (Ray et al., 2008). To determine climate change impacts on runoff and snowpack, various studies were investigated, but original analysis was not performed. The Western Water Assessment did not use the downscaled projections (described above) to run a hydrologic model. Instead, it is concluded that runoff and snowpack are expected to decline by a certain percentage based on the results of previous studies. However, the procedure by which runoff and snowpack projections were obtained in previous studies is not well described. In each study, it is questionable whether a multi-model GCM ensemble was used to obtain large-scale projections, and few details are provided about the downscaling procedure. Additionally, minimal information about the validity of the hydrological model is provided.

3.4 KEY TAKEAWAYS

- It is important to critically analyze reports that produce high-resolution climate change impact maps. Numerous steps and assumptions are required to obtain such maps from large-scale climate projections.
- Reports should clearly describe the procedures used to derive high-resolution information on climate change and its impacts and should discuss the uncertainties and limitations of the results.
- Uncertainties associated with emission scenarios and GCMs should be addressed, and their impact on final results should be assessed.
- Validation of gridded/interpolated datasets and of impact models under current climate should also be provided and discussed.

4.0 CONCLUSION

The downscaling of global climate change projections has been developed to serve the needs of decision makers who require local climate information for impact assessments. GCMs provide information at scales on the order of 100–500 kilometers for studies that focus on large geographic regions and direction of change, e.g., increase or decrease in temperature. Downscaling to 10–50 kilometers is necessary for the assessment of region- and station-scale climate information. GCM output can be downscaled via dynamical and/statistical means that vary in sophistication and applicability.

Dynamical downscaling that involves the use of a regional climate model nested within a GCM is based on physically consistent atmospheric relationships that can result in the simulation of unprecedented values. However, this method is computationally complex and data intensive, produces 20–50 kilometers grid cell information, and may require further statistical downscaling to obtain a spatial resolution of less than20 kilometers.

In statistical downscaling, relationships are established to associate large- and regional-scale climate information. This method is computationally inexpensive and efficient, and station-scale climate information can be generated; however, a sufficient amount of observational data that may be unavailable for many areas is required to develop the equations. Additionally, its primary assumption, that the relationships between present large and local-scale processes will remain the same in the future, is not verifiable.

Various reports that provide high-resolution climate impact information have been produced for the decision-making community but should be interpreted carefully. Climate information at spatial scales of 10–50 kilometers is obtained using various downscaling methods that have limitations and assumptions that are often omitted in reports, and uncertainty inherent in projections is often not highlighted. These factors should be kept in mind when the interpreting the results.

4.1 RECOMMENDATIONS

It is difficult to recommend which downscaling method is best, since the goals and resources of each study are unique. Choosing the appropriate method depends on the user's needs and can vary according to the spatial and temporal resolution of the desired information and the climate variables that have the highest impact on the region and/or sector being considered. For example, a vulnerability assessment that investigates climate change impacts on agriculture in the tropics will focus on total rainfall and dry spells during the growing season, while a water and disaster risk assessment will focus on the variable of extreme rainfall.

Although is it difficult to suggest a particular method, it is possible to make the following recommendations:

- It is best to partner with a climate scientist or downscaling expert who can help to uncover the techniques applied in existing downscaling data and methods, assess them in terms of their limitations, and determine the most appropriate downscaling method — i.e., downscaling should not be undertaken by the user alone.

- In using/interpreting published results:
  - Be wary of high-resolution maps. To produce such maps, downscaling is required, and it is important to research the process to determine limitations and uncertainties.
  - Keep in mind that uncertainties arising from different sources are inherent to the projection process. Therefore, results should not be taken at face value, especially when no explicit uncertainty assessment is provided; alternatively, they should be construed as broad indicators of potential changes and impacts, dependable at larger scales even if presented at fine scales.
- In planning a sub-regional climate change and its impact assessments:
  - Consider whether the decisions/situations at hand really require downscaling. For certain resource assessments, monthly or annual scenarios derived directly from GCM outputs may be sufficient; in some cases, climate information will be used in conjunction with rather broad-scale indicators, and no value would be added by downscaling climate projections.
  - Investigate whether projections at appropriate scales already have been produced. Numerous regional climate change assessment projects provide downscaled data and/or tools that are freely available; however, their relevance for the problem at hand and their limitations still need to be assessed.
  - If an original downscaling is necessary, explicitly include and investigate appropriate methods to downscale and contextualize the climate change information for the area of interest given time and resource constraints.
    - In general, statistical methods are most appropriate if time and financial resources are limited. However, they require a sufficient amount of historical climate data.
    - RCMs are still primarily used by regional or international institutions focusing on climate and in regional assessment projects over larger areas. A validation of the outputs at scales of interest is a necessary first step; further statistical bias correction or downscaling might be required.
  - Include an assessment of uncertainty.
    - Use outputs from various GCMs to quantify the degree of uncertainty in the projections.
    - Ideally, multiple downscaling methods should be utilized to assess further impacts of assumptions on local climate.

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ANNEX A. STATISTICAL METHODS

This appendix provides detailed information about the various statistical downscaling methods presented in Section 2.0 under the three main categories: linear methods, weather classification, and weather generator.

LINEAR METHODS

Linear downscaling methods are applied when the relationship between the predictor and the variable being predicted, termed the predictand, can be approximated by linear equations.

Delta Method

One of the simplest ways to statistically downscale GCM projections is to use the delta or change factor method. The "change factor" is the ratio between GCM simulations of future and current climate and is used as a multiplicative factor to obtain future regional conditions. For example, to determine future regional temperature (T_f), the following steps are involved: (1) the ratio (∂) between future (T^F) and current (T^C) GCM-simulated temperature is computed, and (2) this ratio is multiplied by the currently observed regional-scale temperature (T_c)[6].

$$T_f=\partial\, T_c, \text{ where } \partial = T^F/T^C$$

The predictor is the currently observed temperature, and the GCM output is used to define the change factor by which to multiply the current observed temperature to obtain future values. More generally, the predictor and predictand need to be the same variable. Since the ratio between GCM simulations of future and current climate is used to obtain future regional climate, this method assumes that GCMs more reliably simulate relative change rather than absolute values (Hay et al., 2000). The main caveat is that the same ratio or relative change is applied to all regions lying within the same GCM grid point, which means that local differences in future climate due to local features will not be accounted for.

Simple and Multiple Linear Regression

A simple linear regression is a widely used method that establishes a linear relationship between one large-scale atmospheric predictor, e.g., GCM-simulated temperature, and one local predictand, e.g., local-scale temperature[7], represented in the equation below as *x* and *y*, respectively. This relationship is generated by analyzing observational local-scale data and correlating it with GCM simulations. Once a relationship is established, it can be applied to derive projected local conditions using GCM simulations of the future climate as input.

$$y = \alpha + \beta x$$

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6 Note: this method can also be used to downscale any climate variable and is not limited to temperature.

7 Predictor and predictand do not have to be the same variable. The predictor and predictand can be GCM-simulated surface pressure and observed rainfall, respectively.

When there are two or more predictor variables, e.g., large-scale rainfall and temperature, which influence the regional climate, a multiple regression equation can be built (see the equation below). To establish a multiple regression equation, a procedure known as forward selection is most commonly used in which the predictor variable that explains the most variance is first identified (x_1). The rest of the variables are then searched and the one that most reduces the remaining unexplained variance is selected (x_2). The procedure is repeated until no further improvement is obtained (Hay and Clark, 2003).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k$$

An assumption implicit in the linear regression methods is that the variables are normally distributed, i.e. symmetrically distributed around the mean of a bell-shaped curve and not skewed towards higher or lower values. Large-scale atmospheric circulation data is usually normally distributed but some variables, such as daily precipitation, deviate strongly from normality[8] (Zorita and von Storch, 1999). Thus, linear regression is not suitable for analysis of daily precipitation and other highly skewed distributions (Hay and Clark, 2003).

Spatiotemporal Methods: Canonical Correlation Analysis (CCA) and Singular Value Decomposition (SVD)

Multiple regression analysis, described above, is a method that allows for the prediction of a single predictand variable from a set of predictor variables. However, in some instances, understanding the relationships between sets of multiple predictand and multiple predictor variables and their time evolution may be more valuable (Hair et al., 1998). For example, the predictand variable may no longer be one variable, but rather a collection of data recorded at various locations (Benestad, 2008).

Canonical correlation analysis (CCA) and Singular value decomposition (SVD) are widely used spatiotemporal[9] methods that allow for the study of interrelationships among spatially distributed coarse simulations and observed local-scale variables by determining the sets of patterns that have the strongest relationships over time. Both methods determine pairs of spatial patterns that have the strongest association, but CCA maximizes temporal correlations, while SVD maximizes the covariance (Wilks, 1995).

Again, the main assumption underlying both methods is that the relationship between predictand and predictor is linear and that they are both normally distributed. Another caveat is that co-variance does not imply causality since co-variations between two fields or variables might be caused by a third variable. Therefore, CCA and SVD results should be interpreted carefully with an understanding of underlying physical relationships.

WEATHER CLASSIFICATION

Methods in this category can be applied to variables that have normal as well non-normal distributions. In weather classification schemes, the local variable is predicted based on a limited number of large-scale atmospheric "states". The states can be identifiable synoptic weather patterns or hidden, complex systems. The future atmospheric state, simulated by a GCM, is matched with its most similar observed

8 Describes a variable with a normal distribution.

9 A spatiotemporal method refers to an analysis that addresses factors across both space and time.

atmospheric state. To that historic atmospheric state there corresponds a value, or a class of values, of the local variable, which are then replicated under the future atmospheric state.

This class of methods is particularly well suited for downscaling non-normal distributions, such as daily rainfall or frequencies of occurrence; however, a large amount of observational daily data, e.g., 30 years of daily data for the region of interest, is required in order to evaluate all possible weather conditions. Also, daily data for both historical and future large-scale atmospheric states need to be analyzed, which is computationally demanding.

Analog Method

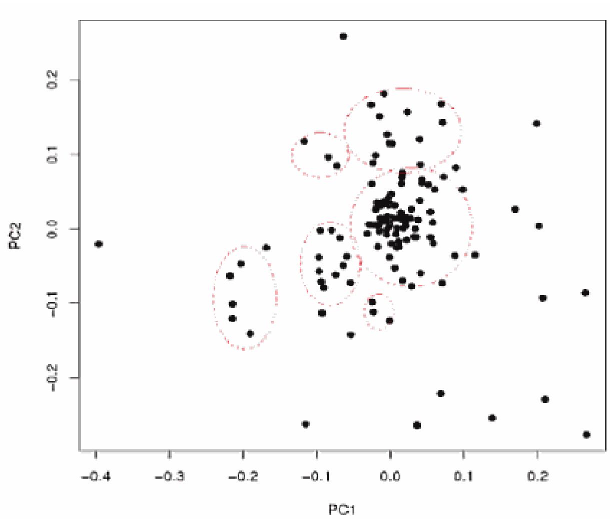
The analog method is a relatively simple statistical downscaling weather classification method. The large-scale atmospheric circulation simulated by a GCM is compared to historical observations and the most similar is chosen as its analog. The simultaneously observed local weather is then associated to the projected large-scale pattern.

In order to find an appropriate analog, a sufficiently long record of observations is required (Zorita and von Storch, 1999). Assessment of the performance of the analog method for predicting normally and non-normally distributed variables determined that the analog method is most appropriate for non-normal distributions, such as daily rainfall. However, this method is incapable of predicting new values that are outside the range of the historical record. Thus, new record-breaking precipitation values, which are likely to become more frequent in the future, cannot be forecasted (Benestad, 2008).

Cluster Analysis

Cluster analysis is a data reduction method that aggregates values within a dataset into a limited number of groups or classes (Schoof and Pryor, 2001). By searching for natural groupings or types, complex relationships can be identified and additional information about large to local-scale relationships can be understood (Gong and Richman, 1995) (Figure A.1).

FIGURE A.1. CLUSTER ANALYSIS



Data is organized into different classes according to their distance to the nearest cluster of points (marked as red circles).

Source: Benestad, 2008

There are different ways in which data can be grouped. The hierarchical method of clustering treats each observation initially like a cluster and aggregates them based on predefined criteria until all observations have been grouped (Schoof and Pryor, 2001); nonhierarchical clustering allows reassignment of observations to different clusters as analysis proceeds (Corti, 2012). K-means is another popular clustering algorithm (Robertson et al., 2004).

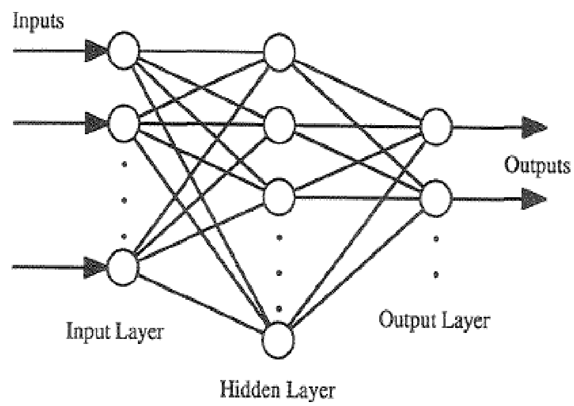
Cluster analysis can be applied to any kind of data: binary[10], discrete, and continuous[11] (Gong and Richman, 1995). Through cluster analysis, daily weather data can be grouped into synoptic types, weather regimes can be defined from upper air flow patterns, and members of ensemble forecasts can also be grouped (Corti, 2012).

As in the analogue method, to estimate future values of a local predictand, the output from a GCM is compared to the large-scale observations over the historical period. Once a large-scale simulation is aggregated to a cluster, a random observation from the batch of data associated with this cluster is chosen as the local-scale prediction (Benestad, 2008).

Artificial Neural Network (ANN)

An artificial neural network (ANN) can be described as an algorithm that transforms an input data into an output data using stepwise nonlinear functions (Benestad, 2008). An ANN can represent any arbitrary nonlinear function given sufficient training and can generalize a relationship from a small subset of data. The topology of the network involves a number of interconnected nodes (neurons) arranged into three layers: input, hidden, and output (Figure A.2). The input and output layers represent large-scale and local climate information, respectively. The ANN must first be calibrated based on historical data. Various weights and biases are applied to each neuron and adjusted during the training period in order to match the network and actual outputs (Dawson and Wilby, 1998). Once the network is appropriately trained, high-resolution local climate data can be derived from large-scale circulation information.

FIGURE A.2. A BASIC OVERVIEW OF ARTIFICIAL NEURAL NETWORK TOPOLOGY



Source: Dawson and Wilby, 1998

ANN derives a nonlinear relationship between atmospheric and local-scale climate variables and provides an alternative to many statistical models that are limited by assumptions of linearity, normality, etc. To derive the relationship, a long time-series of good quality data is required during the training period. ANN is primarily used to obtain daily precipitation at a local scale (Cavazos, 2000). A major drawback is its complexity; it is difficult to interpret physical relationships since the hidden layers result

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[10] Data whose unit can take on only two possible values.

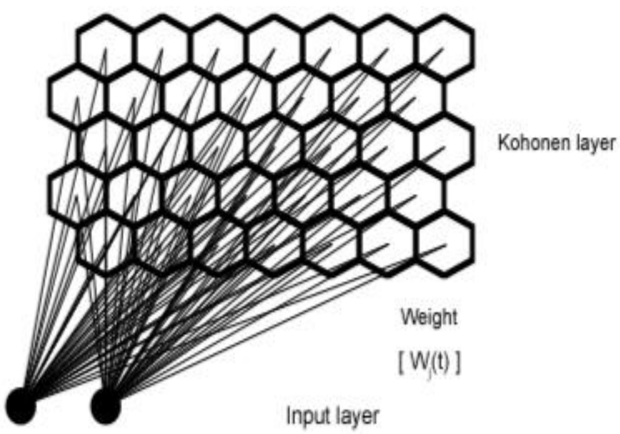
[11] Discrete data contains distinct values, whereas continuous data can assume any value within a range.

in a lack of transparency. The ANN method has thus been coined as a "black box" approach (Benestad, 2008).

Self-Organizing Map (SOM)

A self-organizing map (SOM) is a synoptic-pattern-based model that links observational station data to large-scale synoptic patterns. SOM contains one input layer that is fully connected to the output layer, shown in Figure A.3 (the Kohonen layer). During the training of the model, SOM analyzes the input (large-scale variable) and associates it with the output (local-scale variable), simultaneously. This is not the case in the analog and cluster analysis methods that analyze the large and local-scale variables separately. GCM-simulated large-scale future projections are used as the input to obtain future local-scale conditions (Yin 2011).

FIGURE A.3. STRUCTURE OF TWO DIMENSIONAL SELF-ORGANIZING MAP



Source: Yin, 2011

In comparison to other methods based on discrete data grouping, SOM presents several advantages: no assumptions are made about the data, i.e., distributions can be normal or non-normal; all data is represented in the model without prior reduction to a few states; and the relationship between nodes is easy to visualize, because the training procedure ensures that the least similar patterns will move to opposite corners of the map. SOM output provides probability and risk analysis information for impact studies. It is also commonly used to investigate the synoptic forcing of daily precipitation (Yin, 2011).

WEATHER GENERATORS

A weather generator is a statistical model used to generate sequences of daily variables, e.g. daily precipitation, maximum and minimum temperature, humidity, etc., from monthly GCM output. It is useful for impact models that require local spatial data at a daily time-scale. Weather generators produce multiple daily weather series, which is natural and logically consistent because any number of small-scale weather sequences may be associated with a given set of larger-scale values. In other words, for a particular monthly rainfall projected in the future, the weather generator will produce numerous possible daily rainfall sequences that have the same statistical characteristics of those that occurred in the past with the same monthly average.

Weather generators are data-intensive, require several years of daily data, and are sensitive to missing or erroneous data in the calibration set (Wilby et al., 2009). Also, when multiple variables are predicted, it is often crucial to account for the coherency between them. For example, insolation should be low on a rainy day.

Long Ashton Research Station Weather Generator (LARS-WG)

Long Ashton Research Station Weather Generator (LARS-WG) is a type of weather generator that simulates time series of daily weather at a single site (Semenov, 2012). It is based on a serial approach, which has the ability to adequately describe the length of wet and dry series (CICS, 2006). For LARS-WG in particular, the first step in the weather generation process is the analysis of observed station data in order to calculate its characteristics. Observations for precipitation, maximum and minimum temperature, and sunshine hours are used to create frequency distributions. Synthetic weather data[12] is then generated by combining these statistical characteristics with a scenario file that contains information about changes in precipitation amount, wet and dry series duration, mean temperature, temperature variability, and solar radiation. The software allows for the assessment of the quality of the simulations via a comparison between statistical characteristics of the observed data and that of LARS-WG simulations (CICS, 2006).

MarkSim GCM

MarkSim GCM is a weather generating software that provides daily information of future climatologies for any point on the globe based on existing GCM projections (CCFAS, 2011). This tool produces average annual distribution of daily rainfall, maximum and minimum temperature and solar radiation for the 21st-century (Jones and Thornton, 2013). It is embedded in Google Earth, and the user can choose greenhouse gas emission scenarios and GCM outputs (CCAFS, 2011).

MarkSim GCM generates downscaled projections by: 1) spatially downscaling GCM output using the delta method, 2) stochastically generating daily series based on a previously performed calibration procedure that involved clustering observations from more than 10,000 stations worldwide, and 3) selecting an analogue among the clusters that best matches values generated by the GCMs (CCAFS, 2011; Jones and Thornton, 2013).

However, there are major caveats associated with MarkSim GCM. Since MarkSim GCM simply matches future climate simulations with a current climate cluster that is the most similar, future weather that is different from present day weather cannot be generated. The weather associated with the current climate cluster is associated with the future scenario, which may not be the case. Additionally, high rainfall variances[13] are not well simulated (Jones and Thornton, 2013).

Nonhomogeneous Hidden Markov Model (NHMM)

A Nonhomogeneous hidden Markov model (NHMM) generates daily weather sequences assuming the existence of two processes: an *observed process* and a *hidden process.* The *hidden process* is the atmospheric circulation, which can be classified into a small number of unobserved discrete patterns called "weather states". The succession of weather states is assumed to be stochastic and Markovian. A stochastic process involves some indeterminacy, i.e., there are several directions in which the process can evolve, each with a distinct probability. The probabilities of transitions between hidden states depend on characteristics of the atmosphere (Hughes et al., 1996). The *observed process* is the rain occurrence at a fixed location, which is conditioned by the hidden process (Figure A.4).

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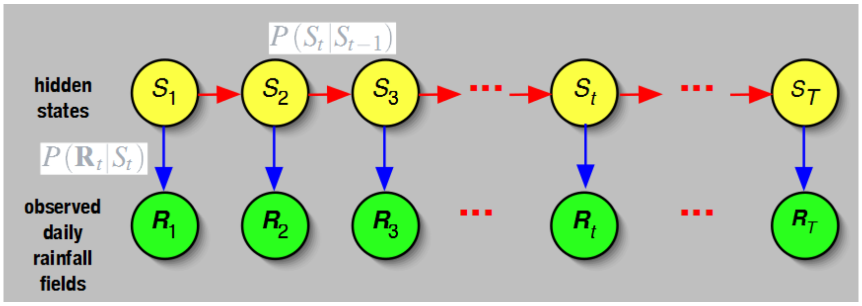
[12] Weather data produced by LARS-WG, which is different than the observed weather data.

[13] For example, the impact of El Niño-Southern Oscillation (ENSO) can lead to high rainfall variance.

FIGURE A.4. GENERAL STRUCTURE AND EVOLUTION OF HMM



Source: Robertson and Verbist

To downscale future climate projections, changes in the probabilities of hidden states under future conditions are estimated and time-series of localized rainfall occurrence are generated. As in other weather generators, multiple time-series are generated. NHMM is a very useful tool for generating realistic simulations of precipitation and understanding the relationships between atmospheric circulation patterns and rainfall. It is commonly used method by hydrologists who need localized daily rainfall information for modeling purposes (Hughes et al., 1996).

But the method relies on hidden states often difficult to interpret. In addition, the correct or optimal order and number of states must be carefully determined. Also, simulation of rainfall occurrence at locations not been explicitly included in the model has not been developed (Hughes et al., 1996).

MIXED METHODS AND TOOLS

Frequently, multiple methods are used sequentially. For example, if the goal is to obtain localized daily precipitation, spatial downscaling may first be applied followed by a weather generator. Methods described below involve both spatial and temporal downscaling.

Bias-Corrected Spatial Disaggregation (BCSD)

Bias-corrected spatial disaggregation (BCSD) is a statistical method that originated from the requirement to downscale ensemble climate model forecasts[14] at spatial and temporal scales appropriate for hydrological modeling. This method involves two steps: bias correction and weather generation. In the bias correction step, GCM monthly averaged climate variables for a baseline time period, e.g., 1950–1999, are compared to a time series of gridded observed data at the same spatial scale and time period. GCM simulations for a future time period are then adjusted based on this comparison. Finally, the weather generation step produces daily weather stochastically and provides possible daily weather sequences for a future time period. Note that in this method, the predictor and predictand variables are the same, e.g., both temperature, but have different spatial or temporal timescales.

The daily patterns of rainfall associated with future monthly projections are an artifact of the historical information from the baseline period. They are not novel and do not reflect changes to statistical

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[14] An ensemble forecast is the average of many forecasts produced by the same model with slightly different initial conditions. By averaging many possible outcomes, the ensemble reduces forecast uncertainty.

properties of future climate, e.g. changes in the frequency of rainfall events that may happen in the future are not represented (Werner, 2011).

The World Bank, The Nature Conservancy, Climate Central, and Santa Clara University have collaboratively used BCSD to produce a standardized set of downscaled climate projections for the entire globe, which are available via the Climate Change Knowledge Portal. BCSD is computationally efficient and it can be suitably used to perform spatial downscaling and bias correction for a large amount of GCM outputs (Ahmed et al., 2013).

Statistical DownScaling Model (SDSM)

The Statistical DownScaling Model (SDSM) is freely available software in which multiple linear regression methods are used to spatially downscale daily predictor-predictand relationships (CICS, 2006). SDSM provides climate information at specific locations for which there is daily data adequate to calibrate the model, as well as archived GCM output (Wilby and Dawson, 2013). Key inputs include quality observed daily data for both local-scale and large-scale climate variables as well as daily GCM outputs for large-scale variables for future climate (UNFCCC, 2013). Outputs can be applied over a range of climate impact sectors and include site-specific daily scenarios for maximum and minimum temperatures, precipitation, and humidity. A range of statistical parameters such as variance, frequencies of extremes, and spell lengths are also produced (UNFCCC, 2013).

ANNEX B. REGIONAL CLIMATE CHANGE ASSESSMENT PROJECTS

This appendix describes some of the most important regional climate change assessment projects that properly perform downscaling. Most of them have undergone intensive research (e.g., used multiple models), to ensure the validity of their results.

PREDICTION OF REGIONAL SCENARIOS AND UNCERTAINTIES FOR DEFINING EUROPEAN CLIMATE CHANGE RISKS AND EFFECTS (PRUDENCE)

The primary goal of Prediction of Regional Scenarios and Uncertainties for Defining European Climate Change Risks and Effects (PRUDENCE), a three-year European Union project that ended in 2004, was to provide high-resolution climate change scenarios for 21st-century Europe via dynamical downscaling. It was the first comprehensive and continental-scale project that evaluated and inter-compared high-resolution climate models and their applications (Christensen et al., 2007).

Several European research groups contributed to the project and the model output is freely available to the general research community. Four GCMs and eight RCMs were used for simulations. Most RCMs were run at a ~50 kilometers spatial scale and some were run at ~20 kilometers and ~10 kilometers (Christensen et al., 2007). For both the A2 and B2 scenarios, summer warming and drying over most of the European region was found. Maximum dry spell length, maximum precipitation intensity, and an interannual increase in variability during the summer were also projected. These simulations are consistent with trends of summer climate observed over Europe in recent decades (Christensen, 2005).

Results from PRUDENCE indicate that application of RCM-based scenarios for impact studies is significantly advantageous in comparison to use GCM-based scenarios. However, sole reliance on RCMs is not appropriate either (Christensen et al., 2007). Multi-model ensembles can be used to address projection uncertainties (Christensen, 2005).

For more information, refer to: http://prudence.dmi.dk/main.html

ENSEMBLE-BASED PREDICTIONS OF CLIMATE CHANGES AND THEIR IMPACTS (ENSEMBLES)

ENSEMBLE-Based Predictions of Climate Change and their Impacts (ENSEMBLES) was a five-year (2004–2009) research project led by the UK Met Office and funded by the European Commission. It involved various partners across Europe. It was established based on the need to make reliable estimates of climate risk, and an ensemble of regional models was deemed the most appropriate method to accomplish this goal. The project was the first effort to develop an ensemble prediction system to construct integrated scenarios of future climate change in Europe for quantitative risk assessment (Hewitt and Griggs, 2004). More specifically, the project succeeded in doing the following:

- Produced probabilistic climate projections of temperature and rainfall for the 21st-century via an ensemble prediction system

- Assessed the impacts of climate change on agriculture, health, energy, water resources, and insurance
- Increased the certainty in predictions by contributing to the understanding of physical, chemical, biological, and human-related feedbacks in the climate system
- Developed high-resolution climate observation datasets for Europe for the purpose of validation of ensemble predictions

A primary goal of the project was to maximize the usage of the results by linking the outputs of the ensemble prediction system to a range of applications which use high resolution climate inputs to feed their models, including agriculture, health, food security, energy, water resources, insurance, and weather risk management, (Hewitt and Griggs, 2004). The ENSEMBLES Downscaling Portal allows users to downscale their own data using existing downscaling techniques and simulation datasets. This alleviates the historical difficulty for end-users to access stored simulations and post-process them according to their needs. Users can choose predictors, predictands, and transfer functions to be used in the downscaling process. They can then perform a quality assessment to verify results and ultimately download downscaled data (Cofiño et al., 2009).

For more information, refer to: http://www.ensembles-eu.org/

A EUROPE-SOUTH AMERICA NETWORK FOR CLIMATE CHANGE ASSESSMENT AND IMPACT STUDIES (CLARIS)

The Europe-South America Network for Climate Change Assessment and Impact Studies (CLARIS) project was a three-year interdisciplinary project established in 2008 to build an integrated European-South American network dedicated to promote common research strategies to observe and predict climate changes and their socio-economic impacts in South America. In order to assess impacts and provide information to policy-makers, obtaining reliable simulations at the regional-scale is a central issue (Menéndez et al., 2010). To accomplish this goal, climate data sets, simulations, and the appropriate framework to compare and exchange methodologies between European and South American scientists were gathered. In addition, a bridge between the climate research community and stakeholders in South America was created to demonstrate the potential of using climate information in agriculture, health, and air-pollution decision-making processes (Boulanger et al., 2010).

Dynamical downscaling was performed with five RCMs (MM5, PROMES, RCA3, REMO, and WRF) and one stretched-grid global model (LMDZ) to simulate extreme precipitation and temperature of the past to determine which models perform best for South America. The results showed that the performance of each model depended on the simulated climate, region, and variable of interest. Despite some consensus that a multi-model ensemble gives in general the best climate depiction, the multi-model composite was not distinctively better than a single good model in this case. Further investigation as to why this occurred is required (Menéndez et al., 2010).

Other climate simulations carried out during the CLARIS project are still being analyzed as well as more recent ones under the new CLARIS-LPB (La Plata Basin) project (Menéndez et al., 2010). This project is a more regionally focused study that aims to predict climate change impacts on La Plata Basin for the design of adaptation strategies in land-use, agriculture, rural development, hydropower production, river transportation, water resources, and ecological systems in wetlands.

For more information, refer to: http://eolo.cima.fcen.uba.ar/objectives.html and http://www.claris-eu.org/.

THE NORTH AMERICAN REGIONAL CLIMATE CHANGE ASSESSMENT PROGRAM (NARCCAP)

The North American Regional Climate Change Assessment Program (NARCCAP) is an international program that provides climate scenario information for the United States, Canada, and northern Mexico. Its development was spurred by the lack of research on the uncertainty in future climate projections from RCMs. More specifically, NARCCAP's scientific motivation is to explore the separate and combined uncertainties in regional climate simulations that result from the use of different GCMs that drive various RCMs. It also serves as a provider of regional climate change projections to the climate impacts and adaptation community. NARCCAP uses a variety of GCMs and RCMs so that climate impacts researchers can characterize multiple uncertainties in their assessments (Mearns et al., 2012).

As a preliminary step to evaluate the performance of RCMs over the region, NCEP Reanalysis II data for the period 1979–2004 is used as the driver. NCEP Reanalysis II data is up-to-date gridded data that represents the large-scale state of the present and past atmosphere. To obtain projections for the current period (1971–2000) and 21st century, RCMs of a 50 kilometers spatial scale are nested within GCMs. For the 21st century projections, SRES A2 emissions scenario is used (UCAR, 2007).

The RCMs that are being used include two from the European PRUDENCE program (HadRM3 and RegCM), the Canadian Regional Climate Model (CRCM), the NCEP regional spectral model (RSM), MM5, and the Weather Research and Forecasting model (WRF). The GCMs include the Hadley Centre HadCM3, National Center for Atmospheric Research (NCAR) CCSM, the Canadian CGCM3, and the GFDL model (UCAR, 2007; Mearns et al., 2012).

Overall, the results are within the range of what has been found in other multi-model studies. It is difficult to determine which models perform best given the inherent spatial and temporal variability of the climate. Performance of the models varies substantially from one sub region to another, but they all simulate temperature more accurately than precipitation. When the ensemble average of all six RCMs is used to obtain metrics for mean temperature and precipitation, most metrics are well represented – but some are better simulated by a single regional model (Mearns et al., 2012).

For more information, refer to: http://www.narccap.ucar.edu/

COORDINATED REGIONAL CLIMATE DOWNSCALING EXPERIMENT (CORDEX)

Several international projects mentioned above have made significant contributions to downscaling efforts over a specific region. However, there has been limited international coordination and transfer of knowledge between these projects. The Coordinated Regional Climate Downscaling Experiment (CORDEX) was developed to bridge this gap and facilitate easier analysis by scientists and end-user communities at the local level. Twelve highly populated regions worldwide areas plus the Arctic and Antarctic have been defined, with Africa as a primary initial focus (Nikulin et al., 2012).

Motivated by the critical concern over the water and food supply in Africa, the quality of RCM-simulated precipitation was investigated. Most RCMs capture the main climatological features of precipitation but with different levels of accuracy. The performance of 10 individual RCMs (ARPEGE, HIRHAM, RegCM3, CCLM, RACMO, REMO, RCA, PRECIS, WRF, and CRCM) and their ensemble average were evaluated and simulations were provided at ~50 kilometers resolution for the entire African continent. Seasonal means, West African monsoon rainfall, and annual and diurnal cycle simulations were obtained. In general, the multi-model average out-performs many of the individual models, most likely due to the cancelation of opposite-signed biases across the models. However, this ensemble average should not always be viewed as the most accurate simulation. Instead, Nikulin et al. (2012) conclude that an ensemble average with increased RCMs and individual GCM-RCM members should be further investigated.

For more information, refer to: http://wcrp-cordex.ipsl.jussieu.fr/

AFRICAN MONSOON MULTIDISCIPLINARY ANALYSES (AMMA)

The African Monsoon Multidisciplinary Analyses (AMMA) was built by an international scientific group to improve knowledge and understanding of the West African Monsoon (WAM) and its variability. The impetus for the establishment of this project is based on the need to predict the WAM and its impacts on West African nations. Dry conditions in recent decades and their devastating impacts on populations and economies have drawn a large amount of financial support from multiple agencies around the globe.

The main goals of AMMA follow:

- Improve the understanding of the WAM's regional and global influence on the physical, chemical, and biological environment.
- Scientifically relate the variability of the WAM to health, water resources, food security, and demography issues in West Africa.
- Implement relevant monitoring and prediction strategies.
- Ensure that the multidisciplinary research conducted by the AMMA project is effectively integrated with prediction and decision-making activity.

It is more difficult to forecast weather of short to medium range timescales in West Africa than in the extra-tropical regions of Europe or North America. This is due to the lack of routine weather monitoring and difficulty in simulating key elements of the WAM. For seasonal to interannual timescales, it is recognized that dynamical models may not be appropriate since they poorly represent the annual cycle and disagree on the sign and amplitude of rainfall changes. Statistical methods are therefore recognized as the most appropriate tool for the region.

For more information, refer to: http://www.amma-international.org/spip.php?rubrique1

STATISTICAL AND REGIONAL DYNAMICAL DOWNSCALING OF EXTREMES FOR EUROPEAN REGIONS (STARDEX)

The goal of Statistical and Regional Dynamical Downscaling of Extremes for European Regions (STARDEX), which began in 2002 and ended in 2005, was to identify robust downscaling techniques to produce future scenarios of extremes for regions in Europe for the end of the 21st century. Statistical, dynamical, and statistical-dynamical downscaling methods were evaluated and inter-compared. An expected outcome of the project was to pinpoint and discover improved methodologies for the development of scenarios of extremes, with recommendations as to which perform best for different regions across Europe and for different variables (Salmon, 2002).

The specific measurable objectives follow:

1. Develop datasets of observed and simulated climate as well as a diagnostic software tool for calculating standard set of extreme event statistics.
2. Analyze recent trends, causes, and impacts of extreme events over a wide variety of European regions.

3. Validate the European GCMs (HadCM3 and ECHAM4/OPYC3), particularly for extremes.
4. Inter-compare various statistical, dynamical, and statistical-dynamical downscaling methods using data from the second half on the 20th century and determine which methods are most robust.
5. Use the most appropriate statistical, dynamical, and/or statistical-dynamical downscaling methods to develop scenarios of extreme events for the late 21st century.

Overall, the project concluded that there are uncertainties in regional scenarios of extremes due to the downscaling procedure, and that a multi-model approach, whether statistical or dynamical, is best. It was determined that in the majority of cases, no consistently superior statistical downscaling model can be identified, especially for the station-scale. It is thus recommended that a range of the most robust statistical downscaling methods be used, which is similar to the common and best practice of using a range of global and regional climate models. STARDEX additionally provided application criteria for dynamical and statistical downscaling general approaches for user needs (STARDEX, 2005).

For more information, refer to: http://www.cru.uea.ac.uk/projects/stardex/

ANNEX C. DOWNSCALING TOOLS AND SOFTWARE

Interactive user-friendly tools are necessary to ease the downscaling process for end users and maximize the application of available projections. Various portals utilizing statistical and dynamical methods exist that directly downscale GCM output to the regional or local scale. Those portals are usually well documented and describe the main methods and datasets. Users can often test and validate different statistical and/or dynamical downscaling methods to ensure simulation accuracy.

These products are accessible to the general public, so there is potential for misuse by users who are unfamiliar with the tools and software. To use them appropriately and obtain accurate downscaling results, the user must understand the kind of data and downscaling techniques inherent in the software.

TABLE C.1. TOOLS, DESCRIPTIONS, AND LINKS TO USER-FRIENDLY DOWNSCALING SOFTWARE

Tool/Source	Description
LARS-WG	Tool for producing time-series of a suite of climate variables at single sites (http://www.rothamsted.ac.uk/mas-models/larswg.html)
SDSM	Software package that produces site-specific daily scenarios of climate variables and statistical parameters (http://co-public.lboro.ac.uk/cocwd/SDSM/)
Clim. pact	R functions for downscaling monthly and daily mean climate scenarios (http://cran.uvigo.es/web/packages/clim.pact/index.html)
ENSEMBLES	Experimental portal for downscaling tools applied to Europe (https://www.meteo.unican.es/downscaling/ensembles)
FINESSI	Multi-sector/multi-variable climate change scenarios for Finland (http://www.finessi.info/finessi/?page=explore)
MAGIC/SCENGEN	Interactive software for investigations of global/regional climate change (http://www.cgd.ucar.edu/cas/wigley/magicc/)
PRECIS	UK Met Office RCM (http://www.metoffice.gov.uk/precis/)
SERVIR	The Climate Mapper and SERVIR Viz (http://www.servir.net/en/The_Climate_Mapper_and_SERVIR_Viz)
World Bank	Climate Change Knowledge Portal (http://climateknowledgeportal.climatewizard.org/)
ASD	Automated statistical downscaling tool (http://loki.qc.ec.gc.ca/DAI/downscaling_tools-e.html)

CIAT	Various models that use statistical and dynamical methods (http://www.ccafs-climate.org/)
MarkSim GCM	Stochastic weather generator (http://gismap.ciat.cgiar.org/MarkSimGCM/)

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