Climate downscaling, Reanalysis and Gridded Climate data

A. Downscaling:

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:

1. **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. 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.

2. **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:
   a. 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.
   b. 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.
   c. 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.

B. 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 inter annual 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 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 amulti-model ensemble mean (or median) is thought to be the most probable future climate

trajectory. 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.

Uncertainty is compounded with downscaling due to assumptions that are inherent in models. With
each modelling 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.

C. Reanalysis and gridded climate data

Reanalysis of past weather data presents a clear picture of past weather, independent of the many varieties of instruments used to take measurements over the years. Through a variety of methods, observations from various instruments are added together onto a regularly spaced grid of data. Placing all instrument observations onto a regularly spaced grid makes comparing the actual observations with other gridded datasets easier. In addition to putting observations onto a grid, reanalysis also holds the gridding model constant—it doesn't change the programming—keeping the historical record uninfluenced by artificial factors. Reanalysis helps ensure a level playing field for all instruments throughout the historical record.

Purpose:

The purpose of reanalysis is as:

- Initialization of operational weather forecasts
- Climate analysis over historical periods
- Provision of initialization and boundary data for atmospheric limited area models (LAMs, e.g., regional climate models)

- Validation of global and regional climate model experiments
- Provision of atmospheric boundary conditions for, e.g, hydrological models

Strengths:

- Global data sets, consistent spatial and temporal resolution over 3 or more decdes, hundreds of variables available; model resolution and buases steadily improved.
- Reanalysis incorporate millions of observations into a stable data assimilation system that would be nearly impossible for an individual to collect and analayze seperately, enabling a number of climate processes to be studied.
- Reanalysis data sets are relatively striaghtforward to handle from standpoint.

Limitations:

- Reanalysis data sets should not be equated with“observations“ or “reality“.
- The changing mix of observations, and biases in observations and models, can introduce spurious variabality and trentd into reanalysis output.
- Observational constraints, and therefore reanalysis reliabality, can considerably vary depending on the location, timeperiod, and variable considered.

D. Gridded Datasets

Gridded datasets enable a systematic analysis of spatio-temporal climate (change) patterns. These datasets allow detection and attribution of human influences on climate, re-analyses important for NWP and climate model initialization and provision of boundary conditions Gridded data sets are important reference for climate model validation.

Limitations:

- Spatio-temporal consistency of gridded data not always given
- E.g., effective resolution < nominal resolution (-> smoothing of spatial variability, smoothing of extremes). E.g., temporal changes in observational network (-> artifical trends)
- Connected to this: long-term gridded time series affected by poor data availability in historic times (e.g., before 1900)
- Systematic biases of surface measurements might not be accounted for
- Uncertainties due to gridding method