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# Climate Scenario Development and Applications for Local⁄Regional Climate Change Impact Assessments: An Overview for the Non-Climate Scientist

## Part II: Considerations When Using Climate Change Scenarios

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Abstract
Although downscaling methods for deriving local⁄regional climate change scenarios have been extensively studied, little guidance exists on how to use the downscaled scenarios in applications such as impact assessments. In this second part of a two-part communication, we review for non-climate scientists a number of practical considerations when utilizing climate change scenarios. The issues discussed are drawn from questions frequently asked by our colleagues on assessment teams and include sources of observational data for scenario evaluation, the advantages of scenario ensembles, adjusting for scenario biases, and the availability of archived downscaled scenarios. Together with Part I, which reviews various downscaling methods, Part II is intended to improve the communication between suppliers and users of local⁄regional climate change scenarios, with the overall goal of improving the utility of climate impact assessments through a better understanding by all assessment team members of the strengths and limitations of local⁄regional climate change scenarios.

### *Introduction*

Climate change impact assessments are typically conducted at the local and regional scales, and thus require climate change scenarios with a fine spatial resolution. These scenarios are usually developed by applying 'downscaling' methods to coarser-scale output from global climate models (GCMs). The scenarios are then employed by an assessment team for analyses and modeling efforts unique to the specific assessment and by stakeholders to inform decision making.

A voluminous literature exists on the development and evaluation of different downscaling methods, sometimes referred to as downscaling 'comparison' studies (Fowler and Wilby 2007, 1543). In general, this literature was written by climate scientists for other climate scientists. In contrast, little published guidance exists on how to use downscaled local⁄regional climate change scenarios in climate impact assessments. Instead, members of an assessment team, most of whom are not climate scientists, must sift through the formal and informal publications of previous assessments to ascertain possible options and potential pitfalls when employing local⁄regional climate change scenarios in an impact assessment. This omission led Fowler and Wilby (2007, 1543) to conclude that 'there has been a disconnection between the suppliers and users of regional climate change scenarios for adaptation and resource planning'.

Fowler and Wilby's concern resonated strongly with our previous experiences as suppliers of climate scenarios and participants of assessment teams. Our colleagues have asked us numerous challenging questions about the nature and limitations of local/regional climate change scenarios and their use in assessments. These questions motivated this two-part communication written expressly for non-climate scientists involved in climate change impact assessments. In Part I, we summarized different downscaling approaches, emphasizing the characteristics of these methods that we feel users need to be aware of in order to knowledgeably and appropriately interpret the resulting scenarios. Here in Part II, we highlight a number of issues that we feel need to be carefully considered when applying local/regional climate change scenarios, specifically observational datasets for scenario evaluation, the construction and use of scenario ensembles, approaches to bias correction, and advantages and disadvantages of archived climate scenarios. The discussion below assumes that an assessment team is using the popular top-down, end-to-end assessment strategy (see Figure 1 in Part I), although it is also applicable for other strategies.

## *Downscaling Terminology*

We utilize the three category classification of downscaling methods provided in Part I, namely dynamic downscaling, empirical-dynamic downscaling, and disaggregation downscaling methods. Dynamic downscaling refers to the use of numerical models to simulate fine-resolution climate fields, particularly the use of regional climate models (RCMs) driven by coarse-scale GCM output. Empirical-dynamic downscaling employs statistical methods to relate local/regional climate variables (e.g. temperature and precipitation) to large-scale circulation and atmospheric state variables that are chosen to represent important dynamical and physical processes in the atmosphere. Disaggregation methods include interpolation and other statistical methods to estimate fine-scale values from coarse-scale spatial fields of a particular variable, or inferring a finer time resolution from temporally aggregated averages or accumulations of climate variables. (See Part I for more details.)

## *Retrospective Data for Scenario Evaluation*

While suppliers of local/regional climate change scenarios will (hopefully!) have performed substantial evaluation[1] of the scenarios, it is the responsibility of the users to conduct evaluations specific for the assessment. This is particularly important when archived scenarios are used and the available metadata contain limited information on evaluation.

For disaggregation and empirical-dynamic downscaling procedures, evaluations are typically conducted between observations of climate variables (e.g. temperature and precipitation) and the downscaled local/regional scenarios of these variables that were developed from climate model output for a period overlapping with the observations, known as the 'control' period (see Part I). Downscaled scenarios for a control climate represent one possible realization of the present-day climate rather than predictions for a specific date. Thus, it is not appropriate to compare observations and scenarios day-by-day, month-by-month, etc. Rather, the evaluation focuses on differences in the probability density functions of the downscaled scenarios and observations, such as differences in the mean, variance, and extremes (Maraun et al. 2010). Often it is also necessary to compare observed and control-period GCM-simulated values of the coarse-scale circulation and free-atmosphere fields used as predictors in empirical-dynamic transfer functions, or the coarse-scale surface climate variables that are being disaggregated to finer resolution fields.

For dynamically downscaled scenarios, evaluation includes comparisons between observations of climate variables and downscaled values obtained from a 'perfect boundary condition' (i.e. 'current' climate) simulation, and between the downscaled values from the control climate and current climate simulations (see Figure 3, Part I). Additionally, it is necessary to evaluate whether the RCM adequately simulates the mesoscale circulation features and processes that influence the climate variables of interest for the assessment.

Whatever the downscaling method, evaluation is an essential step in the scenario development process. However, an important caveat is that 'skill for the present-day climate … may not be a sufficient indicator of skill for the future climate' (Maraun et al. 2010, 23), and therefore it is also necessary to carefully consider whether the projected future changes are physically reasonable and interpretable.

### REANALYSIS FIELDS

Reanalysis datasets, originally developed for climate monitoring and weather-related research, are often used when evaluating GCM and/or RCM simulations.[2] These gridded fields, which can be considered a 'blend' of observations and model output, are constructed using a multi-part data assimilation system that includes an operational weather forecasting model; complex algorithms for quality control of raw observations from balloon soundings, ships, buoys, aircraft, satellites, and surface observing stations; and space and time interpolation schemes (Kalnay et al. 1996). Saha et al. (2010, 1016) succinctly describe a reanalysis as follows:

> the analysis at any given time ($t$) is the result of a short forecast (the guess field), initialized from a previous analysis (valid at time $t - \Delta t$), modified by assimilating new observations available in a narrow window centered at $t$.

The same forecast model and assimilation system are used for the entire period of the reanalysis in order to remove discontinuities and/or spurious trends introduced by changes over time in forecast models and assimilation systems (Saha et al. 2010), although discontinuities may still exist due to changes in the quantity and quality of atmospheric observations. Reanalyses can be classified in terms of their spatial coverage as either 'global' or 'regional' (see Table 1 for a description of currently available reanalysis data sets).

Two of the earliest and most widely used global reanalyses are the National Center for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) Reanalysis (Kalnay et al. 1996), available for 1948–present, and ERA-40 (Uppala et al. 2005) available for 1957–2002 and produced by the European Center for Medium Range Weather Forecasting. Both reanalyses provide a large number of surface and upper air variables at a sub-daily (six-hourly) time step and 2.5° latitude × 2.5° longitude resolution, although the ERA-Interim reanalysis (Simmons et al. 2007), a temporary replacement while the ERA-40 undergoes an extensive upgrade, has a finer 1.5° horizontal resolution for the period 1989–present. More recent global reanalyses, such as JRA-25 (Onogi et al. 2007), MERRA (Bosilovich 2008), and CFSR (Saha et al. 2010), have finer spatial resolutions, or, like the newly available Twentieth Century Reanalysis (20CRV2) (Compo et al. 2011), are available for a longer historical period (more details on these reanalyses are provided in Table 1). Several new global reanalyses are currently under development, such as JRA-55 which is an update to JRA-25 with a longer period

**Table 1. Currently available reanalysis products.**

| Name | Type | Produced by | Spatial resolution | Time step of archived data | Period | Reference/website | Comments |
|---|---|---|---|---|---|---|---|
| NCEP/NCAR Reanalysis 1 | Global | National Center for Environmental Prediction (NCEP), National Center for Atmospheric Research (NCAR) | ~200 km; data archived at 2.5° latitude × 2.5° longitude | 6 hourly | 1948–present | Kalnay et al. (1996); Kistler et al. (2001) http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.html | Continued under the name Climate Data Assimilation System 1 (CDAS1) |
| NCEP-DOE AMIP-II Reanalysis 2 | Global | NCEP, Department of Energy (DOE) | ~200 km; data archived at 2.5° latitude × 2.5° longitude | 6 hourly | 1979–present | Kanamitsu et al. (2002) http://dss.ucar.edu/pub/reanalysis2/ | Improved on NCEP/NCAR Reanalysis 1 (corrected some errors and updated parameterizations); continued under the name CDAS2 |
| ERA-40 | Global | European Center for Medium Range Weather Forecasting (ECMWF) | ~200 km; data archived at 2.5° latitude × 2.5° longitude | 6 hourly | 1957–2002 | Uppala et al. (2005) http://www.ecmwf.int/research/era/do/get/era-40 | Update to an earlier reanalysis referred to as ERA-15 |
| ERA-Interim | Global | ECMWF | ~80 km; data archived at 1.5° latitude × 1.5° longitude | 6 hourly | 1989–present | Simmons et al. (2007) http://www.ecmwf.int/research/era/do/get/era-interim | Temporary replacement for ERA-40 as new reanalysis (tentatively referred to as ERA-75) is being developed |
| JRA-25 | Global | Japan Meteorological Agency (JMA), Central Research Institute of Electric Power Industry (CRIEPI) | ~120 km; data archived at 1.25° latitude × 1.25° longitude and at 2.5° latitude × 2.5° longitude | 6 hourly | 1979–2004 | Onogi et al. (2007) http://jra.kishou.go.jp/JRA-25/index_en.html | Continues as JCDAS |

**Table 1. Continued.**

| Name | Type | Produced by | Spatial resolution | Time step of archived data | Period | Reference/website | Comments |
|---|---|---|---|---|---|---|---|
| JMA Climate Data Assimilation System (JCDAS) | Global | JMA | ~120 km; data archived at 1.25° latitude × 1.25° longitude and at 2.5° latitude × 2.5° longitude | 6 hourly | 2005–present | Onogi et al. (2007) http://jra.kishou.go.jp/JRA-25/AboutJCDAS_en.html | Continuation of JRA-25 |
| 20th Century Reanalysis (C20r) Version 2 | Global | National Oceanic and Atmospheric Organization (NOAA) Earth Systems Laboratory | 2° latitude × 2° longitude | 6 hourly | 1871–2008 | Compo et al. (2011) http://www.esrl.noaa.gov/psd/data/gridded/data.20thC_ReanV2.html | Based only on surface pressure data |
| Modern Era Retrospective Analysis for Research and Applications (MERRA) | Global | National Aeronautics and Space Administration (NASA) Goddard Space Flight Center | 0.5° latitude × 0.667° longitude | Hourly, 3 hourly, and 6 hourly | 1979–present | Bosilovich (2008) http://gmao.gsfc.nasa.gov/research/merra/ | Only run for the period of modern satellite observations; referred to as a 'satellite era' reanalysis |
| CFS Reanalysis and Reforecast (CFSR) | Global | NCEP | ~38°km; archived data at 0.5° latitude × 0.5° longitude | Hourly | 1979–2009 | Saha et al. (2010) http://cfs.ncep.noaa.gov/cfsr/ | Enhancement over NCEP/NCAR Reanalysis 1 and NCEP-DOE Reanalysis 2 |
| North American Regional Reanalysis NARR | Regional | NCEP | ~32 km | 3 hourly | 1979–present | Mesinger et al. (2006)) http://www.emc.ncep.noaa.gov/mmb/rreanl/ | NCEP-DOE R2 is used to provide lateral boundary conditions to the NCEP regional Eta model |

of record (1958–2012) and a finer spatial resolution (~22 km) (Trenberth et al. 2009). These new efforts take advantage of recent improvements to forecast models and data analysis techniques. Regional-scale reanalyses are currently limited to North America but are in development for other areas. The North American Regional Reanalysis has an approximately 32 km resolution (Mesinger et al. 2006), and is an important dataset for validating (and initiating) RCM simulations.

When using either global or regional reanalyses for evaluating the inputs to, and outputs from, climate downscaling techniques, it is important to keep in mind that the reanalyses are unlikely to have the same grid spacing as corresponding GCM or RCM fields, and often regridding of either the reanalysis or model fields is necessary (Wilby et al. 2004). Users should also keep in mind that reanalysis fields are affected by biases and limitations (e.g. resolution) of the operational weather forecasting model used to produce the reanalysis, and, consequently, the reanalysis fields can deviate from observations (Maraun et al. 2010).

### STATION DATA AND GRIDDED FIELDS

Time series observations from climatological recording stations are essential for the evaluation (and development) of downscaled scenarios. These observations are typically obtained from local or national archives, although several regional and global archives of station observations are also available including, for example, the daily resolution European Climate Assessment & Dataset (Klein Tank et al. 2002) and the daily and monthly versions of the Global Historical Climatology Network (GHCN) (Peterson and Vose 1997). The quality of the station observations must be considered, as climate observations contain a myriad of inhomogeneities due to changes in instrumentation and observing practices (see Winkler 2004, 2010 for reviews). All observational data should first be carefully evaluated using one or more of the many methods developed to check for inhomogeneities (see review by Peterson et al. 1998).

Gridded fields of observed variables are also used for evaluation of local/regional climate scenarios, in addition to serving as a baseline for applying change factors (discussed below). The majority of gridded datasets have been developed for precipitation and surface temperature (see Table 2 for a listing of the more widely used gridded datasets and their characteristics), and provide either climatological values (i.e. long-term averages) or time series of anomalies relative to a base period (frequently taken as 1961–1990). The spatial resolution of the gridded fields varies widely from as fine as 1 km to as coarse as 5° latitude by 5° longitude. Most gridded datasets employ a monthly time step, although gridded fields with a daily time step [e.g. E-OBS (Haylock et al. 2008)] are also available. Very generally, the gridded fields are obtained by either (i) averaging anomalies or climatological values for stations located within a grid box [e.g. the GHCN global gridded temperature and precipitation products (Peterson and Vose 1997)], (ii) spatial interpolation of anomaly and climatological fields considering only distance between observing stations [e.g. the University of Delaware global gridded monthly time series and climatological values of terrestrial air temperature and precipitation (Legates and Willmott 1990a,b)], or (iii) spatial interpolation that considers topography such as the thin-plate spline interpolation scheme used for the WorldClim dataset (Hijmans et al. 2005) or the local linear regressions of climate versus elevation and slope used to create the Precipitation-elevation Regressions on Independent Slopes Model (PRISM) gridded fields of temperature and precipitation (Daly 2006; Daly et al. 2002).

Table 2. Gridded datasets of observed climate variables that are commonly used in the development and evaluation of climate scenarios.

| Name | Area | Produced by | Variables/temporal resolution | Spatial resolution | Period (for time series data) | Reference/website | Remarks |
|---|---|---|---|---|---|---|---|
| CRUTEM2 | Global land areas | University of East Anglia Climate Research Unit | Time series of monthly temperature anomalies (calculated as deviation from 1961–1990 base period) | 5° latitude × 5° longitude | 1851–2005 | Jones and Moberg (2003) http://www.cru.uea.ac.uk/cru/data/tem2/#sciref | Although still available, this data set is no longer updated; CRUTEM2V is the variance adjusted version of this dataset (see Jones et al. 2001) |
| HADCRUT2 | Global | Hadley Centre and University of East Anglia Climate Research Unit | Time series of monthly temperature anomalies (calculated as deviation from 1961–1990 base period) | 5° latitude × 5° longitude | 1851–2005 | Rayner et al. (2003) http://www.cru.uea.ac.uk/cru/data/tem2/#sciref | Incorporates both sea-surface and land-based observations; although still available this dataset is no longer updated; HADCRUT2V is the variance adjusted version of this dataset |
| CRUTEM3 | Global land areas | University of East Anglia Climate Research Unit | Time series of monthly surface temperature anomalies (calculated as deviations from 1961–1990 base period) | 5° latitude × 5° longitude | 1985–present | Brohan et al. (2006) http://www.cru.uea.ac.uk/cru/data/temperature/ | Replaces CRUTEM2; CRUTEM3V is the variance adjusted version of this dataset |

**Table 2. Continued.**

| Name | Area | Produced by | Variables/temporal resolution | Spatial resolution | Period (for time series data) | Reference/website | Remarks |
|---|---|---|---|---|---|---|---|
| HADCRUT3 | Global | Hadley Centre and University of East Anglia Climate Research Unit | Time series of monthly surface temperature anomalies (calculated as deviations from 1961–1990 base period) | 5° latitude × 5° longitude | 1851–present | Rayner et al. (2006) http://www.cru.uea.ac.uk/cru/data/tempera ture/ | Replaces HADCRUT2; HADCRUT3V is the variance adjusted version of this dataset |
| Global Historical Climatology Network (GHCN) Global Gridded Temperature Products | Global land areas | National Climatic Data Center | Time series of monthly temperature anomalies (calculated as deviations from 1961–1990 base period) | 5° latitude × 5° longitude | 1880–present | Peterson and Vose (1997) http://www.ncdc.noaa.gov/temp-and-precip/ghcn-gridded-temp.html | Homogeneity adjusted data are the primary data source; station anomalies are aver aged within each grid box to obtain the gridded anomalies |
| Global Historical Climatology Network (GHCN) Global Gridded Precipitation Products | Global land areas | National Climatic Data Center | Time series of monthly precipitation anomalies (calculated as deviations from 1961–1990 base period) | 5° latitude × 5° longitude | 1900–present | http://www.ncdc.noaa.gov/temp-and-precip/ghcn-gridded-prcp.html | Anomalies were calculated on a monthly basis for all stations having at least 25 years of data in the 1961–1990 base period; station anomalies were then averaged within each 5° × 5° grid box to obtain the gridded anomalies |

**Table 2. Continued.**

| Name | Area | Produced by | Variables/temporal resolution | Spatial resolution | Period (for time series data) | Reference/website | Remarks |
|---|---|---|---|---|---|---|---|
| HadGHCND | Global land areas | Hadley Centre and National Climate Data Center | Time series of daily anomalies of maximum and minimum temperature relative to the 1961–1990 base period | 2.5° latitude × 3.75° longitude | 1950–present | Caesar et al. (2006) http://hadobs.metoffice.com/hadghcnd/ | Designed primarily for the analysis of climate extremes and climate model evaluation |
| Global Precipitation Climatology Project (GPCP) | Global | World Climate Research Programme | Time series of monthly mean precipitation | 2.5° latitude × 2.5° longitude | 1979–present | Huffman et al. (1997)http://cics.umd.edu/~yin/GPCP/main.html | Combines *in situ* observations with remotely sensed observations |
| CPC Merged Analysis of Precipitation (CMAP) | Global | NOAA/NWS/Climate Prediction Center | Times series and climatological values of monthly average precipitation rate (mm/day) | 2.5° latitude × 2.5° longitude | 1979–2009; climatological values calculated for period 1979–2000 | Xie and Arkin (1997) http://www.cpc.ncep.noaa.gov/products/global_precip/html/wpage.cmap.html | Rain gage measurements are merged with precipitation estimates from satellites |
| GISS Surface Temperature Analysis | Global | NASA/Goddard Institute for Space Studies | Time series of monthly anomalies of temperature | 2° latitude × 2° longitude | 1880–present | Hansen et al. (2010) http://data.giss.nasa.gov/gistemp/ | A land temperature only data set and a combined land temperature and sea-surface temperature data set are available |

**Table 2. Continued.**

| Name | Area | Produced by | Variables/temporal resolution | Spatial resolution | Period (for time series data) | Reference/website | Remarks |
|---|---|---|---|---|---|---|---|
| CRU CL 1.0 | Global land areas | University of East Anglia Climate Research Unit | Climatological values for 1961–1990 of monthly precipitation, wet day frequency, daily mean temperature, diurnal temperature range, vapor pressure, cloud cover, frost day frequency, wind speed | 0.5° latitude × 0.5° longitude | Average values for 1961–1990 | New et al. (1999) http://www.cru.uea.ac.uk/cru/data/hrg/cru05/cru05_intro.html | The station data were interpolated as a function of latitude, longitude, and elevation using thin-plate splines |
| CRU CL 2.0 | Europe | University of East Anglia Climate Research Unit | Climatological values for 1961–1990 of monthly precipitation, wet days, mean temperature, diurnal temperature range, frost day frequency, wind speed, relative humidity, sunshine | 10′ resolution | Average values for 1961–1990 | New et al. (2002) http://www.cru.uea.ac.uk/cru/data/hrg/tmc/ | The station climate statistics were interpolated using thin-plate smoothing splines |
| CRU TS 1.2 | Europe | University of East Anglia Climate Research Unit | Time series values of monthly precipitation, temperature, diurnal temperature range, vapor pressure, cloud cover | 10′ resolution | 1901–2000 | Mitchell et al. (2004) http://www.cru.uea.ac.uk/cru/data/hrg/timm/grid/CRU_TS_1_2.html | The station climate statistics were interpolated using thin-plate smoothing splines |

**Table 2. Continued.**

| Name | Area | Produced by | Variables/temporal resolution | Spatial resolution | Period (for time series data) | Reference/website | Remarks |
|---|---|---|---|---|---|---|---|
| CRU TS 3.0 | Global land areas | University of East Anglia Climate Research Unit | Time series of monthly precipitation totals and monthly means of daily mean temperature, maximum temperature, minimum temperature, diurnal temperature range, vapor pressure, cloud cover, wet day frequency, frost day frequency | 0.5° latitude × 0.5° longitude | 1901–2006 | Mitchell and Jones (2005) http://badc.nerc.ac.uk/data/cru/ | The station climate statistics were interpolated using thin-plate smoothing splines |
| Terrestrial Air Temperature Gridded Monthly Time Series and Terrestrial Precipitation Gridded Monthly Time Series Version 2.01 | Global land areas | University of Delaware | Time series of monthly precipitation and minimum and maximum temperature | 0.5° latitude × 0.5° longitude | 1990–2008 | Legates and Willmott (1990a) http://jisao.washington.edu/data_sets/ud/ | A lapse rate adjustment was used in the interpolation of temperature observations; elevation was not included in the spatial interpolation of precipitation observations |

**Table 2. Continued.**

| Name | Area | Produced by | Variables/temporal resolution | Spatial resolution | Period (for time series data) | Reference/website | Remarks |
|---|---|---|---|---|---|---|---|
| Terrestrial Air Temperature and Precipitation Monthly Climatologies Version 4.01 | Global land areas | University of Delaware | Climatological fields of monthly average air temperature and precipitation | 0.5° latitude × 0.5° longitude | Averages calculated over the period 1975–2005 | Legates and Willmott (1990b) http://jisao.washington.edu/data_sets/ud/ | A lapse rate adjustment was used in the interpolation of temperature observations |
| WorldClim | Global land areas | University of California, Berkeley | Climatological fields of monthly precipitation and mean, minimum, and maximum temperature | 1 km | Averages calculated over period 1950–2000 | Hijmans et al. (2005) http://www.worldclim.org/ | Employed a thin-plate spline interpolation scheme using latitude, longitude, and elevation to estimate spatially varying elevation relationships |
| Precipitation-elevation Regressions on Independent Slopes Model dataset (PRISM) | United States | Oregon State University | Time series of annual and monthly temperature and precipitation | 4 km or less | 1985–present | Daly et al. (2002) http://www.prism.oregonstate.edu/ | This method employs local linear regressions of climate versus elevation and elevation-varying slope to incorporate the impact of terrain barriers, gradients, and cold air drainage and inversions in addition to spatially varying elevation relationships |

**Table 2. Continued.**

| Name | Area | Produced by | Variables/temporal resolution | Spatial resolution | Period (for time series data) | Reference/website | Remarks |
|---|---|---|---|---|---|---|---|
| Maurer et al. dataset | United States and portions of Canada and Mexico | University of Washington | Monthly and daily precipitation, average, maximum and minimum temperature, wind | 1/8° (~12 km) | 1950–1999 | Maurer et al. (2002) http://www.engr.scu.edu/~emaurer/data.shtml | Daily precipitation interpolated using SYMAP algorithm and gridded values scaled to match PRISM long-term monthly climatology; daily $T_{max}$ and $T_{min}$ data lapsed to the grid cell mean elevation. |
| Hamlet and Lettenmaier dataset | United States | University of Washington | Daily and monthly precipitation, daily maximum and minimum temperature | 1/8° (~12 km) | 1915–2003 | Hamlet and Lettenmaier (2005) | Similar to the Maurer et al. methodology with addition of a temporal adjustment to ensure time series have consistent long-term trends with stations from the US Historical Climatology Network and the Historical Canadian Climate database |
| E-OBS | Europe | Developed as part of the ENSEMBLES project | Time series of daily precipitation and daily mean, maximum, and minimum temperature | Four grids with differing spatial resolutions ranging for ~25–50 km | 1950–present | Haylock et al. (2008) http://eca.knmi.nl/download/ensembles/ensembles.php | Developed from the European Climate Assessment & Dataset; daily standard errors are provided for each grid cell as an estimate of interpolation uncertainty |

The uniform grid and the extensive coverage of gridded observed datasets contribute to their popularity, but users need to be aware of their limitations and realize that employing these datasets in climate scenario evaluation (and development) can be more challenging than it might first appear. One issue is that most climate observing stations are located at relatively low elevations; thus, interpolations in areas of irregular topography need to be interpreted cautiously. Also, Guentchev et al. (2010) recently showed that gridded datasets can suffer from similar inhomogeneity issues as the original station observations. Therefore, extensive comparisons of the gridded product with available high quality meteorological station data are recommended. Furthermore, the variance of the gridded datasets is usually smaller than the observed variance at individual stations (Maraun et al. 2010), especially for those gridded datasets that average the anomalies or climatological values for all stations falling within each grid box. Additionally, users should keep in mind that the fine resolution of gridded datasets can give an appearance of realism that is often not consistent with the spatial resolution of the initial observations (Daly 2006).

### *Scenario Ensembles*

Considerable uncertainty surrounds the current understanding of how climate might change in the future. This uncertainty arises from, among other factors, an incomplete understanding of climate processes and uncertainty as to how greenhouse gas emissions may change in the future (Ahmad et al. 2001). Although some impact assessments still employ a single scenario (e.g. Trapp et al. 2007; White et al. 2006), the use of ensembles (i.e. groups of scenarios) is becoming the standard practice. Ensembles provide a range of projections and hence an estimation of what Jones (2000) refers to as the 'calibrated range of uncertainty'. The calibrated uncertainty range is smaller than the full, but unknown, uncertainty range, and careful selection of the ensemble members is required for the calibrated range to approach the full range of uncertainty (Figure 1). In a similar vein, Stainforth et al. (2007, 2166) argue that climate ensembles provide a 'lower bound on the maximum range of uncertainty'.

When constructing an ensemble, it is important to capture the major uncertainty sources (Figure 2). A typical ensemble will include climate change scenarios developed assuming varying projections of future greenhouse gas emissions, such as the SRES scenarios (named after the *Special Report on Emissions Scenarios*; Nakicenovic et al. 2000) or

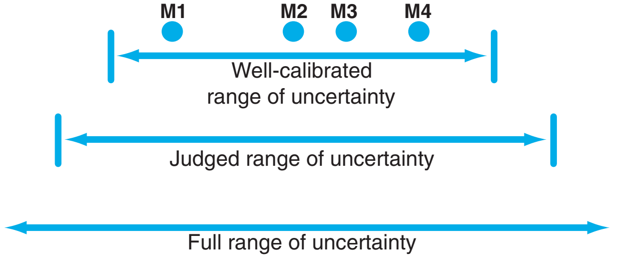


Fig. 1. Schematic depiction of the relationship between 'well-calibrated' scenarios, the wider range of 'judged' uncertainty that might be elicited through decision analytic techniques, and the 'full' range of uncertainty, which is drawn wider to represent overconfidence in human judgments. M1 to M4 represent scenarios produced by four models (e.g. globally averaged temperature increases from an equilibrium response to doubled $CO_2$ concentrations). This lies within a 'full' range of uncertainty that is not fully identified, much less directly quantified by existing theoretical or empirical evidence (modified from Jones 2000). Source: Ahmad et al. (2001).

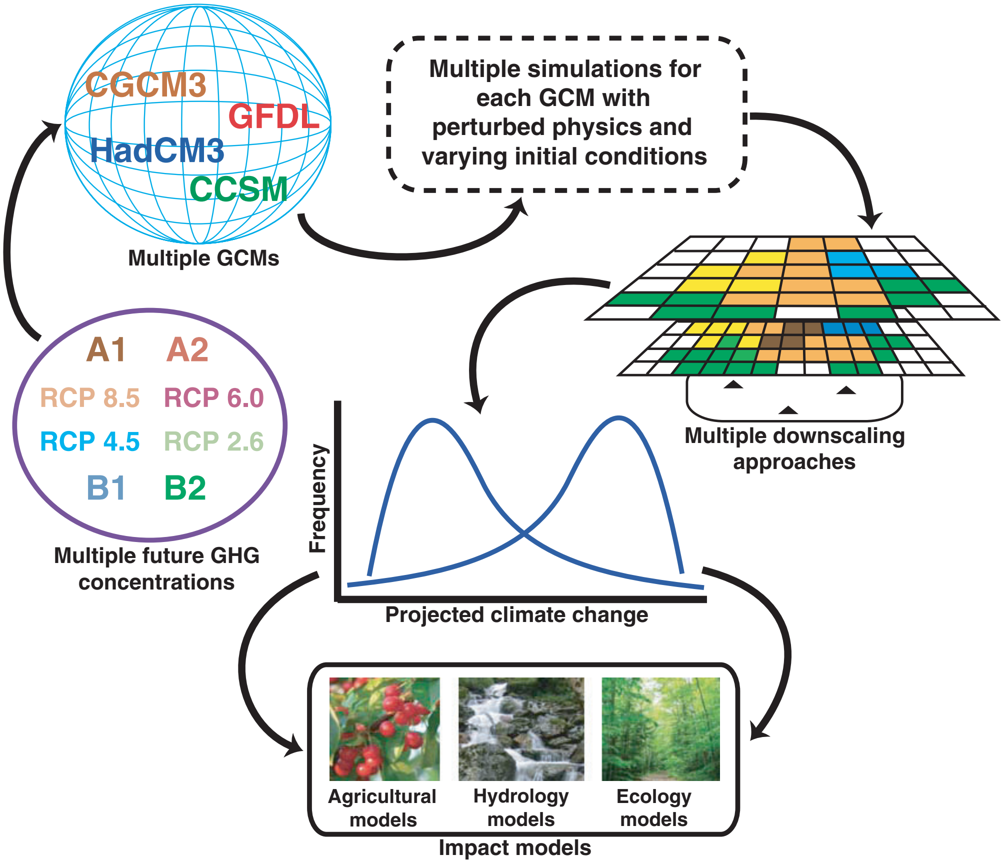


Fig. 2. Sources of uncertainty and possible distributions of an ensemble of projected local/regional climate change. The dashed line indicates uncertainty sources that are infrequently considered.

the newly developed 'representative concentration pathways' (RCPs; Moss et al. 2010). The SRES scenarios were developed around four coherent, internally consistent 'story-lines' that assume different demographic, social, economic, technological, and environ-mental developments. The scenarios represent greenhouse gas emissions as a function of these assumptions. Very broadly, the four storylines represent: (i) strong economic values and increasing globalization (A1 storyline), (ii) strong economic values and increasing regionalization (A2 storyline), (iii) strong environmental values and increasing globaliza-tion (B1 storyline), and (iv) strong environmental values and increasing regionalization (B2 storyline) (Nakicenovic et al. 2000). The SRES scenarios can be considered a sequential approach to projecting future climate, as socio-economic and emissions scenar-ios are used to estimate radiative forcing which in turn is input into GCMs to project the human influence on future climates (Moss et al. 2010). Representative concentration pathways were in part introduced to reduce the time needed for scenario development by allowing for the coordinated development of socio-economic and emissions scenarios in parallel (rather than sequentially) with the modeling of a range of future climates (Moss et al. 2010). Four representative concentration pathways that can arise from a number of different combinations of socio-economic, technological, and policy drivers and that represent a broad range of climate outcomes were drawn from the literature. They include a 'rising' trajectory with greenhouse gas emissions increasing through the 21st century and $CO_2$-equivalent concentrations >1370 parts per million (ppm) by 2100 (referred to as RCP8.5); two 'stabilization without overshoot' trajectories, one with $CO_2$-equivalent concentrations of ~850 ppm (RCP6.0) and the other with ~650 ppm (RCP4.5) by 2100; and a 'peak and decline' trajectory with maximum $CO_2$-equivalent concentrations of ~490 ppm before 2100 and a subsequent decline in emissions (RCP2.6) (Moss et al. 2010). The GCM simulations for the upcoming Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment will use the representative concentration pathways as inputs, whereas the modeling efforts for the IPCC Third and Fourth Assessments utilized the SRES scenarios.

An ensemble should also include scenarios developed from a number of different GCMs (see Randall et al. 2007 for a listing of the major GCMs), in order to capture uncertainty introduced by the structural differences of GCMs and their errors and biases. Giorgi and Coppola (2010) recently recommended that at least 4–5 GCMs need to be included in an ensemble to obtain robust estimates of future change for areas where there are substantial, systemic regional biases in GCM simulations for the control climate. It is also possible to include in the ensemble scenarios developed from multiple simulations from the same GCM, where selected physical parameterizations have been perturbed to evaluate their influence on the projected climate or where initial conditions (i.e. the 'starting state') have been slightly modified to evaluate variability (see http://climateprediction.net/content/experiment-strategy-basic for more information).

Ideally, an ensemble also should include scenarios constructed using different (i.e. dynamic, empirical-dynamic, and disaggregation) approaches to downscaling, although this is still a rarity. An important exception is the STARDEX experiment (Statistical and Regional dynamical Downscaling of EXtremes for European region; http://www.cru.uea.ac.uk/projects/stardex/). When dynamic downscaling is utilized the ensemble preferably includes scenarios developed from multiple RCMs, whereas when using empirical-dynamic and disaggregation methods different approaches to defining the transfer functions or interpolation schemes should be included (CCSP 2008; Déqué et al. 2007; Fowler et al. 2007; Giorgi 2006; Rowell 2005). Also, Winkler et al. (1997) showed that 'user decisions' when applying a particular downscaling methodology, such as choosing to develop empirical transfer functions separately for each season, can introduce uncertainty.

When allocating resources, attention should particularly be paid to developing scenarios from multiple GCM simulations, as several studies suggest that the choice of GCM introduces the largest degree of uncertainty (e.g. Benestad 2002; Wilby and Harris 2006; Winkler et al. 2003). An exception is dynamic downscaling where the use of multiple GCMs *and* multiple RCMs may be required, as some authors (e.g. Déqué et al. 2007) have reported that the choice of RCM can introduce as much uncertainty as the choice of GCM. Also, a number of RCM intercomparison studies have suggested that ensemble means of RCMs are generally in better agreement with observations than any individual model (Fu et al. 2005; Takle et al. 1999).

Interdependence among the ensemble members must be considered when interpreting a scenario ensemble (Tebaldi and Knutti 2007). Many GCMs and RCMs share the same numerical schemes and parameterizations, and consequently scenarios developed from different climate models are not independent (Fowler et al. 2007). Similarly, scenarios developed from the same GCM simulations but using different downscaling methods are not independent. Nor are ensemble members derived using different projections of greenhouse gas emissions but the same GCM and/or downscaling method. This interdependence makes it difficult to assign probabilistic estimates of local/regional climate change based on the scenario ensemble. Furthermore, because of the interdependence among scenarios, scenario consensus should not be confused with skill or reliability (Maraun et al. 2010).

For some applications (e.g. Zavalloni et al. 2006, 2008), all members of a scenario ensemble were weighted similarly, whereas for others varying weights were assigned, often based on the magnitude of the biases between observations and simulations for the control (i.e. present-day) climate (e.g. Blenkinsop and Fowler 2007; Giorgi and Mearns 2002), although Stainforth et al. (2007, 2145) argue that using observations to weight ensemble members is inappropriate given that they are simulating a 'never before experienced state of the [climate] system'. A current avenue of research is the use of Bayesian methods as an alternative means to evaluate multi-member ensembles of climate projections (e.g. Berliner and Kim 2008; Buser et al. 2009; Smith et al. 2009).

### *Bias Adjustments*

The errors and biases of downscaled climate scenarios complicate their use in applications. Below we describe some of the approaches that have been used for adjusting for bias. The discussion is organized around the three major downscaling methods. Evident from the discussion is that adjusting for biases in local/regional climate scenarios is challenging and that agreed upon approaches to bias adjustments do not currently exist. Dialog between climate scenario users and suppliers is particularly important during this phase of an assessment to ensure that the bias adjustments are appropriate for the goals of the assessment, and that the potential impact of biases (and bias adjustments) on the assessment outcomes and decision making is understood.

#### CHANGE FACTORS AND DISAGGREGATION METHODS

A number of assessments have used what is commonly referred to as a 'change factor' (e.g. Wilby et al. 2004), or alternatively the 'delta' method (e.g. CCSP 2008), to adjust for scenario biases. This approach has been particularly popular for ecological assessments, and these applications are used here for illustration. Frequently, bioclimatic envelope models, also referred to as ecological niche models or species distribution models (Jeschke and Strayer 2008), are used to describe the current geographical distributions of organisms as a function of climate and to project future species distributions in a perturbed climate (e.g. Gallego-Sala et al. 2010; Oberhauser and Peterson 2003; Thomas et al. 2004). These models typically relate the current distribution of a particular species to monthly or seasonal climatological (i.e. long term average) values of surface temperature and precipitation (e.g. Bradley 2009), and are generally developed at the local spatial scale using climate observations from individual stations or from finely gridded observed climatological fields such as the aforementioned WorldClim or PRISM datasets. To estimate future species distributions, the observed climatological values are modified by a change factor, and the modified climatological values are input into the bioclimatic model. A simple and commonly used approach to calculating change factors is, for average temperature, to subtract for individual gridpoints the GCM-simulated average temperature for a control period (such as 1970–1999) from that for a future period (such as 2070–2099), and, for precipitation, to calculate the ratio of the projected future average precipitation to the average value for the control period. (Ratios are used for precipitation because it is a zero-bounded variable.) Spatial disaggregation schemes are often used to interpolate the change factors from the GCM grid resolution to a finer resolution, and the interpolated change factors are then applied to the climatological values at observation stations or to finely gridded observed climatological fields. An underlying assumption is that the nature and magnitude of the biases in the downscaled scenarios are similar for the control and future periods, or, in other words, any change in the bias is small compared to changes in the climate between future and control periods (Buser et al. 2009). This assumption was recently criticized by Christensen et al. (2008, 6) who found that 'model biases have the potential to grow when used for climate change simulations under global warming conditions'. Another concern that, in our opinion, has not been sufficiently addressed in the downscaling and assessment literatures is whether it is appropriate to apply the interpolated change factors to gridded observed fields if the interpolation schemes differ between the two datasets, particularly in terms of how elevation is incorporated into the interpolation.

The change factor approach, as outlined above, is most appropriate for monthly, seasonal, or annual averages or accumulations, although a stochastic weather generator (see Part I) can be used to generate daily time series from the adjusted means, or alternatively, the change factors can be used to adjust long-term daily observations of a climate variable at a location. The latter approach was used in a number of earlier assessment studies (e.g. Adams et al. 1990; Bonan et al. 1990; Rosenzweig and Parry 1994), but this method has lost favor as it does not consider changes in the variability of the climate variable and we recommend that its use be limited to sensitivity studies.

Another issue is that a change factor ignores biases in the distributions of the GCM-simulated climate variables. This concern has been addressed by a number of authors, most notably by Wood et al. (2004) who recommended a multi-step approach, that they labeled the 'bias-correction and spatial downscaling (BCSD) method' for calculating change factors. BCSD adjusts for biases using quantile mapping, which relates the quantiles (e.g. 10%, 50%, 90%) of the cumulative frequency distribution (cdf) of an observed series of a climate variable to the cdf of the GCM-simulated series for the control climate. The steps of the BCSD method, as summarized by Barsugli et al. (2009), include (i) map the quantiles of the cdf for the GCM control climate simulation of the time series of monthly accumulations or averages of the climate variables (e.g. precipitation and surface temperature) against the cdf for observed (typically gridded) values that have been aggregated to the scale of the GCM grid, (ii) adjust for GCM biases by applying the quantile mapping to the probability density functions for the future projections of the climate variables, (iii) calculate change factors between GCM future and control periods, (iv) interpolate the change factors to a finer resolution using a distance-only interpolation scheme and apply them to the original fine-scale observed values, and, if needed, (v) apply a weather generator to obtain daily time series. Underlying the BCSD approach is the assumption that GCMs have limited skill at time steps finer than the monthly scale.

### BIAS ADJUSTMENTS WHEN USING EMPIRICAL-DYNAMIC DOWNSCALED SCENARIOS

A well-known limitation of empirical-dynamic downscaling is that the variance of the downscaled climate variables is underestimated, as the large-scale predictors capture only part of the local climate variability (Themeβl et al. forthcoming). A number of authors (e.g. von Storch 1999) have recommended that variance be 'inflated', such as by adding random noise to the downscaled time series. One concern is that the variance inflation procedure developed for the current climate may not be appropriate for a future climate. Error in the predictor variables is also a concern for empirical-dynamic downscaling, and several authors have argued that the large-scale predictor variables be adjusted for known differences between the control climate and observations. For example, Winkler et al. (1997) imposed the same mean and variance on the observed time series and the GCM-simulated control climate time series of the predictor variables.

Another approach to bias adjustment for scenarios developed using empirical-dynamic methods is to first use the projected time series to compute climatological values for selected future periods and for a control period and then compute change factors between these periods, as described above for scenarios developed using disaggregation procedures. Local site conditions are implicitly incorporated into these change factors, given that the empirical transfer functions are developed for individual locations. The BCSD approach could also be used for bias correction, although the spatial interpolation step is unnecessary as the scenarios are usually already at the local scale. Alternatively, the downscaled time series can be fed directly into the downstream (e.g. hydrological, ecological, economic) models of an end-to-end assessment. Bias adjustments, such as simple change factors between future and control periods, can then be applied to the 'intermediate' or 'final' outcomes of the model suite. This approach was used, for example, by Zavalloni et al. (2008) to estimate projected future change in crop yield from local climate scenarios of daily precipitation and minimum and maximum temperature. A concern is that the components of the model suite introduce additional layers of uncertainty (Wilby et al. 2004), and assessing the relative magnitude (and possible interactions) of the uncertainty sources is challenging.

### DYNAMIC DOWNSCALING AND BIAS ADJUSTMENTS

The output of dynamic downscaling is a suite of physically consistent climate variables at sub-daily time steps. These characteristics make dynamically downscaled scenarios very appealing as input to hydrologic models, crop-growth simulation models, or other models that require climate data with fine space and time resolutions. A challenge is dealing with RCM errors, especially in simulated precipitation, an important variable for many applications but one which some authors (e.g. Fowler et al. 2007; Themeβl et al. forthcoming) argue should not be used directly in climate impact assessments because of its dependence on RCM resolution and parameterizations.

No definitive approach to bias adjustments for RCM simulations currently exists, and this remains an active area of research. For some applications (e.g. Salathé et al. 2007), debiasing methods similar to those applied to GCM output have been used. Daily or sub-daily RCM simulations are aggregated to a monthly (or longer) time scale and change factors calculated as the difference between the mean values for future and control period simulations. The change factors can then be used to modify observed values, with stochastic methods used to reintroduce a daily time step if needed. Alternatively, a few authors have used the change factors to directly adjust the RCM-simulated daily time series (e.g. Engen-Skaugen 2007; Themeβl et al. forthcoming). Adjustments to the cdfs of the RCM-simulated variables are also a possibility, similar to the quantile mapping utilized in the BCSD approach described above for disaggregated downscaling. Another option is to feed the daily or sub-daily RCM simulations into application models without prior bias adjustment (e.g. Bell et al. 2007) and calculate change factors for the outcomes of a model suite. Yet another approach is the use of MOS (short for 'model output statistics') techniques (Glahn and Lowry 1972) that were originally developed for short-term weather forecasting. Unlike GCM control simulations, which as mentioned above are just one possible realization of the present climate, RCM perfect boundary layer simulations can be directly compared to observations with the same time stamp. This correspondence allows for the development of transfer functions between the RCM output (as predictors) and observations (the predictand). While these transfer functions can at least in part adjust for error in the RCM simulations, they cannot adjust for error in the GCM simulations of the lateral boundary conditions for the control and future climate.

Recently, Themeβl et al. (forthcoming) compared several approaches for adjusting RCM simulations for biases while at the same time further downscaling the regional scenarios to point locations. When these post-processing approaches were applied to a current climate simulation for the European alpine region obtained using the MM5 (Dudhia et al. 2005) mesoscale climate model, Themeβl et al. found that all of the post-processing methods better represented the median, variance, frequency, intensity, and extremes of daily precipitation of the current climate compared to the 'raw' RCM simulations. They argued that adjustments to the cdf (e.g. quantile mapping) are the preferred approach due to their non-parametric nature and simplicity, but acknowledge that their results are not necessarily transferable to different RCMs or other geographic regions.

### *Utilizing Available Resources*

Because of the often time consuming nature of climate scenario development, it is worthwhile to first investigate whether scenarios with an appropriate domain and spatial resolution and with a sufficient number of time slices already exist for the study area (Mearns et al. 2003).

At least five global archives of spatially interpolated GCM change factors for monthly climatological values of temperature and precipitation are currently available: TYN SC 2.0 (Mitchell et al. 2004; http://www.cru.uea.ac.uk/cru/data/hrg/); WorldClim future scenarios (not to be confused with the gridded observed fields; http://worldclim.org), the10′ Future Climate Grids (Tabor and Williams 2010; http://ccr.aos.wisc.edu/model/ipcc10min/), the Bias Corrected and Downscaled WCRP CMIP3 Climate Projections jointly developed by Santa Clara University/U.S. Bureau of Reclamation/Lawrence Livermore National Laboratory (Maurer et al. 2007, available from Climate Wizard http://www.climatewizard.org), and the International Centre for Tropical Agriculture (CIAT) disaggregated dataset (http://gisweb.ciat.cgiar.org/GCMPage/download_diss.html). The TYN SC 2.0 and WorldClim change factors are based on GCM simulations from the earlier IPCC Third Assessment rather than the more recent IPCC Fourth Assessment, and, although the 10′ Future Climate Grids utilize the IPCC Fourth Assessment models, the developers appear to have used a difference rather than a ratio when calculating the change factors for precipitation. The available time slices are relatively short for the WorldClim and the 10′ Future Climate Grids, whereas the WCRP CMIP3 and TYN SC 2.0 datasets provide change factors for the entire 21st century at a fine (1/8° × 1/8°) resolution for WCRP CMIP3 and somewhat coarser (0.5° × 0.5°) resolution for TYN SC 2.0. The most comprehensive is the recent CIAT dataset that provides change factors for seven overlapping 30-year periods at four spatial resolutions (30 arc-seconds, 2.5 arc-minutes, 5 arc-minutes, and 10 arc-minutes). All use different schemes to interpolate change factors at the coarse GCM grid point scale to a finer resolution. The datasets also vary in terms of the number of scenarios. TYN SC 2.0 includes scenarios developed from four GCMs and four SRES emissions scenarios; scenarios developed from 16 GCMs and three SRES scenarios are included in the global WCRP CMIP3 archive, whereas 24 GCMs and three emissions scenarios were used for the 10′ Future Climate Grids and the CIAT dataset. In contrast, the WorldClim future scenarios are limited to three GCMs and two SRES emissions scenarios. Regional archives of scenarios derived using change factors also exist. An example is the regional version of the WCRP CMIP3 archive for the conterminous USA available at http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections. Similar to the global archive, scenarios of monthly precipitation and average surface temperature for the 21st century at a 1/8° × 1/8° resolution were obtained from 16 GCMs in the Climate Modeling Intercomparison Project 3 (CMIP3; Meehl et al. 2007) archive and three emissions scenarios (SRES A2, A1B, B1). To develop these fine-scale scenarios, gridded temperature and precipitation observations at a 1/8° resolution were 'upscaled' to a 2° resolution, and the GCM projections for the control and future climates were regridded to this resolution. Quantile mapping was used to calculate change factors, which were then downscaled using a simple inverse distance approach and applied to the original finely gridded observed dataset.

Archives of dynamically downscaled scenarios are also available, particularly for Europe. As part of Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects (PRUDENCE; http://prudence.dmi.dk/), simulations with a 50 km resolution from eight different RCMs were archived for selected time slices (1961–1990 and 2071–2100). The follow-up ENSEMBLES project (http://www.ensembles-eu.org/) has made available multiple RCM simulations for Europe at two resolutions (25 and 50 km) for a relatively long time slice (1950–2100). Another potential source of dynamically downscaled scenarios for Europe is an archive maintained by the Model and Data Group (M&D) of the Max-Planck-Institute for Meteorology (http://www.mad.zmaw.de/). For North America, RCM simulations driven by reanalysis fields and by multiple GCMs for two time slices (1960–1990 and 2040–2070) with a 50 km resolution are just now coming online as part of North American Regional Climate Change Assessment Program (NARCCAP; http://www.narccap.ucar.edu). A limitation of these archives is that only one or two greenhouse gas emissions scenarios were included in the experimental design. Recently, the World Climate Research Program initiated the Coordinated Regional Climate Downscaling Experiment, referred to as CORDEX, to provide multi-model high resolution climate simulations for 1950–2100 for land regions worldwide (Giorgi and Jones 2010). These dynamically downscaled scenarios, as they become available, will foster climate impact research for areas that have not received as much attention in the published literature such as South America and Africa. In addition to archived resources, it may be possible to identify individual scientists, either through a review of published literature or via informal networks, who are willing to share RCM simulations that they have performed and archived locally. Whatever the source of the RCM simulations, the assessment team should budget sufficient resources for evaluation of the simulated circulation features of significance to the assessment.

Several software tools and portals are available to assist with empirical-dynamic and disaggregation downscaling. One of the best known is the Statistical DownScaling Model (SDSM) developed by Wilby et al. (2002) (see documentation available at https://co-public.lboro.ac.uk/cocwd/SDSM/SDSMManual.pdf), where multiple regression analyses relating large-scale circulation and moisture patterns to surface temperature and precipitation are used to condition the local-scale parameters, such as precipitation occurrence, of a stochastic weather generator. The system also applies stochastic methods to inflate the variance of the downscaled series. SDSM is composed of several different modules that allow users to check observations for missing data and suspect values, select large-scale predictor variables from a suite of candidate variables, perform initial evaluations of the downscaled scenarios, and display summary statistics for the scenarios. The SDSM software assumes users have considerable expertise in climatology and statistics, and Wilby et al. (2002, 157) warn against using the software 'uncritically as a ''black box'' '. Another software tool is the R package 'clim.pact' that allows users to analyze and downscale monthly and daily climate data with a variety of the statistical techniques including empirical orthogonal function analysis, canonical correlation analysis, and linear stepwise regression (Benestad et al. 2008; http://www.worldscibooks.com/environsci/6908.html). An additional user-friendly resource is the Climate Data Access and Statistical Downscaling Portal, established as one of the ENSEMBLE project aims (http://www.meteo.unican.es/ensembles/). The portal allows a user to choose predictands and predictors from a daily data base and make regional and local projections by applying one of the available downscaling methods (analogs, weather typing, regression, and neural networks). Although the regional focus and the modest number of downscaling options constrain the use of these software systems and portals, they, nevertheless, can be a valuable asset for assessment studies.

### *Moving Forward*

Climate change scenarios are the foundation of climate impact assessments, but the development of these scenarios places large demands on available resources, often to the detriment of other components of the assessment. Even disaggregation downscaling methods, often touted as being less resource intensive than dynamic or empirical-dynamic downscaling, can be time consuming. Clearly, greater collaboration and sharing of resources are needed, if only to reduce the costs of impact assessments. The fact that local/regional climate scenarios are inherently constrained to a small geographic areas limits their usefulness in other assessments. This presents a challenge. One recommendation is the development of informal regional clearinghouses for exchanging scenarios to supplement national-level programs such as ENSEMBLES and NARCCAP. Also, developers of local/regional climate scenarios need to provide a web portal or tool for others to view, use or even download scenario ensembles. Another recommendation is that assessments focusing on different aspects of the same region but with similar scenario needs coordinate scenario development efforts.

Greater sharing of downscaled climate scenarios raises an important but unanswered question of what is the 'shelf life' of a climate scenario. Modifications and improvements to GCMs are ongoing.[3] Because of the time required for development, it is not uncommon for downscaled climate scenarios to be completed around the same time as a new set of GCM simulations is released. The 'knee jerk' reaction is to assume that once a newer version of a GCM is available scenarios based on the older version are obsolete. It is plausible, though, that the uncertainty introduced by the model 'vintage' is less than that introduced by the choice of GCM or downscaling technique. The lifetime of downscaled climate scenarios and implications for the usefulness of scenario portals need to be addressed. This issue is particularly important at the present time, given the phasing out of the SRES scenarios and introduction of the representative concentration pathways along with the coordinated GCM simulations planned and underway for the IPCC Fifth Assessment (Taylor et al. 2008).

### *Concluding Remarks*

Over the course of several assessment projects, our colleagues have asked us many questions about climate scenarios and downscaling. We attempted in this two-part article to address these questions for a broader audience. Our intent was to provide non-climate scientists with the rudimentary background needed to design a scenario ensemble consis-

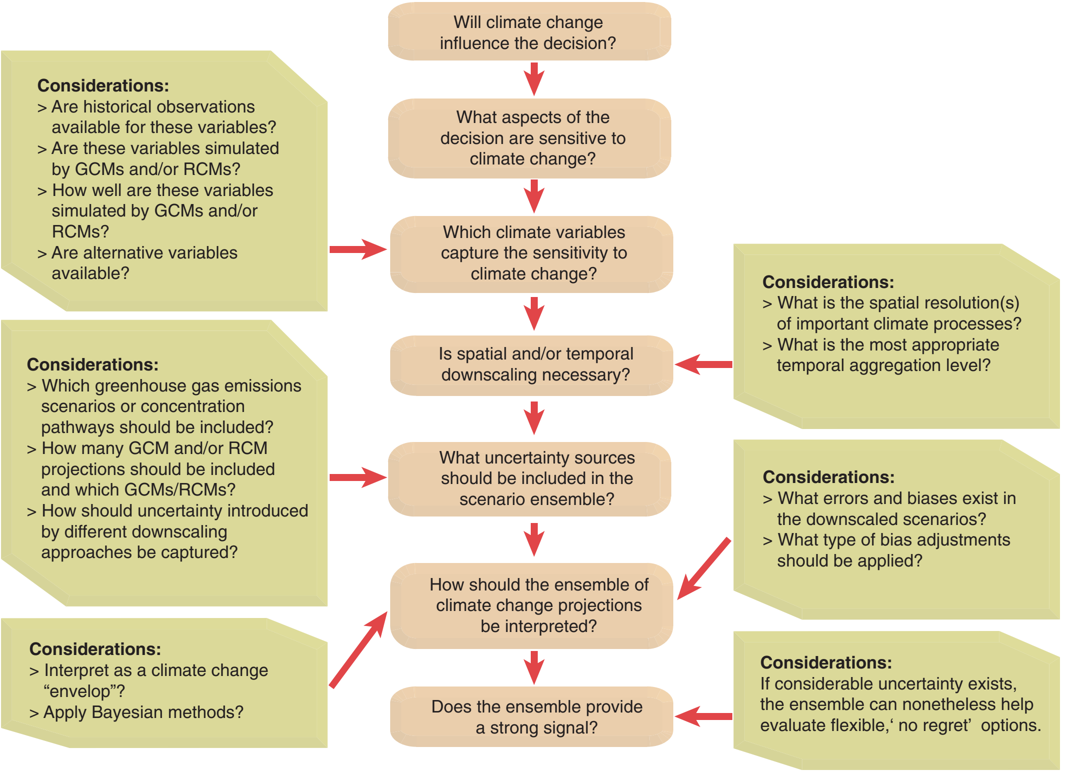


Fig. 3. An analysis pathway for the design and application of local/regional climate change scenarios.

tent with the goals of the assessment, plan for the resources and effort required to build the ensemble, and appropriately use the scenarios in the assessment analyses. We close with a schematic of an 'analysis pathway', modified from Stainforth et al. (2007), that summarizes what we consider key steps in the development and application of climate change scenarios (Figure 3). We recognize that Part I and Part II represent only a one-way communication, from suppliers to users, and encourage users to initiate conversations with suppliers, particularly on the challenges encountered when employing climate change scenarios in an impact assessment.

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[1] While some authors differentiate between 'evaluation' and 'validation', here we use the term 'evaluation' to include formal validation and more informal evaluation.

[2] As pointed out in Part I, reanalysis fields can also be used to initialize climate models. For example, RCM perfect boundary condition simulations are often driven by global reanalysis fields for a recent period.

[3] For convenience, GCM versions are often grouped by the IPCC report in which they are reviewed. It is common to refer to GCMs as Second Assessment Report- (SAR), Third Assessment Report- (TAR) and Fourth Assessment Report- (4AR) era models.

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