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

Part I: Scenario Development Using Downscaling Methods

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Abstract

The majority of climate change impact assessments focus on potential impacts at the local/regional scale. Climate change scenarios with a fine spatial resolution are essential components of these assessments. Scenarios must be designed with the goals of the assessment in mind. Often the scientists and stakeholders leading, or participating in, impact assessments are unaware of the challenging and time-consuming nature of climate scenario development. The intent of this review, presented in two parts, is to strengthen the communication between the developers and users of climate scenarios and ultimately to improve the utility of climate impact assessments. In Part I, approaches to climate downscaling are grouped into three broad categories – dynamic downscaling, empirical-dynamic downscaling and disaggregation downscaling methods – and the fundamental considerations of the different methods are highlighted and explained for non-climatologists. Part II focuses on the application of climate change scenarios.

Introduction

Scientists from many disciplines and stakeholders with a wide range of backgrounds are undertaking climate impact assessments in response to awareness of the potential impacts of climate variability and change on natural and human systems. For the most part, these assessments target a specific phenomenon, activity or system, and are constrained to limited geographic areas (Carter et al. 2007). Climate scenarios are the traditional starting point for a local/regional climate change impact assessment, particularly those employing an end-to-end assessment strategy that links the scenarios in a sequential manner to several models such as ecological/process models, economic models, decision-making models and policy frameworks (Figure 1).

Very simply, a climate scenario is a plausible representation of the future climate (Carter et al. 2001). The terms 'climate scenario' and 'climate change scenario' are frequently used interchangeably, although some authors (e.g. Mearns et al. 2001) have argued that 'climate change scenario' be reserved for the difference between a plausible future climate and a control climate (discussed below). Typically, climate scenarios are derived from projections of the climate system's response to varying greenhouse gas emissions or concentrations (Baede 2007). These projections are usually obtained from global climate models (GCMs[1]). Because GCMs have a spatial resolution of 100–300 km, 'downscaling' methods are employed to infer the high spatial and/or temporal resolution needed for most impact assessments. Climatologists carefully distinguish a climate scenario from a climate prediction, forecast or outlook. These latter terms refer to estimates of the evolution of the climate (Baede 2007), and are reserved for relatively short lead times, usually no more than a few seasons into the future (American Meteorological Society 2000).

The development of local/regional climate change scenarios can be a 'bottleneck' in the assessment process. The research team and/or stakeholder groups conducting an assessment may be unaware of the challenging and time-consuming nature of scenario development or incorrectly assume that standard protocols exist. Consequently, the time and resources needed for this important phase of the assessment are often underestimated. Climatologists and others involved in climate scenario development, ourselves included, are often approached by colleagues from multiple disciplines and or stakeholder groups asking: What software can we use to develop scenarios? Can you run a few climate model simulations for us or show us how to run the model? Would you supervise our graduate students and postdoctoral advisees to develop scenarios? Can we hire your graduate students to quickly and inexpensively develop scenarios? Can we use archived scenarios? Our colleagues are usually disappointed to hear that standard protocols and black box methods do not, and should not exist; that scenario development can be costly, time consuming and demand substantial computer resources; and that archived scenarios may not be suitable for their specific purpose.

This dilemma motivated this article. Although a number of excellent reviews of climate scenario development already exist (e.g. Benestad et al. 2008; Fowler et al. 2007; Giorgi 2006; Giorgi et al. 2001; Hanssen-Bauer et al. 2005; Hewitson and Crane 1996; Maraun et al. 2010; Mearns et al. 2001; Wilby and Wigley 1997; Xu 1999; Yarnal et al. 2001), the majority were written primarily for scientists in climatology or related fields. By contrast, this article is directed toward scientists outside of climatology, who are proposing, leading, or participating in local/regional climate change impact assessments. Our intent is to address the plea by Fowler and Wilby (2007, 1543) that information on the 'technical (and institutional) constraints' of downscaling be provided to the user community and their concern that '… somewhere along the line there has been a disconnection between the suppliers and users of regional climate change scenarios for adaptation and resource planning'. The material presented here builds on earlier guidelines such as those provided by Mearns et al. (2003) and Wilby et al. (2004).

We highlight and explain fundamental considerations and limitations for the design, development, application and interpretation of local/regional climate change scenarios.

Fig. 1. Schematic of an end-to-end assessment strategy, also referred to as a 'feed forward approach', for a local/regional climate change impact assessment. The types of models and the number of 'links' will vary for different assessments. Climate change scenarios serve as a starting point for an end-to-end assessment.

The topics and issues addressed are drawn from the literature and from our experiences developing climate change scenarios for several multidisciplinary impact assessments, including a current project concerning the potential impacts of climate change on specialized agriculture (i.e. commercial fruit production) in Michigan (USA) and central and eastern Europe (Winkler et al. 2010).

Here in Part I, we provide an overview of the methods commonly used to construct local/regional climate change scenarios and the advantages and limitations of the different downscaling approaches. We assume that most readers are unlikely to develop climate scenarios themselves, but rather will employ scenarios developed by other members of their assessment team or obtained from an archive. Hence, we focus on those elements of the scenario development that we think are most important for an informed interpretation of downscaled climate change scenarios. Part II focuses on the application of climate change scenarios in assessment studies.

Overview of Downscaling Methods

Traditionally, downscaling approaches have been classified as either 'dynamic' or 'empirical', with empirical methods alternatively referred to as 'statistical' (e.g. Christensen et al. 2007) or 'empirical-statistical' (e.g. Benestad et al. 2008) downscaling. Dynamic downscaling involves the use of numerical models, such as global models with variable spatial resolution, high-resolution global models, or, more commonly, regional climate models (RCMs) driven by coarse-scale GCM output, to simulate climate fields with a relatively fine spatial resolution, whereas empirical downscaling encompasses a large variety of statistical approaches to deriving fine-resolution climate scenarios. In this review, we instead use a three category classification, namely dynamic downscaling, empirical-dynamic downscaling and disaggregation approaches to downscaling. We believe that this classification scheme better captures the diversity of downscaling methods that previously have been broadly grouped together as empirical downscaling and better conveys the nuances between different empirical downscaling methods. By 'empirical-dynamic' downscaling, we refer to downscaling approaches that empirically relate local or regional surface climate variables to large-scale airflow and other atmospheric state variables chosen to represent relevant dynamic and physical atmospheric processes. By contrast, disaggregation downscaling methods focus on the interpolation of a climate variable from a coarse-resolution field to either a fine-resolution grid or to a specific location, or the inference of a finer (e.g. daily) time resolution from temporal (e.g. monthly, seasonal) averages or accumulations of a climate variable.

To help visualize the different downscaling approaches, a schematic of the outputs when the methods are applied to GCM simulations is shown in Figure 2.

Dynamic Downscaling

Most dynamic downscaling employs RCMs, also referred to as limited-area models. RCMs are driven by lateral boundary conditions obtained from reanalysis fields (a combination of model output and observations, see Part II for more information) or coarse-scale simulations from GCMs. 'Lateral' simply refers to the borders of the RCM domain. Lateral boundary conditions include horizontal wind, temperature, moisture and pressure fields at multiple layers in the atmosphere and surface conditions such as soil moisture or sea-surface temperatures (Giorgi 2006; Rummukainen 2010). RCMs are often described as 'nested' within the global-scale observations or GCMs that provide the lateral boundary conditions,

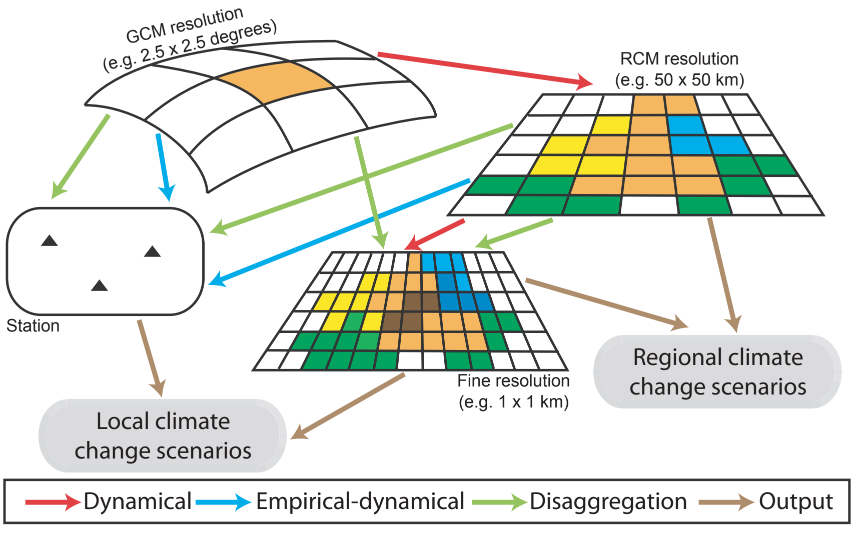

Fig. 2. Schematic of the outputs of dynamic downscaling, empirical-dynamic downscaling and disaggregation downscaling methods when applied to GCM simulations. The products from the downscaling can be gridded fields of climate variables at a range of spatial scales or climate scenarios for specific locations. Different approaches to downscaling can be applied, as shown by the colored arrows. Also, multiple downscaling steps can be used to obtain the desired spatial resolution (RCM, regional climate model; GCM, global climate model).

although for the most part only one-way nesting has been employed. As described by Giorgi (2006), in one-way nesting the large-scale fields drive the RCM but the regional-scale simulation does not feed back to the larger scale. Therefore, the primary role of the RCM is to provide regional-scale detail in response to the large-scale forcing.

ADVANTAGES AND LIMITATIONS OF DYNAMIC DOWNSCALING

Dynamic downscaling is the preferred choice for scenario development when the local/regional climate is strongly influenced by mesoscale (a few to several hundred kilometers) features, such as topography-induced circulation or sea breeze fronts, whose strength and/or location may change in a perturbed climate. In this situation, there should be 'clearly defined regional-scale (mesoscale) phenomena targeted for simulation' (CCSP 2008, 34), and it is essential to evaluate whether the RCM adequately simulates these phenomena. Also, RCMs are often a better choice when an assessment requires a large suite of physically consistent climate variables (Hanssen-Bauer et al. 2005), for example when temperature, humidity, wind and radiation fields are necessary to calculate evapotranspiration and other relevant parameters for a water budget analysis. Another advantage of RCMs is that they can potentially capture regional-scale feedback effects such as the impact of a decrease in snow cover on regional air temperature. However, dynamic downscaling is demanding in terms of time and resources. For example, the ratio of computer processing time to simulation length is currently approximately 1:100 for a RCM with 25–50 km resolution and a domain size approximating that of the USA, assuming a 16 processor computer cluster is used for the simulation. Fortunately, archives of RCM simulations are increasingly becoming available for various regions of the world. However, the typical (25–50 km) resolution of the RCM simulations in current archives may be insufficient for some specific assessments or research questions.

DESIGNING RCM SIMULATIONS

Important considerations when designing a RCM simulation include choice of RCM(s), spatial resolution and simulation length, domain size and placement of the domain boundaries, spin-up, physical parameterization, large-scale forcing and evaluation.

Choice of RCM

Numerous RCMs exist; among the most commonly used are CHRM (Lüthi et al. 1996), CRCM (Caya and Laprise 1999), HadRM3H (Buonomo et al. 2007), HIRHAM (Christensen and van Meijgaard 1992), MM5 (Anthes and Warner 1978; Grell et al. 1994), RAMS (Pielke et al. 1992), RegCM (Giorgi and Bates 1989), REMO (Jacob and Podzun 1997) and WRF (Skamarock et al. 2005). Although these models were all constructed from fundamental conservation laws and numerically solve a similar set of dynamic equations, they differ in a variety of ways including grid structure, numerical schemes, surface boundary conditions and the parameterizations required to account for subgrid-scale physical processes. Comparisons of different models suggest that no single RCM is 'best' with 'different models showing superior performance depending on the field examined' (CCSP 2008, 35). Furthermore, recent model comparisons found that the uncertainty introduced by the choice of RCM can be as large as that introduced by the choice of GCM used to drive the RCM simulation (e.g. Déqué et al. 2007). As pointed out by Giorgi (2006, 110), this indicates that 'internal [RCM] physics can be dominant over the lateral boundary forcing for some climate variables'.

Spatial resolution and simulation length

Typical horizontal resolutions of RCMs are on the order of 25–50 km (Rummukainen 2010), although simulations with resolutions of only a few kilometers are possible using multiple-nested RCMs (e.g. Hay et al. 2006; Liang et al. 2001). One constraint is that the RCM performance deteriorates if the resolution of the RCM is more than 8–12 times finer than the resolution of the driving lateral boundary conditions whether from reanalysis fields, GCMs, or a coarser-scale RCM (CCSP 2008; Giorgi 2006). RCM simulations typically contain 18–40 vertical layers from the surface of the earth to the lower to mid stratosphere (15–25 km).

Spatial resolution and simulation length are intrinsically linked. As the spatial resolution increases, the time step of a model simulation is shorter and the required computational resources increase (Giorgi and Mearns 1999). Thus, while the length of GCM simulations is typically a century or longer, RCM simulations are usually only a few years or several decades in length (e.g. Christensen et al. 2002; Leung et al. 2004; Plummer et al. 2006). A common practice is to perform RCM simulations for two or three relatively short (10–30 years) 'time slices' that are separated by several decades (e.g. Laprise 2008; Leung et al. 2004). The implicit assumption is that conditions for neighboring time periods can be interpolated from the time slices. This assumption is questionable as considerable interdecadal variability is evident in the GCM simulations used to drive RCMs (e.g. Guentchev et al. 2009).

Model domain, spin-up and parameterization

Typically, the model domain for a RCM covers a portion of a continent (CCSP 2008), but the domain size depends on the goals of the assessment. The domain should be sufficiently large to capture the relevant mesoscale circulations (Mearns et al. 2003), but too large of a domain may cause the larger-scale circulation to drift away from that of the driving GCM (Jones et al. 1995). Also, computational costs increase with larger domain sizes (Leduc and Laprise 2009). Domain boundaries should be placed so that the area for which the scenarios are required is located well into the interior of the domain (Mearns et al. 2003), and so that the boundaries do not intersect areas of sharp gradients of topography or surface conditions (CCSP 2008; Giorgi 2006; Giorgi and Mearns 1999).

Model simulations also require time for the large-scale forcings to be felt, or what is known as 'spin-up' (American Meteorological Society 2000). Definitive guidelines for the spin-up period do not exist. In general, land-surface processes (e.g. soil temperature, soil moisture) require longer spin-up periods than atmospheric fields (CCSP 2008; Laprise 2008).

Another important consideration is the choice of model parameterizations. Some processes either occur at scales finer than the RCM resolution or are too complex to be realistically represented within the model (Laprise 2008). These processes are instead 'parameterized', or in other words they are represented in terms of resolved variables and/or simplified parameters. For instance, parameterizations are needed to represent the formation of convective clouds in a RCM with a 25–50 km resolution. Even when a multiple-nested RCM simulation is used to obtain a finer (e.g. 7–10 km) grid size that approximates the resolution of convective clouds, parameterization is still needed to capture microphysical processes. A variety of parameterization schemes exist, and different schemes may perform better for some regions than others (CCSP 2008). A limitation is that the parameterizations are often derived statistically for the current climate and may not be appropriate for future climates (Christensen et al. 2007). As pointed out by Maraun et al. (2010, 24), non-stationarity of RCM parameterizations is a particular concern for RCMs developed for specific regions, and 'there is greater confidence in the parameterization schemes in future climates' if a RCM performs well in multiple regions with diverse climates.

'Current' and 'control' climate simulations

Before simulations can be performed for a future period, it is essential that RCM simulations be conducted for a recent climate period. In our experience, non-climatologists are often not aware that this is a multiple-step process (Figure 3). Initially, in what is often referred to as the 'perfect boundary condition' simulation (Giorgi 2006), the RCM is driven either by observations or reanalysis fields for a recent period (e.g. 1991–2000), referred to in Figure 2 as the 'current' climate. The RCM output is then compared to relevant observed series or fields to identify systematic errors of the model. Special attention should be paid to whether the RCM adequately simulates the mesoscale features and processes that influence the climate variables of interest for the assessment. At this juncture changes to the RCM, such as modifications to the parameterizations or adjustments of the model domain, may be warranted.

Because RCMs 'inherit' the errors of the driving GCM (Giorgi and Mearns 1999), it is essential to also perform a 'control' run (Mearns et al. 2003). For this run, the RCM is driven by GCM-simulated fields for the same time period used for the perfect boundary condition simulation; differences in the climate statistics between the two simulations are assumed to result from error in the driving GCM fields (e.g. Pan et al. 2001). RCM simulations for future periods should always be compared to the control simulation rather than the perfect boundary condition simulation, as the control run captures the error from both the GCM and RCM whereas the perfect boundary condition simulation captures only the RCM error.

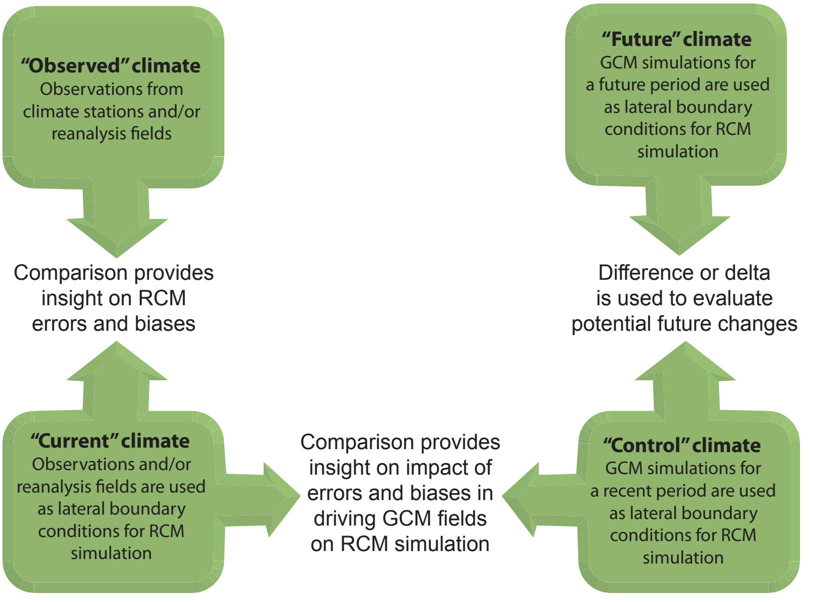

Fig. 3. Definition of 'observed', 'current', 'control' and 'future' climates for RCM simulations and the types of comparisons that must be performed. Note that it is not appropriate to compare future climate projections directly to observations (RCM, regional climate model; GCM, global climate model).

Empirical-Dynamic Downscaling

Although the term 'empirical-dynamic', or alternatively 'statistical-dynamic', has been used before (e.g. Najac et al. 2011), this terminology traditionally has referred to those downscaling methods that used circulation/airflow *patterns* to estimate local or regional surface climate variables. Here, we use the term more broadly to refer to all empirical methods that use patterns or point values of circulation and/or free atmosphere variables that were selected to represent important atmospheric processes. Free atmosphere variables, such as 500 hPa geopotential height, are minimally influenced by surface processes and friction. By contrast, surface climate variables (e.g. surface temperature) are strongly influenced by boundary fluxes that may not be adequately parameterized in a GCM.

Empirical-dynamic downscaling is frequently used when climate scenarios for individual locations are required and/or the climate variables needed for the assessment are poorly simulated by RCMs. Also, because these methods generally are not as resource intensive as dynamic downscaling, it is somewhat easier to build a larger ensemble (i.e. suite) of scenarios and include multiple future time slices. For empirical-dynamic downscaling it is assumed that (i) GCMs better simulate circulation and free atmosphere variables compared to surface climate variables; (ii) circulation and free atmosphere variables are representative of a larger spatial domain compared to surface climate variables; (iii) empirical relationships can implicitly capture the effects of local topography, geography and boundary conditions on the surface variables; and (iv) the relationships observed for the current climate are stationary in time (Winkler et al. 1997). Downscaled scenarios are typically developed for each climate variable (e.g. temperature, precipitation) separately, which may result in less consistency between variables as compared to scenarios obtained from dynamic downscaling.

ANALOGS

The simplest empirical-dynamic downscaling approach is analogs, also referred to as weather typing schemes. Observations of local climate variables are related to the occurrence of different daily weather circulation patterns. The weather types can be identified either manually or objectively using a variety of statistical techniques. Changes in the frequency of the weather types in a perturbed climate are then used to project changes in the local climate variables (e.g. Matulla et al. 2008; Zorita and von Storch 1999). Important assumptions are that the frequency, timing and persistence, but not the character, of the weather patterns will change in the future (Hewitson and Crane 2006); the relationship between the weather types and local climate remains stationary; and future values of the climate variable will be within the range of observed values (Hanssen-Bauer et al. 2005).

EMPIRICAL TRANSFER FUNCTIONS

A more complex approach to empirical-dynamic downscaling is the development of empirical transfer functions that relate large-scale values or patterns of one or more predictor variables to local values of the predictand. Most transfer functions are developed using what in short-range weather forecasting is referred to as the 'perfect prog' approach (Glahn 1985) in that empirical relationships are first developed from observations of both the predictor variables and the predictand(s) and then applied to output from weather and/or climate model simulations.[2] Key considerations when developing empirical transfer functions are temporal resolution and stratification, choice of predictand, potential predictors, definition of calibration and validation periods, and statistical method used to define the function.

Temporal resolution and stratification

Historically, the majority of empirical transfer functions related monthly, seasonal, or annual values of the predictors to values of the predictands with the same temporal resolution. This emphasis on a coarse temporal resolution, rather than daily or sub-daily values, is in part an artifact of the temporal resolution of popular data archives. A major source of GCM simulations for the user community is the IPCC Data Distribution Centre (http://www.ipcc-data.org/), and until recently only monthly averages were available for many of the variables often used as predictors and/or predictands. Although daily and sub-daily values could be obtained by contacting modeling centers directly, this required considerable effort to transfer large data volumes and preprocess the variety of data formats, some of which are unique to the atmospheric sciences. Also contributing to the focus on coarse temporal resolution is the generally higher explained variances obtained for transfer functions with monthly rather than daily resolutions (Yarnal et al. 2001). Empirical-dynamic downscaling efforts are now moving to a daily or finer time step (e.g. Winkler et al. forthcoming), as this temporal resolution is often needed to portray the weather–climate dependency of a phenomenon or system.

Temporal stratification also needs to be considered, as it is possible to develop a single empirical transfer function or separate functions by month or season. The former approach minimizes the risk of unanticipated changes in the timing of seasons in a future climate (Winkler et al. 1997; Yarnal et al. 2001) or that conventional seasonal definitions may not reflect 'natural' seasons (Wilby et al. 2004), but ignores seasonal variations in the processes responsible for the predictand (Wetterhall et al. 2005).

Predictand(s)

The two most widely used predictands are surface[3] temperature and precipitation, but empirical transfer functions can be developed for a range of predictands including variables not directly available from GCMs such as phenological stages (e.g. Matulla et al. 2003). One factor to consider when choosing the predictand is whether a simpler variable that is hopefully easier to simulate can be substituted for a more complex variable that is challenging to simulate. For example, the explained variance of transfer functions simulating daily precipitation is notoriously low (e.g. Buishand et al. 2004), but for some applications, such as estimating the potential impacts of climate change on outdoor recreation, it may be possible to substitute the occurrence of a wet day (a nominal/ordinal variable) for precipitation amount (an interval/ratio variable).

Predictor variables

The choice of predictor variables is a crucial consideration. As stated by Hanssen-Bauer et al. (2005, 264), 'unwise choices of predictors … may lead to dubious results'. The variables selected as large-scale predictors should be well simulated by climate models, capture the climate change 'signal', account for a large portion of the variability in the predictand, and have a stable relationship with the predictand (Giorgi et al. 2001; Wilby et al. 2004). Even with these guidelines in mind, numerous 'user decisions' (Winkler et al. 1997) surround the choice of predictor variables.

One issue is whether to express the predictor variables in terms of point values obtained either from the nearest GCM grid point or interpolated from surrounding grid points or to express them as large-scale atmospheric flow patterns. The latter class of predictors is usually obtained by applying principal component[4] (e.g. Benestad 2001; Kaas and Frich 1995), fuzzy rule (Bardossy et al. 1995; Panagoulia et al. 2006), or self-organizing map (Hewitson and Crane 2006) analyses to circulation fields such as sea-level pressure, although simple circulation indices (e.g. Conway and Jones 1998; Katz and Parlange 1993) or gradients (e.g. Wetterhall et al. 2005) can also be used. An argument for using circulation fields as predictors is that GCMs are thought to more accurately portray the large-scale field of a variable rather than the values at one or a few grid points. A disadvantage is that the domain over which the circulation fields are identified may impact the downscaled scenarios (Benestad 2001; Goodess and Palutikof 1998). The influence of the domain size appears to vary with season and location with the largest effect on the downscaled scenarios when circulation is weak (Benestad 2001), such as during the warm season or at low latitude locations. When selecting the domain size, scenario developers must carefully consider the varying scales of the circulation features important for their location, and recognize that some experimentation is needed to indentify, as suggested by Benestad (2001, 1665) 'the largest size in the range that roughly gives the same answer'.

Murphy (2000) was one of the first authors to raise the issue of whether a climate change signal is present in the predictor variables. He found that, when downscaling monthly precipitation, transfer functions based only on circulation variables performed as well for the present climate as those that also included humidity. But when the transfer functions were applied to GCM simulations for future periods, the projected precipitation was substantially different. This occurred because the projected changes in the circulation predictors were much smaller than the changes in the humidity variables. Humidity in this case is a climate change 'signal bearing predictor' (Hanssen-Bauer et al. 2005, 258).

Careful selection of predictor variables can also help minimize concerns about the stationarity of the relationship between the predictors and predictand(s) (Hewitson and Crane 2006). Predictors should be chosen to mimic as close as possible important, time-invariant physical processes. For example, the thickness (distance) between the 1000- and 500-hPa-pressure surfaces is often used as a predictor variable when downscaling temperature, as the well-known hypsometric relationship states that the mean temperature of a layer is proportional to the layer thickness. Similarly, vorticity (or spin) is frequently included in downscaling functions for precipitation as vorticity changes are physically related to rising motion.

When the predictor variables have a strong annual cycle, the relationship between the predictors and predictands will be inflated. In this situation, the transfer functions are in essence simulating the annual cycle rather than the day-to-day or month-to-month (depending on the temporal resolution) deviations of the predictand. Some, but not all, authors have removed the annual cycle before fitting the transfer function (e.g. Huth and Kysely 2000; Menzel and Burger 2002; Winkler et al. forthcoming).

Calibration, validation and control periods

The time period used for the development of empirical transfer functions is referred to as the calibration period or, alternatively, the development period. The transfer functions are then evaluated against observational data outside of the calibration period, or what is often referred to as the validation period. The choice of calibration and validation periods can impact the stationarity of the functions. If trends are apparent in the calibration period, the transfer functions are unlikely to be stationary with time. Also, greater confidence can be placed in the time invariance of the functions if the calibration and validation periods are well separated in time (Wilby et al. 2004). As for dynamic downscaling, a control period is an essential component of the scenario development. The empirical transfer functions are applied to GCM-simulated values of the predictor variables for a similar time period as the calibration and/or validation periods. Differences in the climate statistics represent uncertainty introduced by error and bias in the GCM fields. Alternatively, the empirical-dynamical transfer functions can be applied to output from RCMs driven by a GCM (e.g. Themeβl et al. forthcoming). In this case, differences in the climate statistics represent the combined uncertainty introduced by the GCM and RCM.

Methods for defining transfer functions

Numerous statistical methods are used to develop transfer functions including, but not limited to, multiple or stepwise regression (e.g. Easterling 1999; Reichert et al. 1999) and other regression techniques such as multi-way partial least squares regression (Bergant and Kaijfež-Bogataj 2005), tree-structured regression (Li and Sailor 2000) and logistic regression (e.g. Beckmann and Buishand 2002); generalized linear models (e.g. Fealy and Sweeney 2007); canonical correlation analysis (e.g. Busuioc et al. 2001; Karl et al. 1990; von Storch et al. 1993); artificial neural networks (e.g. Haylock et al. 2006; Tolika et al. 2007); singular value decomposition (Huth 1999; Widmann et al. 2003); hidden Markov models (Cheng and Tan 2008) and support vector machine algorithms (Tripathi et al. 2006).

Comparisons exist of many of the commonly used methods to develop transfer functions (e.g. Khan et al. 2006; Schoof and Pryor 2001), but any synthesis is complicated by the different locations, predictors and predictands of these studies. In a review of downscaling methods used in hydrology, Fowler et al. (2007) concluded that choice of statistical method generally introduces less uncertainty than the choice of GCM to which the transfer functions are applied. In addition, they found that the choice of predictor variables appears to be as important as the choice of statistical method. Other authors also concluded that, at least for linear methods, different techniques perform similarly as long as the 'information content in the predictors is similar' (Hanssen-Bauer et al. 2005, 260).

Limitations of empirical-dynamic downscaling
One concern of empirical-dynamic downscaling is that, because the explained variance is always <100%, the variance of the predictand is underpredicted and consequently extremes are underestimated (Easterling 1999; Fowler et al. 2007; Karl et al. 1990). Various methods for adjusting or 'inflating' the variance, such as adding white noise to the simulated time series, have been attempted, but all make assumptions regarding variability in a future climate that are not necessarily defendable. Also, even though the transfer functions may validate well for the present climate, they are not necessarily valid for a perturbed climate (Wilby et al. 2004). One reason is that all empirical-dynamic downscaling methods assume that anticipated future changes lie within the range of the natural variability of the predictand. Large changes in the future invalidate this assumption. Yet another limitation is that with a few exceptions (e.g. Karl et al. 1990) transfer functions are developed for each predictand separately. Also, transfer functions must be developed individually for each location, as it is the local conditions that are implicitly captured by the transfer functions.

Disaggregation Methods

In contrast to empirical-dynamic downscaling, disaggregation downscaling methods start with coarse-scale fields of a climate variable and infer higher spatial and/or temporal resolution for that variable. In general, disaggregation methods require fewer resources than either dynamic or empirical-dynamic downscaling. This, along with the availability of archived scenarios, has contributed to the popularity of disaggregation methods for climate impact assessments.

SPATIAL DISAGGREGATION

One approach to spatial disaggregation is to employ statistical methods (often general linear models such as regression) to relate the coarse-scale values (i.e. the predictors) of a variable to the value at an individual location (e.g. Salathé et al. 2007). Using surface temperature as an example, one might average temperature observations over a region approximating the size of a GCM grid cell and then statistically relate the spatial average to the temperature at an observing station. The derived relationship can then be applied to coarse-scale GCM-projected fields of temperature for control and future periods to obtain station-specific projections. This approach is most often used when the focus is on annual, seasonal, or monthly means and accumulations rather than on daily values. Similar to empirical-dynamic downscaling, it is assumed that the effects of local topography, geography and boundary conditions are implicitly captured in the statistical relationship. Evaluation of the GCM simulations of the coarse-scale values is particularly important for this downscaling approach, as substantial errors have been documented in GCM projections of surface temperature and precipitation (e.g. Palutikof et al. 1997). In some cases, in order to account for biases in GCM simulations, the statistical relationships are developed between the coarse-scale fields and the parameters of the probability density function of the local climate variable, and then a random number generator is used to obtain a daily time series for the location (e.g. Notaro et al. forthcoming). A related approach is to include, besides the coarse-scale values of the predictand, additional predictors such as free atmosphere variables to refine the relationship between the large-scale predictor and the local-scale predictand (e.g. Schmidli et al. 2006; Tolika et al. 2007). This latter approach is similar to empirical-dynamic downscaling, but we classify it as a disaggregation downscaling method because the coarse-scale value of the predictand usually is the largest contributor to the explained variance (e.g. Themeβl et al. forthcoming).

A more common approach to spatial disaggregation is to spatially interpolate coarse-scale GCM output to a finer resolution grid. For surface temperature and other variables that are not zero bounded, a spatial interpolation scheme is often applied to the differences at the GCM grid points between the simulated values for a future climate and those for the control climate, to account (at least partially) for biases in the GCM simulation. In the case of precipitation, which is a zero-bounded variable, the ratio of the projected future change compared to the modeled value for the control climate at the individual GCM grid points is used. Common spatial resolutions of the resulting downscaled climate variables are $0.5° \times 0.5°$ (e.g. Mitchell et al. 2004), $0.1° \times 0.1°$ (e.g. Notaro et al. forthcoming) and $10' \times 10'$ (e.g. Tabor and Williams 2010). The spatial interpolation schemes vary from those based on distance only (e.g. Tabor and Williams 2010) to more complex schemes such as thin plate spline interpolation (e.g. WorldClim future projections; http://www.worldclim.org/futdown.htm) that uses elevation (obtained from a digital elevation model) in addition to latitude and longitude to capture the influence of fine-scale topography on the temperature and precipitation fields. As pointed out by Daly (2006, 707), a major consideration when using these fine-resolution scenarios is that interpolated high-resolution datasets 'raise important questions about the tendency to equate resolution with realism'.

TEMPORAL DISAGGREGATION

Because of their smaller size, datasets of monthly aggregated projections from GCMs are much easier to manage than the voluminous data sets of daily or sub-daily projections. Resource constraints (storage space, computer expertise, time) often prohibit the use of the daily or sub-daily GCM projections, even for impact assessments that require fine time steps. In these situations, stochastic weather generators are often employed to disaggregate monthly precipitation totals or temperature means into daily time series (Wilby et al. 2004) that are consistent with the GCM-projected changes (e.g. Dubrovsky et al. 2004; Katz 1996; Qian et al. 2008; Semenov 2008; Semenov and Barrow 1997; Wilks 1992). Typically, weather generators use Markov processes to simulate wet/dry days and then estimate wet day amounts, temperature and solar radiation conditional on precipitation occurrence (Wilby et al. 2004; Wilks 2010). They are usually adapted to climate change studies by modifying the weather generator parameters, primarily the monthly mean and standard deviation, by GCM-projected changes in these parameters, although alternative methods such as using GCM-simulated daily circulation variables to estimate future probabilities of precipitation occurrence have been proposed (Wilks 2010). The majority of applications have used weather generators designed to provide synthetic series of climate variables at a single site, although several multistation variants have been proposed to capture the spatial coherence of the climate variables (see Maraun et al. 2010 for a review). A limitation of weather generators is that the simulated interannual variability of the synthetic series is smaller than the observed variability (what is known as the 'overdispersion' phenomenon) (Qian et al. 2008). Also, future changes in the variable, such as precipitation occurrence, used to condition a

Table 1. Checklist of considerations for evaluating alternative downscaling options (see text for a description of the downscaling methods).

Consideration	Why important?	Downscaling method: Regional climate models (dynamic downscaling)	Analogs (empirical-dynamic downscaling)	Perfect Prog transfer functions with circulation and/or free atmosphere variables as predictors (empirical-dynamic downscaling)	Transfer functions relating large-scale values of a climate variable to local values of the variable (disaggregation downscaling)	Spatial interpolation (disaggregation downscaling)	Weather generators (disaggregation downscaling)
Spatial resolution	For some impact assessments, it is essential to capture the influence of local site characteristics on climate, whereas for other applications regional-scale variations in climate are sufficient	Not appropriate for point (station) scale; multiple-nested RCMs can be used to obtain scenarios on a fine (1–10 km) mesh grid; single nested RCMs are usually used to obtain scenarios on a 25–50 km grid	Can be used for a range of spatial scales, but most often used to obtain scenarios at a point (station) scale	Can be used for a range of spatial scales, but most often used to obtain scenarios at the point (station) scale	Can be used for a range of spatial scales. Frequently used to obtain scenarios for a station or for grid points (the latter requires that observed gridded fields of the climate variable are available)	Not appropriate for point (station) scale; frequently used to obtain scenarios at a fine (1–10 km) resolution grid	Point (station) scale

Table 1. Continued.

		Downscaling method					
Consideration	**Why important?**	**Regional climate models (dynamic downscaling)**	**Analogs (empirical-dynamic downscaling)**	**Perfect Prog transfer functions with circulation and/or free atmosphere variables as predictors (empirical-dynamic downscaling)**	**Transfer functions relating large-scale values of a climate variable to local values of the variable (disaggregation downscaling)**	**Spatial interpolation (disaggregation downscaling)**	**Weather generators (disaggregation downscaling)**
Temporal resolution	Scenarios often serve as input to ecological, process, or activity models. The time step used in these models often determines the temporal resolution required for the climate scenarios	Sub-daily	Typically daily	Scenarios can be generated at sub-daily, daily, monthly and longer temporal aggregations	Most appropriate for monthly or longer temporal aggregations	Most appropriate for monthly or longer temporal aggregations	Daily (some attempts have been made to develop weather generators for sub-daily time steps)

Table 1. Continued.

Consideration	Why important?	Downscaling method: Regional climate models (dynamic downscaling)	Analogs (empirical-dynamic downscaling)	Perfect Prog transfer functions with circulation and/or free atmosphere variables as predictors (empirical-dynamic downscaling)	Transfer functions relating large-scale values of a climate variable to local values of the variable (disaggregation downscaling)	Spatial interpolation (disaggregation downscaling)	Weather generators (disaggregation downscaling)
Physical consistency of downscaled climate variables	Physical consistency is important when more than one climate variable is required for an assessment	Physically consistent	Physically consistent	Typically downscaled scenarios are developed separately for each climate variable; use of the same predictor variables can impart some physical consistency	Downscaled scenarios are developed separately for each climate variable; weak physical consistency	Typically climate variables are interpolated separately; weak physical consistency	Not physically consistent if random sequences are generated for each variable separately; physical consistency is increased if time series of climate variables are generated conditional on a specified climate variable such as precipitation occurrence

Table 1. Continued.

Consideration	Why important?	Downscaling method					
		Regional climate models (dynamic downscaling)	**Analogs (empirical-dynamic downscaling)**	**Perfect Prog transfer functions with circulation and/or free atmosphere variables as predictors (empirical-dynamic downscaling)**	**Transfer functions relating large-scale values of a climate variable to local values of the variable (disaggregation downscaling)**	**Spatial interpolation (disaggregation downscaling)**	**Weather generators (disaggregation downscaling)**
Spatial coherence/ autocorrelation	Important if, for a particular time stamp (day, month, year), a climate variable(s) is needed for multiple locations	RCMs appear to overestimate spatial autocorrelation	Spatially coherent in as much as similar circulation patterns are associated with similar weather conditions at nearby locations	Spatially coherent in as much as the predictor variables are similar for nearby locations	Reasonably spatially coherent as the large-scale average value of the climate variable (i.e. the predictor) is similar for neighboring locations	How well the spatial autocorrelation is reproduced depends on the degree of topographic and land cover variability; interpolation schemes that do not explicitly incorporate topography and/or land cover overestimate the degree of spatial autocorrelation	Not spatially coherent as most often weather generators are applied separately for individual locations; multistation weather generators attempt to simulate spatial autocorrelation, although these are not yet widely used

Table 1. Continued.

Consideration	Why important?	Downscaling method: Regional climate models (dynamic downscaling)	Analogs (empirical-dynamic downscaling)	Perfect Prog transfer functions with circulation and/or free atmosphere variables as predictors (empirical-dynamic downscaling)	Transfer functions relating large-scale values of a climate variable to local values of the variable (disaggregation downscaling)	Spatial interpolation (disaggregation downscaling)	Weather generators (disaggregation downscaling)
Stationarity	Almost all downscaling methods assume that functions developed for current climate are transferable to a future climate	Parameterizations used in RCMs may not be appropriate for a future climate; often best to select RCMs that perform well for a wide range of current climates	The relationship between weather types and local climate may change if, for example, the water holding capacity of the atmosphere is greater in the future than currently	Predictor variables should be chosen to reflect time-invariant physical processes; more confidence if transfer functions perform well for historical periods separated in time and/or with widely differing climate conditions	Future changes in mesoscale circulation can change the relationship between the large-scale average value of a climate variable and local values	Future changes in mesoscale circulation can impact the spatial pattern of a climate variable	Future changes in the variable(s) used to condition the weather generator can have unanticipated effects on the other variables being simulated

Table 1. Continued.

Consideration	Why important?	Downscaling method: Regional climate models (dynamic downscaling)	Analogs (empirical-dynamic downscaling)	Perfect Prog transfer functions with circulation and/or free atmosphere variables as predictors (empirical-dynamic downscaling)	Transfer functions relating large-scale values of a climate variable to local values of the variable (disaggregation downscaling)	Spatial interpolation (disaggregation downscaling)	Weather generators (disaggregation downscaling)
Sensitivity to error in the input data/ predictors	'Garbage in – garbage out'	RCM simulations inherit error from the GCMs used for the lateral boundary conditions; it is important to evaluate whether a GCM adequately simulates the large-scale climate for the region of the RCM domain	Among the downscaling techniques, error in the input data is somewhat less of a concern for analog methods as they are based on circulation patterns which are generally better simulated by GCMs compared to gridpoint values	This method employs large-scale circulation and free atmosphere variables as predictors which are generally better simulated by GCMs compared to surface climate variables; compared to other downscaling methods (such as RCMs), also, one can more easily adjust the predictor variables for error observed between a GCM control run and observations	Error in the predictor variables is a concern, and debiasing (see Part II) is likely necessary, as the predictor(s) is the large-scale value of surface climate variables which are generally not simulated as well as free atmosphere variables; error can also be introduced by the procedures used to calculate the 'observed' large-scale spatial average of the surface climate variables that is used for the transfer function development	This method is sensitive to error in the large-scale GCM-simulated surface climate variables; because of this, spatial interpolation is commonly applied to the difference between the projected future value and the value for the control period	Weather generator parameters are usually adjusted by the difference between the mean and/or variance for a future period and the values for a control period, which in part accounts for error in the GCM simulations

Table 1. Continued.

Consideration	Why important?	Downscaling method: Regional climate models (dynamic downscaling)	Analogs (empirical-dynamic downscaling)	Perfect Prog transfer functions with circulation and/or free atmosphere variables as predictors (empirical-dynamic downscaling)	Transfer functions relating large-scale values of a climate variable to local values of the variable (disaggregation downscaling)	Spatial interpolation (disaggregation downscaling)	Weather generators (disaggregation downscaling)
Additional assumptions and limitations	In order to appropriately interpret climate scenarios, users must be aware of assumptions and inherent limitations of the downscaling method	If a RCM cannot adequately simulate the mesoscale circulation features important to a region, the RCM may provide little value over empirical-dynamic or disaggregation downscaling applied to GCM simulations	It is essential to compare the character of projected future circulation patterns to current patterns as a major assumption is that the frequency, but not the character, of atmospheric circulation changes in the future	Variance of the predictand is underestimated, especially for precipitation; adding a random noise term or inflating the variance may be warranted	Error in the GCM-simulated large-scale values of the climate variable can have a large impact on the downscaled scenarios; adjustments for error in the predictor may be necessary	Interpolation from a coarse to finer grid requires assumptions regarding the shape and continuity of the underlying variable space that may not be realistic	Simulated interannual variability is smaller than observed (referred to as 'overdispersion')

Table 1. Continued.

		Downscaling method					
Consideration	**Why important?**	**Regional climate models (dynamic downscaling)**	**Analogs (empirical-dynamic downscaling)**	**Perfect Prog transfer functions with circulation and/or free atmosphere variables as predictors (empirical-dynamic downscaling)**	**Transfer functions relating large-scale values of a climate variable to local values of the variable (disaggregation downscaling)**	**Spatial interpolation (disaggregation downscaling)**	**Weather generators (disaggregation downscaling)**
Resources required	Downscaling methods differ widely in terms of their data, computational and storage needs and the effort required for evaluation	Resource intensive	Moderately resource intensive	Moderately resource intensive	Relatively modest in terms of resources needed	Relatively modest in terms of resources needed	Relatively modest in terms of resources needed

RCM, regional climate model; GCM, global climate model.

weather generator can have unanticipated (and unrealistic) effects on the other variables (Wilby et al. 2002; Wilks 1992).

Hybrid Downscaling Approaches

A recent development in climate scenario development is the use of more than one downscaling approach, or what we refer to here as 'hybrid' downscaling, to obtain climate scenarios with the resolution and characteristics required for an assessment. Most commonly, empirical-dynamical or disaggregation methods are applied to the outputs from RCMs to obtain scenarios at a local scale and/or to adjust for errors in the RCM simulations (e.g. Themeβl et al. forthcoming). A more elaborate example is provided by Früh et al. (2011) who employed an urban climate model coupled with temporal interpolation to obtain urban-scale scenarios with a short time step from previously developed regional-scale climate scenarios. Hybrid downscaling can potentially maximize the advantages and minimize the limitations of different downscaling approaches.

Choosing a Downscaling Method – A Difficult Decision

The choice of downscaling methodology can have a large influence on the outcomes of an assessment. Scientists and stakeholders involved in a climate impact assessment must clearly outline at the beginning the desirable (and minimal) requirements for climate change scenarios. For example, monthly or seasonal means and totals may be sufficient for some assessments, whereas for others daily or sub-daily values of climate parameters are required. Or in some cases, a large suite of climate variables is necessary, but for others one or two variables, often temperature and precipitation, may be sufficient. To further assist assessment teams in evaluating different downscaling options, we provide in Table 1 a checklist of important considerations, roughly based on the end-user needs identified by Maraun et al. (2010) for precipitation scenarios, and relate these to the strengths and limitations of the downscaling methods described above. When using the checklist, assessment teams must keep in mind that currently it is not possible to argue for one approach being universally 'better' than another (Christensen et al. 2007). Rather, the different approaches should be viewed as complementary, and assessment teams should consider employing multiple downscaling approaches as appropriate. Also, an assessment team is responsible for interpreting the climate change scenarios in light of the assumptions and limitations of the scenarios. In Part II, a number of issues that frequently arise when applying scenarios in climate change impact assessments are addressed.

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Notes

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[1] Although historically 'GCM' is the abbreviation for 'general circulation model', more recently the meaning of this acronym has broadened to also include complex models that couple the atmosphere, ocean and land-surface components of the earth-atmosphere system, or what are generally known as 'global climate models'. The broader meaning is used here.

[2] Another frequently used approach in statistical weather forecasting is 'Model Output Statistics' (MOS), where transfer functions are developed using model simulated, rather than observed, values of the predictor variables. The advantage of MOS over perfect prog is that MOS inherently accounts for model error. Because GCM simulations are only one possible realization of the climate, it is not possible to relate a GCM-simulated value of a predictor variable for a particular time to the observed value for the same time. Consequently, MOS approaches cannot be directly applied to GCM simulations, and perfect prog methods are used instead. However, RCM simulations for the current climate (i.e. perfect boundary condition simulations) can be related to observed values of the predictand for a particular time stamp. Recently, MOS has been used to downscale RCM simulations to finer resolution (e.g. location of a climate observing station) and to adjust for error in the RCM simulations.

[3] Observations of maximum and minimum temperature are taken at 2 m above the surface except in the USA where they are reported at approximately 1.5 m. Sometimes these measurements are referred to as 'near surface' measurements, although more commonly they are simply referred to as 'surface' measurements.

[4] In atmospheric science, principal components are often referred to as empirical orthogonal functions (Wilks 2006).

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