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Statistical Downscaling in Climatology

Abstract

Downscaling is a term that has been used to describe the range of methods that are used to infer regional- or local-scale climate information from coarsely resolved climate models. The use of statistical methods for this purpose is rooted in both operational weather forecasting and synoptic climatology and has become a widely applied method for development of regional climate change scenarios. This article provides an overview of statistical downscaling with a focus on assumptions, common predictors and predictands, and methodological approaches ranging from interpolation and scaling to regression-based methods, weather pattern-based techniques, and stochastic weather generators. Suggestions are made for improved assessment of the fundamental downscaling assumptions as well as reduction of uncertainty associated with application of downscaled climate information across models and greenhouse gas emissions scenarios.

1. Introduction

Atmosphere-ocean general circulation models (AOGCMs) are the primary tools used to assess climate system behavior in response to changes in natural or anthropogenic forcing. With resolution that rarely exceeds 1° × 1°, AOGCMs are unable to explicitly resolve small-scale processes such as convection or the topography of the underlying land surface, resulting in a lack of fidelity at small spatial scales. Downscaling is a term that has been used to describe a range of methods that are used to infer regional- or local-scale climate information from coarsely resolved AOGCMs. When AOGCMs are used with different forcings (e.g., sea-surface temperatures, land surface characteristics, or projected changes in greenhouse gases) downscaling can be used with impact-specific models (e.g., hydrological models) to assess the effects of these forcings on various aspects of climate.

Climate downscaling approaches can be broadly classified as dynamical or statistical with a small number of studies using dynamical-statistical approaches (e.g., Fuentes and Heimann 2000, Boé et al. 2006, Svoboda et al. 2012). Studies comparing statistical and dynamical downscaling approaches have generally found similar skill in reproducing historical climate statistics, although the ability of statistical downscaling to provide point estimates may be an addition consideration for some applications, such as those in hydrology (see, for example, Chiew et al. 2010, Frost et al. 2011). As noted by Murphy (1999), this does not necessarily imply that downscaled estimates of future climate from these methods possess equal skill.

Dynamical downscaling can be conducted by using an AOGCM with variable resolution (i.e., low resolution generally, but high resolution over the region of interest) as in Déqué and Piedelievre (1995), but is most commonly done by using lateral boundary conditions from an AOGCM to force a higher resolution regional climate model (RCM), which is run for a smaller domain. The greatest advantage of dynamical downscaling is the physical consistency with the driving AOGCM. However, the direct boundary forcing from the AOGCM can also lead to inherited bias. Dynamical downscaling is also computationally demanding, which typically precludes application to large suites of AOGCMs with varying greenhouse gas emissions trajectories. To date, the largest coordinated dynamical downscaling experiments have been the North American Regional Climate Change Assessment Program (NARCCAP; Mearns et al. 2009; Mearns et al. 2012) which produced 50 km RCM simulations sampled from the space of 4 AOGCMs and 6 RCMs to produce 12 unique combinations using historical forcing (1971-2000) and a single future emissions scenario, SRES A2 (2071-2100) and the Prediction of Regional Scenarios and Uncertainties for Defining European Climate Change Risks and Effects (PRUDENCE; Christensen et al. 2007) project which included four high resolution atmospheric GCMs and eight RCMs also using SRES A2 forcing. A more recent project, the Coordinated Regional Climate Downscaling Experiment, or CORDEX, aims to establish an international framework for coordinating downscaling projects in different regions. As computational capabilities continue to improve, it may be possible to conduct coordinated dynamical downscaling experiments over a much wider range of AOGCM-RCM combinations and radiative forcing scenarios, to assess and potentially reduce uncertainty associated with the development of regional climate change projections (see Mearns et al. 2012).

Conceptually, statistical downscaling evolved from synoptic climatology (Hewitson and Crane 1996), the subfield of climatology that describes surface climate as a function of both large-scale atmospheric circulation and local environmental conditions (see Yarnal 1994). As such, it relates observed, reanalyzed, or AOGCM-derived large-scale climate descriptors to observed regional- or local-scale descriptors using a statistical function. The function is then applied to AOGCM output to derive the regional- or local-scale descriptor consistent with the AOGCM projection (see Figure 1). Statistical downscaling also has roots in operational weather forecasting (e.g., the Perfect Prognosis and Model Output Statistics approaches) and applications in short-range and seasonal forecasting are still common (e.g., Gutiérrez et al. 2004, Feddersen and Andersen 2005, Diez et al. 2005, Lim et al. 2009, Schoof et al. 2009). The relatively low computational demand makes statistical downscaling an attractive approach for developing regional- to local-scale climate change scenarios using a large suite of AOGCMs and a range of greenhouse gas emissions scenarios. The Statistical and Regional Dynamical Downscaling of

Extremes for European Regions (STARDEX; Goodess et al. 2005) project represents the largest coordinated statistical downscaling effort to date.

Several reviews of statistical downscaling have been conducted since the approach became widely applied following the advent of widely accessible climate model archives associated with coupled model intercomparison projects (see Meehl et al. 2007; Taylor et al. 2012). Recent reviews, however, have focused on specific variables (e.g., the review of precipitation downscaling by Maraun et al. 2010) or on specific applications, such as hydrological modeling (Xu 1999; Wood et al. 2004, Fowler et al. 2007, Chen et al. 2012). This review will provide a broad overview of statistical downscaling for regional climate change investigations with a focus on downscaling assumptions, choices of predictors and predictands, and methodological approaches, with an overall goal of broadly representing current downscaling practice and providing direction for future statistical downscaling research.

2. Assumptions

Successful statistical downscaling requires that several assumptions are met (see Hewitson and Crane 1996, Giorgi et al. 2001, Wilby et al. 2004, Benestad 2008). The assumptions can be summarized as follows:

1) There must be a strong relationship between the predictor variable(s) and the predictand (i.e., the variable being predicted).
2) The predictor variable(s) must be adequately simulated by the AOGCM.
3) The predictor variable(s) must incorporate the climate change signal.
4) The relationship between the predictor(s) and predictand must be stationary (i.e., time invariant).

The first assumption is a general requirement for statistical modeling. The time behavior of the predictand can only be specified on the basis of the predictor(s) if there is a strong degree of covariance and similar time structure (Benestad 2008) and standard methods exist for identifying and quantifying the strength of the predictor-predictand relationship.

The second assumption addresses the fidelity of the model in simulating important aspects of the predictor variables. Clearly, reproducing the statistical moments and spatial distribution of the historical large-scale climate does not guarantee that the future representation in the model is correct, but failure to do so would certainly indicate a shortcoming. It is also possible that the climate model response to enhanced greenhouse gas forcing is incorrect. In this case, downscaling will not improve the model, but simply add precision to the erroneous model projections (Prudhomme et al. 2002). The failure of AOGCMs to produce an accurate regional response to large scale forcing from ENSO and other large-scale climate variations has also led to recent criticism of confidence placed on multi-decadal regional climate projections (see Pielke and Wilby 2012). More discussion of evaluation of predictors simulated by AOGCMs is presented in Section 3.

Since the goal of many (most) statistical downscaling applications is to develop scenarios of regional climate change, the predictor variables must fully represent the climate change signal (Assumption 3). For example, sea-level pressure typically explains a significant proportion of variance in observed temperature, but if used alone in a statistical downscaling application, may lead to unrealistically low temperature change estimates (Huth 2004, Benestad 2008) since the effects of increased radiative forcing from greenhouse gases are not likely to be manifest as changes in sea level pressure alone. Likewise, Zorita et al. (1995) and Zorita and von Storch (1999) note that geopotential height changes may be reflective of changes in atmospheric density in a warmer climate rather than changes in circulation and advocate for the use of sea level pressure instead. The regional response to large scale climate change is also a function of regional feedbacks. A major shortcoming of all downscaling approaches, aside from a small number of two-way nested dynamical techniques, is that there is no opportunity for regional processes to feedback to the driving AOGCM. Changes in the local environment that might also contribute to future changes cannot be accounted for explicitly. Surface-related feedbacks can be especially important in alpine environments where changes in albedo and energy fluxes between snow-covered and vegetated surfaces exist. The importance of land cover has also been demonstrated for temperature and near-surface moisture variations (Fall et al. 2010) with implications for assessing future changes in human heat stress related to changing climate conditions (Schoof et al. 2012a).

The fourth assumption of statistical downscaling is that the relationship between the predictor(s) and predictand is stationary through time. While this assumption cannot be tested explicitly, the ability of a particular statistical model to ‘adapt’ to changed climate conditions can be tested given a sufficiently long historical record. For example, Wilks (1999) built precipitation downscaling models with dry years and then tested them on wet years and vice-versa. Similarly, with a long enough record, a model could be trained on cold years and then tested on warmer years. A model that ‘passes’ such a test would increase the confidence when used in a warmer climate to assess changes in the variable of interest. As noted by Benestad (2004), statistical historical relationships from several published studies appear to hold in perturbed climates. While this does not guarantee stationarity in the relationships used in all downscaling studies, it demonstrates that the assumption of stationary is not necessarily violated in all statistical downscaling applications. Studies have also tested the stationarity assumption within AOGCMs. Frias et al. (2006) use a 1000 year model simulation to test the stationarity of the relationship between sea level pressure and precipitation in two regions with the results differing by region. The assumption of stationarity in the predictor-predictand relationship also extends to validity beyond the historical data range. As noted by Wilby et al. (2004), little research has been done to date to address this issue across a range of predictor variables and AOGCM simulations. A long, high quality observed record, will result in more robust downscaled climate estimates (Wilby and Wigley 1997; Prudhomme et al. 2002) and will also maximize the range of the predictors and allow for testing of stationarity. While often cited as a drawback of statistical downscaling, the stationarity assumptions also applies to the parameterizations within regional climate models used for dynamical downscaling as noted by Wilby et al. (2004).

3. Predictors and predictands

Climate change research has focused primarily on temperature and precipitation since they are likely to produce the greatest impacts on humans via impacts on agriculture and water security and generally have the longest available observed records. While downscaling studies generally follow this trend, downscaling has also been applied to a large range of additional predictands including humidity (Huth 2005, Schoof 2012a), wind (Sailor et al. 2000, Pryor et al. 2005a, 2005b, 2006, Salameh et al. 2009, Michelangeli et al. 2009), and many others including coastal sea-level (Cui et al. 1995) and ocean wave heights (Wang et al. 2010). For some methods (e.g., canonical correlation analysis, CCA) spatial fields are downscaled. For these applications, and many others, pre-processing using empirical orthogonal functions (EOFs) is common. Benestad (2001) described a common EOF approach in which the same EOFs are used for both calibration and future scenario production. To address nonlinearity, studies have frequently transformed predictands in lieu of applying nonlinear downscaling techniques. A number of studies have also downscaled probability distribution or weather generator parameters rather than actual values (e.g., Wilby et al. 2002, Pryor et al. 2005a, Schoof et al. 2010).

The predictor variables used for downscaling are largely determined by availability of long historical time series that can be used for calibration of the downscaling model (Figure 1) and the availability of the predictors from AOGCMs. The synoptic climatological roots of statistical downscaling suggest that circulation variables should be the dominant source of surface climate variability. However, multiple studies (Hanssen-Bauer and Forland 2000, Kaas and Frich 1995, Schubert 1998, Huth 1999) have noted the importance of including upper air temperature as a measure of radiative forcing and the importance of including humidity as a predictor for precipitation (e.g., Cavazos and Hewitson 2005). Other studies, such as Timbal et al. (2008) have investigated the role of absolute vs. relative humidity as predictors for precipitation. Benestad (2008) demonstrated (using the first law of thermodynamics and the continuity equation, respectively) that temperature or precipitation cannot be specified solely on sea level pressure. Therefore, in practice, the large-scale parameters often include thermodynamic variables in addition to circulation variables.

Given the wide availability of reanalysis products available (e.g., Kalnay et al. 1996, Uppala et al. 2005), there are now a wide variety of accessible candidate predictor variables. For example, the widely used Statistical DownScaling Model (SDSM; Wilby et al. 2002) uses 25 candidate predictor variables consisting of standard upper level variables (humidity, geopotential height, temperature, and zonal and meridional winds), surface and near surface variables (sea level pressure, near surface winds), and derived circulation variables (vorticity and divergence).

Studies have also identified reanalysis or AOGCM precipitation fields as useful predictors for precipitation downscaling (e.g., Widmann et al. 2003, Schmidli et al. 2006)

The utility of a candidate predictor variable depends strongly on the nature of the predictand (discrete vs. continuous, daily vs. monthly). For example, monthly mean temperature is likely to be approximately Gaussian and strongly correlated with lower to mid tropospheric temperature and circulation (geopotential height and/or sea level pressure) while daily precipitation is highly skewed with dependence on parameters that govern the horizontal flux and convergence of moisture (e.g., specific humidity, winds, vorticity)(see Cavazos and Hewitson 2005; Schoof , 2012b).

With few exceptions, statistical downscaling work published to date has focused primarily on the strength of the statistical relationship between the predictand and candidate predictor(s) (i.e., Assumption 1 in Section 2) with surprisingly little work addressing (1) the fidelity of predictor simulation by AOGCMs or (2) identification of scales at which AOGCM simulations exhibit agreement with observations. Evaluation of grid-point statistics in GCMs (as demonstrated by Chervin (1981) and Portman et al. (1992) has been adopted by several downscaling studies (Sailor and Li 1999, Schoof et al. 2007). These studies and others implicitly assume that AOGCM performance in the historical period is reflective of AOGCM utility for investigating future climate. While historical skill does not provide any guarantee regarding future climate, identification and elimination of models that do not perform well in the historical period is a useful approach for reducing the variability associated with downscaled AOGCM ensembles.

Taylor diagrams (Taylor 2001) represent one tool that can be used to address multiple aspects of AOGCM performance over a specified spatial domain. Taylor diagrams have the spatial correlation plotted on the radial axis and the ratio of simulated to observed spatial standard deviation on the x-axis. The distance from any plotted point to the origin (spatial correlation = 1 and ratio of spatial standard deviations = 1) is then proportional to the root mean square error. The example provided in Figure 2 demonstrates that for this particular AOGCM (IPSL CM5a; Dufresne et al. 2012), winter (DJF) 850 mb air temperature is better simulated than sea level pressure. The accompanying maps suggest that this is largely due to overestimation of sea level pressure associated within the high elevation regions of the Rocky Mountains.

An additional issue related to predictor choice is scale. While it has been widely acknowledged that AOGCMs should not be used at the grid point scale, there has been relatively little analysis of predictor fidelity across scales and across AOGCMs. When predictor scale has been considered (e.g. Grotch and McCracken 1991), the recommendation has been to use averages over several grid points and has been interpreted differently among studies. For example, Schoof et al. (2010) averaged predictors over a 12.5° × 12.5° area centered on the station of interest while Goyal et al. (2012) averaged predictors over four grid points resulting in 5° × 5° data. Predictor domain can also be taken as the region where correlation with predictand is positive (Benestad 2004, Chu and Yu 2010) or meets a specific threshold. By this standard, the predictor domain may be located ‘upstream’ due to temporal mismatch between reanalysis data and observations (see Brinkmann 2002). The optimal scale is likely to vary among predictors, timescales, AOGCMs, and how ‘optimal’ is defined. Studies have found inconsistent results regarding the effect of predictor scale on results (see Benestad 2001 and Huth 2002). Recent work by Masson and Knutti (2011) and Räisänen and Ylhäisi (2011) identifies the ‘optimal smoothing scale’ at which AOGCM simulated temperature and precipitation exhibit agreement with observations, yet retain regional features of the climate signal. Application of these techniques to the variables commonly used in statistical downscaling and an assessment of optimal scale variations among models and variables should be a high priority for the statistical downscaling community.

4. Methodological choices

In their seminal paper on statistical downscaling, Wilby and Wigley (1997) outlined three categories of downscaling method: regression-based approaches, weather pattern-based approaches, and weather generators. Although methodological developments have continued in the years since their publication and most recent downscaling applications use combinations of these approaches, these categories still adequately represent the canon of available downscaling techniques. However, a number of novel scaling techniques have also emerged within the downscaling literature (e.g., Salathé 2003, Wood et al. 2004). In forecasting parlance, downscaling techniques can also be described as either PerfectProg (PP), if the relationship is derived using observed predictors, or Model Output Statistics (MOS) if the predictors are taken directly from the AOGCM. The MOS approach can be thought of as having a built-in AOGCM bias correction whereas PP requires trust in (or explicit evaluation of) the fidelity of the AOGCM simulations.

In the application of any particular downscaling technique subjective decisions are required (see Winkler et al. 1997) and comparative studies conducted in different regions and using different driving AOGCMs have demonstrated that there is no single statistical downscaling approach that is optimal for all regions and applications. Bürger et al. (2012) compared five statistical downscaling methods for temperature and precipitation extremes in Western Canada. They found that expanded downscaling, a weather pattern-based approach (see

Bürger 1996), performed best. They noted that it is unlikely that their results would extend beyond the fixed framework within which they were derived (i.e., the specific data, AOGCM, and study region). Schmidli et al. (2007) compared six statistical downscaling methods including regression-based, weather pattern-based, and stochastic weather generator approaches for downscaling daily precipitation in the European Alps and found a wide range of results which depended largely on the choice of method. Haylock et al. (2006) compared six statistical and two dynamical downscaling approaches and found that methodological differences were as large as those from emissions scenarios. Harpham and Wilby (2005) compared two artificial neural networks and a conditional resampling method and found the methods to have relative advantages and disadvantages in downscaling heavy precipitation. These studies collectively demonstrate that the choice of method is a major contributor to uncertainty in the resulting downscaled climate. This is especially important if the downscaled climate information is to be used in an additional model to assess impacts, as in Chen et al. (2012). In the description of methods that follows, specific applications are described to provide the reader with the scope of current statistical downscaling practice and methodological considerations.

4.1 Scaling methods

Scaling techniques are perhaps the most intuitive statistical methods for inferring fine scale information from AOGCMs. Spatial interpolation or disaggregation of AOGCM output, for example, provides a baseline against which more rigorous downscaling methods can be compared (see Wheater et al. 1999). For regions of high relief, interpolation can be used with an adjustment for elevation as in Wang et al. (2011). Salathé (2003) describes a scaling technique for precipitation in the northwest USA that consists of applying precipitation anomalies from reanalysis data to a high resolution observed data set. Wood et al. (2004) describes a method in which AOGCM data are first bias corrected and then spatially disaggregated (BCSD) to a fine grid for hydrologic modeling. Wood et al. found that BCSD exhibited less bias than traditional interpolation methods and Hayhoe et al. (2007) applied the method to assess climate change impacts on the northeast United States under different greenhouse gas scenarios. The studies of Salathé (2003), Widmann et al. (2003), Wood et al. (2004) and Salathé (2005) are also among a growing number of studies that use large scale values of the predictand as the predictors.

4.2 Regression-based methods

The term regression is used the downscaling literature to describe the range of techniques from standard ordinary least squares regression applications (e.g., Sailor and Li 1999) and variations (e.g., censored quantile regression, Friederichs and Hense (2007), multi-way partial least-squares regression, Bergant and Kajfež-Bogataj (2005)) to methods that identify relationships between fields, such as singular value decomposition (SVD) and canonical correlation analysis (CCA) (see Bretherton et al. 1992 for a review and intercomparison of such methods). Hertig and Jacobeit (2008) used CCA to downscale geopotential heights to temperature to assess 21st century warming in the Mediterranean. Huth (1999) and Huth (2002) compared CCA, SVD, and multiple linear regression with principal components and grid point values with and without screening for downscaling temperature in central Europe. They found that pointwise multiple linear regression best approximated the temporal structure of the observed data, but that CCA best captured the spatial structure. The generalized linear modeling (GLM) framework has recently emerged as a flexible technique for downscaling precipitation and other variables. An application to precipitation in Ireland can be found in Fealy and

Sweeney (2007) and an overview of applications in other studies is available in Beuchat et al. (2012).

Also included in this category are artificial neural networks (ANNs), and a growing body of computational learning algorithms including tree-based methods (Goyal et al. 2012), genetic programming (Coulibaly 2004), support vector machines (SVMs, Tripathi et al. 2006), and relevance vector machines (RVMs, Ghosh and Mujumdar 2008). ANNs have been widely used for a range of temperature, precipitation, and wind downscaling applications (see, for example, Cavazos 1997, Crane and Hewitson 1998, Schoof and Pryor 2001, Cannon and Whitfield 2002). Coulibaly et al. (2005) and Dibike and Coulibaly (2006) applied an ANN to daily precipitation downscaling and found that performance was improved over regression especially for extremes and variability. Regression and weather pattern-based approaches have also been combined with ANN techniques downscaling studies. For example, Cavazos (1997) combined principal components of multiple circulation variables as predictors in an ANN for winter precipitation in Mexico. ANNs have also been useful for evaluating the need for nonlinear methods. Trigo and Palutikof (2001) compared linear and nonlinear ANNs for downscaling of monthly precipitation over Iberia. The linear (or only slightly non-linear) ANNs were more capable of reproducing the observed precipitation series. When the predictor-predictand relationship is nonlinear, or when the predictand is non-Gaussian, as in the case of daily precipitation, ANNs are typically found to have an advantage over standard parametric approaches (e.g., Ramirez et al. 2006). Cannon (2011) describes a new quantile regression neural network that can be used to downscale mixed discrete-continuous predictands. SVM approaches emerged as an alternative to ANNs which are highly sensitive to network architecture. Tripathi et al. (2006) used a support vector machine approach to downscaling monthly precipitation and found it to outperform ANN. SVMs have also been used by Anandhi et al. (2008) for monthly precipitation downscaling. RVMs are similar to SVMs, but use Bayesian learning framework to determine the model solution (Ghosh and Mujumdar 2008).

4.3 Weather pattern-based methods

Weather pattern-based techniques emerged from the synoptic climatological perspective the surface climate variations are largely determined by the large-scale atmospheric circulation. Early approaches to downscaling in this category used eigentechniques (e.g., EOF analysis) to identify modes of variability in large scale data and then used the temporal variations in the modes (the principal components) in traditional downscaling, such as regression models or ANNs (Huth and Kyselý 2000, Schoof and Pryor 2001). More recently, Li and Smith (2009) downscaled winter seasonal precipitation from four principal components of mean sea-level pressure for southern Australia and found improvement over raw GCM output. Other classification methods, based on fuzzy rules (Stehlík and Bárdossy 2002, Bárdossy et al. 2002, 2005), optimal distinction of surface climate elements (Enke et al. 2005), and self-organizing maps (SOMs) have also been applied within a downscaling context (e.g., Cavazos 2000, Hewitson and Crane 2006).

Among the most widely applied weather pattern-based approaches are analog methods (Zorita and von Storch 1999). In the analog approach, the historical record is searched for a pattern matching the AOGCM simulated pattern. The surface climate conditions observed during the historical analog are then used as the downscaled predictands. The analog method, like all statistical downscaling methods, requires long historical series. As historical records become longer, the likelihood of no-analog situations decreases. The analog method has been widely applied (e.g., Timbal and Jones 2008, Timbal et al. 2009 and references therein). While some comparative studies of precipitation downscaling (Wetterhall et al. 2006; Wetterhall et al. 2007) have generally found that other downscaling approaches outperform the analog method, other studies have shown that analog techniques exhibit skill that is similar to more complex techniques (Zorita and von Storch 1999; Chiew et al. 2010; Frost et al. 2011). Several improvements to traditional analog approaches have been suggested, including constructed analogs (Maurer and Hidalgo 2008) and multivariate adapted constructed analogs (MACA, Maurer et al. 2010). In an application to wildfire, Abatzoglou and Brown (2012) found that MACA outperformed the BCSD method with better representation of relative humidity and wind. Another analog-based method is K-nearest neighbor downscaling (KNN, Gangopadhyay et al. 2005), which applies weights to a number (k) of similar historical analogs which are then used to generate ensembles.

The nonhomogeneous hidden Markov model (NHMM, first introduced by Hughes and Guttorp 1994) has also been widely applied to downscaling (e.g., Hughes et al. 1999, Bellone et al. 2000, Robertson et al. 2004, Fu et al. 2012), particularly for daily precipitation. In the NHMM approach, precipitation occurrence probabilities and amounts at a location are associated with classes of large scale atmospheric fields, such as geopotential height and humidity. The approach has also been extended to multisite precipitation downscaling by Charles et al. (2004) and Frost et al. (2011). Mehrotra and Sharma (2005) used a combination of the k-nearest neighbor approach and NHMM in an application to multisite precipitation occurrence downscaling at 30 stations in Australia. Their approach treated the weather states as continuous, whereas the traditional NHMM approach requires a discrete number of classes.

Since the large-scale atmospheric state will continue to exert influence on surface climate as climate varies and changes, weather pattern-based approaches are likely to remain a preferred method for statistical downscaling. Outstanding issues for downscaling with the weather pattern-based approaches include a lack of systematic studies evaluating the reproduction of synoptic patterns by AOGCMs and their responses to GHG forcing and different surface climate responses within the same large-scale atmospheric state (i.e., within-type variability). Goodess and Palutikof (1998) applied a combined circulation-type and weather generator approach to daily precipitation downscaling in southeast Spain and found that the inability of the GCM to correctly simulate the circulation types was detectable in the weather generator output. McKendry et al. (2006) and Schoof and Pryor (2006) both identified a number of shortcomings in AOGCM representation of synoptic patterns for North American regions.

4.4 Weather generators

Weather generators (WGs) are stochastic models for daily weather elements that can also be regarded as random number generators whose output resembles daily weather data at a station (Wilks and Wilby 1999). As such, WGs can generate sequences of arbitrary length for used in impacts models. WGs were initially developed for use in agricultural modeling where observations were of insufficient length or plagued by missing data. The most widely applied WGs in statistical downscaling work have been variations of the WGEN model (Richardson and Wright 1984) and LARS-WG (Semenov and Barrow 1997). Both models produce daily sequences of precipitation (occurrence and amount) along with maximum and minimum temperature and solar radiation. Precipitation models usually form the basis of WGs since other variables exhibit dependence on precipitation. For example, in the simulation of maximum and minimum temperatures, precipitation occurrence provides a surrogate for cloud cover. Wilks and Wilby (1999) provide an overview of commonly used WG formulations.

To use WGs in a climate downscaling context, the model parameters (e.g., the transition probabilities for precipitation occurrence, the distribution parameters for wet-day precipitation amounts, the means and variances of the non-precipitation variables, etc.) need to be changed to reflect the changed climate. In the first study to apply WGs to climate downscaling, Wilks (1992) perturbed WG parameters by considering AOGCM-projected relative changes. Other studies have suggested alternative means of updating the parameters, such as downscaling them using regression of large-scale atmospheric variables (Schoof et al. 2007, 2010). Zhang (2005) downscaled monthly GCM temperature and precipitation to the station level by calibrating the probability distributions produced by the GCM to the observed probability distributions at the station. For each calendar month, functions were fit to the quartiles of observed vs. simulated values and then used to downscale future values which were used with a weather generator to produce inputs for an agricultural impact assessment model. Weather generators have also been developed for multisite simulation of precipitation under climate change (Wilks 1999) and combined with other downscaling approaches (e.g., the weather pattern-based approaches by Mearns et al. 1999 and Fowler et al. 2005).

In comparisons with other methods, WGs have been found to perform well. Wilby et al. (1998) compared two weather generators, two vorticity-based methods, and two ANNs methods for statistical downscaling of daily precipitation. The weather generators were found to produce series that most agreed with the observed series. Underestimation of variances is a common problem with statistical models and those used for downscaling are no exception (see for example, Schmidli et al. 2007). Some authors have proposed increasing the variance of models using techniques such as inflation (Karl et al. 1990) or addition of random noise (von Storch 1999) with no clear consensus on which method is preferable (see von Storch 1999 and Huth 2002). Furthermore, neither method provides a clear extension to enhancing variability in the downscaled future time series. As noted by Schoof et al. (2007), the inclusion of distribution parameters in WG-based downscaling applications reduces the underestimation of variance relative to regression-based methods. Other authors (Grondona et al. 2000, Wilby et al. 2002) have also conditioned WG parameters on large scale modes of climate variability such as the NAO or ENSO to improve low frequency variability.

5. The future of statistical downscaling

The array of studies cited in this review demonstrates that statistical downscaling has become a preferred method for inferring regional information from coarsely resolved AOGCMs. However, despite a large number of studies comparing downscaling predictors and methods, additional work is needed to translate the derived regional climate change information into climate adaptation (Fowler et al. 2007, Fowler and Wilby 2007). Given the current state of climate science, future climate scenarios developed using downscaling techniques do not include all first order forcings and feedbacks and even the large-scale atmospheric response to changes in greenhouse gas forcing with AOGCMs is uncertain. Large-scale AOGCM errors and shortcomings, such as the lack of balance between global precipitation and evaporation described by Liepert and Previdi (2012), have tremendous implications for climate downscaling. Therefore, downscaled climate projections (whether derived statistically or dynamically) can currently only be presented to the impacts community as a subset of possible future climates (Pielke and Wilby 2012).

Consideration of uncertainty and its role in applied downscaling should be a key theme in the next decade, while the utility of downscaled climate scenarios should remain limited to sensitivity testing and appraisal of adaptation options. Hawkins and Sutton (2009) consider uncertainty due to internal climate variability, choice of AOGCM, and choice of greenhouse gas scenario. The latter two types of uncertainty increase at finer scales and are added to uncertainty associated with the downscaling technique. Application of the downscaled series to an impacts model adds yet another layer of uncertainty. The full uncertainty associated with downscaled climates has not yet been sufficiently addressed in most downscaling studies, yet adaptation to regional climate change may require identification of regional climate projections that are scenario-neutral (i.e., robust across scenarios and therefore 'actionable', e.g., Prudhomme et al. 2010).

As the focus of coordinated AOGCM experiments evolves to include decadal prediction (see e.g., Meehl et al. 2009), statistical downscaling will become better positioned to inform decision making in agricultural and hydrological applications. Recent work combining dynamical and statistical downscaling techniques (e.g., Chen et al. 2012, Svoboda et al. 2012) suggests that even as model resolution increases and dynamical downscaling approaches evolve, statistical downscaling will continue to provide information to the impacts community that cannot be provided by other methodological approaches. As better observed and reanalyzed data sets become available and AOGCM simulations continue to improve, there will be additional opportunities for the statistical downscaling community to evaluate the critical assumption of stationarity and better assess the scales at which statistical downscaling predictors are optimally simulated by AOGCMs. This will improve the confidence with which statistically downscaled climates can be used to assess the impacts of climate variability and change at the regional scale.

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Figure 1. The statistical downscaling process (from Schoof 2012, modified after Maraun et al. 2010). The calibration step consists of developing and validating the statistical model using historical data (observed data for the PP approach or AOGCM data for the MOS approach, see Section 4). The projection step consists of applying the validated model to AOGCM output to derive regional- to local-scale projections.

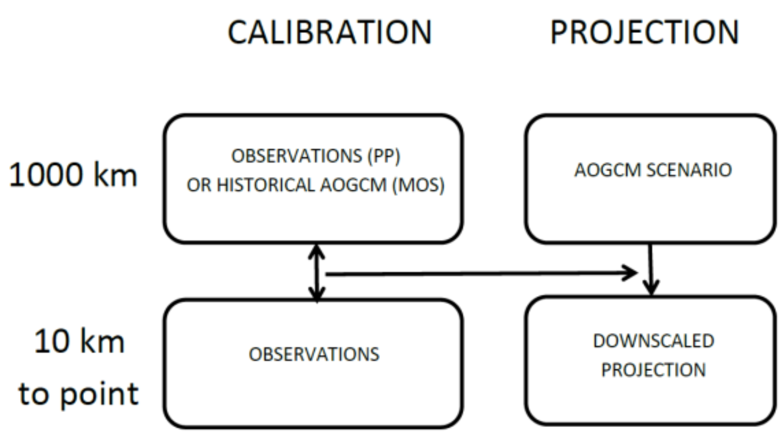

Figure 2. Demonstration of Taylor diagrams (Taylor 2001) as useful tools for assessing the performance of AOGCMs. The examples provided are for sea level pressure (SLP) and 850-mb air temperature simulated by the coupled climate model IPSL CM5 evaluated relative to the NCEP-NCAR reanalysis during winter (DJF).