Challenges, Solutions, and Future Directions for Statistical and Dynamical Downscaling of Global Climate Models

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Introduction

Global-scale models of climate are an irreplaceable element in the search for certainty about the future of Earth's many life-sustaining systems. However, the same scale that gives these models their ability to form a cohesive picture of the earth's climate system also creates challenges in employing the projections created by these models. Namely, the resolution and accuracy of the global models is often insufficient to capture fluctuations in climate variables on a scale that is relevant to the climate impacts community, due mostly to the fact that global climate models project *atmospheric* variables rather than surface variables. Studying the future of living organisms' habitat suitability [Levy et al., 2016] or creating high-certainty hydrological projections [Wood et al., 2004] require projections of surface climate variables at a temporal and spatial resolution not offered by global-scale models. In addition, many global-scale models are not able to capture unique small surface features which can impact the translation of global circulation patterns to surface climate variables. An ecologist attempting to identify suitable future habitat for a species of lizard, for example, requires projections of solar radiation, precipitation, and temperature at hourly and meter-scale [Levy et al., 2015]. A global climate model with 100-km resolution simply does not suffice.

The "downscaling" of climate models intends to address this scale mismatch. The purpose of downscaling is to create for a specific region of interest a climate projection with high spatial (and often temporal) resolution based on information derived from a global model (or set of global models) [Pielke and Wilby, 2012]. The two core approaches to downscaling that have emerged (along with myriad hybridizations thereof) are *statistical* downscaling and *dynamical* downscaling. They differ centrally in their fundamentals. The Intergovernmental Panel on Climate Change (IPCC) defines statistical downscaling as "deriving empirical relationships linking large-scale atmospheric variables (predictors) and local/regional climate variables (predictands) [Flato et al., 2013]." Dynamical downscaling involves either creating regional climate models (RCMs) which "are applied over a limited-area domain with boundary conditions either from global reanalyses or global climate model output" [Flato et al., 2013] or using existing global circulation models (GCMs) run at a higher resolution over a specific area of interest [Pielke and Wilby, 2012]. These models are based on mathematical representations of the driving physical processes for a given region, perhaps specific orography or coastline dynamics [Flato et al., 2013].

This paper first characterizes each of these approaches and the advantages and challenges therein, with an eye toward using the output of these downscaling procedures to inform impact analyses in various study domains external to climatology. We survey the literature of proposed solutions to the problems that face each set of downscaling methods, and conclude with a summary analysis of the suitability of these approaches for applications of interest. The primary focus of this paper is to examine the underlying mechanisms which confound regional climate projections and the ways in which the modeling community has attempted to address them, in light of the models' utility in the climate impacts community.

Statistical Approaches

The natural first step toward a more fine-grained understanding of local climate is the derivation of statistical relationships between global-scale atmospheric patterns and any surface variables of interest. Since the 1970s, researchers have been developing statistical approaches to link large-scale free atmosphere variables to local-scale weather variables. This is mostly because these relationships are particularly relevant to short-term weather forecasting, but their applicability to future climate projection is only a short logical step away [Wilby et al., 1998]. Given a global circulation model which can predict atmospheric variables into the future with some level of uncertainty, a statistical model needs only to apply this information to some previously-derived mathematical relationship to produce a value (or set of values) for a relevant surface climate variable.

Approaches have evolved significantly in recent years (a point that even Flato et al. deemed worth noting in the IPCC AR5 report). Past approaches were characterized by classical linear regression techniques, hidden markov modeling, and some artificial neural networks [Wilby et al., 1998]. As work continued, the state of the art in statistical downscaling was honed for specific applications or to highlight specific phenomena. The "weather classification" method of statistical downscaling correlates groups of days with consistent surface weather to patterns in large-scale atmospheric variables based on subjective assessments of atmospheric circulation, and these methods have limited success reproducing persistent weather states (like wet- or dry-spells) [Wood et al., 2004, Sec. 2.1]. Another method, "weather generation," attempts to replicate (via some Markov process) the statistical attributes of a local climate variable (such as mean and variance) while using large-scale atmospheric variation to compute state transition probabilities. These models often underestimate precipitation persistence and temporal variability, but variants of weather generators can be useful in temporal downscaling (that is, converting a monthly precipitation total into daily rainfall amounts, for example) [Wood et al., 2004, Sec 2.4].

A fundamental challenge for the use and development of statistical models is that the central assumption of these approaches is not verifiable. Namely, the assumption that the statistical relationships derived for our present-day climate also hold under future forcing scenarios cannot be supported [Wilby et al., 2004]. This assumption is known as the statistical stationarity hypothesis, and it is difficult to provide support for stationarity when examining future climate. This theoretical weakness is one of the reasons why statistical downscaling has received less favor in the impacts community than regional or dynamical downscaling, which can take advantage of the uncertainties in GCM models more natively and thus capture the range of potential future variability in climate.

Aside from this disadvantage, however, statistical models have the distinct advantage that they are often much less computationally intensive than some dynamical approaches [Wilby et al., 2004]. This is due mostly to the fact that the derivation of the statistical relationships that drive future projections (a computationally intensive process) only occurs in the creation (but not *use*) of the model. Therefore, when new GCM data become available, statistical downscaling using pre-computed models is much more computationally tractable than re-computing an entire dynamical model for a region.

An important point to note, however, is that while each type of statistical model can be derived to predict a variety of surface climate variables, some model types perform better when predicting certain kinds of climate variables or when predicting certain variables at regional versus continental scales [Gutmann et al., 2014]. For example, one particular approach in the Gutmann et al. analysis of algorithms for hydrological projection predicted rainfall amounts rather poorly at continental scale and performed much better at regional scale, but far over-predicted extreme rainfall events. Another algorithm in the analysis predicted current climate quite well when initialized with past re-analysis data, but is limited in the range of predictable variability in future climate due simply to the mechanics of the algorithm used to generate the model. This is a direct example of the theoretical deficiencies introduced by an inability to support the statistical stationarity hypothesis upon which these methods rely.

The point that emerges here is that a range of statistical techniques for future climate projection must be considered before deciding upon a single approach to use for a given assessment requiring downscaled climate data on account of the extreme variability in the strengths and weakenesses of each type of approach. This is a point mentioned in Flato et al. [2013], Gutmann et al. [2014], Wilby et al. [2004], and Wood et al. [2004], which highlights the importance of choosing the correct model for an intended purpose.

Further, it is quite common in the impacts community to assume that an increased spatial resolution as provided by these statistical methods implies an increased confidence in the climate projections produced. This certainly cannot be the case, as uncertainty propagates from the GCM input data through the statistical models and into the output [Wilby et al., 2004]. The best way to address this particular issue is to compute the statistical models on a range of GCM output data, which can help to incorporate the uncertainty in large-scale climate modeling into the downscaled analysis.

In summary, statistical downscaling approaches can leverage past and current climate to derive mathematical relationships between global-scale climate and local-scale surface climate variables in order to predict these surface variables at spatial and temporal resolutions relevant to the climate impacts community. Though these derived models have a significant computational advantage over the more computationally-intensive dynamical downscaling approaches, they suffer from an inability to predict significantly different future climates as a result of their inevitable adherence to the statistical stationarity hypothesis. Statistical models can also mislead a user into thinking that increased resolution implies increased confidence in the projections—an educated researcher should use a number of global climate projections as input to a given statistical downscaling method to capture the uncertainty inherent in global climate projections. Finally, the choice of statistical downscaling method truly depends on the intended use case, especially in the case of impact assessment. Many models have weaknesses that other methods do not share, therefore choosing the correct approach for a given research question is critical.

Dynamical Approaches

In response to some of the pitfalls of statistical models, and in recognition of the importance of models with more local climatological context, dynamical climate models have taken the stage as a primary form of downscaling. There are several classes of model which fall under the description "dynamical model," and all of them originate from very different starting points. In a 2012 review paper by Pielke and Wilby, the authors propose dividing the space of dynamical climate models into 4 classes, and it is in this proposed order that I present this section.

Short-term numerical weather prediction models are what Pielke and Wilby consider to be a "Type 1" model. This class of models is not particularly relevant for most impacts-related climate projections, mostly due to the inability of these models to project far into the future. The short-term nature of the projection they produce means that the dynamics that they encapsulate are quite sensitive to the input data, which consists of both a global analysis of observations and current regional observations. It is important to note the dependence of Type 1 models on intial conditions, because therein lies the difference between type 1 and type 2 models.

Type 2 models as defined by Pielke and Wilby are similar to Type 1 models in that they are able to produce regional-scale numerical predictions of future climate, but they are free from the constraint of initial conditions in the form of regional observation data. Instead, Type 2 models depend on *boundary conditions* set by some global climate projection (like a GCM). The caveat here is that those boundary conditions come from a model (again, like a GCM) for which initial conditions based on real global observations are important. Therefore, even though a Type 2 regional model does not directly depend on initialization from regional observations, the boundary conditions that constrain its projections originate from a GCM that can be sensitive to initialization.

Removing observation-based initialization from the global model which constrains the boundary conditions for a given regional model leads us to Type 3 regional downscaling, wherein lateral boundary conditions to the regional model are taken from a global model which was not initialized from observations. Rather, the global models used for lateral boundary conditions are forced based on real-world boundary conditions (for the global model) rather than direct observations. Finally, a natural extension of this approach is Type 4 regional downscaling, wherein the global model which constrains the input boundary conditions is one which predicts coupled interactions between the atmosphere, ocean, biosphere, and cryosphere. Aside from human forcings, all components of the climate system are computed by the global model, which provides boundary conditions for a regional model.

Type 4 models are the most commonly-used in the climate impacts community, due primarily to their purported ability to project a wide range of climate variables far into the future. However, Pielke and Wilby [2012] consider the predictive value of Type 4 models to be severely limited in their ability to actually add value to regional climate predictions (over the baseline of statistical interpolation of global models onto terrain).

Indeed, this is a concern among many climate researchers due to several considerable disadvantages exhibited by regional climate models. Generally, the skill of regional climate models is impacted by the location and scale at which they are applied, their ability to communicate with global climate models, and the lateral boundary conditions used to run them. This latter point is particularly important: the boundary conditions used to constrain regional climate variables that are often derived from one of many global climate models strongly influence the output of regional climate models. In one example, a regional climate model of the Arctic demonstrated significantly more sensitivity to initial conditions when a weaker set of boundary conditions were imposed upon it [Rinke and Dethloff, 2000]. The implication here is that any errors that originate in the global climate models or initial conditions are propagated (if not potentially amplified) in the regional simulations. This is a primary concern for many in the climate modeling community, as the sources of error in global climate models are often difficult to pinpoint and control for [Pielke and Wilby, 2012].

In addition, the size of the domain upon which the regional model attempts to predict climate variables can have a significant effect on the performance of the model. There is a tradeoff here: models with a large regional scale are able to capture more synoptic-scale phenomena which can enhance their ability to resolve certain types of variables with higher skill [Flato et al., 2013], but these large scale models have no way to communicate these regional simulations back to the global climate models which are constraining their boundary conditions, so the two models can diverge significantly in their projections in the long term. However, another disadvantage introduced by large-domain models is the introduction of a large amount of internal variability in the model, which can negatively affect predictions which rely on natural variability (like seasonal means that rely on interannual variability to predict) [Flato et al., 2013]. An approach which can attempt to reverse this effect is the use of a technique known as "spectral nudging," which can maintain some of the natural climate variability at the expense of a model's ability to reproduce extreme events [Flato et al., 2013].

Despite these disadvantages, dynamical projections can offer much in the way of predictability over their statistical cousins. The nature of a dynamical model allows it to take into account specific physical processes at the interface of global-scale free atmosphere variables and surface climate, such as coastlines or mountain ranges. Simulating generalized physical processes allows for the projection of a wide range of variables (simply by virtue of requirement), in contrast to statistical methods which are constrained by available data [Mearns et al., 2003]. As a result, dynamical models are often more robust in predicting some weather extremes, especially in regions where topography or coastline dynamics play a large role in local climatology.

This section has thus far only addressed one of the more common approaches to dynamical downscaling, namely the use of a regional climate model applied a small scale that is "nested" within a larger global model (that is, boundary conditions are provided to the regional model by the global model). More recent advances in dynamical modeling have included a "stretched grid" approach, wherein a global model can be instructed to provide a high-resolution projection for a region of interest. In this way a regional climate projection is obtained from a model with global context but without the computational overhead of projecting the entire globe's future climate at high spatial and temporal resolution [Flato et al., 2013]. Additional advances include the coupling of regional climate models with an interactive ocean, which can greatly enhance the projection of variables like precipitation over a non-coupled model. The coupling approach is one that has also been applied to stretched grid models of global climate.

In summary, dynamical models of regional climate use mathematical representations of local physical processes to map global climate variables to a local surface climate variables in one of many ways. Commonly these dynamical approaches rely on a global projection of free-atmosphere variables as boundary conditions for a regional model, and therefore the same caveats that apply to global models of the atmosphere apply to regional models. Other approaches involve global models applied in a "stretched grid" fashion, wherein the context of the global model's projections can be directly applied to a specific region at high resolution. Regional climate models are able to project a wide variety of surface climate variables at fine spatial and temporal scales as a result of their direct modeling of physical processes, and can often better represent climatological extremes than their global counterparts. Despite some challenges in their implementation, dynamical models seem to have claimed the majority of favor in the regional downscaling arena, due mostly to their performance, reliability, and physical basis.

Future Directions

The previous sections have offered a selection of the vast space of statistical and dynamical downscaling approaches. It is important to also note that the field of regional downscaling as a whole is being considered in a critical light, due in part to questionable practices regarding the use of regional climate projections [Kerr, 2011, Xie et al., 2015]. This hard look at downscaling has forced climate modellers to carefully consider their approaches and attempt to develop new methods that address some of the more glaring shortfalls of regional climate modeling. One product that has come from this process is the Coordinated Regional Downscaling Experiment (CORDEX) consortium, which was developed in 2009 to attempt to better understand the ways in which uncertainties propagate from global models to regional models and their projections [Kerr, 2011]. CORDEX is a model intercomparison project (like CMIP5 and CMIP6) for regional climate models, and it is essentially the first of its kind to provide the sort of model comparisons necessary to highlight the levels of uncertainty present in reports of future climate, especially important at regional scales [Gutowski Jr. et al., 2016].

Much of the discourse around questioning the utility of regional climate models comes from the vast quantities of uncertainty that are simultaneously persistent in the models and poorly communicated to the models' users. Xie et al. [2015] address this point directly by claiming that future generations of climate modelers need to take a large step back from the problem and focus on deeply understanding the physical mechanisms that drive climate before attempting to predict it on a fine spatial scale. This suggestion is based on the observation that regional climate is dependent on many interconnected factors, almost all of which are currently poorly understood. Figure 1 illustrates some of these interconnections and highlights the importance of understanding *all* factors involved in regional climate change, especially the ones that introduce feedbacks into the process. Without a more

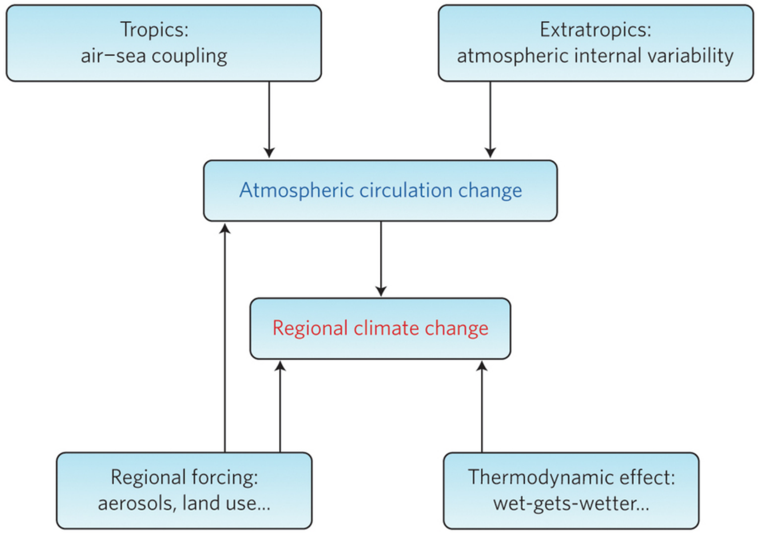

Figure 1: Schematic of physical origins of climate change, from Xie et al. [2015]

well-founded physical basis, regional climate models are particularly subsceptible to amplifications of error in any part of the process as a result of these feedbacks, which is part of the reason that Xie et al. [2015] suggest devoting time and energy toward this pursuit. Specifically, the authors suggest that understanding the global response of factors like temperature, precipitation, global circulation, El Niño, and temperature extremes in the face of anthropogenic forcings is a critical first step in regional climate modeling, and one that is only beginning. It is therefore unreasonable to truly rely on regional models in the ways in which the impact community has been without fully considering the impact of uncertainties on the intended result variable.

It is critical, then, for the impacts community to utilize both statistical and dynamical climate modeling with a keen eye toward the advantages, disadvantages, and appropriateness of each model. It is not likely that the regional modeling community will have a "silver bullet" for downscaling for a very long time, if ever, and therefore it is critical that both regional modellers and users in the impact community acknowledge the pitfalls of regional models as a core part of climate research going forward. This includes understanding the mechanisms, assumptions, internal variability, sources of error, and application applicability for each potential choice of model. This burden is placed both on modellers to make this information transparent, and on users to make an effort to understand and use it. If used well, regional climate models fill an extremely important gap in understanding responses of myriad earth systems to climate change, and their continued use is critical in studying how anthropogenic climate change will impact the future.

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