Correction

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The meeting report "How mathematical models can aid understanding of climate," published in the 20 December 2011 issue of *Eos* (*92*(51), 482, doi:10.1029/2011EO510010), stated that the conference was held by the "Institute for Mathematics and its Applications." It should have read "Institute of Mathematics and its Applications."

FORUM

Regional Climate Downscaling: What's the Point?

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Dynamical and statistical downscaling of multidecadal global climate models provides finer spatial resolution information for climate impact assessments [*Wilby and Fowler,* 2010]. Increasingly, some scientists are using the language of "prediction" with respect to future regional climate change and impacts [e.g., *Hurrell et al.,* 2009; *Shapiro et al.,* 2010], yet others note serious reservations about the capability of downscaling to provide detailed, accurate predictions [see *Kerr,* 2011].

Dynamic downscaling is based on regional climate models (usually just the atmospheric part) that have finer horizontal grid resolution of surface features such as terrain [*Castro et al.,* 2005]. Statistical downscaling uses transfer functions (e.g., regression relationships) representing observed relationships between larger-scale atmospheric variables and local quantities such as daily precipitation and/or temperature [*Wilby and Fowler,* 2010]. These approaches have been successful in improving the skill of numerical weather prediction. Statistical downscaling can also be used as the benchmark (the control) against which dynamic downscaling skill is judged [*Landsea and Knaff,* 2000].

Castro et al. [2005] categorized downscaling into four types (see also Table 1).

Type 1 downscaling is used for short-term, numerical weather prediction. In dynamic type 1 downscaling the regional model includes initial conditions from observations. In type 1 statistical downscaling the regression relationships are developed from observed data and the type 1 dynamic model predictions.

Type 2 dynamic downscaling refers to regional weather (or climate) simulations [e.g., *Feser et al.,* 2011] in which the regional model's initial atmospheric conditions are forgotten (i.e., the predictions do not depend on the specific initial conditions) but results still depend on the lateral boundary conditions from a global numerical weather prediction where initial observed atmospheric conditions are not yet forgotten or are from a global reanalysis. Type 2 statistical downscaling uses the regression relationships developed for type 1 statistical downscaling except that the input variables are from the type 2 weather (or climate) simulation. Downscaling from reanalysis products (type 2 downscaling) defines the maximum forecast skill that is achievable with type 3 and type 4 downscaling.

Type 3 dynamic downscaling takes lateral boundary conditions from a global model prediction forced by specified real-world surface boundary conditions such as seasonal weather predictions based on observed sea surface temperatures, but the initial observed atmospheric conditions in the global model are forgotten [e.g., *Castro et al.,* 2007]. Type 3 statistical downscaling uses the regression relationships developed for type 1 statistical downscaling except using the variables from the global model prediction forced by specified real-world surface boundary conditions.

Type 4 dynamic downscaling takes lateral boundary conditions from an Earth system model in which coupled interactions among the atmosphere, ocean, biosphere, and cryosphere are predicted [e.g., *Solomon et al.,* 2007]. Other than terrain, all other components of the climate system are calculated by the model except for human forcings, including greenhouse gas emissions scenarios, which are prescribed. Type 4 dynamic downscaling is widely used to provide policy makers with impacts from climate decades into the future. Type 4 statistical downscaling uses transfer functions developed for the present climate, fed with large-scale atmospheric information taken from Earth system models representing future climate conditions. It is assumed that statistical relationships between real-world surface observations and large-scale weather patterns will not change. Type 4 downscaling has practical value but with the very important caveat that it should be used for model sensitivity experiments and not as predictions [e.g., *Pielke,* 2002; *Prudhomme et al.,* 2010].

Because real-world observational constraints diminish from type 1 to type 4 downscaling, uncertainty grows as more climate variables must be predicted by models rather than obtained from observations. *Pielke et al.* [2012] assert that type 4 dynamic downscaling fails to improve accuracy beyond what could be achieved by interpolating global model predictions onto a finer-scale terrain or landscape map. This position is based on several reasons:

First, as a necessary condition for an accurate prediction, multidecadal global climate model simulations must include all first-order climate forcings and feedbacks. However, they do not.

Second, current global multidecadal predictions are unable to skillfully simulate regional forcing by major atmospheric circulation features such as from El Niño and La Niña and the South Asian monsoon [e.g., *Annamalai et al.,* 2007; *Paeth et al.,* 2008].

Third, while regional climate downscaling yields higher spatial resolution, the downscaling is strongly dependent on the lateral boundary conditions and the methods used to constrain the regional climate model variables to the coarser spatial scale information from the parent global models. Large-scale climate errors in the global models are retained and could even be amplified by the higher-spatial-resolution regional models. If the global multidecadal climate model predictions do not accurately predict large-scale circulation features, for instance, they cannot provide accurate lateral boundary conditions and interior nudging to regional climate models.

Fourth, apart from variable grid approaches, regional models do not have the domain scale (or two-way interaction between the regional and global models) to improve predictions of the larger-scale atmospheric features. This means that if the regional model significantly alters the atmospheric and/or ocean circulations, there is no way for this information to affect larger-scale circulation features that are being fed into the regional model through the lateral boundary conditions and nudging. For example, recent research indicates that terrestrial evaporation from the Eurasian continent contributes 80% of China's water resources [*van der Ent et al.,* 2010]. In this case, the regional model domain has to be large enough to include areas that are connected by soil moisture feedbacks.

Last, the lateral boundary conditions for input to regional downscaling require regional-scale information from a global forecast model. However the global model does not have this regional-scale information due to its limited spatial resolution. This

Table 1. A Typology of Downscaling Applications

Type	Purpose	Inputs to the Regional Downscaling
1	short-term numerical weather prediction	global analysis of observed data plus observed regional initial conditions
2	regional climate simulation	atmosphere information from global or regional reanalyses in which the regional initial conditions are forgotten
3	seasonal prediction	global atmospheric model prediction with prescribed observed surface conditions (e.g., sea surface temperatures)
4	climate prediction	multidecadal global climate model prediction based on prescribed radiative forcing