Comments on "The North American Regional Climate Change Assessment Program: Overview of Phase I Results"

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The Mearns et al. (2012) article provides documentation of the level of skill of one type of dynamic downscaling. Within that framework is an important new contribution that will be widely cited. However, the paper only provides an upper bound of what is possible with respect to phase II of the North American Regional Climate Change Program

> wherein the boundary conditions are provided by four AOGCMs for 30 years of current climate (1971–2000) and 30 years of a future climate (2041–70) for the Special Report on Emissions Scenarios (SRES) A2 emissions scenario. (Mearns et al. 2012, page 1338)

They write

> and . . . . results of phase I contribute to the characterization of uncertainty in phase II (Mearns et al. 2012, page 1339).

The Mearns et al. (2012, p. 1358) study then concludes with the claim that

> we have shown that all the models can simulate aspects of climate well, implying that they all can provide useful information about climate change. In particular, the results from phase I of [the North American Regional Climate Change Assessment Program] NARCCAP will be used to establish uncertainty due to boundary conditions as well as final weighting of the models for the development of regional probabilities of climate change.

However, this conclusion overstates the significance of their findings in terms of its application to the multidecadal prediction of regional climate (i.e., "climate change"). The Mearns et al. study uses observational data (from a reanalysis) to drive the regional models. Using the classification we have introduced in Castro et al. (2005), Mearns et al. is a type 2 dynamic downscaling study.

As we wrote in Pielke and Wilby (2012, p. 52),

> type 2 dynamic downscaling refers to regional weather (or climate) simulations . . . in which the regional model's initial atmospheric conditions are forgotten . . . 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. . . . Downscaling from reanalysis products (type 2 downscaling) defines the maximum forecast skill that is achievable with type 3 and type 4 downscaling.

In contrast

> 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. . . . 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 downscaling has practical value but with the very important caveat that it should be used for model sensitivity experiments and not as predictions (Pielke 2002; Prudhomme et al. 2010).

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As discussed in Pielke and Wilby, type 1 downscaling is used for short-term, numerical weather prediction, while 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. 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.

One cannot, therefore, use type 2 downscaling to make claims, as Mearns et al. (2012) have, about the accuracy of type 4 downscaling. Type 2 downscaling provides a real-world observational constraint on how much the regional model can diverge from reality. This is not the case with type 4 downscaling. A type 4 downscaling cannot be more accurate than a type 2 downscaling.

A more appropriate approach is to first assess what changes in climate statistics would have to occur in order to cause a negative impact to key resources, as we recommend in Pielke et al. (2012, 2013). Only then can we assess what is plausibly possible and how to mitigate/adapt to prevent a negative effect from occurring.

The type of downscaling used in a study is a critically important point that needs to be emphasized when dynamic downscaling studies are presented. Mearns et al. (2012) did not do this.

Indeed, Mearns et al. (2012) is a study of the current climate, not of changes in climate statistics over the time period of the model runs. The Mearns et al. (2012) study did not look at the issue of their skill to predict changes in climate statistics. Even reproducing the current regional climate in a hindcast mode when the results are not constrained by reanalyses is being shown to be a daunting challenge (Xu et al. 2012; Fyfe et al. 2011; van Oldenborgh et al. 2012; Anagnostopoulos et al. 2010; Stephens et al. 2010; Sun et al. 2012; van Haren et al. 2013; Kundzewicz et al. 2010; Goddard et al. 2013; Driscoll et al. 2012; Mauritsen et al. 2012; Jiang et al. 2012; Sakaguchi et al. 2012).

It is even more challenging to skillfully predict changes in regional climate, which is what is required if the RCMs are to add any value for predicting climate in the coming decades beyond what could be extracted from reanalyses. The impacts community should be aware that the Mearns et al. (2012) paper addresses type 2 dynamic downscaling only. Their results do not provide a measure of the skill of multidecadal regional climate change prediction (i.e. type 4 downscaling)

In summary, the Mearns et al. (2012) BAMS paper with respect to type 2 downscaling is an important new contribution. However, its application to climate change runs (type 4 downscaling) is inappropriate and misleading to the impacts and policy communities on a level of predictive skill that does not yet exist.

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