

ARE PRESENT DAY CLIMATE SIMULATIONS ACCURATE ENOUGH FOR RELIABLE REGIONAL DOWNSCALING?

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INTRODUCTION

The motivation for developing downscaling techniques results primarily from the large spatial scales involved in model simulations of weather and of climate change. Climate variables such as temperature, precipitation, and soil moisture are represented as area-averaged values over model grid cells that are typically several hundred kilometers on a side. However, because of high spatial variability, weather and climate information is most useful when it represents relatively small areas. Techniques have been developed over time designed to take information from large model grids and apply it to single points within the grid domain. For example, a weather forecast is more useful if information from a large model grid can be applied to a specific city or small region within the grid. Similarly, climate model information is more useful to water managers, for example, if climate information about a specific watershed can be obtained from a large grid average. Such applications are known as downscaling.

Downscaling techniques come in two primary varieties. Statistical downscaling uses historical, empirical relationships between large-scale, grid-averaged values and conditions at a single point within the grid box. For instance, under certain weather conditions a specific city within a grid box might, on average, exhibit a historical tendency to be cooler and wetter than the grid average value so that a forecast is then adjusted to reflect this historical relationship. Dynamical downscaling usually implies a second physical model embedded in a forecast or climate model that is driven by conditions in the larger scale model. Such a strategy allows a better representation of, for example, topographical differences across a grid cell and more realistic modeling techniques of some physical processes. Dynamical downscaling can typically be performed with grid cells of tens of kilometers on a side. Hybrid

techniques using a combination of dynamical and statistical methods are also in use.

The first and most important assumption common to both forms of downscaling is that the large scale information used in the downscaling is accurate. No downscaling technique can correct faulty information supplied by the large scale model and therefore weather and climate models must simulate regional variations in climatic fields accurately both in present day and in future change scenarios. We examine the assumption of large-scale accuracy in detail by comparing climate simulations with present climate observations and by comparing recent model predictions of climate changes with observations of actual changes.

COMPARISON OF MODEL SIMULATIONS WITH OBSERVED CLIMATE

Figure 1 compares most of the available atmospheric general circulation model control simulations with observed climate conditions for two important hydrologic variables. In ideal circumstances, we would expect all models to closely reproduce the observed pattern and magnitudes and with little spread among models. Precipitation averaged around latitude bands (Figure 1a) compares roughly in pattern with observations (heavy dark line). The models generally simulate a precipitation maximum near the equator with secondary maxima in the mid-latitudes of each hemisphere. However, there is a large spread in precipitation values between the various models at every latitude band and large differences between any particular model and observations. Because averaging around a latitude band has a smoothing effect on regional differences between models, the spread in simulated precipitation between models would be expected to be much larger for any particular region in a particular latitude band than shown here. This is an indication that the large scale information supplied by a climate model for downscaling varies considerably between models and so results would be highly model-

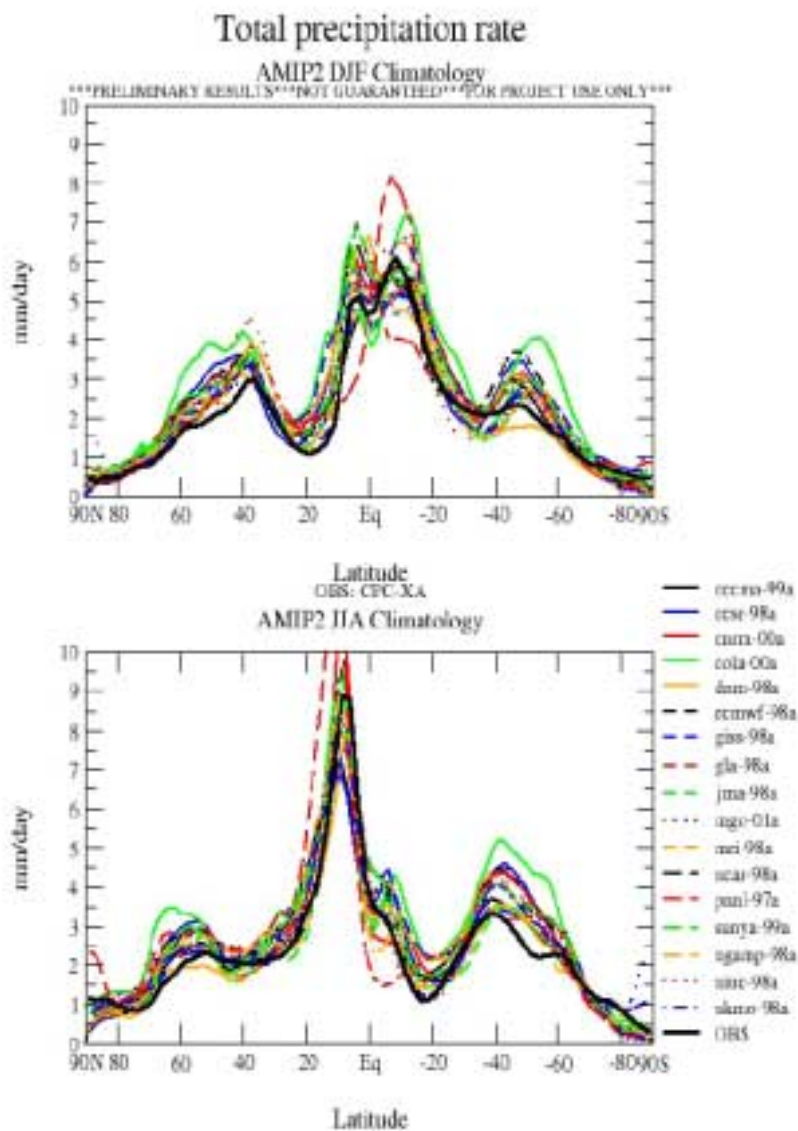


Figure 1a. Comparison of zonally averaged AMIP atmospheric model control simulations with observations: precipitation. From: <http://www-pcmdi.llnl.gov/amip/>

dependent -- an important point for those who would use climate model information for mitigation or adaptation strategies that must be applied to a particular region. Figure 1b compares simulations of cloud cover, again averaged around a latitude band. Here, the differences between observations and any single model are large as is the spread between models. Again, model spread and errors would be expected to be larger in any particular region. This comparison suggests that great caution is in order when applying output from the current generation of climate models to regional decision-making. Regional simulations will often not accurately mirror observations and the specific patterns affecting any region will be heavily

model-dependent (Kittel et al., 1998; Giorgi and Francisco, 2000).

CLIMATE CHANGE PREDICTIONS

Another way to assess the utility of climate change simulations for operational decision-making is to assess the accuracy of predicted changes in recent years. It is well known that climate change simulations under increasing greenhouse gases produce a warmer surface as a global average. What is less known is that climate model simulations show that the largest tropospheric

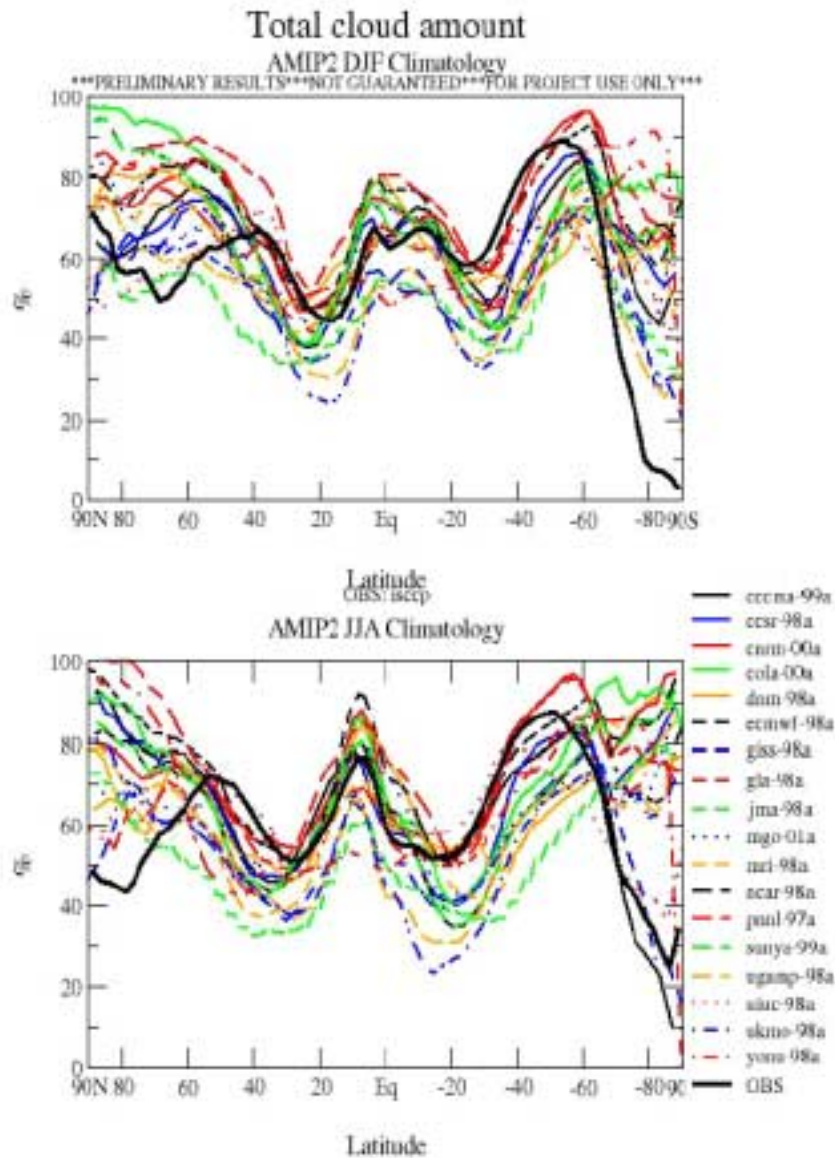
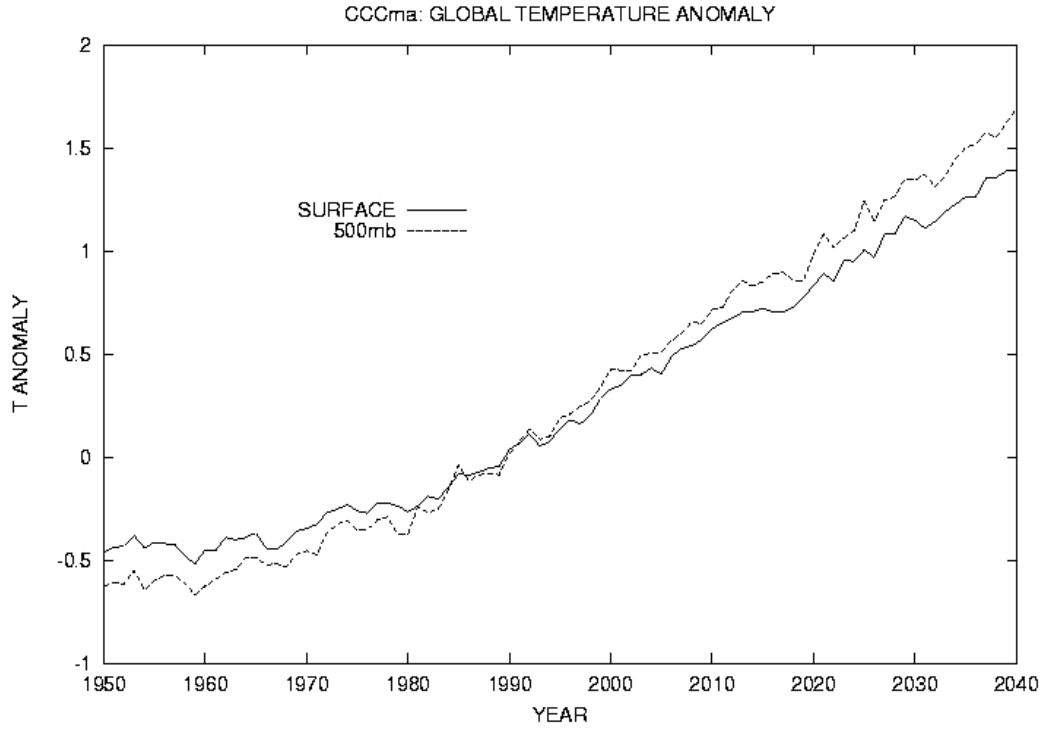


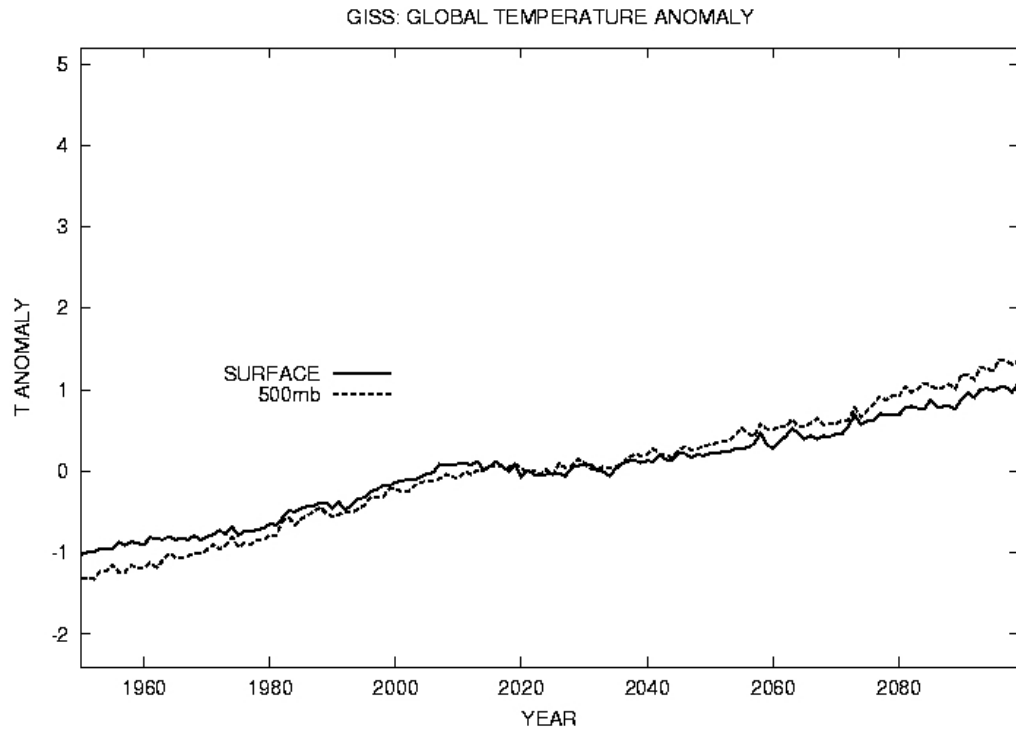
Figure 1b. Comparison of zonally averaged AMIP atmospheric model control simulations with observations: cloud cover. From: <http://www-pcmdi.llnl.gov/amip/>

warming occurs above the surface (IPCC, 2001; Chase et al., in review). Figure 3 compares the warming rates at the surface and at 500mb (about 5km above the surface or mid-troposphere) as simulated in a coupled atmosphere-ocean climate model forced by increasing CO₂ and sulfate aerosols (Russell et al., 2000). This figure clearly shows an accelerated warming above the surface. This is a general prediction of climate change models (IPCC, 2001). Figure 4 compares several measures of tropospheric temperatures (MSU satellite: Christy et al. (2000), Rawinsonde: Sterin (2001), NCEP reanalysis: Kalnay et al. (1996)) and all measures indicate that not only is the troposphere

above the surface not warming faster than the surface as predicted in model simulations, it is not warming at all. A second version of the MSU satellite product (Mears et al., in review) shows more warming in the lower troposphere than the other three measures but less warming than at the surface. The observed situation of a large warming at the surface with no warming above is extremely unlikely in recent model simulations under any conditions (Chase et al., in review). Such an error in the simulation of the vertical temperature structure on the global average would be expected to have large implications for the



(a)



(b)

Figure 2. Globally averaged surface and 500 mb temperature anomaly (relative to 1979-2001 mean) for: a) the Canadian Center for Climate Modeling and Analysis coupled model (CCCm2) ensemble, b) Goddard Institute for Space Studies (GISS) coupled model ensemble

simulation of atmospheric water vapor content, cloud cover and the entire hydrological cycle. Again, errors at the global scale would generally be expected to be larger at any particular point. General circulation models have also generally predicted an increase of the global hydrological cycle in step with a warming climate though there are exceptions particularly over limited time periods (IPCC, 1996, 2001). While precipitation is less easily monitored than air temperatures, the introduction of satellite measurements since the late 1970's has allowed comparison of model simulations with truly global precipitation observations. Figure 5 compares observed precipitation since 1979 (Global Precipitation Climatology Project: <http://precip.gsfc.nasa.gov/>) with that simulated by two model simulations. Both models show an increase in precipitation since 1979 that has no basis in observations. Additionally, regional monsoon systems in the tropics have all shown a decrease in intensity since the 1950s (Chase et al., in press) despite model predictions of an accelerated hydrological cycle.

Finally, and of particular importance to operational decision-making are regular changes in circulation associated with the Southern Oscillation (SO) and

North Atlantic Oscillation (NAO). These natural climate fluctuations have been directly linked to a large portion of the Northern hemisphere winter warming signal (Palecki and Leathers, 1993; Hurrell, 1996; Corti et al., 1999) which is, itself, the primary global surface warming signal. In the observational data, a trend in the NAO index toward more positive values since the early 1960's has been documented (Hurrell, 1996). Similarly, the observed SO index has shown a tendency towards more negative (El Nino-like) values since the middle of the century with a steep change to more negative values in the mid-1970s. The shifts in both these natural circulation regimes are associated with warming and Hurrell (1996) demonstrates that when these two natural circulation influences are removed from the time series, no discernible upward surface temperature trend remains in the Northern Hemisphere (See Figure 4 in Hurrell, 1996). Corti et al. (1999) argue that the observation that recent climate changes are projected on naturally occurring modes of variability is, in itself, not evidence against an anthropogenic origin of the changes. However, if model simulations of past climatic changes do not simulate a similar projection onto natural modes, then questions arise as to whether the correct physical mechanisms are being simulated and whether regional projections can possibly be accurate.

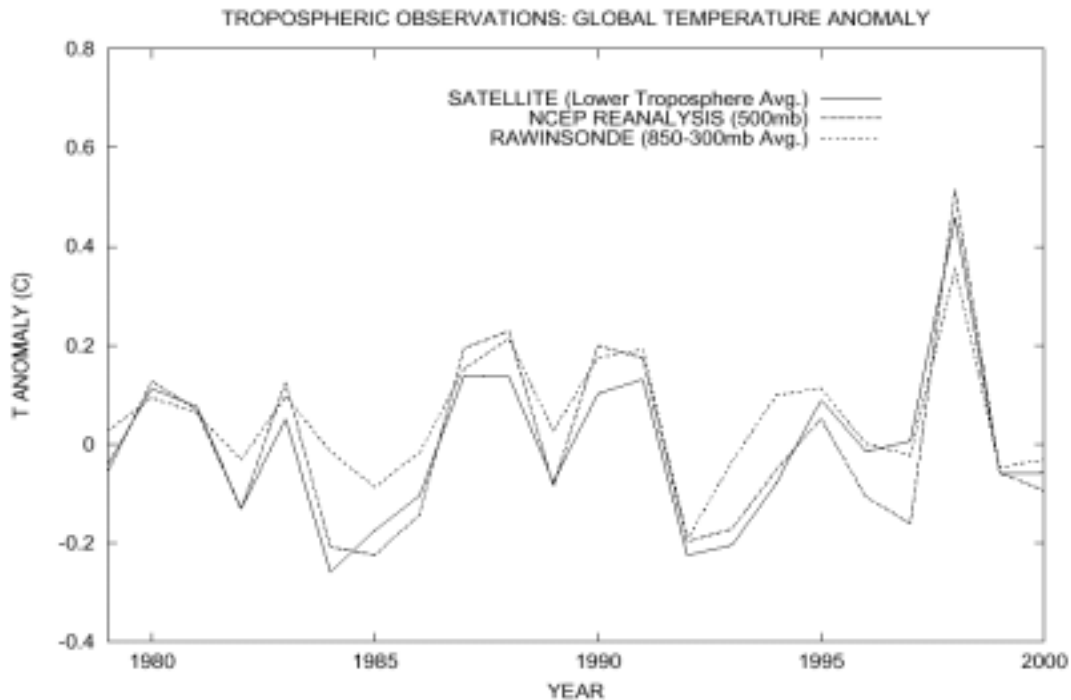


Figure 3. Observed globally averaged temperature anomalies (relative to 1979-2001 mean) for three upper air measures (MSU, radiosonde, NCEP reanalysis) and the surface for 1979-2001

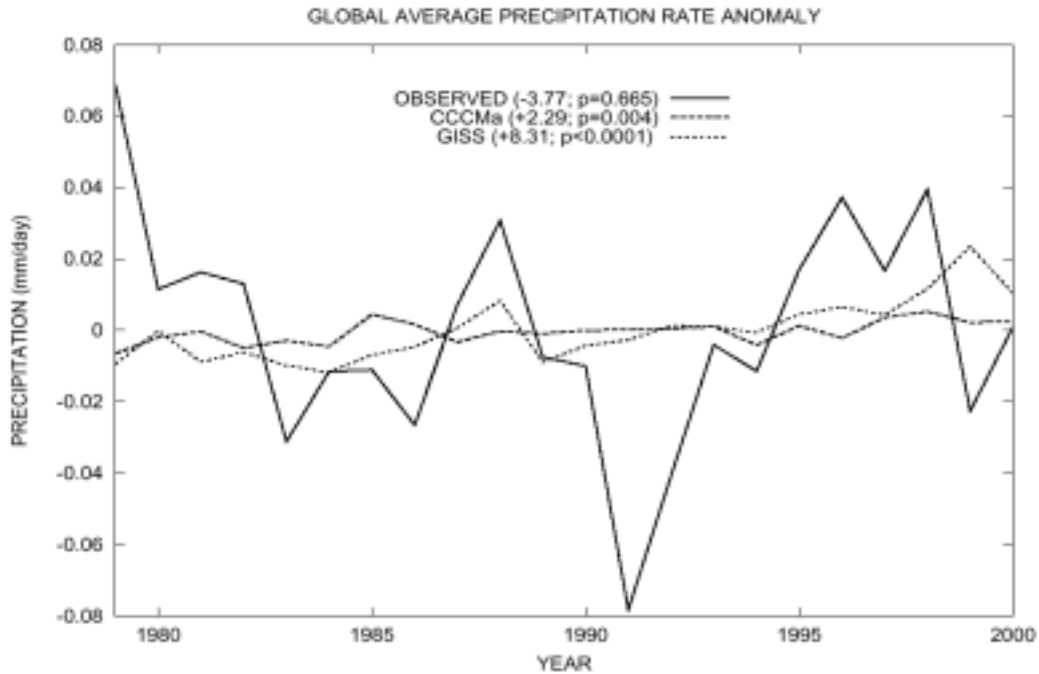


Figure 4. Simulated and observed globally averaged precipitation rate anomalies. Trend and significance p value are given in the legend. Trend units are given as the change in mm/year over the 22 year period 1979-2001

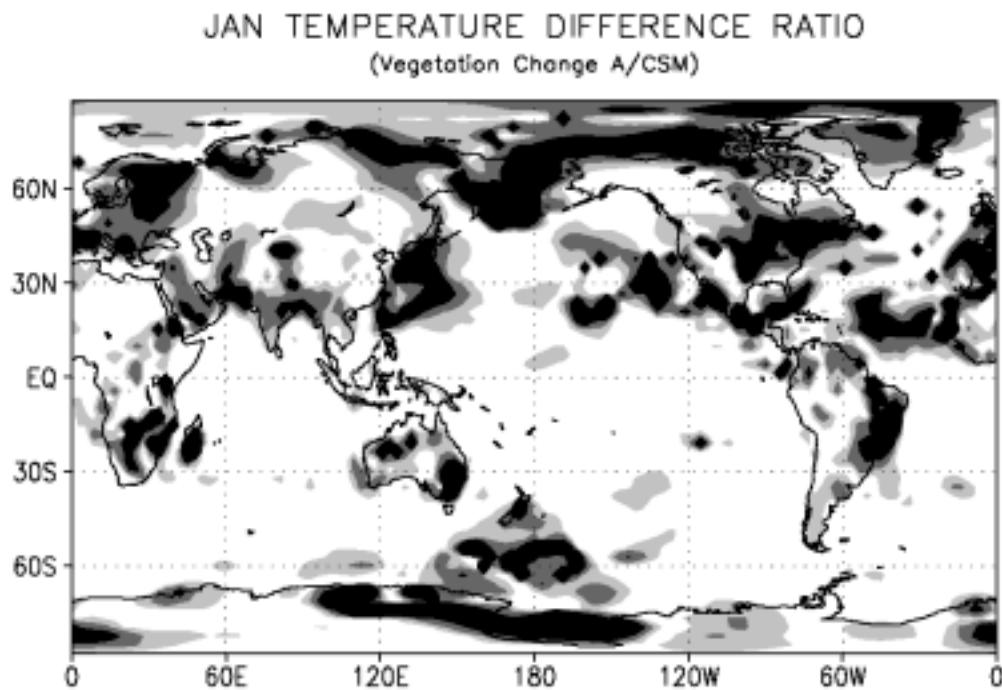


Figure 5. Ratio of simulated surface temperature effects (vegetation change)/(CO₂ change). Shading is, light to dark, 50%, 100%, 200% the effect of CO₂. From Chase et al. (2002)

Reports from model simulations concerning atmospheric circulation changes caused by increasing

greenhouse gases are contradictory. There have been reports of changes which favor a positive shift in the

Southern Oscillation (SO) (more La Nina-like) (e.g. Timmerman et al., 1999, Hu et al., 2001) while others find a tendency for an increasing negative phase (e.g. Collins, 2000; Meehl et al., 2000). Still others find no change (e.g. Tett, 1995) or an increase in amplitude in both phases of the SO but no clear favoring of one phase over the other. Additionally, reported changes in the SO typically occur at CO₂ levels far above present levels of forcing and are therefore in no way applicable to the present day.

Simulated changes in the NAO are also generally non-representative of present day conditions and not robust between models. Paeth et al. (1999) shows a steadily increasing NAO index in climate change simulations starting at about the correct time but conclude that such a trend could happen naturally and the statistical significance cannot be assessed for many more years. Shindell et al. (1999), using the GISS model, demonstrates a positive trend in the model simulating NAO with present day levels of forcing. The large majority of the simulated change in the NAO occurs between 2000 and 2030, however. The trend between 1959 and 2000, the period of observed increase in the NAO index, is static (see Shindell et al., 1999: Figure 2b). Fyfe et al. (1999), using the CCCma model, also demonstrated an increase in the NAO but only at high levels of CO₂ forcing that are unrepresentative of present-day conditions. Osborn et al. (1999) find the opposite effect with a decreasing NAO index in climate change simulations starting at present-day and continuing through the century.

Finally, the robustness of the results from such isolated simulations is unclear. For example, Collins (2000) found a shift towards a more El Nino like state at 4x natural CO₂. However, the simulation produced the opposite change in circulation when small details of the model formulation were changed.

IS EVERYTHING ACCOUNTED FOR?

IPCC (2001) discusses a series of climate forcings both natural and human that are poorly understood and simulated. One such potential climatic influence is changes in landcover due to human activity. Figure 7 (reproduced from Chase et al., 2002) compares the model simulated climate change due to historical landcover changes with that of present day levels of CO₂ and sulfate aerosols. Both simulations show changes in surface temperature that can be either increases or decreases and that are comparable at the regional scale. Any particular region could be warming or cooling under the influences of these factors, making reliable regional action difficult.

Additionally, different models place regions of warming and cooling differently, making any result heavily model-dependent. Accounting for additional influences on the climate would also change regional results.

DYNAMICAL DOWNSCALING WITH A REGIONAL MODEL

We have discussed potential problems with the large scale boundary conditions used as a starting point for any downscaling procedure. We now examine the specific assumptions behind the dynamical downscaling technique. At present, a limited area model (LAM) nested within a larger GCM is used to dynamically downscale for a specific region. The LAM is nudged at its lateral boundaries by the GCM and may be nudged in the interior of its domain. Given an appropriate grid spacing, LAMs can capture the effects of local surface heterogeneity well, though their effects do not upscale to the GCM. With multiple nested grids, it is possible to explicitly simulate cloud microphysical processes. LAMs have proven their utility in short-term numerical weather prediction for several decades. When a LAM is run for a long-term integration (several weeks or more) it is a regional climate model (RCM). Many LAMs originally designed for numerical weather prediction have been adapted as RCMs, such as ETA, MM5, and RAMS. RCMs have their own inherent uncertainties. They are very sensitive to the specification of lateral boundary conditions and grid spacing. As shown by Castro and Pielke (in preparation), for example, RCMs tend to degrade the amplitude and variability of large-scale atmospheric features in the GCM, like ridges and troughs. This can dramatically affect the RCM downscaled results. This worsens as the RCM grid spacing increases and as domain size increases. Dynamical downscaling with a RCM never improves predictability as compared to the GCM. In addition, there may be large sensitivities to the specification of the surface boundary conditions, such as soil moisture and sea surface temperature, and the choice of model parameterizations. Given these caveats, caution should be taken in configuring an appropriate RCM experimental design and interpretation of RCM results.

CONCLUSIONS

We have given several examples in this paper that we believe indicate that present-day climate simulations as input to downscaling techniques designed for day-to-day operations should be used with caution. A case can be made for looking at the output from a variety of models as a way of spanning the space of possible solutions (a technique use for short-term weather prediction), but for longer-term applications, this assumes that each model is fundamentally independent and that the range of

possibilities is fully spanned. Downscaling cannot improve errors in large scale forcing information nor can it provide additional predictability. Present-day climate simulations have large regional errors and a large spread between different models when replicating current climate. Recent climate predictions of accelerated warming above the surface and an accelerated hydrological cycle due to increasing greenhouse gasses and aerosols have not materialized. Moreover, simulations of natural modes of variability (e.g. ENSO and the NAO and the shifts in these modes implicated in most observed climate change) have been poor and the results have not been robust. Processes with the potential to significantly affect regional climate, such as landcover changes, are not generally included in climate change simulations. A specific example of dynamical downscaling indicates that regional climate models, even if provided perfect large-scale boundary conditions, introduce uncertainties and errors of their own.

AUTHOR INFORMATION

Tom Chase works in the areas of interactions between climate and the biosphere, feedbacks within the climate system, and climate change using both models and observational data. He is with the Cooperative Institute for Research in Environmental Sciences (CIRES) at the University of Colorado and is an assistant professor in the Department of Geography.

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