CLIMATE MODEL PROJECTIONS FOR THE CAROLINAS;

TAKING ACCOUNT OF UNCERTAINTY

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The Role of Uncertainty in Climate Science

Assessments of uncertainty have played an increasingly important role in recent reports of IPCC (the Intergovernmental Panel on Climate Change) and CCSP (the US government's Climate Change Science Program). A report by Moss and Schneider (2000) was used for uncertainty assessments in the Third Assessment Report (2001) of IPCC, and was the basis of the current IPCC (2005) recommendations on uncertainty for the Fourth Assessment Report (2007). Elsewhere, Morgan et al. (2008) have given a very comprehensive set of recommendations for CCSP, arguing strongly in favor of a quantitative, probabilistic approach to uncertainty, and explaining the role of methods from Bayesian statistics and decision theory. Although these methods may well be ultimately "the way to go" in this field, they are not currently very widely used by climate scientists, so in this review we outline the more straightforward approach of IPCC (2005).

Type	Indicative examples of sources	Typical approaches or considerations
Unpredictability	Projections of human behaviour not easily amenable to prediction (e.g. evolution of political systems). Chaotic components of complex systems.	Use of scenarios spanning a plausible range, clearly stating assumptions, limits considered, and subjective judgments. Ranges from ensembles of model runs.
Structural uncertainty	Inadequate models, incomplete or competing conceptual frameworks, lack of agreement on model structure, ambiguous system boundaries or definitions, significant processes or relationships wrongly specified or not considered.	Specify assumptions and system definitions clearly, compare models with observations for a range of conditions, assess maturity of the underlying science and degree to which understanding is based on fundamental concepts tested in other areas.
Value uncertainty	Missing, inaccurate or non-representative data, inappropriate spatial or temporal resolution, poorly known or changing model parameters.	Analysis of statistical properties of sets of values (observations, model ensemble results, etc); bootstrap and hierarchical statistical tests; comparison of models with observations.

Table 1: Types of Uncertainty (from IPCC, 2005)

The first step is to recognize that there are different types of uncertainty; see Table 1. "Unpredictability" refers to components of uncertainty that cannot easily be quantified using mathematical or statistical techniques, e.g. projection of future emissions. For this type of uncertainty, IPCC uses "scenarios" to represent a range of possible outcomes, rather than a probabilistic assessment. "Value uncertainties" mostly refers to uncertainties that can be quantified using statistical techniques. In between lie "structural uncertainties", such as the use of inappropriate models; in practice, these are often neglected in formal assessments of uncertainty, though statistical methods for dealing with this kind of uncertainty are becoming increasingly sophisticated (see, e.g., SAMSI 2007).

Because of this recognition that uncertainty assessment is not purely a statistical issue, IPCC (2005) emphasizes the importance of expert judgment and group consensus in the reporting of uncertainty, though also warning against the “tendency for a group to converge on an expressed view and become overconfident in it” (Morgan and Henrion, 1990).

Wherever possible, IPCC (2005) recommends quantitative assessment of uncertainty, and the use of standardized language to express those uncertainties. One possible language is in terms of “likelihoods”, given in Table 2. This allows us to use phrases such as “virtually certain”, “very likely”, etc., with well defined ranges of probability, though it should be emphasized that the probabilities themselves are meant to represent the result of expert judgment and consensus; typically they would not be the result of a single statistical calculation, though statistics may well be used to help inform these assessments.

Terminology	**Likelihood of the occurrence/ outcome**
Virtually certain	> 99% probability of occurrence
Very likely	> 90% probability
Likely	> 66% probability
About as likely as not	33 to 66% probability
Unlikely	< 33% probability
Very unlikely	< 10% probability
Exceptionally unlikely	< 1% probability

Table 2: Likelihood Scale (from IPCC, 2005).

Uncertainty Assessment for Climate Projections from Multi-Model Ensembles

So far, our discussion of uncertainty has been rather general and abstract. For the specific situation in which projections of future climate change are assessed using multiple replications of climate models, a variety of statistical techniques has been proposed. Our discussion here follows Meehl et al. (2007) and also the recent paper of Smith et al. (2008). Applications of the techniques to regional climate model projections are extensively discussed in Christensen et al. (2007).

Replications of the same climate model under the same conditions show some random variation, as a result of the internal variability of the model, but this is of relatively minor importance compared with the structural variability of models due to such factors as different grid sizes and different parameterizations of sub-grid-scale processes. Thus, most assessments of variability in climate projections involve ensembles of model runs from different models. A caveat about such approaches is that they still do not cover all possible sources of inter-model variability, and it is still possible that all the models may contain common sources of bias, which will not be detected by inter-model comparisons.

One approach is via *perturbed physics ensembles*, which use just one model but vary physical parameters of that model (such as the climate sensitivity, the mean global temperature rise in equilibrium associated with a doubling of atmospheric carbon dioxide compared with pre-industrial conditions). A particularly famous example of this approach is Stainforth et al. (2005), who enlisted a large number of volunteers from the general public to run climate models on their personal computers.

The alternative approach, on which we shall concentrate for the present discussion, combines data from several different climate models, where it is assumed that each modeling group has made its own best judgment of climate sensitivity and other model parameters.

To the best of our knowledge, Santer et al. (1990) were the first to propose formal statistical techniques, such as t tests and confidence intervals, to combine data from several climate models. Their ideas were extended by Räisänen (1997), while Räisänen and Palmer (2001) used decision theory techniques to present optimal projections of future climate change based on data from several models. Their methods, however, did not allow for the possibility that different models might have different weights.

A second approach is based on the extension of "detection and attribution" methods to several models. "Detection and attribution" refers to a methodology for expressing climate observations as a linear combination of "signals" or "fingerprints" from various sources of external forcing, plus internal variability. Allen et al. (2000) applied detection and attribution methodology to four climate models, obtaining projections (with confidence bands) for future temperature changes into the middle of the 21^{st} century. Further applications of the same approach were by Stott and Kettleborough (2002) and Stott et al. (2006).

A third approach is based on the *Reliability Ensemble Average* (REA), first introduced by Giorgi and Mearns (2002). This approach was the first to recognize that, for projecting a specific variable in a specific region, it may be appropriate to give different weights to different models. Giorgi and Mearns identified two factors in determining the weights, which they called *bias* and *convergence*. Bias is a measure of the discrepancy between a model's projections of 20^{th} century climate and observational data. Convergence refers to the agreement among different models in their 21^{st} century projections – a model that produces substantially different projections from the other models in the ensemble would typically be assigned lower weight in the REA. The method used by Giorgi and Mearns to assign weights contained some ad hoc features, but an alternative approach introduced by Tebaldi et al. (2004, 2005) recast the methodology in terms of Bayesian statistics. In this approach, a Monte Carlo approach is used to derive posterior distributions of various statistical parameters, and probabilistic projections of future climate change may be obtained by sampling from the Monte Carlo output.

Some comparisons between the detection and attribution approach and the REA approach were presented in Lopez et al. (2006), and further discussed in Meehl et al. (2007). It was pointed out that the Bayesian REA approach typically yields narrower uncertainty bounds than the detection and attribution approach, but that the two may be brought into better agreement by adjusting the prior distributions of the REA approach. Two other approaches to probabilistic projections are due to Greene et al. (2006) and Furrer et al. (2007). It has been pointed out that the Greene approach tends to produce completely different projections from the REA approach, which is attributable to some assumptions in their approach (Christensen et al., 2007), while the Furrer approach is an extension of Tebaldi et al. (2004, 2005).

Recently Smith et al. (2008) have presented an alternative formulation of the Bayesian REA approach that is intended in part to meet some of the objections to the earlier Tebaldi et al. (2004, 2005) approach. In this formulation, there are two versions, a "univariate" methodology that treats each climate variable or region entirely separately from all the others, and a "multivariate" methodology that combines all the variables or regions into a single analysis. The multivariate analysis makes stronger statistical assumptions but one consequence is that typically (though not always) it leads to narrower uncertainty ranges for future projections. We recommend computing both the univariate and multivariate analyses as a check on the robustness of the results to statistical modeling assumptions.

Example: Climate Model Projections for North Carolina

As an illustration of these ideas, we apply the methods of Smith et al. (2008) to projections of future temperature and precipitation from North Carolina.

20th century observational data are represented by "climate normals" (1971-2000) tabulated by the National Climatic Data Center. Specifically, monthly temperature and precipitation means were downloaded for 160 stations within North Carolina, and grouped into three regions, henceforth referred to as "West", "Central" and "East" North Carolina (Figure 1). Averages were computed for each three-month season (Winter=DJF, Spring=MAM, Summer=JJA, Autumn=SON).

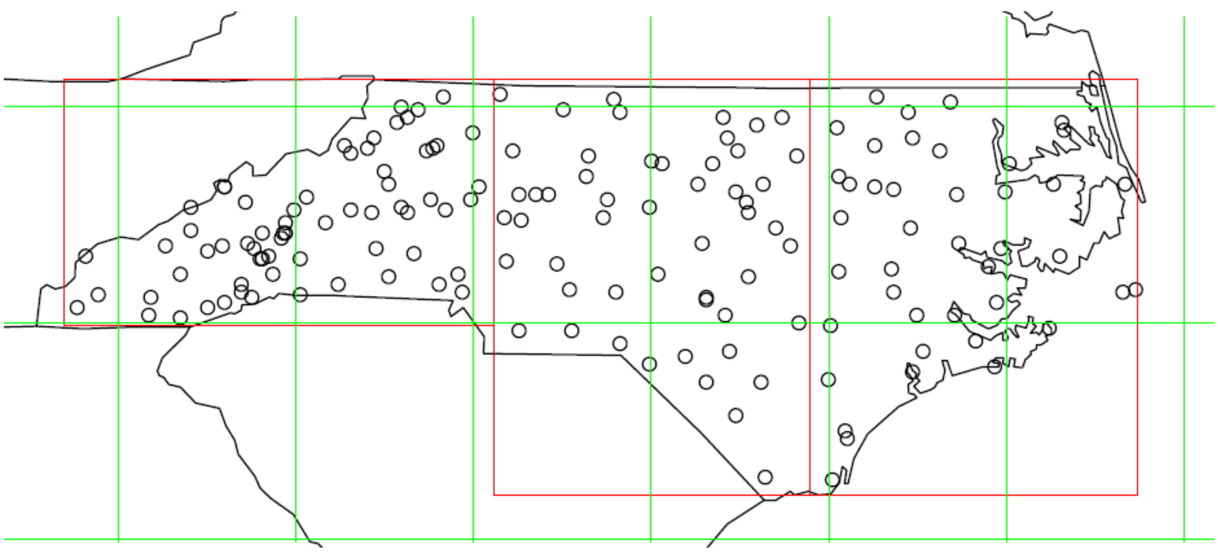

Figure 1: Stations used in computing climate normals, in three regions (West, Central, East) shown in red. Also shown (in green) are the grid boxes of one well-known climate model, the Community Climate System Model (CCSM) from the National Center for Atmospheric Research.

Climate model data were downloaded from the IPCC-AR4 archive at the Program for Climate Model Diagnosis and Intercomparison (http://www-pcmdi.llnl.gov) . Data from seven models were obtained (Table 3), using runs for 20th century model output (1971-2000) and for future projections (2071-2100) under the SRES-A2 scenario. The A2 scenario is often called the "business as usual" scenario and represents projections of greenhouse gases if there are no substantial efforts to curtail emissions over the coming decades. The model data were projected to the three regions shown in Figure 1. It should be pointed out that this projection is rather rough, since in many cases the grid cells of the climate models were as large or larger than the regions being projected. For this reason, it would be of interest to repeat the following exercise with regional climate models, which use smaller grid cells.

Model	Description
1	Canadian Centre for Climate Modelling and Analysis, CGCM3.1 Model, T47
2	CSIRO Atmospheric Research, Australia, Mk3.5 Model
3	NOAA Geophysical Fluid Dynamics Laboratory, CM2.1 Model
4	NASA Goddard Institute for Space Studies, ModelE20/Russell
5	Max Planck Institute for Meteorology, Germany, ECHAM5 / MPI OM
6	NCAR Community Climate System Model, CCSM 3.0
7	Hadley Centre for Climate Prediction, Met Office, UK, HadCM3 Model

Table 3: Climate Models Used for Future Projections

Results for temperature projections are given in Figure 2. For each season and region, we present three estimates with corresponding 95% probability intervals, (a) for 20th century data (based on climate normals, with standard error representing inter-station variability), (b) for 21st century data under the "univariate" model of Smith et al. (2008), (c) for 21st century data under the "multivariate" model of Smith et al. (2008).

In each case, the results show a clear warming trend, of the order of 4-5 degrees F in winter and 6-7 degrees F in the other three seasons. The warming is slightly less in the East region than in the West and Central. The prediction intervals for 21st century mean temperatures typically have width of the order of 2-4 degrees F, which implies some uncertainty about the actual amount of warming but still a very high confidence that the temperature will increase over the 21st century, in all regions and seasons.

Corresponding results for precipitation projections are in Figure 3. Here also, there is a projection of increasing precipitation in all seasons and regions, but the 95% probability intervals are wide compared with the projected increases. The projected increase is quite small, less than 0.5 mm per day in most season/region combinations (i.e. less than 10% overall increase in precipitation). The greatest confidence that there will be an increase in precipitation is in the winter. For the other three seasons, the range of projected mean precipitations for 2071-2100 typically overlaps the current mean precipitation, which implies a lack of confidence that there will be an increase. There is no discernable difference among the three regions. Note that the results are not consistent with 20th century trends discussed elsewhere in this report, which have shown an increase in fall precipitation, a decrease in summer precipitation, and little change in spring and winter.

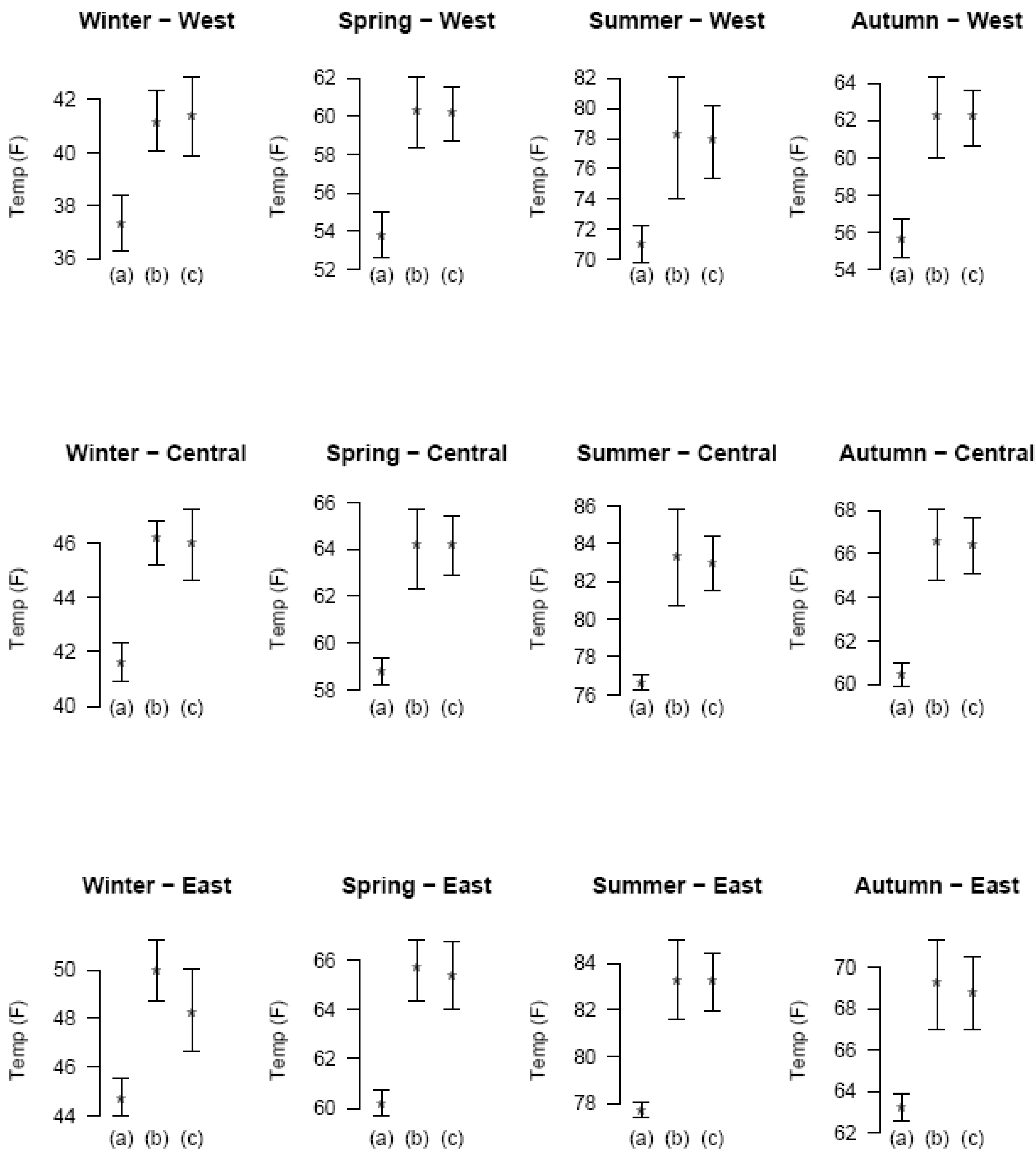

Figure 2: Temperature Projections with 95% Probability Intervals. (a) Climate Normals for 1971-2000; (b) Projections by “univariate” method of Smith et al. (2008). (c) Projections by “multivariate” method of Smith et al. (2008).

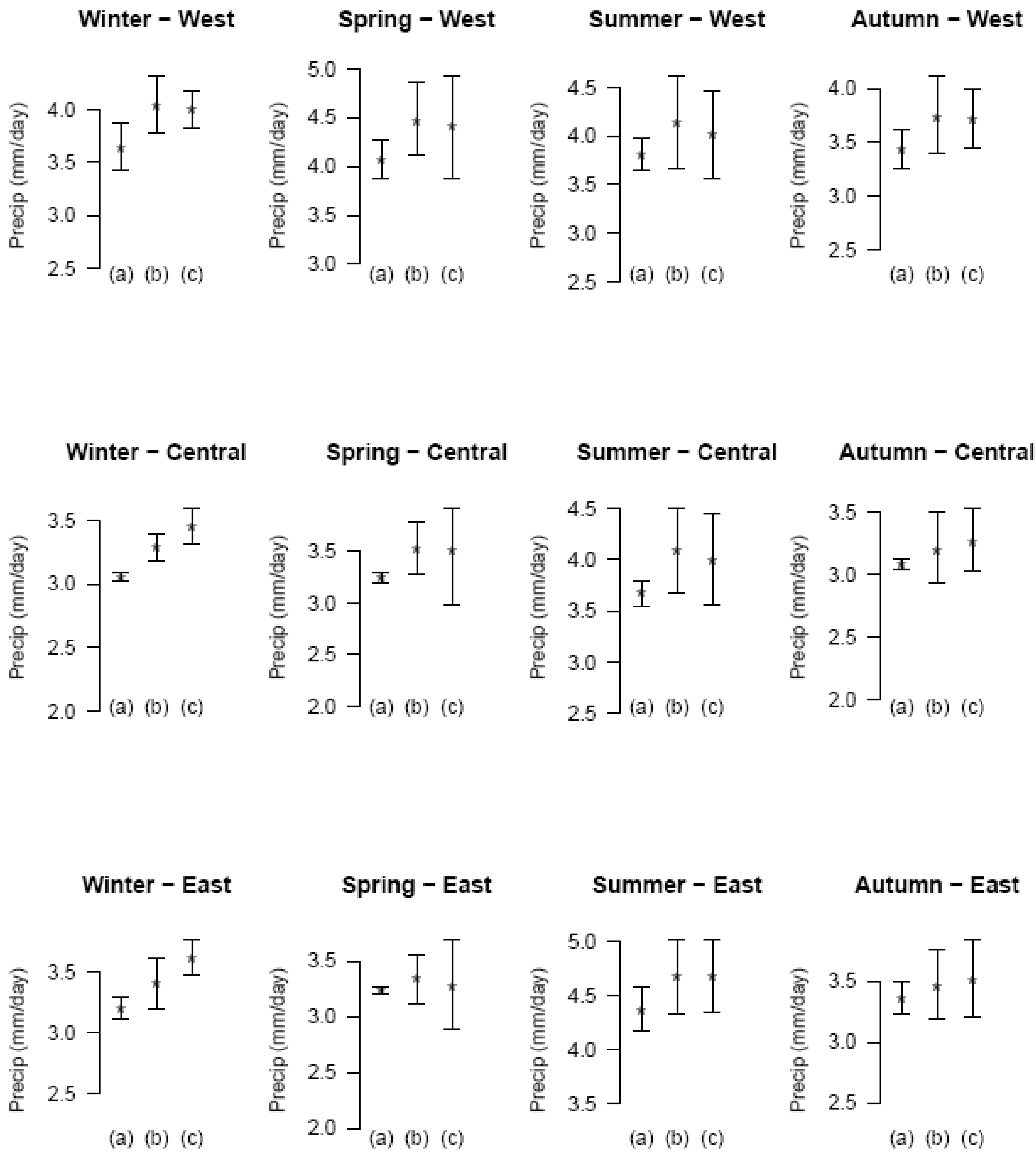

Figure 3: Precipitation Projections with 95% Probability Intervals. (a) Climate Normals for 1971-2000; (b) Projections by "univariate" method of Smith et al. (2008). (c) Projections by "multivariate" method of Smith et al. (2008).

Conclusions

Model projections for North Carolina for the years 2071-2100 show a consistent warming of the order of 5 degrees F over all regions and seasons, slightly lower in winter than the other three seasons, with a high level of confidence that the warming trend is genuine. For precipitation, the models also project an increase over all seasons and regions, but with wide probability intervals compared with the projected increases, implying that there is still considerable uncertainty about the direction of future change.

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