Spatial patterns of probabilistic temperature change projections from a multivariate Bayesian analysis

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[1] We present probabilistic projections for spatial patterns of future temperature change using a multivariate Bayesian analysis. The methodology is applied to the output from 21 global coupled climate models used for the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. The statistical technique is based on the assumption that spatial patterns of climate change can be separated into a large scale signal related to the true forced climate change and a small scale signal due to model bias and variability. The different scales are represented via dimension reduction techniques in a hierarchical Bayesian model. Posterior probabilities are obtained with a Markov chain Monte Carlo simulation. We show that with 66% (90%) probability 79% (48%) of the land areas warm by more than 2°C by the end of the century for the SRES A1B scenario. **Citation:** Furrer, R., R. Knutti, S. R. Sain, D. W. Nychka, and G. A. Meehl (2007), Spatial patterns of probabilistic temperature change projections from a multivariate Bayesian analysis, *Geophys. Res. Lett.*, *34*, L06711, doi:10.1029/2006GL027754.

1. Introduction

[2] Recent work on probabilistic climate change projections has focussed mainly on the evolution of global mean temperature [e.g., *Wigley and Raper*, 2001; *Knutti et al.*, 2002, 2003, 2005; *Stott and Kettleborough*, 2002] or on constraining climate system properties such as climate sensitivity, ocean diffusivity and aerosol forcing [e.g., *Forest et al.*, 2002; *Knutti et al.*, 2002, 2003]. However, impacts and adaptations are determined mostly by local climate change and thus require a quantitative picture of the expected change on regional and seasonal scales. Estimates of the probability density functions (PDF) for regional changes have been constructed using different approaches [e.g., *Räisänen and Palmer*, 2001; *Giorgi and Mearns*, 2003; *Tebaldi et al.*, 2005; *Stott et al.*, 2006; *Greene et al.*, 2007], often either treating individual regions independently or neglecting structural uncertainties due to intermodel differences. In contrast to other techniques, the method applied here [*Furrer et al.*, 2007] is based on an ensemble of 21 global coupled climate models (AOGCMs) and partly takes into account structural uncertainty due to the use of different climate models. It explicitly models the spatial covariance of the global fields, thus providing PDFs of localized climate change that are coherent with the distribution of climate change in neighboring locations. Results are shown for the temperature change at year 2080–2100 for the IPCC SRES A1B scenario [*Nakićenović et al.*, 2000], relative to 1980–2000.

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2. Statistical Model

[3] *Furrer et al.* [2007] introduce a statistical methodology to assess probabilistic climate change fields from different AOGCM results. We review here the fundamental ideas of the approach. The auxiliary material contains a thorough discussion of the method, parameter justification and additional illustrations.[1]

[4] The applied method can be interpreted as an extension of linear regression: instead of individual values, entire fields are regressed. Further, the errors are not assumed to be identically distributed but the fields may have individual error structure. In this analysis, the individual fields are the temperature change from each member of the multi-model ensemble, averaged over the decades and seasons of interest.

[5] The regressors are carefully chosen (basis) functions that are selected to explain the common large scale structure of the climate change signal. For each AOGCM, regression coefficients are determined, which are, on average over all models, assumed to be centered around the true (unknown) coefficients which implies that the true signal of climate change is represented as a linear combination of those basis functions. Further, this means that all AOGCMs have as common component the true climate change that we try to estimate. Inevitably, like for any other method, if a bias is common to all models, this will incorrectly be considered part of the "true" climate signal. Each AOGCM approximates the true signal of change with a precision that is determined by the resolved processes, its resolution, parameterization, etc. This statistical modeling technique is a dimension reduction approach since each field is represented by a few (order of hundreds) coefficients instead of the set of grid cells (order of thousands).

[6] The main statistical assumption of the model is that the true (unknown) climate change can be realistically represented as a linear combination of the basis functions. This signal, common in all AOGCM, is also termed large scale signal. The remaining residual signal, also termed small scale signal, accounts for the spatial correlation remaining in each AOGCM's deviation from the common large scale structure. This AOGCM specific signal is assumed to be due to model bias and internal unforced climate variability and is modelled as (spatially structured) Gaussian noise with constant variance.

[1]Auxiliary material data sets are available at ftp://ftp.agu.org/apend/gl/2006gl027754. Other auxiliary material files are in the HTML.

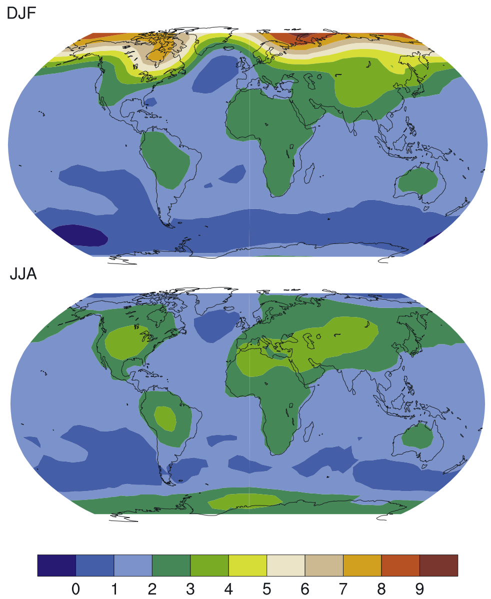

Figure 1. (top) DJF and (bottom) JJA temperature change in °C by 2080–2100 in the A1B scenario (relative to 1980–2000) that is exceeded with 80% probability.

[7] Additional assumptions are that each individual AOGCM is unbiased for each gridpoint, and that all AOGCMs are independent (i.e. their differences from the true climate signal are uncorrelated) and are given the same weight. These assumptions are not entirely satisfied in reality. To some degree, most AOGCMs are known to have similar biases, in particular on small scales. Independence implies that with increasing number of AOGCMs the uncertainty in the climate change estimate decreases. If the number of climate models were to become very large this would lead to unrealistic results as this method ignores that in this case the common biases dominate the uncertainty. This asymptotic behavior would require attention and modifications of the statistical method. However, these assumptions do not imply that all the models have the same climate sensitivity, or that they all have the same transient climate response at a particular time and at some scale. We assume that each design of a AOGCM model is such that it models the truth to the best knowledge of its developers. The differences between the models are expressed by their individual precision. Additionally, a more sophisticated method should incorporate the fact that some models compare more favorably with observations than others. The underlying idea of our approach, namely that each climate model provides realizations of a process centered around the true climate, is fundamentally different from the assumptions that the true climate is one of the physically possible climates described by the AOGCMs.

[8] The statistical model is formulated as a spatial hierarchical Bayesian model [*Banerjee et al.*, 2004] and using a Markov Chain Monte Carlo algorithm we obtain (1) estimates of the true regression coefficients, (2) the uncertainty around them, and (3) estimates of the small scale covariance. As a result we can reconstruct the estimated true climate change field and its uncertainty (posterior field). Since the statistical model accounts for the spatial correlation of the true climate change (through the basis functions) and of the model specific bias and internal variability (through the residual covariance), the probabilistic projections derived for the entire climate change field represent the spatially joint probability of climate change for each of the locations.

3. Results

[9] Results are shown for the surface warming at year 2080–2100 relative to 1980–2000 for the emission scenario A1B, using model simulations calculated for the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC). Surface temperature fields from the following 21 models were used: CCSM3, CGCM3.1(T47), CGCM3.1(T63), CNRM-CM3, CSIRO-Mk3.0, ECHAM5/MPI-OM, ECHO-G, FGOALS-g1.0, GFDL-CM2.0, GFDL-CM2.1, GISS-AOM, GISS-EH, GISS-ER, INM-CM3.0, IPSL-CM4, MIROC3.2(hires), MIROC3.2(medres), MRI-CGCM2.3.2, PCM, UKMO-HadCM3, UKMO-HadGEM1 (for details and model references see http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php). Model data is first interpolated to a common 5° by 5° latitude-longitude grid. Note that the global averages refer to the average between 80°S and 80°N, i.e. the poles are excluded.

[10] The posterior climate fields can be used to calculate pointwise percentile fields. Figure 1 shows the temperature change that is exceeded with 80% probability (i.e. the 20th percentile) for boreal winter (December to February) and summer (June to August). Winter warming is exceptionally large in high northern latitudes, caused by a decrease in sea ice and snow cover, while summer warming is large over most land areas. Although the analysis is carried out on a 5° by 5° resolution, the posterior fields are smoothed by construction and results should not be interpreted on a grid point level but by regions of the order of a few thousand kilometers. The patterns in the posterior climate fields are similar to the corresponding raw (finite sample) multi-model quantities as the analysis is based on all, equally weighted, models. Yet, because of the assumed model structure the present technique can be used to derive arbitrary percentiles independent of the number of models. Of course, the validity of estimates of very large or very small percentiles depends strongly on the statistical model assumptions.

[11] Similarly, Figure 2 shows the probability that the local temperature change exceeds 2°C. This temperature change relative to preindustrial climate is an often quoted, albeit clearly subjective, temperature threshold [*den Elzen and Meinshausen*, 2005].

[12] Figure 3 shows the percentage of the total area and of the land area where the season average warming exceeds a given temperature threshold with 66% and 90% probability, respectively. Note that the IPCC terms >66% and >90% probability as "likely" and "very likely", respectively.

[13] With 66% (90%) probability, about 79% (48%) of the land areas warm more than 2°C relative to the base period 1980–2000 in the annual mean by the end of the century in addition to the global temperature increase of about 0.5°C realized before the base period. The land area fraction exceeding a certain temperature is always substantially larger than the global area fraction, because warming over land is larger than over ocean. A small fraction, about 5% (3%), of the land area warms more than 5°C with 66% (90%) probability.

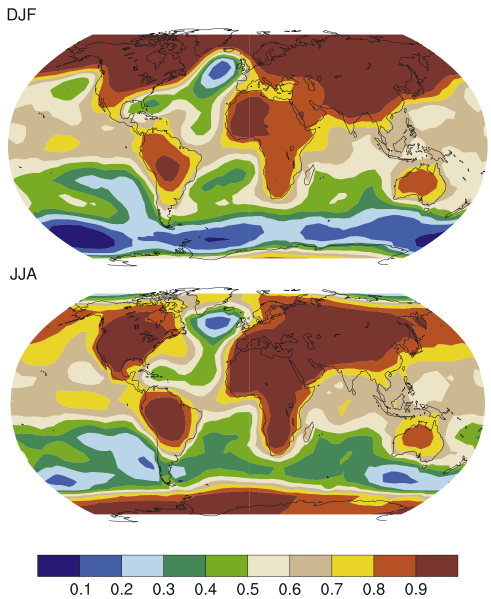

Figure 2. Probability that (top) the DJF and (bottom) the JJA temperature change exceeds 2°C by 2080–2100 in the A1B scenario, relative to 1980–2000.

[14] Naturally, the posterior fields can be used to construct global mean climate changes. Figure 4 compares the seasonal posterior mean climate change with a normal distribution fitted to global mean values of the 21 models.

4. Comparison With Other Techniques

[15] Figure 5 compares regional boreal winter temperature change for four regions obtained with the method presented here with results obtained by *Tebaldi et al.* [2005]. The PDFs of the latter technique are much narrower, and in some cases show multimodality. Multimodal PDFs are not physically meaningful and are likely to be the result of random clustering of the limited number of models and of the use of a model convergence criterion. On large scales, the technique by *Tebaldi et al.* [2005] has been shown to generally underestimate the uncertainty relative to other estimates [*Lopez et al.*, 2007]. The uncertainty of the PDFs calculated here is considerably larger since the developed model was constrained with a global posterior coverage of the climate change. For some regions, e.g., Central America, the regional posterior temperature change is wider than the multimodel forecast. For other regions, e.g., Alaska, the posterior covers all but one or two AOGCM results. We believe that the stationarity assumption of the small scale process (i.e. the assumption that the amplitude of the noise component is

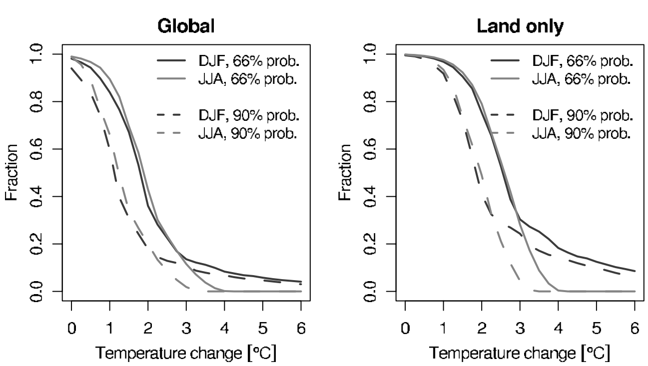

Figure 3. Fraction of (left) total and (right) land area where the season average warming exceeds with 66% and 90% probability a given temperature threshold (period from 1980–2000 to 2080–2100 with A1B scenario).

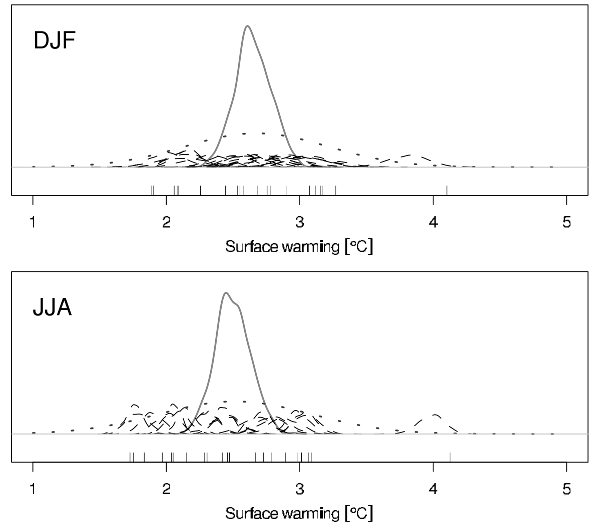

Figure 4. Aggregated (top) DJF and (bottom) JJA PDF of global mean temperature change in °C by 2080–2100 in the A1B scenario, relative to 1980–2000 (solid curve). Dashed curves are the PDFs of respective global mean temperature change for the individual models depicted with a scale reduced by 10. The dotted curve is the normal fit of the 21 models. Ticks mark individual model results.

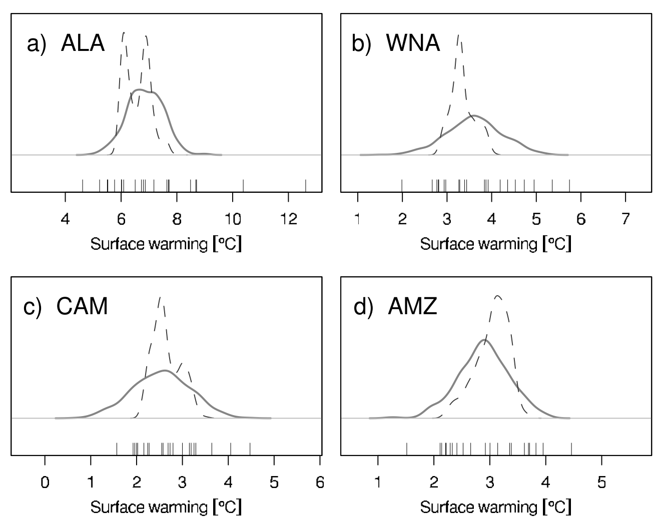

Figure 5. Comparison of PDFs of regional posterior DJF temperature change obtained with the presented method (solid curve) and with the *Tebaldi et al.* [2005] technique (dashed curve). Ticks mark individual model results. The regions are (a) Alaska, (b) West North America, (c) Central America, and (d) Amazon Basin, as defined by *Giorgi and Francisco* [2000].

similar in all regions) is a main factor for this phenomenon. Our PDFs have a comparable variability/uncertainty with the results obtained based on the detection and attribution method, both on global [*Stott and Kettleborough*, 2002] and regional scales [*Stott et al.*, 2006].

5. Conclusions

[16] The statistical model presented here has a simple structure, is based on very few statistical assumptions and it also provides a probabilistic interpretation of the output of a relatively small number of models while incorporating both structural uncertainty due to intermodel differences and the spatial nature of climate fields. The latter is implemented using meaningful covariance functions expressing the geographical and spatial dependence. The posterior fields can be analyzed as such or can be arbitrarily down-scaled or weighted with virtually no computational cost.

[17] However, the model has some limitations and does not incorporate local, systematic biases within individual AOGCMs. Current research consists of extending the statistical model by modelling future and base period climate fields independently and by adding further additive components. For example, the AOGCM climate fields could be represented as additive decompositions of overall large scale effects, specific model bias and internal variability. Further, an ideal technique would take into account the fact that several models in the ensemble are used in different resolutions but are based on identical or similar physical cores.

[18] Finally, by construction of the statistical model, the residual signal has a constant variance. This hypothesis should be relaxed, since, for example, the AOGCMs reveal smaller variability over the ocean compared to over land. Additionally, the statistical method provides a slightly too narrow posterior distribution in the high latitudes (see Figure 5).

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