



Probabilistic projections of climate change fields from a multivariate Bayesian analysis of climate model data

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Motivation and Overview

Impacts and adaptations are determined mostly by 'local' climate change and thus require a quantitative picture of the expected climate change and uncertainty on regional and seasonal scales. 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 IPCC Fourth Assessment Report. The statistical technique is based on the assumption that the simulated 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 from model bias and variability.

Method

Furrer et al. (2006) introduce a statistical methodology that can be seen as a direct extension of the assumptions of linear regression to the treatment of fields, rather than single scalar values. The fields, say future temperature change from different AOGCMs, are regressed upon basis functions, i.e. a series of fields that are chosen to explain the common large scale structure of the climate change signal. The coefficients of the regression are AOGCM specific, but on average assumed to be centered around the true (unknown) coefficients. The main statistical assumption of the method is that the large scale forced signal can be separated from small scale noise and that each AOGCM approximates the true common signal of climate change that we are trying to estimate. The residual signal unexplained by climate change due to model bias and internal unforced climate variability is again AOGCM specific in terms of small scale structure, but is assumed to be (spatially structured) noise with constant variance. The basis functions describing the large scale structure include spherical harmonics, indicators of continents and other geographic features, and the current observations. However, these observations do not attribute weights to the models and we do not have a bias and a convergence weighting as developed by e.g. Tebaldi et al. (2005). The fit of the statistical model through a Markov Chain Monte Carlo algorithm gives (1) estimates of the true coefficients of the regression (2), the uncertainty thereof and (3) estimates of the small scale structure. By recombing the mean coefficient estimates with the basis functions an estimate of the true climate change field is derived. The uncertainty around this field can be determined, for example, by examining ensembles constructed from draws from the posterior distribution of the coefficient estimates. Since the model accounts for the spatial correlation of the large scale (through the basis functions) and of the small scales (through the error covariance), the probabilistic projections derived for the entire globe represent the joint probability of climate change for all locations.

The method currently does not account for the fact that some models perform better than others, and that the models are not entirely independent.

Probabilistic maps

Posterior distributions can be expressed as both maps of temperature change exceeded with any given probability, for both winter and summer, or alternatively as the probability for locally exceeding a given temperature threshold. Warming patterns are similar to the multi model mean, with the typical strong high latitude warming in boreal winter, and warming larger over land than ocean, in particular in boreal summer.

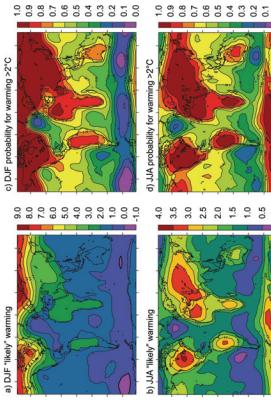


Fig. 2: a/b) DJF and JJA warming probability for 2°C; c/d) Probability that the DJF and the JJA temperature change exceeds 2°C. All changes are for the period 2080-2100 relative to 1980-2000 in the SRES A1B scenario.

Global projections

On the largest scale, the Bayesian method produces probability density functions (PDFs) of global temperature change for various scenarios, decades and seasons. Results compare favourably with other studies based on very different techniques and models. Uncertainty in projections grows over time and projected warming is almost independent of the scenario for the next few decades.

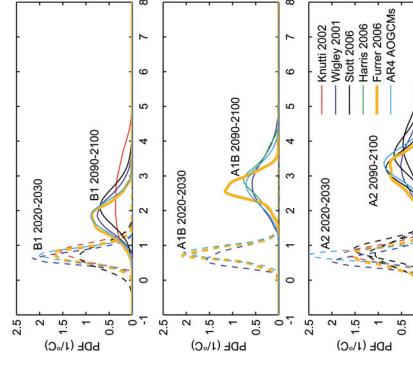


Fig. 3: Fraction of total and land area where the season average warming likely and very likely (66% and 90% probability, respectively) exceeds a given temperature threshold.

Conclusions

The statistical model presented has a simple structure, is based on very few statistical assumptions and provides a probabilistic interpretation of the projected climate change from a relatively small number of models while incorporating both the spatial nature of climate fields as well as structural uncertainty due to intermodel differences. The posterior fields can be analyzed as such or can be arbitrarily down-scaled or weighted with virtually no computational cost. Extensions of the model are possible, e.g. a joint model for temperature and precipitation.

Regional projections

Probability density functions of projected warming can be aggregated for arbitrary regions. However, the separation of the large scale forced patterns from small scale noise necessarily implies some smoothing of the fields (see opposite maps) such that PDFs cannot be interpreted on a grid point level but only on regional to continental scales. PDF widths are similar to the raw model spread and are wider than those derived by methods which weight models by bias and convergence criteria.

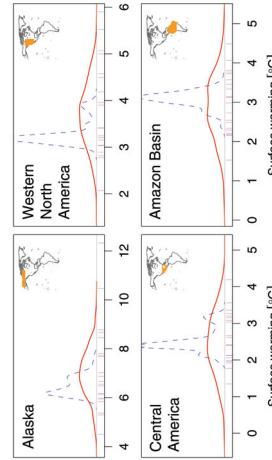


Fig. 4: Comparison of PDFs of regional posterior DJF temperature change obtained with the presented method (red solid) and with the Tebaldi et al. (2005) technique (blue dashed). Ticks mark individual model results. The regions are Alaska, Western North America, Central America and Amazon Basin, as defined by Giorgi and Francisco (2000).

References:

- Furrer, R., S.R. Sain, D. Nychka and G.A. Mehl, 2006: Multivariate Bayesian analysis of atmosphere-ocean general circulation model. *Environmental and Ecological Statistics*, in press, http://www.mines.edu/mines-research/documents/meier_eta_ees_color.pdf.
Tebaldi, C., R.W. Smith, D. Nychka, and L.O. Mearns, 2005: Quantifying uncertainty in projections of regional climate change: A Bayesian approach to the analysis of multi-model ensembles. *Journal of Climate*, **18**, 1524-1540.

Fig. 1: Probability density functions from the presented method (thick yellow lines) compared with other studies that provide probabilistic temperature change projections. Global mean temperature changes are given for the SRES scenarios B1, A1B and A2 and for the decades 2020-2030 and 2090-2100 relative to the 1980-2000 average.