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Probabilistic assessment of regional climate change: a Bayesian approach to combining predictions from multi-model ensembles

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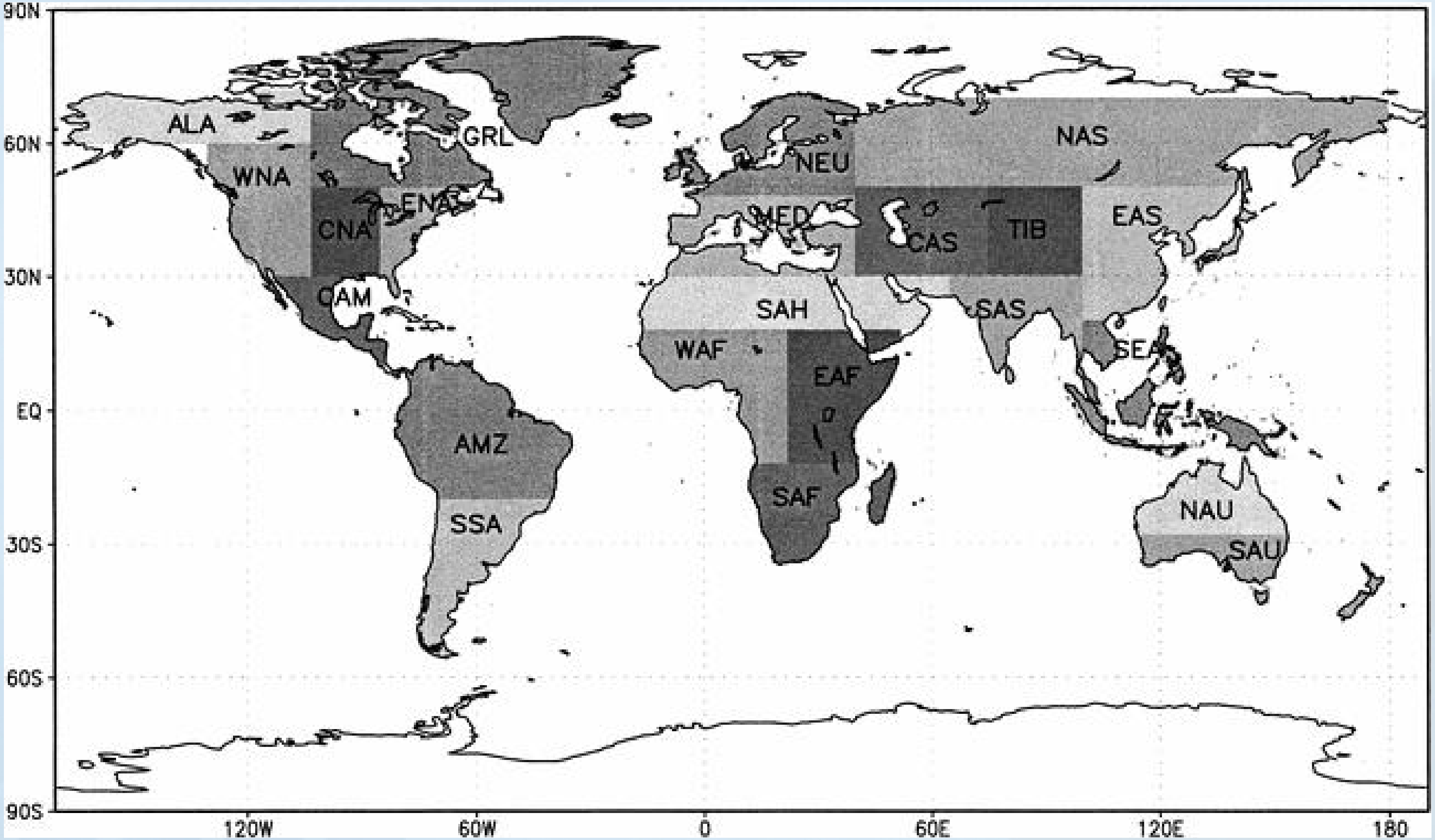
Motivation

- Produce a probabilistic representation of future temperature/precipitation change, at regional scales, relevant to impacts research

- Taking advantage of the information contained in “opportunity ensembles”, reconcile projections from different AOGCMs

- Substitute formal probabilistic assumptions for heuristic criteria of model reliability

Regional Scales



Multi-model Ensembles

- How do we reconcile different projections from different GCMs under the same emissions scenario?

- BIAS and CONVERGENCE criteria:
  - Reward models that perform well in reproducing current climate/discount models that show a large bias
  - Reward models that form the consensus/downweight extreme projections

- Recently formalized as factors in a weighted average of the single models' results by Giorgi and Mearns (*JClim* 2002)

A formal probabilistic approach

We are interested in unknown quantities, the parameters of our analysis

- The true temperature in region A, within current and future climate
- The temperature change in region A

We have data that we want to incorporate in our analysis

- The observed temperature in region A
- 9 AOGCMs experiments simulating current and future climate in region A

A formal probabilistic approach

We write down statistical assumptions for
- the unknown parameters (**prior** distributions)
- the data observed, as a function of the unknowns (**likelihood**)

We combine them, through **Bayes theorem** into the joint **posterior** distribution of the unknowns

Posterior $\propto$ Prior·Likelihood

We estimate the posterior through Markov chain Montecarlo simulation

About prior distributions

We choose extremely wide, non-informative priors:

As non-committed as we can be

Posterior distributions will be shaped by the data, rather than by prior assumptions

Perhaps expert knowledge could/will be included

Likelihood

The observed current temperature is

$$\boldsymbol{X_0 \sim N[\mu, \lambda_0^{-1}]}$$

Model $\boldsymbol{i}$ produces a current temperature reconstruction

$$\boldsymbol{X_i \sim N[\mu, \lambda_i^{-1}]}$$

and a future temperature projection

$$\boldsymbol{Y_i \sim N[\nu, (\theta\lambda_i)^{-1}]}$$

Posterior distributions

Through MCMC techniques we compute estimates of the posterior distribution of all the unknown parameters ($\boldsymbol{\mu}, \boldsymbol{\nu}, \boldsymbol{\lambda}$'s).

Among others, PDFs of Temperature/Precipitation change

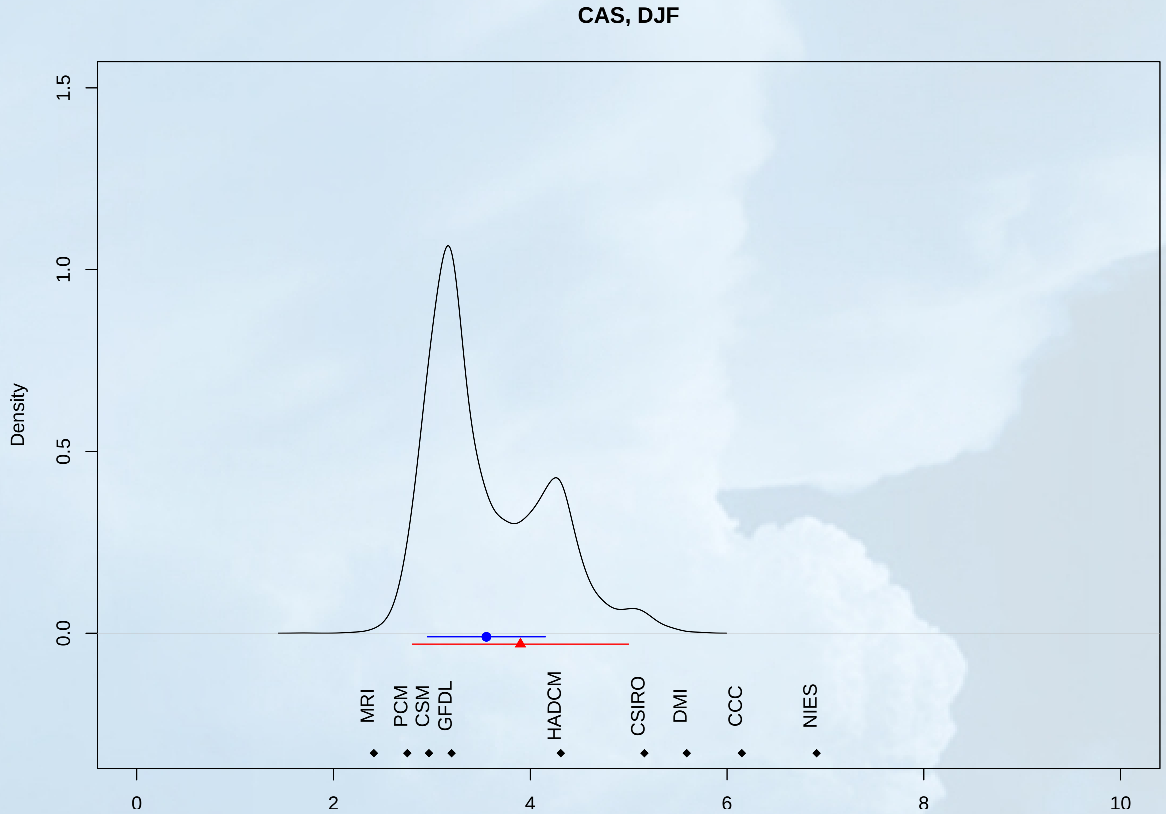
under SRES emissions scenarios A2 and B2,

for the 22 regions,

for winter and summer season.

Temperature Change

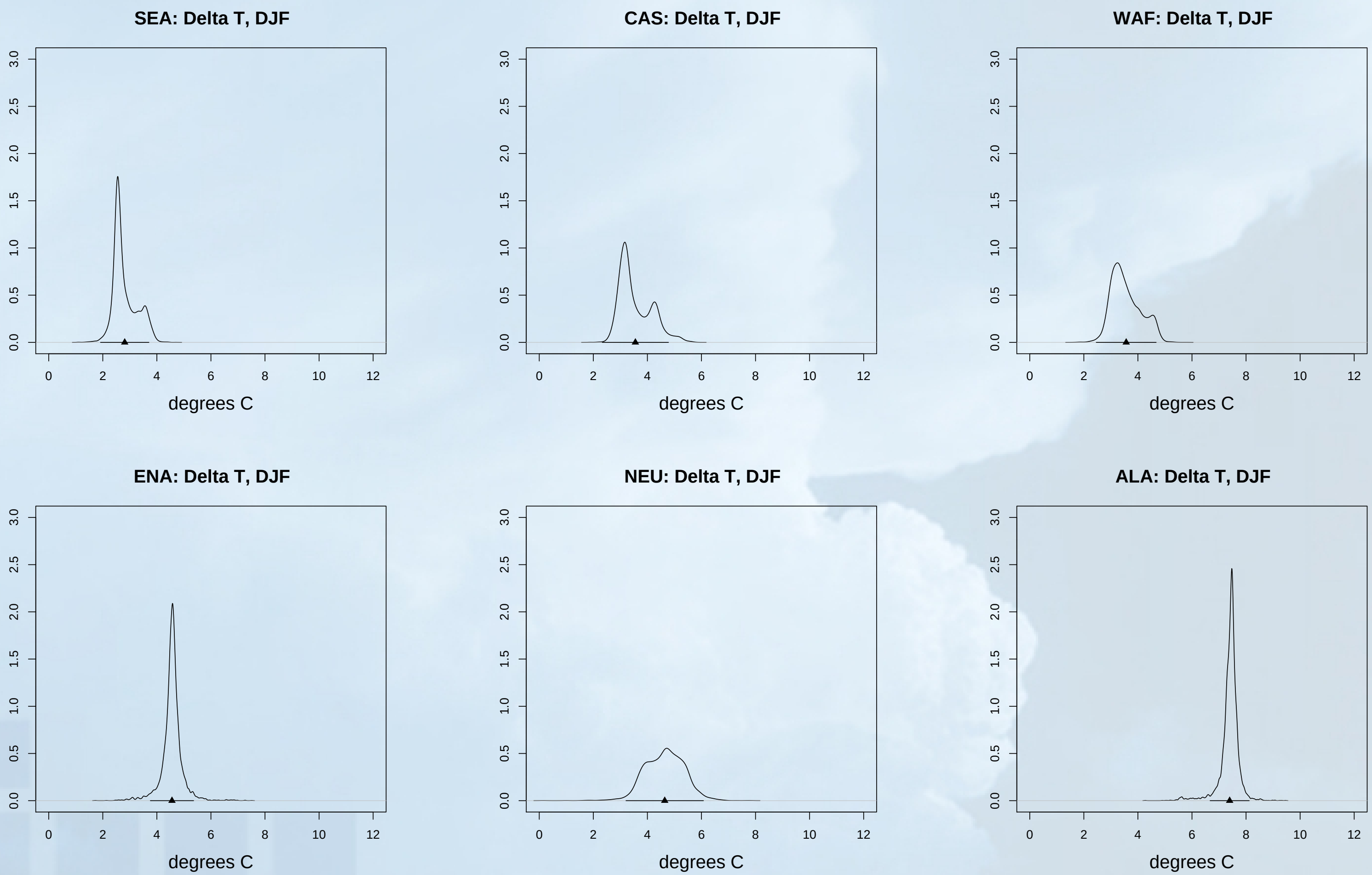
in Central Asia



	NIES	MRI	CCC	CSIRO	CSM	PCM	GFDL	DMI	HADCM
BIAS	5.83	4.81	-7.48	0.50	-0.13	-1.40	-0.96	2.38	1.08

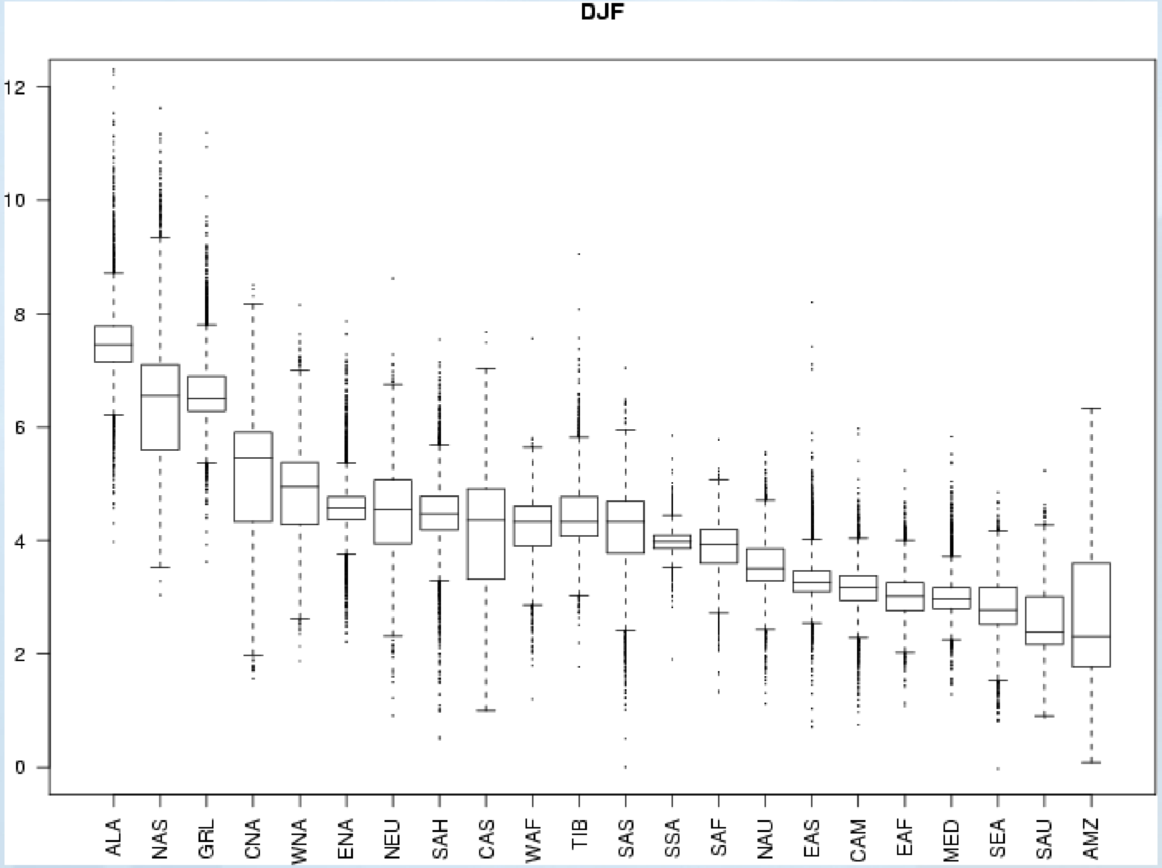
A few more regions

Multimodality and not



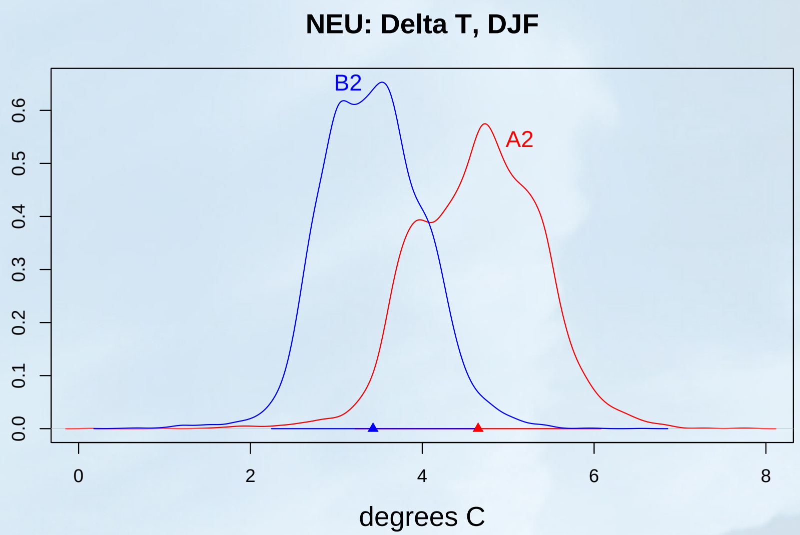
Temperature change in winter

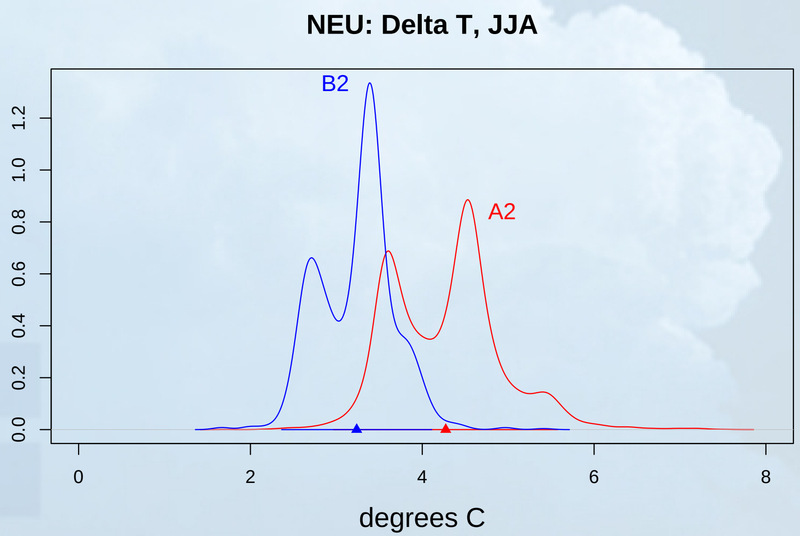
The big picture



Temperature change

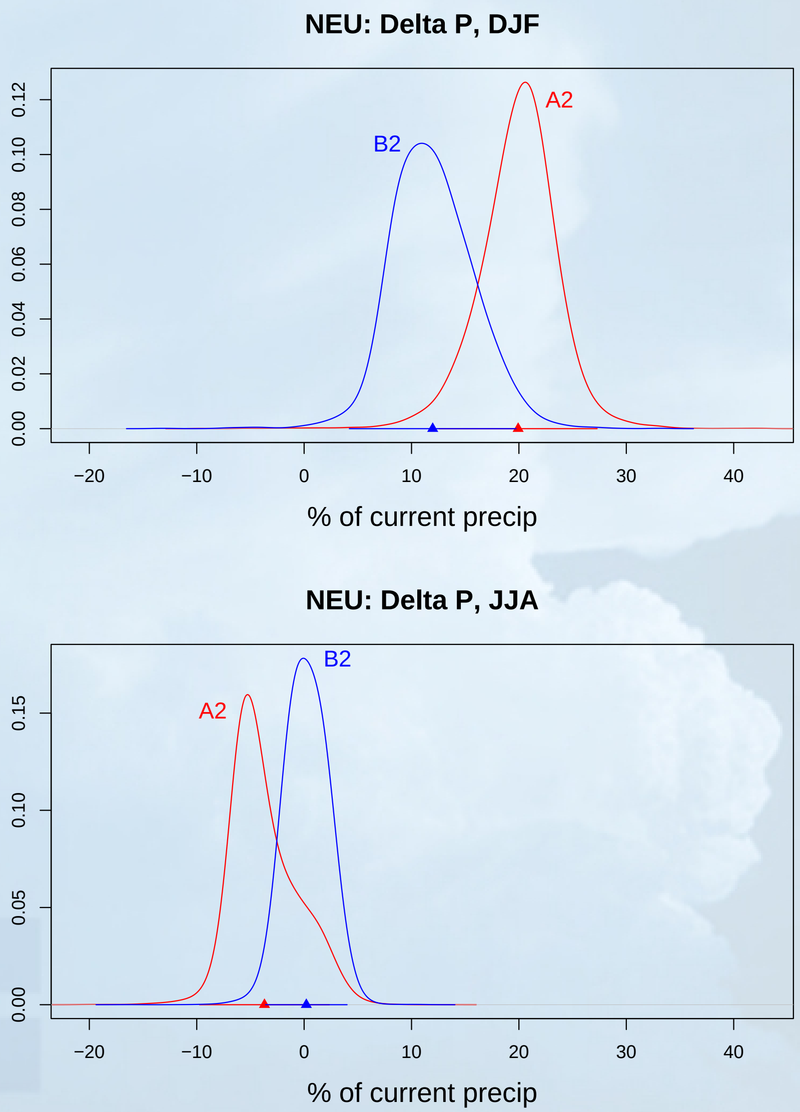
Under two emissions scenarios



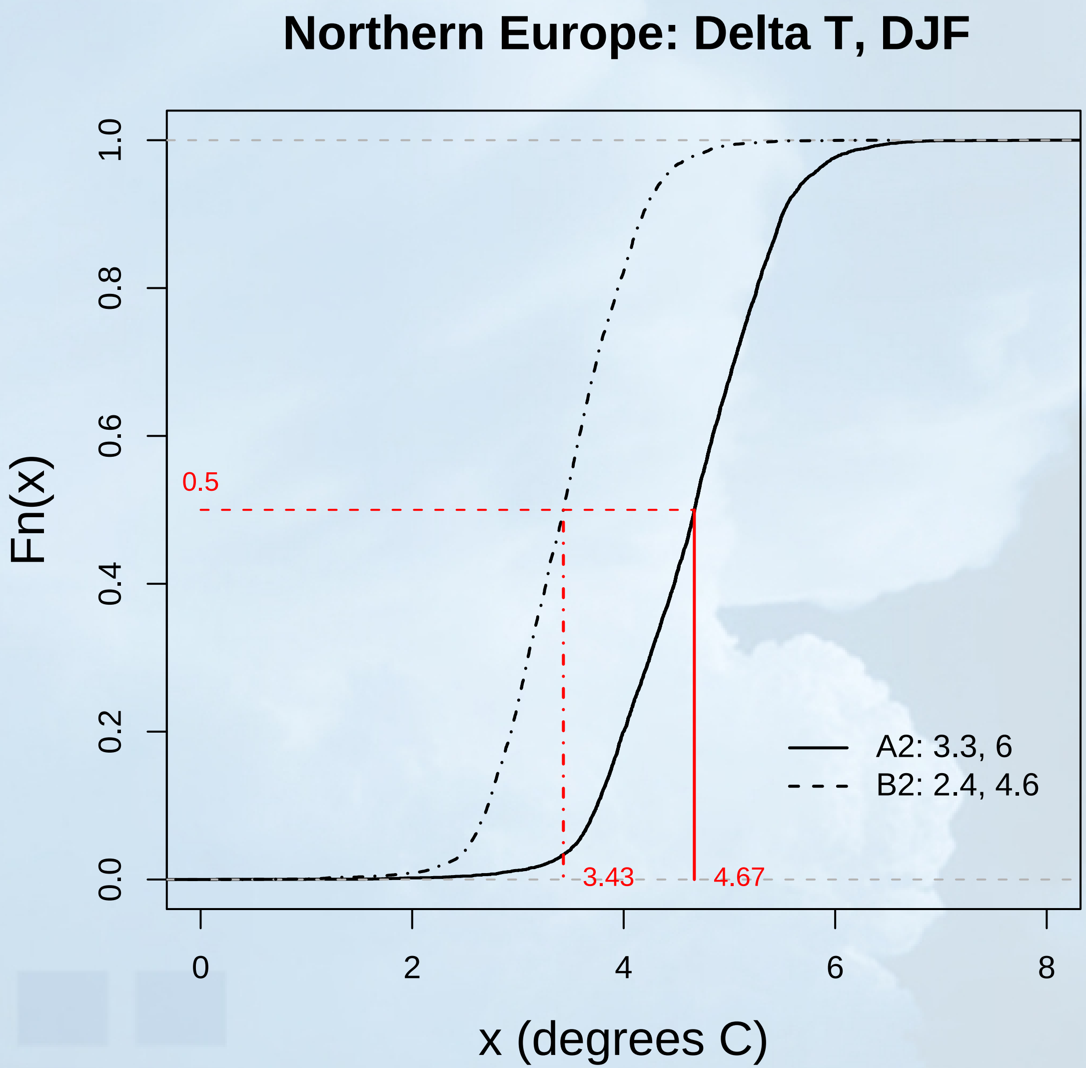


Precipitation change

Under two emissions scenarios



CDF of temperature change



Conclusions

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- We have formalized the criteria of BIAS and CONVERGENCE as a way of analyzing MULTI-MODEL ENSEMBLES.

- We determine POSTERIOR PROBABILITY DISTRIBUTIONS, that summarize all the information in the data, and incorporate the components of uncertainty quantified in the prior and likelihood assumptions.

Uses of the analysis

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- Provide input for downscaling of regional signals, for climate impacts assessment studies

- Elicit decision makers' needs/preferences in looking at probabilistic forecasts

- Alert modelers to gaps in model space and encourage designs of model experiments

- Excite statisticians' interest in the problem of climate change uncertainty

Current and future work (1)

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- Joint treatment of temperature and precipitation, in order to provide forecasts of the bivariate probability density of temperature and precipitation changes
- Hydrologic model, using probabilistic forecast of temperature and precipitation changes over Western North America as input (Dave Yates (RAP/NCAR))
- Higher resolution regional results (Reinhard Furrer (GSP/NCAR) Steve Sain (CU-Denver))
- Extension of this model to probability of changes in extremes (R.L. Smith (UNC-Chapel Hill))

Current and future work(2)

- Application of this model to the collection of experiments fromXS `climateprediction.net` (University of Oxford - Atmospheric Physics and School of Geography)
- Comparison of our results to recent work in the climate change literature, as a service to the research community in the framework of IPCC AR04
- Analysis of experiments for IPCC AR04, to be included in regional projections and global projections chapters

Current and future work(3)

Elicitation of experts' opinion (modelers, climatologists) about

- relative importance of bias and convergence criteria

- shape of prior distributions

Data

- 9 GCMs;
- 22 Regions;
- 2 Seasons;
- Simulated Temperature (and Precipitation) values in 30-years averages
  ($\boldsymbol{X}$, 1961-1990; $\boldsymbol{Y}$, 2071-2100 (A2, (B2)));
- Observed Temperature (and Precipitation) average, $\boldsymbol{X_0}$, for 1961-1990.
- A measure of Natural Variability for Temperature (and Precipitation) for each region.

The unknown quantities

Present and future (under A2) seasonal mean temperatures in a region

$$\mu, \ \nu$$

Measures of each GCM's accuracy in reproducing true temperature

$$\lambda_1, \ldots, \lambda_9$$

Likelihood

Given the true current temperature $\boldsymbol{\mu}$,
the true future temperature $\boldsymbol{\nu}$,
a measure of each GCM's precision $\boldsymbol{\lambda_i}$
a measure of future precision "inflation/deflation" $\boldsymbol{\theta}$

The observed current temperature is

$$\boldsymbol{X_0 \sim N[\mu, \lambda_0^{-1}]}$$

Model $\boldsymbol{i}$ produces a current temperature reconstruction

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and a future temperature projection

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Through Bayes theorem

The joint posterior distribution

$$\prod_{i=1}^{N}\left[\lambda_i{}^{-0.999}e^{-\lambda_i/1000}\cdot\lambda_i\theta^{1/2}\exp\left\{-\frac{\lambda_i}{2}((X_i-\mu)^2+\theta(Y_i-\nu)^2)\right\}\right]\cdot\theta^{-0.999}\cdot$$

$$\cdot e^{-\theta/1000}\cdot\exp\left\{-\frac{\lambda_0}{2}(X_0-\mu)^2\right\}$$