Biases and Uncertainty in Climate Projections

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References

- Christoph Buser, 2009, Dissertation ETH No. 18448
- Buser et al., Climate Dynamics 2009
- Buser et al., Scand. J. Statist. 2010
- Buser et al., Climate Research 2010, in press.

Contents

Ensemble methods

- Assess uncertainty and improve the skill of predictions and projections through a collection of answers (an ensemble).
- Popular in weather prediction, seasonal forecasting and climate studies.
- Ways to generate ensemble members: Single model with perturbed forcing and/or perturbed physics vs. multi-model ensembles.
- Multi-model ensembles in climate studies are small and rather a “sample of opportunities” than a random sample.
- Example of ensembles of global climate models (GCMs): 4th IPCC report with 21 models.
- Examples of ensembles of regional climate models (RCMs): PRUDENCE and ENSEMBLES projects in Europe, NARCCAP in the US.

Regional Climate Models

- Resolution of GCMs is low, typically 2.5° ($\approx$ 250 km in mid-latitudes). Unable to represent varying topography.
- Need higher resolution for regional projections and impact studies.
- RCMs perform dynamic downscaling by using the result of a GCM as driving boundary conditions. Resolution of a RCM typically $0.25^\circ - 0.5^\circ$.
- As a consistency check, run RCMs driven by a reanalysis.
- NARCCAP has 6 RCMs and 4GCMs plus reanalysis. Factorial design for RCM/GCM combinations.
- PRUDENCE and ENSEMBLES have more GCMs and RCMs with a much sparser and less balanced design matrix.

Data used in our analysis

- Output of 5 RCMs from the PRUDENCE project with different driving GCMs (or at least different runs of the same model).
- Observations from CRU (Climate Research Unit).
- Control period: 1961-1990. Scenario period: 2071-2100, Emission scenario A2.
- Averages over seasons and the alpine region ($44^\circ - 48^\circ$N, $5^\circ - 15^\circ$E). No average over different years.
- Use temperature alone or temperature and precipitation jointly.
- Most recent paper considers all PRUDENCE regions, a different set of RCMs from the ENSEMBLES project, E-OBS data, the A1B scenario and the period 2021-2050.

Analyzing yearly values

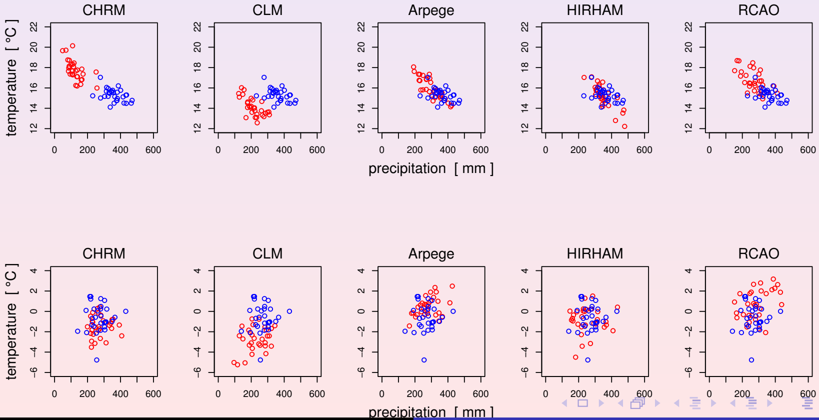
Do not average over years because interest not only in averages, but also in interannual variability.

Problems and solutions:

- Climate not constant over control and scenario period $\rightarrow$ assume linear trend over the period (which cancels by averaging).
- Because of chaotic nature of climate, cannot compare model outputs of two models for the same year (or model output and observation for the same year) $\rightarrow$ assume independence between deviations from linear trend (both within and between models).

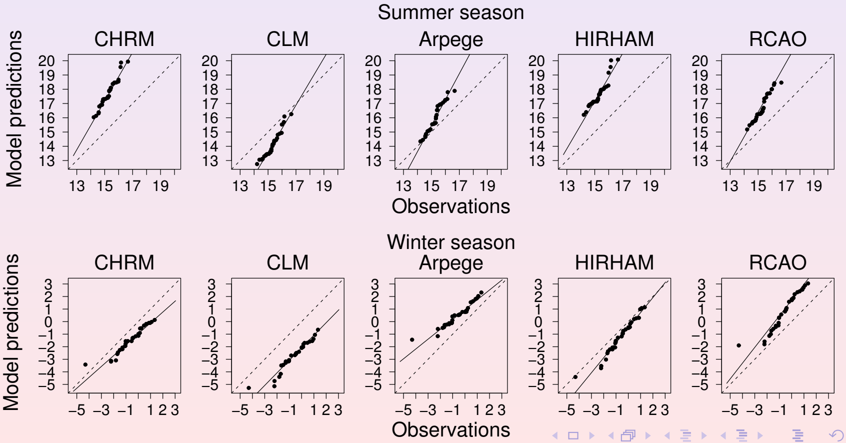
Precipitation and temperature: Alpine region, control

Blue: Observations, Red: Model output.
Top: Summer, Bottom: Winter.



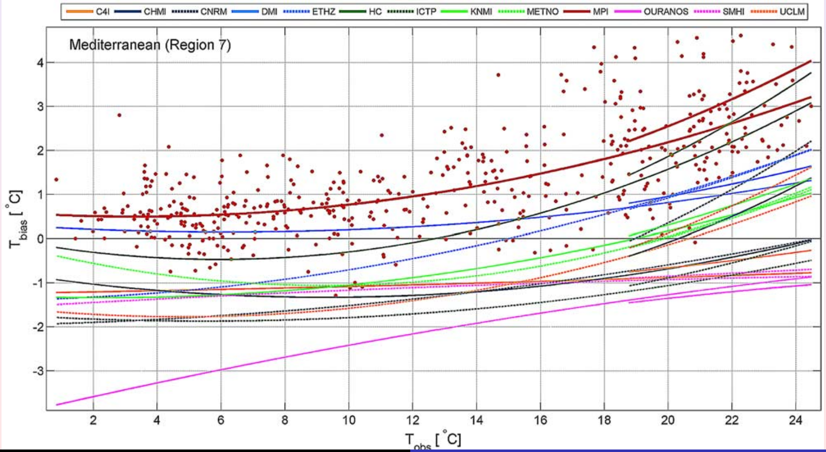
Biases of temperature: Alpine region

Q-Q plots of model output vs. observed values (detrended).



Biases of temperature: Mediterranean

Bias vs. observed monthly values for RCMs driven by reanalysis, from Christensen et al. (2008).



Extrapolation of biases

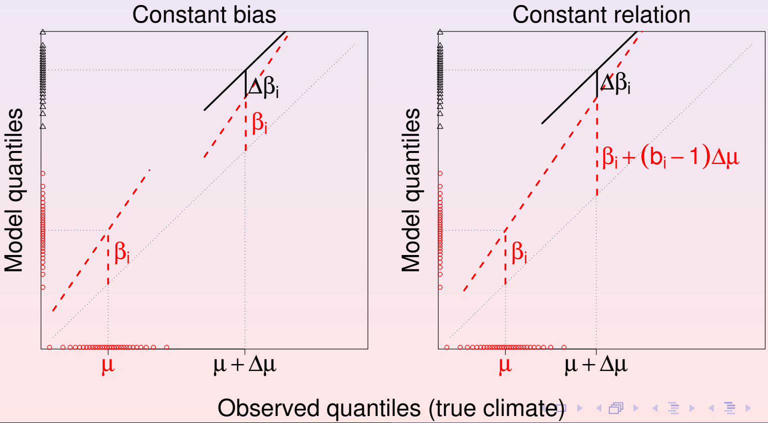
"... one would expect that some sort of extrapolation based on the existing data could make a good first order approximation of the (otherwise undetermined) temperature bias in a simulation." (Christensen et al., Geophys. Res. Letter, 2008)

Which kind of extrapolation ?

- Most studies consider only additive bias and assume no change between control and scenario ($\rightarrow$ no bias left in scenario minus control).
- Q-Q-plots showed also multiplicative bias: models overestimate difference between warm and cold summers $\rightarrow$ 2 possible extrapolations of additive bias (next slide).
- Christensen et al. suggest that additive bias is a function of true value (or boundary conditions driving the RCM).

Graphical illustration of two bias assumption

Values after trend adjustment. Black lines represent additional bias changes (to be discussed later).

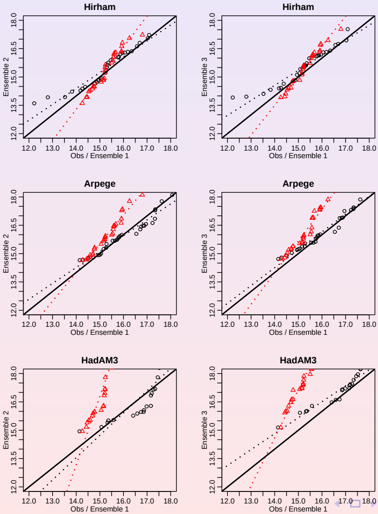


Bias or internal variability ?

Could the biases be explained as internal variability ?
We think no:

- Models are run with observed sea surface temperatures and sea ice conditions which reduces internal variability.
- In those cases where we had additional runs of the same RCM for the control period, estimated biases changed only little.
- We divided GCM preindustrial control runs of 330 years into 11 periods. Estimated additive and multiplicative biases from Q-Q plots of all pairs of periods are smaller than in our plots.

Internal variability versus bias in RCMs



Model averaging in NWP (Raftery et al., 2005)

$x_{t,0}$: observed univariate predictand at day t.
$(x_{t,1}, \ldots, x_{t,I})$: forecast ensemble at day t.
Based on a training period $t = 1, 2, \ldots, T$, fit a predictive distribution

$$x_{t,0} | x_{t,1}, \ldots, x_{t,I} \sim \sum_{i=1}^{I} \hat{w}_i \mathcal{N}(\hat{a}_i + \hat{b}_i x_{t,i}, \hat{\sigma}^2)$$

and use it as forecast distribution at day $T + 1$. Empirically, $T \approx 30$ gives best results.

Bias correction through $\hat{a}_i$ and $\hat{b}_i$. Additional increase of ensemble spread through $\hat{\sigma}$.

In climate, training = control. $x_{t,i}$ attempts to be a draw from the same distribution as $x_{t,0}$, not a forecast.

Notation and basic assumption

Analysis for a fixed region and season.

Notation:

$X_{t,0}$ = observed data for year $1960 + t$,
$X_{t,i}$ = output of model i for the same year,
$Y_{t,0}$ = unobserved future data for year $2070 + t$,
$Y_{t,i}$ = output of model i for the same year.

Distributional assumptions:

All variables are independent and Gaussian $\rightsquigarrow$ Only mean and variances needed.

Mean and variances

$$\begin{aligned}
\mathbb{E}(X_{t,0}) &= \mu + \gamma(t - 15.5), \\
\mathbb{E}(X_{t,i}) &= \mu + \beta_i + (\gamma + \delta_i)(t - 15.5), \\
\mathbb{E}(Y_{t,0}) &= \mu + \Delta\mu + (\gamma + \Delta\gamma)(t - 15.5).
\end{aligned}$$

β_i = additive bias, δ_i = trend bias of model i, $\Delta\mu$ = additive climate change, $\Delta\gamma$ = trend change. By including also biases β_0, δ_0 for observations, we would loose identifiability.

$$\begin{aligned}
\mathrm{Var}(X_{t,0}) &= \sigma^2, \\
\mathrm{Var}(X_{t,i}) &= \sigma^2 b_i^2, \\
\mathrm{Var}(Y_{t,0}) &= \sigma^2 q^2.
\end{aligned}$$

b_i = multiplicative bias of model i, q = change in interannual variability of climate.

Means and variances in the scenario period

Constant bias assumption (used implicitly in most climate studies):

$$\begin{aligned}\mathbb{E}(Y_{t,i}) &= \mathbb{E}(X_{t,i}) + \mathbb{E}(Y_{t,0}) - \mathbb{E}(X_{t,0}) \\ &= \mu + \beta_i + \Delta\mu + (\gamma + \delta_i + \Delta\gamma)(t - 15.5), \\ \mathrm{Var}(Y_{t,i}) &= \sigma^2 q^2 b_i^2.\end{aligned}$$

Constant relation assumption (Same error in estimating climate change as in estimating difference between a warm and a cold year in the control):

$$\begin{aligned}\mathbb{E}(Y_{t,i}) &= \mathbb{E}(X_{t,i}) + b_i(\mathbb{E}(Y_{t,0}) - \mathbb{E}(X_{t,0})) \\ &= \mu + \beta_i + b_i\Delta\mu + (\gamma + \delta_i + b_i\Delta\gamma)(t - 15.5), \\ \mathrm{Var}(Y_{t,i}) &= \sigma^2 q^2 b_i^2.\end{aligned}$$

Bias change and non-identifiability

Allow in addition biases changes between scenario and control. "Constant bias" (keep this terminology!):

$$\begin{aligned} \mathbb{E}(Y_{t,i}) &= \mu + \beta_i + \Delta\mu + \Delta\beta_i + (\gamma + \delta_i + \Delta\gamma + \Delta\delta_i)(t - 15.5), \\ \mathrm{Var}(Y_{t,i}) &= \sigma^2 q^2 b_i^2 q_{b_i}^2. \end{aligned}$$

and similarly for "constant relation".

Problem: Parameters are no longer identifiable (e.g. $\Delta\beta_i$ confounded with $\Delta\mu$).

Frequentist solution: Side conditions

$$\sum \Delta\beta_i = 0, \; \sum \Delta\delta_i = 0, \; \prod q_{b_i} = 1.$$

Bayesian solution: Informative priors for bias changes.

Bayesian analysis

A priori, all parameters are independent. Put flat priors on all identifiable parameters and informative priors for $\Delta\beta_i$, $\Delta\delta_i$ and q_{b_i}, e.g.

$$\beta_i \sim \mathcal{N}(0, (4^\circ)^2), \quad \Delta\beta_i \sim \mathcal{N}(0, (0.7^\circ)^2).$$

A more cautious assumption would use a hierarchical model

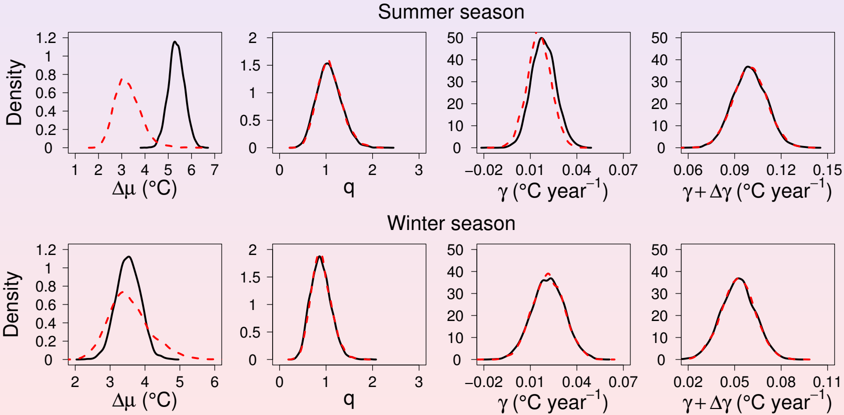
$$\beta_i \mid \mu_\beta, \sigma_\beta^2 \sim \mathcal{N}(\mu_\beta, \sigma_\beta^2) \;\; i.i.d.$$

with a vague prior for μ_β and σ_β.

Compute posteriors and predictive distributions by MCMC. Under "constant relation" some conditionals are non-standard (but log-concave).

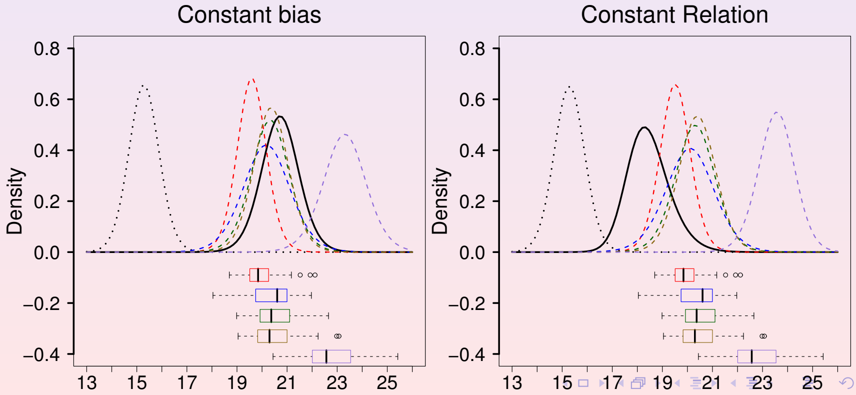
Posteriors for main parameters

Red: Constant relation, Black: Constant bias.



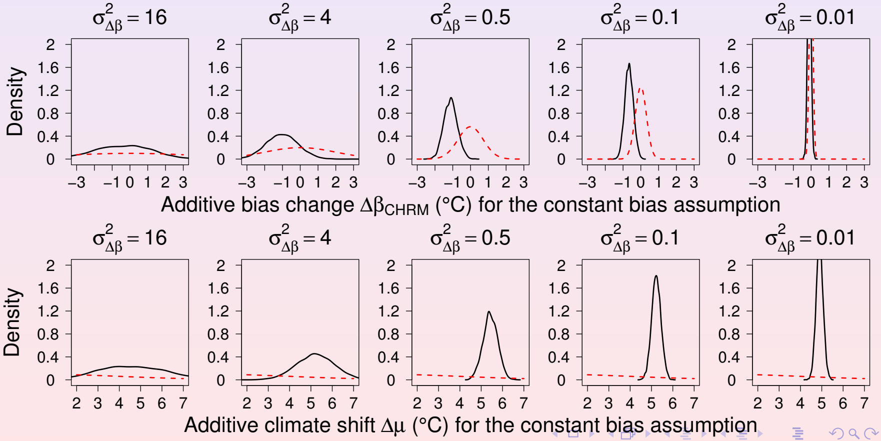
Predictive distributions

Boxplots and corresponding densities: scenario outputs of individual models, adjusted for β_i.



Sensitivity to prior variance of bias change

Red: Prior. Black: Posterior. Upper row: $\Delta\beta_1$. Lower row: $\Delta\mu$.



Cross validation

Take one of the models as reference and use the other 4 to predict the mean change projected by the reference model.
95% confidence intervals:

Reference Model	Truth	SCEN - CTL	Constant Bias	Constant Relation
CHRM	4.17	[5.42,6.23]	[5.01,6.52]	[3.85,7.20]
CLM	4.79	[5.26,6.08]	[4.85,6.33]	[3.23,6.22]
Arpege	4.97	[5.22,6.04]	[4.80,6.31]	[3.86,7.25]
Hirham	5.02	[5.20,6.03]	[4.77,6.29]	[4.33,8.01]
RCAO	8.53	[4.46,5.01]	[3.94,5.44]	[2.94,5.90]

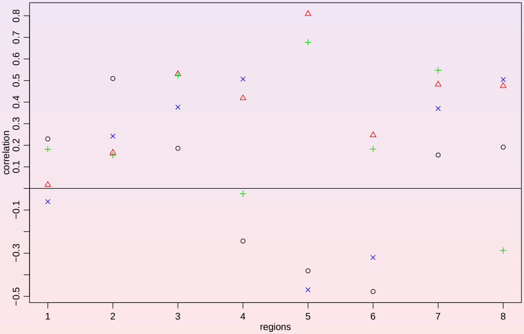
Constant bias or constant relation ?

Ideas to distinguish between “constant bias” and “constant relation”:

- More than one emission scenario: Differences between projections for different scenarios are proportional to b_i under “constant relation”. Results so far are not conclusive.
- Look at correlation between projected change $\bar{Y}_{.,i} - \bar{X}_{.,i}$ and estimated multiplicative bias $\hat{b}_i$.
- Look at the outputs for the whole period 1961 - 2100, or for longer periods in the past. Difficult because trend will not be linear any more.

Projected change and multiplicative bias

Correlation between projected change and multiplicative bias of 16 ENSEMBLES members, estimated for 4 season and 8 regions.

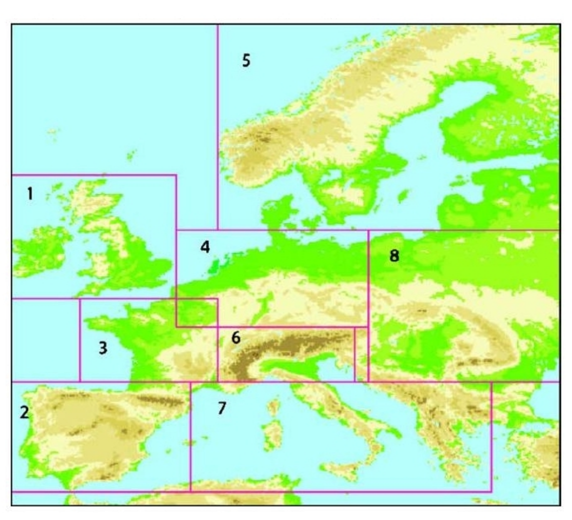


Convex combination of the two assumptions

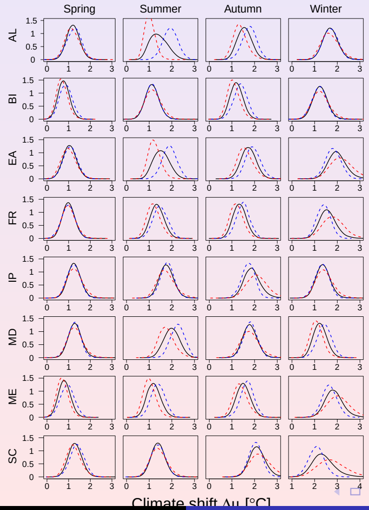
Consider a larger model where $\mathbb{E}(Y_{t,i})$ is a convex combination of the expectation under the constant bias and the constant relation assumption.

Choose uniform prior for the additional parameter κ of the convex combination. Posterior for κ typically still close to uniform, i.e. data cannot decide between the two assumptions. If assumptions matter, spread of posterior for $\Delta\mu$ increases (see next slides).

PRUDENCE regions



Results for ENSEMBLES data



Multivariate analysis: Models

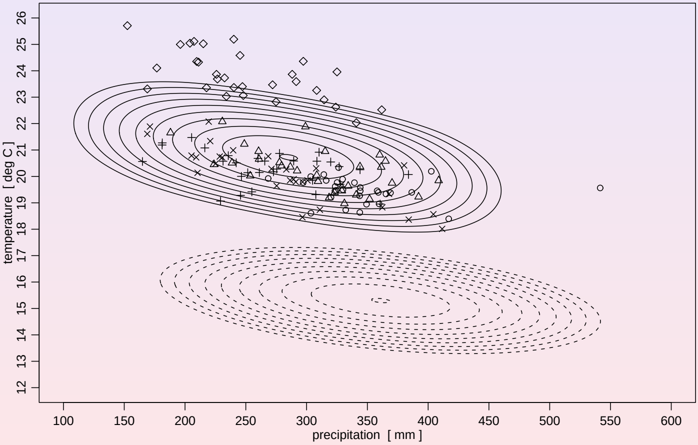
As in Tebaldi and Sanso (2009), regress the k-th variable on the variables $1, 2, \ldots, k-1$. Each regression coefficient then has model bias in the control, true change from control to scenario and bias change.

(Strict) constant relation assumption: There is a matrix M_i such that

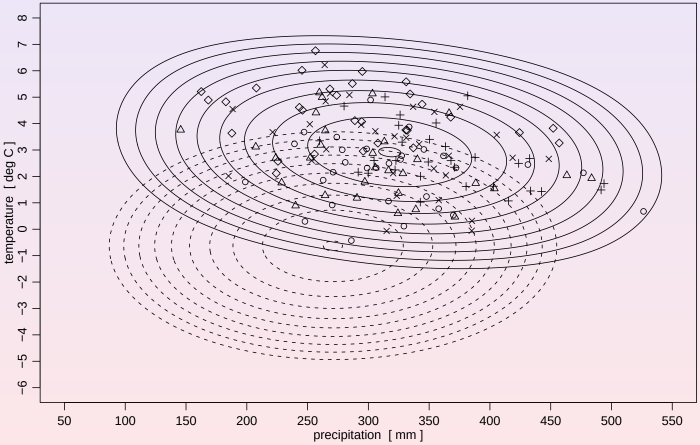
$$
\begin{aligned}
X_{t,i} &\stackrel{d}{=} \mathbb{E}(X_{t,i}) + M_i(X_{t,0} - \mathbb{E}(X_{t,0})), \\
Y_{t,i} &\stackrel{d}{=} \mathbb{E}(X_{t,i}) + M_i(Y_{t,0} - \mathbb{E}(X_{t,0})) \\
&= \mathbb{E}(X_{t,i}) + M_i(\mathbb{E}(Y_{t,0}) - \mathbb{E}(X_{t,0})) + M_i(Y_{t,0} - \mathbb{E}(Y_{t,0})).
\end{aligned}
$$

In the multivariate case, M_i is determined only up to orthogonal transformations.

Posterior predictive for summer temp. + precip.



Posterior predictive for winter temp. + precip.



Monthly data/Finer spatial resolution

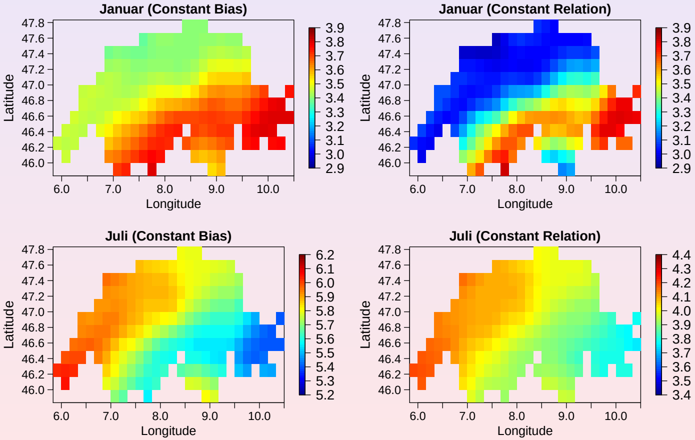
For monthly data, need to take temporal dependence into account. Use AR-models with seasonally varying coefficients.

For analysing individual grid points, need spatially varying smooth parameters μ, β_i, σ etc. Presumably computationally intensive.

A regression model with altitude, longitude and latitude as covariables captures most of the spatial structure in the Alpine region. Can use a 4-dimensional analysis of the estimated regression coefficients (individually for each year and season).

Monthly mean temperature changes for Switzerland

Note the different scales for the two July figures!



RCM/GCM correlations

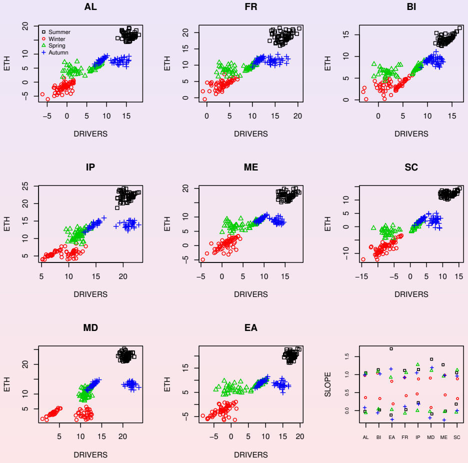
Correlation between RCM and driving GCM is high.
Set $X_{i,t}$ = output of GCM i for year t of control,
$X_{j(i),t}$ = output of RCM j for year t when driven by GCM i.

Possible model (omitting trends for ease of notation)

$$\begin{aligned} X_{i,t} &\sim \mathcal{N}(\mu + \beta_i, \sigma^2 b_i^2), \\ X_{j(i),t} | X_{i,t} &\sim \mathcal{N}(\mu + \alpha_j + \omega_j (X_{i,t} - \mu), \sigma^2 r_j^2) \end{aligned}$$

This means: Additive bias of RCM $= \alpha_j + \omega_j \beta_i$
Multiplicative bias of RCM $= \sqrt{\omega_j^2 b_i^2 + r_j^2}$
Correlation between RCM and GCM $= \omega_j b_i / \sqrt{\omega_j^2 b_i^2 + r_j^2}$.

Relation between driving GCMs and one RCM



Summary and conclusions

- Biases in climate models cannot be ignored.
- Interannual variability is of interest by itself and allows a more detailed analysis of biases.
- There is strong evidence against the hypothesis of no bias change.
- Multiplicative biases lead to 2 equally plausible assumptions (called "constant bias" and "constant relation") for extrapolating additive biases into the scenario. For many seasons and regions they lead to substantial differences in projections.
- Further work is required to deal with several variables, higher temporal and spatial resolution, hierachical dependence in GCM/RCM chains.

The End

Thank you for your attention.