Downscaling or bias adjustment? You name it, the user rules

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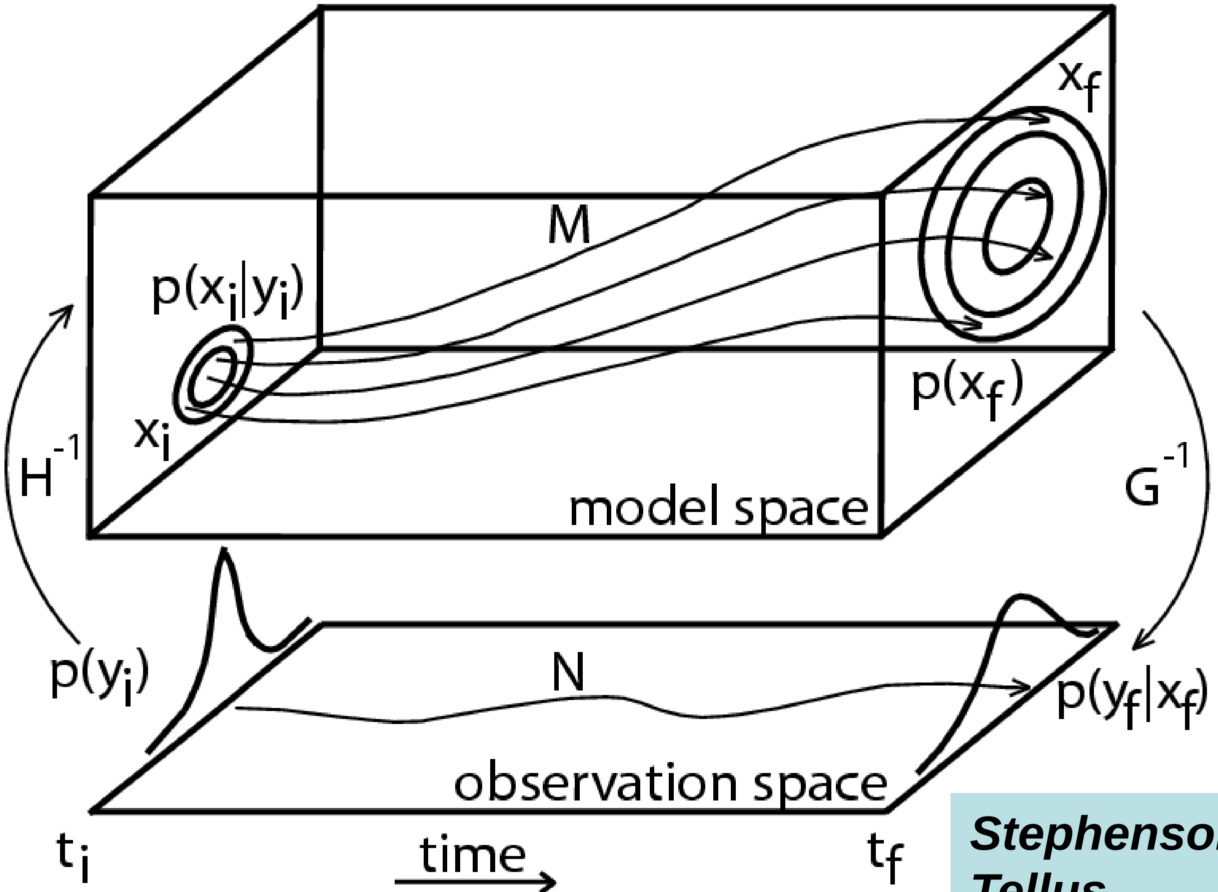
PLAN OF TALK

1. **Introduction: schematic illustrating the practical problem**
2. **Hydro power energy sector example**
3. **Wind energy sector example**
4. **Statistical downscaling examples**
5. **Importance of incorporating parameter uncertainty**
6. **Final remarks**

SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

International Conference on climate science and climate services
Exeter, U.K., 5-7 October 2016

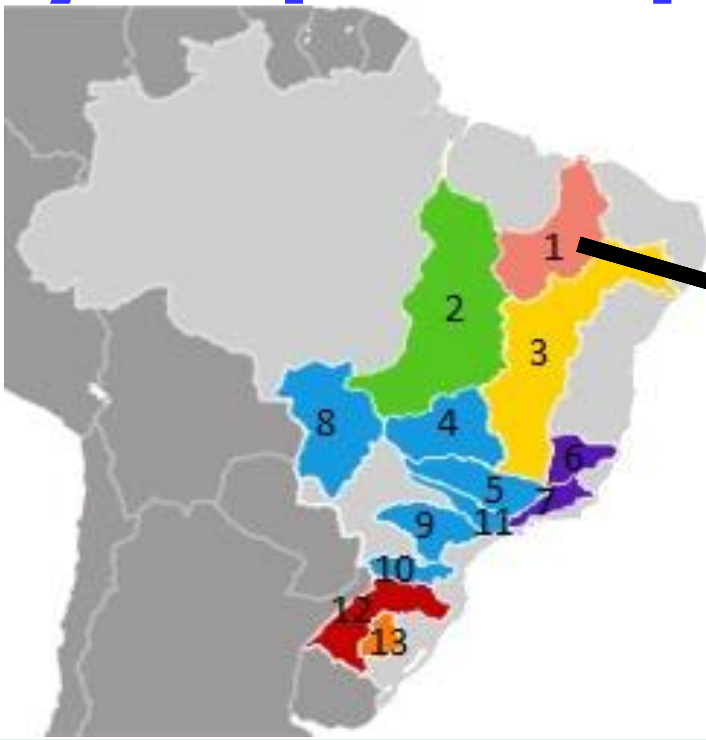
Schematic illustration of the practical problem



Stephenson et al. (2005) Tellus.

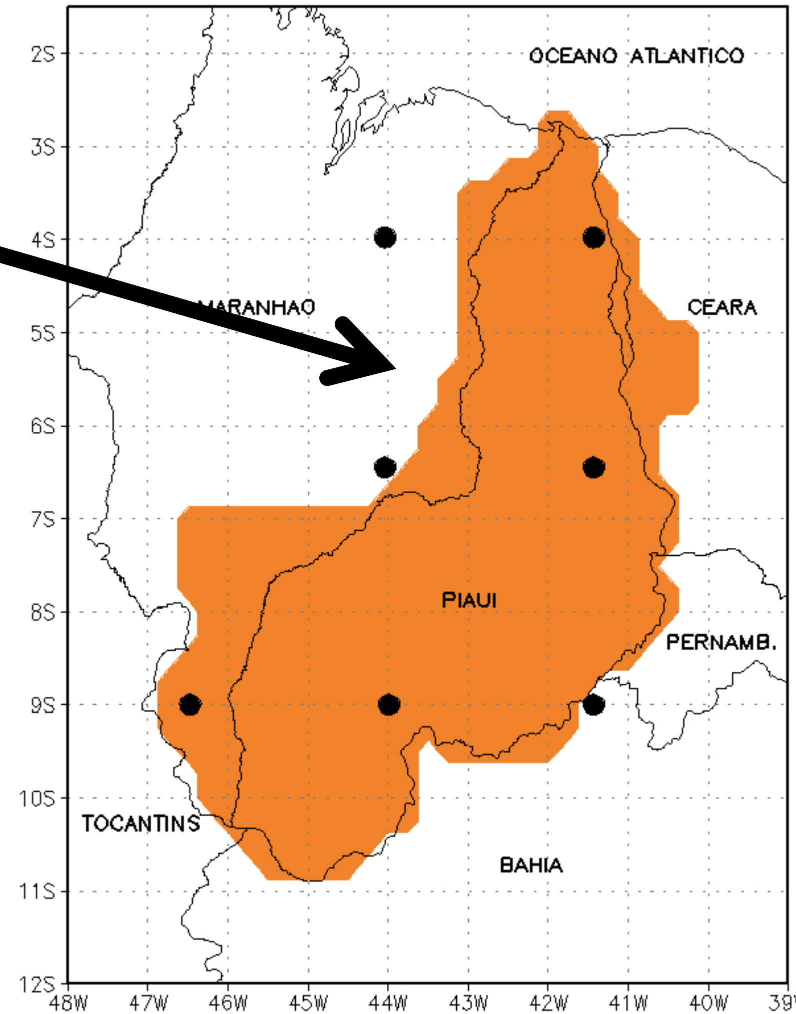
- **Clear need to map predictions into the real world where decision are made**
- **Mapping procedure receives a great variety of names: Downscaling, bias adjustment/correction, forecast calibration/recalibration/assimilation, model output statistics, etc.**

Hydropower production in Brazil



National interconnected system basins

Parnaíba River Basin

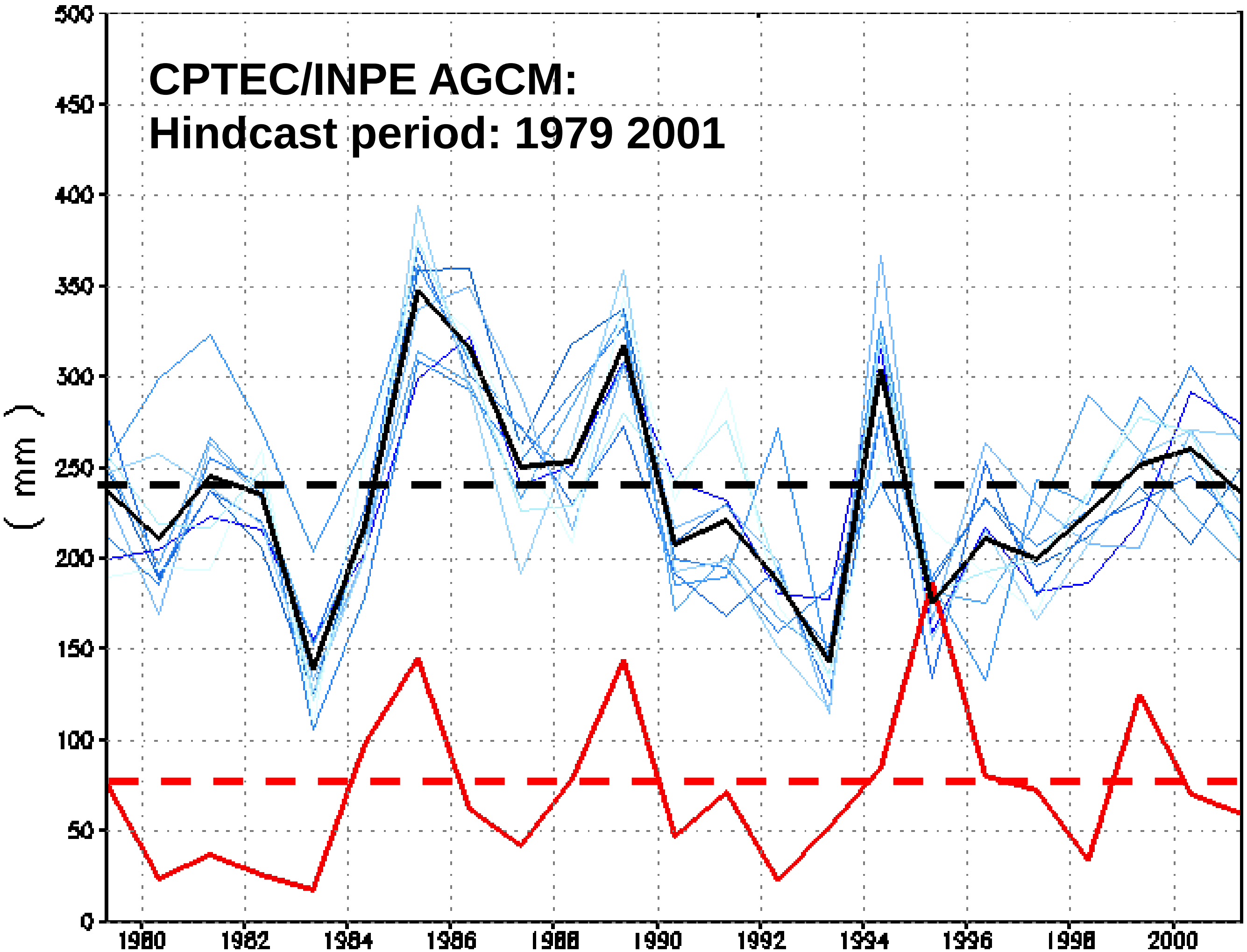


Electricity production in Brazil:
~ 70% hydropower stations

- **Heavily dependent on water availability**
- **Requires precipitation predictions**

Example: May precipitation predictions produced in previous Feb (3-month lead)

Parnaíba River Basin



Observation Ens. mean Ens. members

User: National Electricity System Operator (ONS)

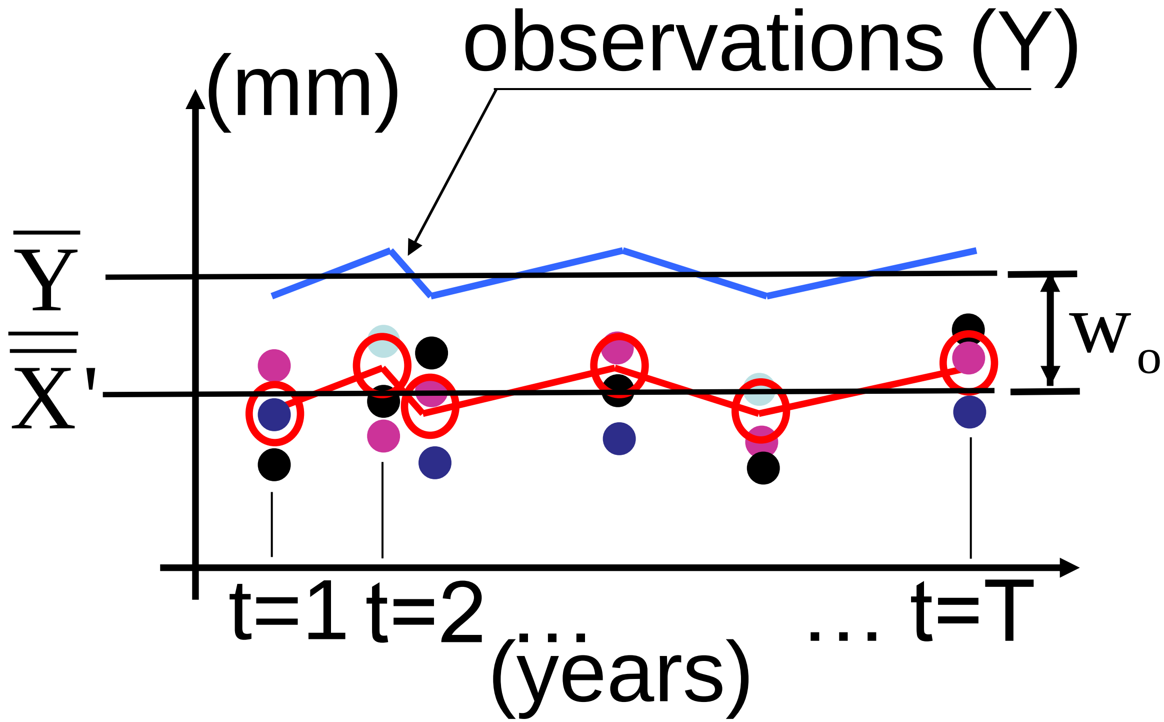
- **Aim: evaluate potential for integrating precip. predictions in decision making process**
- **Aware of biases**
- **Requested assessment of monthly outputs and procedures to remove biases**

Clear wet bias

Addressing model biases

Methodologies evaluated in collaboration with a user (National Electricity System Operator: ONS) responsible for managing energy production and transfer in Brazil

Bias-correction (Constant)



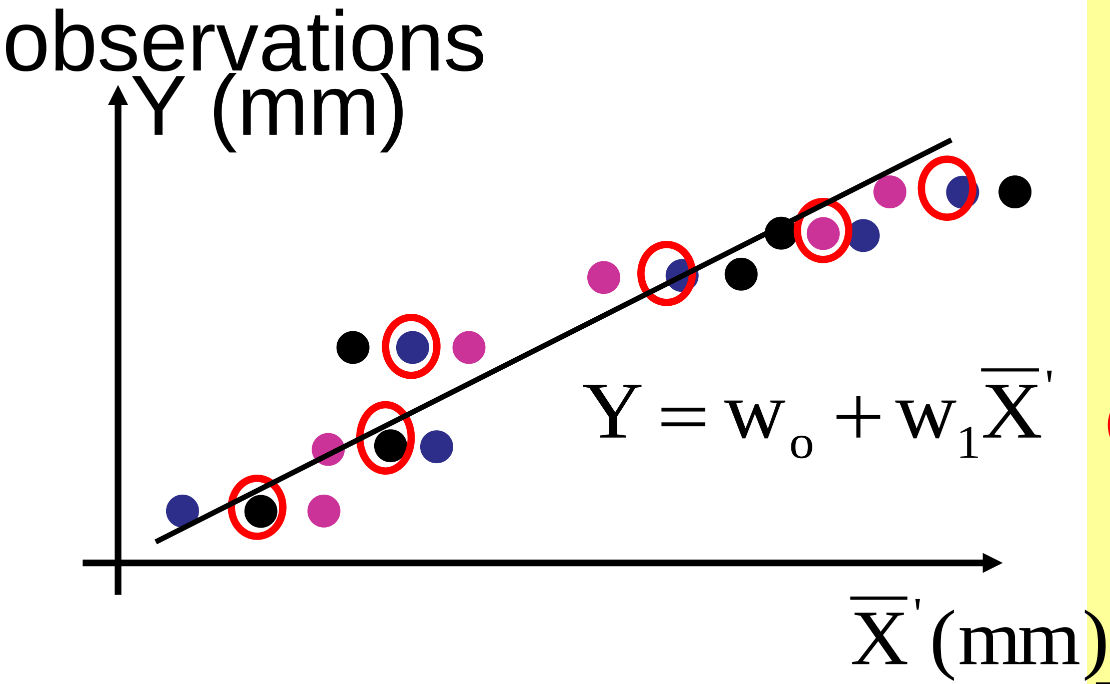
Ensemble fcsts
- Memb. 1 (X_1)
- Memb. 2 (X_2)
- Memb. 3 (X_3)
- O ensemble mean ($\overline{X}'$)

$$\overline{X}' = (X_1 + X_2 + X_3)/3$$

Mean bias ⟶ $$w_o = \frac{1}{T}\sum_{t=1}^{T} Y_t - \overline{X}'_t = \overline{Y} - \overline{\overline{X}}'$$

Corrected forecast ⟶ $$F = w_o + \overline{X}'$$

Bias-correction (Linear regression)



Ensemble fcsts

- Memb. 1 (X_1)
- Memb. 2 (X_2)
- Memb. 3 (X_3)

O ensemble mean ($\overline{X}'$)

$$\overline{X}' = (X_1 + X_2 + X_3)/3$$

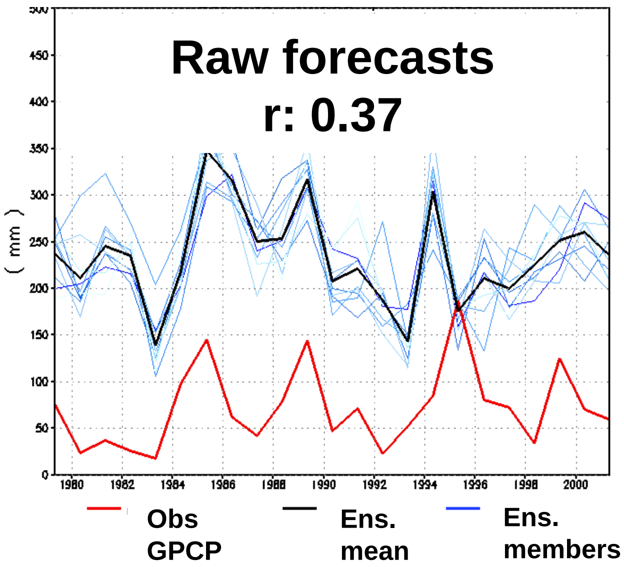
Mean bias $\longrightarrow$ $\hat{w}_o = \overline{Y} - \hat{w}_1 \overline{\overline{X}}'$

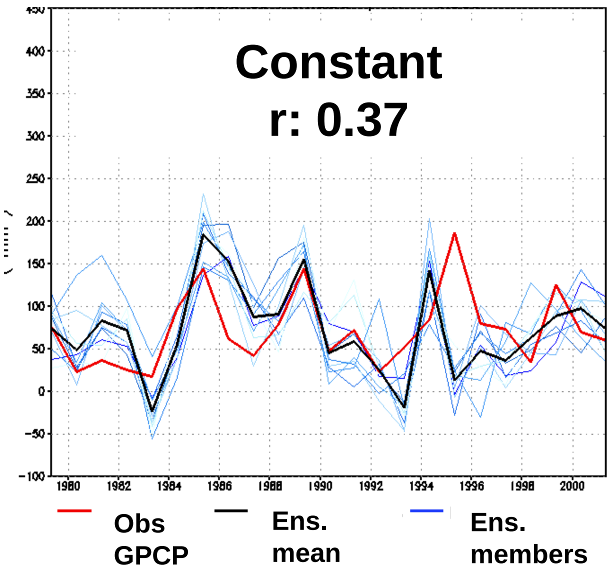
Slope: $\hat{w}_1 = \dfrac{s_{\overline{X}'Y}}{s^2_{\overline{X}'}}$

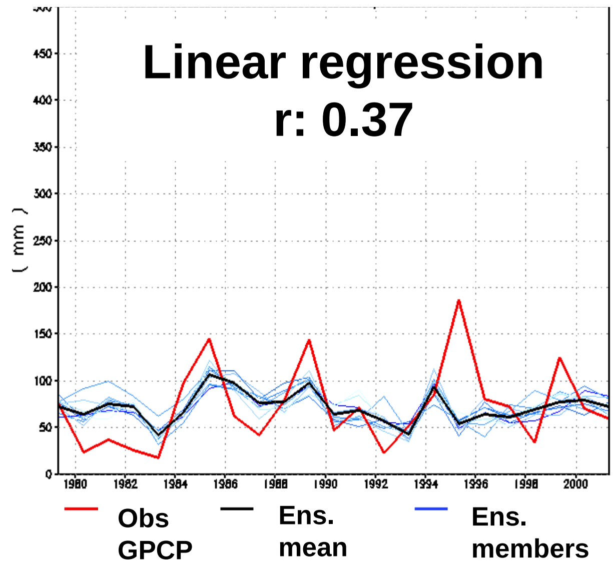
Corrected forecast $\longrightarrow$ $F = w_o + w_1 \overline{X}'$

Comparing bias-correction methods

3-month lead forecasts for May produced in previous Feb

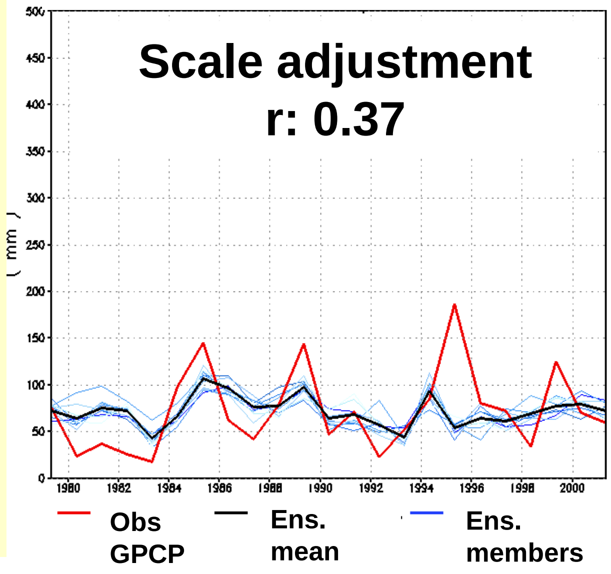


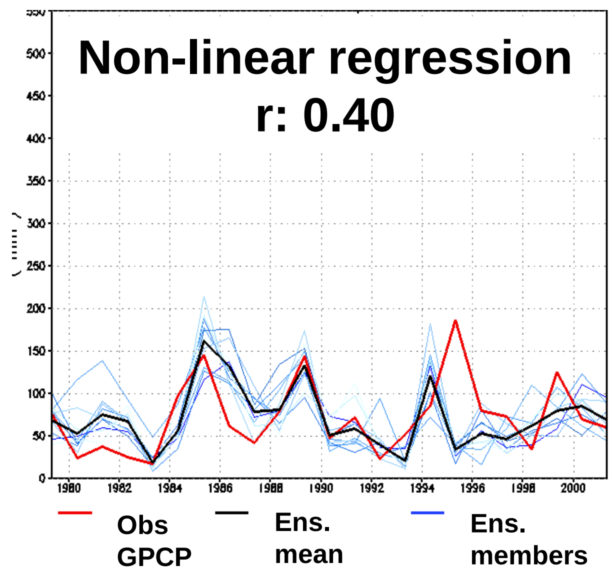




For Parnaíba River Basin:

- **Constant method produces negative precipitation (not recommended)**
- **Overall similar performance among investigated methods**
- **Non-linear regression slightly better than other methods**



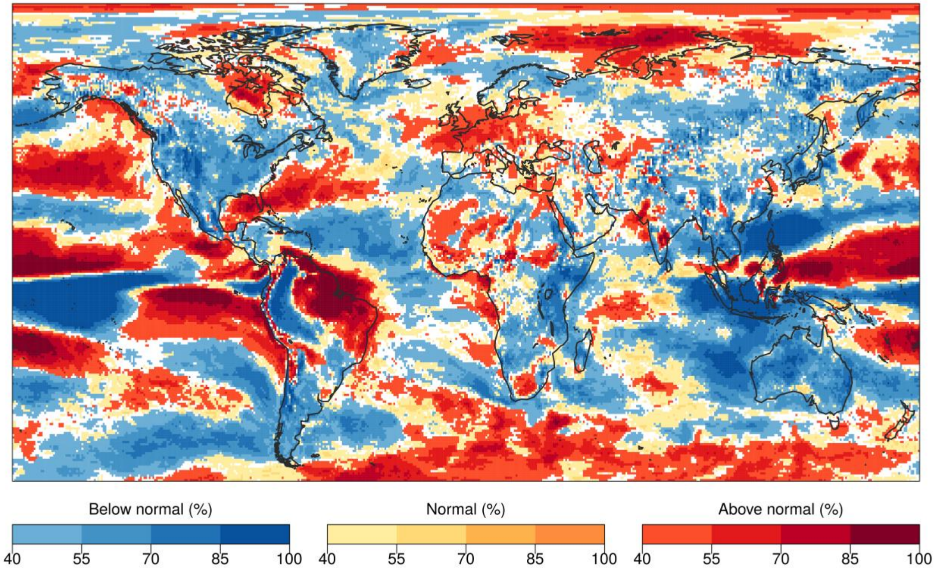


Seasonal predictions for the wind energy sector

Verónica Torralba, Raül Marcos, Doo Young Lee (BSC)

Goal: Perform seasonal prediction system forecast quality assessment to produce usable information for integration on the decision making process of the wind industry

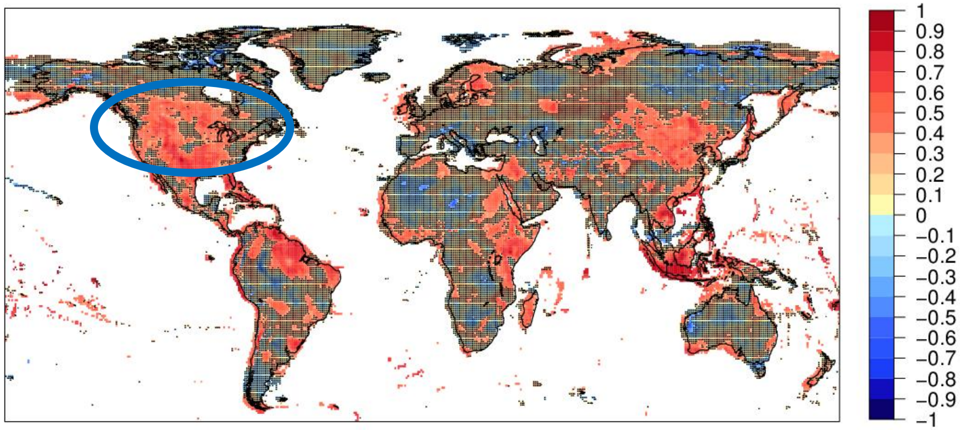
- **Maintenance work**
- **Grid management**



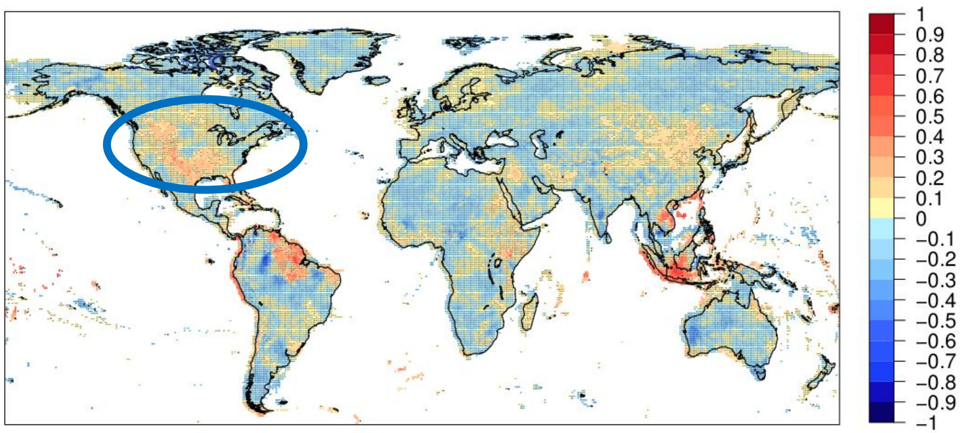
- **Variable** : 10m wind speed
- **Forecast system**:
  ECMWF System 4 (S4)
  51 members
- **Target season:**
  December-January-February (DJF)
- **Issuance month:**
  November (1-month lead)
- **Reference dataset**: ERA- Interim
- **Region of interest:** Canada

Skill assessment: ECMWF System 4
10-metre wind speed seasonal predictions

Correlation btw Fcst and obs
10-metre wind speed



Fair Ranked Probability Score
10-metre wind speed



1-month lead predictions for DJF

Issued in November

Hindcast period: 1991-2012

Reference: ERA-Interim

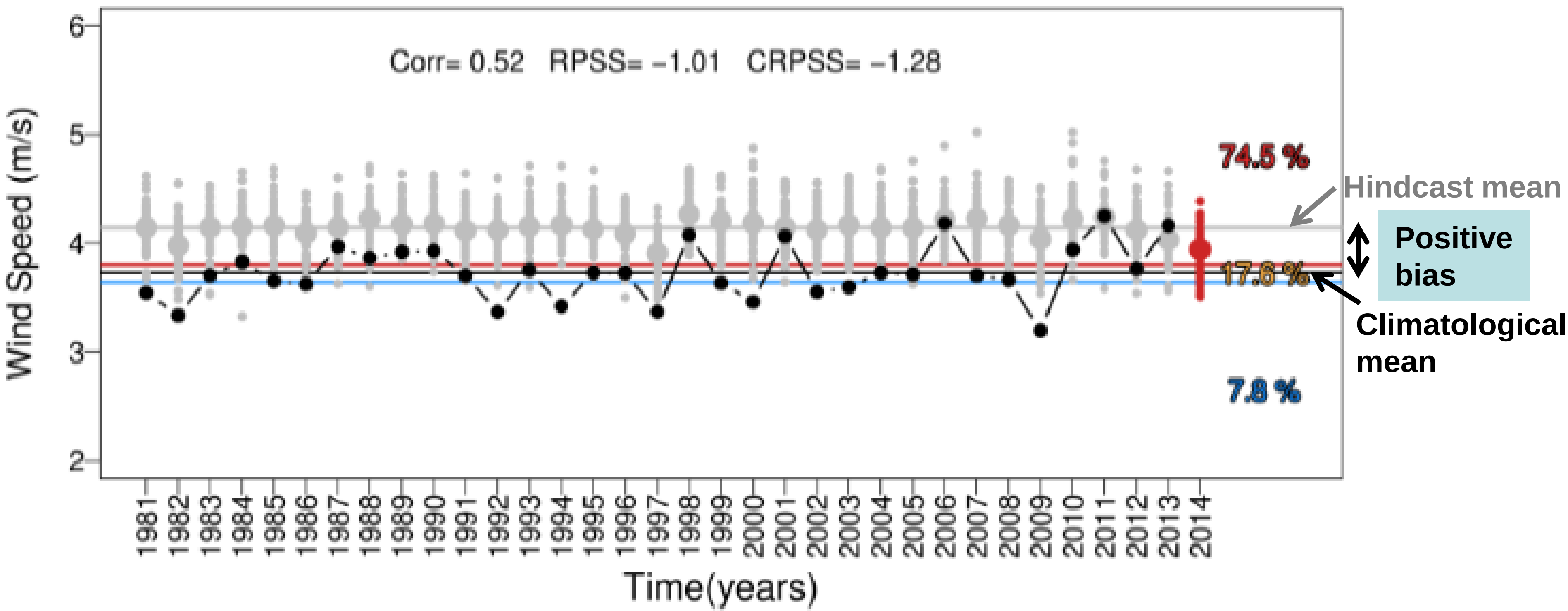
Positive skill over the region of interest in Canada

Raw ECMWF System 4
10-metre wind speed prediction

Barcelona Supercomputing Center
Centro Nacional de Supercomputación
EXCELENCIA SEVERO OCHOA

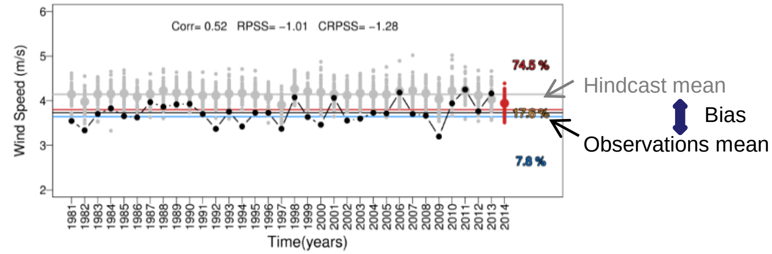
Canada wind farms

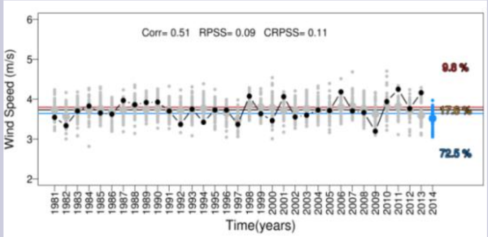
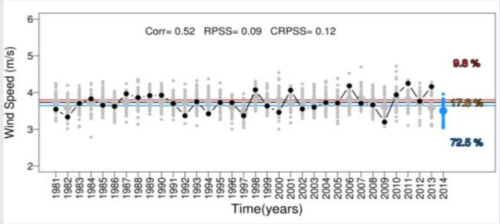
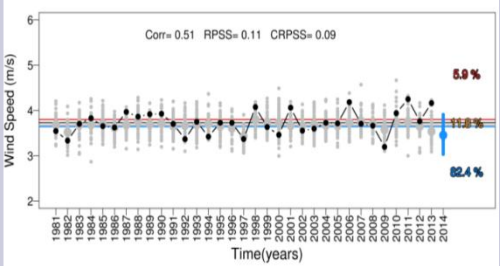
- **1-month lead predictions for DJF**
- **Issued in November**
- **Hindcast period: 1981-2014**
- **Reference: ERA-Interim**



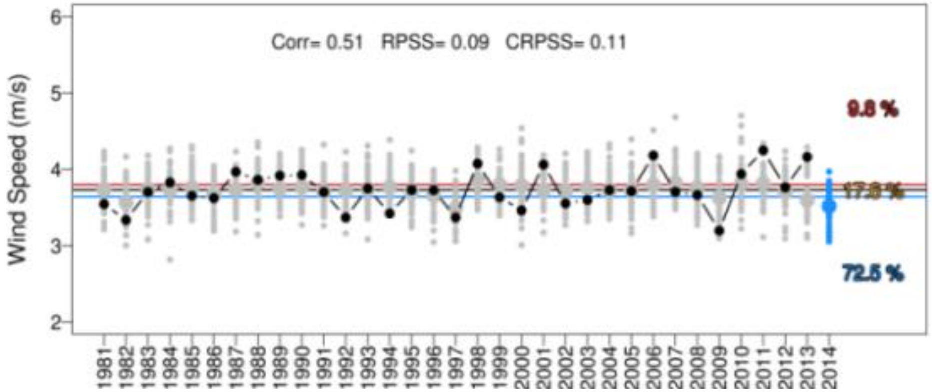
Different bias-adjustment methods

Raw data

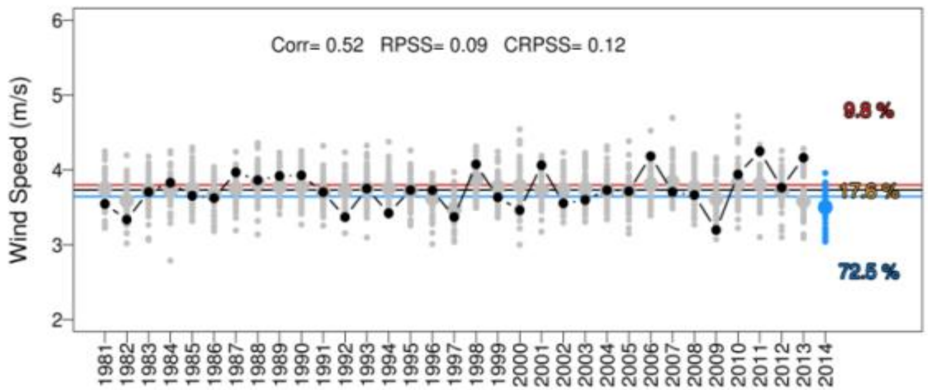


Method	Equation	Description	Result
Simple bias correction	$y_{j,i} = (x_{ij} - \bar{x})\frac{\sigma_{ref}}{\sigma e} + \bar{o}$	Based on the assumption that both the reference and forecasted distribution are well approximated by a Gaussian distribution.	
Calibration method	$y_{j,i} = \alpha x_i + \beta z_{ij} + \bar{o}$	Variance inflation modifies the predictions to have the same interannual variance as the reference dataset and corrects the ensemble spread to improve the reliability.	
Quantile mapping	$y_{j,i} = (ecdf^{ref})^{-1} ecdf^{mod}(x_{ij})$	It determines for each forecast to which quantile of the forecast climatology it corresponds, and then they are mapped to the corresponding quantile of the observational climatology.	

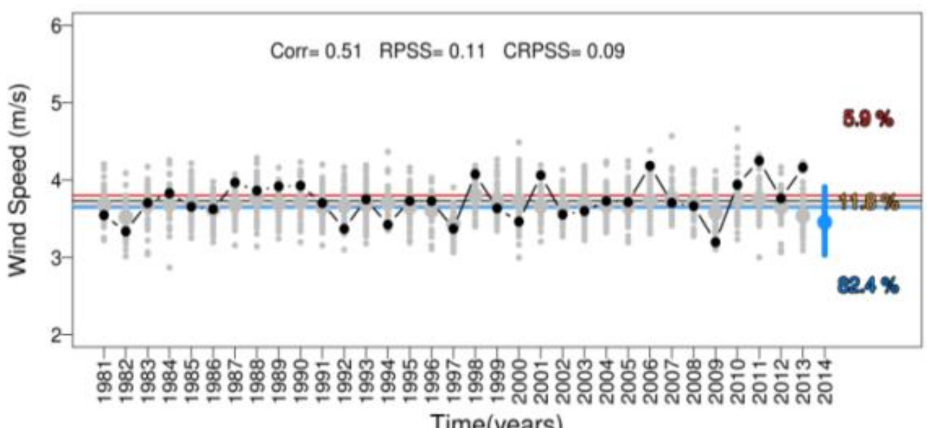
Simple bias correction



Calibration method

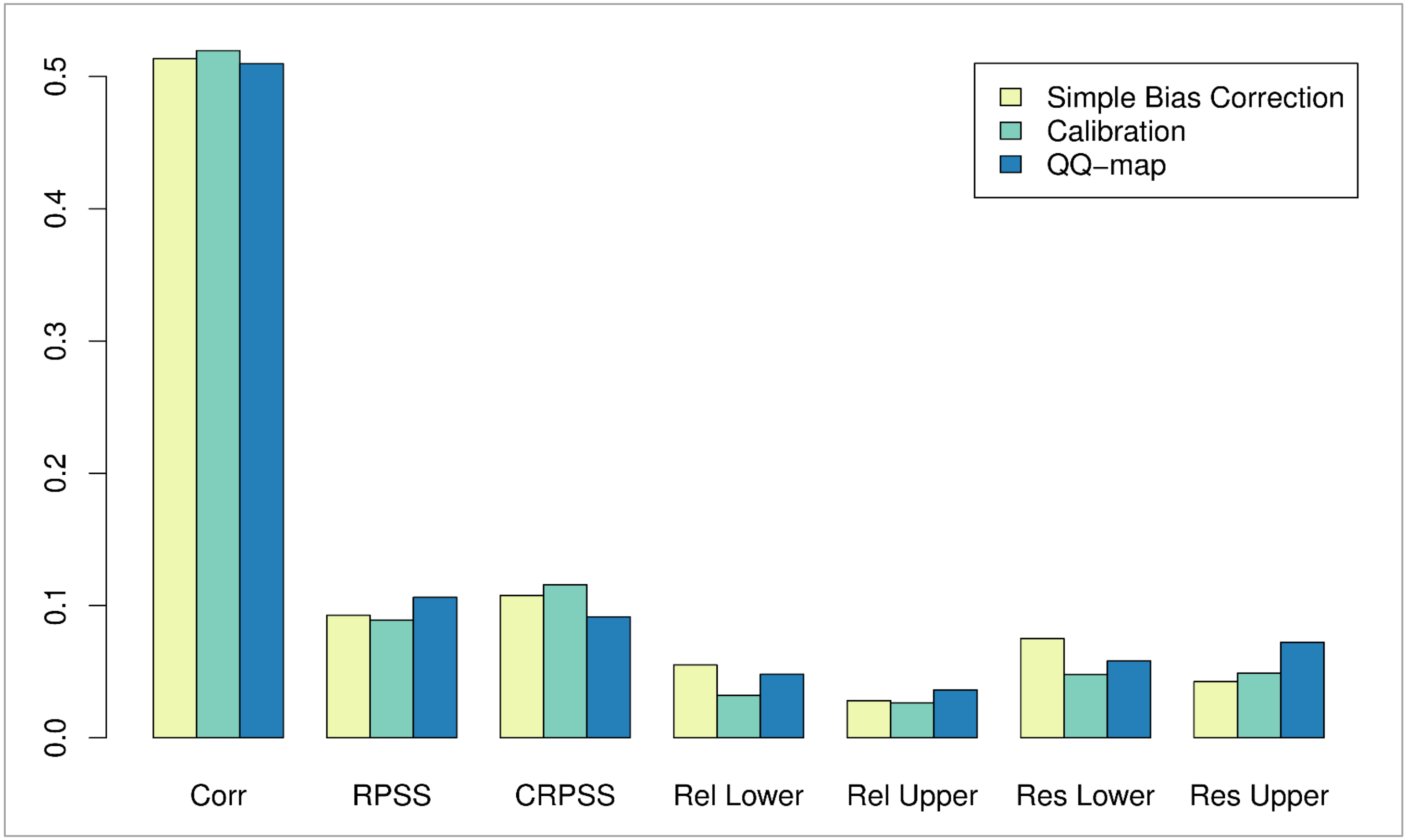


Quantile mapping



Three methods successfully correct previously identified bias

Forecast quality assessment

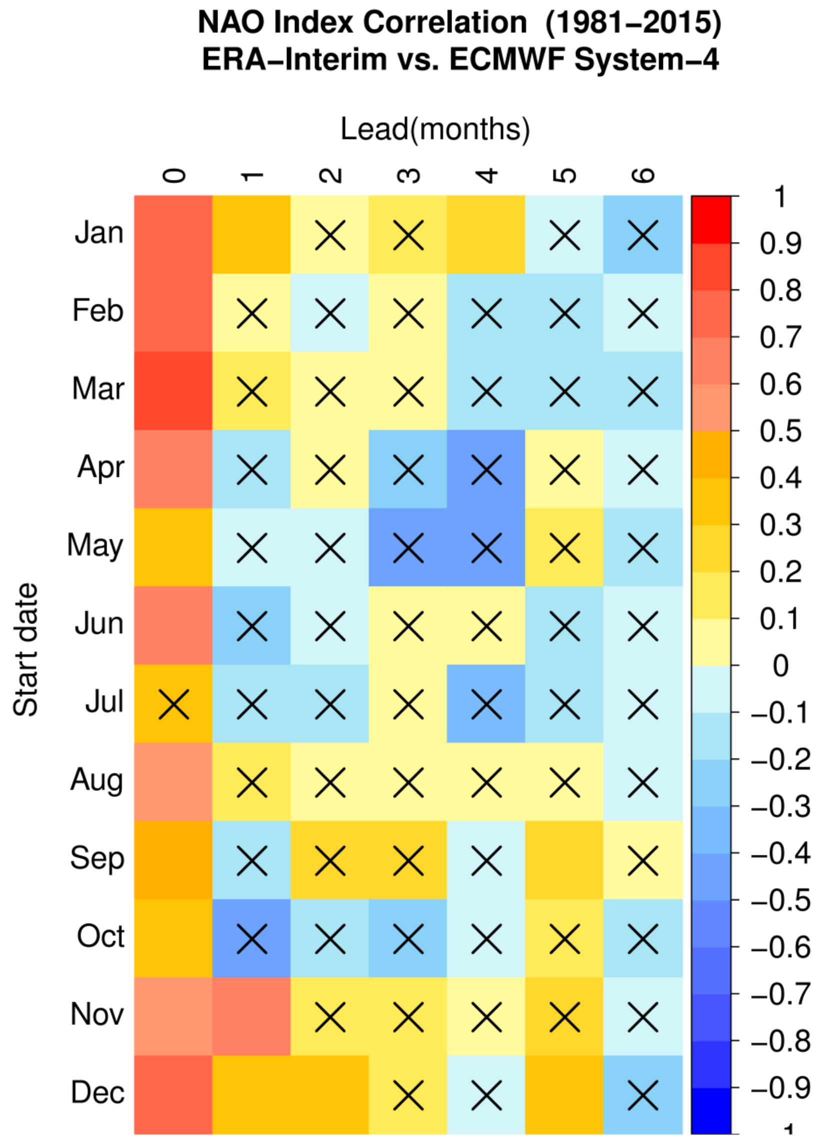


- **Small difference among scores for the three bias-adjustment methods**

NAO prediction skill

Can NAO forecast skill be used to improve the quality of 10-m wind speed forecasts at seasonal time scales?

Downscaling procedure using large scale prediction information to help produce local scale wind predictions



Exploiting NAO seasonal predictions for producing 10-m wind speed

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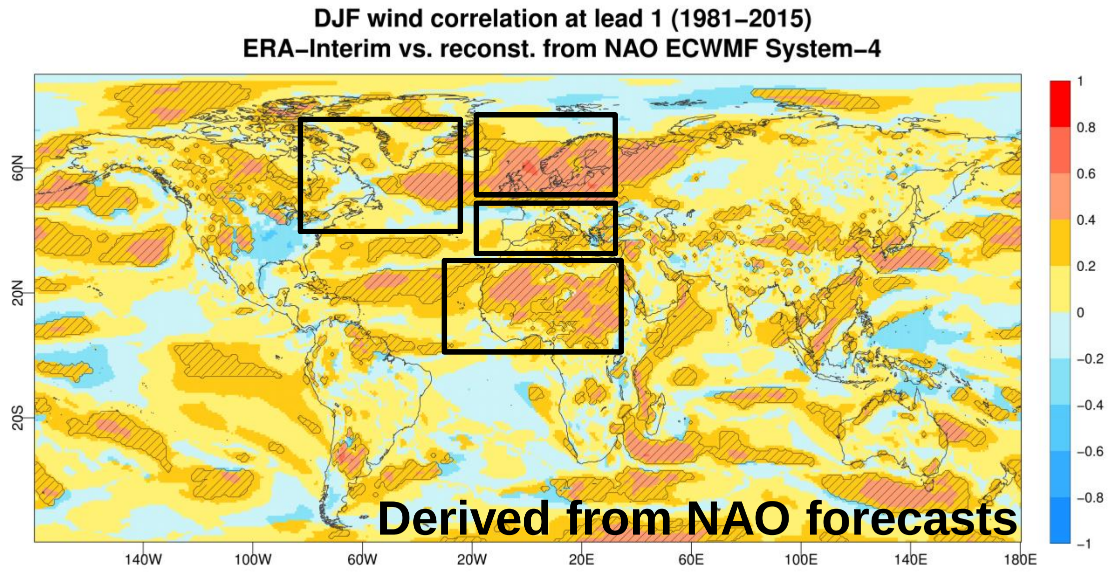
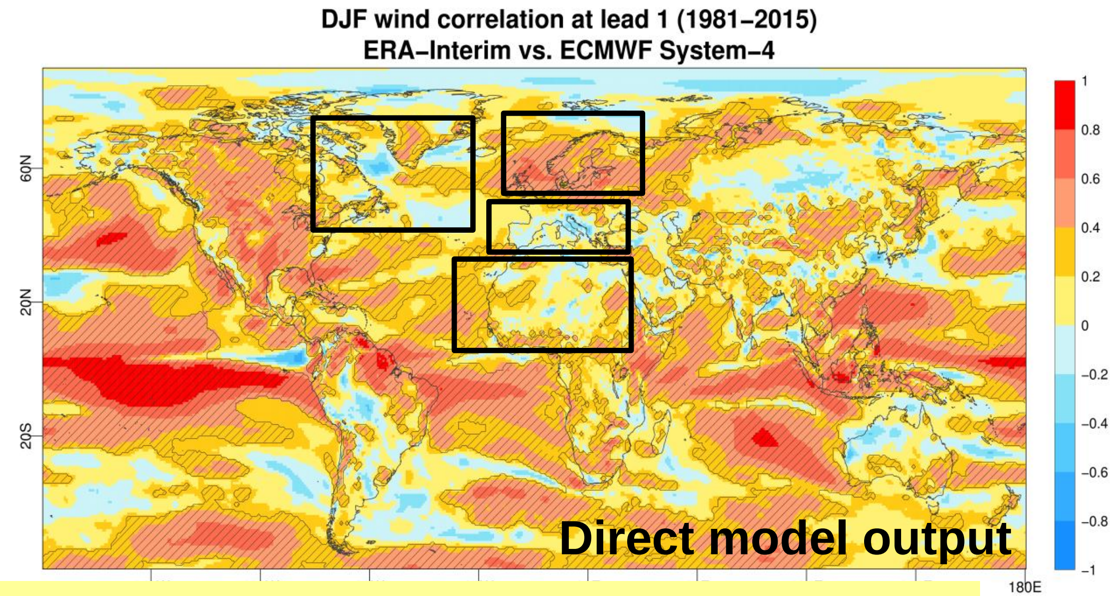
1) Construction of linear regression model: Predictor, observed (ERA-I) DJF NAO. Predictand, DJF 10-m wind speed

2) Compute DJF NAO seasonal prediction (PC-based) from ECMWF S4 SLP seasonal forecasts issued in Nov

3) NAO seasonal forecast is introduced in the linear model (step 1 above) to estimate 10-m wind speed seasonal predictions

4) Validate 10-m wind speed predictions estimated from NAO model with the direct output from S4



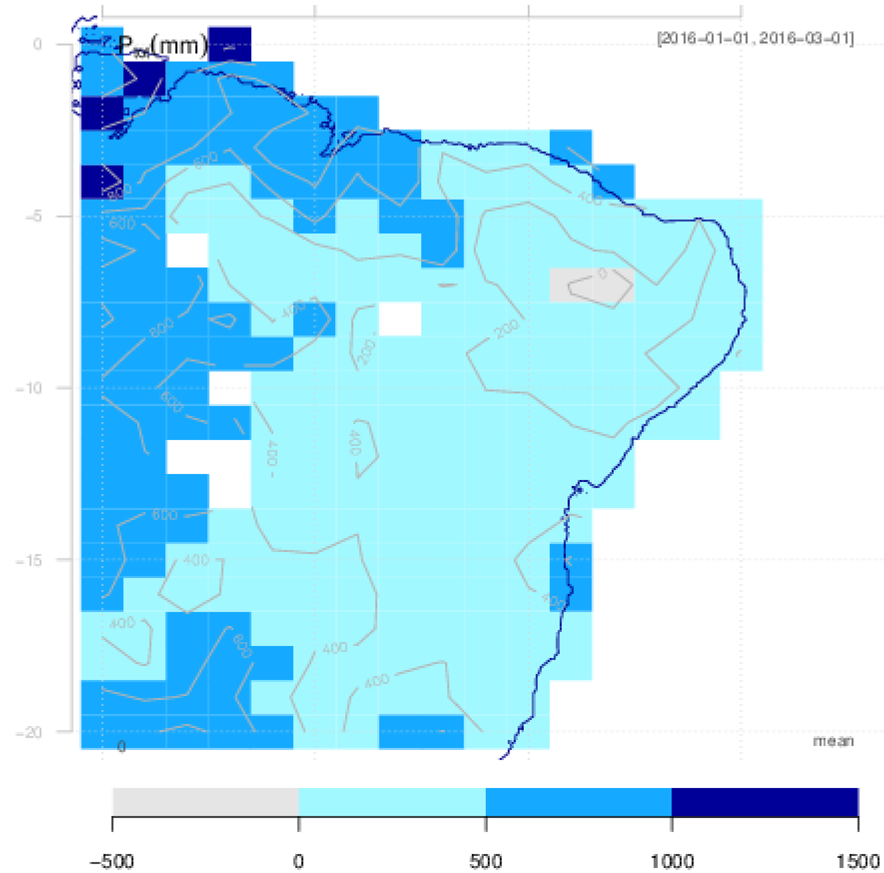


NAO skill helps improve wind speed predictions: over highlighted regions

Exploiting ENSO seasonal predictions for producing NE Brazil precipitation

- Model output statistics (MOS)
- Multiple linear regression based on principal component (PC) analysis
- Predictor:
  ECMWF System 4
  Seasonal T_{2m} over the Pacific
  (Proxy for ENSO)
- Predictand:
  Total precipitation over NE Brazil

NE Brazil precipitation total (mm) downscaled forecast: JFM 2016



Procedure allows production of detailed regional scale forecast information relevant for various user sectors

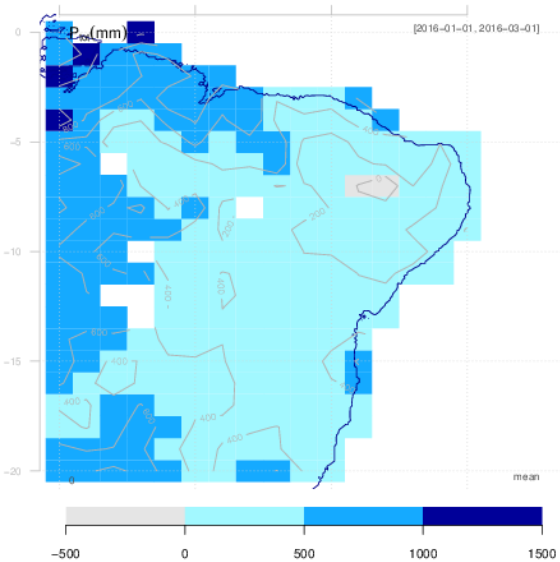
Norwegian Meteorological Institute

Rasmus Benestad

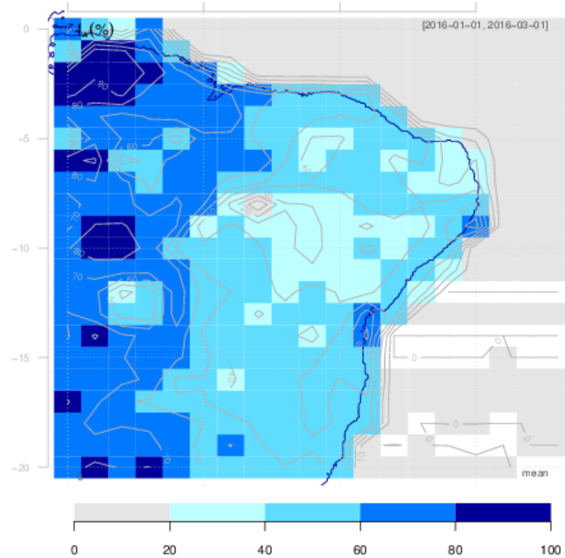
Exploiting ENSO seasonal predictions for producing different aspects of NE Brazil precipitation

Downscaled forecast: JFM 2016

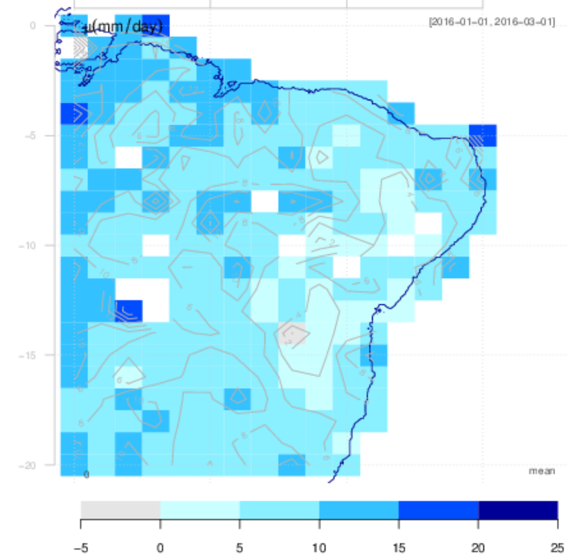
Precip. total: $p_{tot} = n\, f_w\, \mu$



Wet day frequency (f_w)



Wet day mean (μ)



n: total number of days in the JFM season
Wet-day frequency (f_w): dependent on large-scale teleconnections (e.g. ENSO):
Explains the in precipitation total (p_{tot}) signal
Wet-day mean (μ) tends to depend on local aspects: challenging to predict

Procedure allows production of detailed regional scale forecast information relevant for various user sectors

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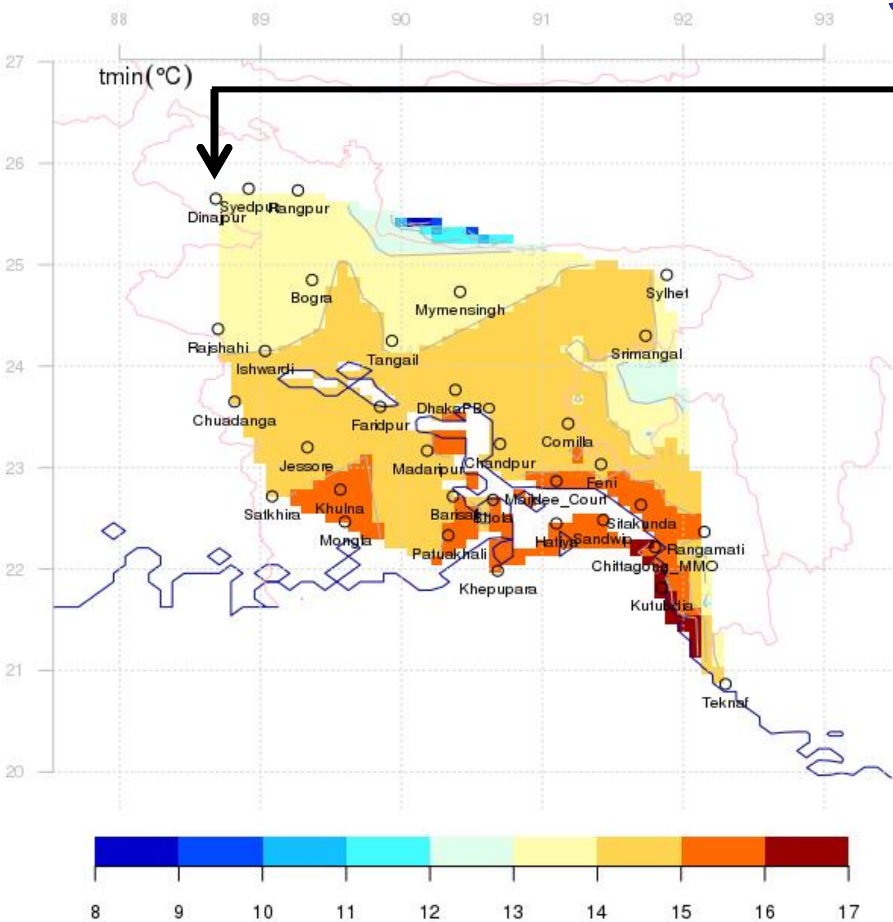
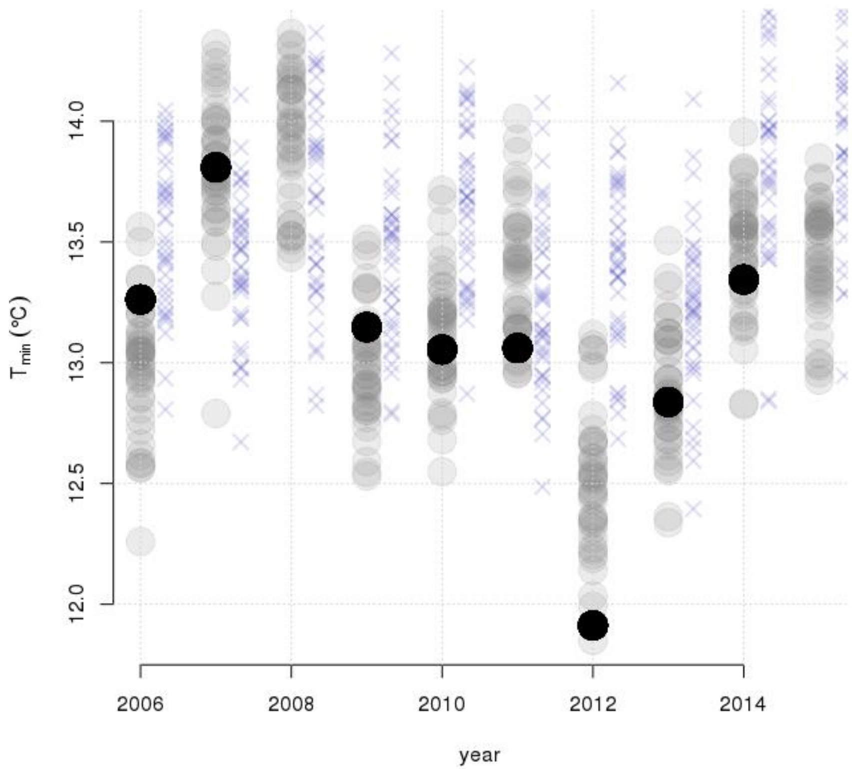
Downscaled seasonal temperature: Local stations in Bangladesh, NDJ 2015/2016



Dinajpur station



Grey circles: Downscaled forecasts
Blue crosses: raw ECMWF S4 forecasts
Back circles: Obs. temperature

Similar MOS procedure as in Brazil helps produce improved local scale information

Procedure allows production of improved local scale forecast information relevant for various user sectors

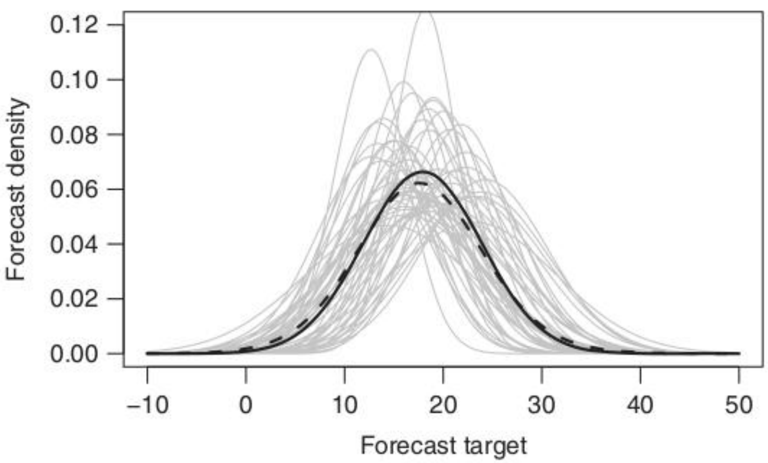
Norwegian Meteorological Institute

Rasmus Benestad

Parameter uncertainty in forecast recalibration

When fitting statistical models for forecast post-processing, there is the need to account for parameter uncertainty. Especially if the number of hindcast years is small.

DJF 1997 NAO forecast



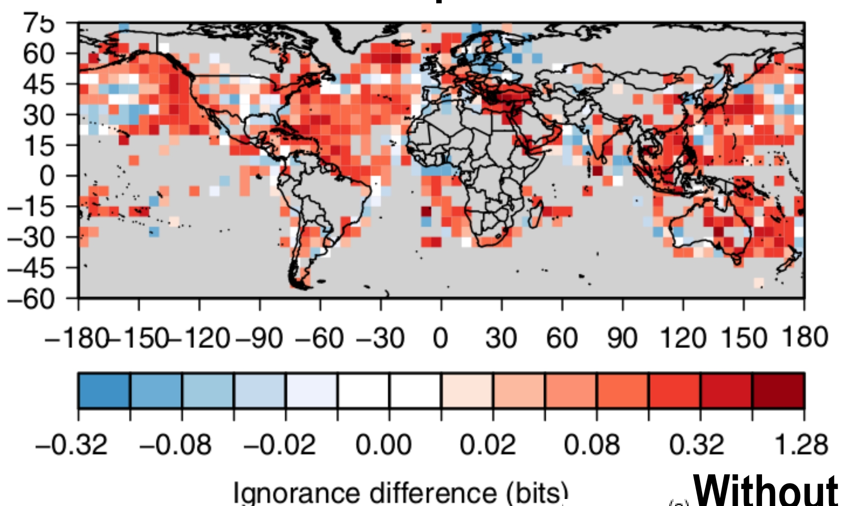
- Each gray line is an equally likely forecast distribution, post-processed by Nonhomogeneous Gaussian Regression, for NAO in 1997. The differences are due to uncertainty in the correct post-processing parameters. By averaging over all possible forecasts, we propagate the parameter uncertainty into the final forecast (dashed line) which is wider than the "best guess" forecast (solid line) that ignores parameter uncertainty.

Siegert, Sansom, Williams (2016) Parameter uncertainty in forecast recalibration. QJRMS, doi: 10.1002/qj.2716

Parameter uncertainty in forecast recalibration

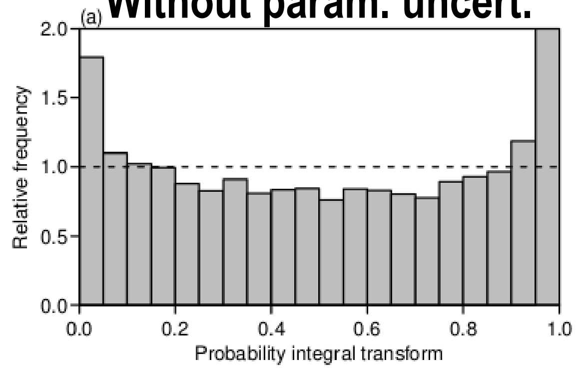
- **By accounting for post-processing parameter uncertainty better quality forecasts are produced**

Ignorance score difference (with minus without param. uncert)
CanCM4 annual temperature forecasts: 1960-2010

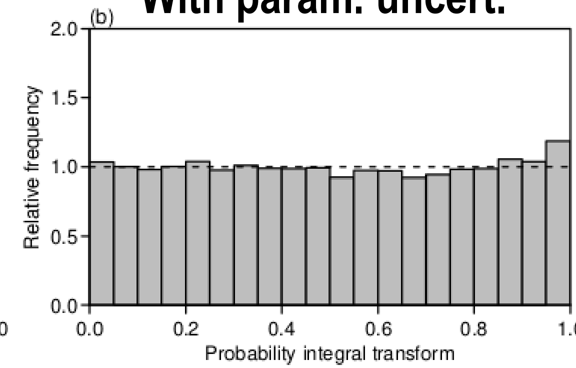


The Ignorance score difference is positive almost everywhere in CANCM4 forecasts. When accounting for parameter uncertainty, the post-processed forecasts assign more probability to the verifying observations.

Without param. uncert.



With param. uncert.



The forecasts become more reliable.
Without parameter uncertainty the rank histogram is U-shaped, with parameter uncertainty the rank histogram becomes flat.

Siegert, Sansom, Williams (2016) Parameter uncertainty in forecast recalibration. QJRMS, doi: 10.1002/qj.2716

Final remarks

• Downscaling and bias adjustment are two aspects of the same problem: Making climate predictions usable by a number of end users, who are unable to deal with direct model outputs and need processed information as close as possible to the observations

• Important to diagnose the impact of these procedures on prediction skill to help users make best use of the tailored climate prediction information

• Recent research suggest importance of incorporating parameter uncertainty in forecast recalibration/bias adjustment procedures

• Hydro power energy sector in Brazil: Interested in co-developing methods to address specific needs. Identification of different best methods for distinct regions/basins and periods well received.

• Bottom line: what matters are the user requirements, and whether the current scientific knowledge allows the co-production of prediction information to help support users decisions

Thank you all for your attention!