

Workshop on Bias correction in climate studies  
6 October 2016  
Berlin, Germany



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# Application of bias correction methods for climate predictions tailored to the wind industry

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**EUPORIAS**

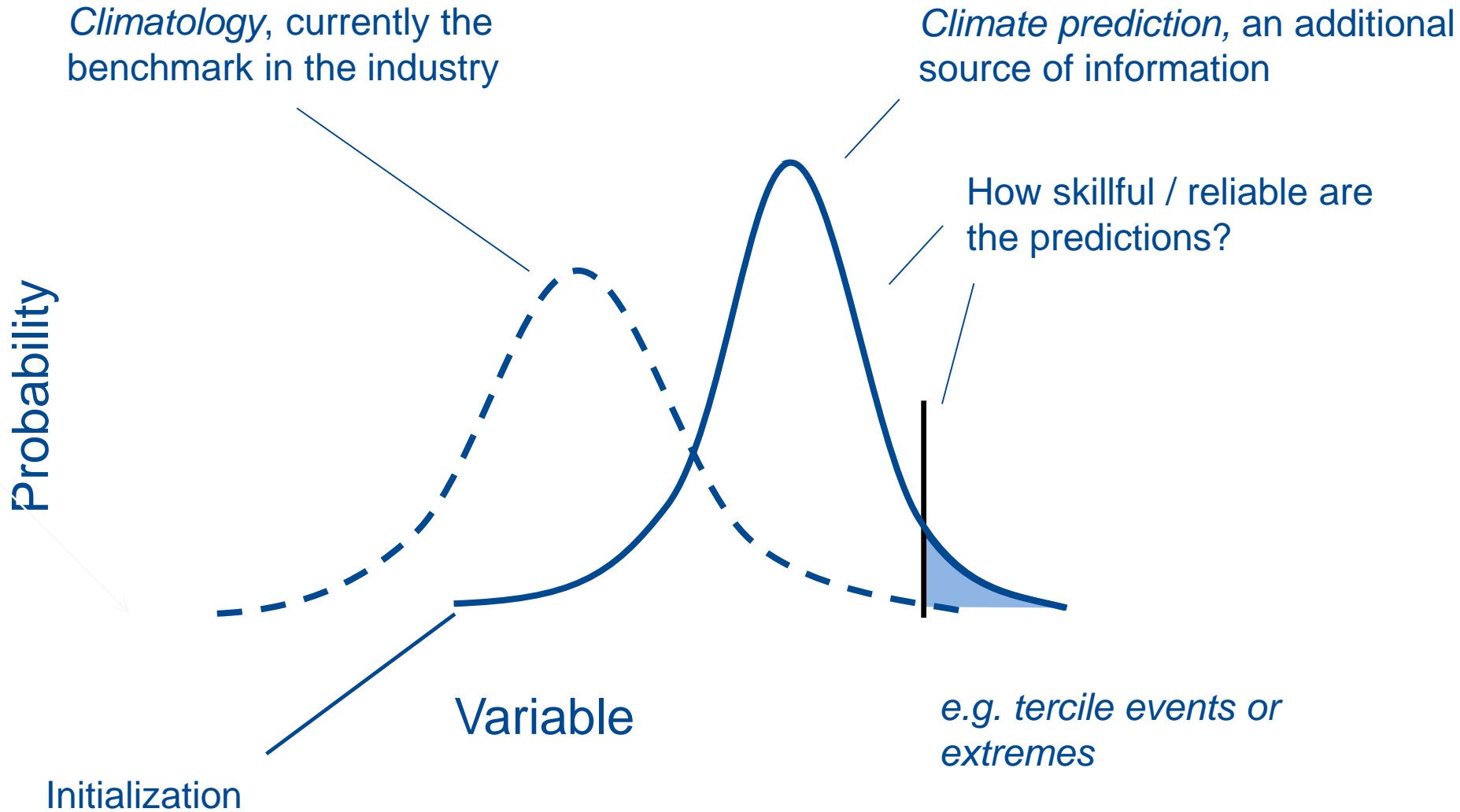


GOBIERNO  
DE ESPAÑA  
MINISTERIO  
DE ECONOMÍA  
Y COMPETITIVIDAD



- Several economic and operational issues as maintenance, matching supply with demand and financial operations require wind forecasting at several time scales.
- Wind energy sector routinely uses weather forecast up to 15 days. Beyond this time horizon a retrospective approach is used.
- Climate predictions can provide additional value to wind energy current approaches.

# Concept climate prediction



## Hydroelectric power management

INTERNATIONAL JOURNAL OF CLIMATOLOGY  
*Int. J. Climatol.* 27: 1691–1705 (2007)  
Published online in Wiley InterScience  
(www.interscience.wiley.com) DOI: 10.1002/joc.1608



### Forecasting precipitation for hydroelectric power management: how to exploit GCM's seasonal ensemble forecasts

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#### Abstract:

The EDF group is the biggest French electric power producer and distributor. Its activities are greatly related to weather and climate. In particular, optimal management of the hydroelectric power production system requires a good forecast of water resources, from several days to several months in advance. Currently, only climatology at the seasonal timescale is used for operational production management. Seasonal probabilistic forecasts would improve watershed management at some months' lead-time if they are skillful enough. For this, two main problems have to be addressed: first, direct precipitation forecasts at this timescale have little, but positive, skill over Europe; second, the spatial scales of seasonal forecasting models are not adequate to predict local precipitation at the river basin scale. This study aims to evaluate the quality of seasonal forecasts of precipitation for 48 catchments in southern France. These are obtained by spatially downscaling global scale seasonal forecasts of geopotential height at 850 hPa. The method used is based on singular value decomposition and multiple linear regression. The statistical downscaling model is calculated from 45 years of observed local precipitation in the watersheds and geopotential fields from ERA40 re-analysis data. The statistical model is then applied to the seasonal hindcasts from the DEMETER project. Two main results arise from this work. First, we show that it is possible to obtain useful and valuable information for EDF at the local scale from global seasonal averaged information. Second, we find that only a probabilistic multi-model ensemble forecast approach provides useful information for EDF catchments, even with quite low skill, and that a deterministic approach, using only the ensemble mean of the forecasts, is not better than a forecast based on climatology. It has, nevertheless, to be pointed out that for operational purposes, being able to know that a forecast for a given location or date is not reliable is, in itself, valuable information. Copyright © 2007 Royal Meteorological Society

KEY WORDS downscaling; hydroelectric power; precipitation; seasonal forecasts; multi-model probabilistic forecasts

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#### INTRODUCTION

EDF group activities are greatly dependent on weather and climate. Electricity demand is directly linked to

skill. Forecasting hydropower production is particularly important in winter, where it is used to meet peak demand at relatively low cost. In summer, it is useful to forecast river flows and temperatures, both to forecast hydropower

## Electricity demand

Applied Energy 137 (2015) 435–444



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### Seasonal climate forecasts for medium-term electricity demand forecasting

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<sup>b</sup>International Pacific Research Center, University of Hawaii at Manoa, Honolulu, HI, USA



#### HIGHLIGHTS

- During the ten years, seasonal climate forecasts have improved their skill.
- We analyzed the link between summer average temperature and demand over Italy.
- Both deterministic and probabilistic forecasting approaches are here considered.
- Climate forecasts show a significant skill in predicting the demand in many regions.

#### ARTICLE INFO

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Probabilistic forecast

#### ABSTRACT

Air temperature is an effective predictor for electricity demand, especially during hot periods where the need of electric air conditioning can be high. This paper presents for the first time an assessment of the use of seasonal climate forecasts of temperature for medium-term electricity demand prediction. The retrospective seasonal climate forecasts provided by ECWMP (European Centre for Medium-Range Weather Forecasts) are used to forecast the June–July Italian electricity demand for the period 1990–2007.

We find a relationship between summer (June–July) average temperature patterns over Europe and Italian electricity demand using both a linear and non-linear regression approach. With the aim to evaluate the potential usefulness of the information contained into the climate ensemble forecast, the analysis is extended considering a probabilistic approach.

Results show that, especially in the Center–South of Italy, seasonal forecasts of temperature issued in May lead to a significant correlation coefficient of electricity demand greater than 0.6 for the summer period. The average correlation obtained from seasonal forecasts is 0.53 for the temperature predicted in May and 0.19 for the predictions issued in April for the linear model, while the non-linear approach leads to the coefficients of 0.62 and 0.36 respectively. For the probabilistic approach, seasonal forecasts exhibit a positive and significant skill score in predicting the demand above/below the upper/lower tercile in many regions.

This work is a significant progress in understanding the relationship between temperature and electricity demand. It is shown that much of the predictable electricity demand anomaly over Italy is connected with so-called heat-waves (i.e. long lasting positive temperature anomalies) over Europe.

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#### 1. Introduction

The main goal of this work is to investigate the use of seasonal climate forecasts for electricity demand over Italy, focusing on the summer period between 1990 and 2007. During the last decade,

climate forecasts have significantly improved their skill on seasonal time-scales (from one month to six months) [27,5,22,4] but their application to decision-making processes are still rare on scientific literature. Considering also the challenges raised by the recent FP7 European Projects on Climate Services (CLMRUN [1], SPECS [3], EUFORIAS [2]), this paper provides an initial assessment of the use of seasonal climate predictions for power systems management with the focus on electricity demand (load) forecast at lead times of one and two months.

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## MONTHLY TO SEASONAL TIMESCALES

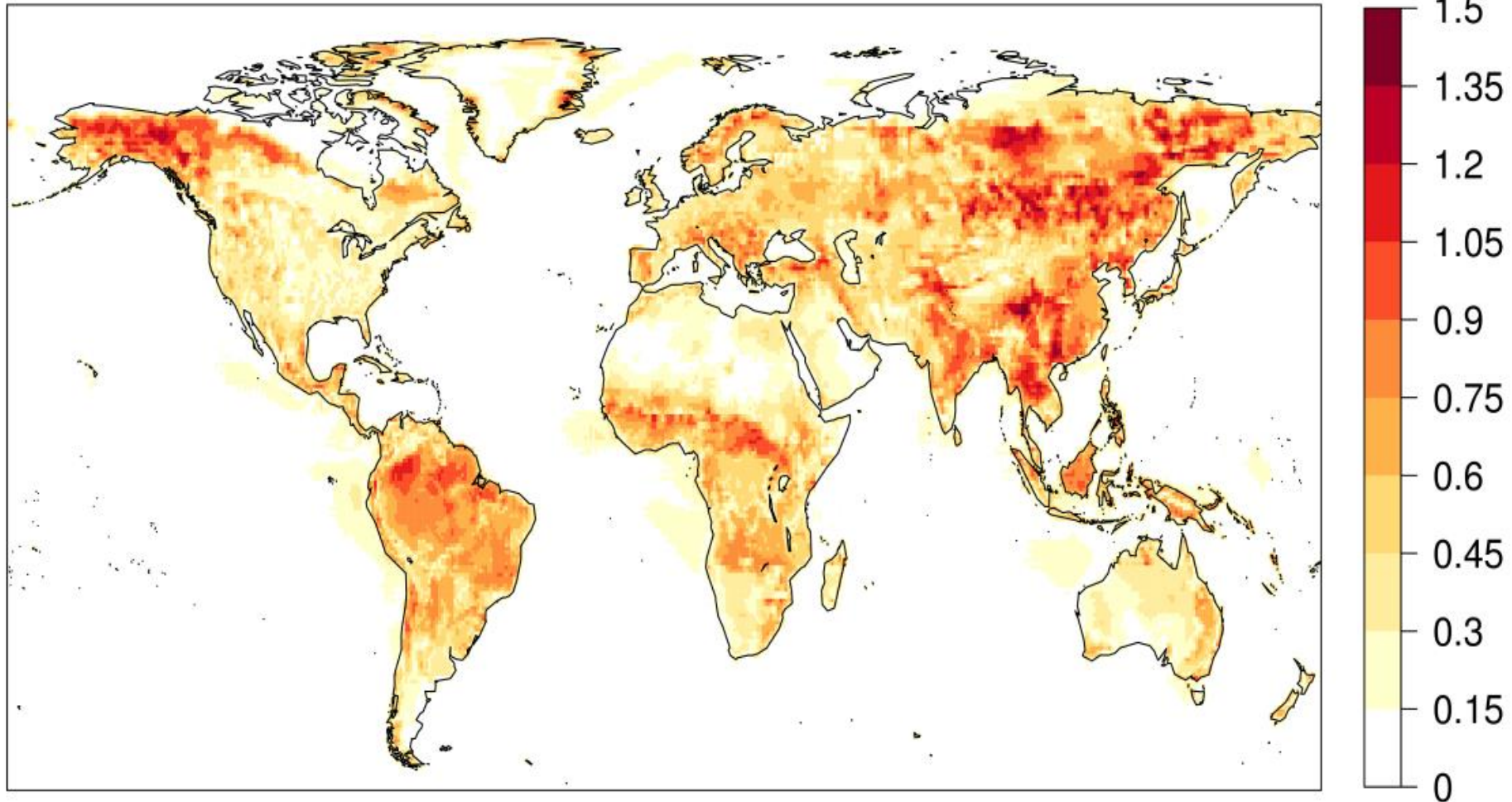
- **Energy producers:** Resource management strategies
- **Energy traders:** Resource effects on markets
- **Wind farm operators:** Planning for maintenance works
- **Wind farm investors:** Optimise return on investments

## ANNUAL TO DECADAL TIMESCALES

- **Wind farm planners:** Site selection
- **Wind farm investors:** Evaluate return on investments
- **Policy makers:** Understand changes to energy mix



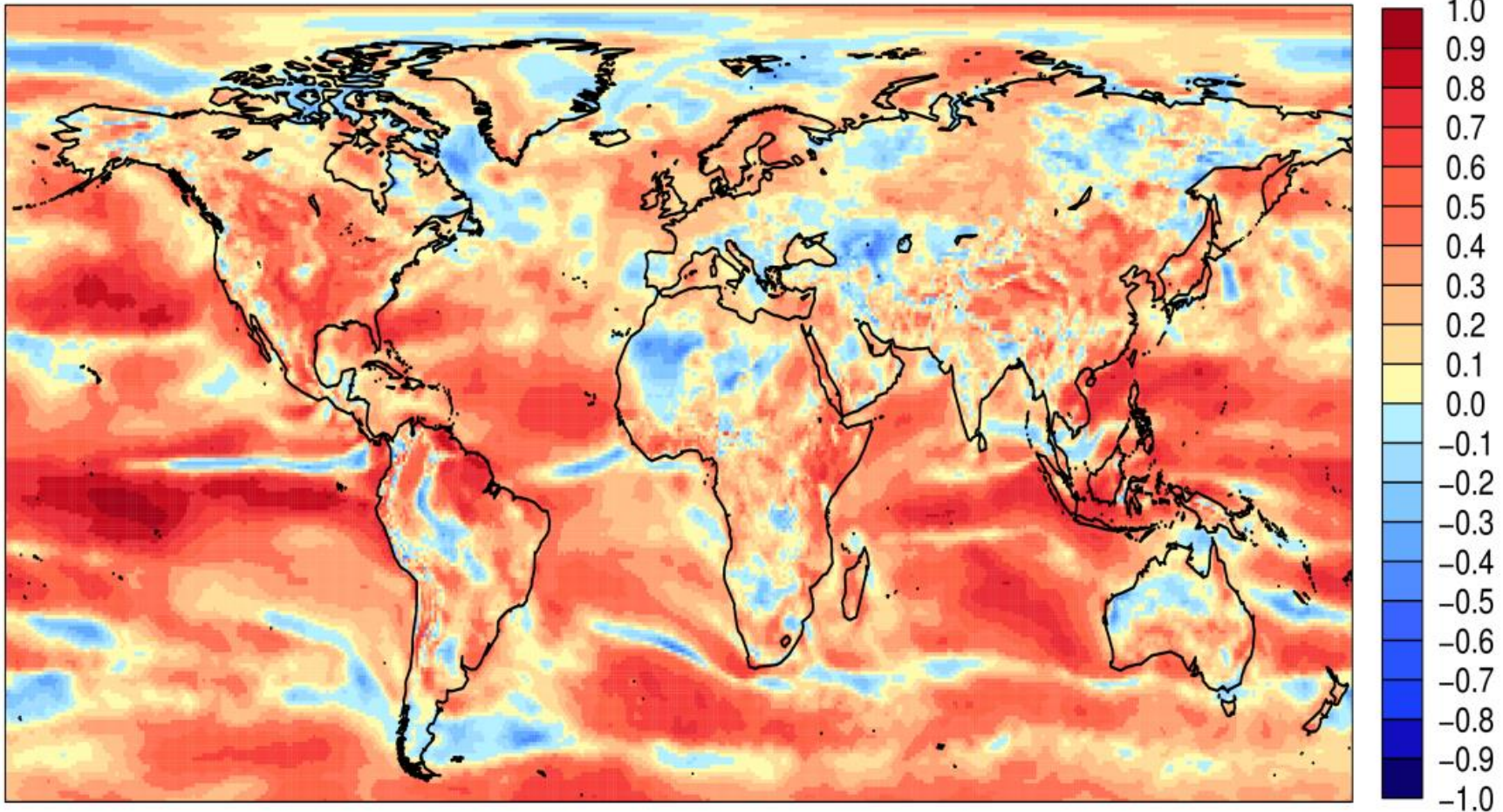
# Challenges for the use of climate information: Observational uncertainty



Range of the differences (m/s) between the 10-m wind speed values produced by ERA-Interim, MERRA and JRA-55

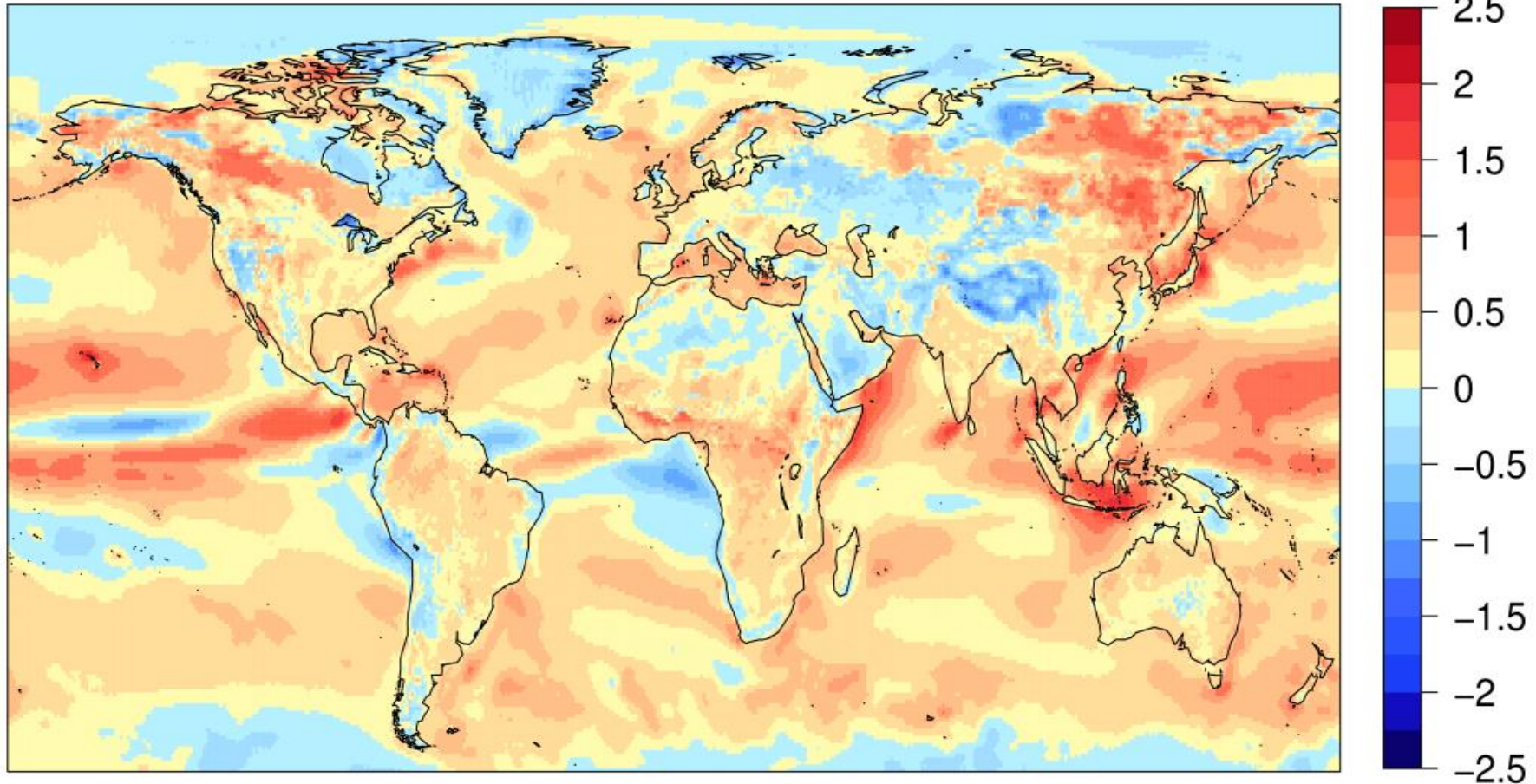


# Challenges for the use of climate information: Predictability



Correlation for 10-m wind speed between the ensemble mean forecasts from ECMWF S4 and ERA-Interim reanalysis in winter

# Challenges for the use of climate information: Biases



Bias of 10-m wind speed between the ensemble mean forecasts from ECMWF S4 and ERA-Interim reanalysis in winter.



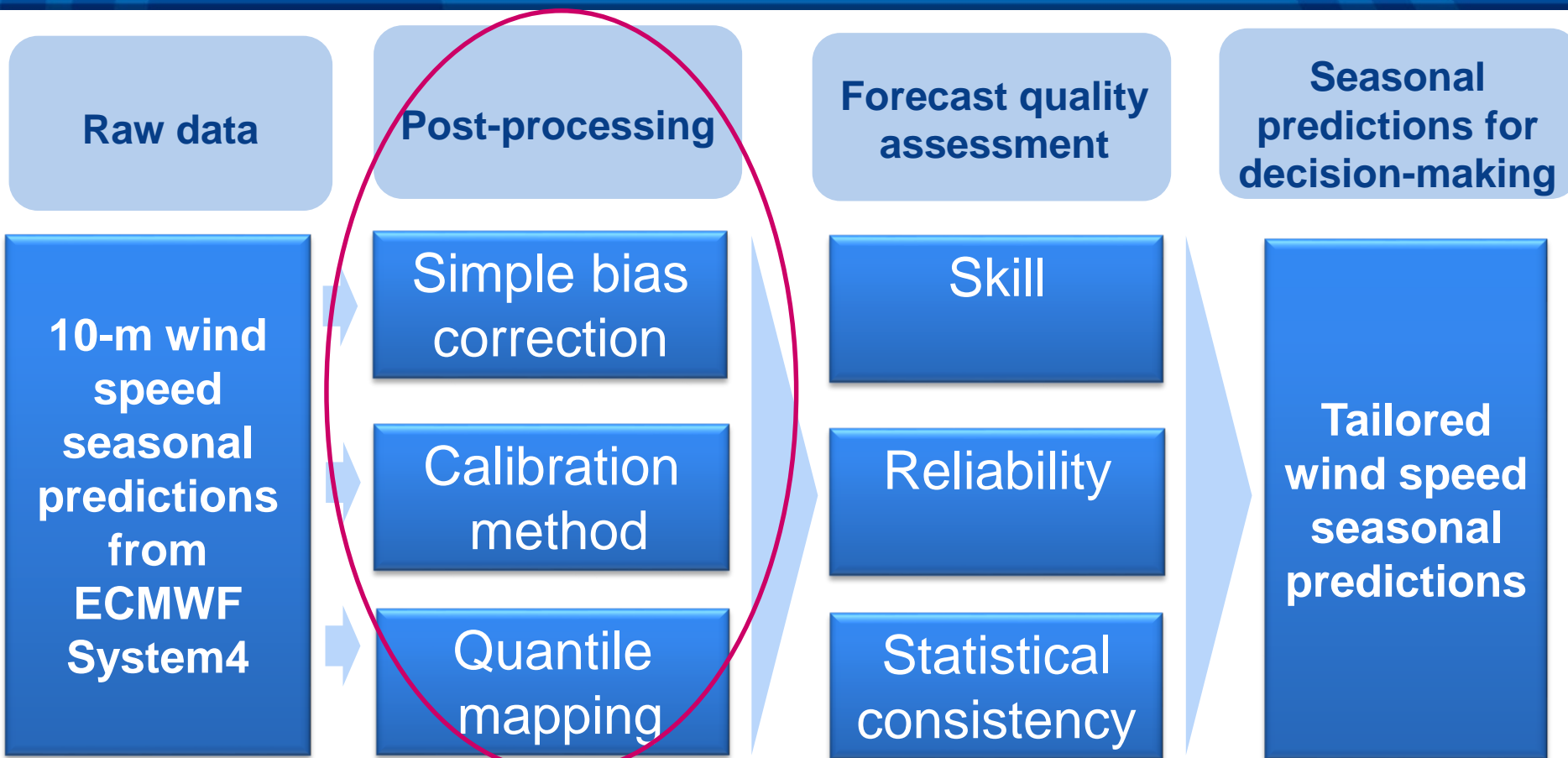


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# Bias-adjustments of seasonal predictions



**Bias-adjustments have been applied to improve the forecast quality of the seasonal climate predictions and allow their application by the wind energy users.**

Simple bias  
correction

Calibration  
method

Quantile  
mapping

$$y_{j,i} = (x_{ij} - \bar{x}) \frac{\sigma_{ref}}{\sigma_e} - \bar{o}$$

Variability  
Observations

Variability  
Ensemble

Simple bias correction is based on the assumption that both the reference and forecasted distribution are well approximated by a Gaussian distribution.



Simple bias  
correction

Calibration  
method

Quantile  
mapping

$$y_{j,i} = \alpha x_i + \beta z_{ij}$$

Variability  
Observations

$$\alpha = |\rho| \frac{\sigma_o}{\sigma_{em}}$$

$$\beta = \sqrt{1 - \rho^2} \frac{\sigma_o}{\sigma_e}$$

Variability  
Esemble

Variability  
Mean Forecast

Variance inflation:

- Predictions with the same interannual variance as the reference dataset
- Correction of the ensemble spread

Simple bias  
correction

Calibration  
method

Quantile  
mapping

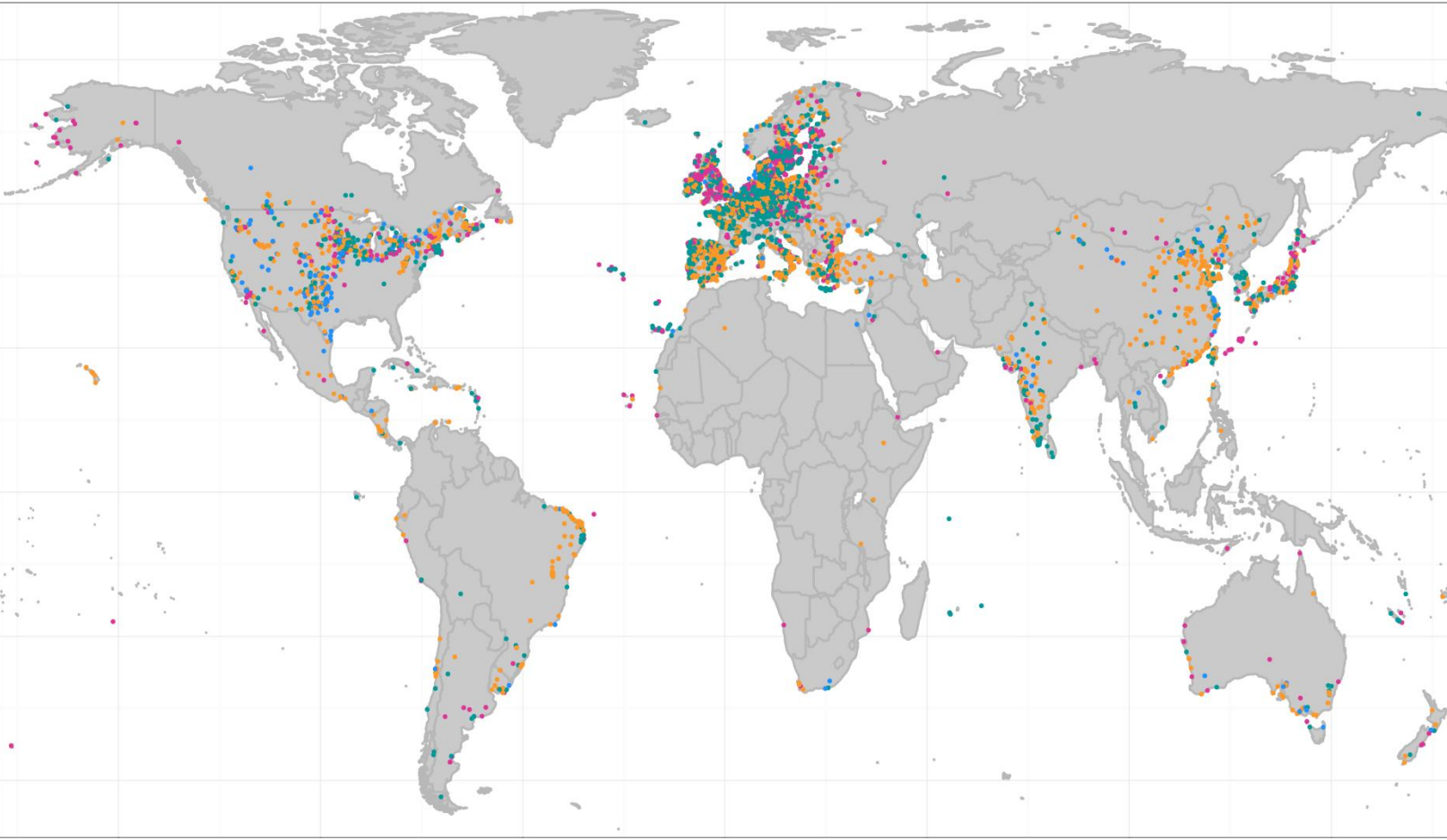
$$y_{j,i} = ecdf^{ref^{-1}} ecdf^{pred}(x_{ij})$$

Inverse cumulative density  
function of the reference  
(quantile function)

Cumulative density function of  
the predictions

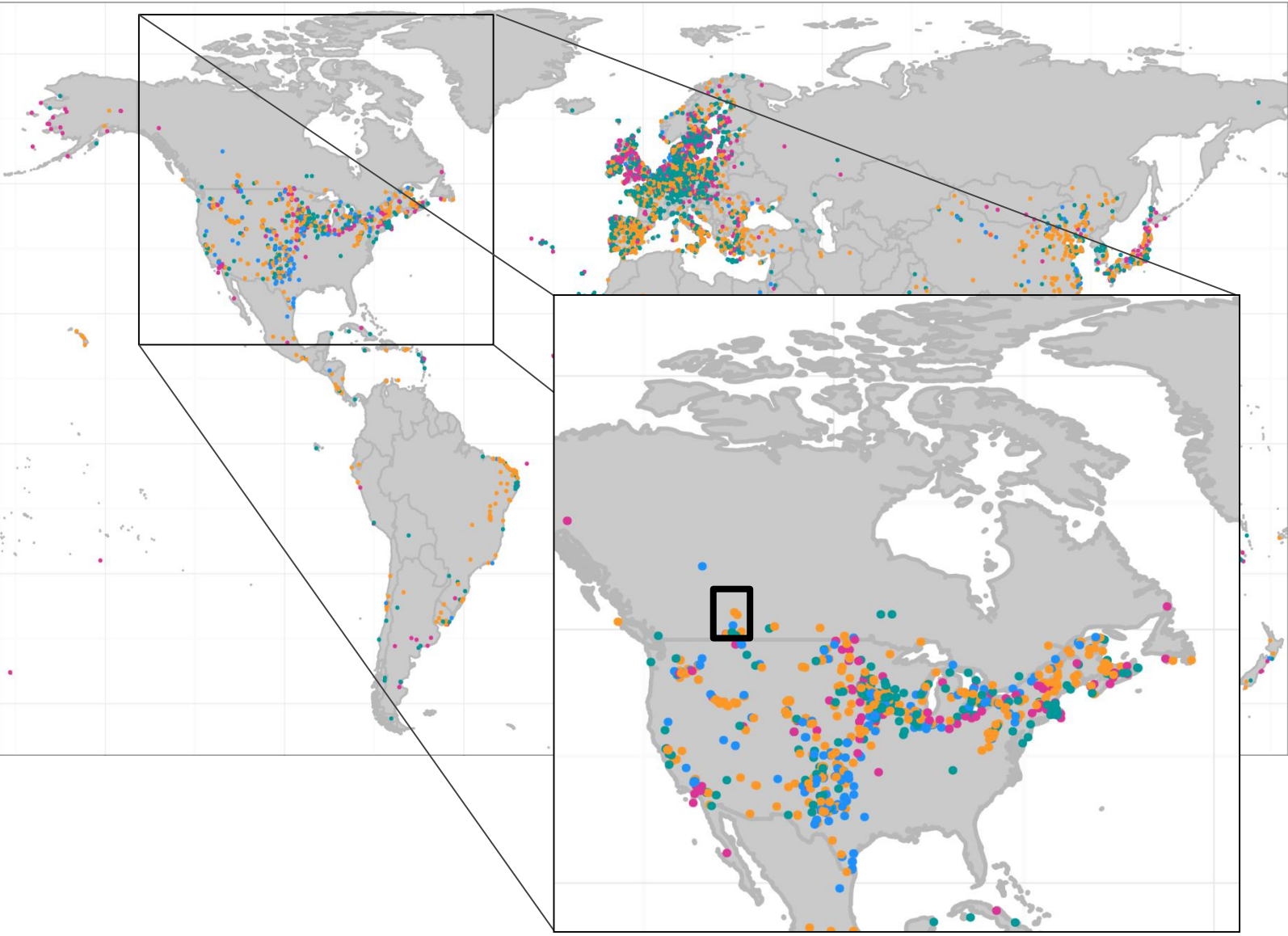
Determines for each forecast to which quantile of the forecast climatology it corresponds, and then maps it to the corresponding quantile of the observational climatology.

# Total installed wind power

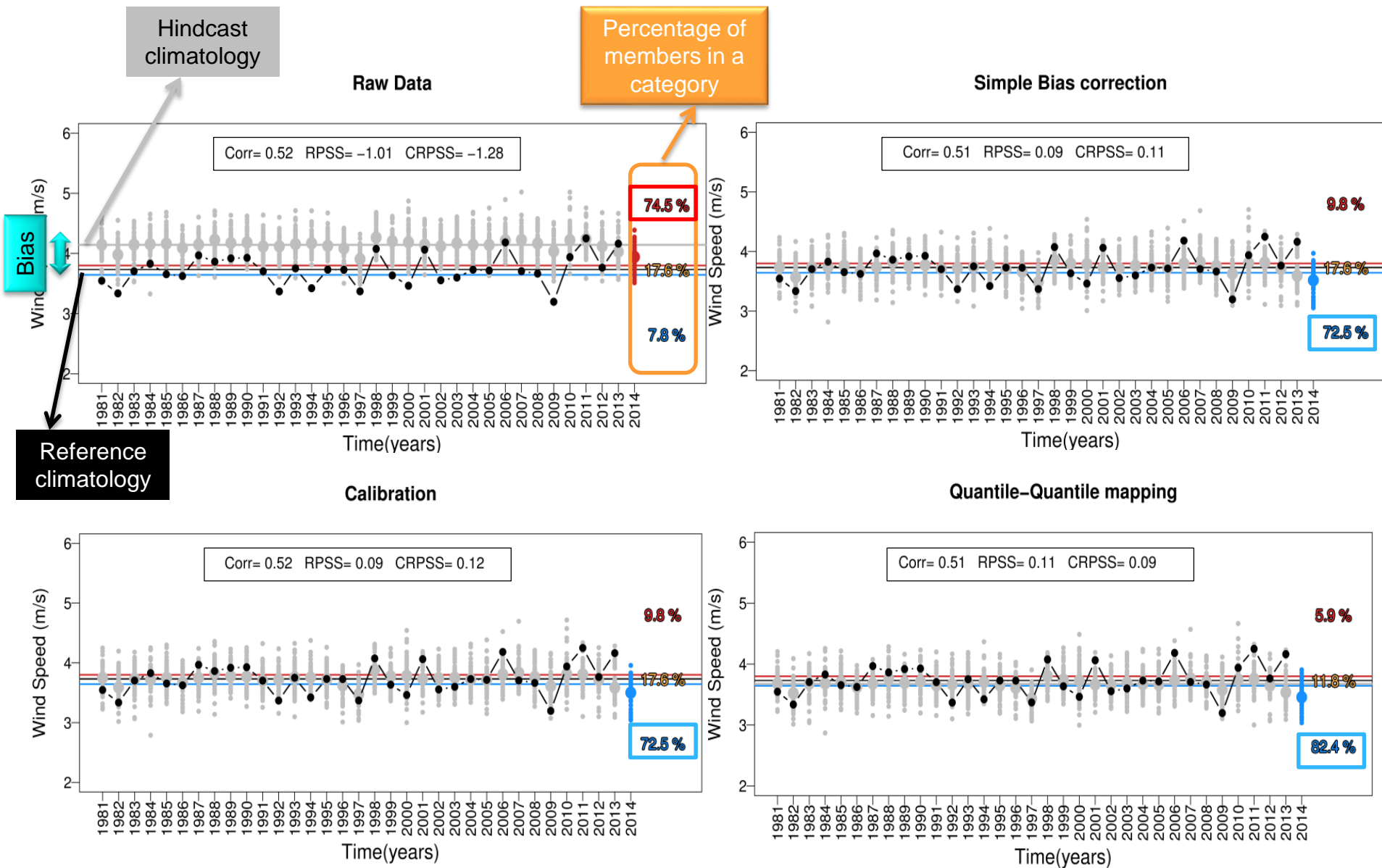




# Total installed wind power



# Impact of bias-correction on skill

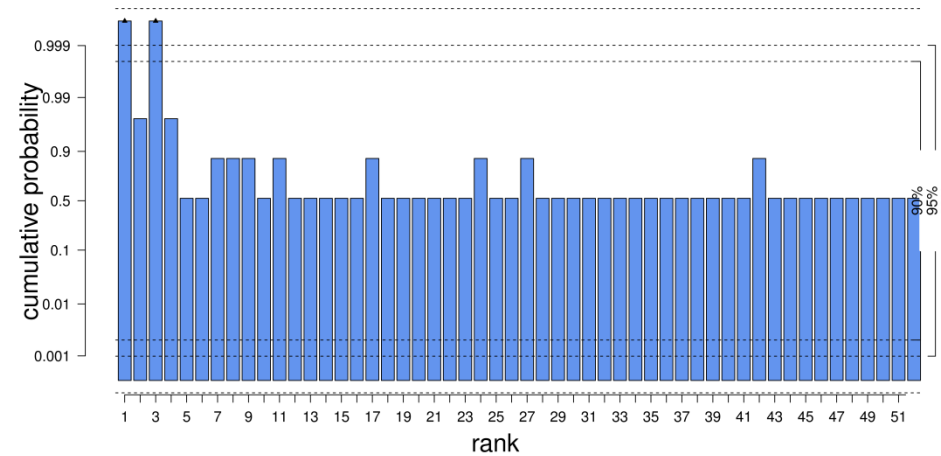


# Impact of bias-correction on statistical consistency

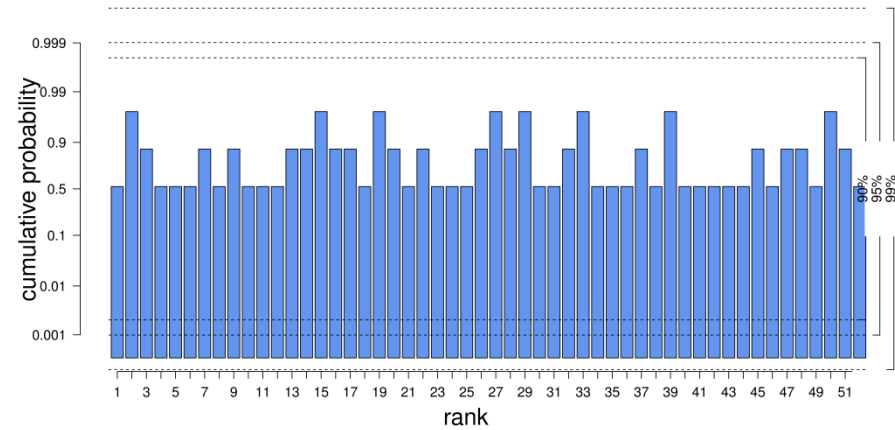


ECMWF S4 seasonal predictions of wind speed in winter (DJF) issued the 1<sup>st</sup> of November and wind speed for the ERA-Interim reanalysis.

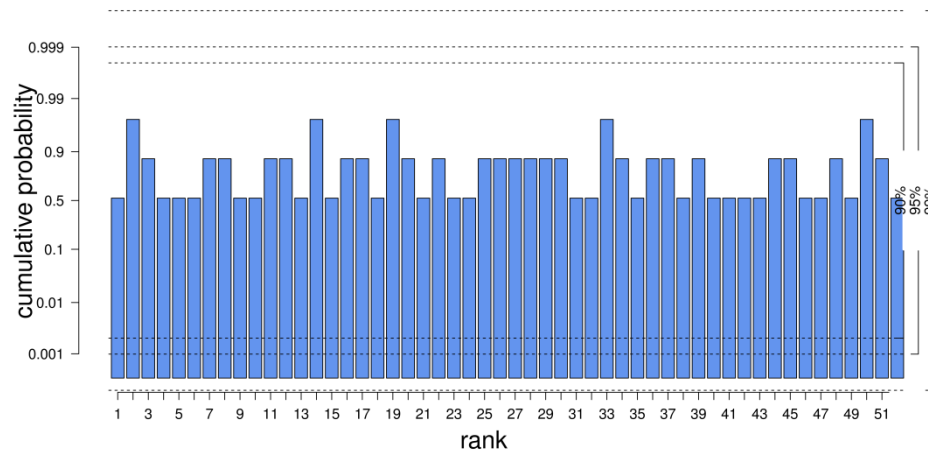
raw



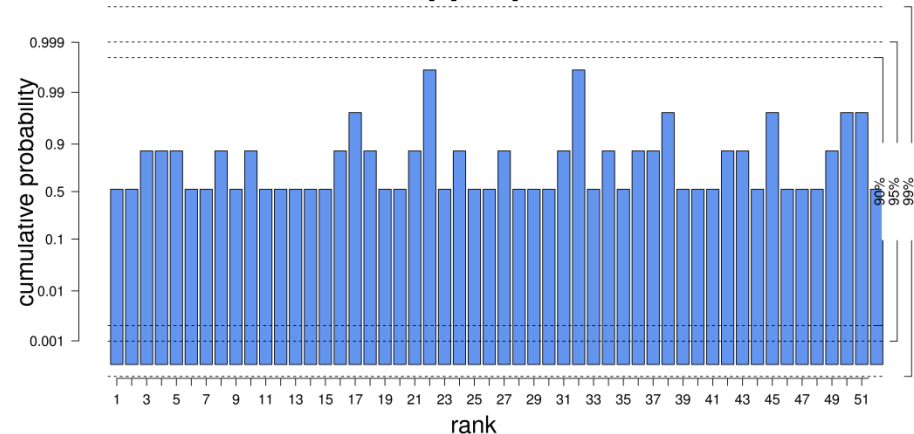
sbcb



cal



qqmap

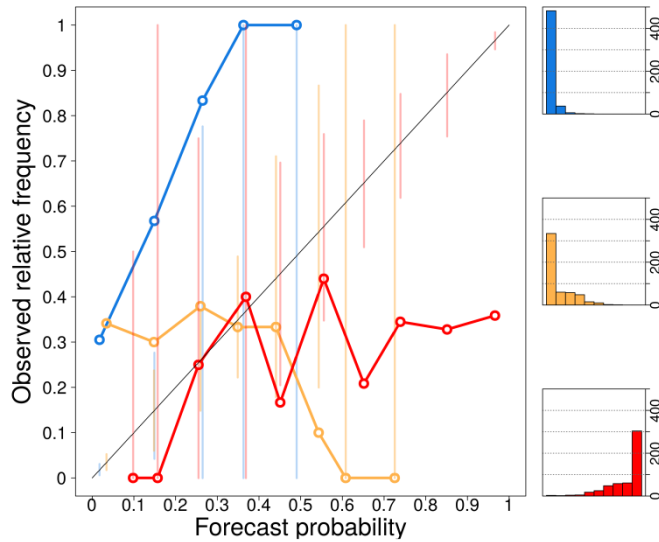




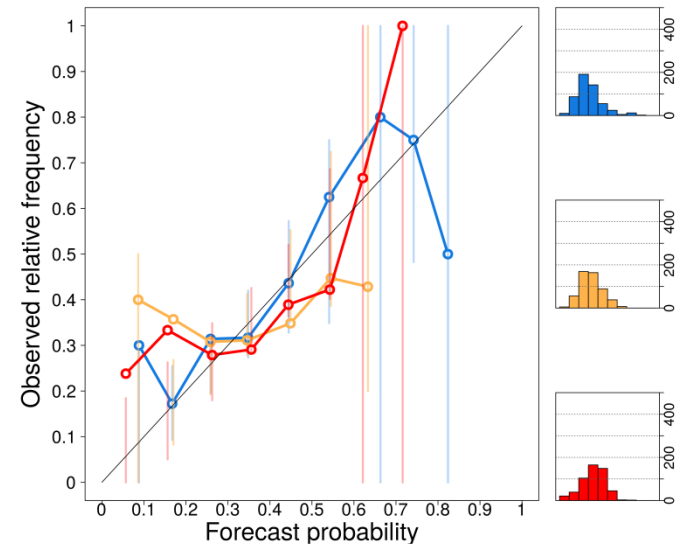
# Impact of bias-correction on reliability



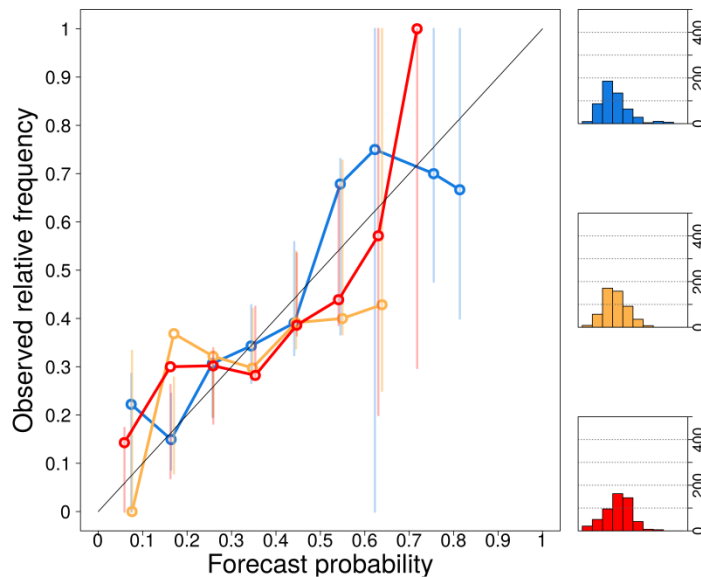
### Raw data



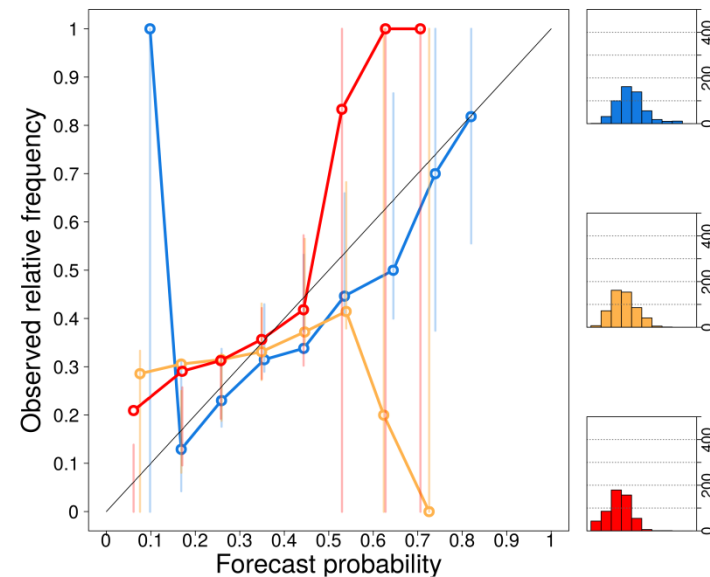
### Simple bias correction in cross-validation



### Calibrated data in cross-validation



### Quantile-Quantile mapping





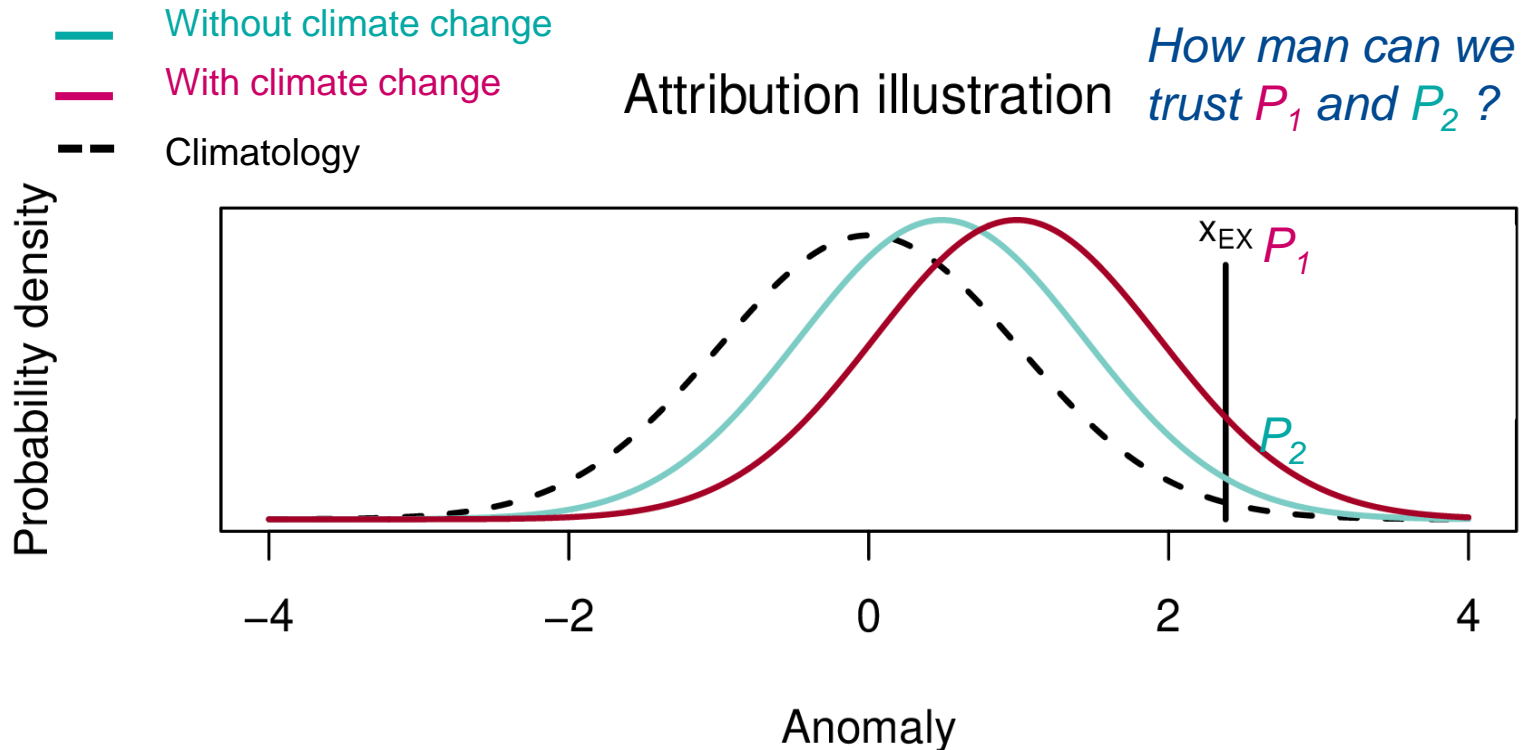
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# Calibration of attributable risk

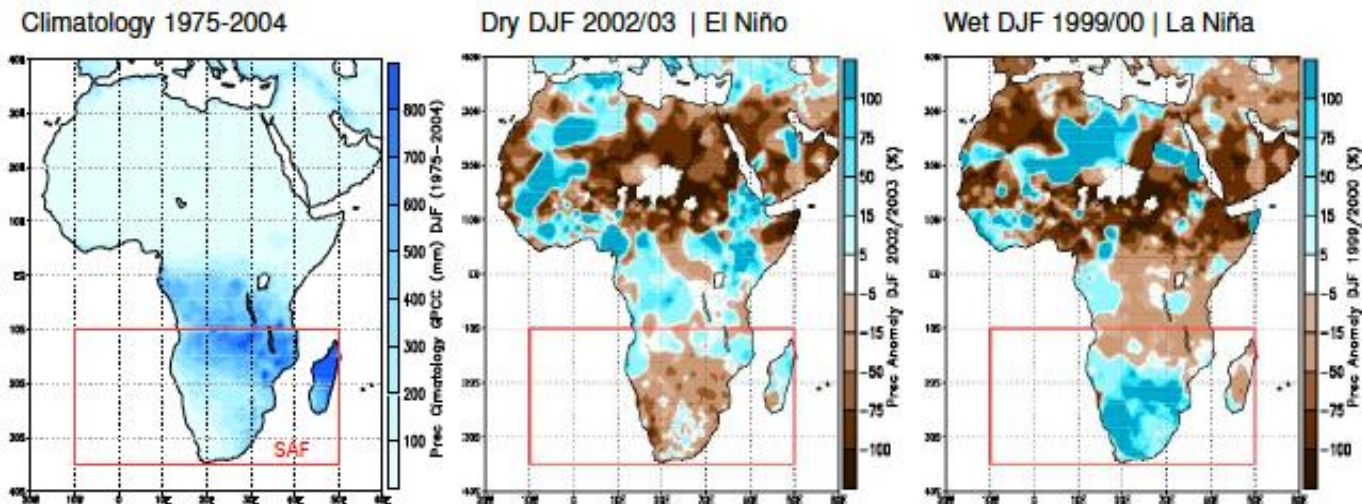
## How accurate are extreme probability estimates from models?



Fraction of attributable risk

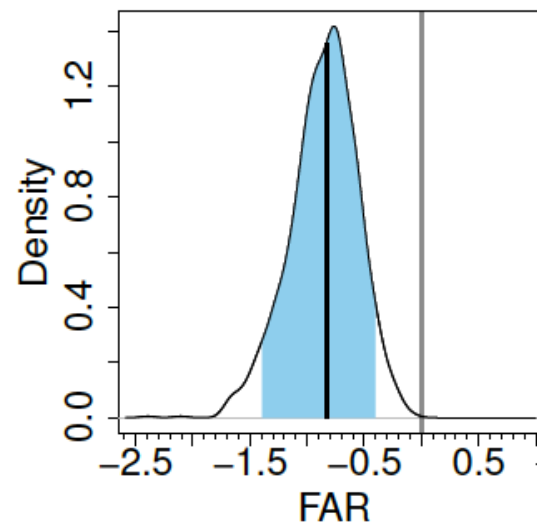
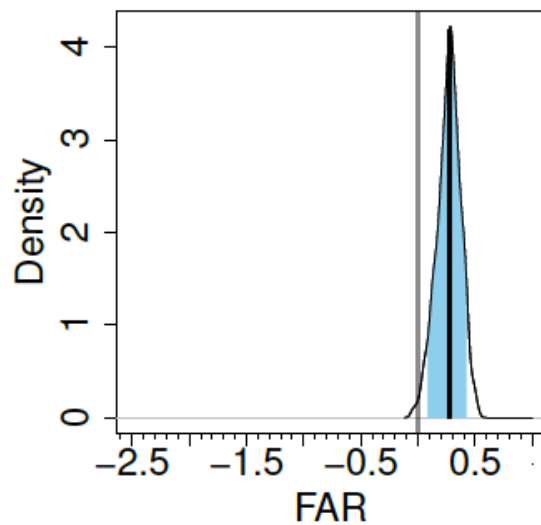
$$FAR = 1 - \frac{P_{NAT}}{P_{ALL}}$$

# Example of attribution



Drought 2002/03

Flood 1999/00





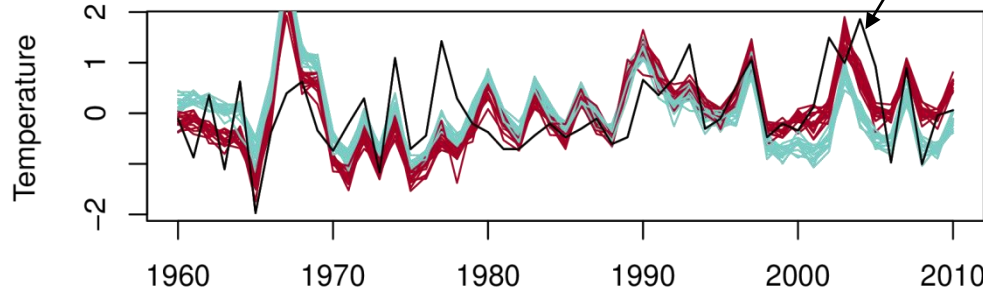
# Attribution of a 30-year summer event



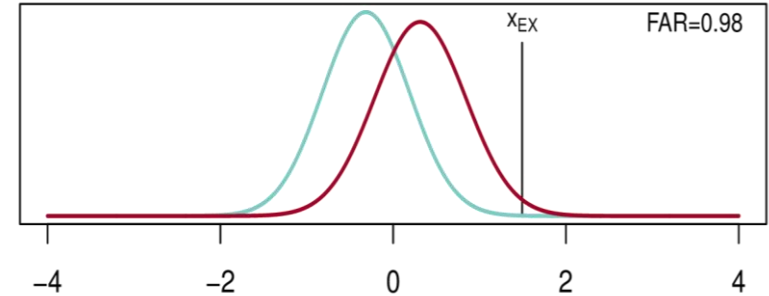
— Without climate change  
— With climate change  
— Climatology

Raw model output

*Not reliable, ensemble too confident*

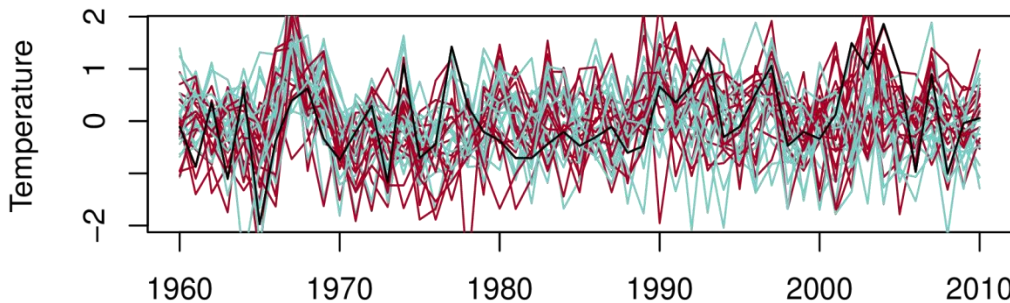


Raw model output

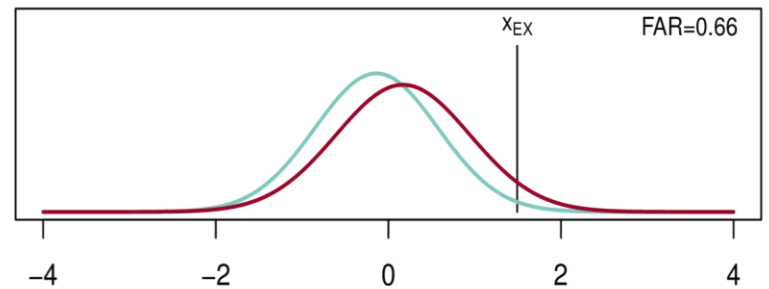


## Reliability can be calibrated by ensemble inflation

Calibrated model output



Calibrated output



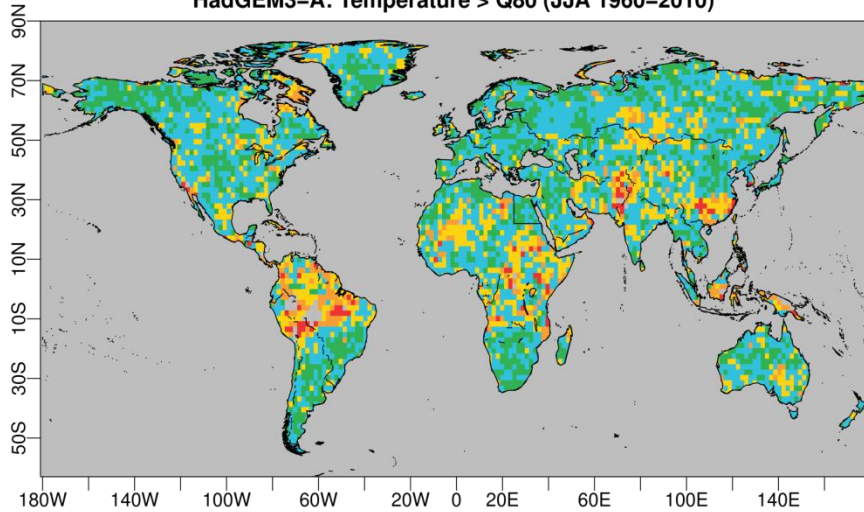
Climate models ensembles tend to be overconfident, ensemble calibration often leads to a reduction in FAR

# Calibrating attributable risk



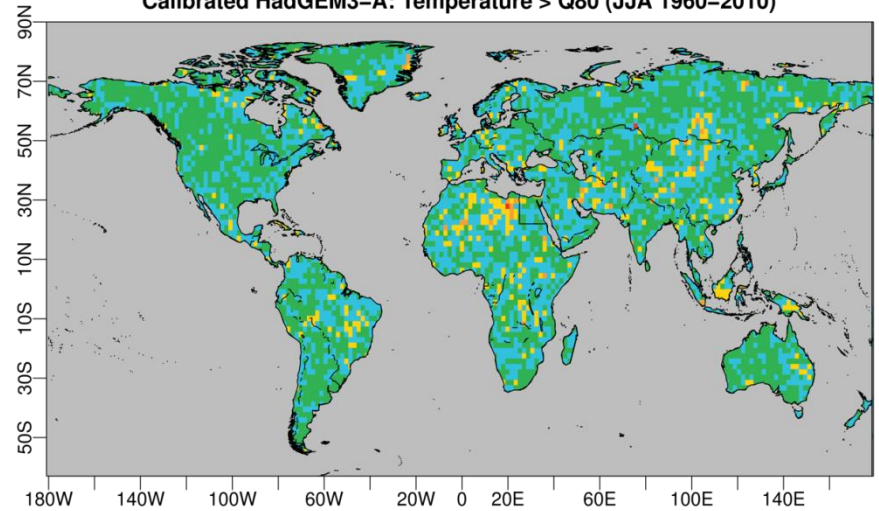
## Reliability (Brier-component)

HadGEM3-A: Temperature > Q80 (JJA 1960-2010)

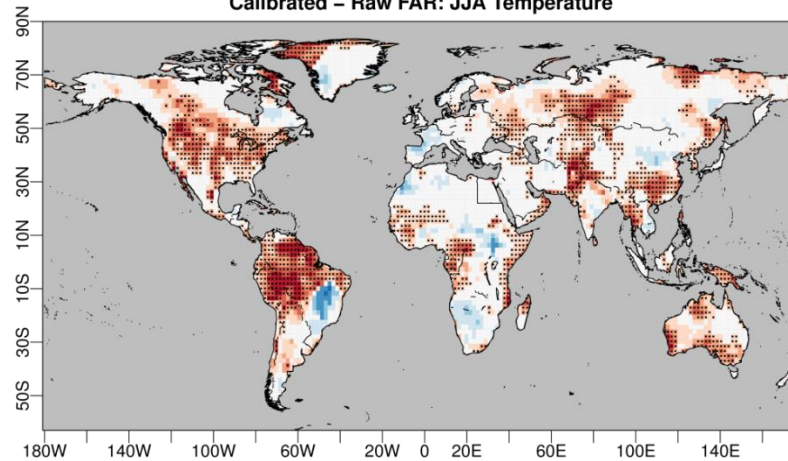


## Reliability (Brier-component)

Calibrated HadGEM3-A: Temperature > Q80 (JJA 1960-2010)



## Calibrated - Raw FAR: JJA Temperature





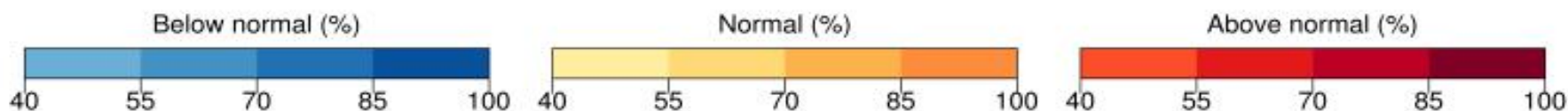
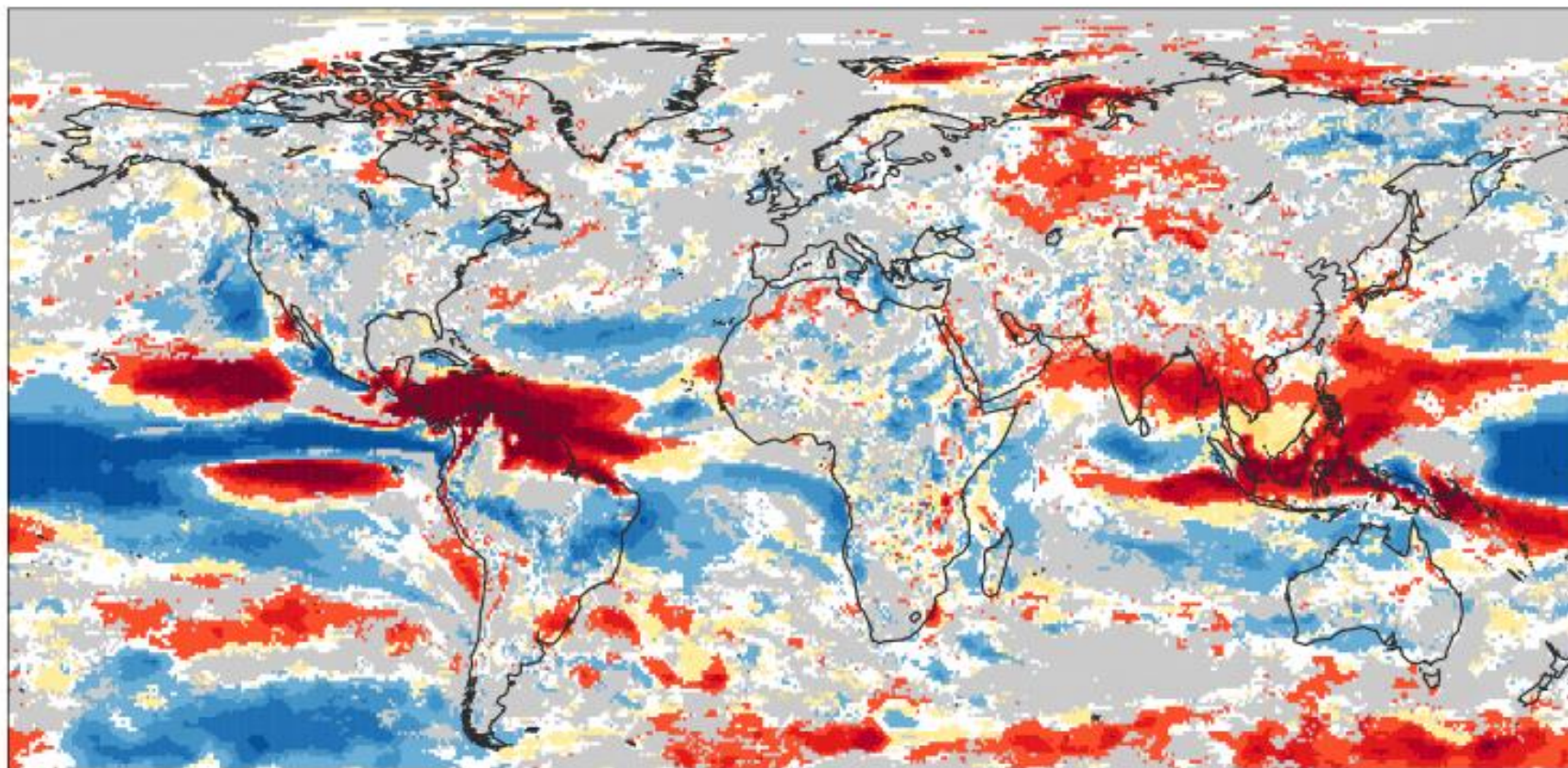
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# Dissemination activities



# Tailored wind speed predictions



ECMWF S4 10-m wind speed seasonal forecast for JJA 2015 initialized the 1<sup>st</sup> of May. The most likely wind speed category (below-normal, normal or above normal) and its percentage probability to occur is shown. White areas show where the probability is less than 40 % and approximately equal for all three categories. Grey areas show where the climate prediction model doesn't improve the climatology.



### RESILIENCE: seasonal wind speed predictions

Seasonal predictions of wind speed need to be tailored to satisfy the information requirements of the energy sector. This is obtained with the transformation of climate variables to capacity factor terms through application of advanced techniques for quality assessment and correction of wind predictions:

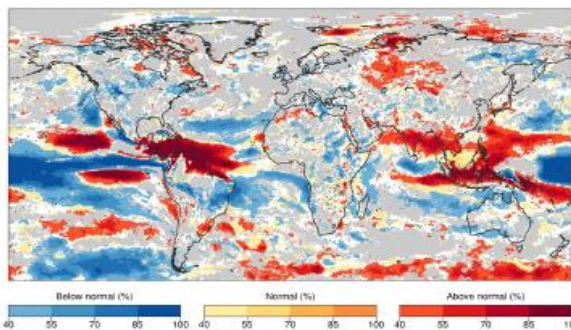


Ten-metre wind speed predictions are produced by a seasonal prediction system called S4 (Molteni et al., 2011) from the European Centre for Medium Range Weather Forecasts which is based on a fully coupled global climate model. These predictions have some limitations and need to be solved to become climate services for the wind industry.

Wind observations are needed to assess the quality of the S4 prediction. Given the sparse wind observations, a reanalysis is used as the best available estimate of wind speed. The S4 prediction is assessed comparing the predicted ten-metre wind speed with the corresponding variable of the ERA-Interim global reanalysis for the period 1981-2016 (Dee et al., 2016) is used as the reference forecast.

Like other variables predicted with a coupled model, wind speed predictions are affected resulting from the inability to perfectly reproduce all the relevant processes responsible for variability in a numerical way. S4 seasonal predictions require bias correction - simple bias correction, calibration and/or quantile mapping - in order to statistically resemble the reference and minimise forecast errors.

This process reduces the uncertainty of wind speed predictions and provides usable information tailored to the wind energy sector.



#### Wind speed probability

Most likely wind speed probability (below normal) at centage probability. Normal represents the average of the past. I show where the <40% and above the three categories show where does not improve current approach projects past climate into the future.

### Use of climate information in the wind stakeholder chain

The high penetration of wind power in the electricity system provides many challenges mainly due to the unpredictability and variability of wind power generation. Therefore, having accurate forecasts of wind power is becoming increasingly important for many stakeholders in the wind energy sector.

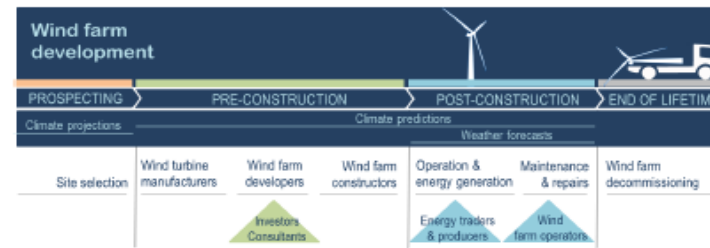


Figure 1: Stages of wind farm development, stakeholders involved at each stage and temporal horizons of climate information used

#### Prospecting

- Climate projections can be used for site selection according to the predicted wind conditions in a particular location in future decades.

#### Pre-construction

- Climate predictions from years to decades can be relevant to understand and quantify the wind resource. For example, they can inform wind energy investors about the volatility of the resource in the future and how this risk can have an impact on the return on investment.

#### Post-construction

- Weather forecasts below 6h are useful to predict sudden events like ramps that can be managed by turbine and farm control.
- Weather forecasts from 6h to 2-3 days are used by transmission system operators for power system management (scheduling reserves, planning, congestion management). Wind farm operators use day-ahead & intraday forecasts for trading in the energy market.
- Weather forecasts from 2-3 days up to a week are used for operation & maintenance planning of wind farms, conventional power plants and transmission lines.
- Climate predictions from sub-seasons to seasons are particularly interesting to support offshore wind farm servicing logistics and onshore operation and energy generation.
- Climate predictions from seasons to decades are relevant to understand and quantify the wind resource, i.e. inform wind energy investors about the volatility of the resource in the future and how this risk can have an impact on the return on investment.



## RESILIENCE

PROTOTYPE

- Data from **ECMWF System 4** (European Centre for Medium-Range Weather Forecasts)
- We assess the global behavior providing **probabilistic seasonal predictions**
- Aggregated output in **terciles**:
  - Above normal
  - Normal
  - Below normal

### ASSESSMENT REPORT 1: Dec-Jan-Feb 2009, US

#### Key event characterisation

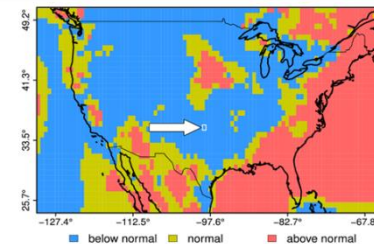
Description

US ERA-Interim 10m wind speed tercile categories (DJF 2009)

AREA: US

SEASON: December-January-February (DJF)

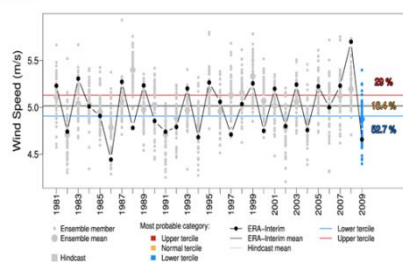
YEAR: 2009/2010



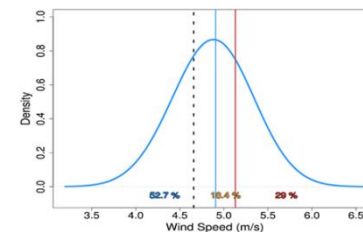
#### RESILIENCE seasonal wind speed prediction

b Time series of 10-m wind speed calibrated from ECMWF System 4 and ERA-Interim reanalysis (DJF 1981-2009)

c Skill assessment and probability density function (DJF 2009 prediction)



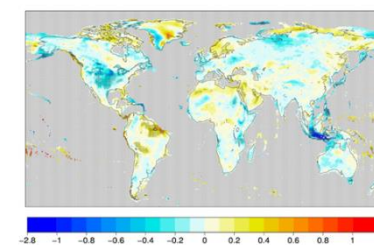
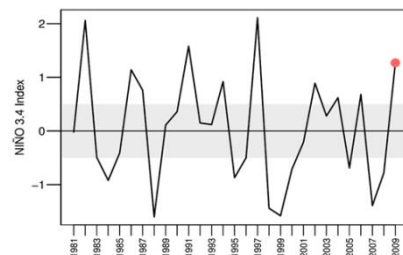
Skill: Corr=0.543 RPSS=0.226 CRPSS=0.115



#### Mechanisms driving seasonal wind speed variability

d Time series of the Oceanic Niño 3.4 Index (ONI) (DJF 1981-2009)

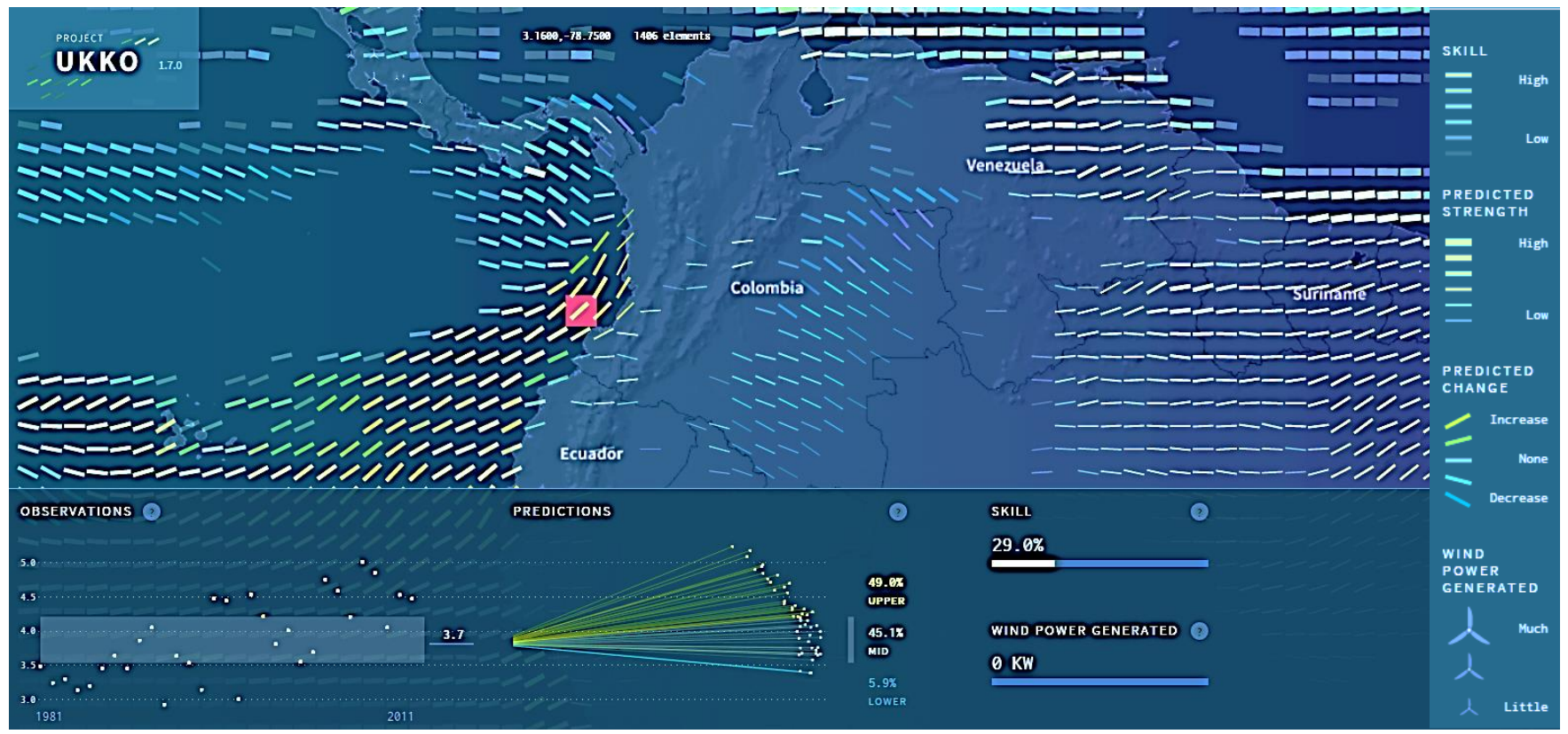
e Impact of the positive phase of Niño 3.4 on the 10-m wind speed (DJF 1981-2014)





# Visualisation tool for wind energy users

<http://project-ukko.net>




**RESILIENCE**  
 PROTOTYPE



# Summary

- This study describes a simple methodology to develop **useful information for the wind industry** that can be easily integrated in their decision-making processes.
- We have used three methods of bias correction which are simple enough to be understandable for the users. They have been used to produce forecasts with **improved forecast quality**.
- The comparison of the three methods indicates that **calibration method displays better reliability** than simple bias correction and quantile mapping, however in terms of skill the three methods produce similar results.
- Event attribution studies should take into account model inadequacies, which are translated in an overestimation of the attributable risk.
- Calibration ensures correct simulated probabilities of extreme events.
- Future work will focus on the formulation of predictions for specific sites. This is a non-trivial task because the bias-adjustments necessary require long-enough observational references that are not readily available.





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EXCELENCIA  
SEVERO  
OCHOA

# Thank you

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