Climate Forecasting Unit

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

Climate predictions for site selection: a new generation of risk management tools

Speaker: Albert Soret [3]
Senior Researcher, Co-leader of the services group

Author: Verónica Torralba Fernandez[1], Melanie Davis[1], Francisco Doblas-Reyes[1,2,3], Nube Gonzalez-Reviriego[1]
1 Climate Forecasting Unit, Catalan Institute of Climate Science
2 Institució Catalana de Recerca i Estudis Avançats (ICREA)
3 Barcelona Supercomputing Center (BSC)

Resource Assessment 2015, 2-3 June 2015, Helsinki, Finland

EUPORIAS

SPECS

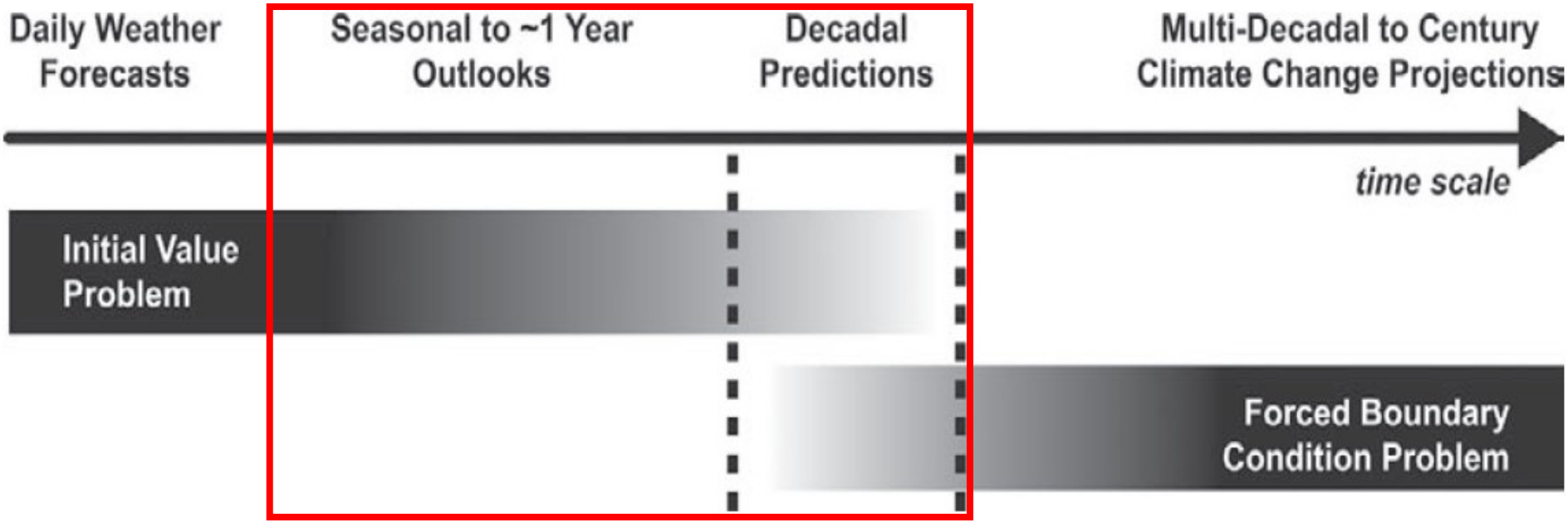
SEVENTH FRAMEWORK PROGRAMME

EUROPEAN UNION
EUROPEAN REGIONAL DEVELOPMENT FUND
A WAY TO MAKE EUROPE

GOBIERNO DE ESPAÑA
MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

NEWA
New European Wind Atlas

- Initial-value problems (weather forecasting) to forced boundary condition problem (climate projections)
- Climate forecasts (sub-seasonal, seasonal and decadal) in the middle

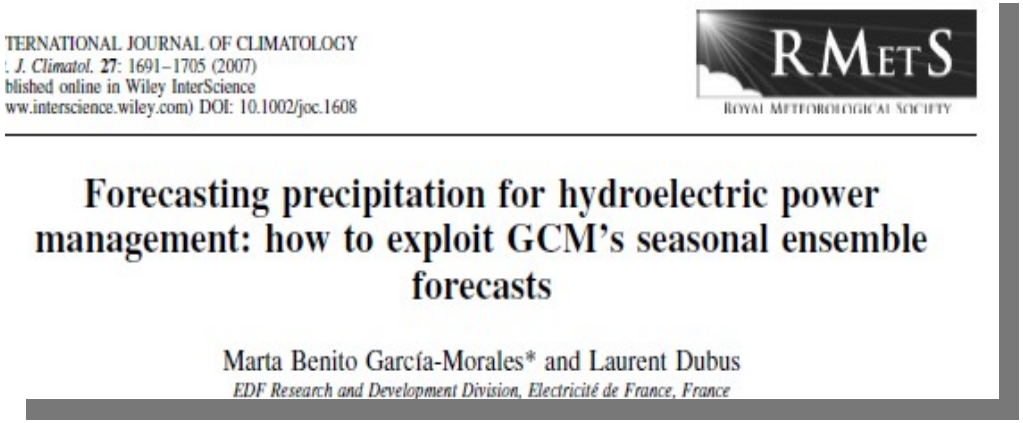


Meehl et al. (2009)

Wind power variability at monthly to decadal time scales has not been traditionally taken into account in wind power facilities planning and management

In other sectors as hydropower or electricity generation and demand balance, climate information on seasonal-to-interannuel time scales have already been illustrated for management decisions.

Hydroelectric power management



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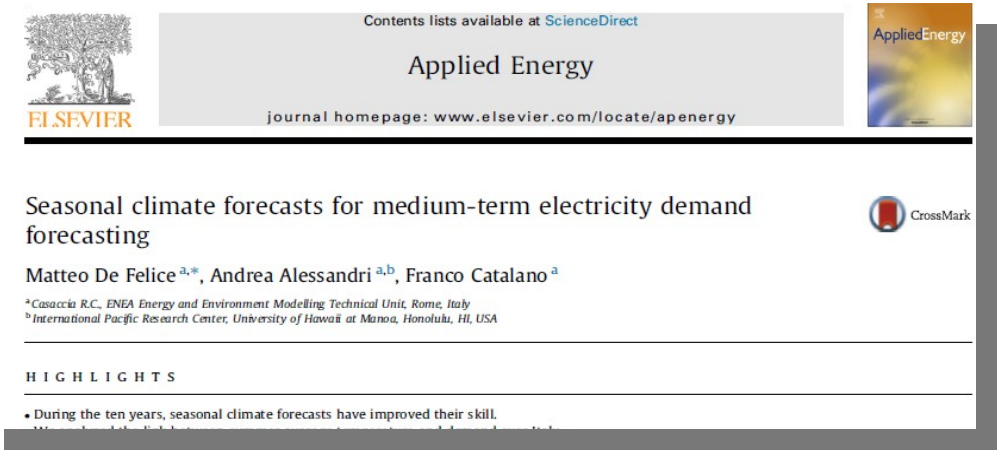
ww.interscience.wiley.com) DOI: 10.1002/joc.1608

RMetS
Royal Meteorological Society

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

Marta Benito García-Morales* and Laurent Dubus
EDF Research and Development Division, Electricité de France, France

Electricity demand



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ELSEVIER

Seasonal climate forecasts for medium-term electricity demand forecasting

Matteo De Felice [a,*], Andrea Alessandri [a,b], Franco Catalano [a]

[a] Casaccia R.C., ENEA Energy and Environment Modelling Technical Unit, Rome, Italy
[b] International Pacific Research Center, University of Hawaii at Manoa, Honolulu, HI, USA

HIGHLIGHTS

- During the ten years, seasonal climate forecasts have improved their skill.

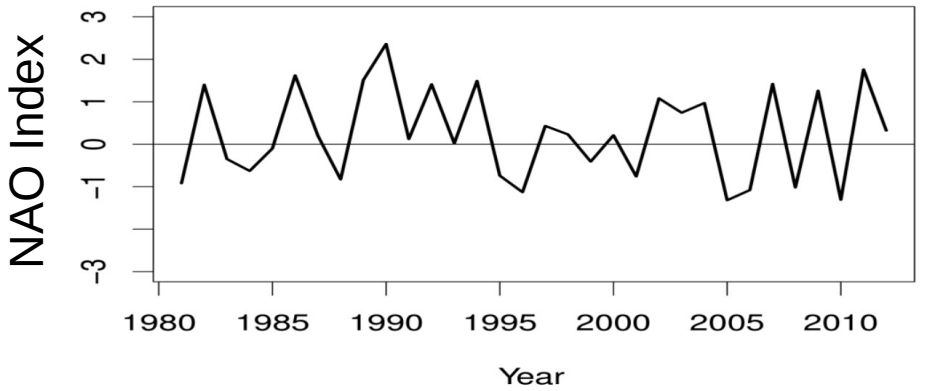
MONTHLY TO SEASONAL TIMESCALES

- **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

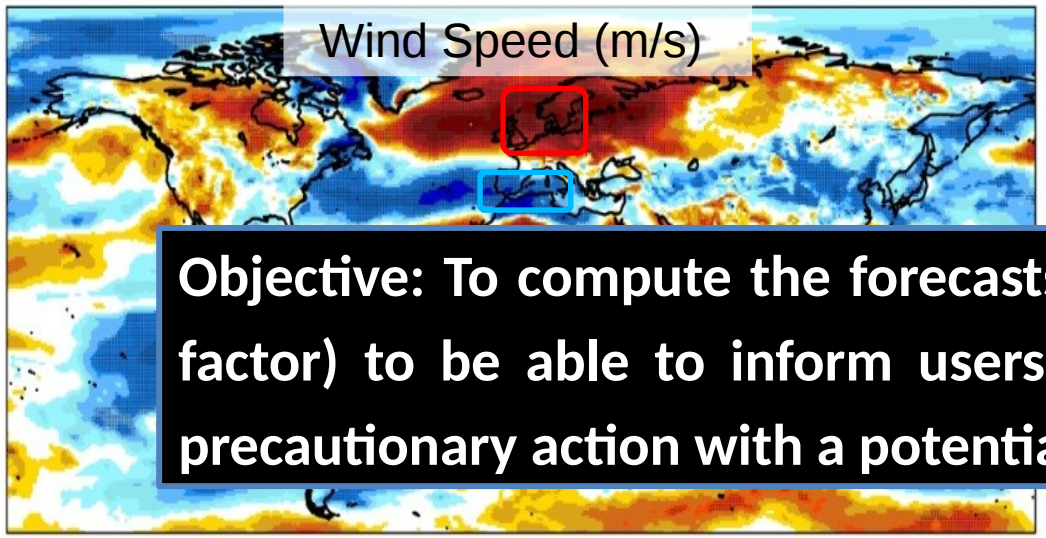
- **Wind farm planners:** Site selection
- **Wind farm investors:** Evaluate return on investments
- **Policy makers:** Understand changes to energy

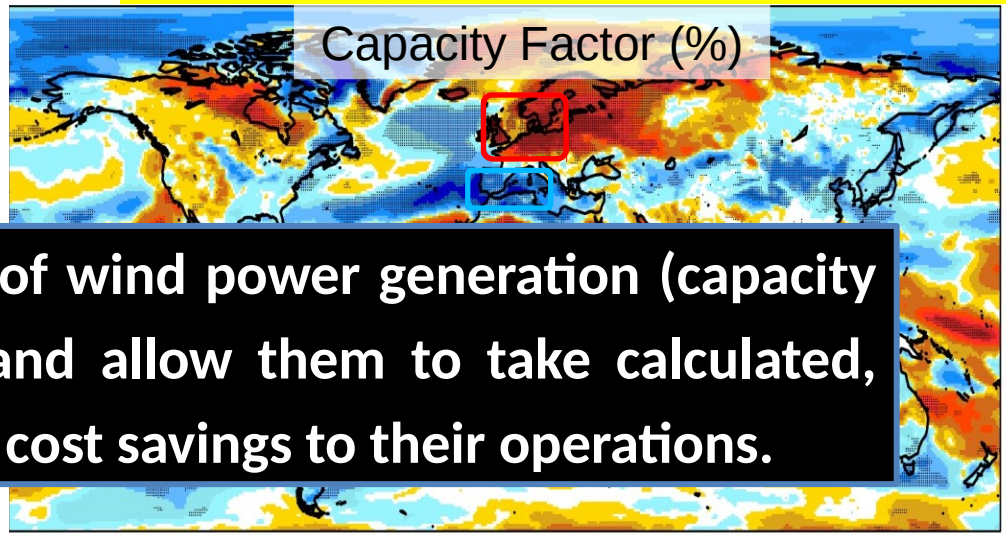
Impact of NAO on Wind Speed and Capacity Factor



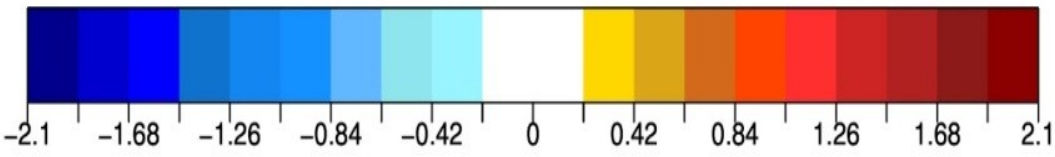
10m wind speed "observations": ERA-Interim
Boreal winter season period 1981-2012

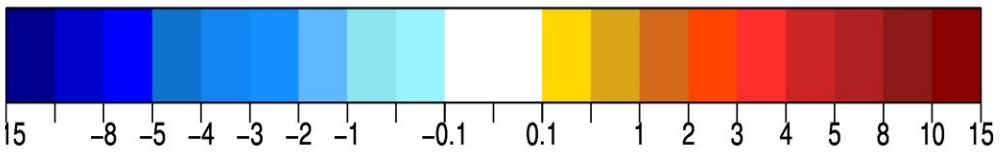
Differences with NAO + and NAO - conditions





Objective: To compute the forecasts of wind power generation (capacity factor) to be able to inform users and allow them to take calculated, precautionary action with a potential cost savings to their operations.





CHALLENGE : models don't provide capacity factor forecasts.

The wind power can be estimated from predictions of wind speeds and temperatures at the surface.

Limitations:

- The wind turbines are at 100m so 10m wind speed must be scaled up.
- Seasonal/monthly means of wind speed and temperature masks sub-seasonal/daily variability.

PREDICTIONS OF CAPACITY FACTOR

POTENTIAL SOLUTION: The wind power can be estimated from predictions of wind speeds and temperatures at the surface.

Forecasts

10m Wind Speed
2m Temperature

+

Past Observations

10m Wind Speed
2m Temperature

PREDICTIONS OF CAPACITY FACTOR

Corrected forecasts

10m Wind Speed
2m Temperature

Post-processing

Forecasts

10m Wind Speed
2m Temperature

Past Observations

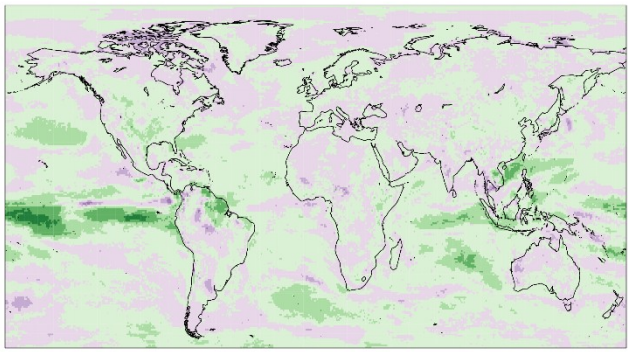
10m Wind Speed
2m Temperature

Forecast quality assessment

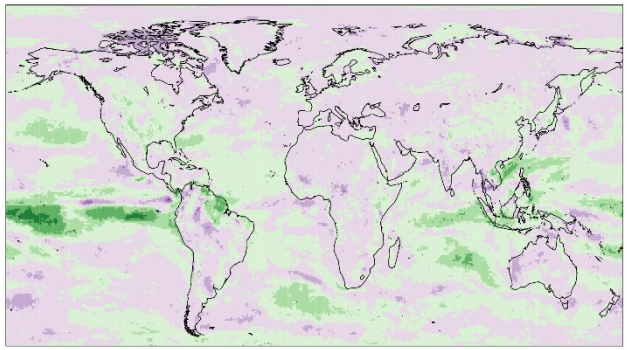
10m Wind Speed
ECMWF S4 1 month lead and ERA Interim
in DJF (1981-2013)

RPSS

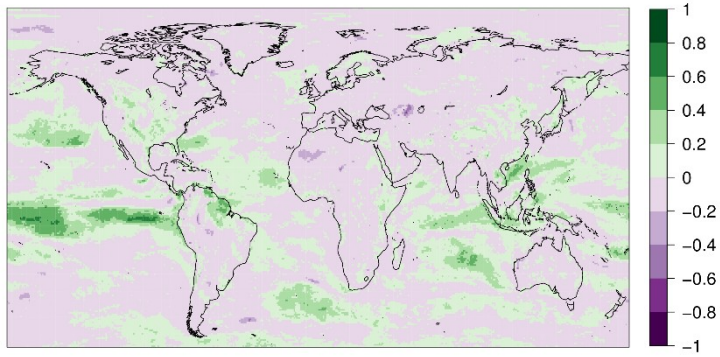
Raw data



Simple bias correction

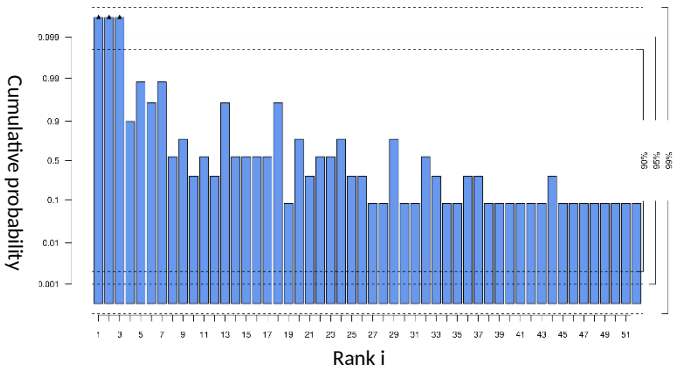


Calibration

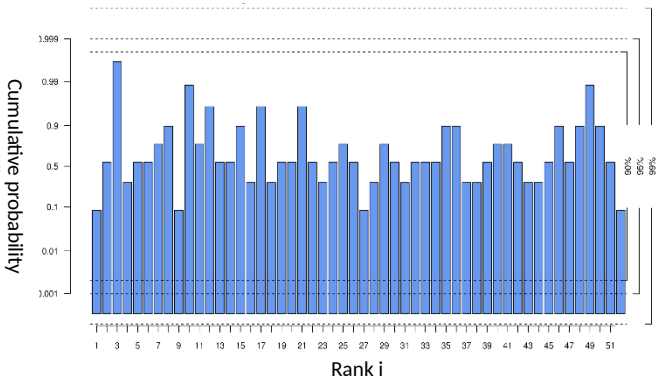


Region of Canada

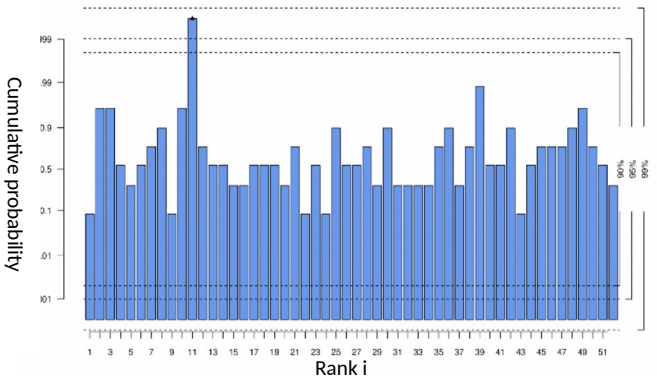
Rank Histograms



	Pearson.Chi2	JP.slope	JP.convex
test statistic	462.69	167.26	83.64
p–value	0	0	0

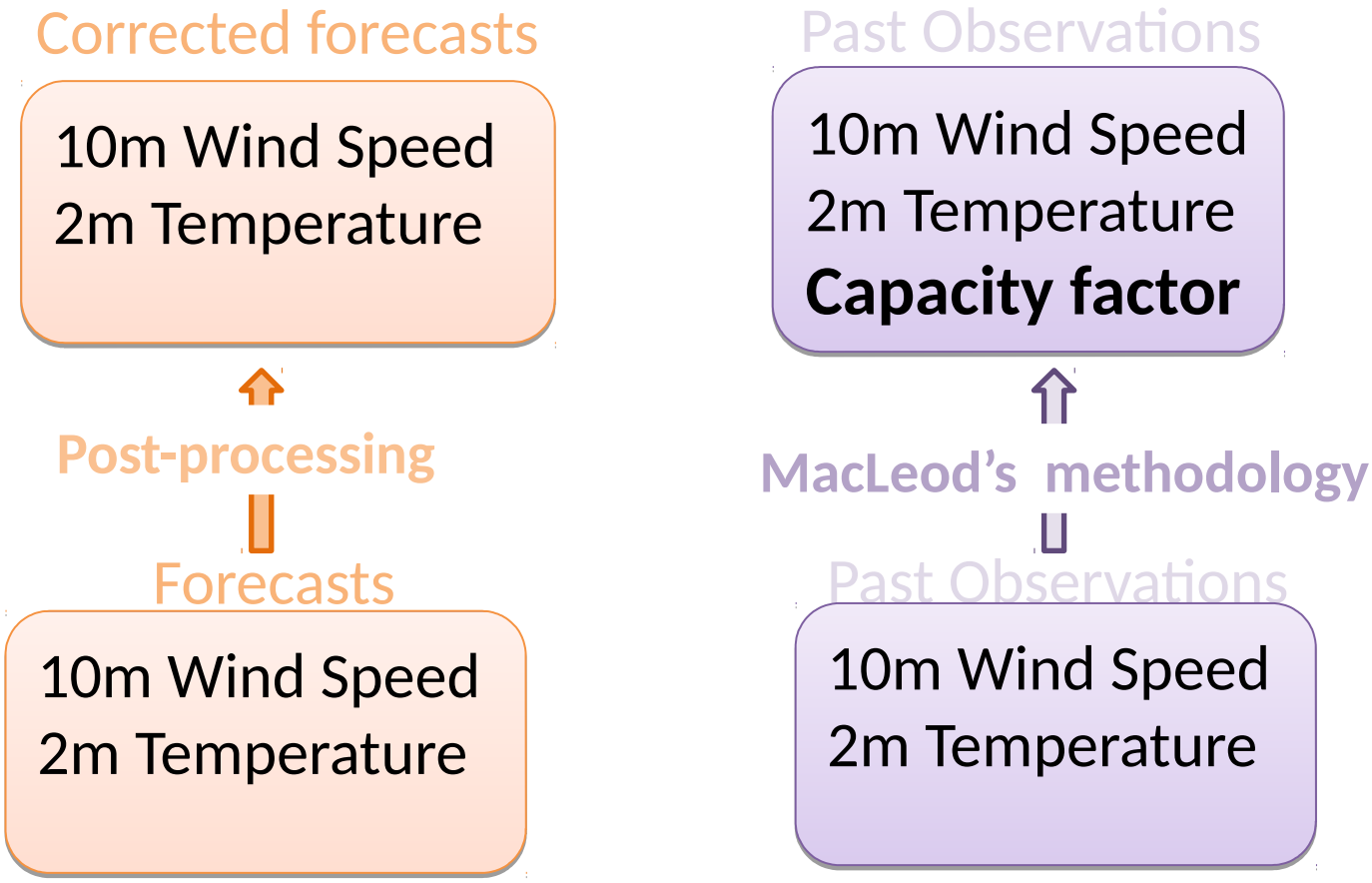


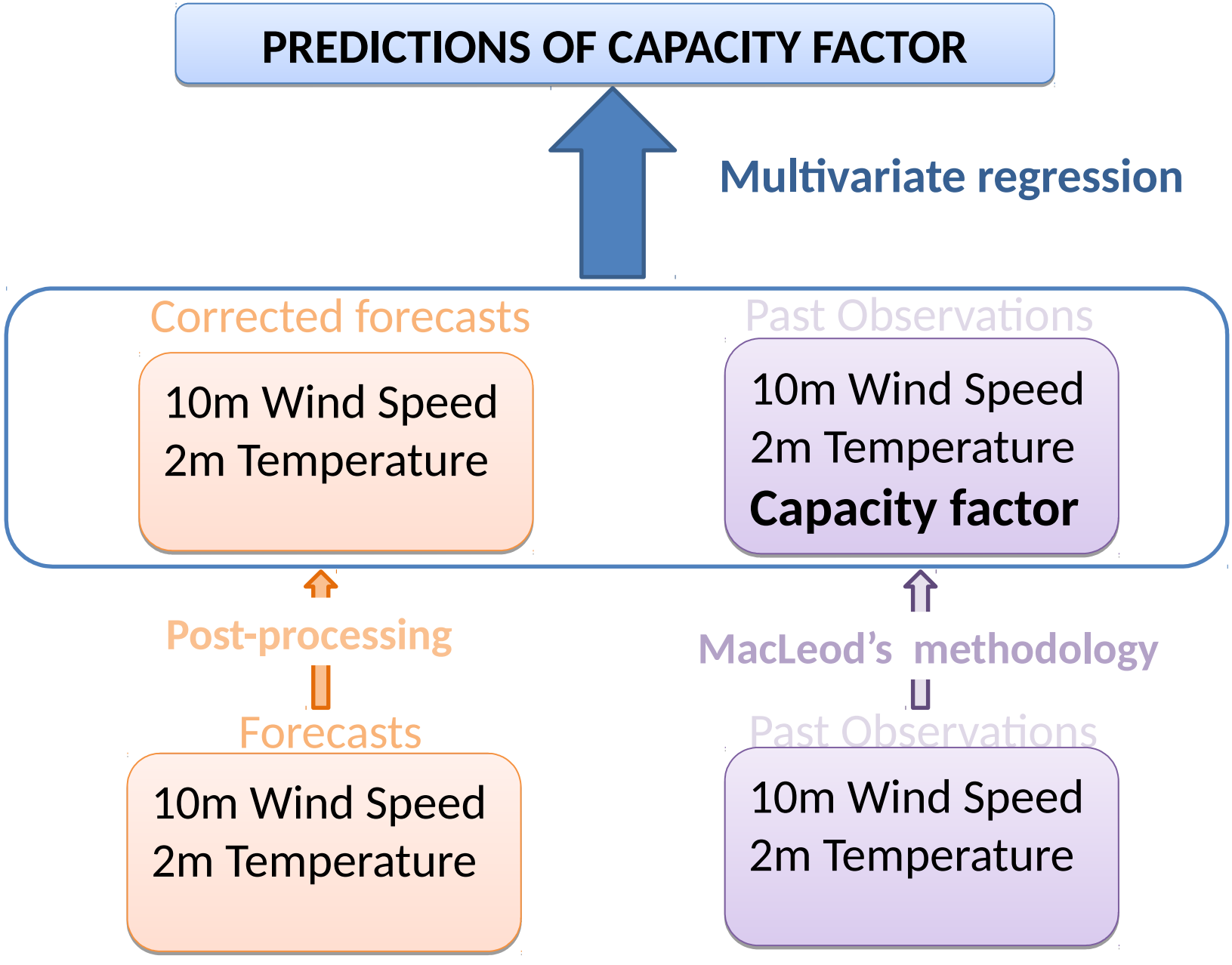
	Pearson.Chi2	JP.slope	JP.convex
test statistic	54	0.15	0.62
p–value	0.36	0.7	0.43



	Pearson.Chi2	JP.slope	JP.convex
test statistic	62.94	0	2.15
p–value	0.12	0.97	0.14

PREDICTIONS OF CAPACITY FACTOR




PREDICTIONS OF CAPACITY FACTOR
Multivariate regression
Corrected forecasts
10m Wind Speed
2m Temperature
Past Observations
10m Wind Speed
2m Temperature
Capacity factor
Post-processing
MacLeod's methodology
Forecasts
10m Wind Speed
2m Temperature
Past Observations
10m Wind Speed
2m Temperature

Multivariate regression

- How can we get a prediction of the capacity factor with a multivariate regression?

1. **Past observations of CF , WS and T are fitted to a multivariate regression and the coefficients A, B and C are obtained.**

$$CF(WS,T) = A\,WS + B\,T + C$$

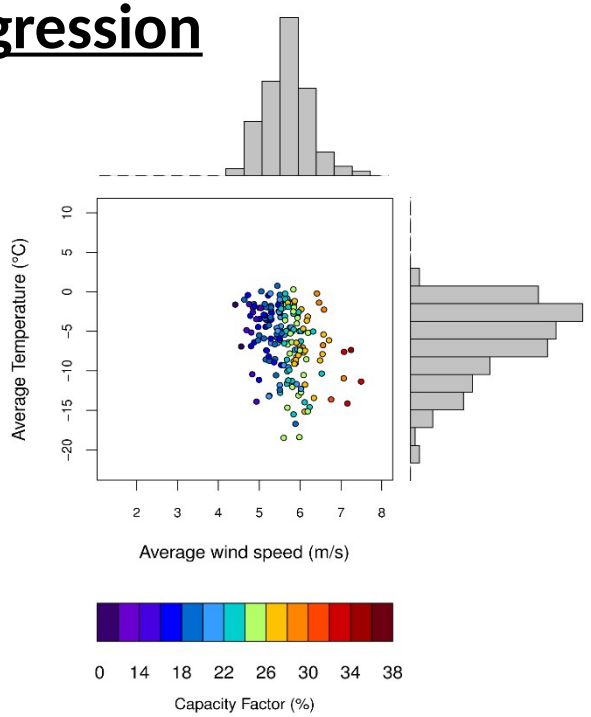
2. **Predictions of WS and T in the target period are introduced in the expression with the coefficients A, B, C and the output is the forecast of the capacity factor.**

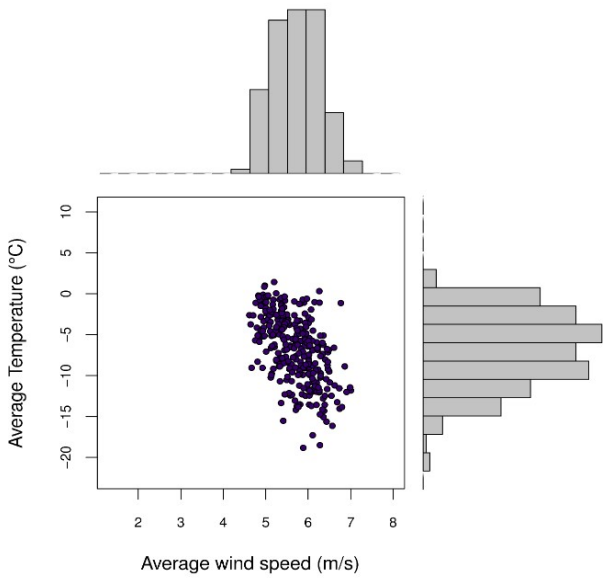
Multivariate regression

Central US region

1

Past observations of CF. December (1981-2011)

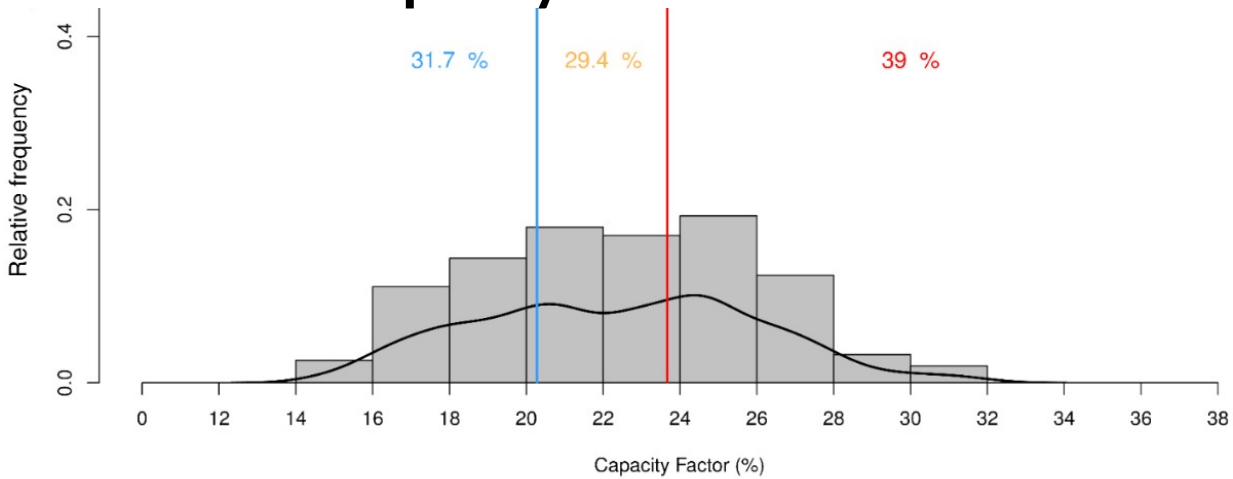




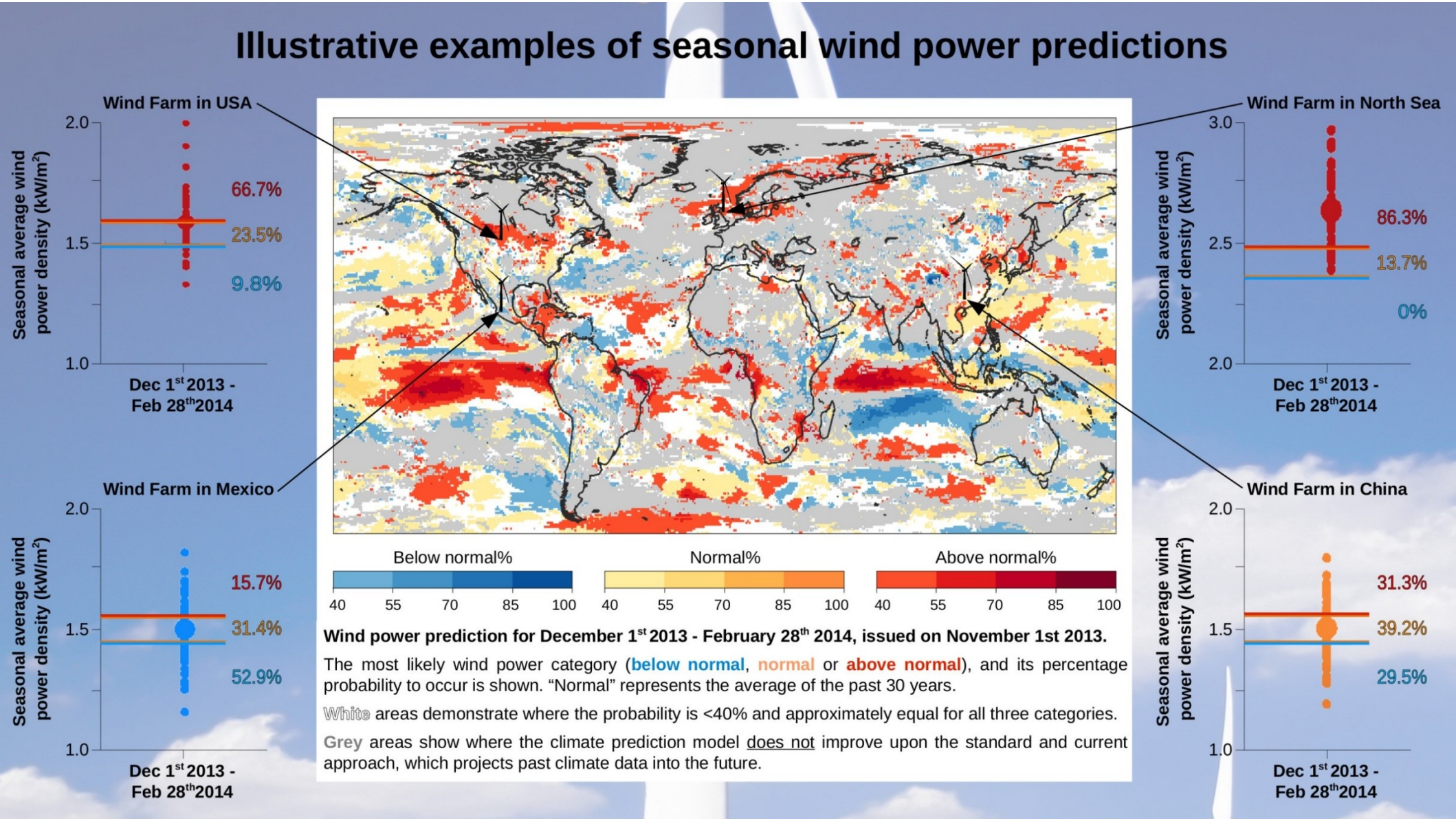
Forecasts of WS and T. Simple bias correction. December (2012)

2

Forecast of capacity factor for December 2012



Illustrative examples of seasonal wind power predictions



Wind power prediction for December 1st 2013 - February 28th 2014, issued on November 1st 2013.

The most likely wind power category (**below normal**, normal or **above normal**), and its percentage probability to occur is shown. "Normal" represents the average of the past 30 years.

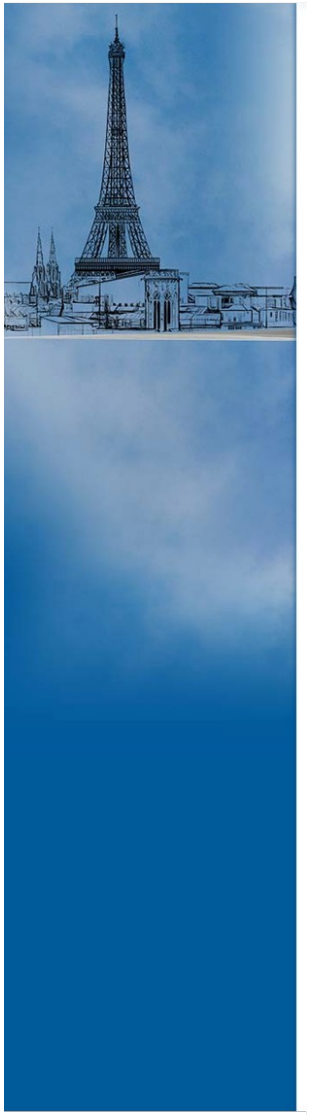
White areas demonstrate where the probability is <40% and approximately equal for all three categories.

Grey areas show where the climate prediction model does not improve upon the standard and current approach, which projects past climate data into the future.

- **Recent advances in climate predictions can provide a more informative view by modelling future wind.**
- **Bias correction is fundamental for climate services, but comes at the cost of a reduction in forecast quality.**
- **For end-users in the wind power industry transforming climate variables (wind speed and temperature) into capacity factor is essential.**
- **Wind speed influence over the capacity factor is higher than temperature.**

- **Assess climate predictions impacts on the wind energy sector at different time scales, from weeks to decades.**
- **Evaluate different methods of post-processing forecasts to reduce the uncertainty and provide usable climate information.**

Thank you!



EWEA 2015
PARIS
EUROPE'S PREMIER WIND ENERGY EVENT
17-20 NOVEMBER

Vortex and IC3 would like to invite you to a lunch on climate predictions for the wind industry at the EWEA event exhibition meeting area.

PRESENTATION OF A SEMI-OPERATIONAL PROTOTYPE TO FORECAST WIND POWER FROM WEEKS TO MONTHS AHEAD

Contact us for further information
info-services-es@bsc.es

Bias correction Simple method

: forecast
: climatology of the ensemble mean
: standard deviation of the reference
: standard deviation of the ensemble mean
: climatology of the reference

Calibration Inflation method

: ensemble mean of the forecast
:difference of the ensemble member with the ensemble mean
: correlation between the ensemble mean and the reference
: standard deviation of the reference
: standard deviation of the ensemble mean : standard deviation of the anomalies of all ensemble members calculated with respect to corresponding (i.e., same start date and lead time) the ensemble mean.

Both methods are applied in 'One-year out cross-validated' mode

Estimation of observational Capacity Factor

Wind Energy:

$$E = \frac{mv^2}{2} = \frac{(Avt\rho)v^2}{2} = \rho\frac{Atv^3}{2}$$

Wind Power:

$$P = \frac{E}{t} = \rho\frac{Av^3}{2}$$

Ideal gas law $\rho = \frac{p}{RT}$

$$P = \frac{p}{RT}\frac{Av^3}{2}$$

p : surface pressure
R : ideal gas constant
T: temperature
v : wind speed
A : area of turbine perpendicular to wind direction

Capacity Factor

CF (%) → **Power output curve from technical turbine specifications: Vestas 2.0 MW**

Assumptions

- **To convert 10 wind speed to the turbine height (100 m) the wind profile power law is used:**

$$\frac{u}{u_r} = \left(\frac{z}{z^r}\right)^{\alpha}$$

: wind speed at vertical height
: wind speed at a reference height
: empirically derived constant (for dry air over land at neutral stability conditions)

- **Daily variability in wind speed and operating limitations (kick-in/kick-out speeds) can be modelled by weighting the wind power over all monthly wind speeds using a Rayleigh distribution:**

$$f(x) = \frac{x}{\sigma^2}e^{-x^2/2\sigma^2}$$

Impact Surfaces

- **What is an impact surface?**

They are a tool to visualise an impact variable in a discretized 'climate space' (Dave MacLeod, Oxford University).

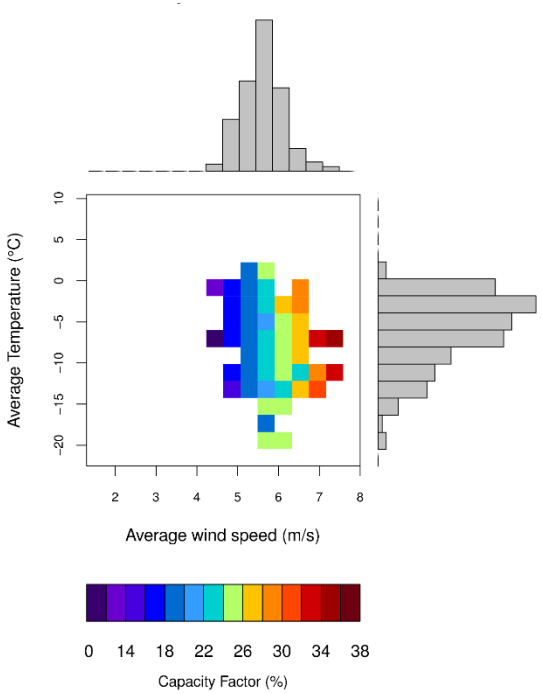
- **How can we get a prediction of the capacity factor from them?**

1. **Past observations of CF , WS and T are discretized and represented in an impact surface.**
2. **Predictions in the target period of WS and T are discretized and represented in an impact surface.**
3. **Each box of the two impact surfaces are combined to provide the capacity factor prediction.**

Impact Surfaces

1

Past observations of CF. December (1981-2011)



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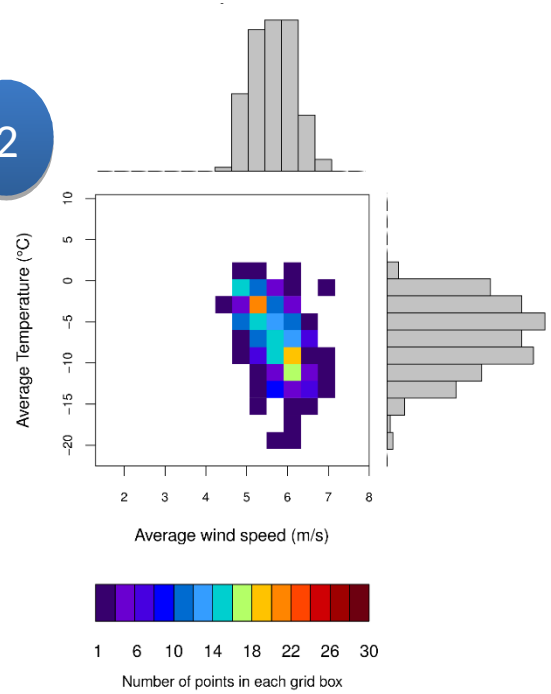
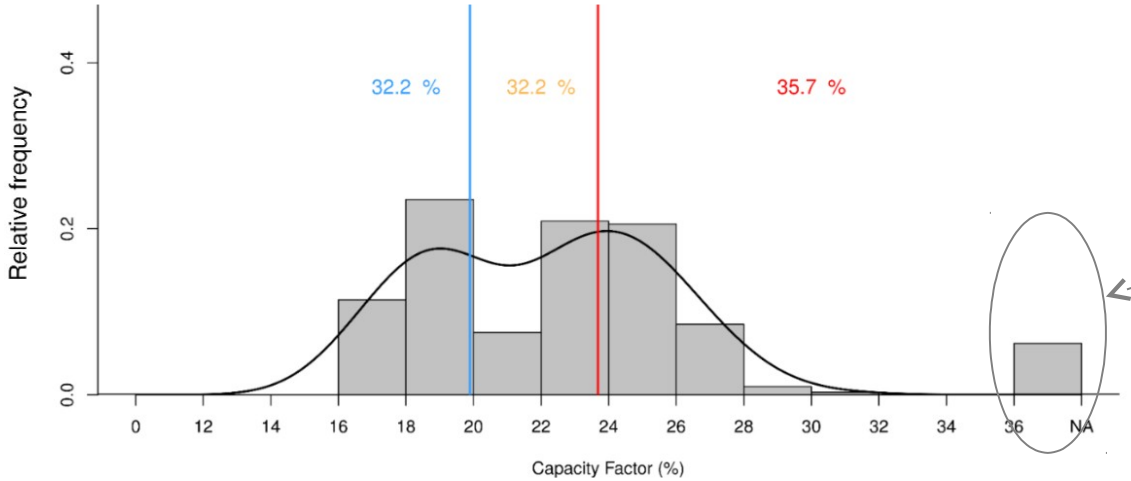


Central US region

Simple bias correction. WS and T bias corrected forecasts. December (2012)

3

Forecast of capacity factor for December 2012



N/A values !!!