From day ahead to decadal wind power forecasting

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EUPORIAS: EUropean Provision Of Regional Impact Assessment on a Seasonal-to-decadal timescale





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





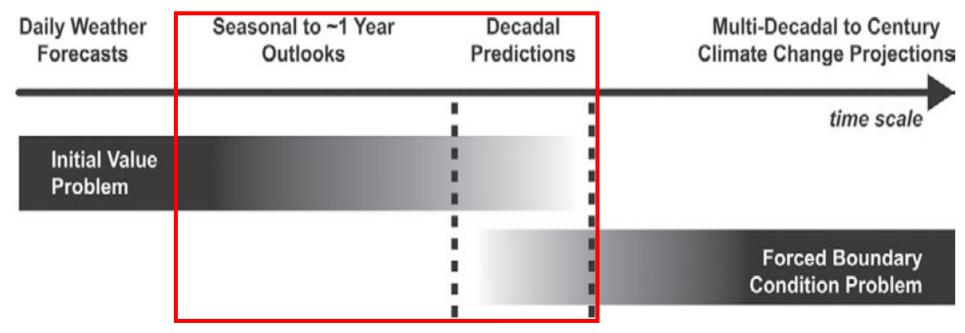
NEWA: New European Wind Atlas







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



3







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

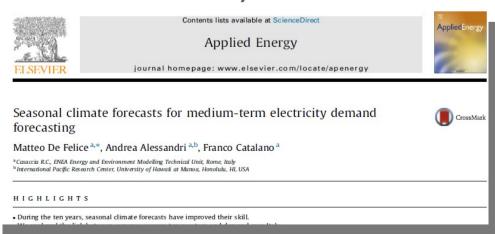
TERNATIONAL JOURNAL OF CLIMATOLOGY : J. Climatol. 27: 1691–1705 (2007) blished online in Wiley InterScience ww.interscience.wiley.com) DOI: 10.1002/joc.1608



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

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Electricity demand







Pre-Constuction Decisions: Annual to Decadal

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





Post-Construction Decisions: 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: Optimize return on investments







Objective within the NEWA project

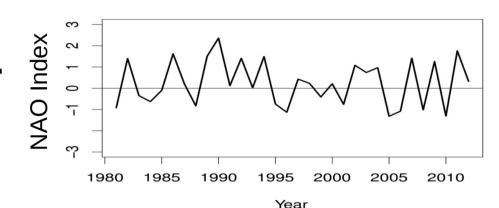
To complement the probabilistic mesoscale model chain with climate predications to produce predictability information at different scales/horizons:

- · hours
- · days
- · weeks
- · seasons
- · and decades



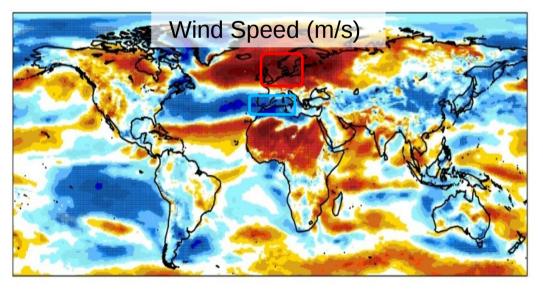


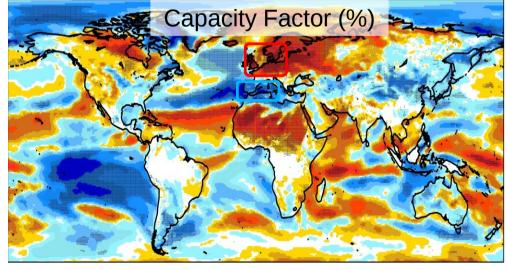
Some examples: Impact of NAO on Wind Speed and Capacity Factor

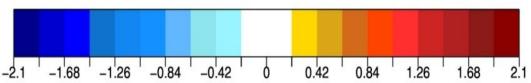


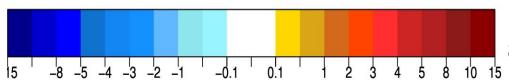
Differences with NAO + and NAO - conditions

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







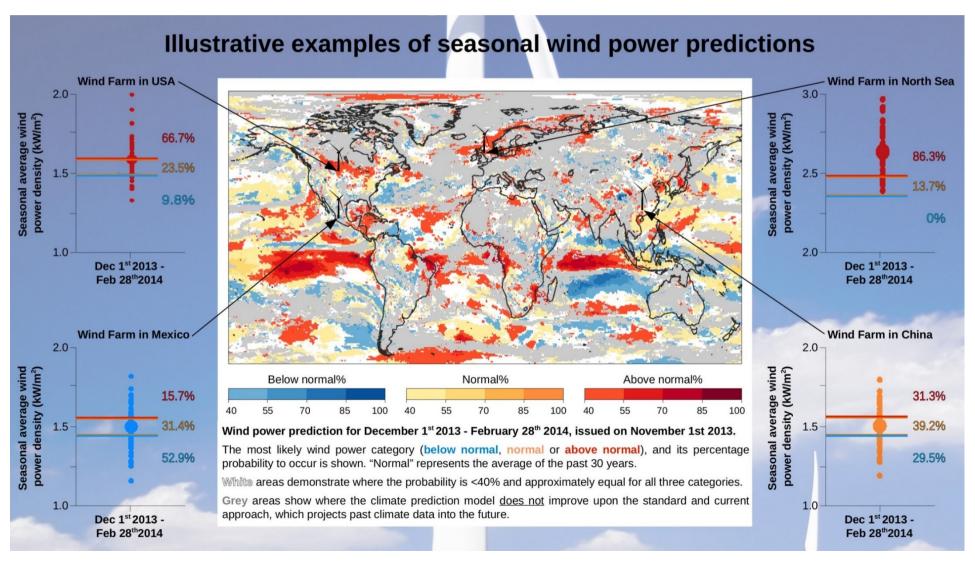








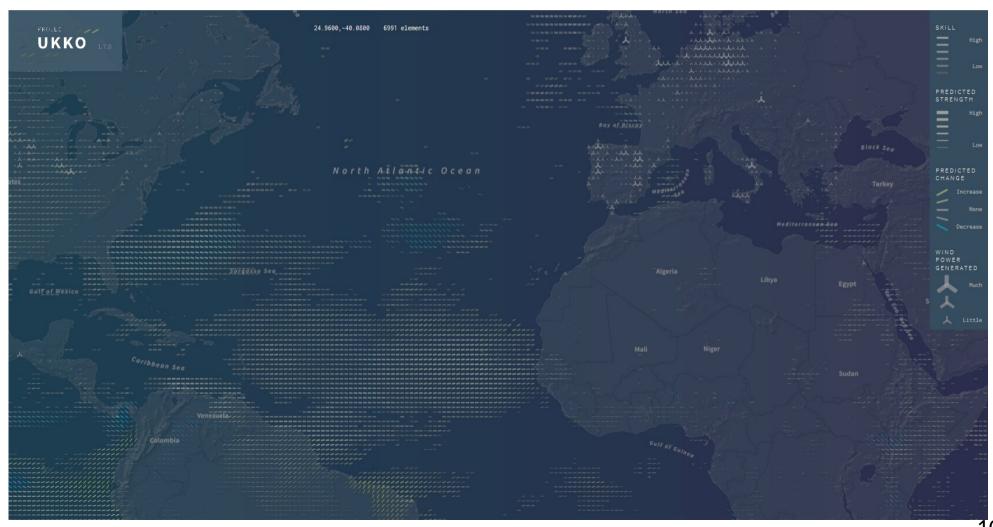
Some examples: Seasonal wind power predictions







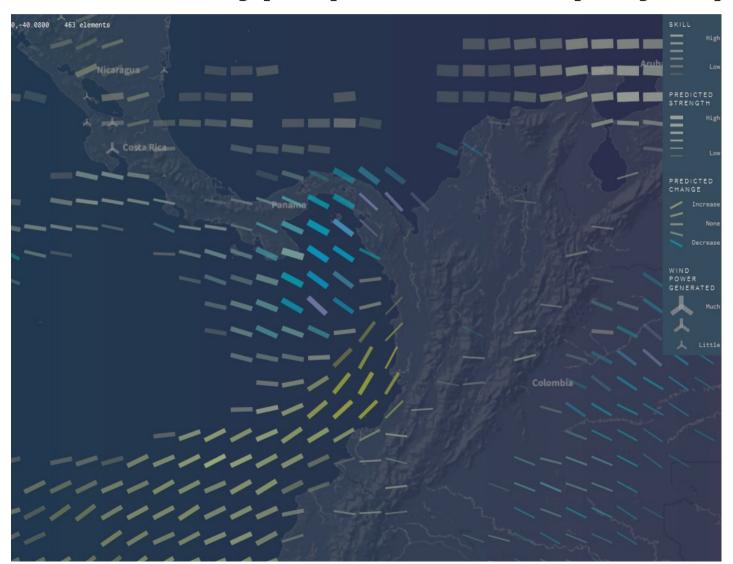
Some examples: RESILIENCE Prototype (EUPORIAS project)







Some examples: RESILIENCE Prototype (EUPORIAS project)

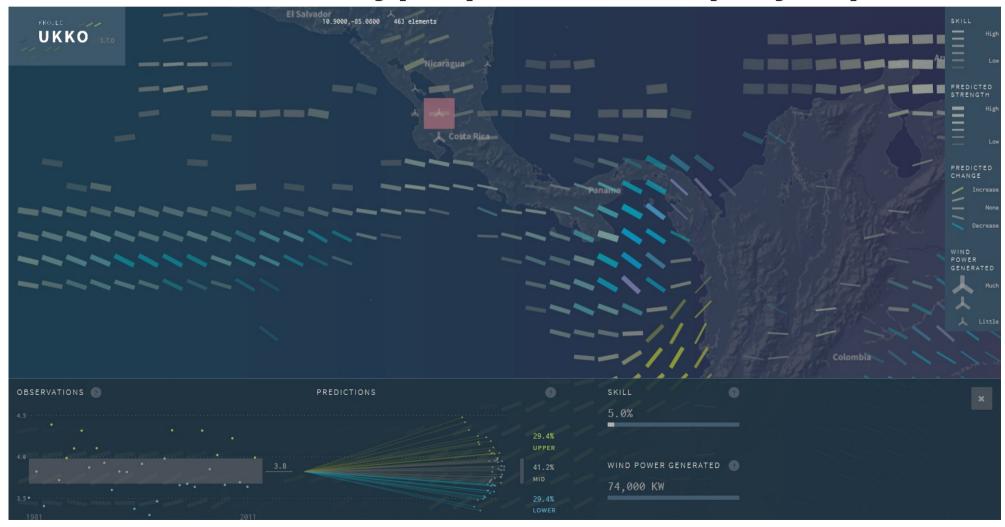








Some examples: RESILIENCE Prototype (EUPORIAS project)









Some examples:

RESILIENCE Prototype (EUPORIAS project)









Thank you!

For further information: albert.soret@bsc.es





Methods

Results

Summary

Future work

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 subseasonal/daily variability.





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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





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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



RPSS



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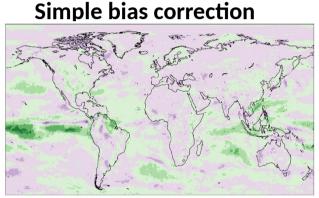
Summary

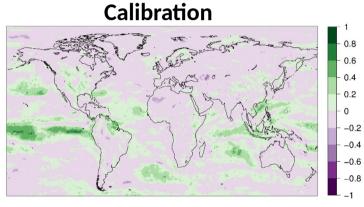
Future work

Forecast quality assessment

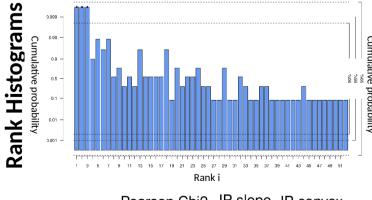
10m Wind Speed ECMWF S4 1 month lead and ERA Interim in DJF (1981-2013)

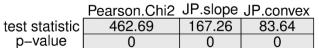
Raw data

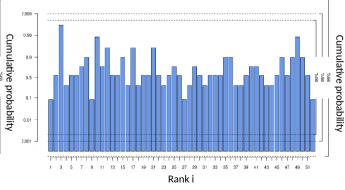




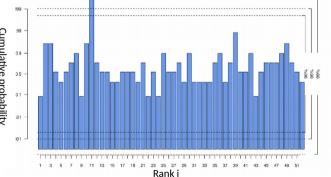
Region of Canada







	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





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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 Capacity factor



MacLeod's methodology



10m Wind Speed 2m Temperature





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PREDICTIONS OF CAPACITY FACTOR



Multivariate regression

Corrected forecasts

10m Wind Speed 2m Temperature

Past Observations

10m Wind Speed

2m Temperature

Capacity factor



Post-processing



Forecasts

10m Wind Speed 2m Temperature



MacLeod's methodology

Past Observations

10m Wind Speed 2m Temperature





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Multivariate regression

- How can we get a prediction of the capacity factor with a multivariate regression?
 - Past observations of CF, WS and T are fitted to a multivariate regression and the coefficients A, B and C are obtained.

$$CF(WS,T) = AWS + BT + C$$

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.





Introduction Methods **Results** Future work **Summary Multivariate regression Central US** region **Past Forecasts of WS** Average Temperature (°C) observations and T. Simple of CF. bias correction. **December December** (1981-2011)(2012)Average wind speed (m/s) Average wind speed (m/s) Capacity Factor (%) 2 **Forecast of capacity factor for December 2012** 31.7 % 29.4 % 39 % Relative frequency 0.0 26 12 18 20 24 14 16 34 36

Capacity Factor (%)



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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

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Estimation of observational Capacity Factor

Wind Energy:

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

Capacity Factor



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

-> 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:

 $\frac{u}{u} = \left(\frac{z}{z'}\right)^{\alpha}$: 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:

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



Introduction Methods Results Summary Future work

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



Past observations of CF. **December** (1981-2011)



Capacity Factor (%)

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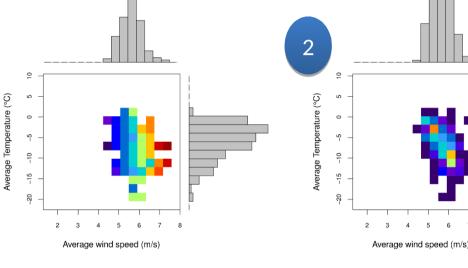
Future work

Central US region

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

Impact Surfaces

Introduction



Number of points in each grid box

Forecast of capacity factor for December 2012

