Stochastic simulation of predictive space-time scenarios of wind speed using observations and physical model outputs

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Wind speed prediction and scenarios simulation

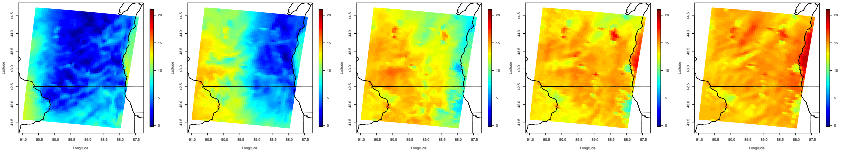
Wind speed prediction and predictive statistical scenarios

- Surface wind predictions are used in a lot of fields: renewable ressources, pollution applications, power grid dispatch [Constantinescu et al., 2011, Li et al., 2015], ...
- Predictive distributions are used to account for the uncertainty associated to a point prediction
- Predictive statistical scenarios enable to inform about this uncertainty at various locations and-or time-step ahead [Pinson et al., 2009]
- Space-time models enable to account for propagations of weather events and improve accuracy of forecasts

Using model outputs and measurements

- Incorporate future and extra information to improve the accuracy of forecast and the spread of scenarios
- Multiple interactions to account for: between variables, space, time

Goals



t = 3pm   t = 5pm   t = 7pm   t = 9pm   t = 11pm

Wind speed at successive times

Goals:

- Provide wind speed predictive scenarios in space and time
- Use Numerical Weather Prediction (NWP) model outputs and measured observations
- Account for space-time information

Plan

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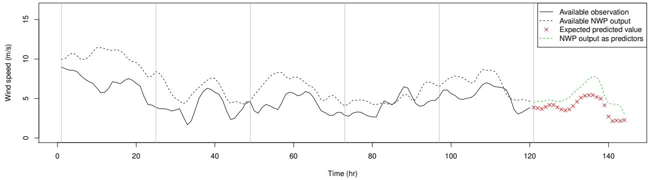
Objectives

Objectives: predict unobserved measurement corresponding to the available 24-hr of NWP using the past measurements and NWP data

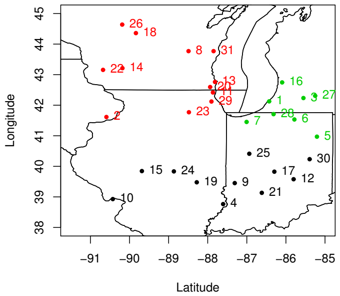


- Observed pairs of measurements (—) and NWP model outputs (– –) → training dataset

- Available NWP data (– –) possibly at different locations but unobserved measurements (×) → predictor dataset

- Include spatial information from neighbors

Two sources of surface wind speed



Homogeneous sub-regions are considered

- NWP model output: WRF data
$\Delta t = 10\text{min}$, $\Delta x = 25\text{km}$
denoted as Y_{NWP}
Every day, the NWP model provides a forecast of 48 hours

- Ground measurements data: ASOS network
$\Delta t = 1\text{min}$, irregular locations
denoted as Y_{obs}

- Data are considered at 10m
- Data are picked every hour

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Modeling choices

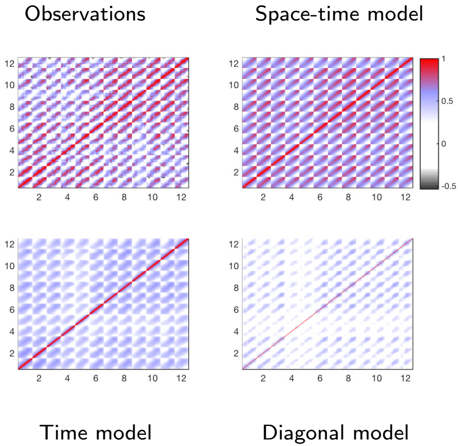
$$\begin{pmatrix} Y_{obs} \\ Y_{NWP} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_{obs} + \Lambda\mu_{NWP} \\ \mu_{NWP} \end{pmatrix}, \begin{pmatrix} \Sigma_{obs|NWP} + \Lambda\Sigma_{NWP}\Lambda^T & \Lambda\Sigma_{NWP} \\ (\Lambda\Sigma_{NWP})^T & \Sigma_{NWP} \end{pmatrix} \right)$$

- NWP outputs modeled as a random process to account for their space-time structure and to provide non-aligned prediction

- Gaussian distribution for convenience in multi-dimension context and conditional distribution expression

- Multi-dimension because of the two processes Y_{NWP} and Y_{obs} that are space-time processes

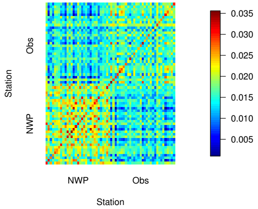
Space-time correlation of wind speed:



Hierarchical bivariate model

A space-time extension of the model proposed in [Royle and Berliner, 1999] is used:

$$\begin{aligned}(Y_{obs}|Y_{NWP}) &\sim \mathcal{N}\left(\mu_{obs|NWP}, \Sigma_{obs|NWP}\right)\\ Y_{NWP} &\sim \mathcal{N}\left(\mu_{NWP}, \Sigma_{NWP}\right)\end{aligned}$$



Associated full joint distribution:

with $\mu_{obs|NWP} = \mu_{obs} + \Lambda Y_{NWP}$

$$\begin{pmatrix} Y_{obs} \\ Y_{NWP} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_{obs} + \Lambda\mu_{NWP} \\ \mu_{NWP} \end{pmatrix}, \begin{pmatrix} \Sigma_{obs|NWP} + \Lambda\Sigma_{NWP}\Lambda^T & \Lambda\Sigma_{NWP} \\ (\Lambda\Sigma_{NWP})^T & \Sigma_{NWP} \end{pmatrix}\right)$$

Specification of the model - Mean structure

$$\begin{pmatrix} Y_{obs} \\ Y_{NWP} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_{obs}+\Lambda\mu_{NWP} \\ \mu_{NWP} \end{pmatrix}, \begin{pmatrix} \Sigma_{obs|NWP}+\Lambda\Sigma_{NWP}\Lambda^T & \Lambda\Sigma_{NWP} \\ (\Lambda\Sigma_{NWP})^T & \Sigma_{NWP} \end{pmatrix} \right)$$

- μ_{obs} and μ_{NWP} are specified with geographical coordinates and time harmonics for account for their space-time patterns;
- μ_{NWP} also with parameter from the NWP model: the land-use

$\bullet \mathrm{E}(Y_{obs}|Y_{NWP}) = \mu_{obs} + \Lambda Y_{NWP}$

$$(\Lambda Y_{NWP})(t,s) = \sum_{i=1}^{h} \alpha^{(\mathrm{LU(s)})}(|t-t_i|) \sum_{k=1}^{3} f_k(\Delta\mathrm{Lat}, \Delta\mathrm{Long})(s, s_k) Y_{NWP}(t_i, s_k)\,, \tag{1}$$

$t_1 \leq t \leq t_h$,

$LU(s)$ is the land-use value of the closest grid point of s

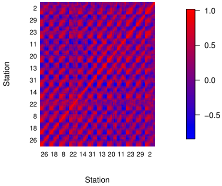
Specification of the model - Covariance structure

The covariance of Y has the structure, inspired by an earlier study [Constantinescu and Anitescu, 2013]:

$$\mathrm{cov}(Y(.,s_i), Y(.,s_j)) = (L_{s_i} K_0 L_{s_j}^T) + \delta_{i-j} K_{s_i}$$

- The matrices K_0 and K_s written as

$$\mathrm{K_j[l,k] = a_j \exp(-b_j(|t_k - t_l|)^2) + \delta_{k-l} c_j}$$



- The matrices L_{s_j} are parameterized in space and time

- The same structure is used for Σ_{NWP} and $\Sigma_{obs|NWP}$ with different parameters

The proposed structure can be interpreted as the following description of the process:

$$\mathrm{Y(b_i, s_j) = \mu + L_{s_j} Y_0(b_i) + \epsilon_{s_j}(b_i)}$$

- b_i: temporal window of 24 hours
- s_j: spatial location
- ϵ_{s_j} are independent from each other and from Y_0

Estimation

- Parameters are estimated by Maximum Likelihood

- The model is trained independently on the 3 sub-regions and independently on 3 months January, May and August 2012

- The parameters are estimated on two thirds of each month, prediction is made on the remaining third
The training period is rolled over the possible permutations

- **Advantages:**
  - avoid the specification of the cross-covariance between Y_{obs} and Y_{NWP}
  - corner stone is the specification of $\mu_{obs} + \Lambda Y_{NWP}$
- **Challenges:**
  - specify Λ to capture of the spatio-temporal scales
  - linear relation between Y_{obs} and Y_{NWP} to capture complex patterns ...
- **What is new?**
  - the idea of using the entire window of 24hr-forecast NWP
  - this model is using space-time information
  - model outputs are modeled as a random process

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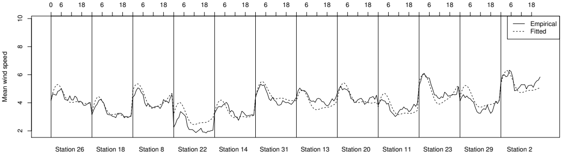
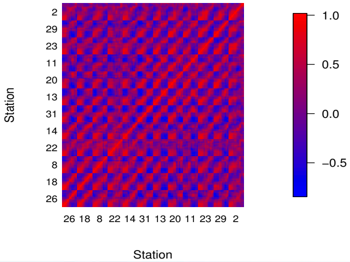
Estimated parameters

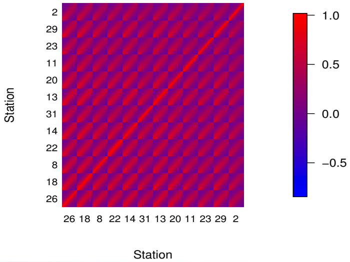
Empirical and fitted mean on Y_{obs}



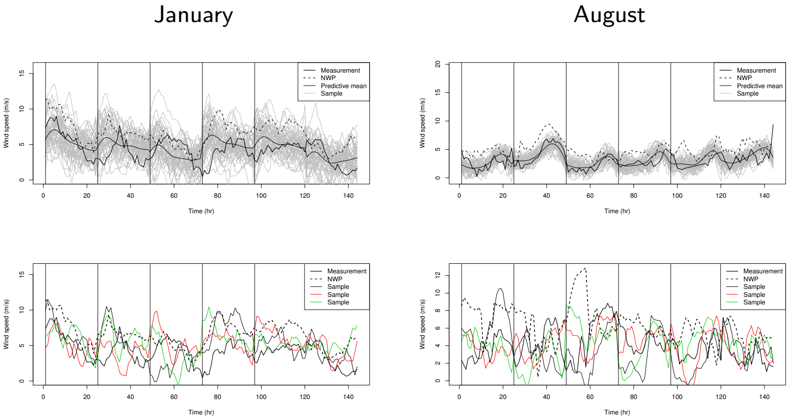
Empirical space-time correlation of $(Y_{obs}|Y_{NWP})$



Fitted space-time correlation of $(Y_{obs}|Y_{NWP})$



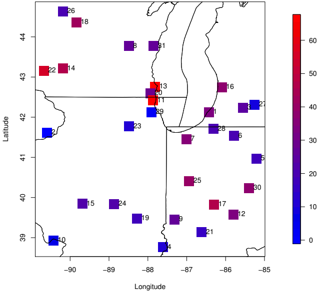
Time series and scenarios



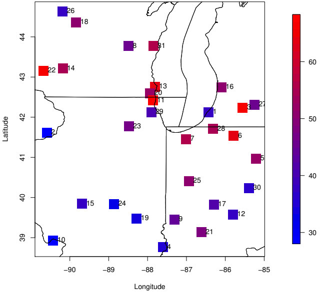
Time series of wind speed at the station with the median RMSE
Upper panels: 50 predictive samples are plotted
Lower panels: 3 samples are plotted

Improvement of Root Mean Square Error

January



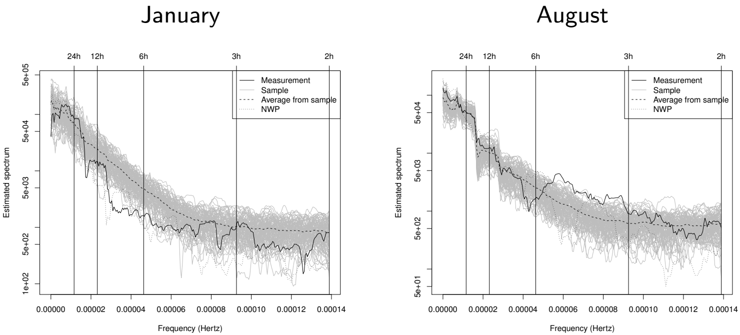
August



Maps of improvement of RMSE of the proposed prediction with respect to the RMSE of the NWP

Each RMSE is computed with respect to the measurements

Temporal spectrum



Estimated spectrum for the station with the median RMSE in subregion C2.

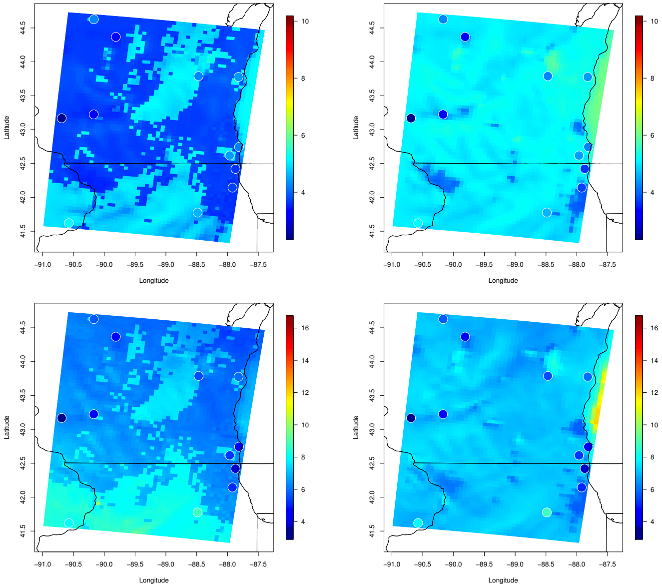
Correction of the mean and variance of NWP outputs - $\Delta x = 5\text{km}$

Krigged observation

NWP

Mean

Variance



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Conclusion and perspectives

- Space-time framework for prediction of surface wind speed based on NWP data and measurements

- Provided predictions improve the RMSE with respect to NWP

- Scenarios have a realistic spectrum respectively to the measurements

- The model enables to correct the first and second order structure of the NWP to match the one of the measurements

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