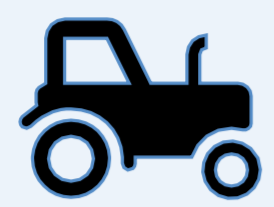


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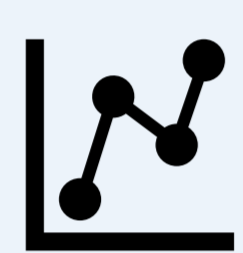
Context

Weather-based forecasting models play a major role in agricultural decision support systems (DSS) but warnings are usually computed at regional level due to a limited amount of automatic weather stations (AWS). Farmers have to refer to the nearest AWS but recommendations are **not always adapted** to their local situation. **Data interpolation could be a solution** to estimate weather conditions in farmer's fields.



Question

What is the best method to perform **operational spatial interpolation** of **air temperature** and **relative humidity** observations at high spatial (1 km x 1 km grid) and temporal (hourly and daily) resolution in Wallonia?



Main results

Hourly air temperature interpolation

Scenario	mean	std	median	75%	90%	95%	99%	max
<i>Pameseb data only</i>								
mulLR-xyz	0.70	0.75	0.46	0.91	1.58	2.17	3.70	11.38
OK-xv	0.73	0.72	0.52	1.00	1.62	2.10	3.40	11.44
KED-xyz	0.62	0.69	0.40	0.81	1.43	1.97	3.33	11.18
NN	0.93	0.95	0.70	1.20	2.00	2.70	4.60	13.40
IDW	0.81	0.77	0.60	1.10	1.77	2.29	3.58	11.34
NAIVE	1.17	0.94	0.95	1.61	2.41	2.99	4.31	11.33
<i>Pameseb + INCA data</i>								
mulLR-xyI	0.67	0.74	0.45	0.87	1.50	2.06	3.70	11.95
mulLR-xyzI	0.66	0.75	0.43	0.85	1.49	2.09	3.76	12.60
KED-xyI	0.64	0.71	0.42	0.84	1.46	2.00	3.42	11.26
KED-xyzI	0.62	0.69	0.40	0.81	1.42	1.95	3.36	11.19
<i>Pameseb + RMI data</i>								
mulLR-xyz	0.67	0.71	0.45	0.88	1.51	2.04	3.48	11.31
KED-xyz	0.59	0.69	0.37	0.76	1.36	1.89	3.41	11.08

mulLR: multilinear regression ; OK: Ordinary Kriging ; KED: Kriging with External Drift
NN: Nearest Neighbor ; IDW: Inverse Distance Weighted ; NAIVE: mean of observations.

Table 1 – Statistics of absolute prediction errors for hourly air temperature interpolation: results of leave-one-out hourly simulations on 2 years.

- (1) Kriging with elevation as external drift => the best score in all cases i.e. both for temperature and humidity and for hourly and daily steps
- (2) Integrating weather forecast as a dynamic explanatory variable does seem to improve the quality of the spatialization but this requires further studies
- (3) Enriching the training dataset by increasing the number of AWS (from 28 to 43) does not dramatically improve the overall performance score but the issue is subtle.

Operational
platform



Real-time weather data dissemination for agricultural DSS in Wallonia.



Datasets

Weather data

- Air temperature and relative humidity
- Hourly and Daily
- From 01/01/2016 to 31/12/2017
- Pameseb network : 28 selected AWS (•)
- RMI network : 15 selected AWS (+)

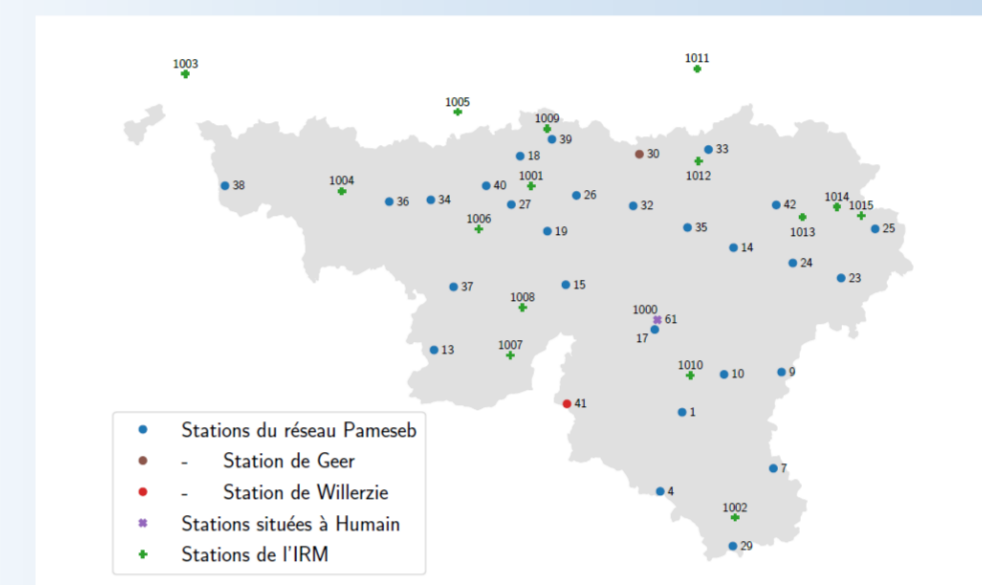


Fig 1 - Map of Pameseb and RMI networks

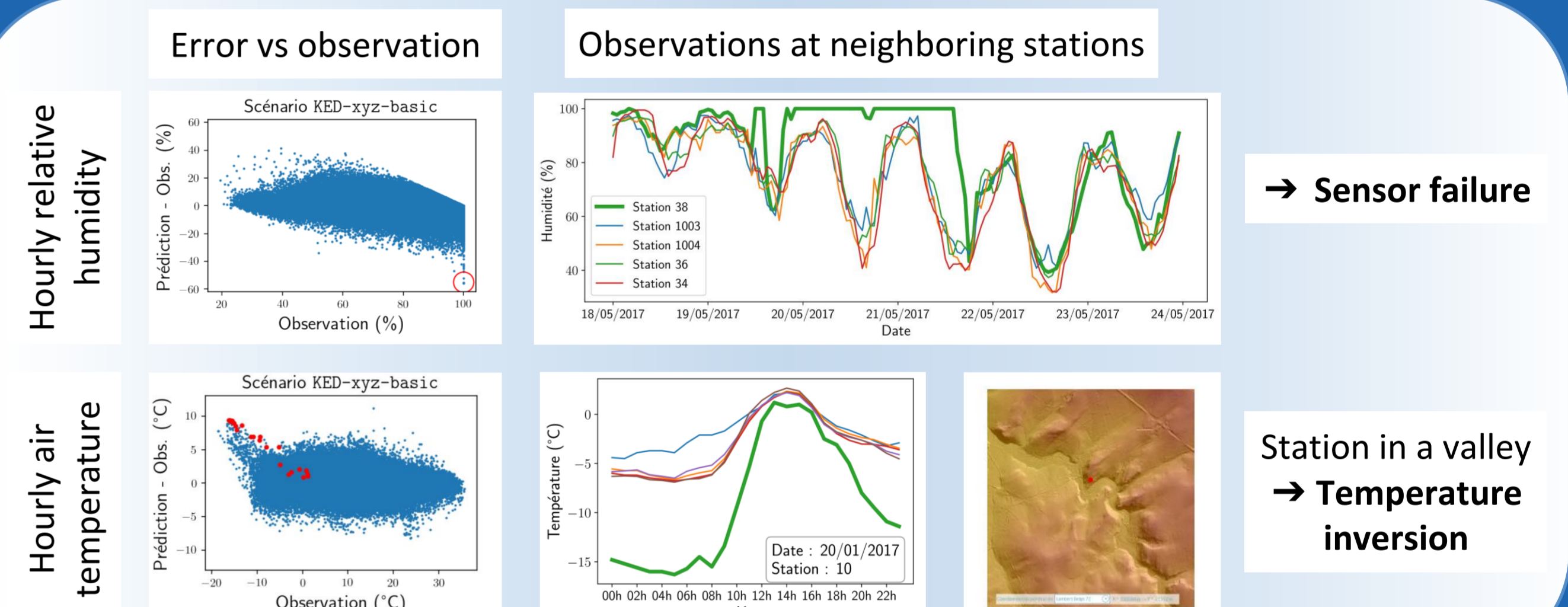


Fig 2 - Automatic Weather Station (AWS)

4 explanatory variables

- Longitude, latitude, elevation (static variables)
- Gridded weather forecast 'INCA' (dynamic variable)

Worst case studies (examples)



Semivariogram

Fixed params by grid-search optimization (not recalibrated every hour)

Best model: Linear without nugget

No significant impact of fine-tuning the semivariogram

Scenario	mean	median
KED-xyz-grid	0,62	0,40
KED-xyz-aver-sph	0,65	0,43
KED-xyz-aver-lin	0,66	0,44

Table 2 – Comparison of optimization techniques for semivariogram parametrization: aver = average of hourly calibrated semivariograms.



Forthcoming

What additional information to improve the interpolation?

Additional data sources to explore:

- Crowd-sourced weather data (farmers' AWS) !Outliers detection!
- Reanalysis of weather data (combination of past short-range weather forecasts with observations through data assimilation)
- Remote sensing: data from meteorological satellites