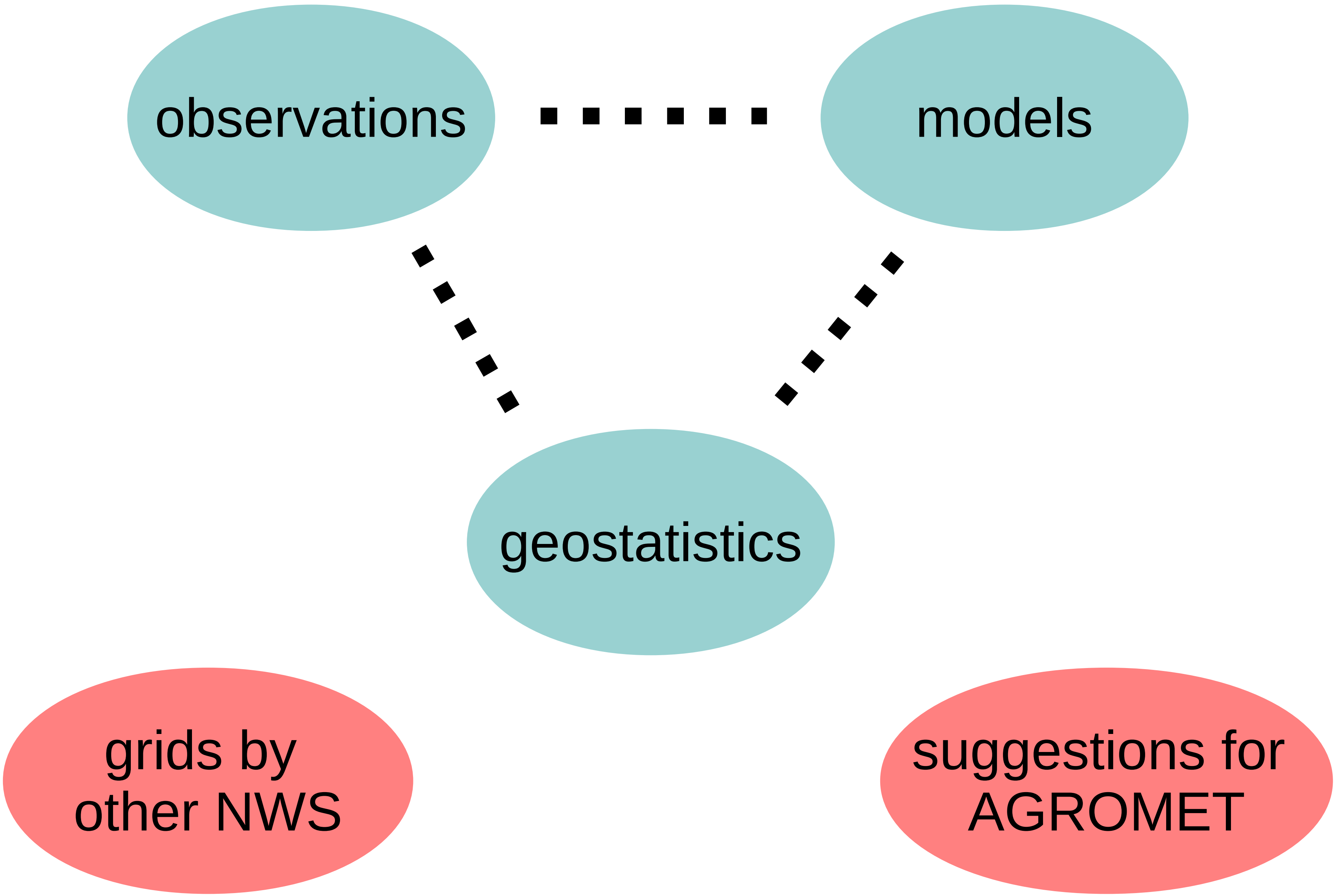
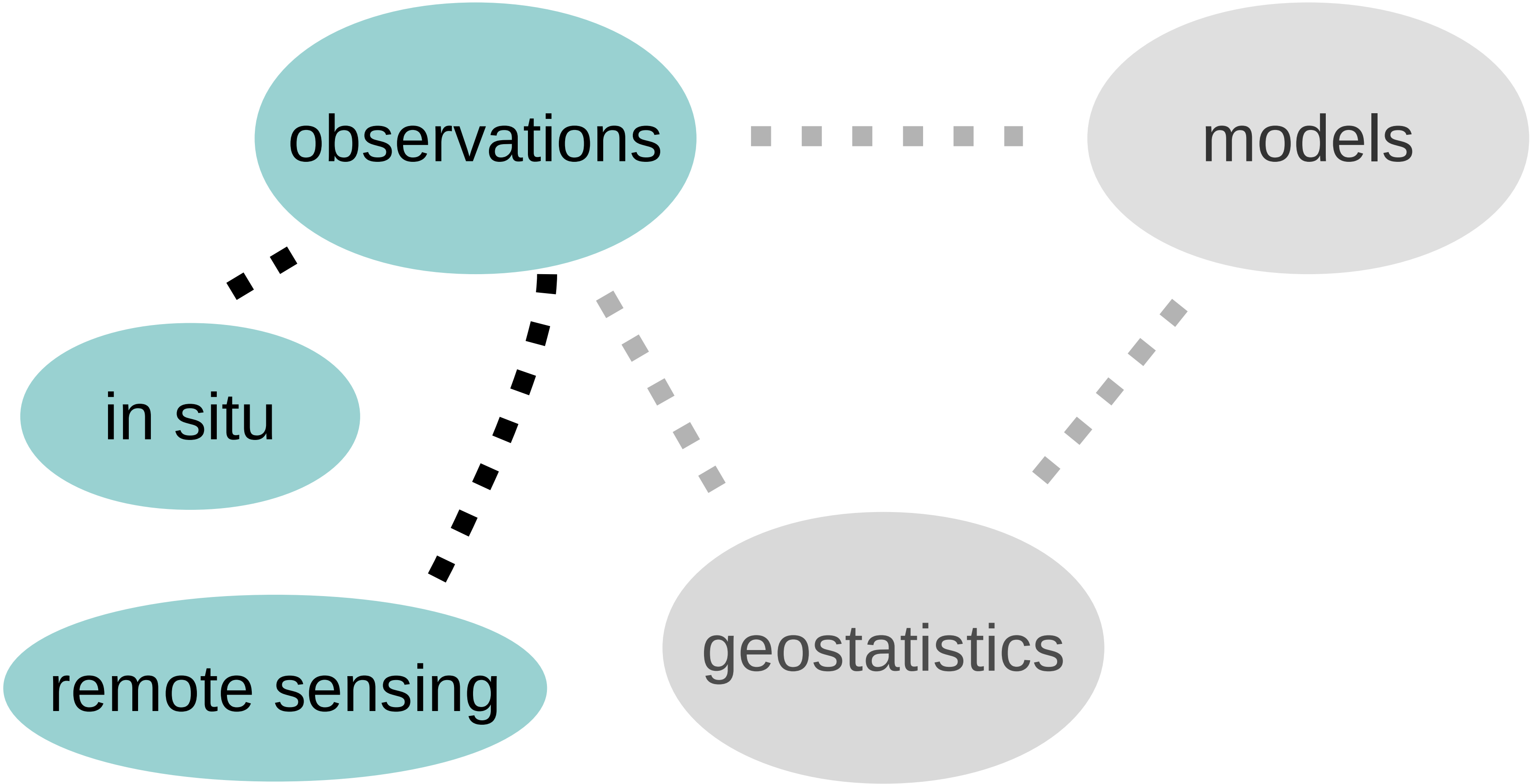
Spatial interpolation workshop @CRA-W, January 2018

Michel Journée, RMI

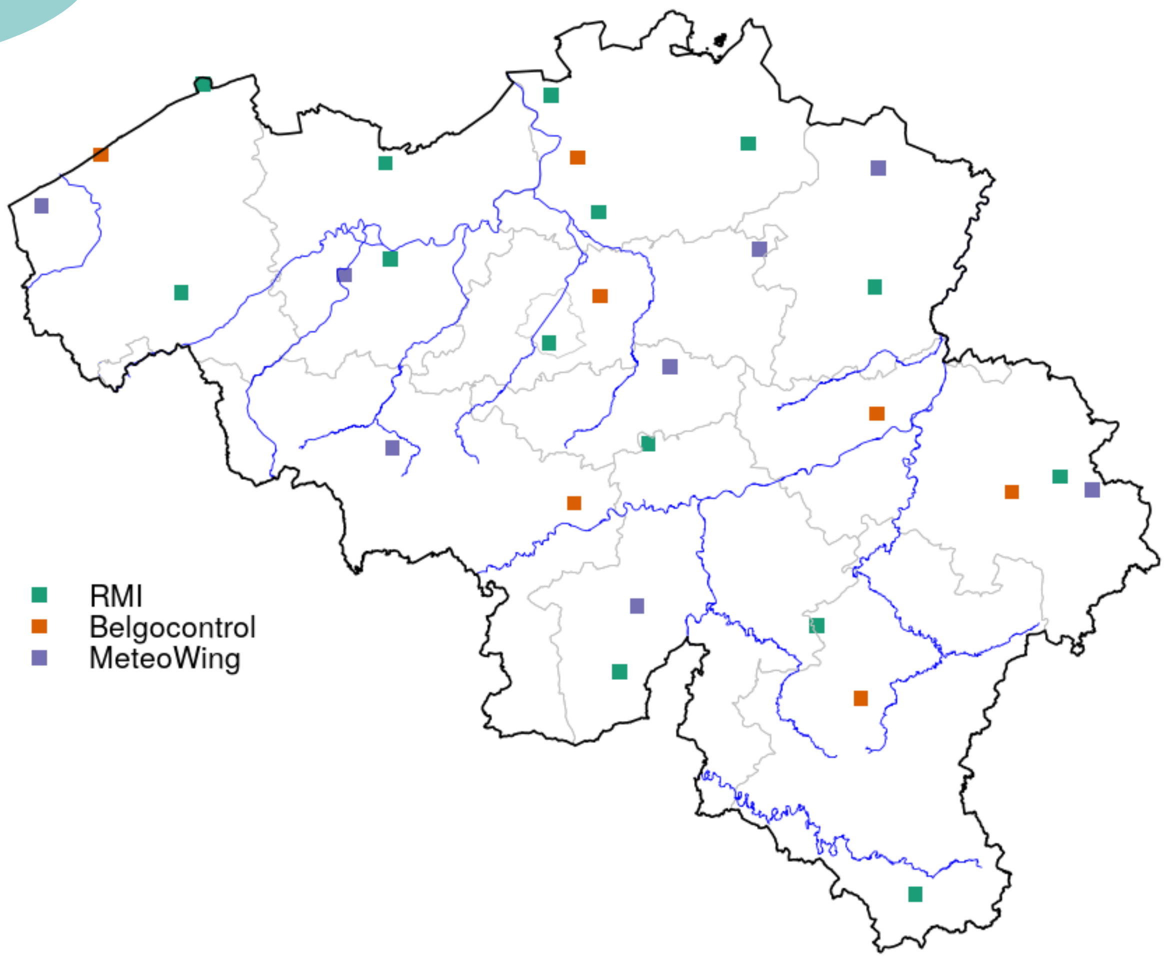



observations
models
in situ
geostatistics
remote sensing

In situ observations in Belgium

Many networks/operators

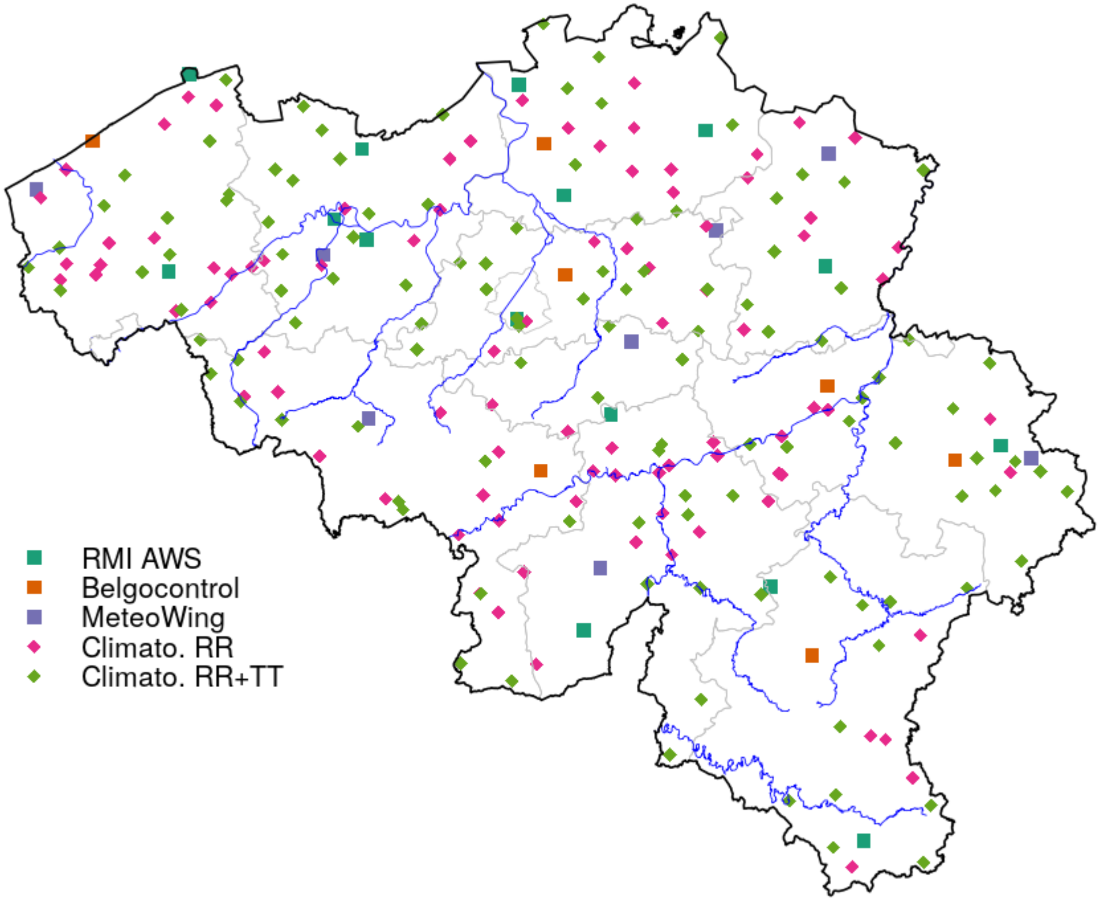
1. synoptic stations (29)



In situ observations in Belgium

Many networks/operators

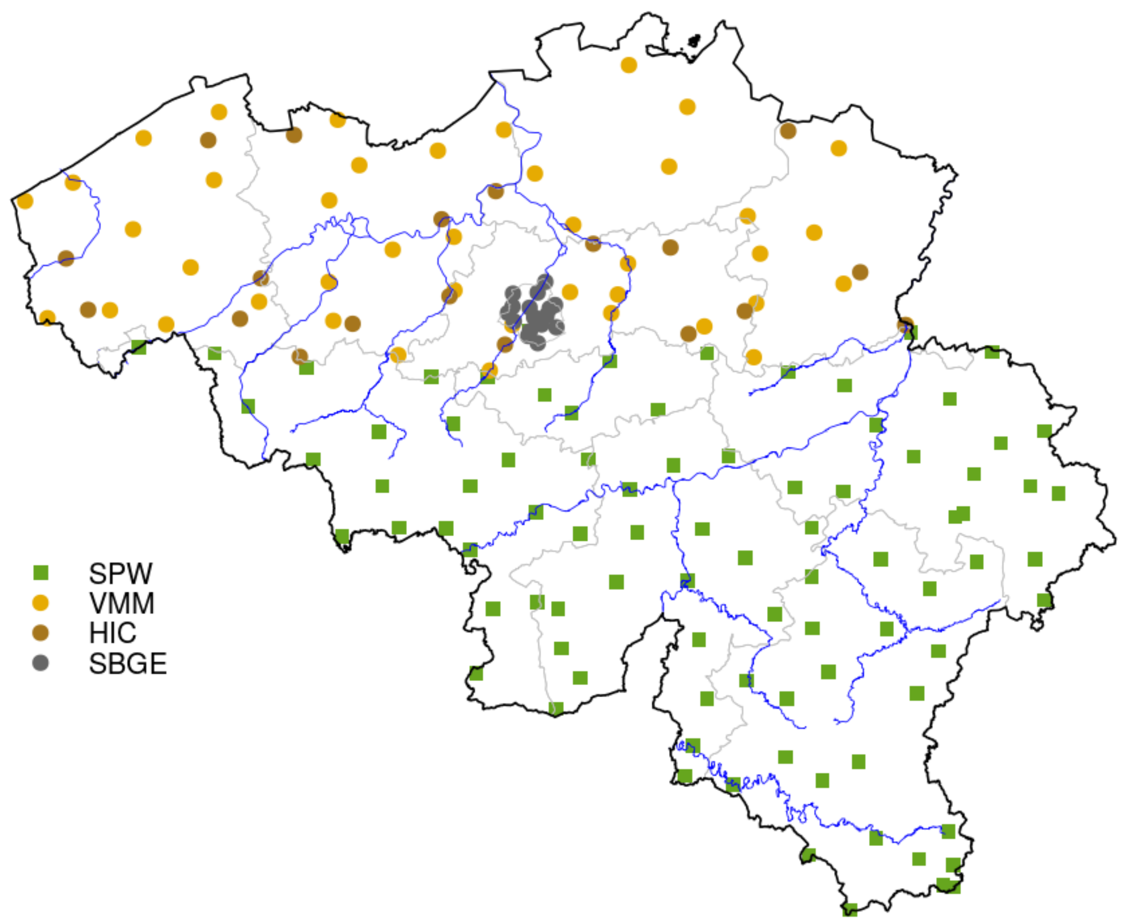
2. climatological stations
(220 RR, 145 TT)



In situ observations in Belgium

Many networks/operators

3. regional hydrological
   networks



In situ observations in Belgium

Many networks/operators

+ agricultural networks (Pameseb, Inagro, etc.)

+ air quality networks

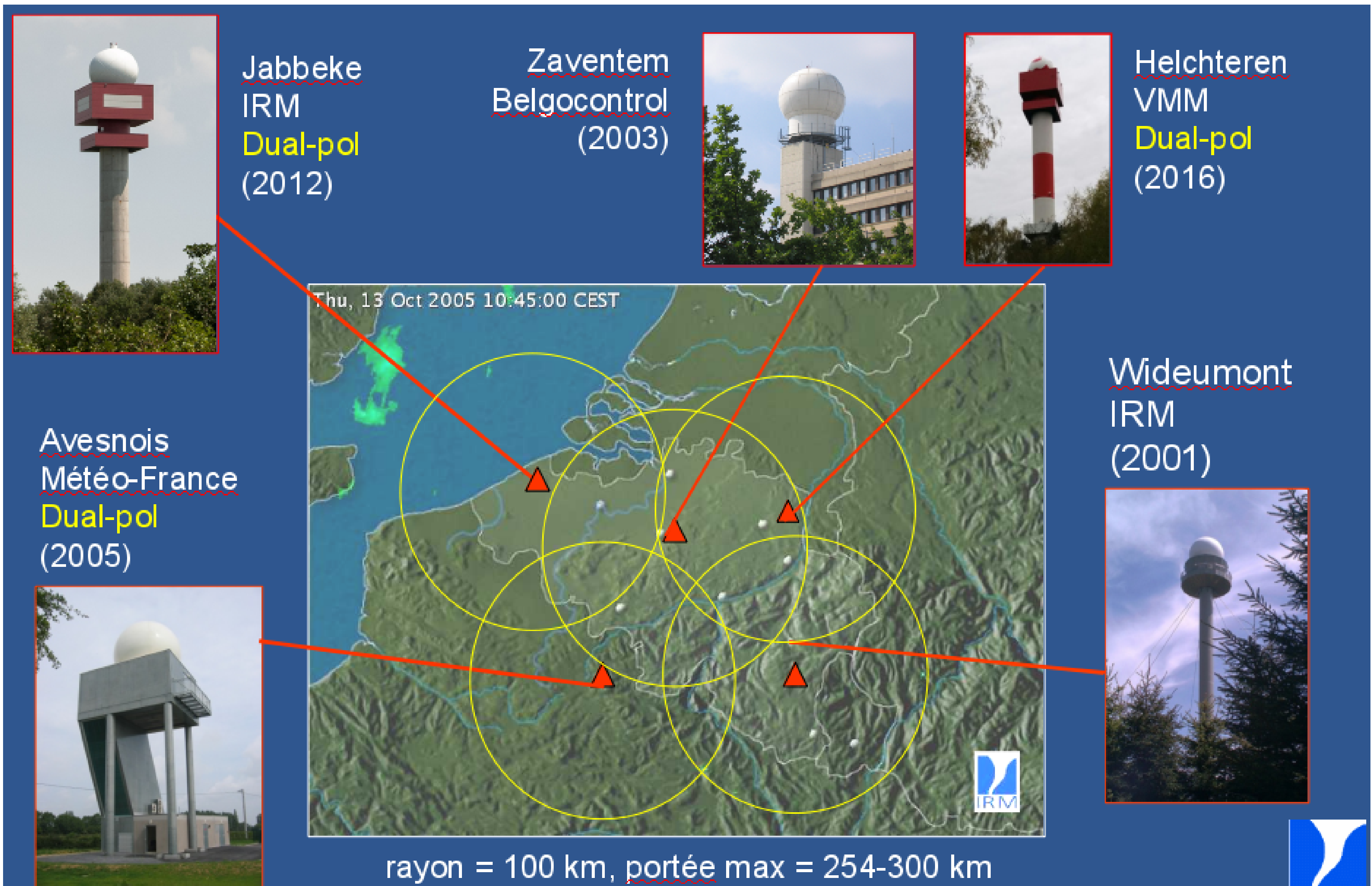
+ traffic management

+ weather enthusiasts observations

etc.

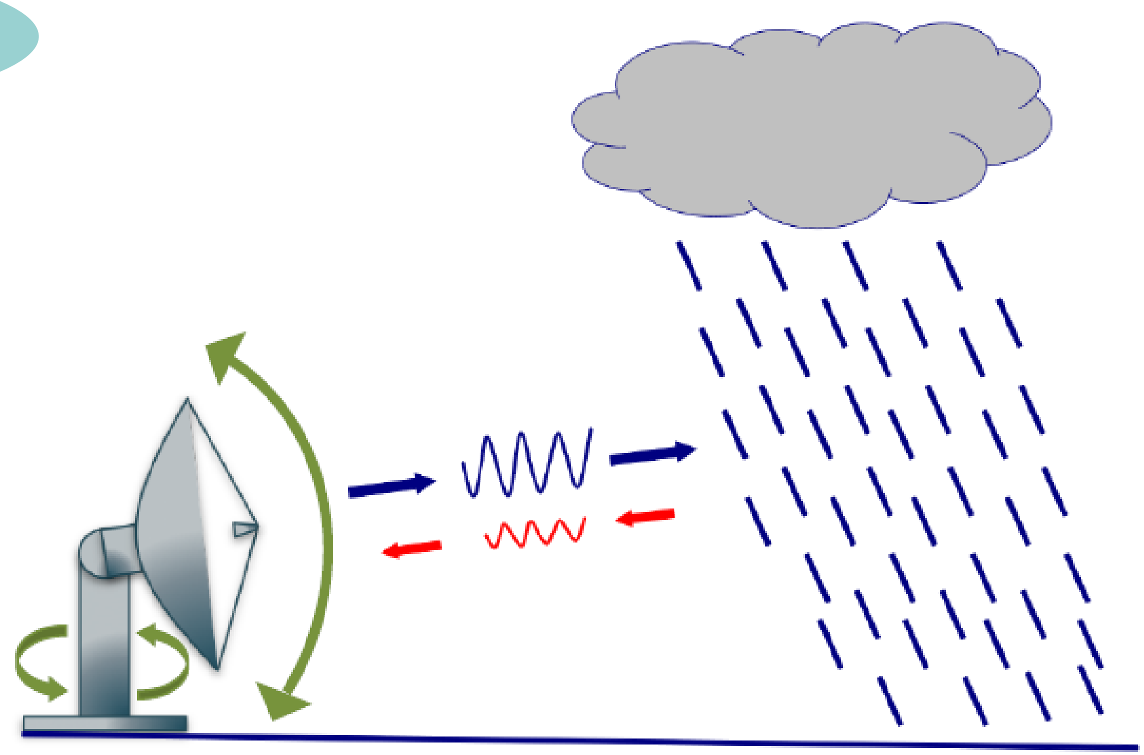
Remote sensing observations

Meteorological radars



Remote sensing observations

Meteorological radars

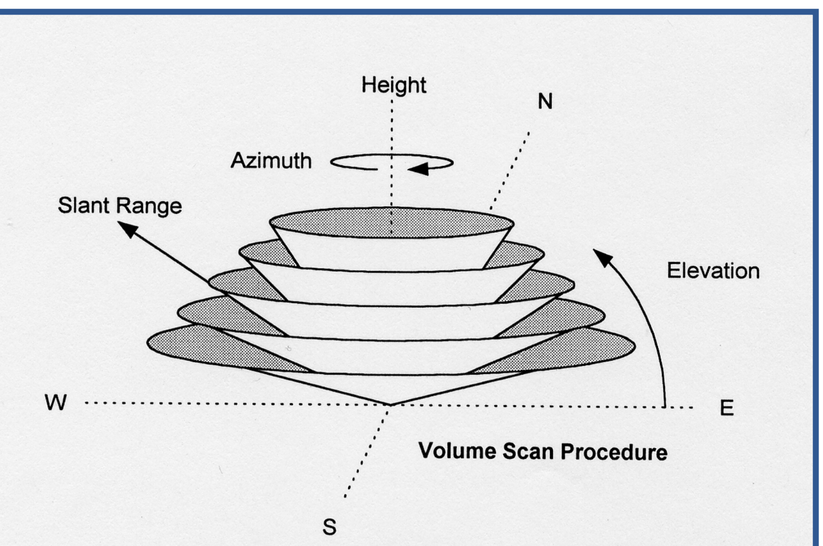


Scan every 5 min

15 elevation angles

Beam width 1°

Azimuthal resolution 1 km at 57 km



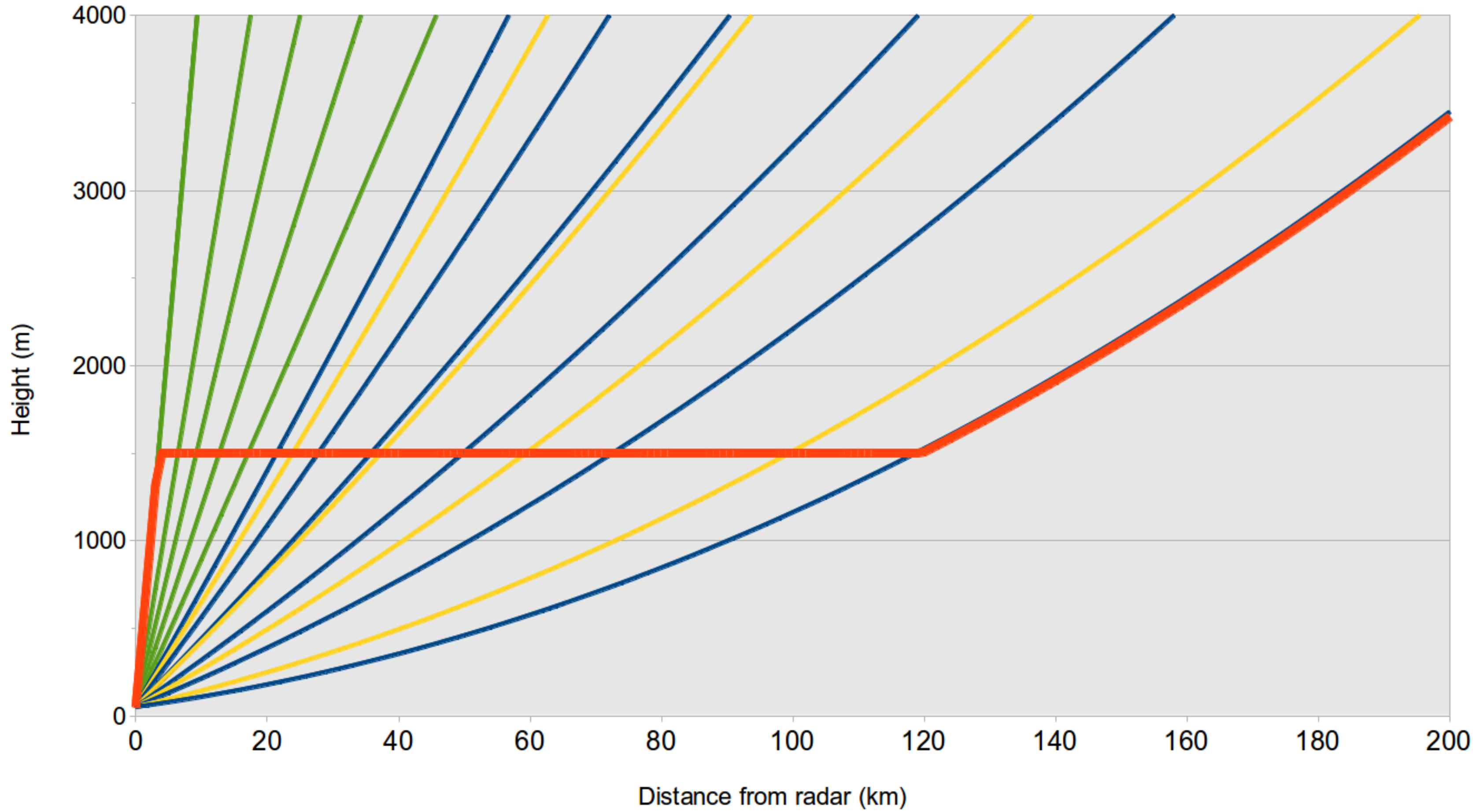
→ **Mesure of the reflectivity Z**

Remote sensing observations

Meteorological radars

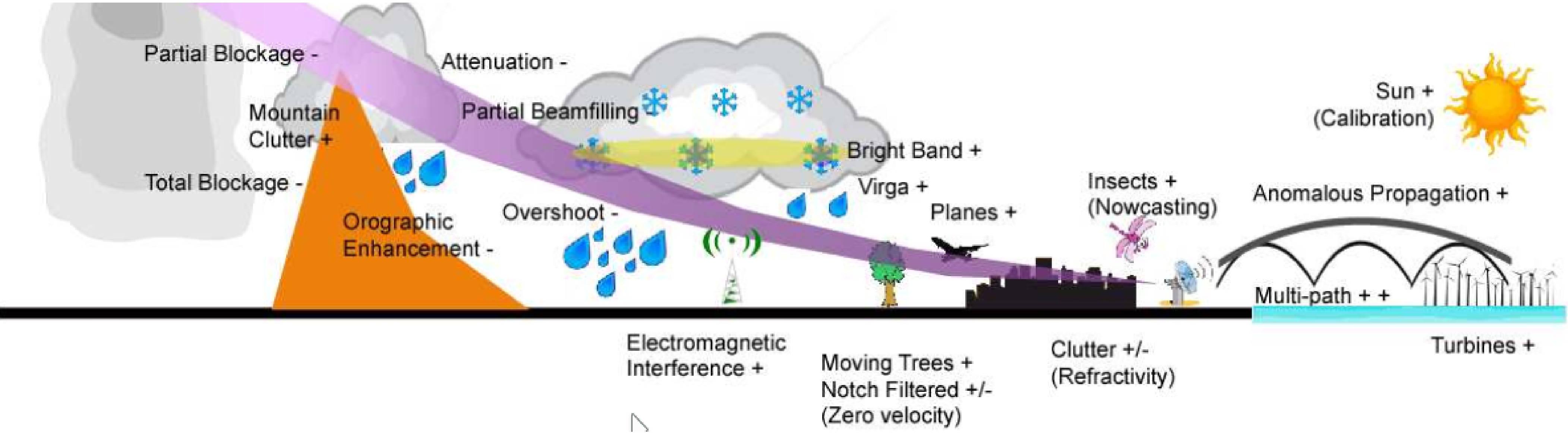
Reflectivity Z → precipitation estimates R

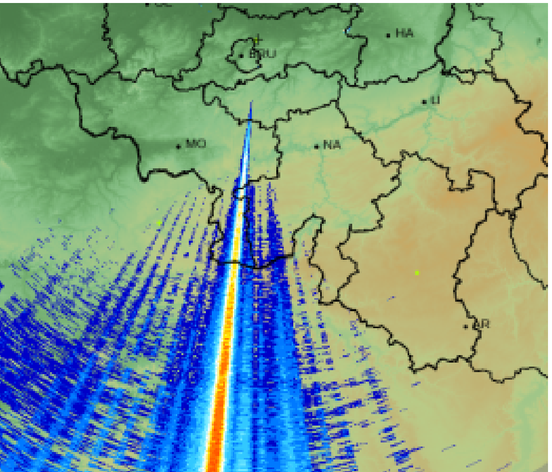
1.5km CAPPI, Marshall-Palmer relationship $Z = 200\,R^{1.6}$

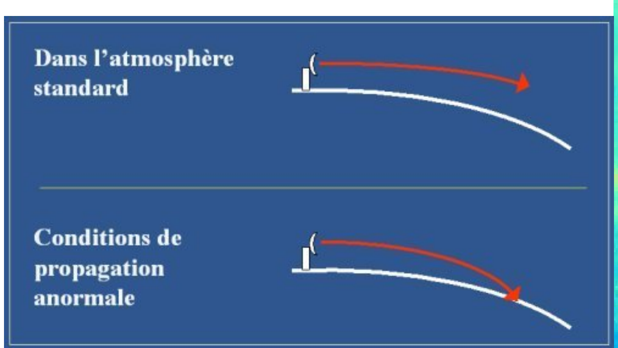


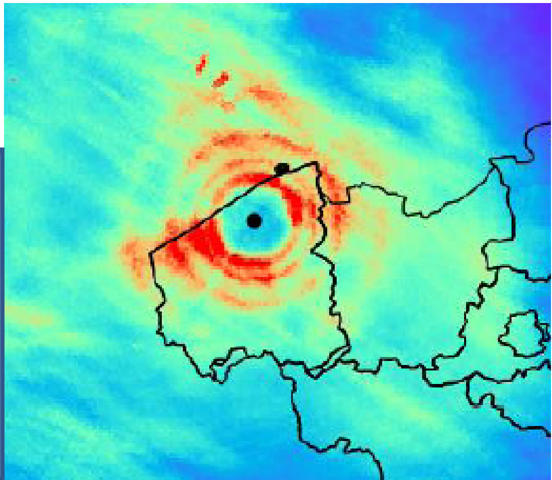
Remote sensing observations

Meteorological radars







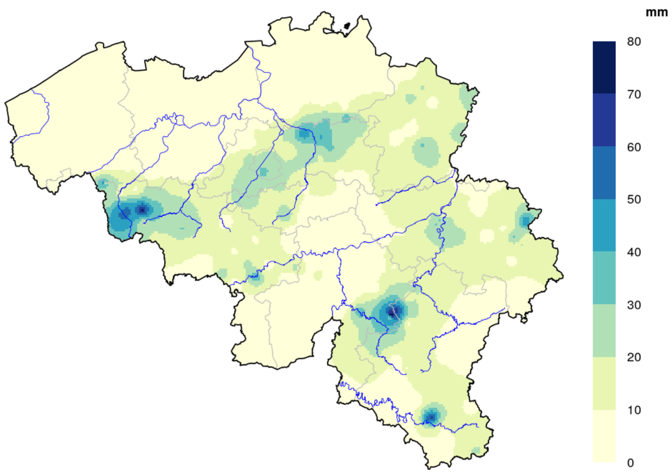


Remote sensing observations

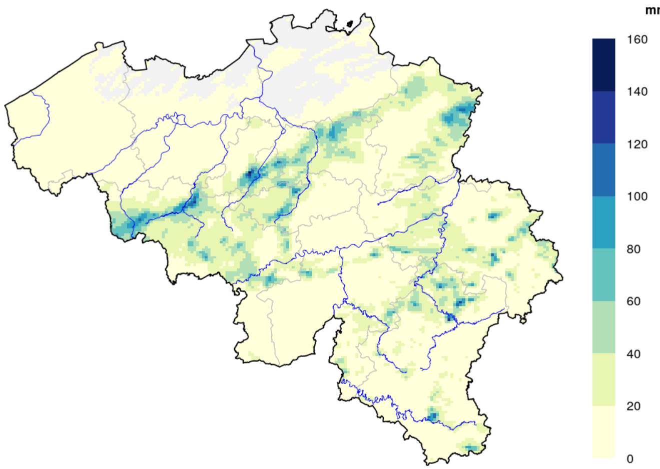
Meteorological radars

Heavy precipitations, 2016/06/07

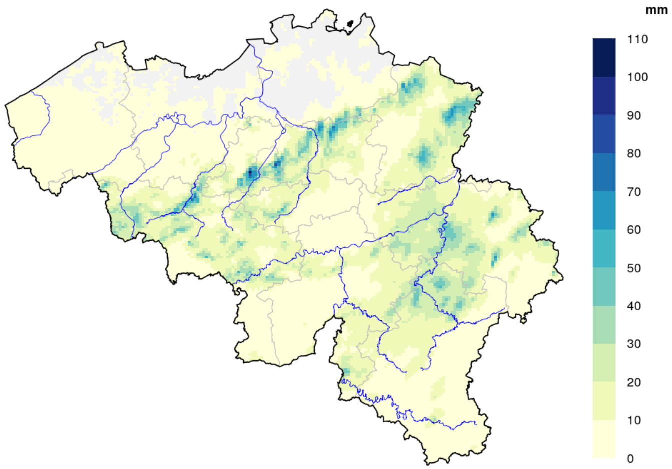
rain gauges

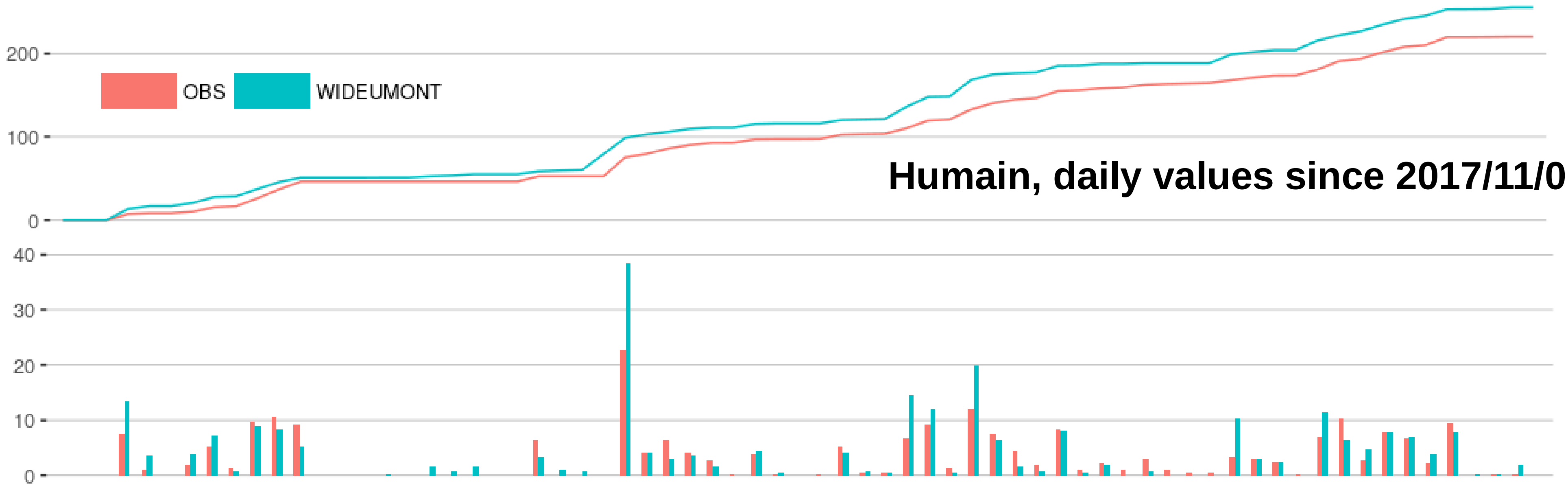


Wideumont radar



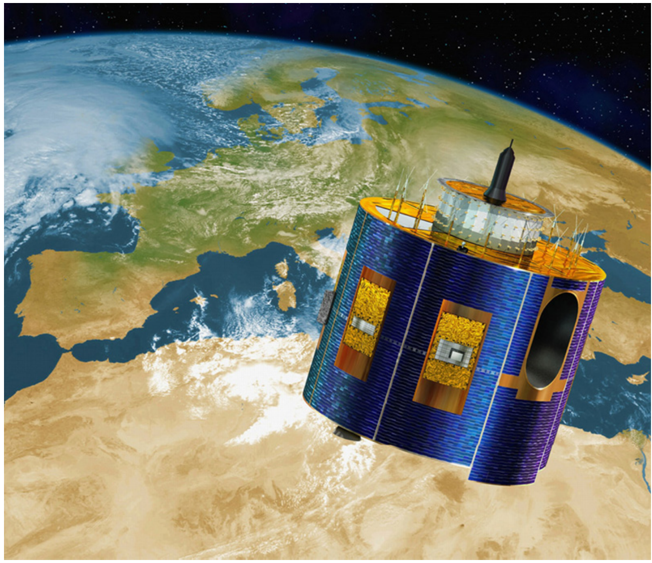
Jabbeke radar





Humain, daily values since 2017/11/01

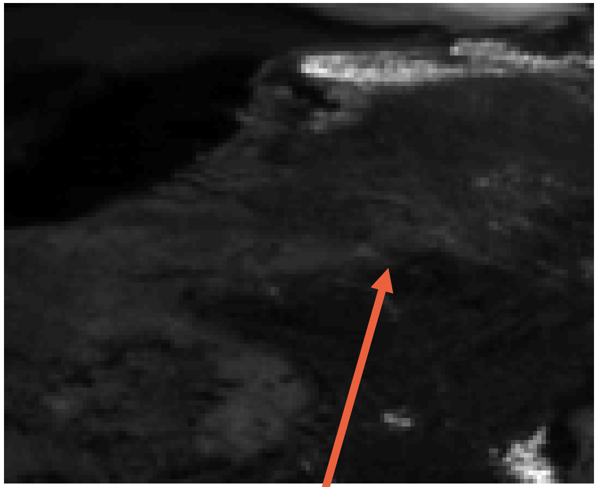
Remote sensing observations



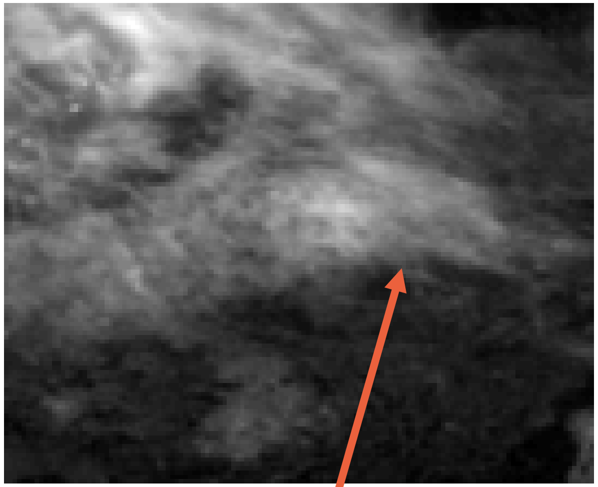
Meteosat

1. cloud index $$n = \frac{\rho - \rho_{\text{clear sky}}}{\rho_{\text{cloudy sky}} - \rho_{\text{clear sky}}}$$

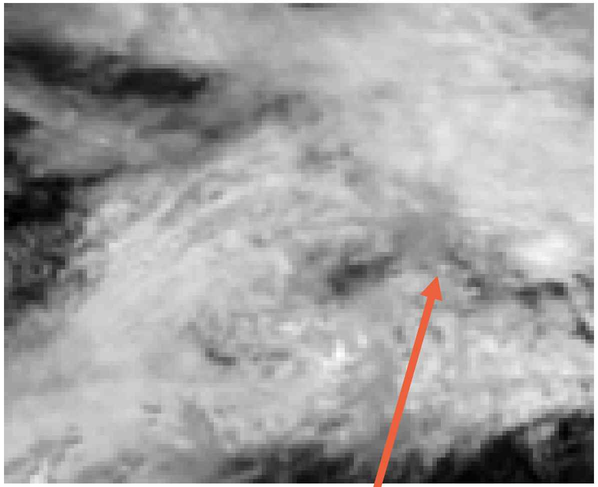
MSG VIS006 channel (6 km x 3.3 km)



clear sky
n=0



partly cloudy
n=0.5



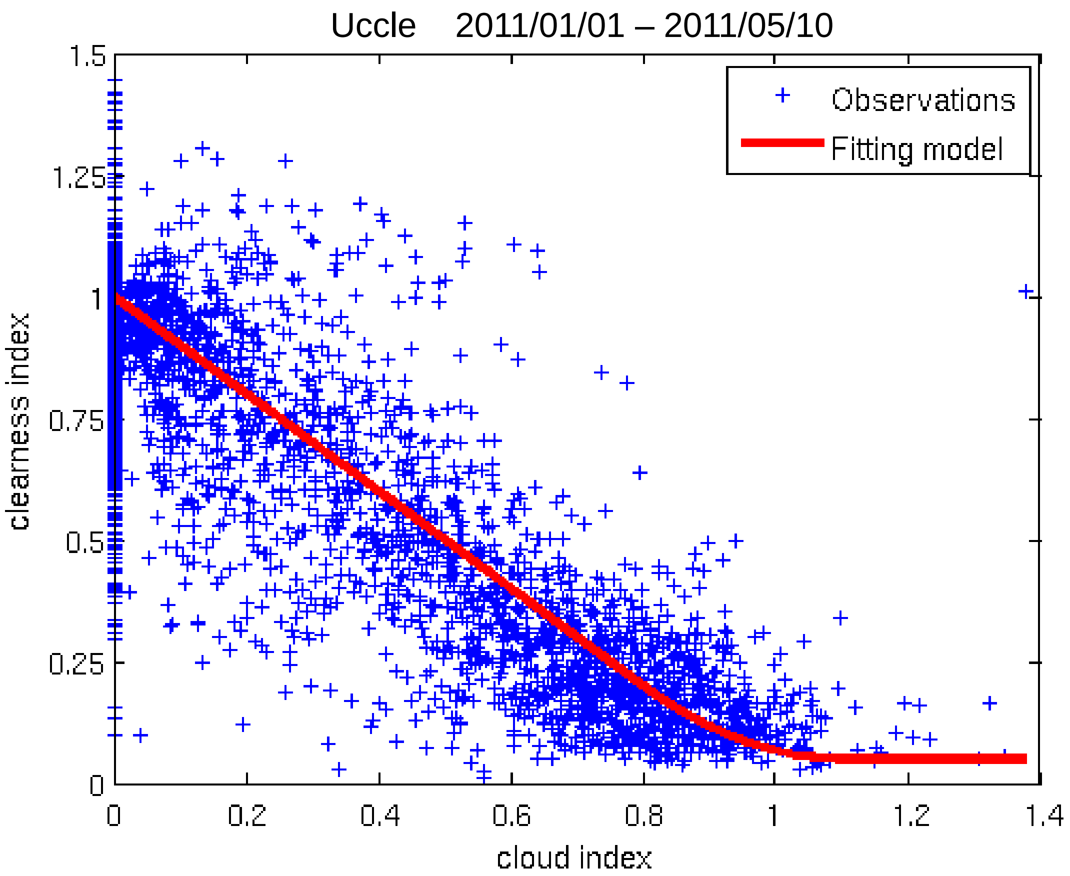
cloudy
n=1

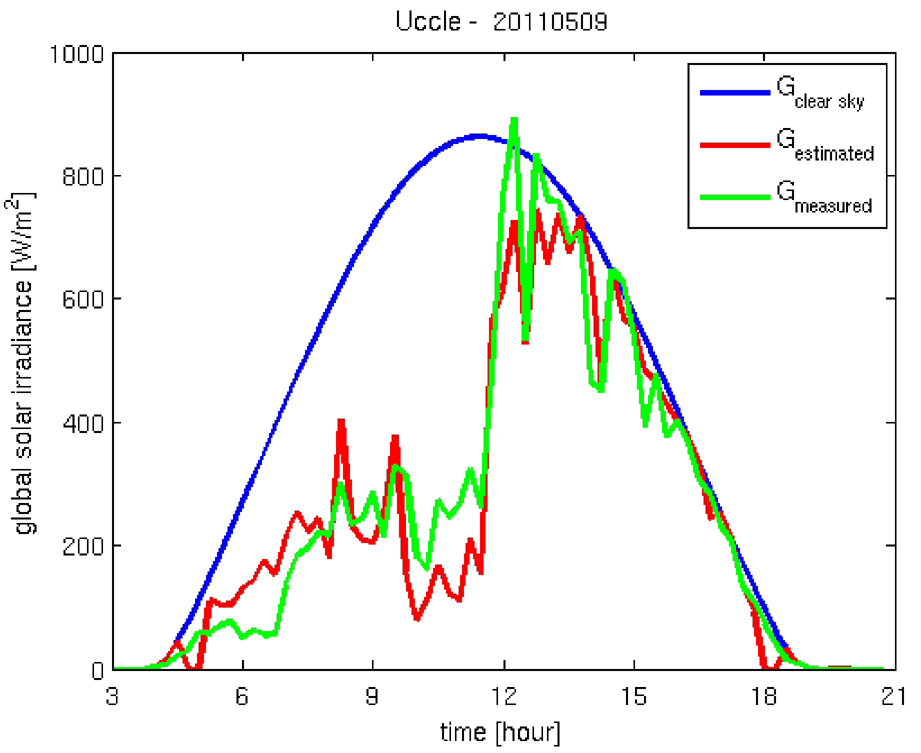
Remote sensing observations

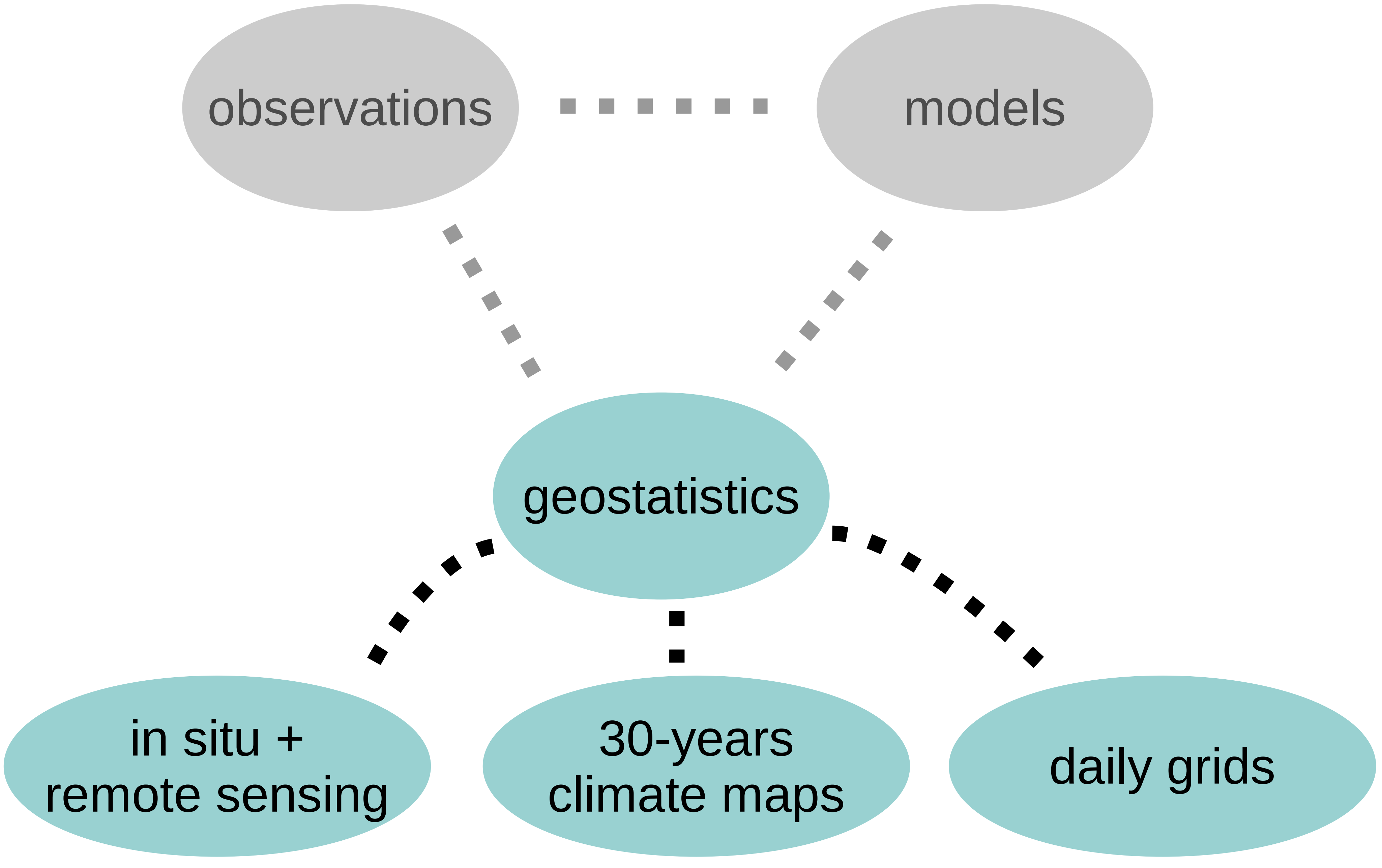
Meteosat

2. cloud index → solar radiation

$$\frac{G}{G_{\text{clear sky}}} = f(n)$$






observations
models
geostatistics
in situ +
remote sensing
30-years
climate maps
daily grids

Rain gauges + radar observations

Mean Field Bias (MFB)

1. pluvios dans un rayon de 100 km du radar
2. minimum 11 paires radar-pluvios avec plus de 0.2 mm
3. le biais est la médiane des ratios

External Drift Kriging (EDK)

1. pluvios dans un rayon de 160 km du radar
2. uniquement si corrélation radar-pluvios supérieure à 0.5
3. variogramme sphérique de 15 km avec une pépite (variabilité ponctuelle) de 0.1
4. transformation des valeurs : racine carrée

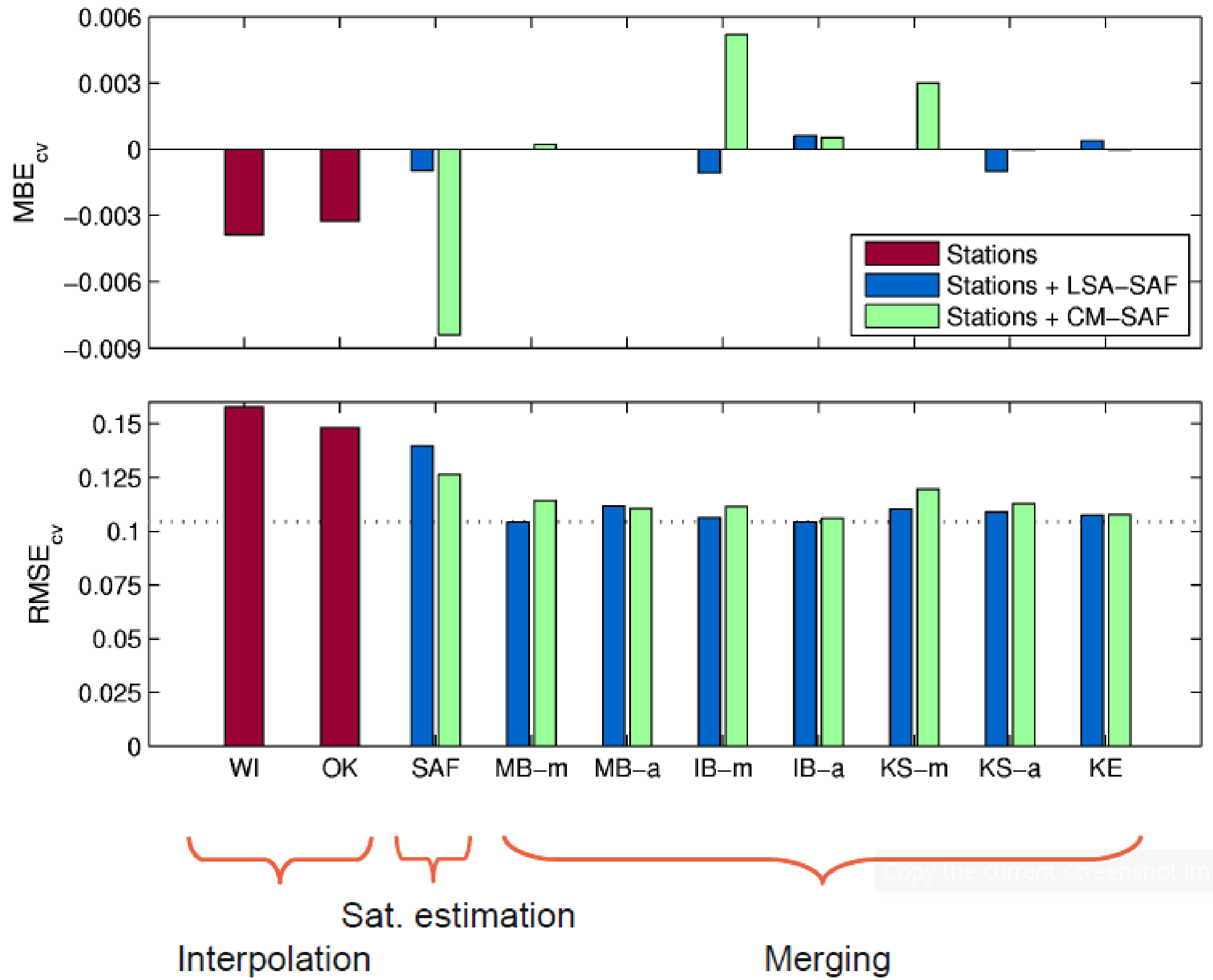
Applied on hourly precipitation totals

Solar radiation: AWS + MSG observations

Normalized
cross-validation errors

Daily totals

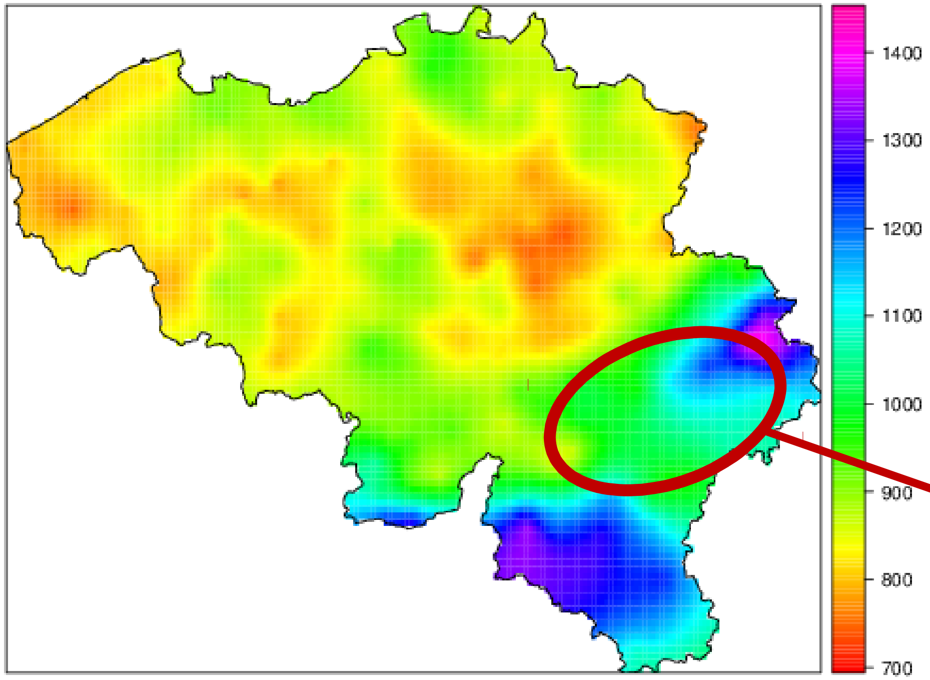
Validation period:
2008 - 2009



Climate maps

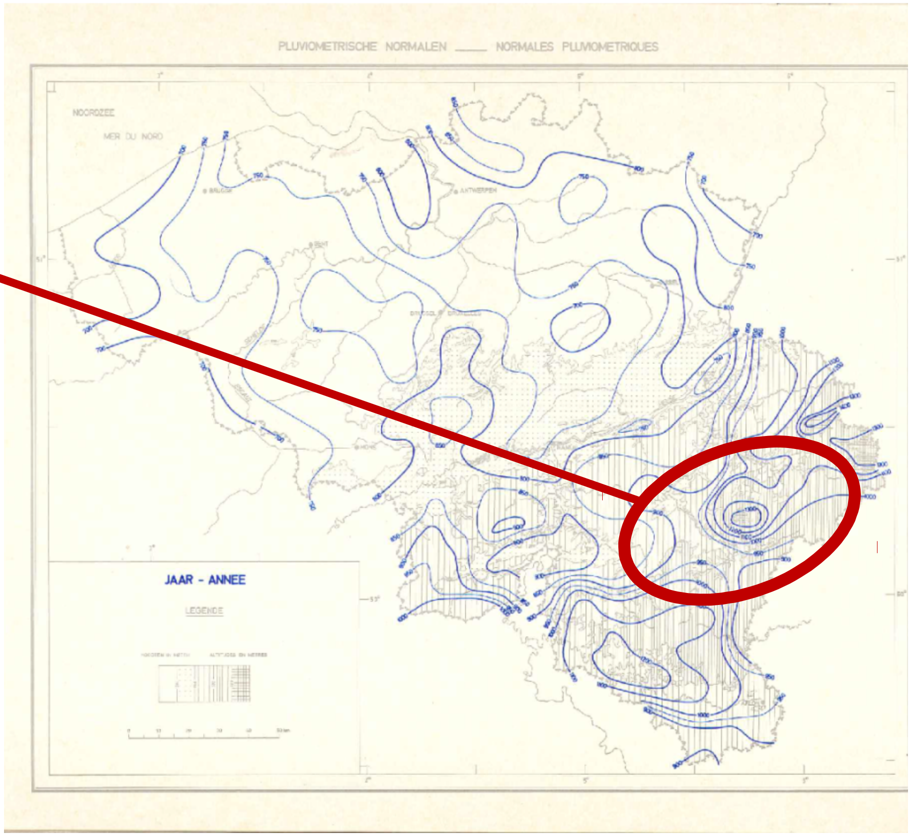
Mean annual rainfall

1981 - 2010



ordinary kriging of
stations mean values

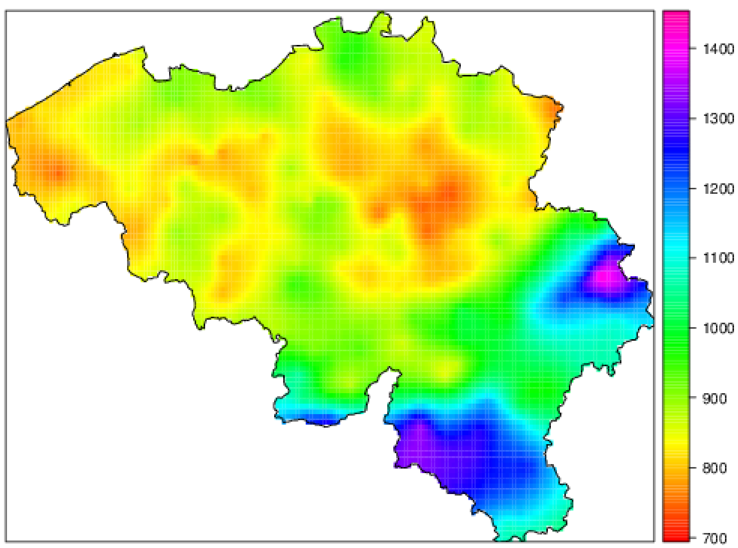
1833 - 1975



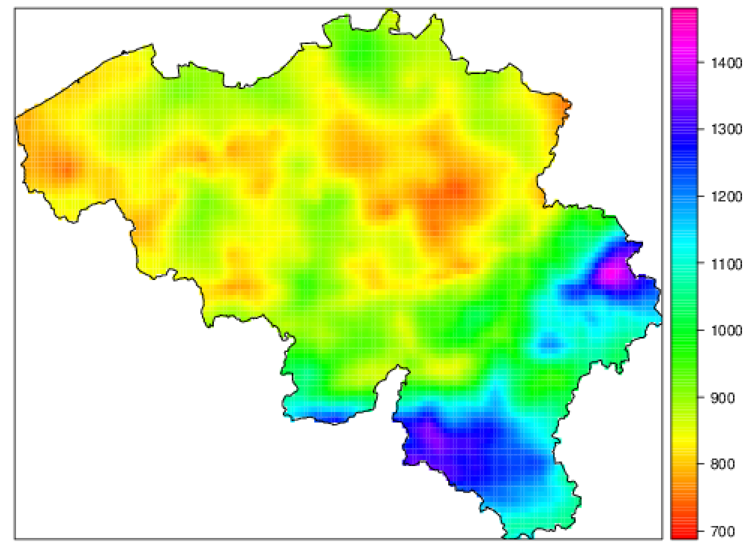
Climate maps

Mean annual rainfall

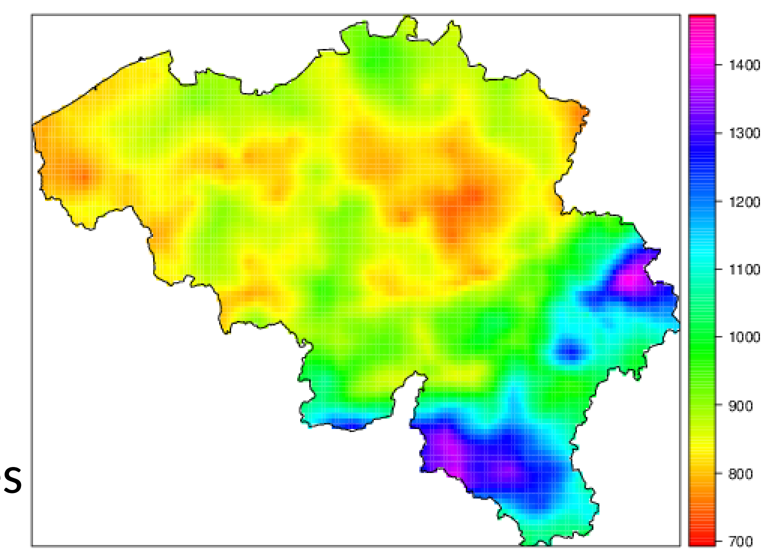
1981 - 2010



+ Terrain elevation



external drift kriging

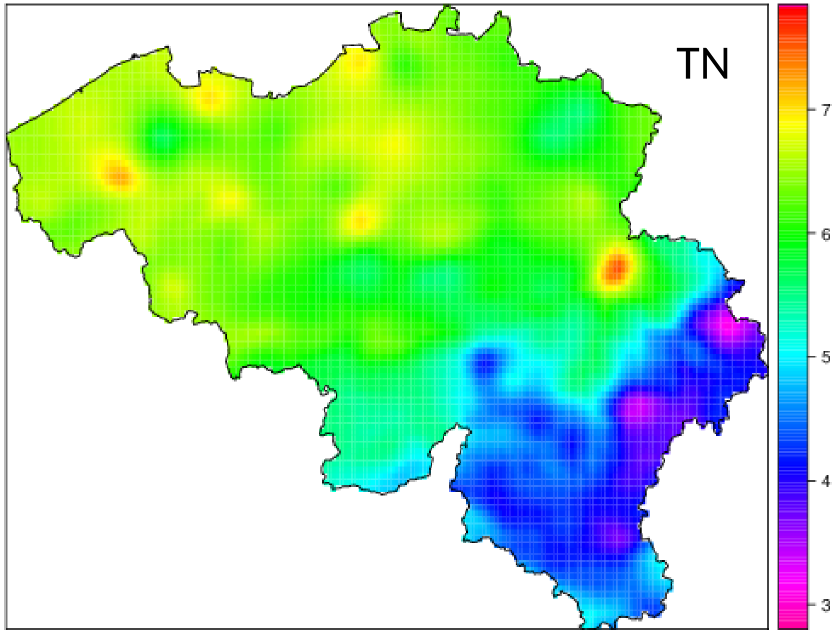


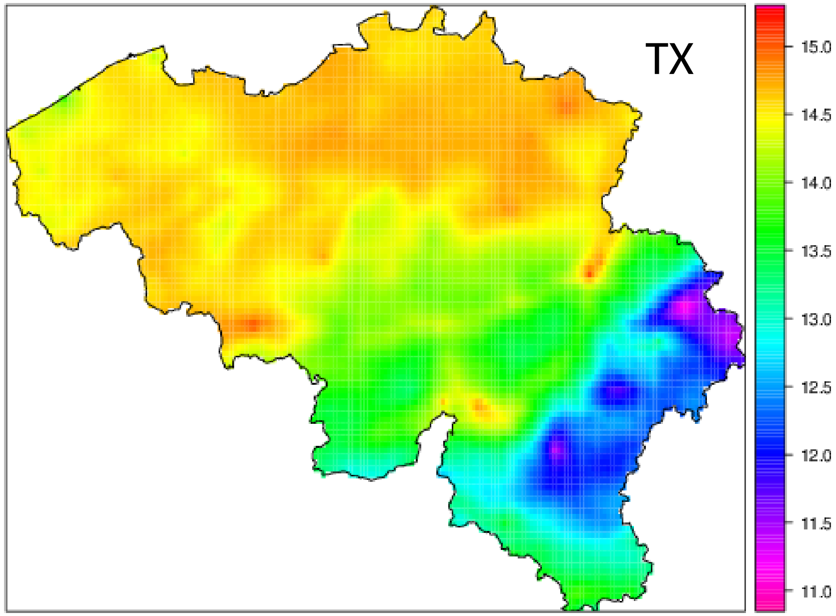
+ Terrain elevation
+ SPW 2005-2013 averages

Climate maps

Air temperature

1981 – 2010 average



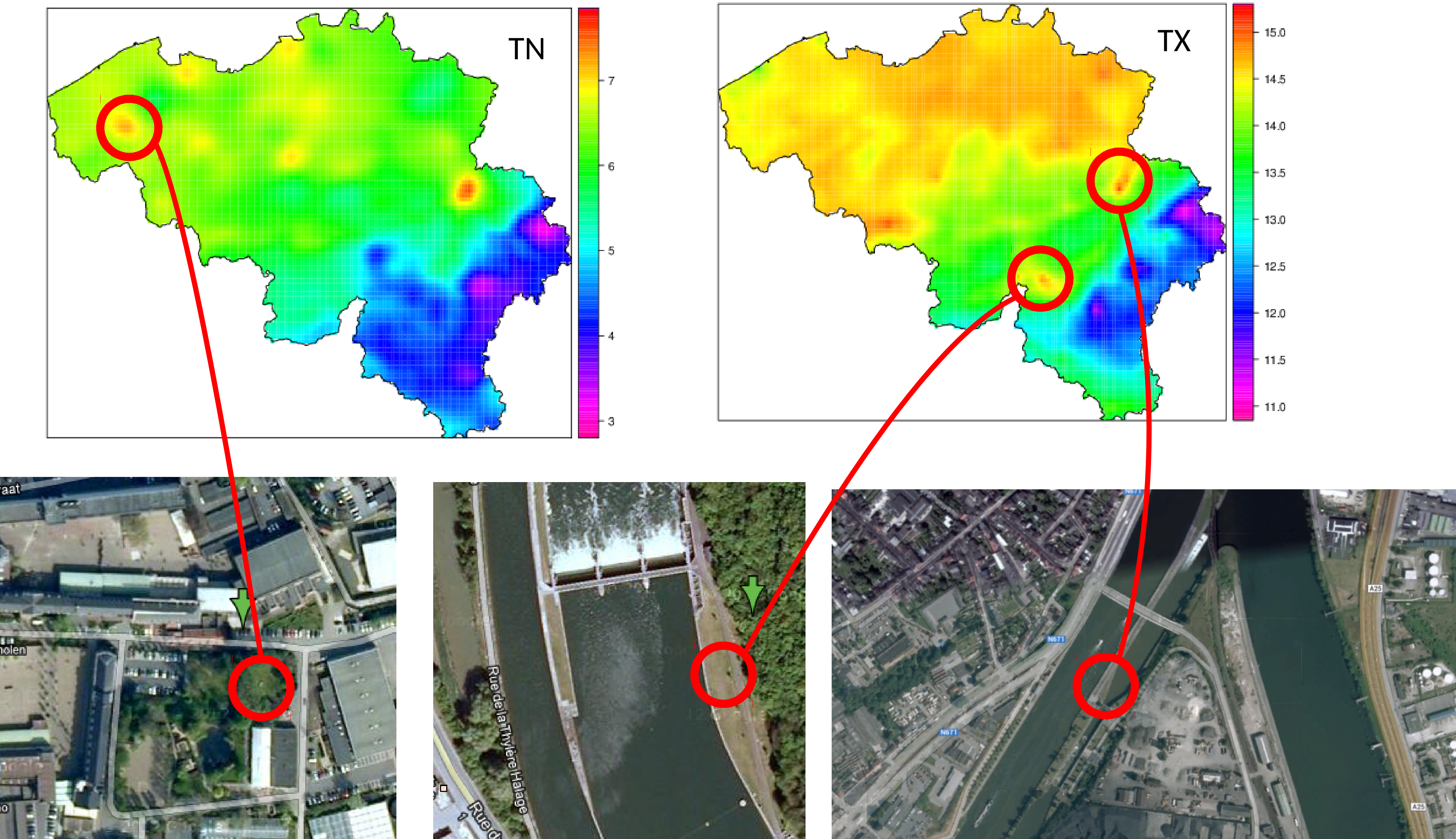


external drift kriging: observations + terrain elevation

Climate maps

Air temperature

1981 – 2010 average



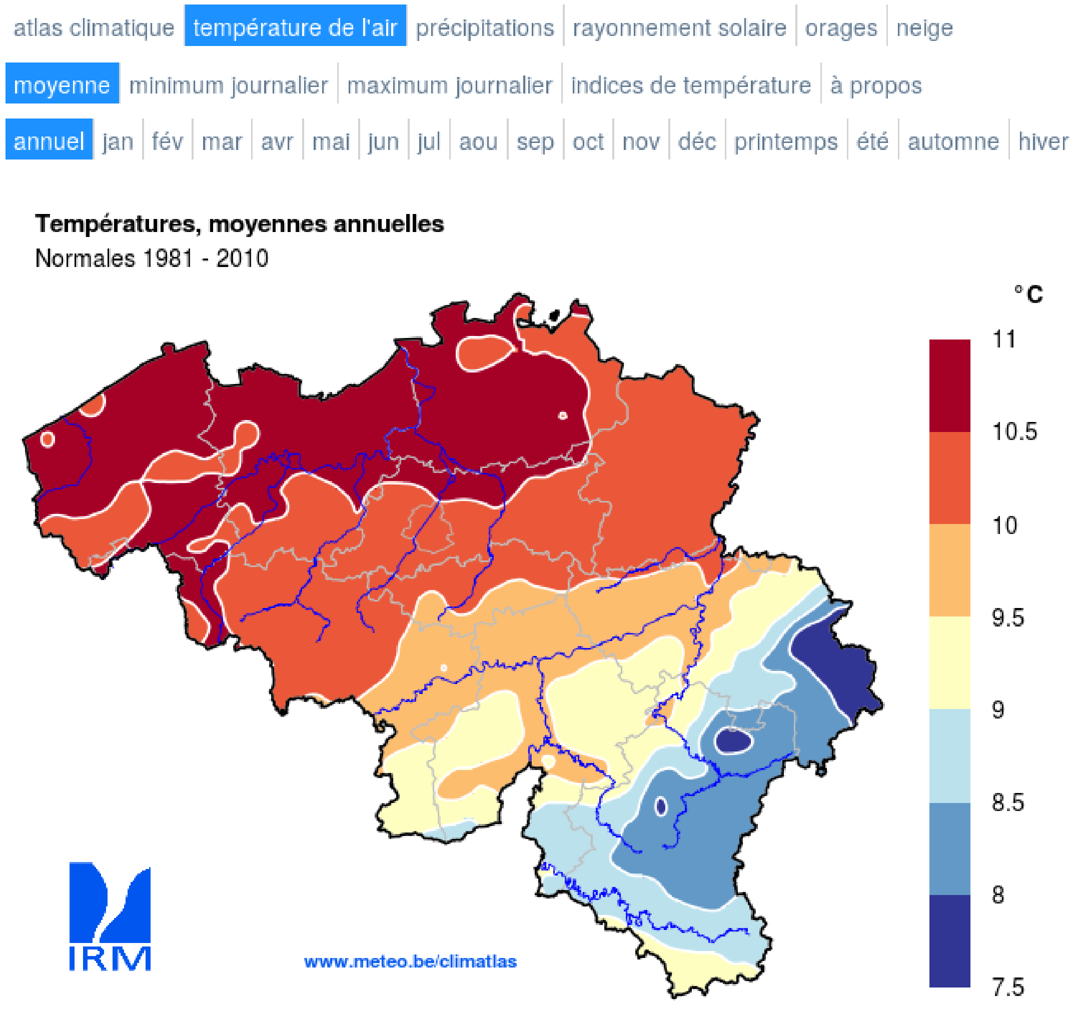
Climate maps

Air temperature

removal of stations with too little spatial representativeness

+

kriging with measurement uncertainty



Daily observational grids

Parameters

min/max air temperature
precipitation quantity
global + direct solar radiation
sunshine duration
10-m wind speed
relative humidity

Resolution

5km x 5km grid + 589 municipality mean values
daily, monthly, seasonal, annual value

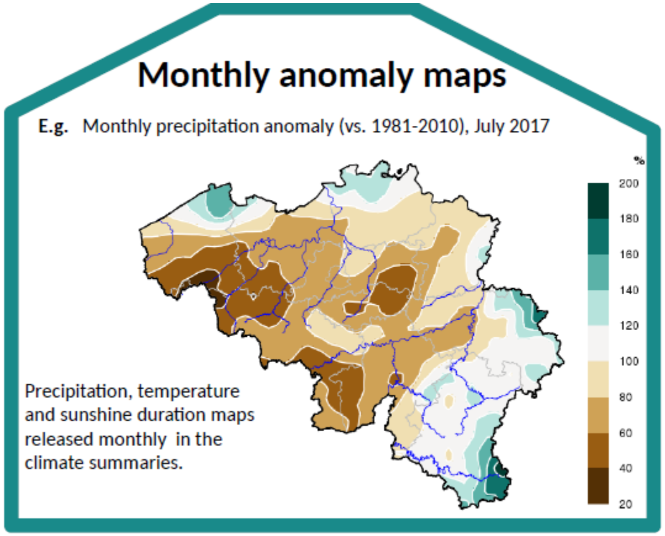
Processing

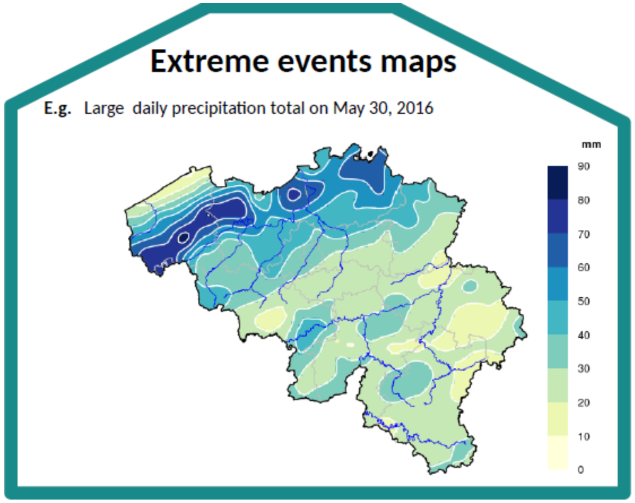
near-realtime processing (next day)
reprocessing for archiving (after fine data quality control)

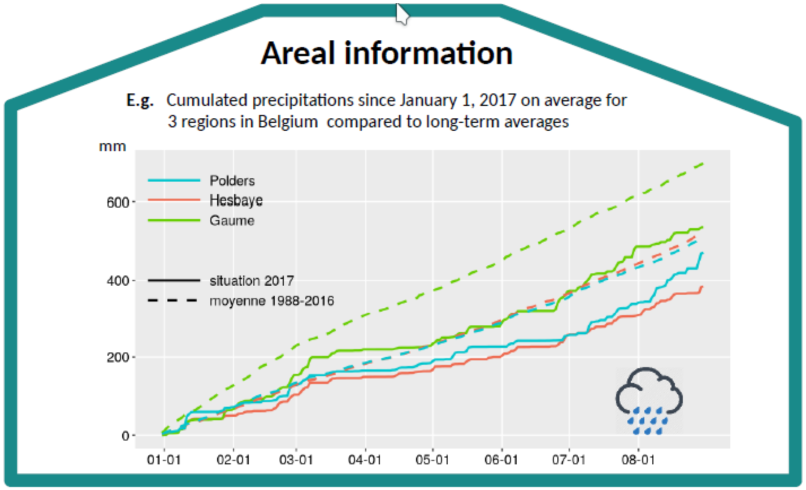
Benefits

climate information for any location and period since 1961
computation of areal averages

→ used for climate monitoring + derivation of climate statistics







Daily observational grids

Observations
from climatological, synoptic and hydrological networks
+ Meteosat Second Generation/MSG

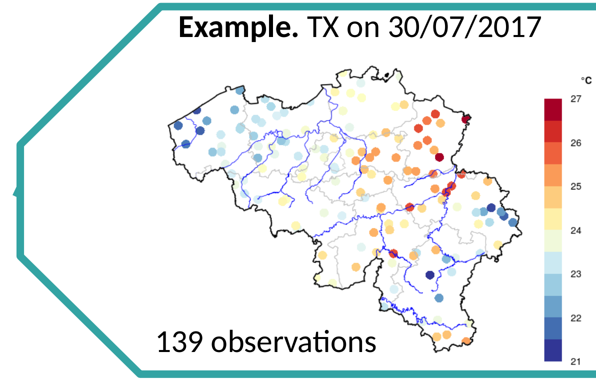
Pre-processing
filtering of raw data (outliers detection, removal of unreliable climatological stations, etc.)

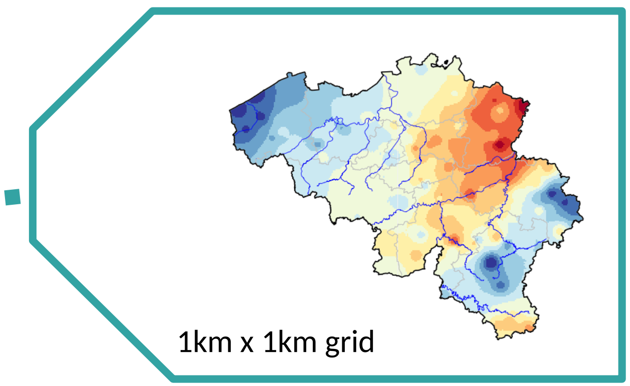
Spatial interpolation
Spatial interpolation on a grid 1km x 1km
External drift kriging with pertinent covariates
→ terrain elevation for TX, TN and RR
→ solar radiation estimates from MSG for G, D and SD
Ordinary kriging otherwise

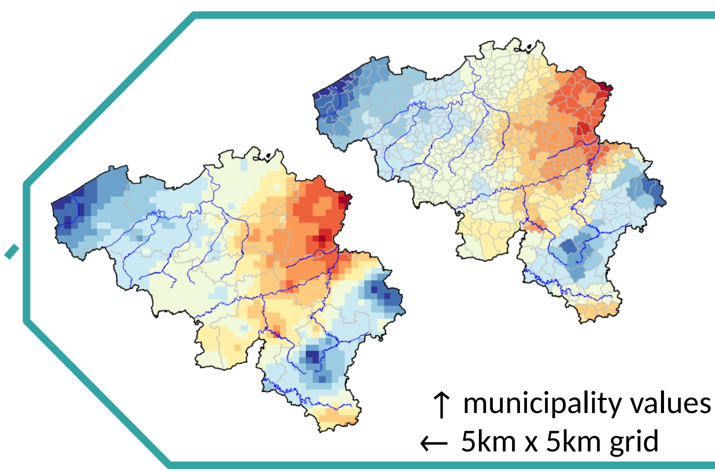
Post-processing
Averaging on 5km x 5km pixels
Computation of municipality values (polygon averages)

Near-realtime grids
Next day morning
Based on filtered raw data

Archiving (1961 - 2017)
Reprocessing with validated data and pertinent covariates (when available)







Daily observational grids

Grid resolution sensitivity

Goal

Determine the most meaningful grid resolution for air temperature.

i.e. Given the stations' density, is a fine grid resolution of 1 km more informative than a coarser grid resolution of 5 km or even 10 km?

Experimental setup

Data from 124 temperature stations from 2012 to 2016

Evaluation of daily grids with a resolution from 1km to 20km by leave-one-out cross-validation

Results

Low impact of the resolution for most stations:

→ RMSE varies by less than 0.2°C for grid resolutions from 1 km to 20 km for 83% of the stations

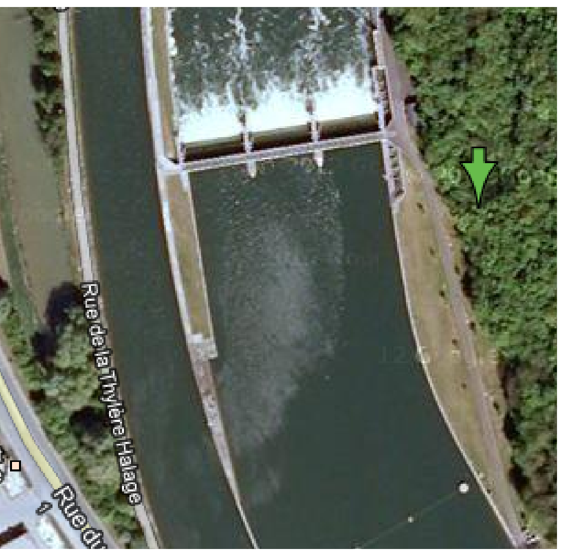
→ P01 and P99 vary by less than 0.2°C for grid resolutions from 1 km to 10 km for 73%

A grid resolution refinement from 5km to 1 km or 2 km improves P01/P99 for 2 stations. No improvement for RMSE. MBE improved by min. 0.2°C for 10 stations but degraded for 14 other stations.

A grid resolution degradation from 5km to 10 km or 20 km improves RMSE for 2 stations and P01/P99 for 21 stations.
→ Some nearby stations are not representative for each other (impact of station's environment and local topography)

Daily observational grids

Challenges: stations' sitting condition



Environmental and Ecological Statistics **8**, 297–309, 2001

Spatial interpolation of air temperature using environmental context: Application to a crop model

PASCAL MONESTIEZ,[1] DOMINIQUE COURAULT,[2] DENIS ALLARD[1] and FRANÇOISE RUGET[2]

[1] *Institut National de la Recherche Agronomique, Unité de Biométrie, Domaine St-Paul, Site Agroparc, 84914 Avignon cedex 9, France*

[2] *Institut National de la Recherche Agronomique, Unité de Bioclimatologie, Domaine St-Paul, Site Agroparc, 84914 Avignon cedex 9, France*

Stations' environment classified according to CORINE landcover database

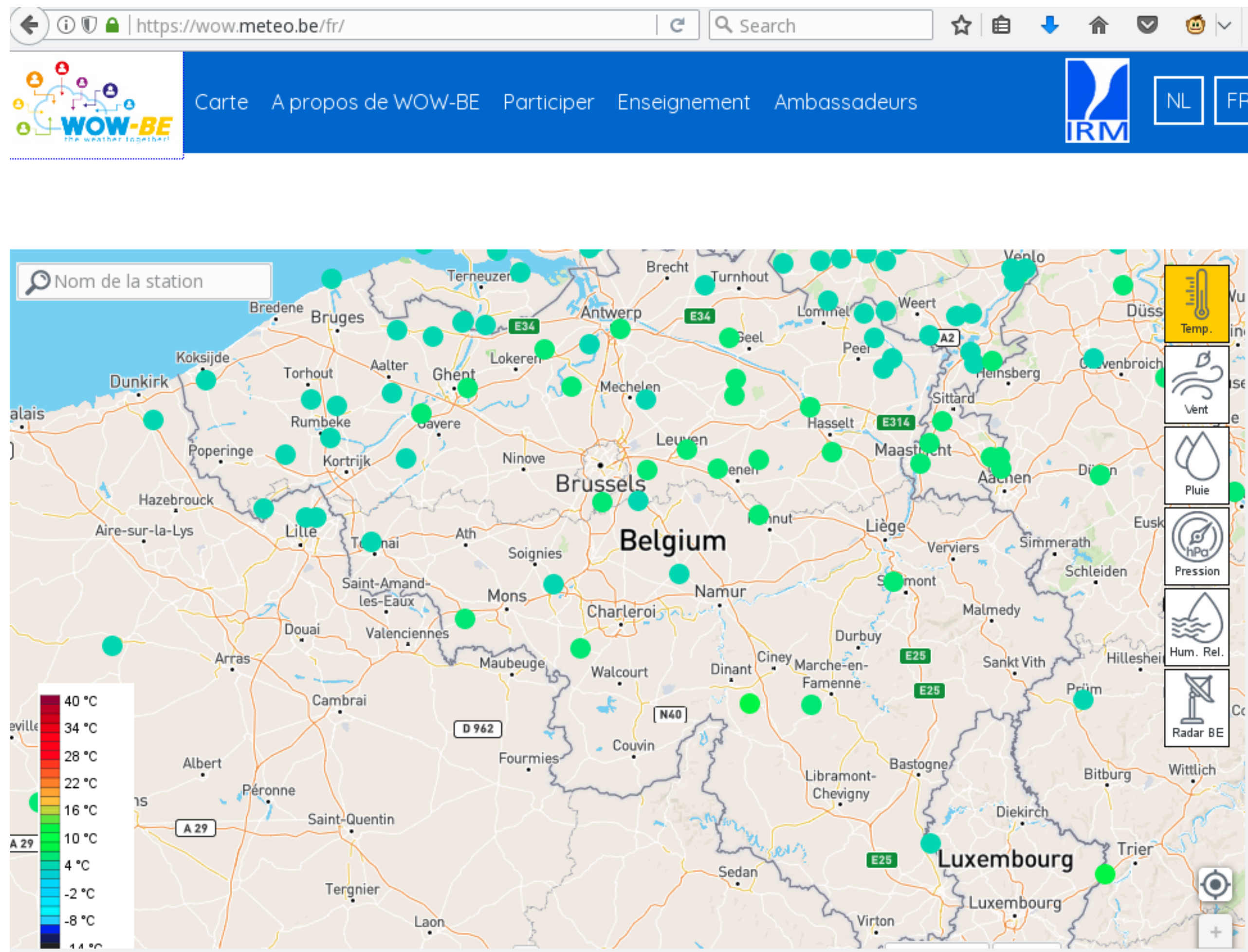
Kriging with categorical external drift

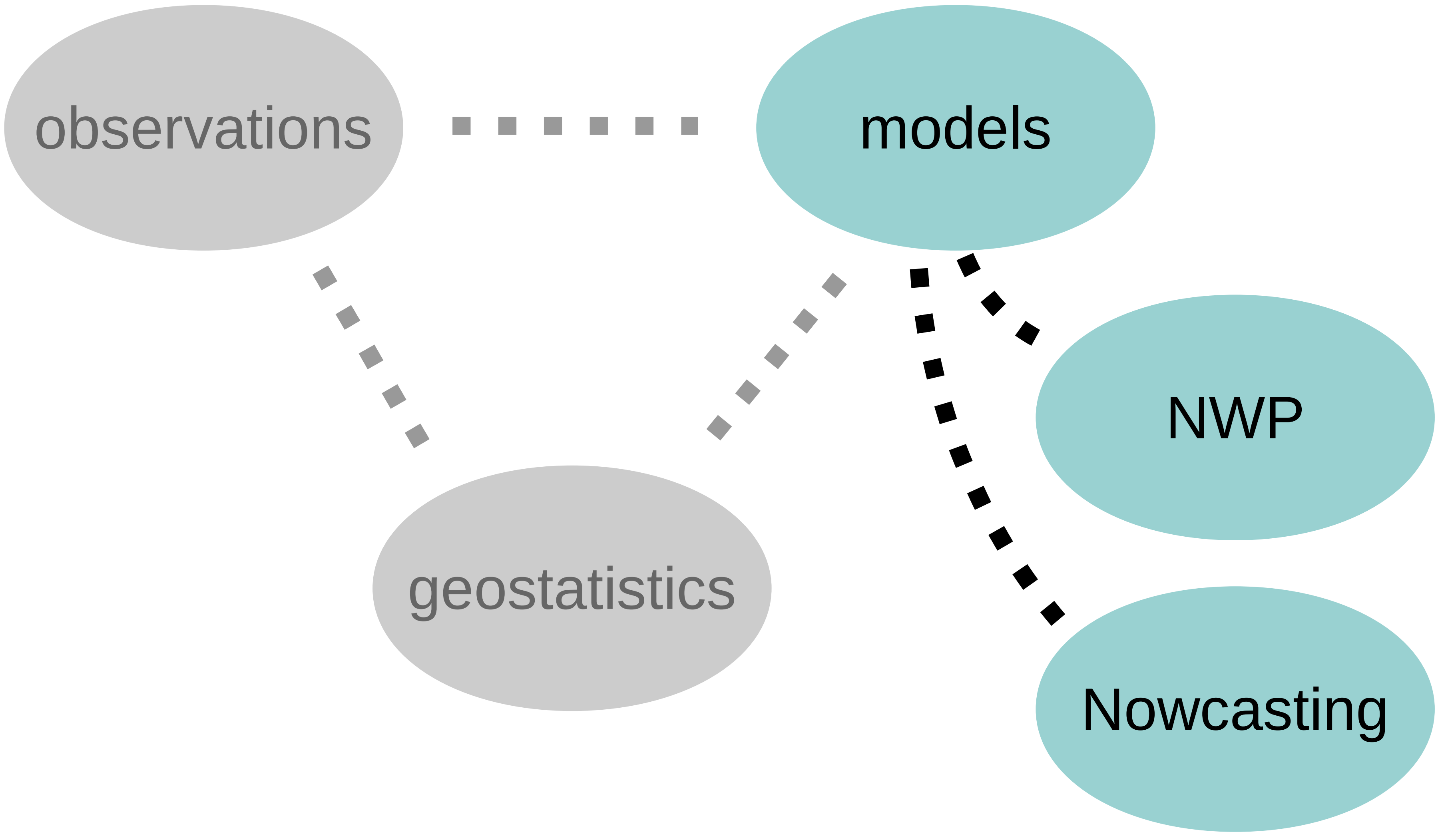
Daily observational grids

Challenges: sensors diversity

Daily observational grids

Challenges: weather enthusiasts data




observations
models
NWP
geostatistics
Nowcasting

Numerical weather prediction

@RMI :
ECMWF IFS, 2 runs/day
+
downscaling by ALARO 4km, 4 runs/day

observations

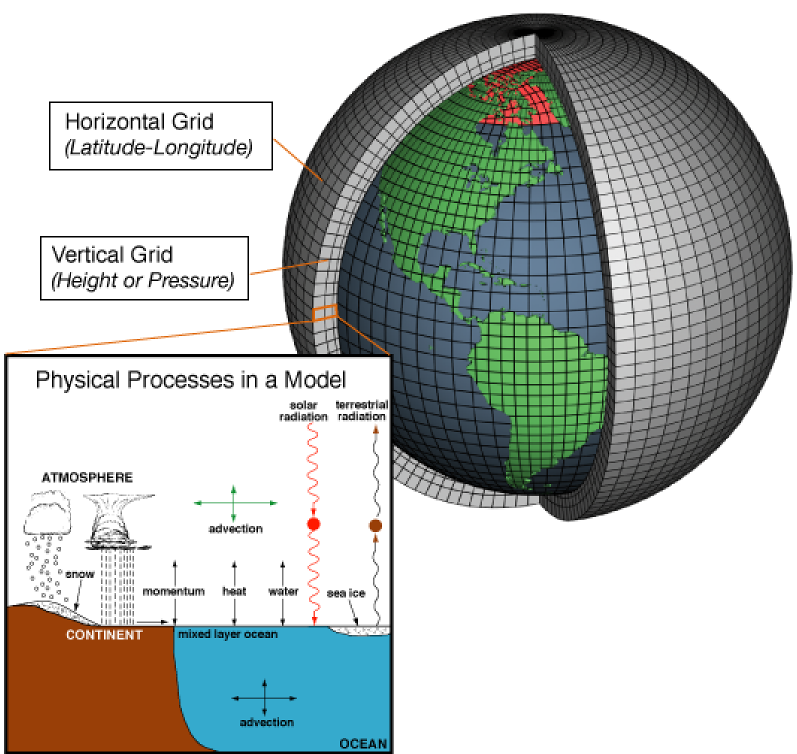
data assimilation

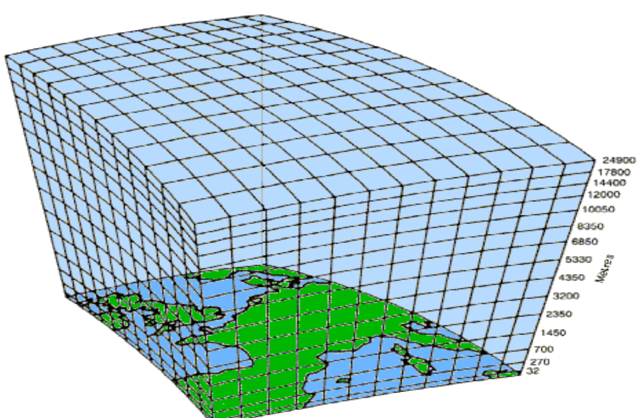
analysis

simulation

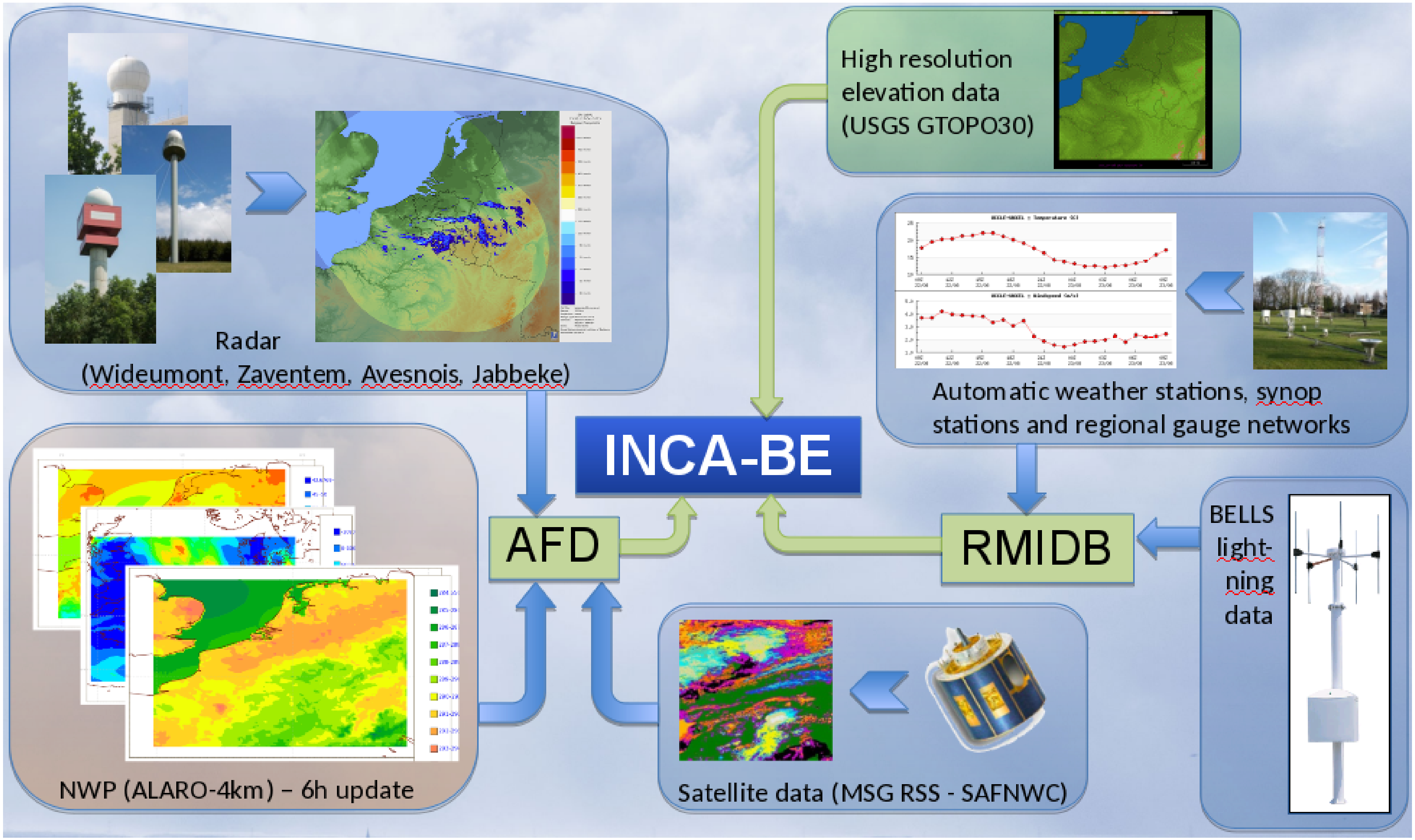
downscaling/ postprocessing

forecast



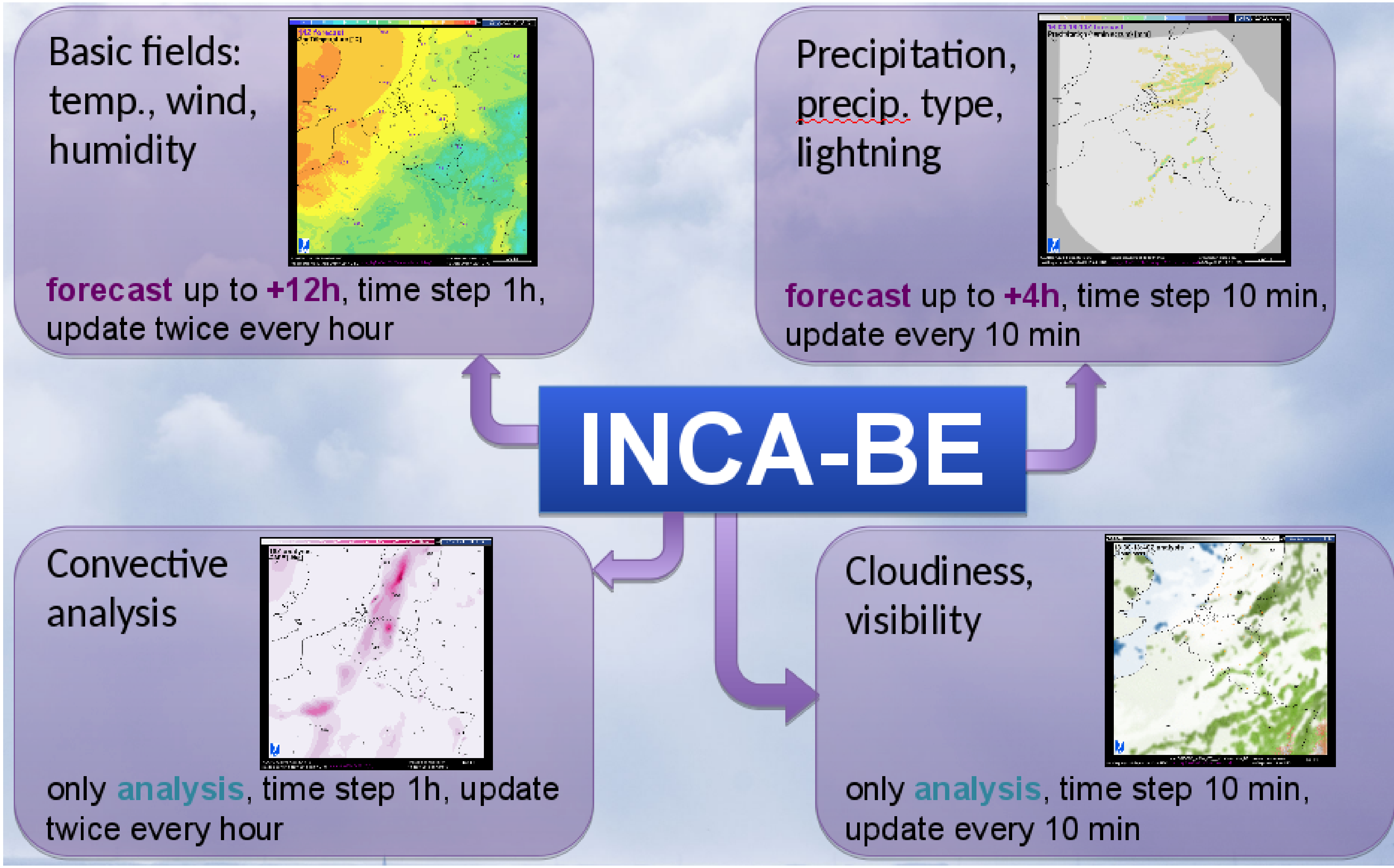


Nowcasting



Radar
(Wideumont, Zaventem, Avesnois, Jabbeke)
High resolution elevation data (USGS GTOPO30)
Automatic weather stations, synop stations and regional gauge networks
INCA-BE
AFD
RMIDB
BELLS light-ning data
NWP (ALARO-4km) – 6h update
Satellite data (MSG RSS - SAFNWC)

Nowcasting


Basic fields:
temp., wind,
humidity
forecast up to +12h, time step 1h,
update twice every hour
Precipitation,
precip. type,
lightning
forecast up to +4h, time step 10 min,
update every 10 min
INCA-BE
Convective
analysis
only analysis, time step 1h, update
twice every hour
Cloudiness,
visibility
only analysis, time step 10 min,
update every 10 min

INCA-BE

temperature and relative humidity analysis

3D NWP output
4km, hourly

↓ **trilinear interpolation**

3D NWP
1km, hourly

↓ **bias correction based on observations**
(2d surface layer + 3d correction model)

3D INCA
1km, hourly

inverse distance interpolation of surface layer bias

+ correction specific to complex orography

+ evaporative cooling due to precipitation

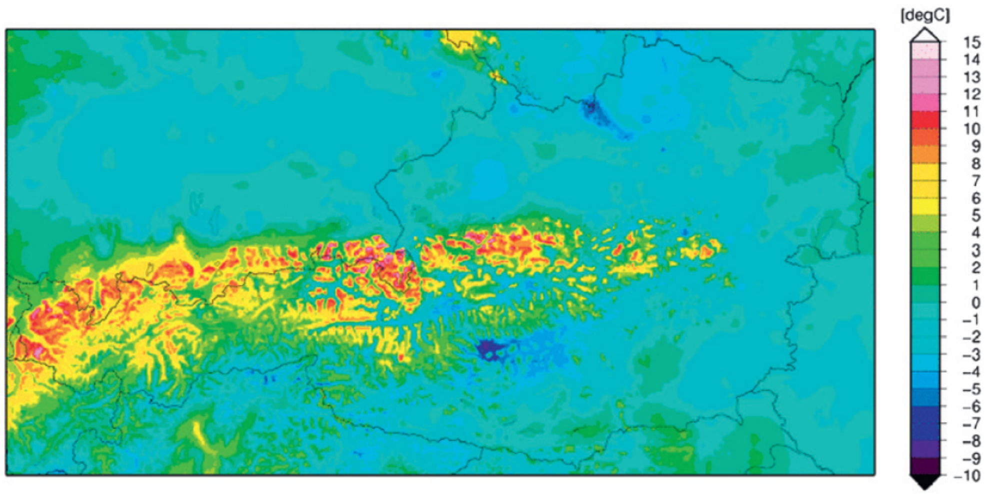
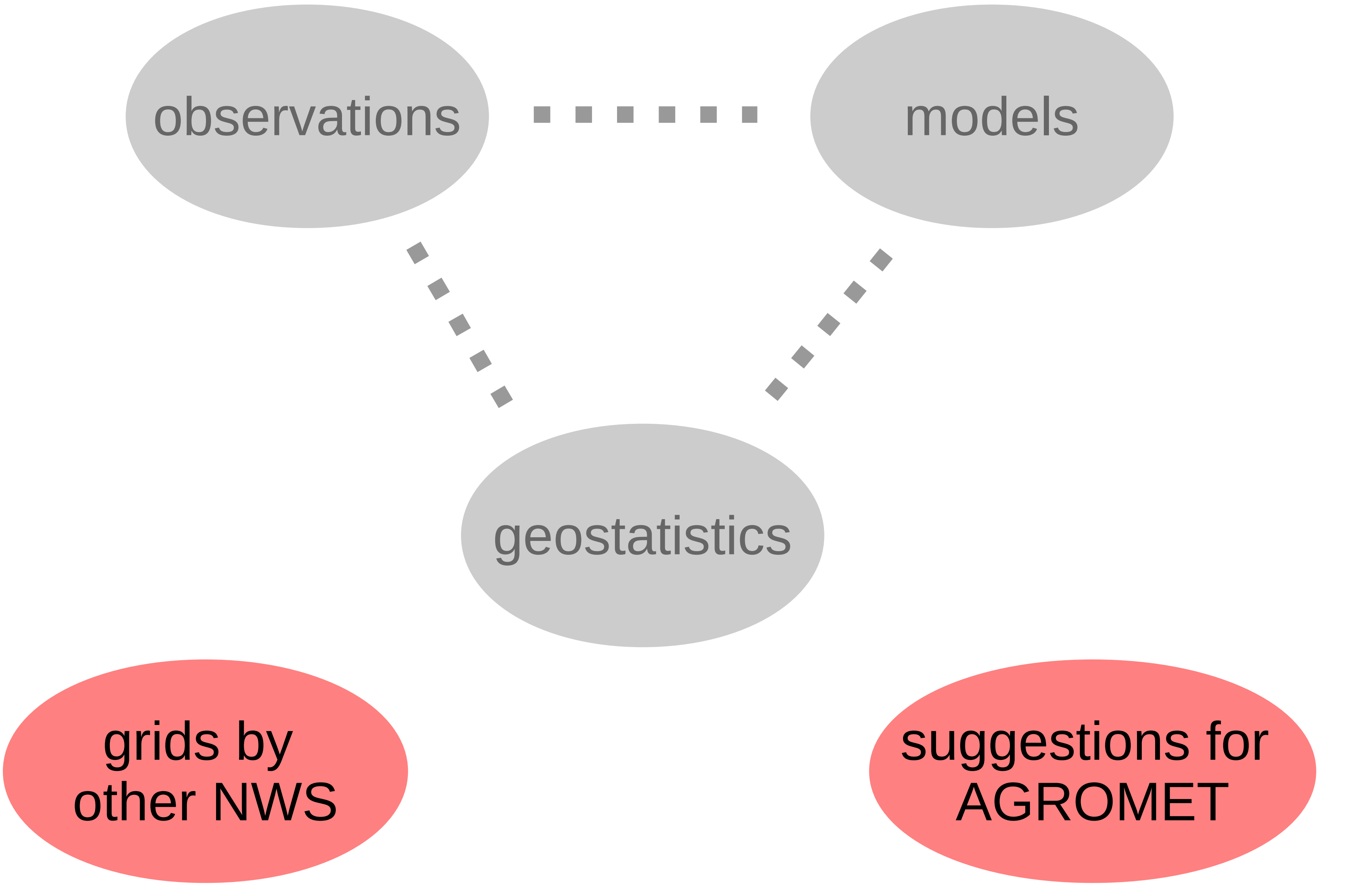


FIG. 7. Example of an INCA temperature analysis during a typical mixed foehn–inversion situation at 0800 UTC 21 Nov 2007. Cold-air pools are present in valleys and basins, while foehn-induced subsidence and mixing create high temperatures at elevations between 1500 and 2000 m.

Seamless weather prediction

→ hourly 1km x 1km forecasts till 10 days = ModelBEST grid


observations
models
geostatistics
grids by
other NWS
suggestions for
AGROMET

Observational grids by other NWS

KNMI

1 km

daily air temperature: block IDW (block size 20km,
search radius 110km)

daily precipitation: OK after square root transformation
daily variogram fitting

(+ hourly precip. grids: rain-gauges adjusted radar data)

MeteoSwiss

2.2 km

Frei et al., 1998
Frei, 2014

daily precipitation, temperature, solar radiation, sun duration
(+ hourly precip. grids: rain-gauges adjusted radar data)

daily air temperature:
1. estimation of a regional non-linear vertical profile
2. interpolation of residuals (non Euclidean distance)

daily precipitation:
interpolation of daily anomalies (non Euclidean distance)

DWD

1 km

Krähenmann et al., 2016

hourly grids, 12 variables, observations + satellite + model

hourly air temperature: adaptation of MeteoSwiss method
based solely on in-situ observations

Observational grids by other NWS

Met Office

5 km

Perry et al., 2009

daily air temperature:

1. regression of daily anomalies with latitude, longitude, altitude, coastal influence, density of urban land use

2. IDW interpolation of residuals

daily precipitation: IDW interpolation of daily anomalies

ECA&D

25 km

Haylock et al, 2008

daily air temperature and precipitation for whole Europe.

1. thin plate spline for monthly averages

2. kriging of daily anomalies (+ elevation for temperature) use of a climatological variogram

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METEO FRANCE

8 km

observations + NWP model = SAFRAN

Optimal interpolation ($\simeq$ external drift kriging)

Suggestions for AGROMET

Before starting to interpolate, **gain in-depth knowledge** about the PAMESEB network:

→ In order to tune the automatic filters:
- inventory of typical measurements errors
- train correction models for systematic errors (based on comparisons in Humain)

Start with the interpolation of **annual (or multiannual) averages**

→ In order to get insight on the spatial representativeness of each station (= impact of sitting condition)

The benefit of INCA-BE analysis as a covariate could be evaluated (e.g., by cross-validation).