Smart4RES

Sponsored by INSTITUT CARNOT M.I.N.E.S

Final conference

Paris, 14 April 2023

ARMINES | MINES PARIS | PSL | METEO FRANCE | INESCTEC | energy & meteo systems | whiffle precision weather forecasting | DNV | DTU | Imperial College London | DLR | Dowel innovation | NEW by EDP & CTG | ICCS | HEDNO

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

Session 2

Advances in Weather Modelling

10:00-11:00	**SESSION 2: ADVANCES IN WEATHER MODELLING** Moderator: Laure Raynaud, Météo France ▪ **RES-dedicated weather forecasting models** Q. Libois (Météo France) ▪ **High-resolution weather models - Large Eddy Simulation (LES): the future** R. Verzijlbergh (Whiffle) ▪ **Improvement of solar forecasting through the use of multi-source observations** J. Lecaza (DLR)

Smart4RES

MORNING SESSIONS

Smart4RES

Final conference
14 April 2023

RES-dedicated weather forecasting models

Quentin Libois, Laure Raynaud, Marie Cassas,
Bastien Alonzo, Ivana Alexovska

Météo-France

METEO FRANCE

This project has received funding from the European Union's Horizon 2020
research and innovation programme under grant agreement No 864337

OUTLINE

1. Context and challenges
2. Enhanced numerical weather prediction (NWP) models
3. Taking advantage of ensemble simulations
4. Key take aways

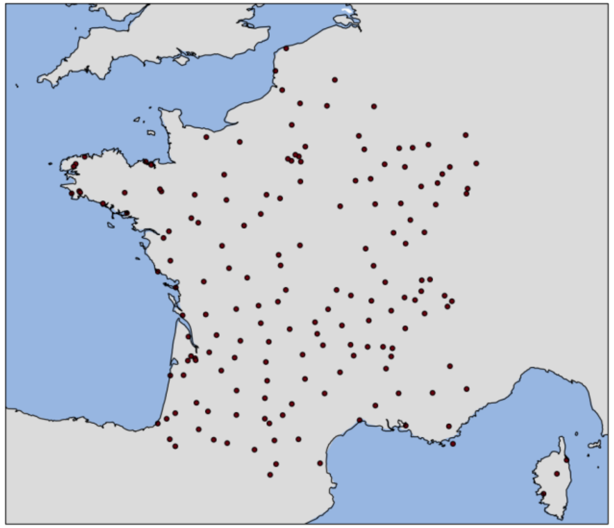
CONTEXT & CHALLENGES

- **Renewable energy sources (RES) prediction is key to increase the share of RES in the electrical grid** (high variability, production anticipation, reduced penalties …)

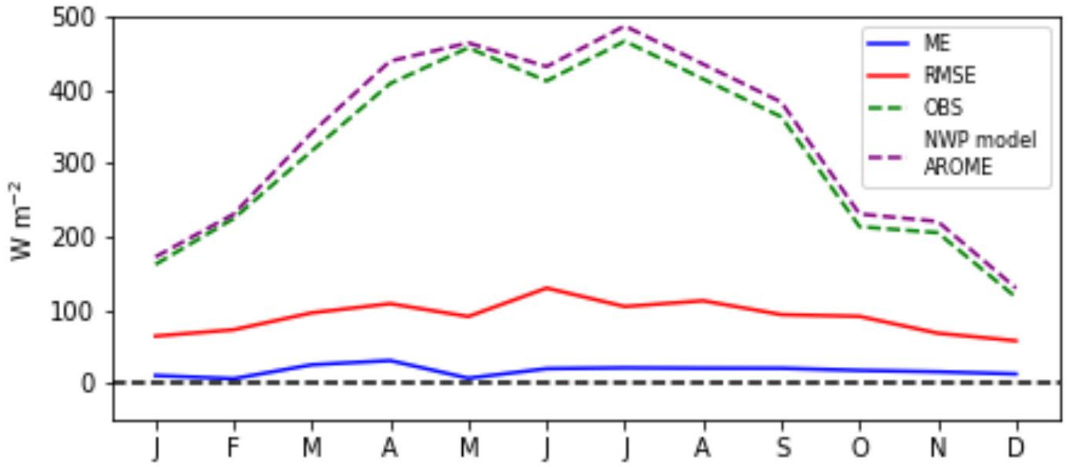
- **Initial challenges**
  - Numerical Weather Prediction (NWP) models do not always perform well for RES-relevant variables
  - Weather scientists and RES experts don't talk much to each other
  - RES users take off-the-shelf weather forecasts from NWP models

- **Challenges tackled in Smart4RES**
  - **How can NWP models contribute to the deployment of RES production?**
  - **How to improve the performance of NWP forecasts for RES prediction?**
  - **How to optimally handle the large amount of NWP models outputs?**
  - **How to increase end-users awareness?**

Enhanced NWP models – tailored for RES needs



Météo-France network for solar radiation observations



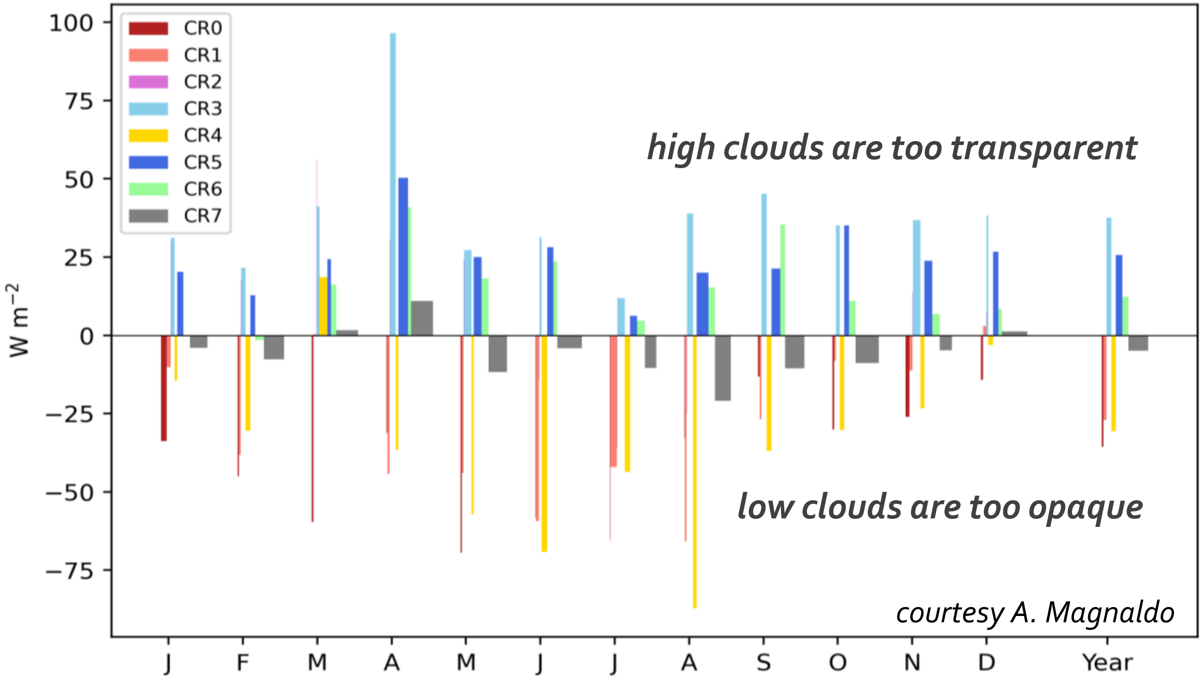
Solar radiation bias (blue) and RMSE (red line) of French operational AROME model over France in 2020 (mean flux = 240 W m^{-2}, bias = 18 W m^{-2}, RMSE = 97 W m^{-2})

NWP models are primarily designed to predict near-surface temperature and wind, and precipitation *(not particularly surface solar radiation or wind at hub height)*

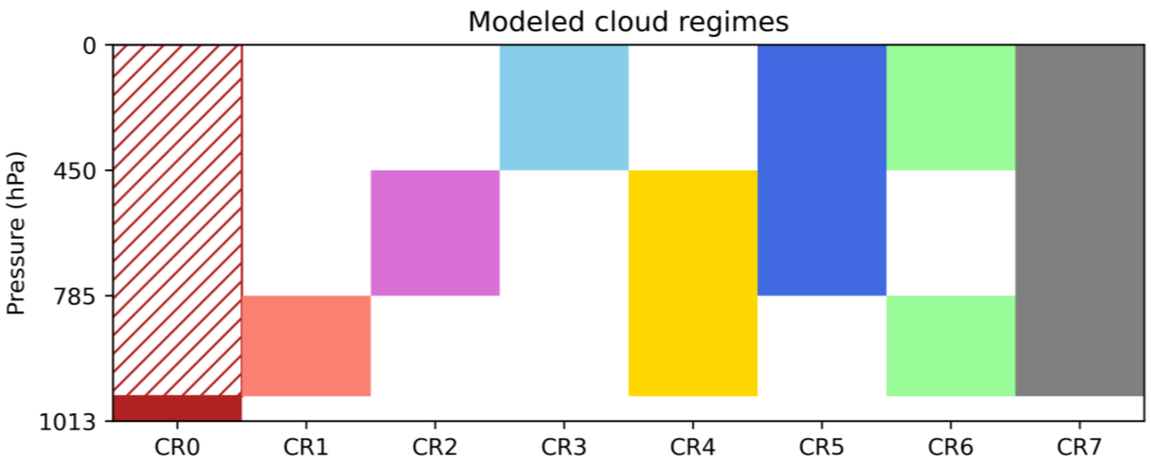
NWP models scores (hence calibration) **do not account for RES-relevant variables**

Errors in wind at hub height and solar radiation **can be significant**

Enhanced NWP models – tailored for RES needs



Monthly solar radiation bias for different AROME cloud regimes (see right) under overcast conditions



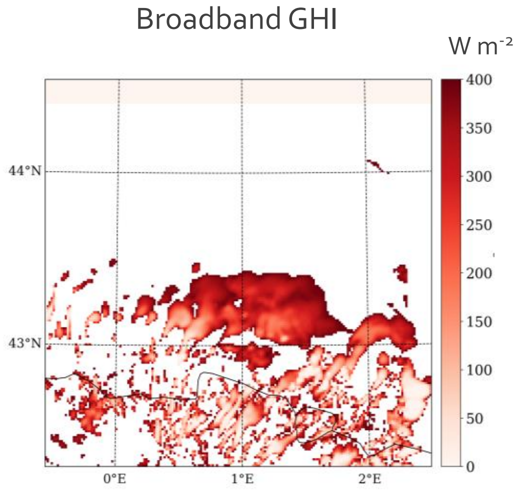
Cloud regimes used to evaluate distinct AROME situations

Detailed analysis of RES variables can help identify forecasting issues

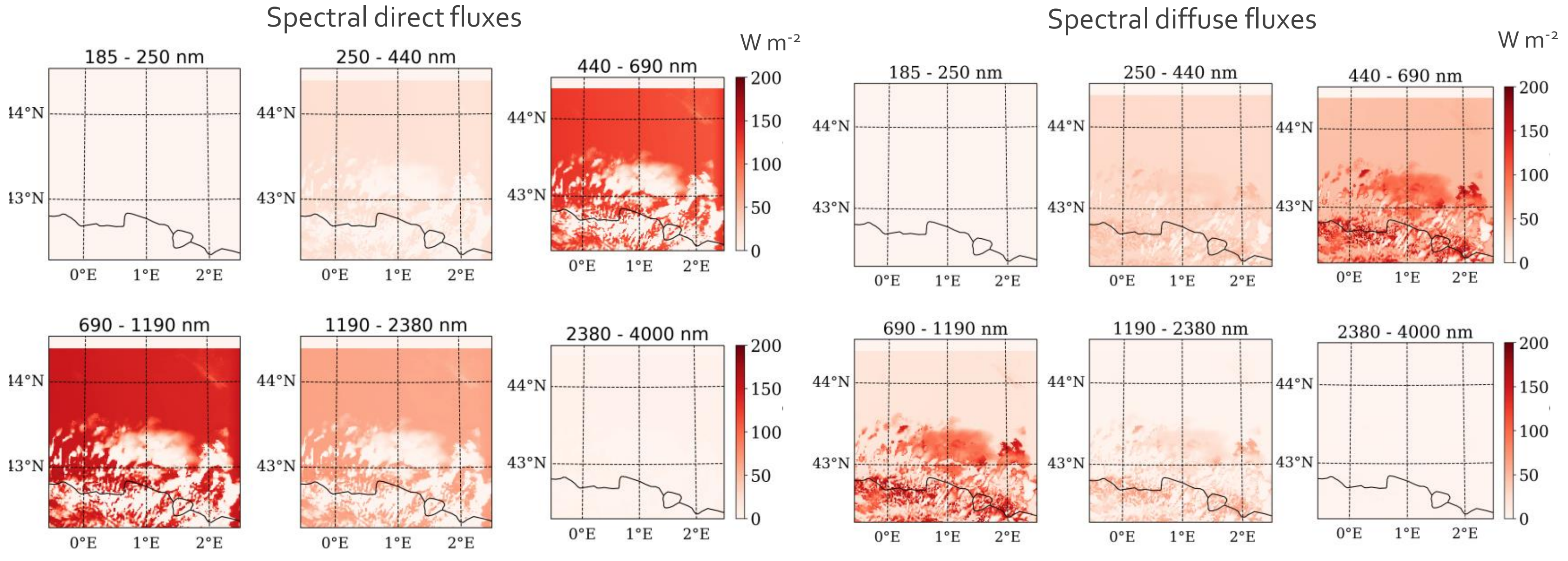
Further developing the **evaluation of RES variables in NWP models will improve RES forecasts**

RES-versions of NWP models could be developed

Enhanced NWP models – new outputs



Standard output



Enhanced outputs

Additional internal variables can be extracted from NWP models

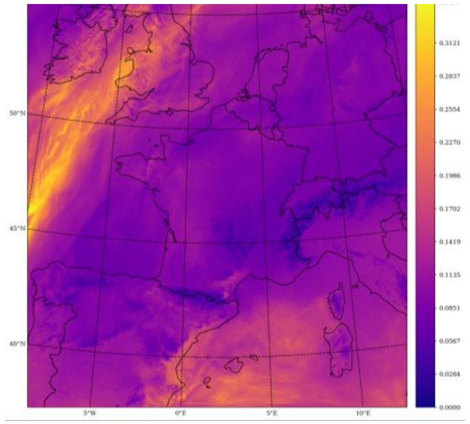
(e.g. cloud optical thickness, direct/diffuse/spectral radiation)

Not yet extracted because extra computation/storage/transfer cost and/or no demand/need

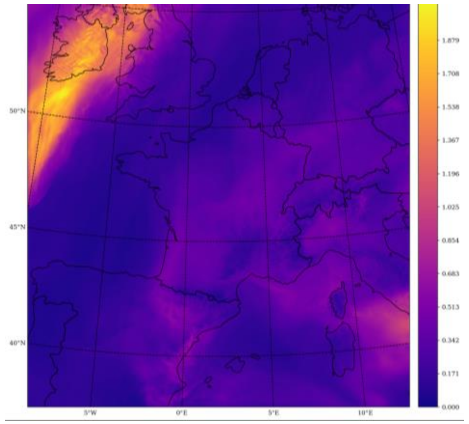
Useful variables to be identified and assessed by final users → user awareness to be developed

Enhanced NWP models – refined physics

Dust event over France on 24 Feb 2021

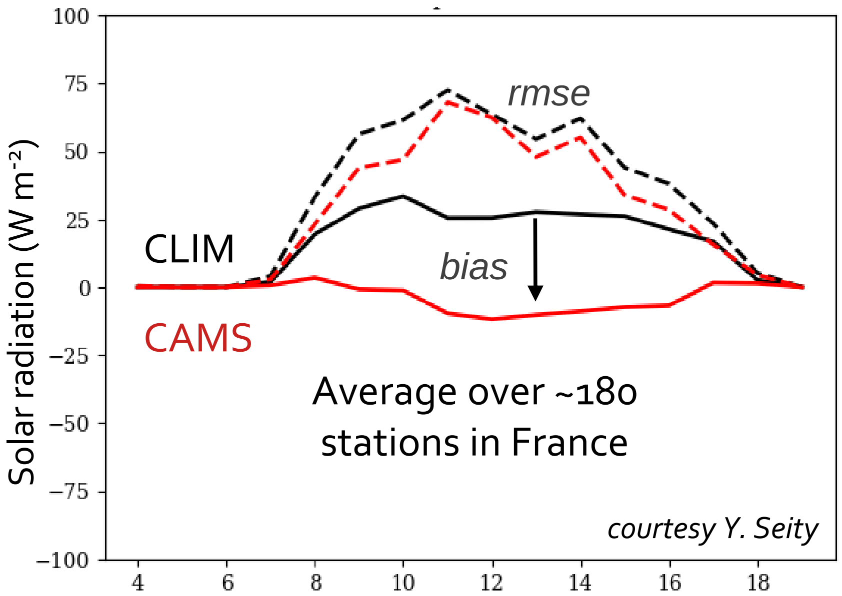


Climatological Aerosol Optical Depth (AOD) over France~0.15
Operational AROME



CAMS (real-time) AOD over France~0.6
Upcoming AROME version

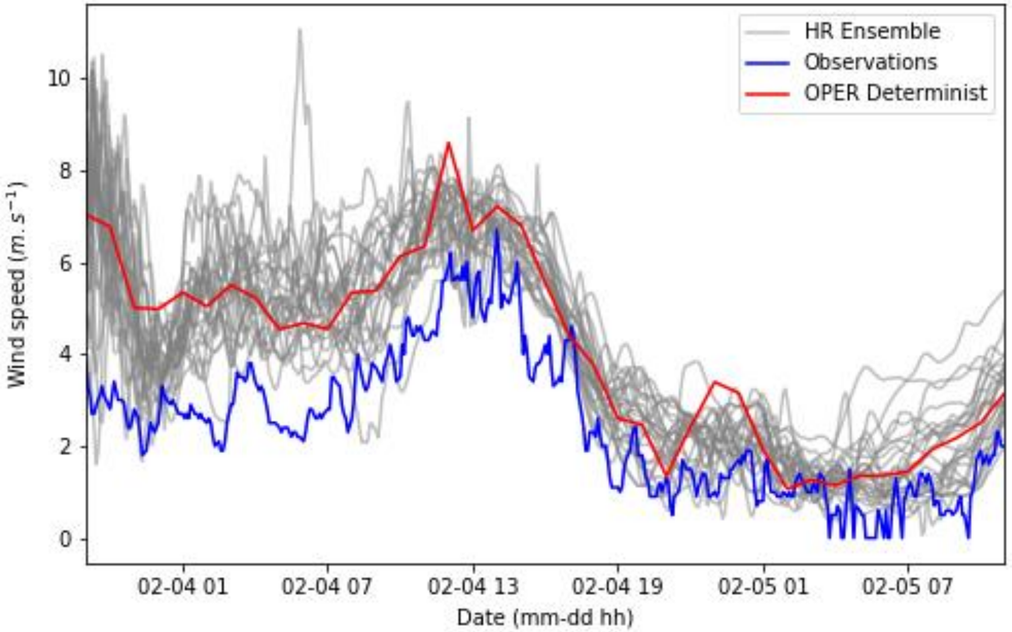
30 W m^{-2} positive bias largely reduced



The representation of aerosols (and their impact on solar radiation) **can be improved** by using real-time aerosols instead of monthly climatologies

Physics development priorities are set by needs → feedbacks from users are essential (e.g. RTE)

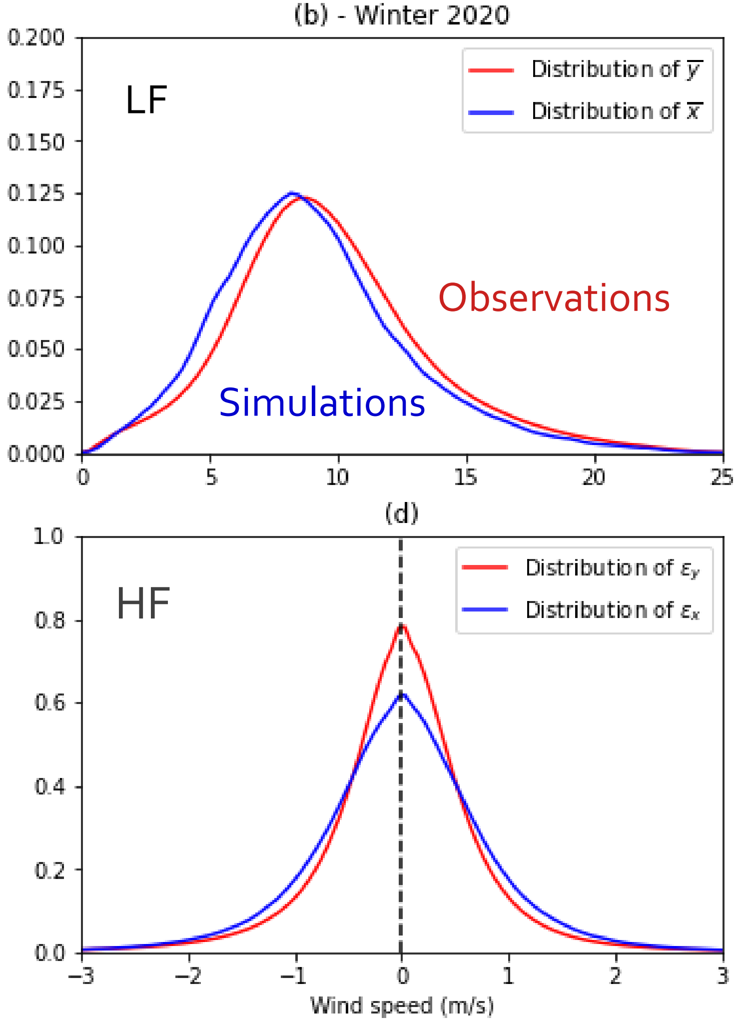
Enhanced NWP models – higher resolution



Comparison between 1-hour (operational, ref) and 5-min (Smart4RES, grey) resolution outputs for wind speed forecasts

Comparison of observed and simulated low-frequency (LF) and high-frequency (HF) variations

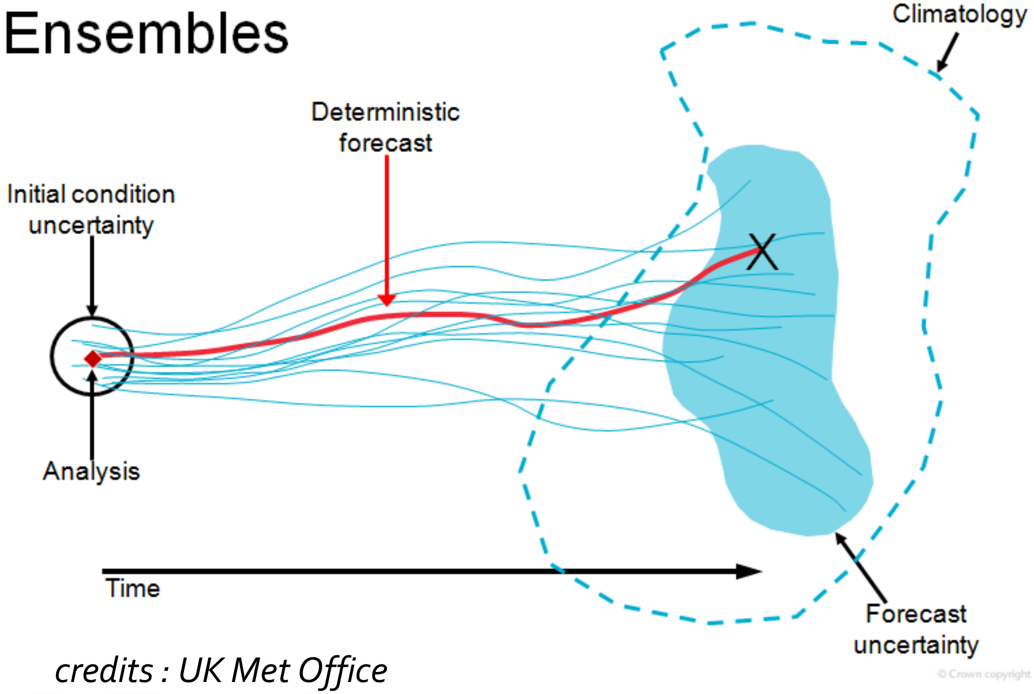
$$x = \bar{x} + \epsilon_x$$



Higher temporal resolution outputs can be available (model time step ~ 1min) **and are physically meaningful**

Data storage issues → full resolution not output

Ensemble simulations



credits : UK Met Office

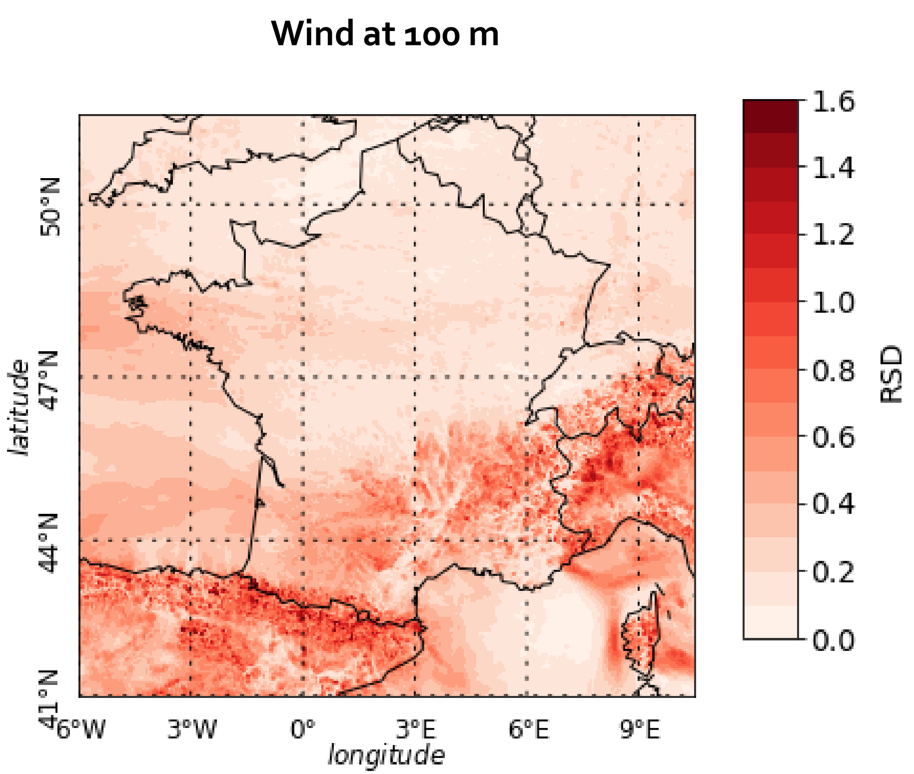
The atmosphere is chaotic
→ ensemble simulations can be used to capture and quantify the uncertainty of its temporal evolution

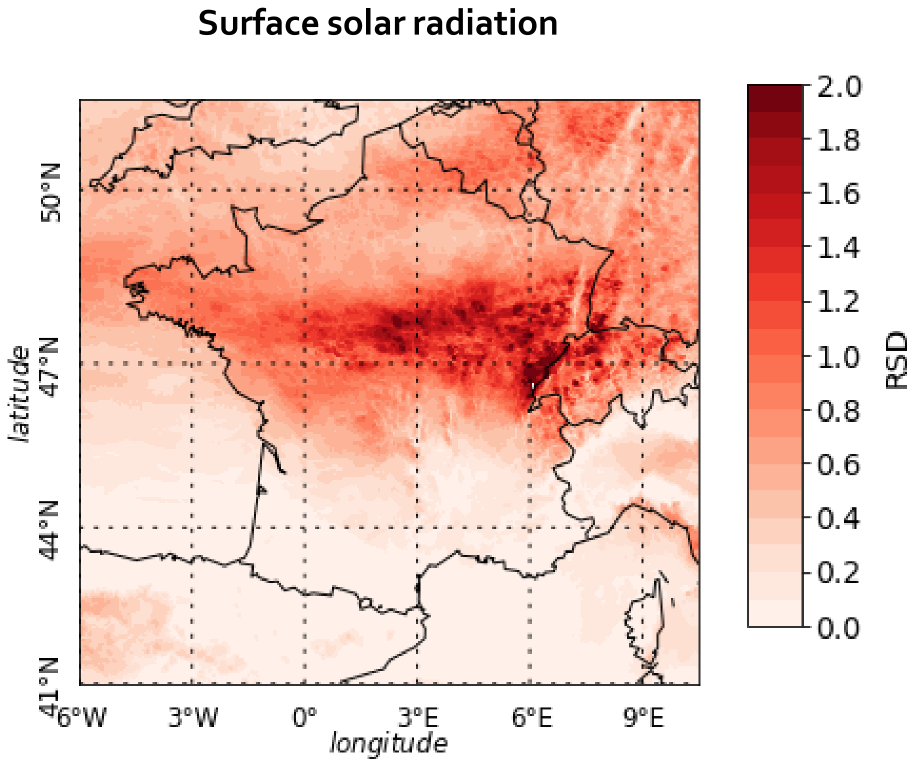
How to **handle the large amount of data** associated to ensemble forecasts?

How to **build user-understandable forecasts**?

How to **build seamless forecasts** from distinct ensembles?

Ensemble simulations – uncertainty





Relative standard deviation (RSD = standard deviation/mean) across an ensemble of 25 AROME members

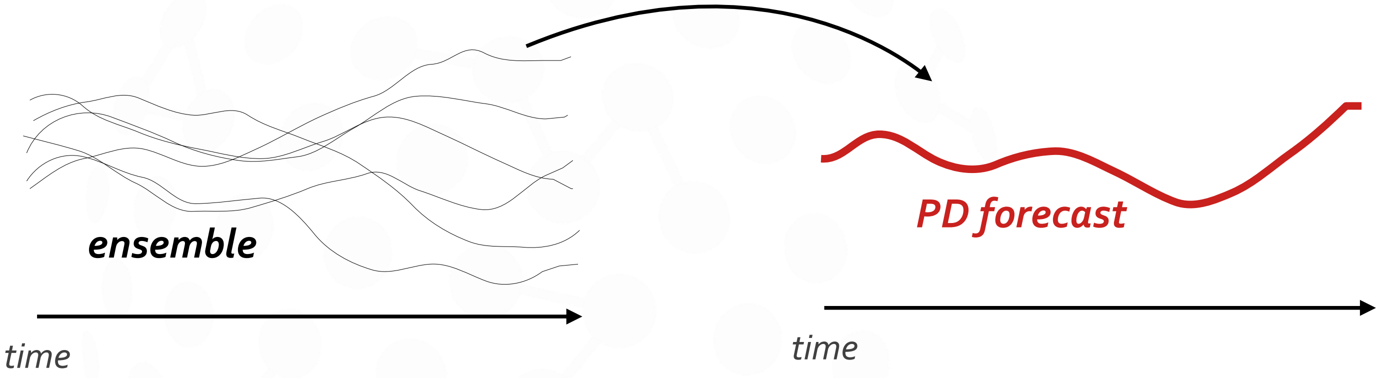
The **variability among ensemble members provides a quantitative estimation of** forecast **uncertainty**

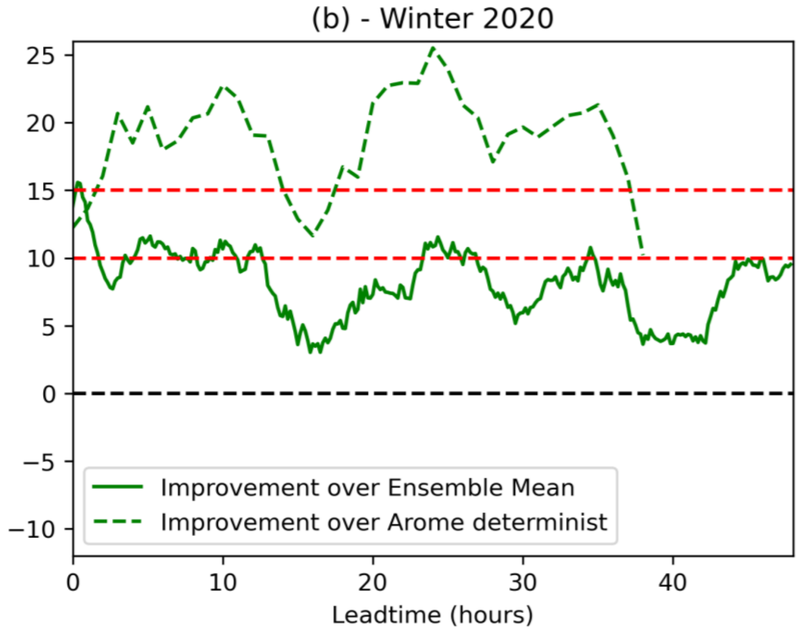
Ensemble simulations – pseudo-deterministic forecasts

Pseudo-deterministic (PD) forecast

=

building a single forecast from an ensemble of simulations





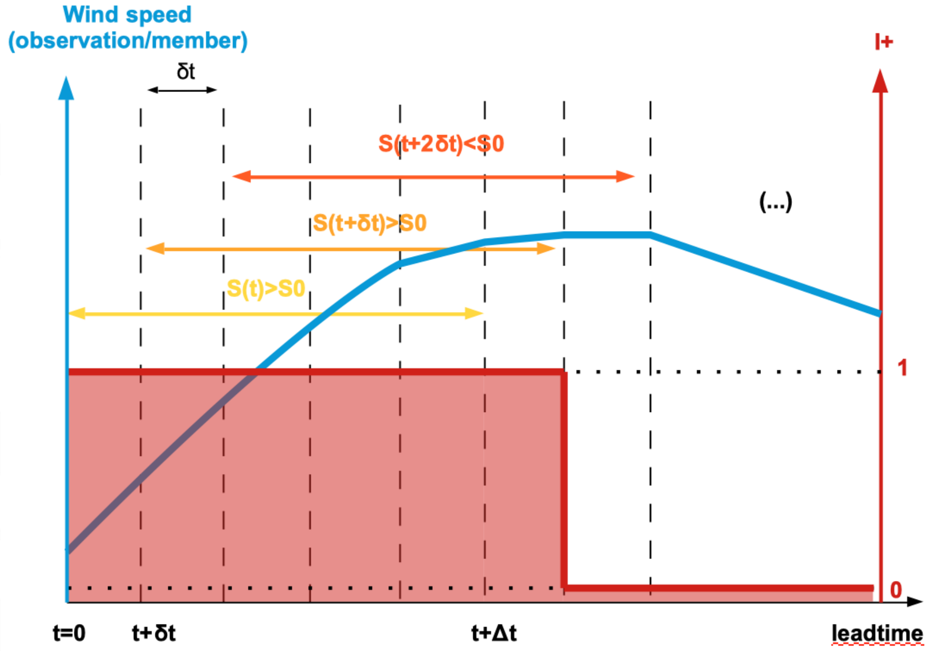
RMSE improvement of PD 100 m wind forecasts

Ensembles contain a wealth of information but **can be hard to handle by the end users**

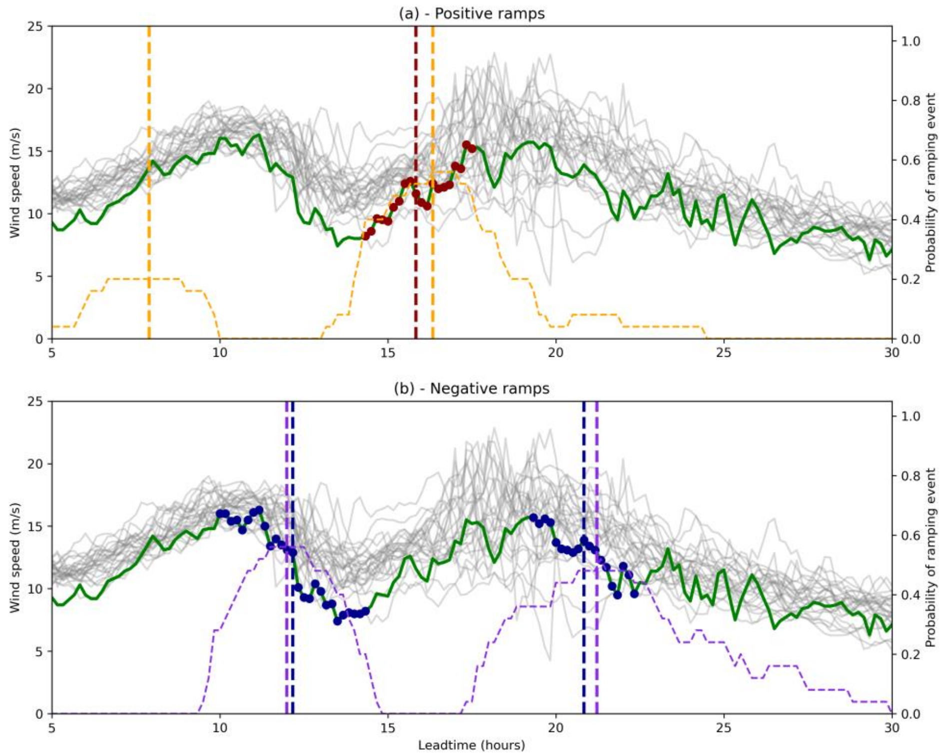
RES production **models often need a single deterministic forecast**

Well designed **PD forecasts** (e.g. percentile) **can outperform ensemble means and deterministic forecasts**

Ensemble simulations – probabilistic products



Schematic description of a positive ramp (threshold S_o)

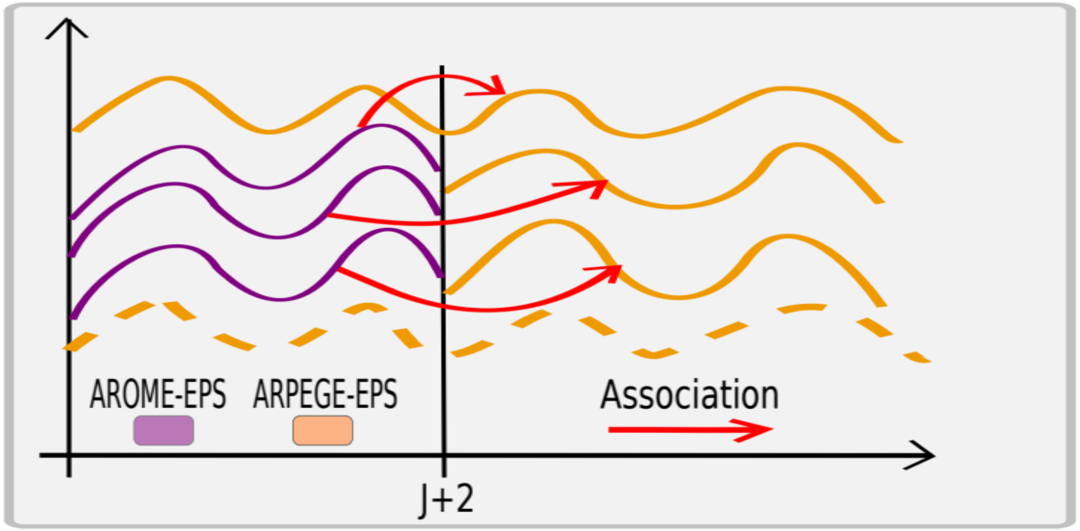


Observed (dots) and simulated (dashed lines) positive (top) and negative (bottom) ram

Rare events (such as wind ramps) **can be detected in ensembles**, sometimes not in deterministic forecasts

Tailored probabilistic products can be built (e.g. different ramp definitions, cut-out)

Ensemble simulations - Seamless forecasts



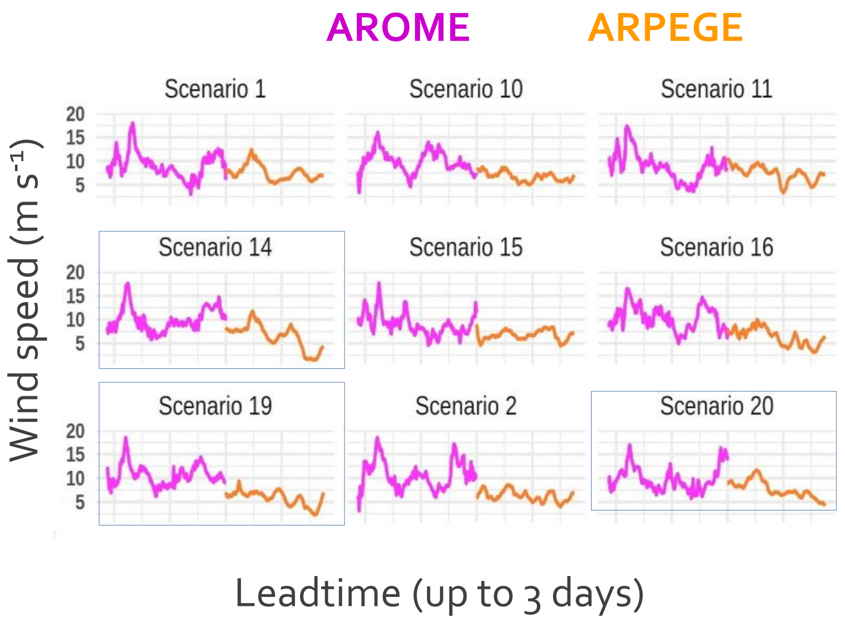
Schematic representation of the seamless junction between the AROME and ARPEGE ensemble forecasts.

Using different models for different leadtimes can be advantageous

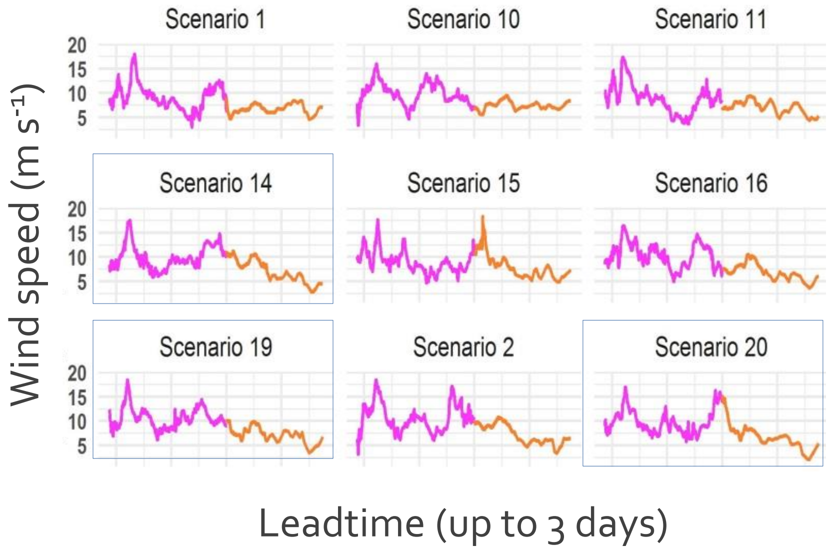
Discontinuity at the junction between models should be minimal for end users

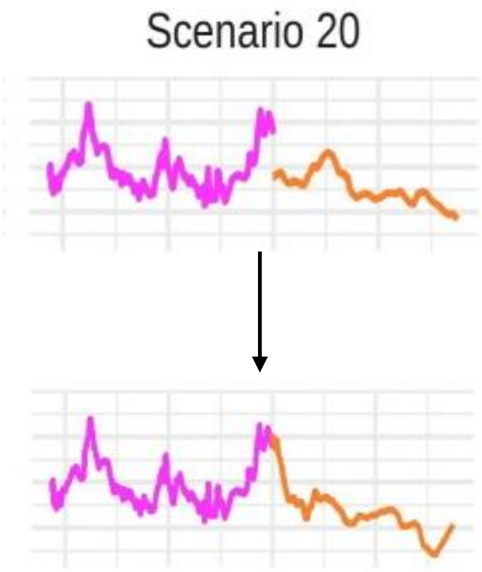
Matching aims at minimizing discontinuity while preserving the number of ensemble members

Ensemble simulations - Seamless forecasts



Random match





Seamless match

Smart matching strategy (e.g. Hungarian method) **ensures minimum discontinuity** of the individual ensemble members

KEY TAKE AWAYS

Weather scientists and RES users should talk more to each other to

- *Get the best out of NWP models (new outputs, finer resolutions ...)*
- *Drive NWP models developments*
- *Derive original RES-dedicated products from weather forecasts*

Ensemble forecasts are becoming the standard of weather prediction

- *They can be used to quantify forecast uncertainties*
- *Post-processing (e.g. PD forecasts, seamless forecasts) can help make them accessible to non-expert users*
- *Tailored probabilistic products can become valuable decision-aid tools*

Quantitative improvements achieved in Smart4RES

- *10-15 % reduction in RMSE for 100 m wind forecasts when using smart PD forecasts*
- *3-5% reduction in RMSE for 100 m wind and solar radiation forecasts with higher spatio-temporal resolution*

FURTHER READING

- Public deliverables : D2.1 and D2.2
- Publications

- Jahangir, E., Libois, Q., Couvreux, F., Vié, B., & Saint-Martin, D. (2021). Uncertainty of SW cloud radiative effect in atmospheric models due to the parameterization of liquid cloud optical properties. *Journal of Advances in Modeling Earth Systems*, e2021MS002742
- Lindsay, N., Libois, Q., Badosa, J., Migan-Dubois, A., & Bourdin, V. (2020). Errors in PV power modelling due to the lack of spectral and angular details of solar irradiance inputs. *Solar Energy*, *197*, 266-278.

Smart4RES

Thank you!

- Quentin Libois, Météo-France: quentin.libois@meteo.fr

Smart4RES

Final conference
14 April 2023

High-resolution weather models
Large Eddy Simulation (LES): the future

Remco Verzijlbergh

Whiffle

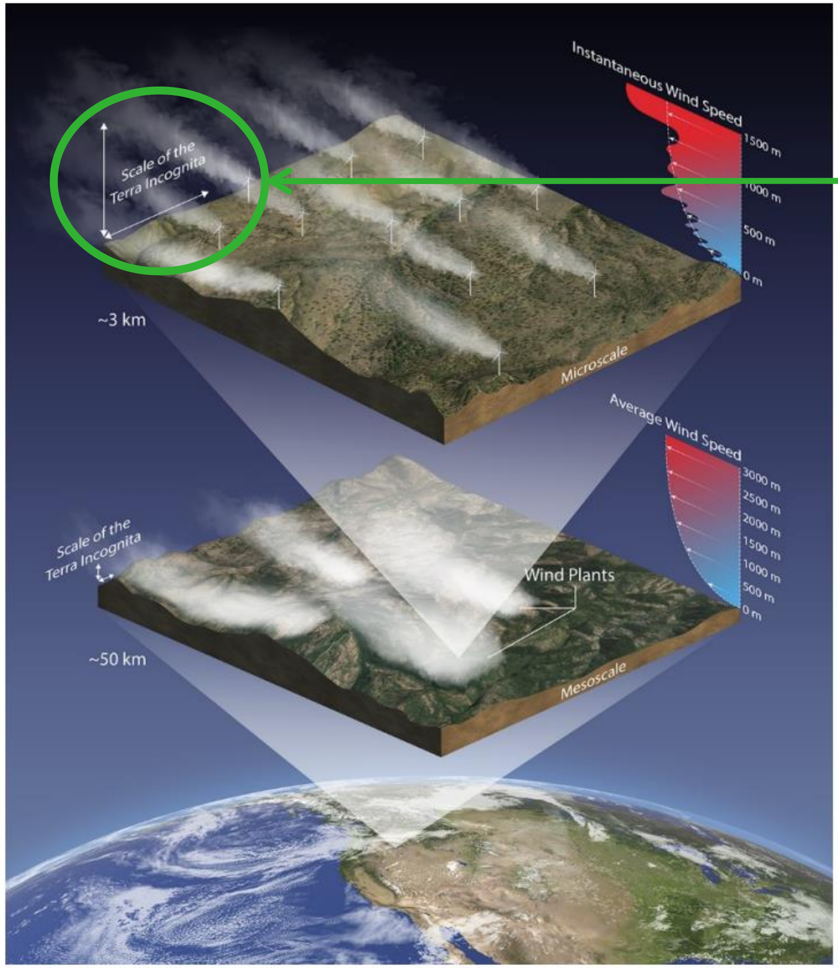
whiffle

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

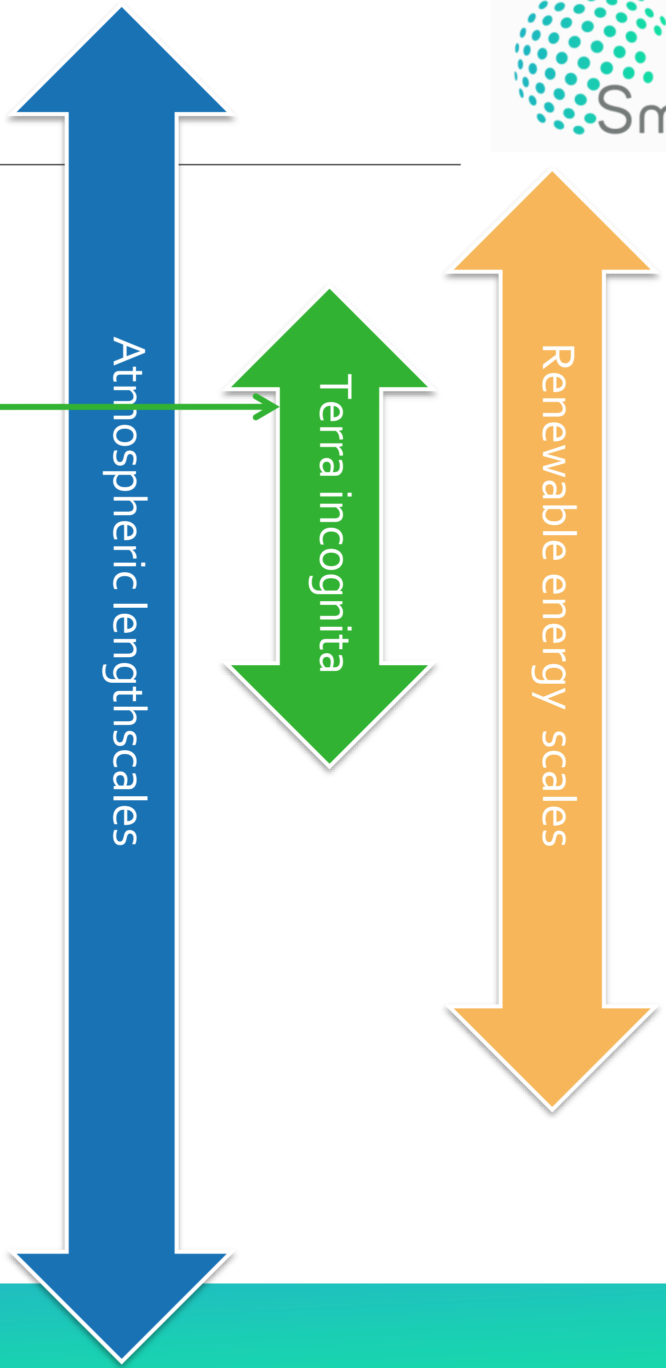
Grand challenges in wind energy

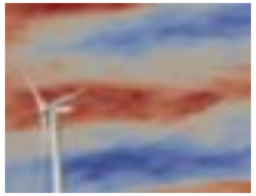
Grand challenges in wind energy:

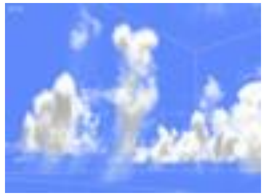
1. Building better turbines
2. Building better wind farms
3. Integrating renewables in the energy system

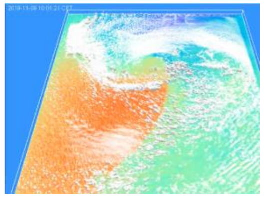


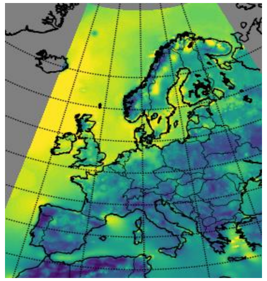
P. Veers et al., Science 10.1126/science.aau2027 (2019)

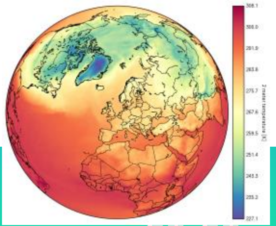




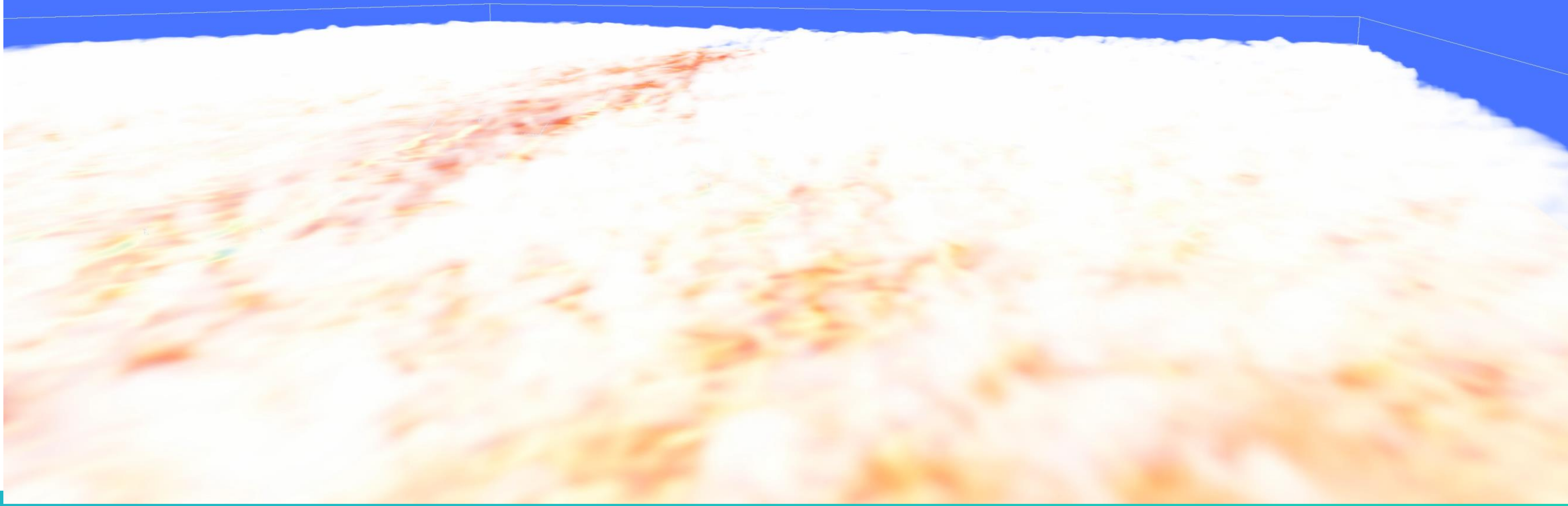








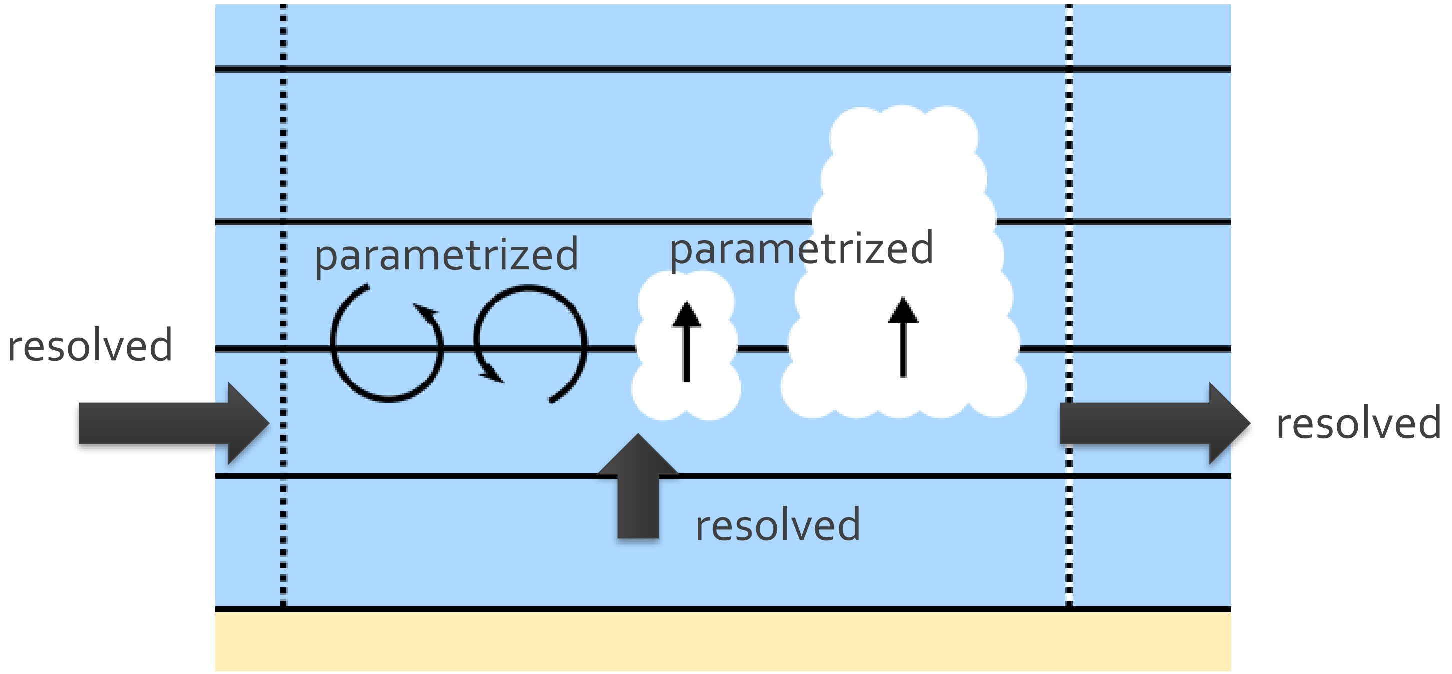
What is Large-Eddy Simulation



Parametrizations in numerical weather prediction (NWP)

Parametrization: **expressing the sub-grid processes in terms of resolved quantities**

Schematic view on transport by sub-grid processes



Typical processes that are parameterized in NWP:

- Turbulence
- Large-scale clouds
- Convective clouds
- Surface drag
- Radiation
- Precipitation
- Surface energy balance

See for example https://www.ecmwf.int/en/elibrary/18714-ifs-documentation-cy45r1-part-iv-physical-processes

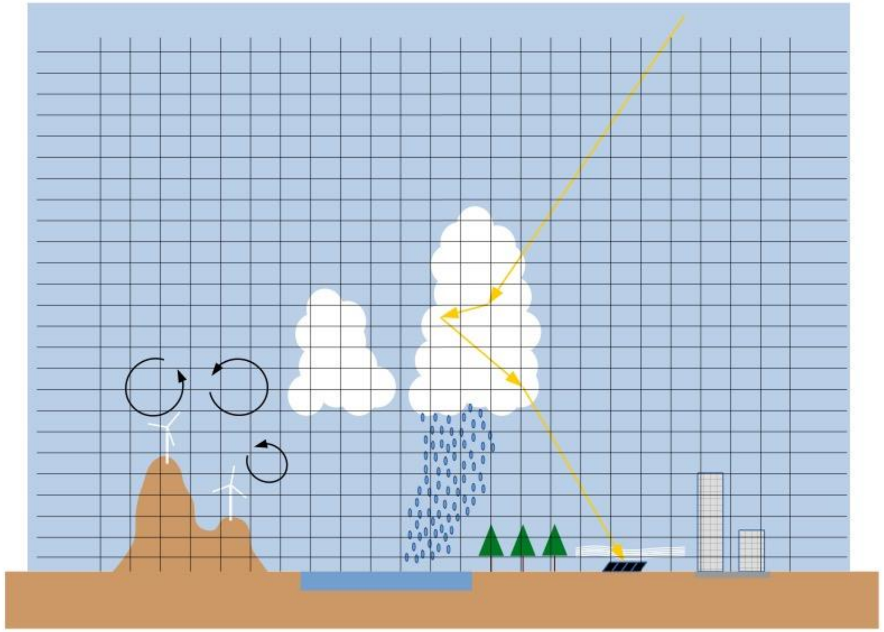
Parametrizations in large-eddy simulation (LES)

Parametrization: **expressing the sub-grid processes in terms of resolved quantities**

The LES grid is fine enough to resolve turbulence, clouds and the surface. "*Assume less, compute more*"

Explicit modelling of:

- Wind turbines
- Canopies
- Buildings
- Turbulence
- Clouds / fog



Picture courtesy Quentin Libois

Typical processes that are parameterized in LES:

- ~~Turbulence~~
- ~~Large-scale clouds~~
- ~~Convective clouds~~
- ~~Surface drag~~
- Radiation
- Precipitation
- Surface energy balance (in high resolution)

See for example https://www.ecmwf.int/en/elibrary/18714-ifs-documentation-cy45r1-part-iv-physical-processes

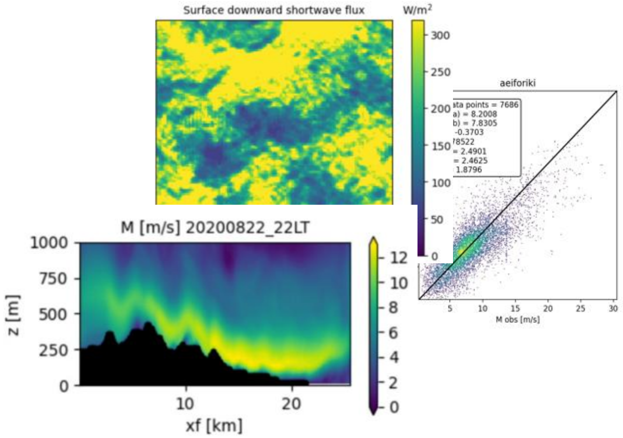
Forecasting with LES: topics addressed in Smart4RES

How can LES models be improved for better RES forecasts for all types of locations?

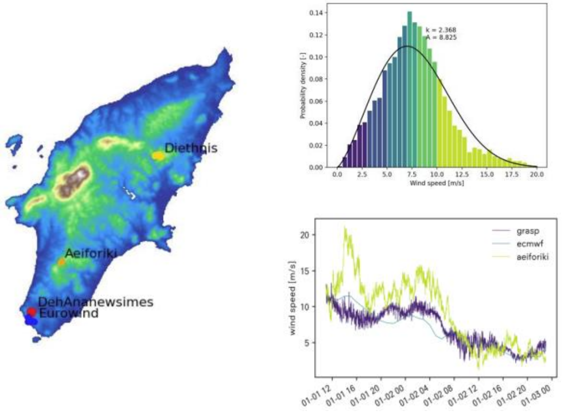
What is the forecast skill for different Smart4RES sites?

How can short-term forecasts be improved by using recent observations?

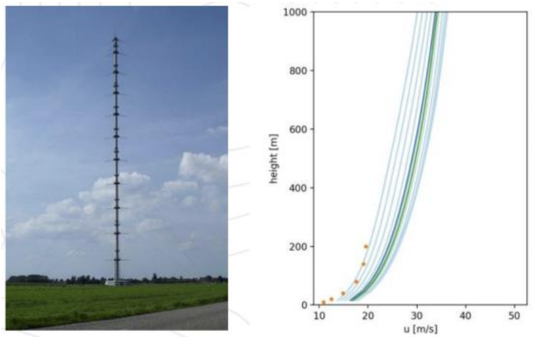
Improving an LES based forecast model



Creating day-ahead RES forecasts for different sites



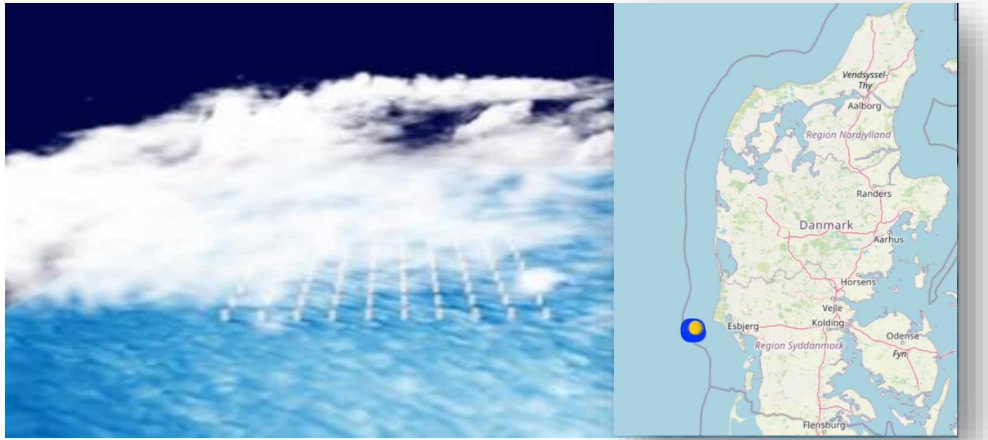
Experimenting with data-assimilation for short-term forecasts



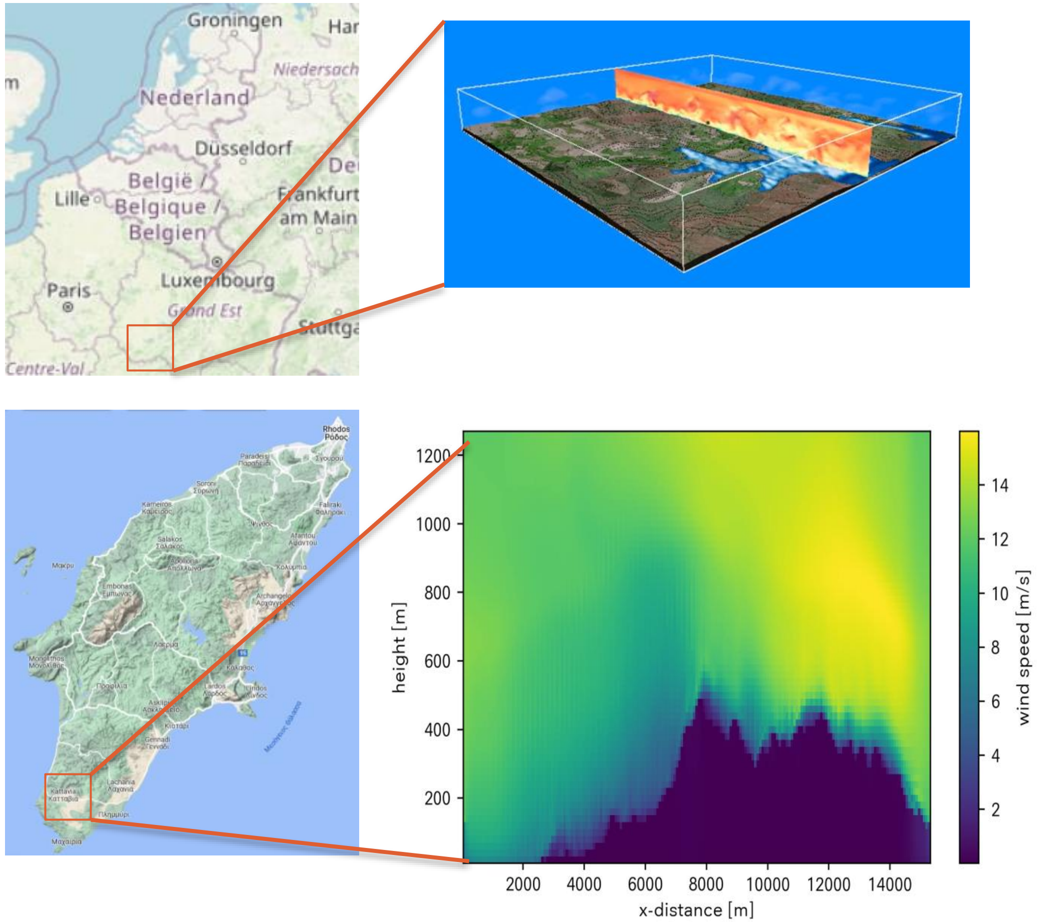
Improving Large Eddy Simulation for operational forecasting anywhere in the world

- Objective: make it ready for production anywhere in the world

2019: LES of windfarms in homogeneous terrain (e.g. offshore wind farms)

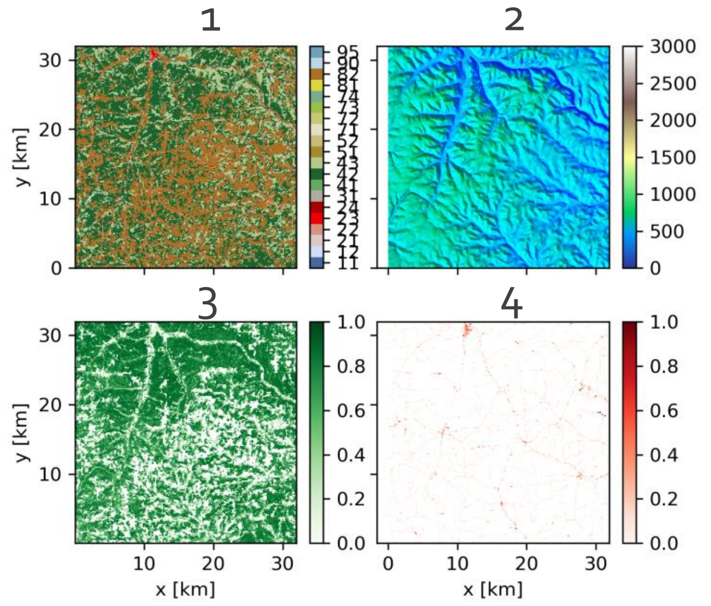


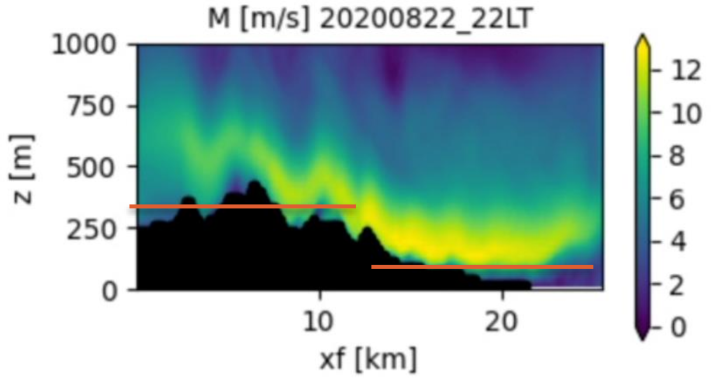
Gilbert, C., Messner, J. W., Pinson, P., Trombe, P., Verzijlbergh, R., Dorp, P. Van, & Jonker, H. (2019). Statistical Post-processing of Turbulence-resolving Weather Forecasts for Offshore Wind Power Forecasting. *Wind Energy*, 1–16. https://doi.org/10.1002/we.2456



Surface representation

- Challenge: NWP (10km) based surface representations do not always work for extremely high resolution (100m)
- Surface energy balance solved on all obstacles
- Mapping ECMWF pressure level fields on LES grid with proper bases level



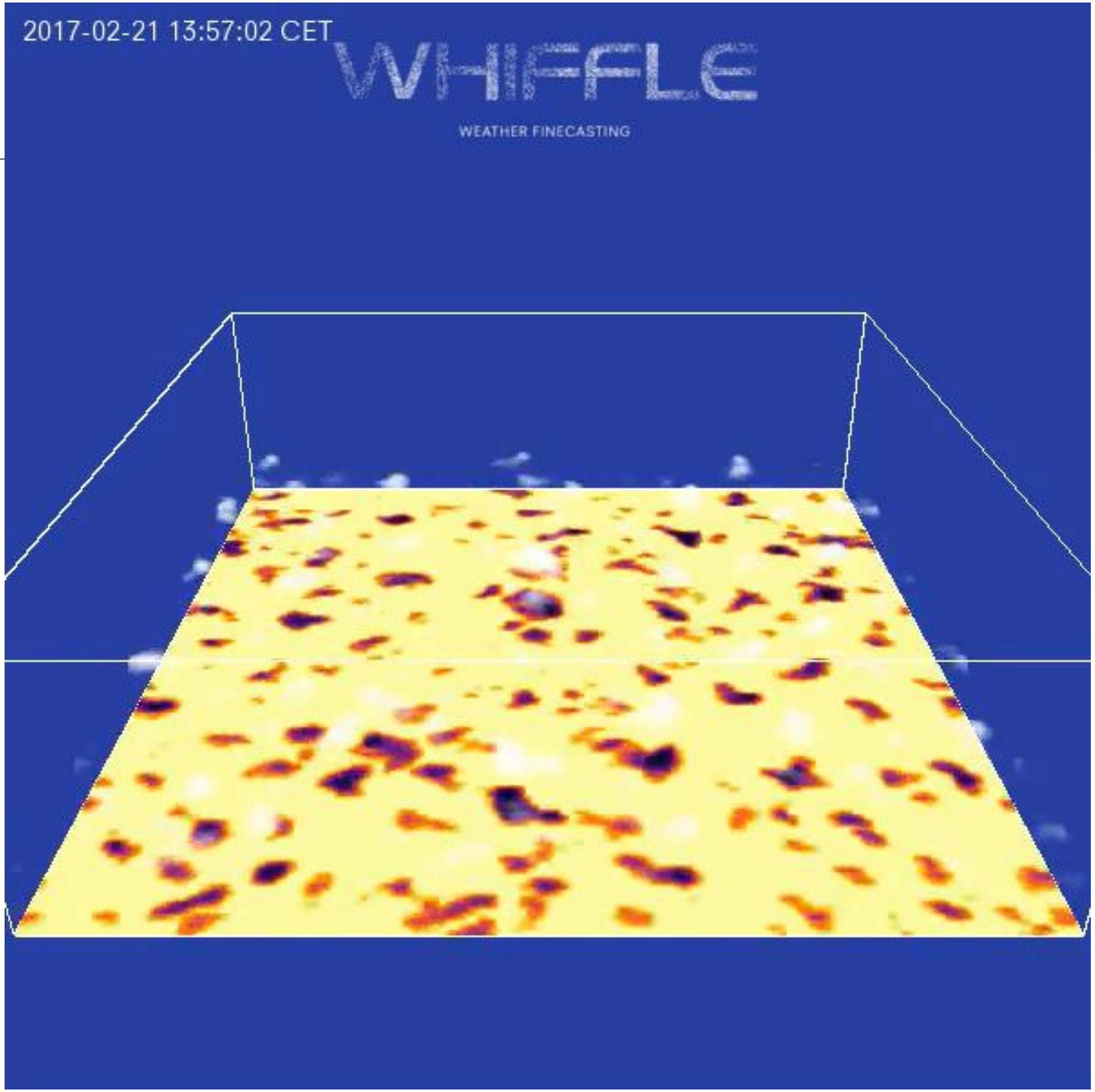


ECMWF surface heights

Example land use:
1. land use class
2. Digital terrain model
3. Canopy density (optional)
4. Urban cover (optional)

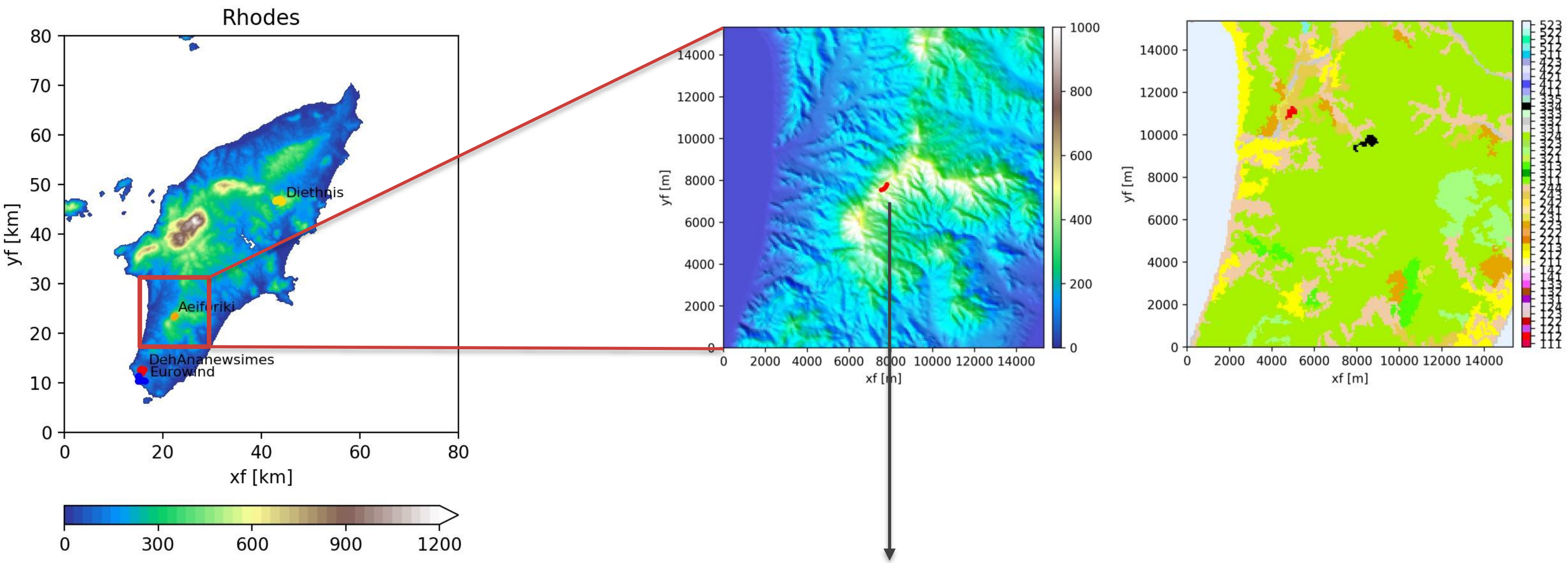
Computationally efficient interactive radiation

- Challenge: radiation modules computationally intensive
- Coupling between LES model and the Ecrad radiative transfer code
- Fully interactive radiation. Radiative fluxes applied every time-step, using a smart implementation
- Side-steps all the ‘trouble’ of cloud overlap assumptions in classical NWP model



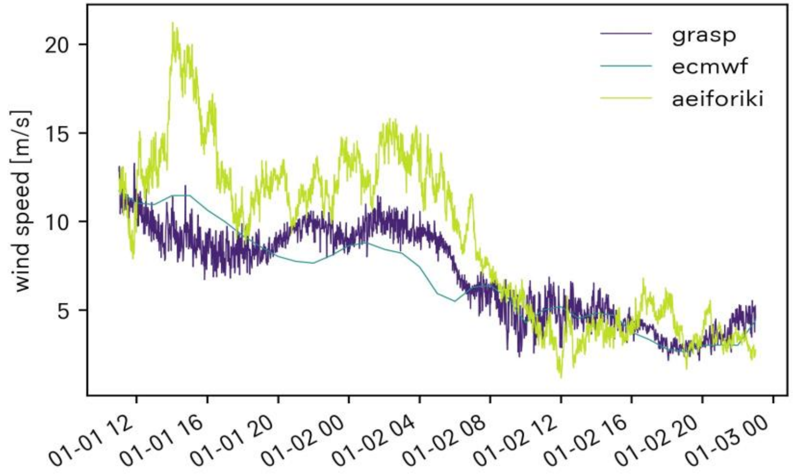
Case highlight: Aeiforiki wind farm on Rhodes

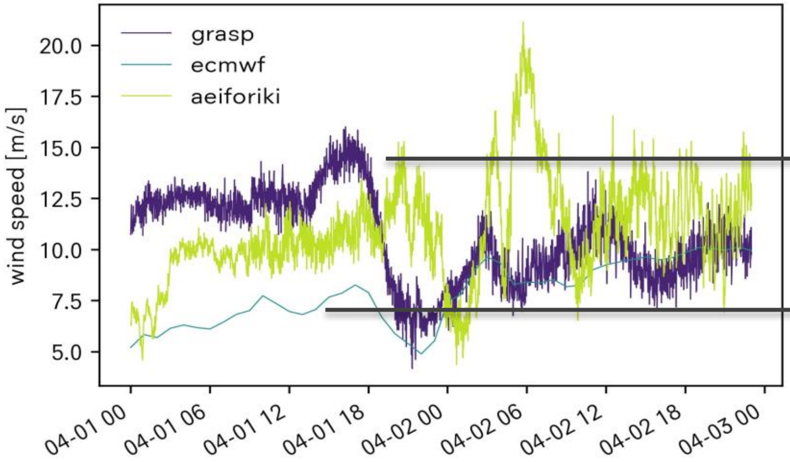
Land use classes



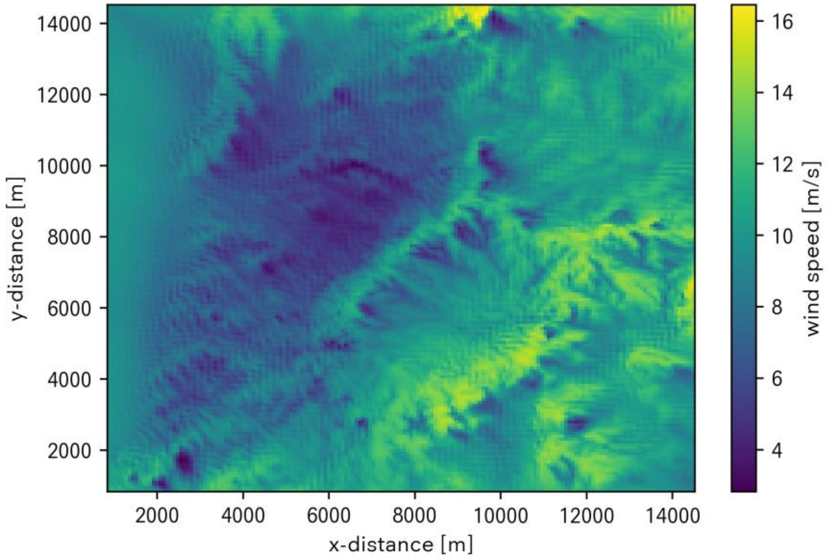
Small wind farm on mountain ridge

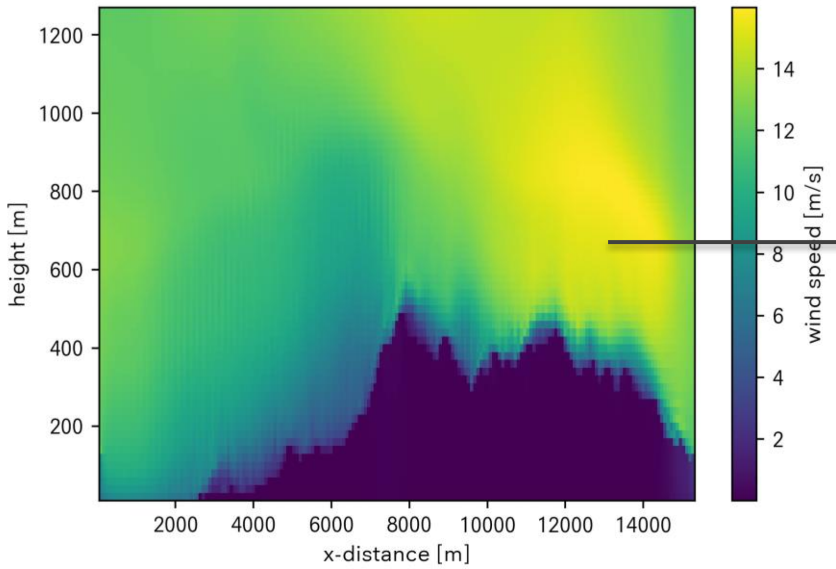
Aeiforiki – A glance at LES results





- Turbulent fluctuations in forecast
- Mean wind very different from ECMWF





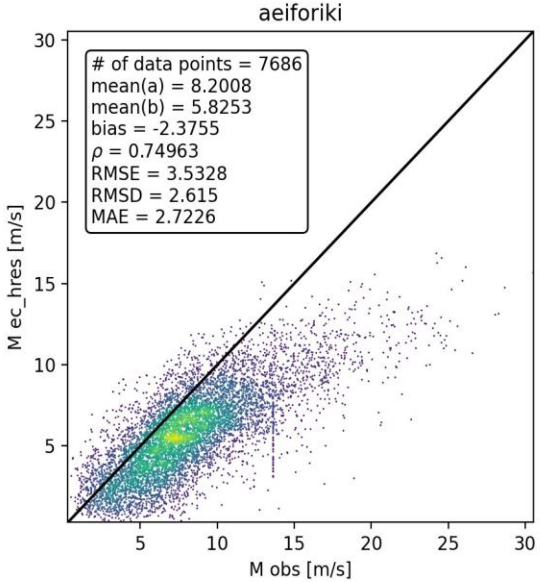
Flow acceleration over the ridge

Quantitative results over a range of sites

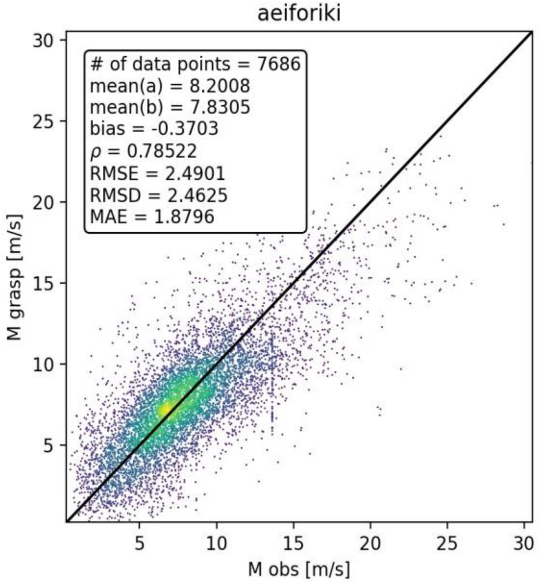
Aeiforiki: MAE improvement of 14%

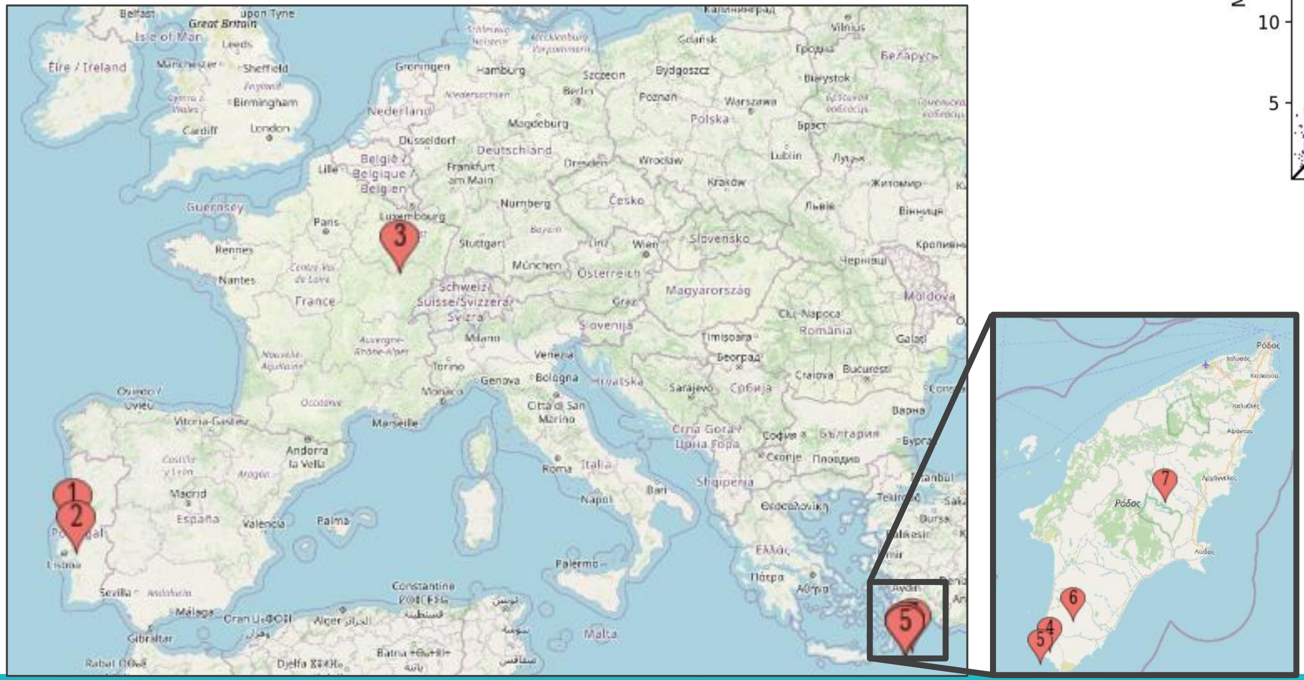
All 7 sites: average 9% improvement in MAE (-2 to 20%)

ECMWF



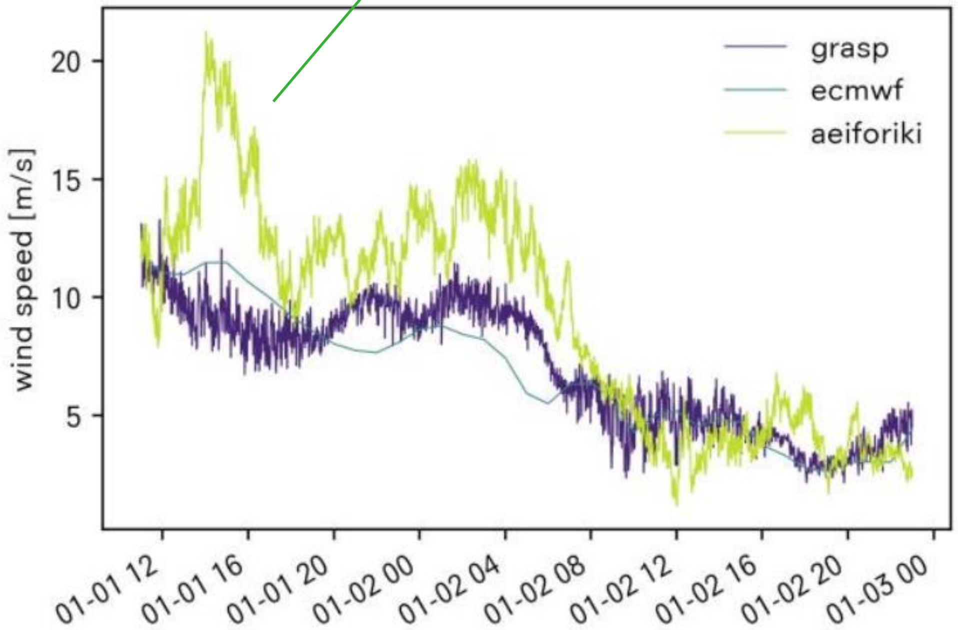
LES



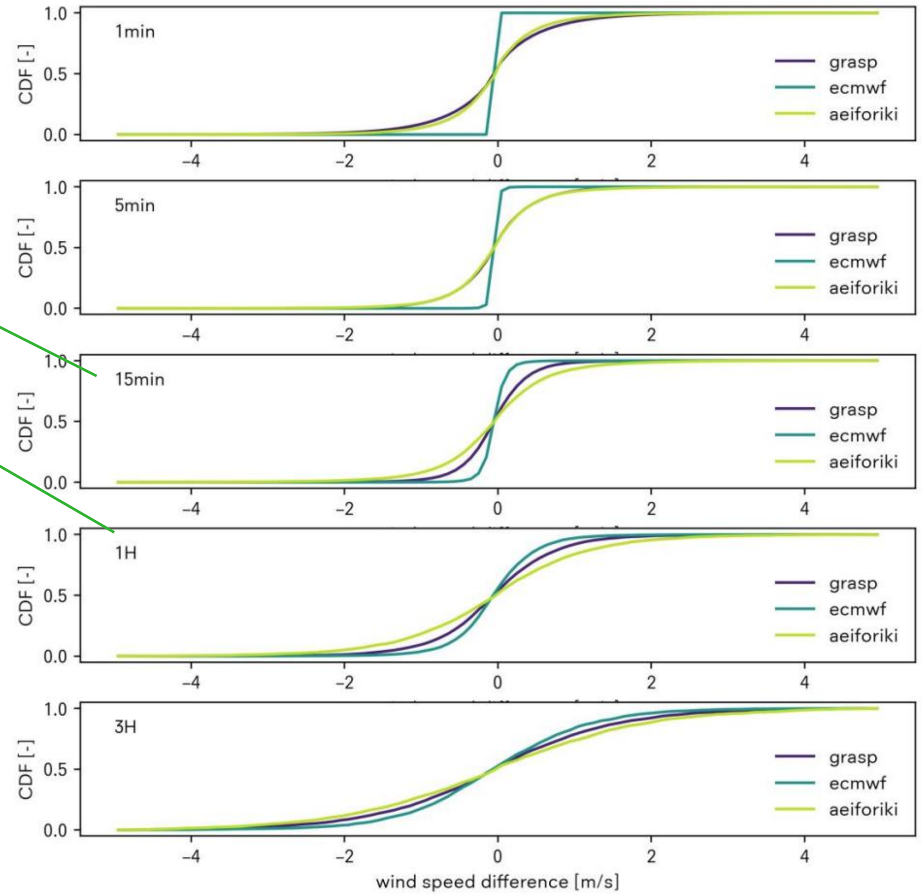


The missing scale

- ✓ Large scale fluctuations from ERA5/ECMWF tendencies
- ✓ Turbulent fluctuations from LES
- × Too little mesoscale fluctuations

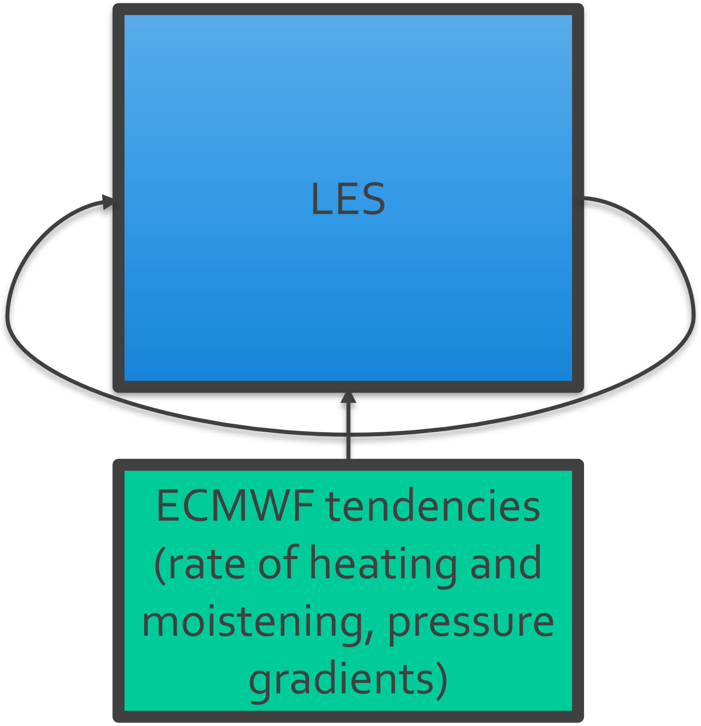


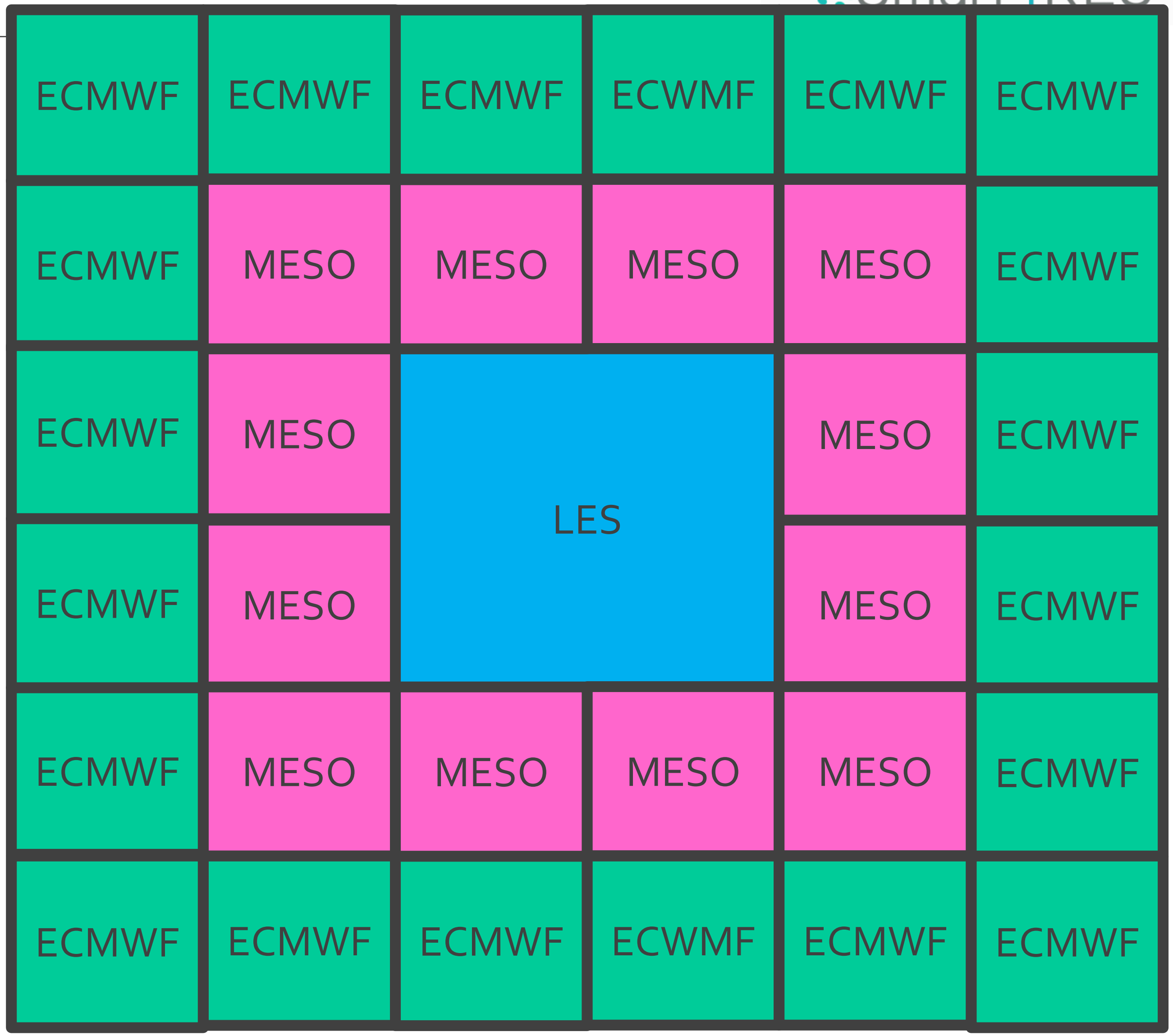
Cumulative distributions of wind speed ramps over different time-scales



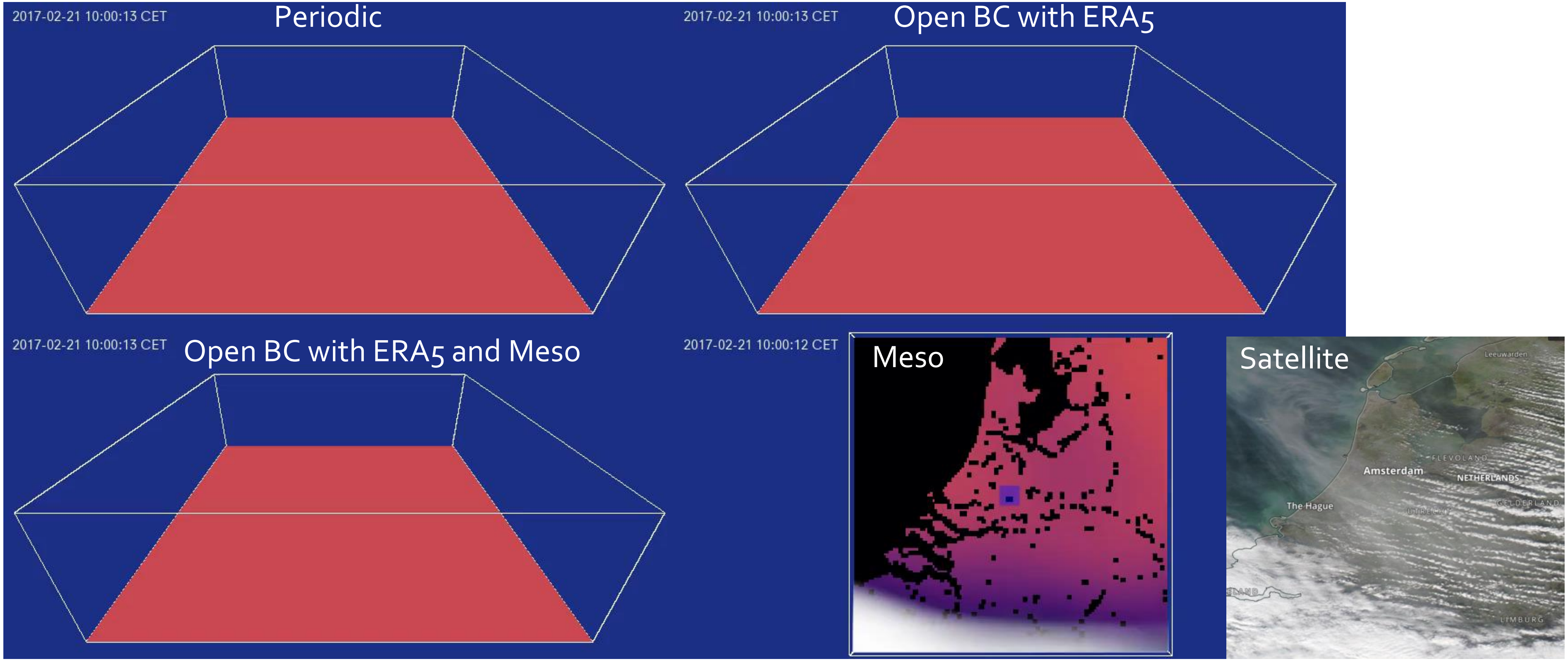
Two changes to our boundary conditions: 1) open boundary conditions 2) mesoscale model as precursor

LES variables are circulated



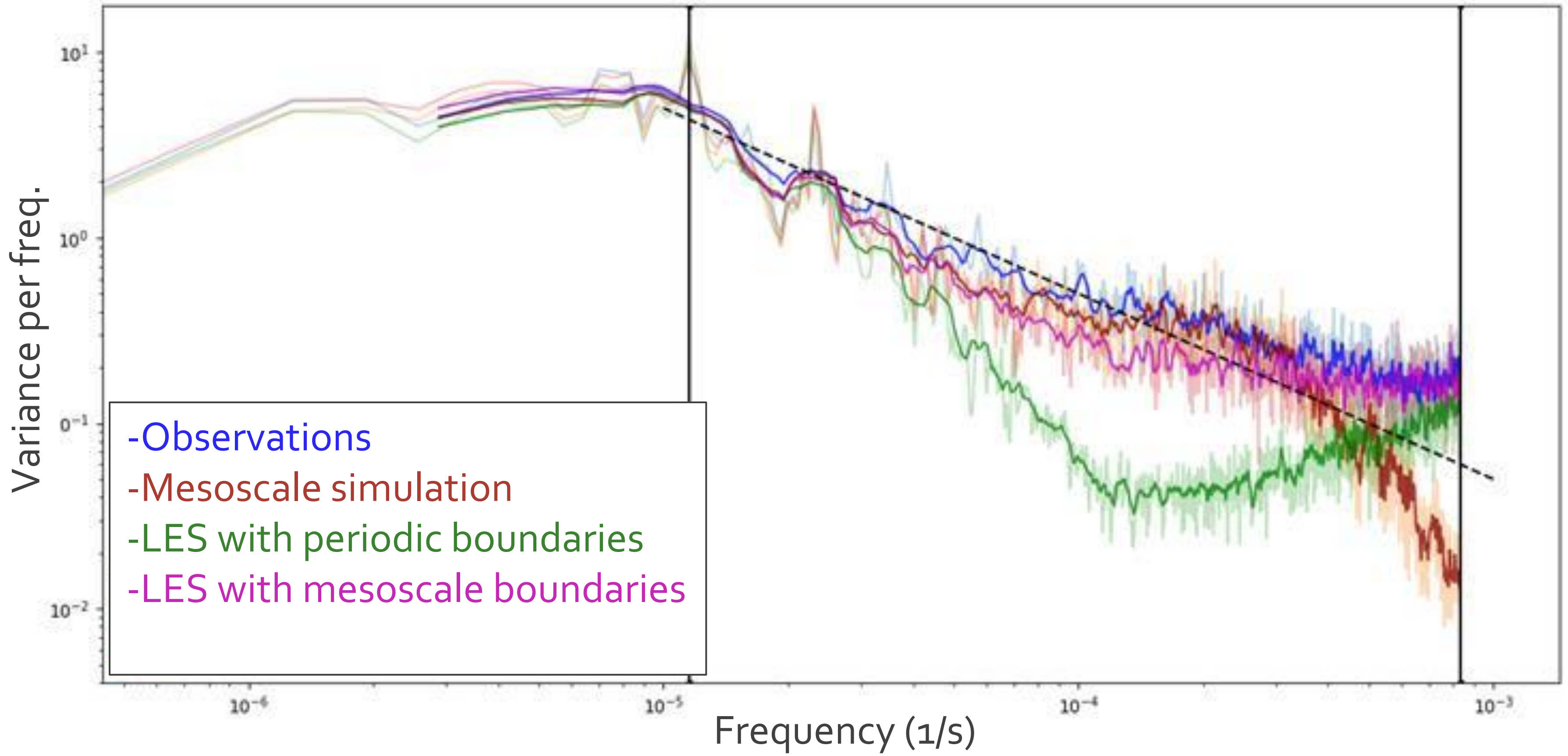


Comparing old and new boundary conditions



https://worldview.earthdata.nasa.gov/?v=1.9500628641860795,50.1453808214975 54,8.2155854716326 75,53.5410173639559 9&l=Reference_Labels_15m,Reference_Features_15m(hidden),Coastlines_15m,VIIRS_NOAA20_CorrectedReflectance_TrueColor(hidden),VIIRS_SNPP_CorrectedReflectance_TrueColor(hidden),MODIS_Aqua_CorrectedReflectance_TrueColor,MODIS_Terra_CorrectedReflectance_TrueColor(hidden)&lg=true&t=2017-02-21-T09%3A08%3A14Z

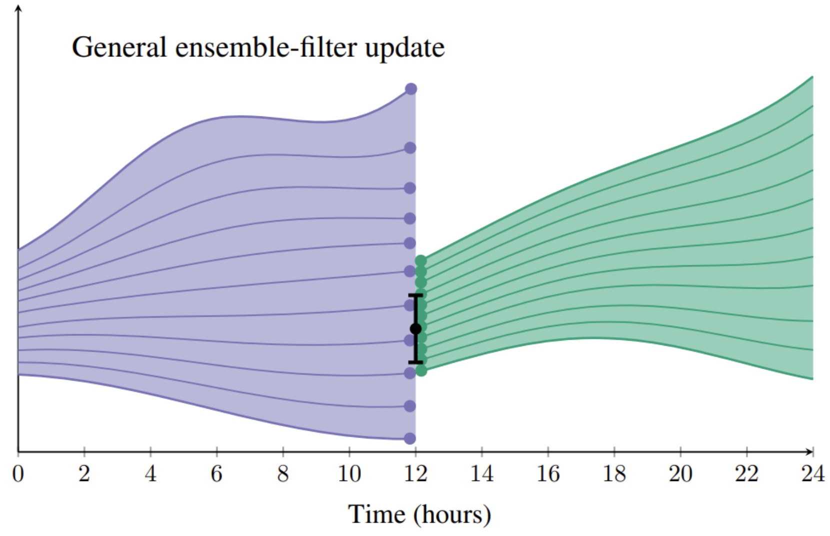
The gap is closed

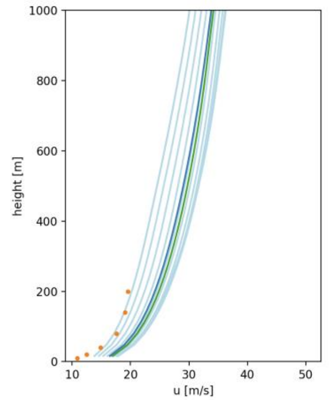


Data assimilation

- Challenge: estimating initial conditions in a local weather model
- Data assimilation: combine measurements and model to estimate the current state of the atmosphere
- Ensemble Kalman Filter suitable for the highly non-linear LES model
- We experimented with tower measurements, surface pressure measurements and a simplified atmospheric model

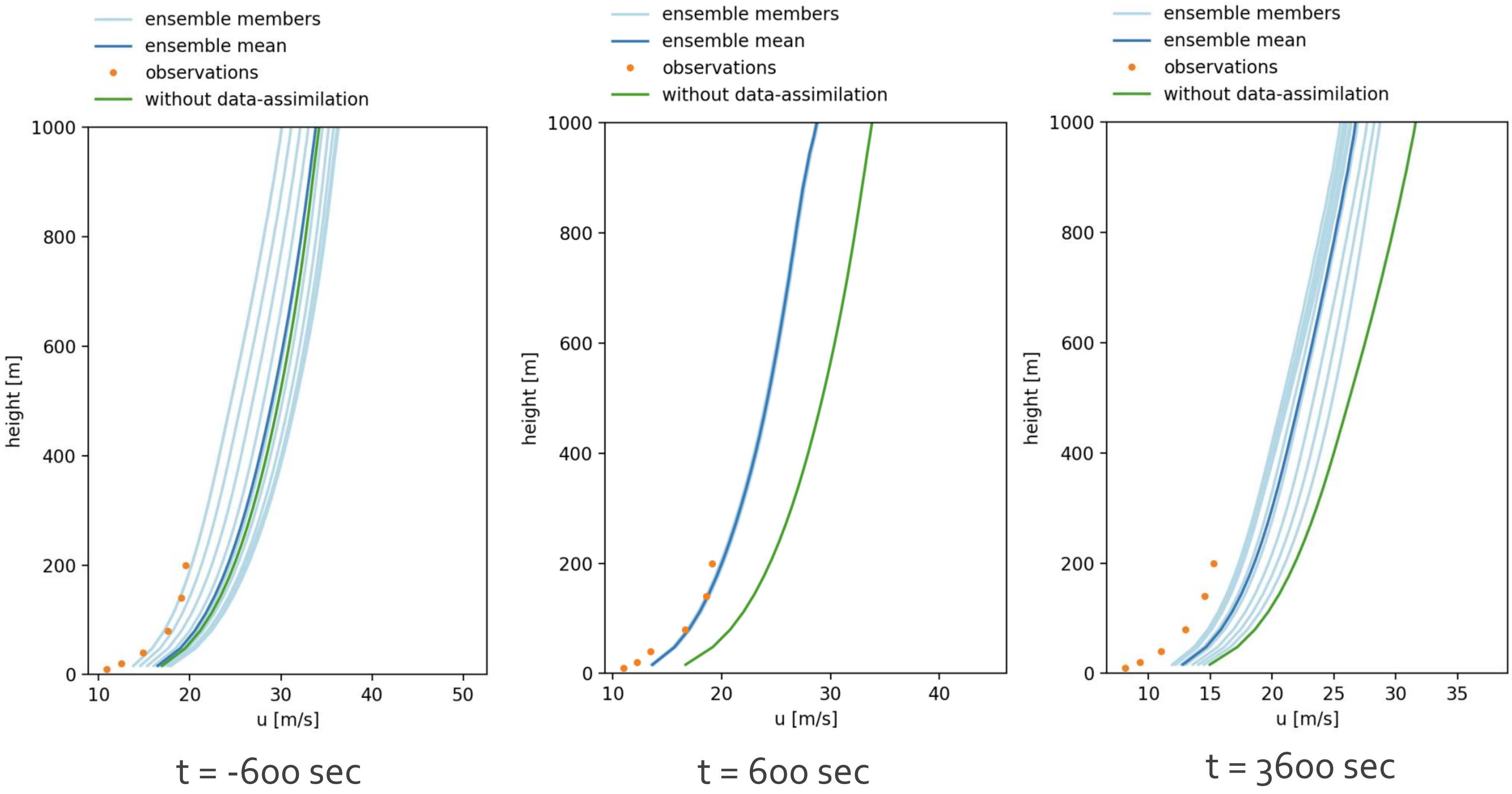
Figure from Van Leeuwen et al (2022) https://doi.org/10.1007/978-3-030-96709-3



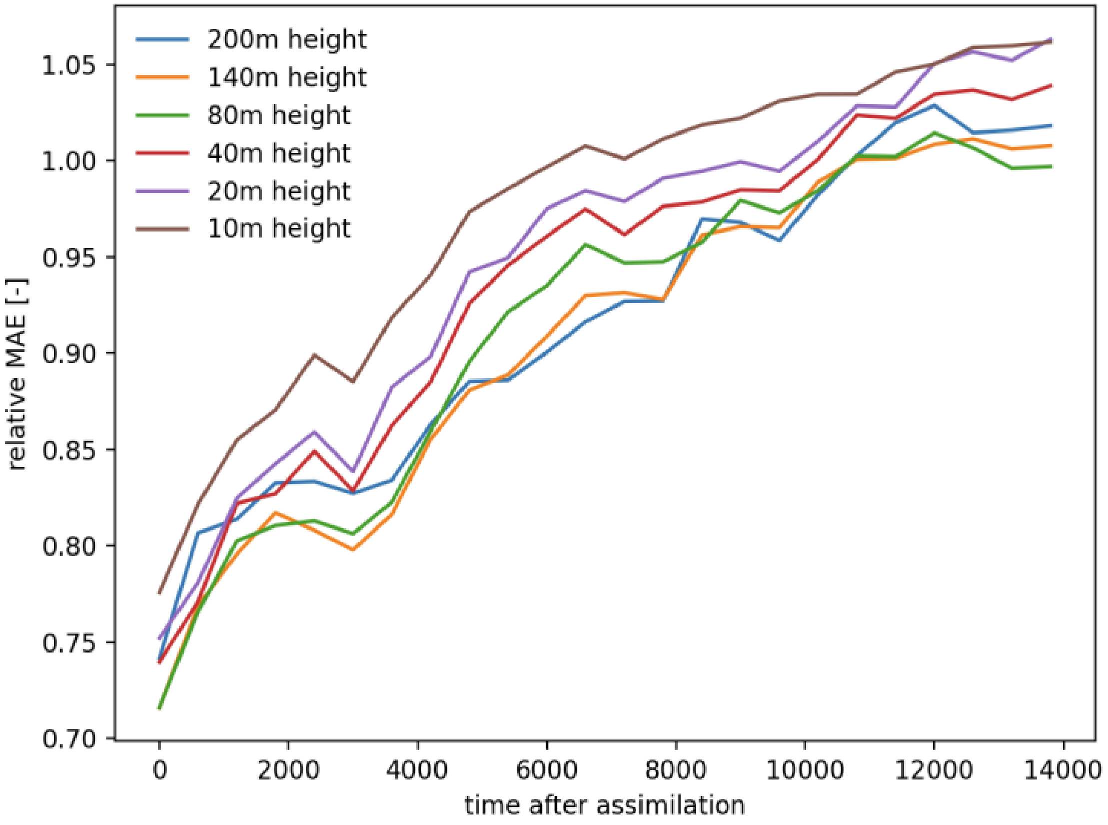


Data assimilation results using a simplified LES model

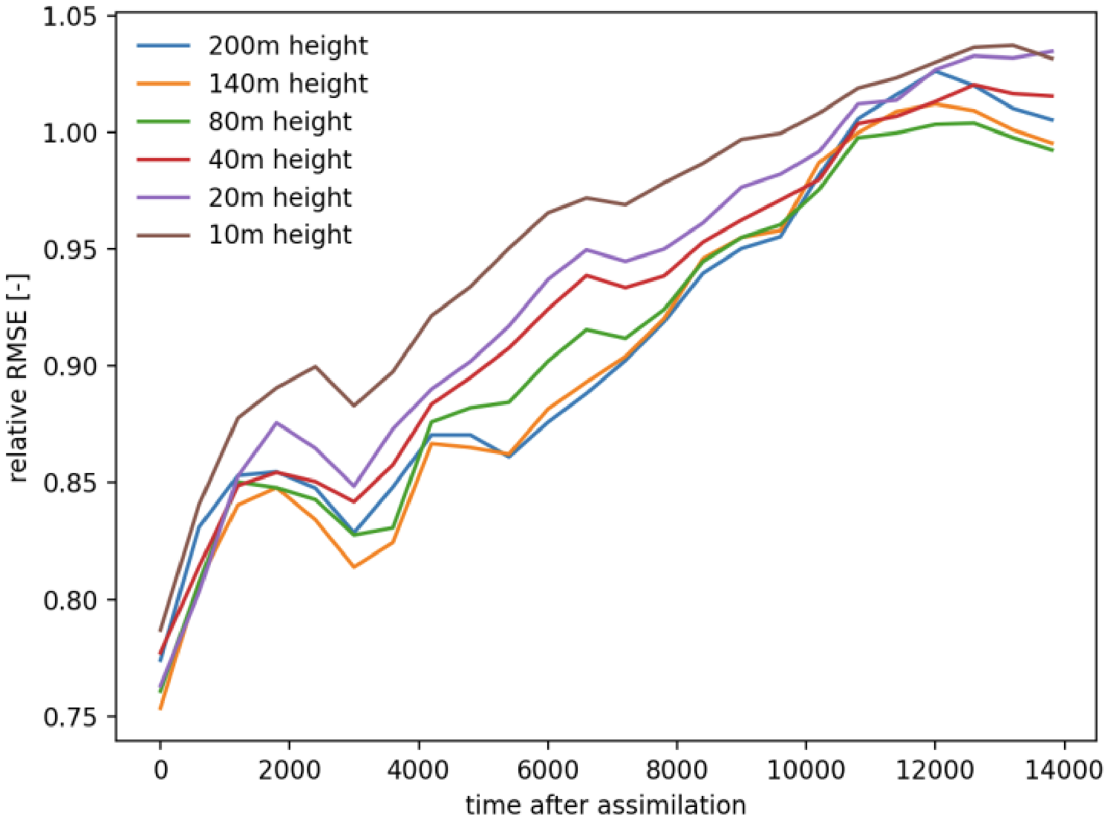
- Start with an ensemble of forecasts
- Adjust each ensemble member to observations
- Use adjusted state as start for new forecast



Relative improvements in the short-term



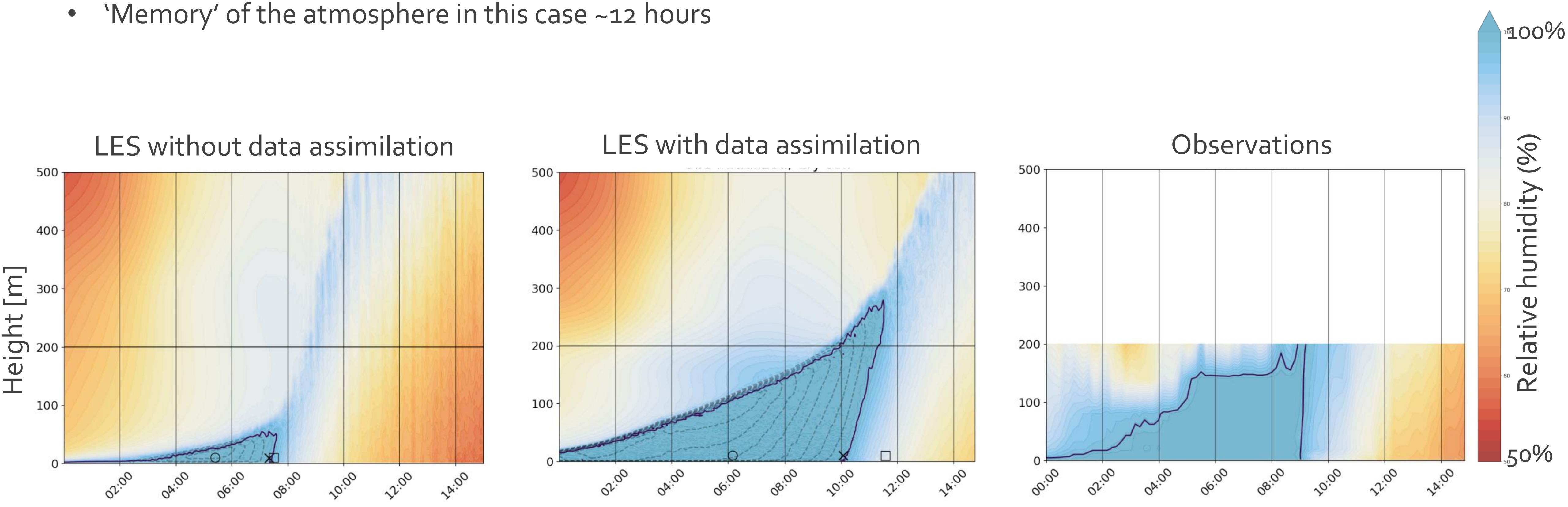
(a) Mean absolute error statistics



(b) Root mean square error statistics

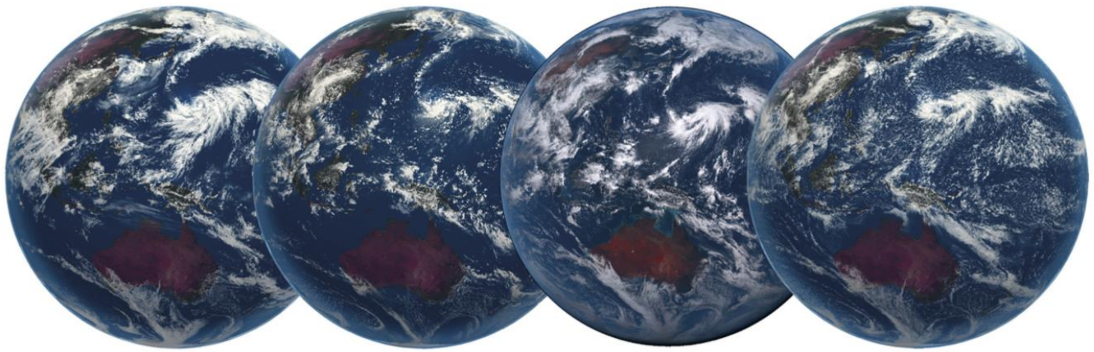
Fog: a difficult forecasting problem

- Initialisation with observations from 2200 UTC
- 'Memory' of the atmosphere in this case ~12 hours

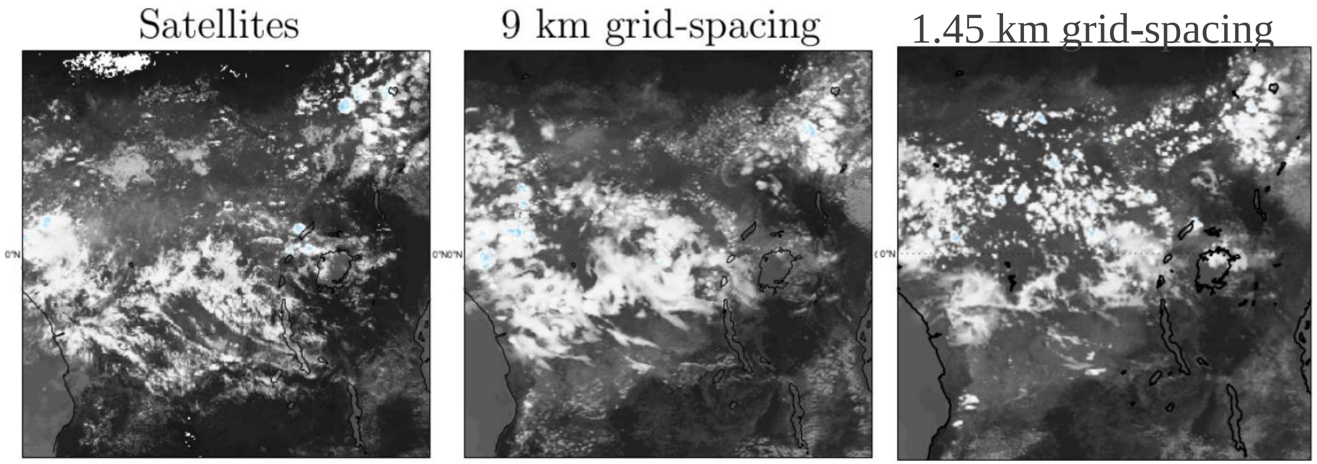


The future of high-resolution weather forecasting: NWP

Which is the satellite image?



Traditional weather and climate models getting finer [1]



ECMWF experimenting with 1km resolution on Piz Daint supercomputer (#20 in Top500) [2]

[1] Palmer, T., & Stevens, B. (2019). The scientific challenge of understanding and estimating climate change. In *Proceedings of the National Academy of Sciences of the United States of America* (Vol. 116, Issue 49, pp. 34390–34395). National Academy of Sciences. https://doi.org/10.1073/pnas.1906691116

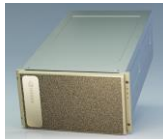
[2] Dueben, P. D., Wedi, N., Saarinen, S., & Zeman, C. (2020). Global simulations of the atmosphere at 1.45 km grid-spacing with the integrated forecasting system. *Journal of the Meteorological Society of Japan*, *98*(3), 551–572. https://doi.org/10.2151/jmsj.2020-016

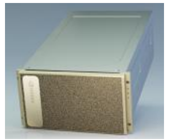
The future of high-resolution weather forecasting: LES

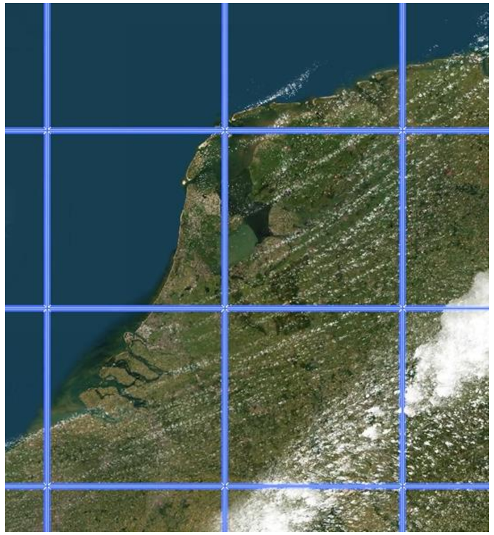
- 2015 (!) proof-of-concept country scale LES
- Uses 256 GPUs on PRACE supercomputer
- 4h wall-clock time for 1h simulation

Schalkwijk, J., Jonker, H. J. J., Siebesma, A. P., & van Meijgaard, E. (2015). Weather forecasting using GPU-based large-Eddy simulations. *Bulletin of the American Meteorological Society*, *96*(5). https://doi.org/10.1175/BAMS-D-14-00114.1

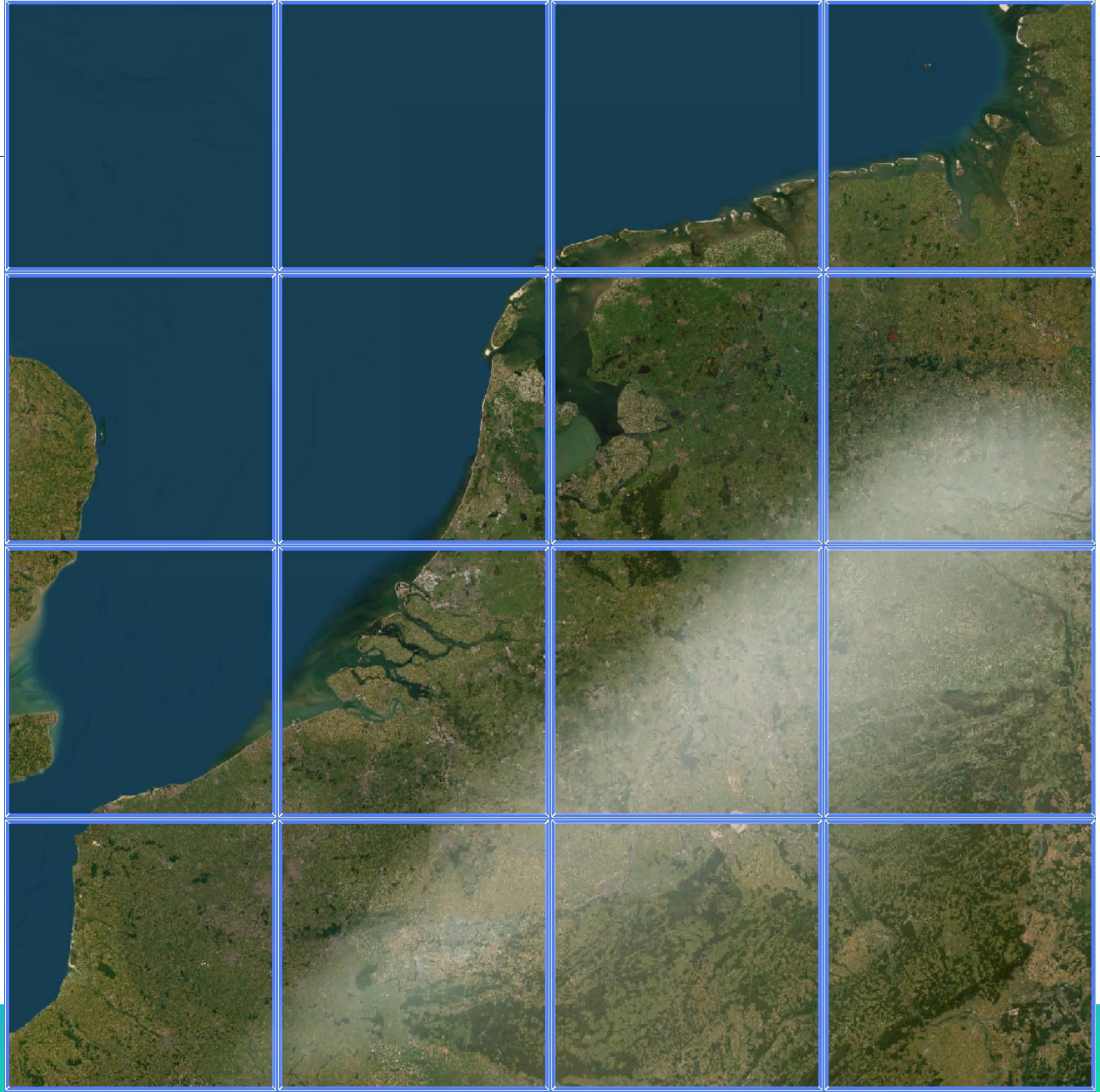
- 2023: beta version of country scale 400x400km LES
- Uses 16 GPUs on 'standard cloud system' (2x DGX A100)
- 2h wall-clock time for 24h simulation







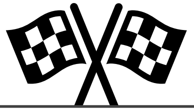
- 202?: proof-of-concept continental scale LES
- Selene GPU supercomputer (#9 Top500)
- 2h wall-clock time for 24h simulation



The future of weather forecasting

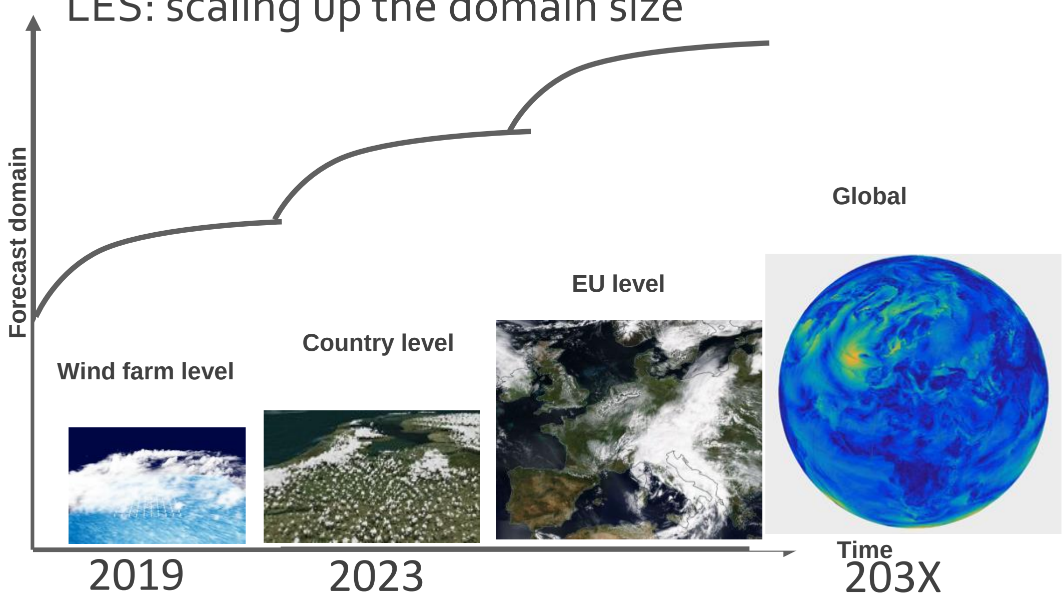
Next generation weather model:

- Turbulence and cloud resolving (= LES !)
- Uses big data and massive computational power
- Supports energy transition and climate adaptation

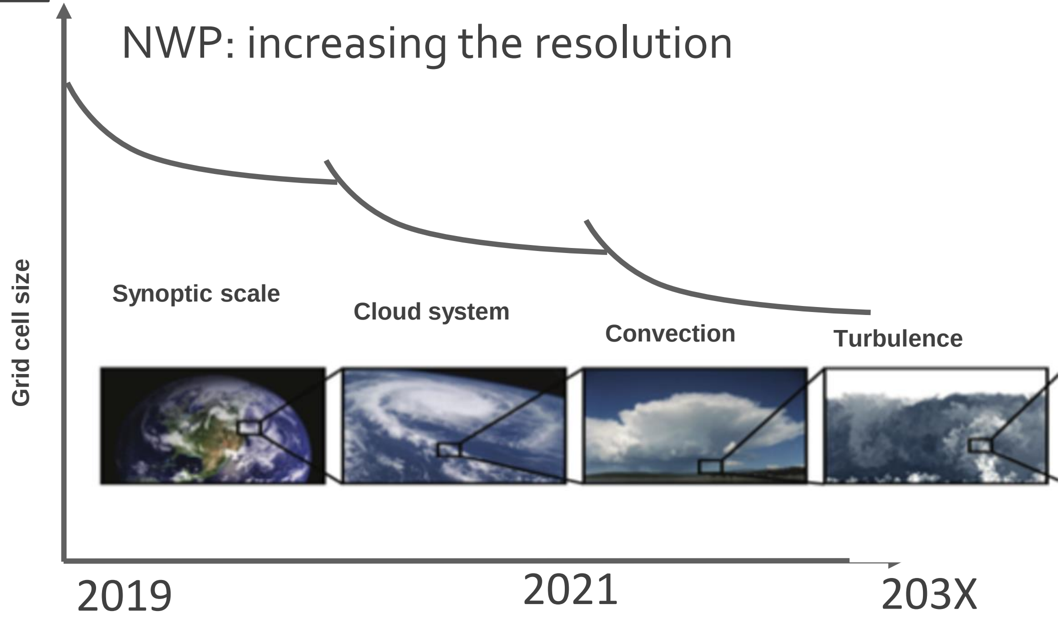


Who will be first?

LES: scaling up the domain size



NWP: increasing the resolution



KEY TAKE AWAYS

- Large-Eddy Simulation provides a high-resolution forecasting technique suitable for RES needs: wake effects, very local wind climate, clouds, etc

- We demonstrated average improvement over industry benchmark forecast of 9% for a range of sites

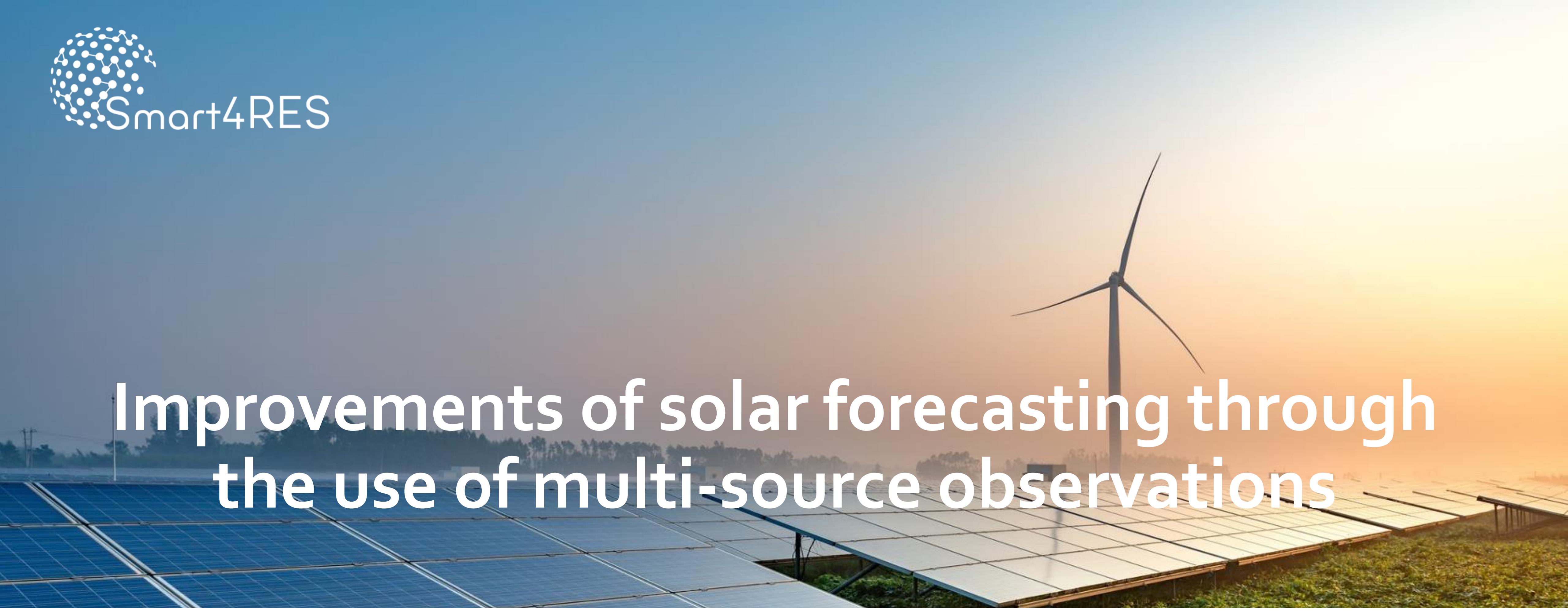
- Data assimilation with Ensemble Kalman filtering can improve short-term forecasts. Initial results show ~25% improvement

- Future weather prediction models will cover the length scales relevant for renewables, from 100m to 10000 km.

Smart4RES

Thank you!

- R.A.Verzijlbergh, Whiffle: remco.verzijlbergh@whiffle.nl
- Thanks to our work-package partners: MeteoFrance & DLR
- Thanks to the entire Smart4RES consortium



Smart4RES

Improvements of solar forecasting through the use of multi-source observations

Jorge Lezaca [1], Niklas Blum [2], Bijan Nouri [2], Annette Hammer [1]

[1] DLR Institute of Networked Energy Systems (VE)

[2] DLR Institute of Solar Research (SF)

DLR

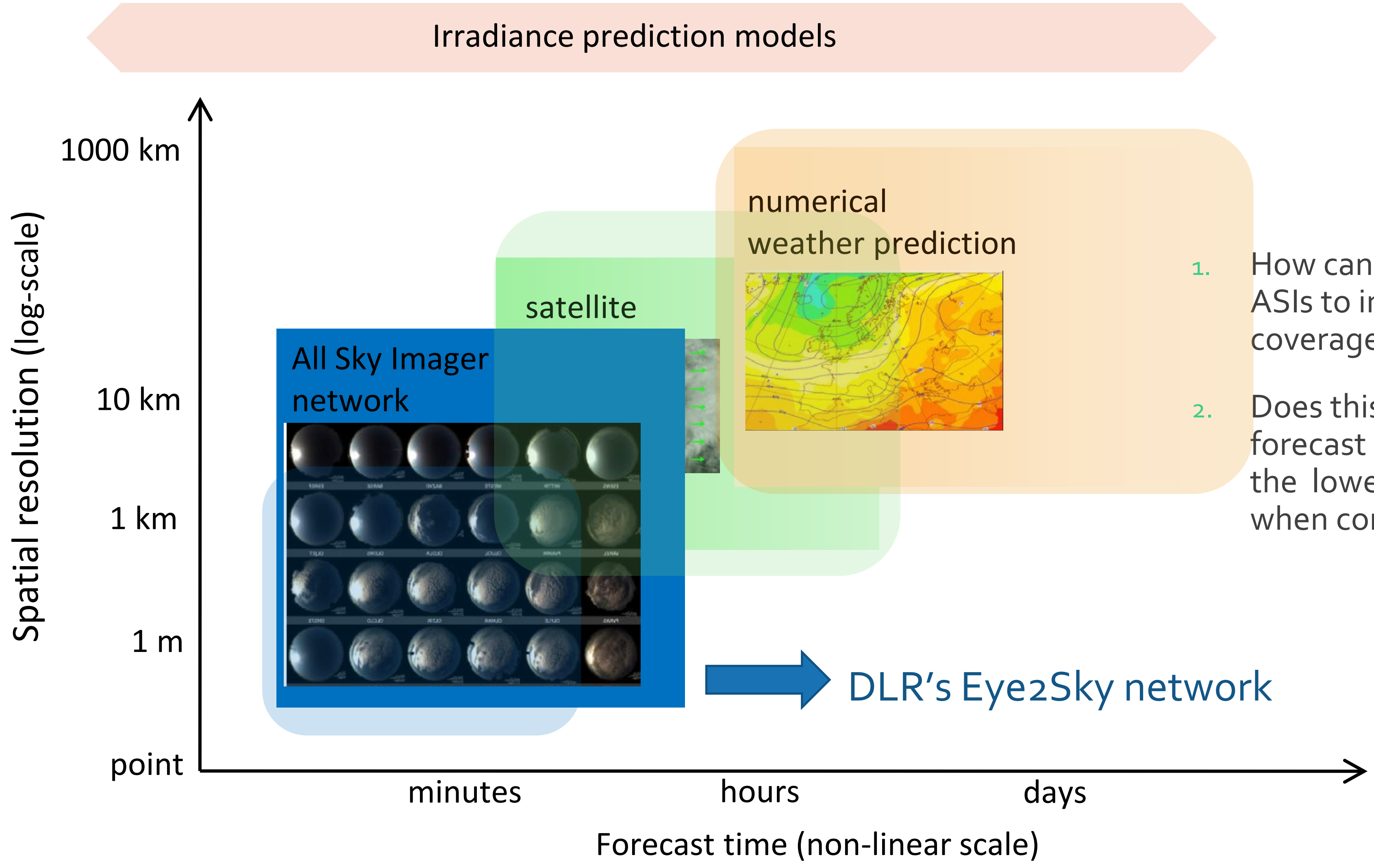
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864337

Agenda

1. Motivation
2. Analysis of a network of all-sky-imagers for solar nowcasting
3. Hibrid combined forcasts using ground observations, all-sky and satellite imagers
4. Conclutions and Outlook

Motivation: challenges and opportunities of weather observations and solar forecasting

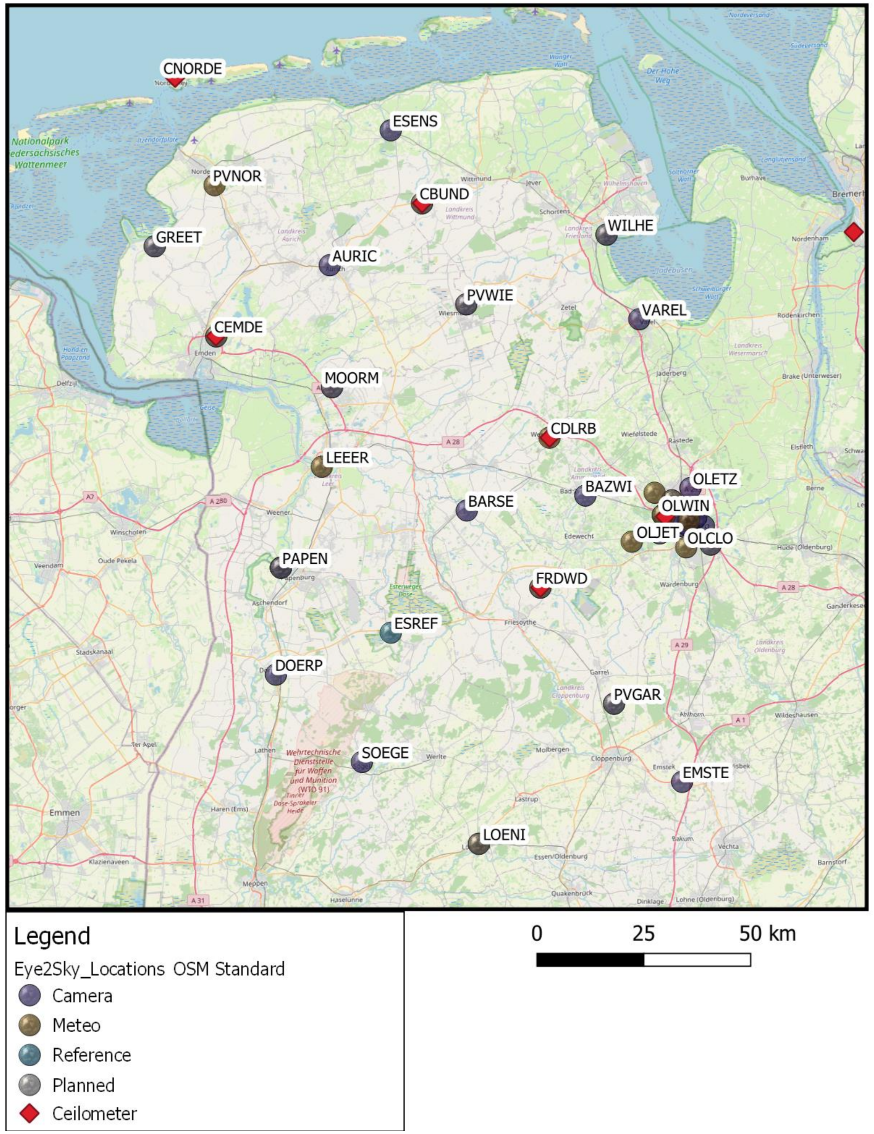
Motivation



Objectives

1. How can we use a dense network of ASIs to improved the accuracy and coverage of the irradiance forecast ?
2. Does this new this new ASI network forecast improves the performance of the lower resolution satellite forecast when combination together ?

Eye2Sky - Cloud camera and meteorological measurement network in Oldenburg



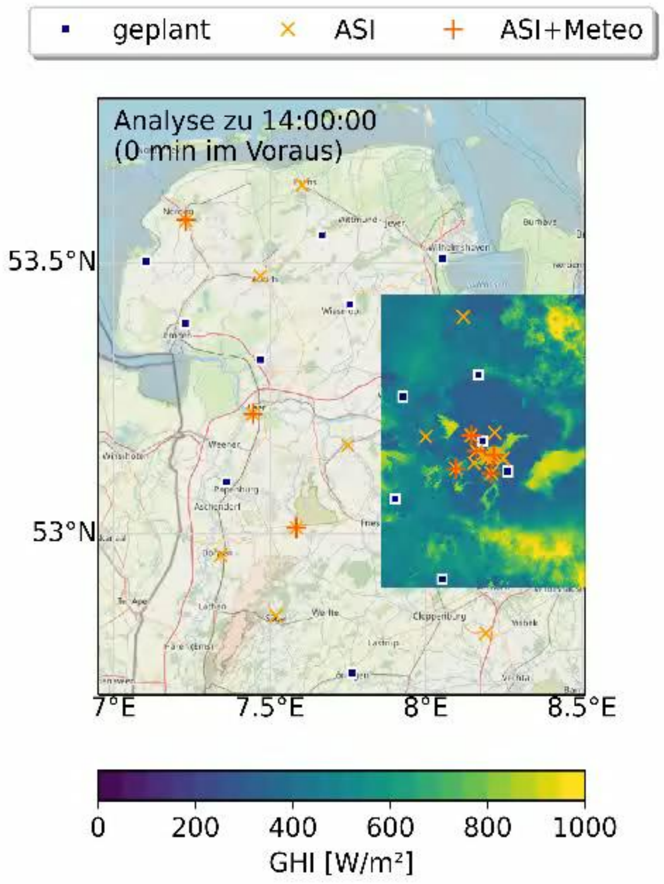
Eye2Sky Overview

- Start of project 2018
- 35 **ASI** in operation (40 planned)
- 14 **meteorological stations**
  - 12 **RSI-based** meteorological stations
  - 2 **solar tracker** stations
- 2 **ceilometer**

Short term solar forecasts with Eye2Sky

Daily video of all cameras

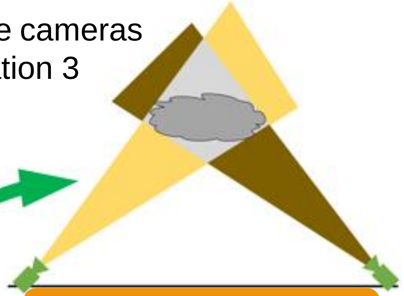
Result: Short-term forecast



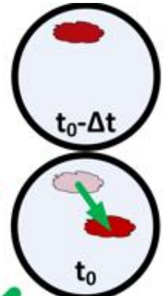
Analysis of a network of all-sky-imagers for solar nowcasting

ASI-network very short-term forecast (up to 1 hour)

- **Height** : stereoscopy from multiple cameras
- **Cloud velocity** : 2D cross-correlation 3 sequential images



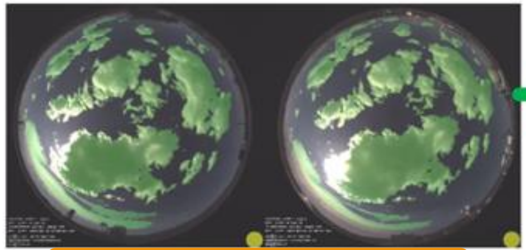
2. Geolocation [2]



3. Tracking

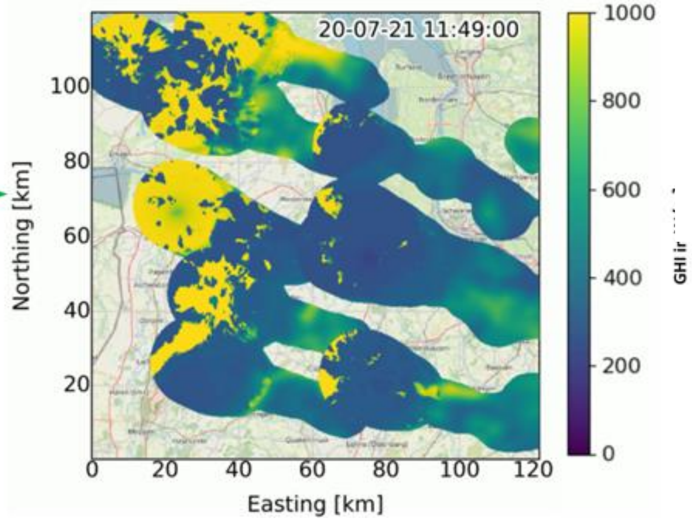
Cloud motion vectors for displacement into the future

Cloud mask : CNN detects and classifies sky/ high/ intermediate/ low clouds

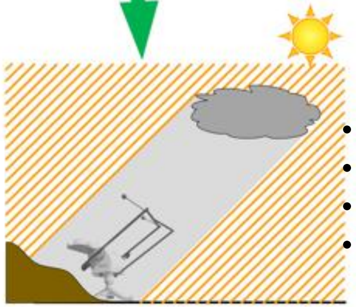


1. Cloud detection [1]

35 ASIs



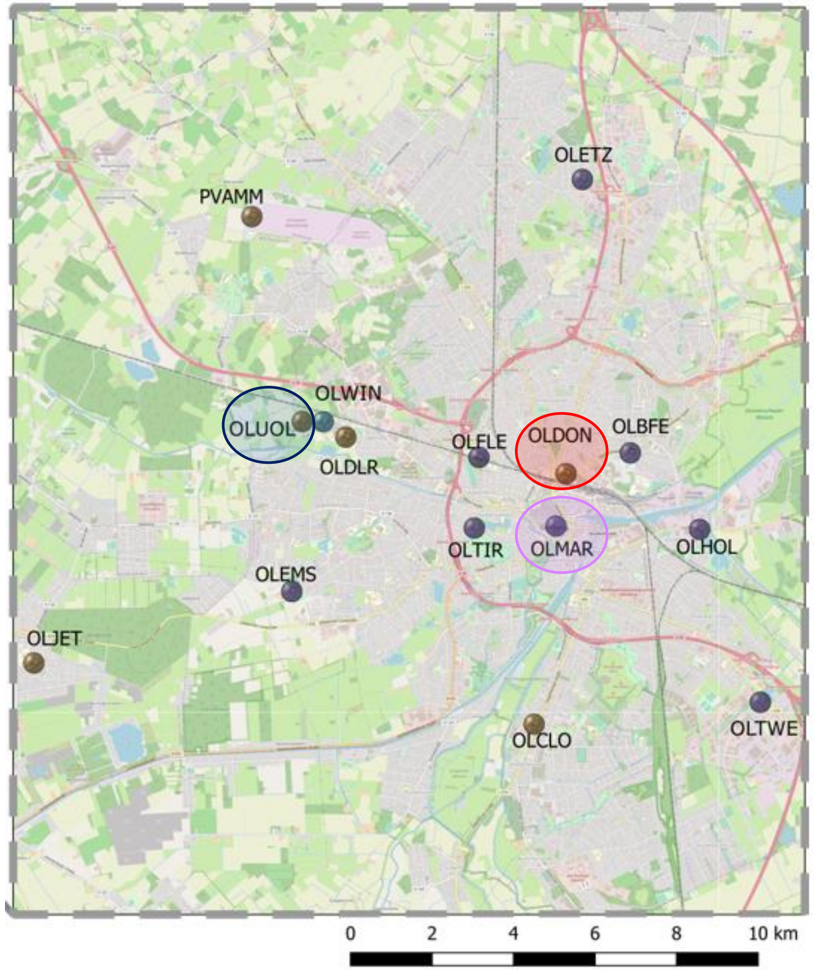
Resolution 50 m x 50 m, every 30s
Area up to 110 km x 100 km



4. Shadow projection & analyze radiative effect [3,4]

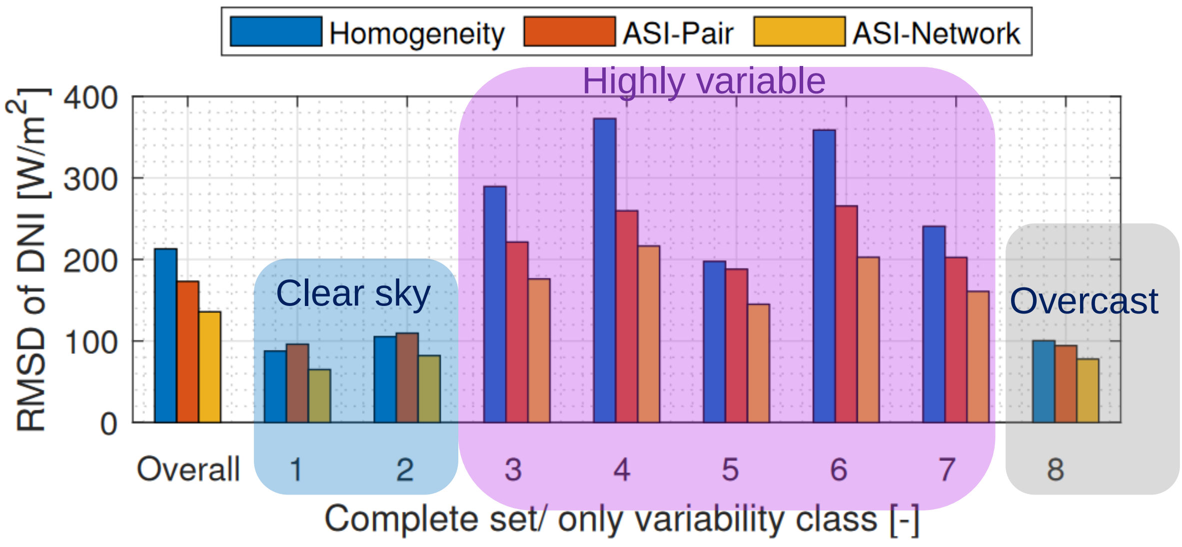
- global elevation model
- DNI, DHI measurements
- Transmittance = DNI / DNI_clear
- Sensitivity analysis : all clouds

Validation of forecast at the site OLUOL



	Eye2Sky network
Available data	92 preselected days in 2020 (all weather conditions)
Validation station	OLUOL
Calibration station	OLDON
Dataset 1 : Homogeneity	OLDON gnd observations extrapolated to OLUOL (spatial persistance)
Dataset 2: ASI-Pair	OLDON - OLMAR
Dataset 3 : ASI-Network	All ASI's except OLUOL
Combi forecast horizon	30 min
Combi forecast resolution	1 min

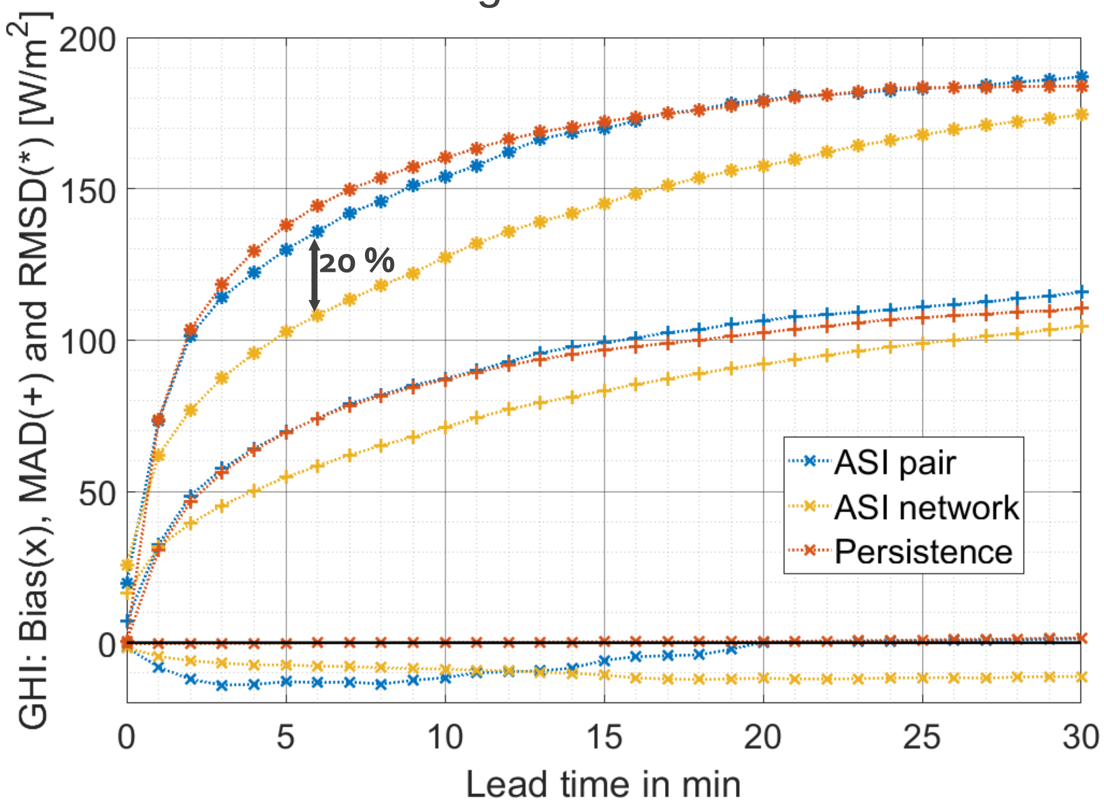
Validation at UOL on DNI using variability classes [5]



- ASI pair predicts DNI at UOL more accurately compared to homogeneity under most conditions
- ASI network has clear advantage over homogeneity & ASI pair under all conditions
- Improvements related to combination of perspectives and also to method to assign transmittance

Validation ASI net vs ASI pair forecast

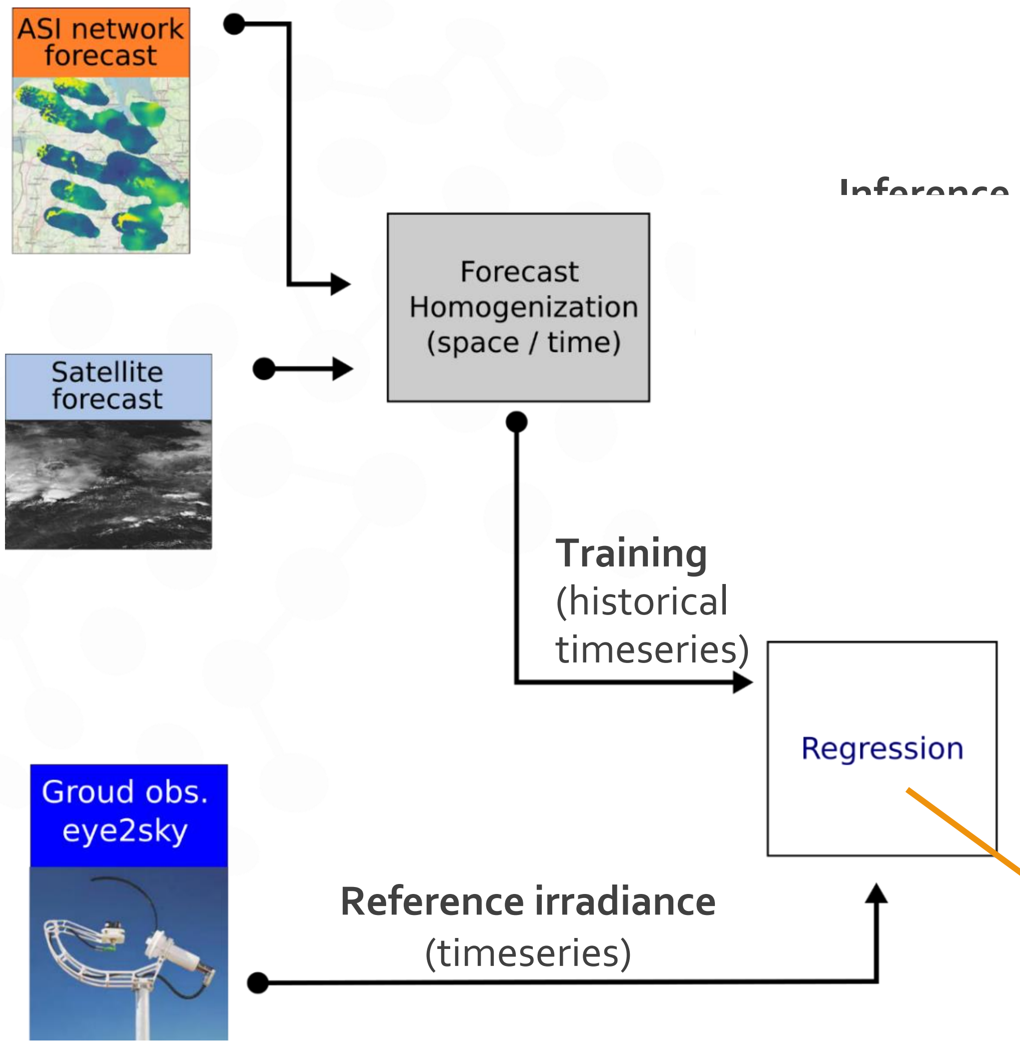
E.g. for GHI at DON:



- ASI network forecast presents a relative improvement on RMSD of around 20% between the leadtimes 2 min to 15 min.
- Advantage of the ASI network over the ASI pair and persistence remains for large lead times
- As expected the ASI network outperforms an ASI pair even more clearly at locations farer from the ASI pairs location (not shown here)

Hibrid combined forcasts using ground observations, all-sky and satellite imagers

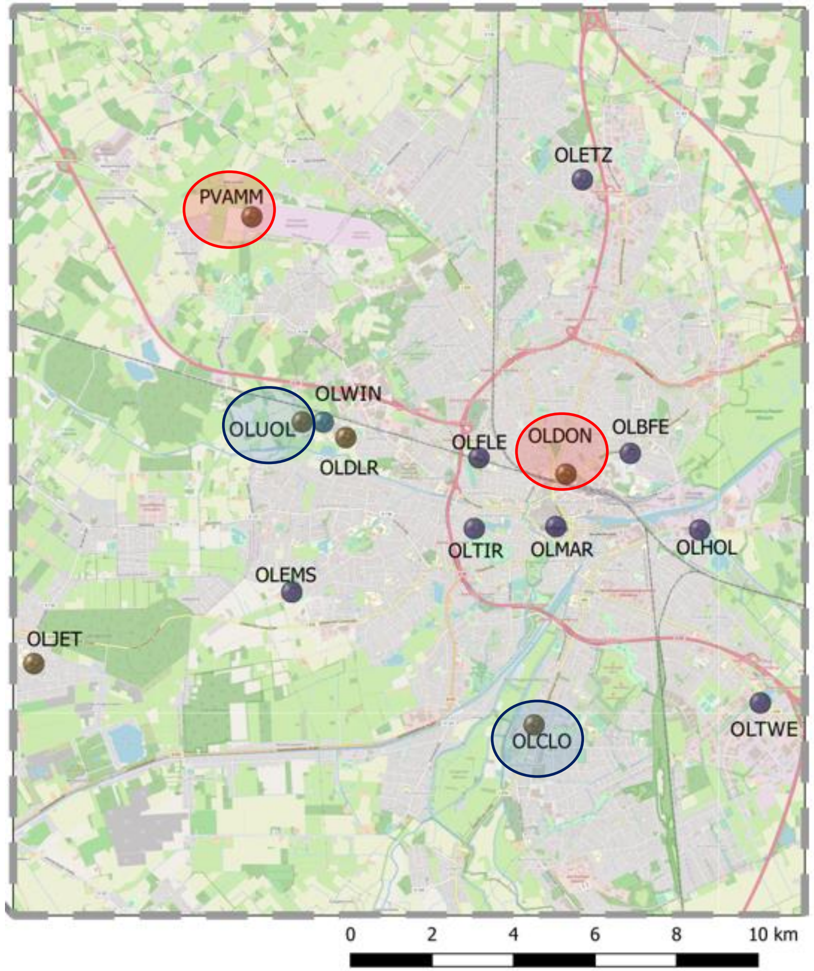
Combination algorithm



$$C = \sum_{n=0} (a_n \cdot F_n) + b \Big|_{\text{per leadtime}}$$

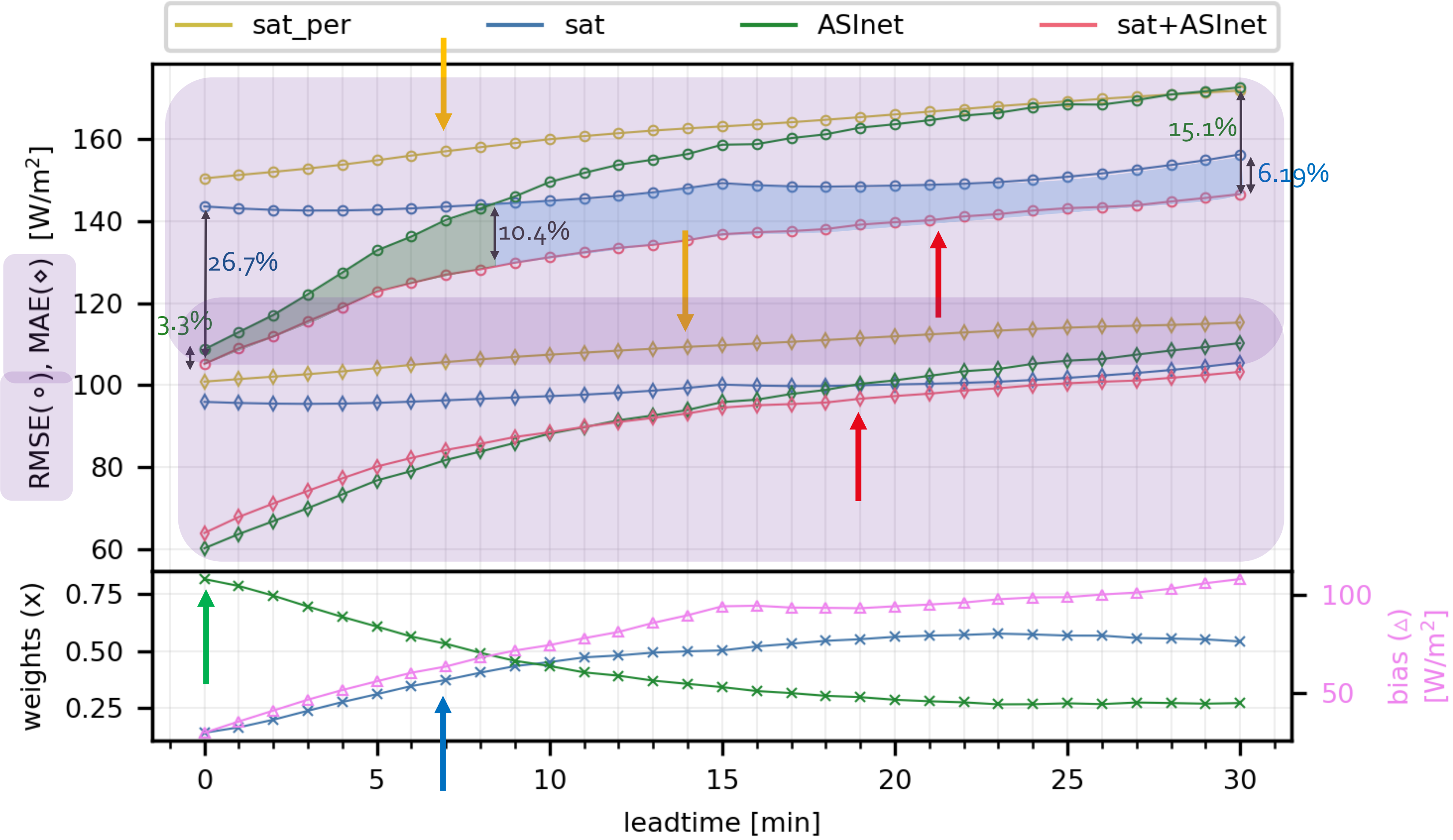
$$lsq.\ \min\left(\sum_{n=0}^{N-1}(a_n \cdot \overline{F_n}) + b - \overline{GHI}\right)\Bigg|_{\text{per leadtime}}$$

Validation of the Hybrid forecast



	Combination SAT + ASInet
Available data	07.2020 - 08.2020 (2 months)
Training range	Last 30 days from forecast instance
Training stations	OLUOL, OLCLO
Validation Range	08.2020
Validation sites	OLDON, PVAMM
Combi forecast horizon	30 min
Combi forecast time resolution	1 min
Data filter	Elevation < 20°

Benchmark of inputs vs combined forecast



- Improv. Over persistance
- RMSE (least squares min)
- MAE improv. Over Sat
- Optimal mix of weigths
- **KPI (10-15% RMSE) : improvement in RMSE of 5% to 14% with respect to satellite forecasts and 3% to 15% with respect to the ASI network**

Key take aways

- The statistical combination of the images of the ASIs in a network help to mitigate the errors which are in the ASI pair configuration (cloud base height, cloud segmentations and cloud velocity).
- The network of ASIs provides instantaneous maps of solar irradiance and outperforms the very-short-term prediction (up to 1 hour) of the state of the art ASI-Pair system.
- Combining the all-sky imagers network and satellite forecasts outperforms individual forecasts and extracts the best of both approaches for short-term forecasts.
- The developed forecasts should be validated at locations in order to assess the performance on different weather conditions (dominant cloud situation, aerosol content, etc.).
- New developments of interpolation an regression strategies (ML) will be implemented to compare performance against this linear base case (is the additional effort/complexity compensated by accuracy?).

FURTHER READING

- Public deliverables on Smart4RES WP2
- Publications
  - [1] Fabel, Y., et al.,(2022). Applying self-supervised learning for semantic cloud segmentation of all-sky images. *Atmospheric Measurement Techniques*, *15*(3), 797-809.
  - [2] Blum, N. B., et al., (2021). Cloud height measurement by a network of all-sky imagers. *Atmospheric Measurement Techniques*, *14*(7), 5199-5224.
  - [3] Blum, N. B. et al.,(2022). Measurement of diffuse and plane of array irradiance by a combination of a pyranometer and an all-sky imager. *Solar Energy*, *232*, 232-247.
  - [4] Blum, N. B., et al., (2022). Analyzing Spatial Variations of Cloud Attenuation by a Network of All-Sky Imagers. *Remote Sensing*, *14*(22), 5685.
  - [5] Schroedter-Homscheidt, M., et all, (2018). Classifying ground-measured 1 minute termporal variability within hourly intervals for direct normal irradiances.. Meteorologische Zeitschrift, 27(2),161-179

Thank you for your attention