

High resolution hybrid forecast based on the combination of satellite and an All-Sky Imager (ASI) network forecasts

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Knowledge for Tomorrow



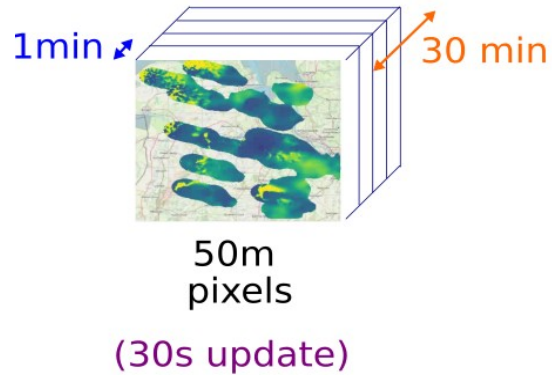
Overview

- Combination inputs description
- Combination method
- Test case
- Results

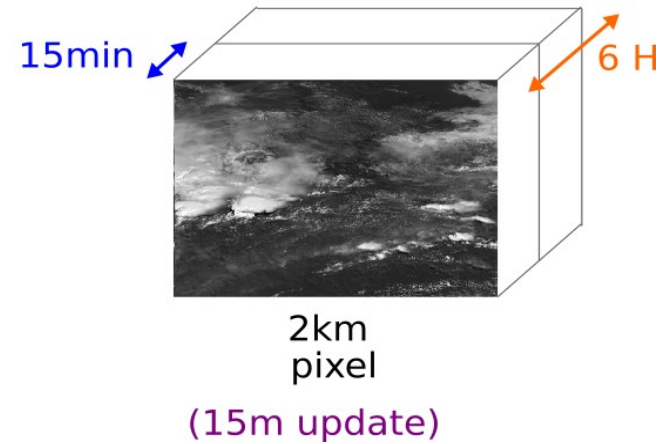


Combination inputs

ASI (All Sky Imager) network forecast



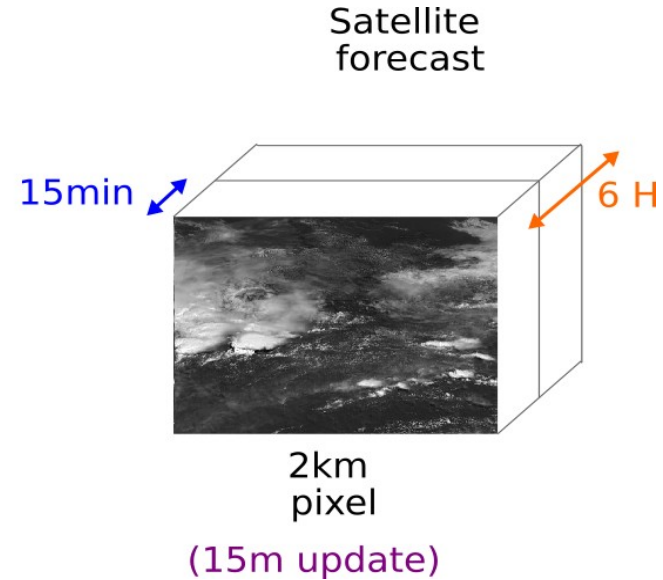
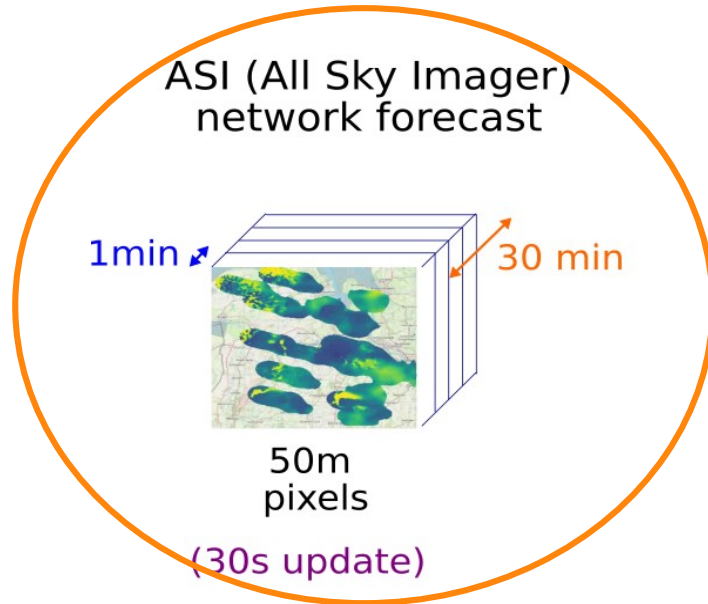
Satellite forecast



Parameter	ASI network	Satellite
Extent	40 x 40 km ² (around Oldenburg)	satellite view (EU wide)
Availability	July and August 2020	operational since 2020



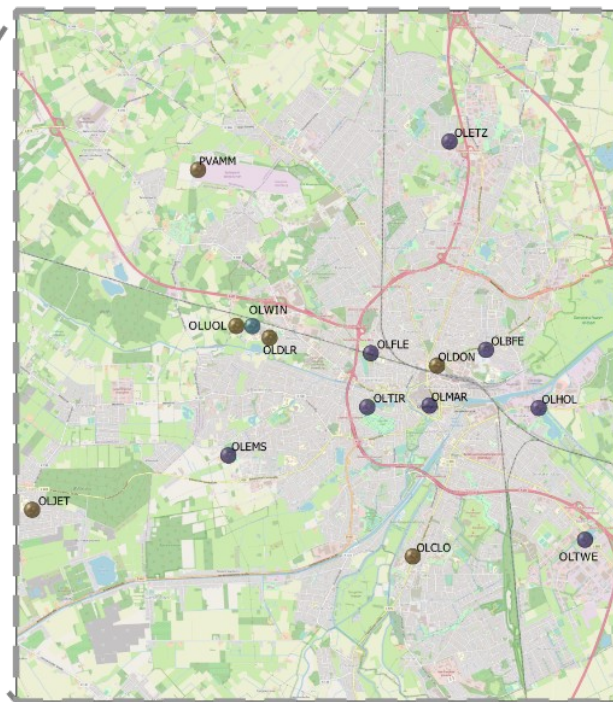
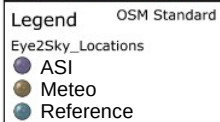
Combination inputs



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Eye2sky : ASI and meteorological measurement network in Oldenburg

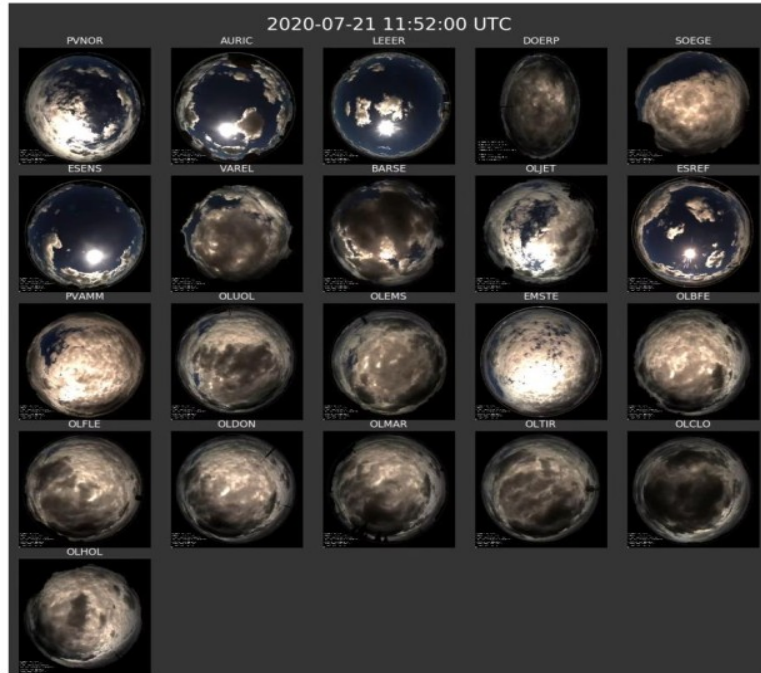


(source: DLR)

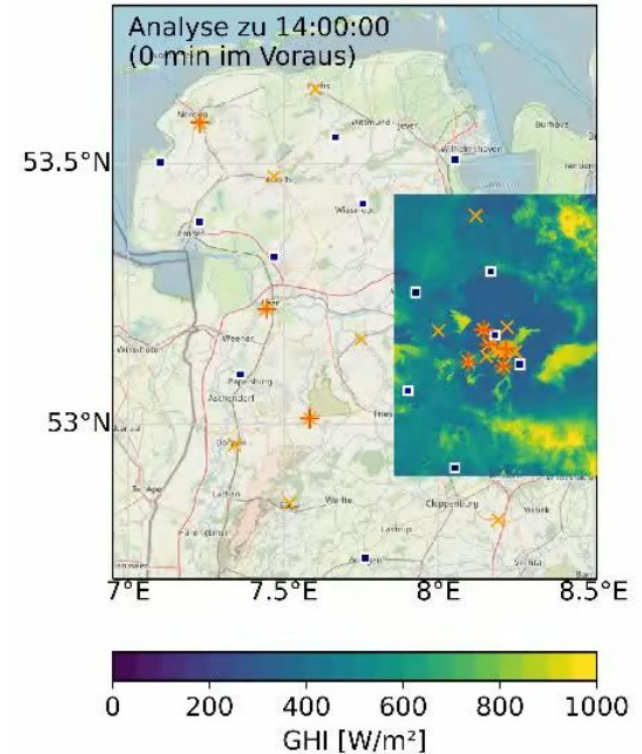
- 30 / 39 measuring stations in operation
 - 2 reference (solar tracker)
 - 10 meteorological stations (RSI + ASI)
 - 18 ASI stations (ASI only)
 - 2 ceilometer
- 14 stations in Oldenburg
- 25 stations around Oldenburg



ASI network forecast *



(source: DLR)



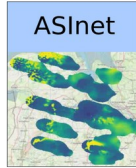
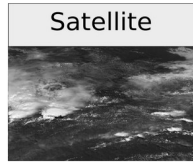
* Blum, N. B. (n.d.). Nowcasting of Solar Irradiance and Photovoltaic Production Using a Network of All-Sky Imagers. PhD dissertation, Rheinisch-Westfälische Technische Hochschule Aachen (under review).

* Blum, N. B et al., Analyzing spatial variations of cloud attenuation by a network of all-sky imagers, Remote Sensing special issue: "Remote Sensing for Smart Renewable Cities" (under preparation).



Combination of satellite and ASI network forecast

Ground
measurements



Forecast Homogenization
(space / time)

Historical

Present

Regression

$a_{i,opt}$

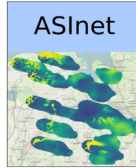
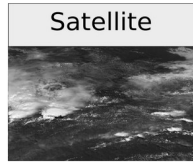
Prediction

Combined
forecasts



Combination of satellite and ASI network forecast

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Forecast Homogenization
(space / time)

Historical

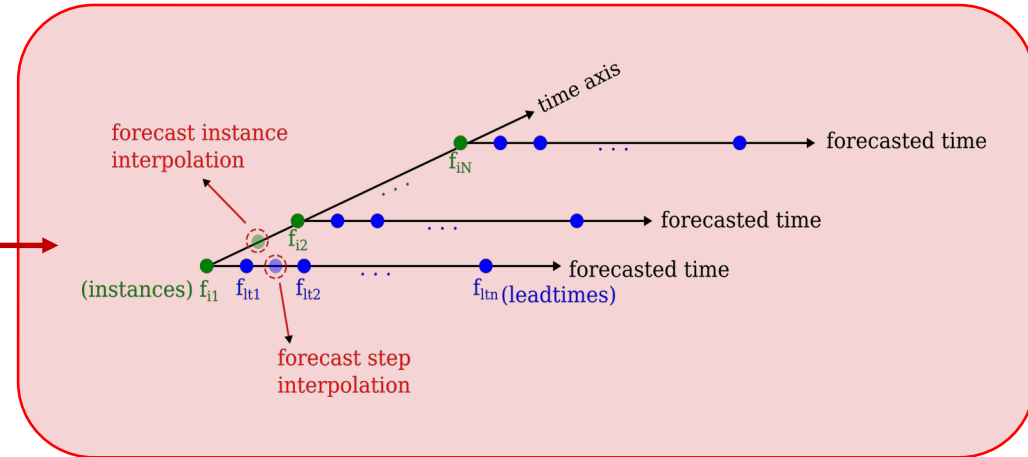
Present

Regression

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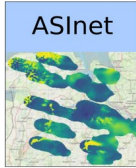
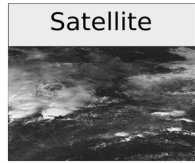
Prediction

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Combination of satellite and ASI network forecast

Ground measurements



Forecast Homogenization (space / time)

Historical

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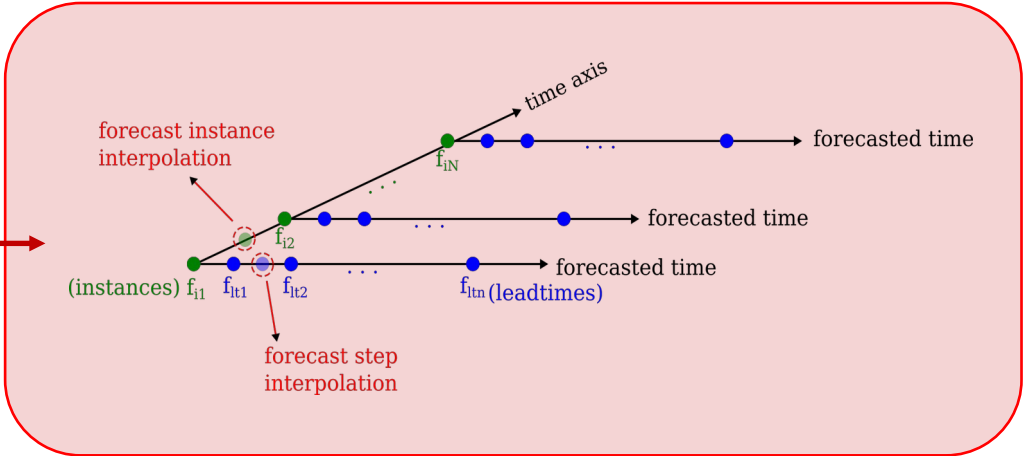
Regression

$a_{i,opt}$

Prediction

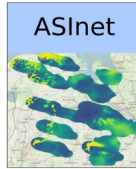
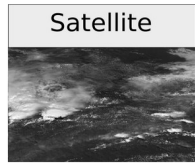
Combined forecasts

$$\min \left(\sum_{n=0}^{N-1} (a_n F_n) + b - GHI \right)$$



Combination of satellite and ASI network forecast

Ground measurements



Forecast Homogenization (space / time)

Historical

Present

Regression

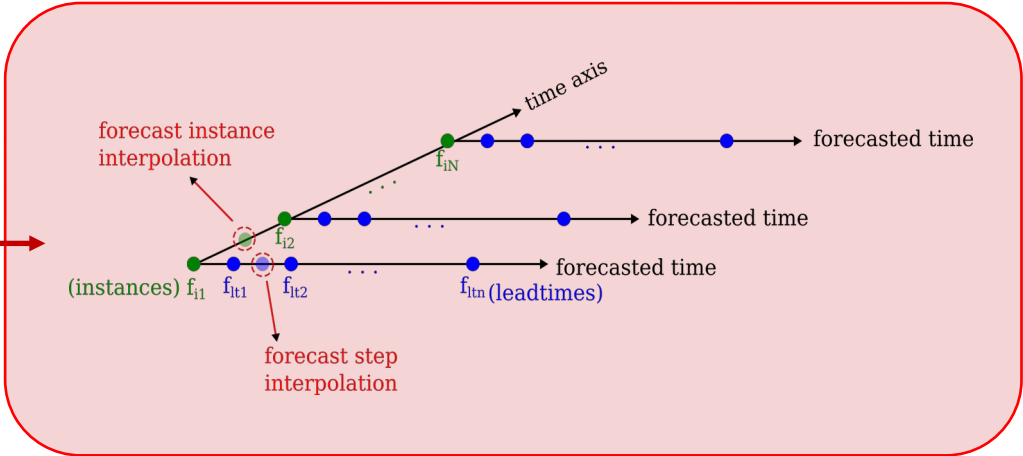
$a_{i,opt}$

Prediction

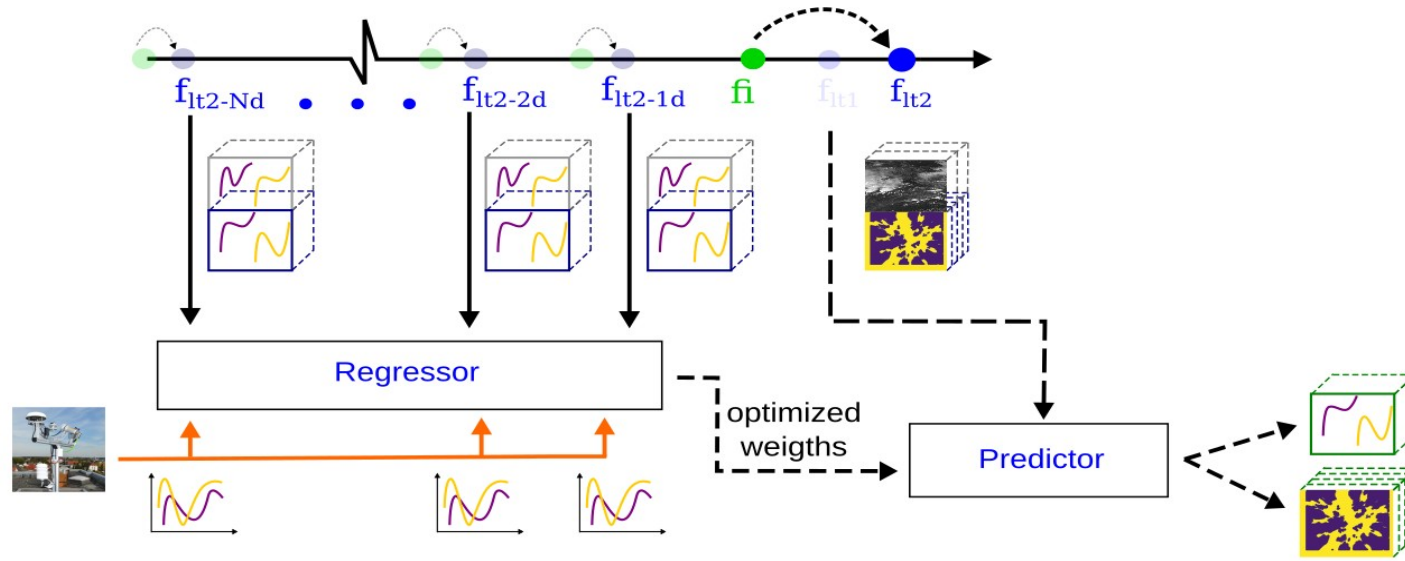
Combined forecasts

$$\min \left(\sum_{n=0}^{N-1} (a_n F_n) + b - GHI \right)$$

$$C = a_0 F_{SAT} + a_1 F_{ASInet} + b$$



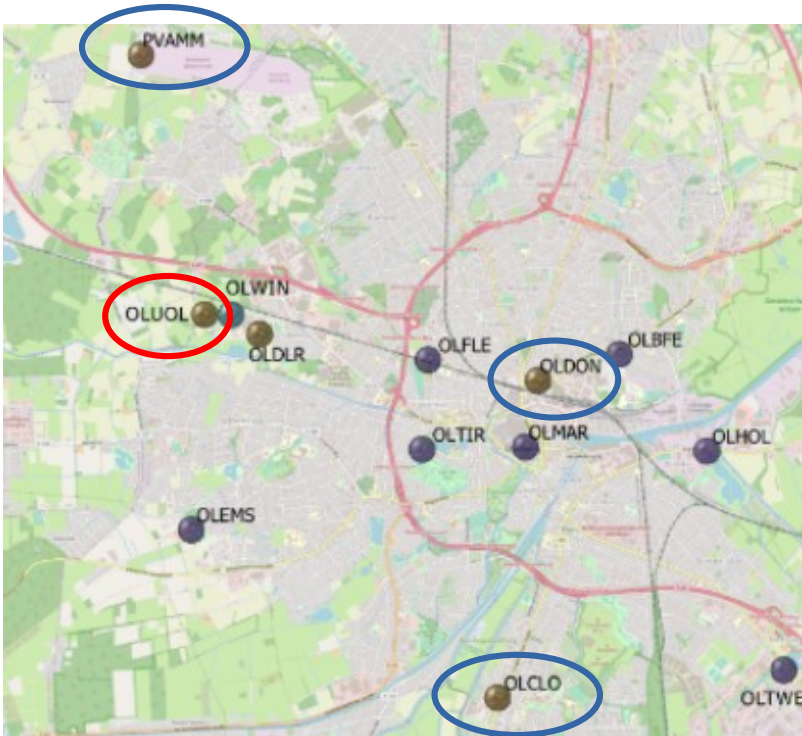
Combination method



Same process repeated per forecast leadtime :
Individual set of optimal weights per leadtime



Combination forecast : test case

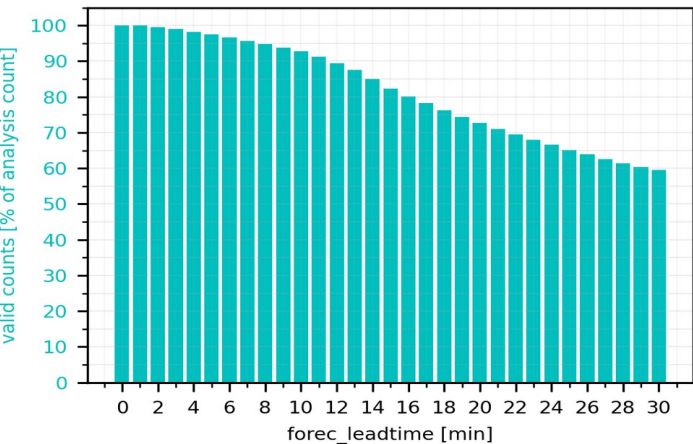
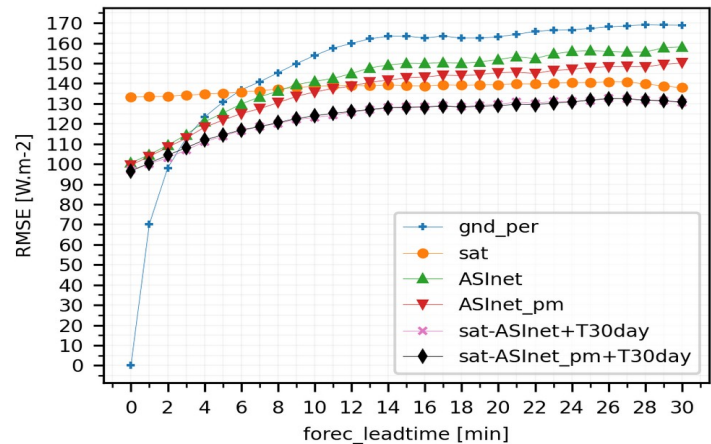
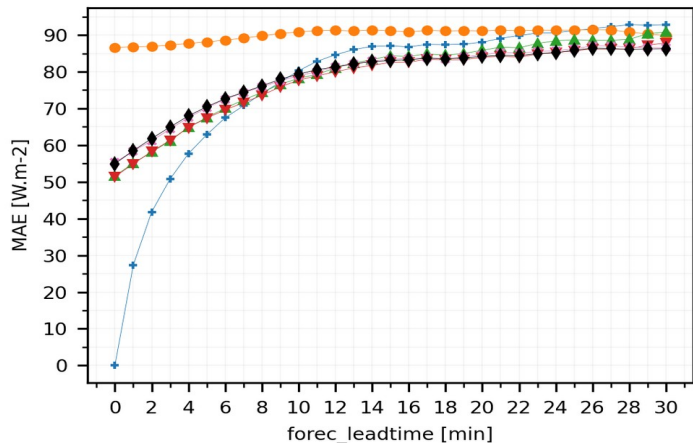
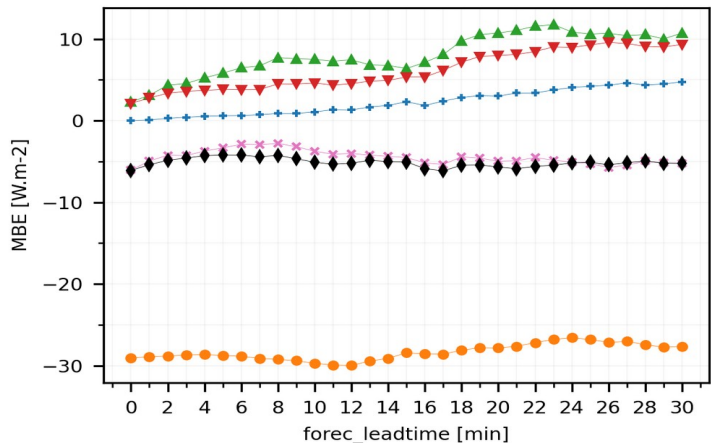


(source: DLR)

- Training :
 - station : PVAMM / OLDON / OLCLO
 - timerange : Last 30 days
- Validation:
 - station : OLUOL
 - timerange : 31.07.2020 to 31.08.2020
- Combined forecast:
 - forecast horizon : 30 min
 - forecast resolution : 1 min
- Data filtering:
 - Elevation > 5°

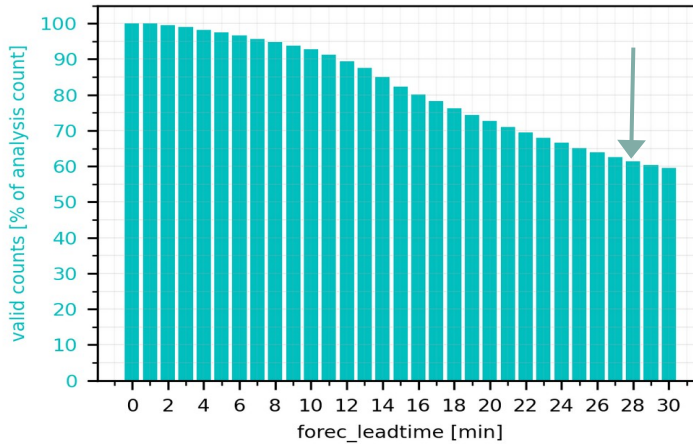
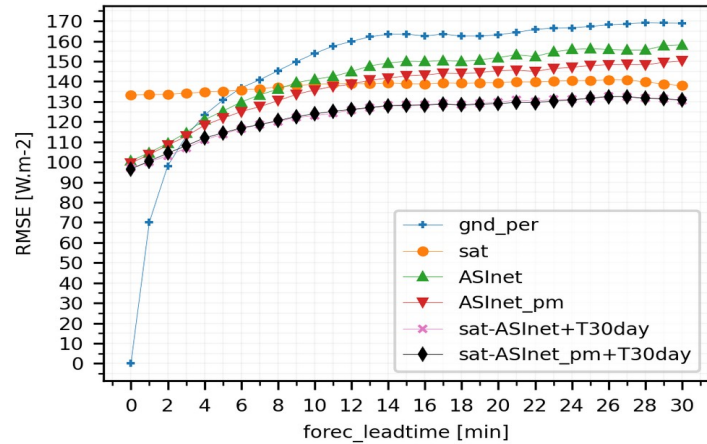
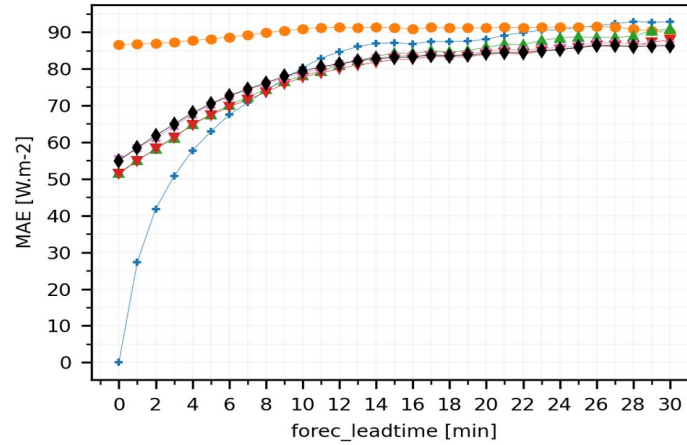
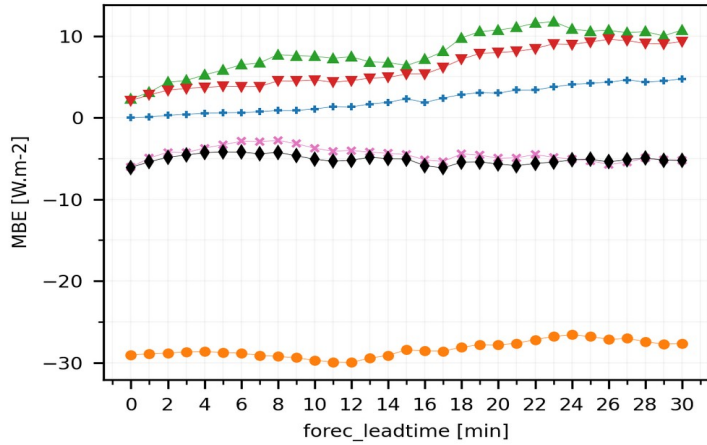


Combination error metrics



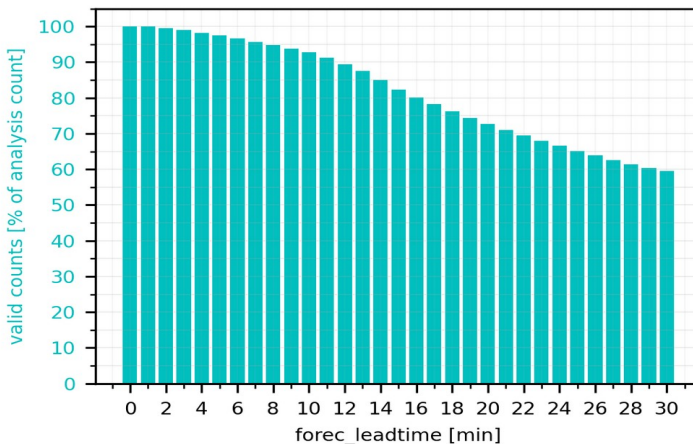
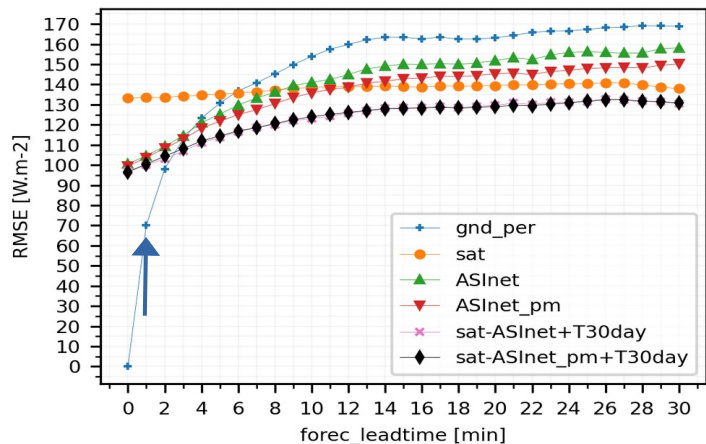
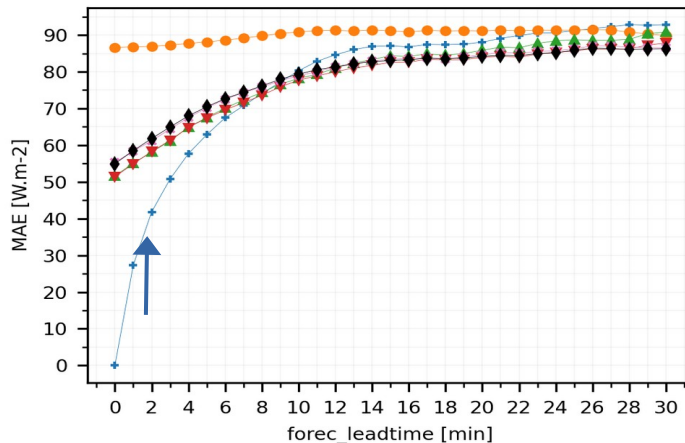
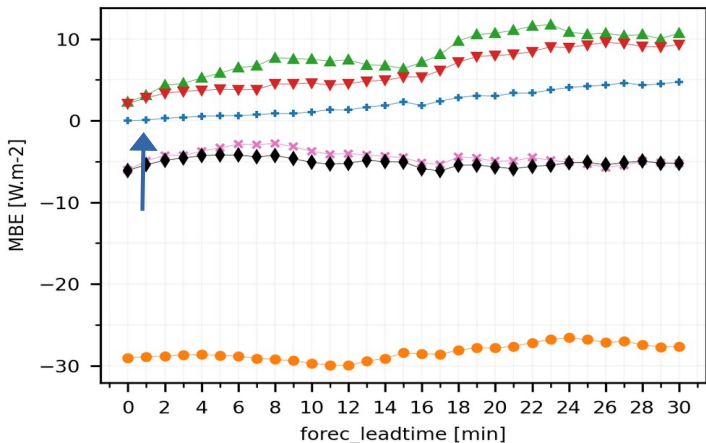
Combination error metrics

- NaN values at higher leadtimes

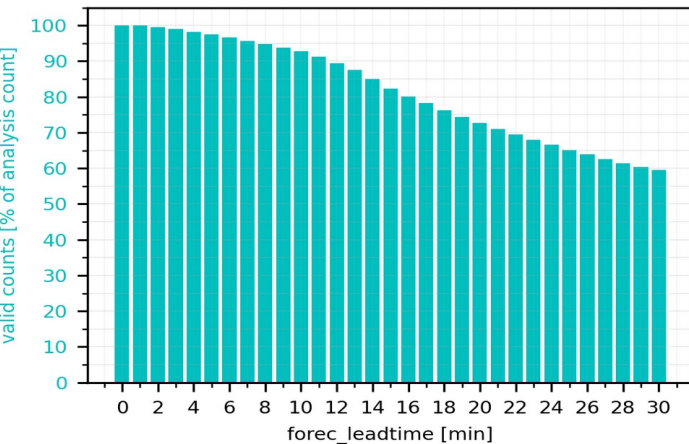
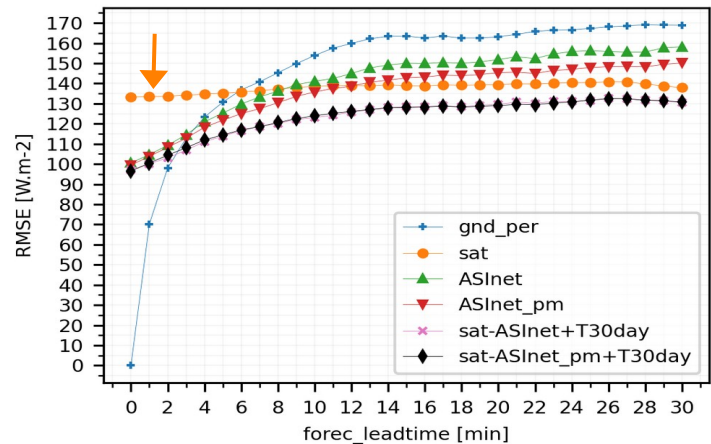
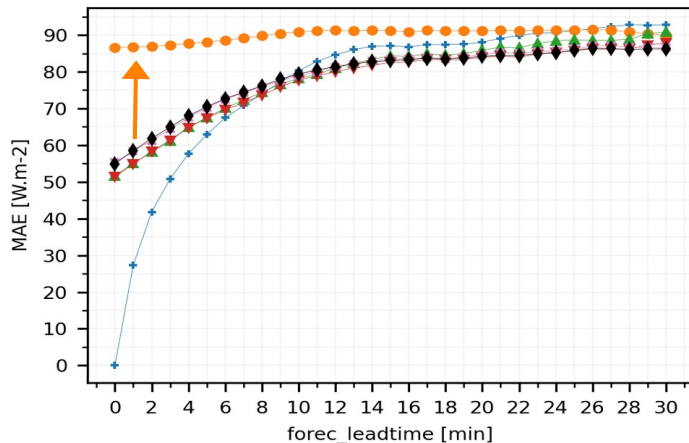
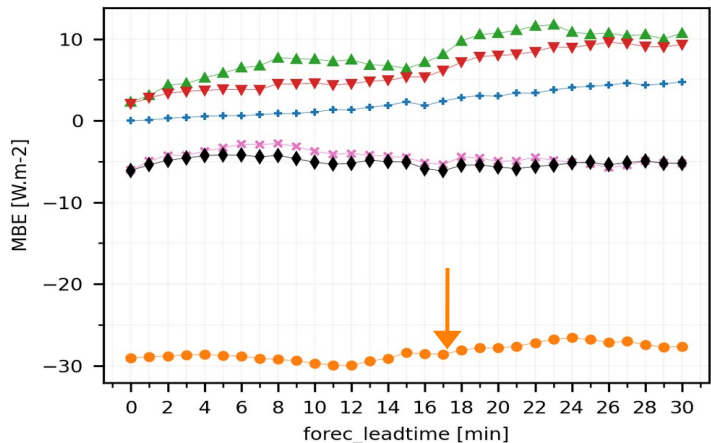


Combination error metrics

- NaN values at higher leadtimes
- Improvement over persistence



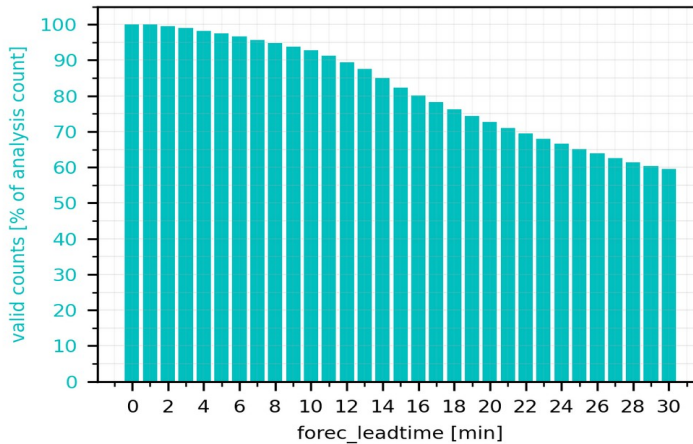
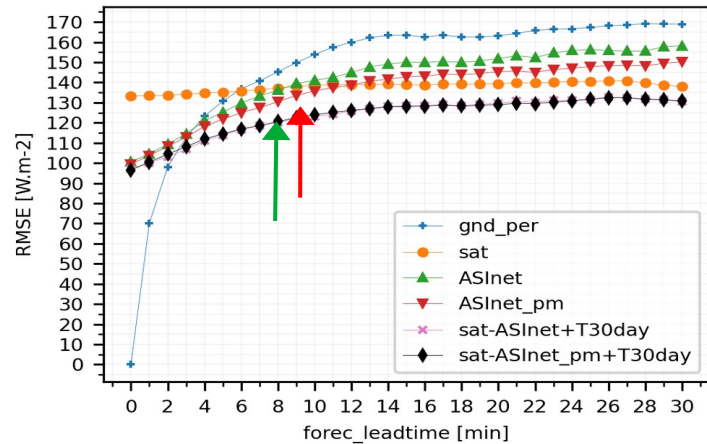
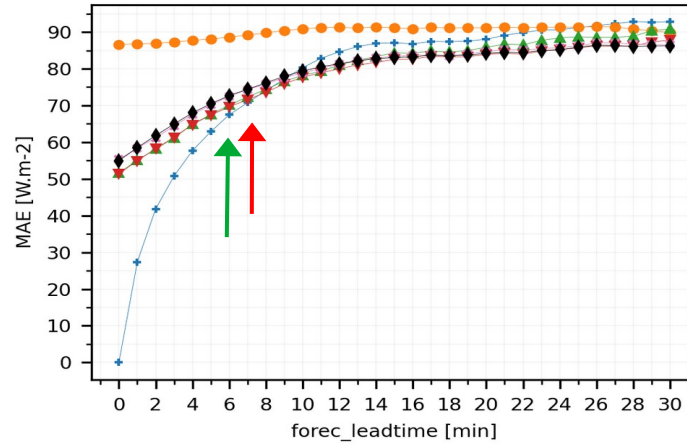
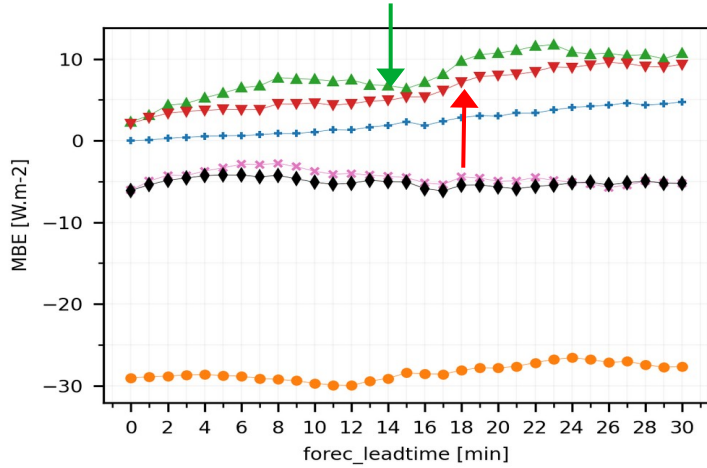
Combination error metrics



- NaN values at higher leadtimes
- Improvement over persistence
- Satellite
 - Underestimation
 - average behavior



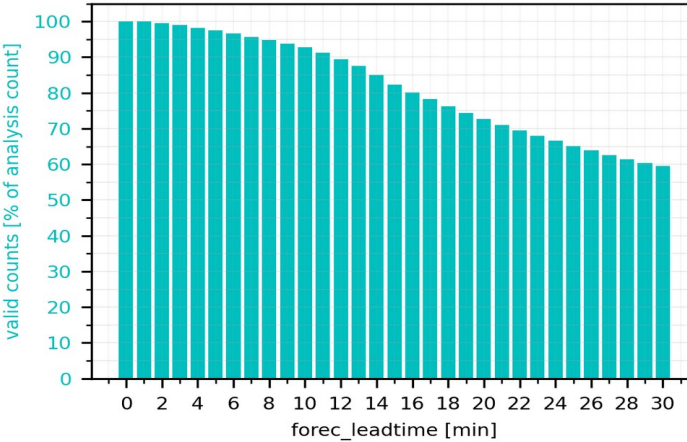
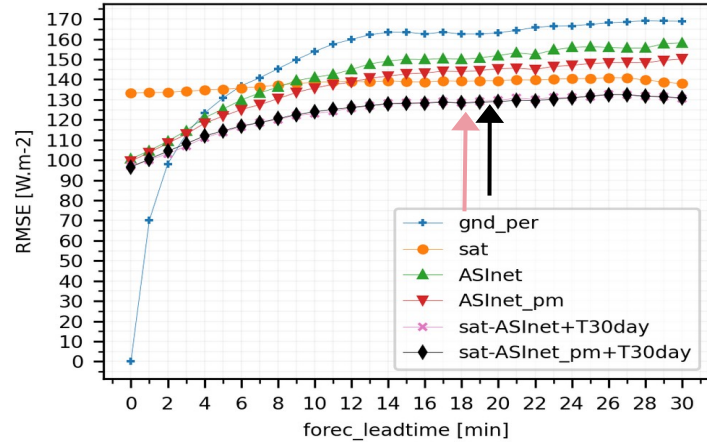
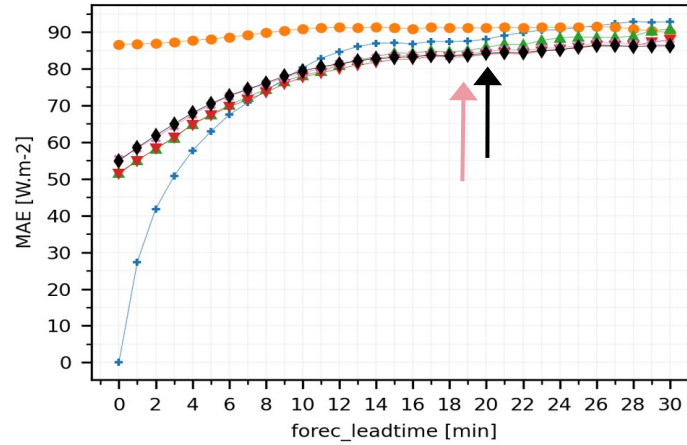
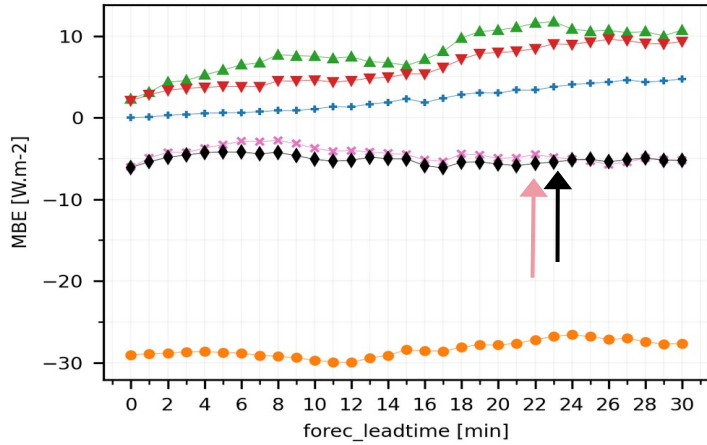
Combination error metrics



- NaN values at higher leadtimes
- Improvement over persistence
- Satellite
 - Underestimation
 - average behavior
- ASInet:
 - Basic vs persistence merger
 - MAE improv. at 9 min
 - RMSE improv. at 3 min



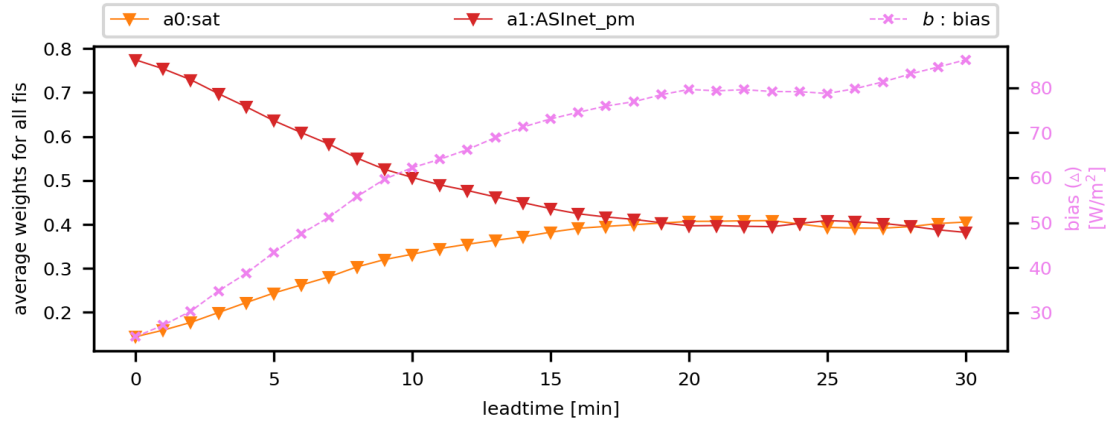
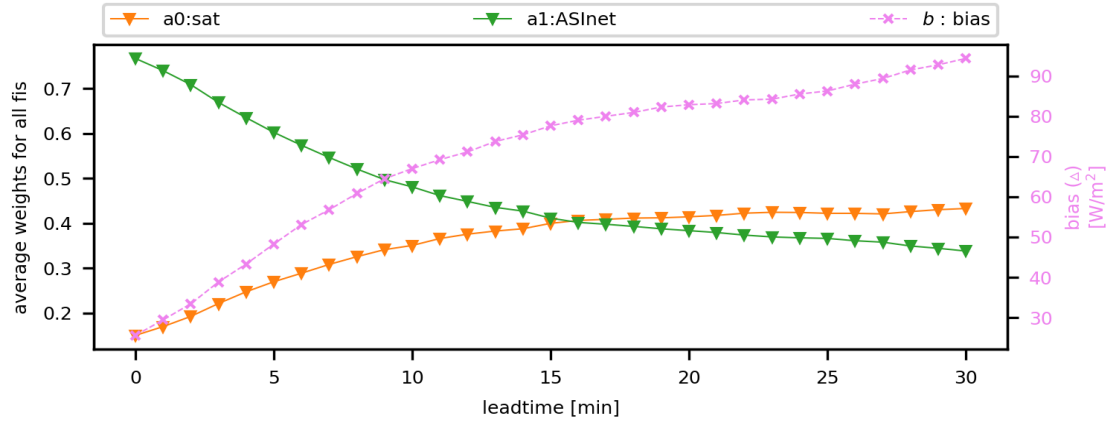
Combination error metrics



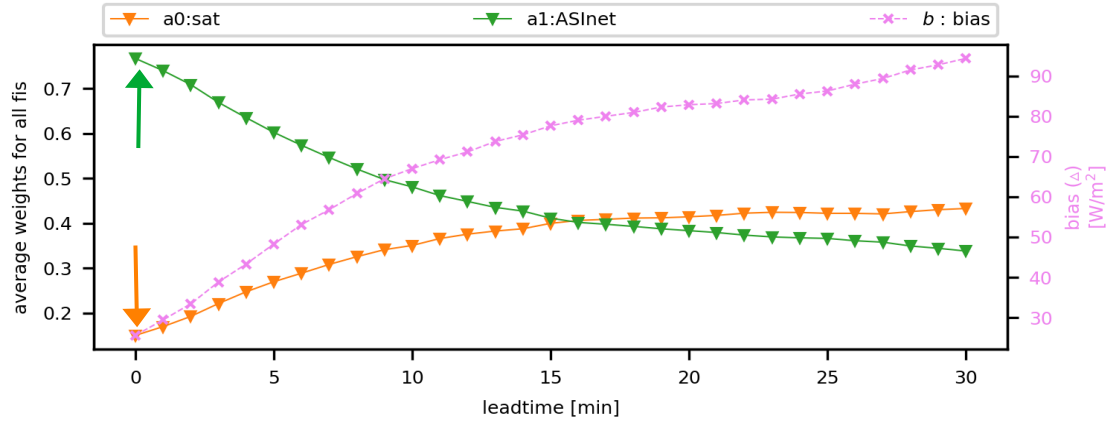
- NaN values at higher leadtimes
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 - Basic vs persistence merger
 - MAE improv. at 9 min
 - RMSE improv. at 3 min
- Combi1, Combi2
 - RMSE improved over all (LSE)
 - relative improv. ~ 8 % (5 – 14 min)
 - BIAS in between inputs
 - MAE ~ behavior as for ASI
 - No noticeable difference between the combis



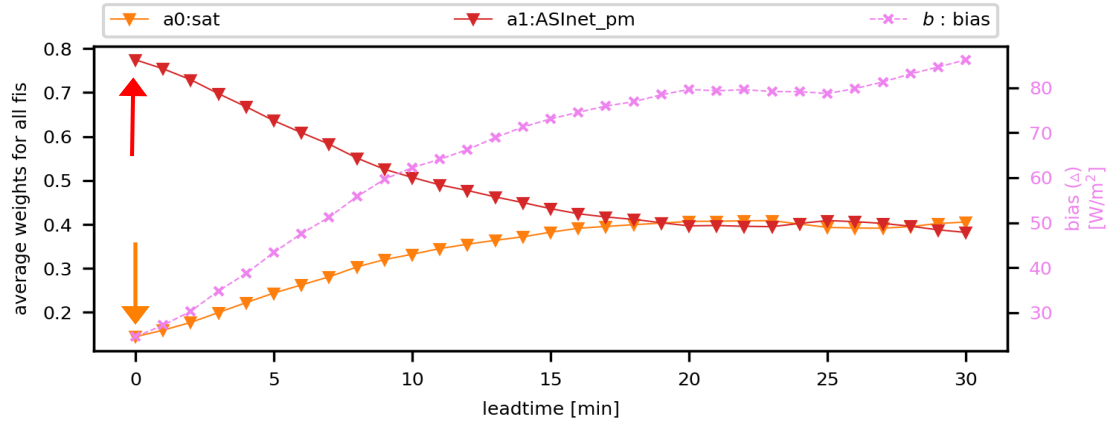
Combi Coeficients



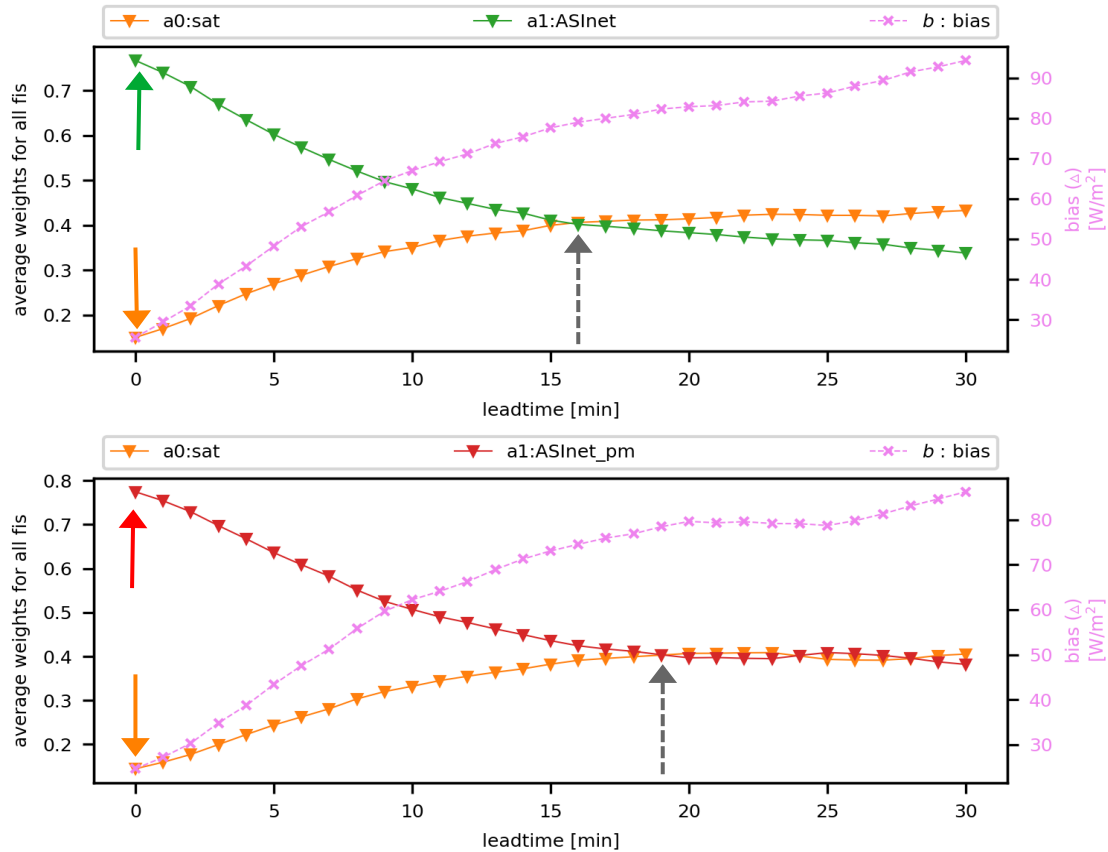
Combi Coefficients



- ASI high weights on lower leadtimes while satellite has low weights



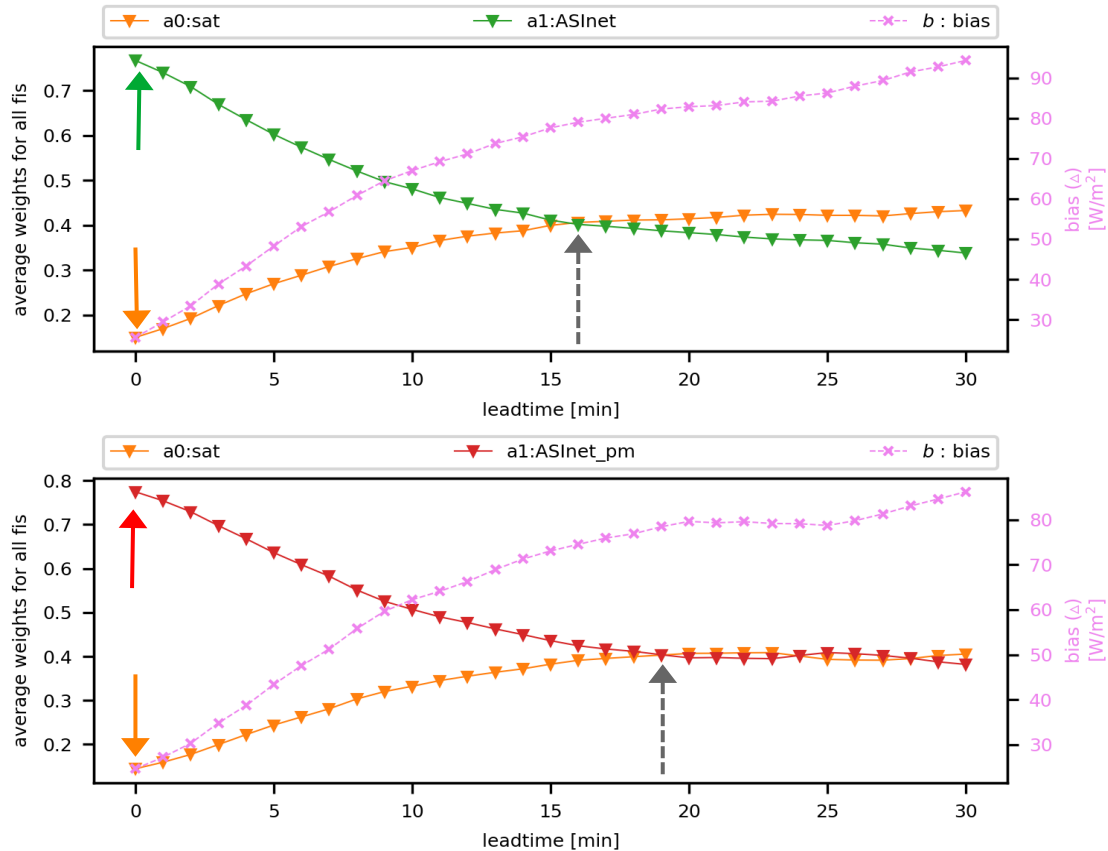
Combi Coefficients



- ASI high weights on lower leadtimes while satellite has low weights
- Same weight:
 - at 16 min for combi with ASInet
 - at 19 min for combi with ASInet_pm
 - ASI forecast influence > 15 min
 - Crosspoint dependent of local weather conditions (low clouds in Oldenburg).



Combi Coefficients



- ASI high weights on lower leadtimes while satellite has low weights
- Same weight:
 - at 16 min for combi with ASInet
 - at 19 min for combi with ASInet_pm
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 - Crosspoint dependent of local weather conditions (low clouds in Oldenburg).
- Bias correction increases over time until ~ 90W.m-2



Conclusions

- The newly developed hybrid forecast outperforms the RMSE of persistence and the input forecasts for all lead times calculated. It shows an improvement on RMSE of around 8 % with respect to the ASI network forecast on lead times going from 5 to 14 min.
- The processing of input data for more months during the year is needed to assess the seasonal transfer ability of the results
- The combined forecast should be validated at locations with different characteristics as the ones found in Northwest Germany in order to assess the differences on performance due to different weather conditions (dominant cloud situation, aerosol content, etc.).
- New developments of interpolation and regression strategies (AI techniques) should be implemented/ tested to compare performance against this linear base case (... is the additional effort/complexity useful).





This work was partially funded by the **Smart4RES Horizon 2020 EU project, grant number 864337**

Thank you for your attention

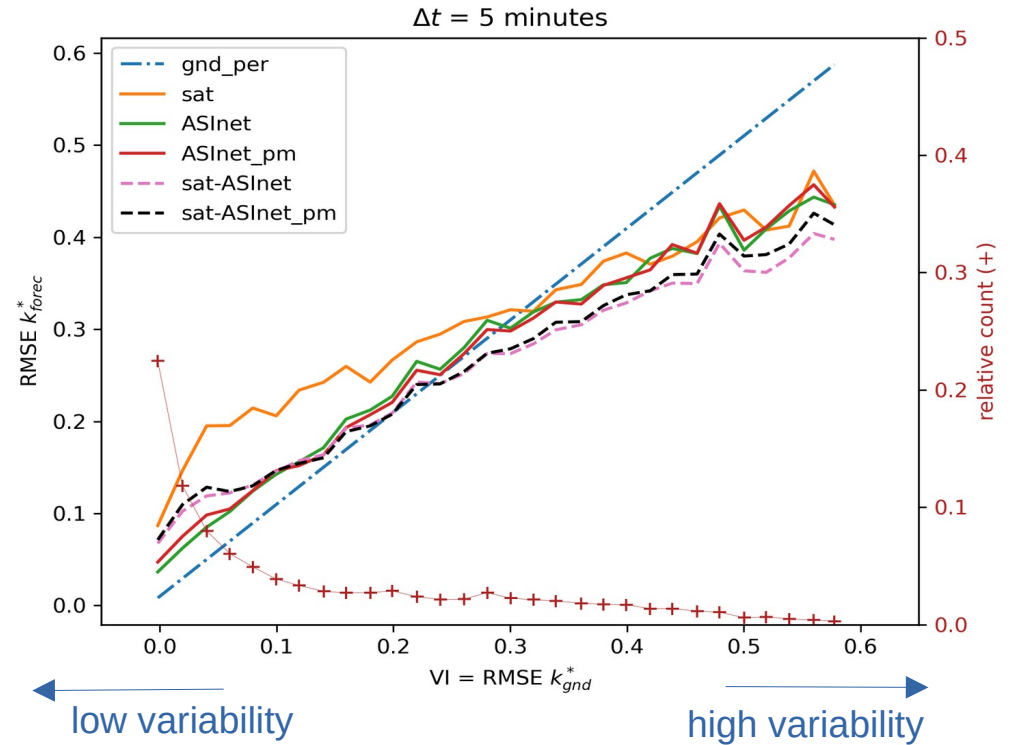
Questions ?



Benchmark on prevailing irradiance conditions

$$VI = \sqrt{\frac{1}{N} \sum_{i=1}^N (K(t_i + \Delta t) - K(t_i))^2}$$

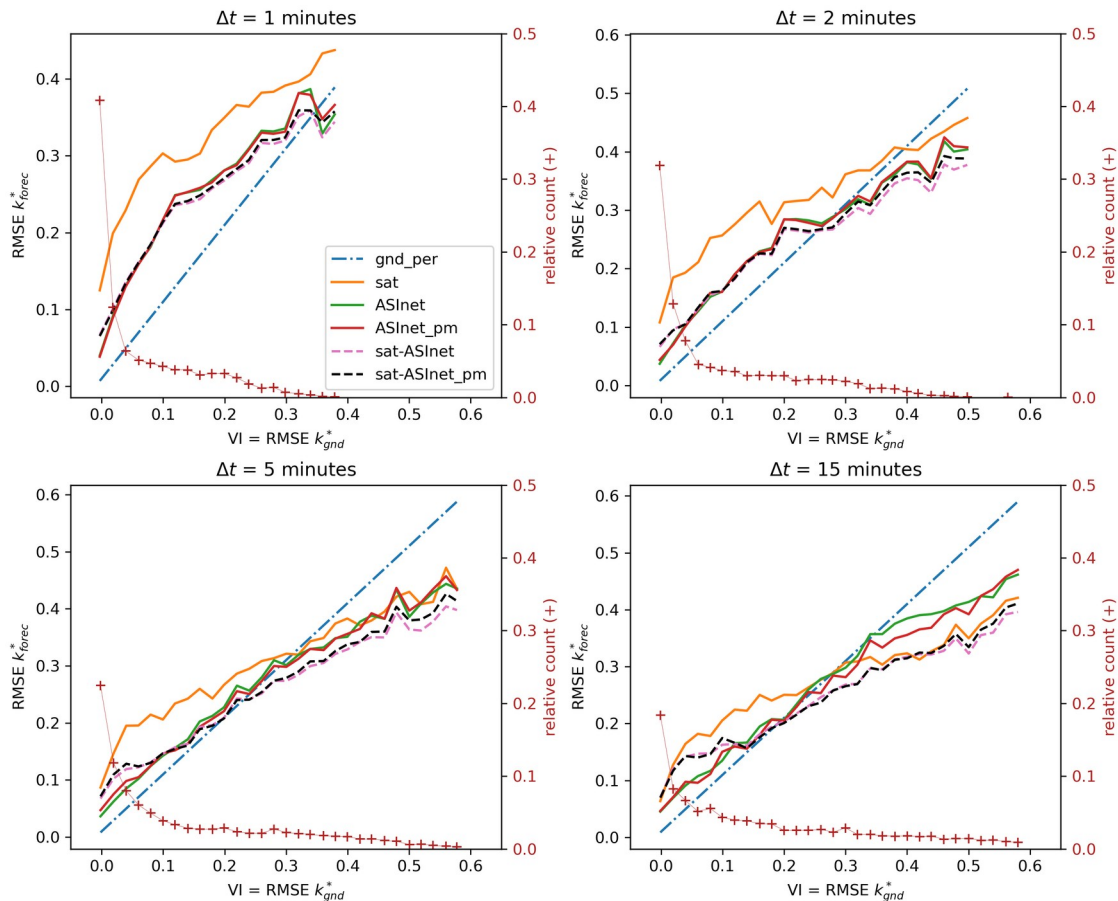
- > Standard deviations of the increments Δt of clear sky index \mathbf{K} (Marquez, R., 2013)
- > N = number of forecast in a sliding window of 25 minutes
- > Δt = increment (5 min in this case)
- > Persistence in diagonal line



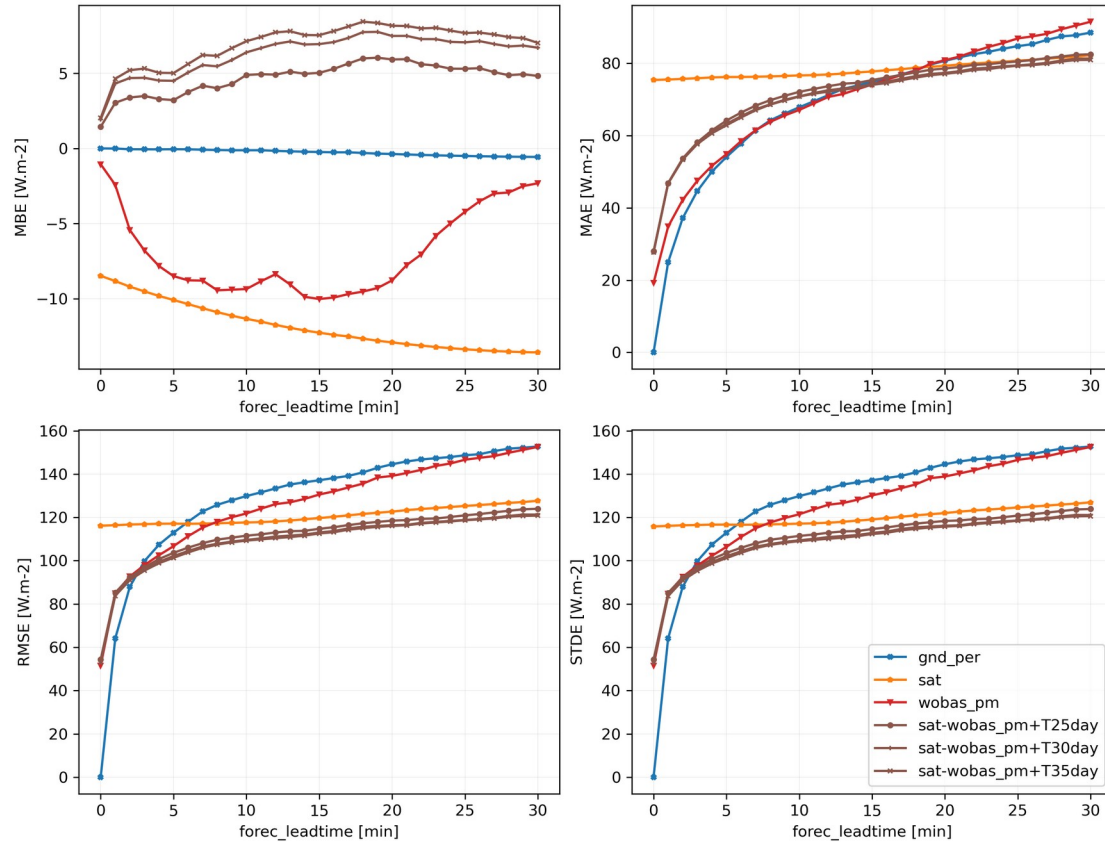
Marquez, R. and Coimbra, C. (2013), "Proposed Metric for Evaluation of Solar Forecasting Models", Journal of Solar Energy Engineering, 135 (1):011016-011016. doi: 10.1115/1.4007496



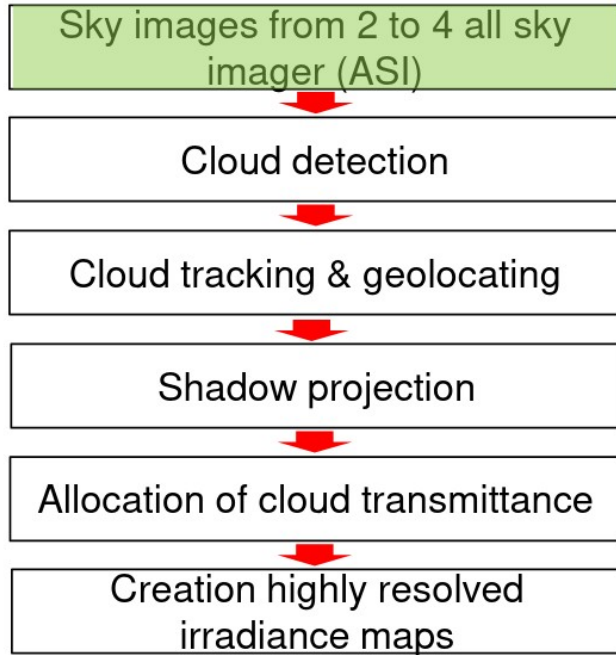
Behavior on different increments



Combination sensitivity on training days: case PVNOR



ASI forecast principle



- Images from 2 to 4 Mobotix surveillance cameras
- Direct Normal Irradiance (DNI) measurements (e.g. Pyrheliometer or Rotating Shadowband Irradiometers RSI)



(source: DLR)

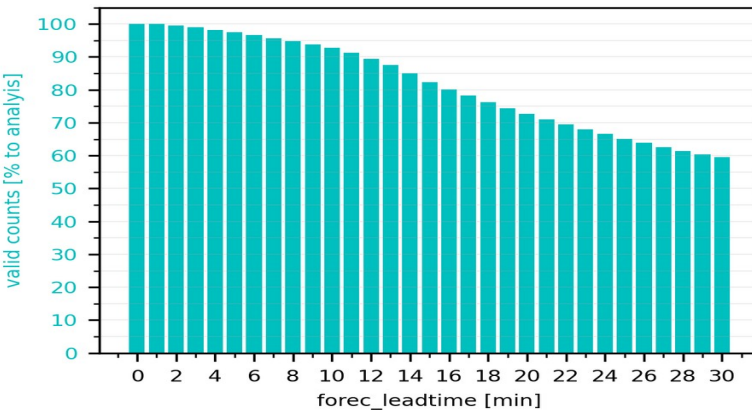
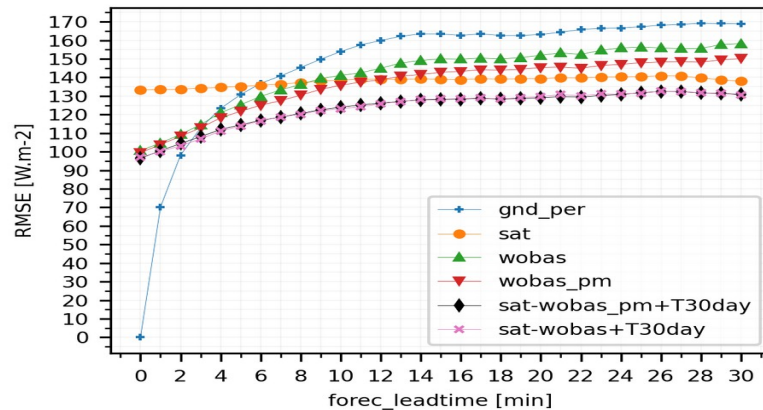
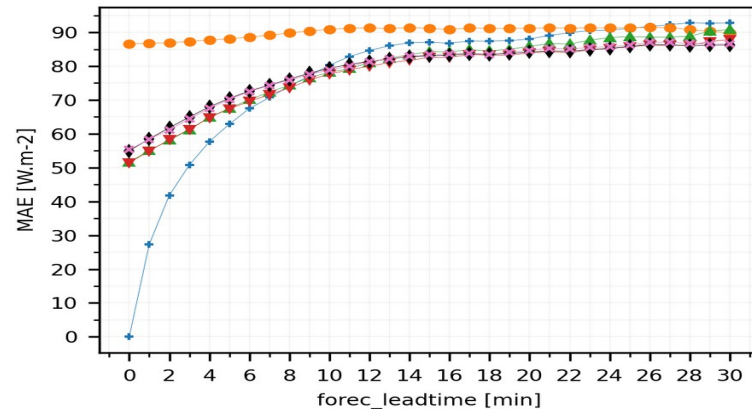
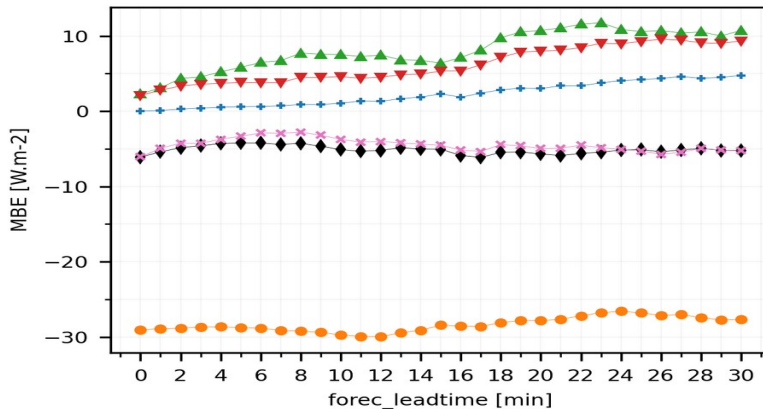


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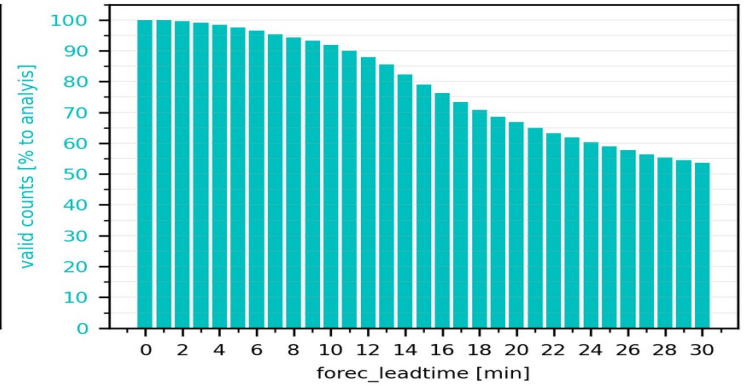
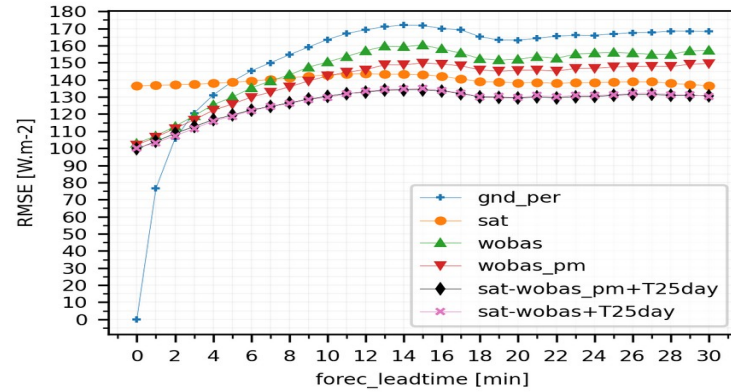
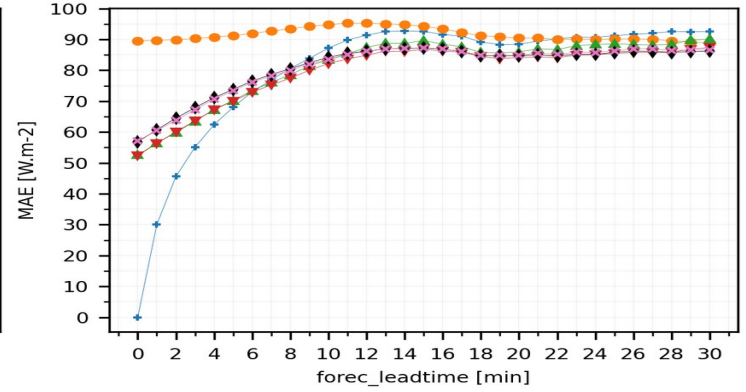
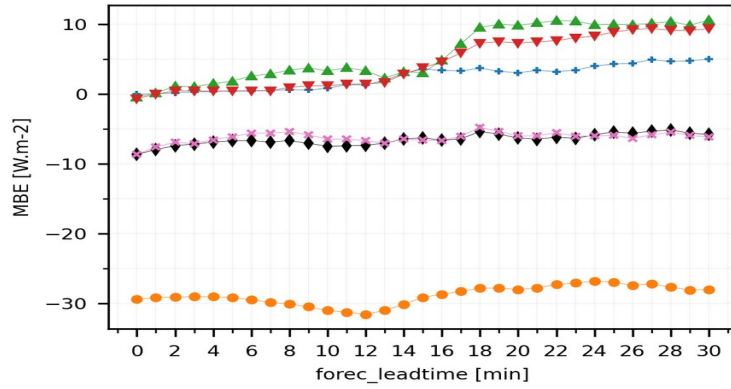


Plots

Cal : PVAMM, OLCLO, OLDON
 forec: OLUOL
 train : 30 days



Cal : PVAMM, OLCLO, OLDON
 forec: OLUOL
 train : 25 days



Cal : PVAMM, OLCLO, OLDON
forec: OLUOL
train : 35 days

