

THE BENEFIT OF A DENSE NETWORK OF ALL-SKY IMAGERS FOR REGIONAL SATELLITE-BASED SHORT-TERM FORECASTS OF SOLAR IRRADIANCE

Jorge Lezaca ^{1*}, Annette Hammer ¹, Thomas Schmidt ¹, Jonas Stührenberg ¹, Niklas Blum ², Bijan Nouri ²

¹ DLR Institute of Networked Energy Systems (VE)

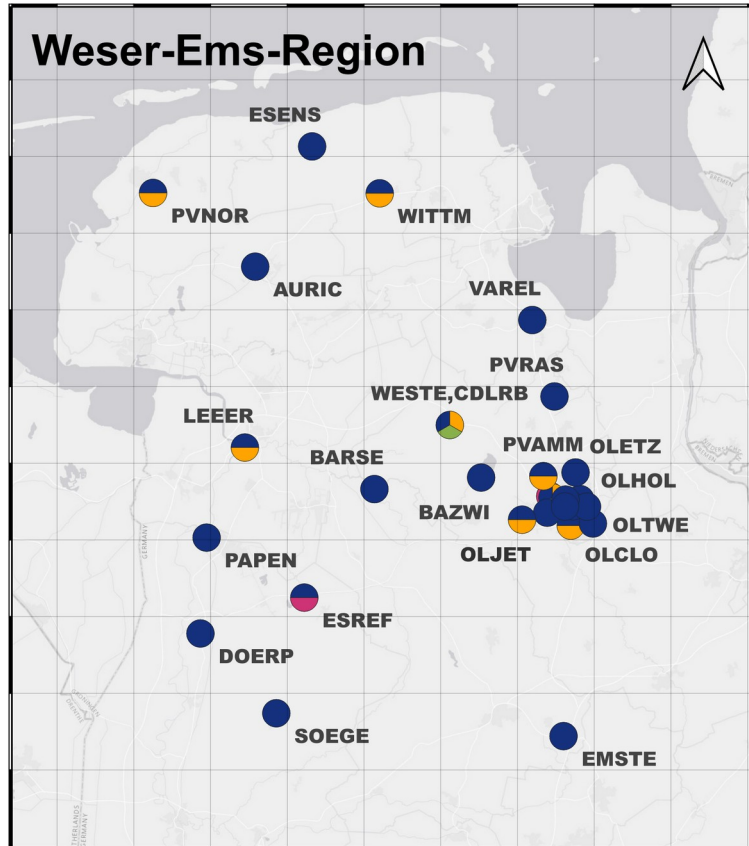
² DLR Institute of Solar Research (SF)

* corresponding author : jorge.lezaca@dlr.de



EYE2SKY NETWORK

DLR's Eye2Sky Measurement network

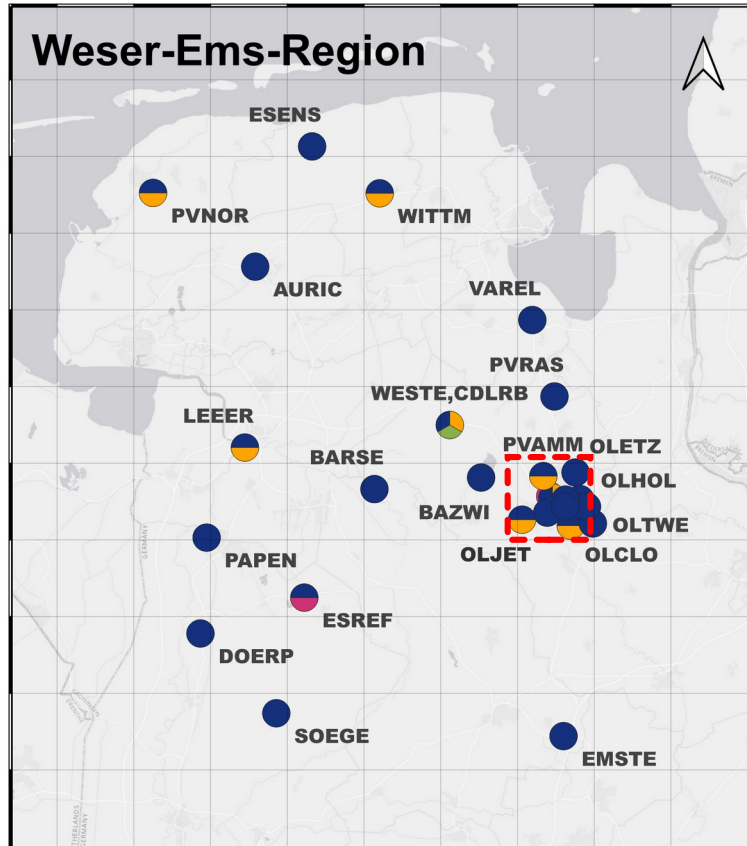


Eye2sky in numbers:

- 110 km x 100 km
- 30 stations with an All-Sky Imager (ASI)
- 12 stations with meteorological instrumentation:
 - 10 with RSI (MET) stations
 - 2 with solar tracker based stations (REF)
- 2 ceilometers (CEI) + data from 8 other in the region from EWE

Background: OpenStreetMap ESRI light gray

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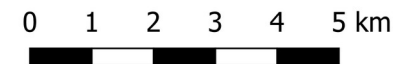
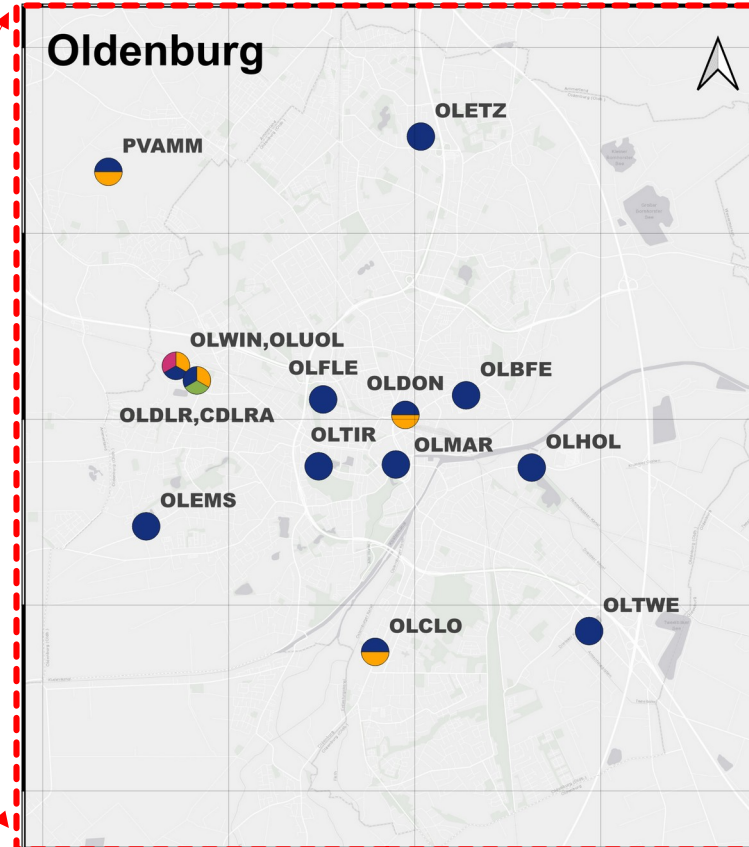
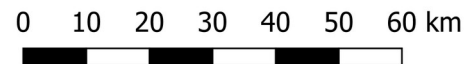
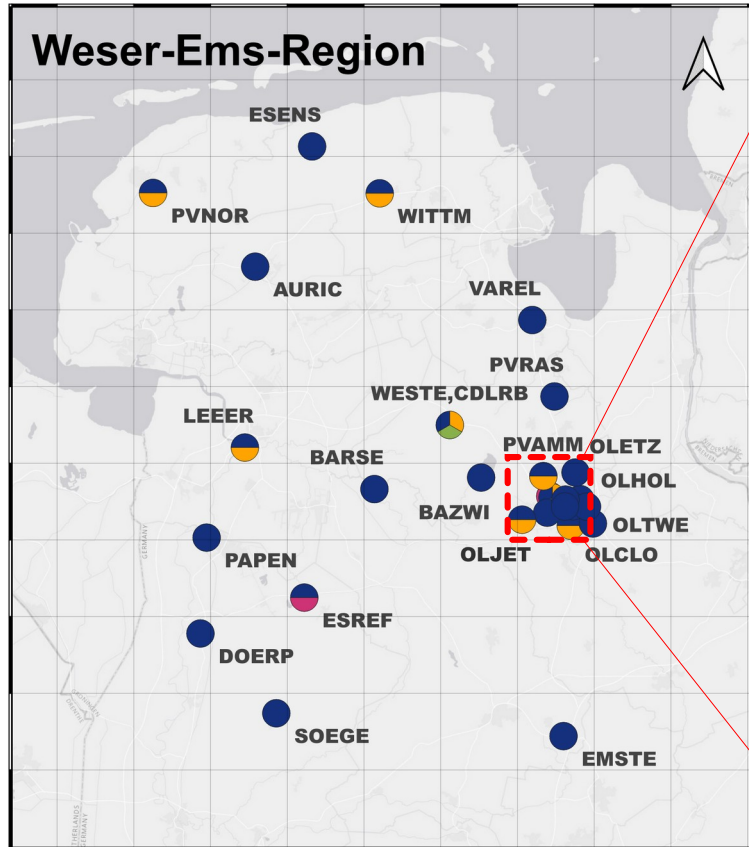


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Eye2Sky Instruments on the MET stations



Meteorological Measurements

- Irradiance (GHI, DHI, DNI, GTI)
- Air temperature and relative humidity

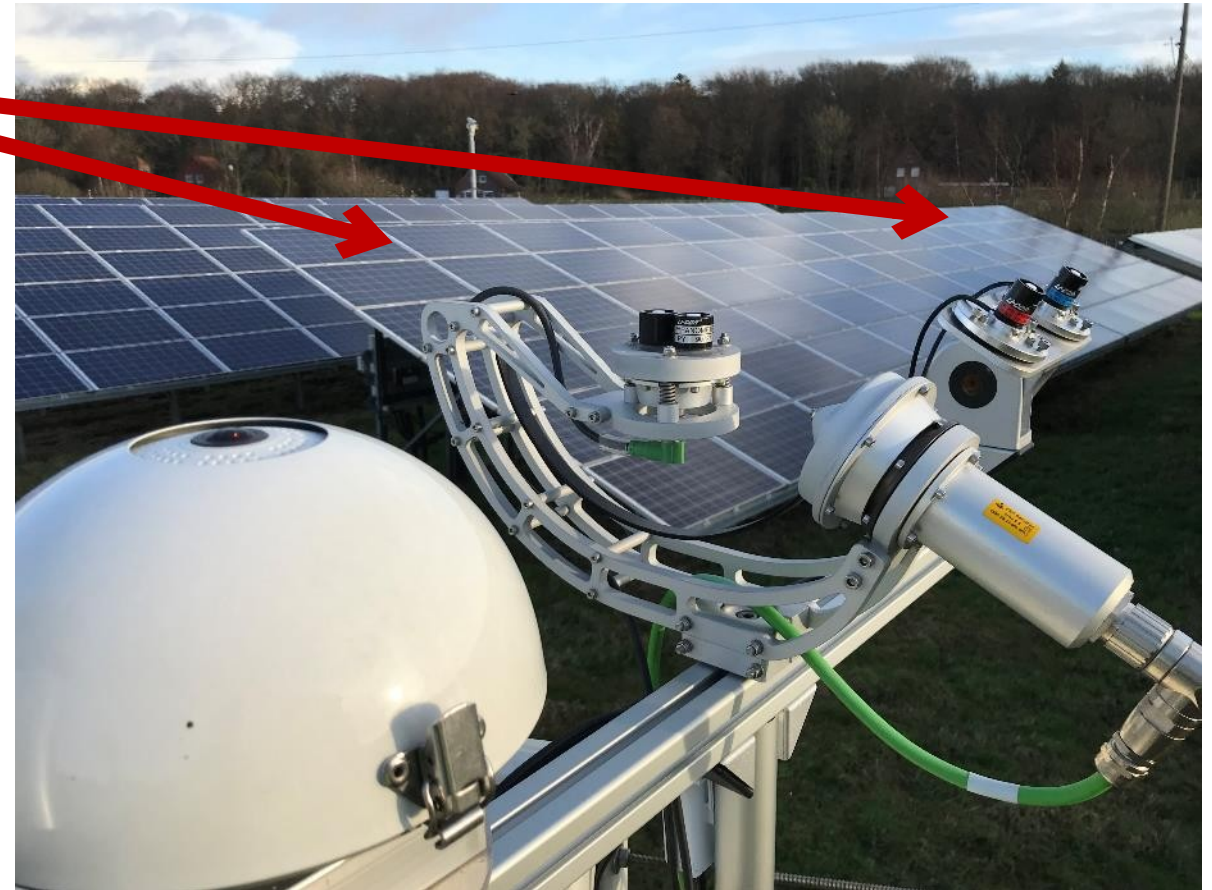


Photography of Eye2Sky station PVNOR

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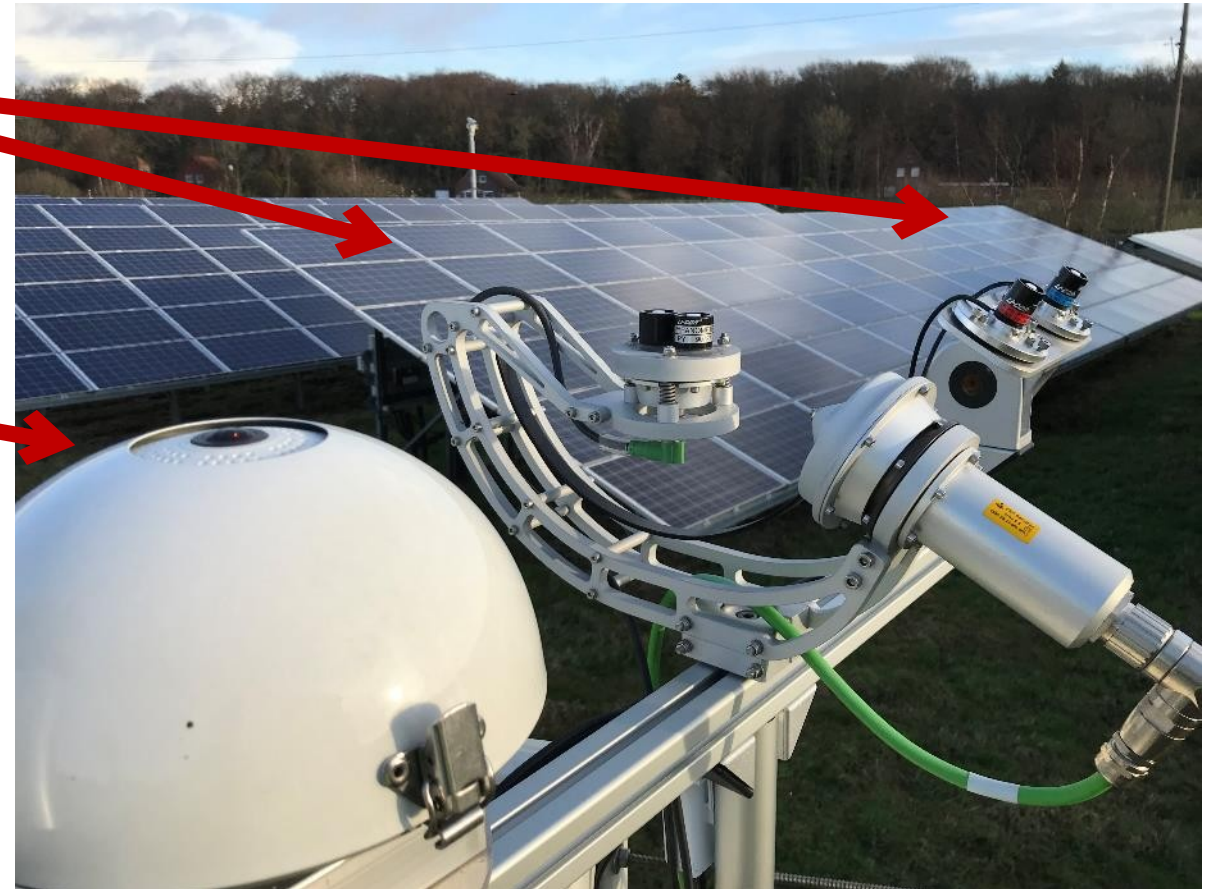
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All-sky imagers (ASI)

- Commercial surveillance cameras
- Fisheye lens with 180° viewing angle
- Data recording every 30s



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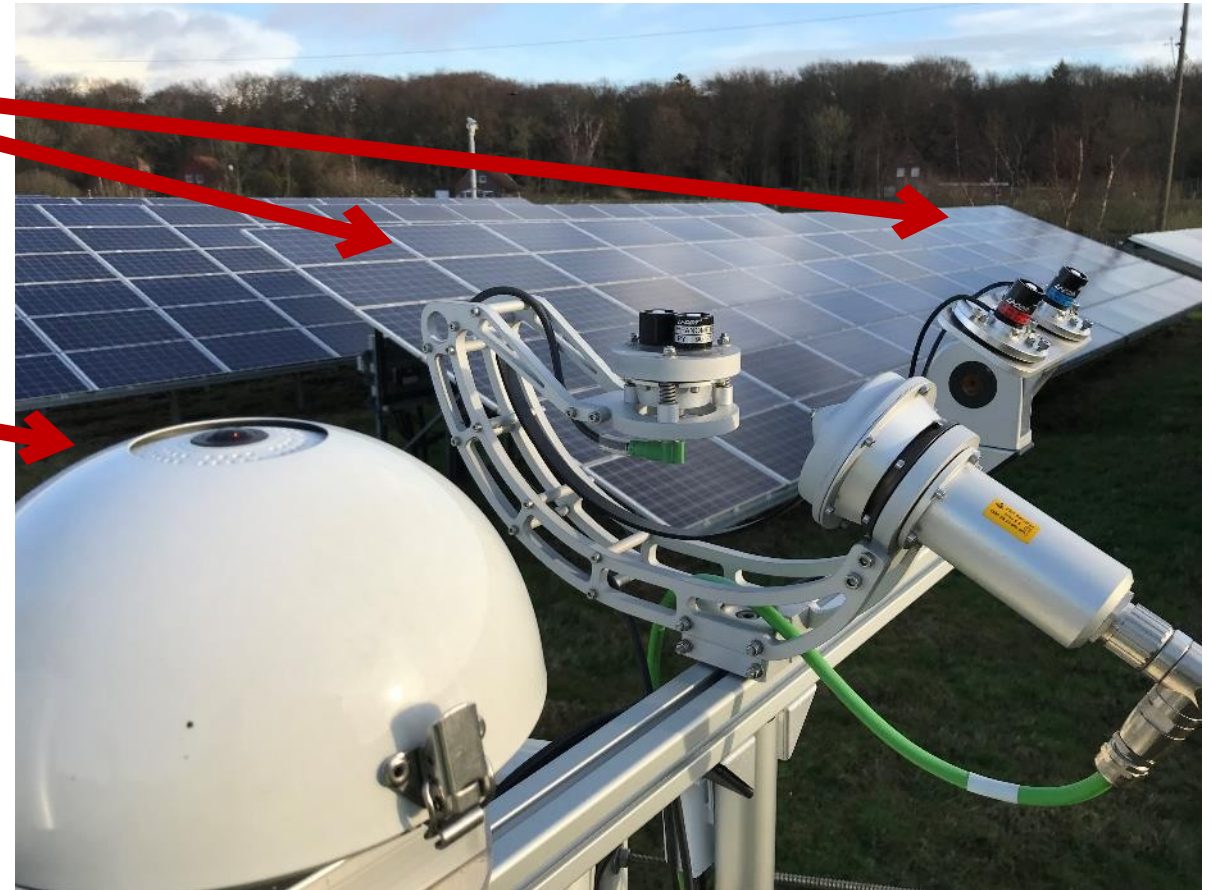
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Open DATASET in preparation (2024)

- 1 year of data to be published
- ASI images + MET measurements
- Expert QC + Logbook included



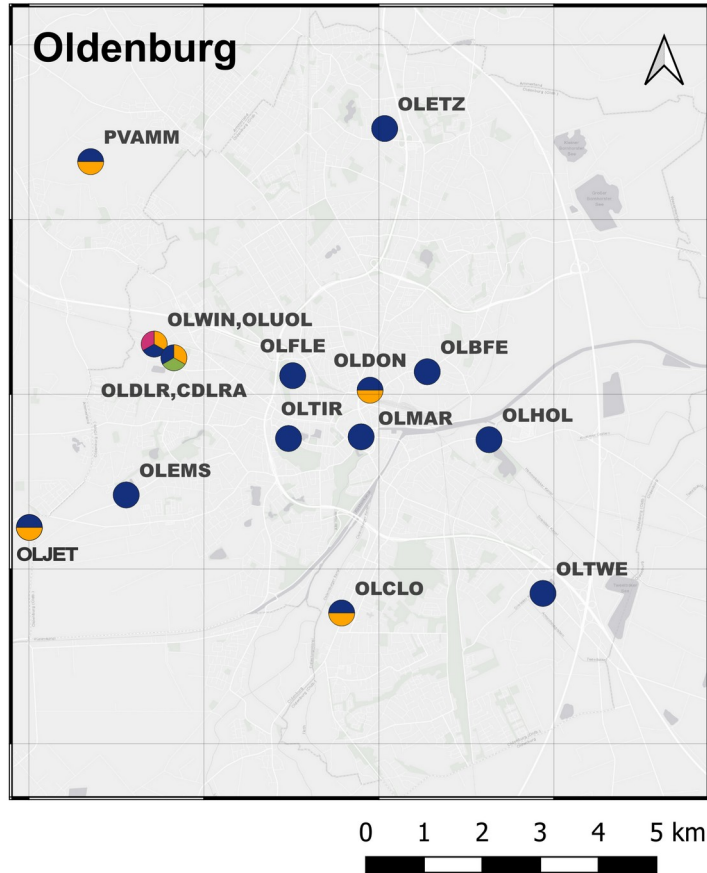
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CONTEXT

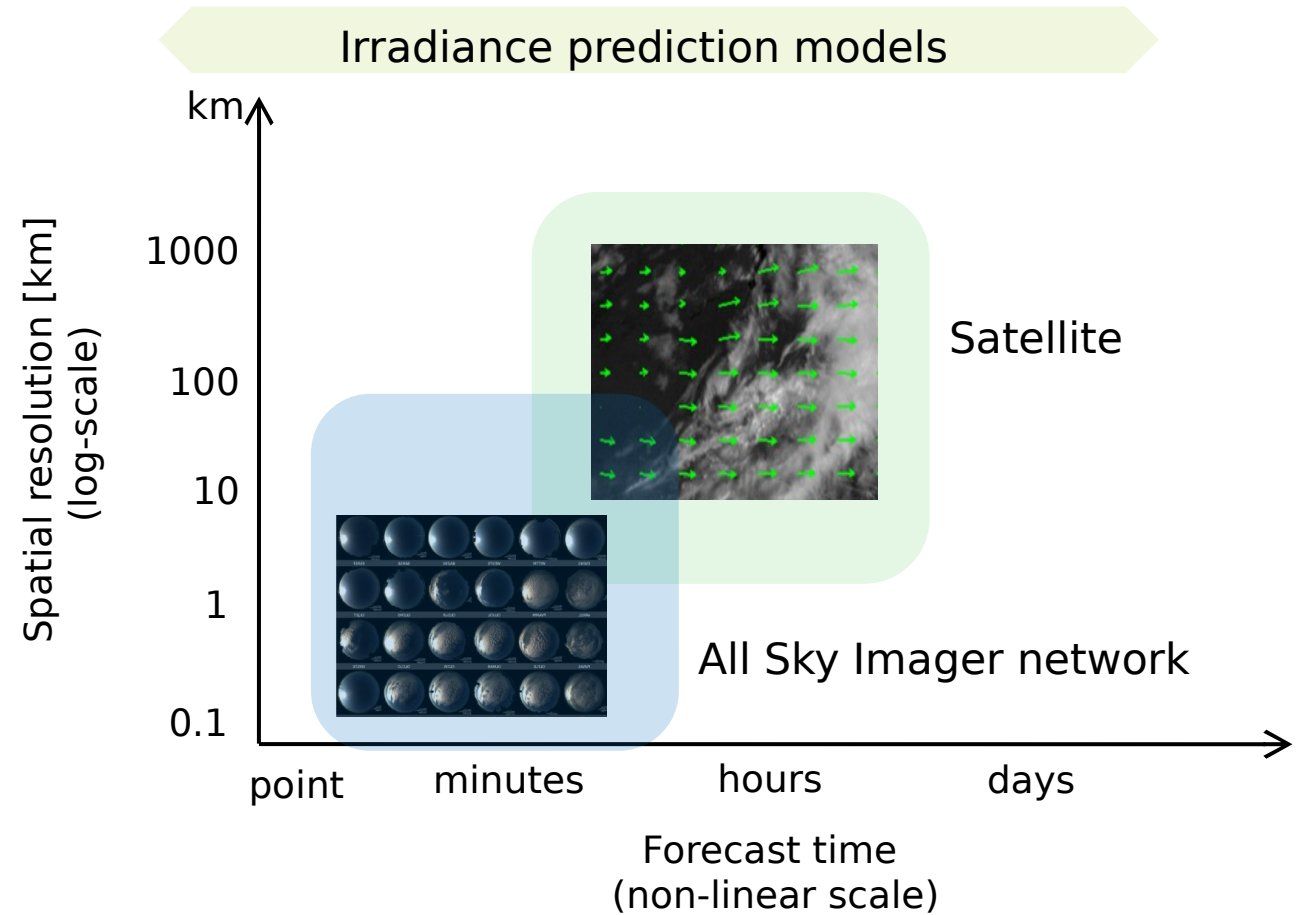
Forecast inputs



Eye2Sky : city region of interest



Background: OpenStreetMap ESRI light gray



Satellite : Heliosat3 (Hammer 2015)
ASI-network (Blum 2022)

Data availability



Characteristic	Satellite	ASI network
Source	Meteosat Second Generation	10 ASI imagers from the Eye2Sky network
Domain	Europe	25 km x 25 km around Oldenburg
Spatial resolution	2 km	50 m
Forecast horizon	6 hours	30 min
Forecast step	15 min	1 min
Temporal availability	from 2005 until today	from 2019 until today
Availability of forecasts for this study	01.07.2020 to 31.08.2020	01.07.2020 to 31.08.2020

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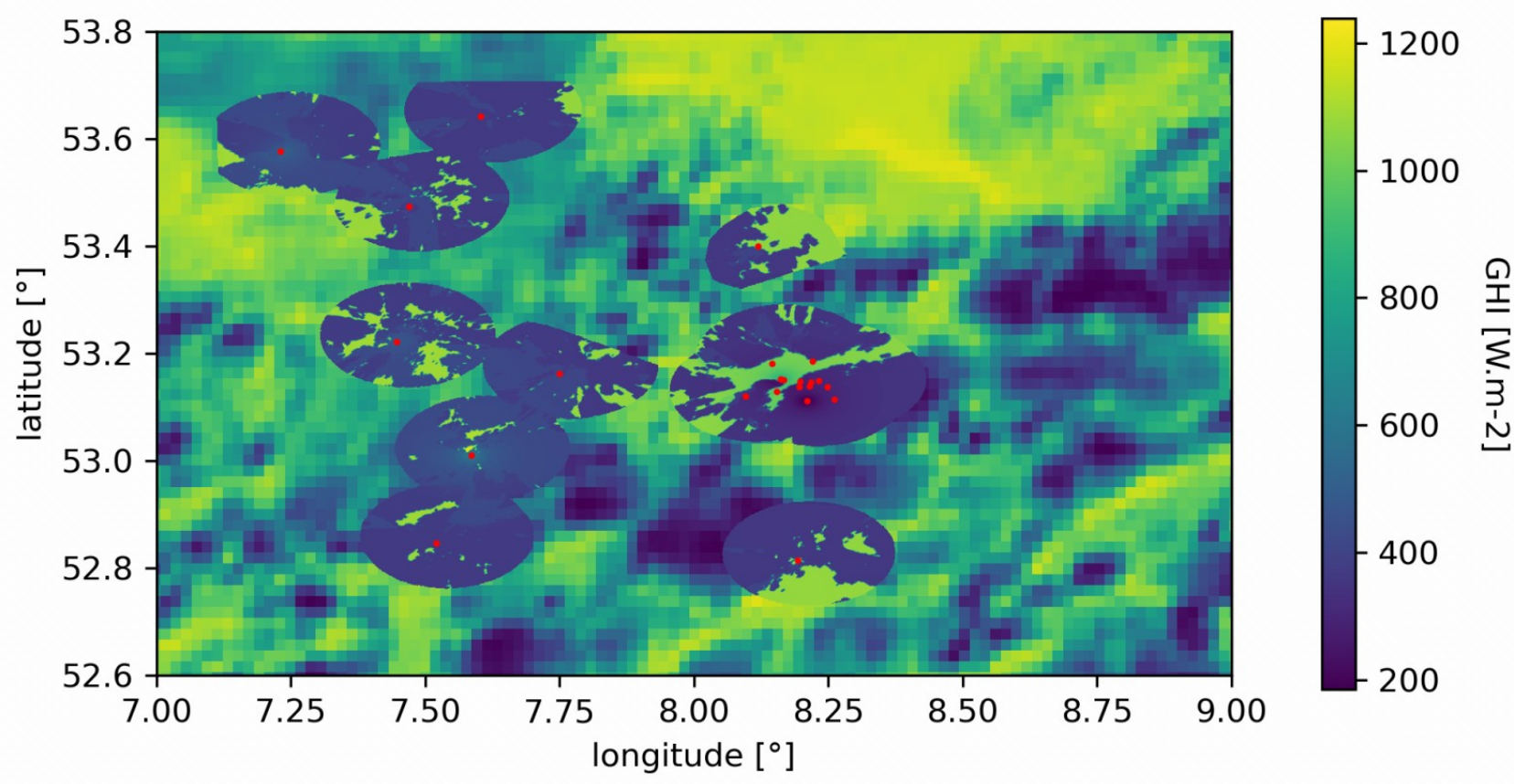
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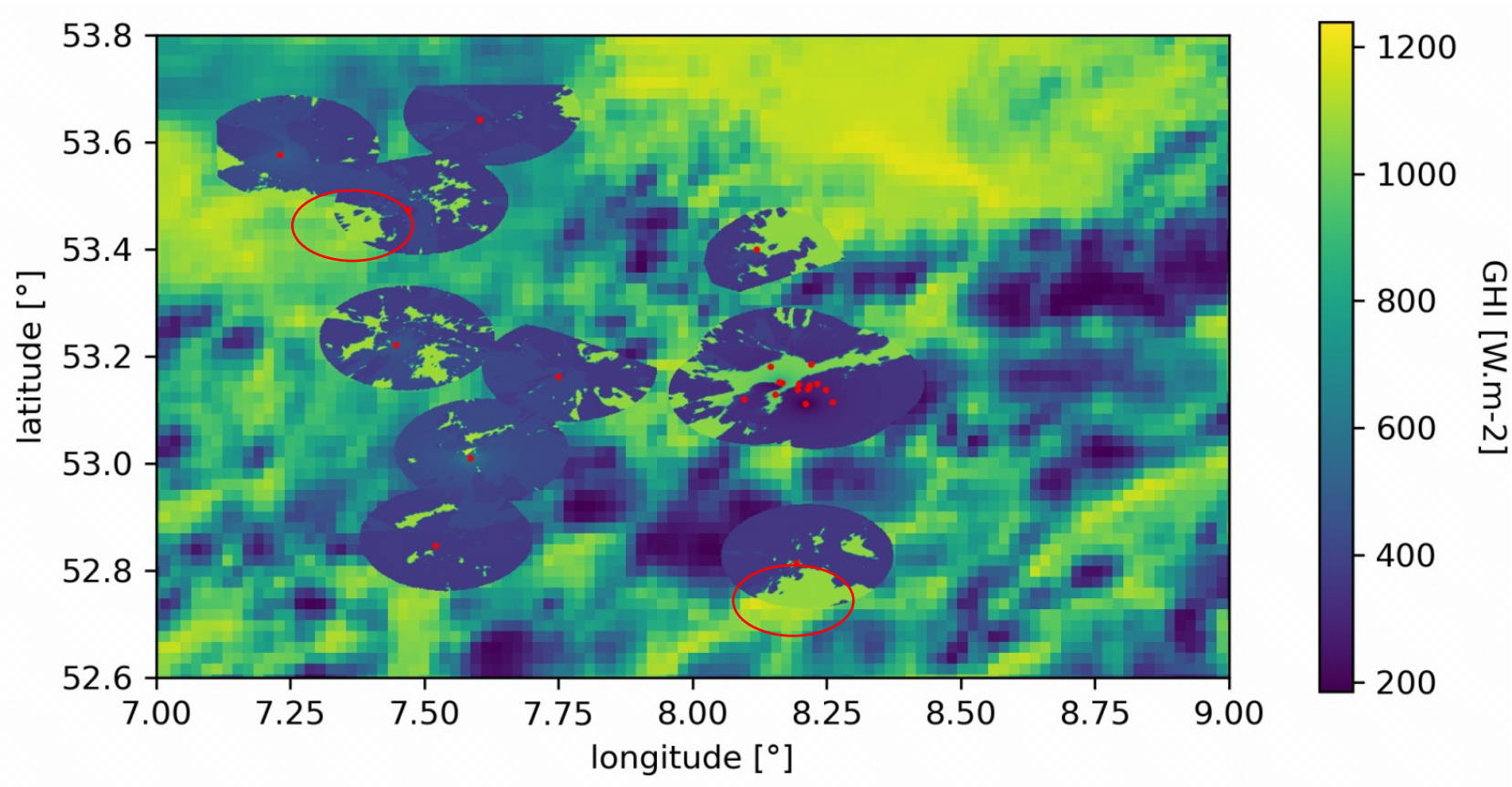


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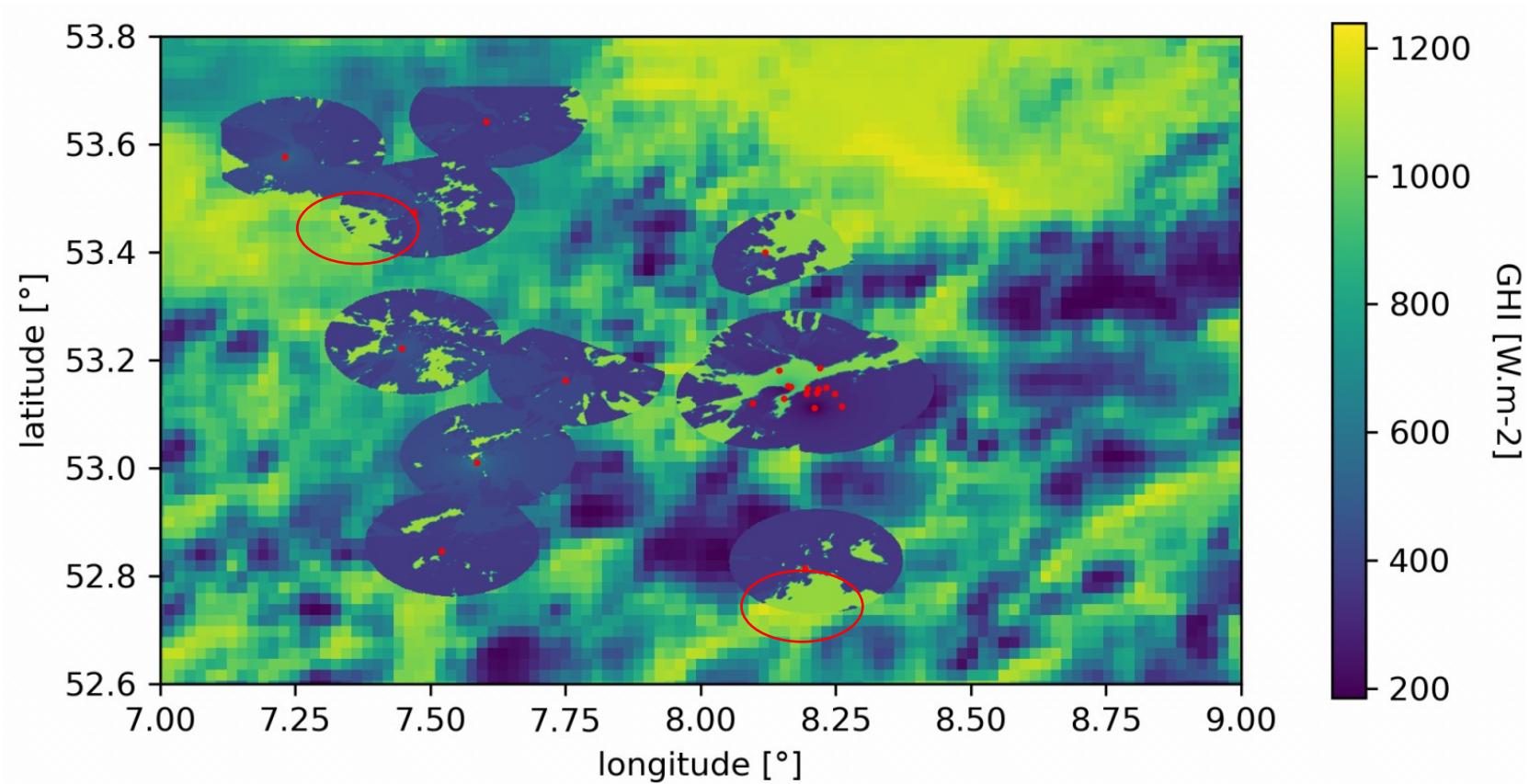
Forecast inputs : 21.07.2020 @ 13:26 UTC



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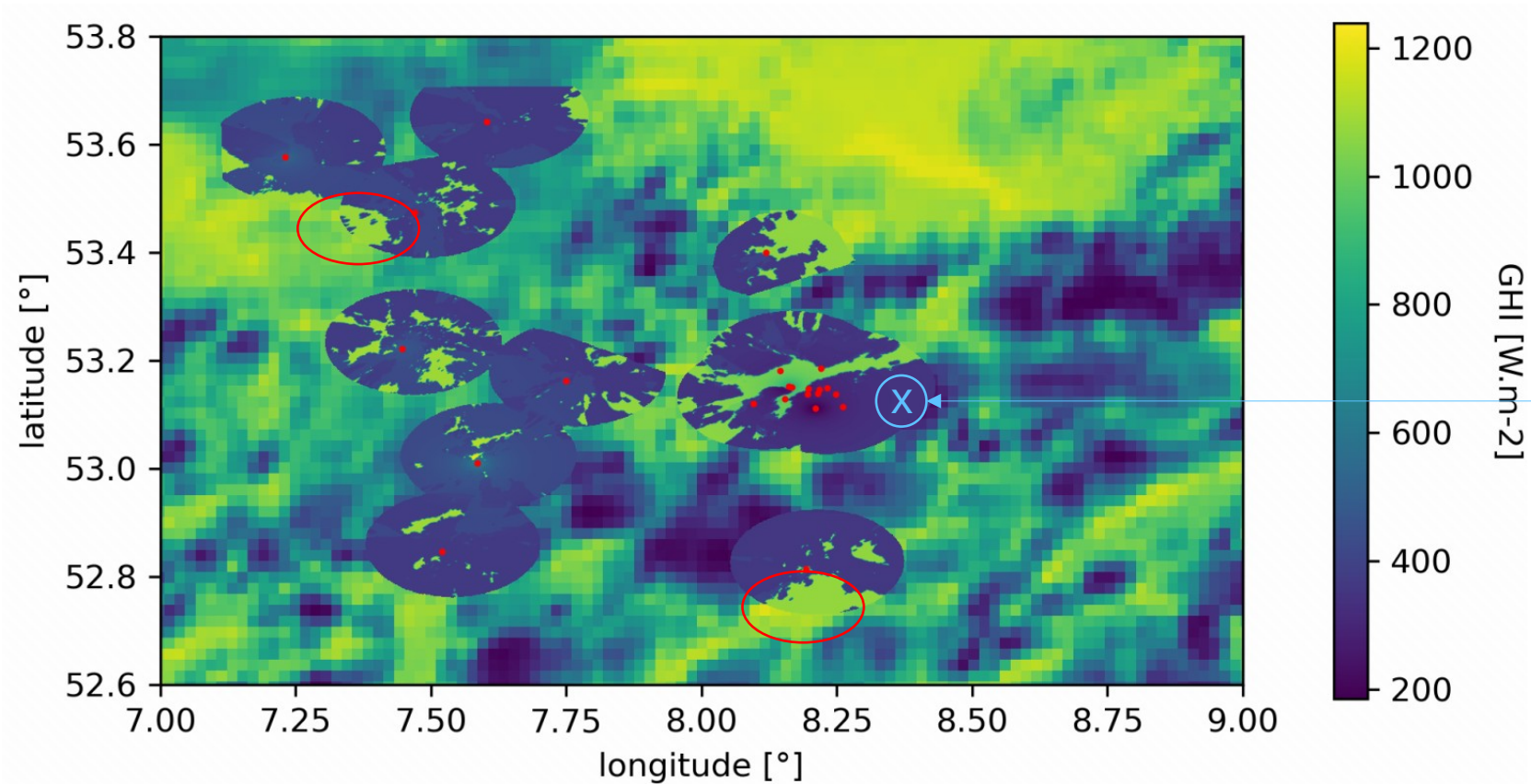


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✓ Can the high resolution information from the ASI network forecast be used to improve the quality of the satellite forecast?

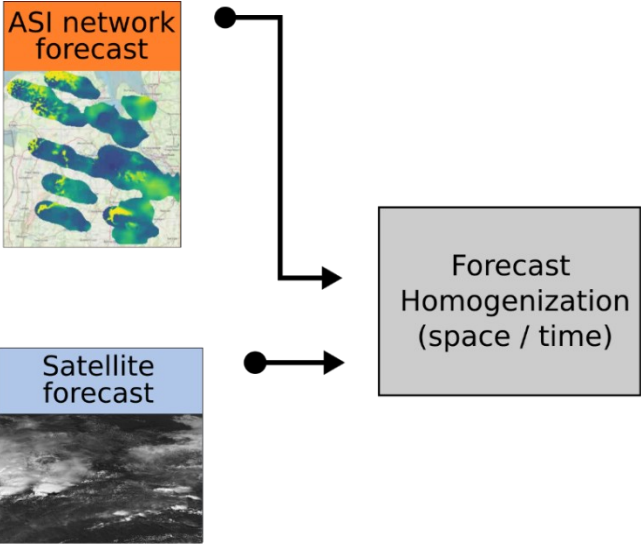
Forecast inputs : 21.07.2020 @ 13:26 UTC



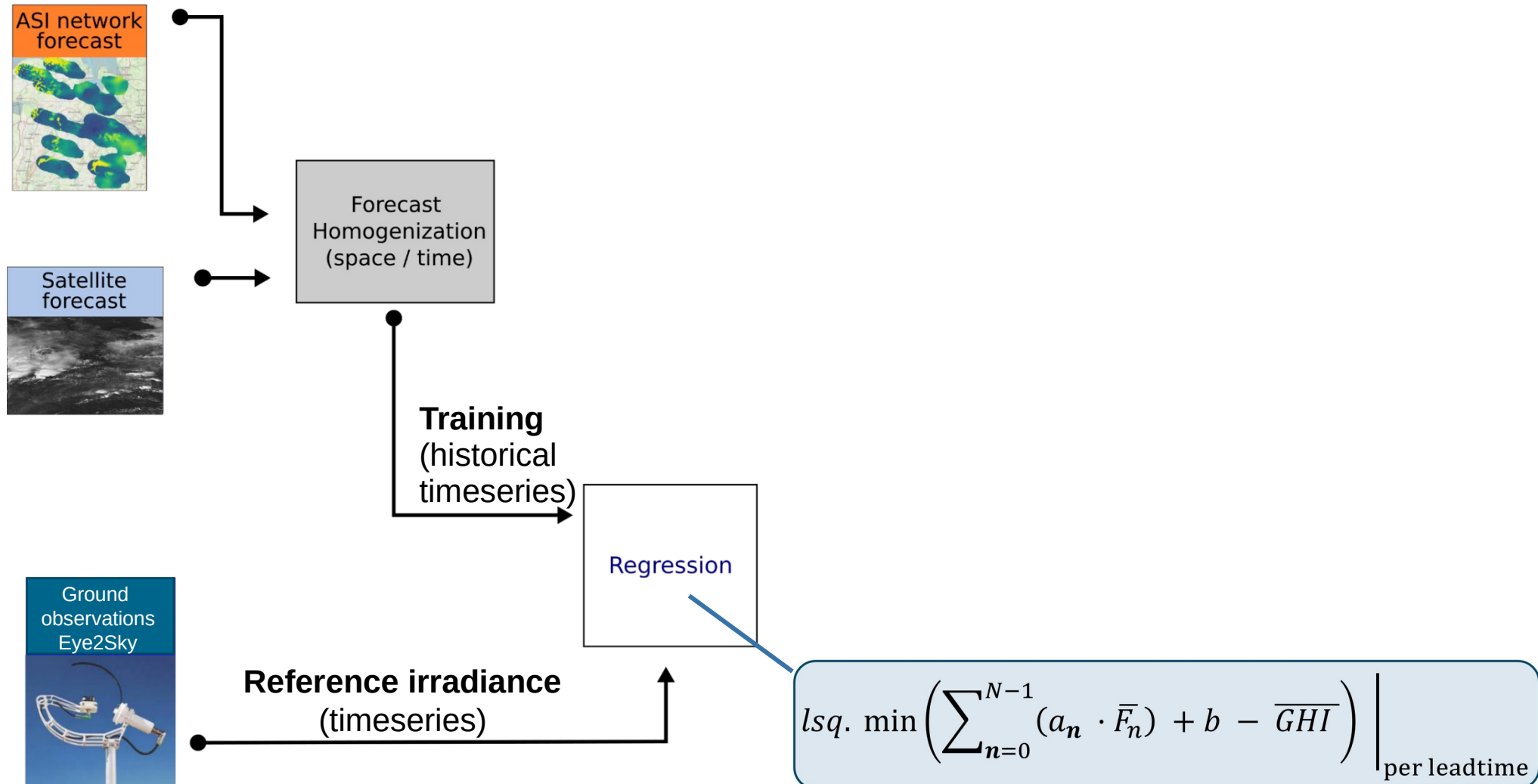
- ✓ Can the high resolution information from the ASI network forecast be used to improve the quality of the satellite forecast?
- ✓ Can we assess the benefit of the improvement at any location on the domain (independently if it has ground observations or not)?

BLENDING METHOD

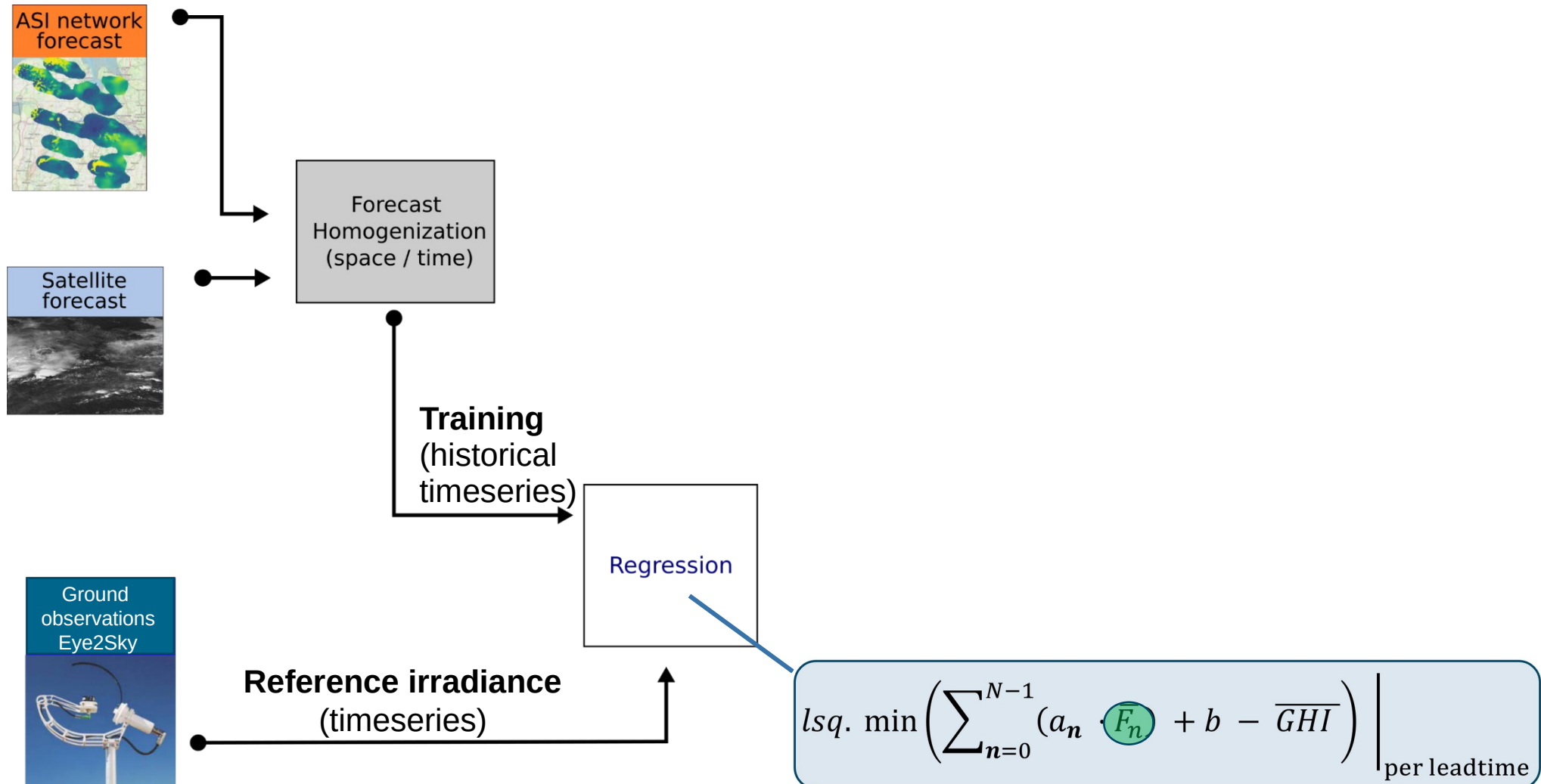
Principle of the blending method



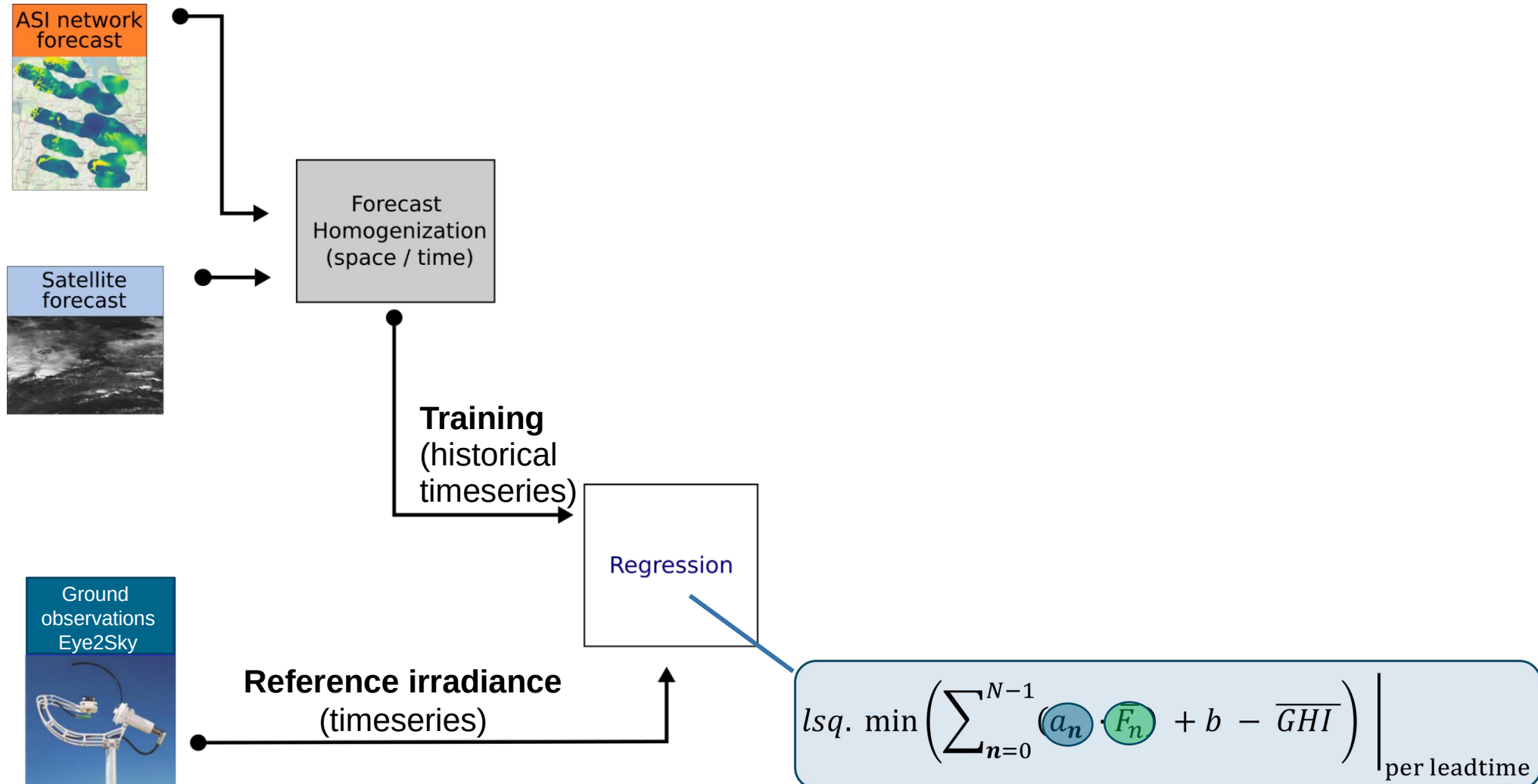
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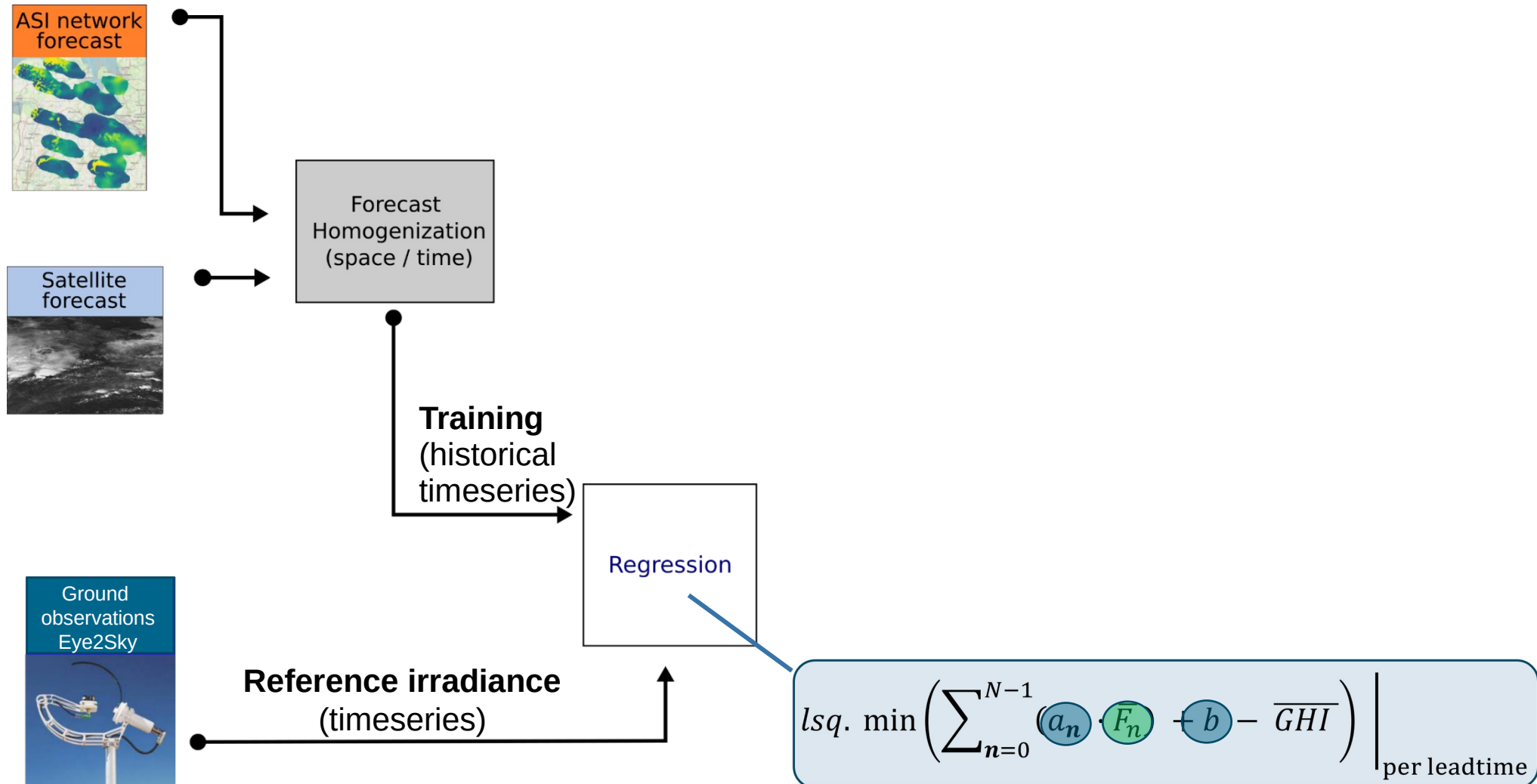
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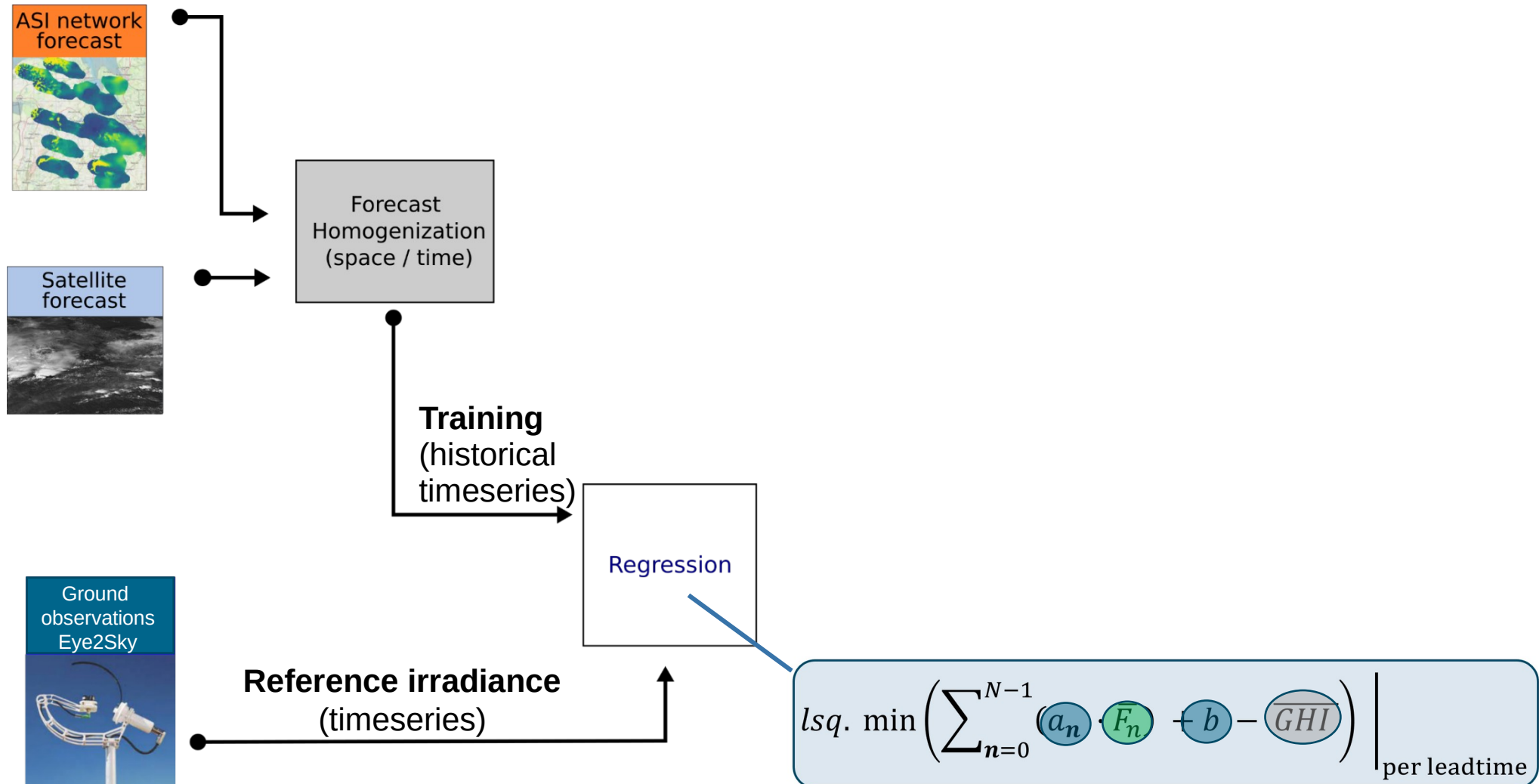
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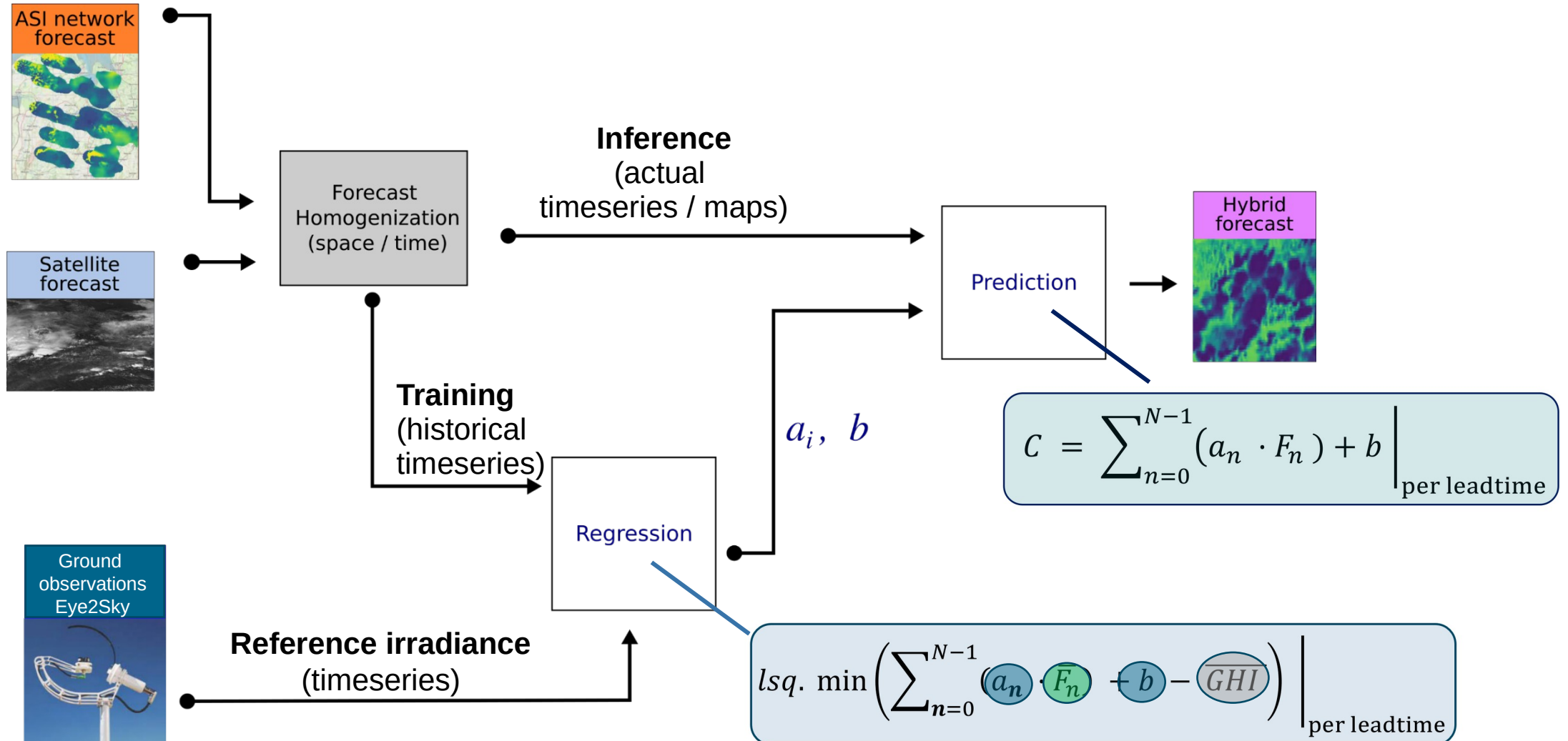
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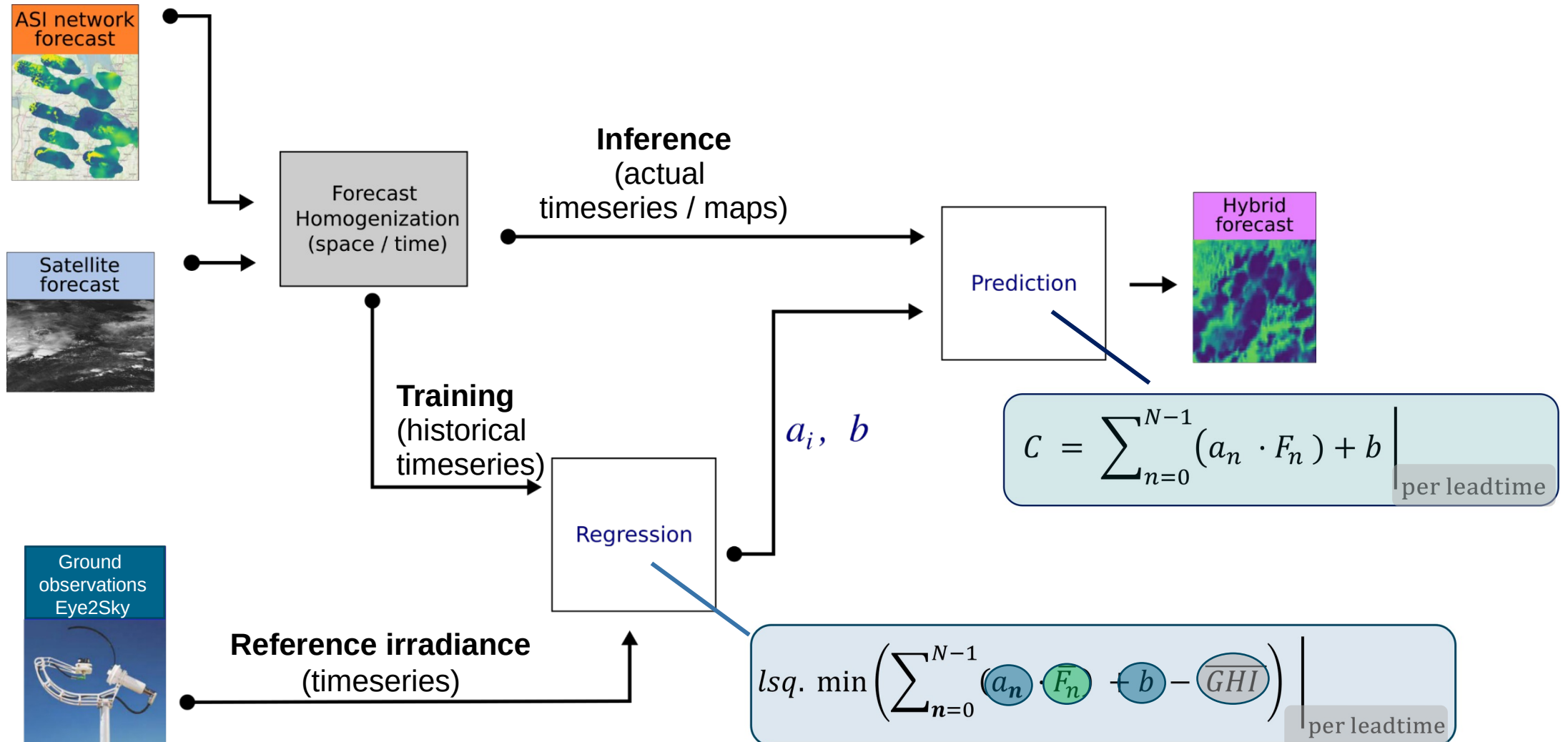
Principle of the blending method



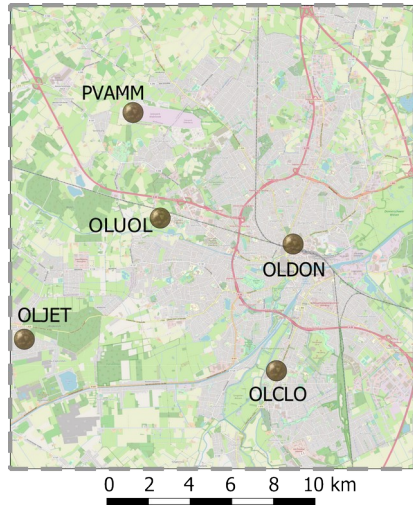
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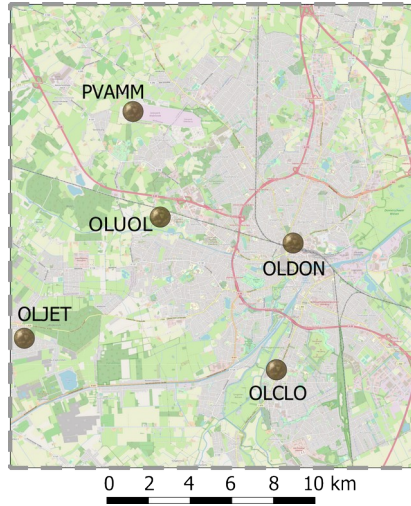
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Training strategy

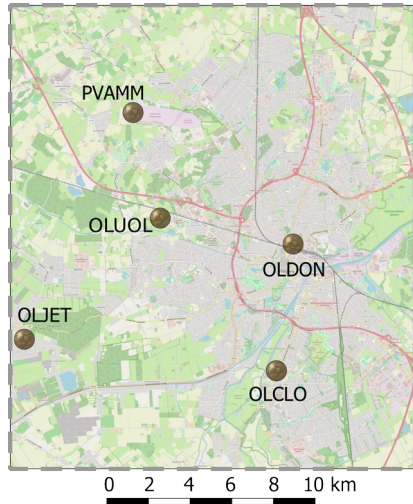


Training strategy

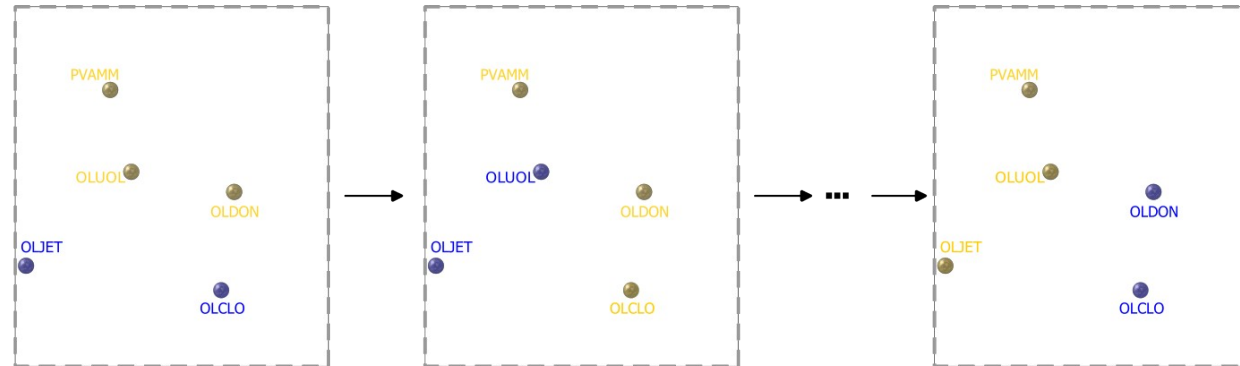


$$\sum_{i=\{2,3,4\}} 5C_i$$

Training strategy



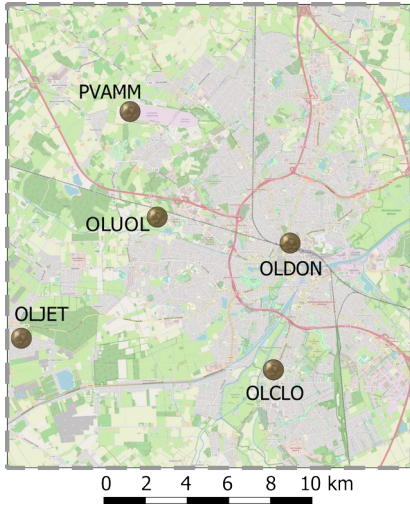
$$5C_2$$



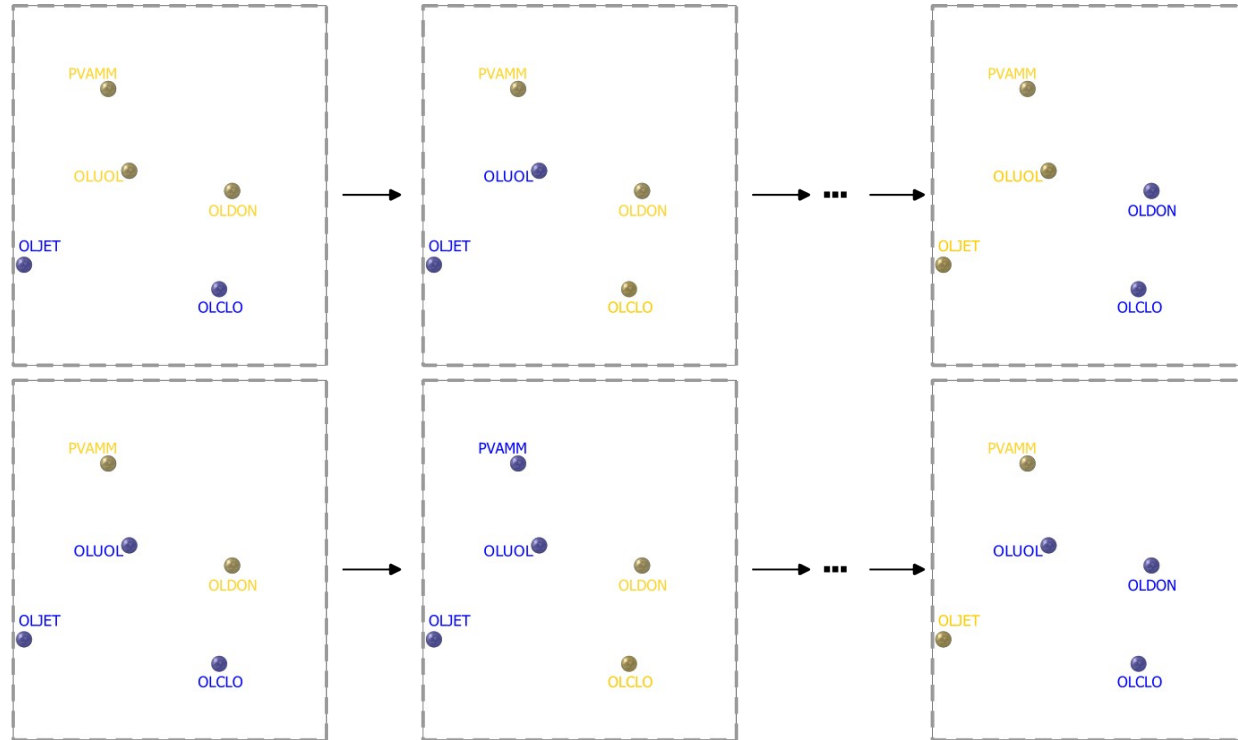
= 10 cases

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Training strategy



$5C_2$

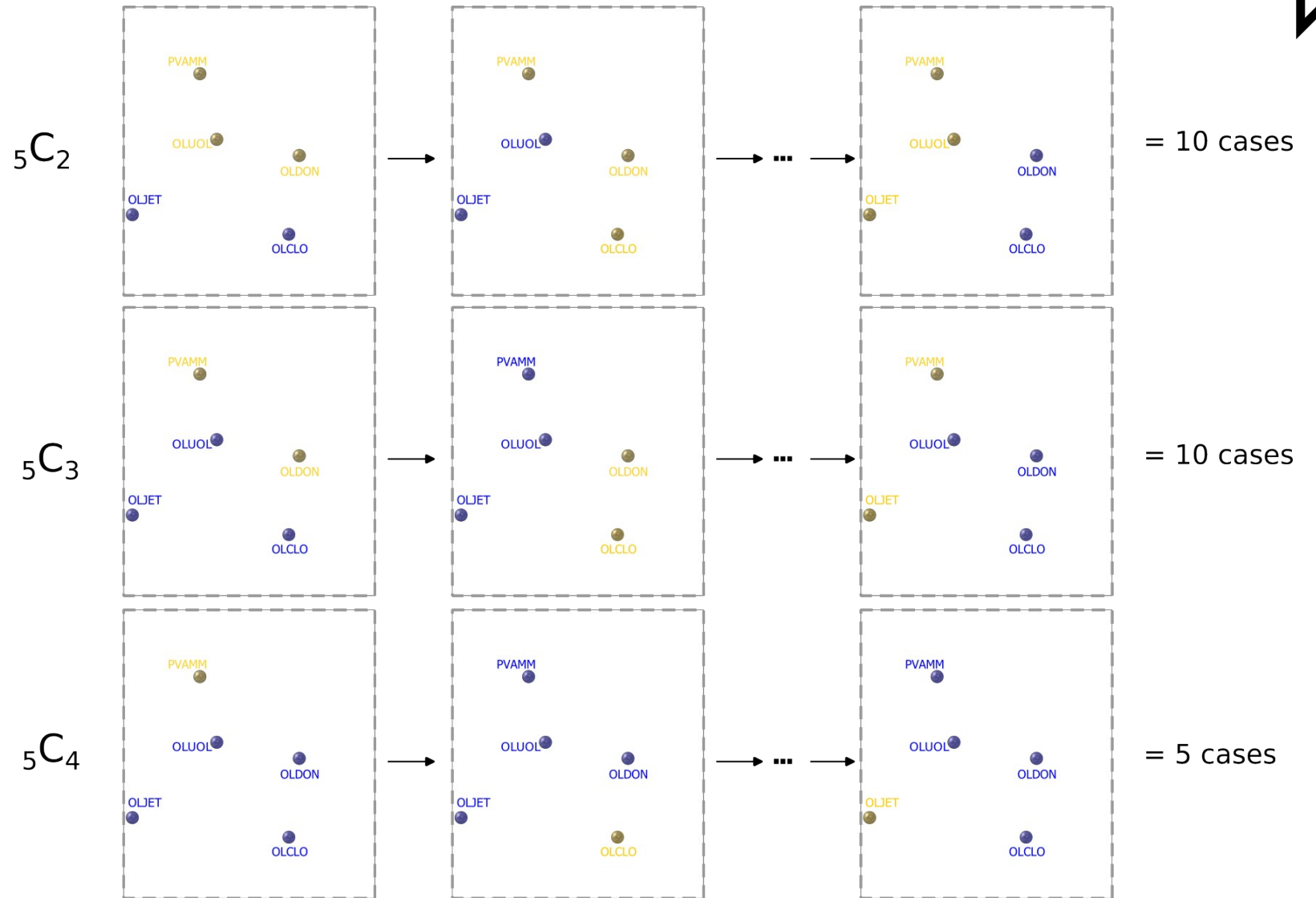
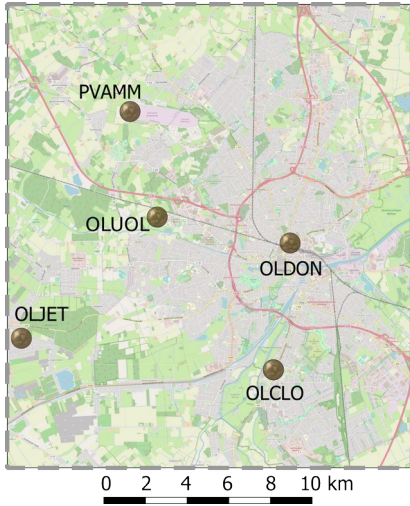


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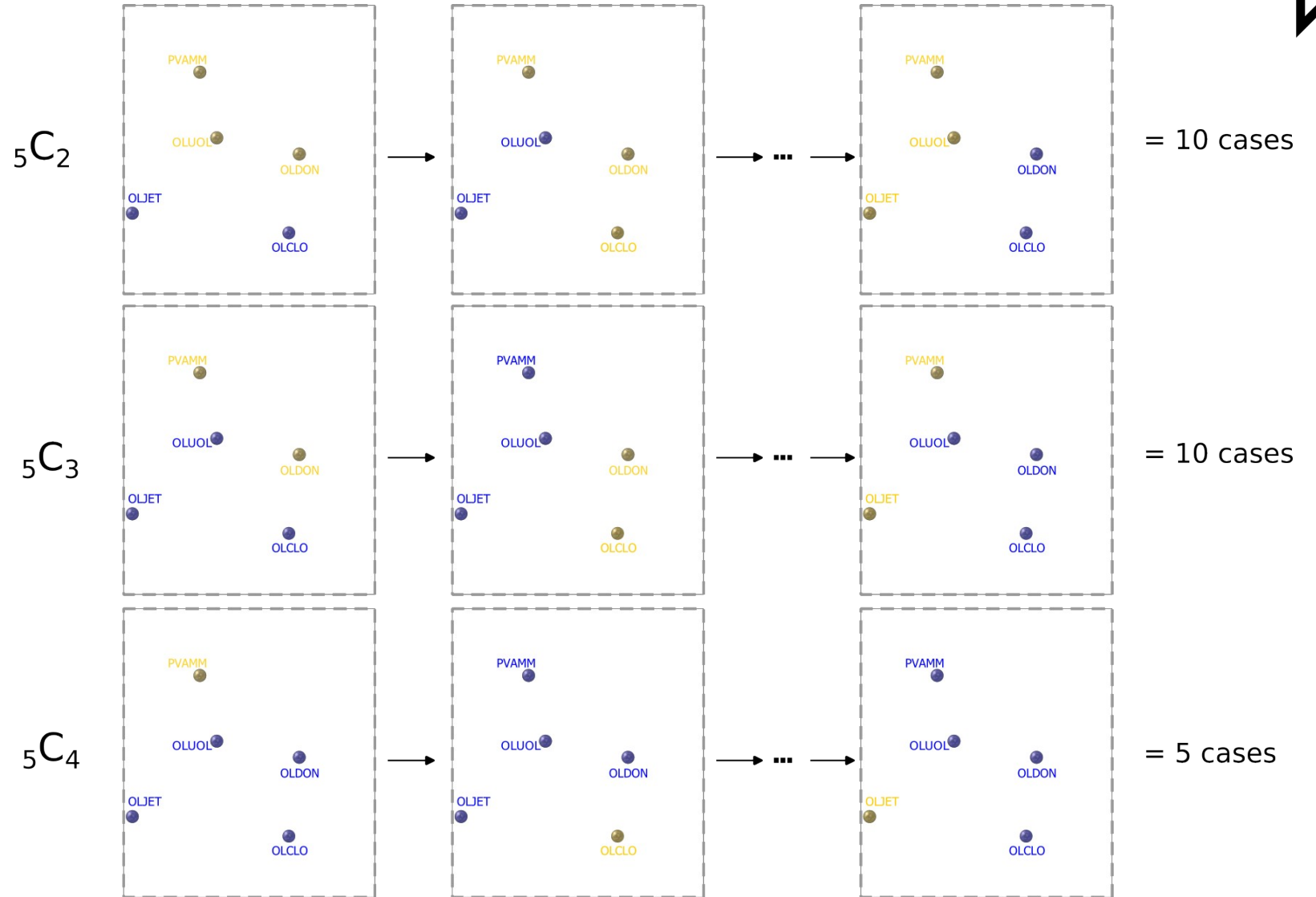
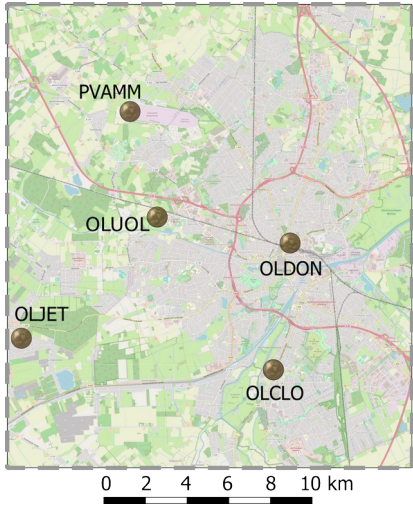
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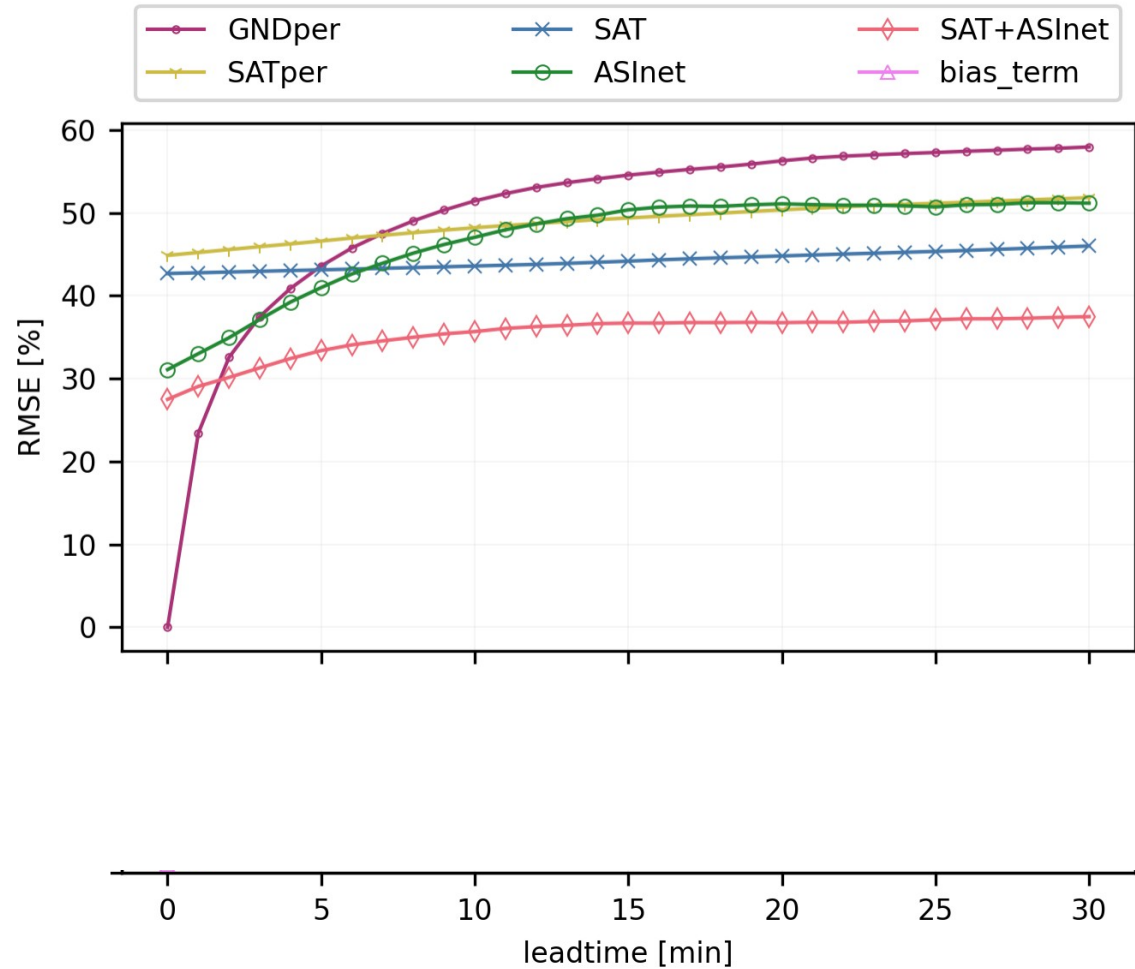


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25 different cases

Blending results* :

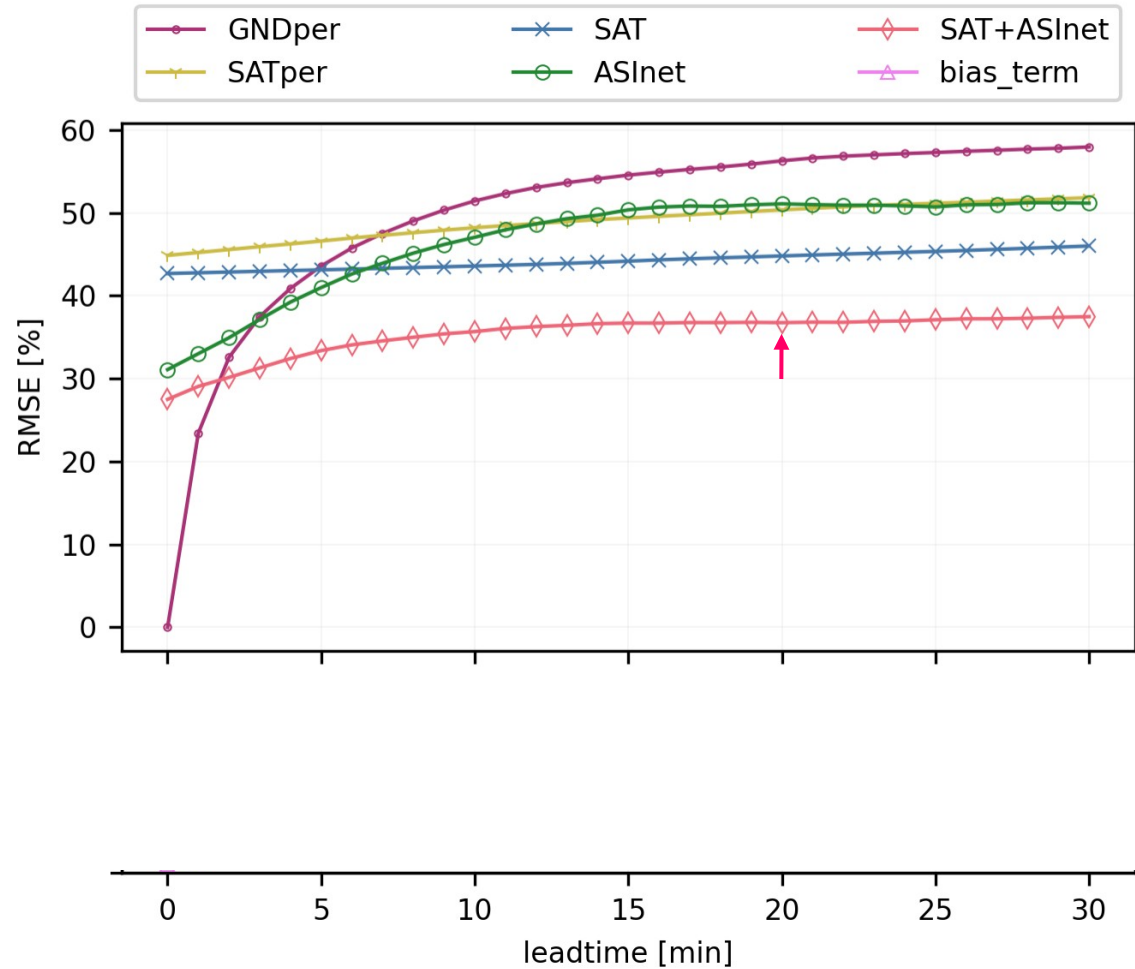
average metrics for the 25 training cases



* The results shown from here onwards are part of a publication being prepared for submission in Meteorologische Zeitschrift.

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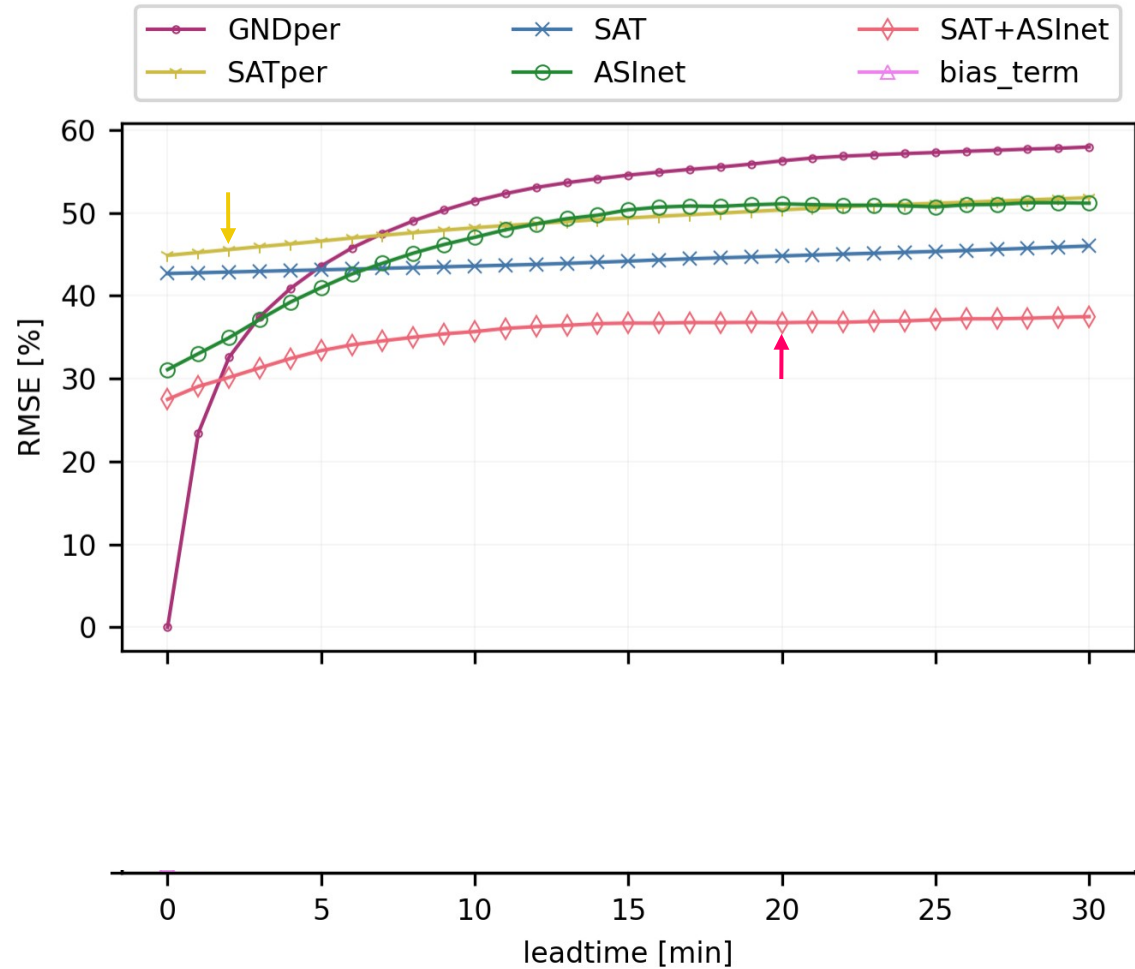


- SAT+ASInet improves over

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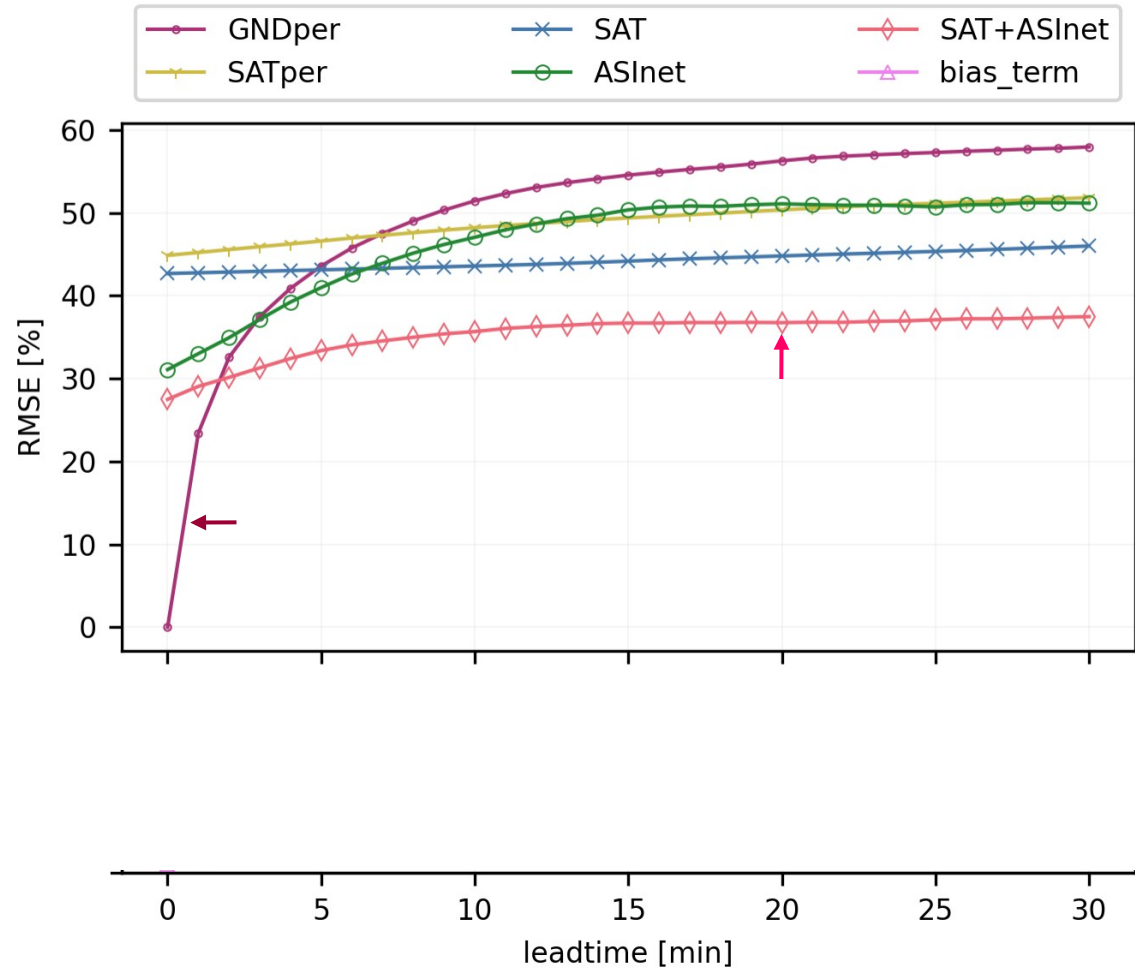


- **SAT+ASInet** improves over
 - **satellite persistence** : all leadtimes

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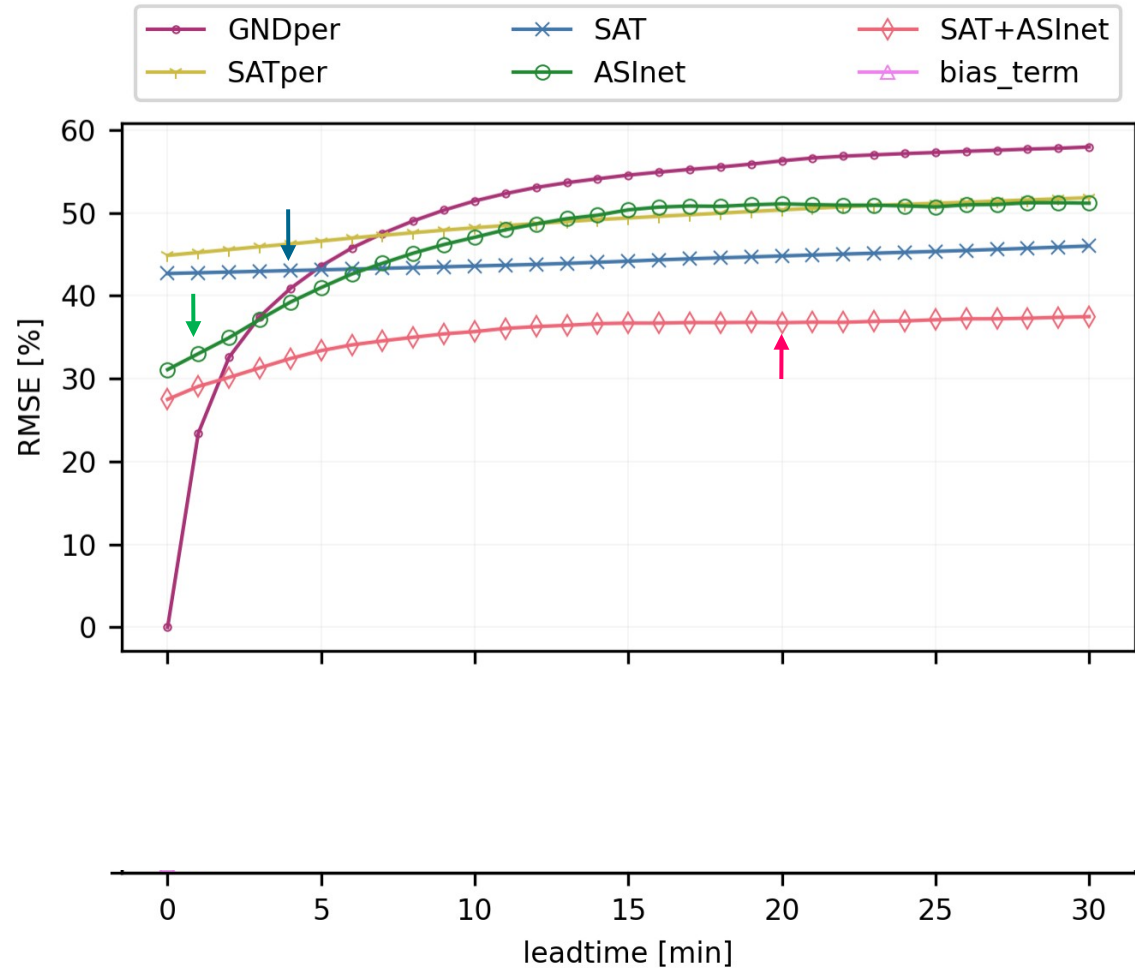


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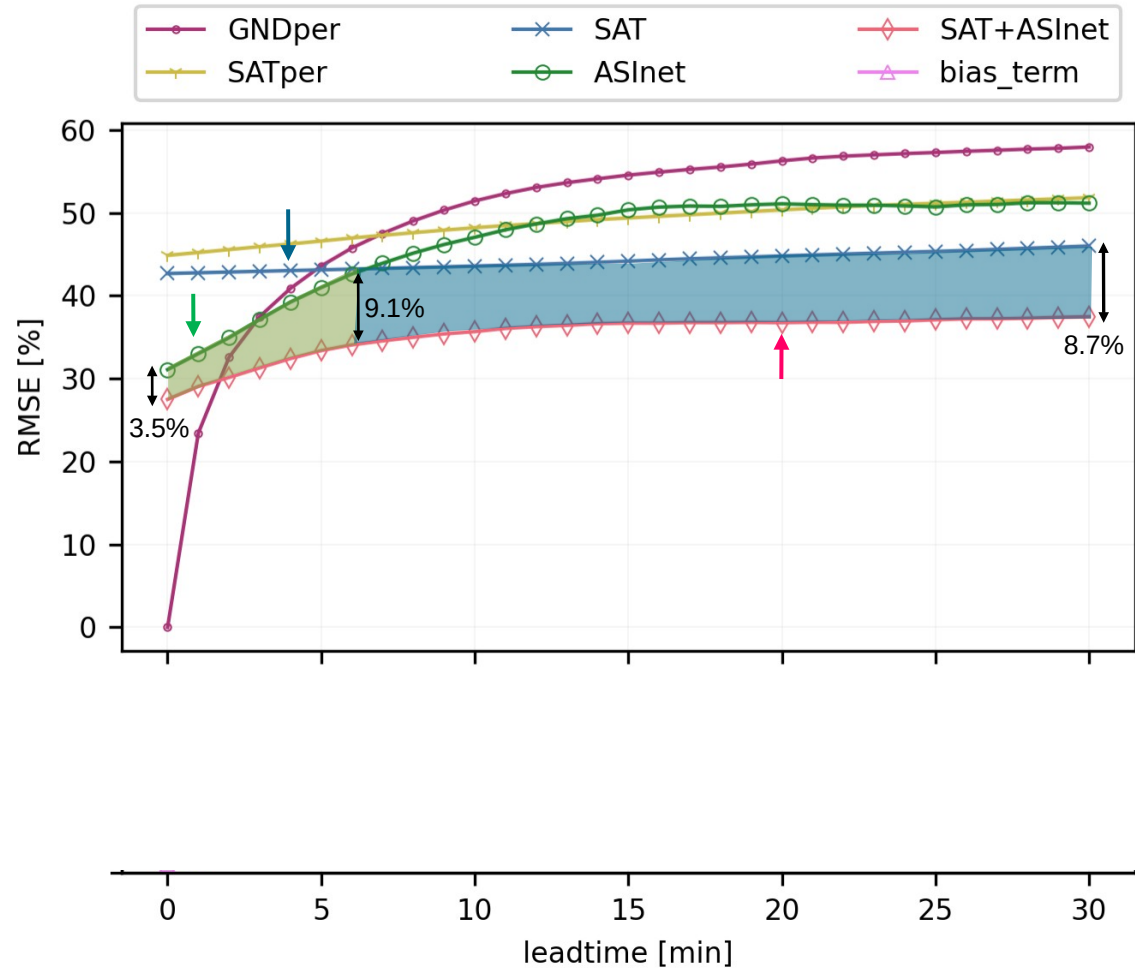


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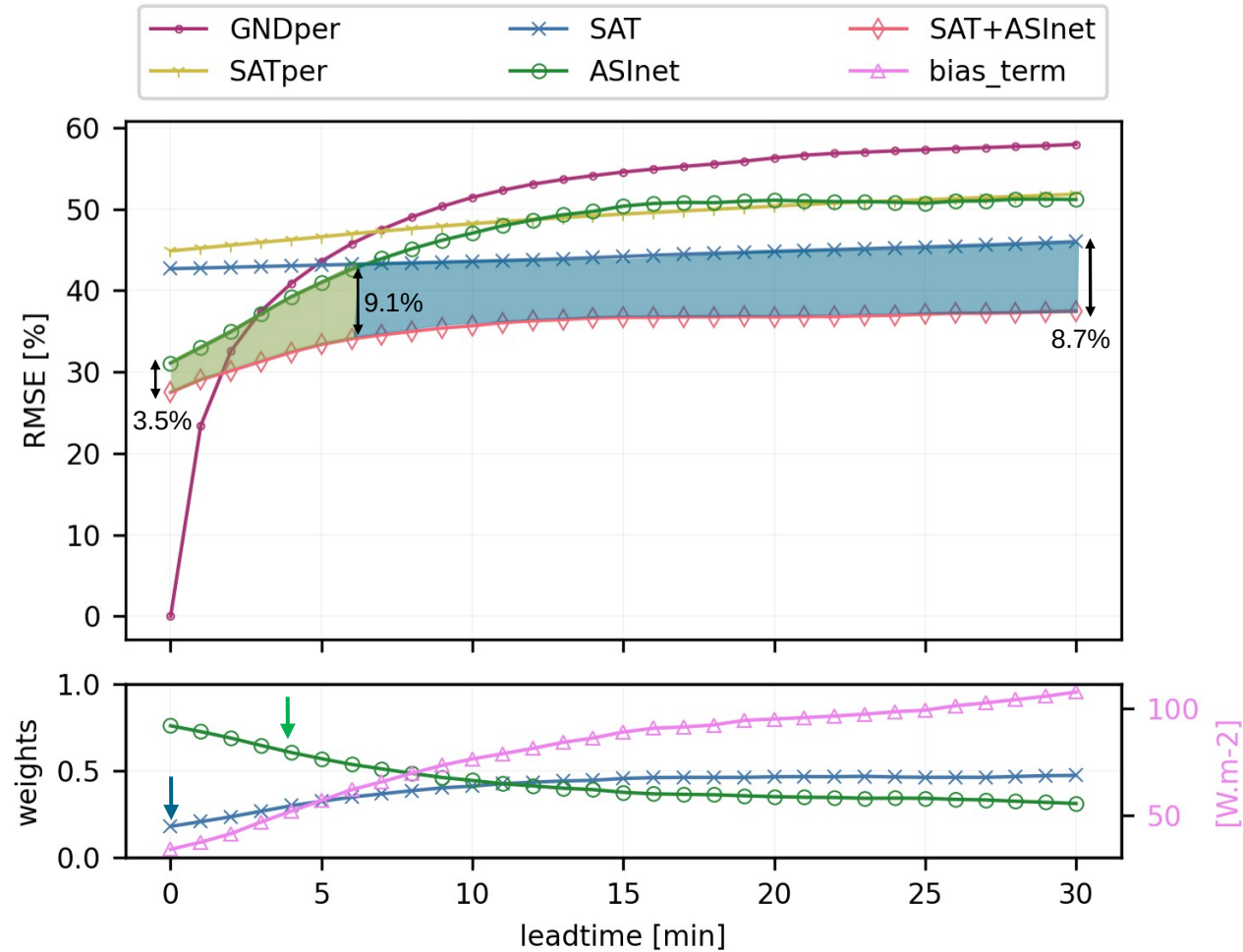


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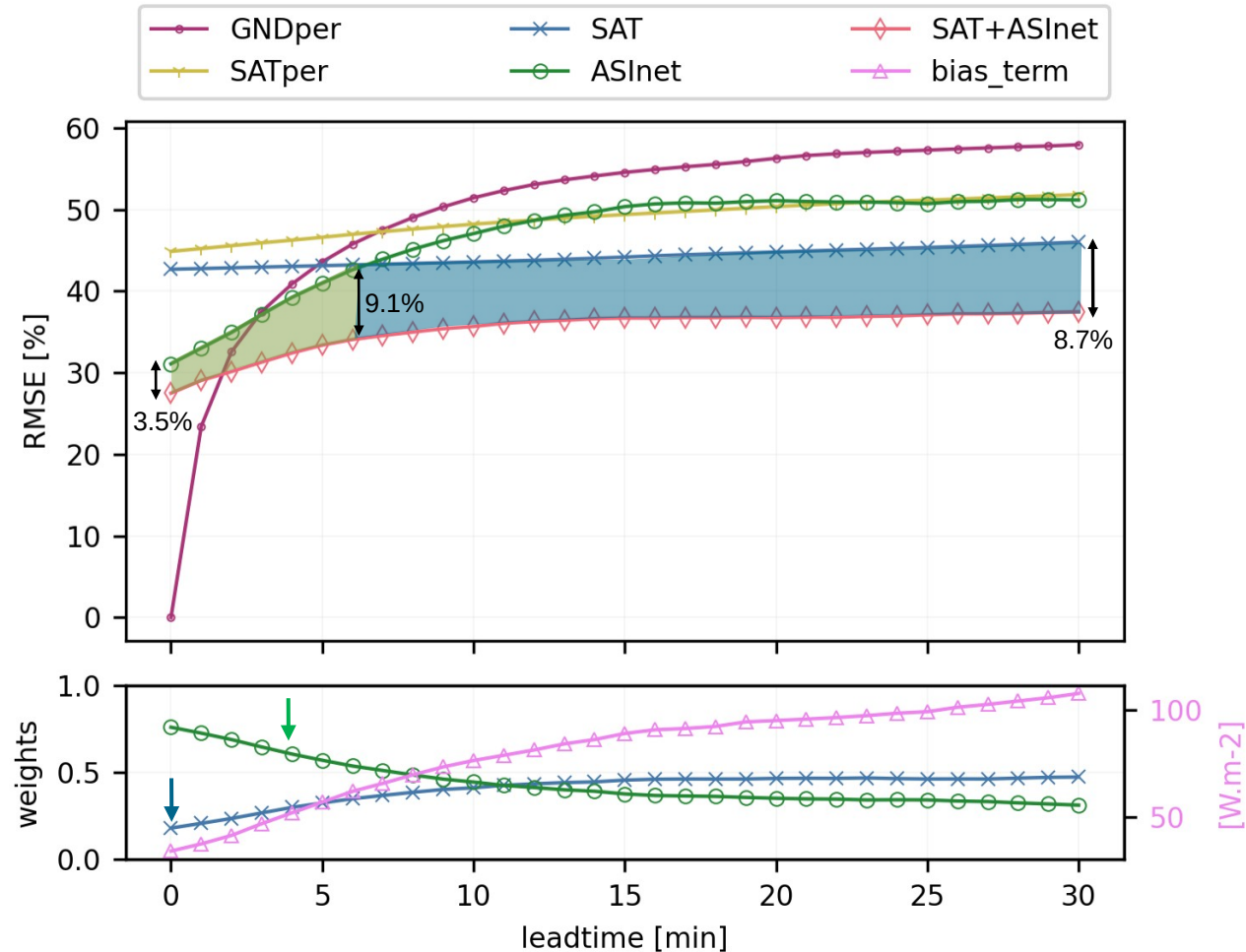


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 - ASInet dominates from 0 to 10 min
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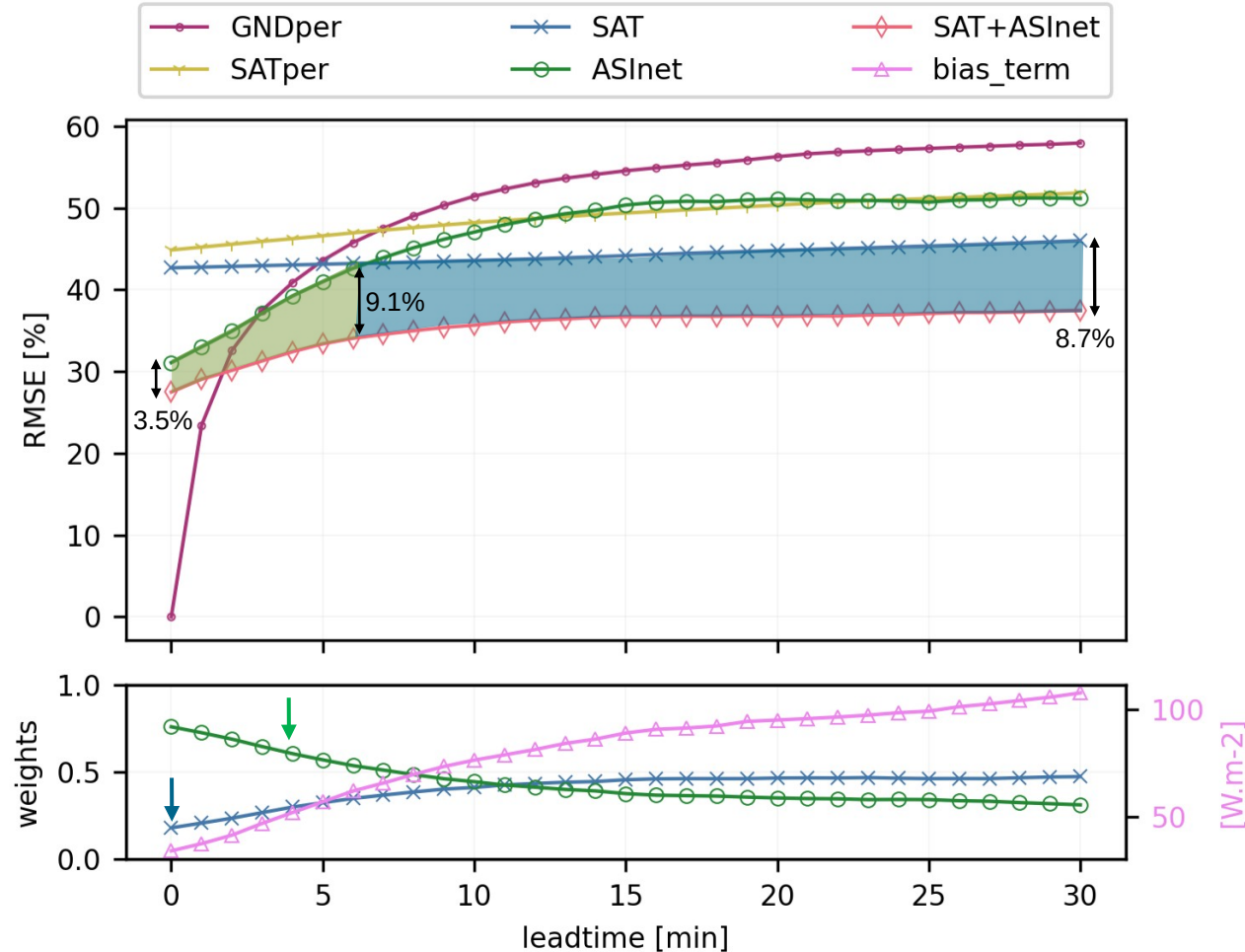


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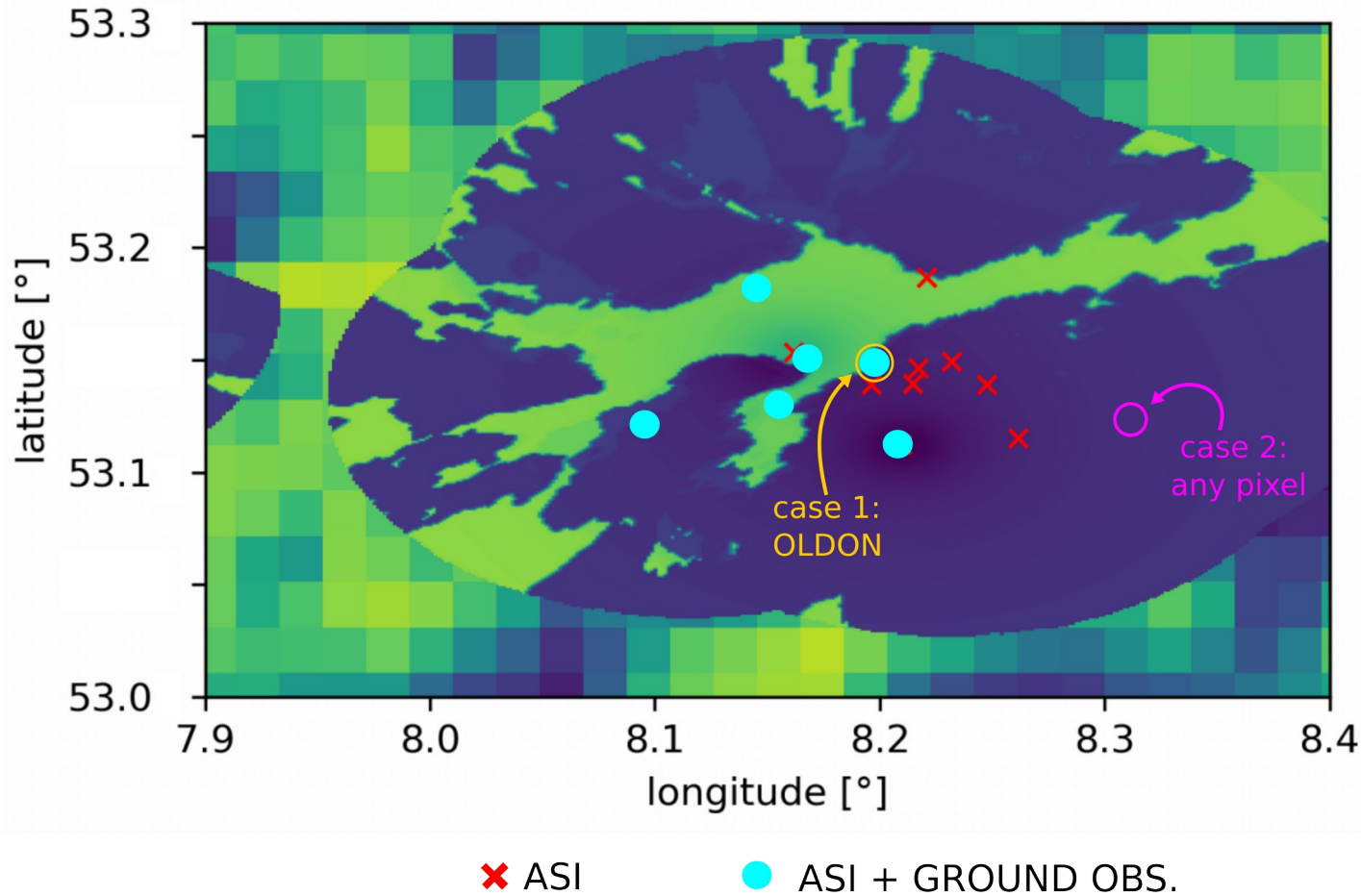
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Wouldn't we obtain better/same performance by blending satellite with the less expensive ground persistence ?

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VALUE OF THE ASI NETWORK

Test cases for blending of different inputs



Test case 1 : Prediction on location where ground observations are available

Test case 2 : Prediction on any location on the irradiance map (not restricted to locations with ground observations)

Blendings to compare:

- 1) SAT+ASInet
- 2) SAT +GNDper

Test case 1 : Blending evaluation at OLDON

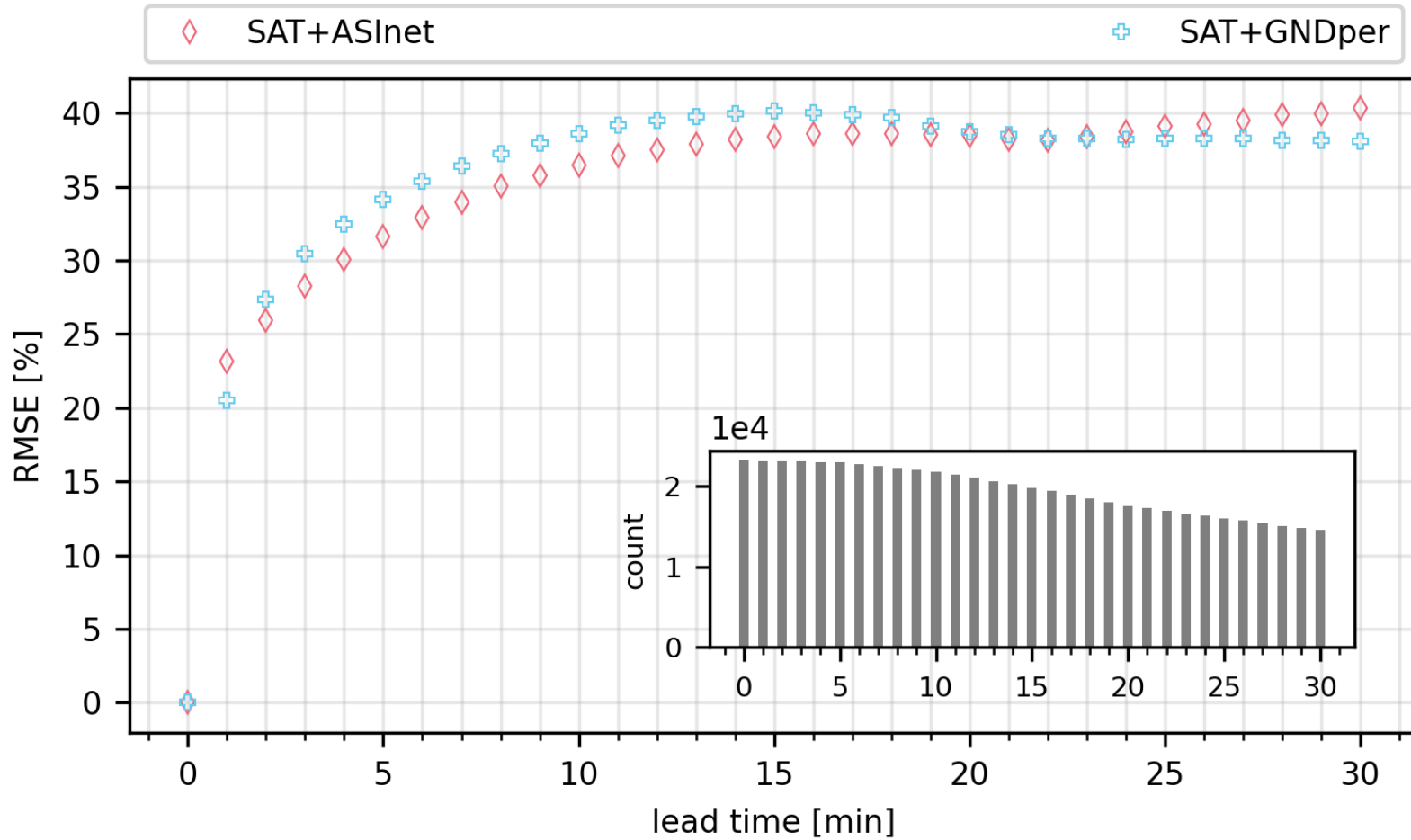


Training	
Stations used	OLDON
Time range	30 days history

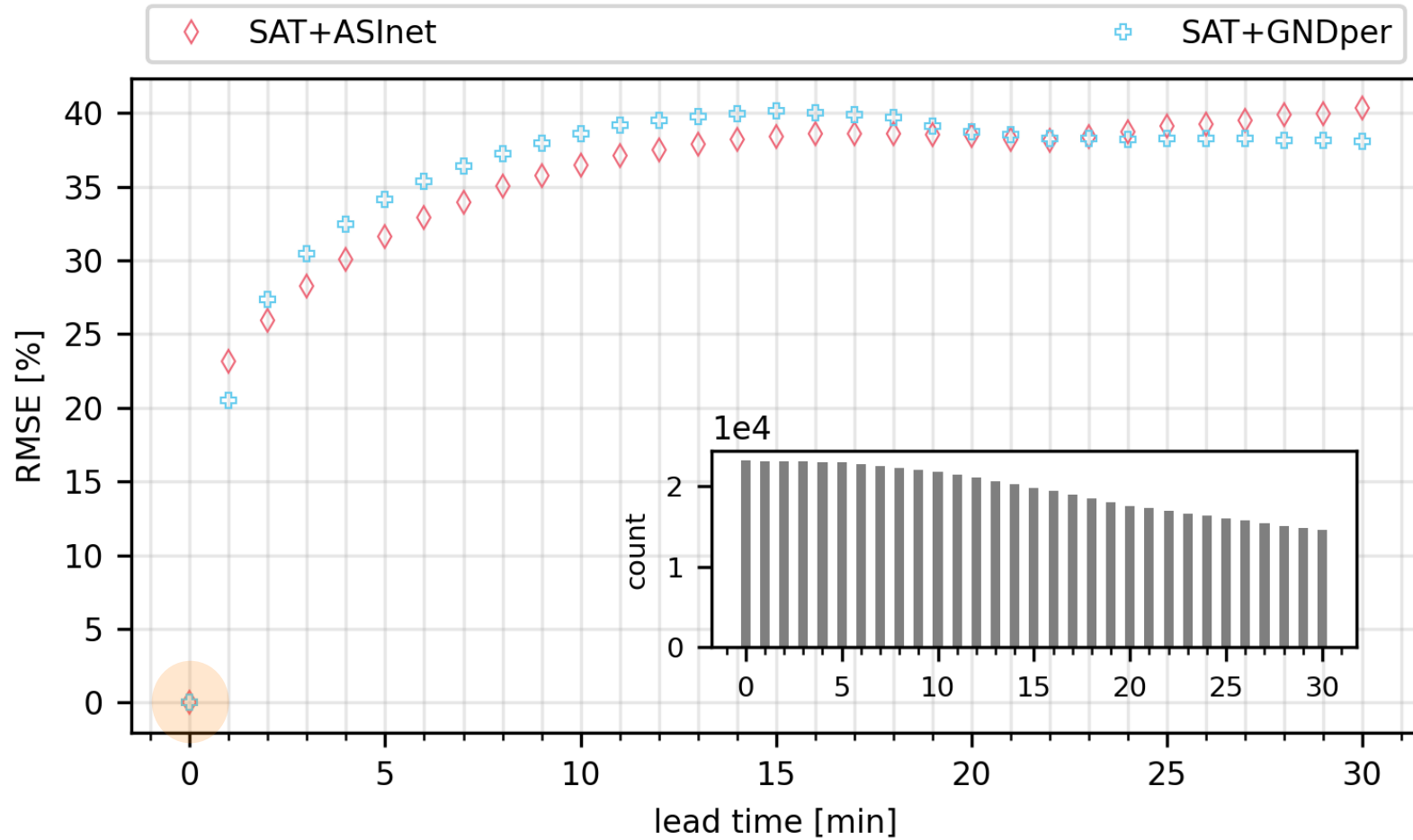
Prediction	
Stations used	OLDON
Time range	From 01.08.20 to 31.08.20

- ✓ 25 times less data compared to previous evaluation !
- ✓ OLDON selected because the station GND observations were used on for the calculation of the attenuation of the cloud scene on the ASI network forecast processing (Blum 2022)
- ✓ To evaluate in the other locations, the ASInet forecast should be reprocessed using the ground observations of the location in question

Test case 1 : evaluation at OLDON

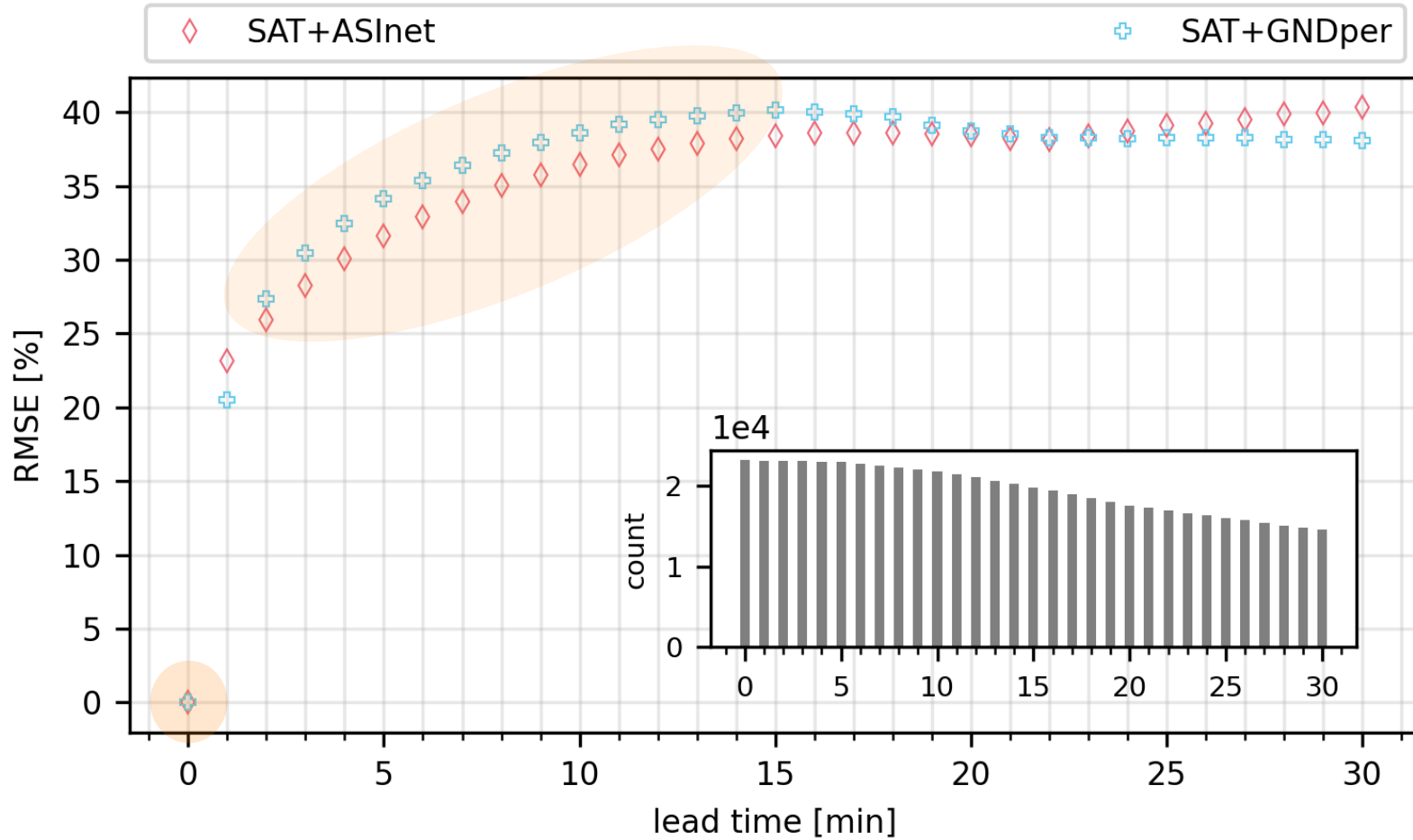


Test case 1 : evaluation at OLDON



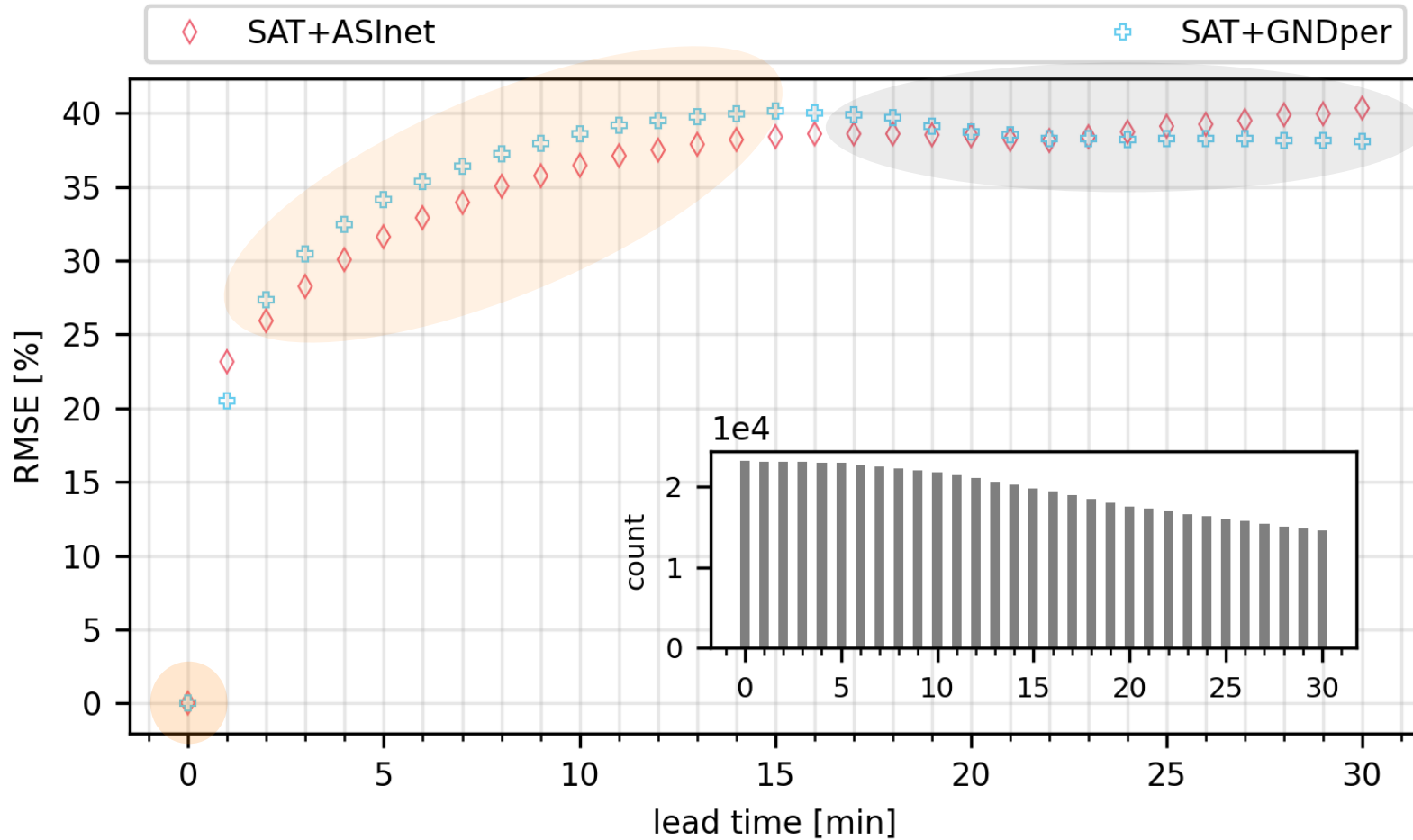
- RMSE 0% at LT0 for both

Test case 1 : evaluation at OLDON



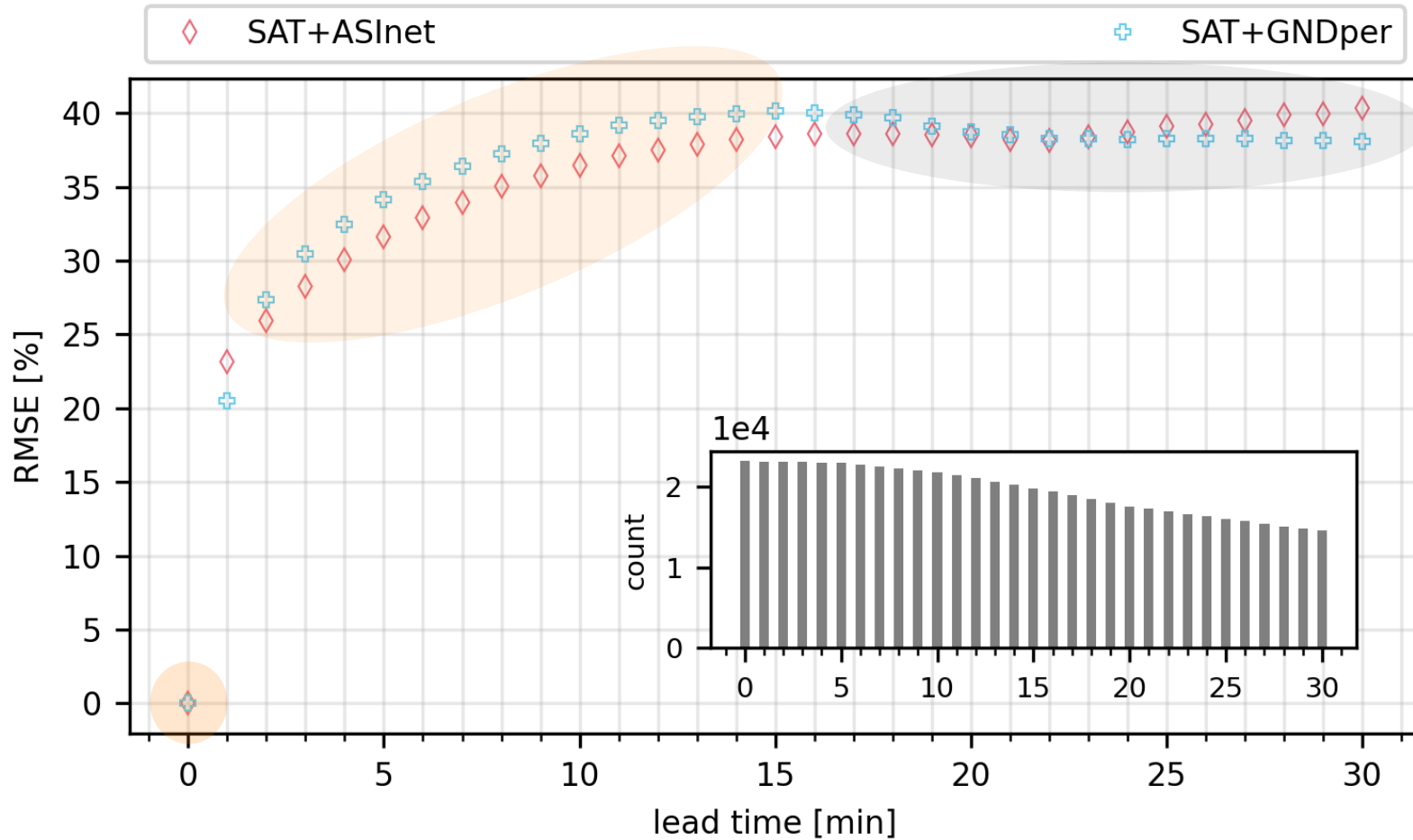
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- Improvement of **SAT+ASInet** from LT2 to LT15 (around 2.5% points)

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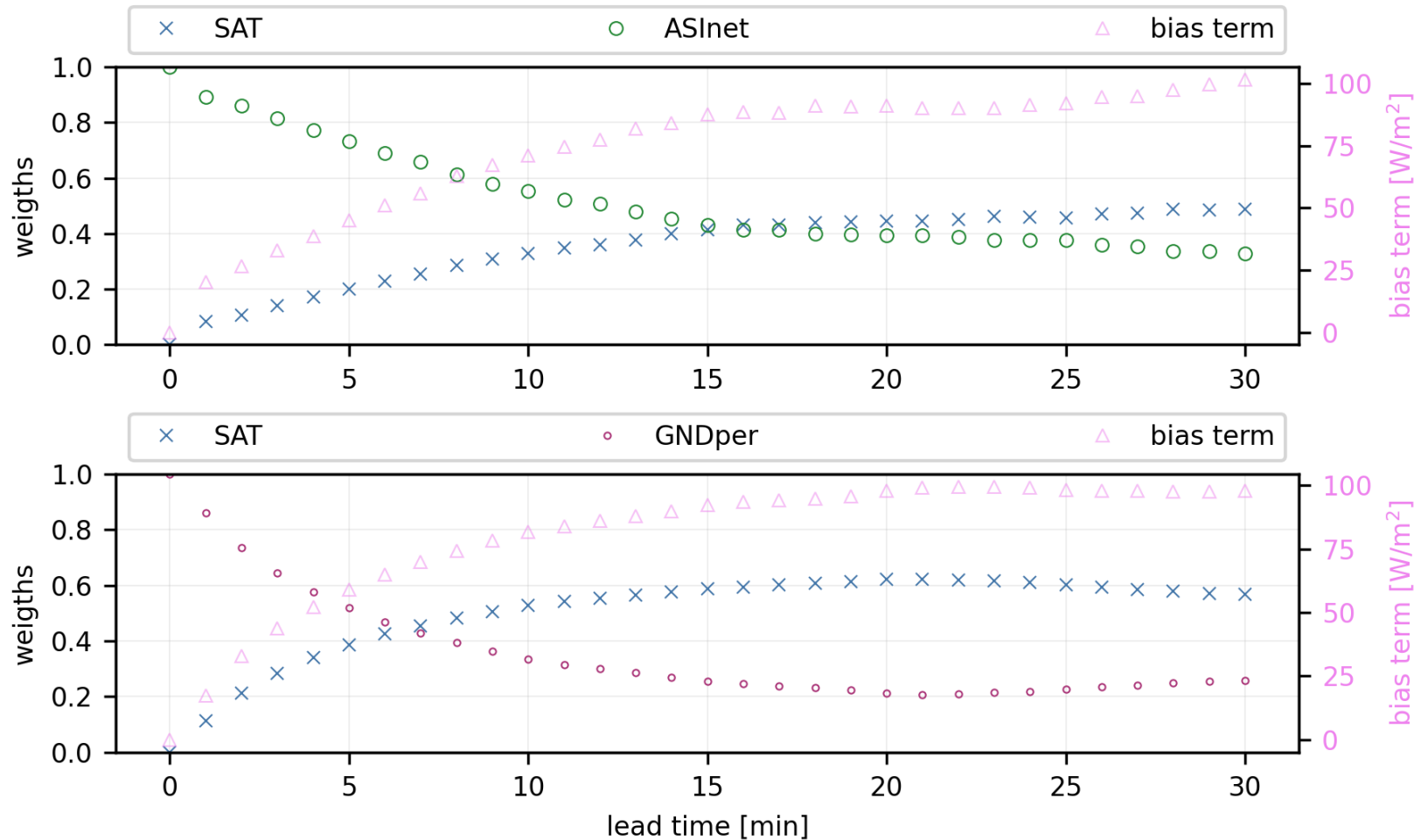
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- Values > LT15 (not sufficient data)

Test case 1 : evaluation at OLDON



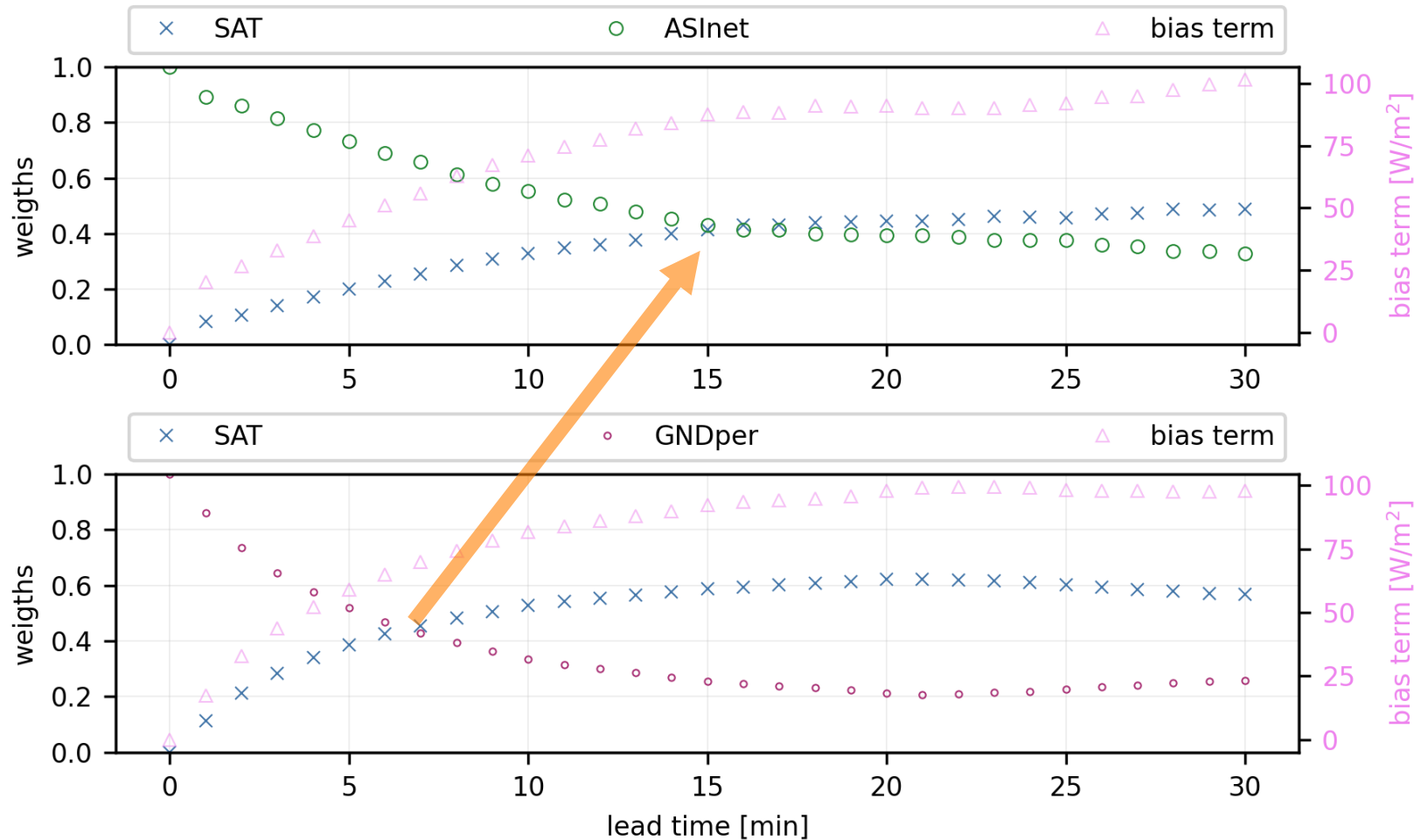
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- This is evidenced on the weights found on the blendings

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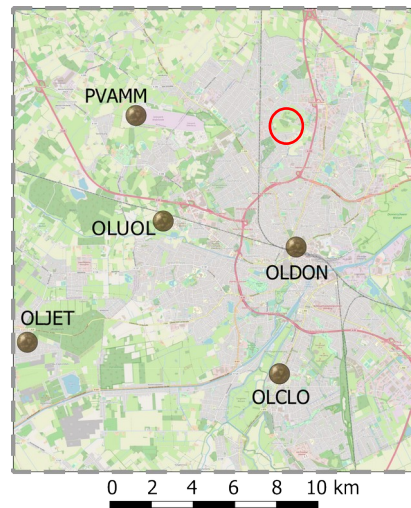


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Test case 2 : evaluation at any pixel in map

If forecast predictions are not limited to locations with ground observations ...

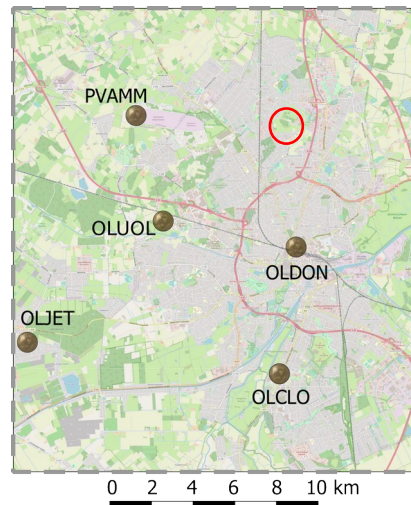
Any location on the domain



Test case 2 : evaluation at any pixel in map

If forecast predictions are not limited to locations with ground observations ...

Any location on the domain



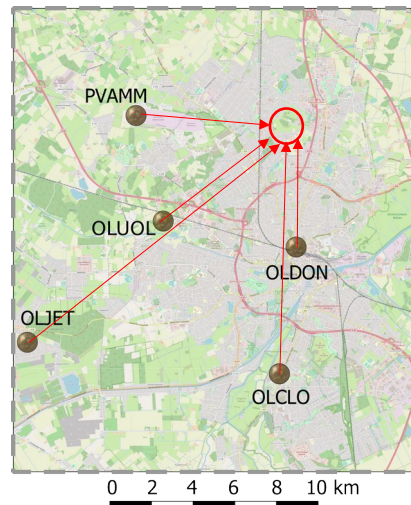
ground neighborhood observation :

$$\text{gnd}_{\text{ngh}}^{\text{p}} = \frac{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \cdot \text{gnd}_i \right)}{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \right)}$$

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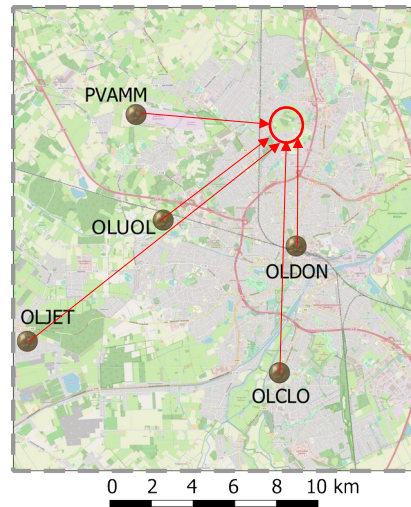
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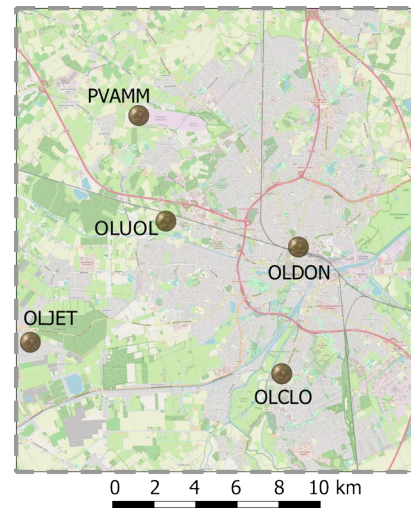
Test case 2 : evaluation at any pixel in map

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Proxy in our study



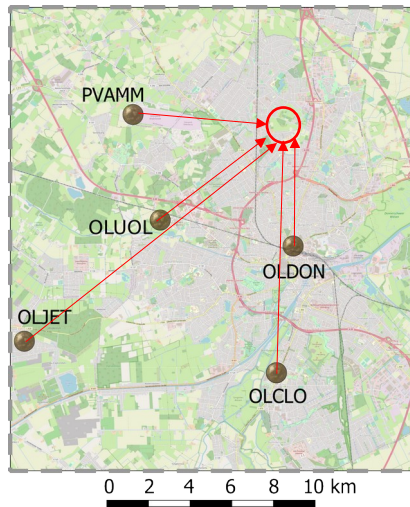
ground neighborhood observation :

$$\text{gnd}_{\text{ngh}}^{\text{p}} = \frac{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \cdot \text{gnd}_i \right)}{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \right)}$$

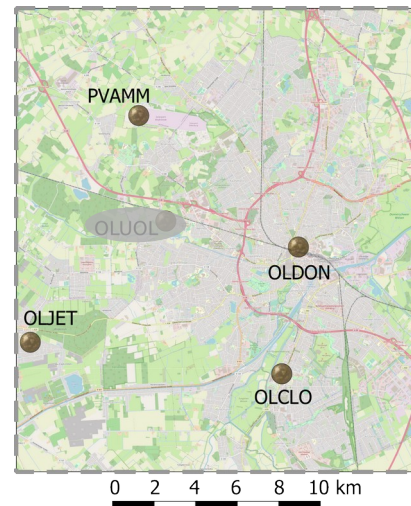
Test case 2 : evaluation at any pixel in map

If forecast predictions are not limited to locations with ground observations ...

Any location on the domain



Proxy in our study



- Neglect a site ground observation

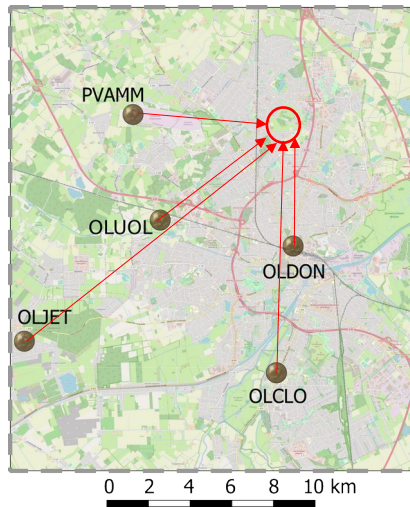
ground neighborhood observation :

$$\text{gnd}_{\text{ngh}}^{\text{p}} = \frac{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \cdot \text{gnd}_i \right)}{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \right)}$$

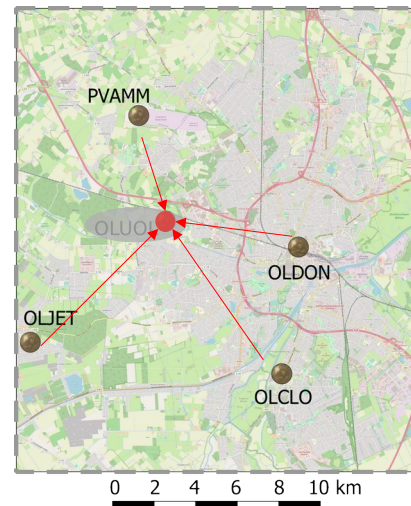
Test case 2 : evaluation at any pixel in map

If forecast predictions are not limited to locations with ground observations ...

Any location on the domain



Proxy in our study



- Neglect a site ground observation
- Calculate ground neighborhood persistence forecast

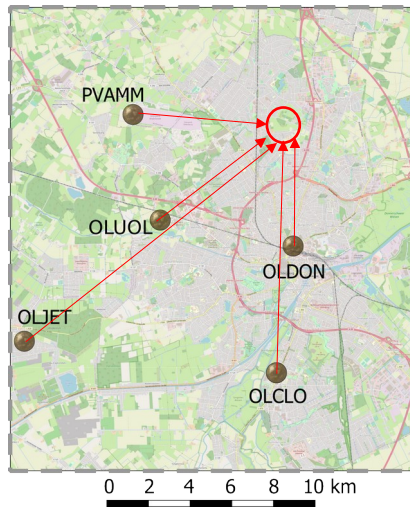
ground neighborhood observation :

$$\text{gnd}_{\text{ngh}}^{\text{p}} = \frac{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \cdot \text{gnd}_i \right)}{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \right)}$$

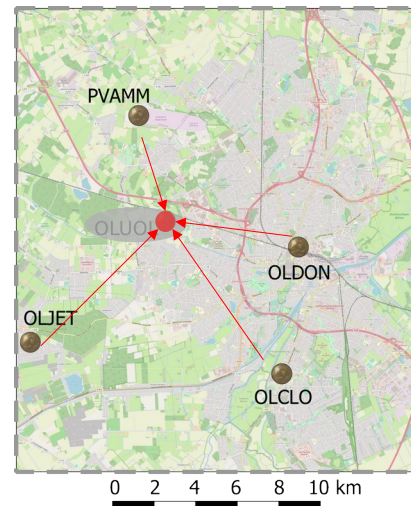
Test case 2 : evaluation at any pixel in map

If forecast predictions are not limited to locations with ground observations ...

Any location on the domain



Proxy in our study



- Neglect a site ground observation
- Calculate ground neighborhood persistence forecast
- Blend satellite with ground neighborhood persistence

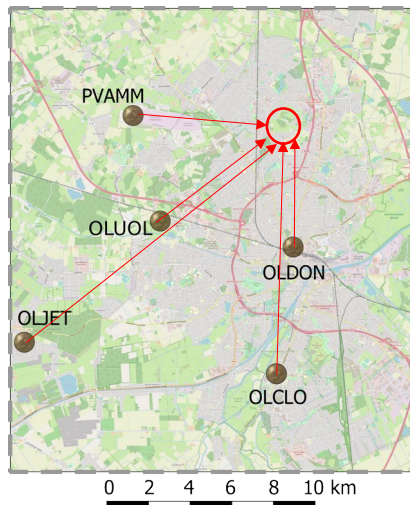
ground neighborhood observation :

$$\text{gnd}_{\text{ngh}}^{\text{p}} = \frac{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \cdot \text{gnd}_i \right)}{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \right)}$$

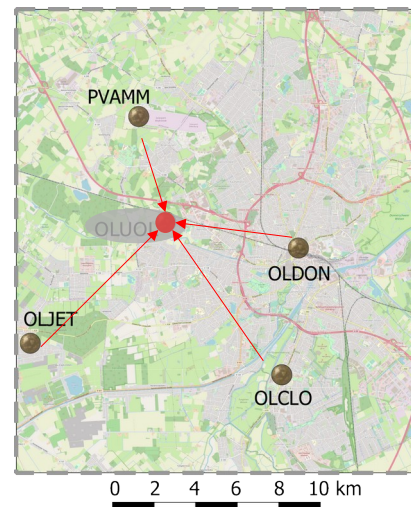
Test case 2 : evaluation at any pixel in map

If forecast predictions are not limited to locations with ground observations ...

Any location on the domain



Proxy in our study



- Neglect a site ground observation
- Calculate ground neighborhood persistence forecast
- Blend satellite with ground neighborhood persistence
- Only use neglected ground observation on validation

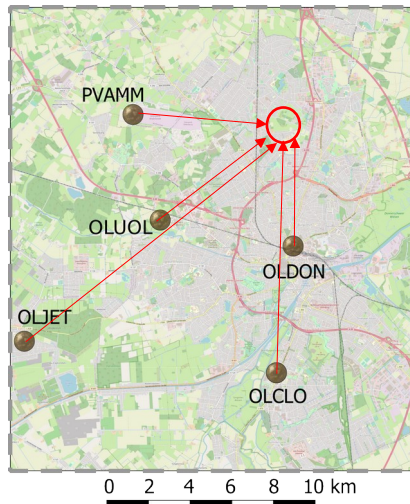
ground neighborhood observation :

$$\text{gnd}_{\text{ngh}}^{\text{p}} = \frac{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \cdot \text{gnd}_i \right)}{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \right)}$$

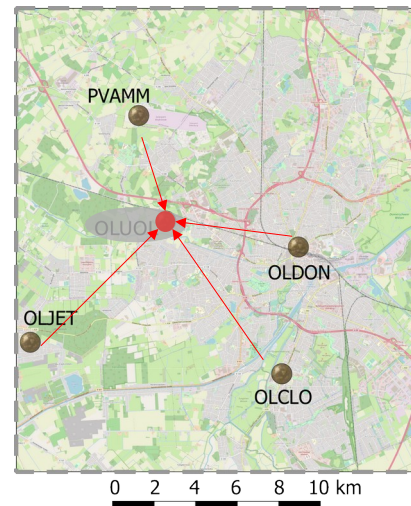
Test case 2 : evaluation at any pixel in map

If forecast predictions are not limited to locations with ground observations ...

Any location on the domain



Proxy in our study



- Neglect a site ground observation
- Calculate ground neighborhood persistence forecast
- Blend satellite with ground neighborhood persistence
- Only use neglected ground observation on validation

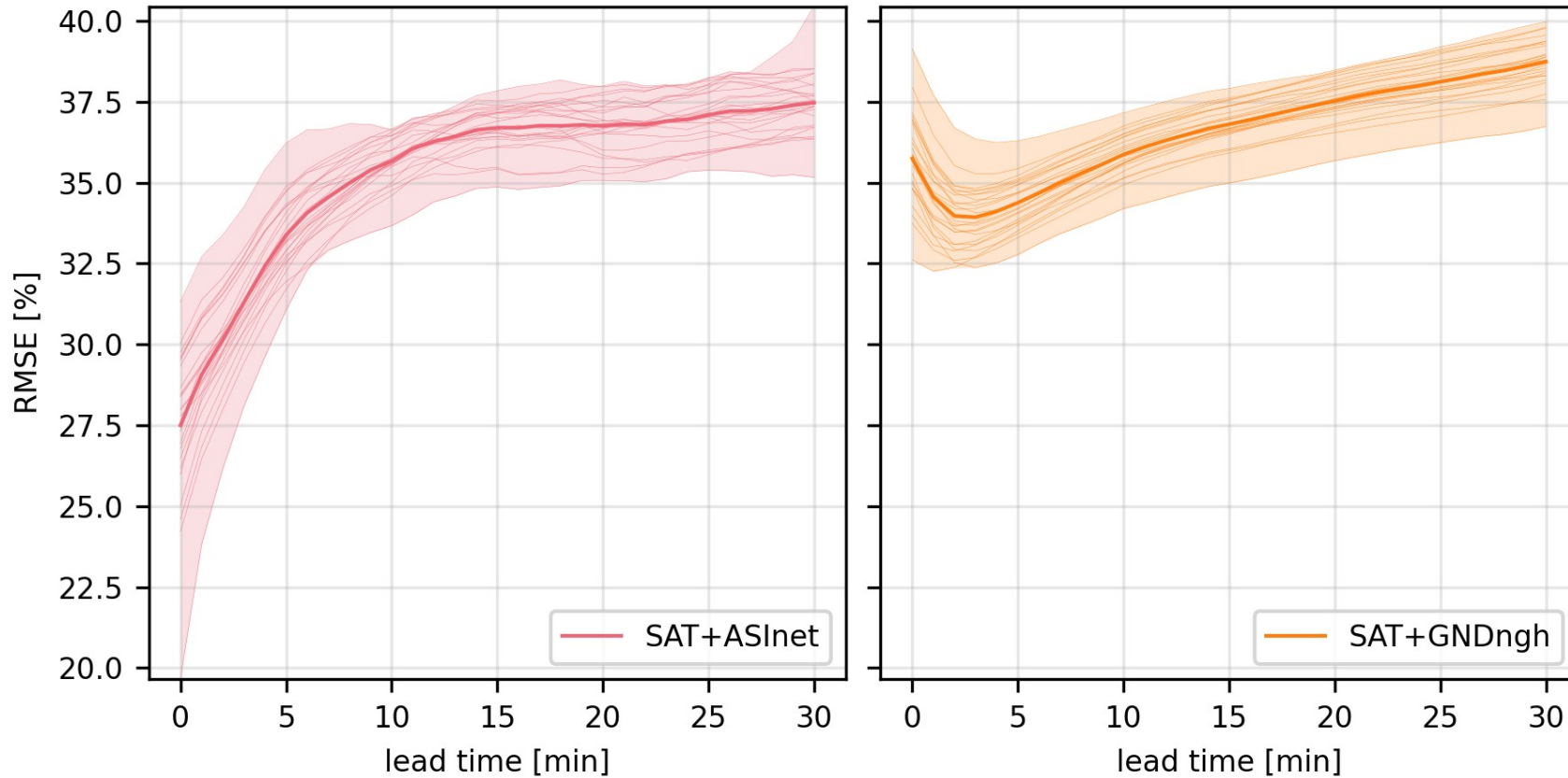
ground neighborhood observation :

$$\text{gnd}_{\text{ngh}}^{\text{p}} = \frac{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \cdot \text{gnd}_i \right)}{\sum_{i=1}^N \left(\frac{1}{d_{ip}} \right)}$$

Proxy for validation :

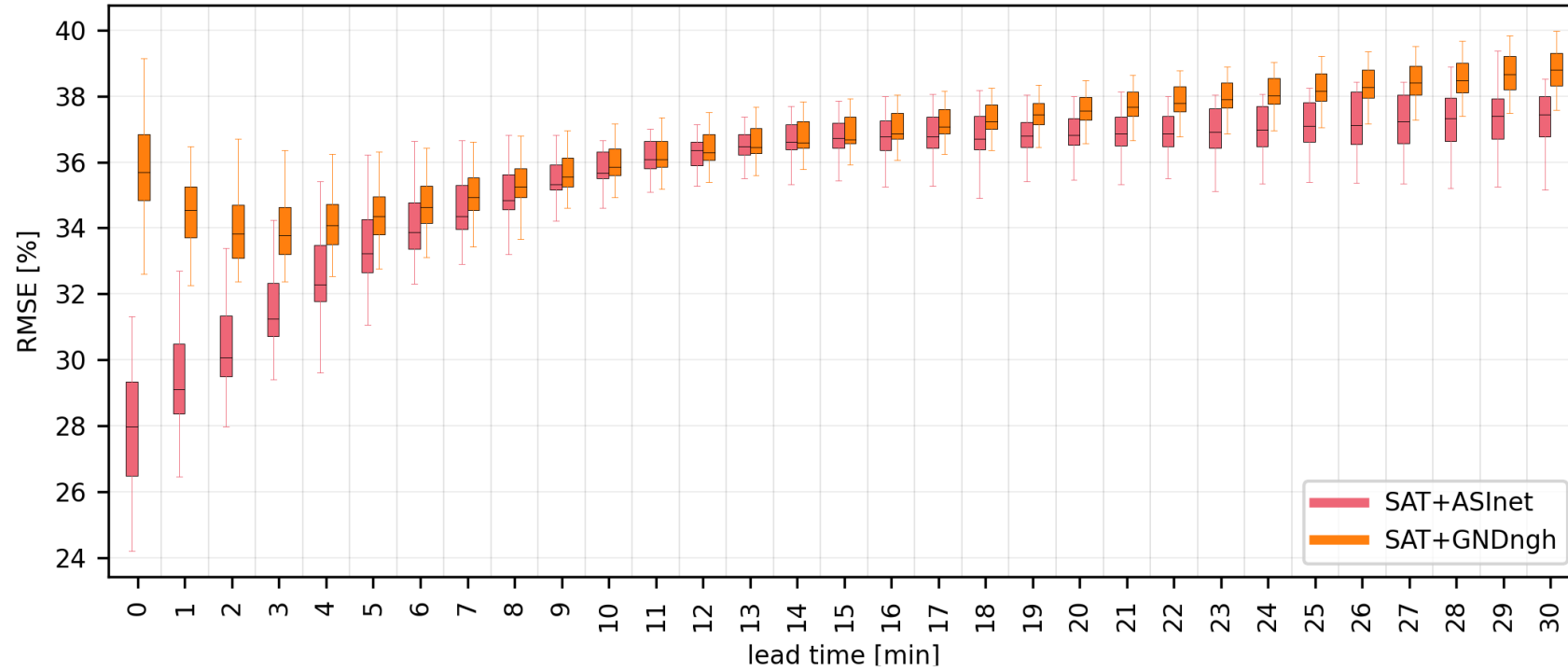
- ✓ find GNDngh persistence on each of the 5 locations
- ✓ Blend satellite with GNDngh persistence for all possible training cases (${}_5C_1$) → 25 cases

Test case 2 : evaluation at any pixel in map



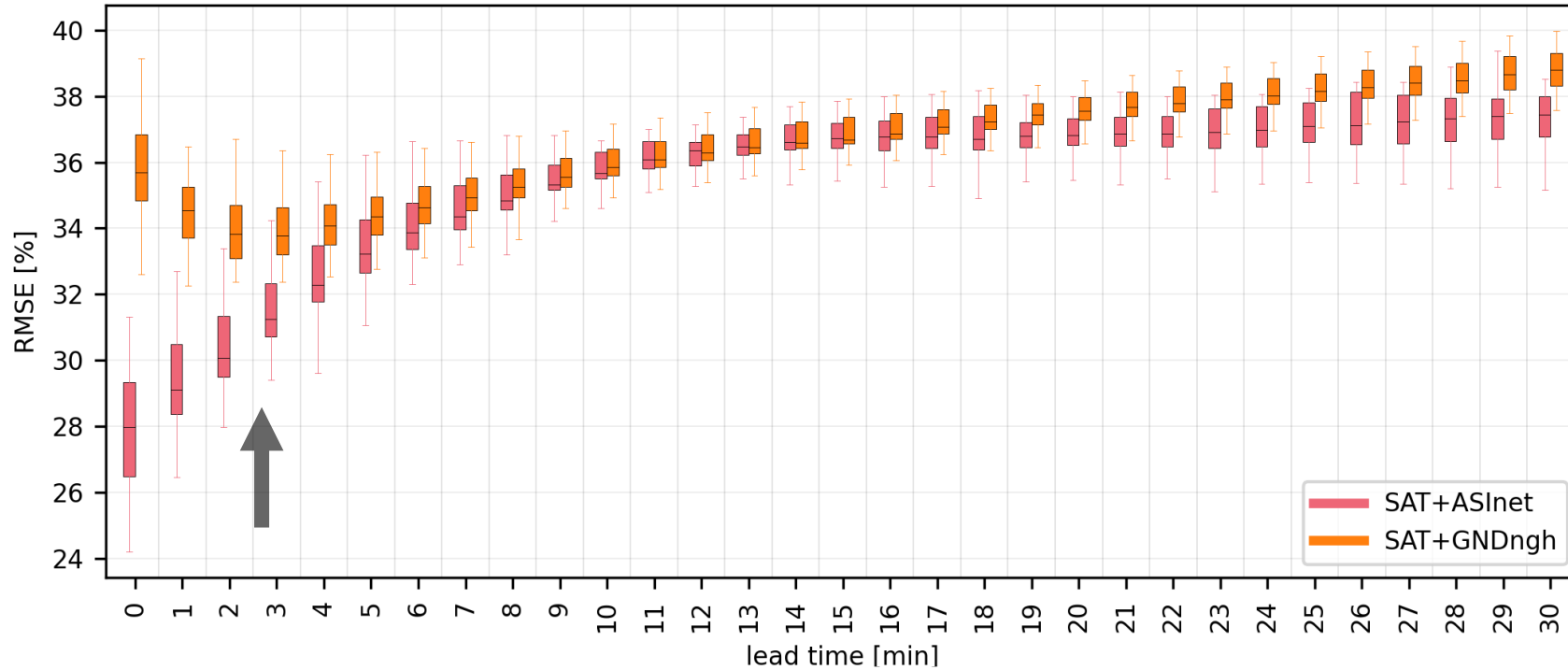
- 25 runs per blending

Test case 2 : evaluation at any pixel in map



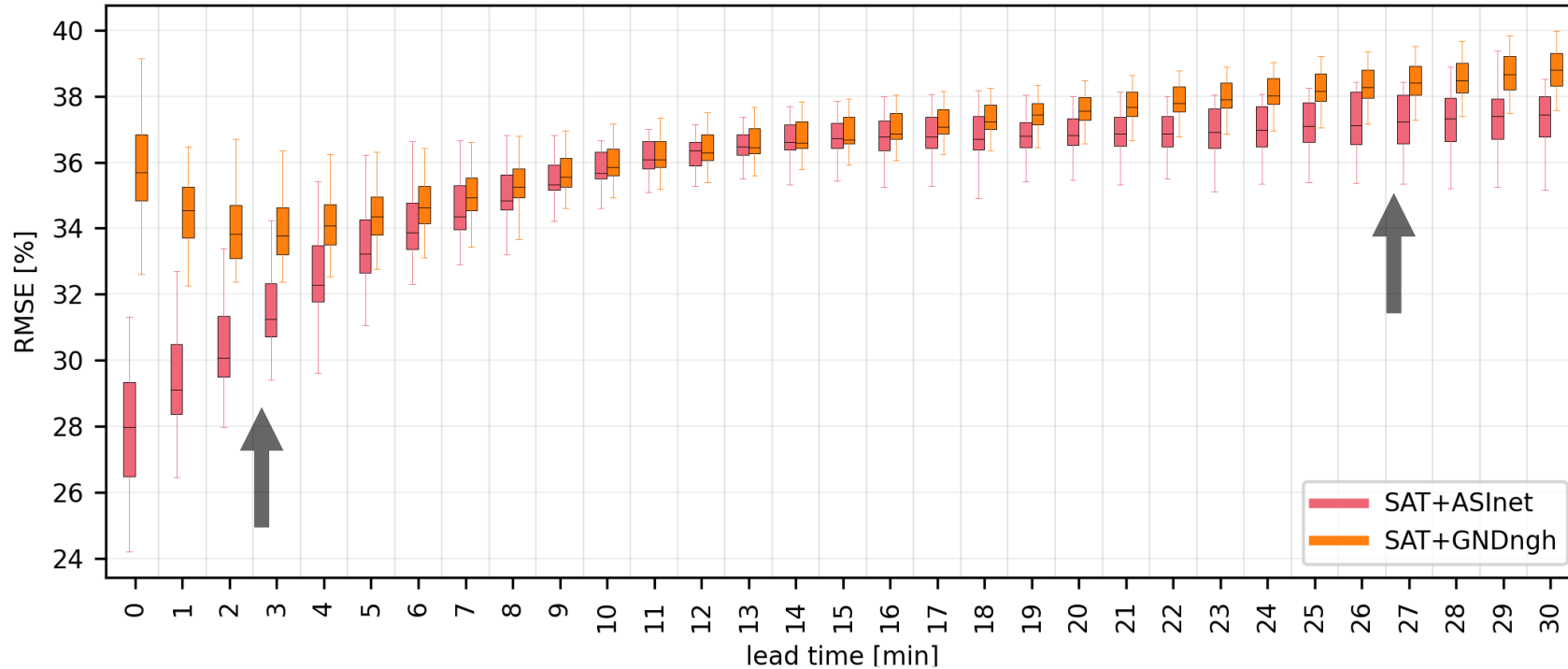
- 25 runs per blending

Test case 2 : evaluation at any pixel in map



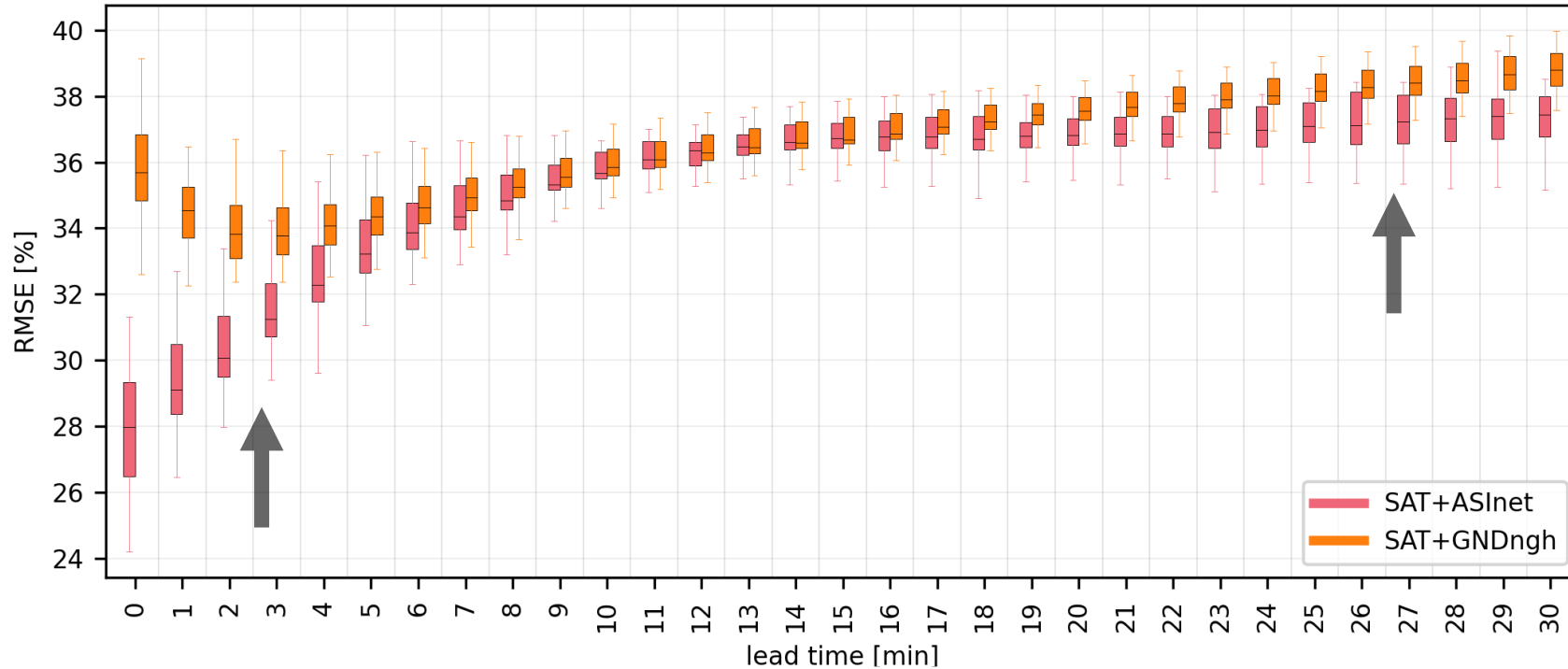
- 25 runs per blending
- Clear lower RMSE for **SAT+ASInet** on lower lead times

Test case 2 : evaluation at any pixel in map



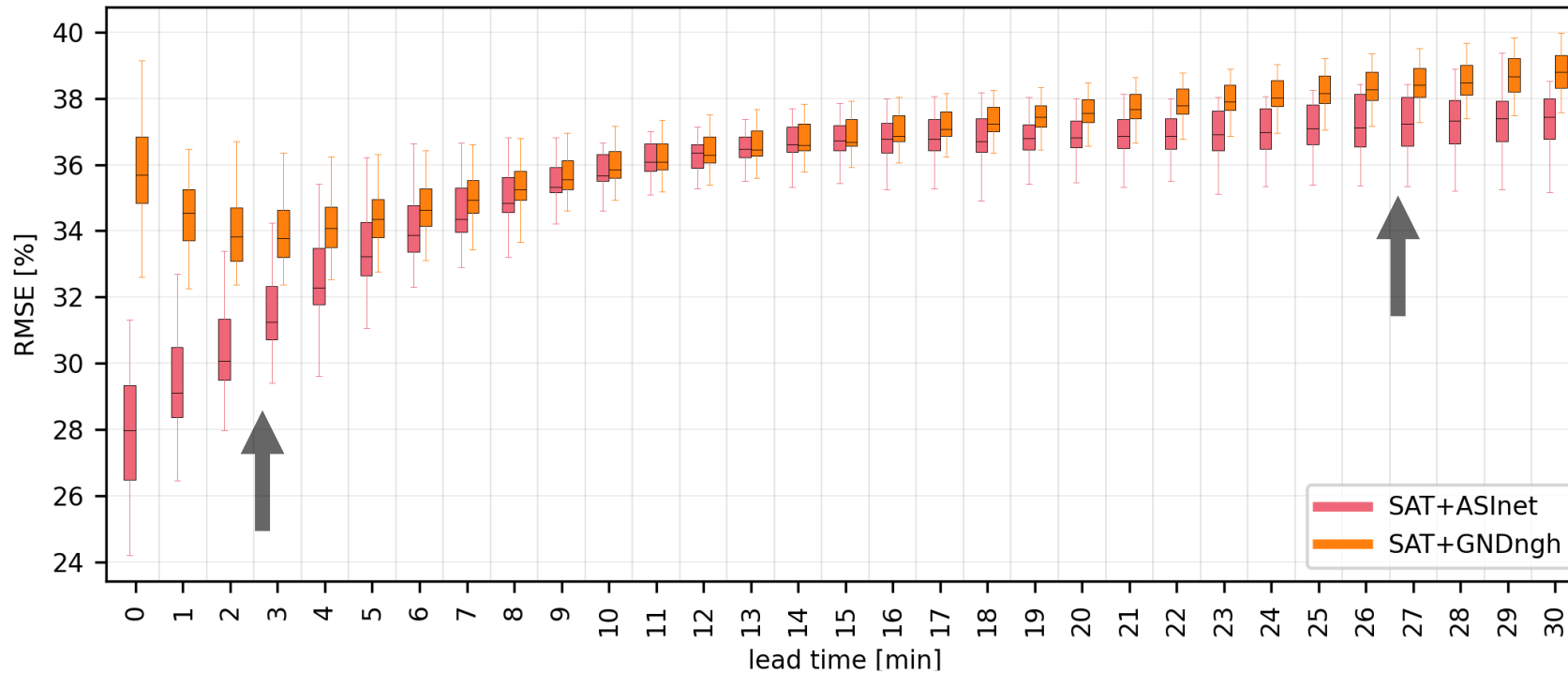
- 25 runs per blending
- Clear lower RMSE for SAT+ASInet on lower lead times
- For higher lead times the SAT+ASInet blend maintains a better performances (weights)

Test case 2 : evaluation at any pixel in map



- 25 runs per blending
- Clear lower RMSE for **SAT+ASInet** on lower lead times
- For higher lead times the **SAT+ASInet** blend maintains a better performances (weights)
- Overall better median on complete forecast horizon

Test case 2 : evaluation at any pixel in map



- 25 runs per blending
- Clear lower RMSE for **SAT+ASInet** on lower lead times
- For higher lead times the **SAT+ASInet** blend maintains a better performances (weights)
- Overall better median on complete forecast horizon

For predictions on pixels where there is no ground observations, the highly resolved spatial-temporal ASInet forecast will provide a better improvement on the blending with Satellite than the one provided by the ground derived persistence.

CONCLUSIONS / OUTLOOK

Conclusions and outlook



- The blending of satellite and ASI network showed an absolute RMSE improvement of 3.5% to 9% over the forecast inputs (SAT and ASI network)
- In point forecasts, the blending of satellite with ground persistence-based forecasts is not able to outperform the satellite and ASI network blending. This is valid for locations with and without ground observations.
- This study assess the performance of the blending only on a point forecast base. Other methodologies based on spatial structures like forecast of spatial variability or ramp rate detection should be done in order to asses the benefit of ASI network on these other metrics.
- The blending should be done on:
 - bigger time range (1 year) → see the season transferability
 - Other climates → increased benefit ?
- Compare linear regression blending with machine learning based methods

References



Blum, N., Wilbert, S., Nouri, B., Stührenberg, J., Lezaca, J., Schmidt, T., Heinemann, D., Vogt, T., Kazantzidis, A., Pitz-Paal, R., *Analyzing Spatial Variations of Cloud Attenuation by a Network of All-Sky Imagers*. Remote Sens. 2022, 14, 5685. <https://doi.org/10.3390/rs14225685>

Hammer, A., Kühnert, J., Weinreich, K., Lorenz, E., *Short-Term Forecasting of Surface Solar Irradiance Based on Meteosat-SEVIRI Data Using a Nighttime Cloud Index*, Remote Sens.7, 2015
DOI:10.3390/rs70709070

Hammer, A., Kühnert, J., Weinreich, K., Lorenz, E., *Correction: Short-Term Forecasting of Surface Solar Irradiance Based on Meteosat-SEVIRI Data Using a Nighttime Cloud Index*, Remote Sens.7, 2015, DOI:10.3390/rs71013842

**THANK YOU FOR YOUR
ATTENTION !**

