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Underestimation of satellite-based surface solar radiation in the Swiss Alpes: a bias correction approach

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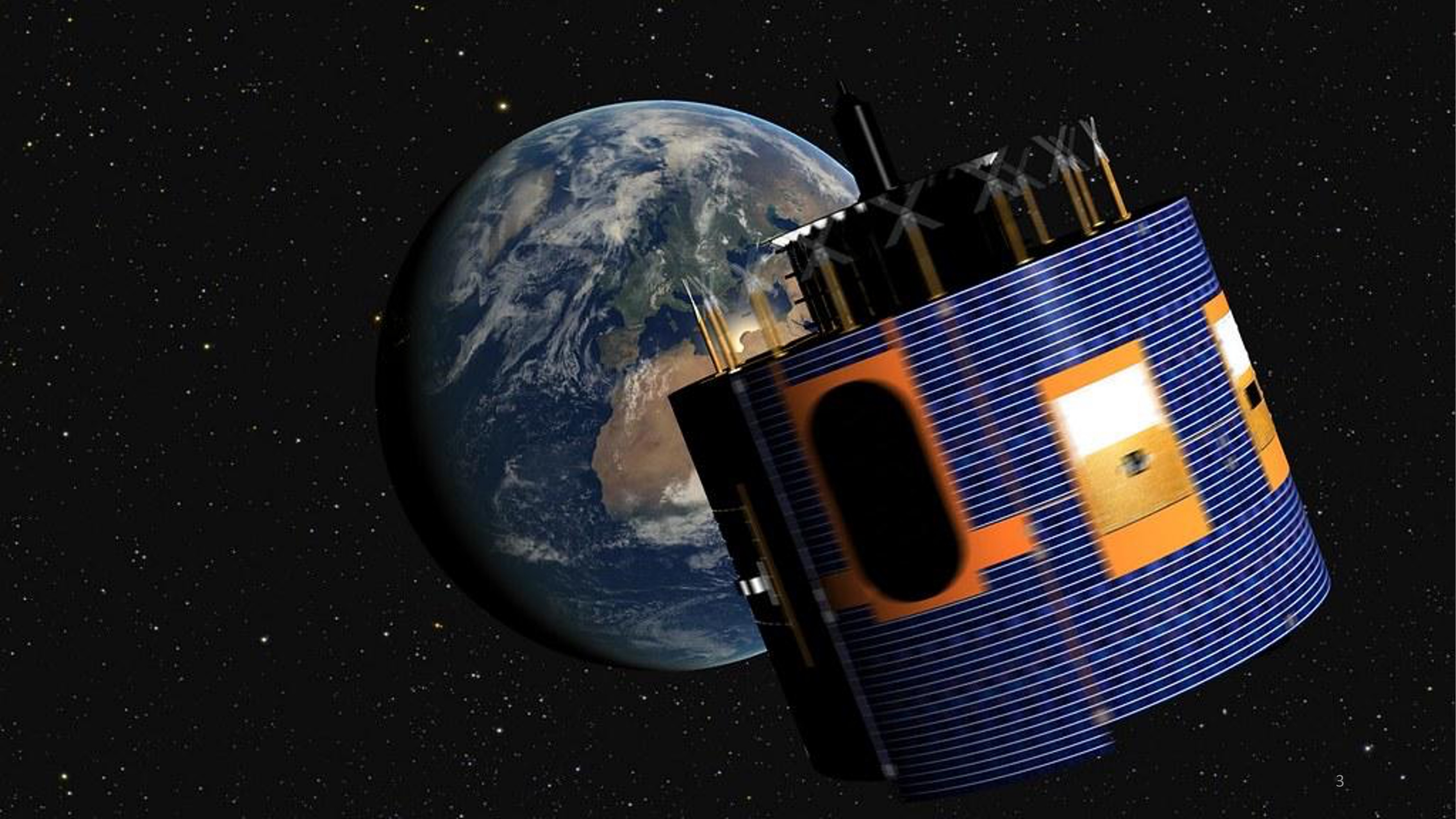
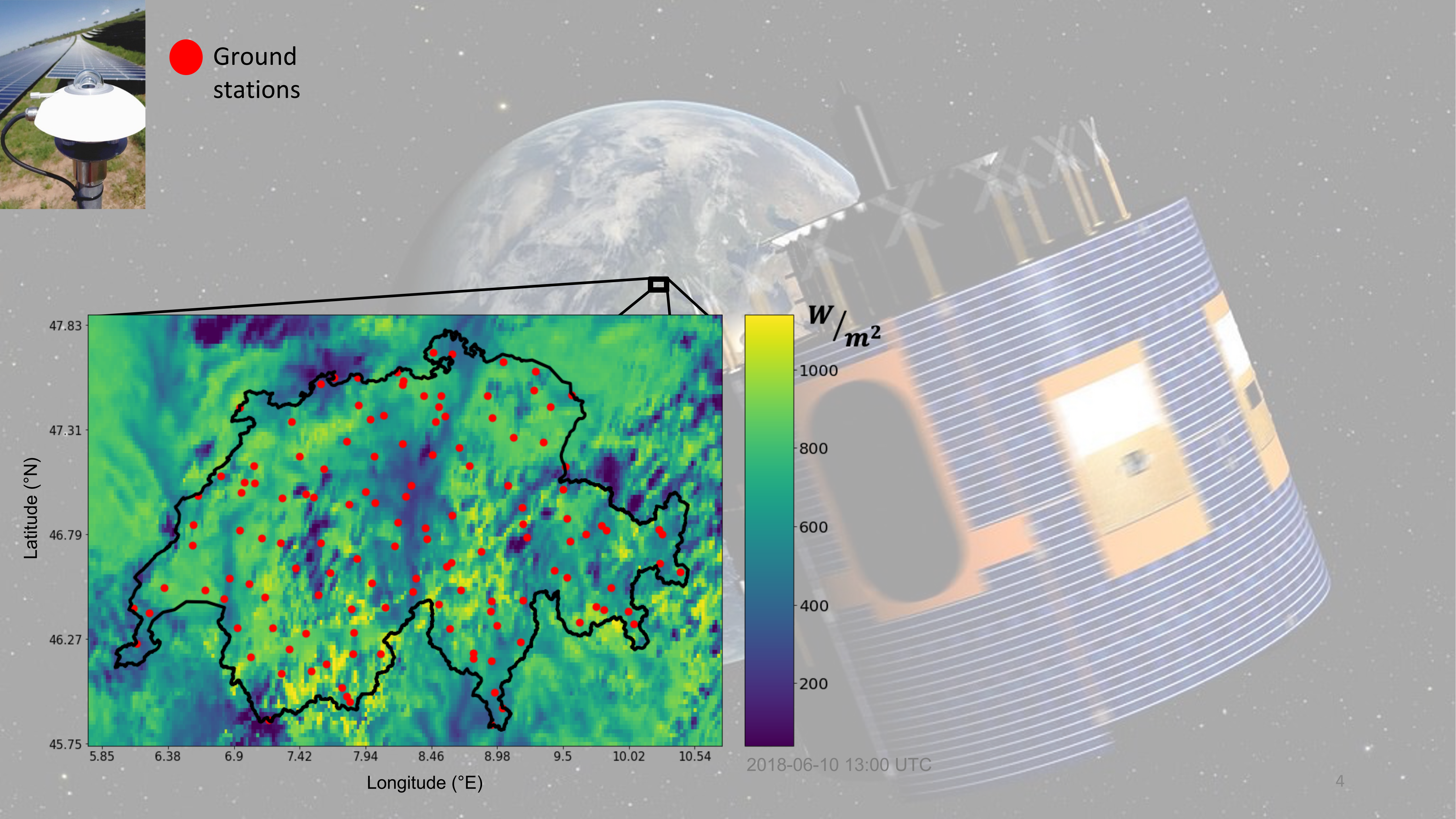



Ground
stations
W/m²
1000
800
600
400
200
47.83
47.31
46.79
46.27
45.75
Latitude (°N)
5.85
6.38
6.9
7.42
7.94
8.46
8.98
9.5
10.02
10.54
Longitude (°E)
2018-06-10 13:00 UTC

Bias

$$bias_{lon,lat,t} = SSR_{lon,lat,t}^{sat} - SSR_{lon,lat,t}^{ground}$$

Bias

$$bias_{lon,lat,t} = SSR^{sat}_{lon,lat,t} - SSR^{ground}_{lon,lat,t}$$

- (lon, lat, t): point in space-time, $(lon, lat) \in S, t \in T$
- SSR^{sat} : satellite-derived SSR measurement
- SSR^{ground} : ground station SSR measurement

Bias

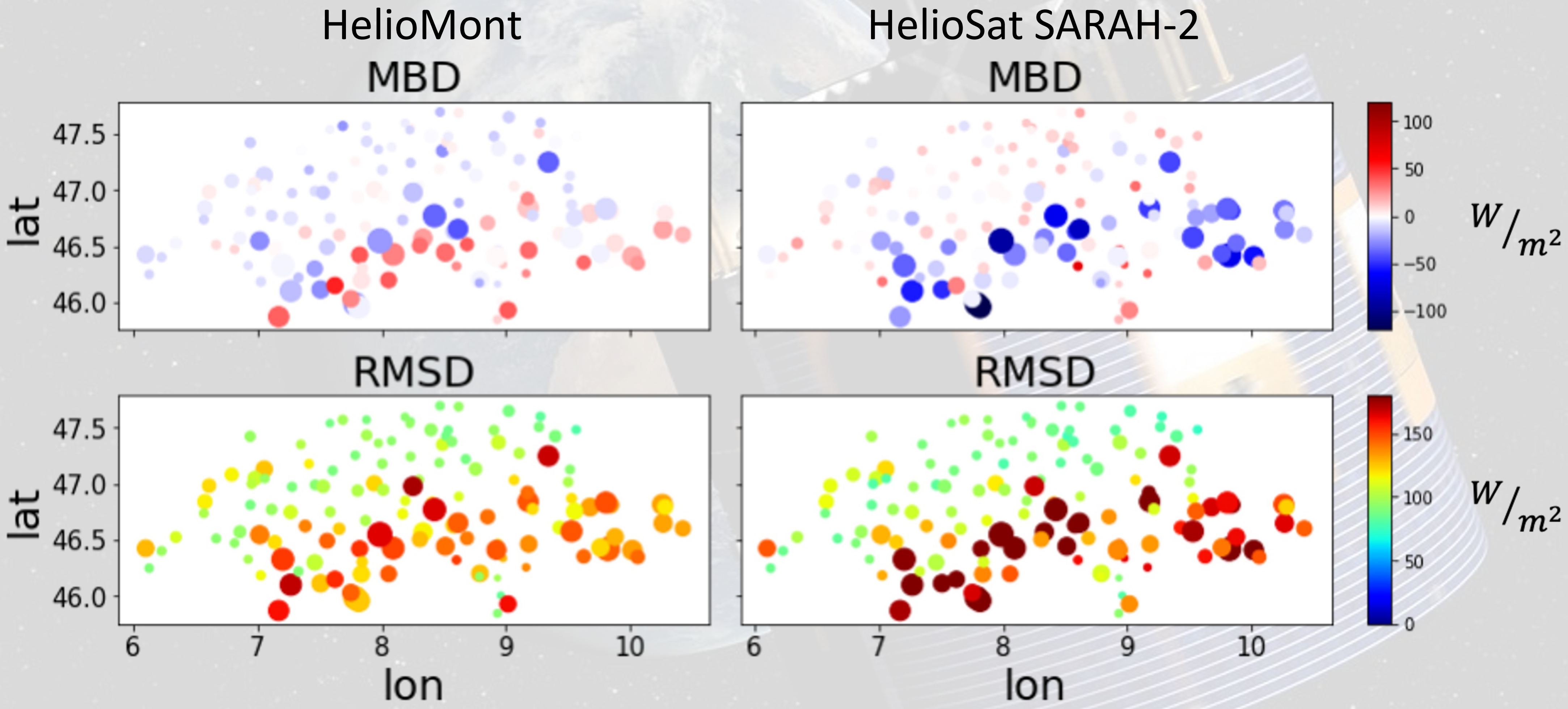
$$bias_{lon,lat,t} = SSR^{sat}_{lon,lat,t} - SSR^{ground}_{lon,lat,t}$$

- (lon, lat, t): point in space-time, $(lon, lat) \in S, t \in T$
- SSR^{sat} : satellite-derived SSR measurement
- SSR^{ground} : ground station SSR measurement

GOAL

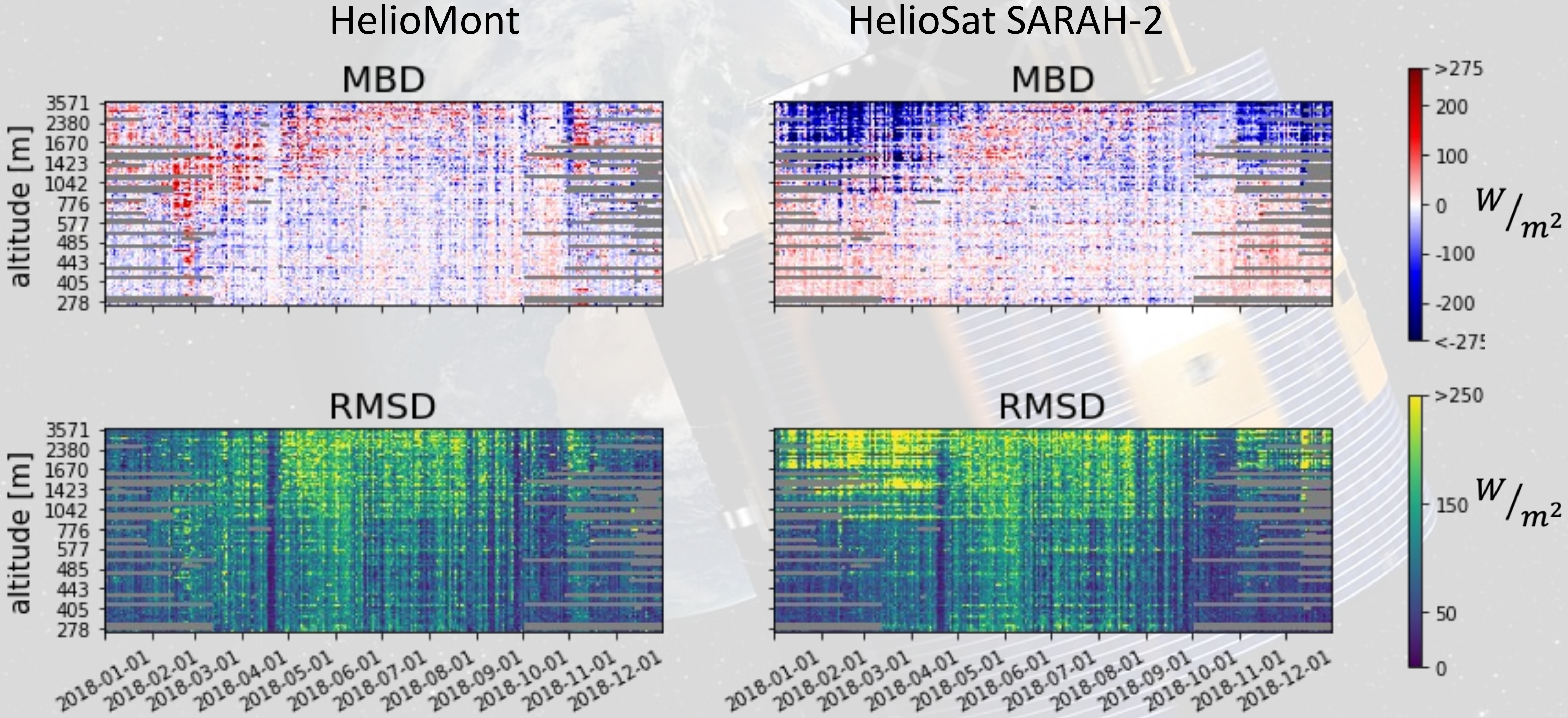
$$\boxed{\min \sum_{lon,lat,t}^{S,T} \left(bias_{lon,lat,t}\right)^2}$$

Bias



RMSD vs altitude R^2: 0.77 0.84

Bias


HelioMont
HelioSat SARAH-2
MBD
MBD
RMSD
RMSD
altitude [m]
3571
2380
1670
1423
1042
776
577
485
443
405
278
2018-01-01
2018-02-01
2018-03-01
2018-04-01
2018-05-01
2018-06-01
2018-07-01
2018-08-01
2018-09-01
2018-10-01
2018-11-01
2018-12-01
>275
200
100
0
-100
-200
<-275
>250
150
50
0
W/m²

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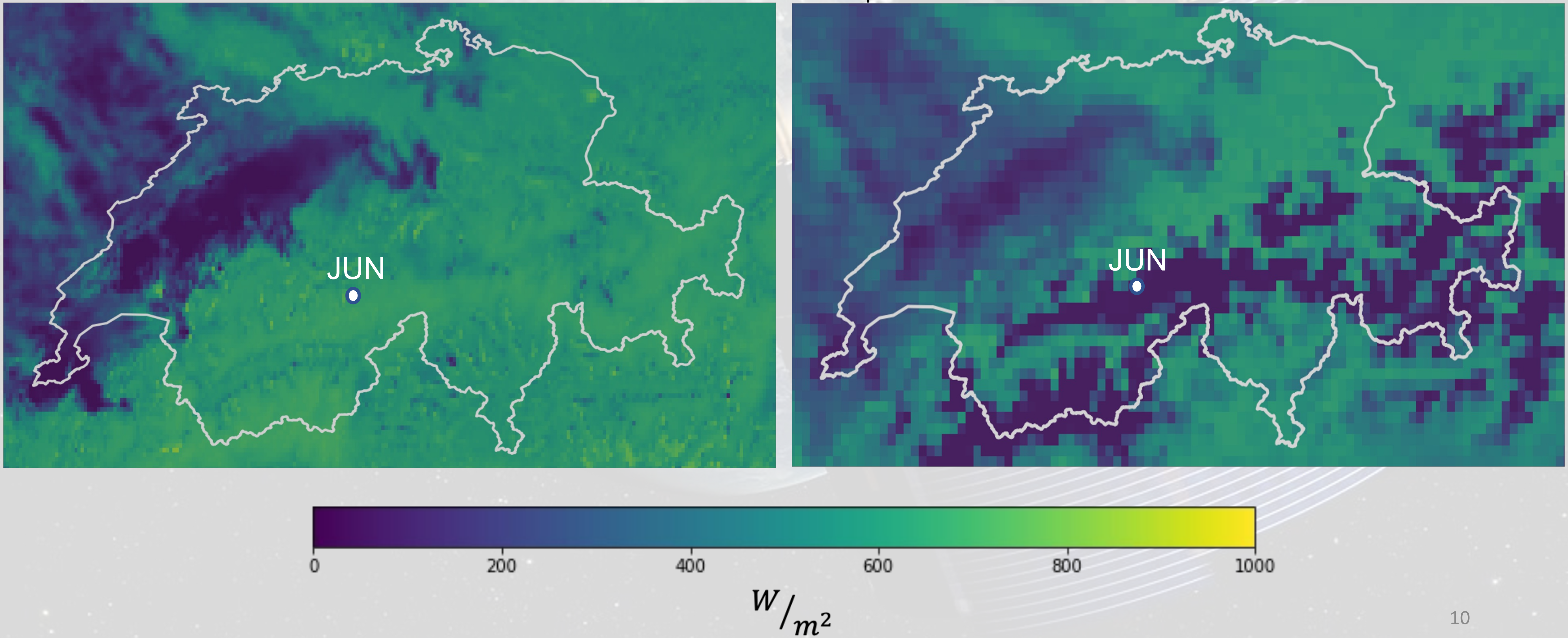
Bias

HelioMont

2018-03-20 12:10pm

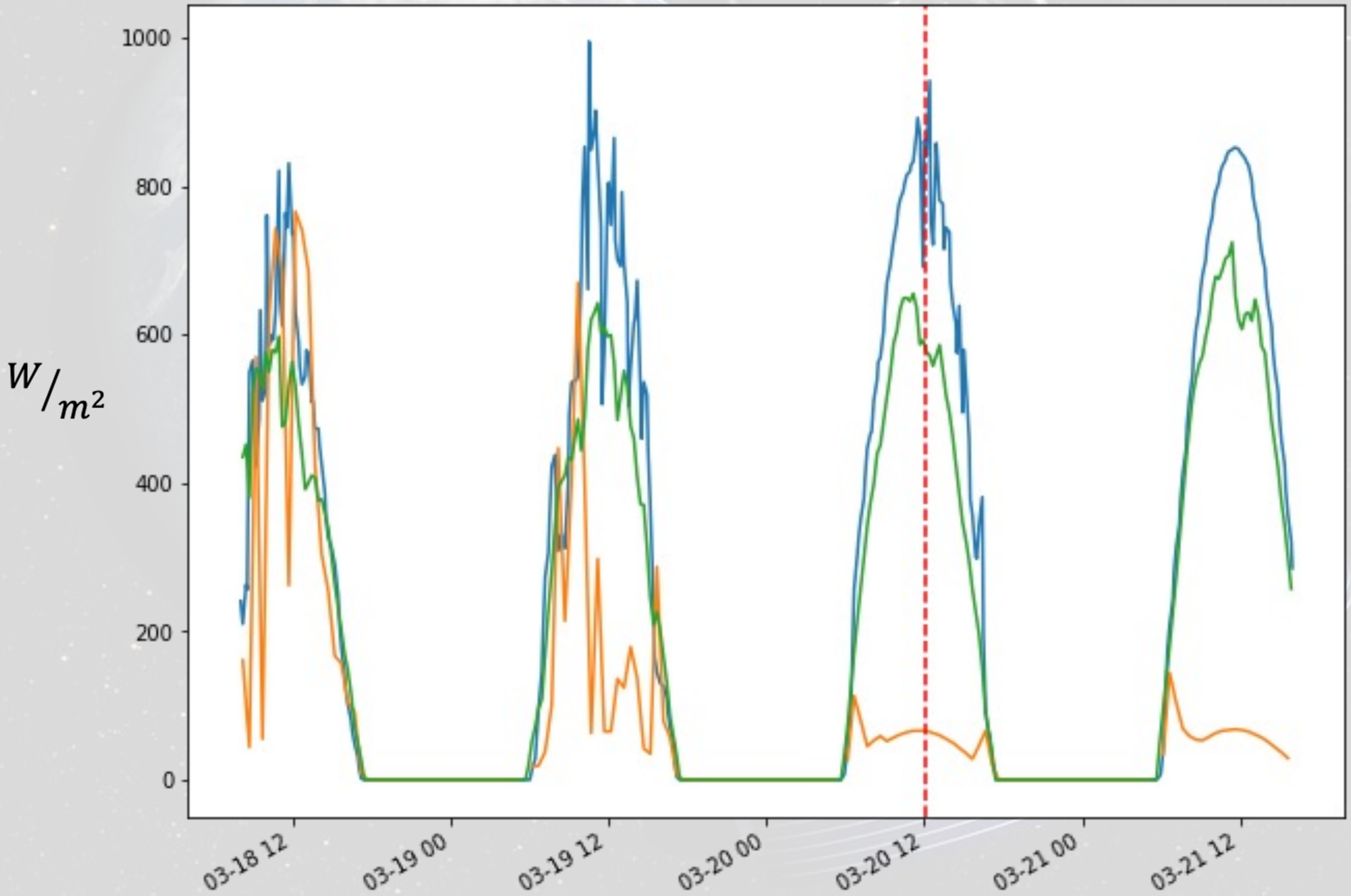
HelioSat SARAH-2



Bias

- In-situ
- SARAH-2
- HelioMont

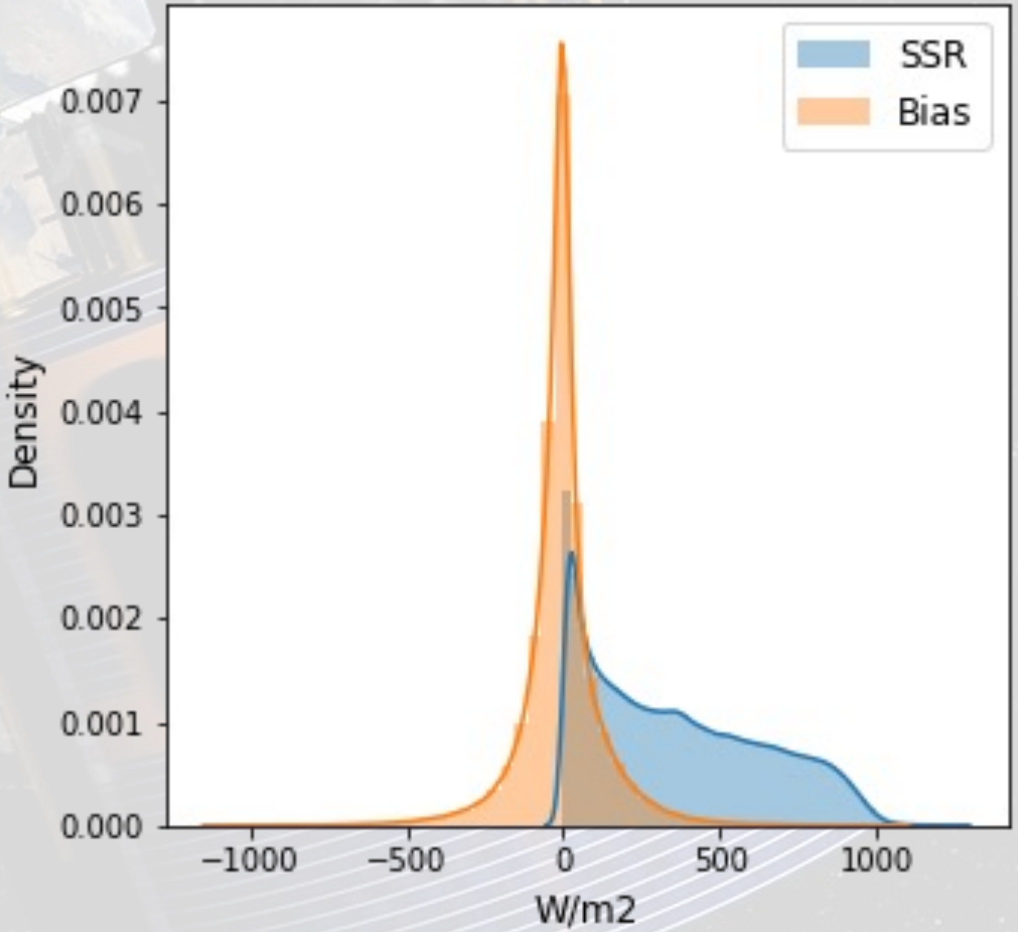
JUN



Bias

- SARAH-2 and HelioMont biases show normality with a confidence of 99%*

- Predicting the bias instead of the ground measurements showed an improvement on the performances



* D'agostino Pearson test on normality

Regression Models

- HelioMont BC Model

$$
\begin{aligned}
bias_{t,lon,lat} &= SSR^{sat}{}_{t,lon,lat} - SSR^{ground}{}_{t,lon,lat} \\
&\sim SSR^{sat}{}_{t,lon,lat} + SZA_{t,lon,lat} + KI_{t,lon,lat} + TE_t + lon + lat + alt_{lon,lat}
\end{aligned}
$$

Regression Models

$$KI = SSR^{sat} \Big/ SSR^{sat}_{clear-sky}$$

HelioMont BC Model

$$bias_{t,lon,lat} = SSR^{sat}{}_{t,lon,lat} - SSR^{ground}{}_{t,lon,lat}$$

$$\sim SSR^{sat}{}_{t,lon,lat} + SZA_{t,lon,lat} + \boxed{KI_{t,lon,lat}} + TE_t + lon + lat + alt_{lon,lat}$$

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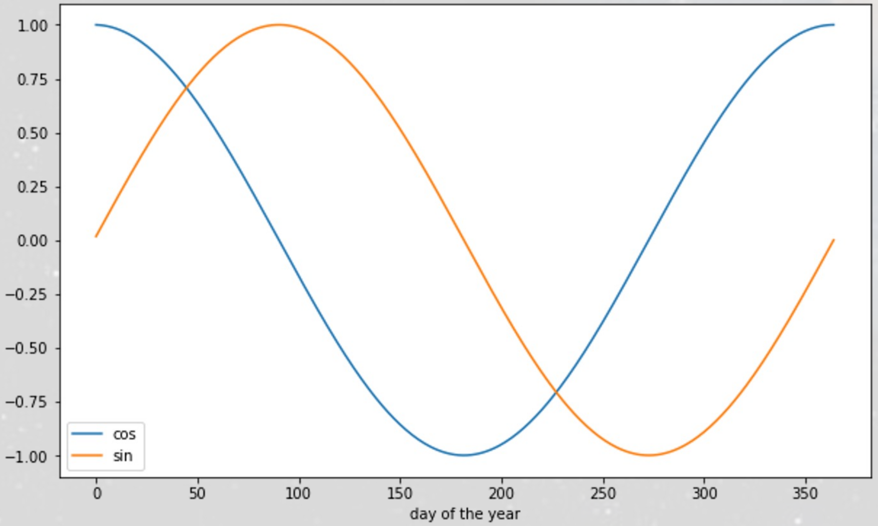
Regression Models

- HelioMont BC Model

$$bias_{t,lon,lat} = {SSR^{sat}}_{t,lon,lat} - {SSR^{ground}}_{t,lon,lat}$$
$$\sim {SSR^{sat}}_{t,lon,lat} + SZA_{t,lon,lat} + KI_{t,lon,lat} \boxed{+ TE_t +} lon + lat + alt_{lon,lat}$$



$$TE_t = f\left(2\pi \times t_{day}/365\right)$$

Regression Models

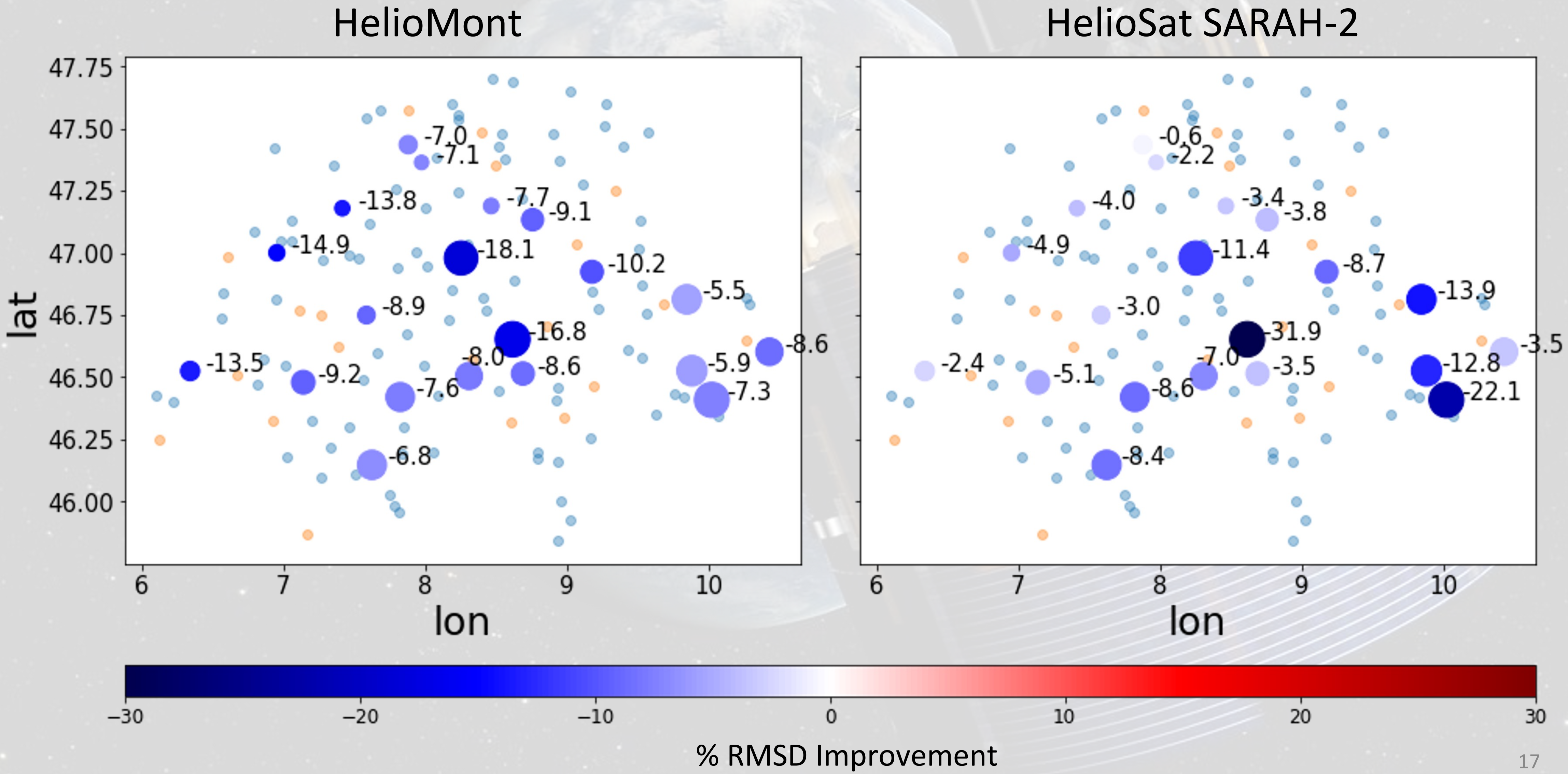
HelioMont BC Model

$$bias_{t,lon,lat} = {SSR^{sat}}_{t,lon,lat} - {SSR^{ground}}_{t,lon,lat}$$
$$\sim {SSR^{sat}}_{t,lon,lat} + SZA_{t,lon,lat} + KI_{t,lon,lat} + TE_t + lon + lat + alt_{lon,lat}$$

SARAH-2 BC Model

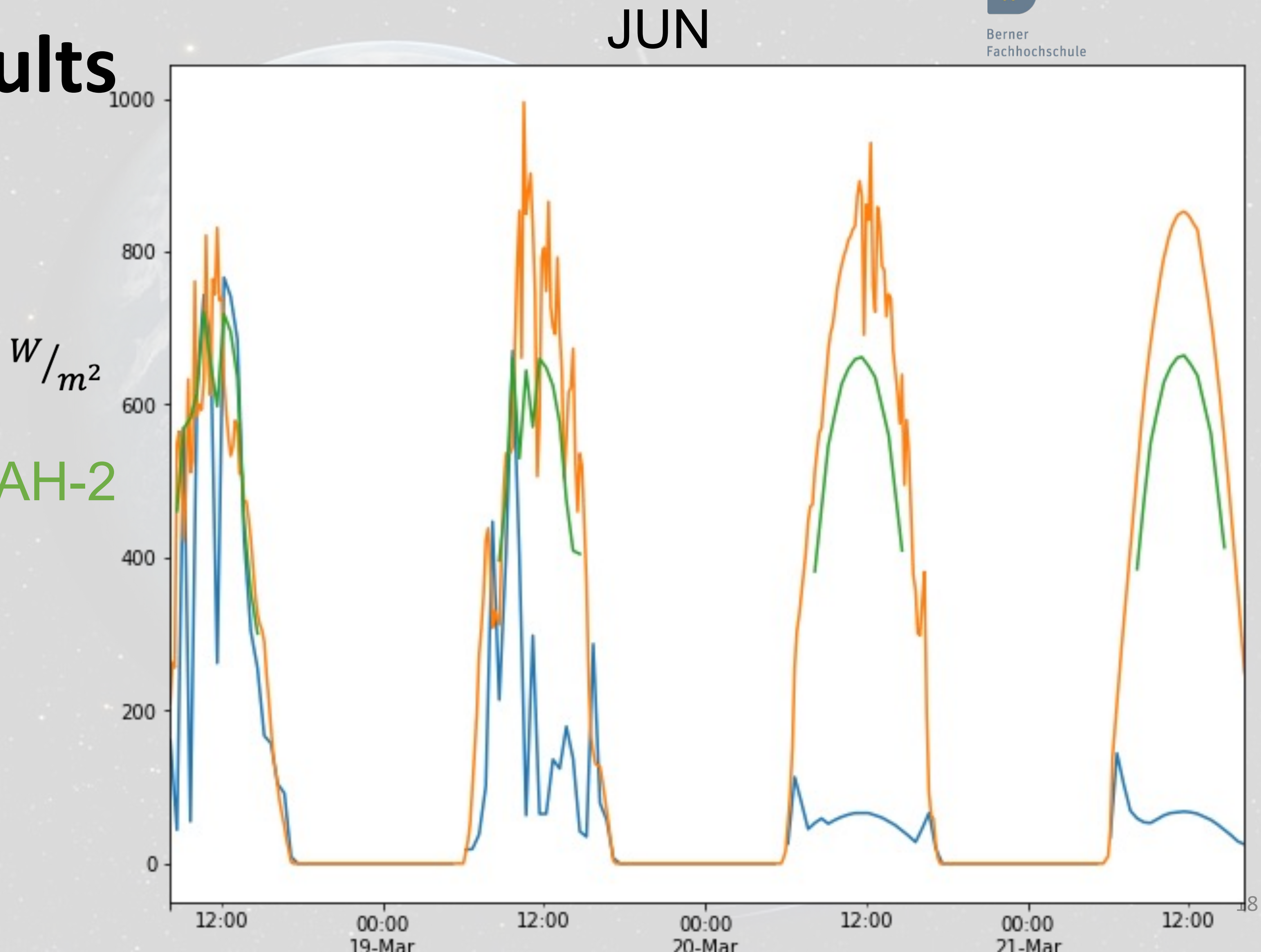
$$bias_{t,lon,lat} = {SSR^{sat}}_{t,lon,lat} - {SSR^{ground}}_{t,lon,lat}$$
$$\sim {SSR^{sat}}_{t,lon,lat} + SZA_{t,lon,lat} + TE_t + lon + lat + alt_{lon,lat}$$

First Results



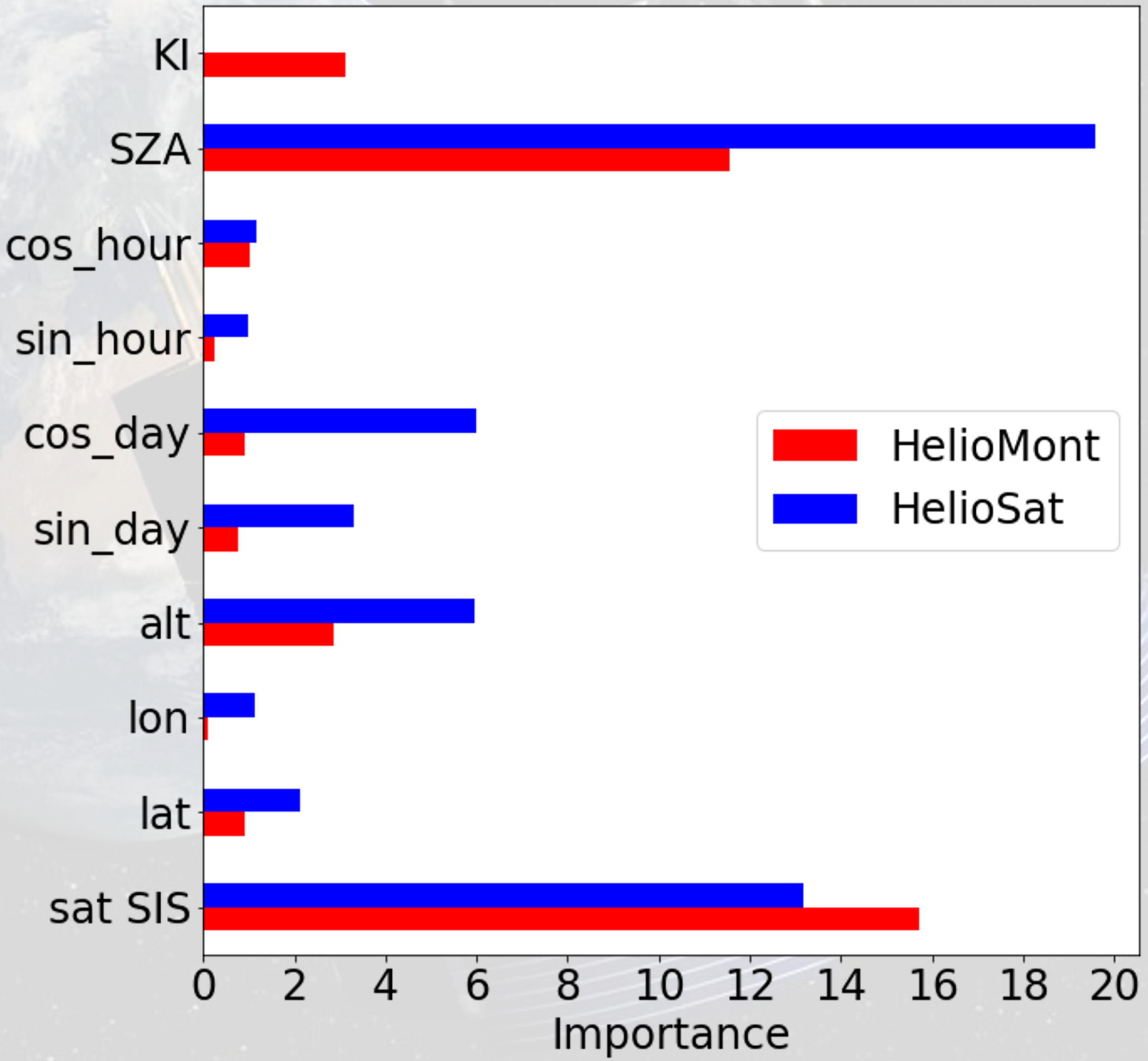
First Results

- SARAH-2
- In-situ
- Corrected SARAH-2



First Results

Feature Importance
Permutation algorithm based on Fisher et al., 2018



+ Time of year
+ Snow cover

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Strong altitude bias

Bias correction of solar radiation

Up to 31% RMSD reduction

Additional bias correction features

Thank you!

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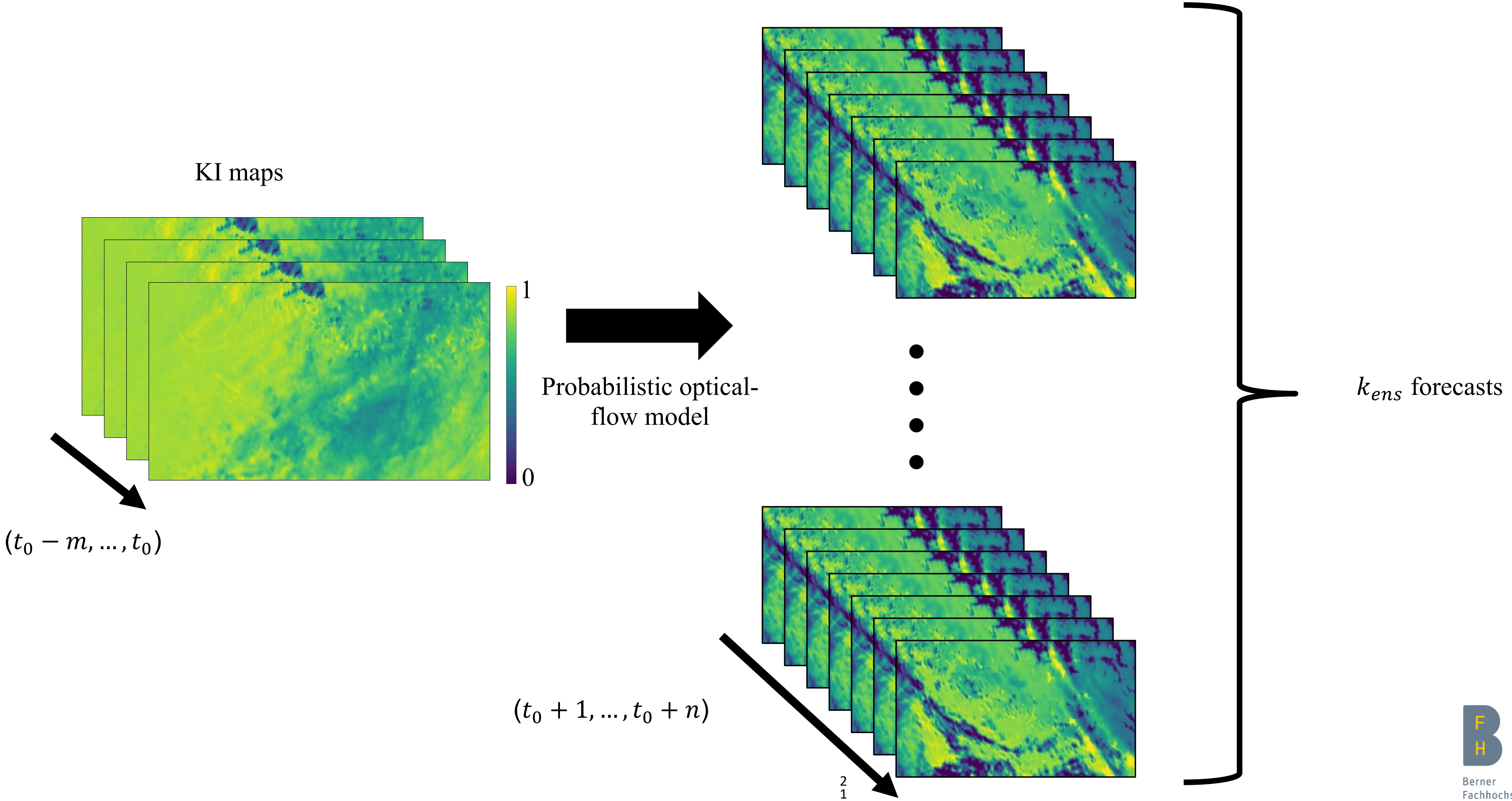
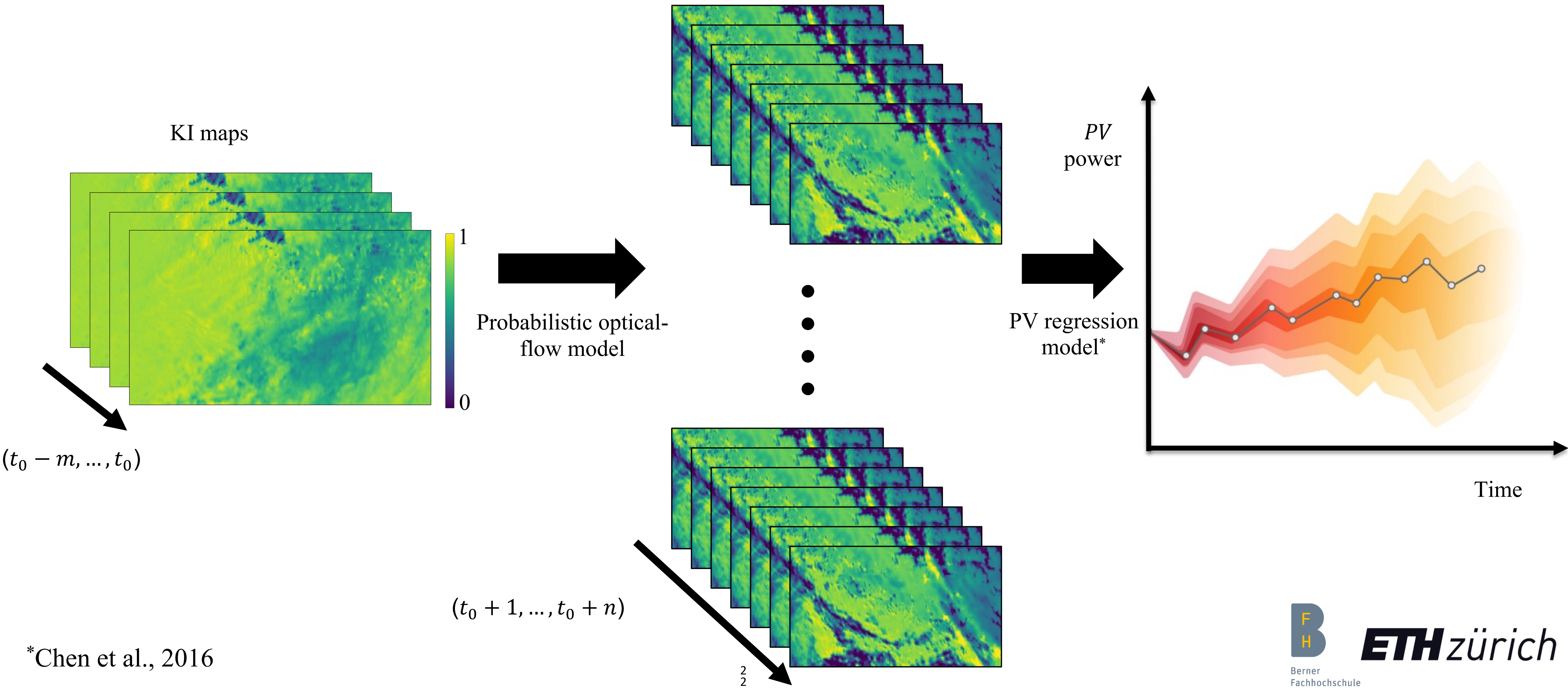
Forecasting Setup



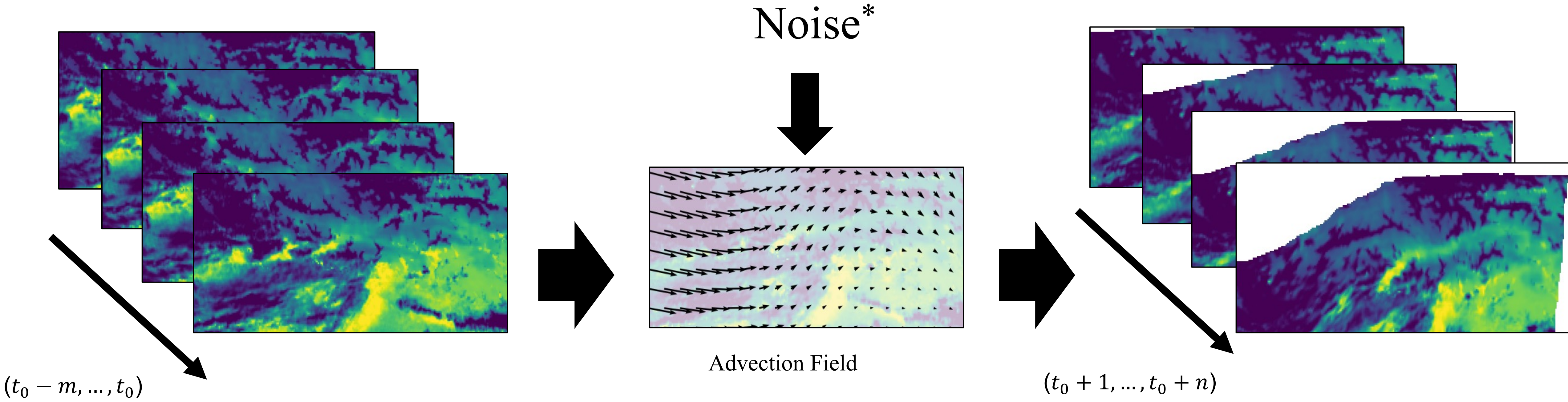
Forecasting Setup



*Chen et al., 2016

Forecasting Setup

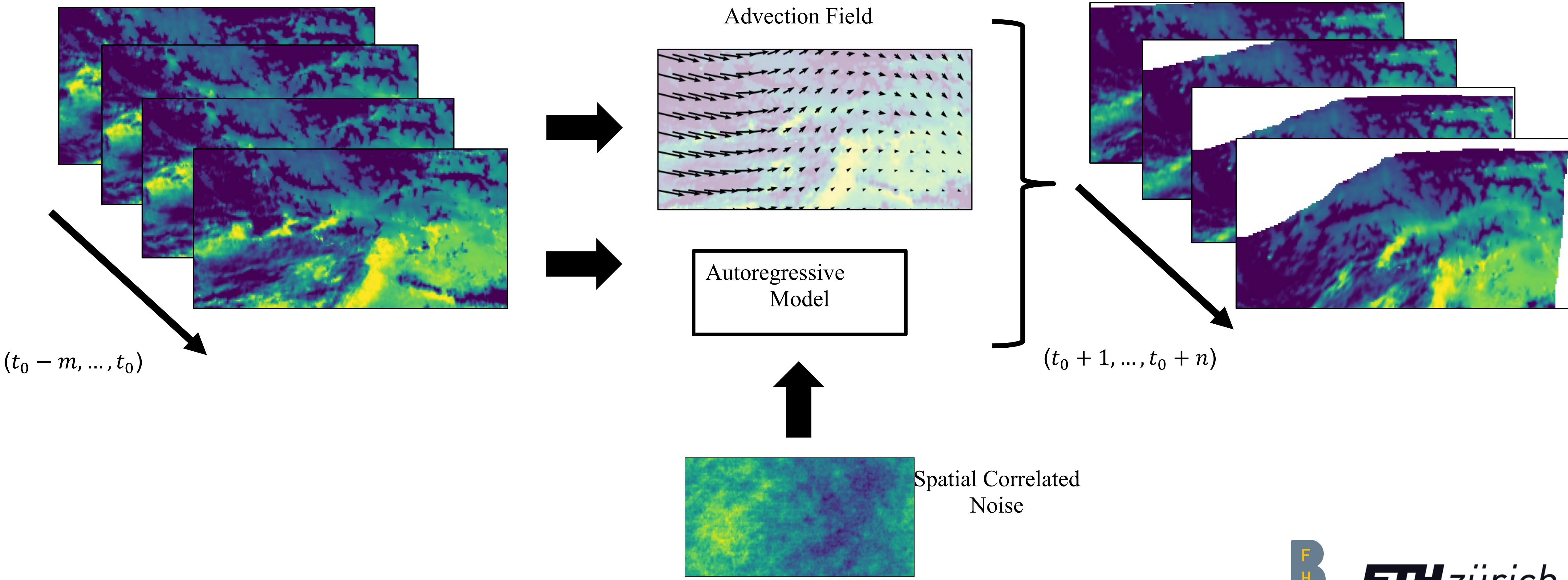
Probabilistic Optical-Flow Model - Extrapolation



*Carriere et al., 2021

Forecasting Setup

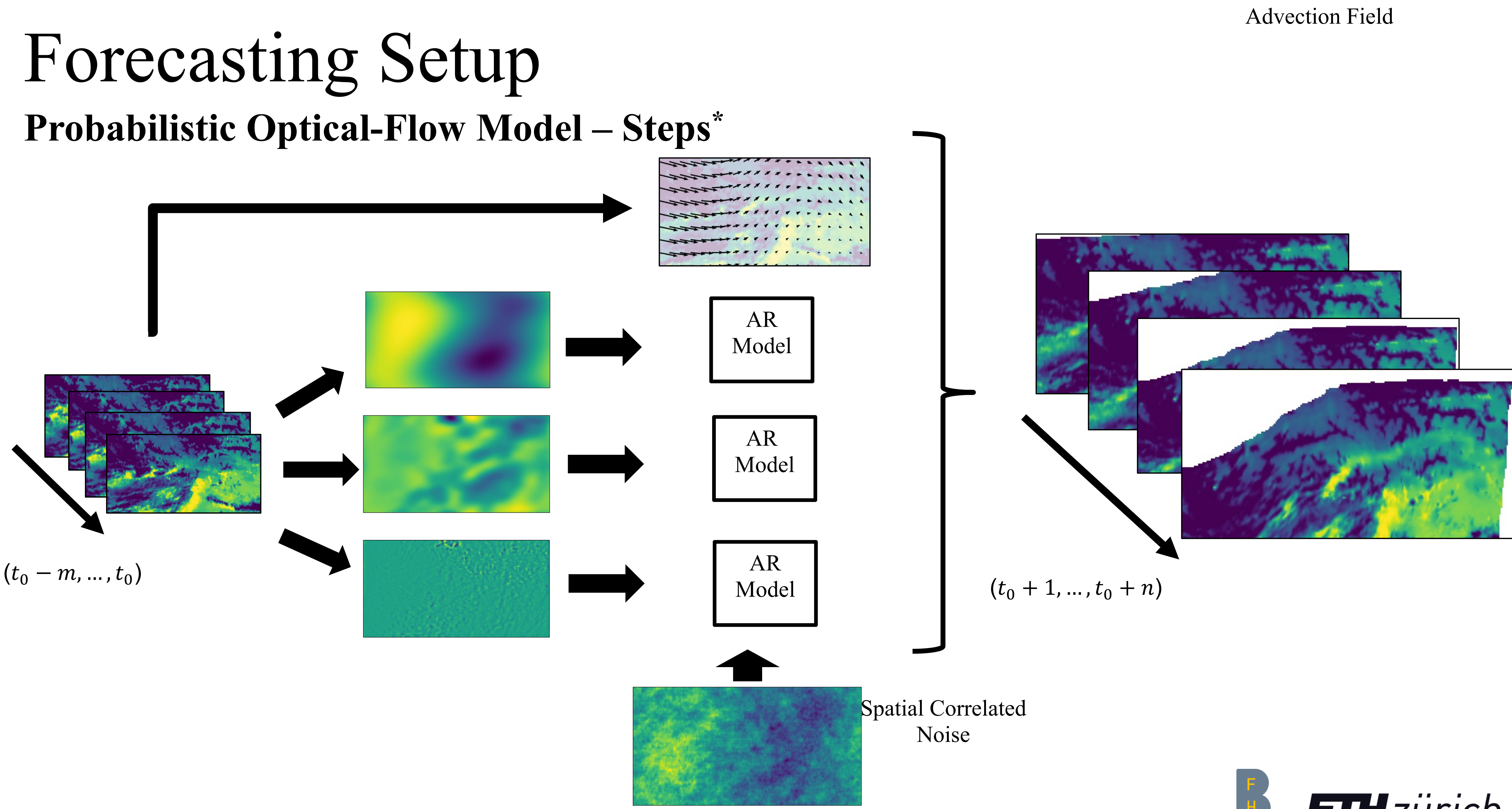
Probabilistic Optical-Flow Model – Steps* without decomposition



*Pulkkinen et al., 2019

Forecasting Setup

Probabilistic Optical-Flow Model – Steps*



*Pulkkinen et al., 2019

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Benchmark Models

Moreover, we also compared our models to other two benchmark models not based on KI forecasting:

1. Persistence Ensemble (PeEn, Alessandrini et al., 2019)

$$\widehat{PV}_{t,j} = PV_{t-j\times 24h} \qquad \forall j \in (1, \dots, k_{ens})\ \forall t \in (t_0+1, \dots, t_0+n)$$

2. Persistence (Pe)

$$\widehat{PV}_t = PV_{t_0} \qquad \forall t \in (t_0+1, \dots, t_0+n)$$

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Case Study

We tested the different models to forecast the cantonal aggregated PV power in Switzerland with a time resolution of 15 min and a lead time of 4 hours.

- The input is composed by one hour of data (m = 4)
- The output is 4 hours of PV production (n = 16)
- 7 Swiss cantons are considered in this study: [ZH, BE, TG, AG, BL, ZG, VD]
- For the prob. optical-flow models k_{ens} is set to 25, while for PeEn k_{ens} is set to 12
- The data is limited to Solar Zenith Angle < 88 degrees
- The test set is composed by 60 days of 2018 and the remaining days of 2018 are used for train and validation

Start date	End date
2018-01-05	2018-01-10
2018-02-05	2018-02-10
⋮	⋮
2018-11-05	2018-11-10
2018-12-05	2018-12-10

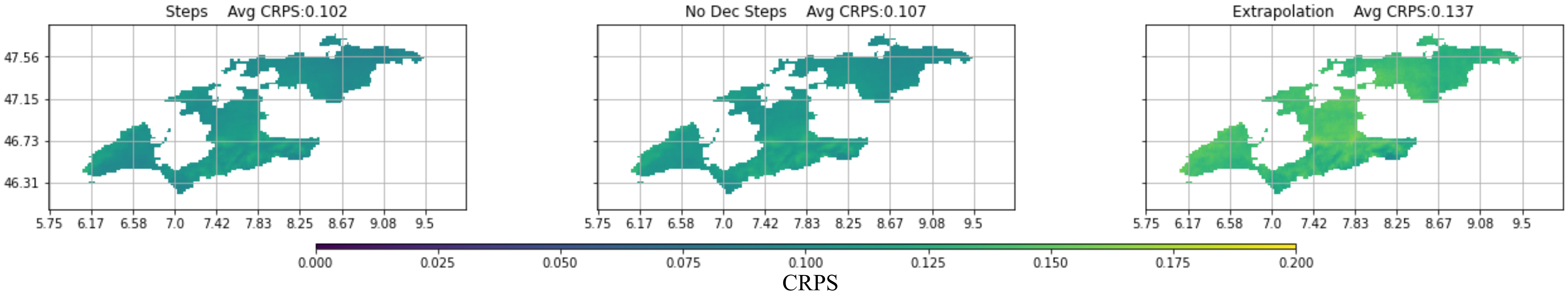
Results – PV Regression

- The regression performance on the different cantons is measured looking at the normalized RMSE and normalized MAE.
- The normalization factor is the maximum power generated in the respective canton in 2018.
- The model performs better for bigger regions. In fact, there is a strong negative linear correlation between nRMSE and the number of pixels representing the regions.

Canton	nMAE	nRMSE	N Pixels
ZH	2.94%	4.23%	478
BE	2.41%	3.35%	1616
TG	3.04%	4.42%	270
ZG	3.82%	5.77%	65
VD	2.39%	3.4%	840
AG	2.94%	4.2%	386
BL	3.43%	5.18%	144

Results – KI Forecast

The average CRPS on the test set is computed for every pixels belonging to the mentioned cantons:



- The autoregressive model clearly improves the quality of the forecasted ensemble of KI maps. With respect to the probabilistic extrapolation method, it reduces the average CRPS by 25.5%.
- The cascade decomposition has a small impact on the prediction.
- The models struggle to precisely forecast on the Alps region.