Probabilistic Forecasting of Regional PV Power based on Satellite-derived Cloud Motion

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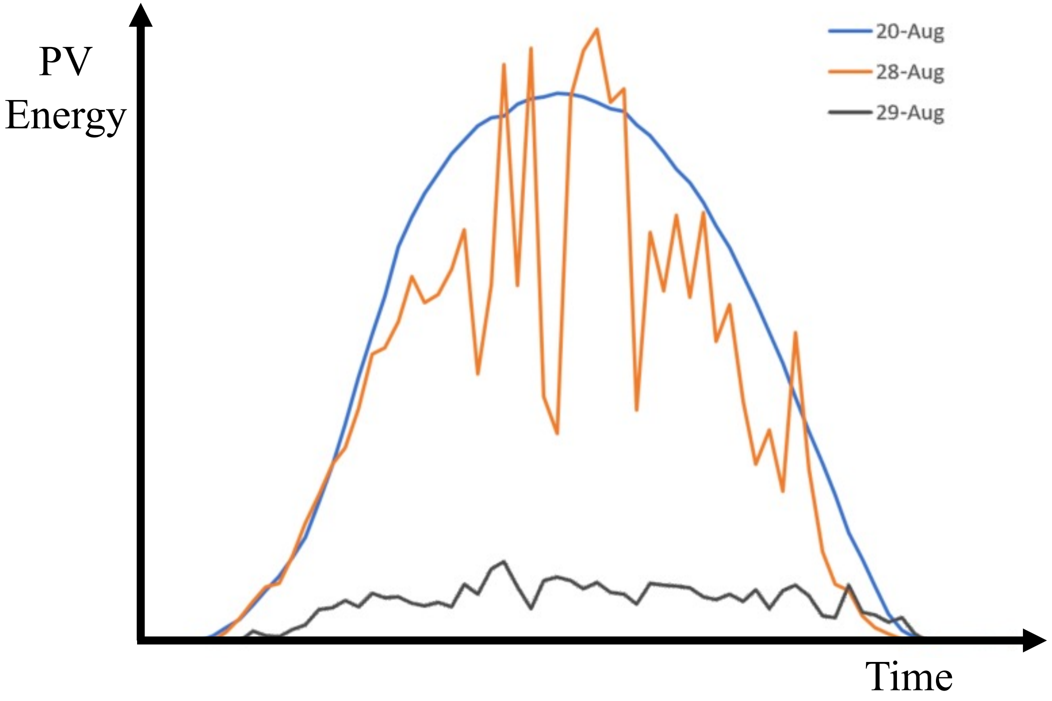
Photovoltaic Energy

WHY

To obtain a 20% reduction of greenhouse gases, we need to generate ~50% of the energy from renewable sources (IPCC)

PROBLEM

The **high volatility** of low-output intermittent generators (PV panels) decreases the energy grid resilience (Smith et al., 2022)



SOLUTION

Accurate probabilistic forecasts based on satellite maps to capture clouds motion dynamics

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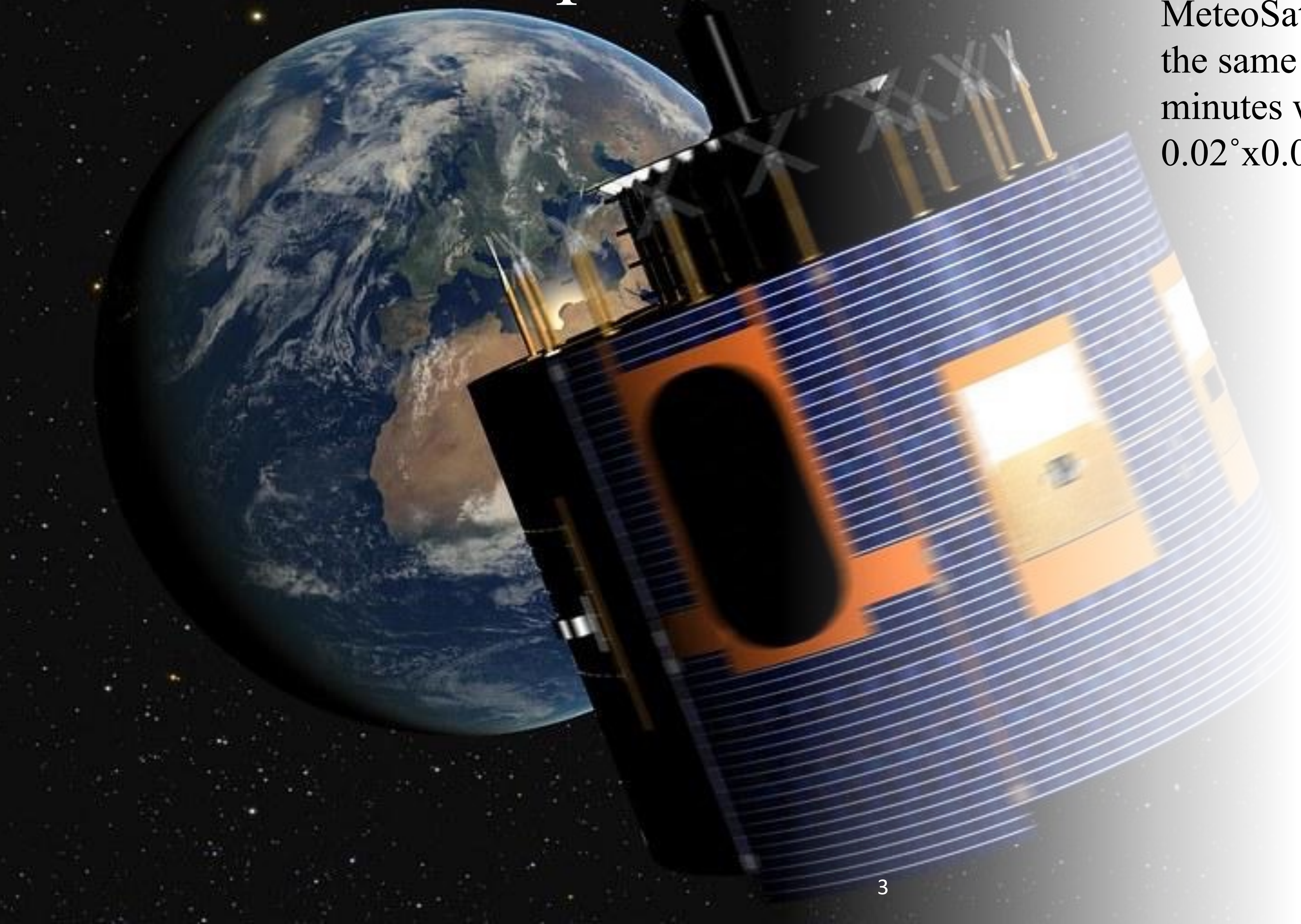
MeteoSat Maps



The satellite maps are retrieved by a MeteoSat geostationary satellite. It scans the same part of the Earth surface every 15 minutes with a spatial resolution of 0.02˚x0.02˚.

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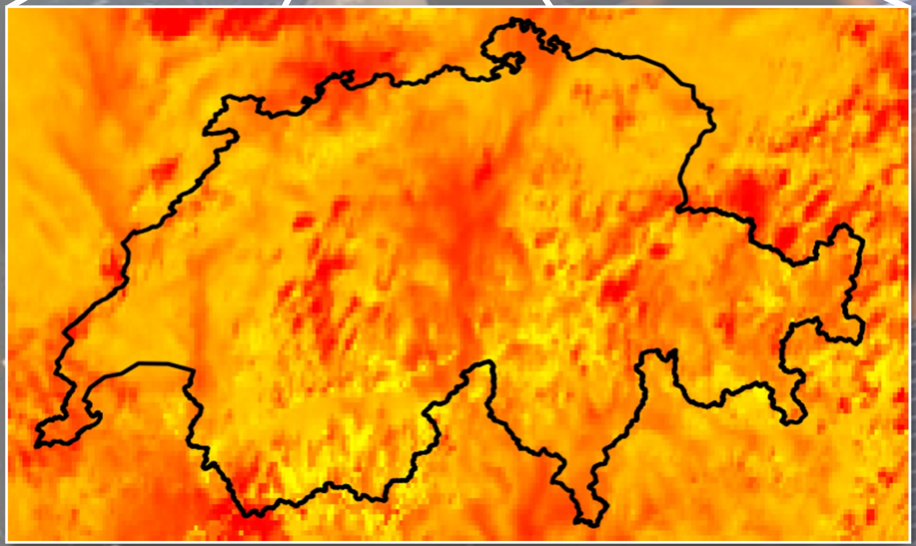
MeteoSat Maps



SSR map of Switzerland

The HelioMont algorithm (Castelli et al., 2014) transforms the raw satellite images into surface solar radiation (SSR) maps.

The solar radiation can be described using two components:

$$SSR = KI \times SSR_{cs}$$

Where:

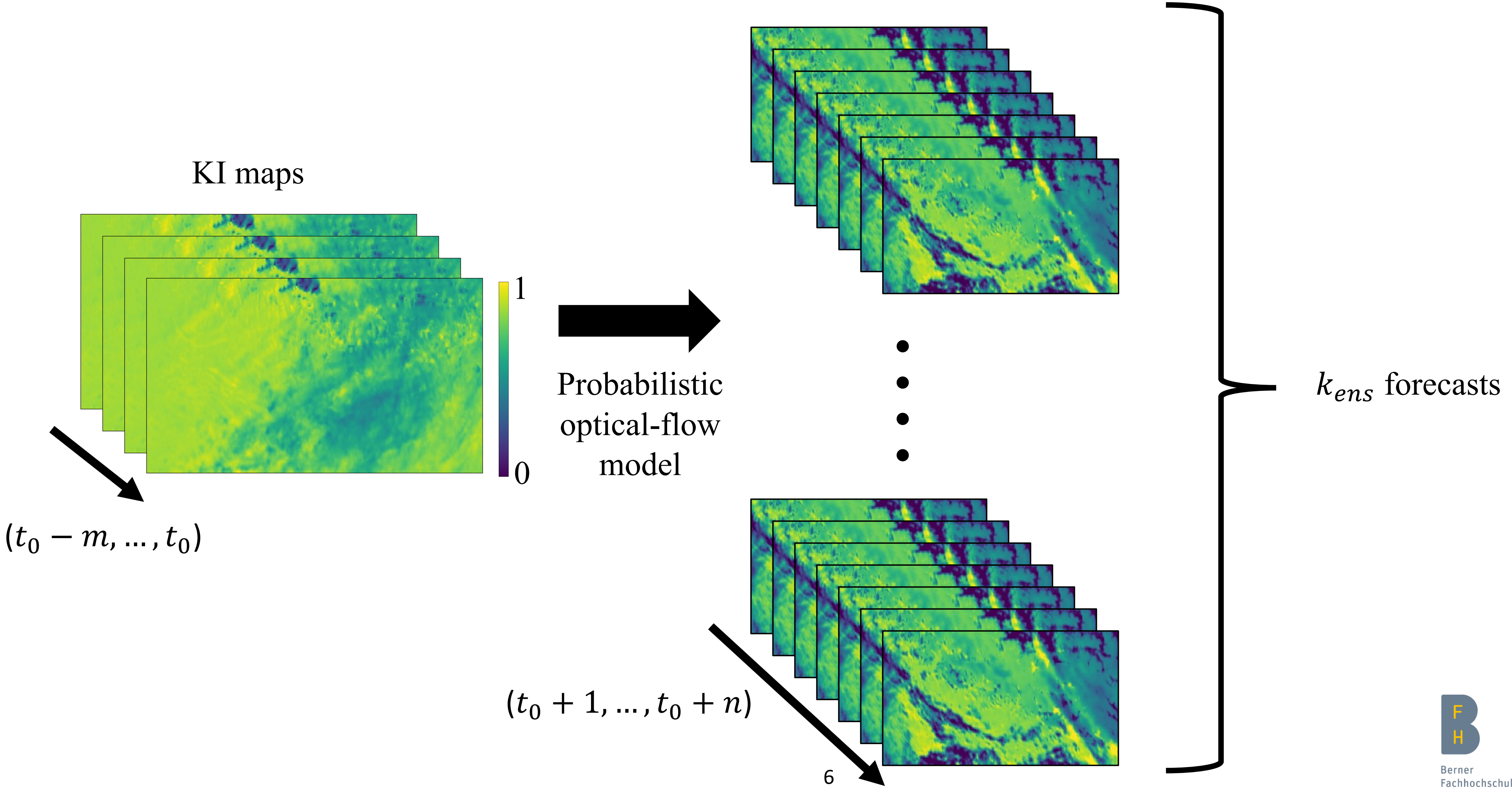
- SSR_{cs}: clear-sky SSR, theoretical value determining the SSR in case of completely clear sky conditions.
- KI: clear-sky index, cloudiness coefficient measuring the effect of clouds on the actual SSR.

Problem Setup

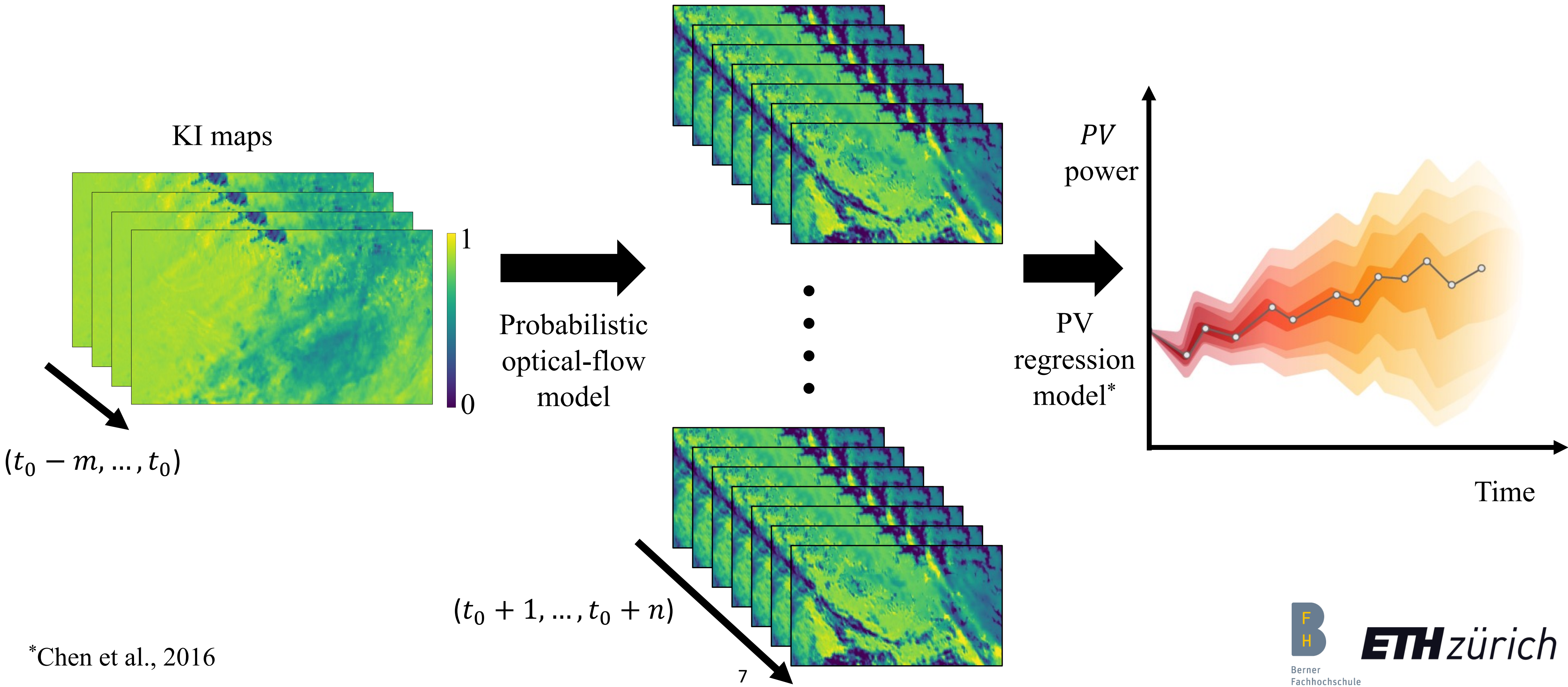
- Given a sequence of m KI maps $(KI_t)_{t_0-m}^{t_0}$, we want to forecast the probability densities distributions of the successive n steps of PV production $\left(p\left(\widehat{PV}\right)_t\right)_{t_0+1}^{t_0+n}$. Where $p\left(\widehat{PV}\right)_t$ is described by a forecast ensemble $\left(\widehat{PV}_t{}^1, \dots, \widehat{PV}_t{}^{k_{ens}}\right)$.

- We apply a 2-step approach:
    1. Forecast an ensemble of future satellite images
    2. Estimate the regional PV power from the forecasted ensembles

Forecasting Setup



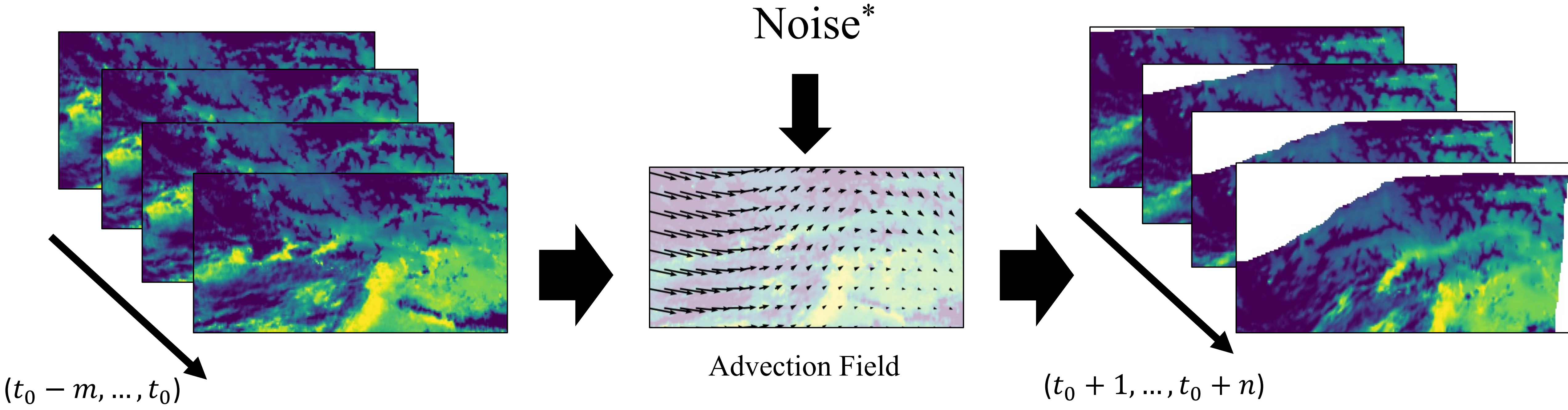
Forecasting Setup



*Chen et al., 2016

Forecasting Setup

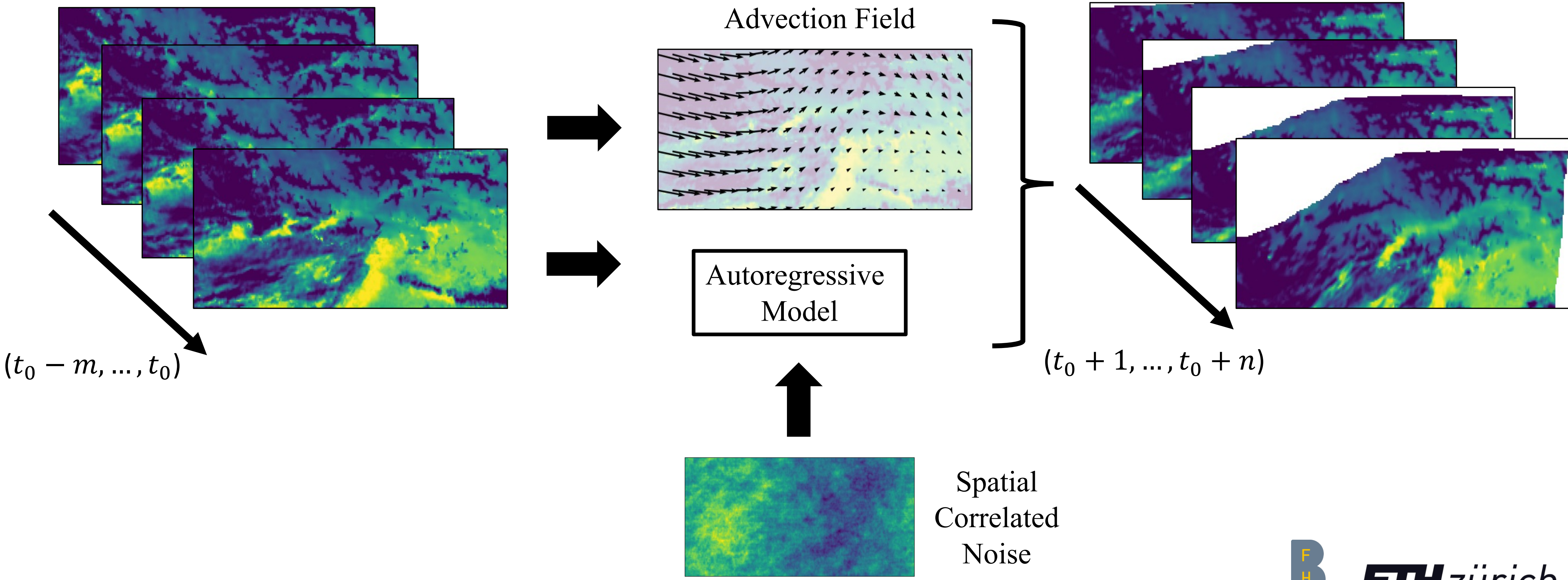
Probabilistic Optical-Flow Model - Extrapolation



*Carriere et al., 2021

Forecasting Setup

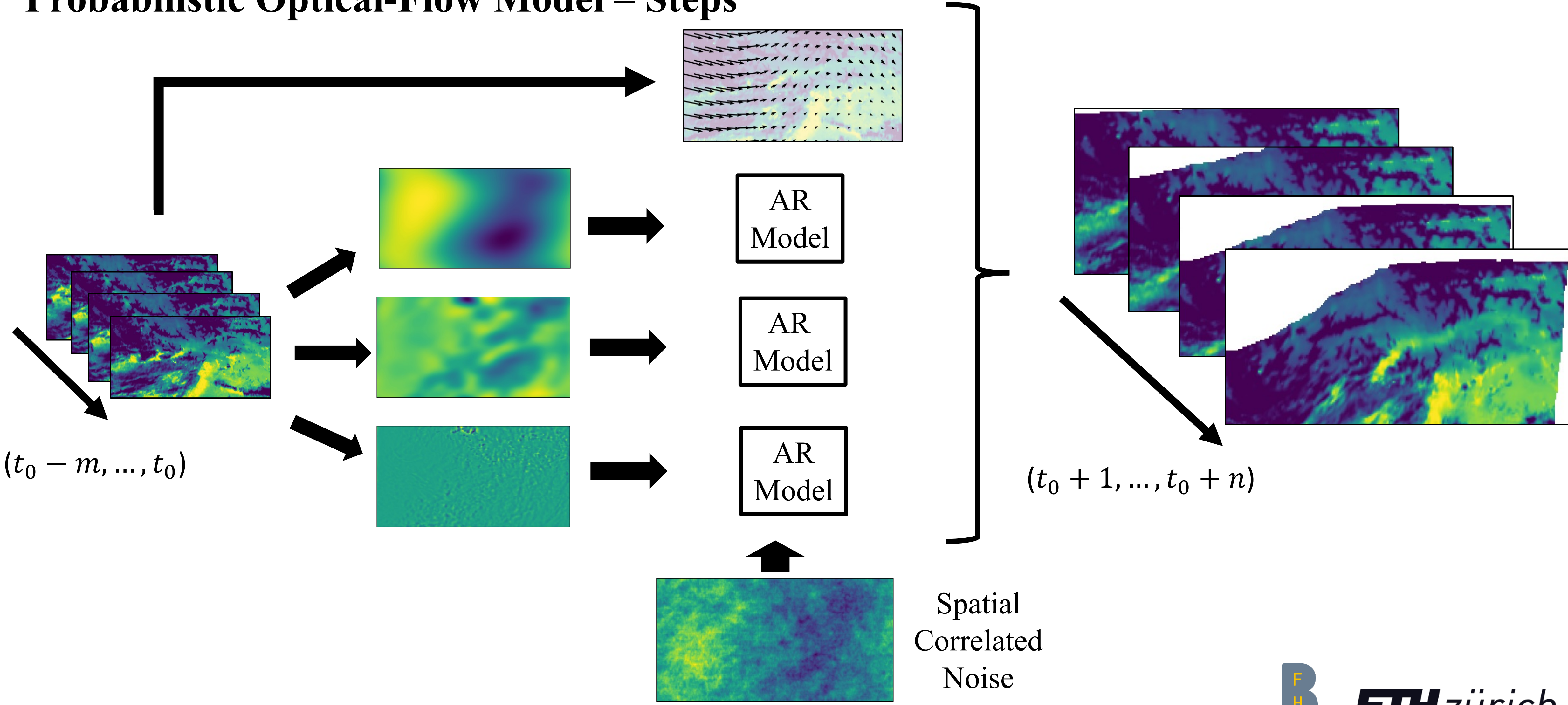
Probabilistic Optical-Flow Model – Steps* without decomposition



*Pulkkinen et al., 2019, Bowler et al., 2006

Forecasting Setup

Probabilistic Optical-Flow Model – Steps*



*Pulkkinen et al., 2019, Bowler et al., 2006

Benchmark Models

Moreover, we also compared the advection models to 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)

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

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

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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

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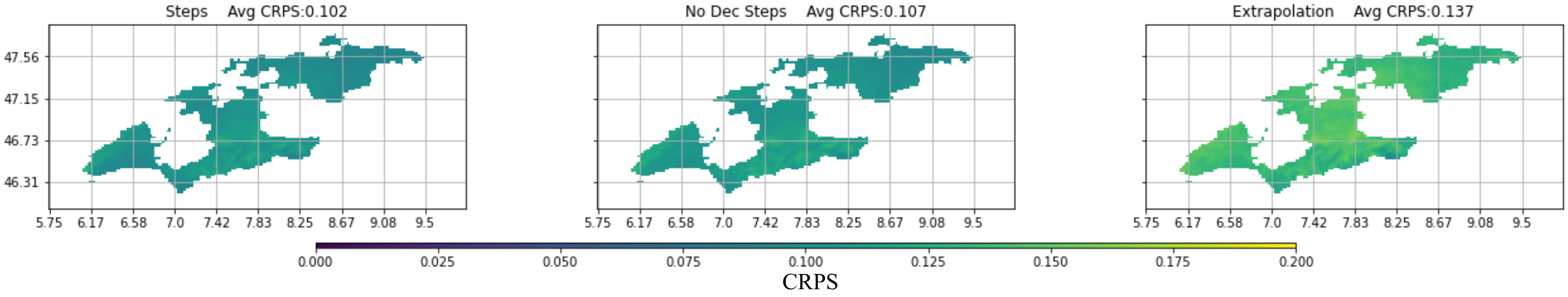
Results – KI Forecast

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



- The autoregressive model clearly improves thequality 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.

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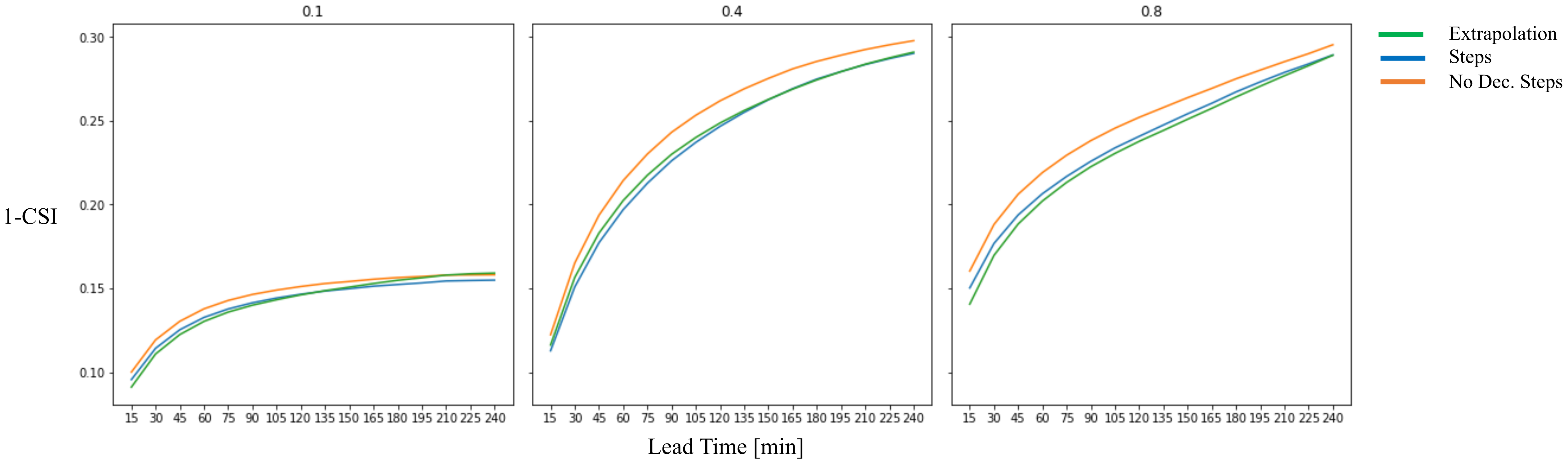
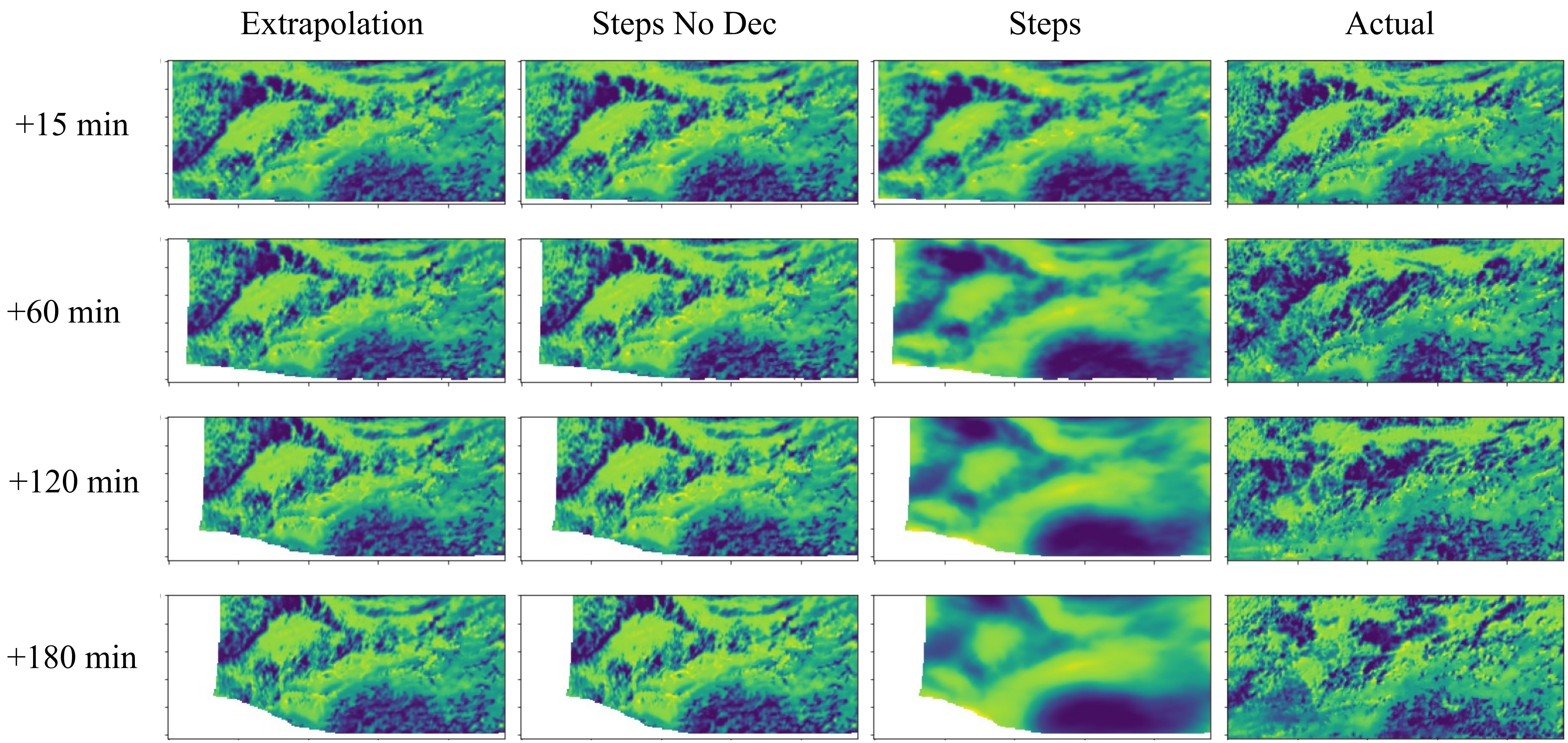
Results – KI Forecast

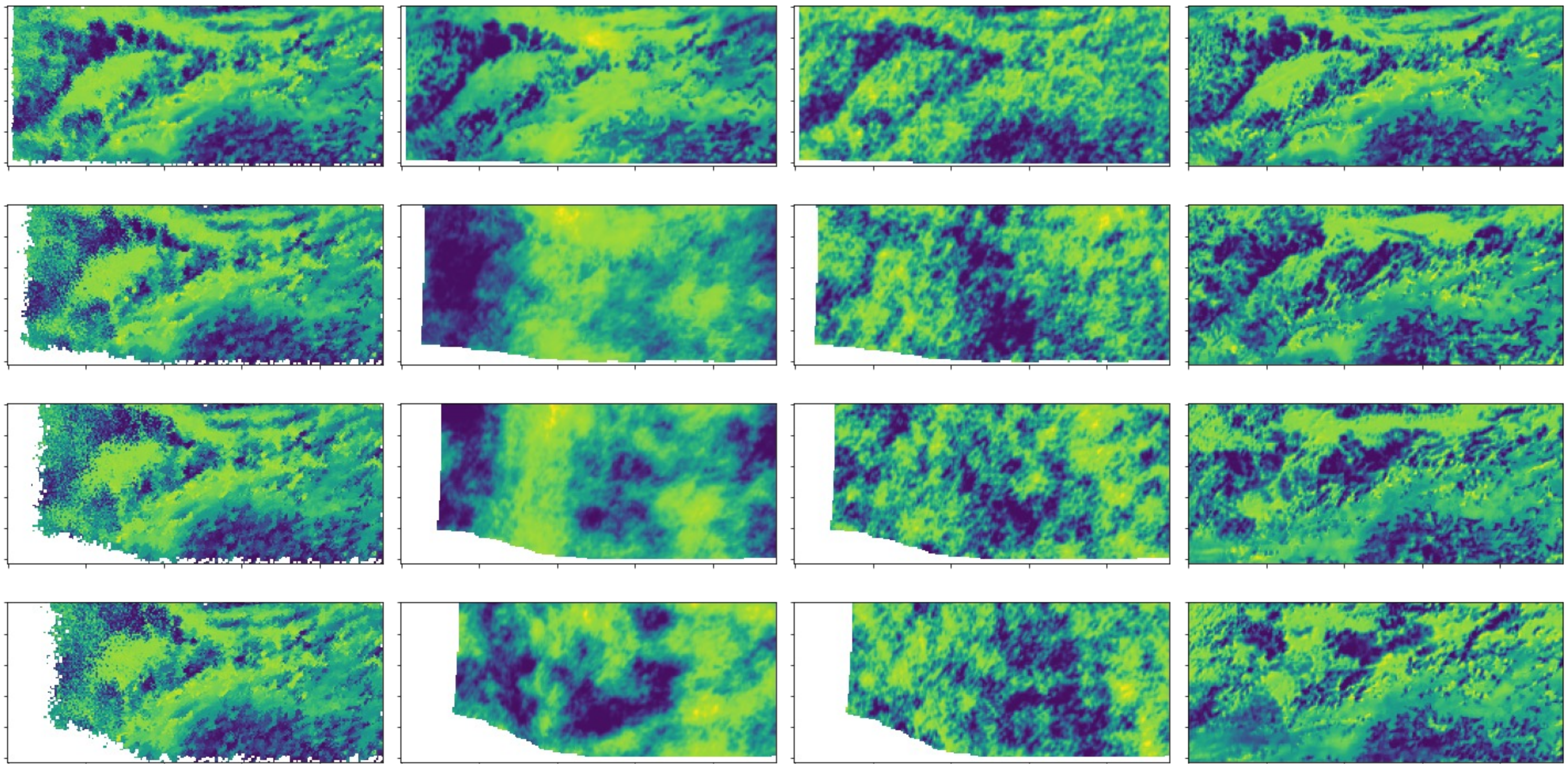
We measured the average Critical Success Index (CSI) for 3 thresholds (0.1, 0.4, 0.8) covering the distribution of KI values.



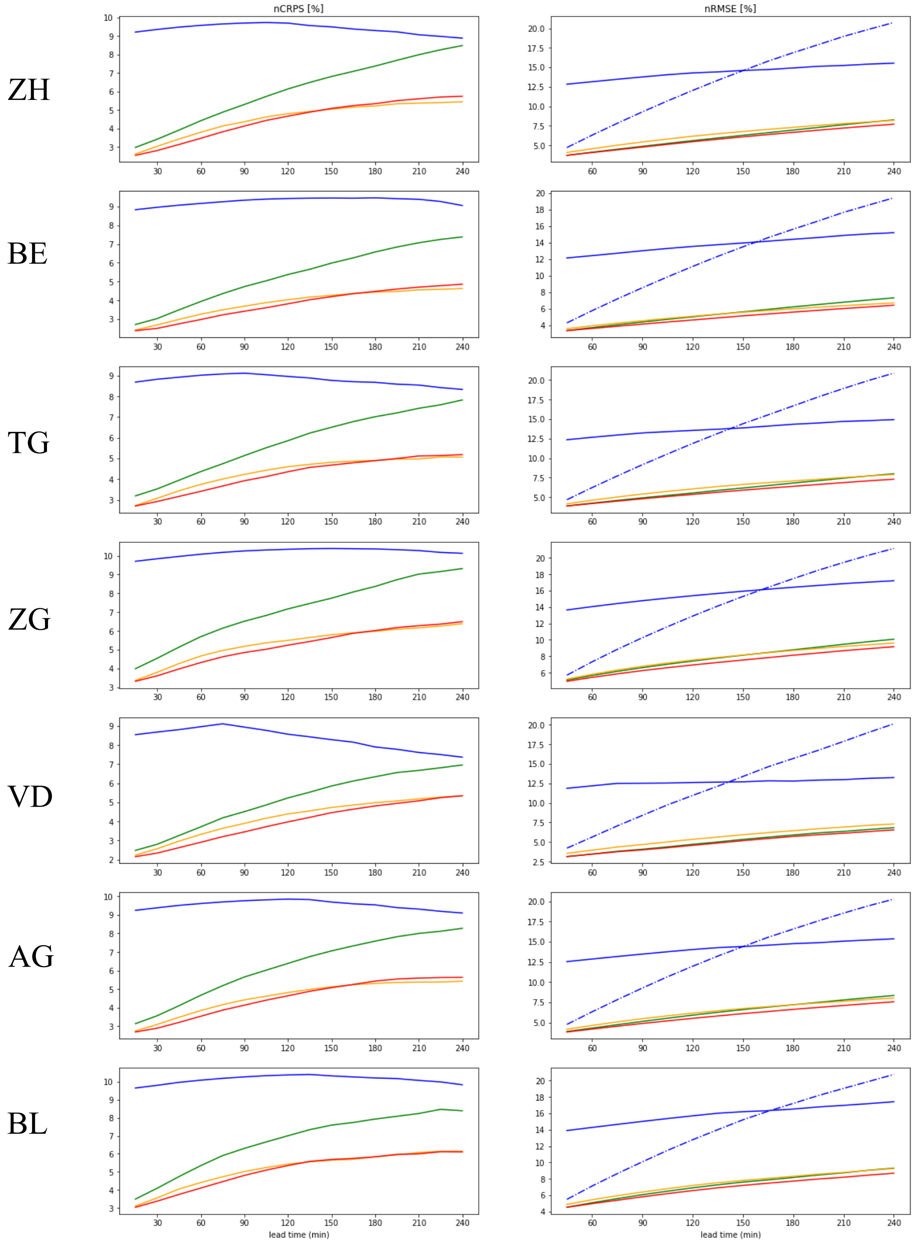
Results – KI Forecast



Results – KI Forecast

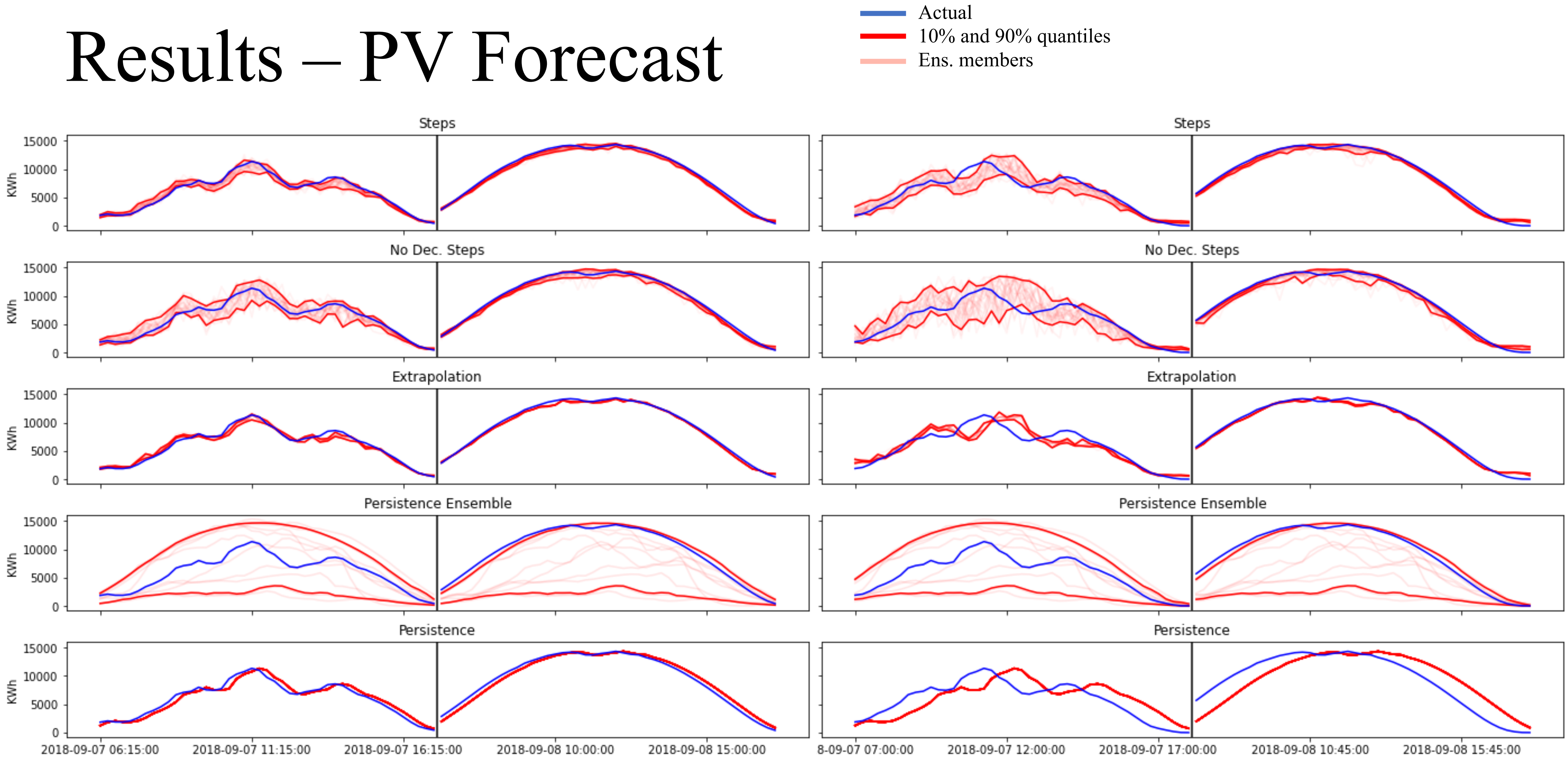


Results – PV Forecast



- The advection-based models (Extrapolation, No Dec. Steps and Steps) outperform the persistence-based models (Pe, PeEn).
- Modeling the growth and decay of cloudiness significantly improved the quality of the ensemble forecast
- On the other hand, analyzing the ensemble mean, the performance of the advection models is similar. Having a closer look, we can notice that Steps is the best performing model for all the different cantons. This is probably due to the cascade decomposition, which reduces the ensemble bias.

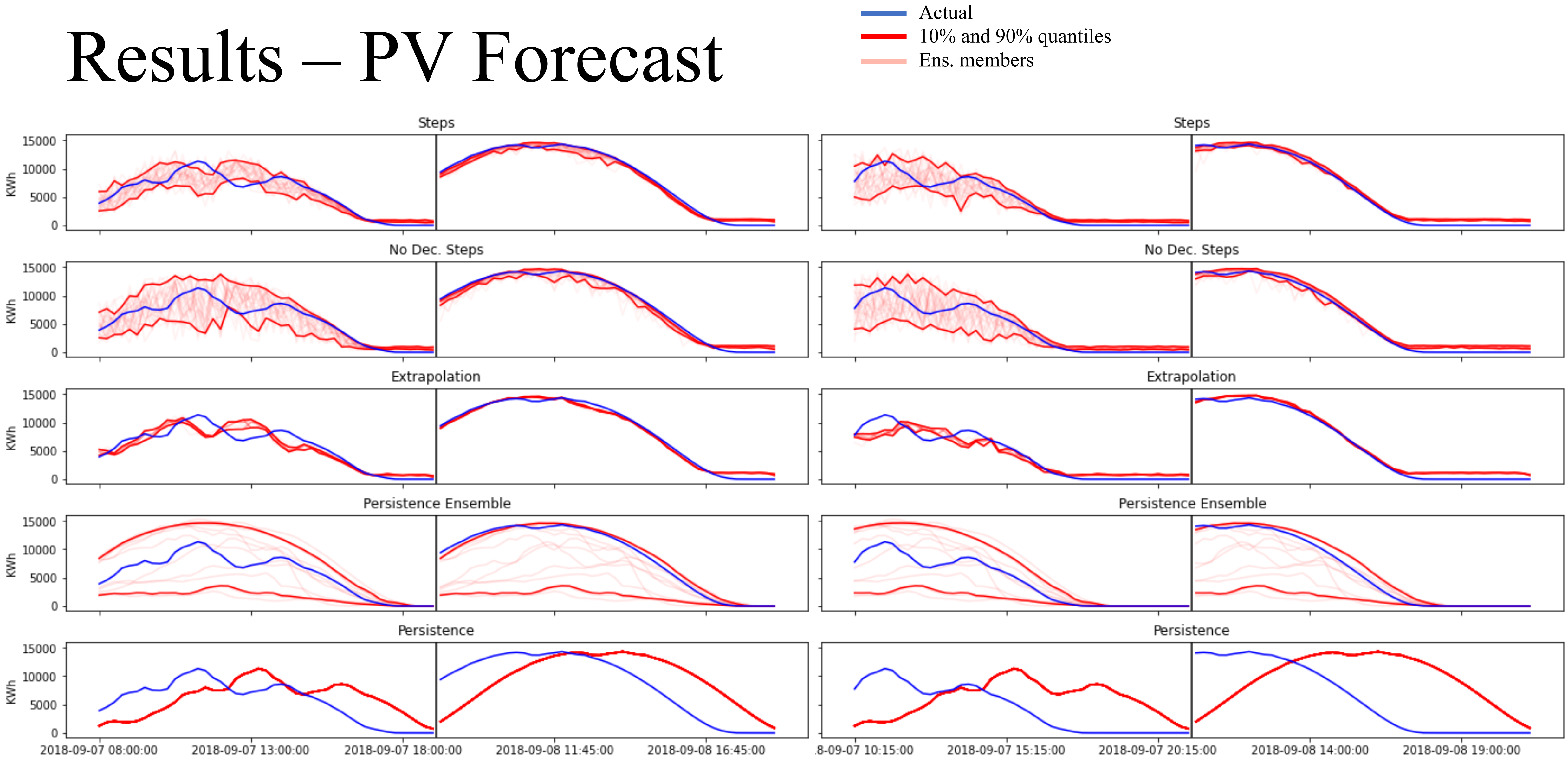
Results – PV Forecast



15 min

60 min

Results – PV Forecast



120 min

240 min

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Results – PV Forecast

- Steps is the best performing model in all the considered regions.
- The decomposition makes Steps reducing the nRMSE up to 10% compared to the same model without decomposition

Canton	PeEn	Extrapolation	No Dec. Steps	Steps
ZH	9.38%	6.05%	4.54%	4.50%
BE	9.28%	5.36%	3.87%	3.79%
TG	8.79%	5.80%	4.35%	4.23%
ZG	10.19%	7.12%	5.33%	5.20%
VD	8.34%	5.12%	4.20%	3.95%
AG	9.53%	6.23%	4.59%	4.53%
BL	10.13%	6.71%	5.16%	5.06%

Normalized CRPS

Canton	Pe	PeEn	Extrapolation	No Dec. Steps	Steps
ZH	20.74%	15.53%	8.26%	8.20%	7.70%
BE	19.41%	15.19%	7.30%	6.69%	6.41%
TG	20.86%	14.92%	8.00%	7.90%	7.29%
ZG	21.14%	17.21%	10.07%	9.61%	9.16%
VD	20.12%	13.25%	6.83%	7.31%	6.55%
AG	20.27%	15.36%	8.35%	8.04%	7.56%
BL	20.76%	17.42%	9.30%	9.24%	8.67%

Normalized RMSE

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