

Nowcasting Solar Power by Deep Learning at Sahara Dust Events

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Abstract

With the rapidly increasing use of solar power accurate predictions of the site-specific power production are needed to ensure grid stability, energy trading, (re)scheduling of maintenance, and energy transfer. Particularly in systems relying on many factors such as solar energy, extreme events can be a threat to the power grid stability and accurate nowcasts. Thus, warnings within a reasonable amount of time ahead for preparation are essential. In the MEDEA project, funded by the Austrian Climate Research Program, we aim at improving the definition and detection of extreme events relevant for renewable energies and using these findings to improve both weather and climate predictions of such extreme events.

In the presented case study, we investigate selected (extremes) cases **of Sahara dust events in 2021** where various weather prediction models were unable to properly reproduce the amount of aerosols in Central Europe resulting in a discrepancy between actual solar power production compared to predictions being off by more than 5 GW. Here, several solar production forecasts gave impaired results based on raw NWP model output. To tackle such events and improve the predictability, **a deep learning framework including an LSTM** (long short-term memory; type of an artificial neural network) and **random forest** will be adopted for nowcasting with multiple heterogeneous data sources available. Relevant features include 3D-fields from different NWP models (**AROME, WRF**), satellite data and products (**CAMS**), point-interpolated radiation time series from remote sensing, and observation time-series (**site observations, close meteorological sites**). We investigate up to **6 hours ahead** nowcasts at several Austrian solar power farms with **an update frequency of 15 minutes**.

Results obtained by the developed method yield, in general, high forecast-skills, where we elaborate on interesting cases studies from a meteorological point of view. Different combinations of inputs and processing-steps are part of the analysis. We compare obtained forecast results to available forecast methods, e.g., an analogs-based method, ***pvlb forecasts driven with AROME*** and AROME RUC.

Data for CASE STUDY 2021

We optimize **site specific models** and select data for each site from:

INPUT:

- **AROME+WRF:**
forecasts in various p/z levels of solar radiation related parameters (e.g.: short-wave radiation, cloud cover, ...)
- **CAMS – site interpolated radiation timeseries:**
radiation related parameters
- **observation site:**
observed solar power (from a power plant)
- **TAWES/INCA** – closest observation/analysis at surface level:
global radiation, temperature, wind, humidity

Check missing, normalize, etc.

OUTPUT: solar power forecasts
in 15 min. resolution
+6 hours, hourly runs

CASESTUDY

Training:

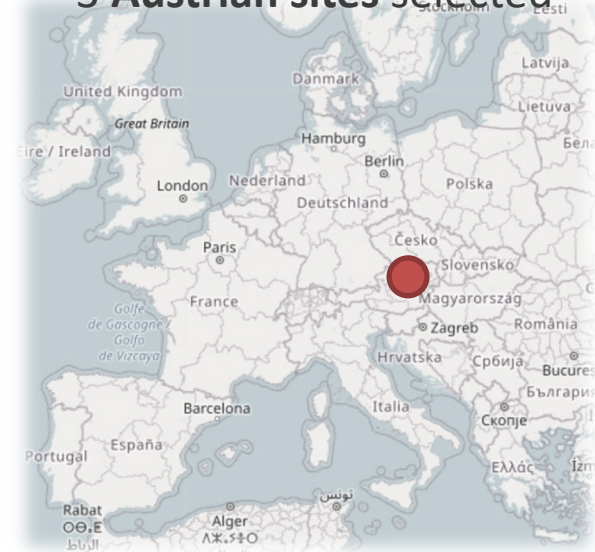
- ✓ 2015-2020 (incl. artificial)
- ✓ 2020 (real only / WRF)

Testing:

- ✓ 2021 or 2020

+ computed **climatology**

3 Austrian sites selected

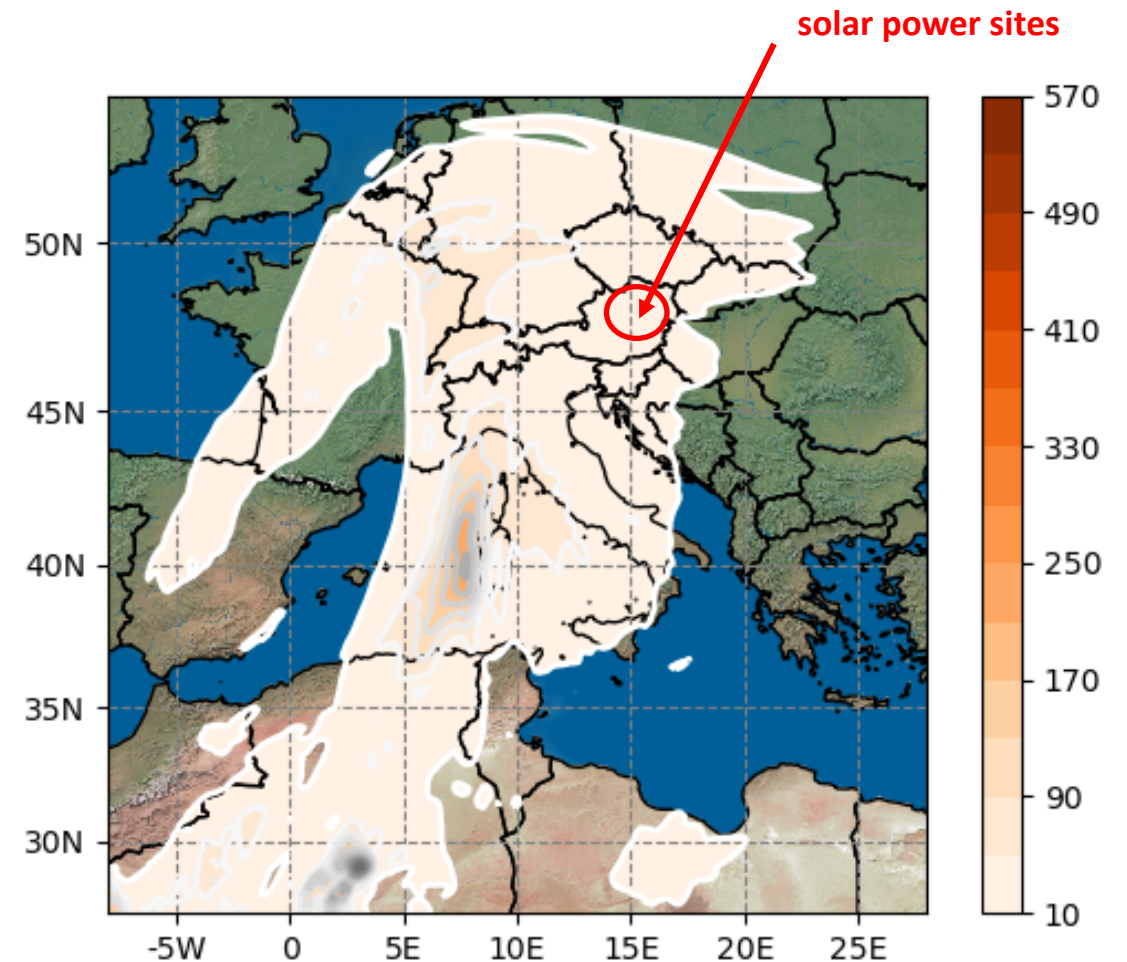


Sahara Dust Events

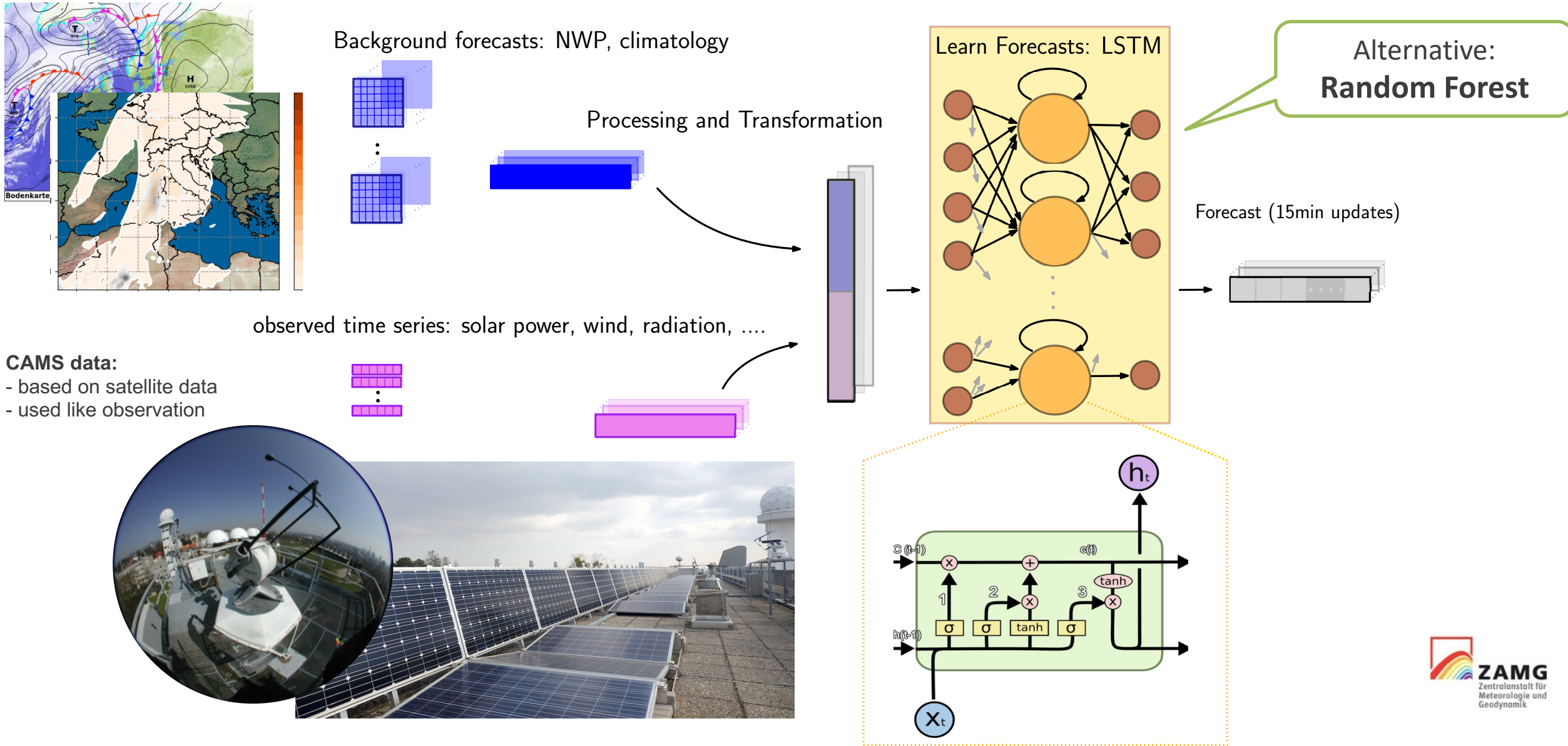
- **2021/01-04:**
 - NWP's unable to properly reproduce the amount of aerosols in Central Europe, i.e.,
 - solar power production/prediction offset > 5 GW.
 - impaired results based on raw models
- A frequent and recurring issue of an „extreme“
- important for energy providers / estimating production



<https://medea.zamg.ac.at/index.html>

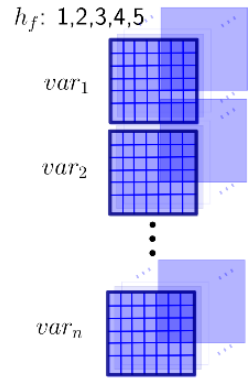


Post-processing Methodology: update a Background Model(s) by ML



Sequence-to-Sequence LSTM - postprocessing a background model

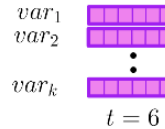
„background model“
climatology + NWP



flatten spatial, concatenate variables

Concatenate: (var, h_f)

observed time series

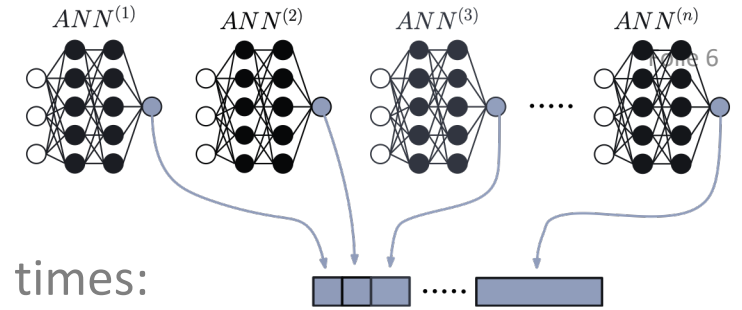


flatten history, concatenate variables

$\times |h_f|$

$h_f = 5$ [copy $h_f = 1$]

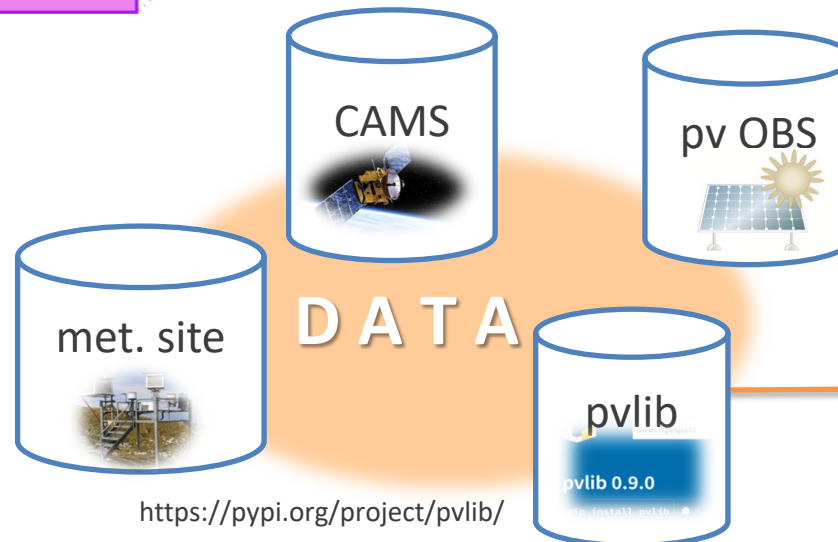
To deal with 24 lead times:
3-6 **LSTM**s for lead time intervals



Flatten

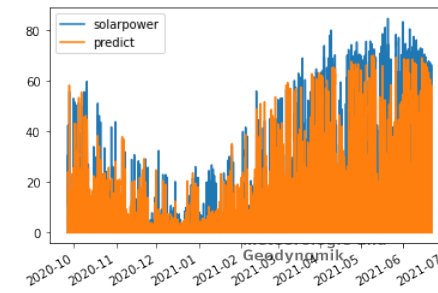
15 min. updates

Includes
pvlib + CAMS

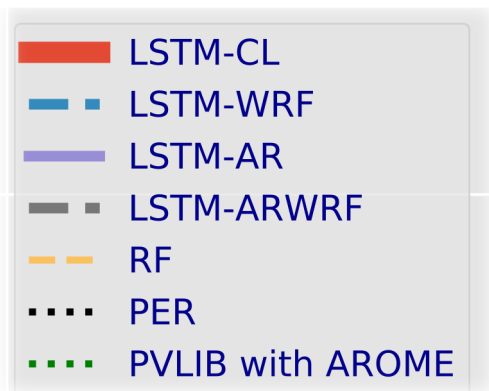
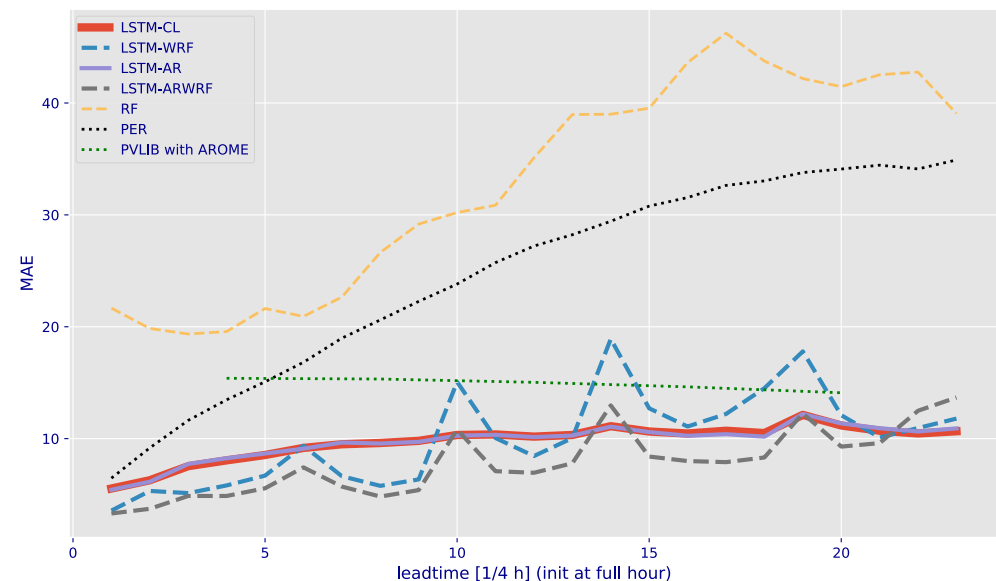


ML/RF:
long, robust
production

2015-2021



Case Study Results – Scores Austrian Locations (2021)



MAE of stations

[x]y...x year of training, e.g.: 3y=3 years

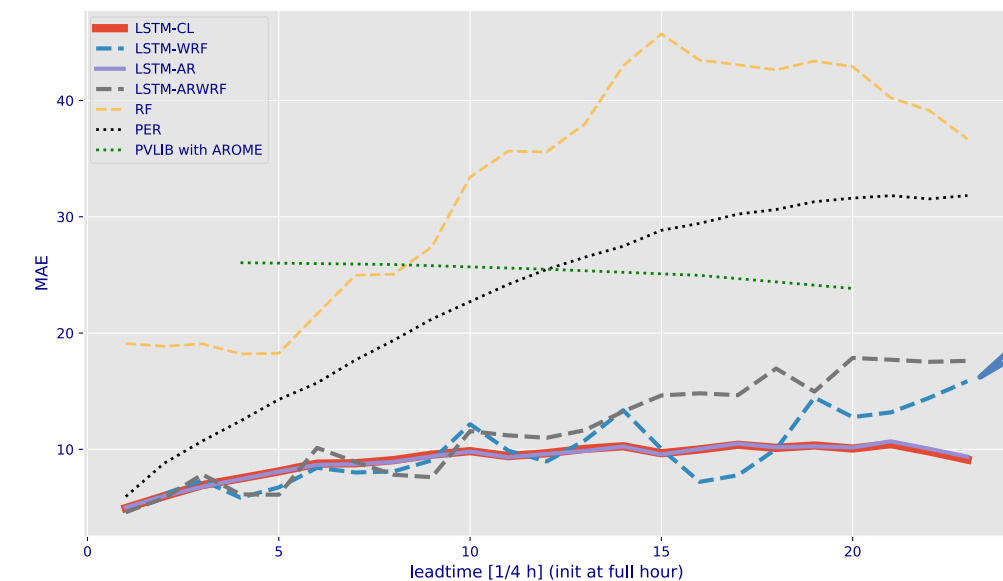
i[x] ... x intervals of leadtimes, e.g.: i3=3 intervals

CL ... basic climatological transformation

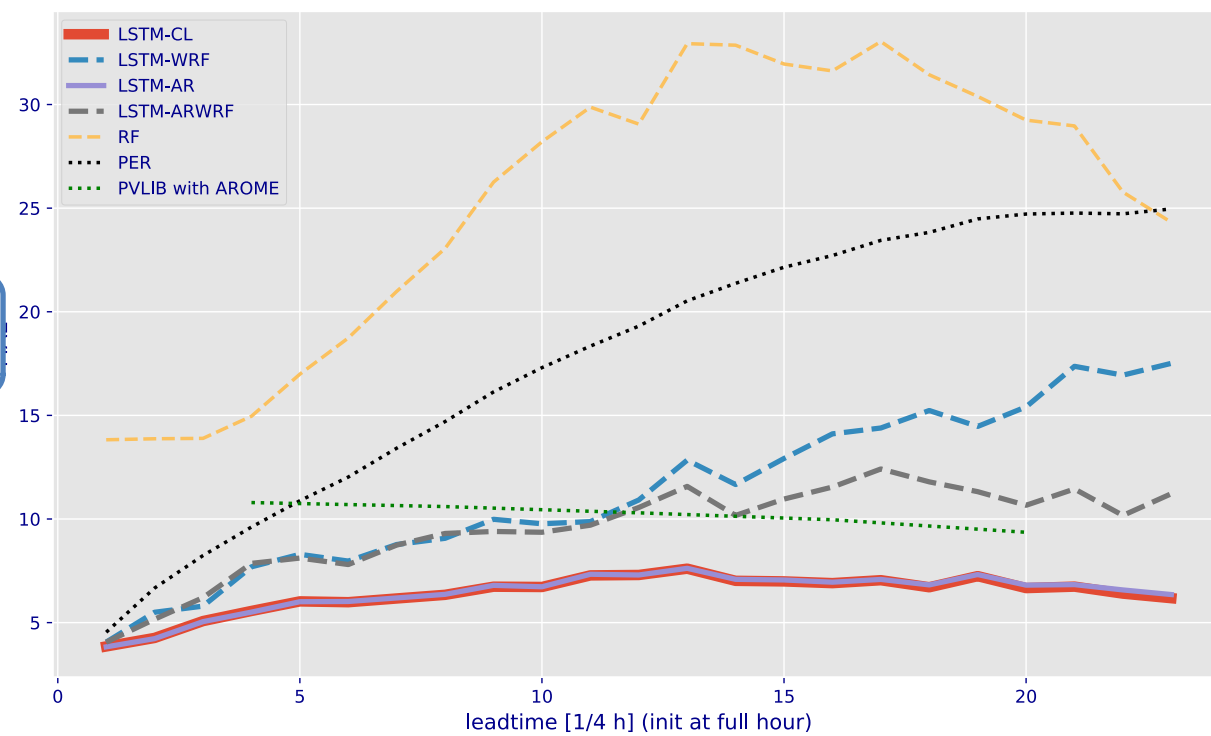
LSTM ... sequence-to-sequence LSTM trained on observation and climatology

RF ... random forest trained on same input as LSTM

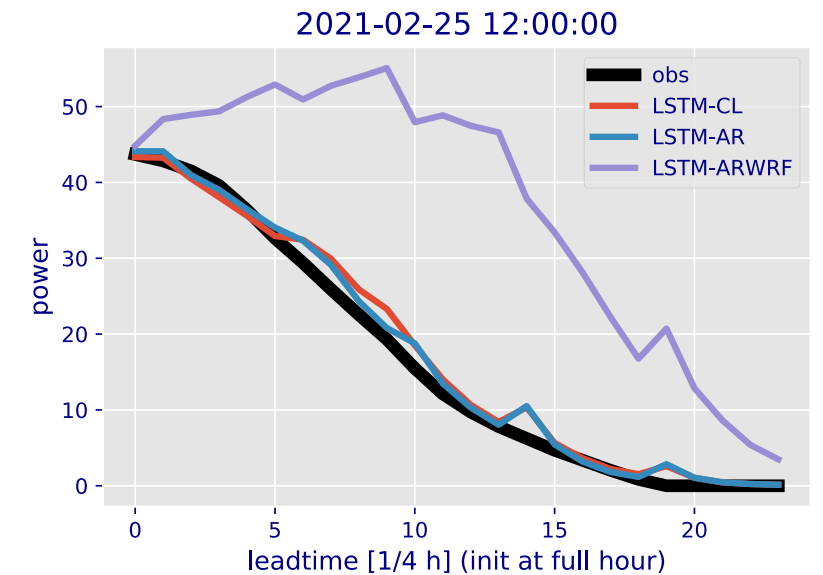
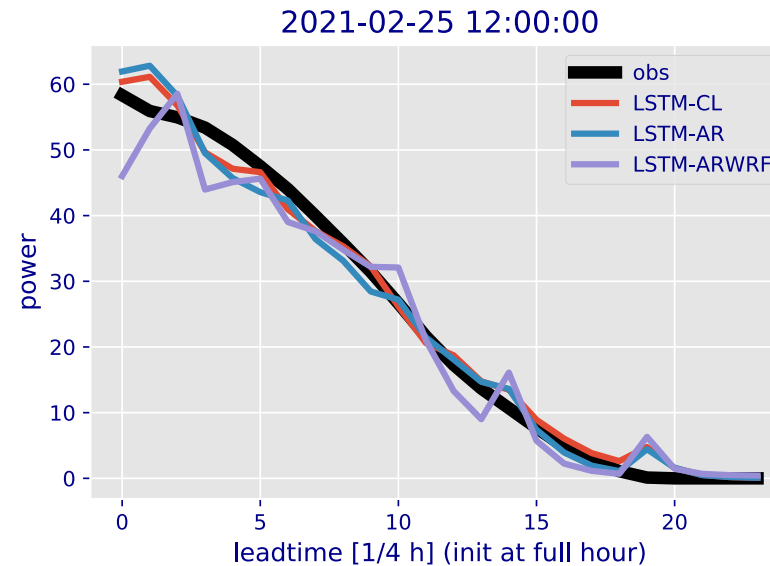
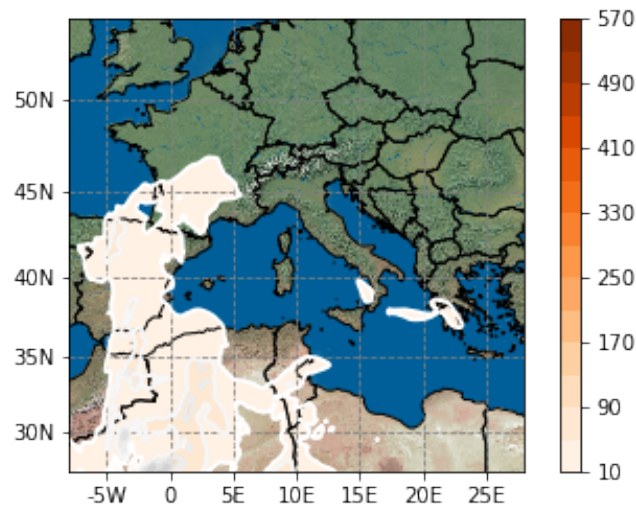
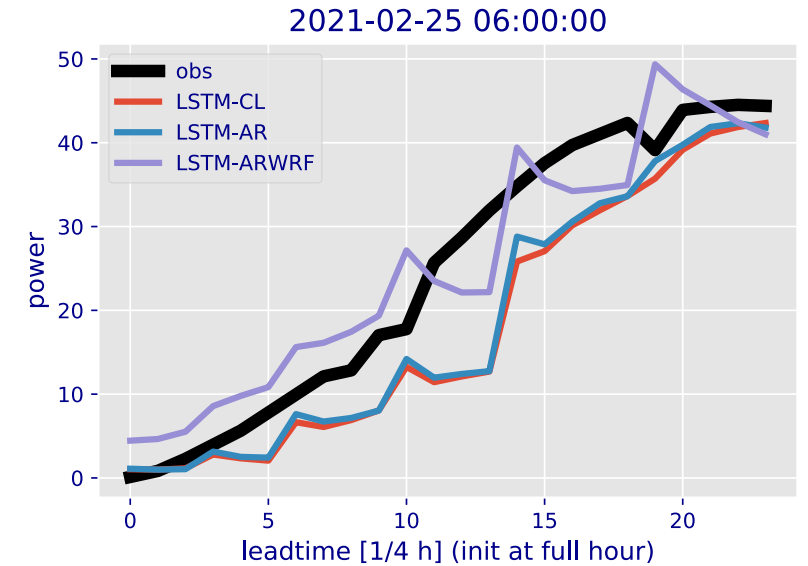
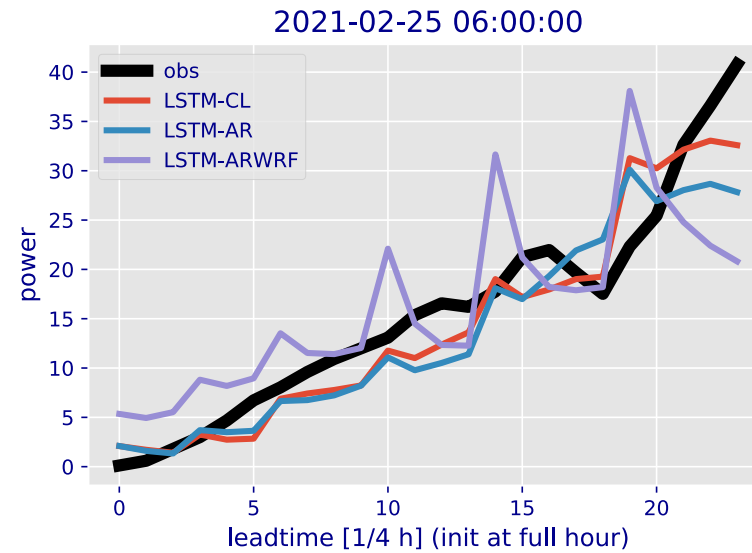
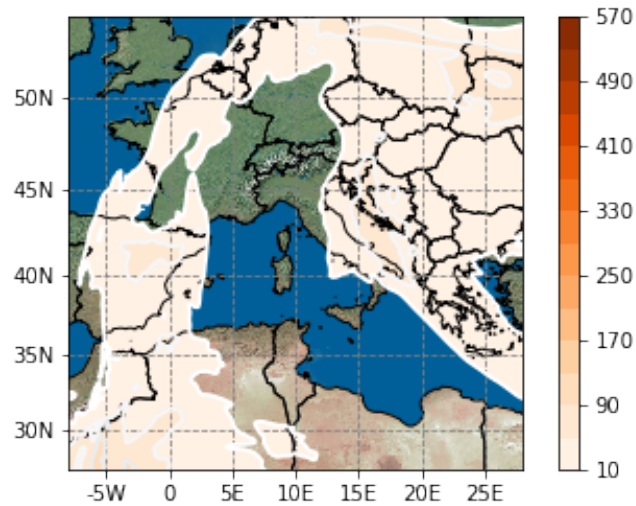
PER ... persistence



incl. WRF:
few cases



Case Study Results – Sample Forecasts





location specific **solar production nowcasts** by a **deep learning** (needed by energy providers):

- **LSTM** promising results for high resolution post processing in nowcasts
- shown in real test cases challenging in operational systems
- efficient computation once trained – suitable for implementing operational systems fast
- diverse data sources available – various temporal and spatial resolution
- BUT: sufficient **data** is needed – synthetic observation data investigated

topics of **future** and **ongoing work**:

- extension of data **transformations** (e.g.: including climatology and feature engineering)
- extend **input data** (e.g.: spatial related time-series', satellite and synthetic)
- feature, hyperparameter, and model optimization
- more locations in different topographic situation and longer test episodes to investigate



Thanks for your attention

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