What drives performance in data-driven and weather-based techniques for short-term PV Forecasting?

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Motivation:

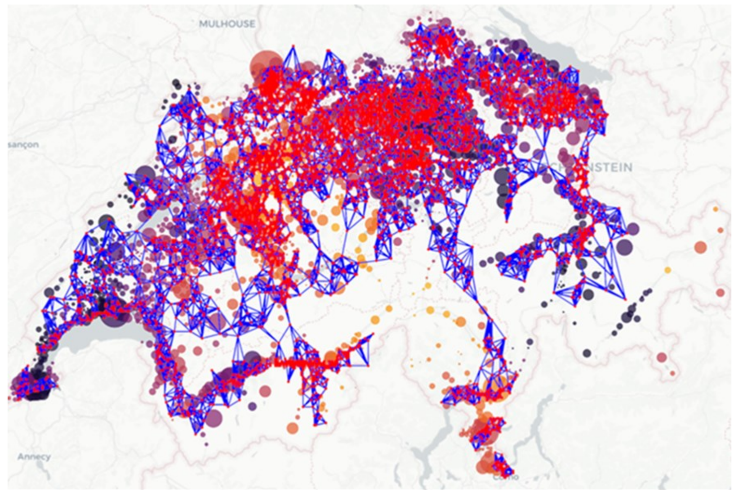
- CloudMove solution from Meteotest offers a nowcasting service for irradiance and PV production with SoA accuracy up to six hours ahead (15 min. resolution)
- CloudMove is based on satellite images and numerical weather models to propagate the cloud movements in the future
- Additionally, CloudMove uses online ground data to correct the forecasts
- Recently, CSEM developed a data-driven forecast model for multi-site PV production forecasting based on Graph neural networks (GNNs)
- These methods can accelerate the computation of forecasts by a factor 100 (after initial training)

Objective: compare CSEM's data-driven solution with CloudMove for different scenarios to provide insight into their performance drivers

Graph-based multi-site PV forecasting

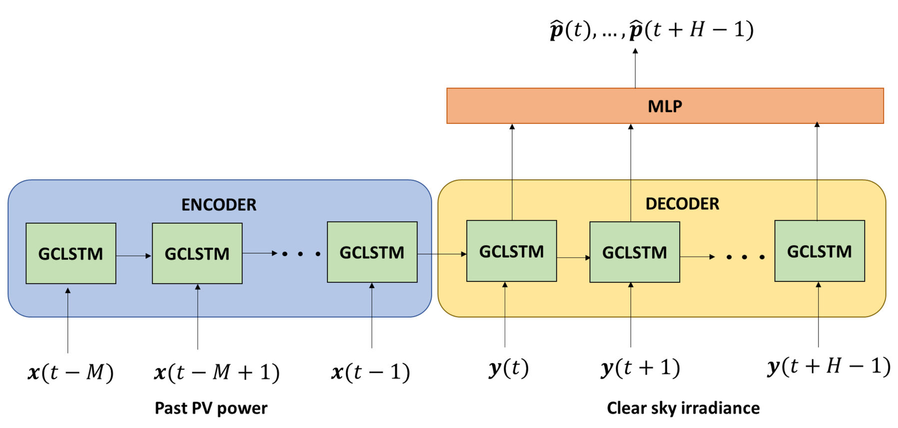
Intuition

- CSEM's data-driven solution relies entirely on production data
- PV stations can be used as a network of virtual weather stations
- By exploiting the spatio-temporal relations of the power production data, cloud movements can be forecasted



Architecture

- The GNN model is an encoder-decoder architecture with graph-convolutional Long-Short-Term-Memory (GCLSTM) cells[1]
- Inputs: production data from past 3 hours and clear-sky irradiance for the forecasting horizon
- Output: power production for all sites in the forecasting horizon (6 hours ahead, 15 min, resolution)

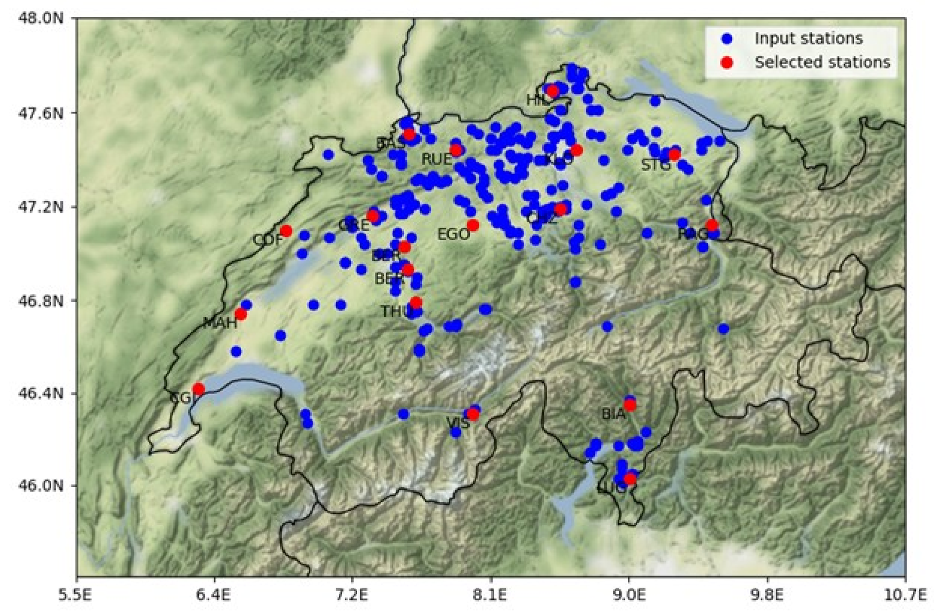


[1]J. Simeunović, B. Schubnel, P. -J. Alet and R. E. Carrillo, "Spatio-Temporal Graph Neural Networks for Multi-Site PV Power Forecasting," in IEEE Transactions on Sustainable Energy, vol. 13, no. 2, pp. 1210-1220, April 2022.

Evaluation set-up

Dataset:

- Power production data from 304 PV stations over Switzerland
- Data from all stations (blue) used as input to GNN (training and evaluation)
- GNN trained using data from whole 2016
- Evaluation in 18 stations (red) for 21 representative days in 2017



Selection criteria: sites

- Regional coverage
- Climate
- Proximity of SwissMetNet stations
- Density of PV stations around selected sites

Selection criteria: days

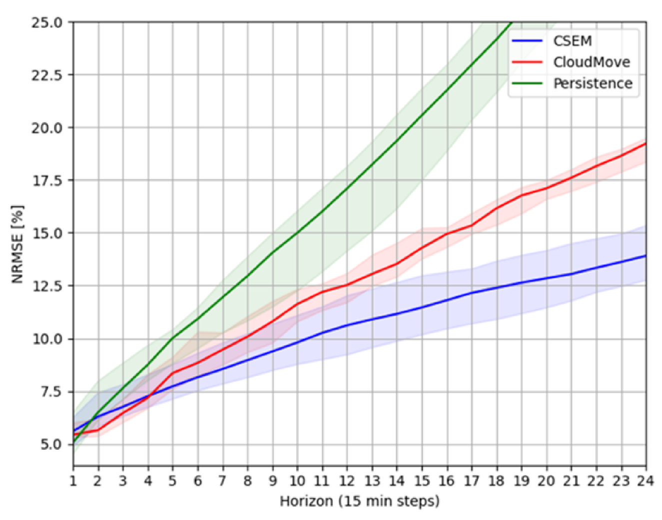
- At least 5 representative days per season
- Mixture of different day categories (according to cloud level)

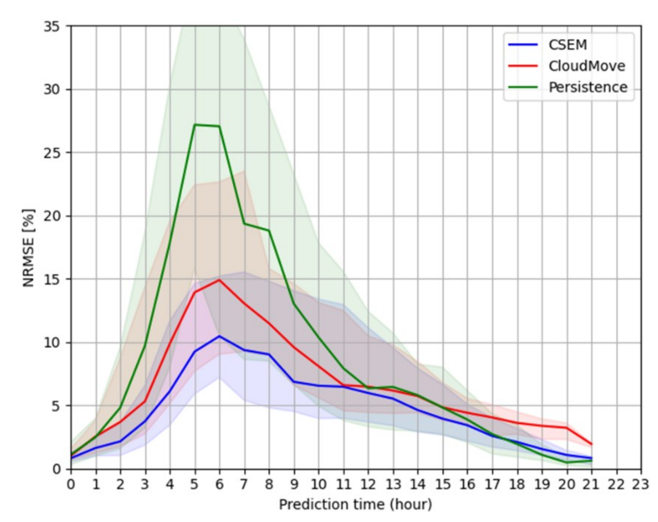
Evaluation metric: Peak-Normalized Root Mean Squared Error (NRMSE)

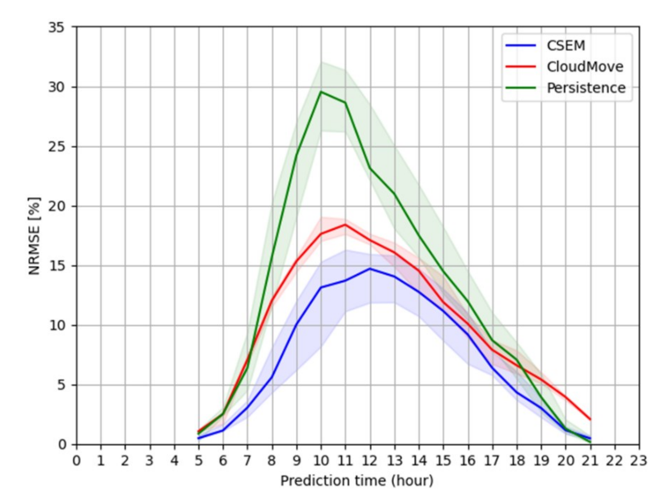
Results and Discussion

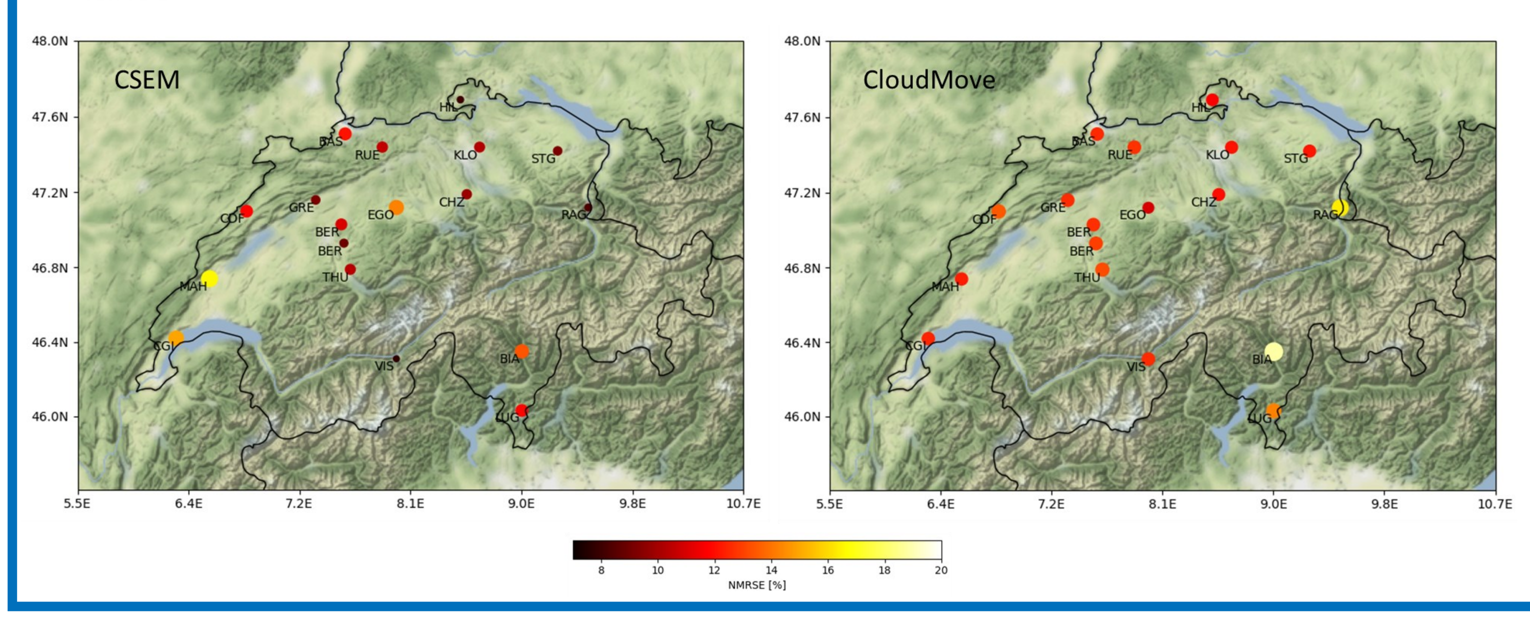
Overall results

- NRMSE vs forecasting horizon:
  - Errors very similar up to two hours ahead (8 steps)
  - More pronounced slope for CloudMove after 2.5 hours ahead (10 steps)
  - Larger spread for CSEM's GNN
- NRMSE vs prediction time of the day (hourly):
  - Largest errors in early morning (5:00 – 7:00) due to scarcity of information due to zero production over night
  - Large spread in errors between 7:00 and 12:00 because forecasting horizon includes peak of solar noon
- NRMSE vs target time of the day (hourly): largest errors near solar noon
- The spatial error distribution is almost uniform for CloudMove, except for the Alpine regions where no weather station was available nearby
- CSEM's solution yields a spreader spatial error with highest errors near borders and lakes



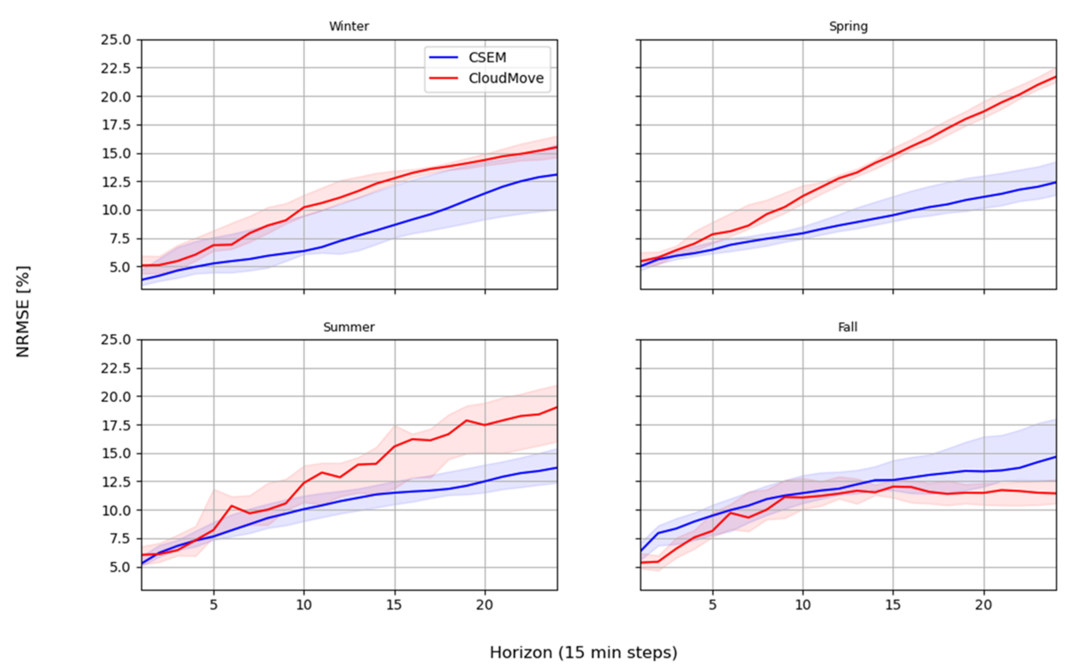


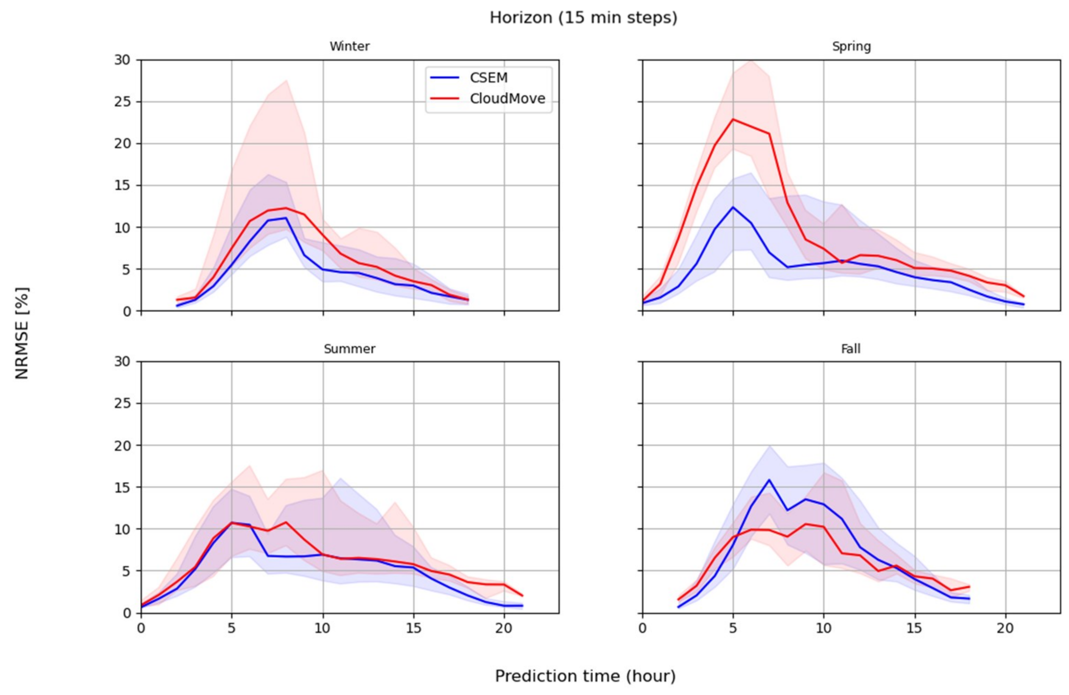




Seasonal dependency

- NRMSE vs forecasting horizon:
  - Larger errors for CloudMove in winter and summer
  - Significantly larger slope in the error evolution in spring for CloudMove
  - Larger errors for CSEM's GNN in fall
  - Larger spread for CSEM's GNN except in summer
- NRMSE vs prediction time of the day (hourly):
  - Larger errors for CloudMove for winter and summer and significantly larger errors in spring
  - Larger spread of errors in winter for CloudMove
  - CSEM's GNN has a large error spread summer around the solar noon due to large peak production





Discussion

- CloudMove and CSEM data-driven method yield a similar error between 0-2 hours ahead predictions but CSEM' method yields smaller errors from 2-6 hours ahead
- CloudMove has a smaller spread of errors across sites and days benefiting from the larger coverage of satellite images except in sites where there aren't nearby weather stations available
- CSEM data-driven method yields a larger spread of errors across sites and days. The error can be very low for sites with a high density of PV stations but high for sites with low density and at the border of the graph
- CloudMove achieves a lower error in fall but CSEM's solution yields lower errors (and spread) during summer when the production is the highest