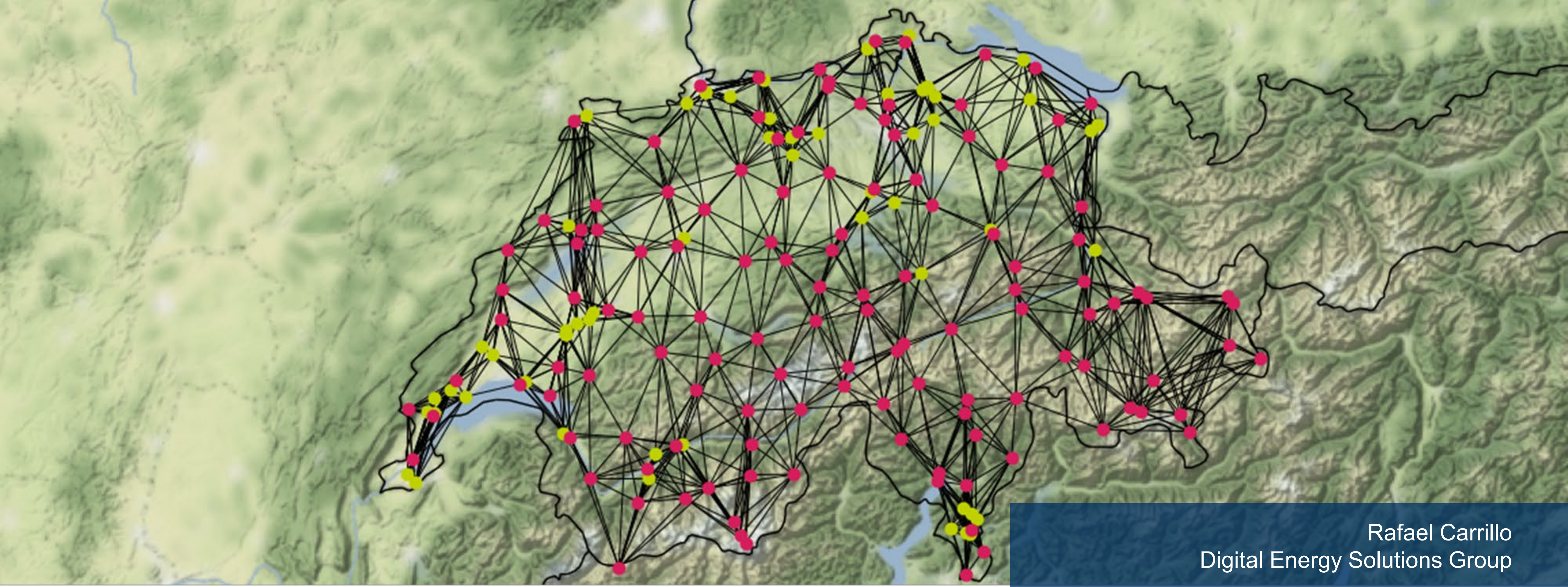

Rafael Carrillo
Digital Energy Solutions Group

Intelligent Maintenance Conference

04-09-2024

GRAPH MACHINE LEARNING FOR SHORT-TERM SOLAR FORECASTING

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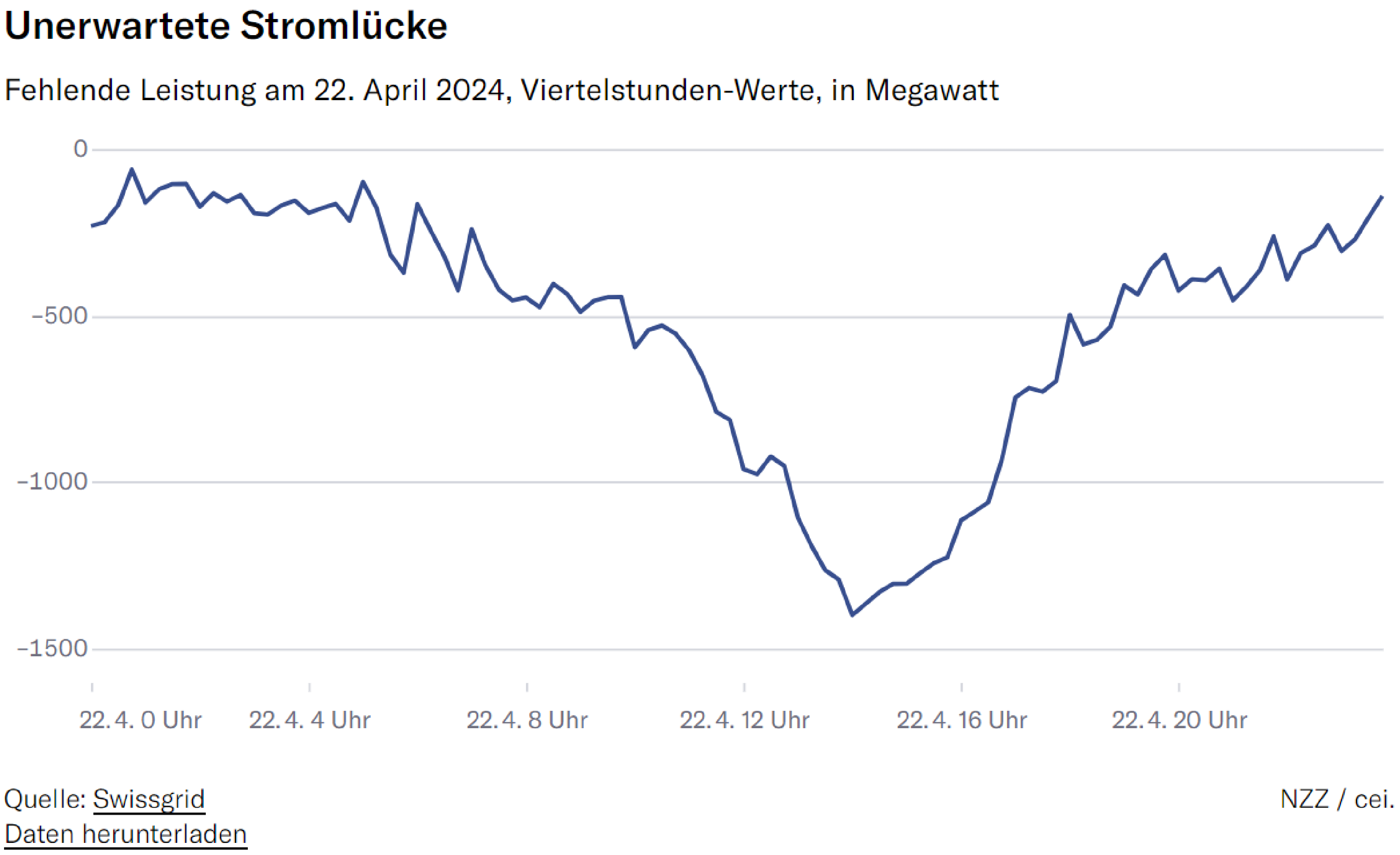
40 YEARS OF INNOVATION

WHY IS SOLAR FORECASTING IMPORTANT?



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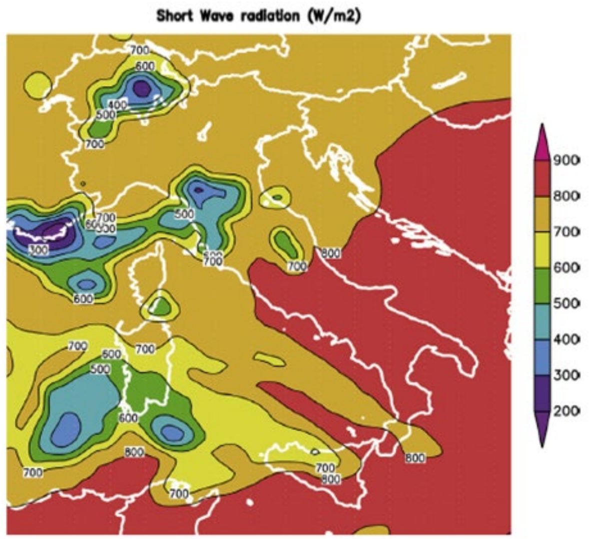
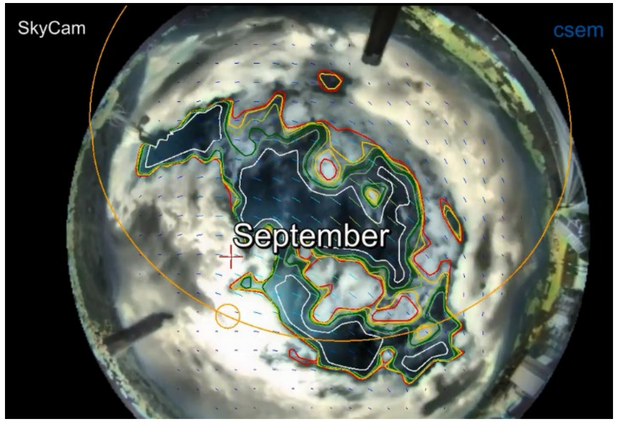
SOLAR FORECASTING

- **Up to 3 days ahead:** numerical weather predictions (NWP) + statiscal (or ML) model
  - Day ahead markets, unit commitment, transmission scheduling
- **Up to 6h ahead:** satellite-derived cloud motion tracking + numerical model
  - Load forecasting, trading
- **Up to 30 min. ahead:** all sky imagers with cloud motion tracking
  - Ramping events



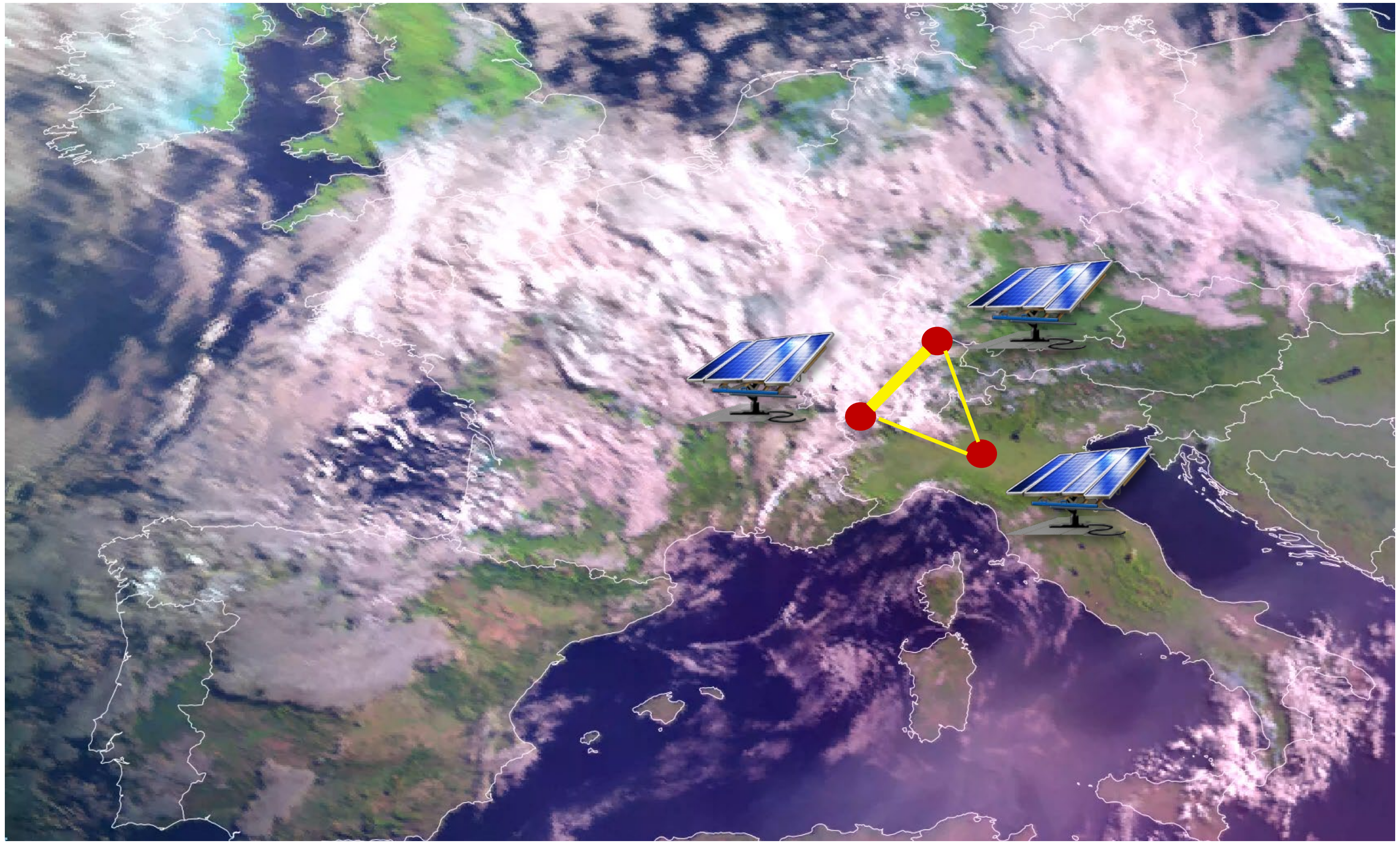
NWP data from the Weather Research and Forecasting (WRF–NWP 3.6.1) mesoscale model by NCAR



SHORT-TERM SOLAR FORECASTING

Cloud motion prediction

- **State of the art:** Numerical weather models + satellite images
- **Limitations:** limited resolution and high computational cost
- What if we use other data sources?
  - Track cloud motion by looking at different ground systems in time
  - Dense network of sensors?



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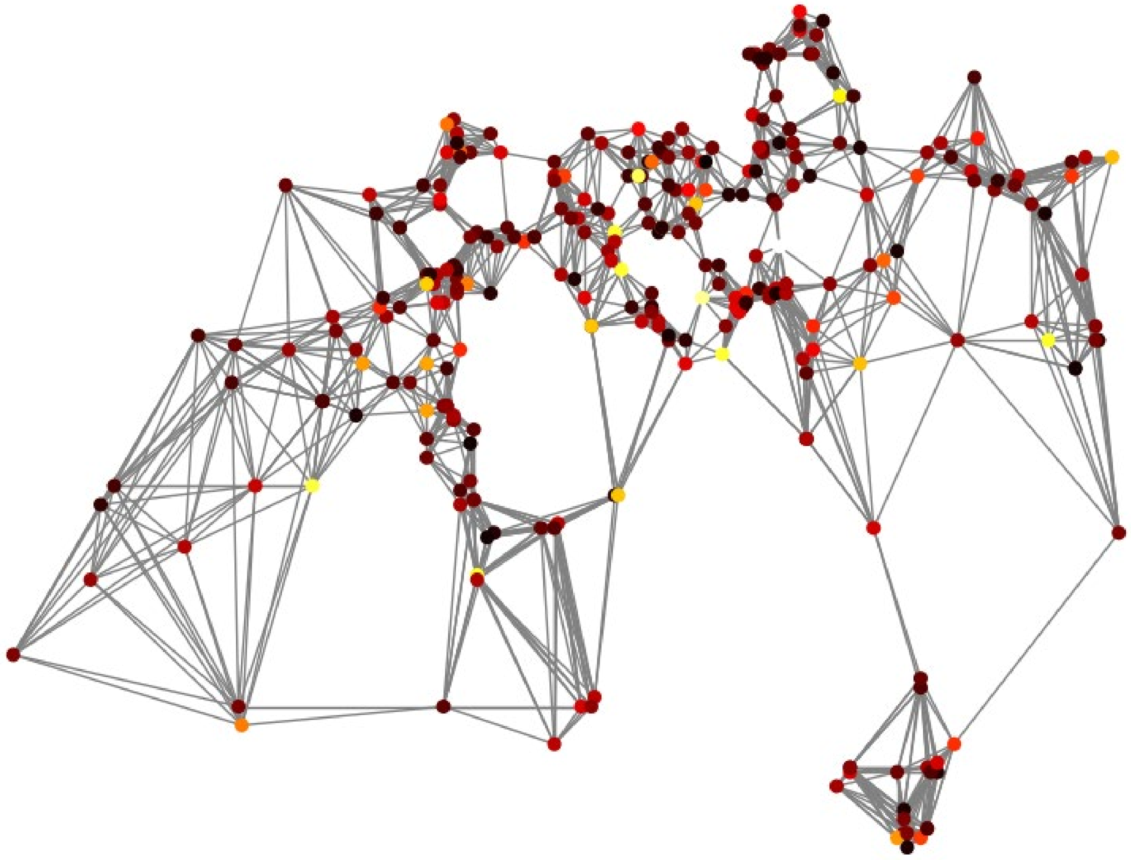
MODELING COMPLEX DYNAMICS WITH GRAPHS

- **Times series** data from:
  - PV systems
  - Meteorological stations
- Graph neural networks model **spatio-temporal relations**

- Potential for improved temporal and spatial resolution
- In Switzerland
  - ~200 meteorological stations
  - ~200.000 connected PV systems



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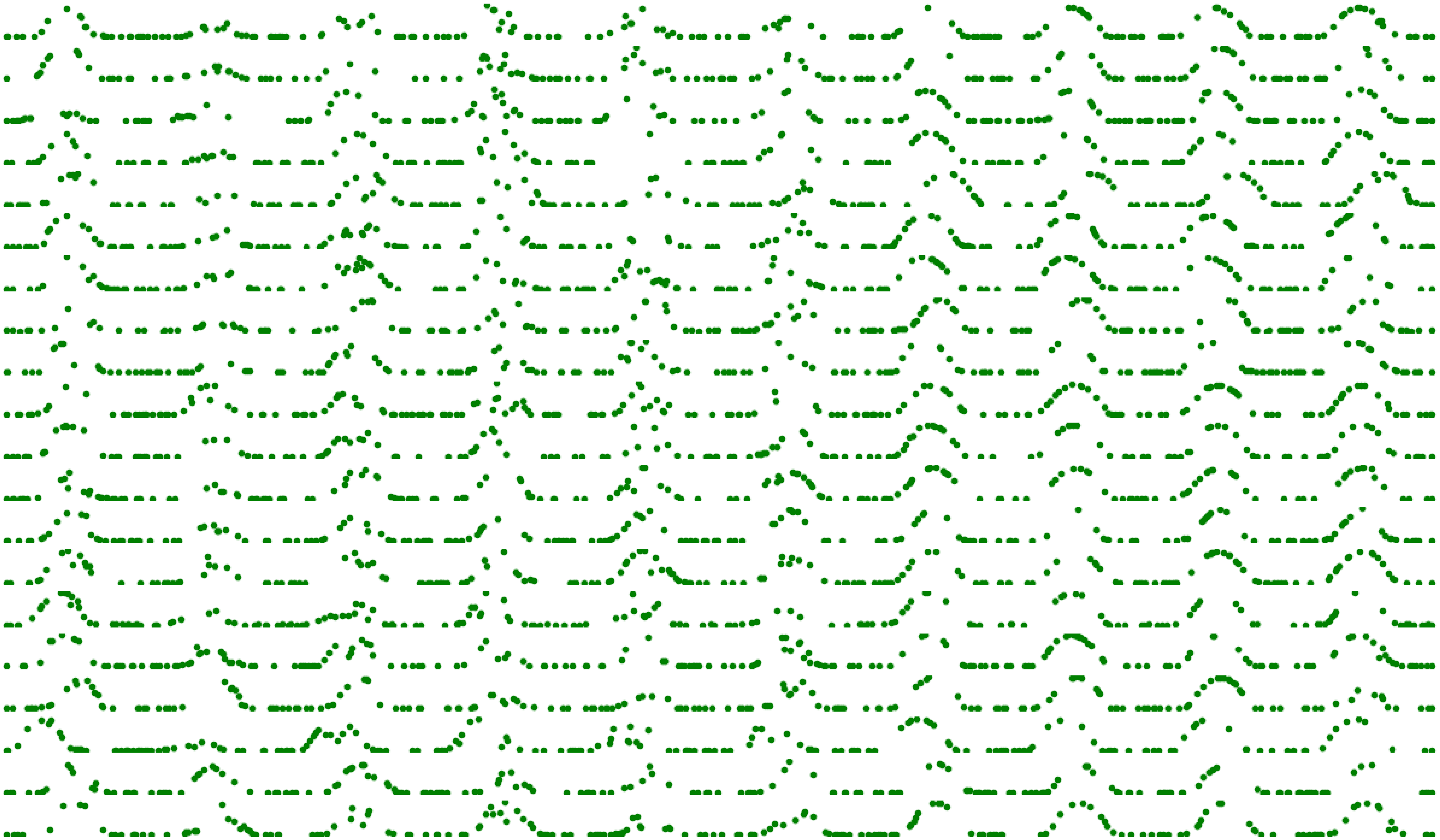
CHALLENGE: DYNAMIC CHANGES IN THE NODE SET



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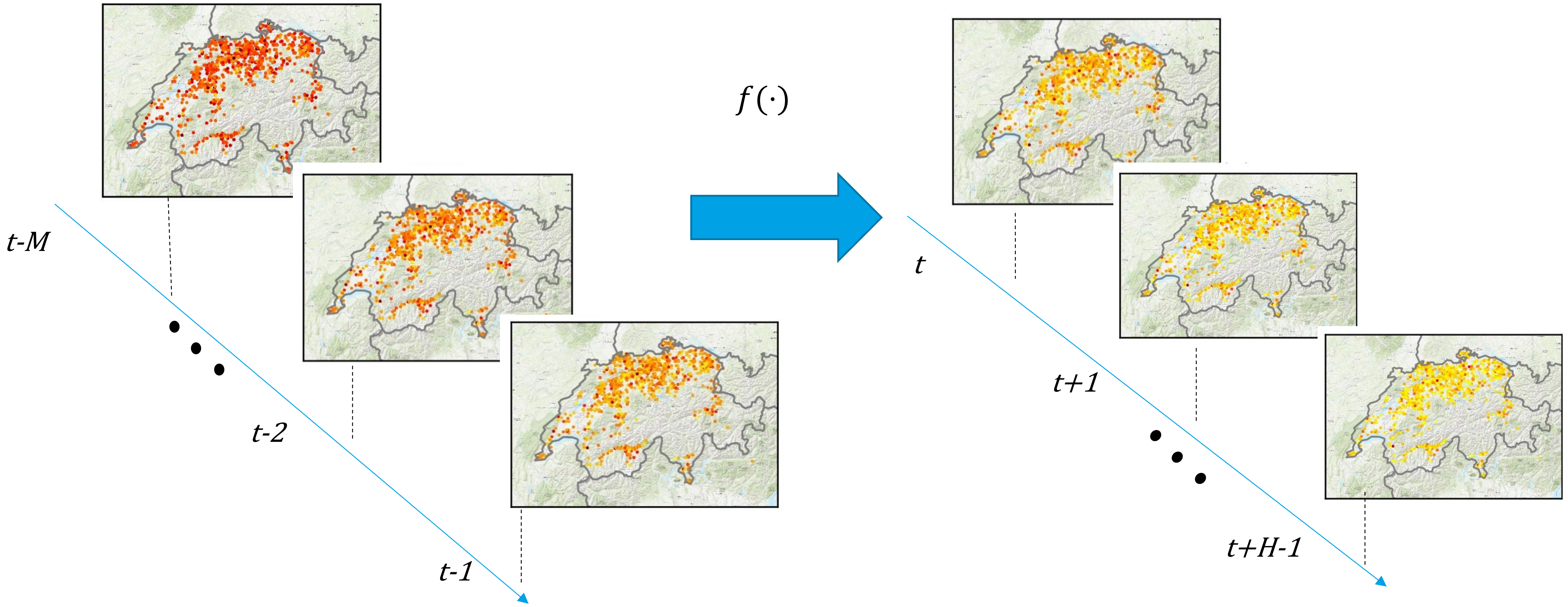
FORECASTING PROBLEM



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DIGERATI

- Short term probabilistic forecast solution
- Six hours ahead horizon with temporal resolution of 15 minutes

Heterogeneous data embeddings → Dynamic graph feature extraction → Fixed graph forecast model → Graph interpolation model →

$\{\boldsymbol{S}(k)\}_{k=t-M}^{t-1}$
Past measurements (4 hours) from available sources (variable number)

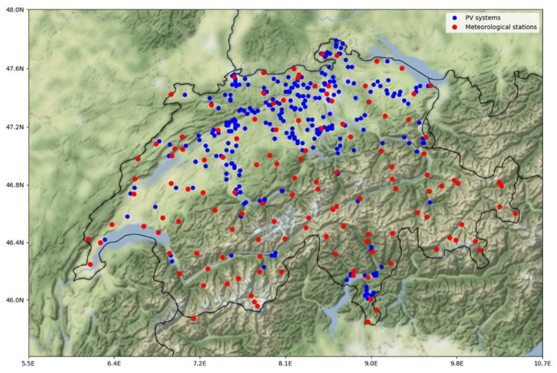
$\{\boldsymbol{X}(k)\}_{k=t-M}^{t-1}$
Features embedded in a common space (variable number)

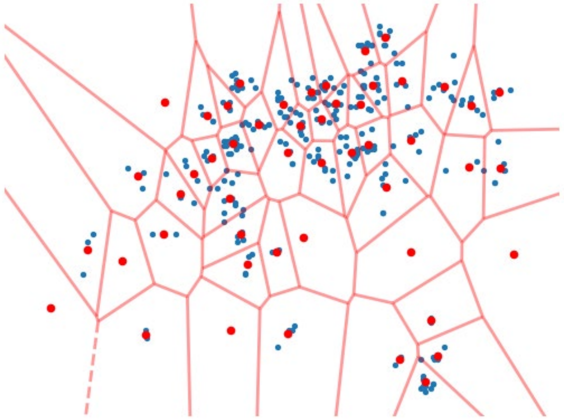
$\{\widehat{\boldsymbol{X}}(k)\}_{k=t-M}^{t-1}$
Features on fixed node set (graph)

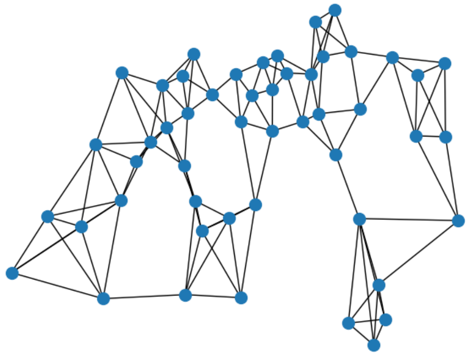
$\{\boldsymbol{y}(k)\}_{k=t}^{t+H-1}$
Forecasted signals on fixed graph

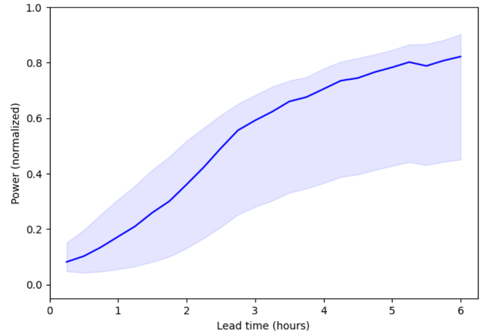
Coordinates of points of interest

$\{\widehat{\boldsymbol{y}}(k)\}_{k=t}^{t+H-1}$
Output forecast at points of interest (6 hours ahead)









R. Carrillo et al., “Dynamic Graph Machine Learning for Multi-Site Solar Forecasting," in Proc. EUPVSEC, 2023, doi: 10.4229/EUPVSEC2023/4CO.8.5

FORECAST MODEL: TEMPORAL SPATIAL MULTIWINDOW GRAPH ATTENTION NETWORK

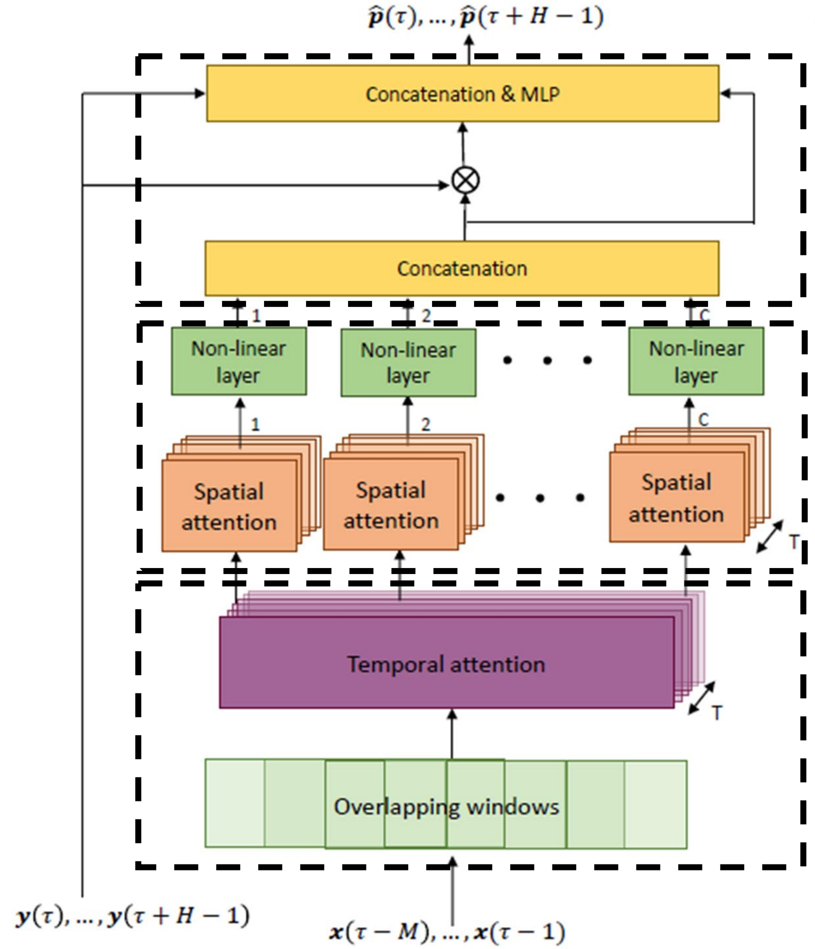
Encoder

- Temporal attention to capture time dependencies
- Spatial attention block to capture dynamically changing spatial correlations between nodes
- Multi-window mechanism: different spatial attention for different forecasting horizon windows
  - (0-2h)
  - (2-4h)
  - (4-6h)

Decoder

- MLP and multi-quantile heads

Future Irradiance (power), 6 hours ahead



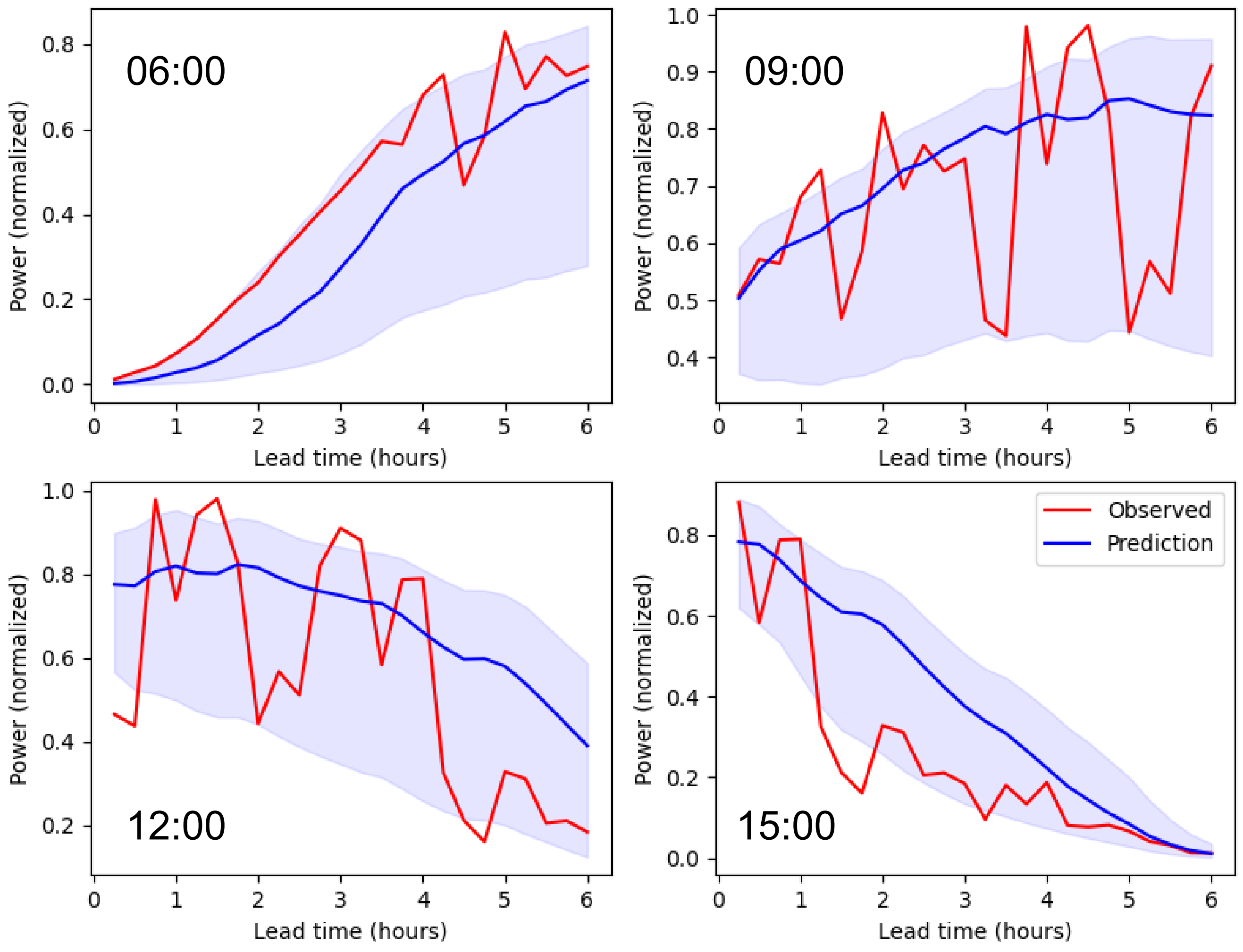
Clear-sky irradiance

Past features, 6 hours

J. Simeunović et al., "Interpretable *Temporal-Spatial Graph Attention Network for Multi-Site PV Power Forecasting," in Applied Energy, 2022, doi:* 10.1016/j.apenergy.2022.120127

PROBABILISTIC FORECASTS

- Quantile regression approach
- DIGERATI produces forecasts for:
  - Median value
  - Upper bound (95% quant.)
  - Lower bound (5% quant.)
- System can be adapted:
  - Less conservative confidence intervals (e.g., for economic optimization)
  - More points of the distribution, e.g., 5%, 25%, 50%, 75%, 95%



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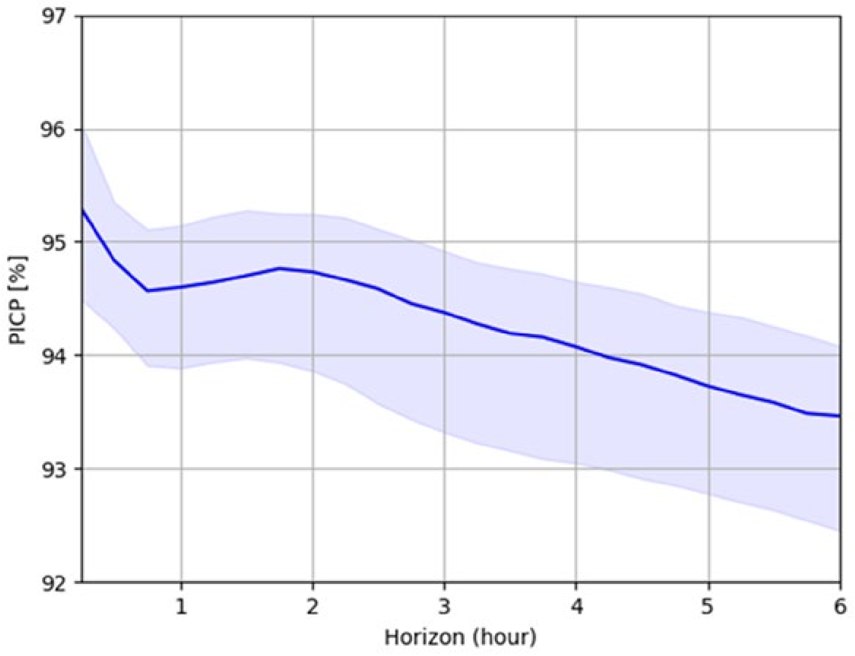
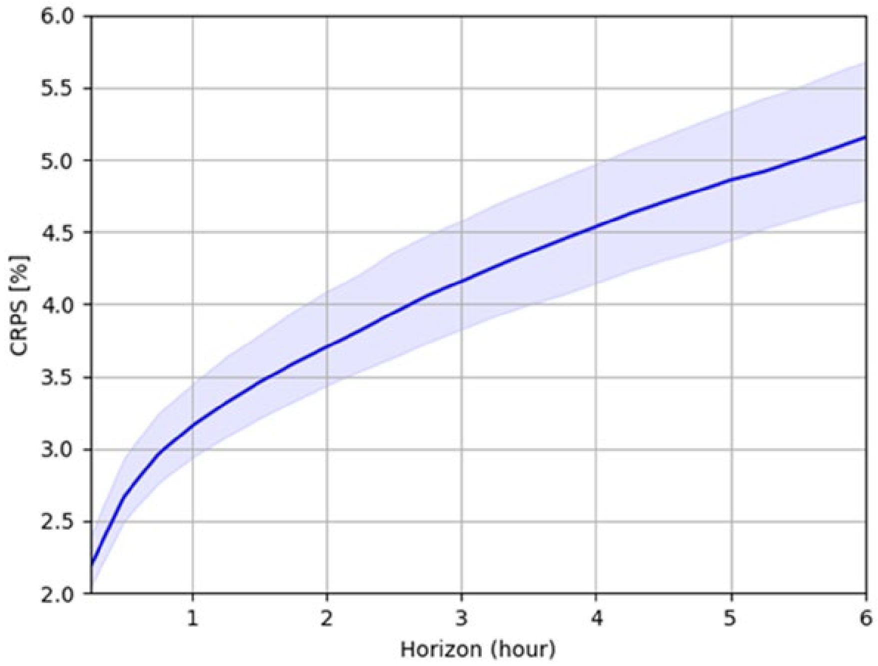
QUANTITATIVE EVALUATION





- **Reliability** of the probabilistic forecasts evaluated on one year of historical data
- Prediction interval coverage probability (PICP) used as metric
- More than 90% probability for the entire forecasting horizon

- Normalized continuous rank probability score (CRPS) evaluated on one year of historical data
- Forecasted quantiles follow the empirical distribution of the data
- CRPS smaller than 6% for the entire horizon

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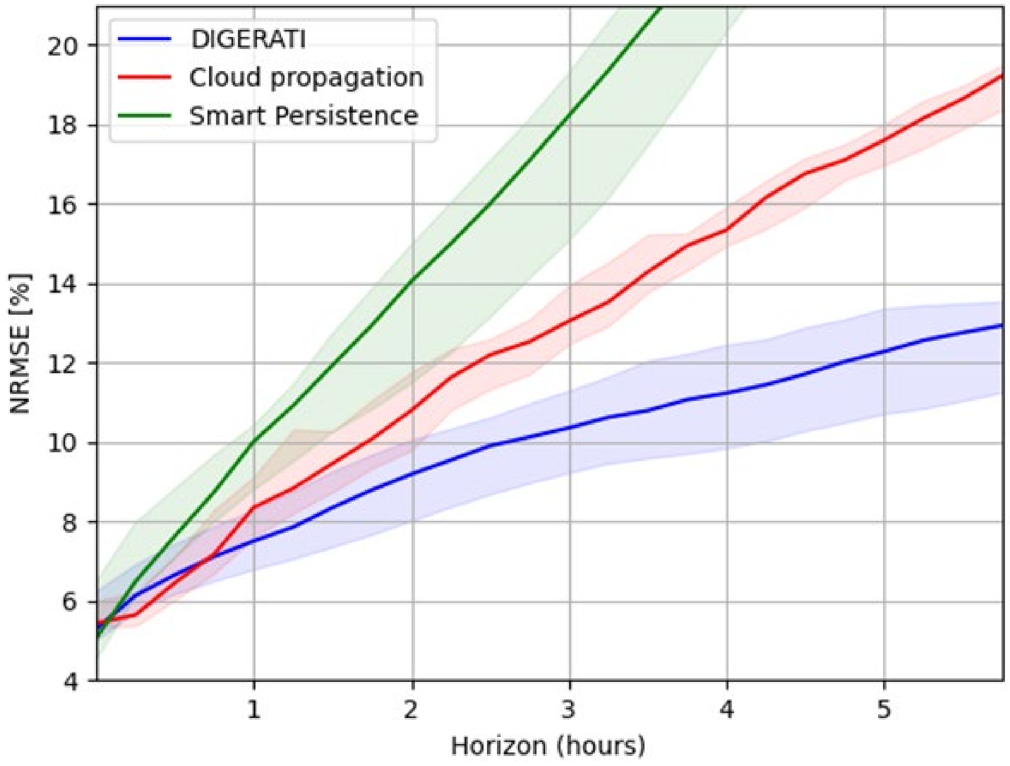
BENCHMARK

- Comparison with a SoA commercial solution based on satellite images and cloud propagation
  - 18 locations in Switzerland
  - 21 days over different weather conditions
- **25% reduction of forecasting error**
- Acceleration on the computations of forecasts by a factor 100



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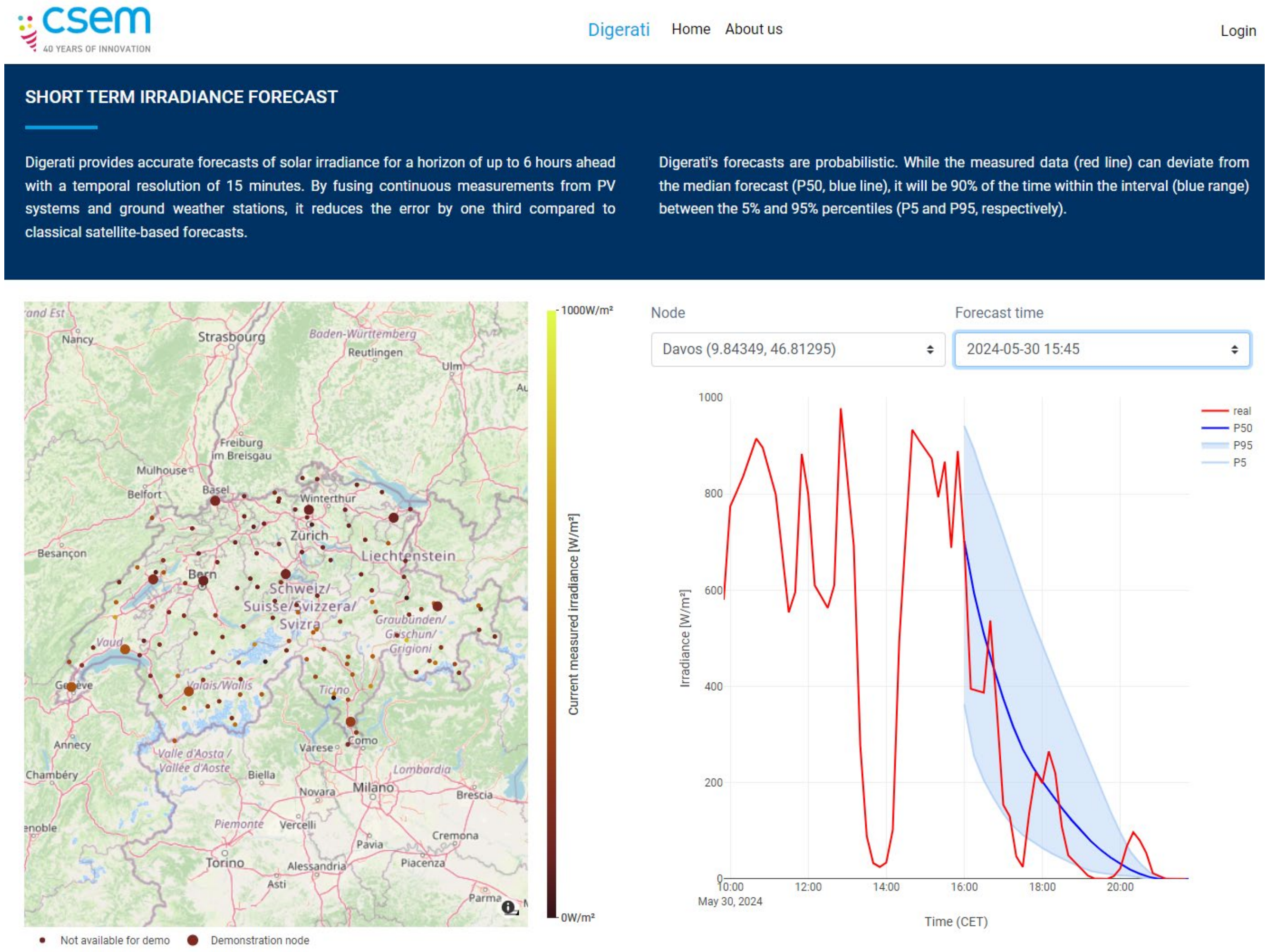
DIGERATI: SHORT TERM FORECASTING SOLUTION

- Live demo yields forecasts for a horizon of six hours ahead with a temporal resolution of 15 minutes
- API available to get forecasts in real time
- Do you want to try it?
  - Go to: https://digerati.portal.csem.ch/



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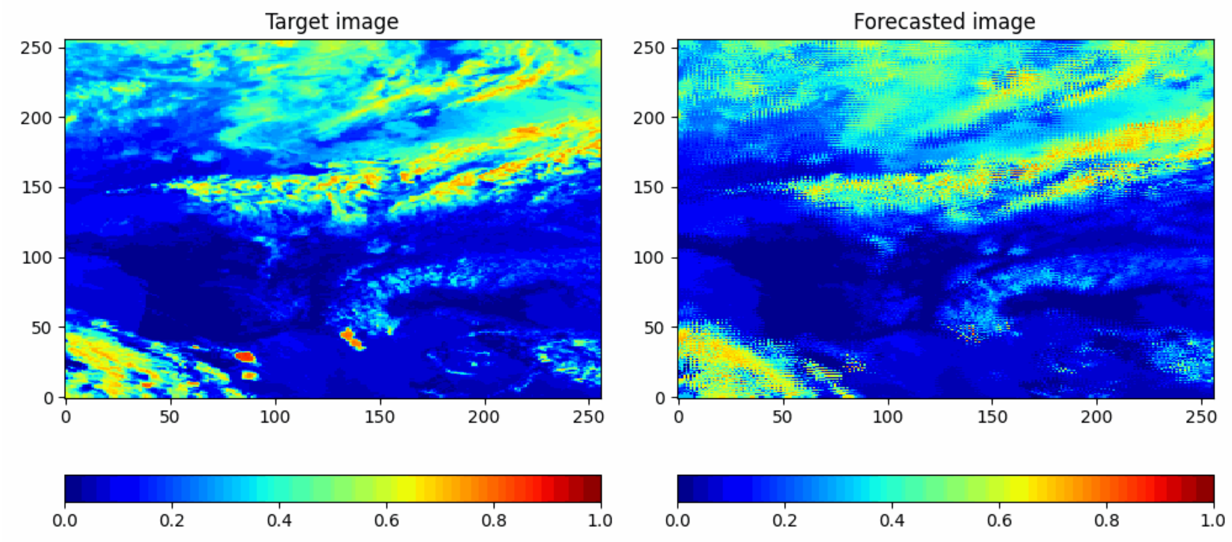
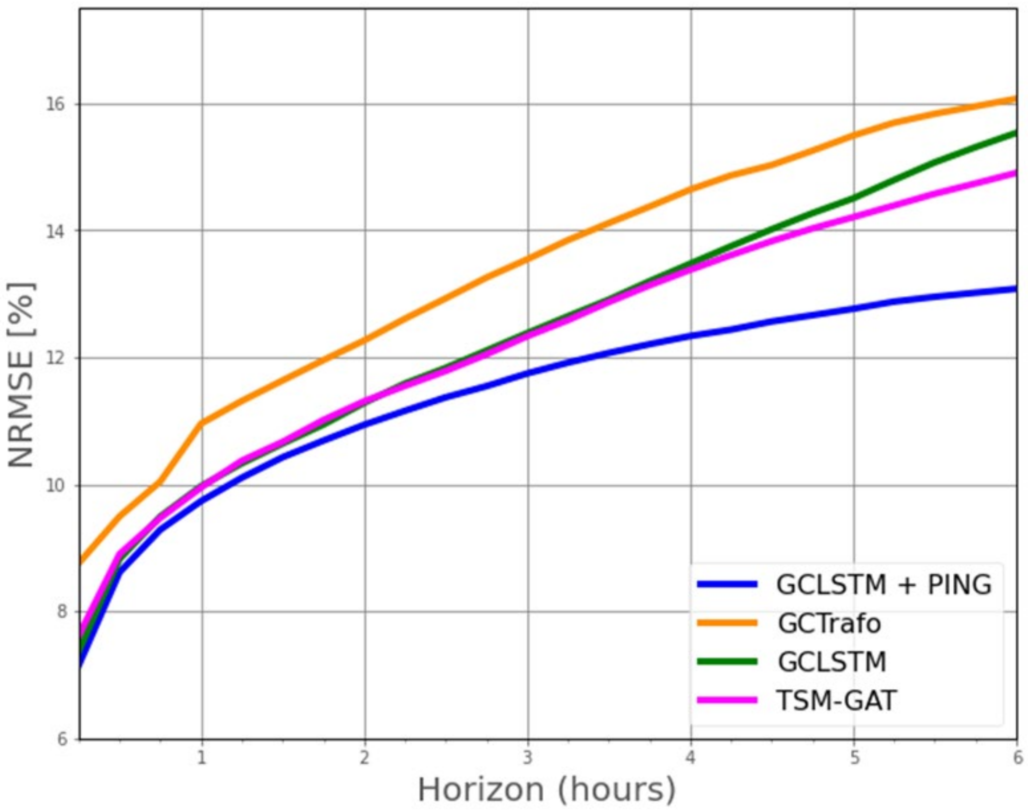
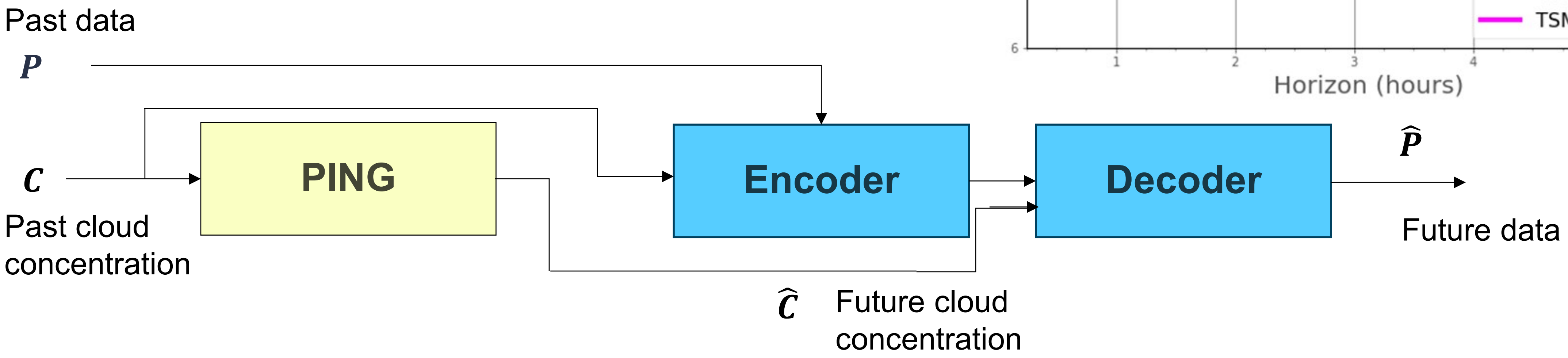
PHYSICS INFORMED GNN (PING): PRELIMINARY RESULTS







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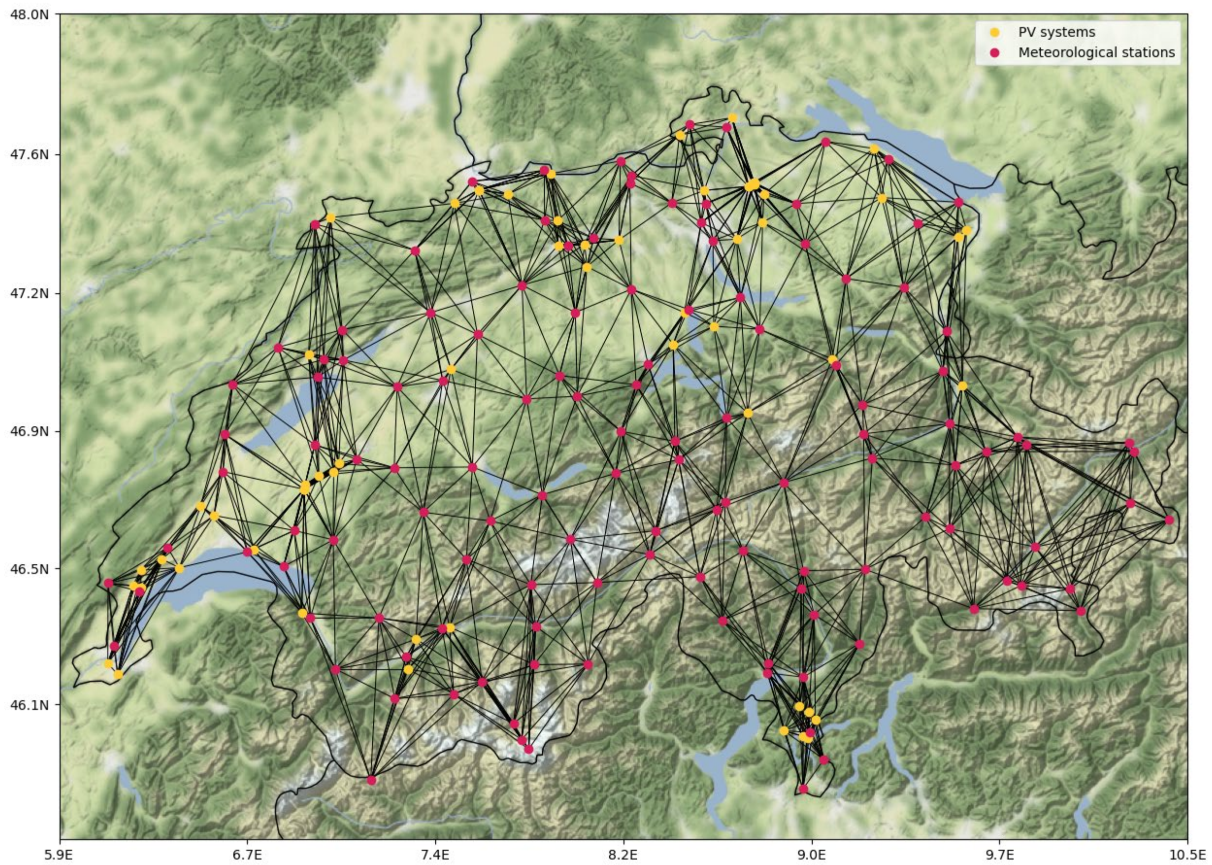
CONCLUSIONS

- DIGERATI produces probabilistic forecasts of solar irradiance (or power) for up to 6 hours ahead with a resolution of 15 minutes
- It uses a network of distributed sensors (**PV systems** and **weather stations**) as inputs
- It uses GNN to learn **spatio-temporal relations** of multisource data
- Solution robust to changing conditions on the input's node set thanks to **dynamic graph machine learning**
- **Outlook:** inclusion of heterogeneous data sources (e.g. satellite images or NWP) to increase spatial context and prediction horizon



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