COMBINING DEEP LEARNING AND PHYSICAL MODELS FOR SOLAR NOWCASTING

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Agenda

- Motivation & Introduction
- Hybrid Nowcasting Models
- Validation
- Conclusion

MOTIVATION & INTRODUCTION

Motivation

What is the problem?

- Short-term irradiance fluctuations induced by clouds pose a challenge for the power system

How to deal with this?

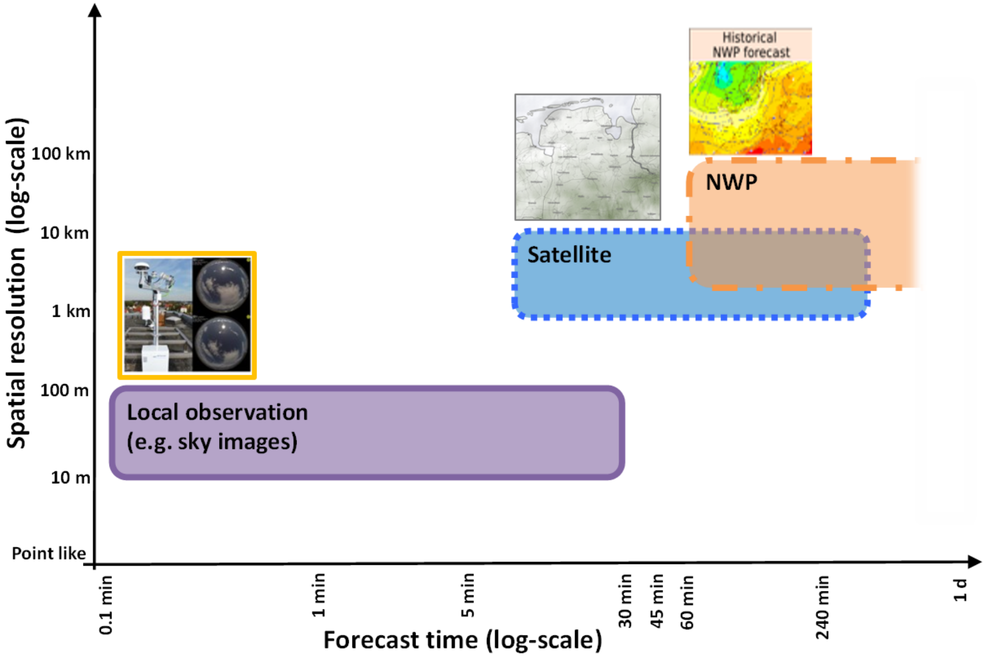
- Apply solar nowcasting to anticipate changes in solar irradiance and adapt plant operation

What are potential benefits?

- Optimized real-time trading
- Ramp rate control
- Frequency control

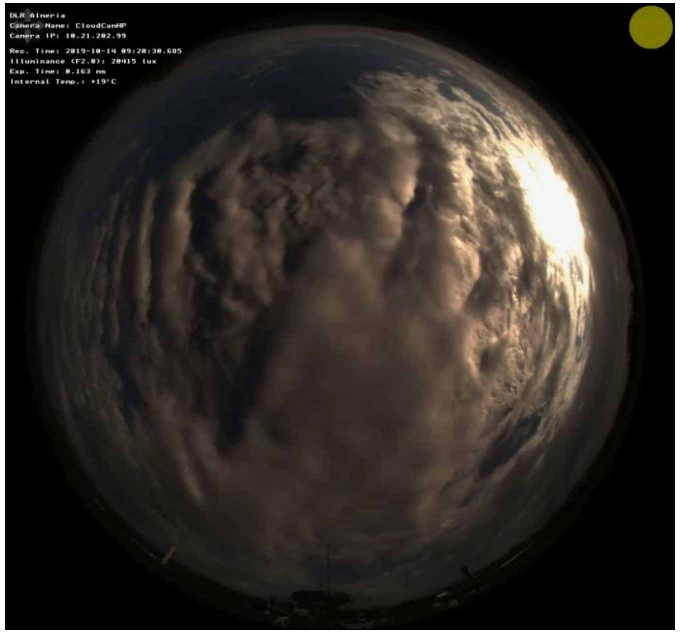
What are the requirements?

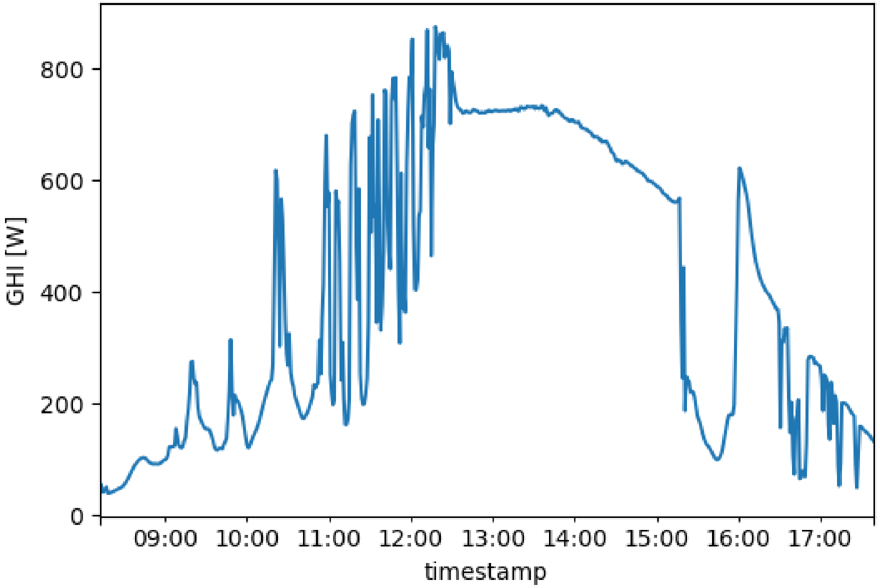
- Cloud information in spatially and temporally high resolutions



ASI Nowcasting

- All-Sky Imager
  - Ground-based camera observing complete hemisphere using fish-eye lens
- Image analysis
  - <u>Physical approach</u>
    - Explicit modelling of clouds, their motion and transmittance
  - <u>Data-driven approach</u>
    - Model learns correlation of clouds and irradiance directly from images
- Nowcast: intra-hour irradiance forecast





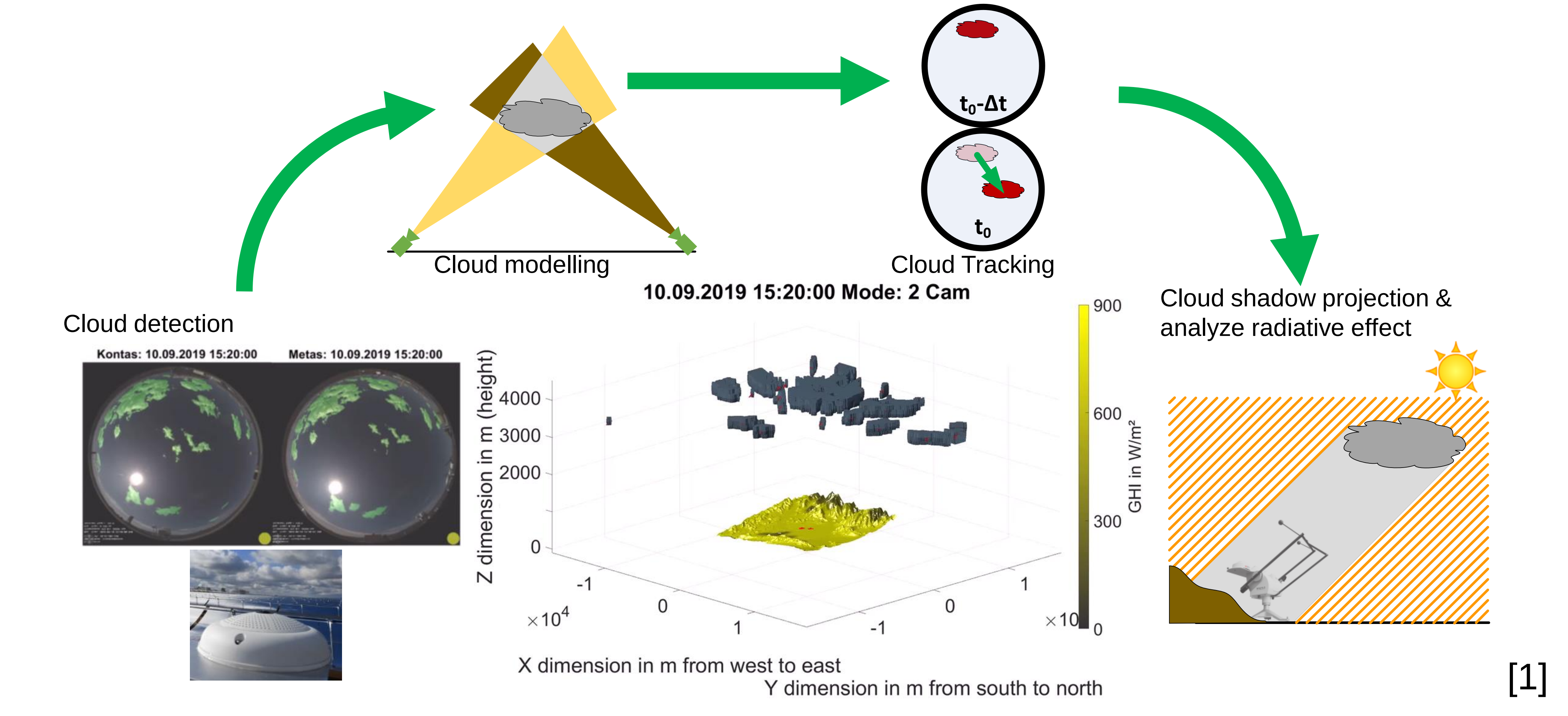
HYBRID NOWCASTING MODELS

Hybrid Model

Physical model

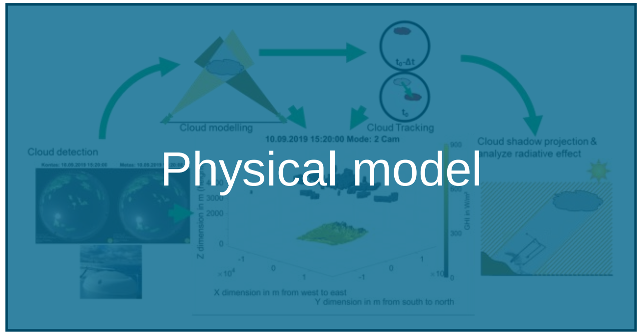
Hybrid Model

Physical model



[1]

Hybrid Model

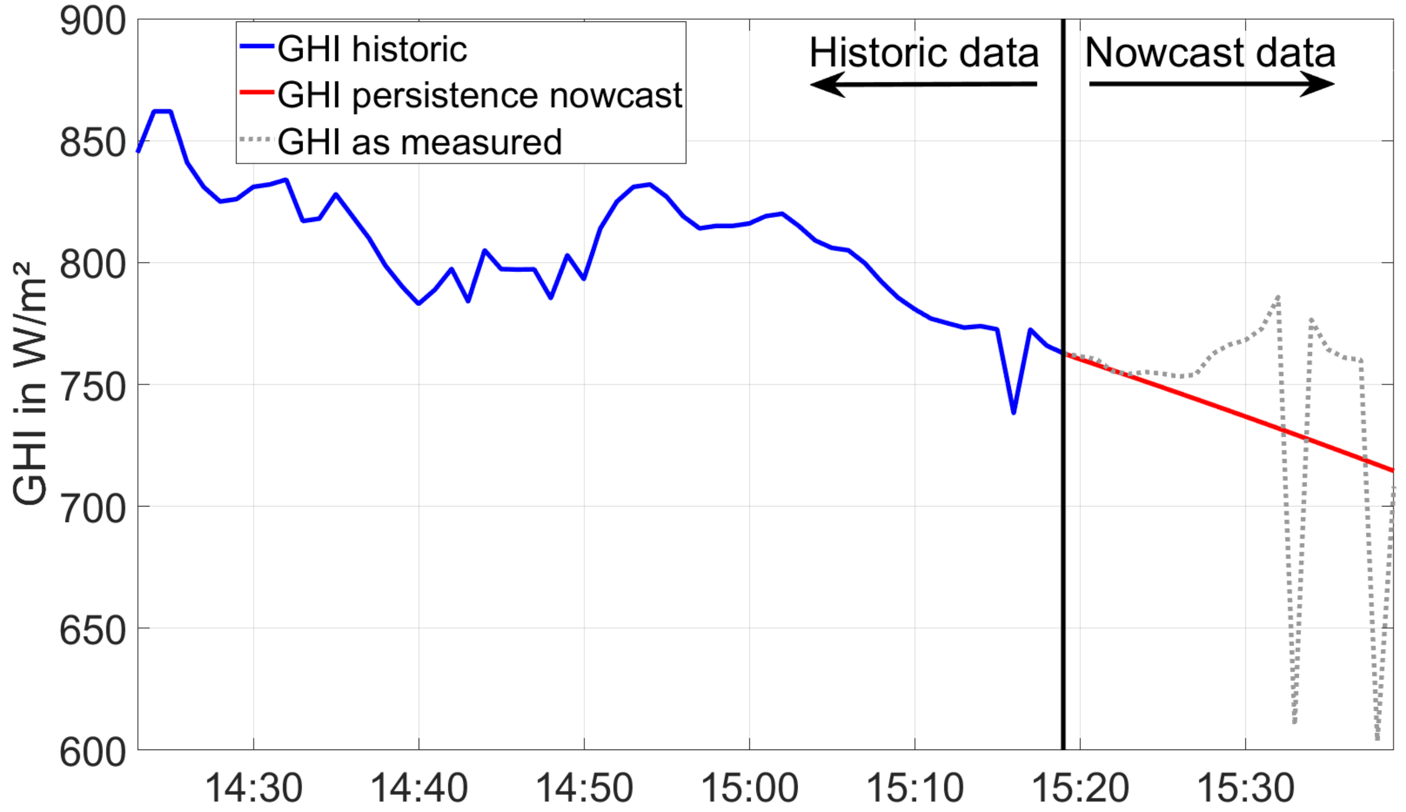


Physical model

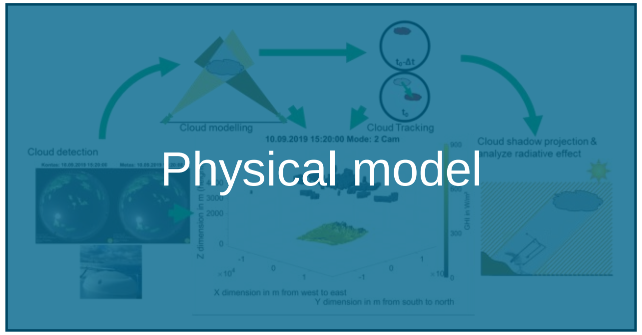
Persistence model

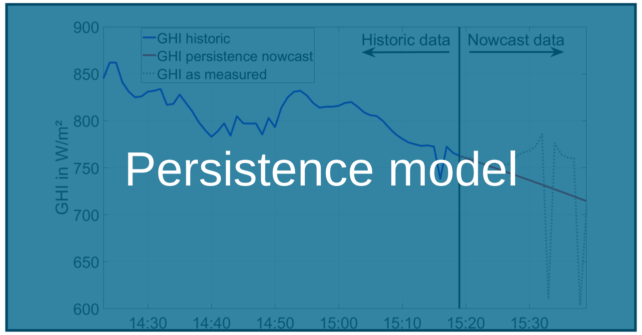
Hybrid Model

Persistence model



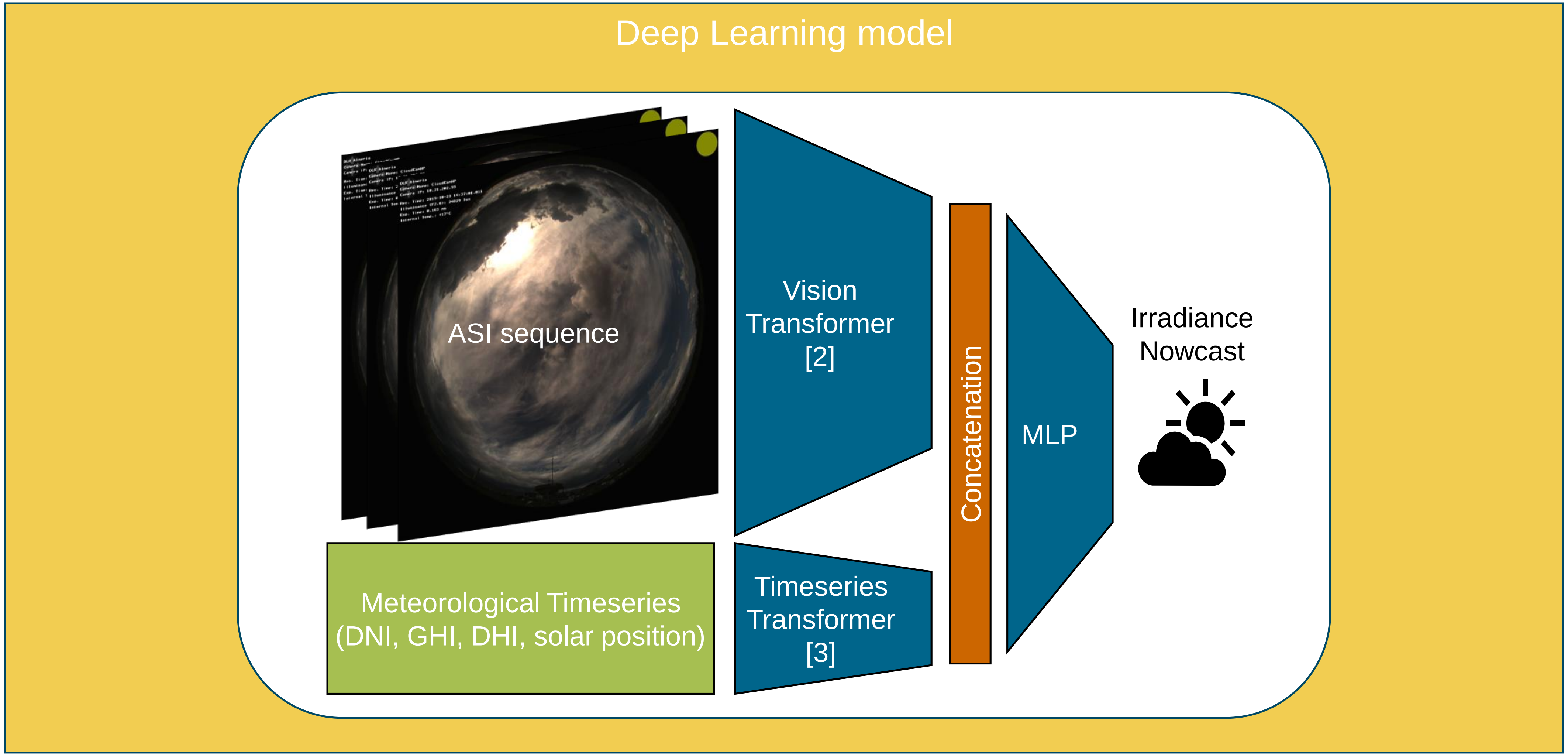
Hybrid Model



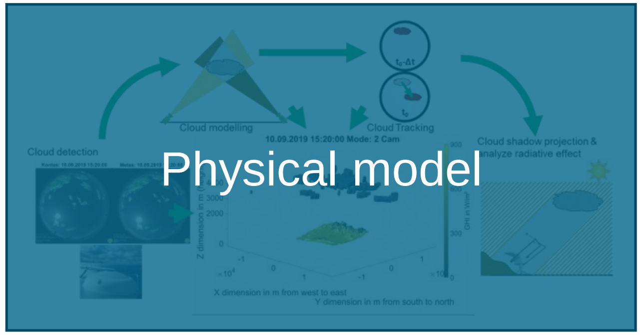


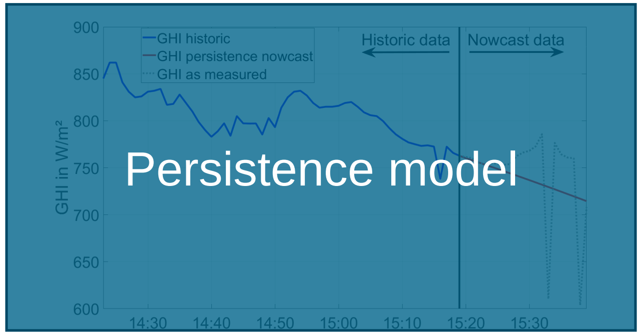
Deep Learning model

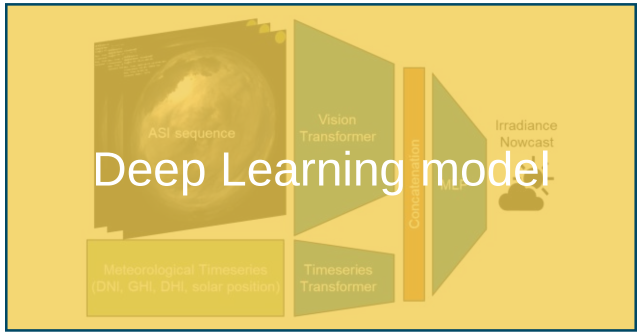
Hybrid Model



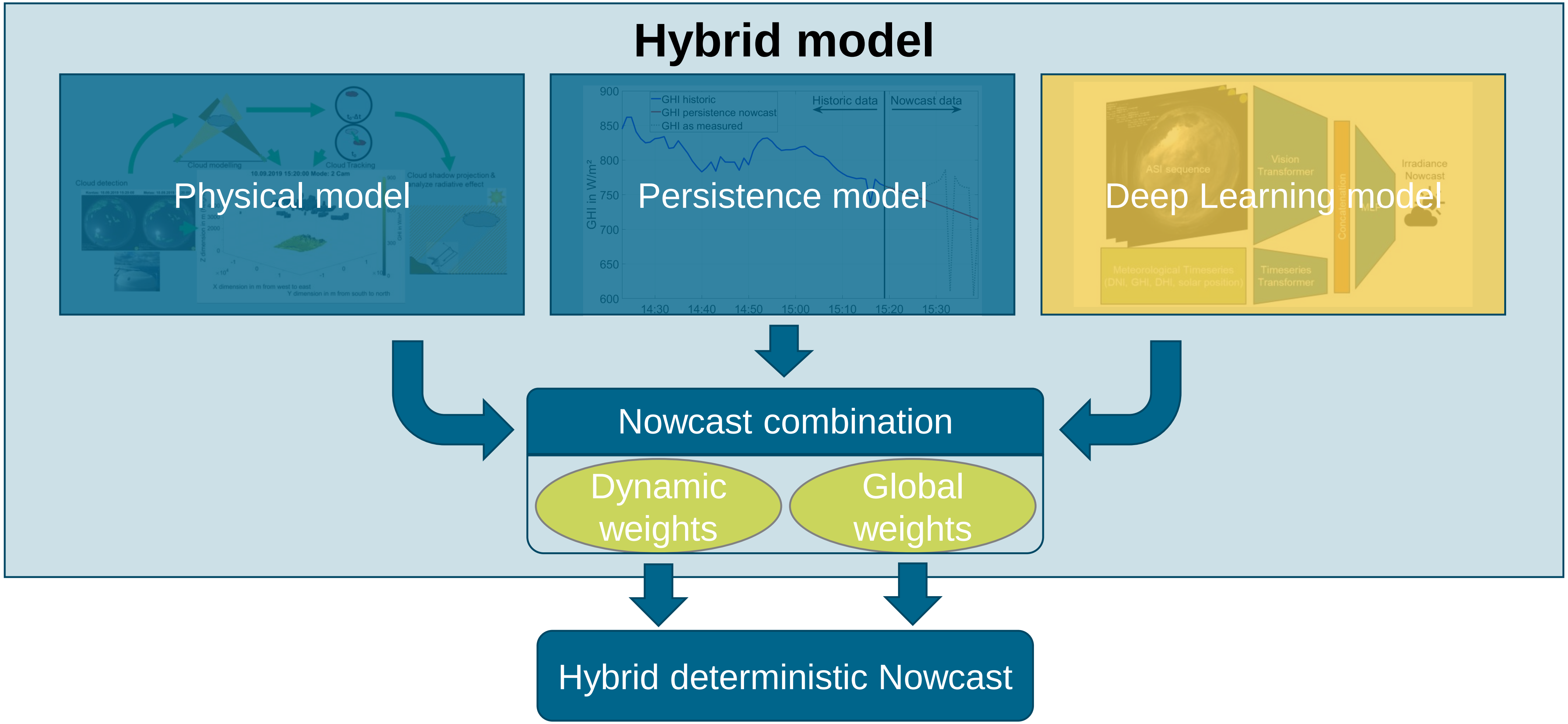
Hybrid Model







Hybrid Model

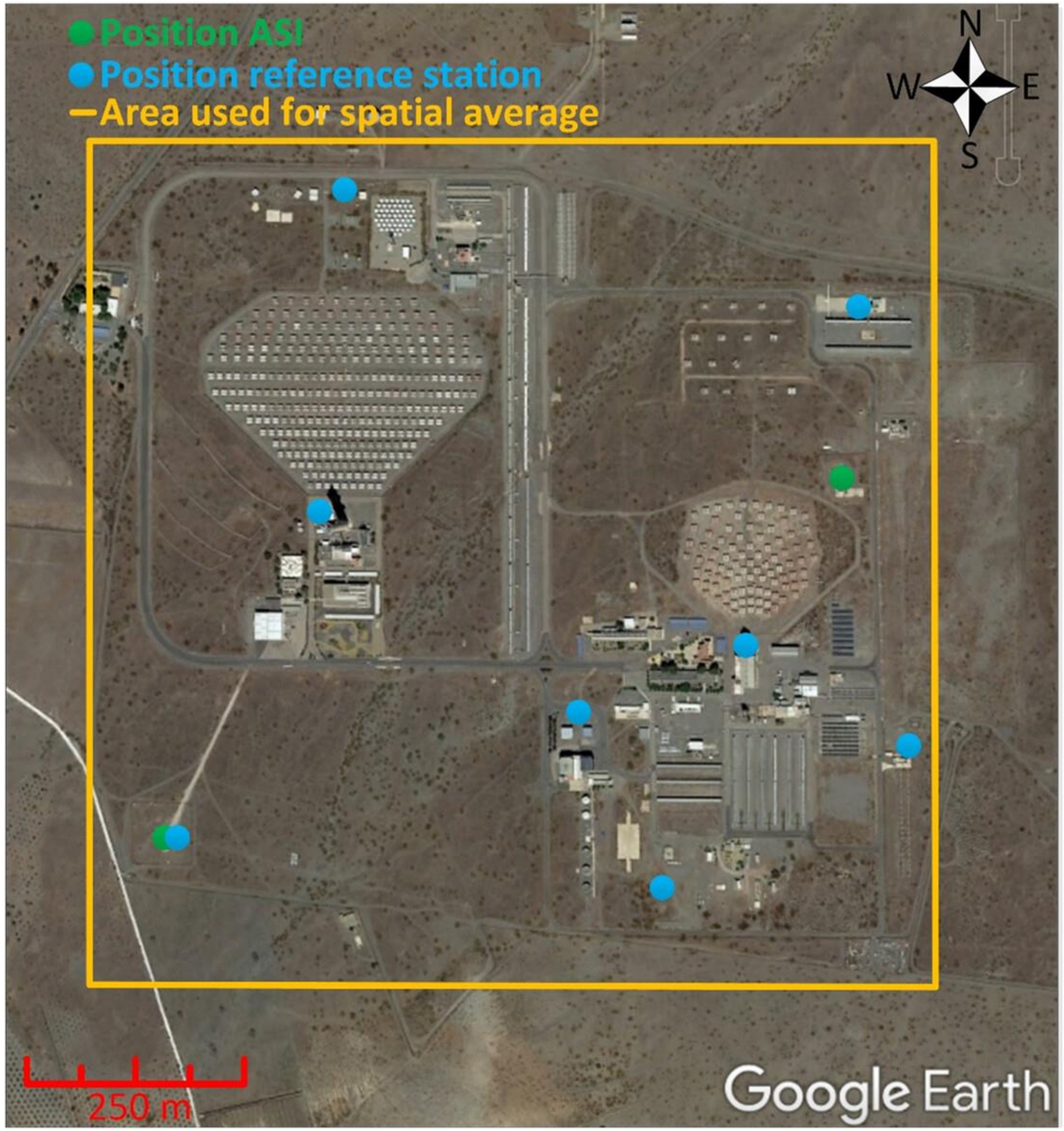


VALIDATION

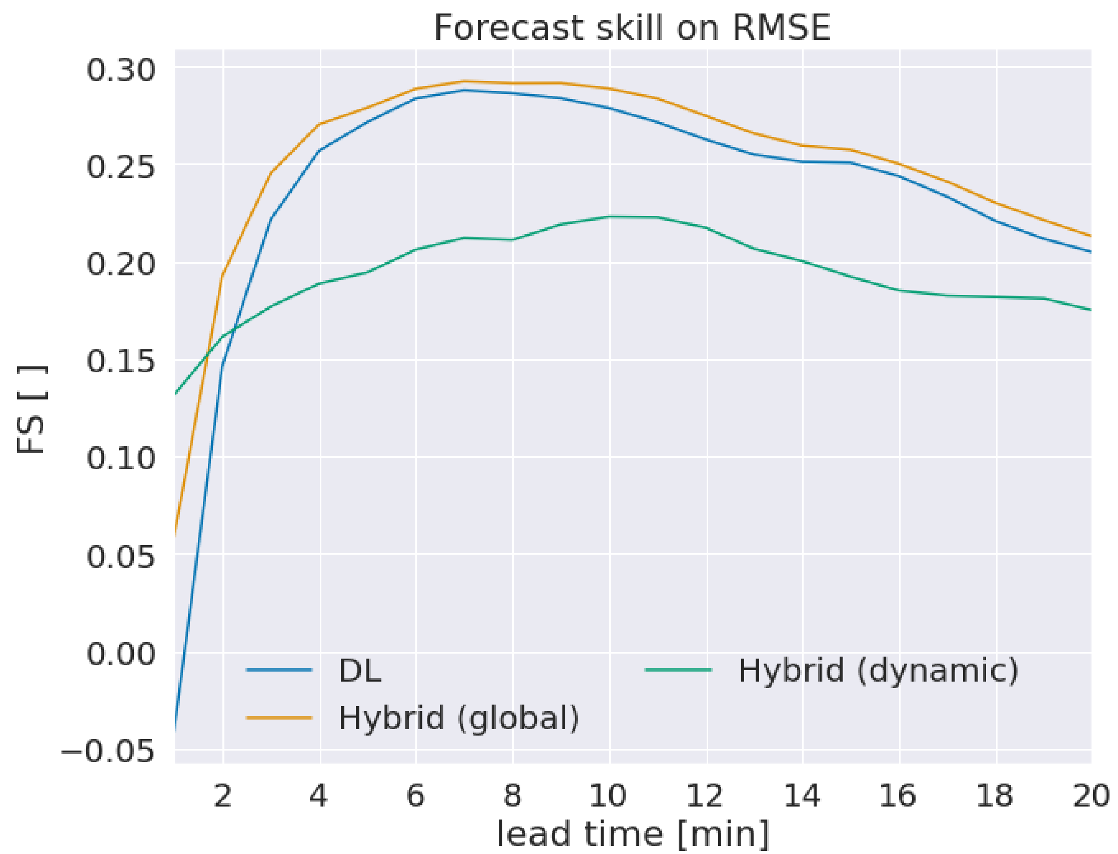
Validation

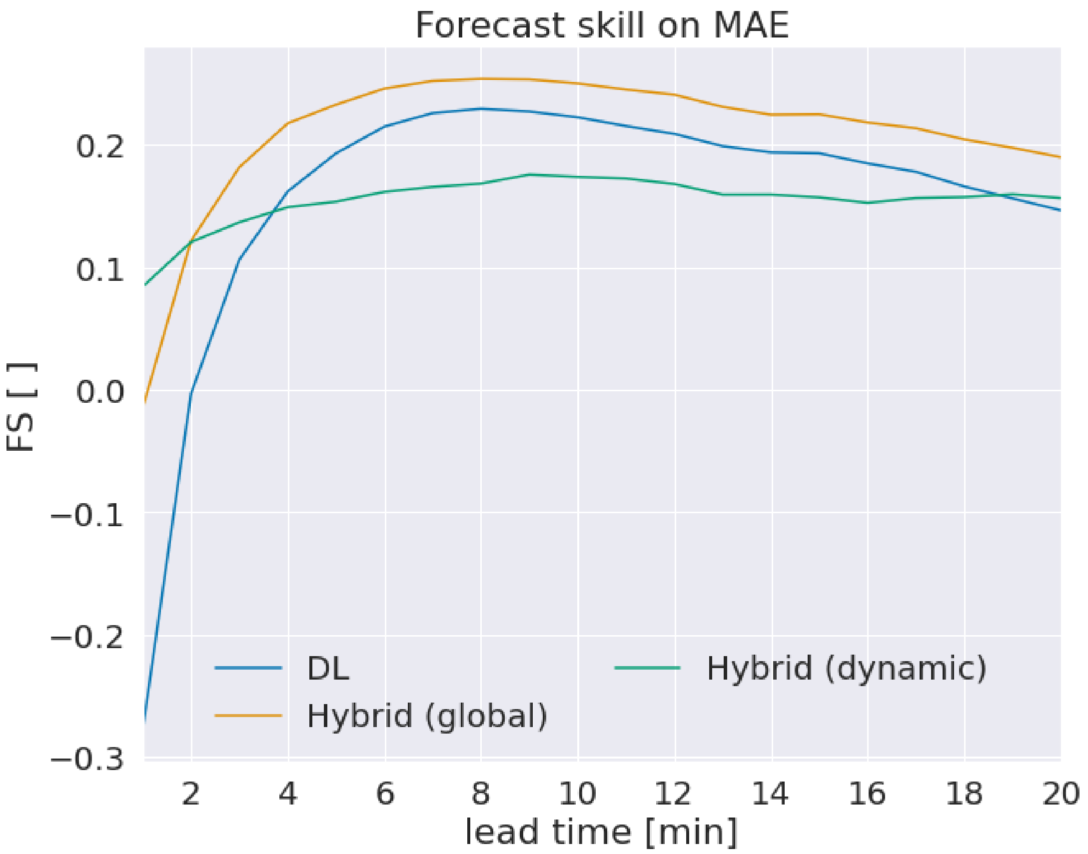
- Comparison of standalone deep learning model with hybrid models (global vs dynamic weights)
- Reference data
  - GHI field average from 9 measurement stations at CIEMAT's PSA (Spain)
  - Benchmark dataset [4]: 28 selected days from 2019 covering different atmospheric conditions
- Validation metric:
  - Forecast skill based on persistence

$$FS = 1 - \frac{error_{model}}{error_{persistence}}$$



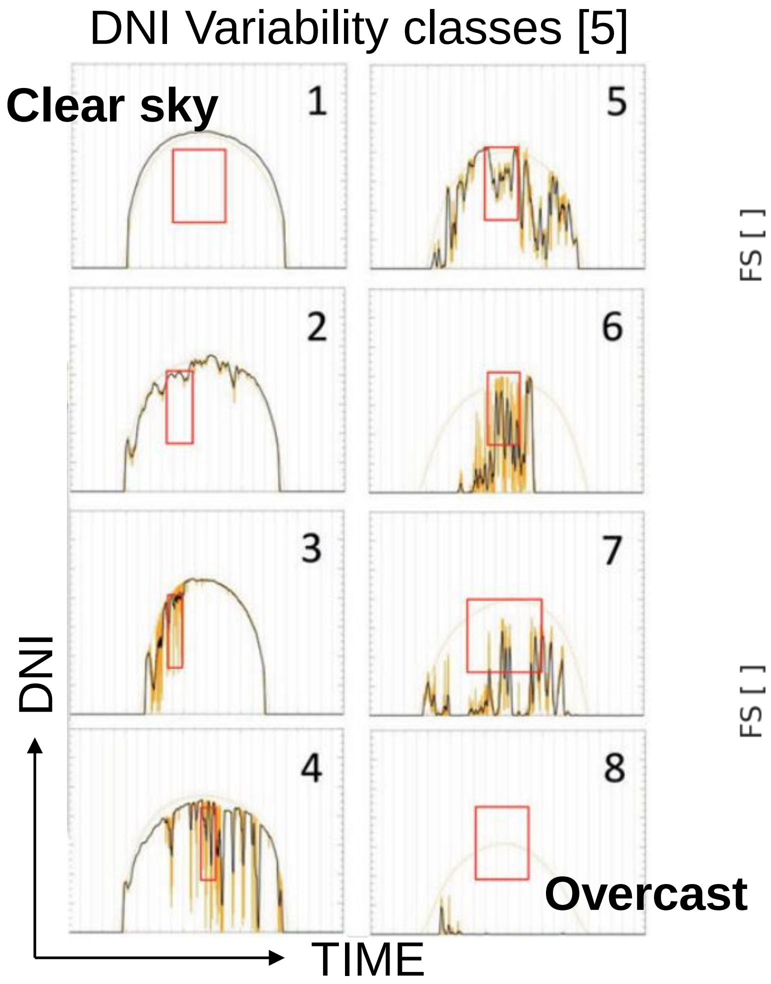
Validation Results

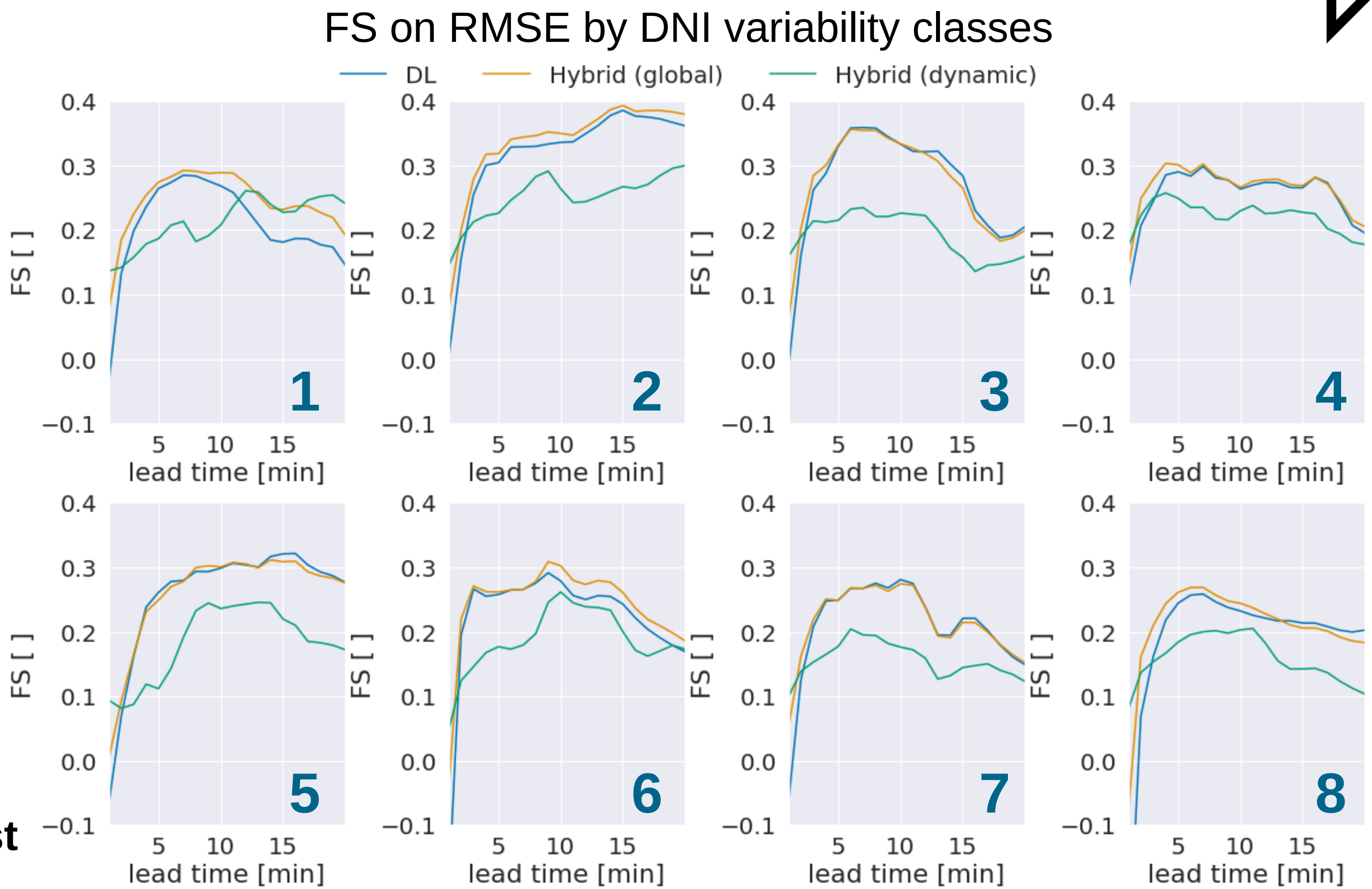




- DL point forecasts work well on field average (optimization on MSE leads to low RMSE)
- Forecast quality of hybrid models depends on combination method
- Generally persistence is already quite good in the first minutes → lower FS for all models

Validation Results





- DNI variability classification as representation of different cloud conditions
- Generally higher FS for more variable conditions
- Difference between Hybrid (dynamic) and Hybrid (global)/DL greater for variable conditions

CONCLUSION

Conclusion

Study presents a benchmark of purely data-driven and hybrid models confirming potential for data-driven models in solar nowcasting

For limited regions (~1km²) data-driven point forecasts can compete with spatial forecasts from physical models in terms of FS

Advantage of hybrid models strongly depends on combination of nowcasts

Forecast skills assess nowcast quality only partially
→ further metrics need to be established in solar nowcasting community

Analysis of probabilistic nowcasts shows benefit from deep learning model [6]

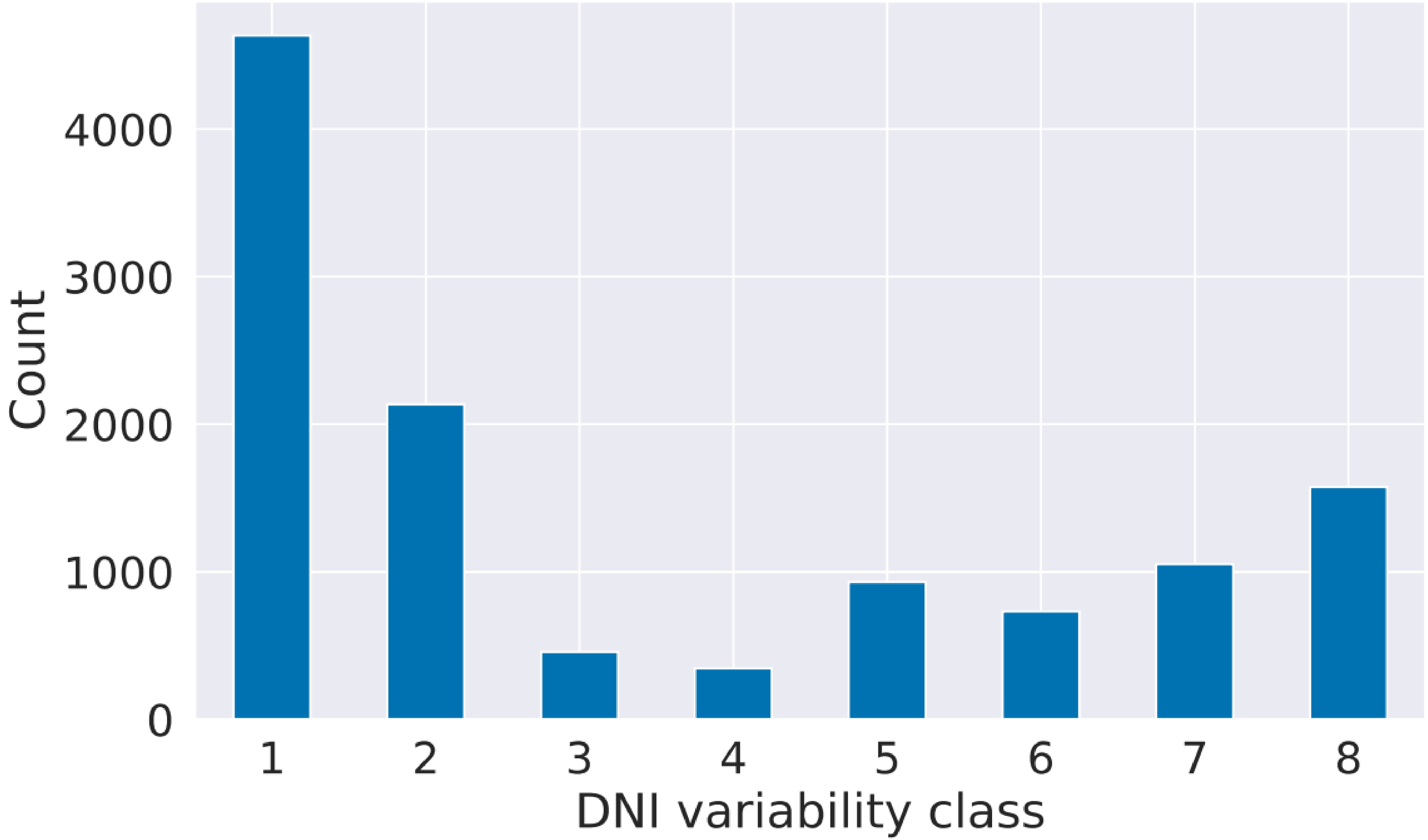
THANK YOU FOR YOUR ATTENTION

References

1. Nouri, B. / Blum, N. / Wilbert, S. / Zarzalejo, L. F., 2022
   A Hybrid Solar Irradiance Nowcasting Approach: Combining All Sky Imager Systems and Persistence Irradiance Models for Increased Accuracy
2. Bertasius, G. / Wang, H. / Torresani, L., 2021
   Is Space-Time Attention All You Need for Video Understanding?
3. Zerveas, G. / Jayaraman, S. / Patel, D. / Bhamidipaty, A. / Eickhoff, C., 2021
   A Transformer-based Framework for Multivariate Time Series Representation Learning
4. Logothetis, S. A. / Salamalikis, V. / Wilbert, S. / Remund, J. / Zarzalejo, L. F. / Xie, Y. / Nouri, B. / Ntavelis, E. / Nou, J. / Hendrikx, N. / Visser, L. / Sengupta, M. / Po, M. / Chauvin, R. / Grieu, S. / Blum, N. / van Sark, W. / Kazantzidis, A., 2022
   Benchmarking of solar irradiance nowcast performance derived from all-sky imagers
5. Schroedter-Homscheidt, M. / Kosmale, M. / Jung, S. / Kleissl, J., 2018
   Classifying ground-measured 1 minute temporal variability within hourly intervals for direct normal irradiances
6. Fabel, Yann / Nouri, Bijan / Wilbert, Stefan / Blum, Niklas / Schnaus, Dominik / Triebel, Rudolph / Zarzalejo, Luis F. / Ugedo, Enrique / Kowalski, Julia / Pitz-Paal, Robert, 2023, *(Under review)*
   Combining deep learning and physical models: a benchmark study on all-sky imagerbased solar nowcasting systems

BACKUP SLIDES

DNI Variability Class Distribution

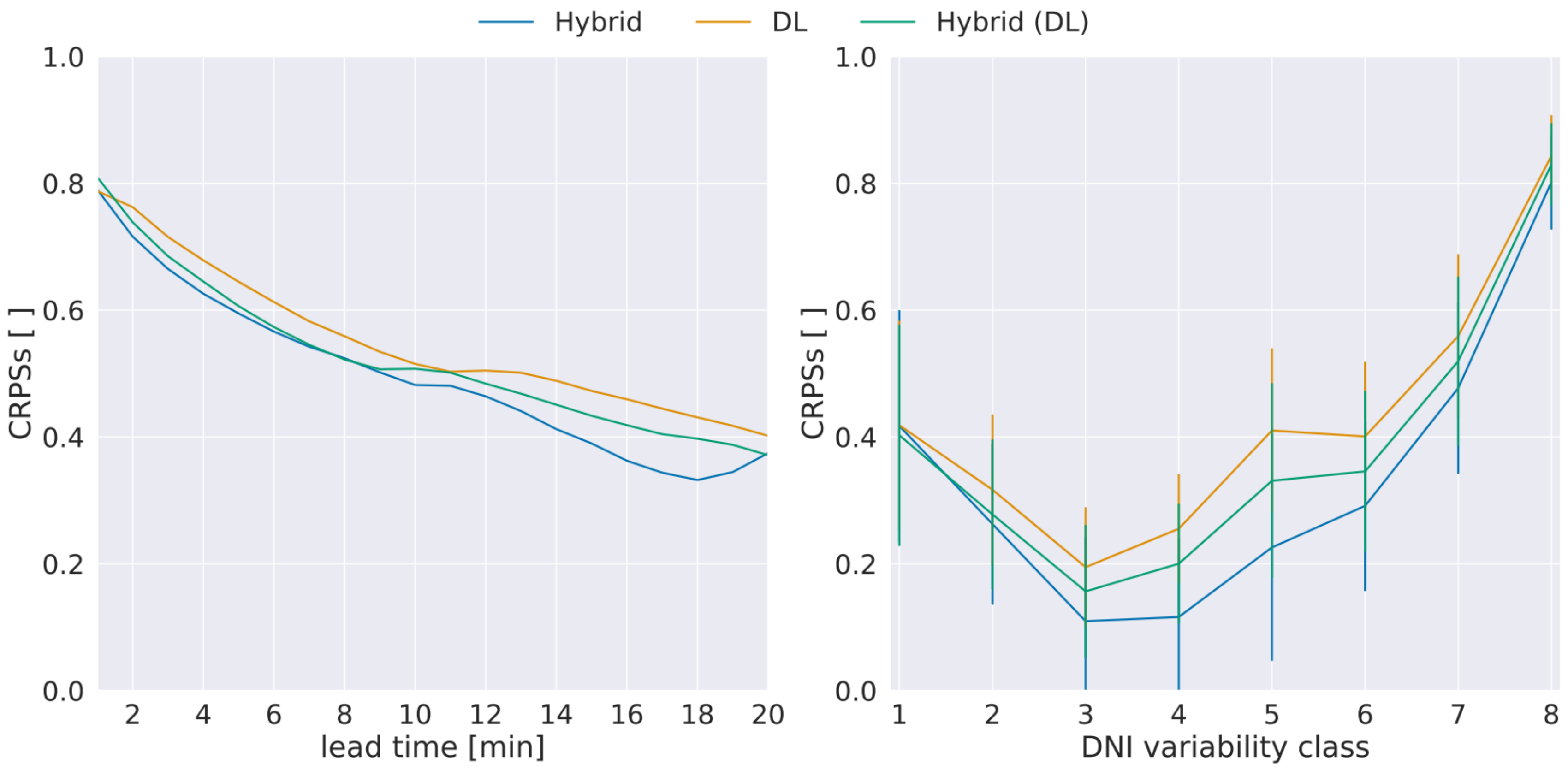


Probabilistic results

$$CRPSs = 1 - \frac{CRPS_{model}}{CRPS_{baseline}}$$

$$CRPS = \frac{1}{N}\sum_{i=1}^{N}\int_0^1 [F_{\hat{y}_i}(x) - F_{y_i}(x)]dx$$

Climatological baseline model:
CSDClim



- DL achieves best CRPSs in terms of lead time and discretized by DNI variability classes
- Higher values for CRPSs under less variable conditions indicate less uncertainty