ALL-SKY IMAGER BASED IRRADIANCE NOWCASTS: COMBINING A PHYSICAL AND A DEEP LEARNING MODEL

IEA PVPS Task 16 All Sky Imagers Benchmarking

15.12.2022

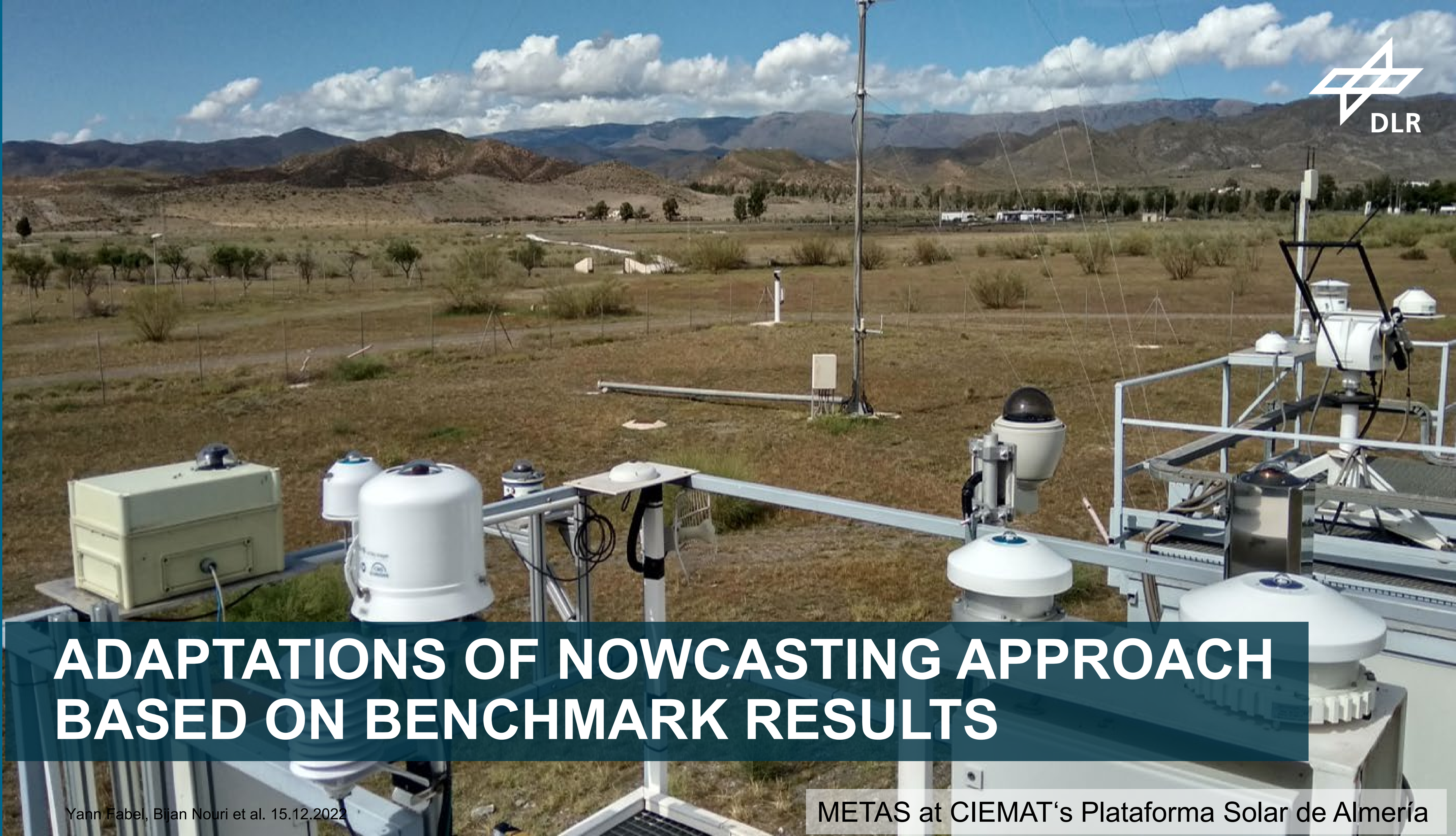
Yann Fabel[1], Bijan Nouri[1], Stefan Wilbert[1], Niklas Blum[1], Luis F. Zarzalejo[2], Robert Pitz-Paal[1]

1) DLR Institute of Solar Research 2) CIEMAT Energy Department – Renewable Energy Division

DLR

Agenda

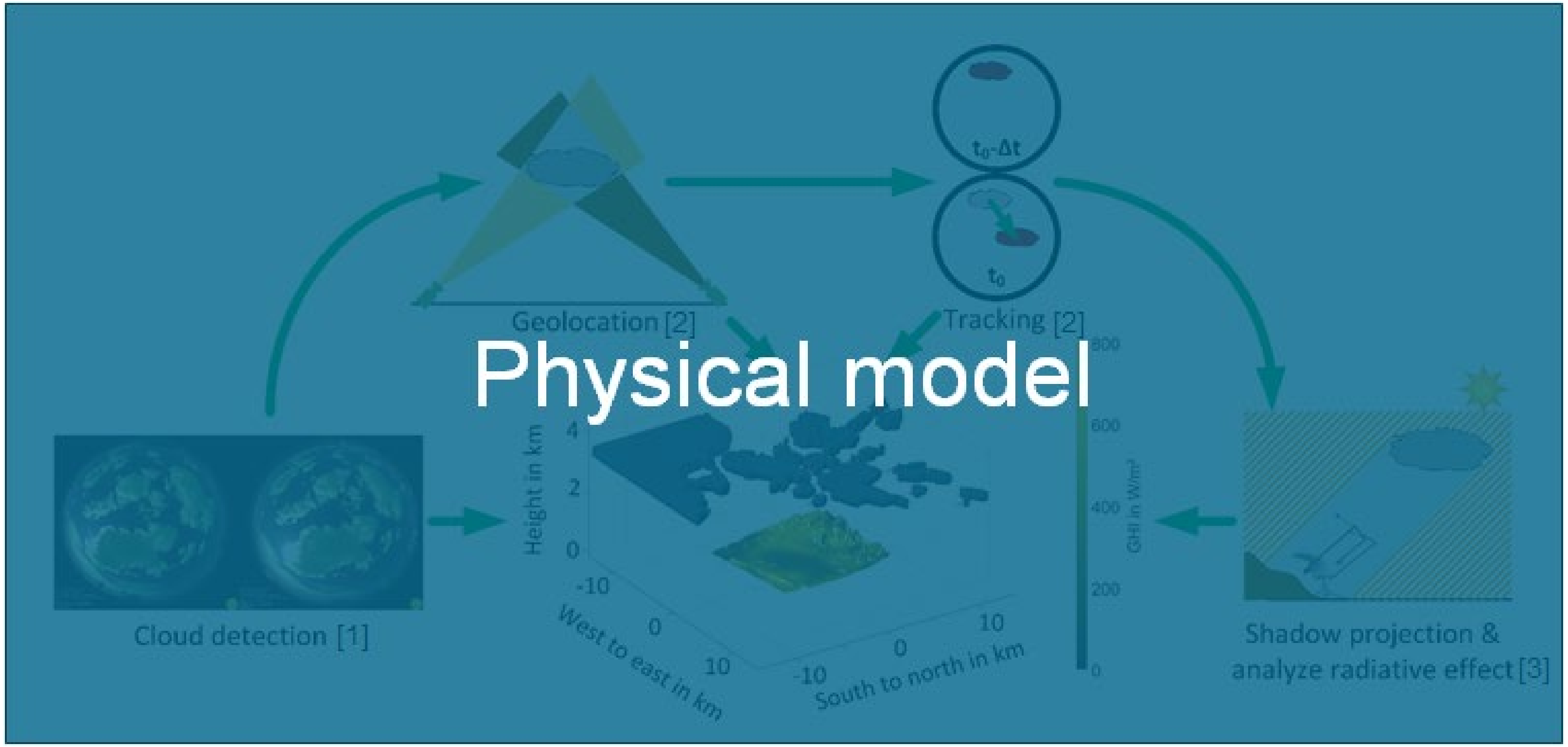
- Adaptations of nowcasting approach based on benchmark results
  - Physical-based approach
  - Machine learning-based approach
- Improvement compared to benchmark status
  - Skill score
  - Ramp rate
- Conclusion



ADAPTATIONS OF NOWCASTING APPROACH BASED ON BENCHMARK RESULTS

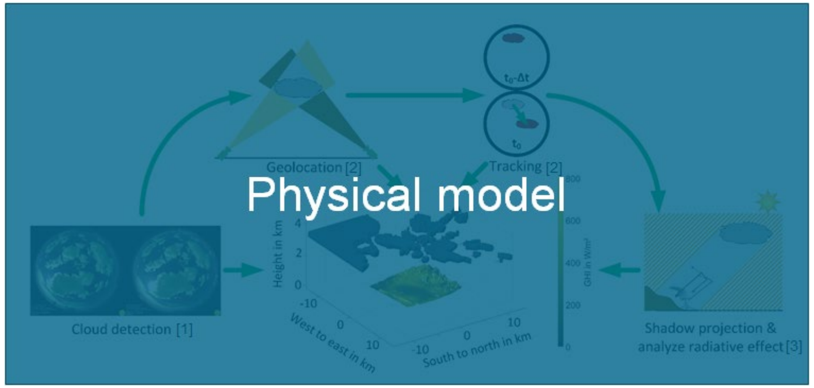
METAS at CIEMAT‘s Plataforma Solar de Almería

Overview– A physical nowcasting approach



Overview – A hybrid nowcasting approach

Hybrid model as used during the benchmark



Combined hybrid nowcasts using an accuracy weighting approach [4]

- Real-time validation over recent past (5 min windows)
- Lead time 0 min as reference
- $RMSE_{LTX,j} = \left[\frac{1}{n}\sum_{i=1}^{n}\left(GHI_{LT0}(t_i) - GHI_{LTX,j}(t_i)\right)^2\right]^{0.5}$
- $GHI_{LTX} = \frac{1}{\sum_{j=1}^{2}\frac{1}{RMSE_{LTX,j}}} \cdot \sum_{j=1}^{2}\frac{GHI_{LTX,j}}{RMSE_{LTX,j}}$

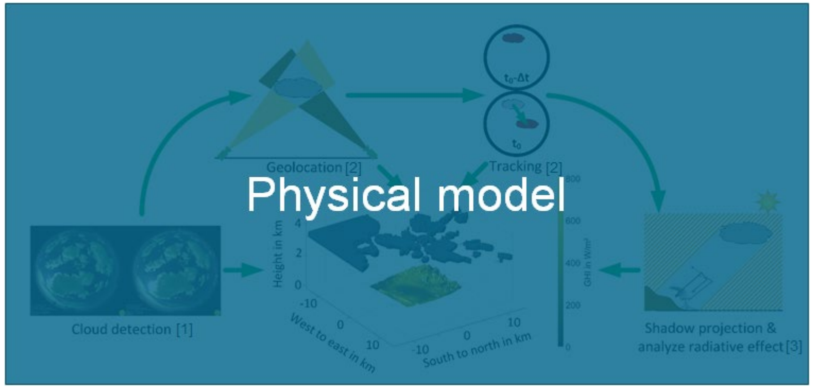
Persistence model

Hybrid model

The hybrid approaches exploit clear divisions in strengths between fundamentally distinct models for distinct prevailing conditions and outperform each model by itself.

Overview – A improved hybrid nowcasting approach

Improved hybrid model developed after the benchmark



Combined hybrid nowcasts using an accuracy weighting approach [4]

- Real-time validation over recent past (5 min windows)
- Lead time 0 min as reference
- $RMSE_{LTX,j} = \left[\frac{1}{n}\sum_{i=1}^{n}\left(GHI_{LT0}(t_i) - GHI_{LTX,j}(t_i)\right)^2\right]^{0.5}$
- $GHI_{LTX} = \frac{1}{\sum_{j=1}^{2}\frac{1}{RMSE_{LTX,j}}} \cdot \sum_{j=1}^{2}\frac{GHI_{LTX,j}}{RMSE_{LTX,j}}$

Persistence model

Machine learning model

Hybrid model

The hybrid approaches exploit clear divisions in strengths between fundamentally distinct models for distinct prevailing conditions and outperform each model by itself.

End-to-end Nowcasting – A data-driven approach

Sky images

Cloud detection

Cloud modelling

Cloud tracking

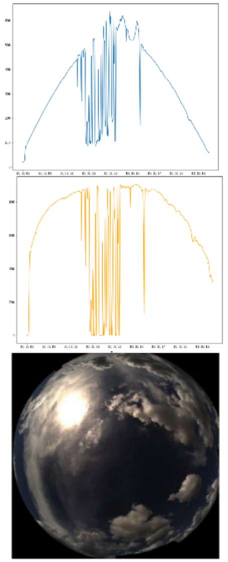
Shadow projection

Allocation of cloud transmittance

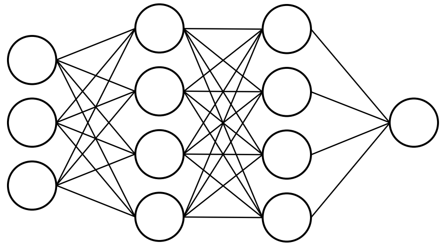
Irradiance nowcast

Time series data

- **Use end-to-end machine learning (ML) models to generate nowcast directly from raw data**
  - ML models are trained on large amounts of observations or features extracted from observations to learn patterns in the data



(Feature Extraction)

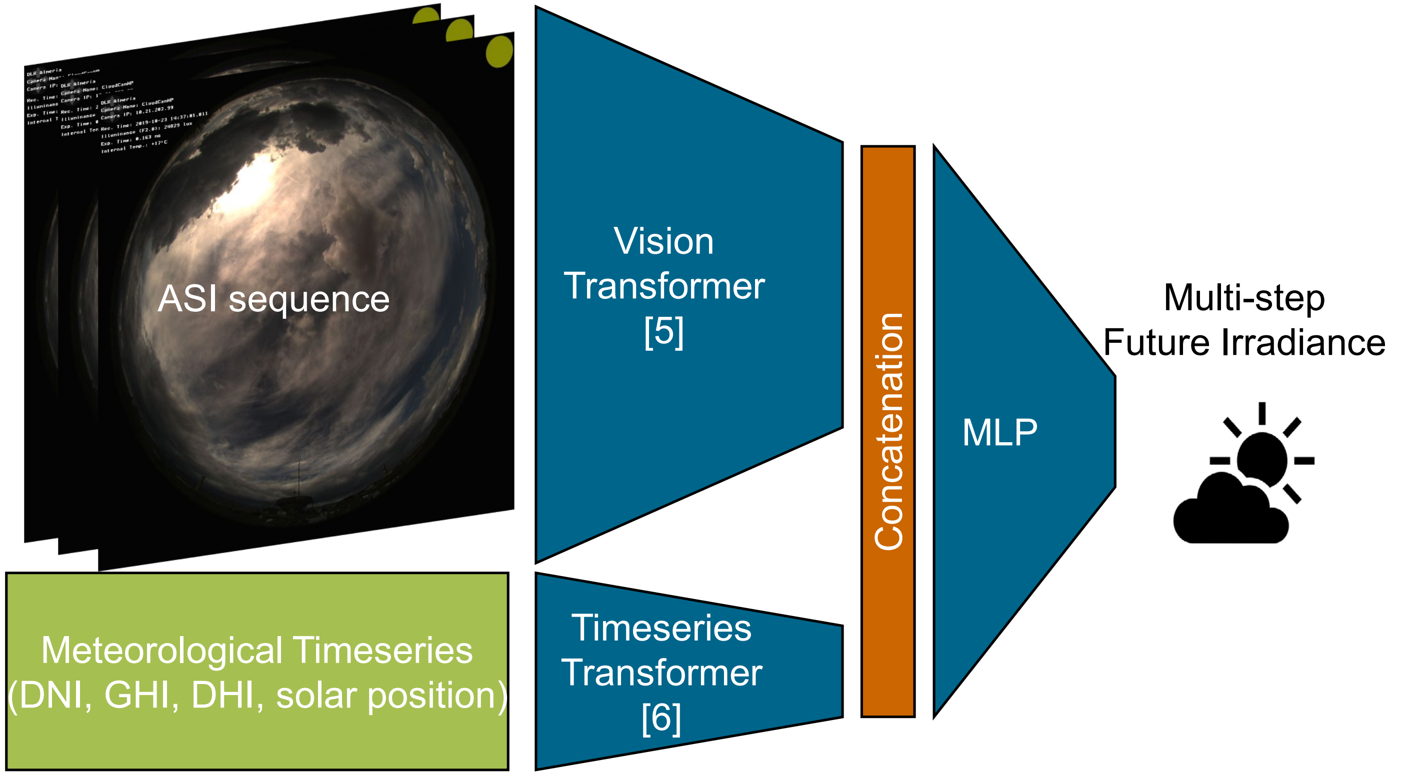


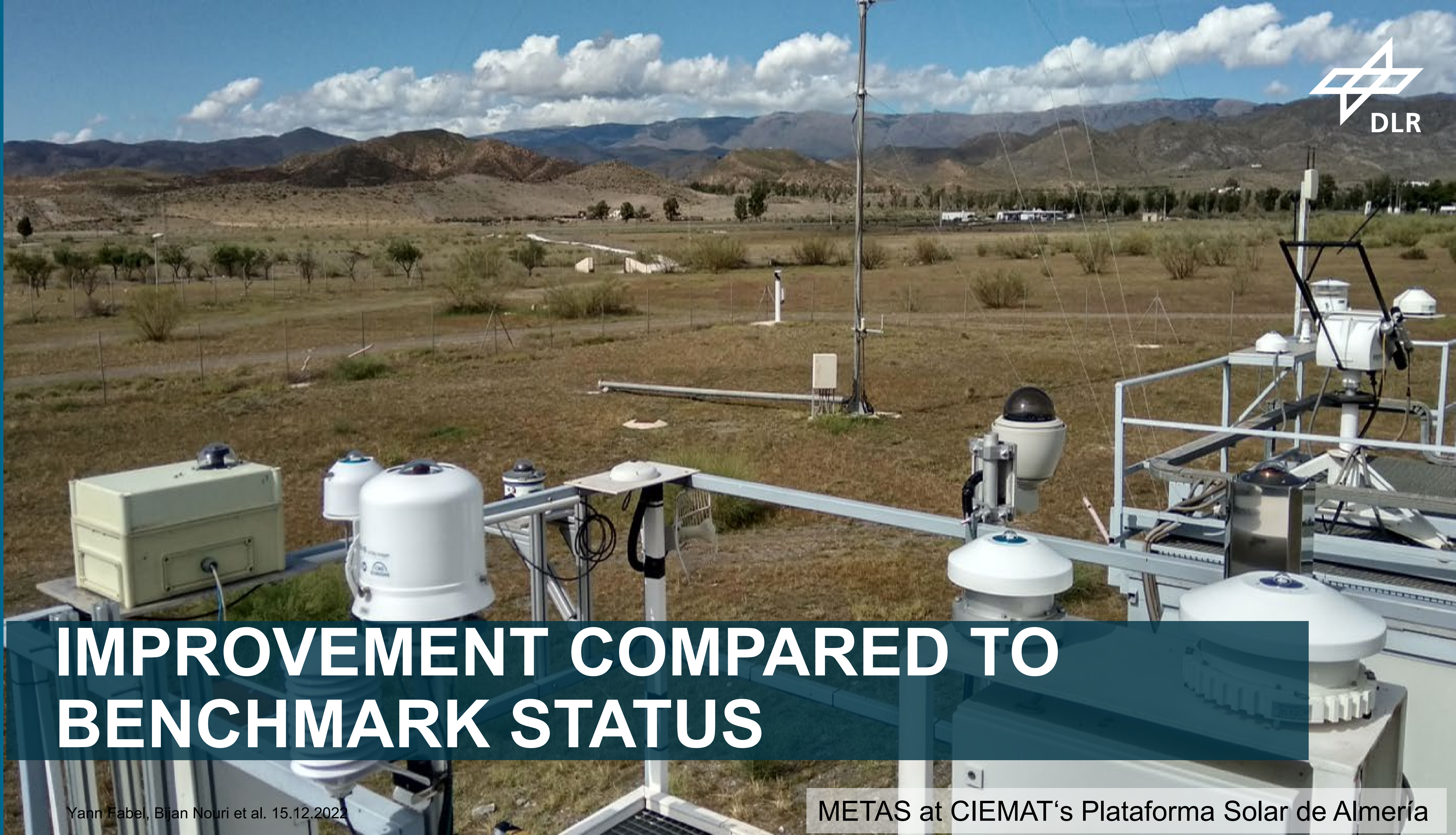
Irradiance nowcast

Multi-modal Deep Learning Model

<u>Solution approach:</u>
- Combined Vision Transformer and Timeseries Transformer
  - Vision Transformer
    - Input: 5 min all-sky imager (ASI) sequence
    - Output: Feature vector (512x1)
  - Time Series Transformer
    - Input: 30 min time series
    - Output: Feature vector (512x1)
  - Combination via a multilayer perceptron (MLP)
    - Input: stacked feature vectors
    - Output: 20min GHI/DNI

Training Size: ~ 400 000 data points (filtered data from 2016-2019)



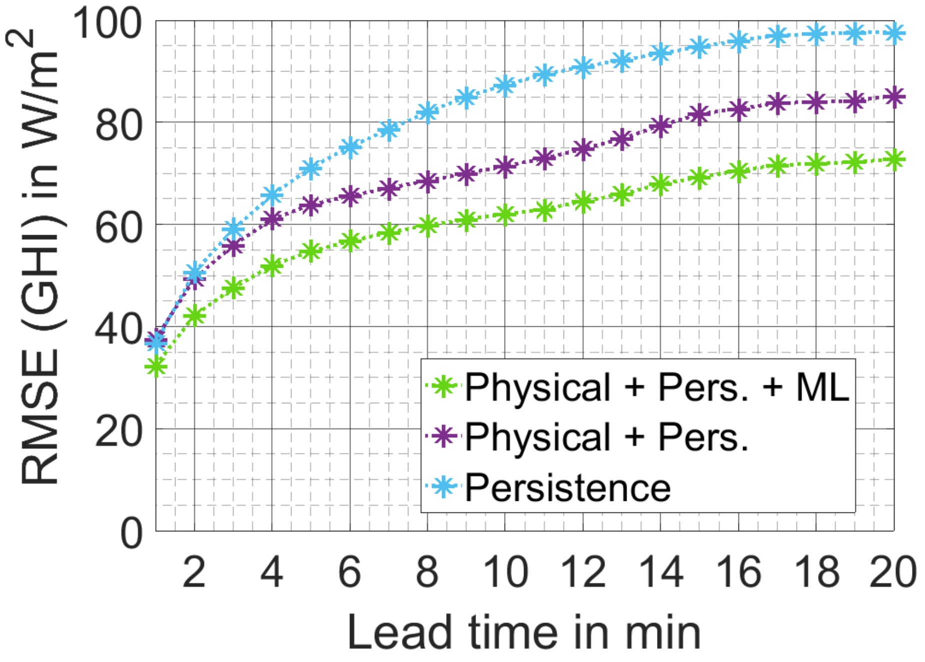


IMPROVEMENT COMPARED TO BENCHMARK STATUS

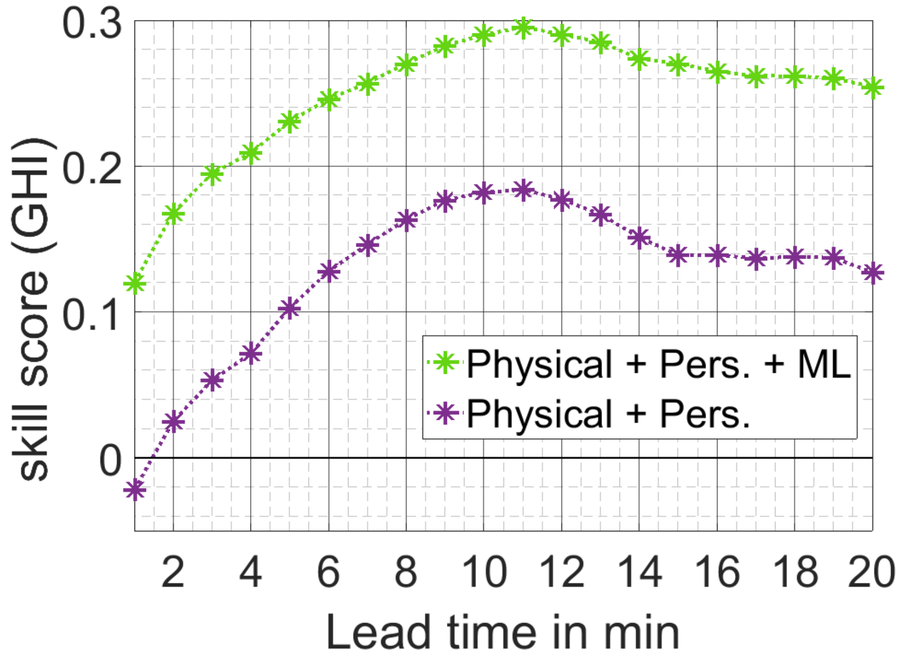
METAS at CIEMAT‘s Plataforma Solar de Almería

Comparison of hybrid nowcasting approaches – skill score

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}$$



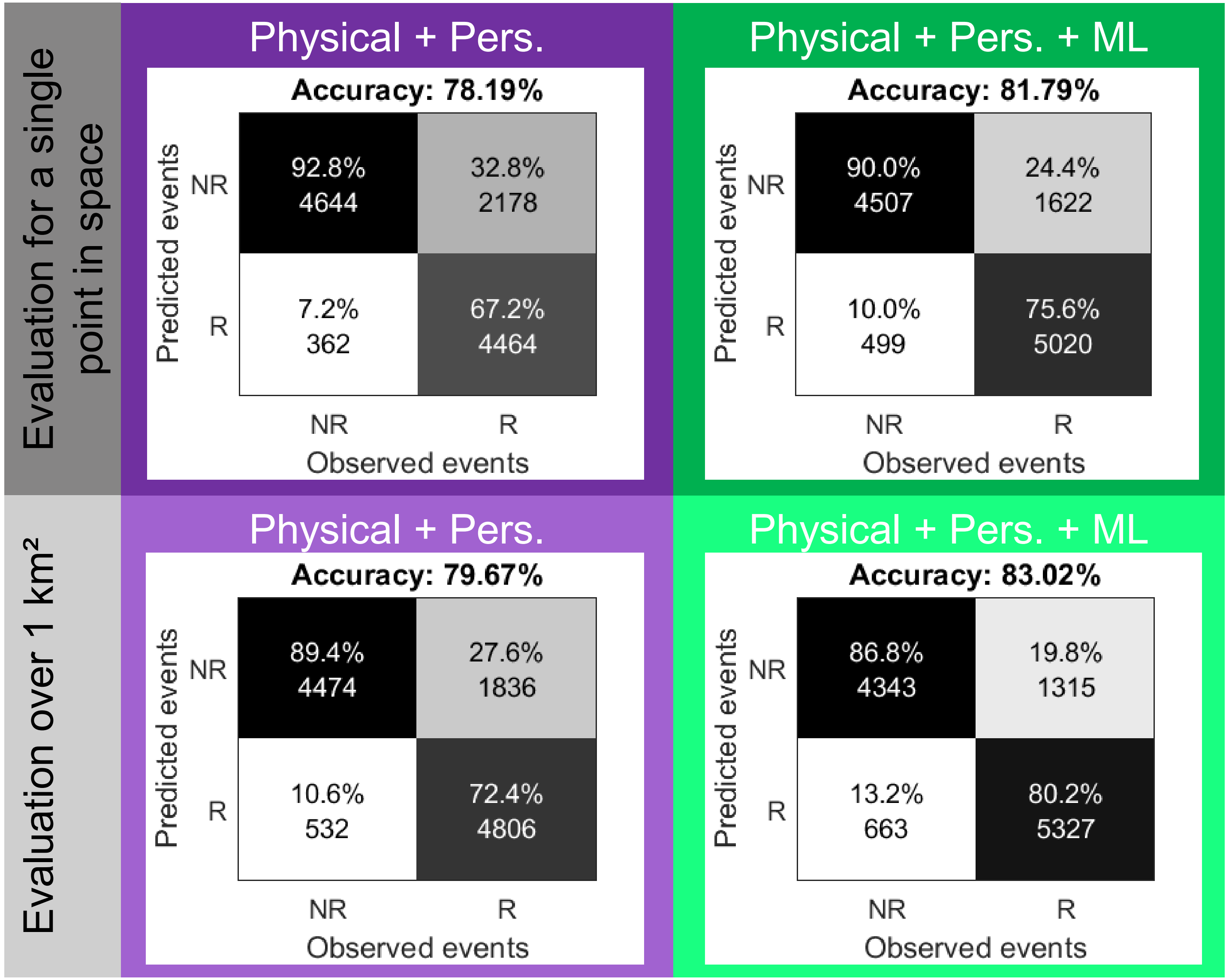
$$skill\ score = 1 - \frac{RMSE_{Model}}{RMSE_{Pers.}}$$



- Validation based on 28 day lasting benchmark data set as described in [7]
- Both hybrid approaches show an overall positive skill score
- The approach used during the benchmark archives an average skill score of 12.6±5.5%
- Significant improvements were achieved by the new hybrid approach with an average skill score of 24.9±4.5%

Comparison of hybrid nowcasting approaches – ramp rate

The presented hybrid nowcasting approaches provides spatial resolved irradiance maps with coverages > 60 km².



- Ramp rate validation according to Stavros et al. 2022 [8] (time horizon range 1 to 20 min)
- Overall improvement since the benchmark >3% points in accuracy
- Further improvement >1% point in accuracy when spatial information are considered (1 km²)

METAS at CIEMAT‘s Plataforma Solar de Almería

CONCLUSION

Conclusion

- Possible improvements of the ASI system have been identified based on the benchmark results.
- The hybrid approach used in the benchmark that is based on real-time validation was enhanced.
  - The physical model was not only combined with the smart persistence model as in the original benchmark, but another 3rd method is also included:
    - end-to-end multi-modal deep learning model (combined Vision Transformer and Timeseries Transformer)
- Significant improvements could be reached:
  - Overall skill score improvement >12% points
  - 8% points more ramps are correctly predicted, overall ramp accuracy improvement >3% points
- The hybridization approach exploits strengths of fundamentally distinct models

Thank you!

[1] Fabel, Y., Nouri, B., Wilbert, S., Blum, N., Triebel, R., Hasenbalg, M., ... & Pitz-Paal, R. (2022). Applying self-supervised learning for semantic cloud segmentation of all-sky images.*Atmospheric Measurement Techniques*,*15*(3), 797-809.

[2] Nouri, B., Kuhn, P., Wilbert, S., Hanrieder, N., Prahl, C., Zarzalejo, L., ... & Pitz-Paal, R. (2019). Cloud height and tracking accuracy of three all sky imager systems for individual clouds. *Solar Energy*, *177*, 213-228.

[3] Nouri, B., Wilbert, S., Segura, L., Kuhn, P., Hanrieder, N., Kazantzidis, A., ... & Pitz-Paal, R. (2019). Determination of cloud transmittance for all sky imager based solar nowcasting. *Solar Energy*, *181*, 251-263.

[4] 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. *Solar RRL*, *6*(5), 2100442.

[5] Bertasius, G., Wang, H., & Torresani, L. (2021, July). Is space-time attention all you need for video understanding?. In *ICML* (Vol. 2, No.3, p. 4).

[6] Zerveas, G., Jayaraman, S., Patel, D., Bhamidipaty, A., & Eickhoff, C. (2021, August). A transformer-based framework for multivariate time series representation learning. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining* (pp. 2114-2124).

[7] Logothetis, S. A., Salamalikis, V., Wilbert, S., Remund, J., Zarzalejo, L. F., Xie, Y., ... & Kazantzidis, A. (2022). Benchmarking of solar irradiance nowcast performance derived from all-sky imagers. *Renewable Energy*, *199*, 246-261.

[8] Logothetis, S. A., Salamalikis, V., Nouri, B., Remund, J., Zarzalejo, L. F., Xie, Y., ... & Kazantzidis, A. (2022). Solar Irradiance Ramp Forecasting Based on All-Sky Imagers. *Energies*, *15*(17), 6191.

Bundesministerium für Wirtschaft und Klimaschutz

The benchmark was funded within the WobaS-A project (GA no. 0324307A)
The recent developments presented here received funding within the SolarFuelNow project (GA no. 03EE5042A)

Comparison of hybrid nowcasting approaches – skill score

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \qquad Bias = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_i - y_i$$

$$SS_{RMSE} = 1 - \frac{RMSE_{Model}}{RMSE_{Pers.}}$$

$$SS_{MAE} = 1 - \frac{MAE_{Model}}{MAE_{Pers.}}$$