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

IEA PVPS Task 16 All Sky Imagers Benchmarking

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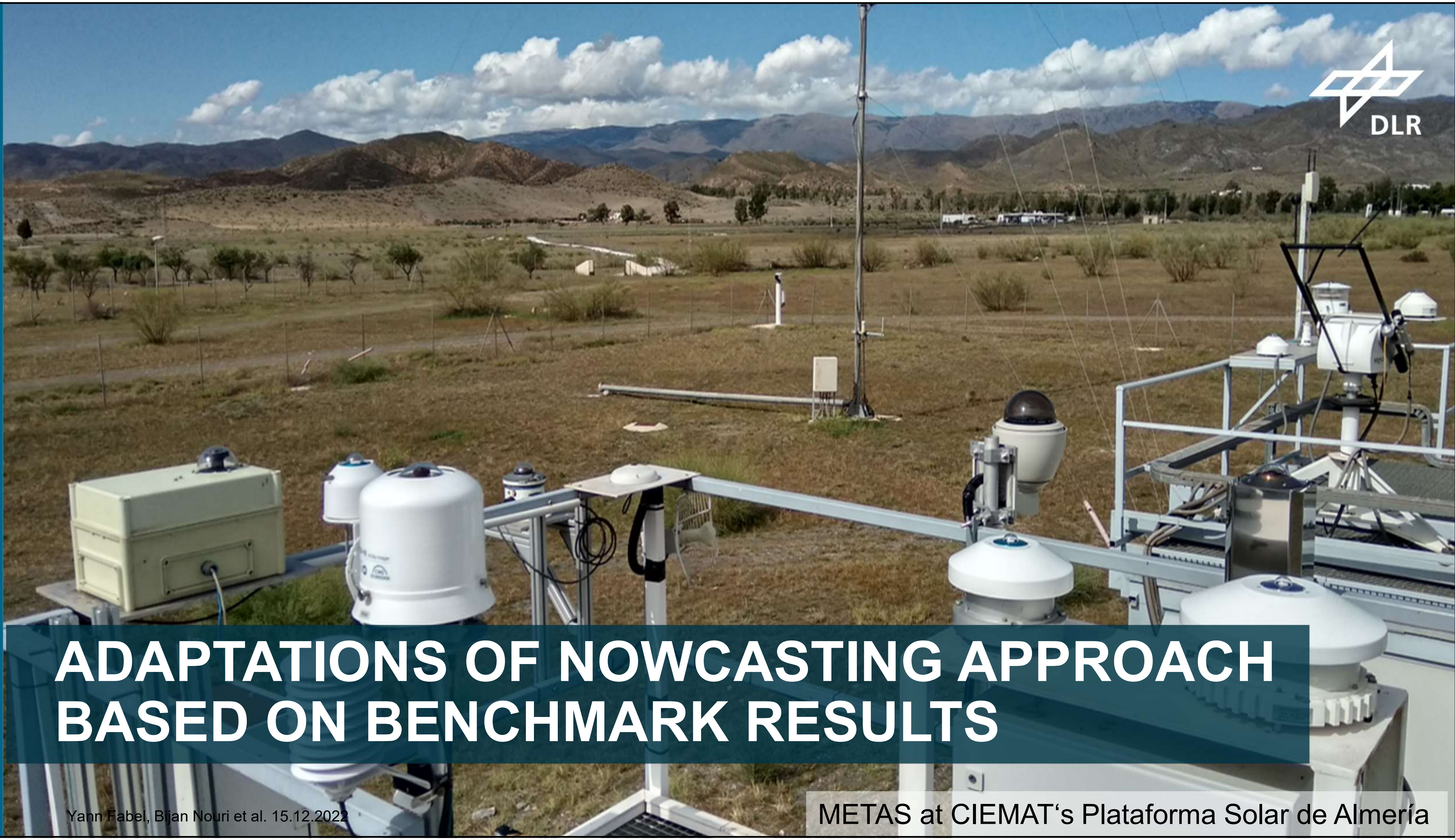
DLR

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



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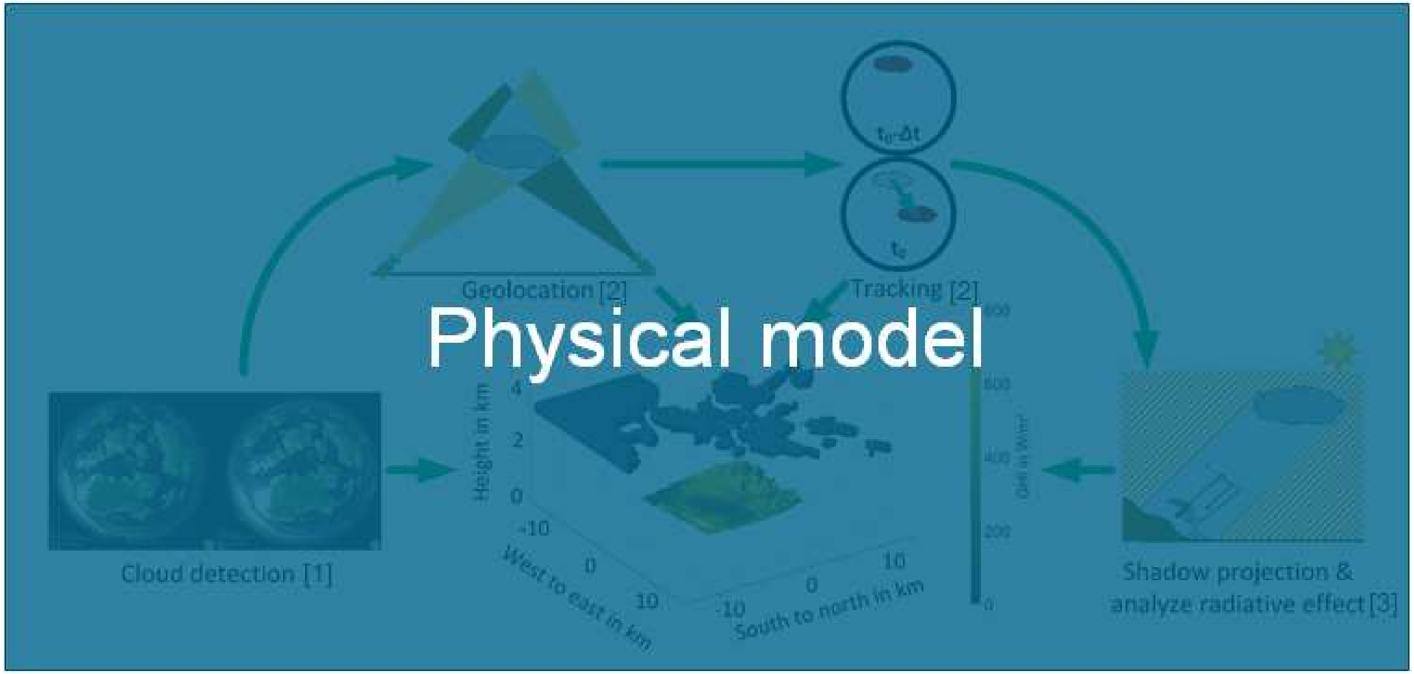
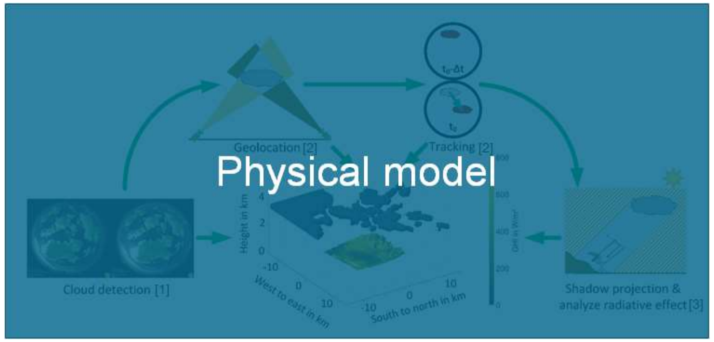
Overview– A physical nowcasting approach



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
- $RMSE_{LTX,j} = \left[\frac{1}{n}\sum_{i=1}^{n}\left(GHI_{LT0}(t_i) - GHI_{LTX,j}(t_i)\right)^2\right]^{0.5}$
- $GHI_{LTX} = \frac{1}{\sum_{j=1}^{2}\frac{1}{RMSE_{LTX,j}}} \cdot \sum_{j=1}^{2}\frac{GHI_{LTX,j}}{RMSE_{LT\ \ ,j}}$

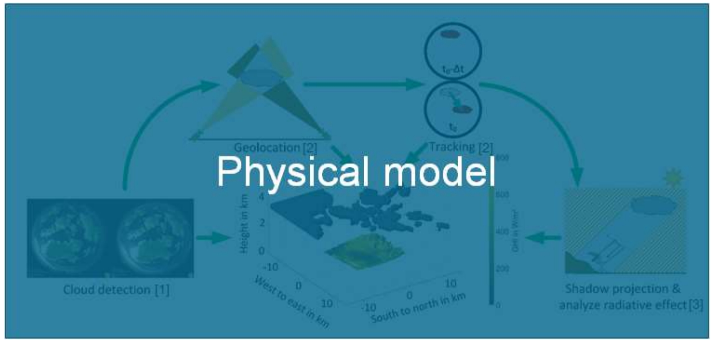
Persistence model

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
- $RMSE_{LT\ ,j} = \left[\frac{1}{n}\sum_{i=1}^{n}\left(GHI_{LT0}(t_i) - GHI_{LTX,j}(t_i)\right)^2\right]^{0.5}$
- $GHI_{LT} = \frac{1}{\sum_{j=1}^{2}\frac{1}{RMSE_{LTX,j}}} \cdot \sum_{j=1}^{2}\frac{GHI_{LT\ ,j}}{RMSE_{LTX,j}}$

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

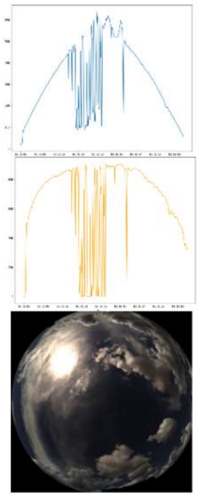
Shadow projection

Allocation of cloud transmittance

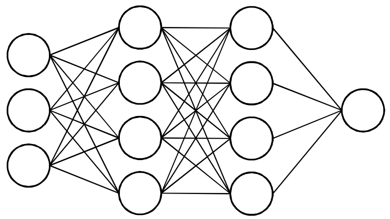
Irradiance nowcast

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)



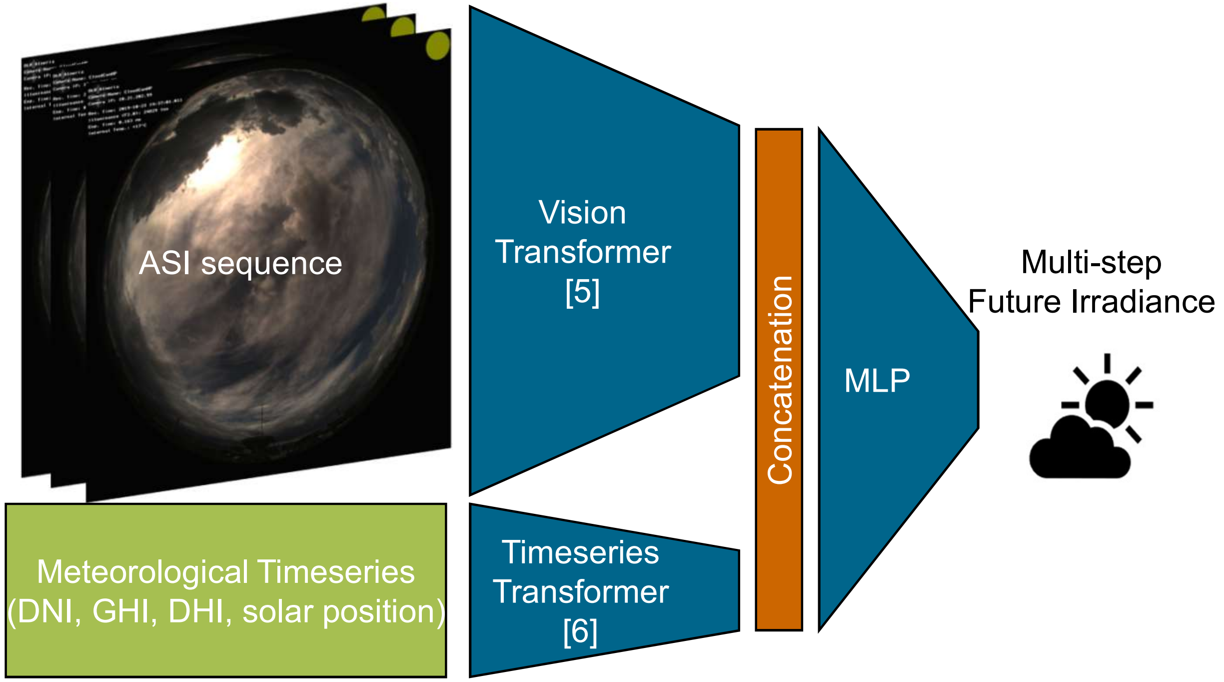
Irradiance nowcast

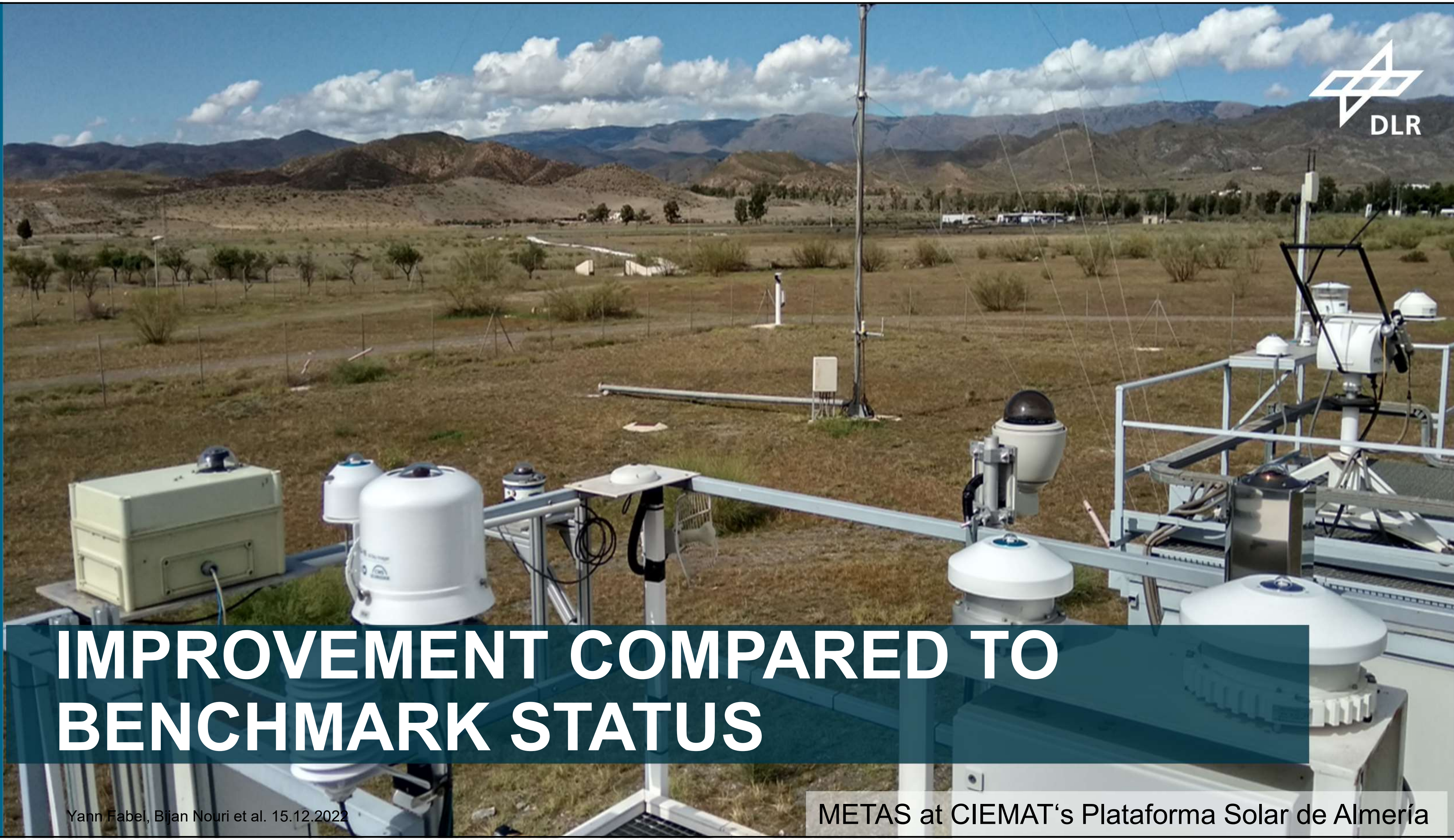
Multi-modal Deep Learning Model

Solution approach:

- 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

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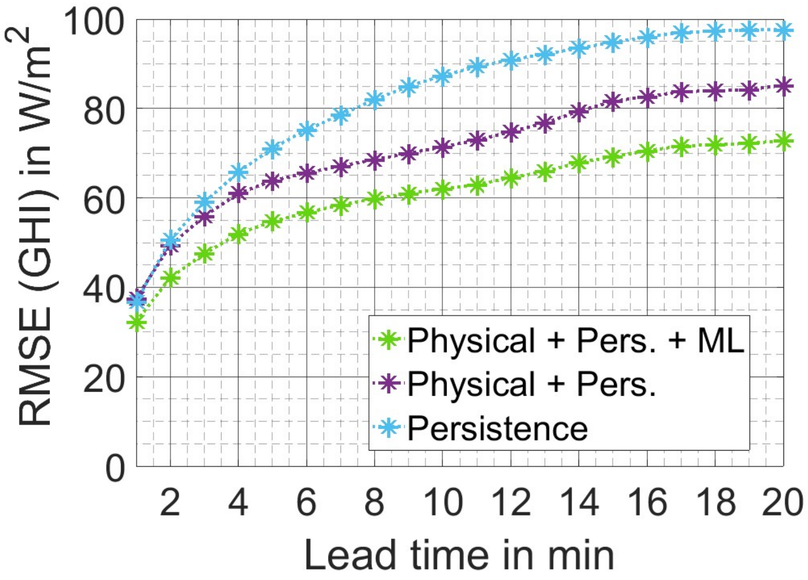
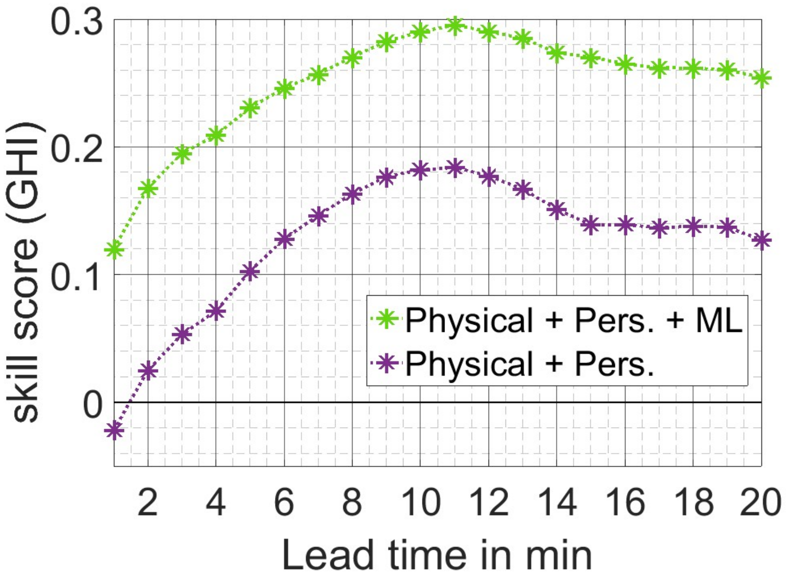
Comparison of hybrid nowcasting approaches – skill score

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



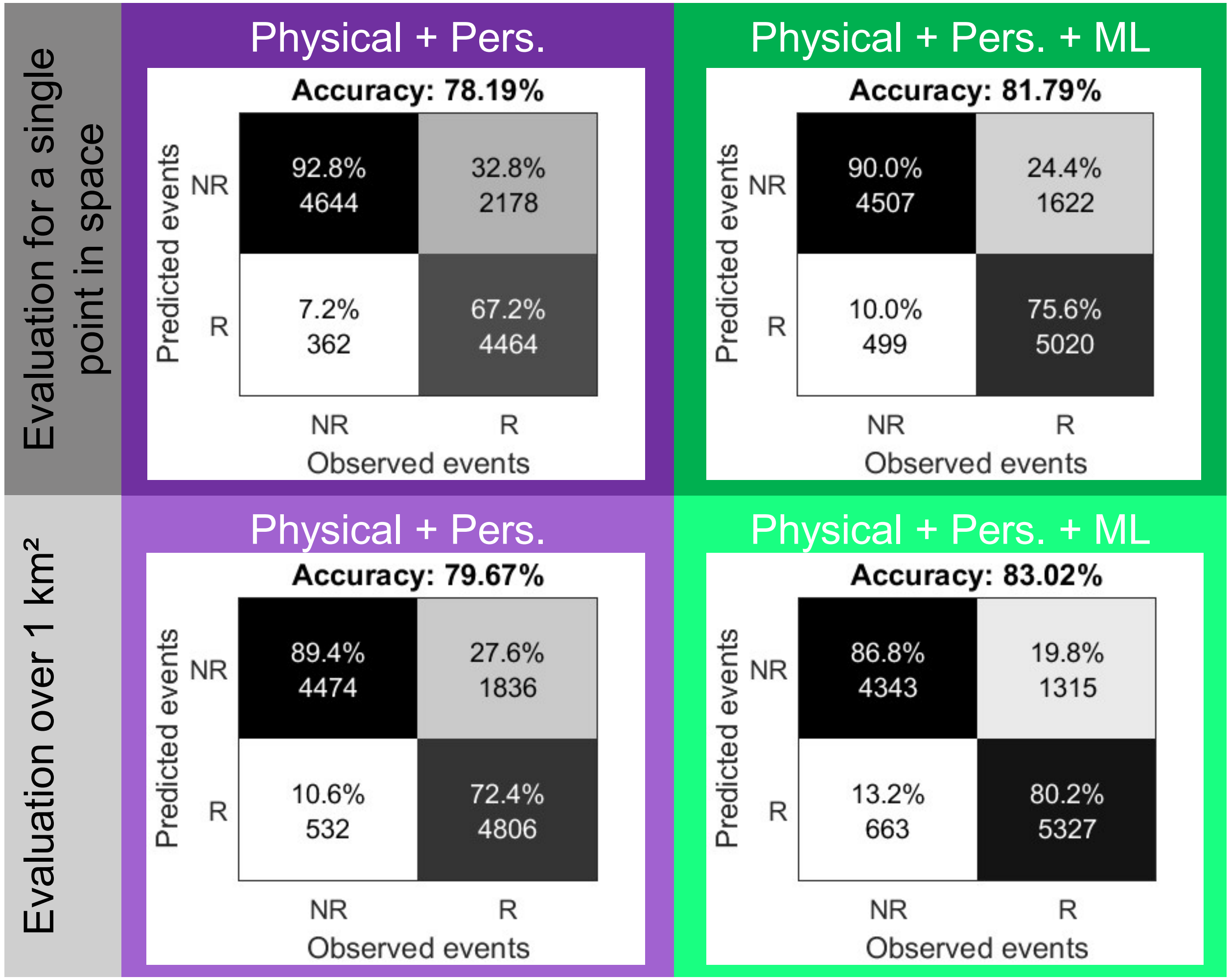
$$skill\ score = 1 - \frac{RMSE_{Model}}{RMSE_{Pers.}}$$



- 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)

CONCLUSION

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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!

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[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.

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Comparison of hybrid nowcasting approaches – skill score

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

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

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

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