

LEVERAGING GENERATIVE MODELS FOR ASI-BASED SOLAR NOWCASTING

Yann Fabel, Dominik Schnaus, Bijan Nouri, Stefan Wilbert, Niklas Blum, Luis F. Zarzalejo, Robert Pitz-Paal

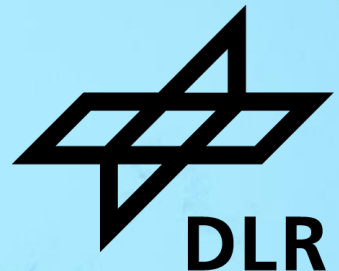
EMS Meeting 2024

4th of September 2024, Barcelona, Spain

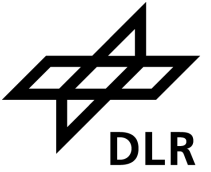


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Agenda



- Motivation for Solar Nowcasting
- Generative Nowcasting Approach
- Qualitative Analysis of Generative Model
- Quantitative Evaluation
- Conclusion & Outlook

The background of the slide is a photograph of a solar field. Large, rectangular solar panels are mounted on metal poles in a grassy field. The panels are tilted and reflect the sky. The sky is blue with some light clouds. The foreground is filled with green grass and small yellow flowers.

MOTIVATION FOR SOLAR NOWCASTING

Motivation

What is solar nowcasting?

- Forecast of solar irradiance (e.g. GHI) for the next minutes

What are ramp events and what are their effects?

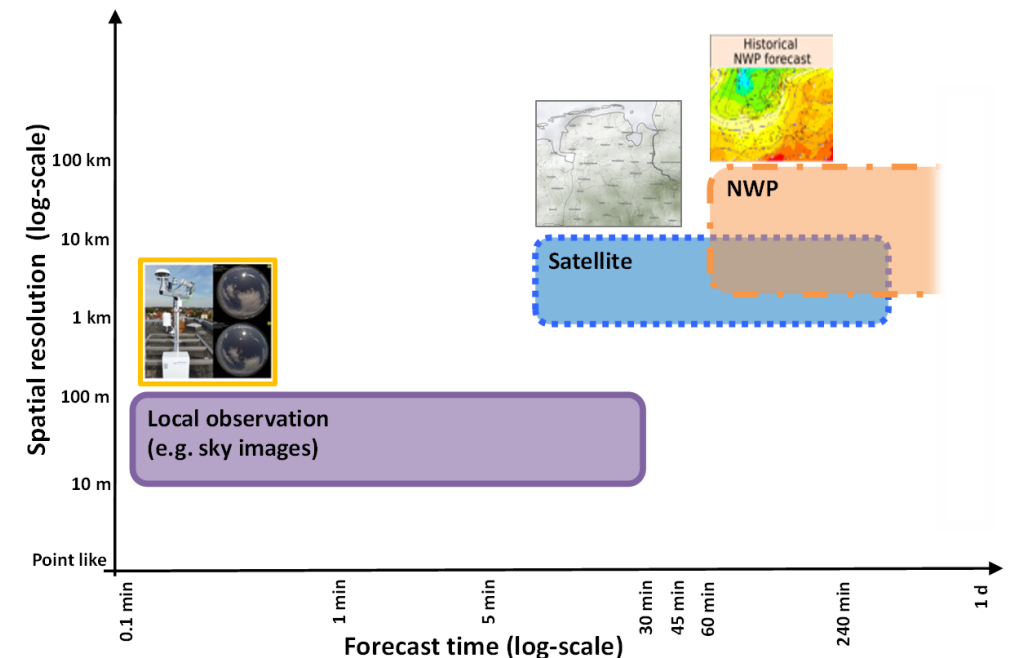
- Sudden local changes in irradiance due to cloud passings
 - Local fluctuations of generated power
 - Represents challenge for integration of solar energy

What are the benefits of nowcasting?

- Anticipate ramp events, leading to:
 - Increased awareness for plant/grid operator
 - Minimization of storage requirements

What are the requirements?

- Cloud information in spatially and temporally high resolutions
 - All-Sky-Imagers
- Model chaotic cloud dynamics → Data-driven models

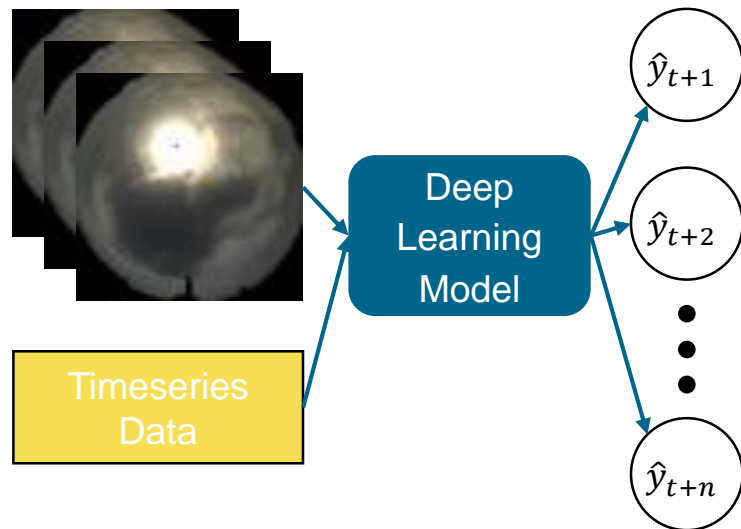


GENERATIVE NOWCASTING APPROACH

Data-driven Solar Nowcasting

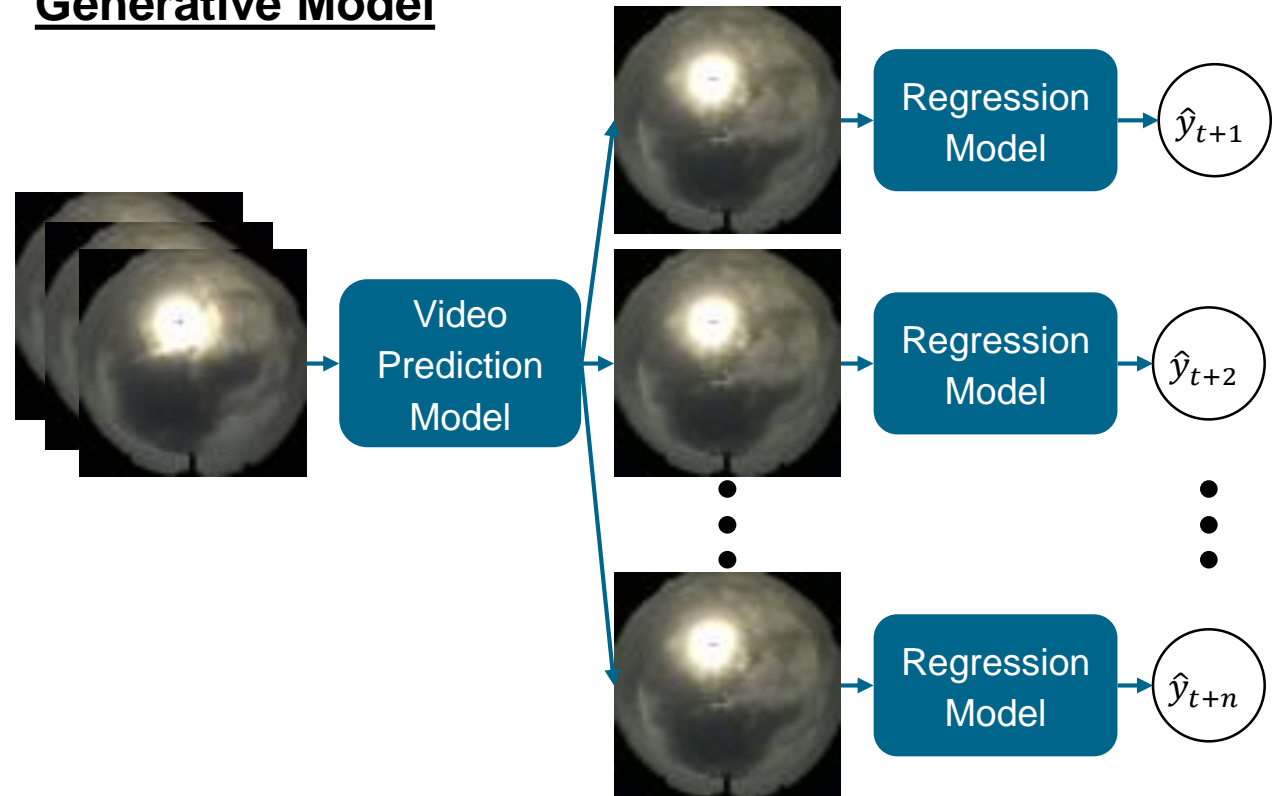
State-of-the-art vs Generative Models

State-of-the-art



- DL model generates forecast directly from input (sky images and/or time series data)
- Optimized on RMSE of irradiance

Generative Model



- 2-step approach:
 - VP model predicts next frames
 - Regression model computes corresponding irradiance
- Independent optimization of VP and regression model

Data-driven Solar Nowcasting

State-of-the-art vs Generative Model



State-of-the-art

- High errors are reduced due to RMSE optimization
→ good approximations of expected energy yield
- **But:** Smoothing of forecast curve
→ short-term fluctuations are not well represented
- Black-box model
→ forecasts cannot be interpreted so easily

Generative Model

- Cloud motion is modelled implicitly by video prediction model
→ Increased interpretability due to additional intermediate results
→ Fluctuations are better represented
- Video prediction models can create multiple „future scenarios“
→ Uncertainty estimation

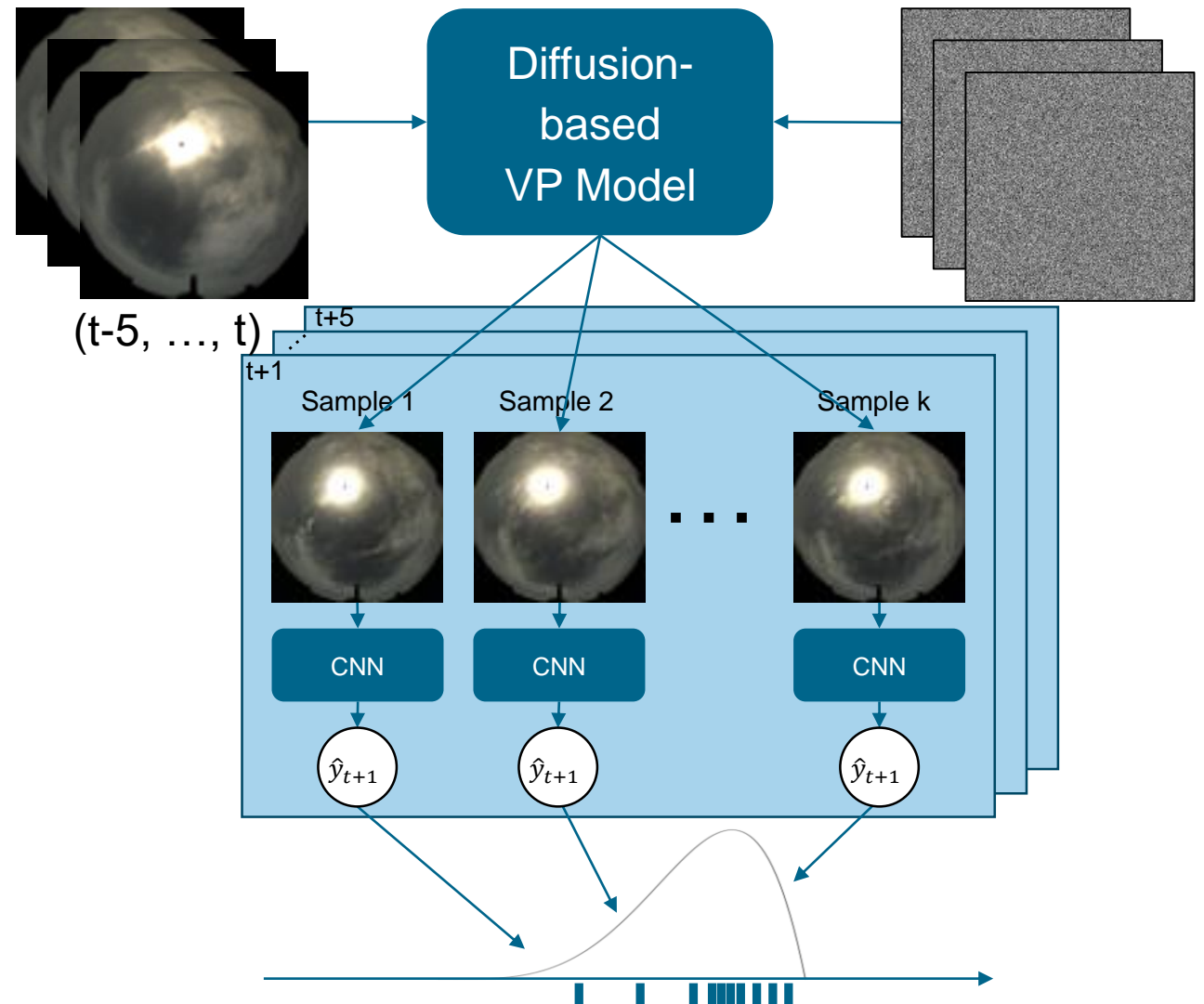
Generative Nowcasting Model Architecture

■ VP-Model:

- Architecture: Diffusion-transformer [1,2]
- Input: sky images of past 5min
- Output: next 5min sky images
- Image Size: 128x128

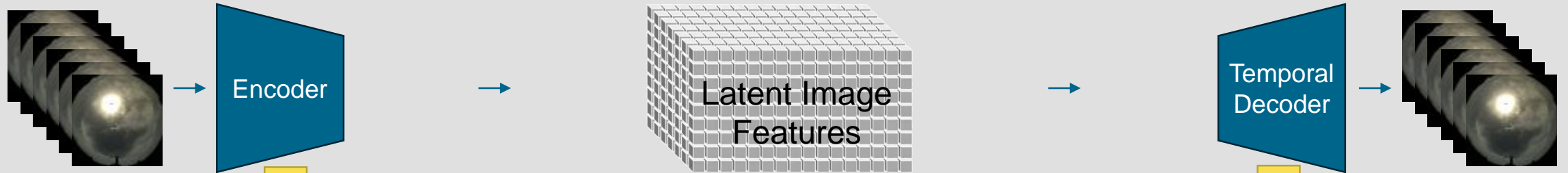
■ Regression Model:

- CNN (ResNet34 architecture [3])
- Input: Single sky image
- Output: GHI (clear-sky-index)
- Trained on real sky images

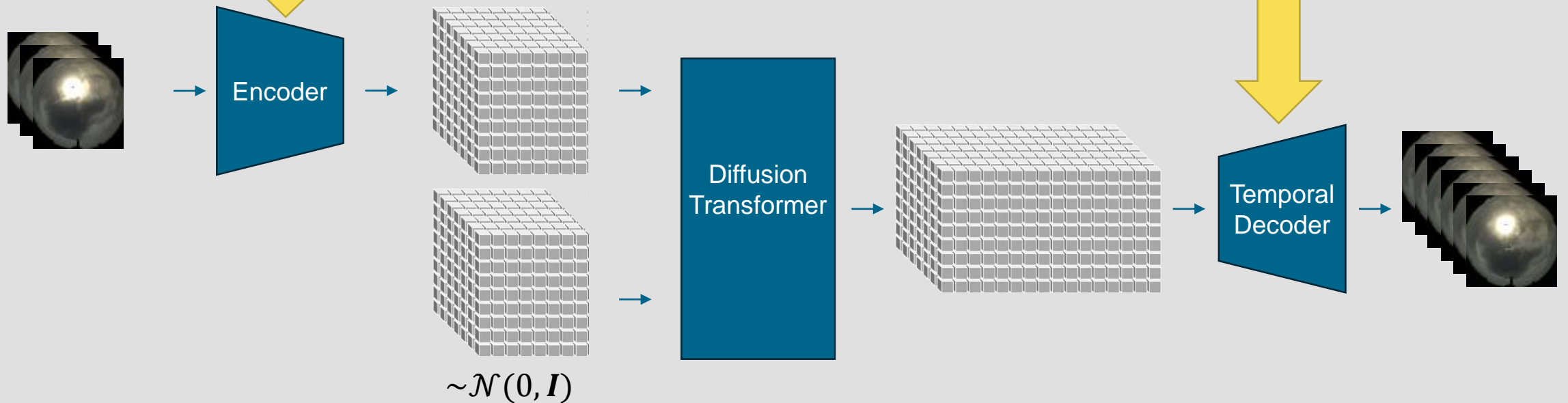


Generative Nowcasting Diffusion-based Video Prediction

Pretraining (Variational Autoencoder)



Latent Diffusion

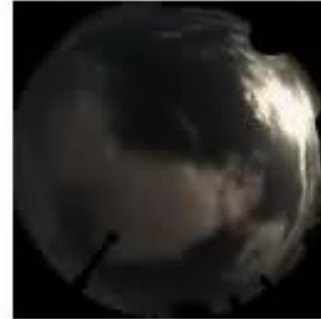
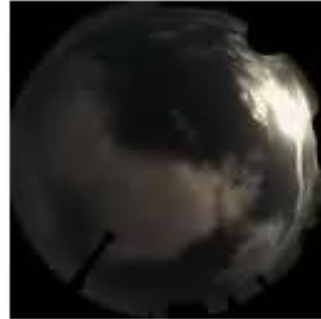
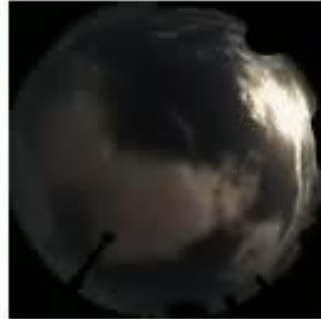


QUALITATIVE ANALYSIS OF VIDEO PREDICTION

Qualitative Analysis of Video Prediction

Samples of generated images

2019-10-01 08:15:00+00:00 (LT=0min)



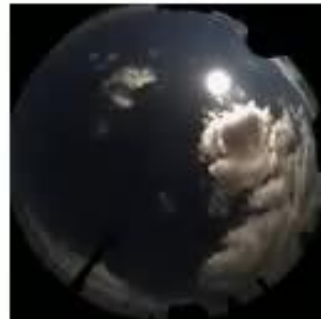
Observed sky



2019-11-19 14:34:00+00:00 (LT=0min)

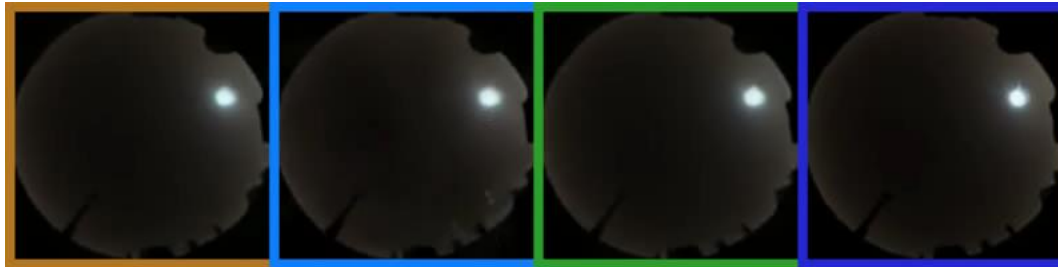


2019-10-08 10:40:00+00:00 (LT=0min)

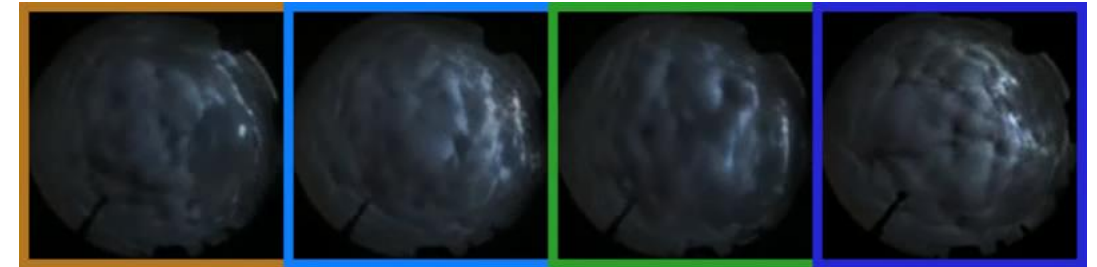
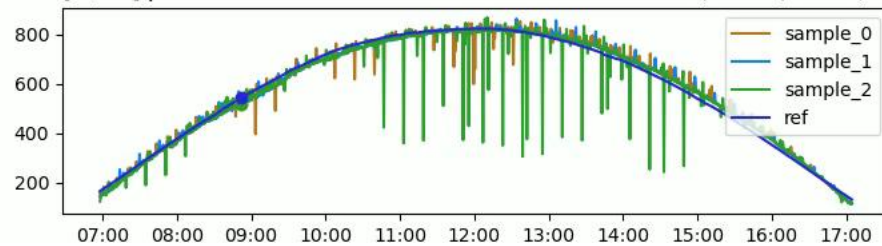


Qualitative Analysis of Video Prediction Nowcasts

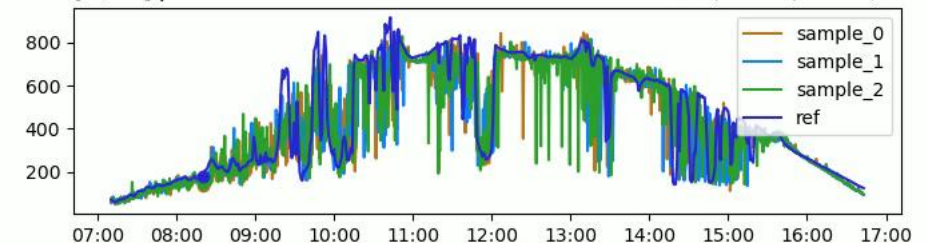
Forecasts for Clear Sky and Cloudy Examples for LT 5min



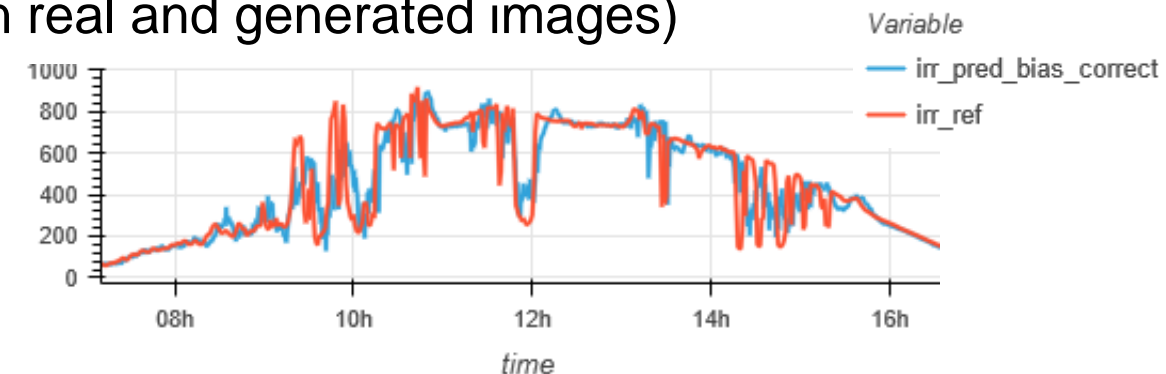
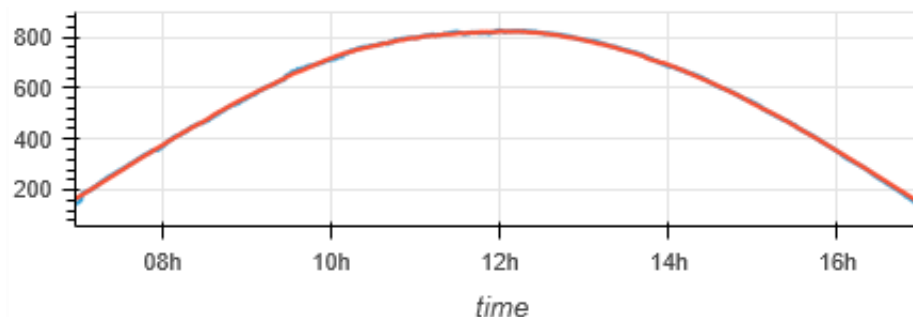
GHI [W/m²] pred vs ref at 2019-09-24 08:51:30+00:00: 517.7, 532.2, 517.2, 541.2



GHI [W/m²] pred vs ref at 2019-10-08 08:20:00+00:00: 134.6, 157.9, 147.6, 181.1



- Artifacts in generated images lead to outliers in irradiance predictions
→ Deterministic forecast by median of all samples
- Additional bias correction (reality gap between real and generated images)



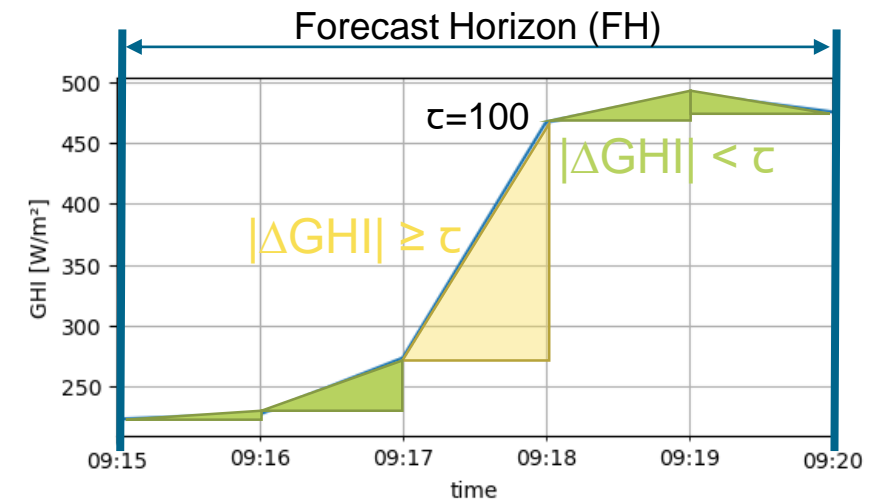
QUANTITATIVE EVALUATION

Quantitative Evaluation

Evaluation of Deterministic Forecasts



- **Dataset:**
 - 28 manually selected days of previous benchmark study of 2019 [4]
- **Comparison to state-of-the-art:**
 - DL model based on vision and timeseries transformer [5]
- **Forecasting Metrics:**
 - RMSE, MAE, MBE
- **Ramp Event Validation:**
 - Ramp Event Definition:
$$\frac{|\Delta GHI|}{\Delta t} > \tau \Rightarrow Ramp$$
$$t: \text{if } \exists Ramp \text{ in } FH \Rightarrow Ramp \text{ Event}$$
 - Evaluation by confusion matrices and f1-score:



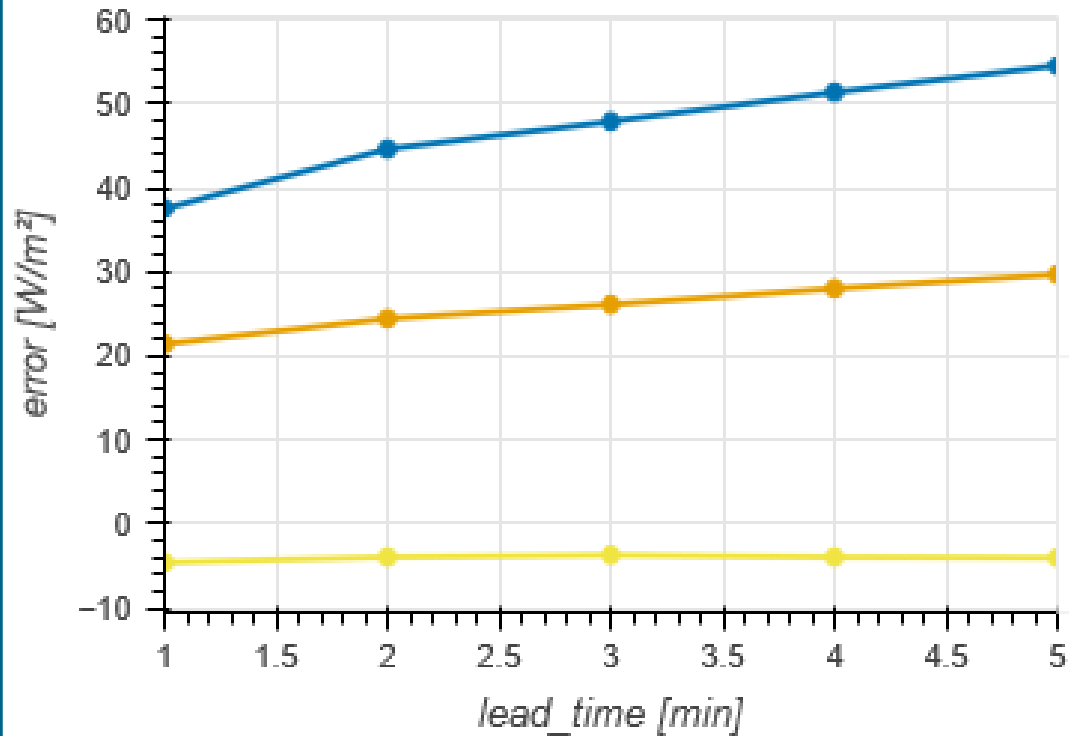
$$F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

$$\text{precision} = \frac{TP}{TP + FP}$$

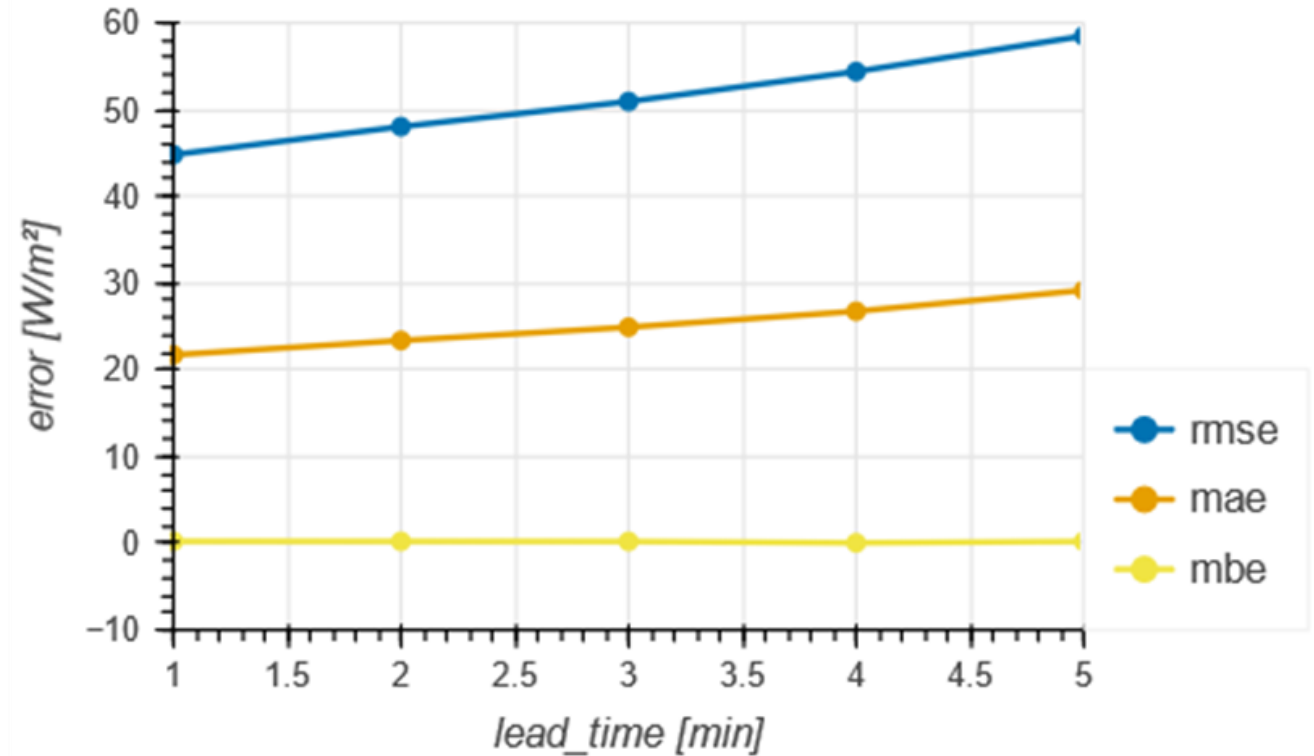
$$\text{recall} = \frac{TP}{TP + FN}$$

Quantitative Evaluation Deterministic Forecasting Metrics

State-of-the-art Model



Generative Model

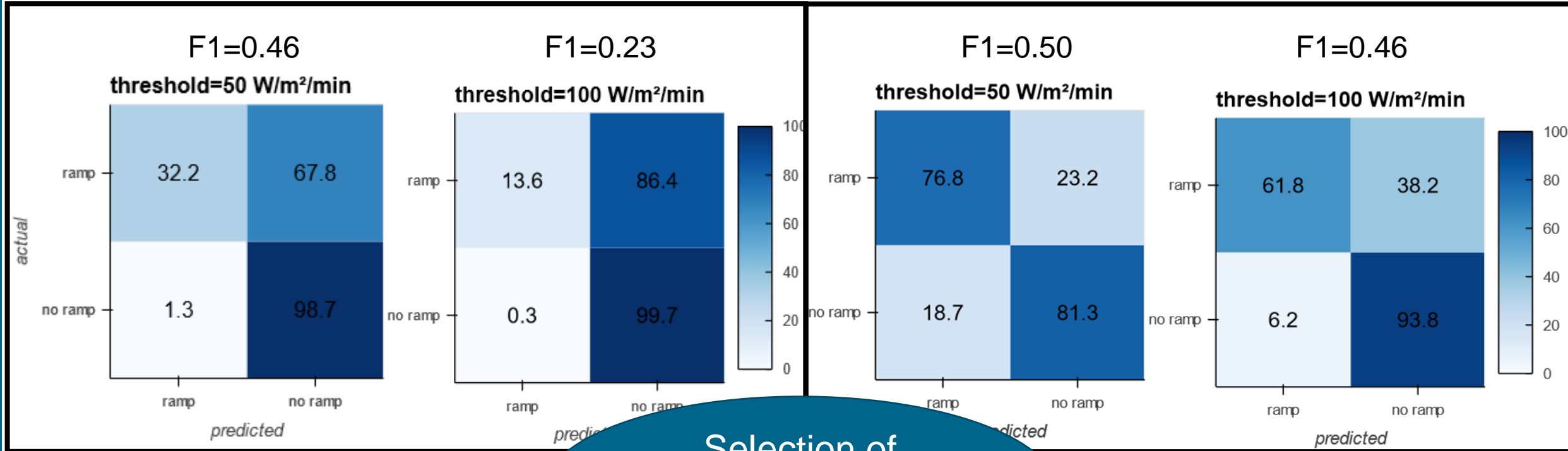


- SOTA still slightly better in RMSE
- MAE almost identical
- No bias for generative model

Quantitative Evaluation Ramp Event Detection

State-of-the-art

Generative Model



- The SOTA DL models detect less than 50% of observed ramps
- Strong decrease in F1-Score for higher thresholds
- Generative model predicts majority of ramp events (76.8%) while maintaining high accuracy (81.3%) of no-ramp events
- Only slight decrease in F1-Score for higher thresholds

Selection of threshold depends on application [6]

CONCLUSION & OUTLOOK

▪ **Summary:**

▪ **Quality of solar nowcasting models depends on use case**

- State-of-the-art models often achieve good error scores but may not be well-suited for ramp event detection (optimization on RMSE)

▪ **Presentation of diffusion-based generative model for solar nowcasting**

- Diffusion transformer for predicting future synthetic sky images
- CNN regression model for predicting irradiance (GHI)

▪ **Validation of nowcasts based on standard metrics and ramp events**

- SOTA and generative model achieve similar results on standard metrics
- Generative model superior in ramp event detection

▪ **Outlook:**

- Improve video prediction model by training on larger, more versatile dataset
- Combined optimization of both models (video prediction & irradiance model)

1. Ho, Jonathan / Jain, Ajay / Abbeel, Pieter (2020)
Denoising diffusion probabilistic models
2. Blattmann, A., Dockhorn, T., Kulal, S., Mendeleevitch, D., Kilian, M., Lorenz, D., ... & Rombach, R. (2023)
Stable video diffusion: Scaling latent video diffusion models to large datasets
3. He, Kaiming / Zhang, Xiangyu / Ren, Shaoqing / Sun, Jian (2016)
Deep Residual Learning for Image Recognition
4. Logothetis, S. A., Salamalakis, V., Nouri, B., Remund, J., Zarzalejo, L. F., Xie, Y., ... & Kazantzidis, A. (2022)
Solar Irradiance Ramp Forecasting Based on All-Sky Imagers
5. Fabel, Yann / Nouri, Bijan / Wilbert, Stefan / Blum, Niklas / Schnaus, Dominik / Triebel, Rudolph / Zarzalejo, Luis F. / Ugedo, Enrique / Kowalski, Julia / Pitz-Paal, Robert (2023)
Combining deep learning and physical models: a benchmark study on all-sky imagerbased solar nowcasting systems
6. Bijan Nouri, Yann Fabel, Niklas Blum, Luis F. Zarzalejo, Andreas, Kazantzidis, Stefan Wilbert (EUPVSEC 2024)
Ramp Rate Metric Suitable for Solar Forecasting and Nowcasting

A large field of solar towers (heliostats) in a grassy field under a blue sky with scattered clouds. The towers are arranged in rows and reflect the sky. A dark blue banner with white text is overlaid at the bottom.

**THANK YOU FOR YOUR ATTENTION!
QUESTIONS? YANN.FABEL@DLR.DE**