RAMP RATE METRIC SUITABLE FOR SOLAR FORECASTING AND NOWCASTING

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Agenda

- Motivation for solar nowcasting
- Present a state-of-the-art and a novel generative nowcasting approach
- Qualitative analysis of generative model
- Quantitative evaluation including ramp rate evaluation
- Conclusion & Outlook

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?

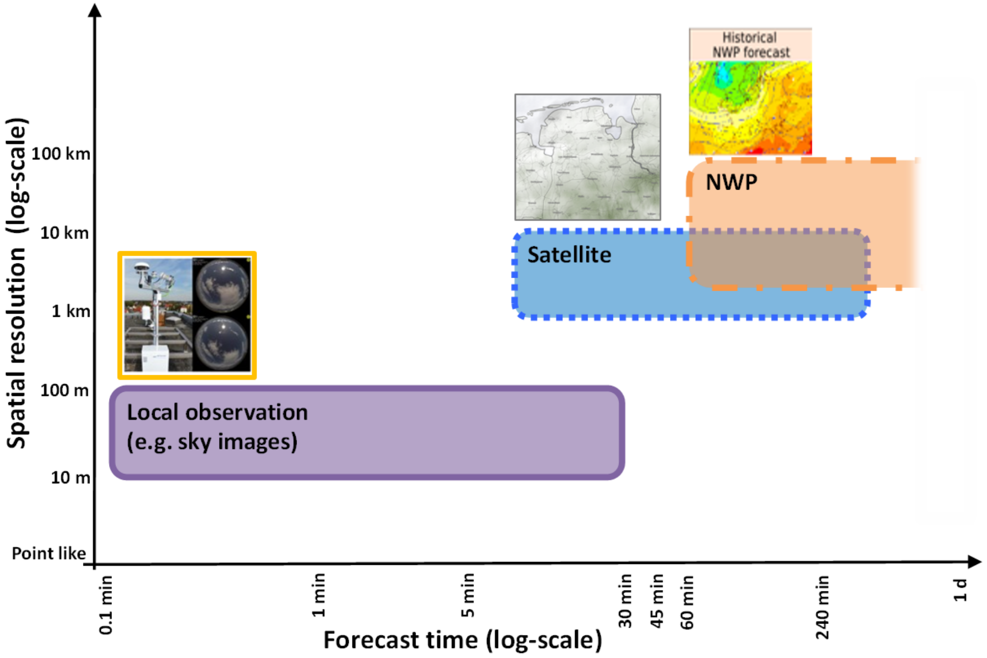
- Sudden local changes in irradiance due to cloud passings
  → Inhomogeneous distribution of the solar resource
  → Local fluctuations of generated power
  → Represents challenge for integration of solar energy

What are the benefits of nowcasting?

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

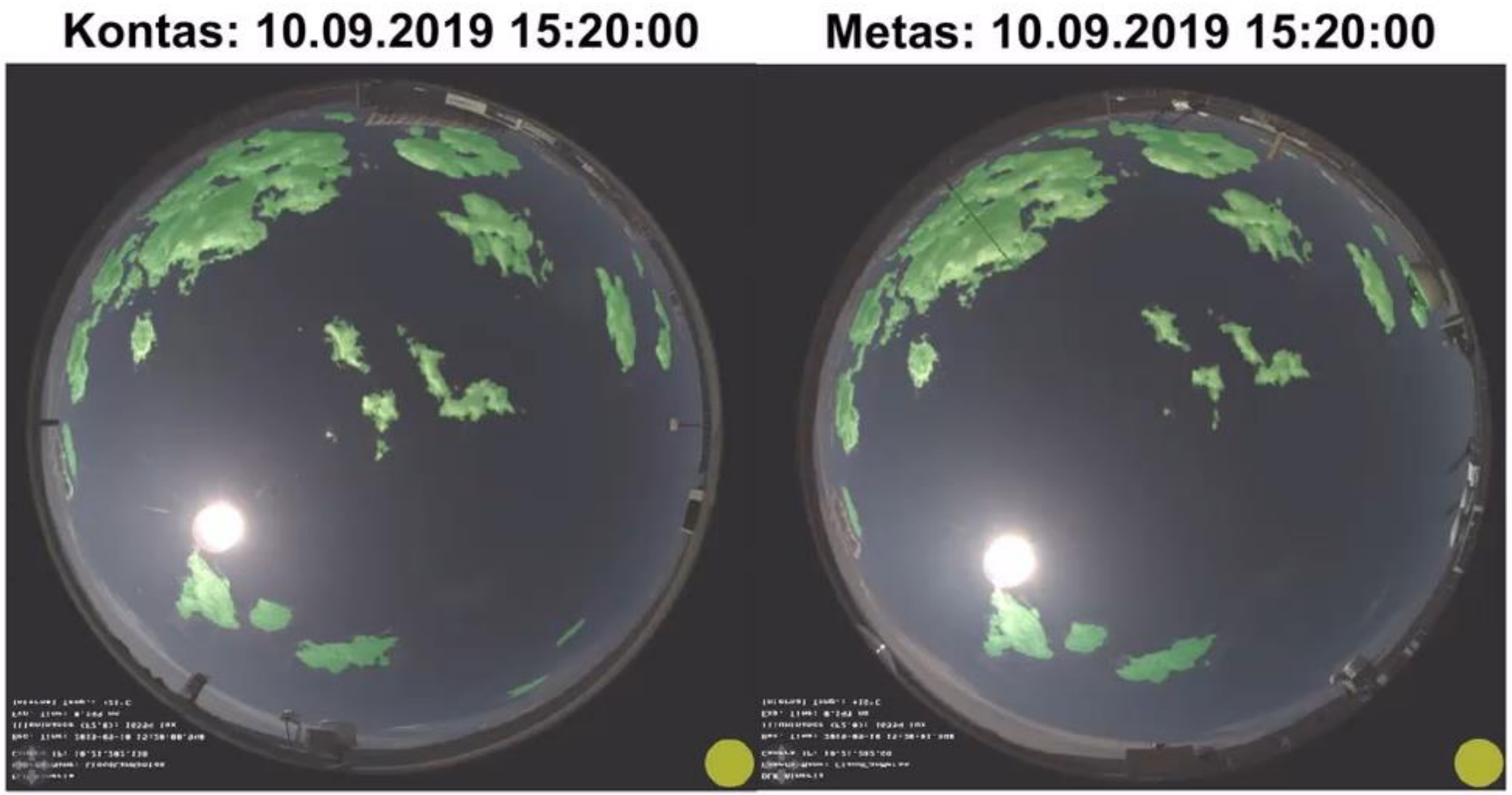
What are the requirements?

- Cloud information in spatially and temporally high resolutions → All-Sky-Imagers



Motivation

All-Sky-Imager: Ground-based camera observing complete hemisphere using fish-eye lens

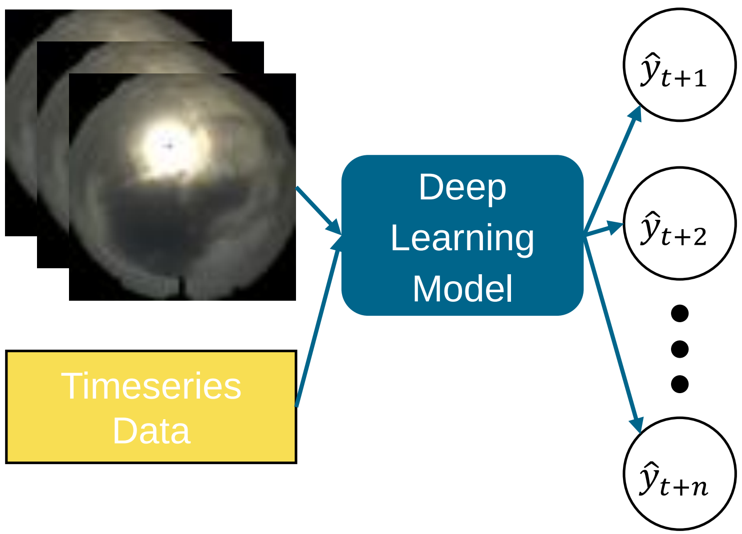


GENERATIVE NOWCASTING APPROACH

Data-driven Solar Nowcasting
State-of-the-art vs Generative Models

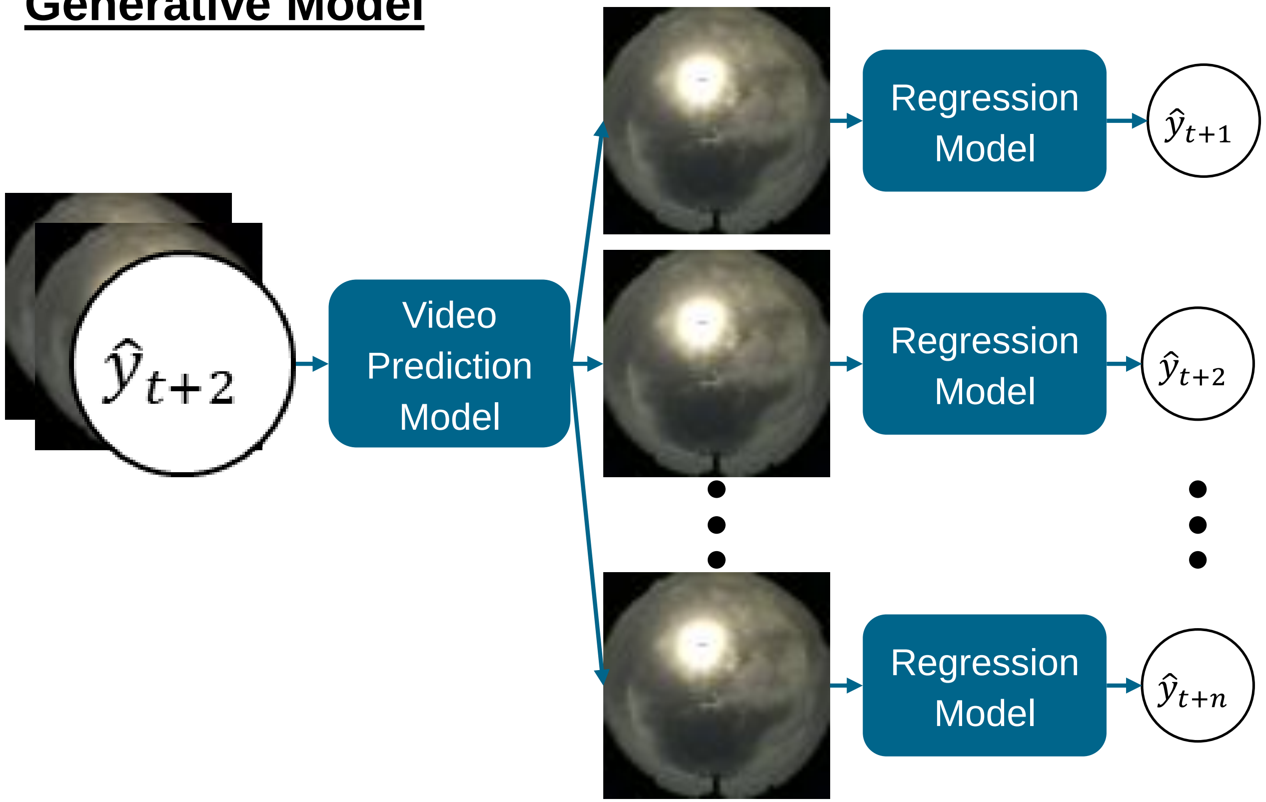
DLR

<u>State-of-the-art</u>



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

<u>Generative Model</u>



- 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**: Smoothening of forecast curve
  - short-term fluctuations are not well represented
- Black-box model
  - forecasts cannot be interpreted so easily

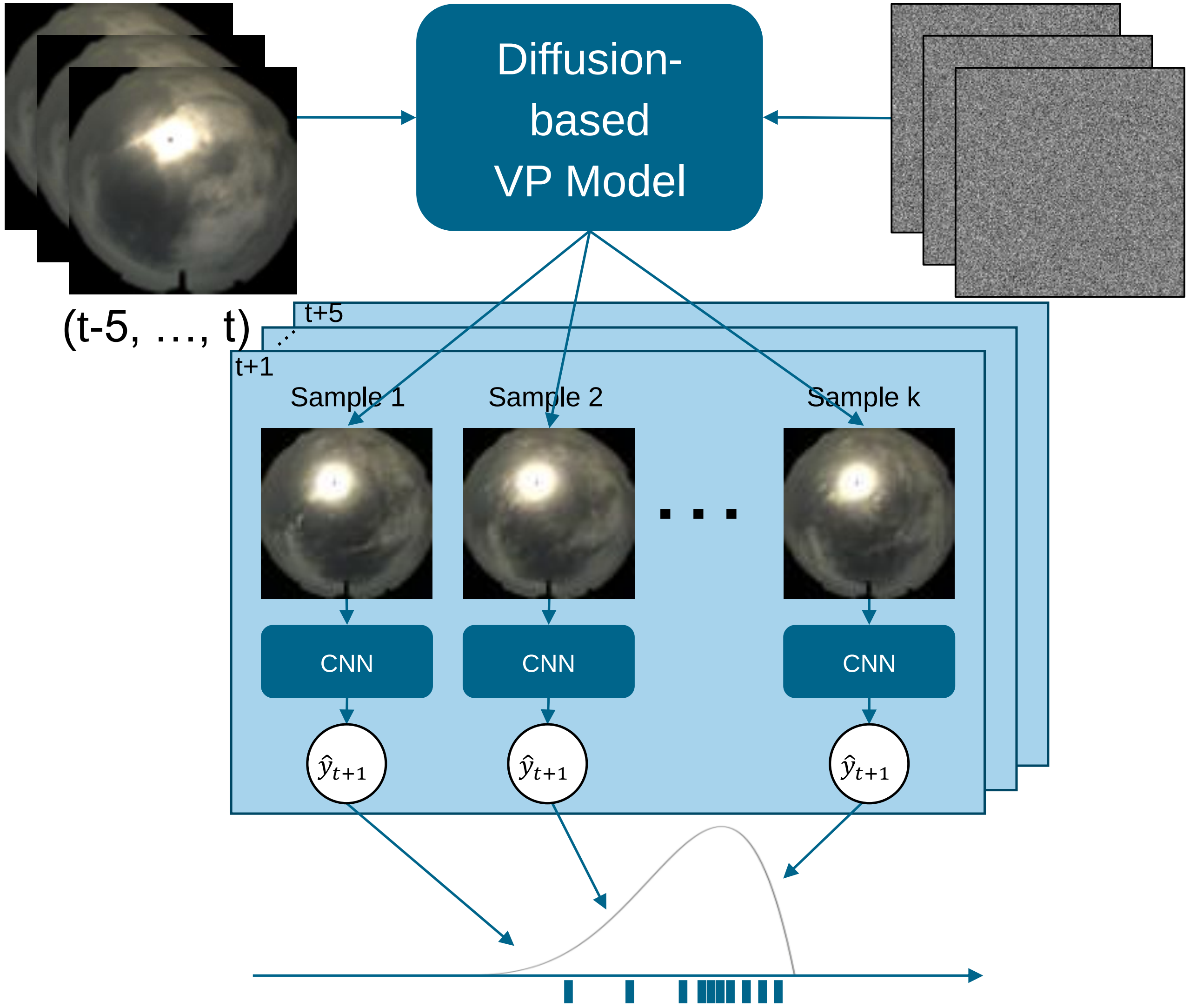
Generative Model

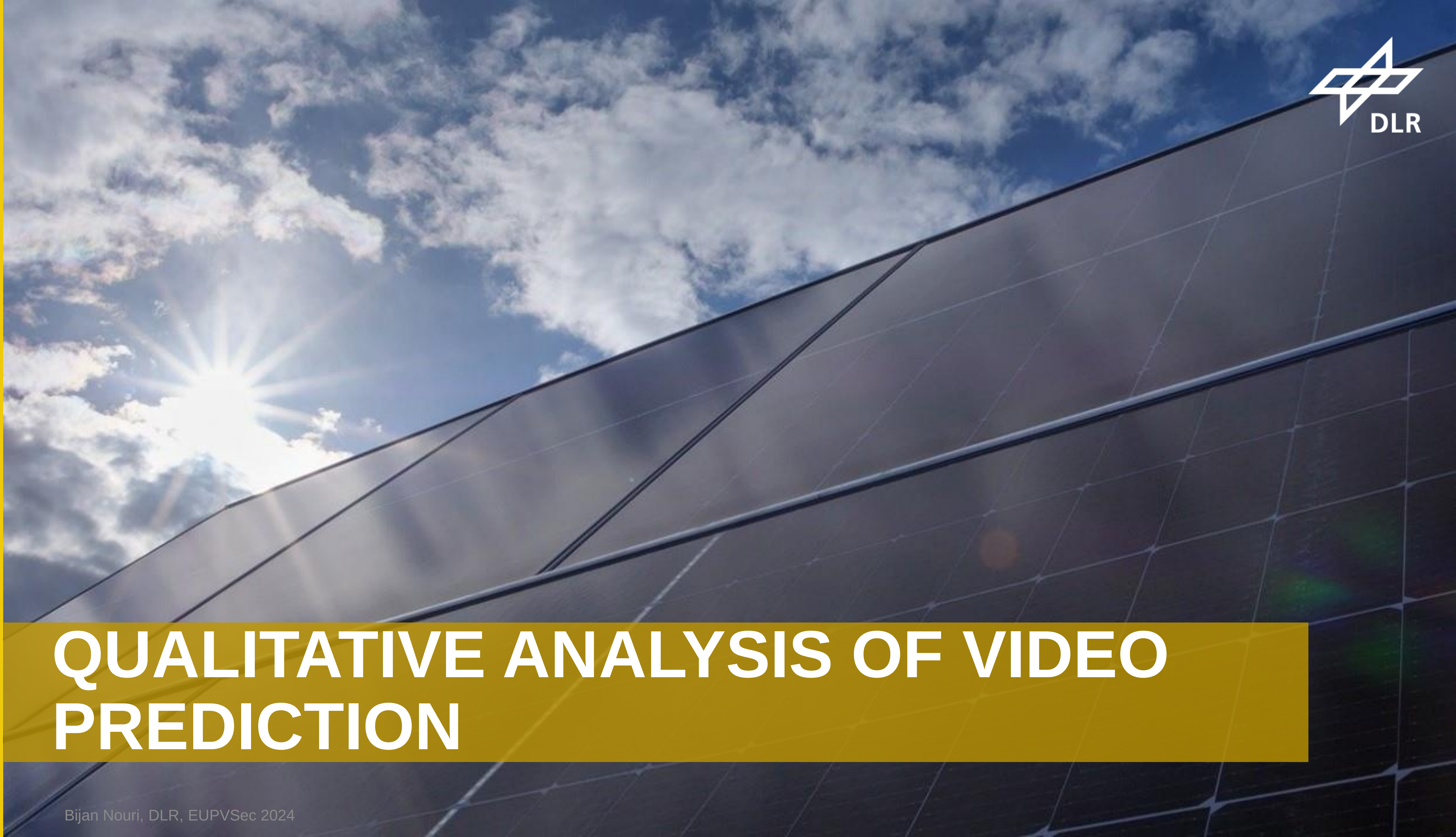
- Cloud motion, shape change, and dissipation are implicitly modeled by the video prediction model.
  - Increased interpretability due to additional intermediate results
  - Fluctuations are better represented
- Video prediction models can create multiple „future scenarios“
  - Uncertainty estimation

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



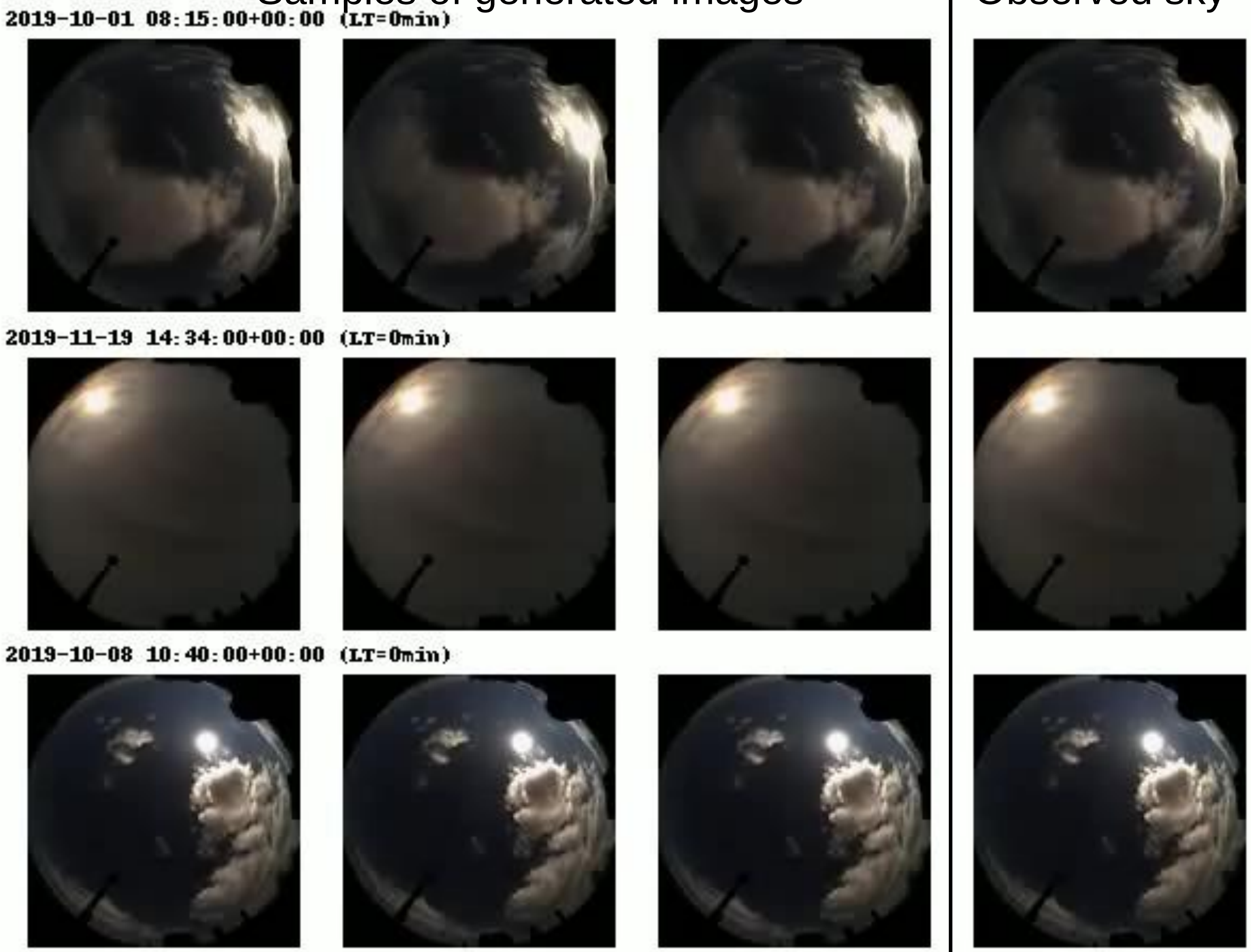


QUALITATIVE ANALYSIS OF VIDEO PREDICTION

Qualitative Analysis of Video Prediction

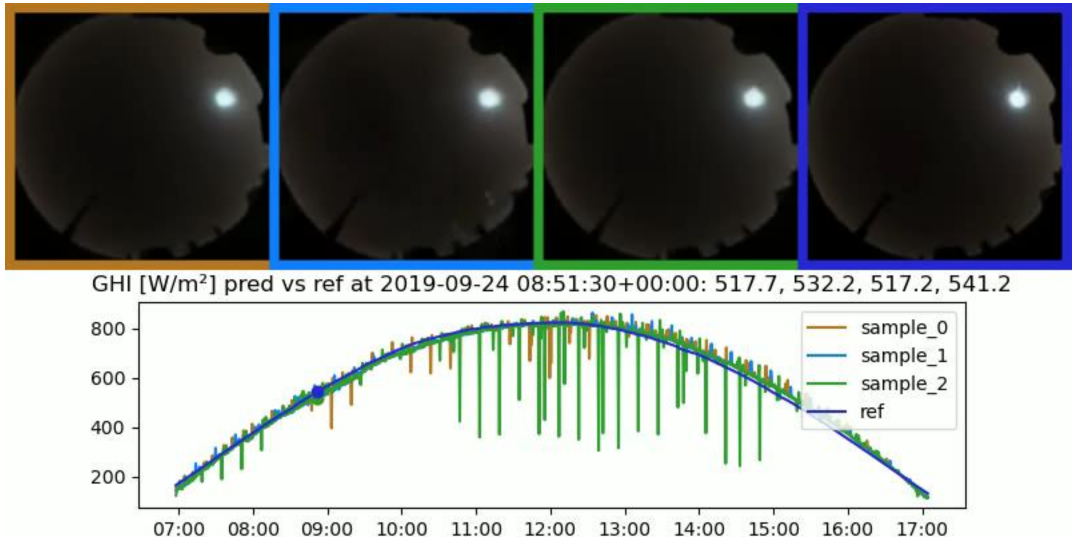
Samples of generated images

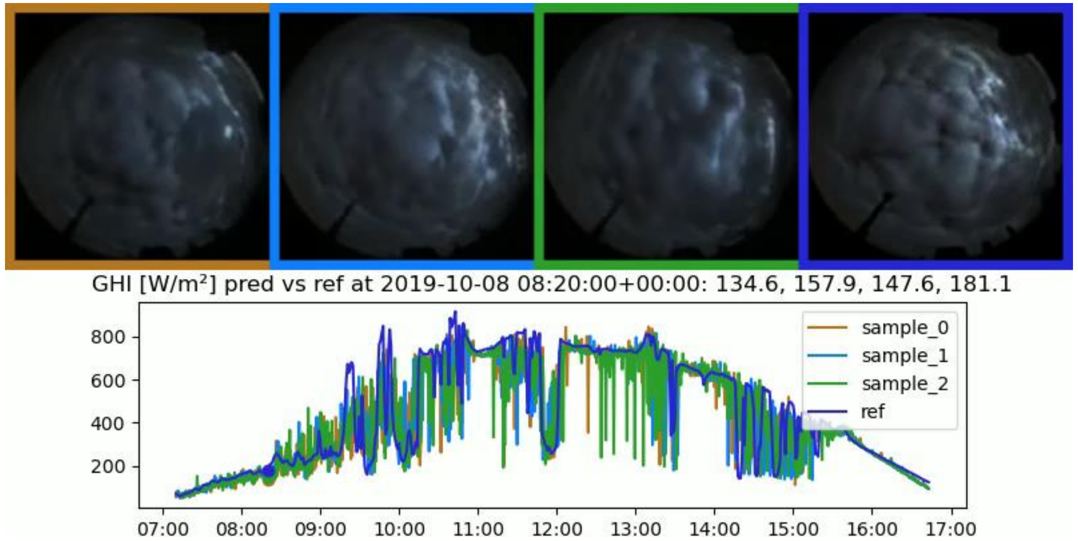
Observed sky



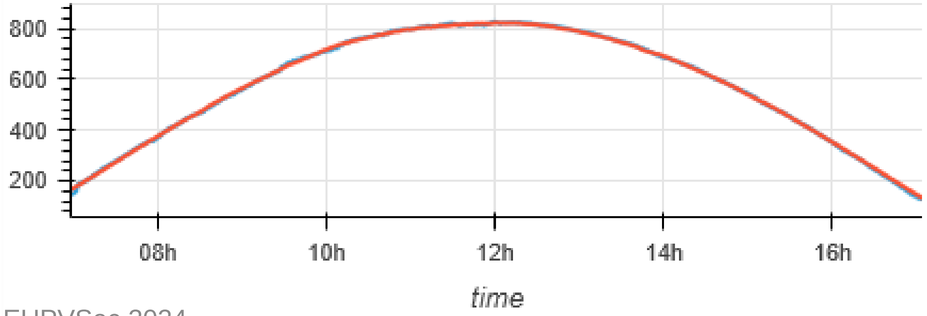
Qualitative Analysis of Video Prediction
Nowcasts

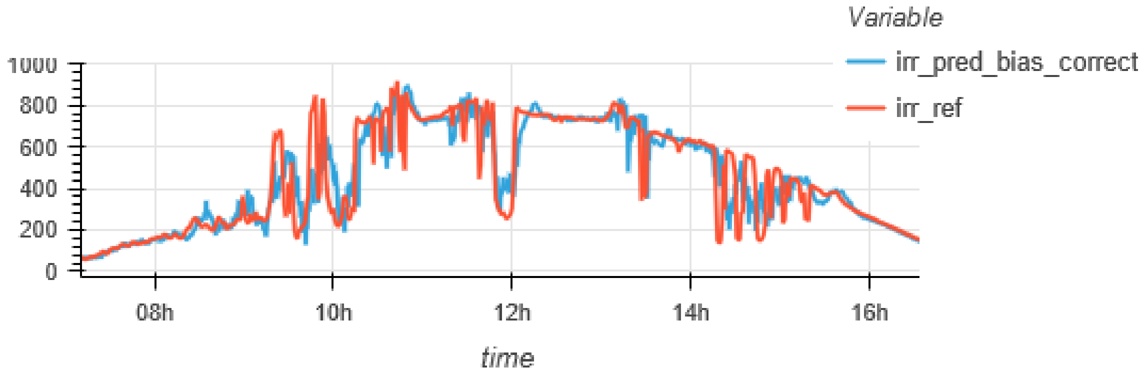
Forecasts for Clear Sky and Cloudy Examples for **LT 5min**





- Artifacts in generated images lead to outliers in irradiance predictions
  → Deterministic forecast by median of all samples





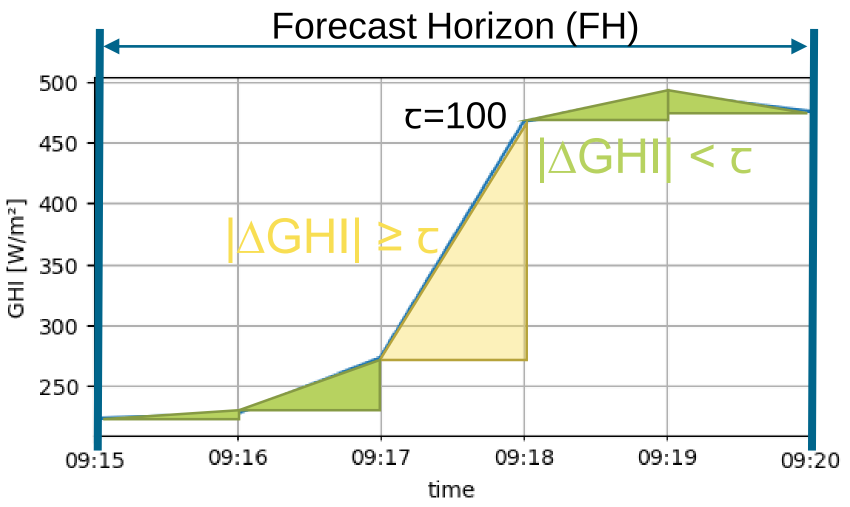
QUANTITATIVE EVALUATION

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:

$$\frac{|\Delta GHI|}{\Delta t} > \tau \Longrightarrow Ramp$$

$$t:\ if\ \exists\ Ramp\ in\ FH \Longrightarrow Ramp\ Event$$

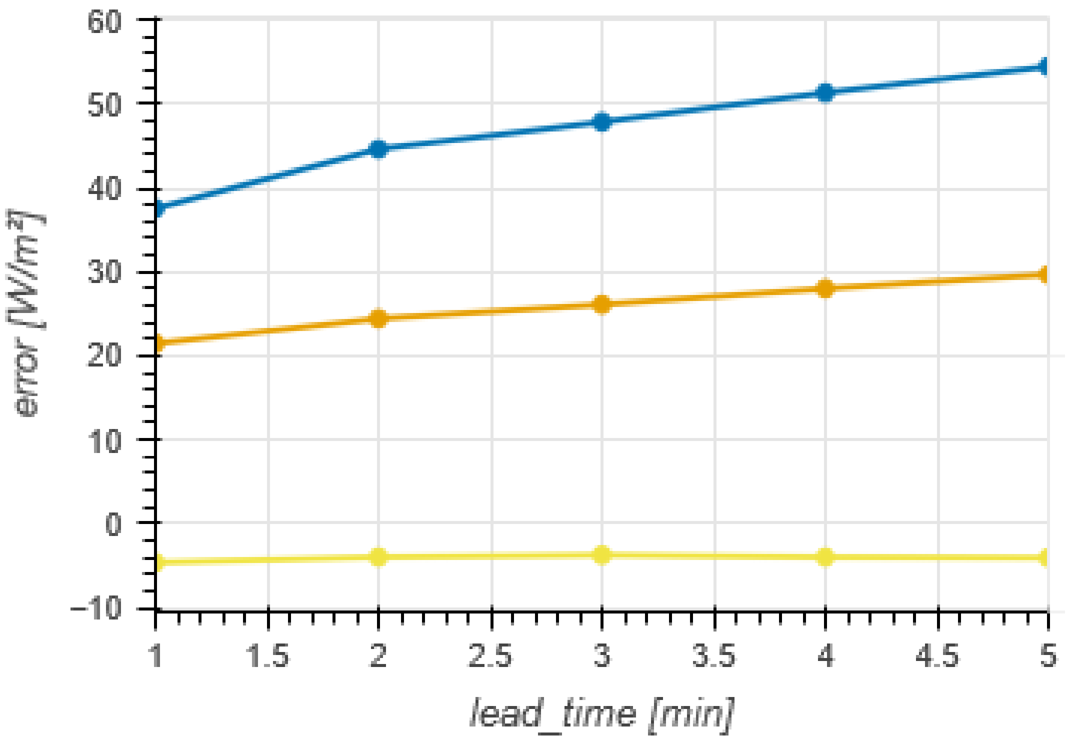


  - Evaluation by confusion matrices and f1-score:

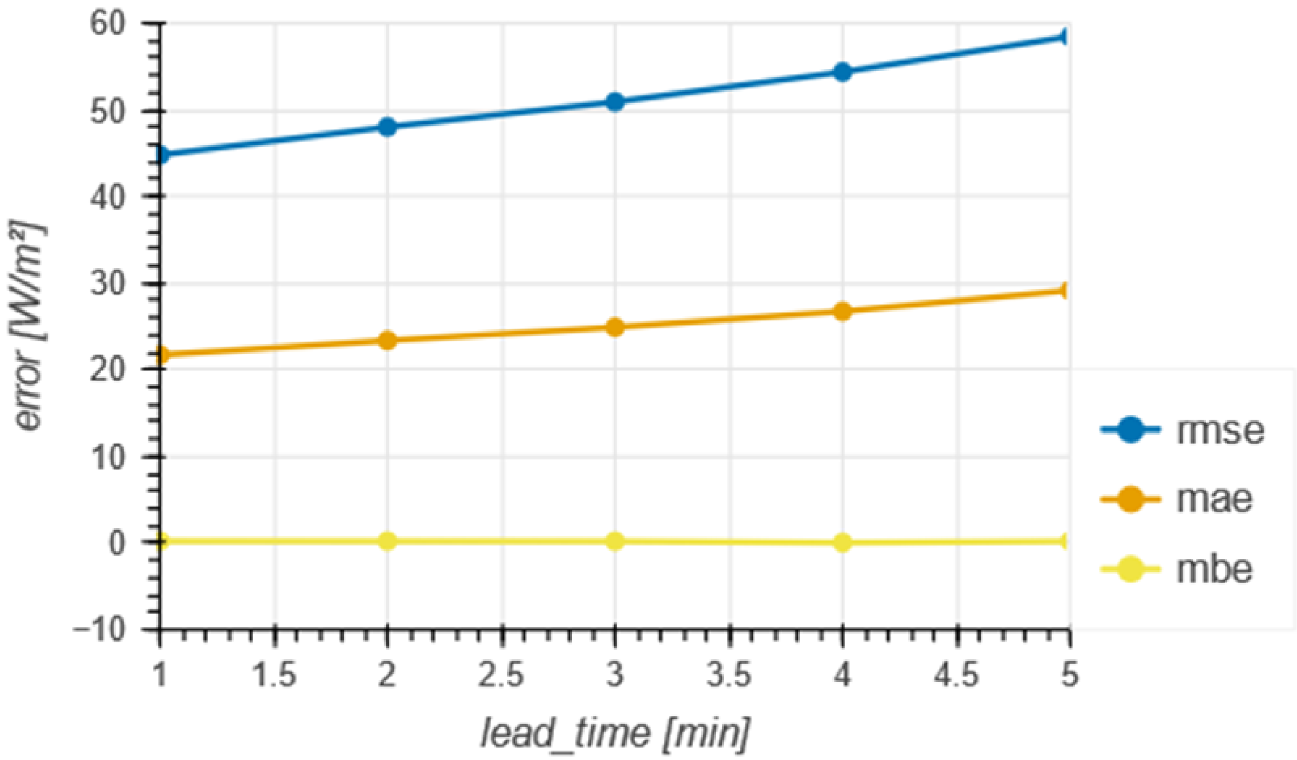
$$F1 = 2 \times \frac{precision\ \times recall}{precision + recall} \qquad precision = \frac{TP}{TP + FP} \qquad recall = \frac{TP}{TP + FN}$$

Quantitative Evaluation
Deterministic Forecasting Metrics

State-of-the-art Model



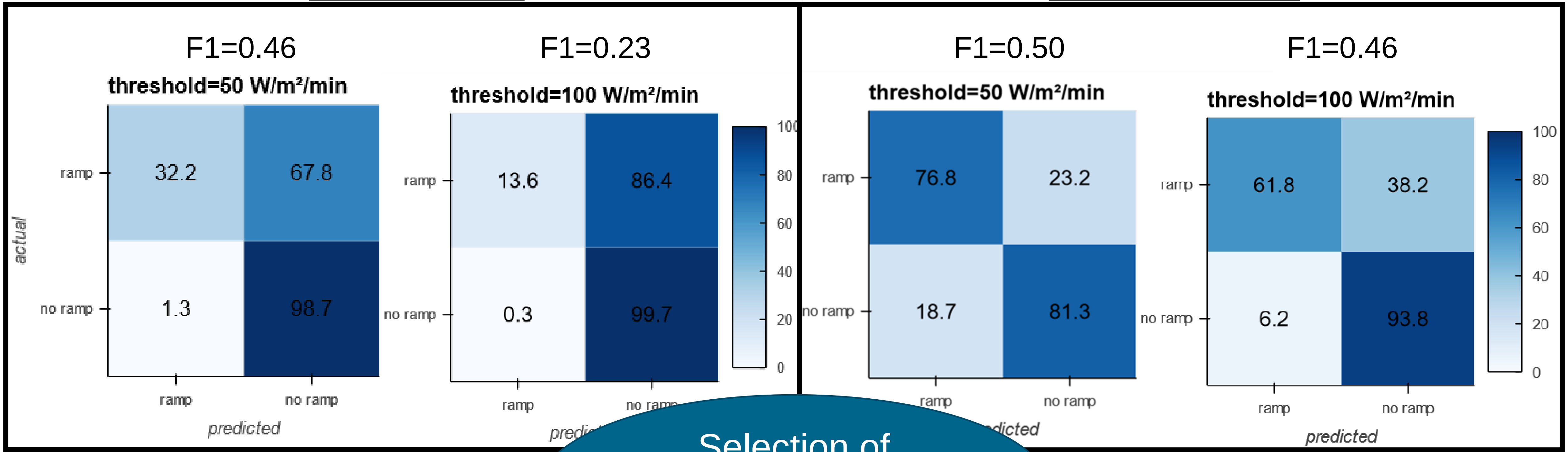
Generative Model



- 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**



Selection of threshold depends on application [6]

- The SOTA DL models detect le[...] observed ramps
- Strong decrease in F1-Score for higher thresholds

- [...]ive model predicts majority of [...] events while maintaining high [...]%) of no-ramp events
- Only slight decrease in F1-Score for higher thresholds

CONCLUSION & OUTLOOK

Conclusion

- **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
  - Increase the resolution of synthetic images and extend the forecast horizon (~30 min ahead)
  - Combined optimization of both models (video prediction & irradiance model)

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   Ramp Rate Metric Suitable for Solar Forecasting and Nowcasting

THANK YOU FOR YOUR ATTENTION!
QUESTIONS?
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