LEVERAGING GENERATIVE MODELS FOR ENHANCED SOLAR IRRADIANCE RAMP DETECTION

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

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Agenda

- Introduction & State-of-the-art
- Generative Nowcasting Approach
- Ramp Event Validation
- Conclusion & Outlook

INTRODUCTION & STATE-OF-THE-ART

Introduction
Motivation

What are solar ramp events?

- Sudden local changes in solar irradiance due to cloud passings

What are the effects of ramp events?

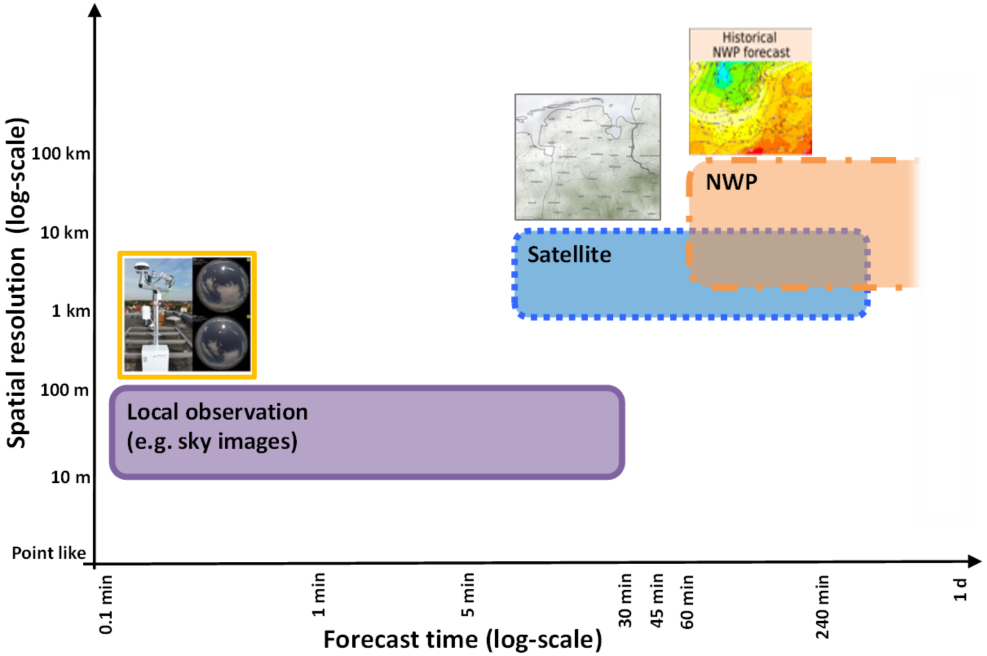
- Local fluctuations of generated power
  - Negative ramps might cause grid code violations

What are the benefits of nowcasting?

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

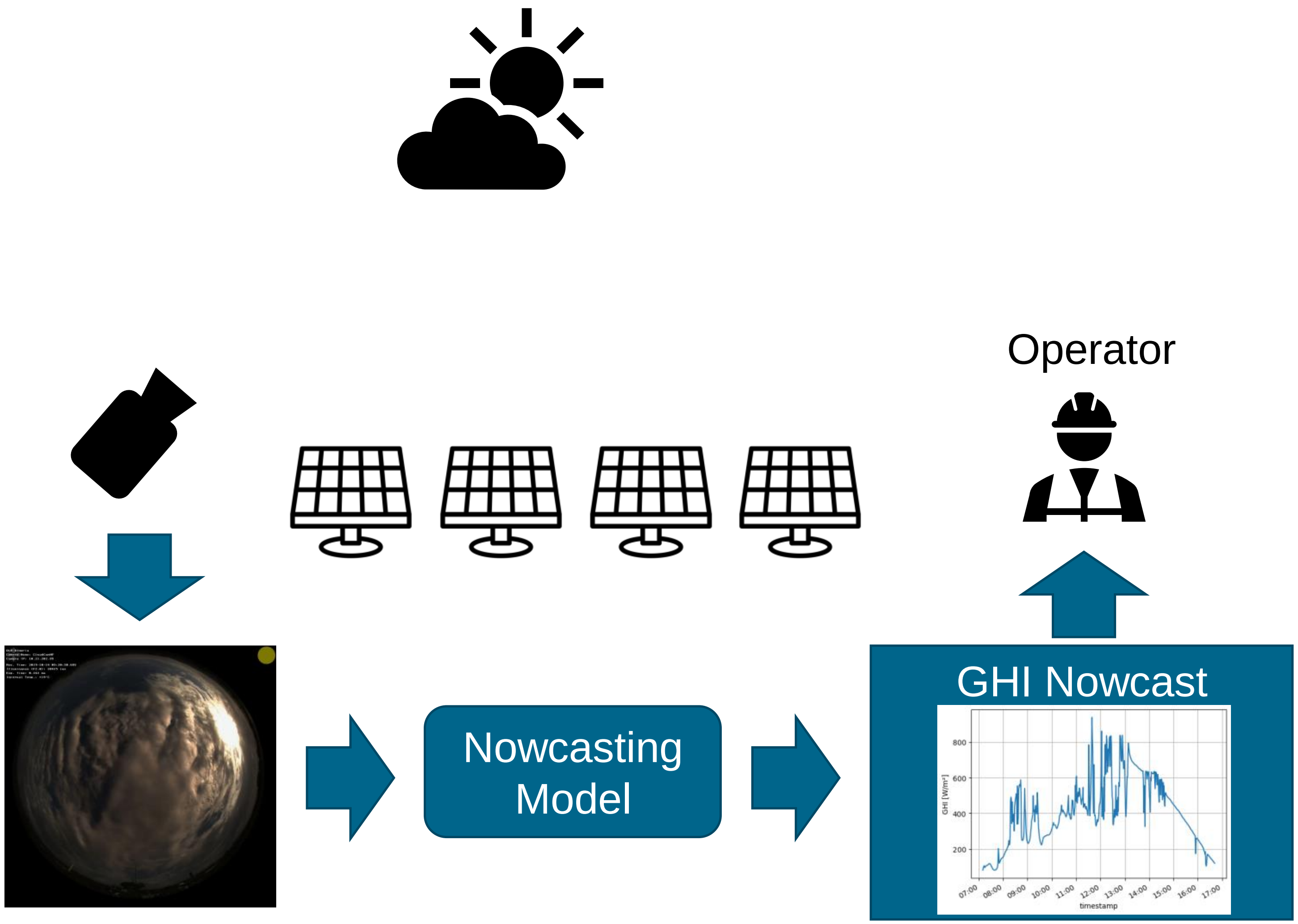
What are the requirements?

- Cloud information in spatially and temporally high resolutions → ASI



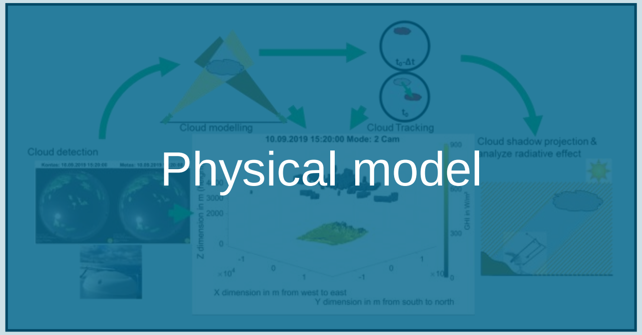
Introduction
ASI Nowcasting

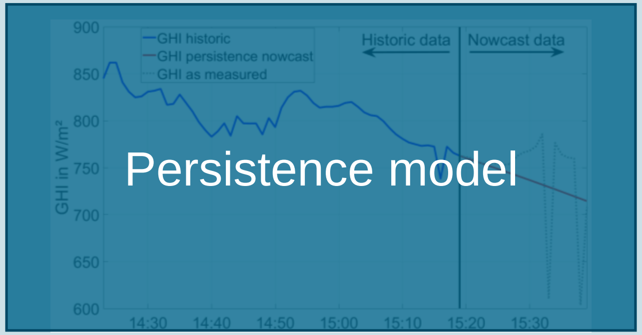
- **All-Sky Imager**
  - Ground-based camera observing complete hemisphere using fish-eye lens
- **Image analysis**
  - Physical approach
    - Explicit modelling of clouds, their motion and transmittance
  - Data-driven approach
    - Model learns correlation of clouds and irradiance directly from images
  - Hybrid approach:
    - Combine physical and data-driven approach
- **Result**:
  - Multi-step intra-hour irradiance forecast (nowcast)

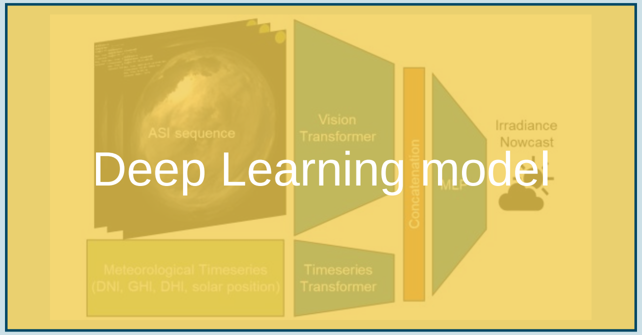


State-of-the-Art
Hybrid Solar Nowcasting

Hybrid model [1,2]







Nowcast combination

Global Weights

Hybrid deterministic Nowcast

State-of-the-Art
Hybrid Solar Nowcasting

Advantages

- Combines strenghts of physics- and data-driven approaches
- Achieves better error metrics and forecast skills than each individual model

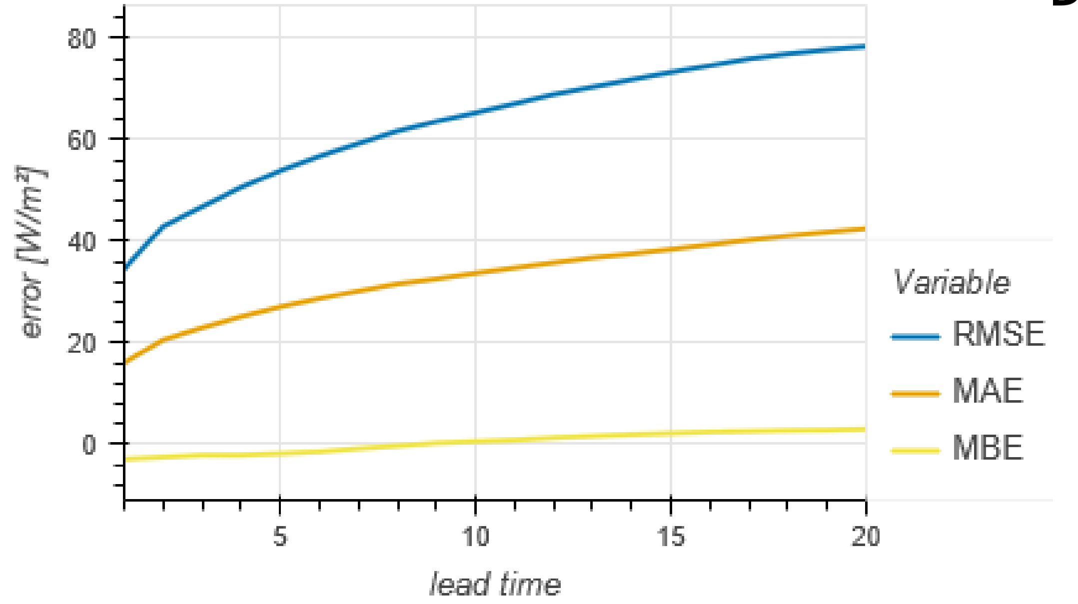
→ **Well-suited for predicting average GHI**

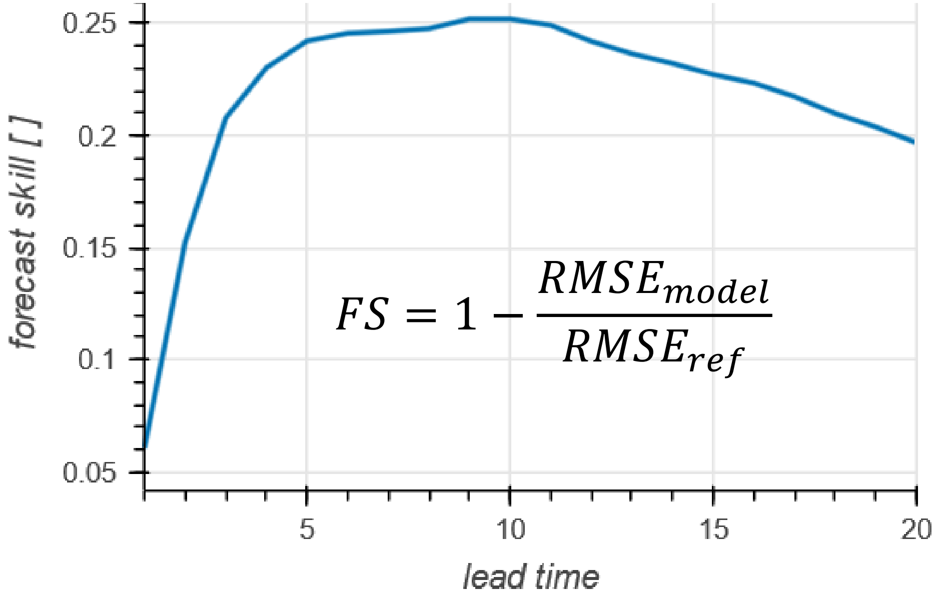
Disadvantages

- Decreased model interpretability
- Hybridization leads to smoothing
  - Persistence and deep learning model generate rather flat forecast curves
  - Combination based on reducing RMSE causes further smoothing

  → **Limited capability to predict ramp events**

GHI Error Metrics



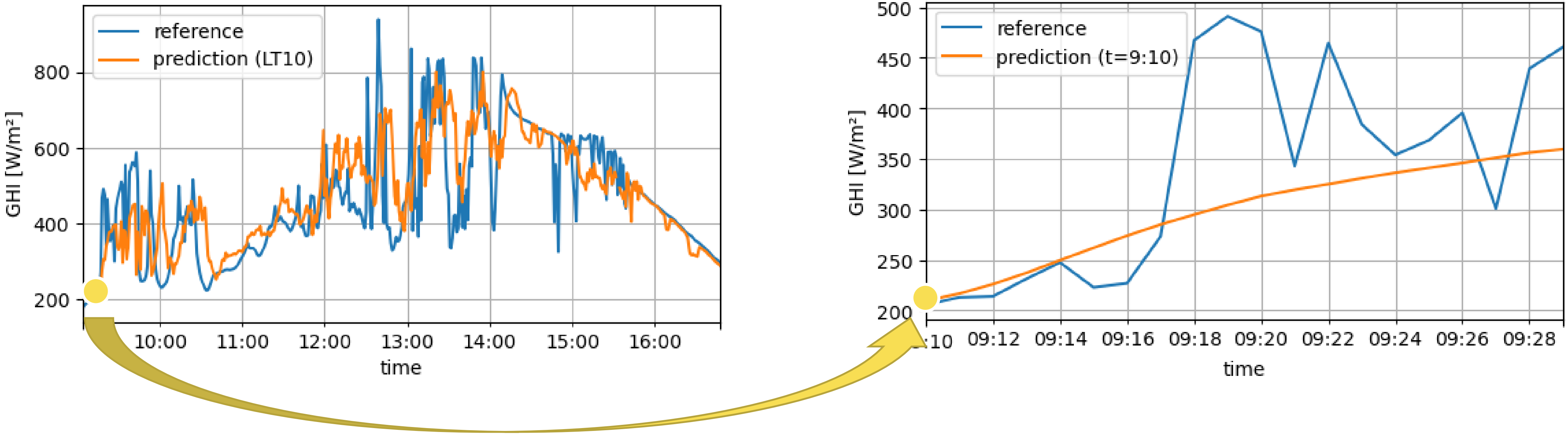


$$FS = 1 - \frac{RMSE_{model}}{RMSE_{ref}}$$

State-of-the-Art
Shortcomings

- **Optimization/Combination based on reducing MSE leads to smoothing**
  - RMSE and FS most common metrics in solar forecasting but they do not assess ramp event detection capability
  - Forecast curves (of fixed lead times) are similar to persistence (shifted reference curve)

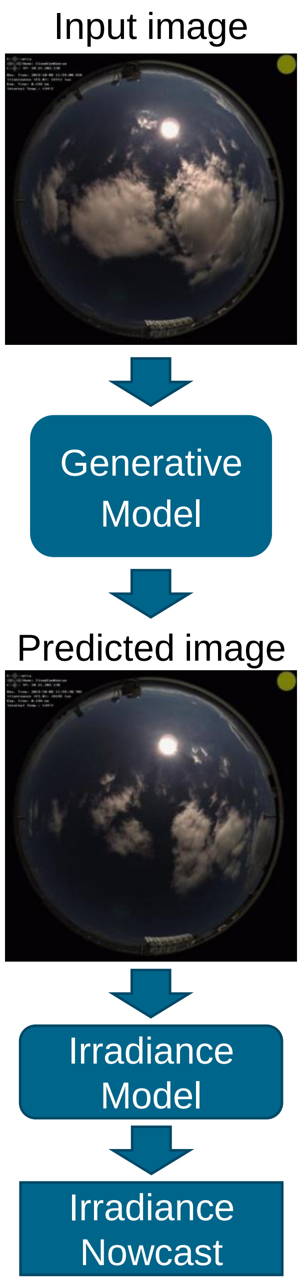
Lead time- vs datetime-specific forecast



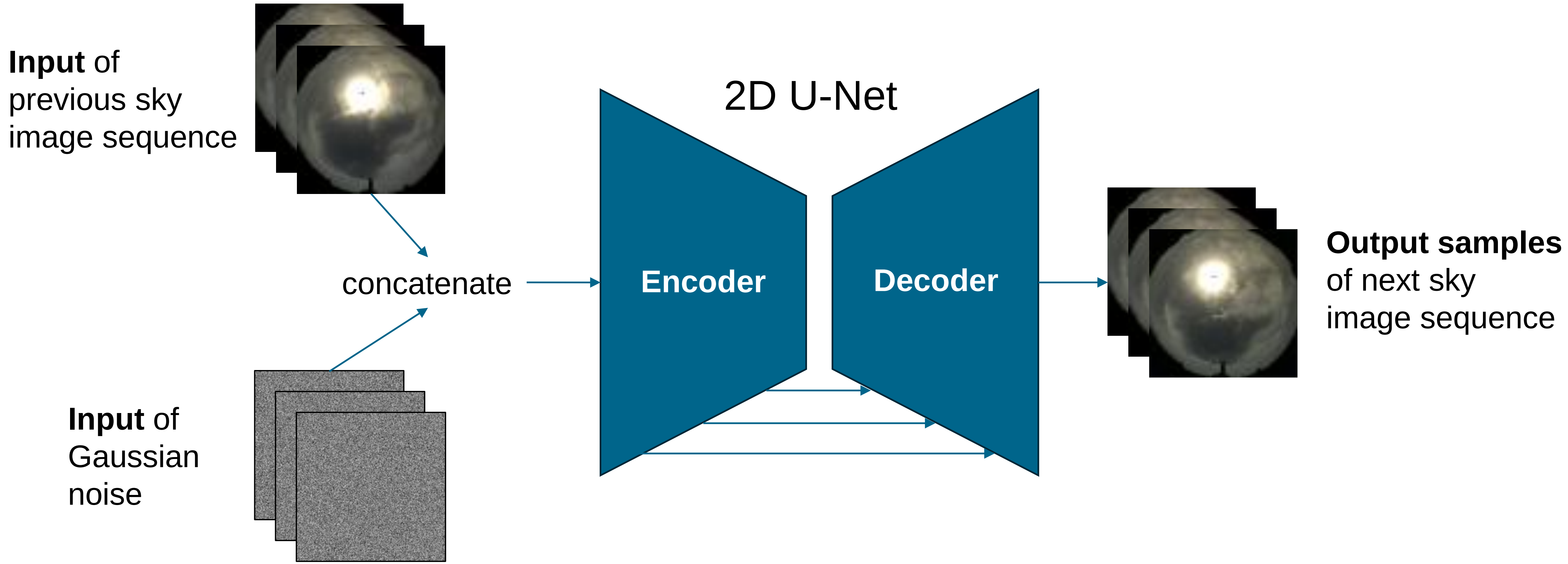
GENERATIVE NOWCASTING APPROACH

Generative Nowcasting Approach

- **Two-stage Method**
  1. <u>Predict future (synthetic) sky image</u>
     - Use sequence of recent sky images to predict next images
     - Generative Model: Diffusion model
  2. <u>Predict irradiance of future sky image</u>
     - Use synthetic images as input to predict corresponding GHI
     - Data-driven and physics-based models are applicable
- **Advantages**
  - Cloud motion is modelled implicitly by generative model
  - Increased interpretability due to synthetic images compared to previous data-driven model
  - Model uncertainty can be achieved through different samples of future sky images

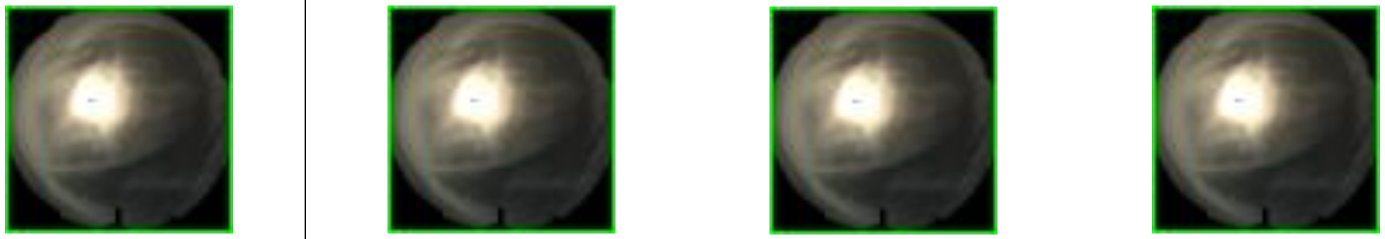


Generative Nowcasting Approach
Video Prediction Architecture: Diffusion Model [3]



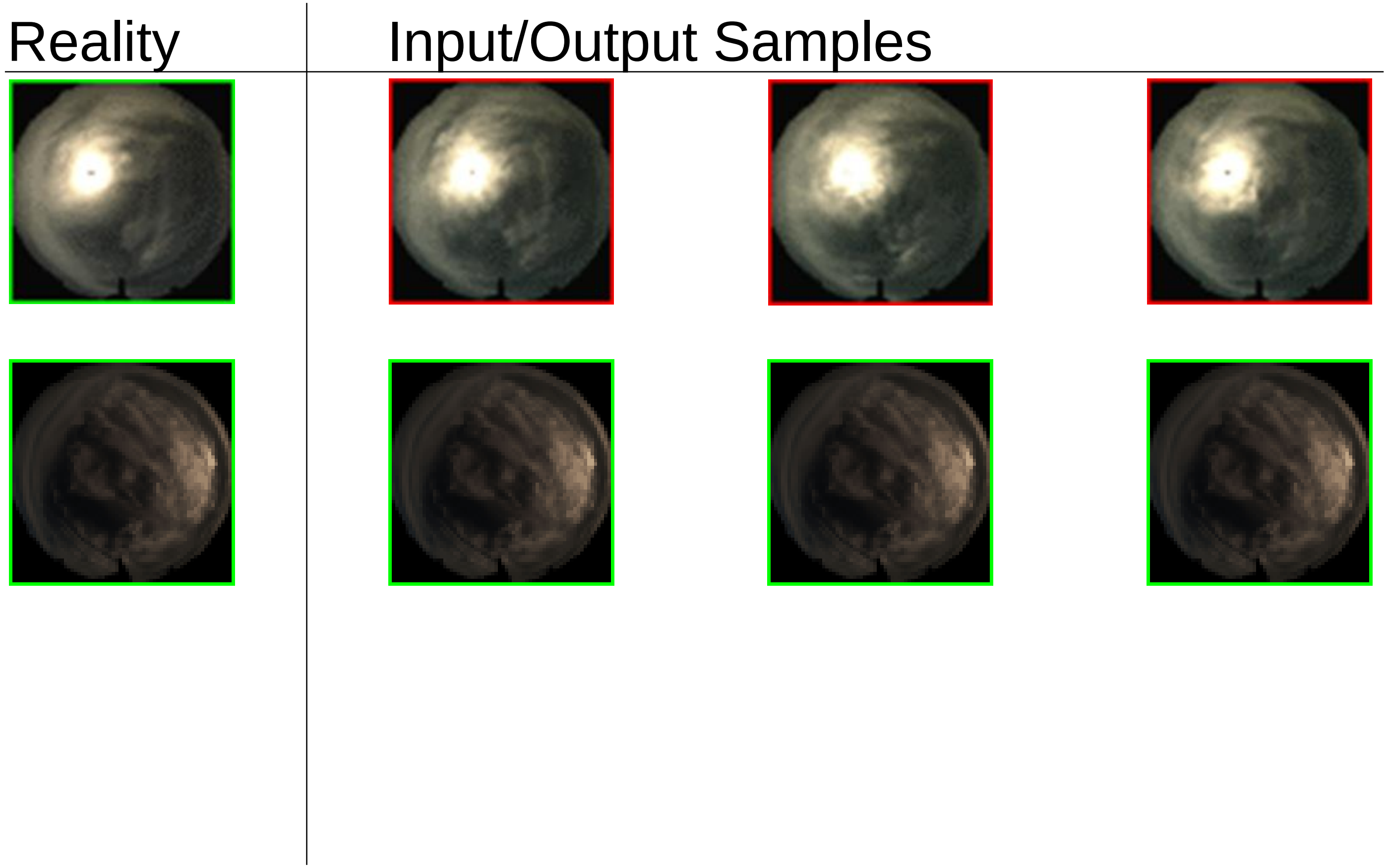
Generative Nowcasting Approach
Examplary Video Prediction Results

Reality | Input/Output Samples



- Green margin: real (input) image
- Red margin: synthetic (output) image

Generative Nowcasting Approach
Examplary Video Prediction Results



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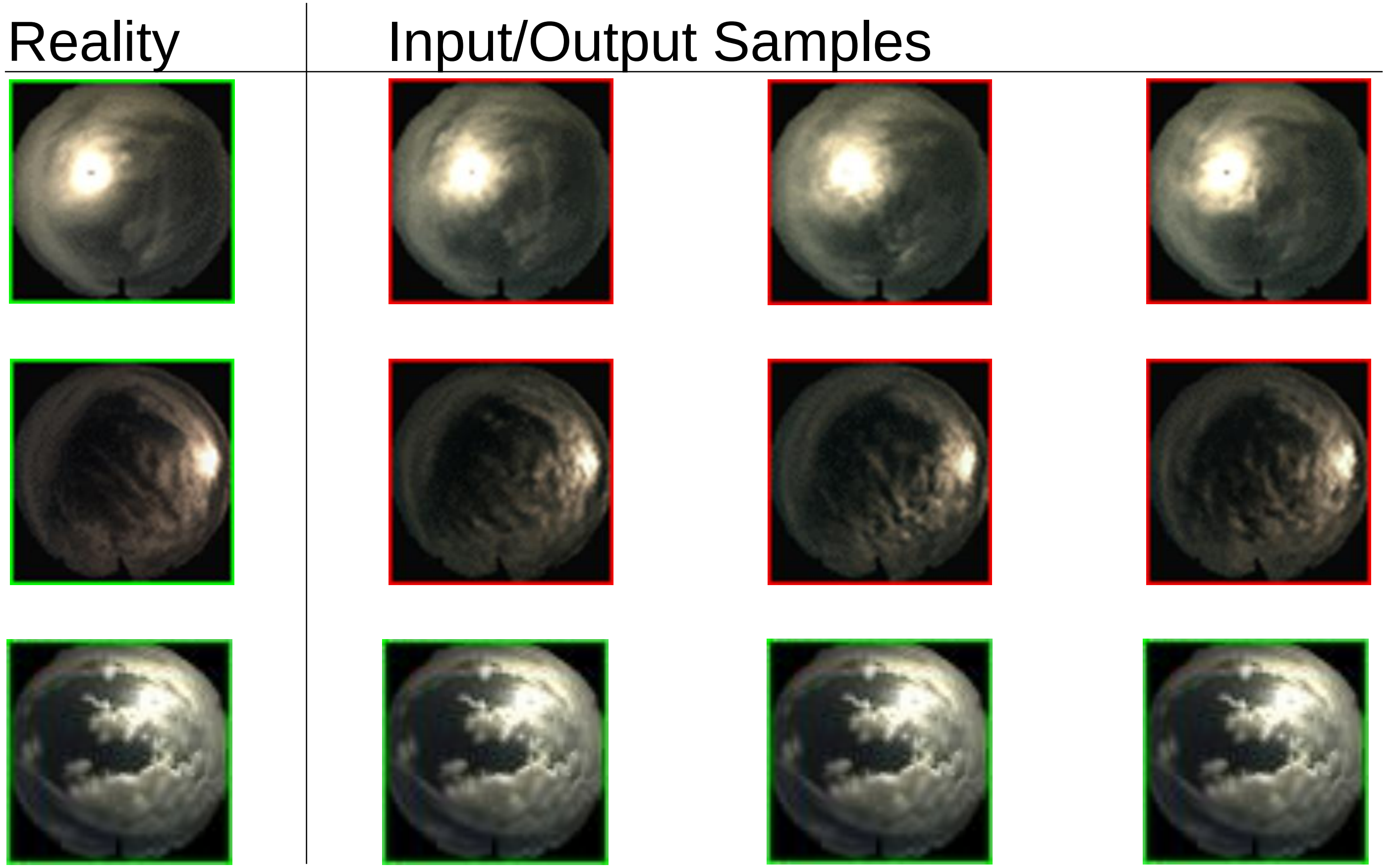
Generative Nowcasting Approach
Examplary Video Prediction Results



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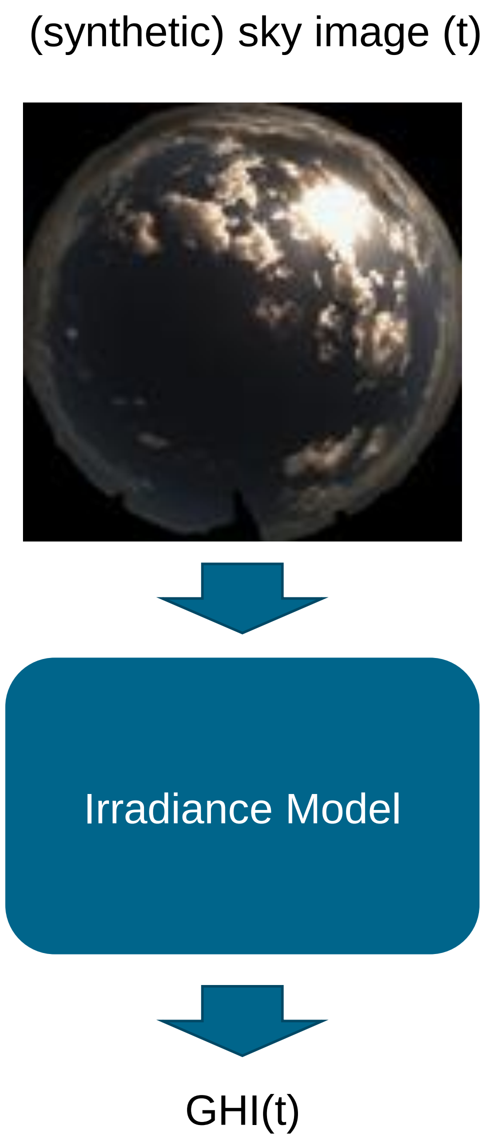
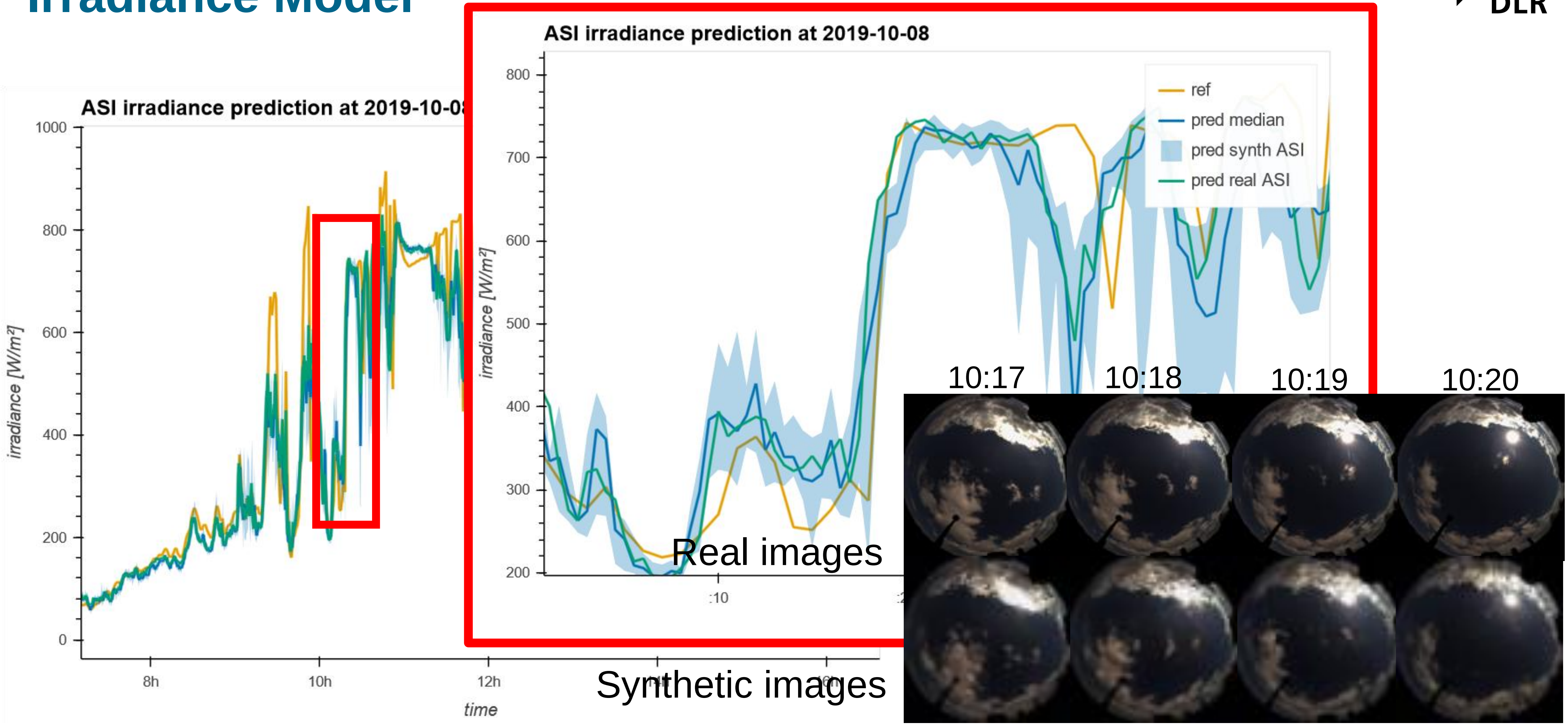
Generative Nowcasting Approach
Irradiance Model

Regression Model

- Input:
  - Single sky image
- Output:
  - GHI (corresponding to image)
- Architecture:
  - CNN (ResNet34)
- Training:
  - Using real sky images
  - Resizing to synthetic image size
  - Adding gaussian noise to simulate characteristics of synthetic images
- Validation:
  - On real and synthetic images (not used for training)



Generative Nowcasting Approach
Irradiance Model



RAMP EVENT VALIDATION

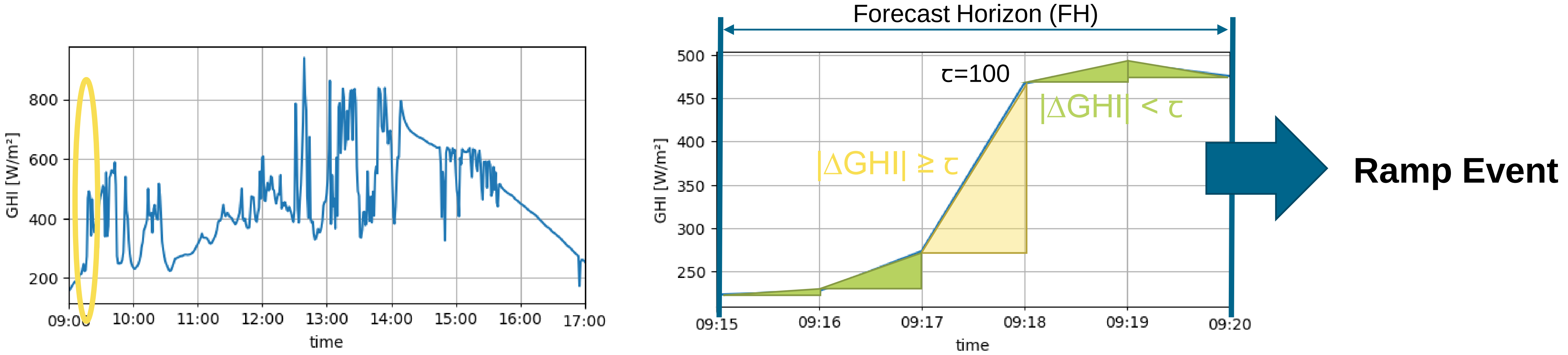
Ramp Event Definition

- Ramp (event) definition in solar forecasting strongly depends on use-case
- Existing definitions often complex and/or too sensitive [4]

Simplified definition:

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

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



Ramp Event Validation

- Validation against reference (on-site GHI measurements)
  - E.g. a predicted ramp event that was observed in the measurement curve is a true positive
- Validation based on 5min forecast horizon
- Validation via confusion matrices (in percentage) and F1-score

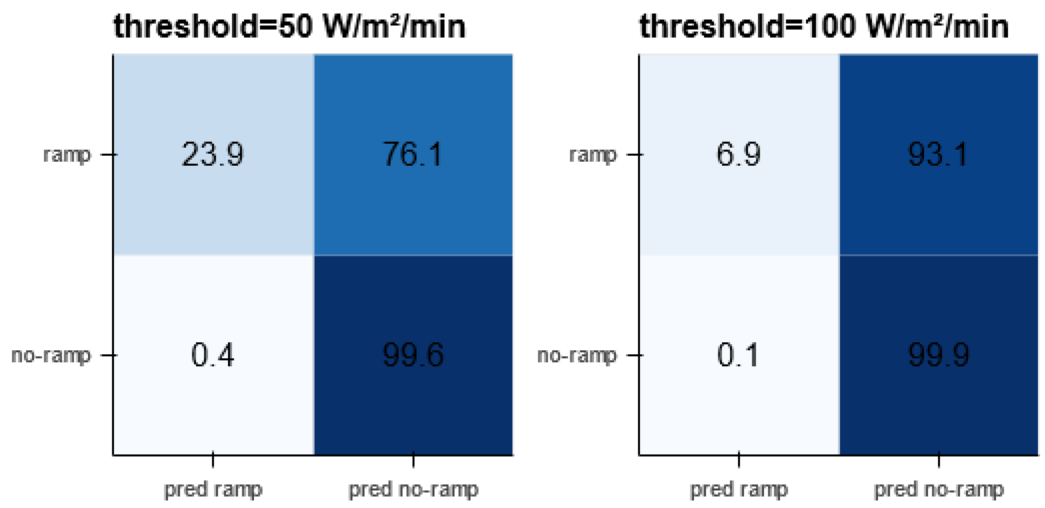
Confusion Matrix

Ramp Event	**True Positives (TP)**	**False Negatives (FN)**
No-Ramp Event	**False Positives (FP)**	**True Negatives (TN)**
	Predicted Ramp Event	Predicted Ramp Event

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

Ramp Event Validation

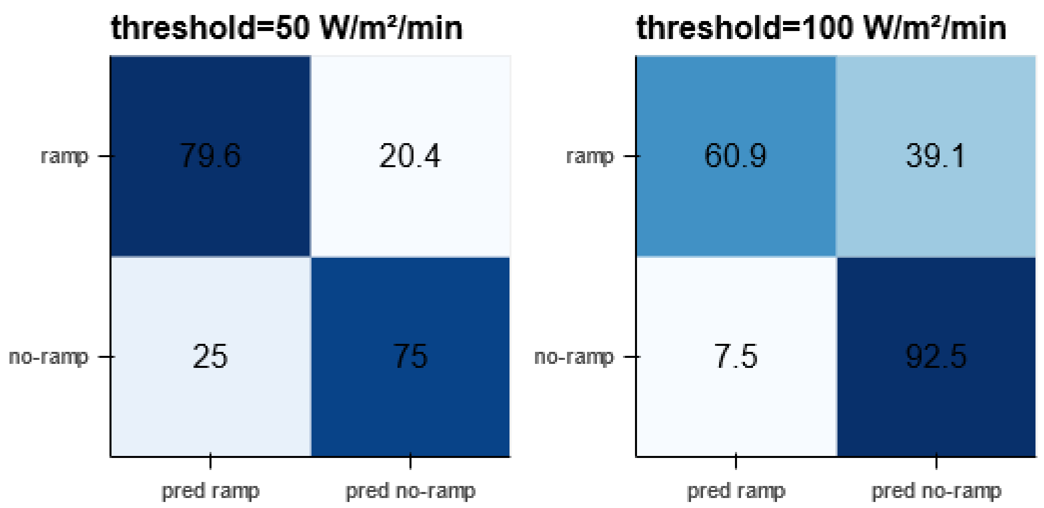
Hybrid Model



F1 = 0.38

F1 = 0.13

Generative Model



F1 = 0.44

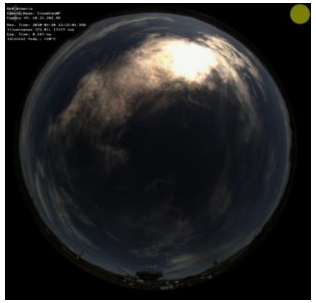
F1 = 0.42

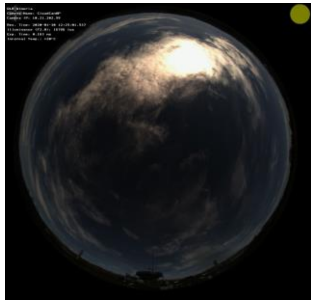
- Hybrid model very good in FS but cannot predict strong ramps
- Generative model predicts majority of actual ramp events while maintaining high rate (>75%) of no-ramp events
- Selection of threshold depends on application/technology

Improving the Irradiance Model

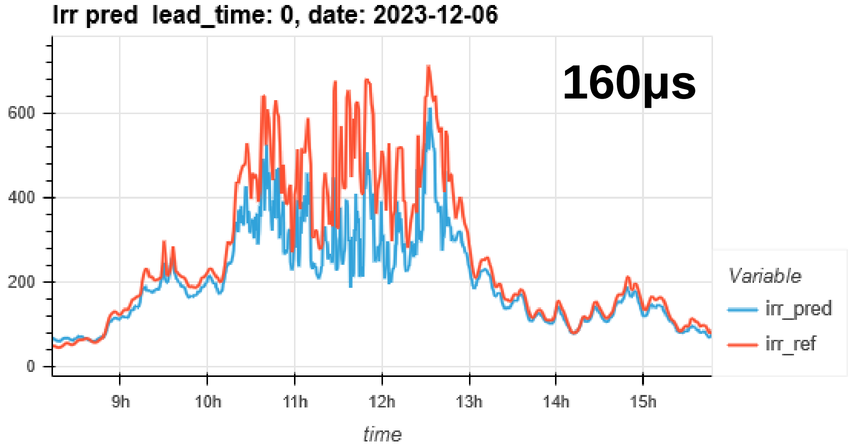
- Oversaturation in circumsolar region poses challenge to estimate irradiance (e.g., large bias)
- Lower exposure times can help to improve accuracy

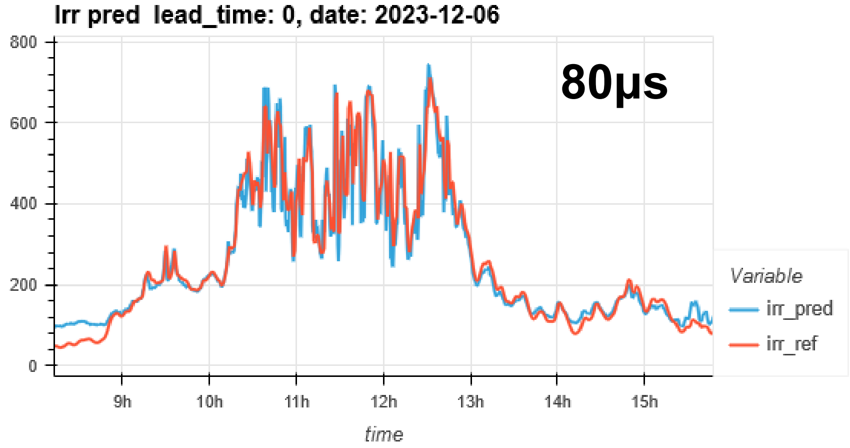
400 W/m² vs 200 W/m²





Exposure Time [µs]	RMSE [W/m²]	MAE [W/m²]	MBE [W/m²]
160	101	70.3	-64
80	60.7	42.2	-1.5





CONCLUSION & OUTLOOK

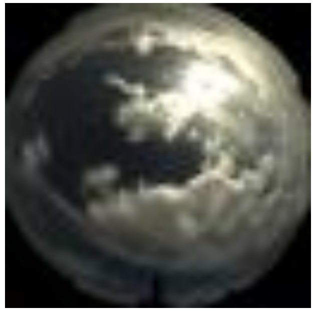
Conclusion

- **Quality of nowcasting models depends on use case**
  - Data-driven and hybrid models often achieve good error scores but may not be well-suited for ramp event detection (optimization on RMSE)
- **Presentation of novel generative approach for ASI-based solar nowcasting**
  - Diffusion model for predicting future synthetic sky images
  - Irradiance model for predicting irradiance (GHI)
- **Validation of ramp event detection of a hybrid model and novel generative approach**
  - Hybrid model misses most ramps due to flattened nowcast curve
  - New generative model superior in ramp event prediction
    → Predicts majority of true ramp events while having few false negatives

Outlook
Improving Generative Model

Video Prediction Model

- Train on sky images with different exposure times
- Reduce training effort to increase image resolution and forecast horizon
  - Low resolution of images (64x64)
  - Short forecast horizon (5 min)



→ Ablate better design (e.g. apply diffusion in latent space)

Irradiance Model

- Reduce error metrics to be compatible with hybrid model in terms of forecast skill

→ Include auxiliary features

→ Test more complex model architectures (e.g. VisionTransformers)

→ Use sky image series (with different exposure times) or HDR

References

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2. 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)*
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   Denoising diffusion probabilistic models
4. 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

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