BLENDED AND GENERATIVE ALL SKY IMAGER NOWCAST

20251016: IEA PVPS Task 16 meeting

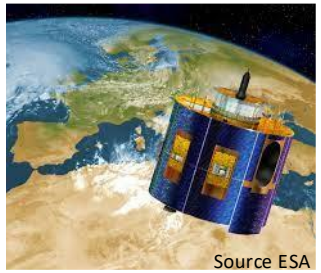
Agenda

- Blended Forecasting System
- Generative Forecasting System

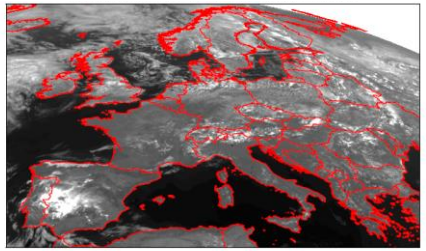
BLENDED FORECASTING SYSTEM

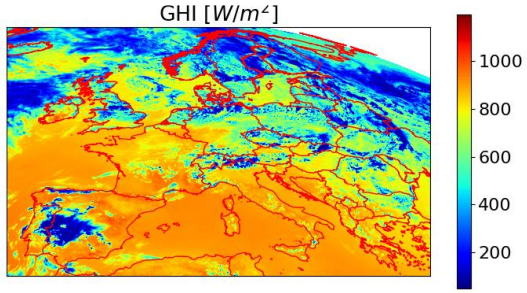
Blended Forecasting System: Forecasting systems

Meteosat based forecasts



Heliosat method [1]

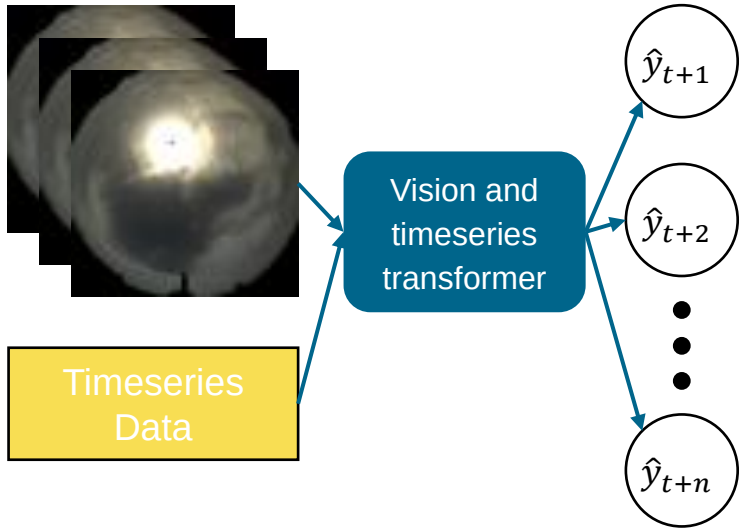




- Horizon ~6h
- Spatial resolution ~ 2km
- Temporal resolution and update rate 15 min

All sky imager (ASI) based forecast

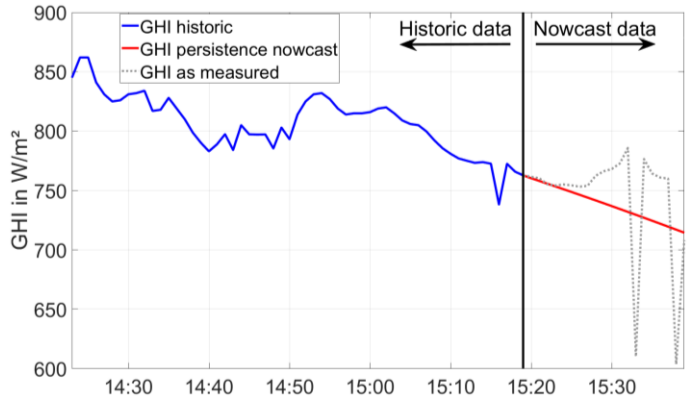
Deep learning transformer method [2]



- Horizon 1h
- Temporal resolution 1 min
- Update rate 30 s
- Model trained on data set in southern Spain
- >3000000 data points distributed over 7 years

Persistence forecast

Scaled persistence method [3]

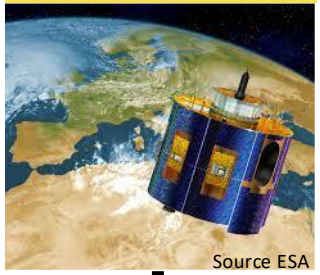


- Update rate 1 min

Blended Forecasting System: Blending methods

Ground measurements

Satellite



ASI

Ground measurements

Forecast

Ground truth

Training data

Testing data

Homogenization

Blending
- Linear regression
- XGBoost
- LSTM
- Transformer

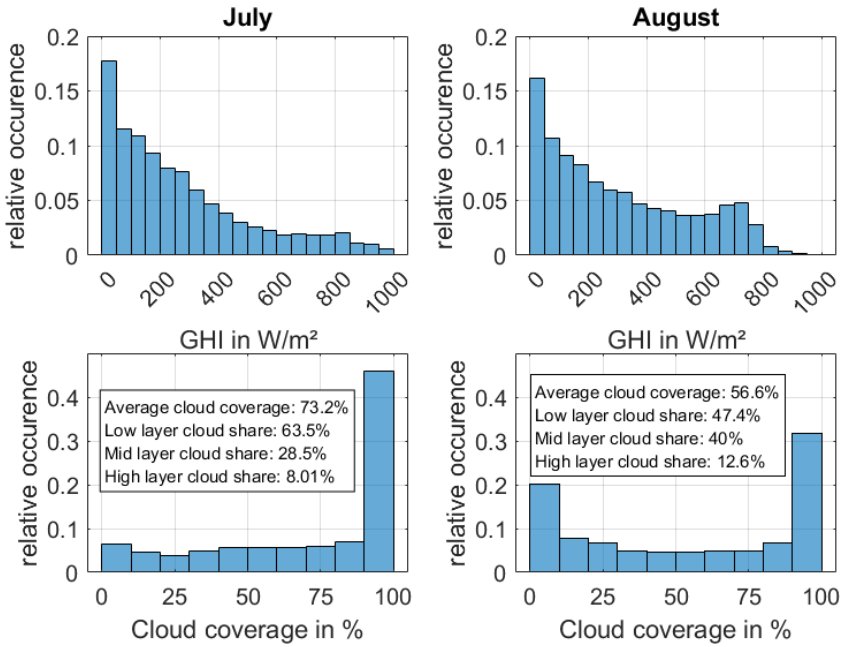
Hyperparameter tuning is performed

Inference blending

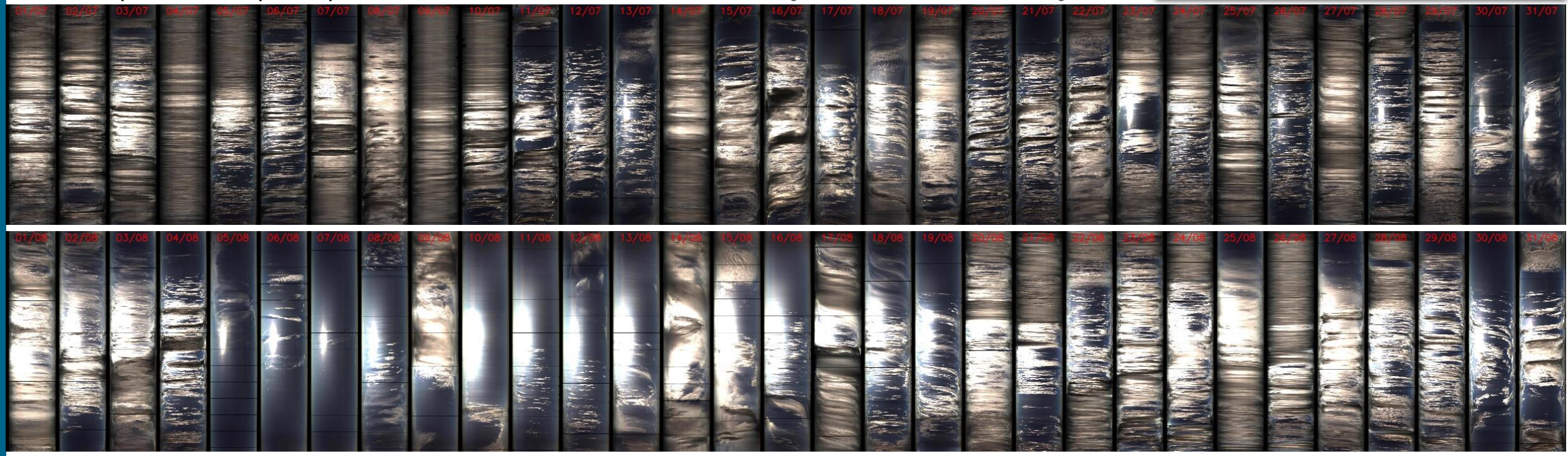
Blended forecasts
- Satellite+Persistence
- Satellite+ASI+Persistence

Used datasets

- Site: Oldenburg (Germany)
  - OLDON station of Eye2Sky Network [4]
  - 53°8´46.96´´N / 8°13´2.41´´E
- Used data
  - Training/Validation: July 2020 (50373 datapoints)
  - Testing: August 2020 (45163 datapoints)

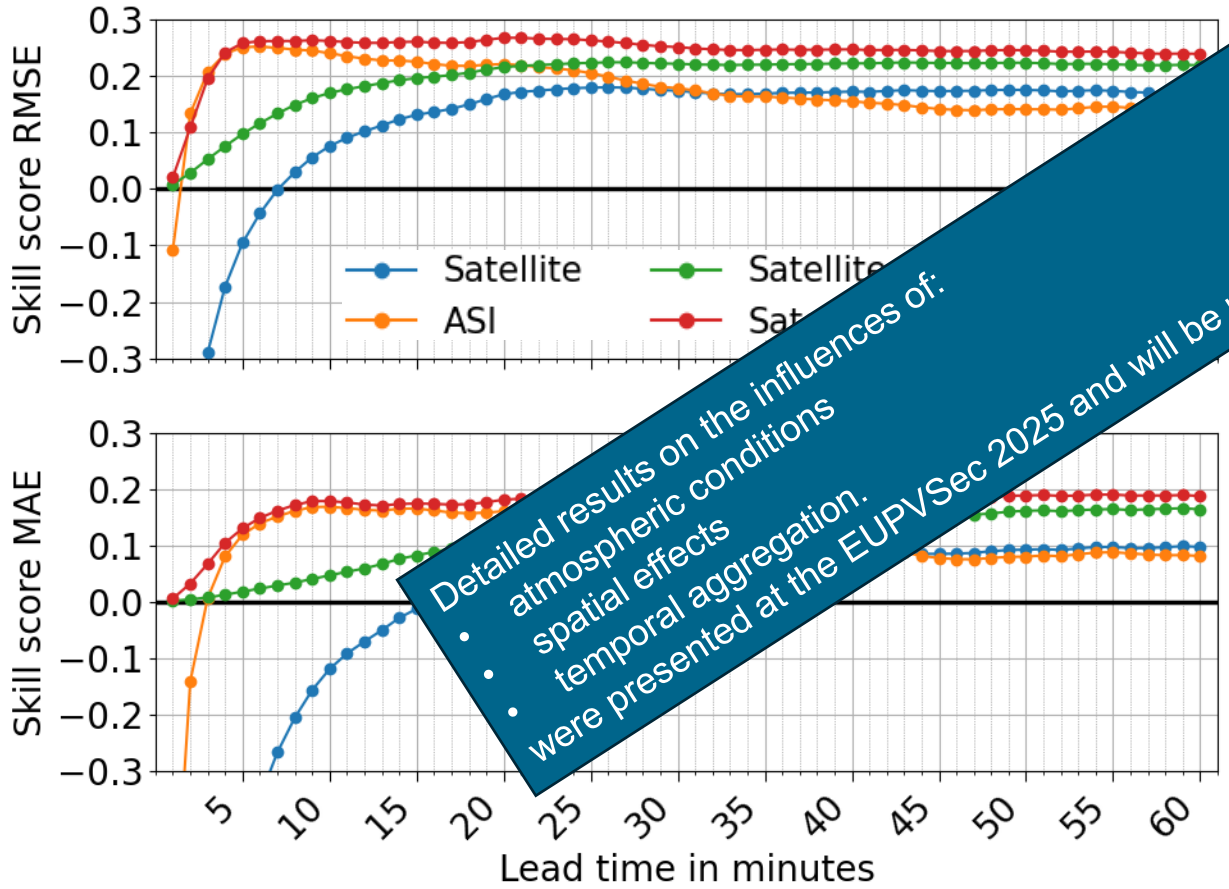


	July	August
$\overline{GHI}$	321.7 W/m²	358.1 W/m²
Max GHI	972.3 W/m²	840.0 W/m²
$\overline{DHI}$	192.1 W/m²	166.7 W/m²
Max DHI	505.4 W/m²	442.1 W/m²
$\overline{DNI}$	209.9 W/m²	323.5 W/m²
Max DNI	876.4 W/m²	847.7 W/m²



General benchmark forecasts

$$RMSE = \sqrt{{}^{1}/_{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \qquad MAE = {}^{1}/_{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \qquad Skill\ sc\ \ldots\ sistence$$



Detailed results on the influences of:
- atmospheric conditions
- spatial effects
- temporal aggregation.

were presented at the EUPVSec 2025 and will be published in a paper in the near future.

	…+Persistence			
	…LR	XGBoost	LSTM	Transfor-mer
…W/m²] ↓	121.8 ±16.9	120.8 ±17.2	119.7 ±17.4	120.4 ±17.2
MAE [W/m²] ↓	77.6 ±14.2	80.3 ±14.9	78.1 ±14.5	79.5 ±14.6
MBE [W/m²] ↓	-1.7 ±1.6	-5.5 ±1.5	-2.8 ±3.0	-1.8 ±5.1
Skill Score (RMSE) ↑	0.24 ±0.04	0.25 ±0.02	0.26 ±0.01	0.26 ±0.02
Skill Score (MAE) ↑	0.17 ±0.03	0.14 ±0.04	0.17 ±0.03	0.15 ±0.05

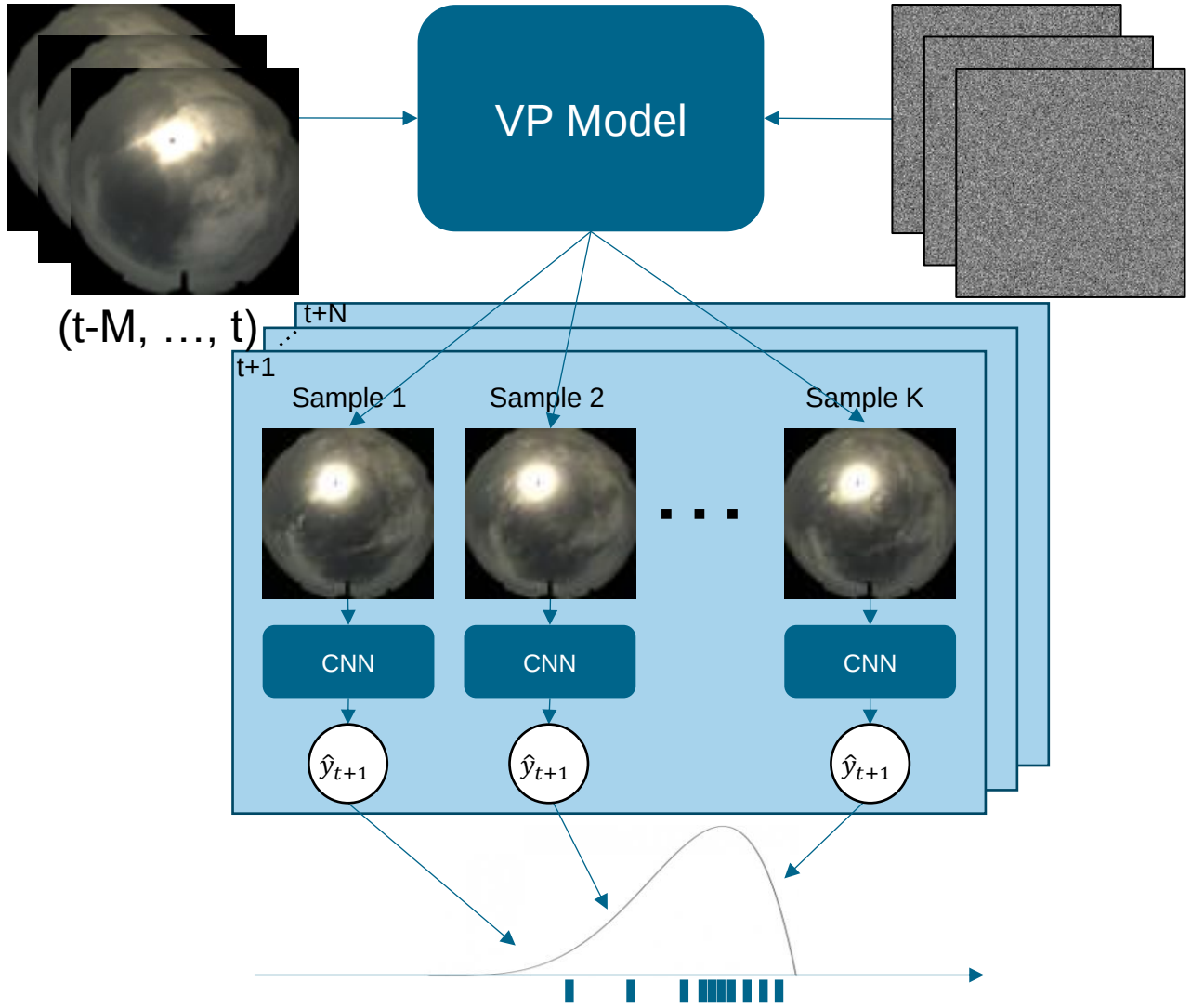
Averaged results over all lead times (± std)

GENERATIVE FORECASTING SYSTEM

Generative Forecasting
Model Architecture

- **Video Prediction (VP)**:
  - Given sequence of M past images next images for N lead times are predicted
  - K future scenarios are generated from the same input sequence by sampling from Gaussian noise
    → Measure for uncertainty

- **Downstream tasks:**
  - Given individual predicted future frames, a second model (e.g. CNN) is used to derive target quantity
  - E.g., classifier predicts directly **ramp events** or **irradiance** based on predicted sky images
  - Trained separately on real images



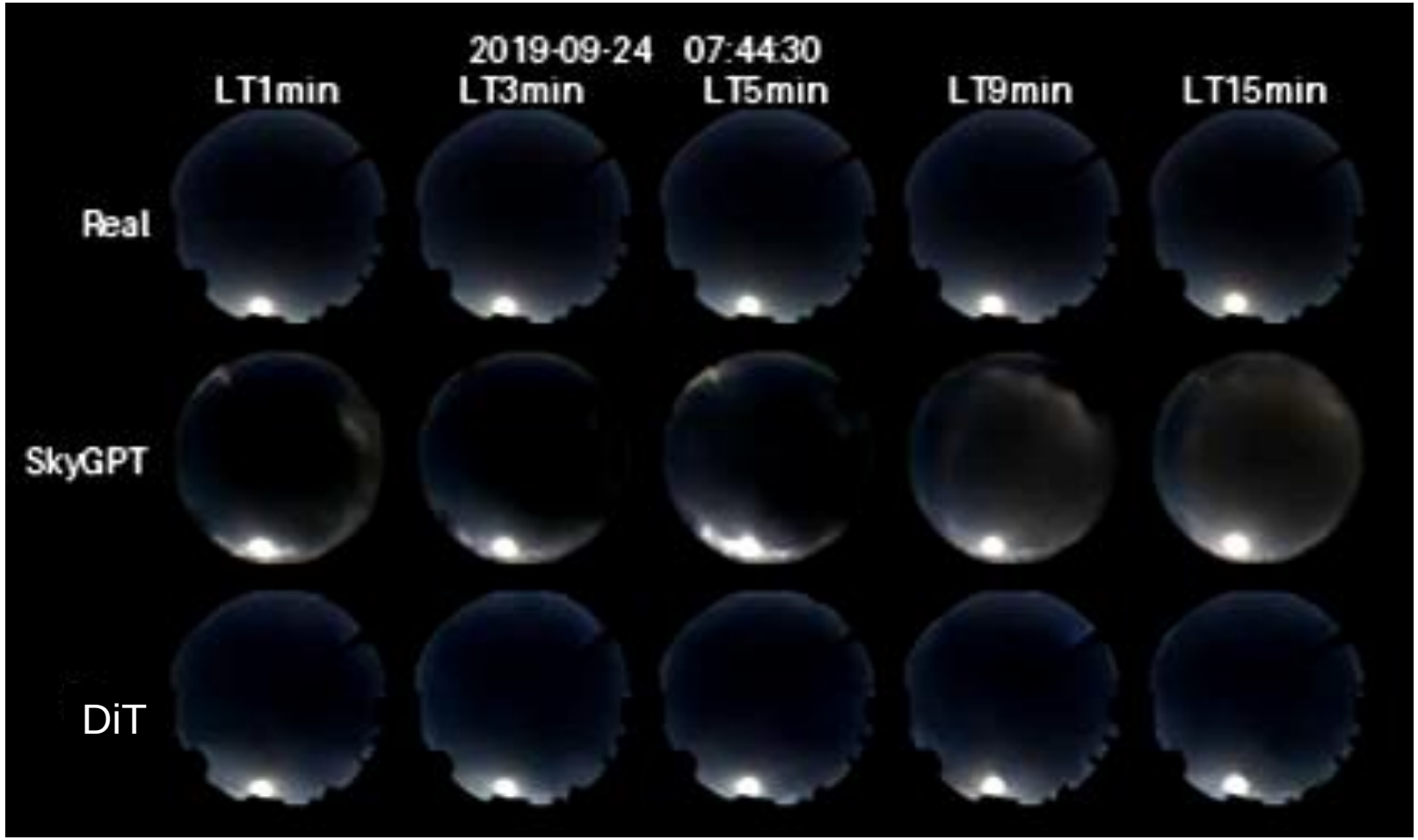
Video Prediction Models
Model options / Train and Test setup

- Two different generative models were tested
  - SkyGPT [5]: Adaptation of the VideoGPT [6] model combined with PhyCell [7]
  - DiT: Adaptation of the diffusion-based transformer model [8]
- Training
  - Both models were trained on selected camera data from CIEMAT‘s PSA
- Testing
  - Evaluation on separate benchmark dataset defined in All-Sky Imager-based forecasting study [9]
  - 28 selected days from a single camera at PSA representing diverse sky conditions
  - 4 image samples per model were generated for each lead time

Image taken at CIEMAT‘s PSA

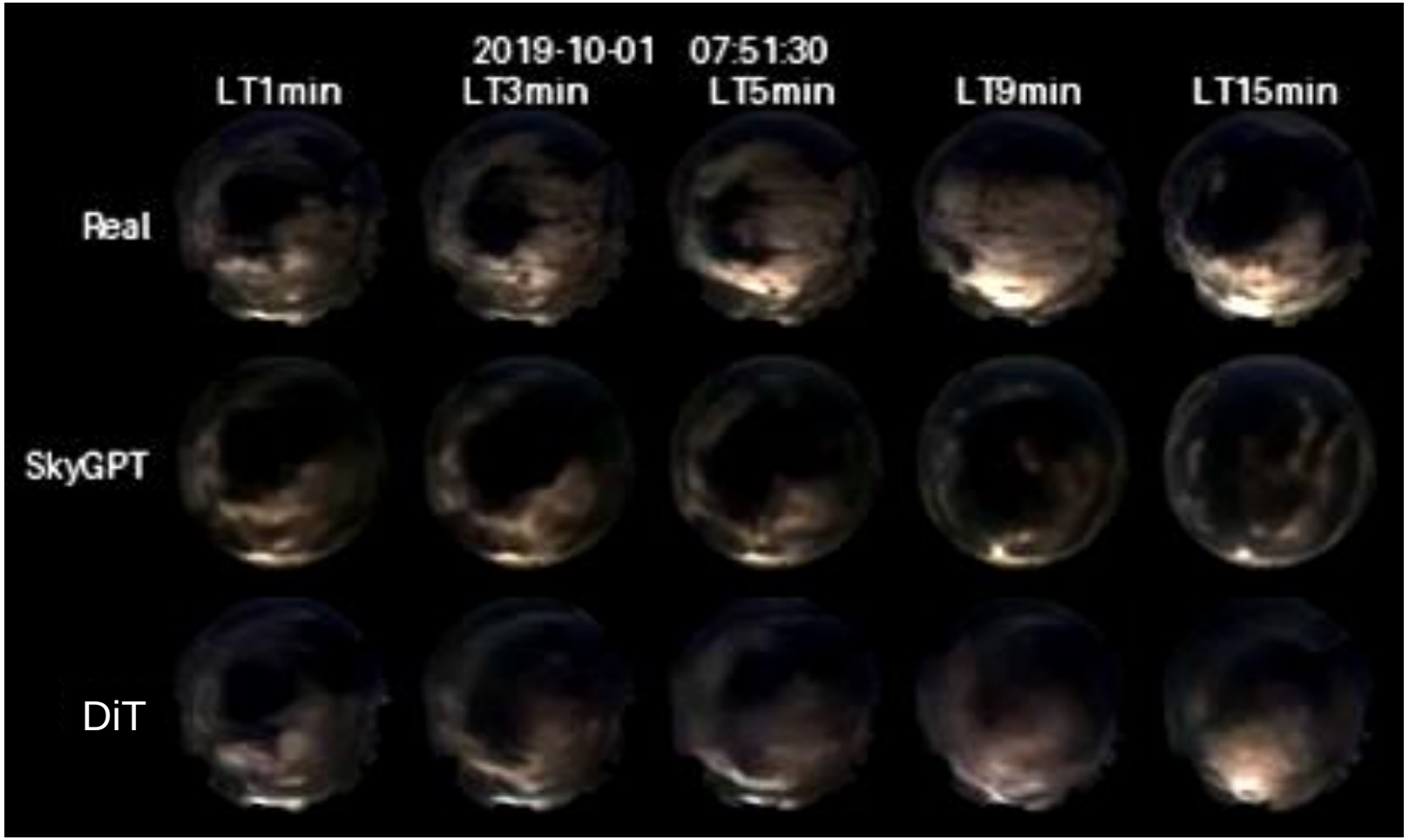
	SkyGPT	DiT
Image res.	64x64	128x128
Temporal res.	2min	1min
Forecast horizon	15min	30min
Variational Auto Encoder	VQ-VAE [6]	Pretrained VAE [9]

Video Prediction Evaluation
Exemplary Results – Single Sample, Selected Lead Times



→ A lot of „hallucinations“ even for clear sky conditions

Video Prediction Evaluation
Exemplary Results – Single Sample, Selected Lead Times



→ Strong deviations in terms of cloud coverage for larger lead times

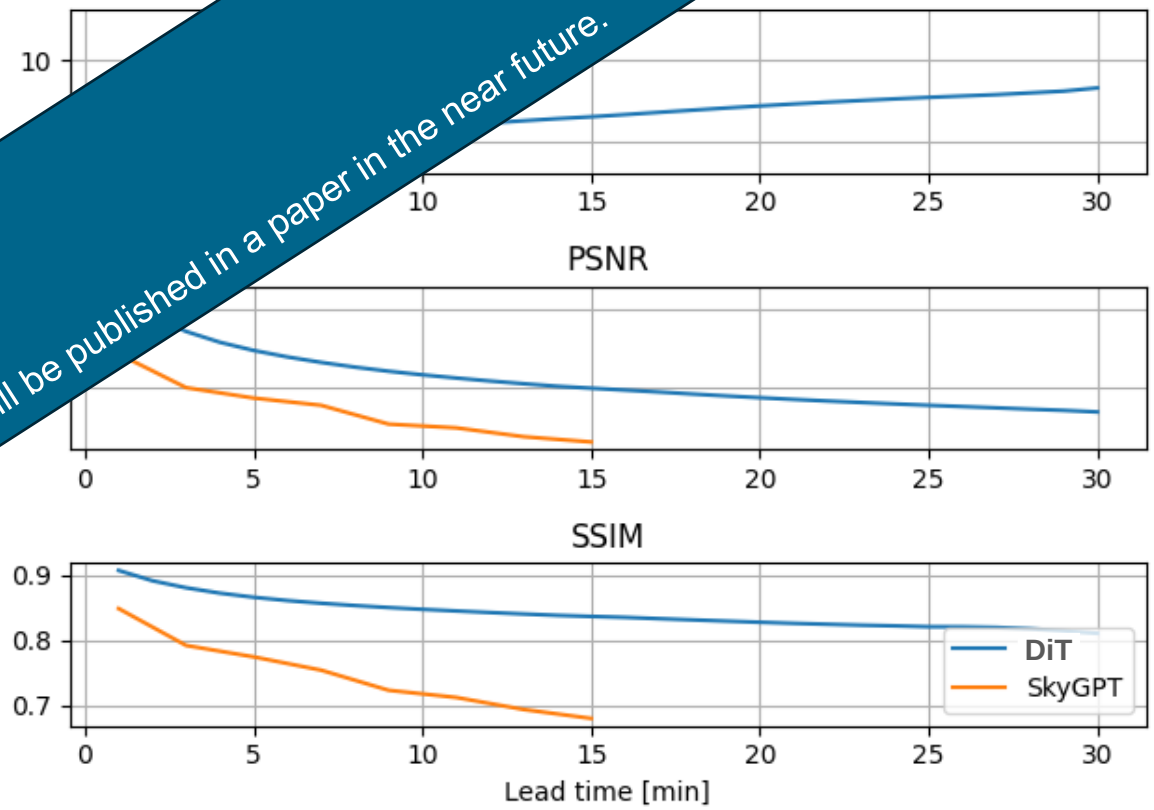
Video Prediction Evaluation
Quantitative Evaluation of Images

- Evaluation of predicted sky image frames
  - Image pixel value data range: [0, 255]
  - Lead-time specific calculation averaged over all generated future scenarios

- Image-wise pixel metrics
  - Mean Absolute Error (MAE)↓:
    - Average error per pi
  - Peak Signal-to-N ↑:
    - Ratio of m al to error in decibe
  - Structural S x (SSIM)↑:
    - Measure fo ptual similarity (capturing sharpness a d structure)

Detailed results on downstream tasks:
- Ramp event prediction
- Irradiance prediction
- Cloud coverage prediction

were presented in part at the EUPVSec 2025 and will be published in a paper in the near future.



→ Better performance of DiT model in terms of image quality

Conclusion

- Blended Forecasting System: Strong for overall irradiance, less for ramp events.
- Generative Forecasting System: Generate multiple realistic sky scenarios for each lead time.
  - Preliminary results show superior ramp event detection capabilities compared to the current state-of-the-art
  - Future work
    - Assessment of further generative model architectures
    - Detailed evaluation of downstream tasks
    - Deriving irradiance maps based on generative approaches

References

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7. LeGuen et al. 2020, **Disentangling Physical Dynamics From Unknown Factors for Unsupervised Video Prediction**, DOI: 10.1109/cvpr42600.2020.01149
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THANK YOU FOR YOUR ATTENTION!
QUESTIONS?
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