Sky image prediction using generative adversarial networks (GANs) for solar forecasting

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Tackling Climate Change with Machine Learning
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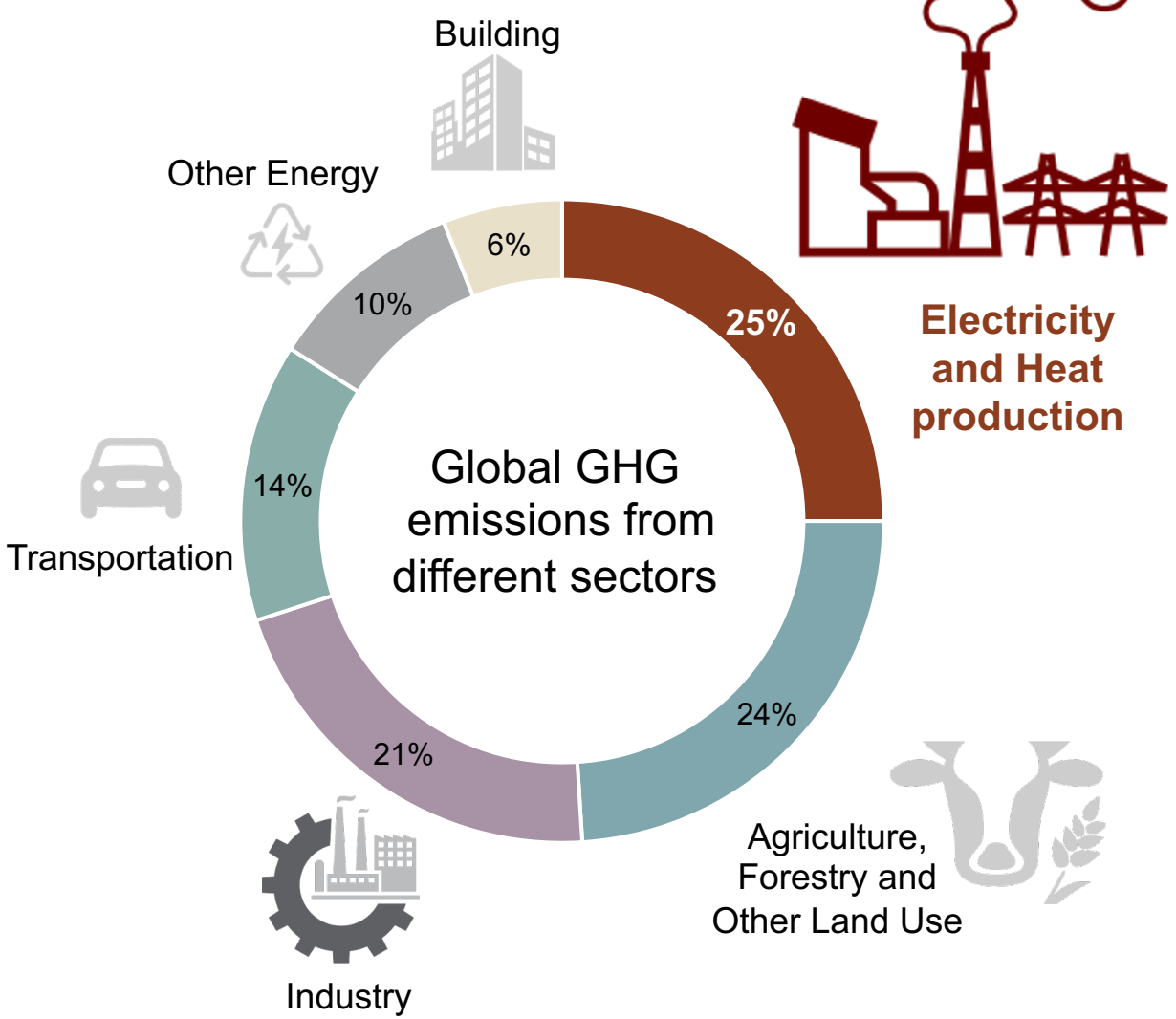
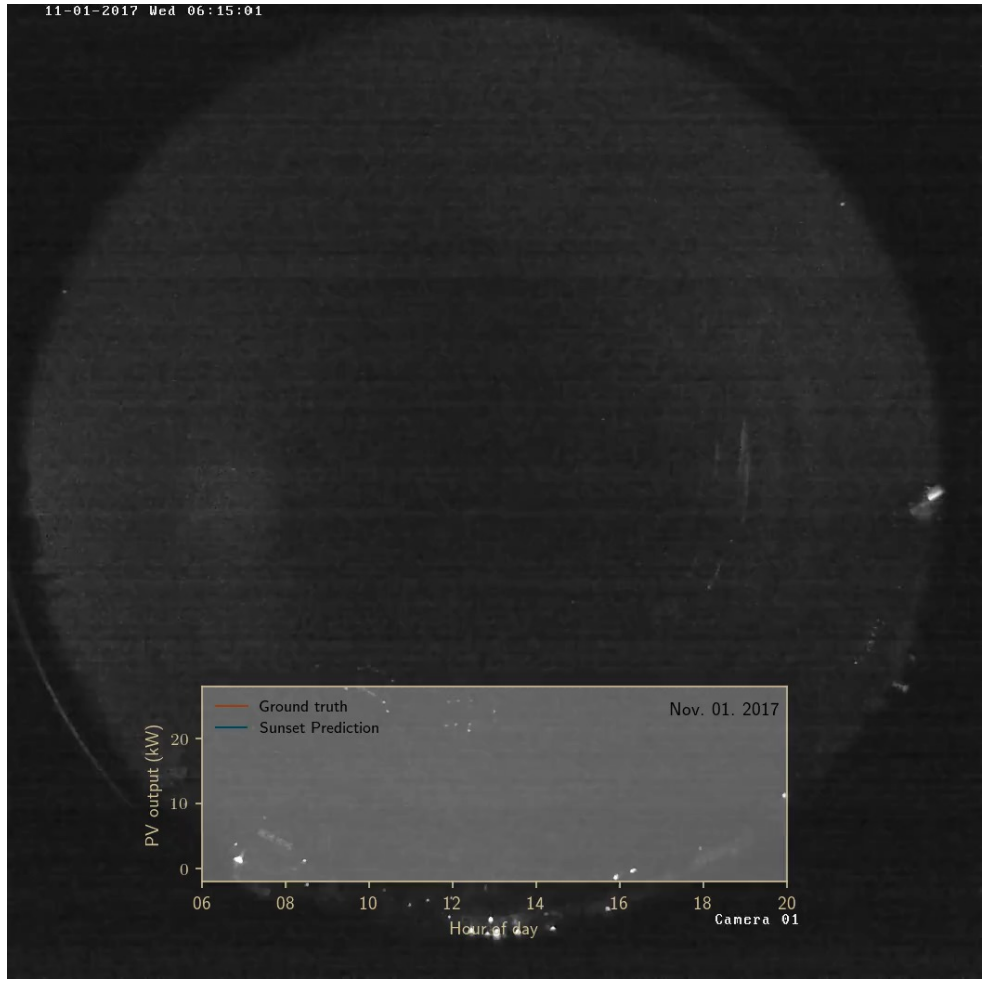
Global GHG emissions from different sectors

Climate Change



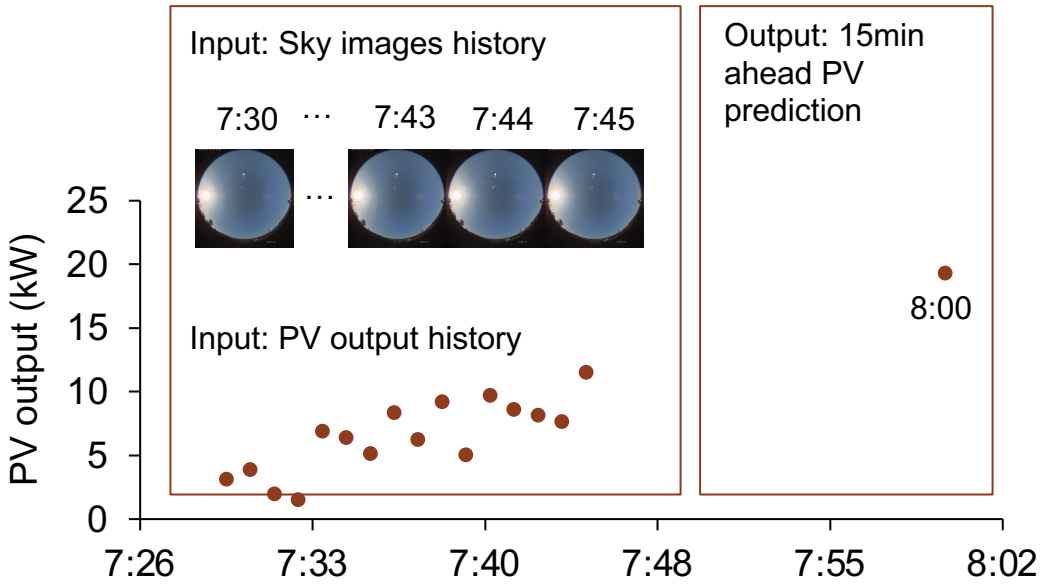
PV integration challenged by solar intermittency



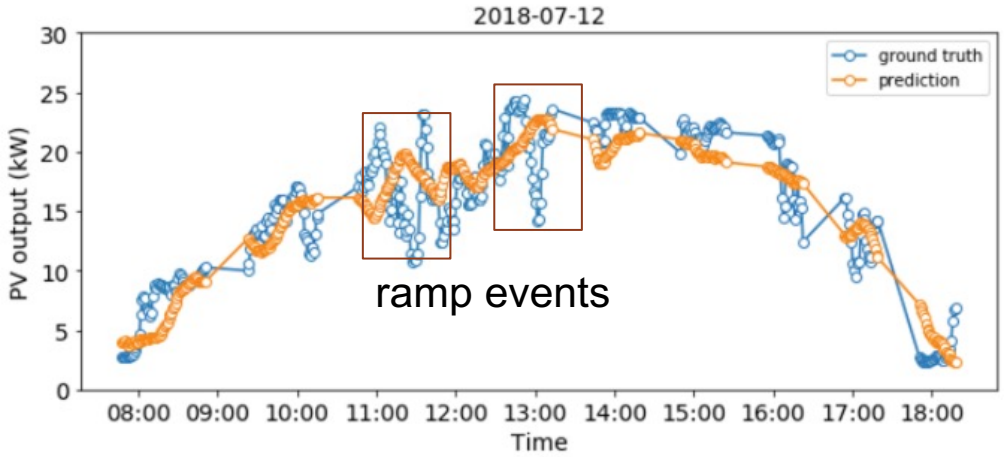
- Integrating solar photovoltaics (PV) is promising to reduce the GHG emissions from power generation
- Large-scale PV integration is challenged by solar intermittency, mainly caused by short-term cloud events
- 70%~80% loss of power could happen on partly cloudy day
- Solar forecasting is critical to alleviate the uncertainty in PV power generation

Image-based solar forecasting

An end-to-end convolutional neural network (CNN) model for solar forecasting[1] (SUNSET)



Performance on a cloudy day: 13% relative mean squared error (30 kW PV system)



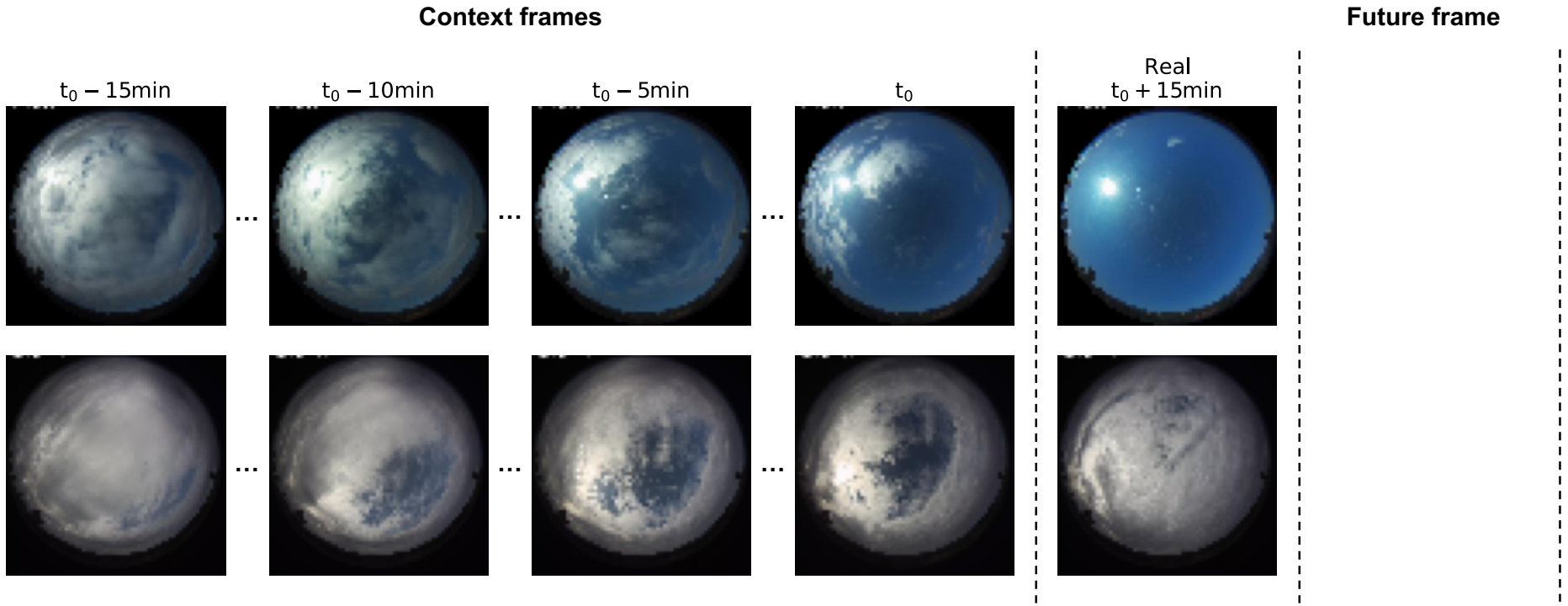
Key challenges

- Temporal lags in predicting the ramp events (sudden power output changes)
- Accurately predicting the motion of clouds is pivotal to accurate solar forecasting

[1] Sun et al. (2019). Short-term solar power forecast with deep learning: Exploring optimal input and output configuration. *Solar Energy*.

Cloud motion prediction via deep learning models

- Predict the **future** sky frame (f) based on the **context** sky image frames (c)
- Learn a mapping G: $\{c_{t-T}, \ldots, c_{t-1}, c_t\} \rightarrow f_{t+T}$ using deep learning models
- Commonly used deep learning models, e.g., ConvLSTM, could capture the cloud dynamics to certain degree, but the generated images look blurry.
- In this study, we explore generative adversarial networks (GANs) for future sky image generation



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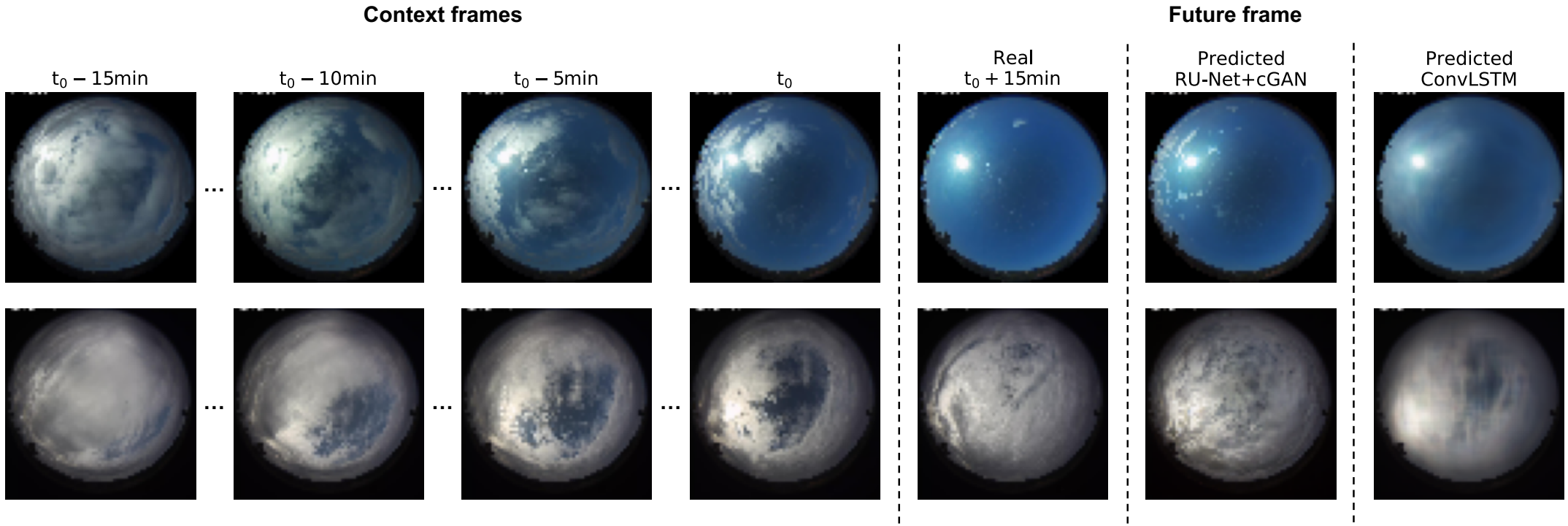


GAN framework and experiments

Real future image frames (F_{t+15})

Sample

Experiment 2

$+\lambda = [5, 15, 30, 50, 75, 100, 200]$ $\mathcal{L}_1$

$\mathcal{L}_G^{GAN}$

Context frames ($C_{t-15}, \ldots, C_{t-1}, C_t$)

Generator (G)

Generated future frames ($\hat{F}_{t+15}$)

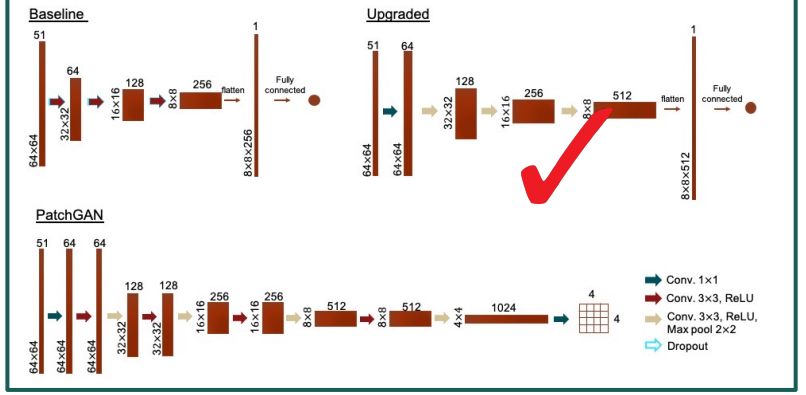
Sample

Discriminator (D)

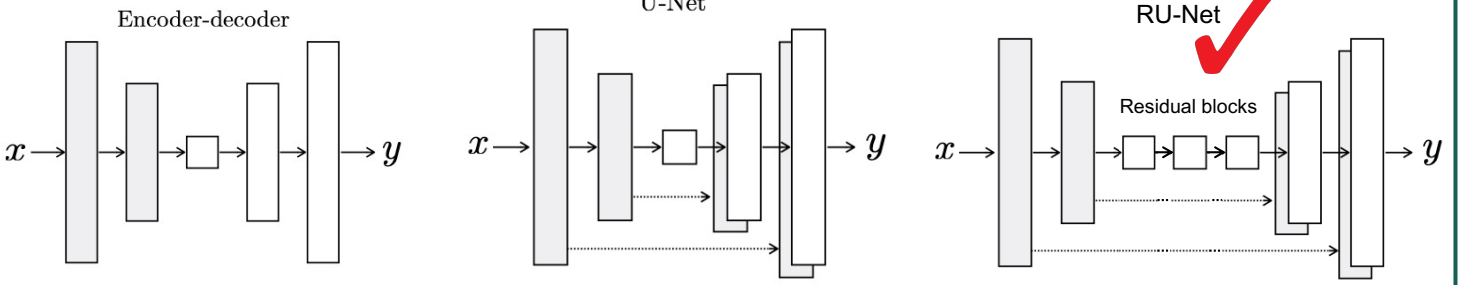
Score (real | sample)

$\mathcal{L}_D^{GAN}$: W-loss with gradient penalty

Experiment 3



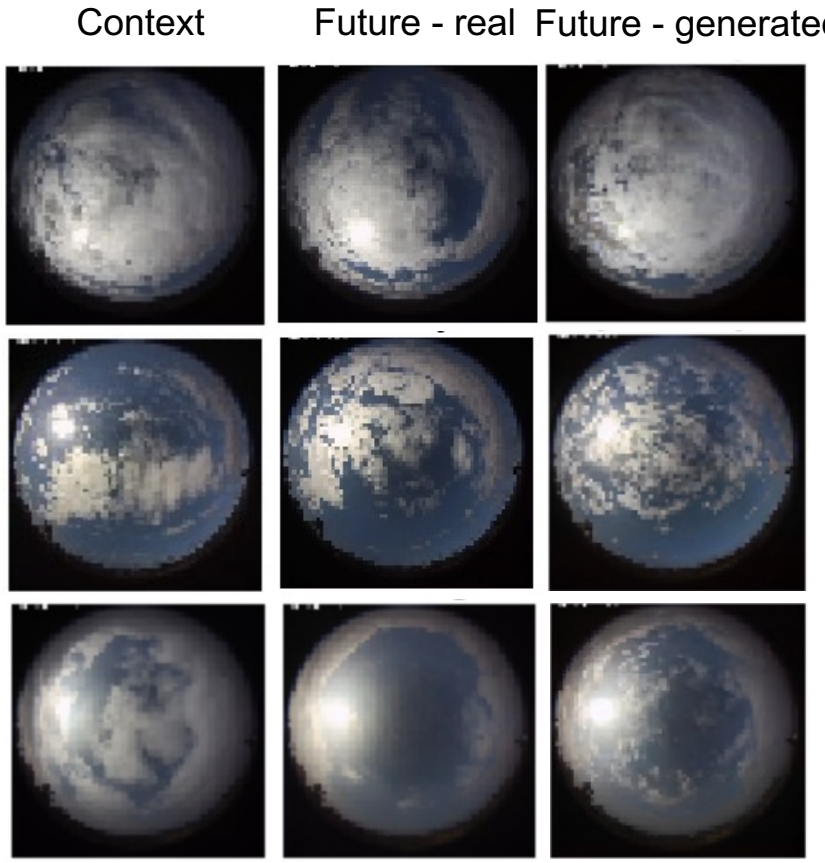
Experiment 1



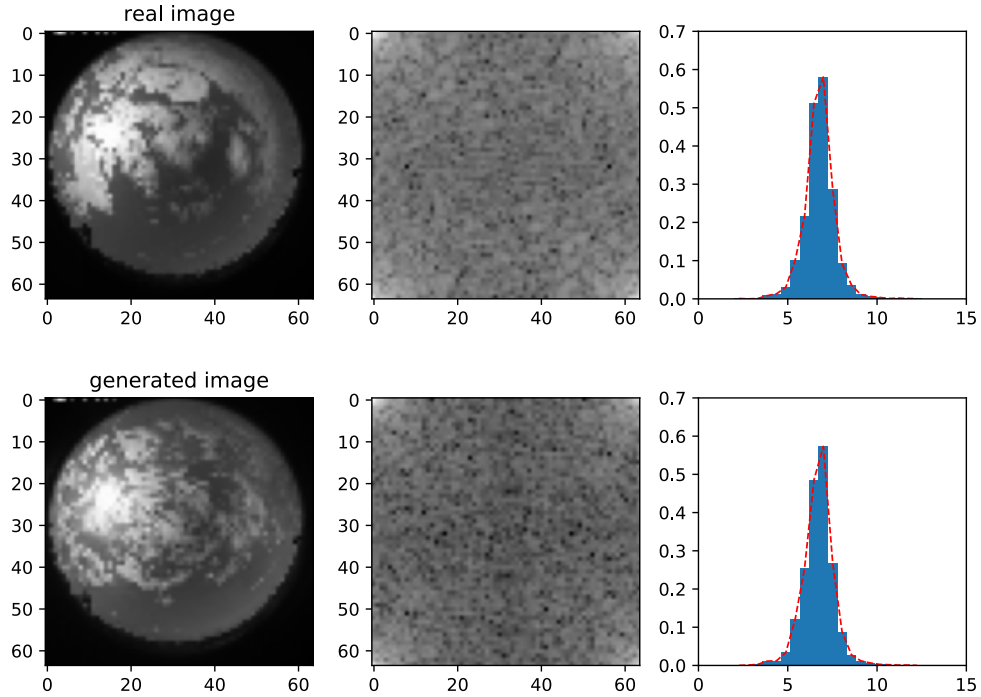
Results and discussion

Fidelity of predicted future images

Visual inspection

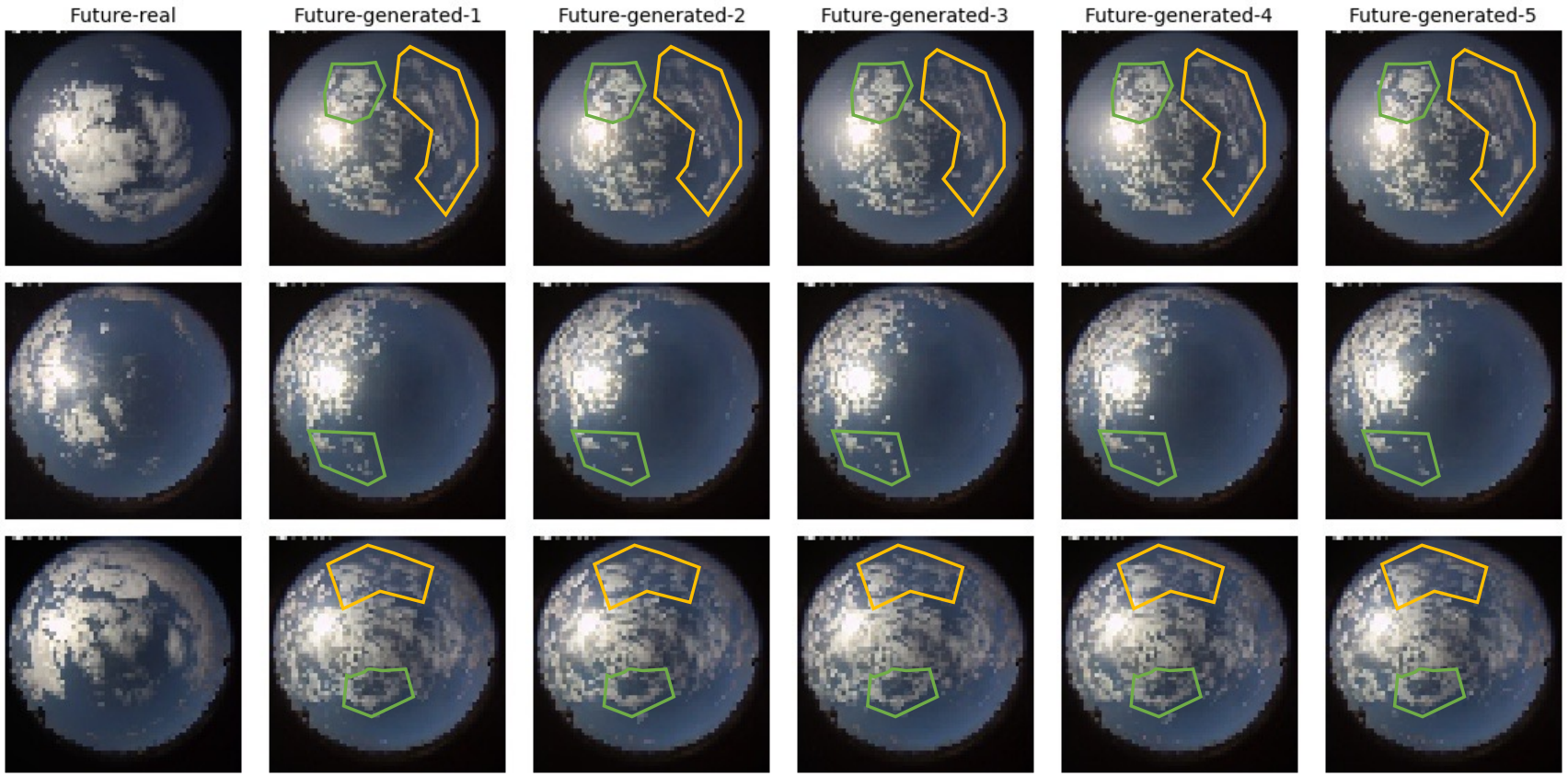


2D Discrete Fourier Transform



Results and discussion

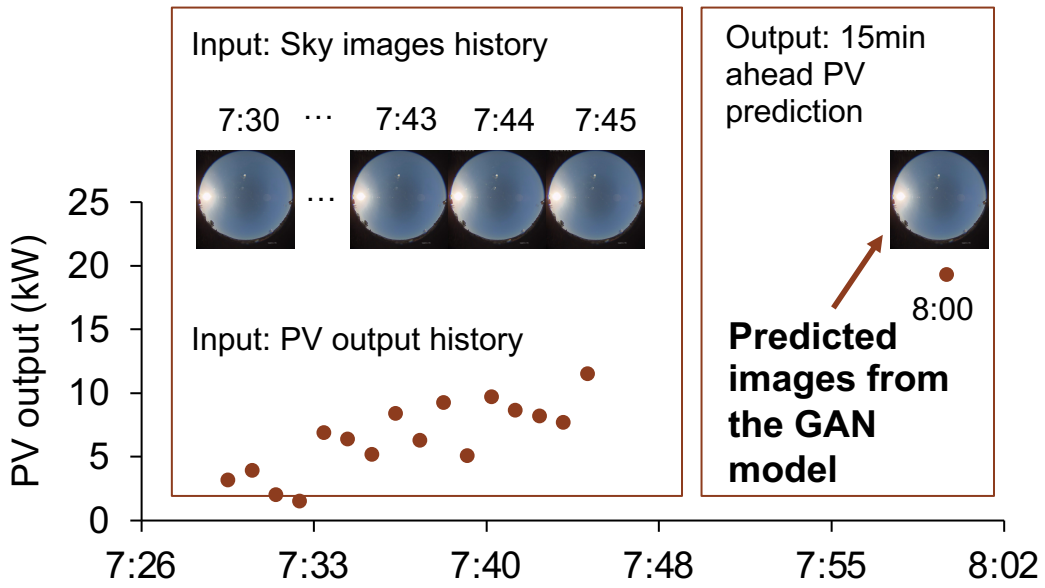
Diversity of predicted future images



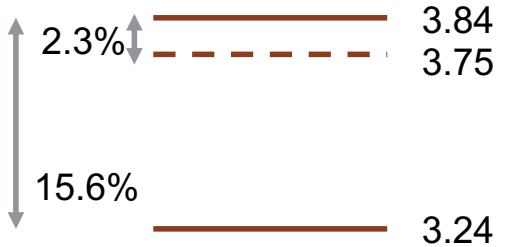
Results and discussion

Predicted future images for downstream solar forecasting

Baseline: SUNSET Model[1]



Test set RMSE (kW)



Baseline

Upgraded: Feed in 16 image history + 1 generated future image

Theoretical upper bound: Feed in 16 image history + 1 real future image

[1] Sun et al. (2019). Short-term solar power forecast with deep learning: Exploring optimal input and output configuration. *Solar Energy*.

Conclusions

- The GAN model we developed can capture the cloud motion of the corresponding context frames and generate realistic future sky images
- The generated images can also be plugged in for the downstream solar forecasting tasks and achieve promising performance

Future work

- The diversity of the model needs to be improved to account for the stochasticity of cloud motion
- Integrate sequential models, such as ConvLSTM, as part of the GAN generator architecture to extract the temporal dynamics from the input sequence