

A NEW DEEP LEARNING NOWCAST MODEL OF RADAR IMAGERY USING GENERATIVE ADVERSARIAL NETWORK FOR OPERATIONAL RAINFALL NOWCASTING

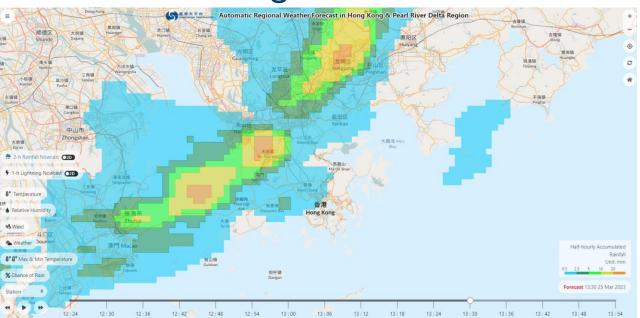
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Our Nowcasting Service to the Public:



Web-based 2-hour Rainfall and 1-hour Lightning Nowcast over the Pearl River Delta Region

> Location-based Nowcast via MyObservatory Mobile App









Severe Weather Warnings

Need a high-resolution and accurate rainfall nowcast algorithm



Past Development on AI Rainfall Nowcast:

Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting

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Wai-kin Wong Wang-chun Woo Hong Kong Observatory Hong Kong, China {wkwong, wcwoo}@hko.gov.hk

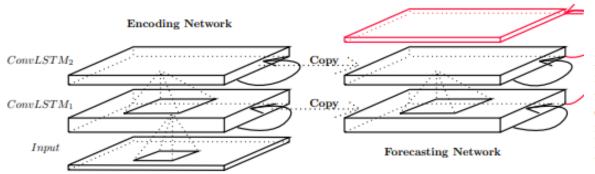


Figure 3: Encoding-forecasting ConvLSTM network for precipitation nowcasting

Deep Learning for Precipitation Nowcasting: A Benchmark and A New Model

Xingjian Shi, Zhihan Gao, Leonard Lausen, Hao Wang, Dit-Yan Yeung

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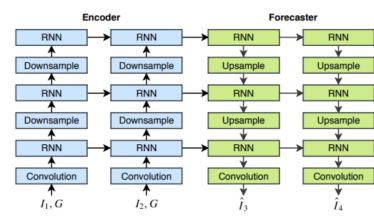
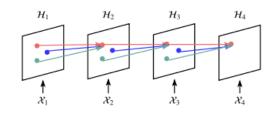
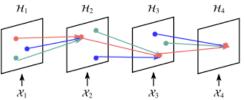


Figure 1: Example of the encoding-forecasting structure used in the paper. In the figure, we use three RNNs to predict two future frames \hat{I}_3 , \hat{I}_4 given the two input frames I_1 , I_2 . The spatial coordinates G are concatenated to the input frame to ensure the network knows the observations are from different locations. The RNNs can be either ConvGRU or TrajGRU. Zeros are fed as input to the RNN if the input link is missing.



(a) For convolutional RNN, the recurrent connections are fixed over time.



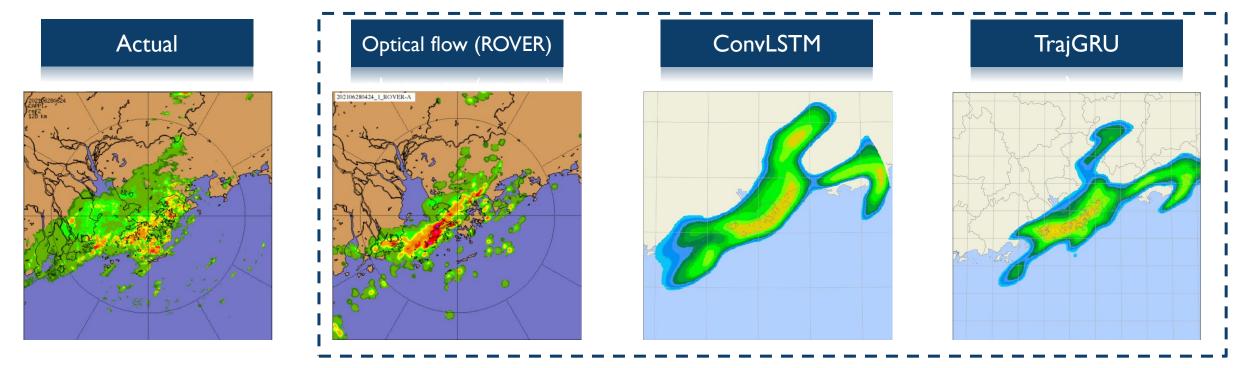
(**b**) For trajectory RNN, the recurrent connections are dynamically determined.

Figure 2: Comparison of the connection structures of convolutional RNN and trajectory RNN. Links with the same color share the same transition weights. (Best viewed in color)



A Quick Comparison of Rainfall Nowcast Methods

2-hour Rainfall Nowcast



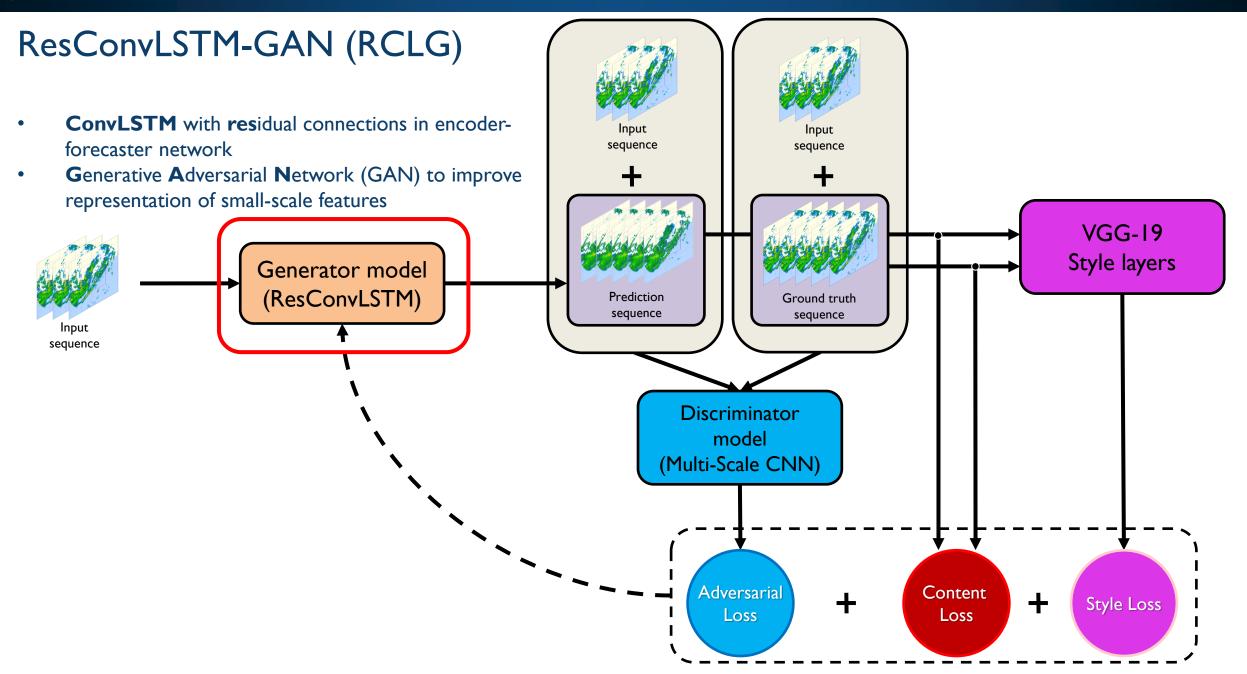
Al Methods:

- Movement Prediction, Intensity Evolution
- Blurring Problem = Reduced Resolution
- ⇒ Inefficient in Nowcast Operation



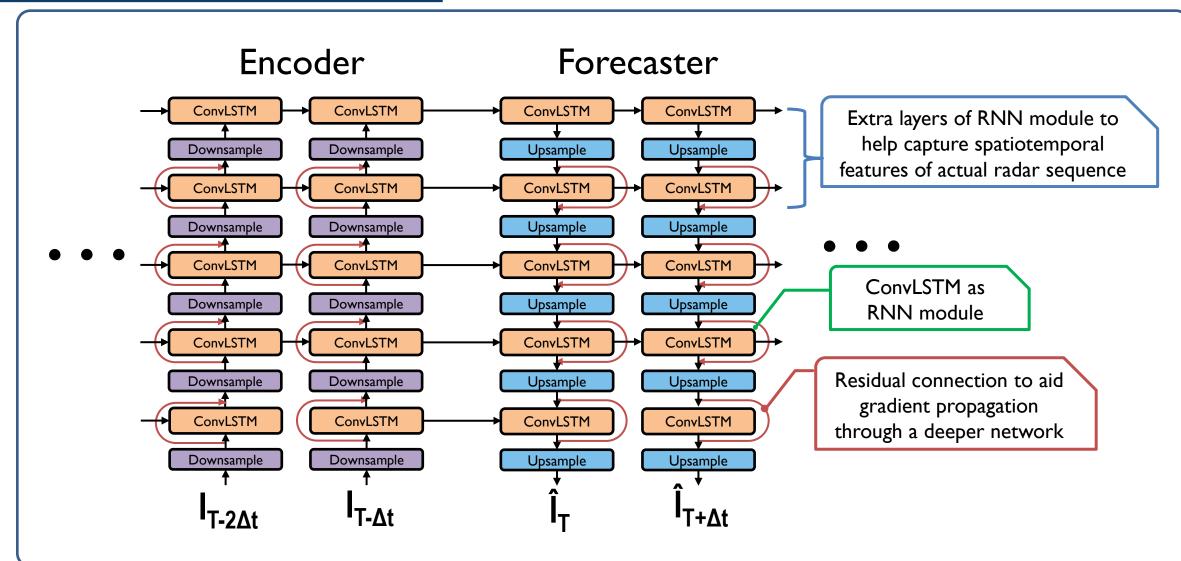
Need a Better Model & Loss Function







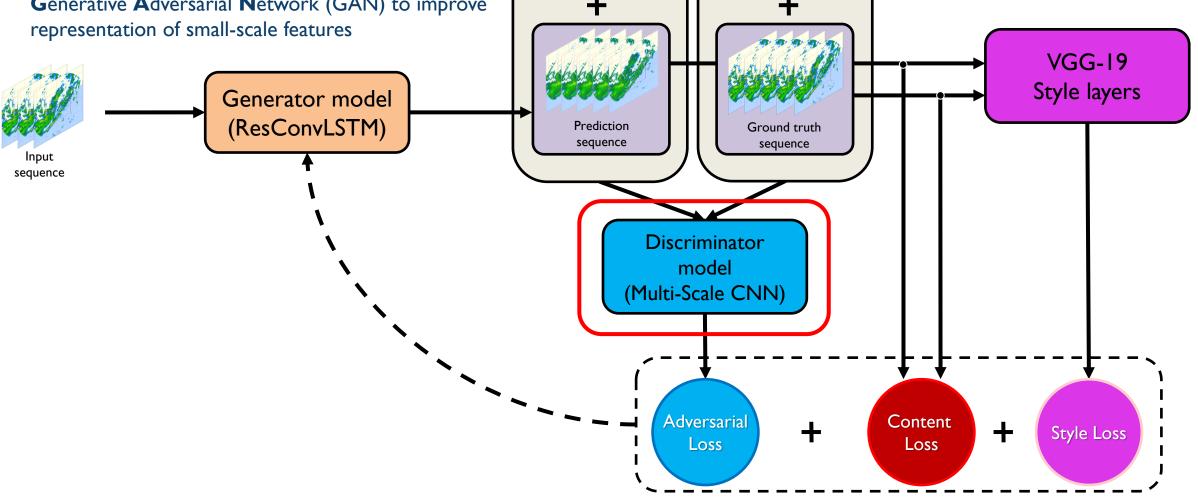
Generator: ResConvLSTM





ResConvLSTM-GAN

- **ConvLSTM** with **res**idual connections in encoderforecaster network
- Generative Adversarial Network (GAN) to improve representation of small-scale features



Input

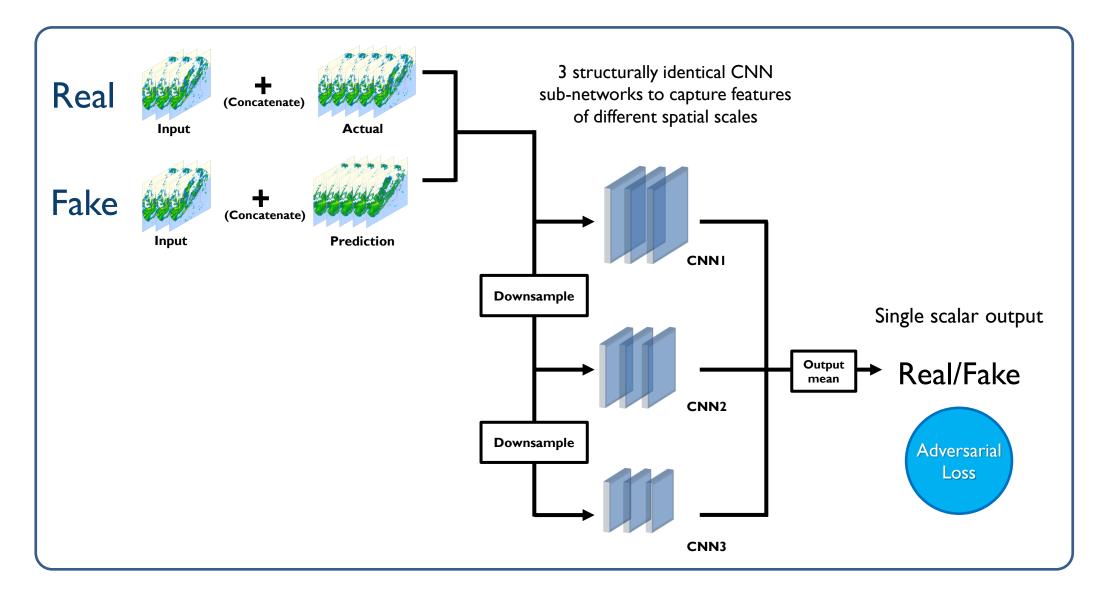
sequence

Input

sequence



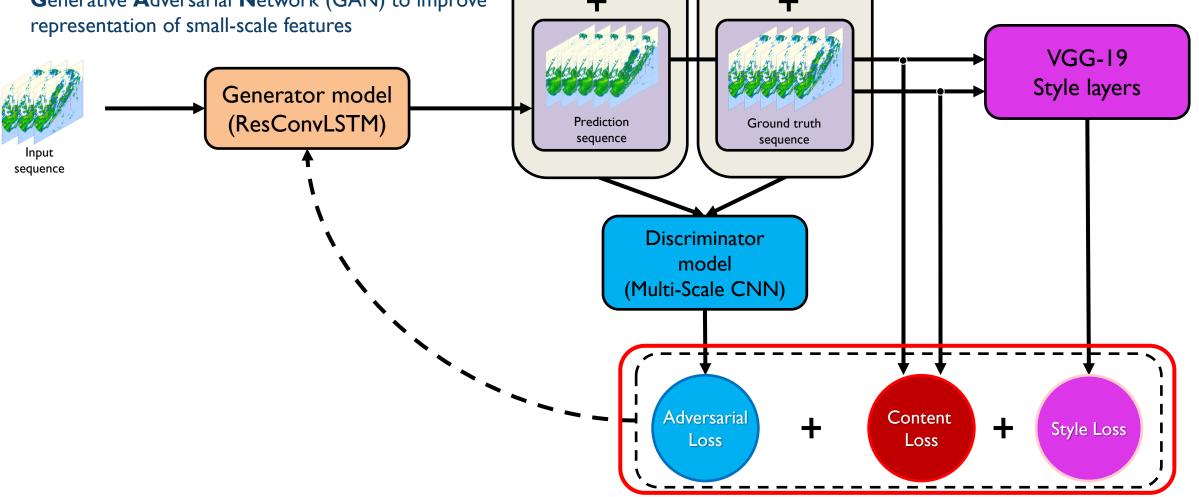
Discriminator: Multi-layer Convolutional Neural Network (CNN)





ResConvLSTM-GAN

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Input

sequence

Input

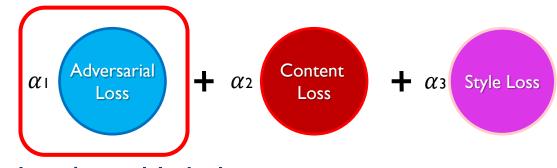
sequence



3 Loss Components

Adversarial Loss – Discriminator Loss

- Binary Cross-entropy (BCE) Loss : Predicted Label vs Actual Label
- Aim : To generate realistic radar sequence





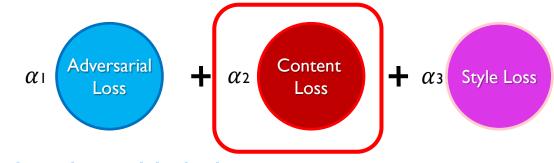
3 Loss Components

Adversarial Loss – Discriminator Loss

- Binary Cross-entropy (BCE) Loss : Predicted Label vs Actual Label
- Aim : To generate output similar to the actual radar sequence

Content Loss – Part of Generator Loss

- Balanced-MAE-MSE Loss : 50% MAE and 50% MSE with Sample Balancing
- Aim : To generate accurate radar nowcast





3 Loss Components

Adversarial Loss – Discriminator Loss

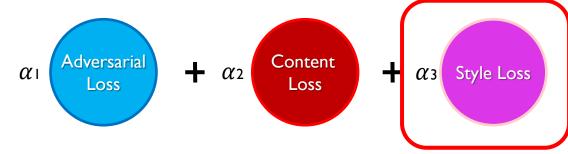
- Binary Cross-entropy (BCE) Loss : Predicted Label vs Actual Label
- Aim : To generate output similar to the actual radar sequence

Content Loss – Part of Generator Loss

- Balanced-MAE-MSE Loss : 50% MAE and 50% MSE with Sample Balancing
- Aim : To generate accurate radar nowcast

Style Loss – Part of Generator Loss

- Neural Network-based Loss
- Aim : To mimic style of spatial features from input radar sequence





Adversarial Loss – Discriminator Loss

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- Aim : To generate accurate radar no

Style Loss – Part of Generator Loss

- Neural Network-based Loss
 - Aim : To mimic style of spatial features from input radar sequence
 - Example from: https://www.tensorflow.org/tutorials/generative/style transfer



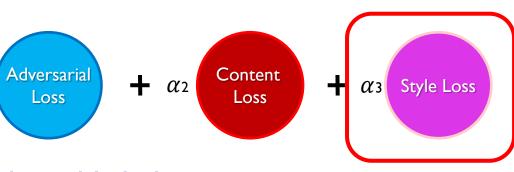
Content





Output







Adversarial Loss – Discriminator Loss

- Binary Cross-entropy (BCE) Loss : Predicted Label vs Actual Label
- Aim : To generate output similar to the actual radar sequence
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As the loss components are in different scale, α_{1-3} are dynamically balanced and determined during the training process, and will be fixed once they have converged.

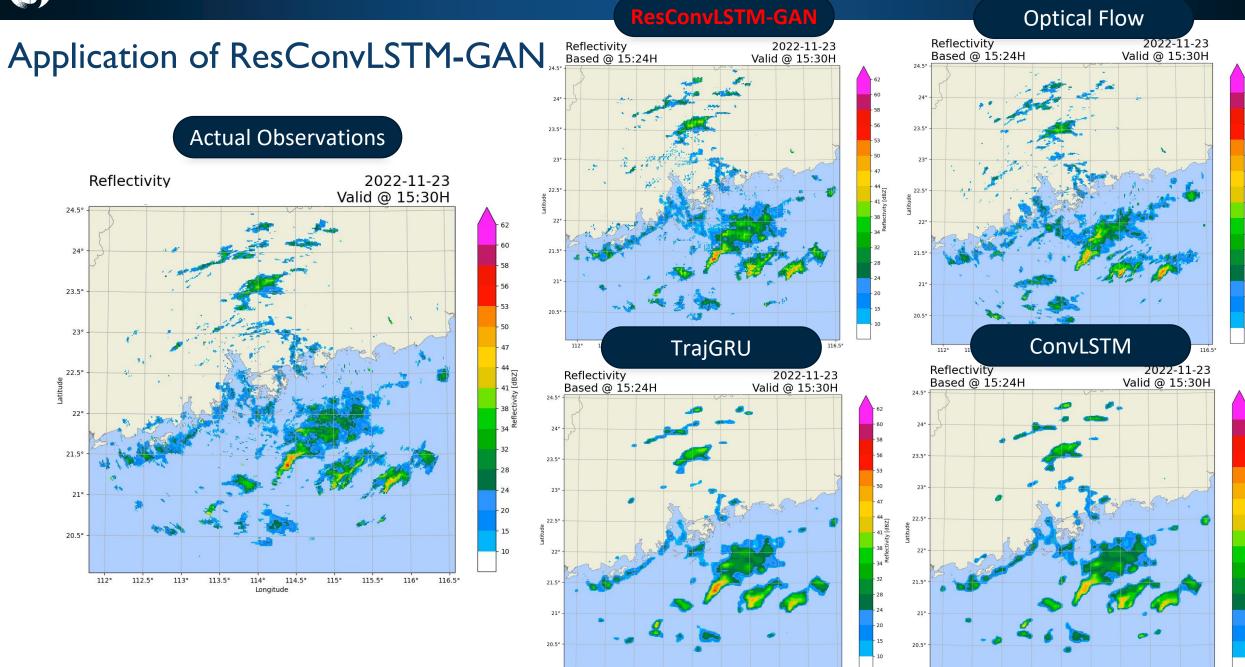


Training Dataset

HKO 2km CAPPI Radar Reflectivity Data

Date range	Train / Valid set: 2009-01 to 2021-05 92000 train sequence 2730 valid sequence	Evaluation set: 2021-06 to 2021-10 5130 test sequence	
Domain coverage	256km radius in 480x480 grid		
Input data	5 radar imageries in 6 minutes interval (past 30 minutes)		
Output data	20 radar imageries in 6 minutes interval (2-hour local precipitation nowcast)		





112.5°

112°

113°

113.5°

115.5°

116° 116.5°

114.5°

114°

115°



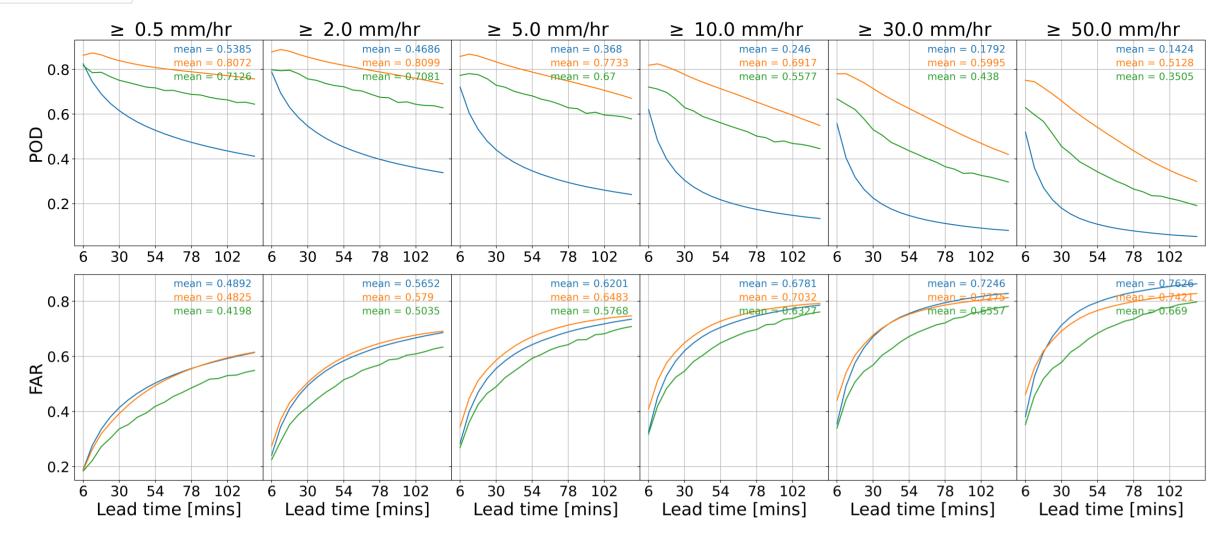


Verification

— trajGRU
— ResConvLSTM-GAN

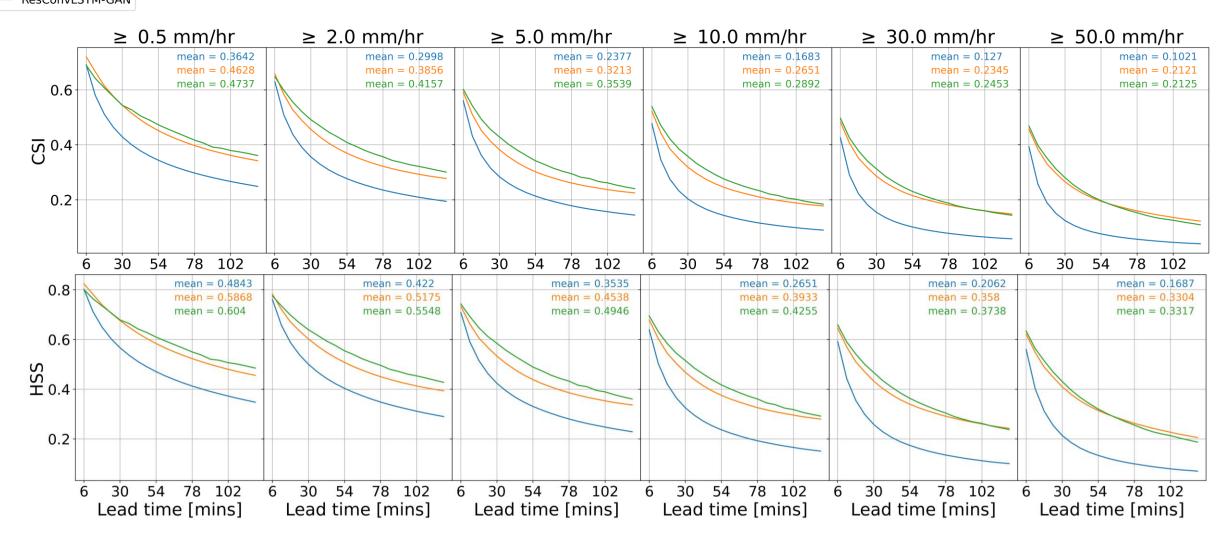
rover_nonlinear

• RCLG produces less blurry output, so lower POD and FAR



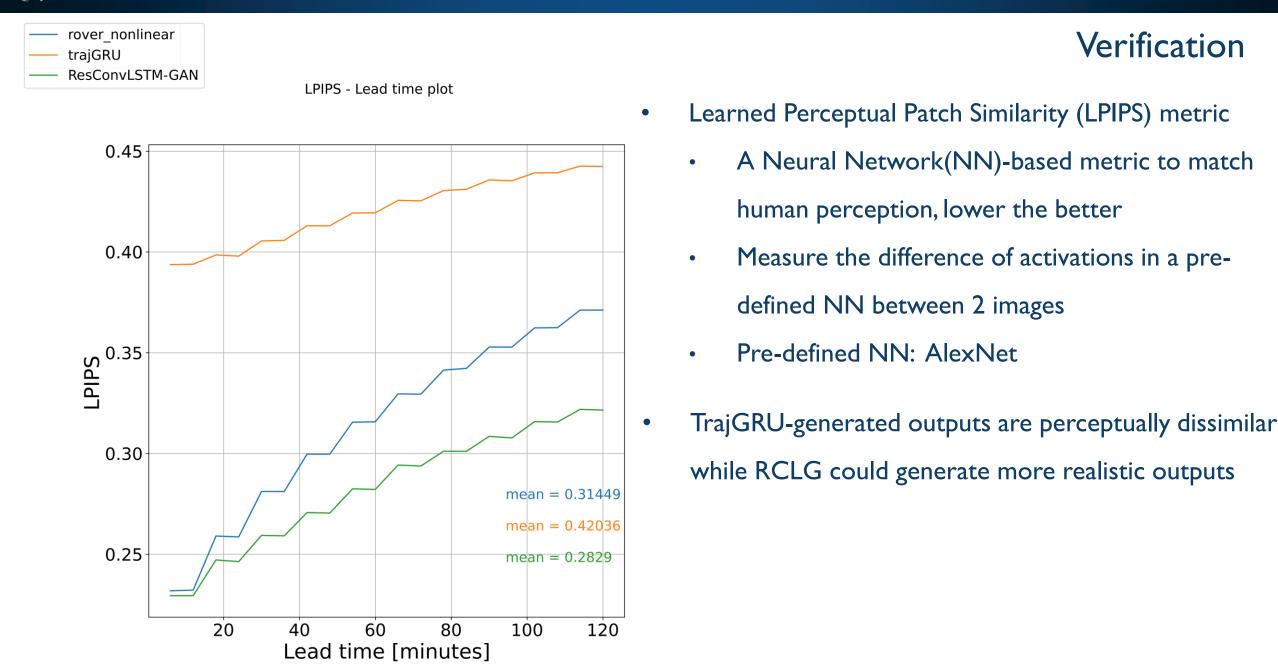


• RCLG has better overall skills compared to TrajGRU



Verification

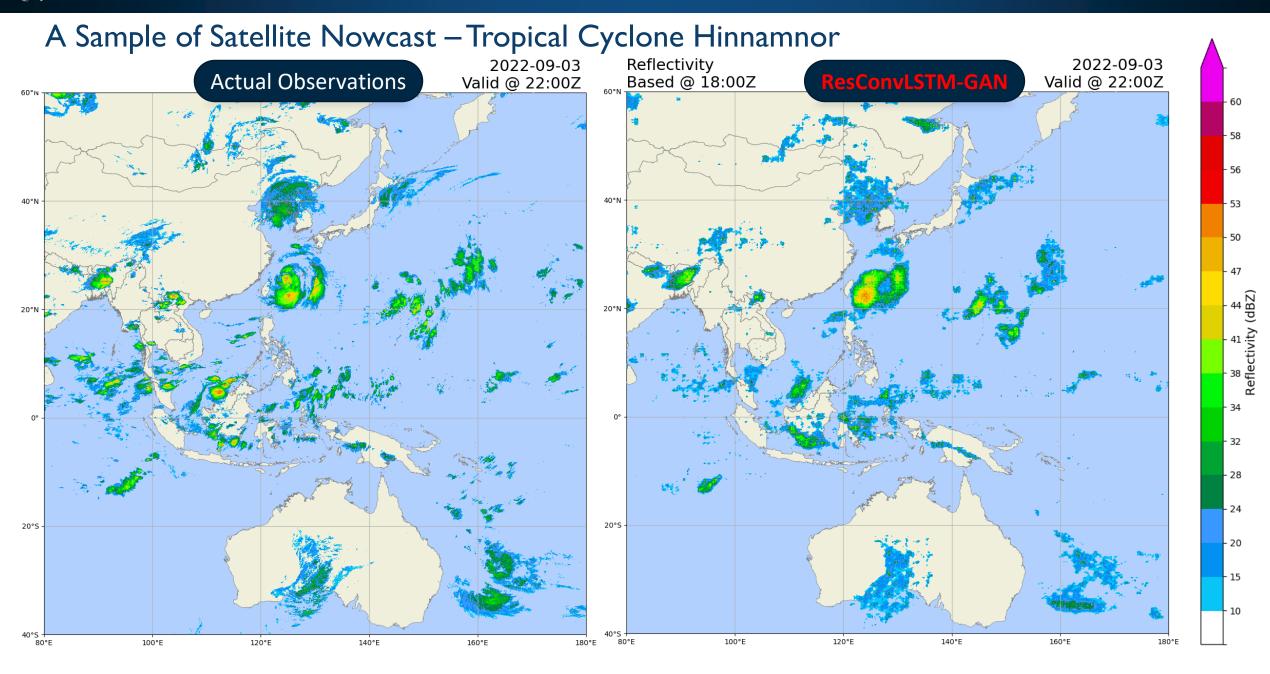






HKO 2km CAPPI Radar Reflectivity Data			H8-GK2A Satellite Simulated Reflectivity Data	
Date range	Train / Valid set: 2009-01 to 2021-05 92000 train sequence 2730 valid sequence	Evaluation set: 2021-06 to 2021-10 5130 test sequence	Train / Validation set: 2021-02 to 2022-09 66320 train sequence 11180 valid sequence	Evaluation set: 2022-10 to 2023-02 13580 test sequence
Domain coverage	256km radius in 480x480 grid		2501x2501 grid from (lat 60°N, lon 80°E) to (lat 40°S, lon 180°E)	
Input data	5 radar maps of 6 minutes interval (past 30 minutes)		6 satellite maps of 20 minutes interval (past 2 hour)	
Output data	20 radar maps of 6 (2-hour local precip		12 satellite maps of (4 hours regional satellit	







Concluding Remarks and Future Work

- ResConvLSTM-GAN is capable of generating more accurate and realistic radar nowcasts over the next 2 hours and the framework is applicable to satellite nowcast
- To replace the generator and discriminator by more efficient deep learning modules
 - e.g. Transformer-based model, Wasserstein GAN
- To implement a physics-driven nowcast framework



Thank you very much

