

Short-term forecasting of Typhoon rainfall with deep learning-based disaster monitoring model

Climate Informatics 2023

Doyi Kim, Yeji Choi, Seungheon Shin, Minseok Seo, and Hyun-Jin Jeong

SI Analytics

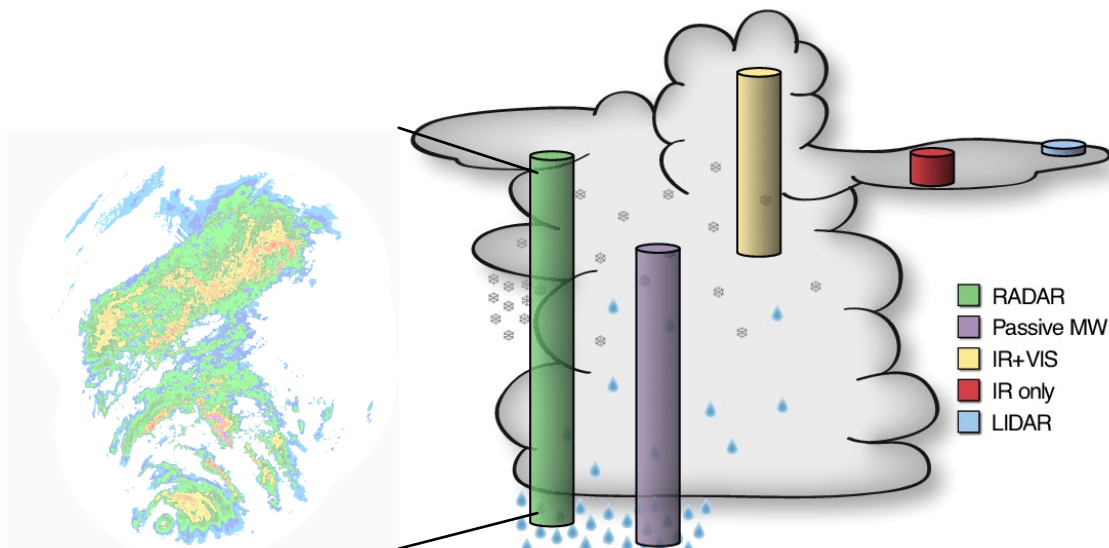
19, April, 2023

Chapter 01

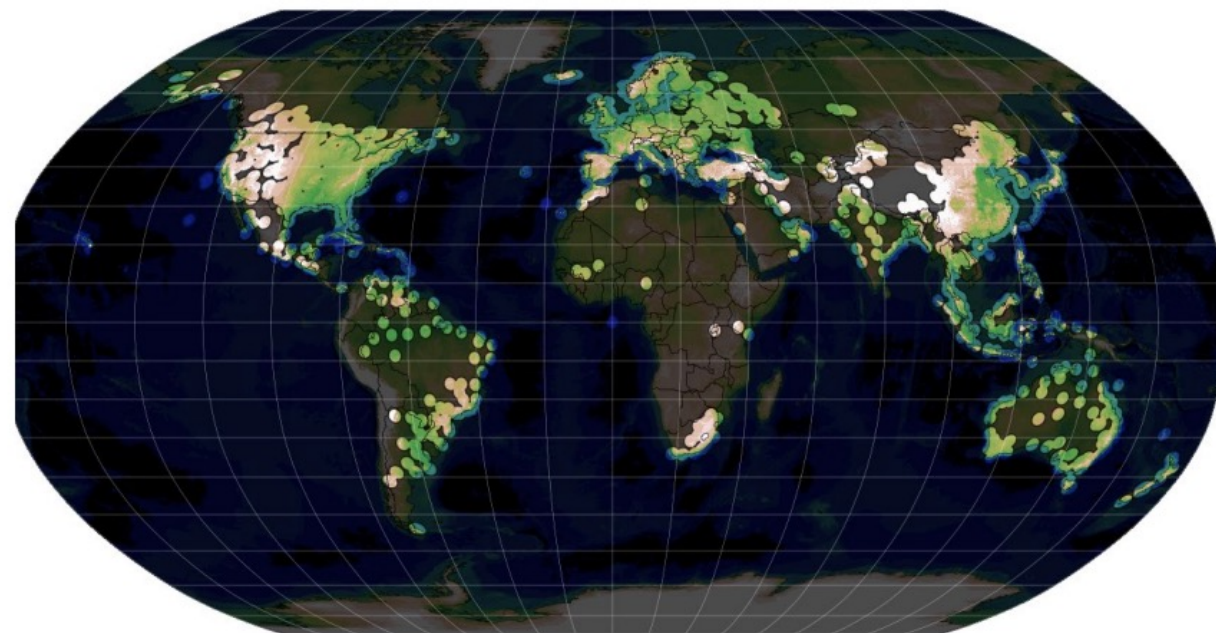
Background

Background

- Weather radar detects and quantifies precipitation and severe weather
- It covers densely populated areas, but still insufficient to cover some regions and oceans



Different measurement techniques in a thick cloud [1]



A map of weather radar coverage [2]

[1] Eliasson, Salomon, et al. "Assessing observed and modelled spatial distributions of ice water path using satellite data." *Atmospheric Chemistry and Physics* 11.1 (2011): 375-391.

[2] Saltikoff, Elena, et al. "An overview of using weather radar for climatological studies: successes, challenges, and potential." *Bulletin of the American Meteorological Society* 100.9 (2019): 1739-1752.

Goal

Accuracy Weather Forecasting without Radar System

Spatio-temporal limited detection → Future Satellite video prediction

Insufficient Radar system → Proxy radar map from satellite images

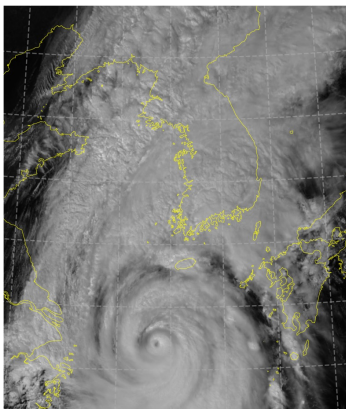
Chapter 02

Data and Method

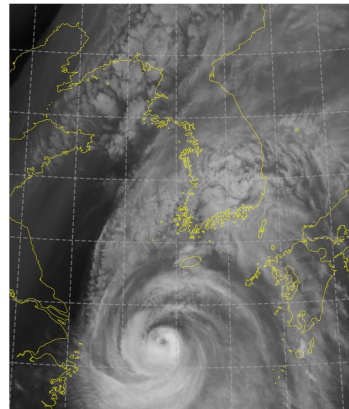
Data

- **Geo-KOMPSAT-2A (GK2A)**
 - Geostationary orbit satellite
 - 2-minutes interval and 0.5 to 2 km spatial resolution
 - 16 channels – Visible (0.06 μm), Water vapor (6.04 μm), and Infrared (10.5 μm) channels
- **KMA Weather Radar**
 - 5-minutes interval and 0.5 km spatial resolution
- **Test Case: Typhoon Hinnamnor**
 - 2022/09/05 0100 to 0700 UTC

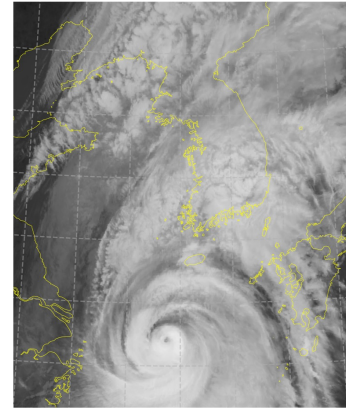
(a) VIS 0.06



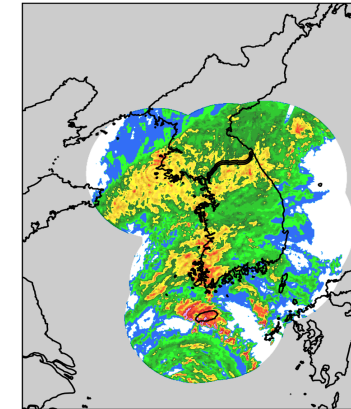
(b) WV 6.04



(c) IR 10.05

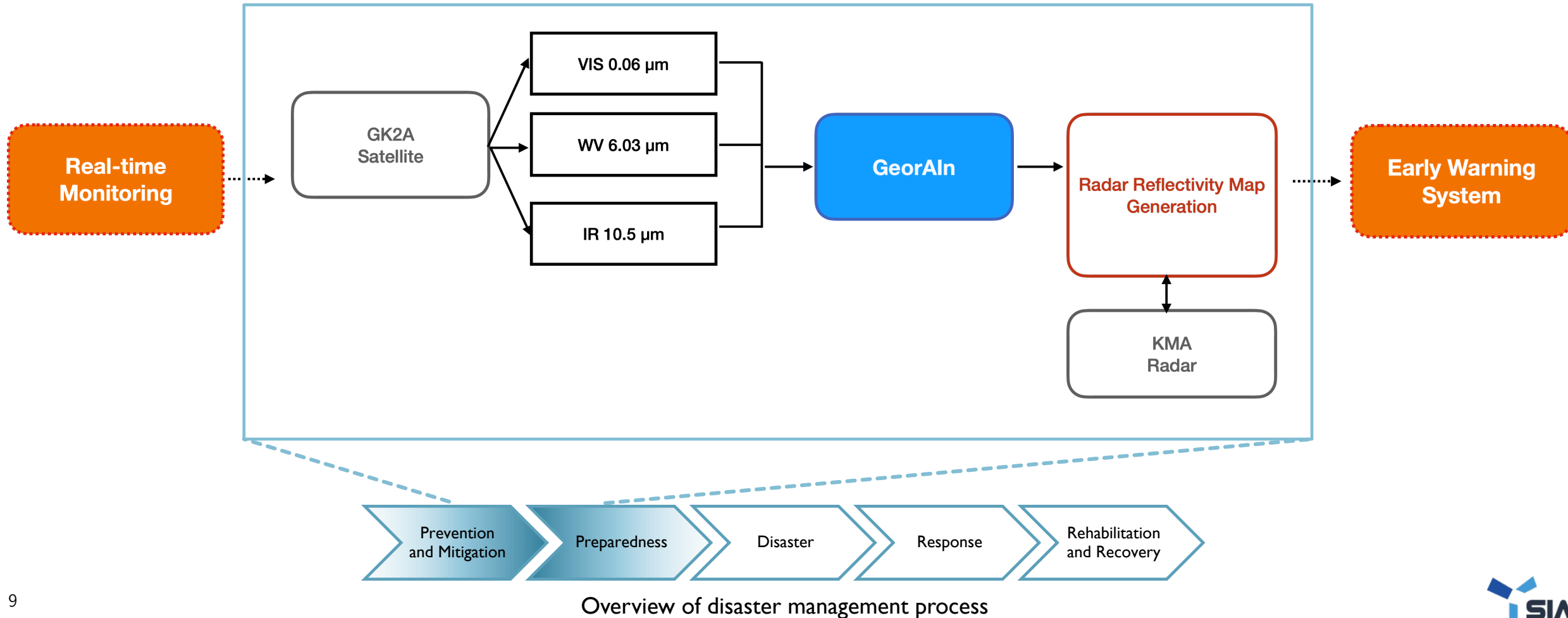


(d) Radar



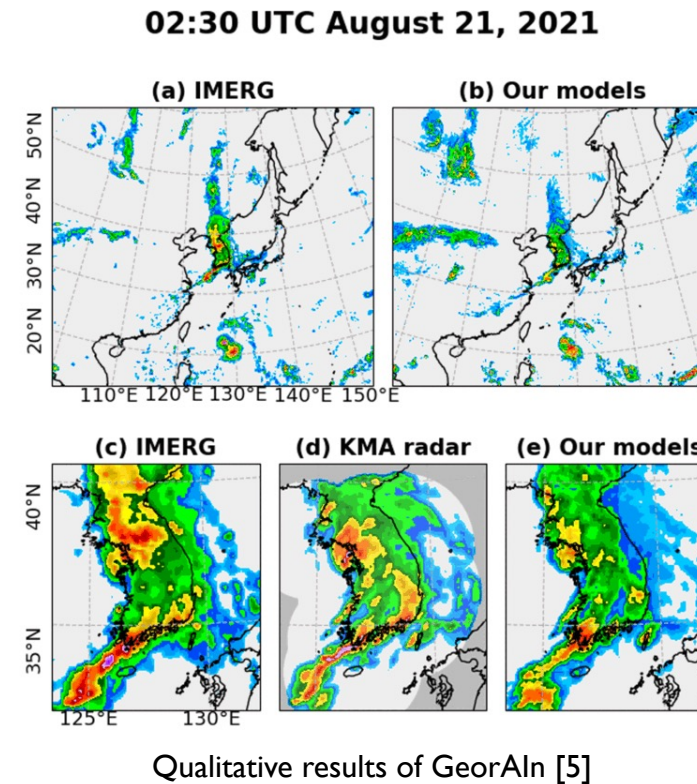
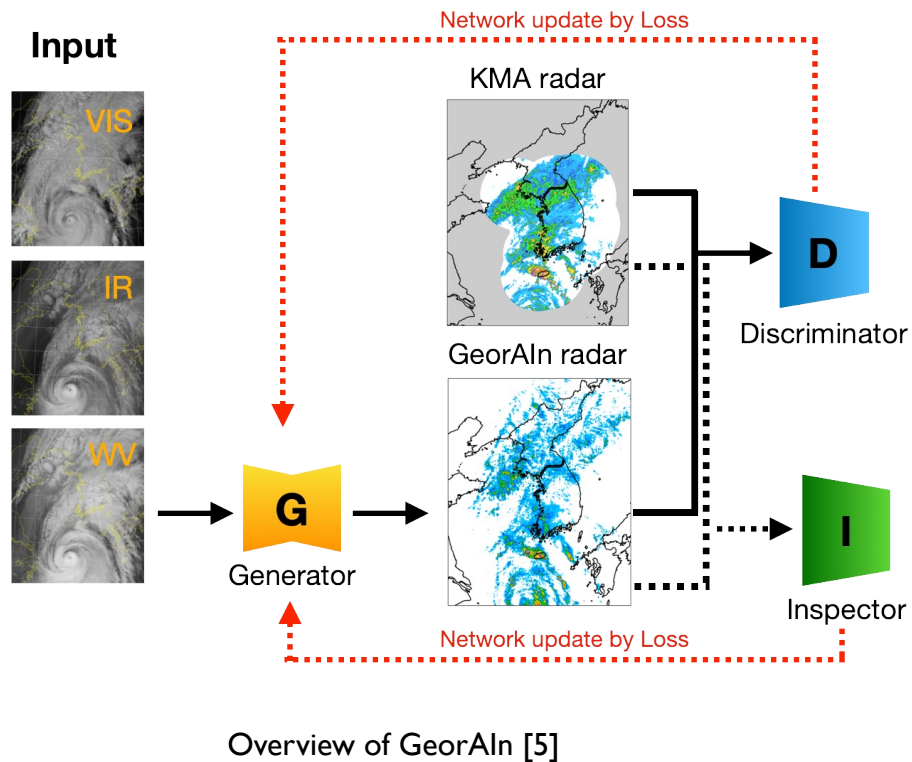
Disaster Monitoring Model

- two-step process, consists of WR-Net and GeorAIIn
 - Rain forecasting over the next few hours for early warning



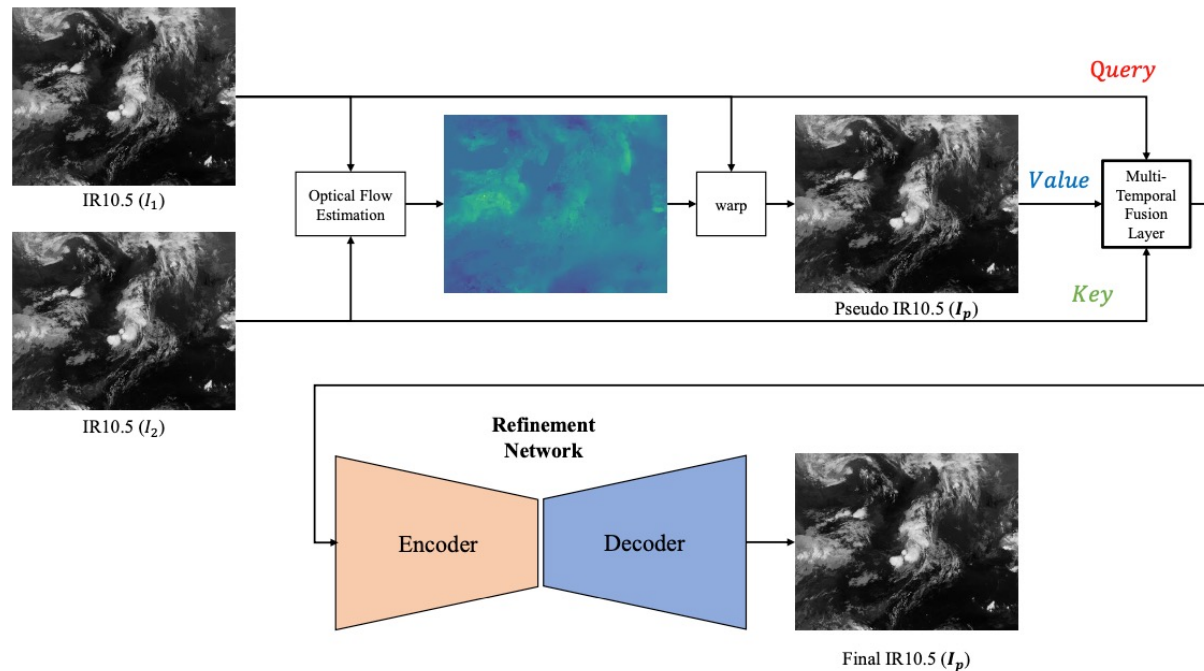
Disaster Monitoring Model

- **Generative Adversarial Network for rain – GeorAI**
 - Generate proxy radar reflectivity map using Pix2PixCC model ([6])
 - Inspector guides the generated image to be physically consistent with the real image



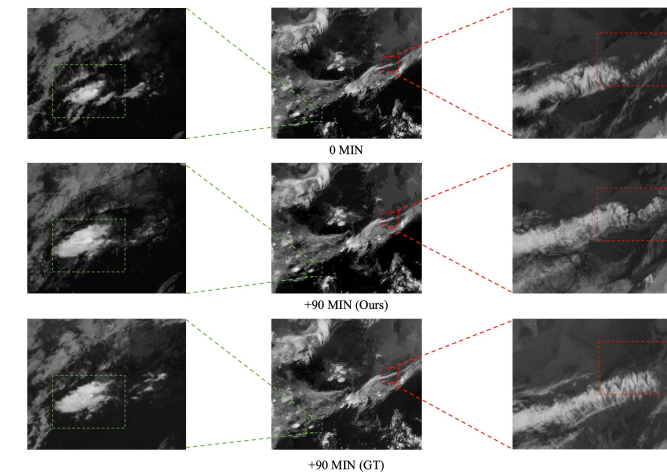
Disaster Monitoring Model

- Video Frame Prediction Network – Warp and Refine Network (WR-Net)
 - Warping component for extracted optical flow
 - Refinement component for intensity changes of each pixel



Overview of WR-Net [7]

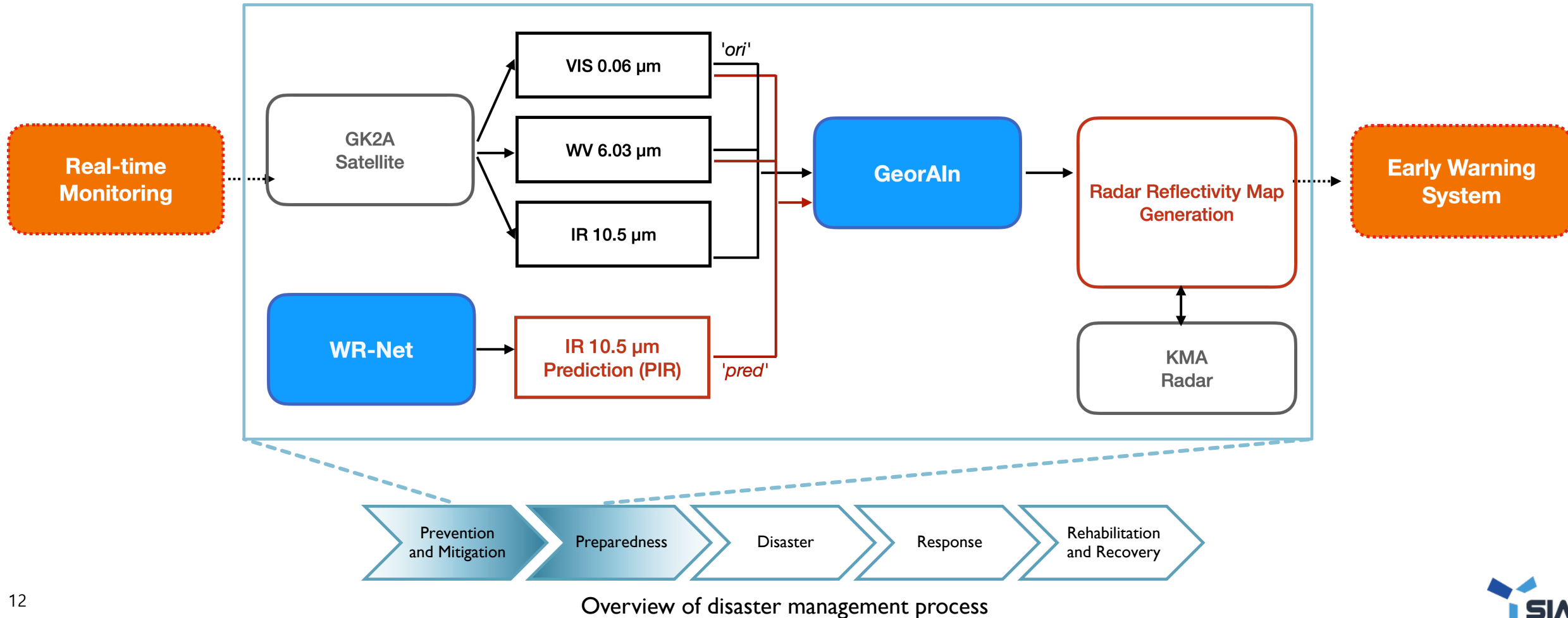
Method	Channels	PSNR \uparrow	SSIM \uparrow
Linear	IR	38.667	0.745
SSM-T	IR	43.285	0.831
WR-Net (Warp Only)	IR	44.213	0.904
WR-Net (Full)	IR	46.527	0.934



Qualitative results of WR-Net [7]

Disaster Monitoring Model

- two-step process, consists of WR-Net and GeorAI
 - Rain forecasting over the next few hours for early warning



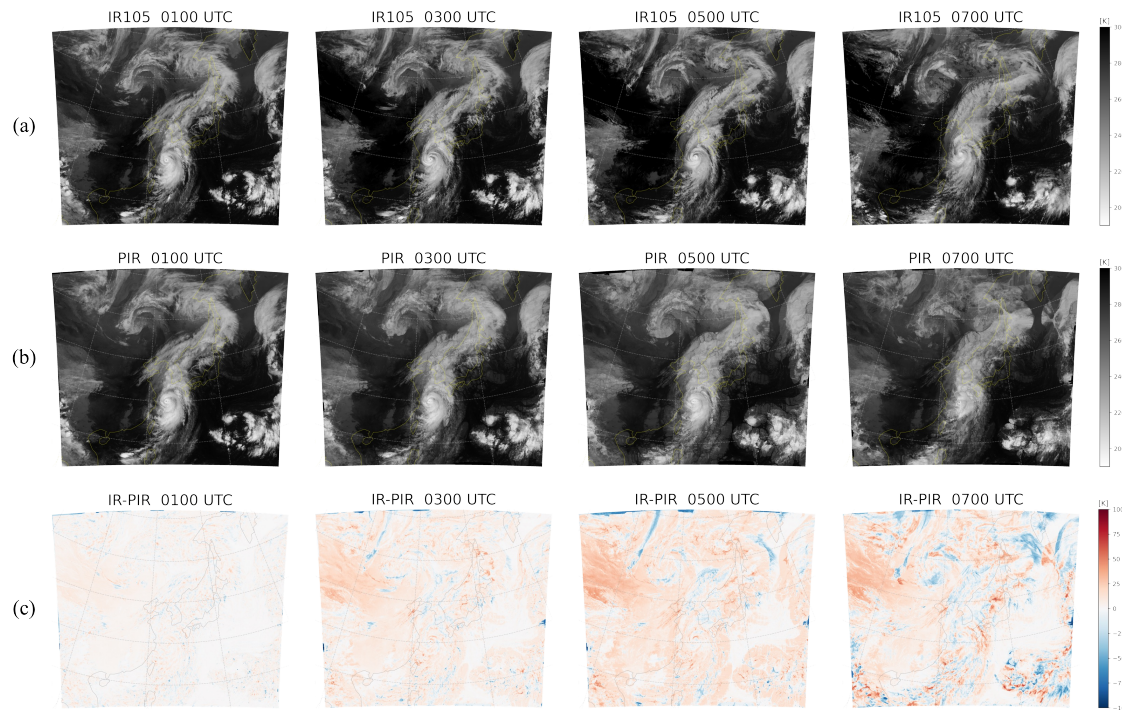
Chapter 03

Results

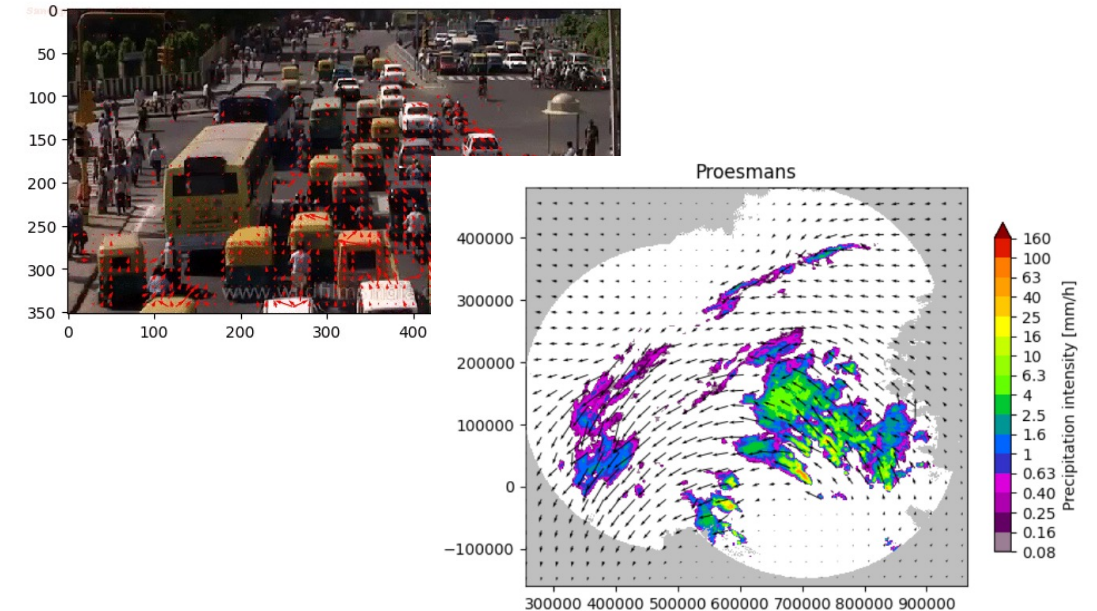
Results: Hinnamnor Case Study

1) Predicting satellite images from WR-Net

- WR-Net prediction images preserve cloud locations and shapes compared to the original (GK2A) image
- The predicted clouds are divided and dimmed by the reduced cloud amount (limitation of optical flow)



IR images from (a) GK2A and (b) WR-Net predicted result, and difference map between them.

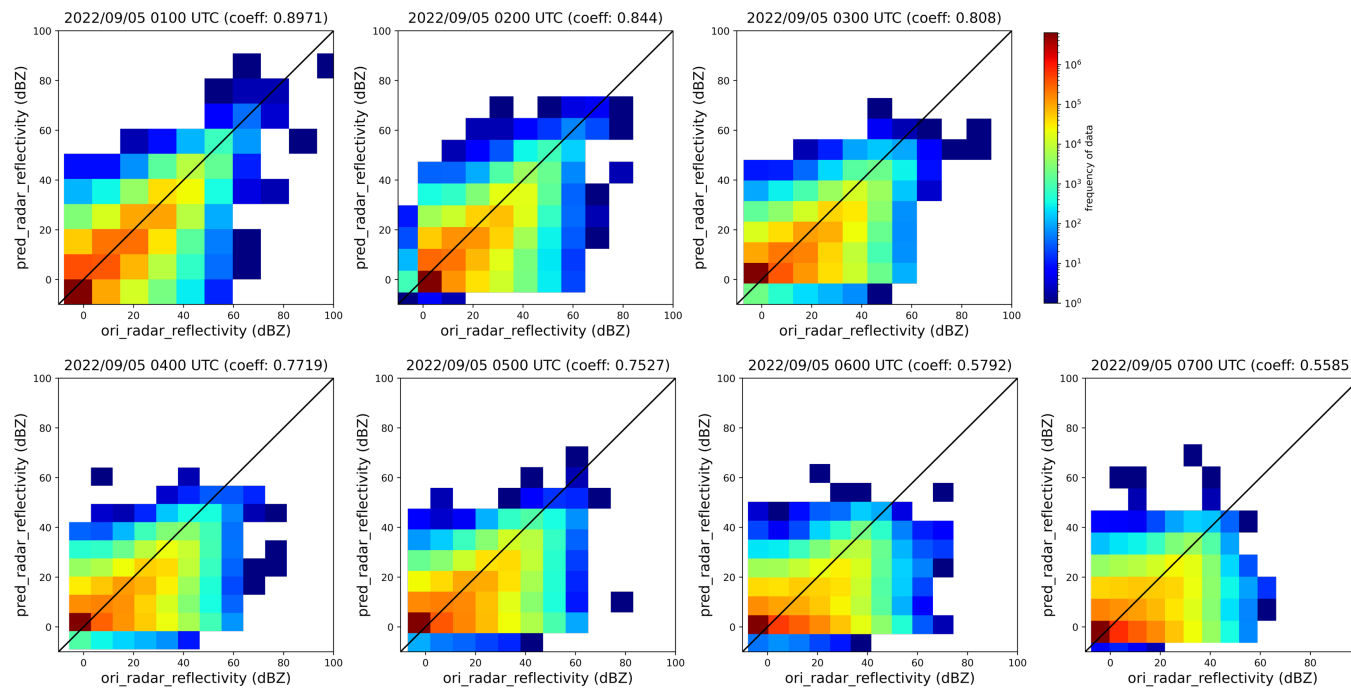


Optical flow only detect the movement and intensity of objects, act as wind vector in weather task

Results: Hinnamnor Case Study

2) Generating radar reflectivity by GeorAI

- Shown a high correlation coefficient of over 0.8 at the future 3 hours and 0.75 at 5 hours
- '*Pred*' results tend to underestimate the radar reflectivity more than the '*Ori*' results



* Convert the radar reflectivity to rain rate by using the Z-R relationship:
 $Z = 200R^{1.6}$

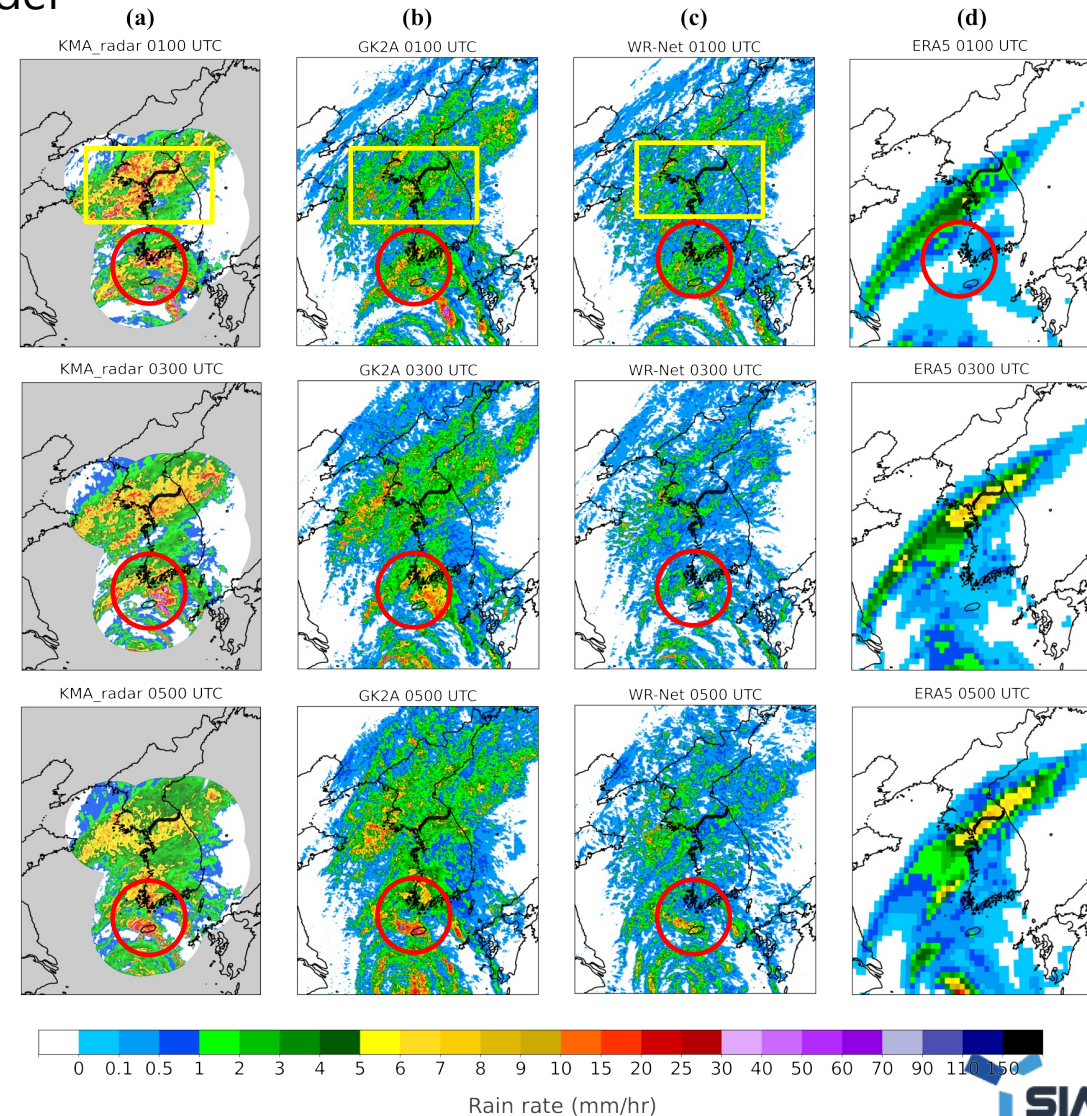
The 2D histogram of the radar reflectivity from the GeorAI results

- '*ori_radar_reflectivity*' is the result of original GK2A three channels (VIS, WV, and IR)
- '*pred_radar_reflectivity*' is the result of two GK2A channels (VIS, WV) and one WR-Net predicted channel (PIR)

Results: Hinnamnor Case Study

3) Monitoring Typhoon rainfall by disaster monitoring model

- Compared with (a) KMA radar, (d) Reanalysis data – ERA5
- (b) GeorAI result and (c) GeorAI + PIR from WR-Net
- Our results show similar patterns with radar, but free of spatial constraints (masked areas in (a))
- Our results are highly accurate in heavy rainfall area (red circle) and slightly underestimated in the moderate rainfall area (yellow box)



Chapter 04

Conclusion

Conclusions

- We predict rainfall in Typhoon Hinnamnor case by our disaster monitoring model with geostationary satellite images
- We utilize the WR-Net results as the input data of the GeorAI model to predict future rainfall
- The GeorAI results show our model can predict the accurate timing, location, and intensity of heavy rain area

- We expect our results to help communicate preemptive and precise warning systems
- We plan to expand our disaster monitoring model to flood and storm cases on the global scale

Thank you for attention

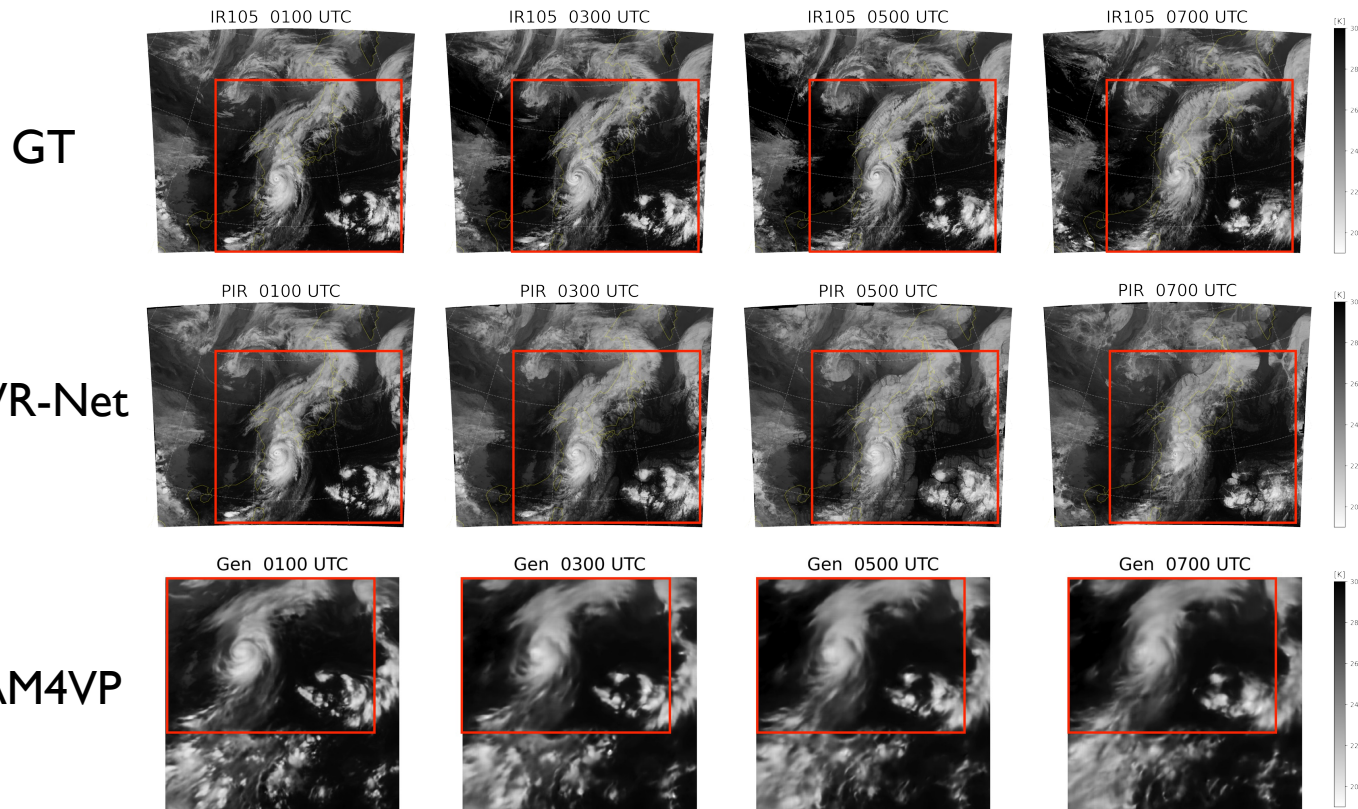
doyikim@si-analytics.ai

www.si-analytics.ai

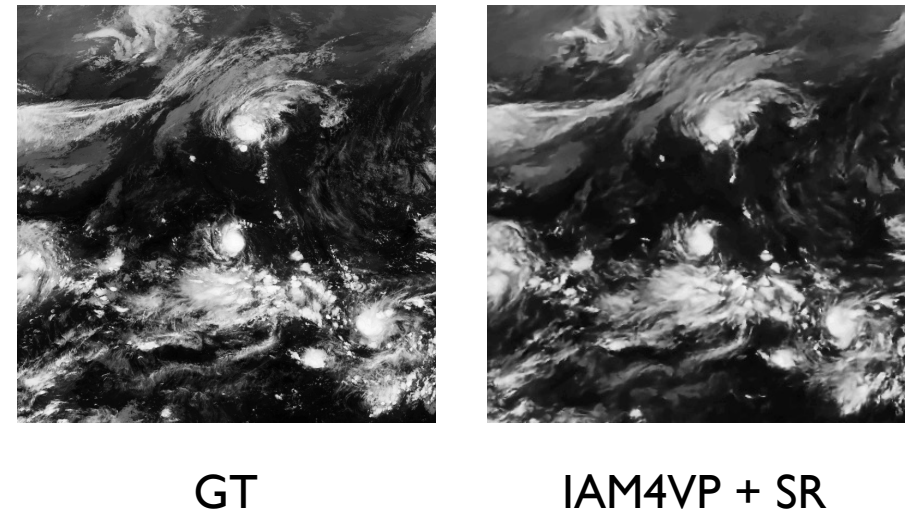


Appendix

- Improved video prediction model: IAM4VP [8]
 - Solving the diminishing problem and generating new cloud cells

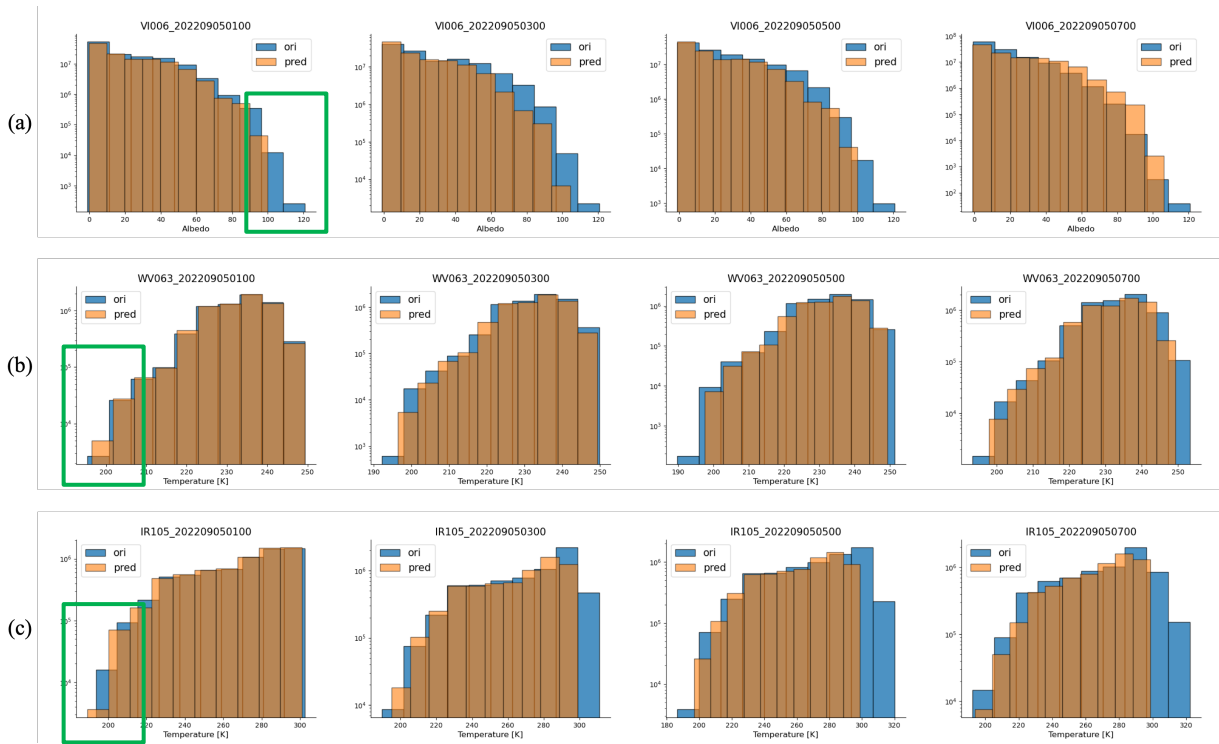


Typhoon Forecasting with IAM4VP model

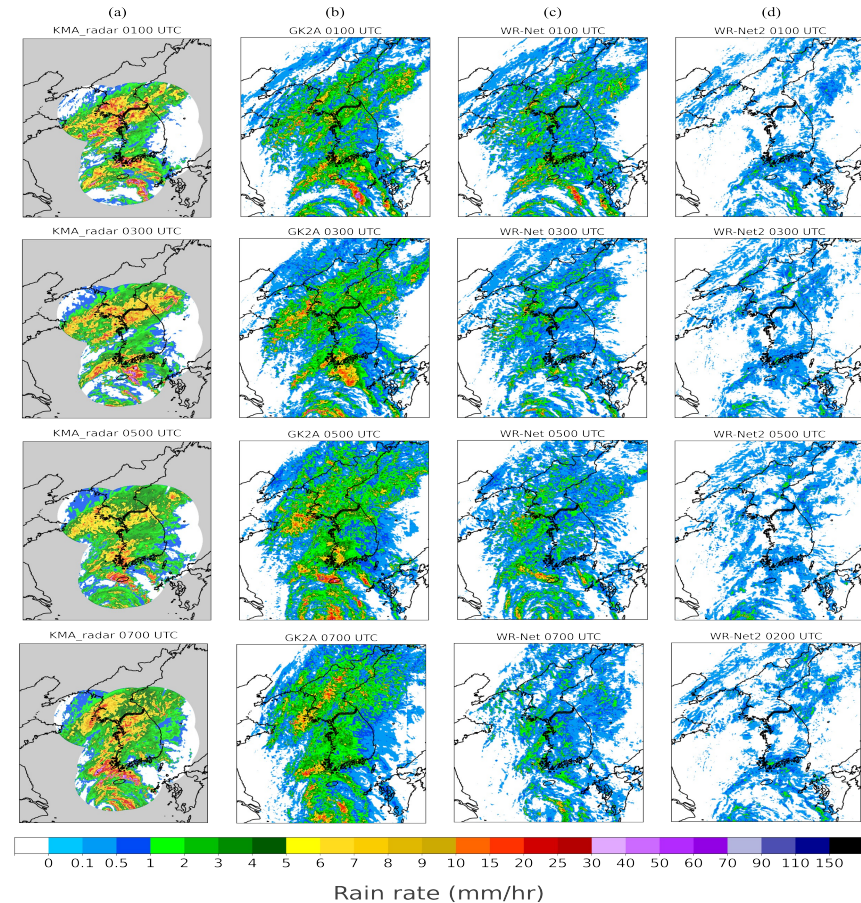


Appendix

- Replacing three channels with WR-Net



Comparison histograms of each channel. (a) is visible $0.06 \mu\text{m}$, (b) is water vapor, $6.04 \mu\text{m}$ and (c) is infrared $10.5 \mu\text{m}$ channels. The Blue bar means GK2A image and the Brown bar is WR-Net predicted image.



Qualitative results of each input combination.

(a) KMA radar, (b) GK2A three channels, (c) two GK2A channels + one WR-Net result, and (d) three WR-Net results

Appendix

- Training information – WR-Net and GeorAIn

	WR-Net	GeorAIn
Training data	GK2A 2020.08-2021.07, 2 min	GK2A 2019.08-2021.07. 10 min
Base model	TV-L1 algorithm (optical flow)/ U-Net based VGG16 (refinement)	Pix2PixCC model
Loss function	PSNR, SSIM	LSGAN, FM loss, CC loss
Optimizer	Adam	Adam
Learning Rate	1e-4	0.0002