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RESEARCH ARTICLE

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

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Abstract

Accurate and reliable disaster forecasting is vital for saving lives and property. Hence, effective disaster management is necessary to reduce the impact of natural disasters and accelerate recovery and reconstruction. Typhoons are one of the major disasters related to heavy rainfall in Korea. As typhoon develops in the far ocean, satellite observations are the only means to monitor them. This study uses satellite observations to propose a deep-learning-based disaster monitoring model for short-term typhoon rainfall forecasting. We apply two deep learning models: a video frame prediction model, WR-Net, to predict future satellite observations and an image-to-image translation model, GeorAIn (Pix2PixCC model), to generate rainfall maps from predicted satellite images. Typhoon Hinnamnor, the worst typhoon case in 2022 in Korea, was selected as a target case for model verification. The results showed that the predicted satellite images could capture the structures and patterns of the typhoon. The precipitation map generated from the GeorAIn model using predicted satellite images showed a correlation coefficient of 0.81 for the three-hour prediction and 0.56 for the seven-hour prediction. The proposed disaster monitoring model can provide practical implications to disaster alerting systems and can be extended to flood monitoring systems.

Impact Statement

The development of a deep learning-based disaster monitoring model using satellite observations has the potential to significantly improve disaster response efforts by providing real-time, accurate, and comprehensive information about affected areas on a global scale.

1. Introduction

Monitoring heavy rainfall can help to assess the risk of potential disasters and enable authorities to alert communities for their safety. Accurate and timely detection of heavy rainfall under the current weather system has been effective in reducing damage from related disasters such as floods and storms. A ground-based radar has high detection accuracy by directly measuring the returned signals from surrounding objects. It is possible to measure rainfall intensity according to particle size since radar beams strike raindrops in the atmosphere. Therefore, most meteorological administrations operate radar systems to detect precipitation. However, radar systems have limitations in detecting precipitation over larger areas and making broader spatiotemporal predictions. Although these systems can predicts the next 0 to 2 hours of rainfall pattern change (e.g., amount, timing, and location) by simple extrapolation, their accuracy decreases over longer periods and they cannot predict the development and dissipation of the system.

Recent studies have utilized deep learning (DL) approaches with satellite images to alleviate these limitations in nowcasting. DL-based models learn the pattern change of rain events from past datasets and then predict future patterns instead of extrapolating continuous snapshots. Ravuri et al., 2021 suggests that a deep generative model improved the quality of the next 0-2 hours of precipitation nowcasting by inputting only radar images and predicting the precipitation probability. Other studies (Shi et al., 2017; Espeholt et al., 2022; Seo, Kim, et al., 2022) used RNN-based models to predict future precipitation probabilities from satellite images. While these state-of-the-art models have shown significant development in short-term weather forecasts regarding cost and accuracy, they still rely on ground-based radar as input or target data. Furthermore, the stochastic results can identify the intensity categories (e.g., high or low) to some extent, but that cannot provide an accurate rainfall rate. Hence, these prediction models still require further improvements.

Countries with satellite systems can complement their entire territory with airborne observations. However, most developing countries cannot afford to do so. Even in countries with radar systems, the equipment is often insufficient to cover the entire region, and the systems are not operated sustainably. In the same manner, observations over oceans are still necessary. Given this situation, the insufficient observational data hinders the use of ML-based models.

We propose a disaster monitoring model combining our DL-based models to predict heavy rainfall from satellite images, which can help authorities monitor and respond to potential disasters. Our model can predict rain rates by proxy radar reflectivity for up to six hours without the need for a ground radar. In Sections 2 and 3, we explain the data and models we used, respectively. In Section 4, we present the predicted results of our trained model against the Typhoon Hinnamnor case, which occurred in 2022 over South Korea, and analyze the findings in Section 5. Additionally, we conducted tests using the generated satellite images by WR-Net, which allow for predicting rain patterns over a longer time than existing nowcasting approaches. Overall, our study aims to overcome the spatial and temporal limitations of radar-based forecasting and contribute to improving disaster response efforts.

2. Data

2.1. GEO-KOMPSAT-2A

GEO-KOMPSAT-2A(GK2A) is the second generation of meteorological geostationary (GEO) satellite launched in 2018 to capture meteorological phenomena by the Korean Meteorological Administration (KMA). The GK2A uses the Advanced Meteorological Imager (AMI) sensor with a 0.5 to 2 km spatial resolution for 16 visible and infrared channels. We trained our model using visible (VIS), water vapor (WV), and infrared (IR) channels, respectively. As an example, figure 1 shows slightly different cloud features for each of the three channels.

The VIS products are produced by reflecting sunlight from the earth's surface and clouds, so they are only available during the daytime. We use 0200 to 0600 UTC (1100 to 1500 KST) images of 0.64 μm visible channel, considering the data quality from GK2A over the South Korean region. Usually, as with Fig 1. (a), the darker areas represent land and water surface, and clouds typically appear as brigh pixels. The significant advantage of the visible channel is a higher resolution (0.5 km) observation than compared to other channels (2 km). It is possible to distinguish small clouds and cloud shapes with fine resolution.

Next, the WV products show the amount of water vapor in the atmosphere. GK2A provides products at three different altitudes, and we use a high-level channel as a 6.03 μm water vapor channel for this study. Similarly, high moisture regions appear on the brighter pixels in Fig 1. (b). It is used to monitor severe weather potential with turbulence existence or estimate wind direction.

Finally, the 10.5 μm infrared channel is known as a 'clean' window channel, which is less sensitive to atmospheric gas absorption. This channel measures the emitted radiation as heat from the earth or clouds, and we can estimate clouds top height and particle properties using this brightness temperature. IR channels provide images day and night by using thermal radiation. Therefore, it could be utilized to identify convective severe weather events anytime.

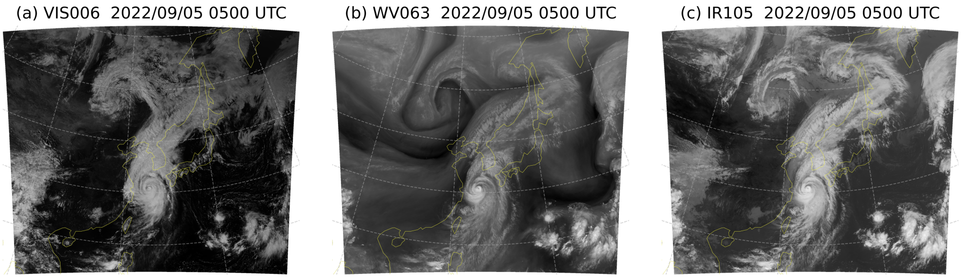

Figure 1. *Model input satellite channels. (a) is 0.64 μm visible channel, (b) is 6.03 μm water vapor channel, and (c) is 10.5 μm infrared channel. In common, bright areas indicate clouds or high moisture areas. Each channel shows different characteristics associated with cloud states.*

2.2. KMA Weather Radar

We use weather radar data from the KMA as a prediction target. A weather radar is a general detection equipment for monitoring severe weather events. Previous studies widely used the constant altitude plan position indicator (CAPPI) product for precipitation nowcasting and flood prediction, but this product tends to underestimate the gauge rainfall (Yoon et al., 2014). Recently, several studies have shown the composited column maximum (CMAX) provides significant prediction results for flood forecasting. CMAX represents the maximum precipitation possible in a column, so it has been used to detect severe thunderstorms. In this study, we selected CMAX radar data to represent the rainfall.

2.3. Data Preprocessing

We perform the data pre-processing in spatial resolution for optimized training. The VIS channel has a higher resolution than other channels, so we used bi-linear interpolation to decrease the image resolution from 0.5 to 2 km, which is the same as IR and WV channels. We normalized all data within the [-1, 1] range for model training. We trained with 10-minute interval data from October 2019 to July 2021 and tested the case of Typhoon Hinnamnor, which occurred the first week of September 2022 and significantly impacted South Korea and Japan as a category-5 strength Super Typhoon. Among the typhoon season, we selected the closest case to South Korea, which was 0100-0700 UTC on September 9, 2022. We generated predictions for the rain rate for the next seven hours, without tracking the typhoon movement, and compared our results to weather radar and other precipitation products.

For qualitative comparison, we used the climate reanalysis data and satellite-based precipitation product. The ERA5 from ECMWF (European Centre for Medium-Range Weather Forecasts) provides an hourly total precipitation parameter, which is the accumulated water that falls to the earth's surface. We also used the IMERG-Late Run data from GPM (Global Precipitation Measurement), which is calibrated precipitation based on the multi-satellite microwave estimates. It is noted that while KMA radar and our results are hourly precipitation (mm/hr), the compared datasets show cumulative rainfall. The ERA5 data has a resolution of 25 km and is hourly, while the IMERG has a resolution of 10 km and is half-hourly. Although the resolution is low, the reanalysis data combined with ground observation are useful for confirming uncertainties in satellite-based precipitation. We also chose the GPM product because IMERG is the only product that provides a global map for satellite-based precipitation.

3. Method

The short-term forecasting model for typhoon rainfall consists of a 2-step process (see figure 3). First, we used a DL-based video frame prediction model (Seo, Choi, et al., 2022) to predict future sequences of GK2A satellite imagery. Then, we applied an image-to-image translation model (Jeong et al., 2022) to generate a proxy radar reflectivity map from predicted satellite images.

3.1. Video Frame Prediction Network - WR-Net

Satellite imagery has been mainly used for near-real-time monitoring of atmospheric conditions or as auxiliary data to improve the initial condition of the numerical forecasting model. However, recent advances in deep-learning-based video frame prediction technique have made it possible to predict future satellite images. In this study, we aim to generate future satellite images using deep-learning technique to prepare for typhoon-related disasters in advance.

Warp and Refine Network (WR-Net), proposed by Seo, Choi, et al., 2022, is a deep-learning based model that generate future images from two consecutive past images. Initally developed for frame interpolation to increase temporal resolutions of GEO satellite observations, WR-Net uses a two-step network: a warping component with manually extracted optical flow and refinement component for intensity changes of each pixel. In the weather and climate community, optical flows have traditionally been used for short-term precipitation forecasting by extrapolating the movement of precipitation systems from weather radar observations. However, the extrapolation method had a limitation in being unable to predict the development and disappearance of clouds. To solve this problem, the WR-Net added a learning-based refinement network. The results from WR-Net showed significantly improved skill scores compared with WR-Net without a refinement network.

3.2. Generative Adversarial Network - GeorAIn

Meteorological GEO satellites provide precipitation rate information according to the reflectivity or brightness temperature observed from the VIS and IR channels. Although GEO satellites have relatively high spatial and temporal resolutions, the physical relations between precipitation rate and brightness

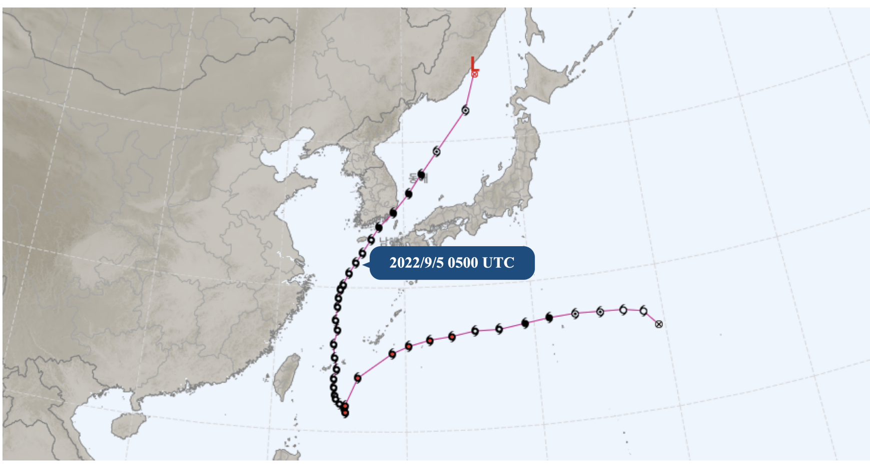

Figure 2. *Track of Super Typhoon Hinnamnor (https://www.weather.go.kr/w/typhoon/typ-history.do).*

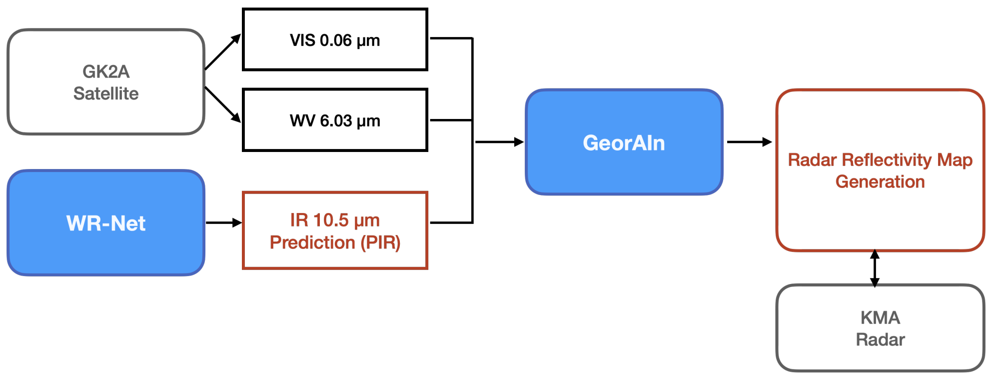

Figure 3. *A disaster monitoring model, which consists of the 2-step models. The WR-Net, a video frame prediction network, predicts future satellite images based on cloud movements. Using the generative adversarial network, the GeorAIn generates the proxy radar reflectivity map from the satellite images.*

temperatures (T_B) are complex and highly non-linear due to the different characteristics of each channel. Because of this, precipitation measurement from the GEO satellite is known to be difficult. However, deep learning-based precipitation retrieval algorithms can handle these complex relationships by using multiple hidden layers to model the non-linear interactions between input (T_B) and output (radar reflectivity).

In this study, we applied the Pix2PixCC model to GK2A satellite images to generate (Jeong et al., 2022) a precipitation map named the geostationary rainfall products (GeorAIn). Pix2Pix is one of the popular methods of image-to-image translation using a Conditional Generative Adversarial Network (GAN). GAN is known to produce high-quality image generation models using an adversarial training process between the generator and the discriminator. The early version of Pix2Pix has a limitation when generating high-resolution images. To solve this, Pix2PixHD (Wang et al., 2018) is proposed to handle high-resolution images. However, GAN is limited in lack of interpretability since they generate images inconsistent with the input data. In addition, GAN is difficult to understand, as they consist of two complex models working against each other. To solve this problem, Jeong et al., 2022 developed Pix2PixCC, adding an inspector that guides the generator to be trained by calculating the correlation coefficient between real and generated images to make physically consistent images.

4. Results: Hinnamnor Case Study

4.1. Predicting Satellite Images from WR-Net

We predict future satellite images with a Video frame prediction model (as explained in Section 3.1). Figure 4 is a case of the IR channel. Using two continuous IR images (0000 and 0100 UTC), WR-Net predicts the future 6-hours (until 0700 UTC) IR images with an hour interval. Figure 4.(a) is the original GK2A IR images, (b) is the WR-Net predicted results, and (c) is the difference map between them. The WR-Net predicted images preserve the location and shape of the clouds to some extent. However, the predicted clouds are divided and dimmed as the prediction time increases. Figure 4.(c) shows that errors accumulate gradually and the image differences increase. This is because, WR-Net only learned how clouds move by optical flow and do not involve in newly generated clouds or dissipating, the overall cloud amount is gradually decreasing. Despite considering this drawback, the longer lead time is a significant advantage in the disaster monitoring model.

About the other channels, the histograms between the GK2A original image and the WR-Net predicted image are compared in Fig 5. As shown in the figure, two histograms have similar distributions about the albedo and temperature. However, the longer the prediction time, the more noticeable the difference in distribution extremes. Cloud pixels generally have high albedo and low temperatures in satellite images, so this area of the tails of distribution means clouds. Therefore, this result indicates that the image predicted by the WR-Net lacks cloud areas and information. For this reason, we conducted additional experiments by replacing only the IR channel that can most identify convective clouds among the three channels with WR-Net results.

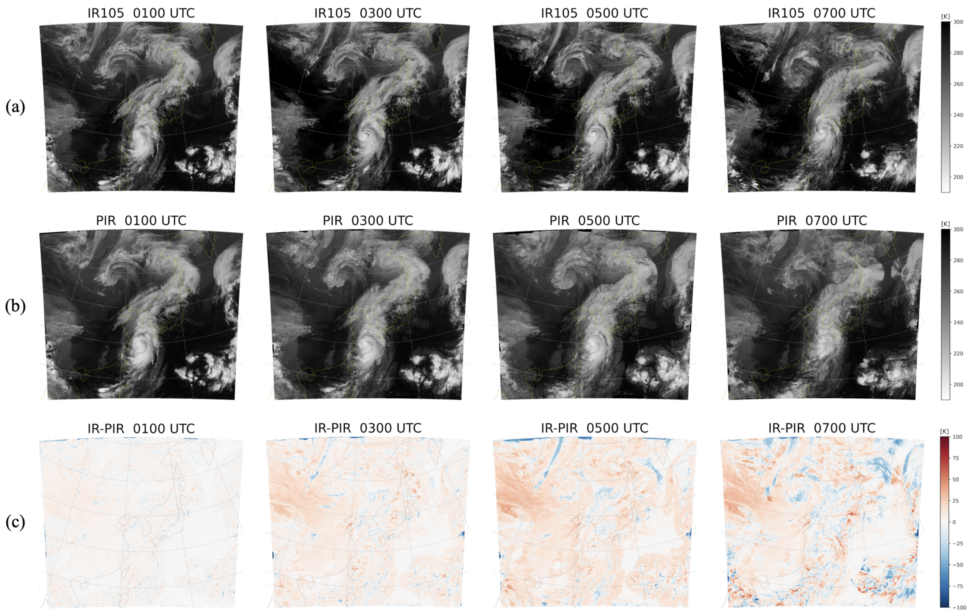

Figure 4. *IR images from (a) GK2A IR 10.5 μm channel, and (b) WR-Net predicted results on September 9, 2022. The bright pixels represent the cloud area. (c) is the difference between (a) and (b). Each colorbar means temperature (K).*

4.2. Monitoring Typhoon Rainfall by GeorAIn

We generate the radar reflectivity from three satellite images with the GeorAIn model and then compare it with KMA radar products. Figure 6 is a 2D histogram representing the correlation of the GeorAIn model results between the three original input channels of GK2A and the two original channels with one WR-Net predicted IR channel. The color bar means the frequency of data, and it was calculated with a log scale. Since images were normalized within the [-1, 1] range for model training, prediction results include negative values during reconstruction. Generally, above 35 dBZ radar reflectivity indicates moderate to heavy precipitation. In this figure, most pixel values appear near 0 dBZ, which means clean-sky pixels. This is because satellite imagery has a much higher percentage of non-cloud pixels than cloud pixels. Closer to the black line means two results have an accurate prediction, so the correlation coefficient is 1.0 on this line. In the prediction after the first hour (0100 UTC), the results of the two predictions show a high correlation of about 0.89 and decrease as the prediction time increase. Despite this decrease, it offers a significant correlation of about 0.75 until 5 hours later (0500 UTC). This means that after up to 5 hours, the WR-Net predicted satellite images could replace the original satellite image, and they showed similar proxy radar reflectivity results.

For the comparison, the predicted radar reflectivity (Z) data were converted to rain rate (R) by using the Z-R relationship (Marshall, 1948) as follows: $z = aR^b$. The coefficients, a and b, are empirically

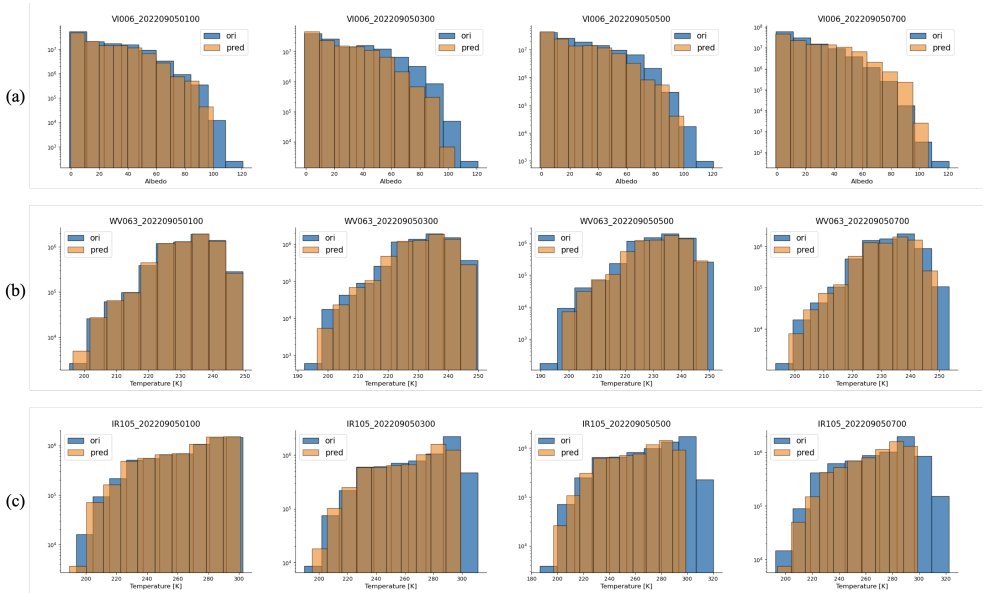

Figure 5. *Comparison between the histogram of the original GK2A image (blue bar) and WR-Net predicted image (brown bar) at each channel. (a) is 0.64 μm visible channel, (b) is 6.03 μm water vapor channel, and (c) is 10.5 μm infrared channel. It is calculated on a log scale.*

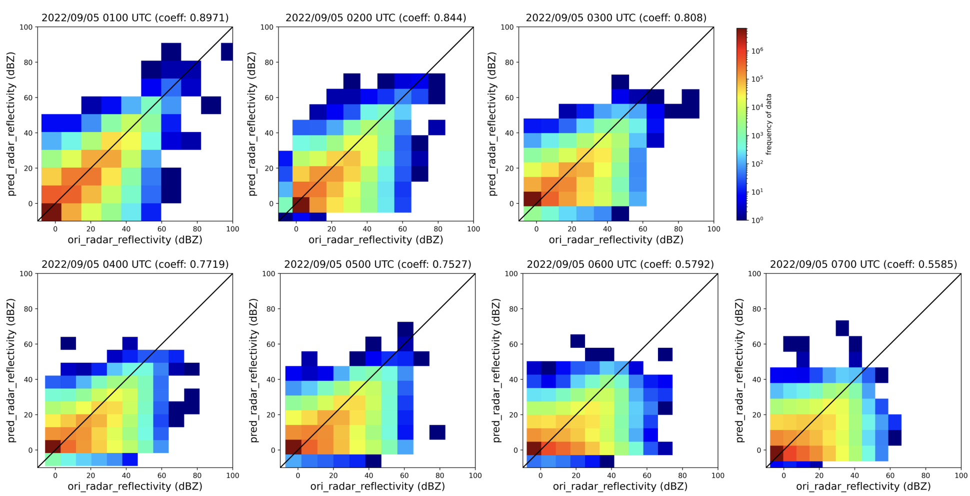

Figure 6. *A 2D histogram of the radar reflectivity generates results from the GeorAIn model, depending on the combination of the input channel. 'ori_radar_reflectivity' is the result of original GK2A three channels (VIS, WV, and IR), and 'gen_radar_reflectivity' means the results of the combination of GK2A two channels (VIS, WV) and WR-Net predicted IR image. The 'coeff' in the subtitle means the correlation coefficient between two results in each graph.*

determined depending on the precipitation type and regions. We use the most general coefficient, a = 200 and b = 1.6, for stratiform precipitation (Marshall-Palmer equation) over Korea.

Figure 7 compares the GeorAIn predicted results with the KMA radar product, climate reanalysis data (ERA5), and GPM IMERG product over the Korean domain. In the KMA radar image (Fig 7.(a)),

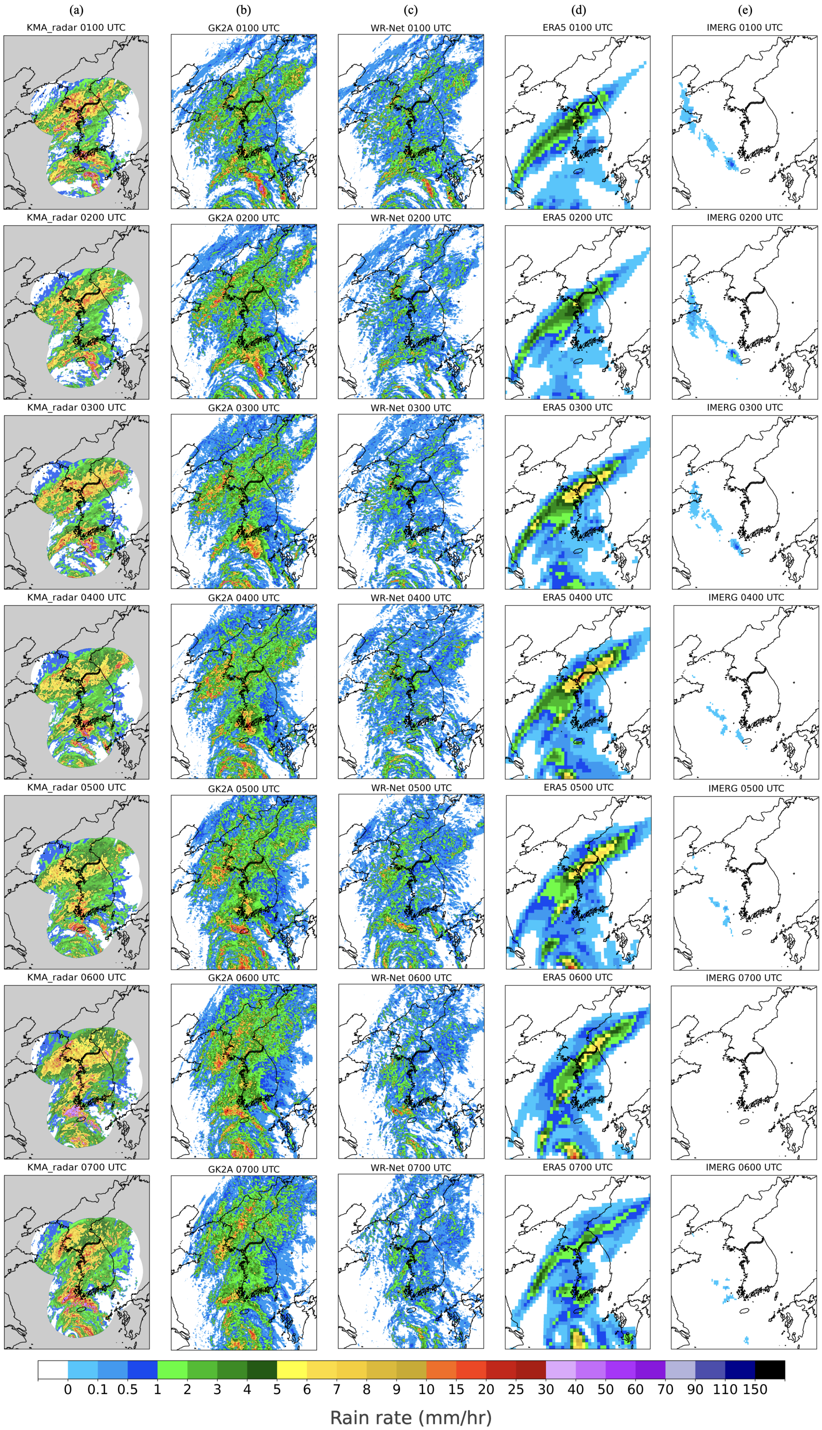

Figure 7. *Comparison of KMA radar data and predicted results. Figures are the rain rate from the KMA radar product(a), (b) from the GeorAIn model with GK2A channels, and (c) from the GeorAIn model with GK2A and WR-Net predicted IR channel. (d) is the hourly total precipitation from ERA5, and (e) is the IMERG precipitation product. The colorbar means rain rates (mm/hr).*

the edges of the image are masked by gray pixels, which represent areas where ground-based radar is not observable. It means radar has spatial limitations in North Korea and the maritime areas. Figure 7.(b) and (c) are the projection map of the predicted results from the GeorAIn, respectively. Because the results are predicted from satellite images, they are free of spatial limitations. The location and shape of precipitation are predicted similarly to radar, and in particular, the results at the input of original GK2A channels (Fig 7.(b)) capture the heavy precipitation (above 10 mm/hr) around Jeju Island located in the southern part of the Korean Peninsula. This shows that the GeorAIn model not only estimates the location, such as the precipitation probability prediction of typical deep learning models, but also accurately predicts the rainfall intensity. However, the result of Fig 7.(c) of inputting the predicted image from WR-Net has significantly fewer rain areas and intensity than the other two results. This might be affected by a gradual decrease in the amount of cloud, as noted in Section 4.1. Nevertheless, the location of heavy precipitation near the typhoon is predicted to some extent. Figure 7.(d) and (e) is ERA5 hourly total precipitation data and the IMERG-Late precipitation from GPM. ERA5 data has nearly ten times greater resolution (25 km) than GK2A (2 km), so they only capture the overall cloud pattern. This accumulated rainfall data shows that heavy precipitation appeared in clouds near the central part of the Korean Peninsula and Jeju Island. On the other hand, the IMERG product offers the least or almost no precipitation of all results.

5. Conclusion and Discussion

We predict rainfall in Typhoon Hinnamnor case by our disaster monitoring model with geostationary satellite images. In this model, we exploited our two models, WR-Net and GeorAIn. The WR-Net is the video frame prediction network to generate future satellite images with optical flow and refinement methods. The GeorAIn is the deep learning-based model to generate proxy radar reflectivity maps from VIS, WV, and IR images of GK2A. GeorAIn can produce high-quality target products such as KMA radar reflectivity but can only be generated for a scene of input data, not future scenes. However, accurate and extended forecasting is essential for disaster monitoring models. To solve this limitation, we utilize the WR-Net results as the input data of the GerAIn model to predict heavy rainfall. The generated IR results with WR-Net had shown a high correlation coefficient of over 0.8 at the future 3 hours and 0.75 at 5 hours with the results from GK2A original channels. Compared with the rain rate from the KMA radar and climate model product, our predicted results show a significantly similar pattern and position of clouds. Moreover, the heavy rainfall area (over 10 mm/hr) is preserved in future frames. It means our model can predict the timing, location, and intensity of heavy rainfall events.

Further studies improve the cloud diminishing issues found in WR-Net and explore cloud cell generation conditions based on physical meaning. In addition, research such as Kim et al., 2019 can be used to generate images of VIS channels that are not available at night and use them for the input of our model. In the GeorAIn, we plan to apply conditional weighting functions to preserve characteristics according to the region and precipitation type.

Our model can be used in disaster monitoring and forecasting related to heavy precipitation. We can make radar reflectivity and rain rate products without ground-based radar systems. We expect our results to help communicate preemptive and accurate warning alarms. To utilize these results globally, we also plan to produce a global radar map with this model by using other GEO satellites and adjusting the bias and loss function.

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Competing Interests. None

Data Availability Statement. The GK2A data used in this study can be found in NMSC: https://nmsc.kma.go.kr/enhome/html/main/main.do. The radar data can be found in KMA: https://data.kma.go.kr/resources/html/en/aowdp.html

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