Deep learning-based monitoring and forecast of the intensity of tropical cyclones

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ABSTRACT

The accurate monitoring and forecast of tropical cyclone intensity can effectively reduce the cost of disaster preparedness and risk mitigation. In this paper we estimated the real-time intensity of tropical cyclones and predicted cyclone intensity in 6-12 hours through a combination of the Communication, Ocean and Meteorological Satellite (COMS) Meteorological Imager (MI) satellite images and European Centre for Medium-Range Weather Forecasts Era-interim (ECMWF ERA-Interim) numerical model output with deep Learning. This study used tropical cyclones that occurred in the western North Pacific between 2011 and 2016. Two schemes considering different combinations of input data and machine learning methods were evaluated. Scheme 2, which applied the fusion network model by using satellite data and the numerical model output, yielded the higher accuracy than Scheme 1.

Index Terms— tropical cyclones, intensity, monitoring, forecasting, deep learning

1. INTRODUCTION

In recent years, the frequency of natural disaster occurrence has significantly increased over the world due to global warming [1]. About twenty-four to thirty typhoons annually occur over the western North Pacific basin, and approximately 20% of the typhoons result in direct damages to Korea and Japan [2]. As one of various types of natural disasters, typhoons cause critical damages for human beings and infrastructure in a short period of time. Thus, it is necessary to mitigate typhoon-derived risks such as death and property damages, by timely and appropriately responding to such meteorological hazards. The accurate estimation and prediction of the intensity of tropical cyclones can lead to reducing the cost for disaster preparedness and risk mitigation.

A typhoon is a tropical cyclone that develops between 180° and 100° E in the Northern Hemisphere. It is a characterized by a low pressure center, a closed low level atmospheric circulation, strong winds, and a spiral arrangement of thunderstorms that produce heavy rainfall. Satellite imagery can be used to provide various information about tropical cyclones, including their intensity, size, and direction. In addition, numerical models have been used to identify and predict such information of typhoons. However, each method has pros and cons, and there is a need to synergistically combine both data to improve the predictability and monitoring of tropical cyclones. Researchers have recently tried to predict weather phenomena and other natural disasters using deep learning, one of the state-of-the-art modeling techniques [3,4]. In this paper, we developed deep learning-based models to estimate and predict the intensity of typhoons. A concept of fusion network deep learning was adopted and a typical convolutional neural network(CNN)-based deep learning was compared to the fusion network approach. The objectives of this research was to 1) estimate real-time tropical cyclone intensity for the western North Pacific area, and 2) predict the intensity in 6-12 hours using satellite images and numerical model data through two deep learning approaches.

2. DATA AND METHOD

2.1. Input variable processing

The data employed in this study included infrared (IR) channels, U wind (U), V wind (V), Vertical Wind Shear (VWS) as independent variables. IR channels were extracted from the Communication, Ocean and Meteorological Satellite (COMS) Meteorological Imager (MI) operated by the Korea Meteorological Administration (KMA). COMS-MI, a geostationary satellite sensor, has five channels including four IR channels with 4 km spatial resolution and one visible (VIS) channel with a 15 min interval and 1 km spatial resolution. Since the VIS channel cannot be used for observation of the area of interest during the nighttime, the four IR channels were used in this study. U, V and VWS were acquired from European Centre for Medium-Range Weather Forecasts Era-interim (ECMWF ERA Interim) with a 6-hour interval and $0.70° \times 0.70°$ horizontal resolution. The historical intensity and track for the tropical cyclones were collected from the best track data provided by Regional

Specialized Meteorological Centers Tokyo (RSMCs-Tokyo, https://www.jma.go.jp). The maximum wind speed of tropical cyclone was used as an intensity indicator (i.e., reference data). Moreover, the maximum wind speed of tropical cyclone 6 to 12 hours later were used as reference data for predicting tropical cyclone intensity.

We extracted the 301×301 sized area from the four satellite channel images (Short Infrared (SI), Water Vapor (WV), Infrareds (IR-1 and IR-2)) based on the center of the typhoons and resampled them to 101×101 size. The processed 101×101 sized images were fed into a CNN classifier. When compared to satellite data, ERA Interim has coarser spatial resolution. To use model data along with the satellite data, we drew 500 km length square frame around the center of each typhoon and the U, V and VWS within this frame were averaged and used as input data. The location of a typhoon (latitude and longitude), the location before 6 hours (latitude and longitude) and the occurrence date (Julian day) were obtained from the best track data at a 6-hour interval and used as input variables.

2.2. Scheme design

We designed two schemes for estimation and prediction of tropical cyclone intensity. Scheme 1 only used satellite data as input variables and ran the model based on CNN. Four convolutional layers and three max-pooling (i.e. average) layers were used in the CNN (Fig. 1). The kernel sizes were 10, 5, 3 and 3 for the convolutional layers, respectively. We used rectified linear unit (ReLu) as the activation function in the convolutional layers and utilized the L2 regularization. In Scheme 2, we used not only the satellite data but also the best track and model (ERA-Interim) data in the framework of fusion network (FN). After building the model with CNN using the satellite data, a vector-based Neural Network (NN) was run using the best track data and model data. We fed the satellite image into the CNN and otherwise put the best track and model into NN. We fused their two last layers in Scheme 2 (Fig. 2).

This study focused on the tropical cyclones of western North Pacific occurred during the period between 2011 and 2016. The samples were divided into three groups by typhoon track: 60% for training, 20% for validation, and 20% for testing the models. To assess the accuracy of the proposed models, coefficient of determination (R^2), bias, and root mean square error (RMSE) were used.

3. RESULTS

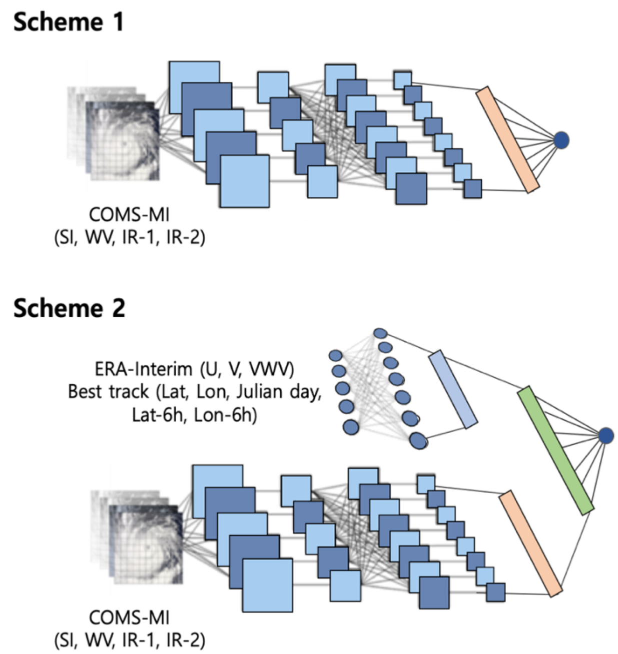

Fig. 1. Schematic diagrams of schemes 1 and 2.

Tab.1. shows the mean and standard deviation values of the test results of the models for 5 runs. In terms of real-time intensity estimation, scheme 1 shows a lower RMSE and scheme 2 shows a higher R^2. When considering the standard deviation, it is interpreted that the two schemes did not show significant difference in performance. However, scheme 2 (FN) shows higher performance than scheme 1 for prediction of the intensity in 6 to 12 hours. It is surprising that the RMSE values of 6h-forecast were lower than those of the real-time monitoring. One possible reason is while past information was included in the models for prediction, it was not included for real-time estimation, resulting in smaller variation of the intensity.

Fig. 2. shows the scatter plot of estimation and prediction results of tropical cyclone intensity by schemes 1 and 2. Both schemes showed similar results for estimation of real-time tropical cyclone intensity and prediction of tropical cyclone intensity in 6 hours. However, for prediction of tropical cyclone intensity in 12 hours, scheme 2 ($R^2 \sim 0.82$ and RMSE ~ 14.76 kt) produced better performance than scheme 1 ($R^2 \sim 0.78$, RMSE ~ 15.94 kt). This might be because scheme 2 used numerical model data, latitude and longitude variables as auxiliary variables which possibly provided potential

Tab. 1. The accuracy metrics (i.e., RMSE and R^2) of schemes 1 and 2 for estimation and prediction of tropical cyclones. The results are the averaged values (and standard deviation) of 5 runs for each scheme.

	Real-time		**6h-forecast**		**12h-forecast**	
	RMSE	R^2	RMSE	R^2	RMSE	R^2
Scheme 1	15.52 (0.25)	0.80	14.58 (0.19)	0.83	16.13 (0.22)	0.78
Scheme 2	15.75 (0.20)	0.81	14.40 (0.13)	0.84	15.16 (0.25)	0.82

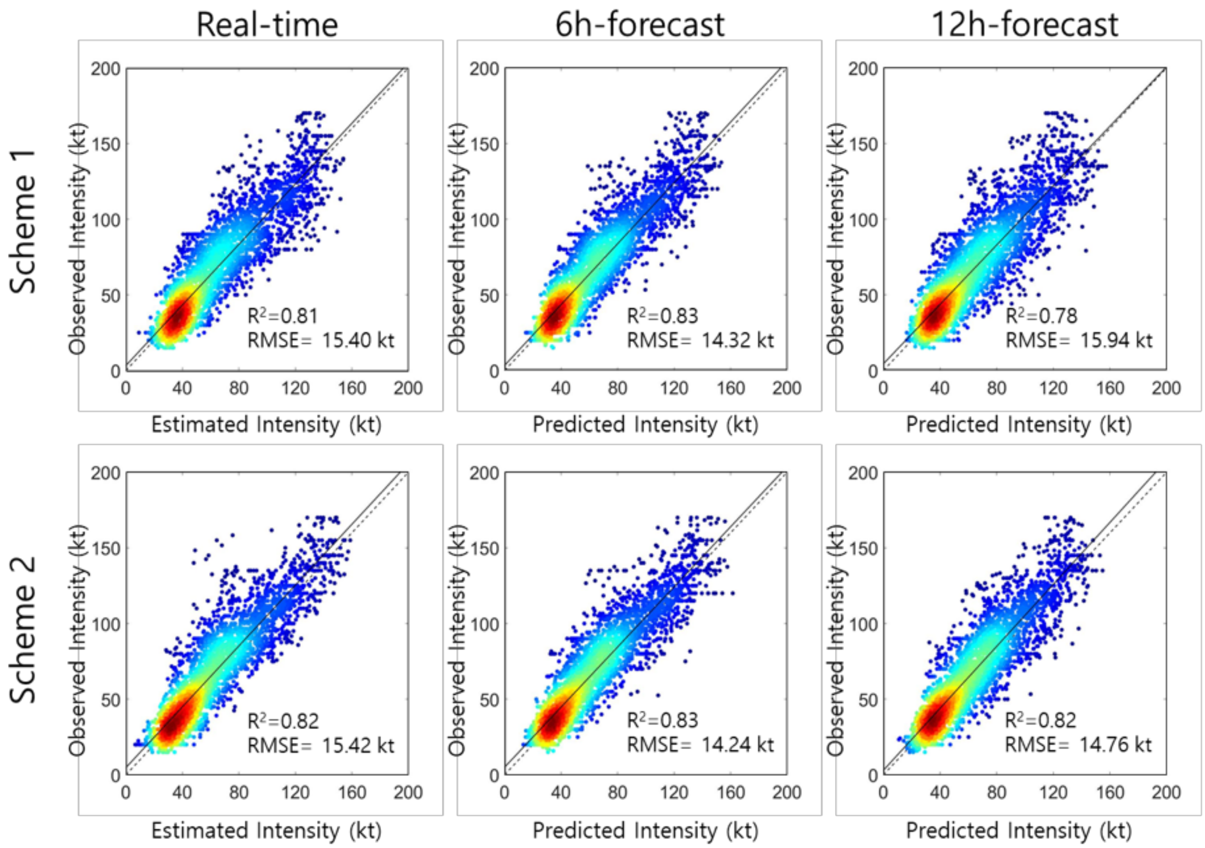

Fig. 2. Scatter plot of estimation and prediction results of tropical cyclone intensity by scheme. The models ran 5 times and the best model results were used to produce the scatterplots.

information of changes in tropical cyclones, which cannot be produced by satellite images. It implies that it is crucial to combine different data sources (i.e., satellite images and numerical models) to improve the prediction of tropical cyclone intensity.

4. CONCLUSION

This study used satellite images and numerical model data to monitor the intensity of tropical cyclones and to predict cyclone intensity in 6-12 hours based on deep learning approaches. Two schemes were tested: Scheme 1 used satellite data as input variables in a typical CNN. Scheme 2 used satellite data, best track data, and numerical model output as input variables by combining CNN and NN in a framework of fusion network. The results showed that the performance of the two schemes did not reveal a significant difference in the real-time monitoring of tropical cyclone intensity. However, for the longer term prediction of tropical cyclone intensity, scheme 2 produced better performance than scheme 1. It is expected that the prediction accuracy can be further improved by incorporating additional input variables or adopting more advanced deep learning approaches.

5. REFERENCES

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