A Deep Convolutional Neural Network Model for Improving WRF Simulations

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Abstract—Advancements in numerical weather prediction (NWP) models have accelerated, fostering a more comprehensive understanding of physical phenomena pertaining to the dynamics of weather and related computing resources. Despite these advancements, these models contain inherent biases due to parameterization of the physical processes and discretization of the differential equations that reduce simulation accuracy. In this work, we investigate the use of a computationally efficient deep learning (DL) method, the convolutional neural network (CNN), as a postprocessing technique that improves mesoscale Weather Research and Forecasting (WRF) one-day simulation (with a 1-h temporal resolution) outputs. Using the CNN architecture, we bias-correct several meteorological parameters calculated by the WRF model for all of 2018. We train the CNN model with a four-year history (2014–2017) to investigate the patterns in WRF biases and then reduce these biases in simulations for surface wind speed and direction, precipitation, relative humidity, surface pressure, dewpoint temperature, and surface temperature. The WRF data, with a spatial resolution of 27 km, cover South Korea. We obtain ground observations from the Korean Meteorological Administration station network for 93 weather station locations. The results indicate a noticeable improvement in WRF simulations in all station locations. The average of annual index of agreement for surface wind, precipitation, surface pressure, temperature, dewpoint temperature, and relative humidity of all stations is 0.85 (WRF:0.67), 0.62 (WRF:0.56), 0.91 (WRF:0.69), 0.99 (WRF:0.98), 0.98 (WRF:0.98), and 0.92 (WRF:0.87), respectively. While this study focuses on South Korea, the proposed approach can be applied for any measured weather parameters at any location.

Index Terms—Bias correction, convolutional neural network (CNN), machine learning (ML), pressure, RH, temperature, weather simulation, wind speed.

I. INTRODUCTION

The atmosphere sciences, particularly weather forecasting, have at their disposal a deluge of data from space, in situ monitoring, and numerical simulations. These diverse data sources offer new opportunities, still largely underexploited, to improve our understanding, modeling, and reconstruction of geophysical dynamics. A number of academic studies devoted to the problem of forecasting difficult-to-retrieve weather events and their associated uncertainties typically employ weather forecasting techniques that fall into three main categories: numerical weather predictions (NWP), statistical forecasting, and artificial intelligence (AI-forecasting). Dynamical (physical) models, such as the Weather Research and Forecasting (WRF) model, use meteorological and topological information to determine the mesoscale weather parameters of a specific region [1], and statistical methods mainly use historical meteorological data to simulate the state of the weather [2]–[6].

To obtain the various meteorological parameters, NWP models generally entail the parameterization of physical phenomena using initial and boundary conditions and a series of partial differential equations [7]. Unfortunately, despite advancements in these models, the shortcoming in resolving horizontal grid resolutions through discretization and interpolation has led to unreliable weather simulations [8]. NWP models are also computationally expensive, particularly with regard to fine-resolution simulations [6]. In addition, because of the misrepresentation of unresolved small-scale features or neglected physical processes, parts of numerical models are represented by empirical submodels or parameterizations [9]–[11], which tends to simplify involved physics that may lead to uncertainties in simulations.

Unlike NWPs, statistical models require a large amount of historical data and completely neglect the physics of the atmosphere; thus, they do not consider meteorology [5], [12]. Since statistical methods are easily implemented and less computationally intensive than NWPs, they are popular among researchers. Nevertheless, due to the scarcity of representing complex meteorological phenomena and nonlinear patterns in the training data, statistical models are unreliable and inaccurate for simulating extreme weather episodes, which exacerbates long-range forecasting.

Because of the chaotic nature of the weather system, errors in weather models are unavoidable but quite often significant regardless of the implemented modeling approach. The parameterization of physical process and discretization of differential equations lead to biases, which increases at every step of space and time in a numerical model. Overcoming these limitations still remains a challenging task. In the past several decades, the volume and quality of observations have increased dramatically, particularly thanks to remote sensing. At the same time, new developments in machine learning
Researchers have applied various ML algorithms in a variety of fields in the earth and atmospheric sciences, including air-quality forecasting (AQF) [2]–[4], [6] and hurricane tracking [15]. ML has also been applied to nowcasting based on real observations, such as the sea surface temperature [16] and precipitation [17]. Most studies for the bias correction using statistical methods or ML methods focus on only one meteorological parameter, or the temporal resolution is very coarse (3-hourly to daily mean values) [18], [19]. Moreover, most studies use the convolutional neural network CNN model for either image processing or classifications of images. The CNN models were used as a nonlinear regressor for air-quality forecasts (ozone and pollen) [2]–[4], [6]. In this study, we apply an alternative approach: a fully data-driven system, using a measurement error of the WRF model. The model developed a real-time weather simulating model that reduces the model-complex weather system. We have developed a weather-AI as a study, we apply an alternative approach: a fully data-driven approach.

II. METHODOLOGY

A. WRF Configuration

WRF v3.8 covers the eastern part of China, the Korean Peninsula, and Japan, with a 27-km horizontal grid spacing for the years 2014–2018. Detailed configurations of the WRF model are available in [21]. The WRF simulation used for this study was conducted in hindcast mode by using one-degree by one-degree National Centers for Environmental Prediction FNL (final) operational global analysis data as initial and boundary conditions, as well as 0.5° real-time global sea surface temperature (RTG SST) for a reasonable sea surface temperature. Thus, we applied a 4-D data assimilation (FDDA) option every 6 h for the temperature, the water vapor mixing ratio, and wind components in conjunction with the indirect soil moisture and temperature nudging technique [22], [23].

B. Deep CNN

The deep architecture of the CNN used in this study is similar to the model in [6]. In general, CNN models are used for image processing and image classifications. The CNN models have proven to be an effective tool in developing regression models for air-quality forecasts [2], [6], [15], [24]–[27]. Since all meteorological parameters are interdependent, the convolution feature of a CNN layer provides an excellent tool for convolving different parameters. Several recent studies have tried to leverage this feature by either convolving a single parameter in time and variables using 1-D CNN [28] or established spatial inter-correlation using 2-D CNN [29]. Although these studies have shown some promising results, the forecast is either a shifted time series [28] by the same amount as the prediction window, or they do not provide time series to evaluate the shifting [29]. For this study, we developed a generalized architecture of the CNN model, which is capable of bias-correcting various weather parameters modeled (by WRF) weather parameters. The use of the numerical model (WRF) enabled us to remove the shifts in time series by removing the previous day’s observations from the inputs for forecasting. The model entails five 1-D convolutional layers (Fig. S4(a) in the Supplementary Document shows the model architecture), a fully connected layer, and an output layer. Each convolutional layer, with 8, 16, 32, 32, and 32 filters, respectively, is activated by the rectified linear unit. In order to find the best architecture, several architectures were tested for wind speed. Fig. S5 shows the comparison of the CNN model with a different number of layers for windspeed, u-wind, and v-wind, respectively. However, the model with three layers performs equivalent to the model with five layers for wind speed. The results from the figure show that the model with five layers performs better for u-wind and v-wind components over the CNN models with fewer layers. In order to have generalized model architecture, we selected a five-layer model for this study. The input for the first layer consists of various hourly meteorological parameters extracted from the WRF model (Table T1 in the Supplementary Document lists all the WRF meteorological parameters used as input). The convolutions are applied to the input features with the elements of a randomly initialized kernel (with a kernel window size of 2 × 1). The feature maps are obtained through the output of the first layer and then used as input for the second layer. The same process is applied in the succeeding layers. The output of the fifth convolutional layer is then passed to the fully connected layer, which contains 264 nodes (neurons) (selected by using grid-search CV [30]). Furthermore, several learning rates, optimizers, and batch sizes were tested for the model, and the best configuration (based on the highest index of agreement (IOA) and correlation on out of box test set) was selected (i.e., 0.001 learning rate, adam optimizer [31], and 72 batch size). The hourly output is obtained at the last layer (output layer). A deep CNN, like any neural network, is an optimization problem that attempts to minimize the loss function. In general, DL models use mean squared error or mean absolute error as loss function to optimize the model. In this study, we used a loss function developed by Sayeed et al. [26] based on the IOA [32].

C. Data Preparation and Model Training

We obtained observed meteorology from the 93 automated synoptic observing system (ASOS) stations operated by the
Korea Meteorological Administration (KMA) for the years 2014–2018 across South Korea. Fig. 2 displays the location of all the meteorology monitoring stations in the country. The meteorological parameters obtained from these stations were wind speed, wind direction, precipitation, relative humidity, temperature, dewpoint temperature, and surface pressure.

Upon completion of the WRF run, we identified the closest WRF grid to each station, to which we assigned a grid point (Table T2 in the Supplementary Document), and then extracted hourly meteorology at each grid point (Table T1 in the Supplementary Document). After acquiring hourly meteorological fields from the output of the WRF model, we prepared the input for each station in the form of a 2-D matrix in which each column represented a specific meteorology parameter from the WRF model and each row represented hourly values. As each column represented a specific meteorological parameter (Fig. S4(b) in the Supplementary Document shows the arrangement of inputs and outputs), it displayed a range of values. To establish uniformity over all inputs, we normalized each column between 0 and 1 with a global minimum and maximum [6]. The output dataset consisted of the hourly observed meteorology. To construct a matrix for training/testing a generalized deep CNN model across the spatial domain, we combined all stations data rowwise and further split the training dataset into a 50–50 ratio (randomly) for training and validation. Then, we trained the model for four years (i.e., 2014–2017) and evaluated it for the year 2018 (note: we did not use 2018 in the model training). We trained a separate model for each of the observed meteorological parameters. One of the major challenges with any ML algorithm is overfitting. In order to minimize the overfitting, we did several test runs by varying the number of iterations (epoch) for the model and evaluated the model on the evaluation set in terms of IOA and correlation. In all these sets, we found out that the model performed best just before when the validation loss becomes larger than the training loss. Thus, for the final model, we trained the model until this point (i.e., the point before the intersection of train and test curve).

1) Special Case: Precipitation Model:: Simulating the amount of hourly rainfall for a specific region requires complex physics and chemistry pertaining to atmospheric conditions. Thus, we divided the simulated rainfall into two sections: a classification model (Rain-CM: Rain Classification model) that identified rain hours and an hourly quantity prediction model (Rain-RM: Rain Regression Model). The two models are combined to simulate the hourly and daily accumulated total rainfall (in mm).

The Rain-CM model is similar to the model discussed in previous sections but differs in its output, which consists of 0’s for no rain and 1’s for rain hours. The data setup of the Rain-RM model differed slightly from that of the models discussed in this study (Fig. S4(c) in the Supplementary Document shows the data arrangement of the Rain-RM model). The output consisted of observed 24 hourly rain amounts (in mm) arranged in rows, and the inputs consisted of the daily simulated meteorology and simulated 24-hourly rain amounts (in mm) by the WRF (this model has 87 inputs instead of 64 inputs and 24 outputs instead of 1). Therefore, each row in the setup consisted of daily values instead of hourly values.

III. RESULTS AND DISCUSSION

For the Weather-AI model, we obtained the following meteorological parameters: wind speed, wind direction, temperature, pressure, dewpoint temperature, relative humidity, vapor pressure, and precipitation at the surface. We then applied this model and the WRF model to obtain predictions for all of 2018. The CNN models, developed for each meteorological variable, were evaluated against the WRF model performance in Section III. In addition to using WRF as a benchmark, we also used linear regression and lasso regression models for the evaluation of the performance of wind speed. We only evaluated windspeed as a benchmark as it is a more difficult meteorological parameter to simulate. Both regression models were fitted as a generalized model and a station-specific model (the generalized model used all stations as input). The average performance of the CNN model (generalized) exceeds the performance of the best regression model (see Table T3 in the Supplementary Document). However, the station-specific CNN model was better than the generalized model in terms of IOA and correlation. The problem with the station-specific model is that it takes greater computational time to train, and
we would need 93 different models for each variable for each station (93 stations). Furthermore, a generalized model can be used at any station apart from 93 used in this study. Thus, in order to have a generalized and easy-to-use model, we will further discuss the performance of the CNN generalized model for each variable.

### A. Wind Speed and Direction

Fig. 3 shows the performance of the WRF model [see Fig. 3(a)] and the Weather-AI model [see Fig. 3(b)] for each station in terms of IOA. The Weather-AI models show an average increase of 27% in IOA for all stations; IOA increased from 0.67 (correlation = 0.66) for the WRF model to 0.85 (correlation = 0.75) for the Weather-AI model. Overall, the Weather-AI model improved the performance of WRF simulations for all stations, with more than two-thirds (64 out of 93) of the stations showing an IOA increase greater than 20% (Fig. S1 shows the percentage change in the IOA at all stations).

Fig. 4 shows Taylor diagrams (separated by month) comparing the performance of the two models for all stations combined. The figure shows that the model closest to the observed point on the diagram performs the best [33], demonstrating the superior performance of the Weather-AI model in all months. Although the root mean squared error (RMSE) for the WRF varied each month, those of the Weather-AI remained stable throughout the year. From Fig. 4, one can conclude that seasonality does not affect the performance of the Weather-AI model for wind speed.

Predicting the wind direction is challenging because of its circular nature. To do so, we first predict the u and v components of winds and calculate the direction. To evaluate the performance of the wind direction, all the predictions that are in the bin of ±45° from observed values are treated as true predictions, and all other values are treated as false predictions. Hence, categorical statistic evaluations, in this case, are as follows:

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\begin{align*}
HR_{wd}, Hit Rate & = \frac{\text{No.of hours when both predictions and observations are in the range of ±45° from observed values}}{\text{Total no.of hours of observations}} \\
FAR_{wd}, False Alarm Rate & = \frac{\text{No.of hours when predictions are not in the range of ±45° from observed values}}{\text{Total no.of hours of observations}}
\end{align*}
\]

The HR\(_{wd}\) for all stations combined for the Weather-AI was 54.83%, and HR\(_{wd}\) for the WRF was 52.16%. Fig. S2(a) shows the yearly time series of wind speed, and Fig. S2(b) shows the wind direction at station 115. This station is unique because it is situated near the southeastern
coast of a small island, Ulleng-do (120 km east of the Korean Peninsula). The WRF model significantly overpredicted wind speeds during the cold months [see Fig. S2(a)]. As summer approached, its performance improved (also shown in Fig. 4) with the most dramatic improvement in the June July August (JJA) season. The Weather-AI model was able to reduce the seasonal biases of the WRF, out-performing it in all months for predicting wind speed and more accurately predicting the wind direction [see Fig. S2(b)]. Furthermore, the model significantly improved the wind direction predictions by successfully predicting dominant southwestern and northeastern wind directions.

B. Precipitation

The bias correction of precipitation consisted of two models. Therefore, we used different techniques to evaluate them. We evaluated Rain-CM based on categorical statistics, that is, the hit rate (HR) and the false alarm rate (FAR), defined as follows:

$$HR_{\text{rain}}, \text{HR Rain Condition} = \frac{\text{No.of hour when both prediction and observation are a rain hour}}{\text{Total no.of hours when observation is a rain hour}}$$

$$FAR_{\text{rain}}, \text{FAR Rain Condition} = \frac{\text{No.of hours when prediction is rain and observation is no rain hour}}{\text{Total no.of hours when observation is a rain hour}}$$

$$HR_{\text{no-rain}}, \text{HR No-Rain Condition} = \frac{\text{No.of hours when both prediction and observation are no rain hour}}{\text{Total no.of hours when observation is a no rain hour}}$$

$$FAR_{\text{no-rain}}, \text{FAR No-Rain Cond.} = \frac{\text{No.of hours when prediction is rain observation is no rain hour}}{\text{Total no.of hours where observation is a no rain hour}}$$

Tables I and II show the HR and FAR of the WRF and Weather-AI models, respectively, for the year 2019 for all stations combined (observations with “NaN” values were removed). The Weather-AI Rain-CM model showed 7% and 1% improvement over the WRF model in the HR for rain and
o-rain hours, respectively, and 37.5% and 6.25% decrease in the FAR for rain and no-rain, respectively.

After obtaining the predictions from the classification model, we applied the regression model (Rain-RM) to predict the hourly amount of precipitation. To merge both models and predict rain more accurately, we converted all the nonrain hours from the Rain-CM to zero. The average IOA for all stations for hourly rain was 0.62 (WRF = 0.56), and the correlation was 0.51 (WRF = 0.43). According to Fig. 5, which presents a stationwise IOA comparison for hourly rain, 90% of the stations show an improved IOA, and 95% show an improved correlation for hourly rain.

The next step in rainfall prediction was daily accumulated rainfall, calculated from the hourly rain predicted by the Rain-RM model. Fig. 6 represents a stationwise IOA comparison of the WRF and Weather-AI models. The average IOA and correlation of the Weather-AI model were 0.87 (WRF = 0.86) and 0.79 (WRF = 0.77), respectively.

C. Other Weather Variables

Fig. 7(a) and (b) presents the stationwise IOA of hourly temperature for 24 h predictions by the WRF and Weather-AI models, respectively. Both models performed well in predicting temperature, with an average IOA for all stations
combined of 0.98 from the WRF and 0.99 from the Weather-AI models. The range of the IOA for the WRF was 0.92–0.99 and for the Weather-AI 0.98–0.99. Even though the temperature predictions of the WRF were exceptionally accurate, those of the Weather-AI still showed improvements in all stations. A similar improvement occurred for the dewpoint temperature [see Fig. 7(c) and (d)]. Monthly Taylor diagram comparisons of both models for temperature and dewpoint temperature are shown in Fig. S6(a) and (b). The results have shown that the RMSE and the SD from WRF were slightly larger during the December, January, and February (DJF) season with a weaker correlation, whereas, during the warmer months, WRF had
Fig. 7. Stationwise IOA comparison of the forecasts of the WRF and Weather-AI models for temperature, dew-point temperature, surface pressure, and relative humidity. (a), (c), (e), and (g) IOA for temperature, dewpoint temperature, pressure, and relative humidity respectively for the WRF model. (b), (d), (f), and (h) IOA for temperature, dewpoint temperature, pressure, and relative humidity respectively for the Weather-AI model.
smaller RMSE and SD with a higher correlation. In contrast, the Weather-AI generated more accurate predictions than the WRF for all months. The RMSE and SD did not vary or exceed 2 °C for each month throughout the season.

The IOA for the hourly surface pressure predictions for 24 h increased significantly, as shown in Fig. 7(e) and (f). The average IOAs of the WRF and Weather-AI models were 0.69 and 0.91, respectively. For several of the stations, the WRF produced uniform bias in simulating surface pressure, which was adjusted by the Weather-AI (see Fig. S3 in Supplementary Document). Since the bias from the WRF was uniform, the correlation was stronger for these stations, but the IOA was weaker. However, as the bias from the Weather-AI decreased, the IOA increased.

Fig. 7(g) and (h) shows the yearly IOA of the hourly simulations of relative humidity from the WRF (IOA=0.87) and Weather-AI (IOA=0.92) models, respectively. All, except for five (Station 169, 165, 129, 140, and 170), stations show improvement in the IOA. According to Fig. S6(c), the Weather-AI model performed better than the WRF model for relative humidity. Also, the bias corrections by the Weather-AI model were slightly more accurate than the simulations of the WRF model in all months.

IV. CONCLUSION

In this article, we developed and discussed a deep CNN model that reduced bias in an NWP model and significantly improved predictions. Although we retained the same model configuration, we developed several meteorology-specific models based on the target/output. The models showed improved predictions over the WRF model and significantly reduced predictions.

The IOA for wind speeds from the Weather-AI model improved for all 93 stations in South Korea. Improvement fell within the range of 2.3–39.3%, with a mean of 17.83% in absolute terms. For wind direction, the predictions of the Weather-AI model improved in 52 out of 93 stations. Moreover, the performance remained consistent throughout the year. Since the Weather-AI model uses the WRF meteorology as an input, it does not indicate any time-series shift as the input does not have true observations (Fig. S7 in the Supplementary Document shows the best, the median, and the least performing station based on IOA). The Rain-CM improved the hit rate by 6% over the WRF model for the prediction of rain hours, but it remained the same as the WRF for the prediction of no-rain hours. The bias correction of the hourly rainfall amount by the Rain-RM model improved in most of the stations; nevertheless, simulating the absolute amount of hourly rainfall remains a challenge.

Predictions of the daily accumulated rainfall amount showed a slight improvement in the IOA and a 2% improvement in the correlation. The performance statistics of other meteorological parameters—temperature, dewpoint temperature, and relative humidity—also improved.

The Weather-AI model significantly improved and bias-corrected the simulated wind speed, relative humidity, and hourly precipitation by the WRF model. As WRF predictions were already relatively accurate, they did not show significant improvement in the bias correction of temperature and dewpoint temperature. The correlation and IOA for temperature

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Fig. 7. (Continued.) Stationwise IOA comparison of the forecasts of the WRF and Weather-AI models for temperature, dew-point temperature, surface pressure, and relative humidity. (a), (c), (e), and (g) IOA for temperature, dewpoint temperature, pressure, and relative humidity respectively for the WRF model. (b), (d), (f), and (h) IOA for temperature, dewpoint temperature, pressure, and relative humidity respectively for the Weather-AI model.
were in the range of 0.92–0.99 for the WRF model. However, for the CNN, the range of correlation and IOA was 0.97–0.99 and 0.98–0.99, respectively. For the CNN model, the range of IOA and correlation were 0.96–0.99 and 0.97–0.99, respectively. The simulation of surface pressure from WRF contained a uniform bias in several stations that were corrected by the Weather-AI model. Even though the Weather-AI model was trained for South Korea WRF simulation, a similar model can be trained and reproduced for any numerical model (simulations and forecasts).

In addition, the system can be utilized for any location to bias-correct any number of meteorological parameters while being computationally fast. Although the AI model showed significant improvement over the WRF model, it does not cover WRF domains over the sea/ocean (because of the lack of observations). In addition, unlike the WRF and more advanced architectures of CNN, the Weather-AI model has no spatial gridded structure. Therefore, we need to develop AI models capable of spatial and temporal simulation and forecasting, specifically long-range forecasting, based on Weather-AI.

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DATA AVAILABILITY

The test/train/validation data are available for noncommercial research purposes by contacting the corresponding author.

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