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Development of a daily PM_{10} and $PM_{2.5}$ prediction system using a deep long short-term memory neural network model

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Abstract. A deep recurrent neural network system based on a long short-term memory (LSTM) model was developed for daily PM_{10} and $PM_{2.5}$ predictions in South Korea. The structural and learnable parameters of the newly developed system were optimized from iterative model training. Independent variables were obtained from ground-based observations over 2.3 years. The performance of the particulate matter (PM) prediction LSTM was then evaluated by comparisons with ground PM observations and with the PM concentrations predicted from two sets of 3-D chemistry-transport model (CTM) simulations (with and without data assimilation for initial conditions). The comparisons showed, in general, better performance with the LSTM than with the 3-D CTM simulations. For example, in terms of IOAs (index of agreements), the PM prediction IOAs were enhanced from 0.36–0.78 with the 3-D CTM simulations to 0.62–0.79 with the LSTM-based model. The deep LSTM-based PM prediction system developed at observation sites is expected to be further integrated with 3-D CTM-based prediction systems in the future. In addition to this, further possible applications of the deep LSTM-based system are discussed, together with some limitations of the current system.

1 Introduction

Over the past several decades, South Korea has made continuous economic growth; however, in accordance with this rapid economic development, emissions of air pollutants from various sources such as industrial, transportation, and power generation sectors have increased, and air quality has thus deteriorated (Wang et al., 2014). Among the atmospheric pollutants, particulate matter (PM) plays an important role in human health and climate change (Davidson et al., 2005; Forster et al., 2007). Several epidemiological studies have reported clear statistical relationships between aerosol concentrations and human mortality and morbidity (Dockery et al., 1992; Hope III and Dockery, 2006). To minimize the public damage caused by air pollution and to alert Korean citizens about high-PM events, the National Institute of Environmental Research (NIER) of South Korea has carried out daily air quality (or chemical weather) forecasting using multiple 3-D chemistry-transport models (CTMs) since 2014.

However, the accuracy of the 3-D CTM simulations has been reported to be low. Researchers believe that this low accuracy originates from uncertain sources of emission inventory, meteorological fields, initial and boundary conditions, and CTMs themselves (Seaman, 2000; Berge et al., 2001; Liu et al., 2001; Holloway et al., 2008; Tang et al., 2009; Han et al., 2011). Many efforts have been made to enhance the accuracy of the 3-D CTM-based forecasting system. As a part of the efforts, the Korean government decided to de-

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4 Outlook and future works

In this study, we established a deep RNN system for daily PM_{10} and $PM_{2.5}$ predictions and evaluated the newly developed system's performance by comparing its PM_{10} and $PM_{2.5}$ predictions with the observed and CMAQ-predicted levels. In the comparisons, the LSTM-based PM predictions were, in general, superior to the CMAQ-based PM predictions. In terms of IOA, the accuracies of the LSTM predictions were 1.01–1.72 times higher than those for the CMAQ-based predictions. Based on this, we concluded that the LSTM-based system could be applied to daily "operational" PM_{10} and $PM_{2.5}$ forecasts. The LSTM-based predictions at the observation sites can provide useful and complementary information for air quality forecasters, synthesizing all the information available such as CTM air quality predictions, AI predictions, weather predictions, and satellite-derived information.

In the future, Korea's air quality forecasting system will be improved by continuous development of the CTM-based prediction system including the use of more advanced DA techniques, together with continuous sophistication of the AI-based prediction system. If the AI-based predictions at the observation sites are consistently better than the CTM-based predictions, the two elements will be more systematically combined within a prognostic mode, which will be our final research goal. In addition, a similar LSTM-based prediction system can also be applied to the daily forecasts of gas-phase air pollutants such as NO_2, SO_2, CO, and O_3. These works are also now in progress.

Although the current LSTM-based system can accurately predict PM_{10} and $PM_{2.5}$, it also has some limitations. For better prediction accuracy, we need more air quality data for model optimization. Because $PM_{2.5}$ has only been monitored in South Korea since 2015, there are too few observations to optimize the $PM_{2.5}$ predictions, which require continuous accumulation of $PM_{2.5}$ observations. In addition, the limited number of input variables is another obstacle to optimal model performance. The current LSTM-based PM_{10} and $PM_{2.5}$ prediction system contains 10–12 input parameters. If more useful parameters such as mixing layer height (MLH) and barometric distribution are available, its performance would improve further (Hooyberghs et al., 2005; Liu et al., 2007). Therefore, future efforts should be made with more $PM_{2.5}$ data and more input variables such as mixing layer heights entered into our system.

Code availability. The source code is available upon personal request to the corresponding author.

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Competing interests. The authors declare that they have no conflict of interest.

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