STATISTICAL ASSESSMENT OF THE INFLUENCE OF HYDROMETEOROLOGICAL FACTORS ON FINE DUSTS

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ABSTRACT: Fine dust, also known as particulate matter, refers to very small matters floating in the atmosphere, and has become one of major concerns in modern society. Fine dust arises not only by anthropogenic emissions, but also by natural sources, and previous studies have revealed that it intensifies, migrates and decreases by several hydrometeorological factors, such as solar radiation, wind and precipitation. The people of South Korea get information of fine dust concentration from Air Quality Monitoring Systems (AQMS). However, due to the spatial imbalance of the AQMS observatories, those who live in places without observatories are using nearest-neighbor-interpolated fine dust information. Therefore, it is crucial to monitor fine dusts across large area to assess spatial variability of fine dust concentration. In this study, we tried to analyze the influences of hydrometeorological factors on fine dust concentration and investigate the capability of the developed model in estimating spatial variability of fine dust, by using Bayesian Model Averaging (BMA). By analyzing Posterior Inclusion Probabilities (PIP) of the hydrometeorological variables chosen from Global Land Data Assimilation System (GLDAS), we could assess positive/negative influences of each variable on the variance of fine dust concentration (e.g. positive influence of solar radiation, negative influence of precipitation). The optimal regression model from weighted average of the models developed by BMA showed moderate correlation with ground-based observation of fine dust. Compared with the nearest neighbor method, the model performed better in expressing spatial variability, implying the possibility of global scale monitoring of fine dust.

1. INTRODUCTION

Recently, fine dust is receiving very high social attention than any other time, with increasing days with high concentration of fine dust. Fine dust refers to dusts floating in the atmosphere in form of aerosol, and is classified into PM10 (<10μm in diameter) and PM2.5 (<2.5μm in diameter). These particles are known to be easily inhaled and cause respiratory- (Ristovski et al., 2012), lung- (Zelikoff et al., 2003) and cardiovascular- (Nishiwaki et al., 2012) related diseases. Also, in serious cases, they can cause premature deaths (Dominici et al., 2015; Zúñiga et al., 2016). Therefore, it is crucial to establish the sources of fine dusts and investigate ways to reduce the damage.

Fine dust has characteristics of both primary pollutants directly emitted from pollution sources such as cars and factories, and secondary pollutants which are formed from chemical reactions in the atmosphere (Choi et al., 2013; Kim et al., 2016). At the same time, in case of Korea, there are numerous long-distance dust events originating from central Asian desert and nearby countries. Therefore, it is hard to estimate the exact reason or sources of fine dust events and assume damages (Han et al., 2006; Jung et al., 2010). As mentioned, fine dust events are not only affected by anthropogenic sources, but also the location at which the events take place, and hydrometeorological factors controlling their migration, mitigation and intensification. Therefore, it is essential to grasp hydrometeorological factors' role in driving variations in fine dust concentration (Nam et al., 2018). There were several studies conducted dealing with the relationships between fine dust concentration and hydrometeorological variables, such as precipitation (Ouyang et al., 2015), soil moisture (Kim and Choi, 2015), solar radiation and temperature (Préndez et al., 1995), and relative humidity (Shin et al., 2007).

The Korean ministry of environment is operating an Air Quality Monitoring System (AQMS) and providing real-time domestic air pollution data through the website (www.airkorea.or.kr). AQMS, although suitable in showing local air pollution concentration in real-time, has limitations in spatially and temporally assess movement of fine dusts (Kim et al., 2018), and in providing accurate information in rural areas, in which the observatories are not present. This kind of problem has been solved through incorporating satellite data (Engel-Cox et al., 2004; Gupta et al., 2006; Van Donkelaar et al., 2010), since they are better in representing an area.

In this study, we tried to analyze hydrometeorological variables that are thought to have impact on the variation in fine dust concentration, especially PM2.5, with hydrometeorological data from Global Land Data Assimilation System (GLDAS). First, we assessed the effects of each hydrometeorological variable has on fine dust concentration by Bayesian Model Averaging (BMA), and we developed multi-variate regression model with the selected variables and aerosol data from two satellites (Terra and Aqua). Finally, by using the developed model we made fine dust concentration maps to investigate the possibility of the model in grasping spatial distribution of fine dusts.

2. STUDY AREA & DATA

2.1. Study Area

The study area of this study is given in Figure 1. South Korea is located at 125° - 131° in longitude and 33° - 38° in latitude. The whole country mainly consists of forest regions, followed by crop land and urban areas. Due to the location of the country, it suffers from long-distance travel of Asian dust, originating from central Asian desert, every spring. There includes over 300 AQMS observatories through the country, which was used as reference data. As mentioned above, spatially non-continuous observatories forces people living in rural areas to use nearest-neighbor-interpolated concentration information.

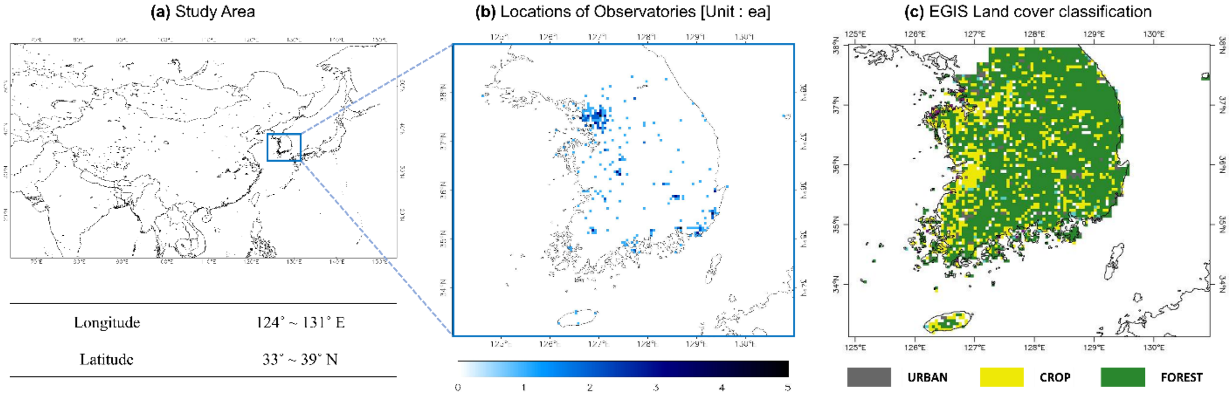

Figure 1. (a) Study area (South Korea), (b) Distribution of AQMS observatories and (c) land cover classification from Environmental Geographic Information System (EGIS).

2.2. Dataset

First of all, daily fine dust concentration data were acquired from the AQMS (Figure 1-b). The number of observatories was 340 and among those, data from only 199 observatories providing PM2.5 concentration were used in this study. For the analysis about the relationships between hydrometeorological variables and PM2.5, we selected Shortwave/Longwave Radiation (SW, LW, respectively), Air Temperature (Ta), Precipitation (P), Soil Moisture (SM), Specific Humidity (SH), Evapotranspiration (ET), Wind Speed (WS) and Air Pressure (Pa) from GLDAS, which is reanalysis data. They were given in 3-hourly temporal resolution, so they were averaged to be daily.

For developing multi-variate regression model, which will be described in section 3, Aerosol Optical Depth (AOD), which is the degree of light extinction by aerosol in a column of atmosphere, from MODerate resolution Imaging Spectroradiometer (MODIS) onboard on satellites Terra and Aqua of National Aeronautics and Space Administration (NASA) were used. Finally, Planetary Boundary Layer Height (PBLH) data from Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) were used to calibrate AOD data.

3. METHOD

The whole dataset was collocated spatially and temporally to match with the AQMS data. Two AOD products from Terra and Aqua (MOD04 and MYD04, respectively), which were given in level 2 data, were preprocessed into gridded data and averaged to produce daily AOD values. Every gridded data was resampled to be matched in pixel size, 5km, and classified according to the land covers and the locations of the observatories.

3.1. Bayesian Model Averaging

BMA was used to analyze the degree of impact each hydrometeorological factor has on fine dust concentration variation and select factors that have effect large enough (Tran et al., 2018). First, 2^k number of regression model is developed using k variables, as in equation 1.

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \quad (1)$$

Here, y refers to the dependent variable, which is fine dust in our case, x refers to k explanatory variables (9 hydrometeorological factors), α a constant, β coefficients and ε an error term. By applying Bayesian theory as given in equation 2, we get Posterior Model Probability (PMP), which is the percentage of dependent variable's variance explained by the model. $P(M_j|Obs)$ refers to the probability of model M_j being true when given the data, $P(M_j)$ refers to the belief of model's prior probability beforehand. In this study, it was assumed that all models were independent to each other and had uniform prior probability distribution.

$$P(M_j|Obs) = \frac{P(Obs|M_j)P(M_j)}{\sum_{i=1}^{2^k} P(Obs|M_i)P(M_i)} \quad (2)$$

Finally, by summing up the PMPs of the models including each explanatory variable, we get Posterior Inclusion Probability (PIP), which implies the degree of impact each hydrometeorological factor has on the variation of fine dust concentration. With these PIP values we selected hydrometeorological factors that are thought to have significant impact on fine dust concentration variation.

3.2. Multi-variate Regression Model

As an indirect quantity of the total aerosol in the column of atmosphere, AOD can be defined as an integral of extinction of light along the column, as in equation 3 (E. Emili et al., 2010):

$$AOD = \pi \int_0^{\infty} Q_{ext}(\lambda, r) N(r, z) r^2 dr dz \tag{3}$$

where Q_{ext} refers to the extinction efficiency and N(r,z)drdz refers to the size distribution function, which represents number of particles between z and z+dz and between r and r+dr.

PM2.5 can be expressed as in equation 4, assuming spherical particles.

$$PM_{2.5} = \frac{4\pi}{3} \int_0^{1.25} N(r, 0) r^3 dr \tag{4}$$

The extent of the integral means that only the particles with diameter under 2.5μm are considered.

Combining the two equations yields a linear relationship as in equation (5) and then can be simplified as in equation (6).

$$PM_{2.5} = \frac{AOD}{H_{eff}} \frac{4\rho r_{eff}}{3[Q_{ext}]} \tag{5}$$

$$PM_{2.5} = \beta + \frac{\alpha AOD}{PBLH} \tag{6}$$

We added the selected hydrometeorological variables following the method of Yang et al., 2005, which can be expressed as in equation (7):

$$\ln(PM_{2.5}) = \beta_{AOD} \ln(AOD) + \beta_{PBLH} \ln(PBLH) + \beta_0 + \beta_1 V_1 + \cdots + \beta_k V_k \tag{7}$$

where β is the coefficient and V is the selected variable.

4. RESULT

4.1. Posterior Inclusion Probability

Figure 2 shows the result of PIP values in three different land cover types. The black bars imply that the variable has positive effect on PM2.5 variation and the white bars imply that the variable has negative effect on PM2.5 variation. PIP value closer to 1 means that the variable has meaningful impact on PM2.5 variation. The variables that have positive effects were long wave radiation and air pressure and the others showed negative effects. However, there were not much difference between the land cover types and except specific humidity in crop land and air pressure in forest, the PIP values were all 1. This might be due to the temporal coverage of the data, which includes 3 years, and therefore the dependent and independent variables have shown yearly patterns. PM2.5 concentration in Korea in highest in spring, followed by winter, fall and summer,

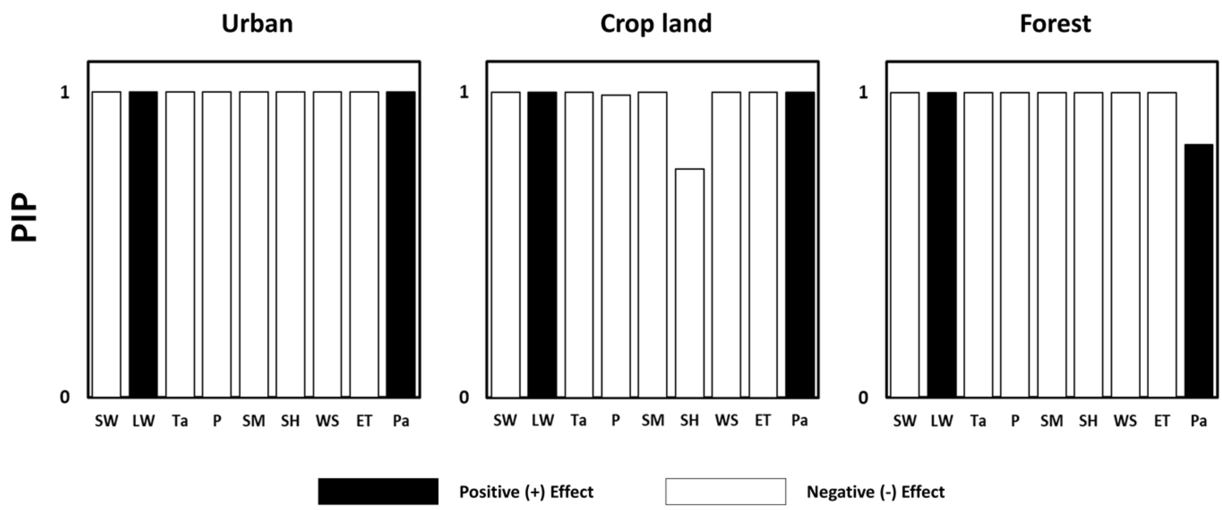

Figure 2. PIP values of 9 different hydrometeorological variables, in three different land cover types.

mainly because of the Asian dust events in spring and occasional smog's occurring in winter. Therefore it makes a convex downward pattern and the hydrometeorological factors that have similar convex downward patterns appeared to have positive relationships with PM2.5 concentration and the factors that have the opposite patterns have shown negative relationships.

Since the total analysis wasn't able to detect the differences in PIP values in different factors, we divided the data into seasons instead of land cover types to remove seasonal effect inherent in the dataset. The result is shown in Figure 3. Significantly positive impacts were found in case of shortwave radiation and air pressure, which is thought to be related to the formation of secondary pollutants in former case. The reason of the positive impact of air pressure is that, it is negatively correlated with boundary layer height, which is again negatively correlated with PM2.5 concentration at the ground level. Significantly negative impacts were found in case of longwave radiation, precipitation, soil moisture and wind speed, except soil moisture in winter, which has shown positive value of under 0.2, implying that it's meaningless. Negative relationship of longwave radiation was appeared because there was an opposite pattern between shortwave radiation and longwave radiation. In case of precipitation and soil moisture, PIP values showed dust wash out effect by precipitation and soil moisture's restraining role of natural dust outbreaks. Wind speed's high PIP values through the whole seasons were thought not to be related with natural phenomenon, but with the way measurement of PM2.5 is done: that is, the device measures PM2.5 concentration by inhaling ambient air and counting or weighing them, and with higher wind speed, there might be less dust deposited, given same pollution level. The PIP values of the

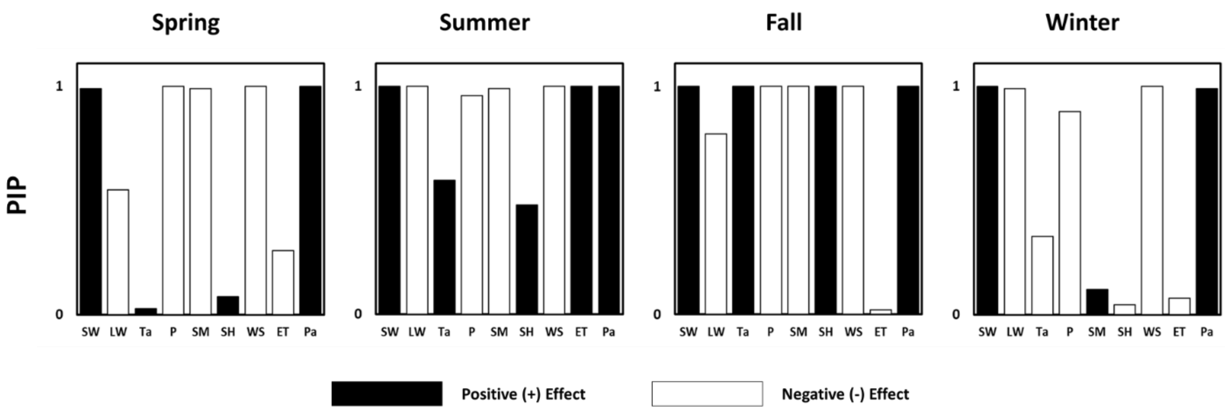

Figure 3. PIP values of 9 different hydrometeorological variables, in four different seasons.

other factors differed from season to season, both in magnitude and sign.

4.2. Model Performance

The variables with PIP values larger than 0.6 were selected from the result in section 4.1, by means of trial and error. In the process of developing models, these variables were significant with 99% confidence level in each model. The developed models were compared with observed PM2.5 concentration, as shown in Figure 4. Overall, the statistics showed moderate to good performances of the models, highest in winter and lowest in spring, which can be attributed to relatively stable meteorological condition in winter and the highest variability of PM2.5 concentration in spring due to frequent dust events, respectively. The slope values were less than 1 for all seasons, resulting in underestimation of PM2.5 concentration in high concentration level and overestimation in low concentration level. This is mainly due to very low number of samples in very high and very low concentrations, compared to those in the middle. Also, overestimation in low concentration level could also be associated to high uncertainties in aerosol product in lower level. Figure 5 shows geographical differences in model performances, in winter. The data from

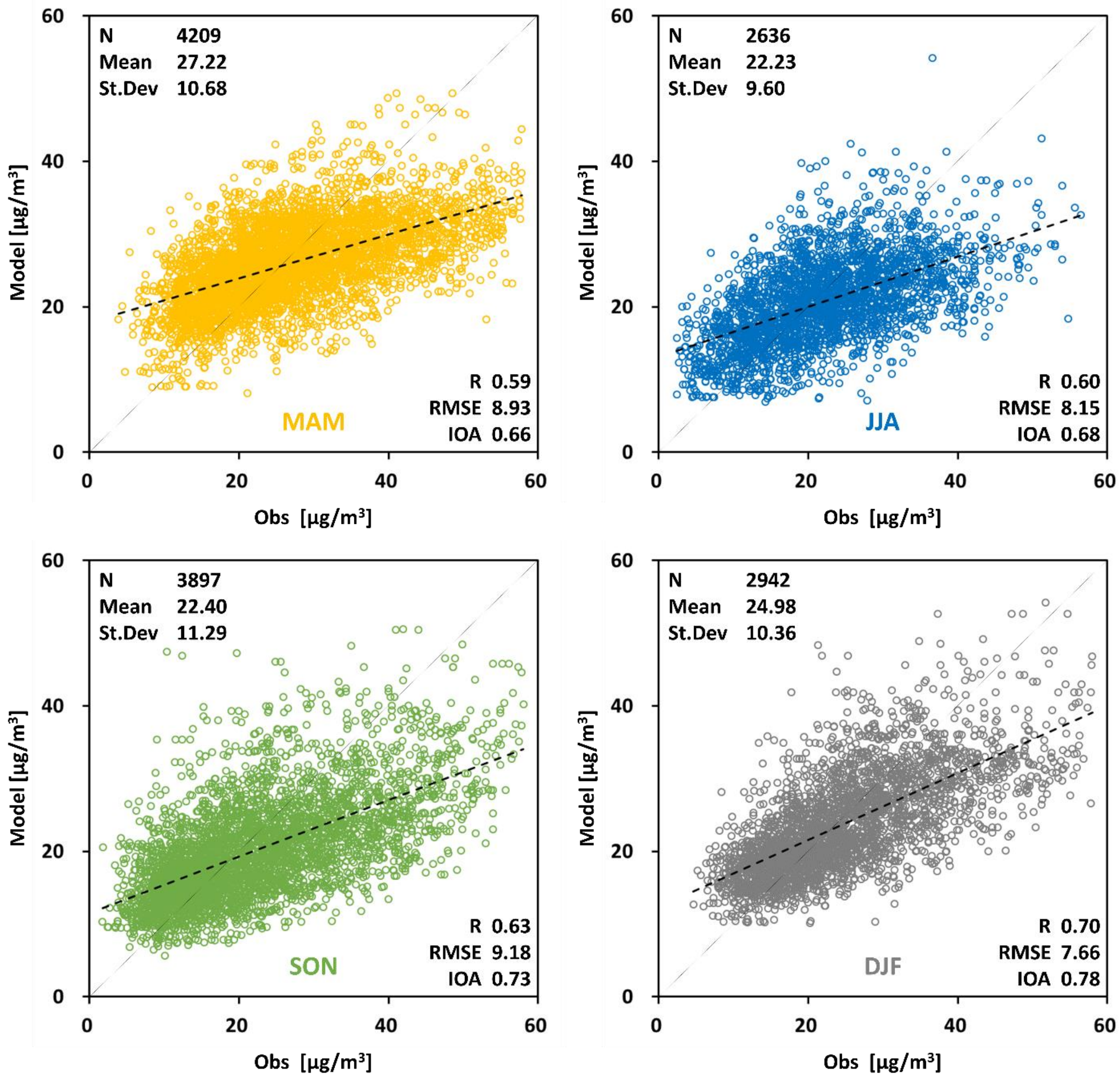

Figure 4. Scatter plots between modeled, observed PM2.5 concentration in different seasons.

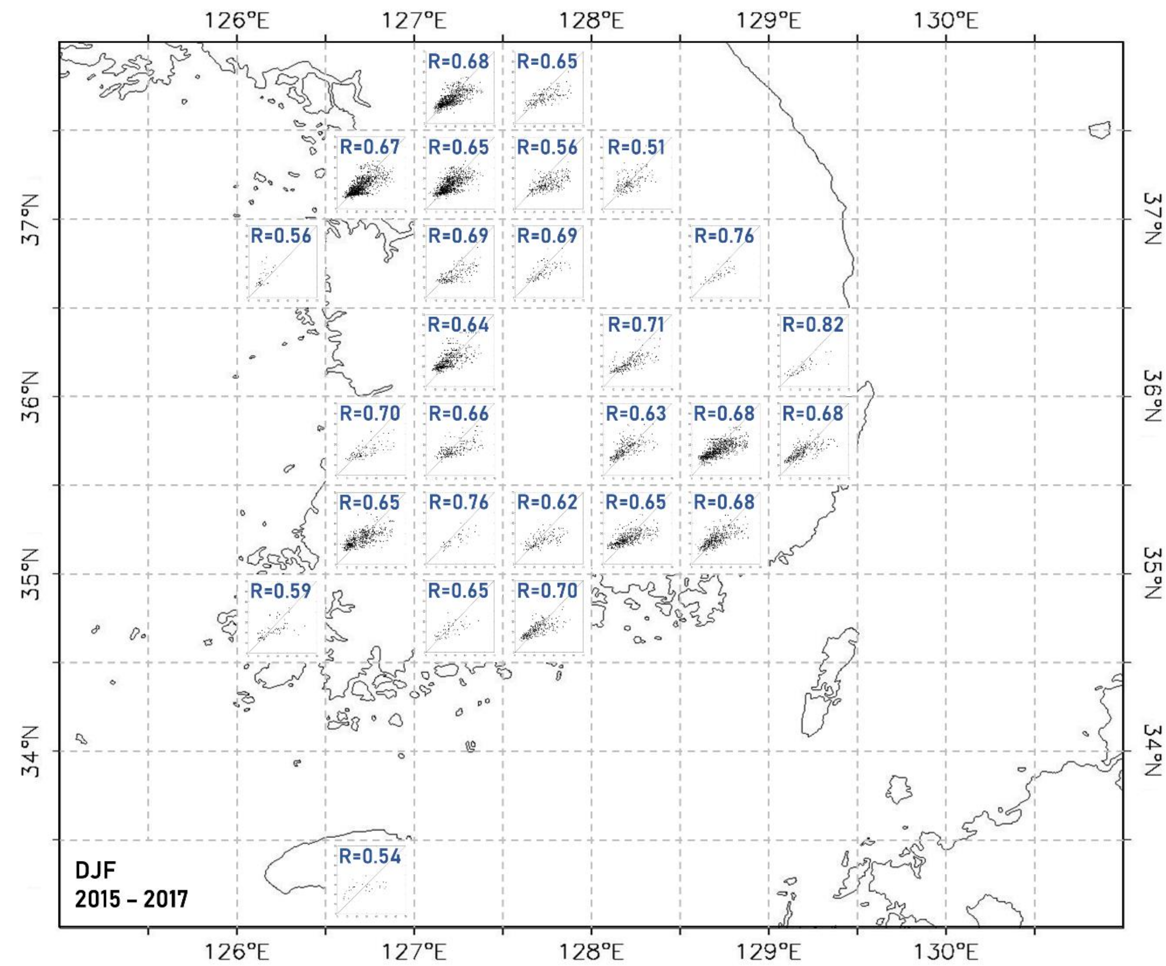

Figure 5. Geographical differences in model performances with correlation coefficient, in winter.

all observatories falling in each 5km x 5km grids were collected and combined. the grids without even one observatory are leaved empty. The overall spatial pattern of the correlation coefficients not much differed season to season. The correlation coefficients ranged from 0.54 to 0.82, coastal areas being generally lower than inland. This could be due to the uncertainty of aerosol retrieval process in coastal areas, which has been mentioned in previous study (Gupta and Christopher, 2009). Therefore, the lowest correlation coefficient was found in the island at the bottom of the country, where almost every pixel of the data was including coastal area.

4.3. Development of PM2.5 Concentration Maps

We applied developed model to every pixel available from MODIS, GLDAS to produce PM2.5 concentration maps. Figure 6 shows the concentration maps from 12 to 21, march, 2015. The upper maps are developed by using models and the bottom ones illustrate ground-based interpolated maps, by means of nearest-neighbor, which is the method being used in Korea to provide PM2.5 information to people living in rural areas. There were two Asian dust events in this period, from 14 to 16 and 21. In the middle of the two events, there was rainfall over the country. We could observe that they look very similar in overall colors and temporal variation, increasing with dust event and decreasing significantly by precipitation, indicating the developed model can capture increasing or decreasing temporal trends. Furthermore, the modeled maps have

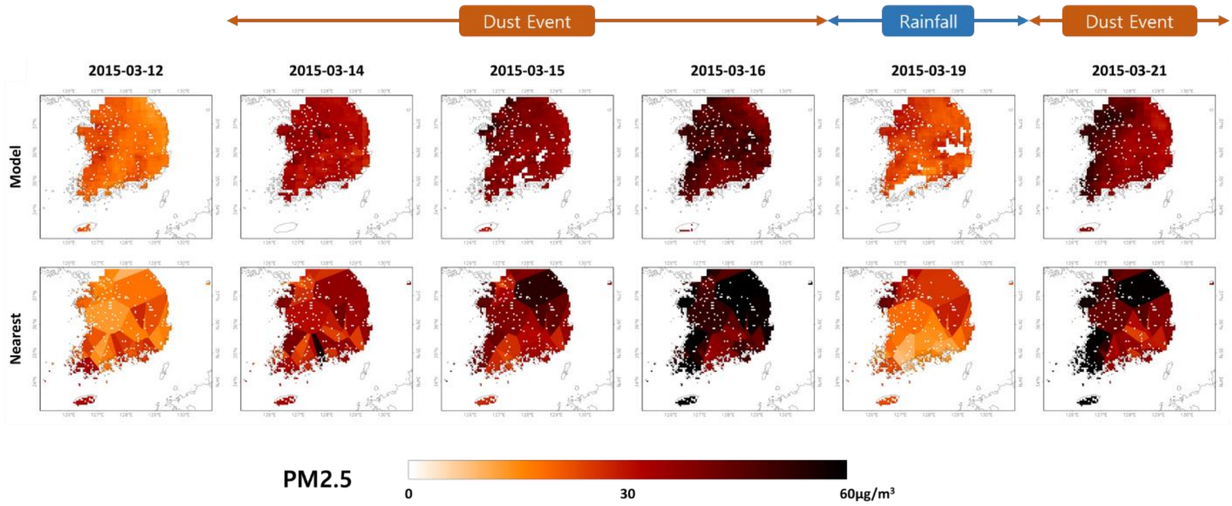

Figure 6. Two types of PM2.5 concentration maps (modeled, interpolated) in march, 2015.

shown ability to better visualize spatial variation. Still, the range of the concentration was relatively small, centered around middle level of the concentration.

5. CONCLUSION

BMA showed its powerful ability to assess each hydrometeorological variable's impact on PM2.5 concentration variation. The results included not only well-known roles of hydrometeorological variables such as precipitation's dust wash out effect and solar radiation's acceleration on formation of the secondary pollutants, but also new insights that there're also roles of air pressure and wind speed. Further classifications using topography, location or elevation might yield somewhat new, or different results that can help deeply understand hydrometeorological influences on air pollution.

Although there were some erroneous estimations from the developed model, mainly due to high variability and skewed distribution of PM2.5 concentration level, the models correlated quite reasonable to the observed values (R ~ 0.82). The developed concentration maps also showed its possibility to be used as a proxy of interpolated concentration information, to those who are living in areas without observatories. Still, their limitation such as under/overestimation should be carefully dealt with on further study by, for example, setting different kinds of thresholds on concentration level or hydrometeorological factors.

6. ACKNOWLEDGMENT

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7. REFERENCES

Choi, J. K., Heo, J. B., Ban, S. J., Yi, S. M., & Zoh, K. D. (2013). Source apportionment of PM2. 5 at the coastal area in Korea. Science of the Total Environment, 447, 370-380.

Dominici, F., Wang, Y., Correia, A. W., Ezzati, M., Pope III, C. A., & Dockery, D. W. (2015). Chemical composition of fine particulate matter and life expectancy: in 95 US counties between 2002 and 2007. Epidemiology (Cambridge, Mass.), 26(4), 556.

Emili, E., Popp, C., Petitta, M., Riffler, M., Wunderle, S., & Zebisch, M. (2010). PM10 remote

sensing from geostationary SEVIRI and polar-orbiting MODIS sensors over the complex terrain of the European Alpine region. Remote sensing of environment, 114(11), 2485-2499.
Engel-Cox, J. A., Holloman, C. H., Coutant, B. W., & Hoff, R. M. (2004). Qualitative and quantitative evaluation of MODIS satellite sensor data for regional and urban scale air quality. Atmospheric environment, 38(16), 2495-2509.
Gupta, P., & Christopher, S. A. (2009). Particulate matter air quality assessment using integrated surface, satellite, and meteorological products: Multiple regression approach. Journal of Geophysical Research: Atmospheres, 114(D14).
Gupta, P., Christopher, S. A., Wang, J., Gehrig, R., Lee, Y. C., & Kumar, N. (2006). Satellite remote sensing of particulate matter and air quality assessment over global cities. Atmospheric Environment, 40(30), 5880-5892.
H. Tran, et al. "Impact of air pollution on cause-specific mortality in Korea: Results from Bayesian Model Averaging and Principle Component Regression approaches." Science of The Total Environment 636, 2018.
Han, J. S., Kim, Y. M., Ahn, J. Y., Kong, B. J., Choi, J. S., Lee, S. U., & Lee, S. J. (2006). Spatial distribution and variation of long-range transboundary air pollutants flux during 1997~ 2004. Journal of Korean Society for Atmospheric Environment, 22(1), 99-106.
Jung, J., Kim, Y. J., Lee, K. Y., Cayetano, M. G., Batmunkh, T., Koo, J. H., & Kim, J. (2010). Spectral optical properties of long-range transport Asian dust and pollution aerosols over Northeast Asia in 2007 and 2008. Atmospheric Chemistry and Physics, 10(12), 5391-5408.
K.P. Nam, D.K. Lee, & J.H. Park. (2018). Analysis on the Characteristics of PM10 Variation over South Korea from 2010 to 2014 using WRF-CMAQ: Focusing on the Analysis of Meteorological Factors. J. Environ. Impact Assess, 27(5), 509-520.
Kim, B. U., Kim, O., Kim, H. C., & Kim, S. (2016). Influence of fossil-fuel power plant emissions on the surface fine particulate matter in the Seoul Capital Area, South Korea. Journal of the Air & Waste Management Association, 66(9), 863-873.
Kim, H., & Choi, M. (2015). Impact of soil moisture on dust outbreaks in East Asia: Using satellite and assimilation data. Geophysical Research Letters, 42(8), 2789-2796.
Liu, Y., Sarnat, J. A., Kilaru, V., Jacob, D. J., & Koutrakis, P. (2005). Estimating ground-level PM2. 5 in the eastern United States using satellite remote sensing. Environmental science & technology, 39(9), 3269-3278.
M. M. Préndez, et al. "Correlation between solar radiation and total syspended particulate matter in Santiago, Chile—Preliminary results." Atmospheric Environment, 29.13, 1995.
M.K. Shin et al, C.D. Lee, H.S. Ha, C.S. Choi & Y.H. Kim. (2007). The Influence of Meteorological Factors on PM_{10} Concentration in Incheon. Journal of Korean Society for Atmospheric Environment, 23(3), 322-331.
Nishiwaki, Y., Michikawa, T., Takebayashi, T., Nitta, H., Iso, H., Inoue, M., & Tsugane, S. (2012). Long-term exposure to particulate matter in relation to mortality and incidence of cardiovascular disease: the JPHC Study. Journal of atherosclerosis and thrombosis, 15347.
Ouyang, W., Guo, B., Cai, G., Li, Q., Han, S., Liu, B., & Liu, X. (2015). The washing effect of precipitation on particulate matter and the pollution dynamics of rainwater in downtown Beijing. Science of the Total Environment, 505, 306-314.
Ristovski, Z. D., Miljevic, B., Surawski, N. C., Morawska, L., Fong, K. M., Goh, F., & Yang, I. A. (2012). Respiratory health effects of diesel particulate matter. Respirology, 17(2), 201-212.
S.M. Kim, J.M. Yoon, K.J. Moon, ... & Y.G. Lee. (2018). Empirical Estimation and Diurnal Patterns of Surface PM2.5 Concentration in Seoul Using GOCI AOD. Korean Journal of Remote Sensing, 34(3), 451-463.
Van Donkelaar, A., Martin, R. V., Brauer, M., Kahn, R., Levy, R., Verduzco, C., & Villeneuve, P. J. (2010). Global estimates of ambient fine particulate matter concentrations from

satellite-based aerosol optical depth: development and application. Environmental health perspectives, 118(6), 847-855.
Zelikoff, J. T., Chen, L. C., Cohen, M. D., Fang, K., Gordon, T., Li, Y., ... & Schlesinger, R. B. (2003). Effects of inhaled ambient particulate matter on pulmonary antimicrobial immune defense. Inhalation Toxicology, 15(2), 131-150.
Zúñiga, J., Tarajia, M., Herrera, V., Urriola, W., Gómez, B., & Motta, J. (2016). Assessment of the possible association of air pollutants PM10, O3, NO2 with an increase in cardiovascular, respiratory, and diabetes mortality in Panama City: a 2003 to 2013 data analysis. Medicine, 95(2).