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Dynamical Characteristics in Time Series Between PM_{10} and Wind Speed

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***Abstract*—We study the temporal variation characteristics of PM_{10} and wind velocity in eight South Korean cities. We employ the detrended cross-correlation analysis (DCCA) method to extract the overall tendency of the hourly variation. We ascertain from three-daily and one-weekly intervals that Busan has the negative largest, while Donghae has the positive largest in the DCCA cross-correlation coefficient between PM_{10} and wind velocity. As a result of Asian dust events, the cross-correlation is statistically significant for the hourly time series data less than two days. Particularly, we discuss whether a cross-correlation is statistically significant or not from random number surrogation and shuffled time series surrogation.**

Keywords— PM_{10}; Wind speed; Asian dust; DCCA; Random number surrogation; Shuffled time series surrogation

I. INTRODUCTION

Particulate matter is composed of organic and inorganic mixtures such as natural sea salt, soil particle, vehicle exhaust, construction dust, and soot. Some of these particles with aerodynamic diameters of less than 10 microns that can enter the body's respiratory system are known as PM_{10} [1,2]. PM_{10} concentration has an effect on climate change by causing an imbalance of the global radiative equilibrium through direct effects that block the stoma of plants and cut off the solar radiation, these are different from the indirect effect that change the optical properties of clouds, cloudiness, and the lifespan of clouds [3,4]. Various factors contribute to the degree of PM_{10} concentration. Notable among these are the type of land use and surface vegetation coverage, as well as meteorological factors [5].

The temporal data of the PM_{10} concentration that occurs in metropolitan areas were affected depending on the source, seasonal fuel usage, urban layout, commuting traffic environment, and micrometeorological change. Especially, concentration distribution is influenced greatly according to changes in temperature, the wind speed, and humidity [4,6]. Jang et al. [7] analyzed the spatio-temporal occurrence period of the fluctuation of particulate matter by using a power spectrum analysis. Giri et al. [8] also examined the relationship between meteorological parameters and urban air pollutants via the Pearson's correlation. Particularly, Xue et al. [2] investigated the trend of PM_{10} concentration variations and correlations between suspended particles and meteorological variables by using correlation analysis via data of time series. However, the methods and techniques used in such studies are fundamentally based on the correlation method. These were not able to remove the specific trend of various time series data like meteorological data, and the premise that time series have normality, when non-normality may actually be the case. Therefore, the reliability of the results is lacking for judging a correlation.

In this study, we analyze and simulate cross-correlations along time scale between PM_{10} concentration and wind speed using the detrended cross-correlation analysis (DCCA) method [9-11] through the removal of specific trends in eight South Korean cities. We discuss the effect of meteorological factors on the fluctuation of PM_{10} concentration during Asian dust events and other time periods. In addition, in order to quantify whether cross-correlations are significant or not, we examine statistical cross-correlation tests and random permutations of the original data.

II. THEORETICAL METHODOLOGY

A. DCCA Method

In this section, for the purpose of simplicity, we are concerned with two time series of PM_{10} differences $\{x_i\}$ and wind velocity differences $\{x_i'\}$, where $i = 1, 2, ..., N$. Then, we introduce statistical quantities $X_k = \sum_{i=1}^{k} x_i$ and $X_k' = \sum_{i=1}^{k} x_i'$, where $k \le N$. Next, we let to introduce the DCCA method, which is a generalization of the detrended fluctuation analysis method and implemented in two published papers [10,12]. For two time series of equal length *N*, we compute two integrated signals X_k and X_k', where $k = 1, 2, ..., N$. We also divide the entire time series into *N*− *n* and ends at *i* + *n*, we define the local trend, $\overline{X_{k,i}}$ and $\overline{X'_{k,i}}$ $(i \le k \le i+n)$, to be the ordinate of a linear least-squares fit. The detrended walk is defined as the difference between the original walk and the local trend as well. The covariance of the residuals in each box is calculated as

$$f^2{}_{DCCA}(n,i) = \frac{1}{n+1}\sum_{k=1}^{i+n}(X_k - \overline{X_{k,i}})(X'_k - \overline{X'_{k,i}}) . \qquad (1)$$

From (1), we calculate the detrended covariance function by summing over all overlapping $N-n$ boxes of size *n* as follows:

$$F^2{}_{DCCA}(n) = \frac{1}{N-n}\sum_{i=1}^{N-n} f^2{}_{DCCA}(n,i) \sim n^{2\gamma} . \qquad (2)$$

Here, the γ exponent quantifies the long-range power-law cross-correlations and also identifies seasonality, but γ does not quantify the level of cross-correlations. Lastly, we find the DCCA cross-correlation coefficient and compare our result to other findings. The DCCA cross-correlation coefficient ρ_{DCCA} is defined as the ratio between the detrended covariance function $F^2{}_{DCCA}(n)$ and the detrended variance functions, $F_{DFA}(n)$ and $F'_{DFA}(n)$, i.e.,

$$\rho_{DCCA}(n,\alpha,\alpha',T) = \frac{F^2{}_{DCCA}(n)}{F_{DFA}(n)F'_{DFA}(n)} . \qquad (3)$$

From (3), the value of ρ_{DCCA} ranges between $-1 \le \rho_{DCCA} \le 1$, and $F_{DFA}(n) \propto n^{\alpha}$ and $F'_{DFA}(n) \propto n^{\alpha'}$ are, respectively, characterized by the detrended fluctuation analysis exponents α and α', and box size *n*. Equation (3) is also dependent upon two time series of length T. When the variables *i* and *j* are perfectly cross-correlated, the value of ρ_{DCCA} is 1. On the other hand, $\rho_{DCCA} = -1$ if two variables are perfectly anti cross-correlated. $\rho_{DCCA} = 0$ corresponds to the case where the relation between two variables have no cross-correlation. Furthermore, we can calculate for an infinitely long time series when ρ_{DCCA} =0. For finite time series, even if cross-correlations are not present, ρ_{DCCA} has presumably some small nonzero value. Hence the DCCA cross-correlation coefficient can serve as an indicator of cross-correlations.

B. Data

In this study, we selected 4 coastal cities (Busan, Incheon, Mokpo, and Donghae) and 4 inland cities (Daegu, Daejeon, Wonju, and Andong) in South Korea peninsula. Inland cities were designated to be those located more than 50 km from the coast, while those located closer to the coast were designated to be coastal cities.

We analyzed PM_{10} concentration in the data of the Air Quality Monitoring network that the Ministry of Environment runs, and a period of data of 5 years from 2006 to 2010. The meteorological factor used in this analysis is wind speed, and we use the data of the manned regional meteorological offices of the Korea Meteorological Administration in order to ensure reliability of data, and it is data of five years from 2006 to 2010 years, as is the case with the PM_{10} concentration data.

The number of Asian dust days was decided by observed days of Asian dust KMA, while the number of non-Asian just days was the remaining days of the analysis period. To perform the DCCA, we use hourly data of the day that Asian dust was observed.

C. Random Number Surrogation and Shuffled Time Series Surrogation

For finite time series, because of the size effect, even if cross-correlations are not present, ρ_{DCCA} is presumably some small nonzero value. Therefore the DCCA cross-correlation coefficient serves only as an indicator of the presence of cross-correlations. If ρ_{DCCA} is 0.2 or 0.3, this value must be judged to be present or absent. In order to test whether the cross-correlations are significant or not, we examine them using the method that generates random number surrogates suggested by Podobnik and Stanley [9]. In addition, we conduct random permutations of the original data to find out the distribution effect of the time series on ρ_{DCCA}, since time series data generally appear to have a non-normal distribution. First, we determine the null hypothesis in random number surrogation. Because this is not a unique choice, we begin by assuming that, with the null hypothesis, the time series are independent and identically distributed random variables and calculate the range of ρ_{DCCA} that can be obtained under the assumption that the time series are independent and identically distributed random variables. We calculate critical points $\rho_{rc}(T,n)$ for the 90% confidence level defined such that the integral between $-\rho_{rc}(T,n)$ and $\rho_{rc}(T,n)$ is equal to 0.90. Thus, we determine the range of ρ_{DCCA} within which the cross-correlations can be considered statistically significant. In the Asian dust, we determine this for each of two different choices of time series length-ranging from *T*=1134 and calculate the probability distribution function (PDF) $P(\rho_{DCCA})$ for the DCCA cross-correlation coefficient ρ_{DCCA} in (3) for different values of box size *n*. Each PDF is obtained by generating 100 independent and identically distributed time series pairs taken from a Gaussian distribution. We use a trend based on a first-order polynomial fit.

Second, let us introduce shuffled time series surrogation. This is also assumed for the null hypothesis. The time series data is obtained through random permutations of the original data and the range of ρ_{DCCA} hat can be obtained under the assumption is calculated. This method guarantees that the surrogate data will be consistent with the null hypothesis of a δ -correlated random process, while exactly preserving the distribution of the original data. We calculate critical points $\rho_{sc}(n)$ for the 90% confidence level. We thus determine the range of ρ_{DCCA} within which the cross-correlations can be considered statistically significant. We determine this for both Asian dust days and non-Asian dust days by city. In addition, we calculate the PDF $P(\rho_{DCCA})$ of the DCCA cross-correlation coefficient ρ_{DCCA} in (3) for four different values of box size n. Each PDF is obtained by generating 100 time series pairs which are shuffled. We also use a trend based on a first-order polynomial fit. To confirm the normality of the shuffled time series, we introduce skewness S_w and kurtosis K_t as

$$S_w = \sum_i (x_i - \bar{x})^3 / [\sum_i (x_i - \bar{x})^2]^{3/2} \qquad (4)$$

and

$$K_t = \sum_i (x_i - \bar{x})^4 / [\sum_i (x_i - \bar{x})^2]^2 , \quad . \qquad (5)$$

where skewness means a symmetric degree of distribution, and the value of skewness is zero at normal distribution. Kurtosis measures the flatness of a distribution, and normal distribution has a kurtosis value of three.

III. NUMERICAL CALCULATIONS AND RESULTS

A. DCCA Method in the Asian Dust Events

First of all, we examine the DCCA analysis between PM_{10} and wind speed during Asian dust events during the five years in the in eight cities. We decide on box size n from 3 hours to 168 hours (a week). We report the ρ_{DCCA} between PM_{10} and wind speed in Table I and Fig. 1.

TABLE I. CORRELATION COEFFICIENTS ρ_{DCCA} BETWEEN PM_{10} AND WIND SPEED.

Box size n	Incheon	Donghae	Mokpo	Busan	Daejeon	Wonju	Daegu	Andong
3	-0.010	-0.006	-0.064	0.060	-0.012	-0.020	0.039	-0.051
6	-0.009	-0.032	-0.020	0.075	0.032	0.012	0.028	-0.012
12	-0.024	0.009	0.027	0.086	0.057	0.015	0.000	0.056
24	0.012	0.104	0.027	-0.010	0.085	0.056	0.007	0.113
48	0.080	0.127	-0.002	-0.056	0.083	0.051	0.079	0.146
72	0.084	0.124	-0.016	-0.052	0.051	-0.016	0.092	0.129
168	0.062	0.195	-0.033	-0.069	0.008	-0.064	0.122	0.141

As shown in Fig. 1, in the case of PM_{10} and wind speed, there exists a positive correlation with $15 \le n \le 51$ in Andong. In Busan and Donghae of the coastal area, there exist positive correlations with $n \le 12$ and $27 \le n \le 45$, respectively. The cross-correlation with $12 \le n \le 48$ is used the mean duration time of Asian dust. Furthermore When Asian dust flows into the Korean peninsula, humidity is in inverse proportion according to the increase or decrease of PM_{10} concentration according to Jang et al. [7]. On the other hand, the change of pressure and temperature is similar with a case in which Asian dust does not occur.

B. Critical Values for the Random Number Surrogation

The range of ρ_{DCCA} which can be considered statistically significant is shown in this section. Fig. 2 shows the PDF $P(\rho_{DCCA})$ of the DCCA cross-correlation coefficient ρ_{DCCA} for four different values of box size n. As it is the PDF which based on independent and identically distributed random variables followed in a Gaussian distribution, $P(\rho_{DCCA})$ is symmetric. This is influenced by two parameters, time series length T and box size n. For each T the PDF converges to a Gaussian distribution as the value of n increases because of the central limit theorem. Table II is the critical value $\rho_{rc}(1134, n)$ for the 90% confidence level. Because of an unfound form of PDF for values of n, we calculate the critical values numerically. As most of correlation coefficients between temperature and PM_{10} show positive values, but in case of humidity show largely negative values, we calculate the upper limit value and the lower limit value through a two-sided test.

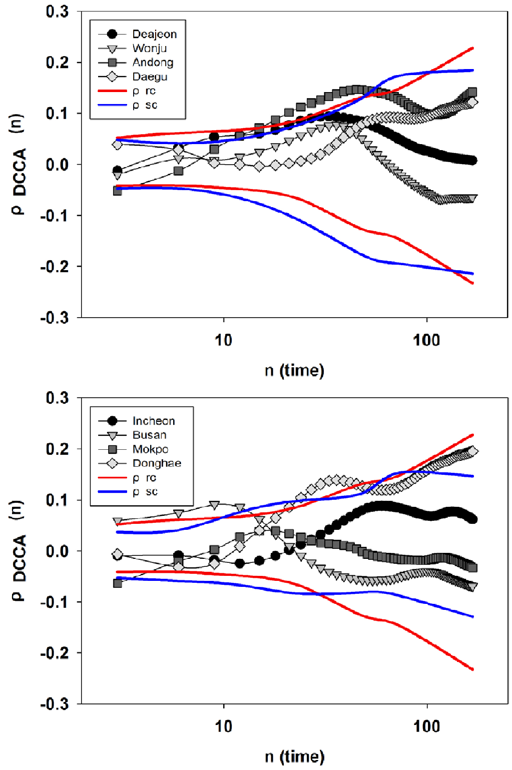

Fig. 1. ρ_{DCCA} between PM_{10} and wind speed.

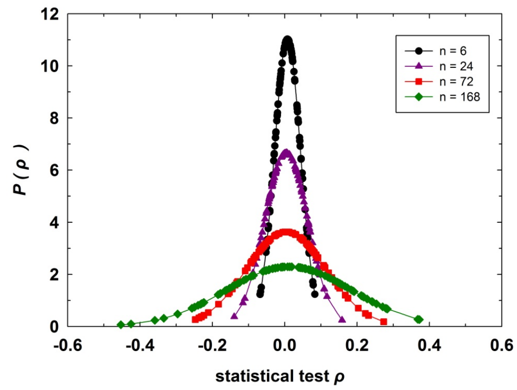

Fig. 2. PDFs of critical value $\rho_{rc}(1134, n)$ for the statistical test.

TABLE II. CRITICAL VALUE $\rho_{rc}(1134, n)$ FOR THE DCCA CROSS-CORRELATION COEFFICIENT WHEN EACH SERIES IS GAUSSIAN IN 90% CONFIDENCE LEVEL WITH ZERO MEAN AND UNIT VARIANCE (T=1134).

T = 1134	n = 3	n = 6	n = 12	n = 24	n = 48	n = 72	n = 168
$Z_{0.05}$	0.0523	0.0612	0.0676	0.0882	0.1315	0.1469	0.228
$-Z_{0.05}$	-0.0412	-0.041	-0.0483	-0.0689	-0.127	-0.1451	-0.2325

C. Critical Values for Shuffled Time Series Surrogation

Fig. 3 is the plot of the PDF $P(\rho_{DCCA})$ of the DCCA cross-correlation coefficient ρ_{DCCA} between PM_{10} and wind speed for four different values of box size n in the four cities of inland areas. As it is the PDF which is based on random permutation of the original data, $P(\rho_{DCCA})$ is non-symmetric. Fig. 4 is a histogram of shuffled original data for values of skewness and kurtosis in Daejeon (representative value of the inland area). The values of skewness and kurtosis indicate that the data of meteorological factors and PM_{10} assume non-normality.

In Tables III and IV, we can find the critical value $\rho_{sc}(n)$ between PM_{10} and wind speed for the 90% confidence level in the eight cities. Because of an unfound form of PDF for greater values of n, we calculate the critical values numerically. When we judge cross-correlation, we use the average of critical values. Likewise, we can calculate upper limit and lower limit values through a two-sided test. Because of the non-normality of the time series data, the moduli of the upper and lower limit values are shown small differences.

We compare ρ_{DCCA} with the critical point $\rho_{rc}(1134,n)$ and $\rho_{sc}(n)$ for each n. If $\rho_{DCCA} > \rho_{rc}(1134,n)$ and $\rho_{DCCA} > \rho_{SC}(n)$, the cross-correlations are considered statistically significant, and we reject the null hypothesis that ρ_{DCCA} comes from a Gaussian independent and identically distributed time series and the random permutation of the original data with no cross-correlations. This means that the area below $\rho_{rc}(1134,n)$ and $\rho_{sc}(n)$ to 0 means insignificant correlations.

TABLE III. CRIRICAL VALUE FOR CROSS-CORRELATION COEFFICIENTS ρ_{DCCA} BETWEEN PM_{10} AND WIND SPEED IN COASTAL AREAS.

	Z value	n = 3	n = 6	n = 12	n = 24	n = 48	n = 72	n = 168
Incheon	$Z_{0.05}$	0.032	0.066	0.056	0.060	0.093	0.102	0.098
	$-Z_{0.05}$	-0.016	-0.045	-0.065	-0.076	-0.114	-0.136	-0.073
Donghae	$Z_{0.05}$	0.031	0.034	0.044	0.018	0.060	0.049	0.157
	$-Z_{0.05}$	-0.070	-0.049	-0.069	-0.065	-0.089	-0.080	-0.109
Mokpo	$Z_{0.05}$	0.036	0.046	0.028	0.025	0.094	0.113	0.063
	$-Z_{0.05}$	-0.028	-0.054	-0.046	-0.067	-0.099	-0.101	-0.103
Busan	$Z_{0.05}$	0.034	0.025	0.019	0.018	0.020	0.050	0.073
	$-Z_{0.05}$	-0.073	-0.037	-0.033	-0.059	-0.140	-0.148	-0.171
Average	$Z_{0.05}$	0.037	0.041	0.076	0.099	0.113	0.153	0.147
	$-Z_{0.05}$	-0.053	-0.059	-0.067	-0.084	-0.081	-0.087	-0.129

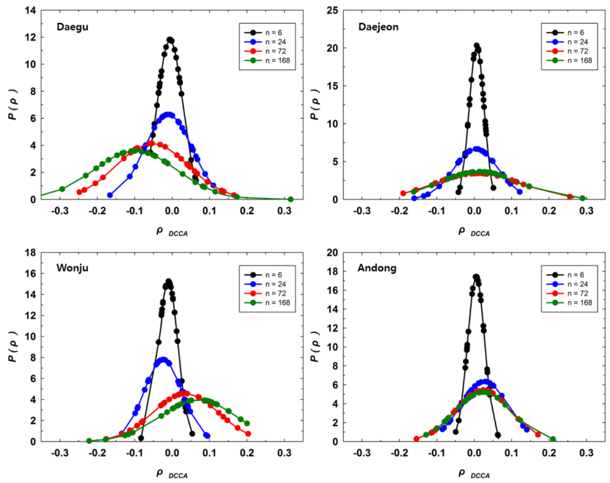

Fig. 3. PDFs of critical value between PM_{10} and wind speed.

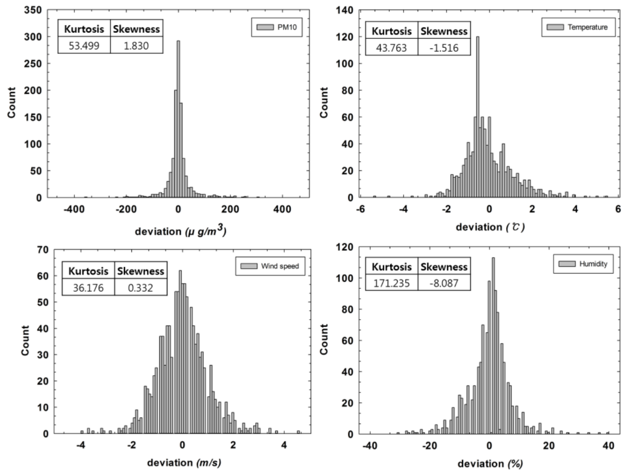

Fig. 4. Shuffled original data for values of Kurtosis and Skewness in Daejeon during Asian dust.

TABLE IV. COEFFICIENTS ρ_{DCCA} BETWEEN PM_{10} AND WIND SPEED IN INLAND AREAS.

	Z value	n = 3	n = 6	n = 12	n = 24	n = 48	n = 72	n = 168
Daejeon	$Z_{0.05}$	0.032	0.029	0.056	0.090	0.161	0.147	0.146
	$-Z_{0.05}$	-0.026	-0.025	-0.030	-0.044	-0.120	-0.156	-0.162
Wonju	$Z_{0.05}$	0.044	0.034	0.053	0.140	0.146	0.170	0.210
	$-Z_{0.05}$	-0.025	-0.034	-0.054	-0.043	-0.060	-0.052	-0.026
Daegu	$Z_{0.05}$	0.038	0.051	0.043	0.064	0.074	0.044	-0.012
	$-Z_{0.05}$	-0.059	-0.041	-0.030	-0.098	-0.176	-0.205	-0.231
Andong	$Z_{0.05}$	0.036	0.032	0.051	0.042	0.096	0.137	0.183
	$-Z_{0.05}$	-0.041	-0.029	-0.051	-0.093	-0.099	-0.078	-0.117
Average	$Z_{0.05}$	0.048	0.041	0.050	0.079	0.130	0.173	0.184
	$-Z_{0.05}$	-0.047	-0.047	-0.066	-0.111	-0.177	-0.194	-0.214

TABLE V. ESTIMATED RESULTS OF CROSS-CORRELATION COEFFICIENTS BETWEEN PM_{10} AND WIND SPEED IN COASTAL AREAS.

	Incheon		Donghae		Mokpo		Busan	
Value	T-test (P-value)	X-square (P-value)	T-test (P-value)	X-square (P-value)	T-test (P-value)	X-square (P-value)	T-test (P-value)	X-square (P-value)
n=3	1.040 (0.302)	2.763 (0.251)	-3.890 (0.000)	6.813 (0.033)	3.940 (0.000)	30.165 (0.000)	-2.190 (0.031)	36.860 (0.000)
n=6	-0.599 (0.550)	5.353 (0.069)	-0.762 (0.448)	1.017 (0.601)	0.413 (0.680)	7.665 (0.022)	-3.020 (0.003)	10.444 (0.005)
n=12	-2.040 (0.044)	14.302 (0.001)	-3.110 (0.002)	3.801 (0.149)	-3.480 (0.001)	7.732 (0.021)	-1.290 (0.201)	11.410 (0.003)
n=24	3.770 (0.000)	119.13 (0.000)	-4.320 (0.000)	8.544 (0.014)	-4.330 (0.000)	3.187 (0.203)	-3.230 (0.002)	6.302 (0.043)
n=48	3.480 (0.001)	90.785 (0.000)	-3.640 (0.000)	8.503 (0.014)	-0.938 (0.350)	5.409 (0.067)	-5.690 (0.000)	0.908 (0.635)
n=72	3.620 (0.000)	94.104 (0.000)	-3.110 (0.002)	4.895 (0.0865)	-0.040 (0.968)	12.768 (0.002)	-5.730 (0.000)	18.824 (0.000)
n=168	3.190 (0.002)	37.475 (0.000)	3.150 (0.002)	10.208 (0.006)	-1.190 (0.238)	10.204 (0.006)	-7.310 (0.000)	30.110 (0.000)

TABLE VI. ESTIMATED RESULTS OF CROSS-CORRELATION COEFFICIENTS BETWEEN PM_{10} AND WIND SPEED IN INLAND AREAS

	Daejeon		Wonju		Daegu		Andong	
Value	T-test (P-value)	X-square (P-value)	T-test (P-value)	X-square (P-value)	T-test (P-value)	X-square (P-value)	T-test (P-value)	X-square (P-value)
n=3	2.970 (0.004)	1.805 (0.406)	3.860 (0.000)	4.548 (0.103)	-4.020 (0.000)	10.185 (0.006)	-5.400 (0.000)	6.489 (0.039)
n=6	3.220 (0.002)	9.597 (0.008)	2.180 (0.032)	0.816 (0.665)	-1.720 (0.088)	12.310 (0.002)	-4.050 (0.000)	8.667 (0.013)
n=12	2.500 (0.014)	3.859 (0.145)	1.710 (0.010)	2.770 (0.250)	-2.310 (0.023)	5.249 (0.073)	-3.690 (0.000)	10.450 (0.005)
n=24	0.780 (0.437)	7.785 (0.020)	4.300 (0.000)	9.217 (0.010)	-1.640 (0.101)	3.743 (0.154)	-4.720 (0.000)	0.397 (0.820)
n=48	0.920 (0.360)	7.447 (0.024)	3.510 (0.001)	10.133 (0.006)	-3.380 (0.001)	4.753 (0.093)	0.584 (0.561)	2.281 (0.319)
n=72	0.788 (0.423)	9.009 (0.011)	3.170 (0.002)	2.347 (0.309)	-5.480 (0.000)	2.607 (0.272)	4.120 (0.000)	8.695 (0.013)
n=168	1.220 (0.226)	16.275 (0.003)	3.110 (0.002)	46.887 (0.000)	-8.790 (0.000)	7.529 (0.023)	7.010 (0.000)	16.558 (0.000)

Tables V and VI present the estimation results of the cross-correlation coefficient between PM_{10} and wind speed in coastal and inland areas, with both the Student-t and X-squared tests. First, To discuss the T- and P-values of the cross correlation coefficient for the 90% confidence level, the cross-correlation coefficients, except for n=12 in Busan, are closer to normal except for n=12, while those in Mokpo are not practically significant for n=6 and 12. In inland areas, the cross-correlation coefficients in Daejon for n=3, 6, and 12 are statistically significant, while those are not statistically significant in Wonju (Daegu) for n=12 (24). To consider the normality test of statistical data via the X- and P-values for the cross correlation coefficient between PM_{10} and wind speed in coastal areas, the cross-correlation coefficients in all values n of Busan are statistically significant, while the cross-correlation coefficient is not statistically significant in Mokpo for n=168. The cross-correlation coefficients in Daejon for n=24, 48, 72, and 168 can be considered statistically significant, while those are not statistically significant in Mokpo for n=24 and 48 in inland areas.

IV. SUMMARY

We have analyzed correlations from time scales between PM_{10} concentration and wind speed by using the DCCA method through the removal of specific trends in eight South Korean cities. We introduced time series data into non-Asian dust events to analyze the change of wind speed due to a fluctuation in PM_{10} concentration. We have also examined statistical cross-correlation tests in order to quantify whether the cross-correlations are significant or not. The processes to quantify whether cross-correlations are significant or not are as follow: first, we calculate the values of correlation coefficients using the DCCA method. Secondly, we generate critical values to test whether cross–correlations are genuine or not using a random number surrogate and a shuffled data surrogate. Thirdly, we determine the range of correlation coefficients within which the cross-correlations can be considered statistically significant.

As a result of Asian dust events, a cross-correlation was considered significant when $12 \le n \le 48$. This is considered to be the mean and max duration time of Asian dust events. However, there is no cross-correlation between PM_{10} and meteorological factors with the exception of time interval. It is found that fluctuation of PM_{10} concentration is greater than the meteorological factors.

In the case of correlation between PM_{10} and wind speed, cross-correlations are more significant in inland areas than in coastal areas. Particularly, there exist negative correlations in Daegu and Wonju. It was assumed that when the source of particles is domestic, the wind has a diluting effect and thus produces a negative correlation. But in case of coastal areas, when a pollutant is injected from external sources, there could be a positive correlation. For this reason, there exists a positive correlation in Incheon when n is 24, 48, 72, and 168. The correlation between humidity and PM_{10} is mostly negative in cities other than Busan and Daegu [12]. We noticed that the values of cross-correlations between PM_{10} and meteorological factors could be quantified by way of the DCCA cross-correlation coefficient [9,11]. In the future, we hope that this study will be extended to treat other types of climatological data, due to the general applicability of the DCCA cross-correlation coefficient.

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