

# Dynamical Behavior of the Correlation between Meteorological Factors

Cheol-Hwan YOU

*National Research Center for Disaster-free & Safe Ocean City, Dong-A University, Busan 49315, Korea*

Ki-Ho CHANG

*Applied Forecast Meteorology Research Division, National Institute of Meteorological Sciences, Seogwipo 63568, Korea*

Jun-Ho LEE\* and Kyungsik KIM†

*Department of Physics and Training Ship Administrative Center,  
Pukyong National University, Busan 48513, Korea*

(Received 29 June 2017, in final form 31 July 2017)

We study the temporal and spatial variation characteristics of meteorological factors (temperature, humidity, and wind velocity) at a meteorological tower located on Bosung-gun of South Korea. We employ the detrended cross-correlation analysis (DCCA) method to extract the overall tendency of the hourly variation from data of meteorological factors. The relationships between meteorological factors are identified and quantified by using DCCA coefficients. From our results, we ascertain that the DCCA coefficient between temperature and humidity at time lag  $m = 24$  has the smallest value at the height of 10 m of the measuring tower. Particularly, the DCCA coefficient between temperature and wind speed at time lag  $m = 24$  has the largest value at a height of 10 m of the measuring tower

PACS numbers: 05.10.-a, 05.45.Df, 05.45.Tp, 89.75.-k, 89.90.+n

Keywords: DCCA coefficient, Meteorological factor, DFA, Temperature, Humidity, Wind speed

DOI: 10.3938/jkps.71.875

## I. INTRODUCTION

Over the last three decades, the research of complex systems has been ubiquitous in physical, biological, ecological, technological, and informational issues [1–5]. This offers both a powerful and successful method and technique for the detailed analysis of real systems. Recently, there has been tantalizing interest in the cross-correlation of collective modes of time-series data from atmospheric geophysics, aerology, seismology, finance, physiology, and genomics [6–15]. The interaction gives rise to collective modes when two other systems interact mutually. This phenomenon can be discussed by analyzing the random matrix theory, the traditional cross-correlation method, and the detrended cross-correlation analysis method. The detrended cross-correlation analysis (DCCA) method [16] was particularly used in the past to analyze several models such as autoregressive fractionally integrated moving average processes, stock prices and their trading volumes, taxi accidents, and electroencephalography.

On the other hand, natural phenomenon such as El

Nino and La Nina caused by global warming is a concern of many scientists around the world. The change in the components of climate has resulted in a considerable climate variation for this complex system [17,18]. Through the numerical weather prediction of the World Meteorological Organization (WMO), the statistical quantities of heat transfer, solar radiation, wind, humidity, and surface hydrology have been calculated within each grid cell of our earth, and these interactions are presently continuing to be calculated in order to shed light on the atmospheric properties. The study of climates can help us to prevent these natural disasters, a large number of deaths and a great economic loss. For the particulate matter, Giri *et al.* [19] have shown the relationship between meteorological parameters and urban air pollutants through the Pearson's correlation. Xue *et al.* [20] have particularly insisted on the trend of PM<sub>10</sub> concentration variations and correlations between suspended particles and meteorological variables by using correlation analysis via data of time series. Here, some of these particles with aerodynamic diameters of less than 10 microns are known as PM<sub>10</sub> [6,7].

The description of meteorological factors in the DCCA method is very interesting and much worth. To our knowledge, this research for meteorological factors will

---

\*E-mail: leejh@pknu.ac.kr

†E-mail: kskim@pknu.ac.kr

be an ongoing problem from now into the future. In this paper, we simulate and analyze cross-correlations along time scale between meteorological factors (temperature, humidity, and wind speed) using the DCCA method. Data are hourly time series of meteorological factors (temperature, humidity, and wind velocity) at a meteorological tower located on Bosung-gun of South Korea during one year of 2015.

## II. THEORETICAL BACKGROUND

First of all, we are simply concerned with one difference set  $\{x_i\}$  and another difference set  $\{x'_i\}$  of meteorological factors, selected on hourly time series of three meteorological factors (temperature, humidity, and wind velocity), where  $i = 1, 2, \dots, M$ . Then, for time series  $\{x_i\}$ , the mean and the variance are, respectively, defined by

$$\mu = \bar{x}_i = \frac{1}{M} \sum_{i=1}^M x_i \quad (1)$$

and

$$\sigma^2 = \overline{(x_i - \mu)^2} = \frac{1}{M} \sum_{i=1}^M (x_i - \mu)^2, \quad (2)$$

where  $\mu' = \bar{x}'_i$  and  $\sigma'^2 = \overline{(x'_i - \mu')^2}$  for series  $\{x'_i\}$ . It is assumed from the mean and the variance that the autocorrelations for series  $\{x_i\}$  and  $\{x'_i\}$ ,  $A_m$  and  $A'_m$ , are given by

$$A_m = \overline{(x_i - \mu)(x_{i+m} - \mu)}/\sigma^2 \quad (3)$$

and

$$A'_m = \overline{(x'_i)(x'_{i+m} - \mu')}/\sigma'^2, \quad (4)$$

respectively. Next, the cross-correlation function is defined by

$$C_m = \overline{(x_i - \mu)(x'_{i+m} - \mu')}/\sigma\sigma'. \quad (5)$$

Here, the autocorrelations scale as power laws  $A_m \sim m^{-\alpha}$  and  $A'_m \sim m^{-\alpha'}$  with  $0 < \alpha, \alpha' < 1$ , and the cross-correlations also scale as power laws  $C_m \sim m^{-\beta}$  with  $0 < \beta < 1$ , where  $m$  is the time lag.

From this point on, we will introduce the DCCA method, which is a generalization of the detrended fluctuation analysis (DFA) method which has been implemented in two published papers [14, 21]. For two time series of equal length  $M$ , we compute two integrated signals  $X_k$  and  $X'_k$ , where  $k = 1, 2, \dots, M$ . We also divide the entire time series into  $M - m$  overlapping boxes, each containing  $m + 1$  values. For both time series, in each box that starts at  $i$  and ends at  $i + m$ , we define the local trend,  $\bar{X}_{k,i}$  and  $\bar{X}'_{k,i}$  ( $i \leq k \leq i + m$ ), to be the

ordinate of a linear least-squares fit. The covariance of the residuals in each box is calculated as

$$F^2_{DCCA}(m, i) = \frac{1}{m-1} \sum_{k=1}^{i+m} (X_k - \bar{X}_{k,i})(X'_k - \bar{X}'_{k,i}). \quad (6)$$

From Eq. (6), we calculate the detrended covariance function by summing over all overlapping  $M - m$  boxes of time lag  $m$  as follows:

$$F^2_{DCCA}(m) = \frac{1}{N-m} \sum_{i=1}^{M-m} f^2_{DCCA}(m, i) \sim m^{2\gamma}. \quad (7)$$

Here, the  $\gamma$  exponent quantifies the long-range power-law cross-correlations and also identifies seasonality, but  $\gamma$  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  $\rho_{DCCA}$  is defined as the ratio between the detrended covariance function  $F^2_{DCCA}(m)$  [21] and the detrended variance functions,  $F_{DFA}(m)$  and  $F'_{DFA}(m)$ , *i.e.*,

$$\rho_{DCCA}(m, \alpha, \alpha', T) = \frac{F^2_{DCCA}(m)}{F_{DFA}(m)F'_{DFA}(m)}, \quad (8)$$

where  $F_{DFA}(m)$  and  $F'_{DFA}(m)$  are, respectively, the detrended fluctuation functions for two difference sets  $\{x_i\}$  and  $\{x'_i\}$  in the DFA method. From Eq. (8), the value of  $\rho_{DCCA}$  ranges between  $-1 \leq \rho_{DCCA} \leq 1$ , and  $F_{DFA}(m) \propto m^{\bar{\alpha}}$  and  $F'_{DFA}(m) \propto m^{\alpha'}$  are, respectively, characterized by DFA exponents and  $\bar{\alpha}$ ,  $\alpha'$  and box size  $m$ . Eq. (8) is also dependent upon two time series of length  $T$ . The value is 1 when the two variables are perfectly cross-correlated.  $\rho_{DCCA} = -1$  if two variables are perfectly anti-cross correlated.  $\rho_{DCCA} = 0$  corresponds to the relation that has no cross-correlation between two variables. Furthermore, we can calculate for an infinitely long time series when  $\rho_{DCCA} = 0$ . Even if cross-correlations are not present for finite time series,  $\rho_{DCCA}$  has presumably some small nonzero value. Hence the DCCA cross-correlation coefficient can serve as an indicator of cross-correlations.

## III. NUMERICAL CALCULATIONS AND RESULTS

We select meteorological factors measured at Boseong global standard weather observatory located on Boseong-gun (33.22°N, 127.99°E) that is an area in South Jeolla Province. The observatory was assigned as a standard observatory approved by the World Meteorological Organization in 2012.

To analyze the DCCA method using more accurate data measured at different heights, the data measured at the integrated weather observational tower of the observatory were selected. For this purpose, a 307 m-high

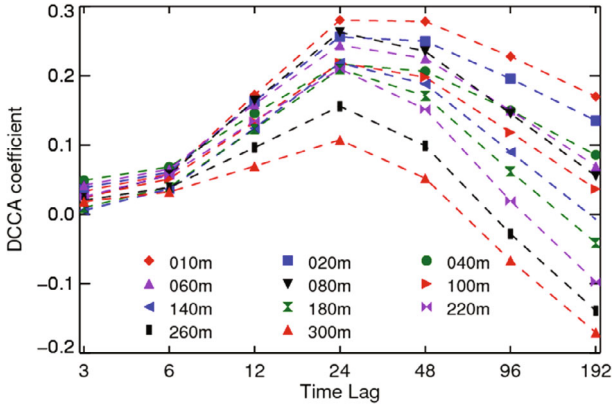


Fig. 1. (Color online) DCCA cross-correlation coefficient  $\rho_{DCCA}$  versus a function of times lag  $m$  between temperature and wind speed, where the time lags  $m$  are 3, 6, 12, 24, 48, 96, and 192 hours during one year of 2015. We measure time series at the heights of 10, 20, 40, 60, 80, 100, 140, 180, 220, 260, and 300 m on the meteorological tower of Boseong-gun in South Jeolla Province, Korea.

measuring tower was installed on the ground at 2.8 m above sea level on the central ridge of Boseong-gun in December of 2013. In order to measure some factors, the meteorological sensors were installed at the heights of 10 m, 20 m, 40 m, 60 m, 80 m, 100 m, 140 m, 180 m, 220 m, 260 m, and 300 m of the measuring tower, respectively. These meteorological factors have been measuring since 2013.

The three meteorological factors used in this analysis are temperature, humidity, and wind speed. The hourly data of the tower are qualified by the Korea Meteorological Administration in order to ensure reliability of data. First of all, we examine the DCCA analysis between meteorological factors (temperature, humidity, and wind speed) during one year of 2015. We decide on time lag  $n$  from 3 hours to 192 hours (8 days). Table 1 summarizes the DCCA cross-correlation coefficient  $\rho_{DCCA}$  between temperature and wind speed in seven different values of time lag  $n$  at the heights of 10 m, 20 m, 40 m, 60 m, 80 m, 100 m, 140 m, 180 m, 220 m, 260 m, and 300 m of the measuring tower. We calculate the  $\rho_{DCCA}$  between temperature and humidity in Table 2, and  $\rho_{DCCA}$  between humidity and wind speed in Table 3.

From Fig. 1, in the case of temperature and wind speed, we find that there exists a positive trend with time lag for the DCCA cross-correlation coefficient. The maximum value of  $\rho_{DCCA}$  is 0.280 with time lag  $m = 24$  hour at a 10 m height, while the minimum one of is  $-0.170$  with time lag 192 hour at a height of 300 m. In the case of temperature and humidity of Fig. 2, results show all negative trends with time lag  $3 \leq m \leq 192$  for the DCCA cross-correlation coefficient. The minimum value of  $\rho_{DCCA}$  is  $-0.880$  with time lag  $m = 24$  hour at 10 m height, while the maximum one of  $\rho_{DCCA}$  is  $-0.284$  with time lag  $m = 192$  hour at a height of 300 m. In Fig. 3,

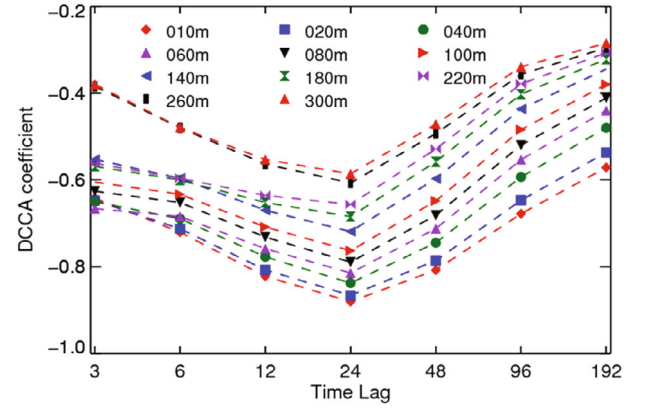


Fig. 2. (Color online) DCCA cross-correlation coefficient  $\rho_{DCCA}$  between temperature and humidity, where the time lags  $m$  are 3, 6, 12, 24, 48, 96, and 192 hour during one year of 2015.

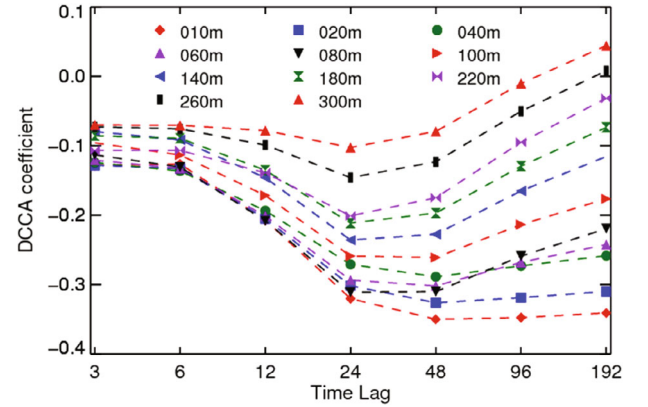


Fig. 3. (Color online) DCCA cross-correlation coefficient  $\rho_{DCCA}$  between humidity and wind speed, where the time lags  $m$  are 3, 6, 12, 24, 48, 96, and 192 hours during one year of 2015.

the DCCA cross-correlation coefficient between humidity and wind speed has a negative trend with time lag  $3 \leq m \leq 220$ . The minimum value of  $\rho_{DCCA}$  is  $-0.349$  with time lag  $m = 48$  hour at 10 m height, while the maximum one of  $\rho_{DCCA}$  is 0.044 with time lag  $m = 192$  hour at a height of 300 m.

#### IV. SUMMARY

The temporal and spatial variation characteristics of meteorological factors are studied at a meteorological tower located on Bosung-gun of South Korea. We employ the DCCA method to extract the overall tendency of the hourly variation from data of meteorological factors. In this analysis, the data of meteorological factors used were time series of temperature, humidity, and wind speed. The relationships between meteorological factors are identified and quantified by using DCCA cross-

Table 1. Values of DCCA cross-correlation coefficient  $\rho_{DCCA}$  between temperature and wind speed in seven different values of time lag  $nm$  at the height (10, 20, 40, 60, 80, 100, 140, 180, 220, 260, and 300 m) of the meteorological tower.

Time Lag	Heights of meteorological tower										
	10 m	20 m	40 m	60 m	80 m	100 m	140 m	180 m	220 m	260 m	300 m
3	0.033	0.038	0.049	0.041	0.023	0.024	0.005	0.009	0.025	0.020	0.018
6	0.058	0.061	0.068	0.065	0.057	0.051	0.036	0.039	0.057	0.038	0.032
12	0.172	0.163	0.145	0.159	0.164	0.133	0.124	0.122	0.134	0.096	0.069
24	0.280	0.256	0.217	0.244	0.262	0.218	0.218	0.209	0.209	0.156	0.107
48	0.278	0.249	0.206	0.225	0.235	0.197	0.188	0.170	0.151	0.099	0.052
96	0.227	0.195	0.150	0.149	0.145	0.118	0.089	0.061	0.019	-0.028	-0.066
192	0.170	0.135	0.085	0.069	0.055	0.036	-0.007	-0.040	-0.097	-0.138	-0.170

Table 2. Values of DCCA cross-correlation coefficient  $\rho_{DCCA}$  between temperature and humidity for seven different values of time lag  $m$  at the height (10, 20, 40, 60, 80, 100, 140, 180, 220, 260, and 300 m) of the meteorological tower.

Time lag	Heights of meteorological tower										
	10 m	20 m	40 m	60 m	80 m	100 m	140 m	180 m	220 m	260 m	300 m
3	-0.641	-0.647	-0.649	-0.666	-0.625	-0.604	-0.552	-0.568	-0.561	-0.384	-0.379
6	-0.720	-0.712	-0.689	-0.684	-0.651	-0.632	-0.596	-0.600	-0.596	-0.479	-0.478
12	-0.822	-0.807	-0.777	-0.758	-0.731	-0.708	-0.669	-0.651	-0.635	-0.563	-0.552
24	-0.880	-0.866	-0.837	-0.814	-0.789	-0.763	-0.718	-0.684	-0.656	-0.606	-0.586
48	-0.807	-0.785	-0.744	-0.712	-0.681	-0.648	-0.597	-0.557	-0.528	-0.492	-0.471
96	-0.677	-0.646	-0.593	-0.553	-0.519	-0.483	-0.436	-0.402	-0.378	-0.356	-0.339
192	-0.571	-0.536	-0.479	-0.439	-0.410	-0.379	-0.344	-0.321	-0.306	-0.295	-0.284

Table 3. Values of DCCA cross-correlation coefficients  $\rho_{DCCA}$  between humidity and wind speed for seven different values of time lag  $m$  at the height (10, 20, 40, 60, 80, 100, 140, 180, 220, 260, and 300 m) of the meteorological tower.

Time lag	Heights of meteorological tower										
	10 m	20 m	40 m	60 m	80 m	100 m	140 m	180 m	220 m	260 m	300 m
3	0.128	-0.128	-0.124	-0.120	-0.112	-0.095	-0.079	-0.085	-0.106	-0.072	-0.069
6	0.126	-0.132	-0.136	-0.132	-0.130	0.113	-0.091	-0.089	-0.106	-0.075	-0.070
12	-0.206	-0.204	0.193	-0.201	-0.207	0.171	-0.145	-0.135	-0.138	-0.098	0.077
24	-0.320	-0.301	0.270	-0.293	-0.310	0.258	-0.235	0.211	-0.200	-0.145	0.102
48	-0.349	-0.326	0.288	-0.301	0.310	0.260	-0.227	0.196	-0.174	-0.122	-0.079
96	-0.347	0.318	0.272	-0.267	0.258	0.213	-0.164	-0.129	-0.094	0.050	-0.010
192	0.340	0.309	0.258	-0.242	-0.219	0.176	0.115	-0.073	0.031	0.008	0.044

correlation coefficients. From our results, we ascertain that at  $m = 24$  intervals the DCCA cross-correlation coefficient between temperature and humidity has the smallest value at the heights of 10 m of the measuring tower. Particularly, the DCCA cross-correlation coefficient between temperature and wind speed at  $m = 24$  intervals has the largest value at the heights of 10 m of the measuring tower. Interestingly, it is remarkable from our results that a robustly anti-cross correlation exists between temperature and humidity, similar to the DCCA cross-correlation coefficient  $\rho_{DCCA} = -0.80$  at Medan of Indonesia in Table A.1 of Ref. [21].

We have noticed that the values of the cross-correlation between meteorological factors may be quan-

tified by way of DCCA and DFA methods. In the future, we hope that this study will be extended to treat other types of meteorological and climatological data, due to the general applicability of the DCCA cross-correlation coefficient.

## ACKNOWLEDGMENTS

This work was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2016R1A6A1A03012812). This work was also

supported by “Research and Development for KMA Weather, Climate, and Earth system Services (NIMS-2016-3100)” of the National Institute of Meteorological Sciences (NIMS) funded by the Korea Meteorological Administration (KMA). The authors also thank the National Institute of Meteorological Sciences for providing Boseong global standard weather observatory data used in this study.

## REFERENCES

- [1] S. Tang, S. Yan, S. Pei and Z. Zheng, *J. Korean Phys. Soc.* **66**, 1783 (2015).
- [2] S. Lee, *J. Korean Phys. Soc.* **67**, 1703 (2015).
- [3] A. Nobi, S. E. Maeng, G. G. Ha and J. W. Lee, *J. Korean Phys. Soc.* **66**, 1153 (2015).
- [4] S. J. Yu, Y. Cho, M-H. Lee, J. Lim and J. Yoo, *J. Korean Phys. Soc.* **67**, 1692 (2015).
- [5] H-Y. Kim and G. Oh, *J. Korean Phys. Soc.* **69**, 455 (2016).
- [6] M. Campillo and A. Paul, *Science* **299**, 547 (2003).
- [7] K. Yamasaki, A. Gozolchiani and S. Havlin, *Phys. Rev. Lett.* **100**, 228501 (2008).
- [8] B. Podobnik, D. Horvatic, A. M. Petersen and H. E. Stanley, *Proc. Natl. Acad. Sci.* **106**, 22079 (2009).
- [9] M. Takayasu and H. Takayasu, *Statistical Physics and Economics* (Cambridge University Press, Cambridge, 2010).
- [10] B. Podobnik, I. Grosse, D. Horvatic, S. Ilic, P. Ch. Ivanov and H. E. Stanley, *Eur. Phys. J. B* **71**, 243 (2009).
- [11] P. Samuelsson, E. V. Sukhorukov and M. Buttiker, *Phys. Rev. Lett.* **91**, 157002 (2003).
- [12] A. Cottet, W. Belzig and C. Bruder, *Phys. Rev. Lett.* **92**, 206801 (2004).
- [13] I. Neder, M. Heiblum, D. Mahalu and V. Umansky, *Phys. Rev. Lett.* **98**, 036803 (2007).
- [14] B. Podobnik and H. E. Stanley, *Phys. Rev. Lett.* **100**, 084102 (2008).
- [15] W-X. Zhou, *Phys. Rev. E* **77**, 066211 (2008); L-Y. He and S-P. Chen, *Physica A* **390**, 3806 (2011).
- [16] R. T. Vassoler and G. F. Zebende, *Physica A* **391**, 2438 (2012).
- [17] P. D. Jones, T. J. Osborn and K. R. Briffa, *Science* **292**, 662 (2001).
- [18] P. Lynch, *J. Comput. Phys.* **62**, 3431 (2008).
- [19] D. Giri, V. K. Murthy and P. R. Adhikary, *Int. J. Env. Res.* **2**, 49 (2008).
- [20] Y-S. Xue, L. Yu and P. Xu, *Analysis of PM<sub>10</sub> concentration time series and climate factor in Hangzhou 2004* (Int. Workshop on Geosci. and Remote Sens. 2008), p. 575.
- [21] R. T. Vassoler and G. F. Zebende, *Physica A* **391**, 2438 (2012).