ISSN: 0973-4929, Vol. 14, No. (3) 2019, Pg. 400-410

Current World Environment

www.cwejournal.org

Temporal Assessment on Variation of PM_{10} Concentration in Kota Kinabalu using Principal Component Analysis and Fourier Analysis

MUHAMMAD IZZUDDIN RUMALING[1], FUEI PIEN CHEE[1]*, JEDOL DAYOU[1], JACKSON HIAN WUI CHANG [3,4], STEVEN SOON KAI KONG[4] and JUSTIN SENTIAN[2]

[1]Faculty of Science and Natural Resources (FSNR), Universiti Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia.
[2]Climate Change Research Group (CCRG), FSNR, Universiti Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia.
[3]Preparatory Centre for Science and Technology, Universiti Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia.
[4]Cloud and Aerosol Laboratory, Department of Atmospheric Science, National Central University, Taoyuan, Taiwan (ROC).

Abstract

Introduction: PM_{10} (particulate matter with aerodynamic diameter below 10 microns) has always caught scientific attention due to its effect to human health. Predicting PM_{10} concentration is essential for early preventive measures, especially for cities such as Kota Kinabalu. Temporal data clustering may enhance accuracy of prediction model by group data in time range. However, the necessity of temporal data clustering has yet to be studied in Kota Kinabalu.

Objective: This research is conducted to compare significance of meteorological and pollutant factors for PM_{10} variation in clustered and unclustered data.

Methodology: This study is focused in Kota Kinabalu, Sabah. The data for meteorological factors (Ws, Wd, Hum, Temp) and pollutant factors (CO_2, NO_2, O_3, SO_2, PM_{10}) from 2003 to 2012 provided by Department of Environment are used for this research. Missing data are imputed using nearest neighbour method before it is clustered by monsoonal clustering. Unclustered and clustered datasets are analysed using principal

Article History

Received: 26 August 2019
Accepted: 9 October 2019

Keywords

Fourier Analysis;
Particulate Matter;
Principal Component Analysis;
Temporal Clusterin;
2-D Regression Analysis.

CONTACT Fuei Pien Chee fpchee06@ums.edu.my Faculty of Science and Natural Resources (FSNR), Universiti Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia.

Doi: http://dx.doi.org/10.12944/CWE.14.3.08

component analysis (PCA) to check significance of factors contributing to PM_{10} concentration.

Findings: PCA results show that temporal clustering does not have noticeable effect on the variation of PM_{10} concentration. For all datasets, humidity and x-component wind speed have highest factor loading on PC_1 and PC_2 respectively. Further statistical analysis by 2-D regression shows that humidity (ρ = -0.60 ± 0.20) and temperature (ρ = 0.63 ± 0.11) have moderate to strong correlation towards PM10 concentration. This may be due to high humidity level and strong negative correlation between temperature and humidity (ρ = -0.91 ± 0.03). In contrast, both x- and y-component wind speed generally show weak correlation towards PM_{10}, with ρ value of 0.09 ± 0.14 and 0.24 ± 0.18 respectively probably because of varying direction of particle dispersion. Fourier analysis further confirms this result by showing that human activity contributes major effect to variation of PM_{10} concentration.

Introduction

Particulate matter is an ambient respiratory particle suspended in the air. It has been attracting scientific attention because of its effects on human health (Shahraiyni & Sodoudi, 2016). PM_{10} (particulate matter with size less than 10 μm) is considered to be one of major air pollutants. One of major sources of PM_{10} is from biomass burning, brought by haze. This has becoming a typical and reoccurring challenge in Southeast Asia since 1980s (Shaadan *et al.,* 2015). Other than that, motor vehicle usage and industrial activities also contribute to emission of PM_{10}. PM_{10} is more hazardous to human health compared to other pollutants such as carbon monoxide and ground-level ozone (Kim *et al.,* 2015; Ny & Lee, 2010). One study suggested that PM_{10} increases the risk of children (between 5 to 15 years old) with asthma to visit emergency department (Cadelis *et al.,* 2014). Also, short to medium-term exposure to PM10 among infants leads to risk of respiratory syncytial virus (RSV) bronchiolitis (Carugno *et al.,* 2018).

Located in Malaysia, Kota Kinabalu experiences monsoon season twice a year: northeast monsoon (NEM) and southwest monsoon (SWM). NEM originates from China and northern Pacific, while SWM originates from deserts in Australia. NEM occurs between November to March and is characterized by cool temperature (Ho *et al.,* 2013). Meanwhile, SWM occurs between May to September as climate becomes warmer. According to Teong *et al.,* (2017), SWM recorded greater amount of rainfall compared to NEM. Outside monsoon season is known as inter-monsoon, happening on April and October (Naing *et al.,* 2011). Inter-monsoon during April is characterized by hot and dry climate, while inter-monsoon in October is cooler and has higher rainfall (Teong *et al.,* 2017).

Short-term prediction of PM_{10} concentration is essential as it enables community to reduce health risks by early preventive measures. Meanwhile, long-term forecasting model is crucial for urban planning, transportation networks, industrial and residential area management in such a way that minimizes health risks to public (Shahraiyni & Sodoudi, 2016). This is important for developing city such as Kota Kinabalu. Prediction model may become more accurate when seasonal factor such as monsoon is considered. This is because climate may affect PM10 concentration differently, depending on season. However, it has not been studied yet whether monsoonal clustering may show difference in PM10 variation with respect to meteorological and pollutant factors. Hence, this study aims to find out whether monsoonal clustering for Kota Kinabalu, Sabah shows difference with unclustered data.

Data and Methods

Study Area and Data

This research focuses on Kota Kinabalu (5.98°N, 116.07°E, altitude: 13 m), capital city of Sabah, Malaysia. As shown in Figure 1, Kota Kinabalu is located at west coast of Sabah. The climate in Kota Kinabalu is characterized by hot and humid climate, influenced by circulation of monsoons (Ho *et al.,* 2013). Kota Kinabalu experiences uniformly high and invariant temperature and high humidity. Heavy rainfall recorded usually occurs in the afternoon (Djamila *et al.,* 2011). In terms of economic activity, Kota Kinabalu is the gateway to the islands of Borneo. Consequently, activities such as trade, industry and tourism are concentrated in Kota Kinabalu (Noor *et al.,* 2014).

Fig.1: Location of Kota Kinabalu

Air quality monitoring station, located in SMK Putatan, Kota Kinabalu is operated by Alam Sekitar Sdn. Bhd. (ASMA), a private company working under Department of Environment Malaysia (DOE). PM_{10} concentration in μg m^{-3} is measured in this station using tapered element oscillating microbalance (TOEM), with temporal resolution of 1 h. Along with other meteorological data Ws (wind speed), Wd (wind direction), Hum (relative humidity), Temp (ambient temperature) and air pollutant concentration data for CO (carbon monoxide), NO_2 (nitrogen dioxide), O_3 (ozone), SO_2 (sulfur dioxide), PM_{10} concentration data is made available by Air Quality Division under DOE. For this research, data from 2003 to 2012 is studied. Statistics of PM_{10} concentration data collected in CA0030 from 2003 to 2012 is summarized in Table 1.

Table 1: Summary of statistics of PM_{10} concentration data from 2003 to 2012

Statistics	
Mean	35.73
Standard Deviation	19.16
Minimum	5.00
Maximum	495.00
Median	32.00
1st quartile	23.00
3rd quartile	44.00
Coefficient of Variation (%)	53.63

As Wd is angular quantity, it is not usually used for principal component analysis or regression analysis (Gvozdic *et al.,* 2011). Furthermore, higher magnitude of Wd does not reflect higher intensity of that property, which may present inaccuracy in both principal component analysis and regression analysis. Thus, Ws and Wd are transformed into east-west component (Wx) and north-south component (Wy) of wind speed using equations (1) and (2). Positive values indicate wind blowing eastward and northward respectively (Gvozdic *et al.,* 2011).

$$W_x = W_s \sin W_d \qquad \text{...(1)}$$

$$W_y = W_s \cos W_d \qquad \text{...(2)}$$

Nearest Neighbour Method

Some data from monitoring stations are missing either due to power outage, calibration, or relocation of monitoring station. Due to missingness of data, it must be imputed before it is used for this research. Data imputation is crucial for further analysis that requires complete dataset such as principal component analysis and Fourier analysis. One of the most common applicable method known as nearest neighbour method (Dominick *et al.,* 2012; Li & Liu, 2014) is used in this paper. Given starting point of a gap (x_1, y_1) and end point of the gap (x_2, y_2), the interpolant y at corresponding time x can be calculated using equation (3) (Zakaria & Noor, 2018). As for Ws and Wd, nearest neighbour method is performed before both are transformed into Wx and Wy to reduce further data loss due to missingness.

$$y = \begin{cases} y_1, when\ x < \dfrac{x_1 + x_2}{2} \\ y_2, when\ x \geq \dfrac{x_1 + x_2}{2} \end{cases} \qquad \text{...(3)}$$

Clustered and Unclustered Data

Data is clustered when data is grouped into a set with same characteristics. In contrast, data is unclustered when they are ungrouped. For this research, two sets of temporal clusters are tested and compared with unclustered data. Due to geographic location of Kota Kinabalu, this city experiences monsoonal season. Thus, monsoonal clustering is studied. In this case, data is divided into four groups: NEM (November to March), IM^4 (April), SWM (May to September), and IM_{10} (October). Data is grouped based on the month the data is observed. The number of samples for all clusters are summarized in Table 2.

Table 2: Number of samples in unclustered and clustered data

Cluster	Number of samples
Unclustered data (total)	87672
Monsoonal cluster:	
NEM	36312
IM_4	7200
SWM	36720
IM_{10}	7440

Principal Component Analysis (PCA)

PCA is a method used to identify the most significant variable that contributes to variation (Dominick *et al.,* 2012). This method is usually used to transform a set of variables to n new variables, known as principal component (PC). PCs account for more significant variation compared to observed variable X. Given that l is loading factor, principal component of ith component is given by equation (4) (Gvozdic *et al.,* 2011).

$$PC_i = l_{1i} X_1 + l_{2i} X_2 + \ldots + l_{ni} X_n \qquad \text{...(4)}$$

Explained variation is the total variation of data included in principal component. Usually, explained variation is highest in PC_1, followed by PC_2, and so on. Gvozdic *et al.,* (2011) and Dominick *et al.,* (2012) had demonstrated that the first two principal components PC_1 and PC_2 are used to create factor loading plot. This is because both PCs usually account at least 90% of variation of data, as evaluated in cumulative explained variation.

Fourier Analysis

Fourier analysis involves transforming data in time domain into frequency domain using fast Fourier transform (FFT) (Kim & Son, 2011). The results obtained from Fourier analysis gives important insights on time series data (Gvozdic *et al.,* 2011). Output from frequency domain displays cyclical behaviour of time series data as seasonal or diurnal data. Due to the nature of meteorological and air pollutant data as time series data, Fourier analysis is a suitable method in analysing the data (Gvozdic *et al.,* 2011). A function of time series data *y(t)* is expressed in the form of Fourier series in equation (5), where $\bar{y}$ is arithmetic mean of data *y(t)*, *T* is measurement period, A_K and B_K are Fourier coefficients and k is a harmonic number.

$$y(t) = \bar{y} + \sum_{k=1}^{\infty}\left[A_k \cos\left(\frac{2\pi kt}{T}\right) + B_k \sin\left(\frac{2\pi kt}{T}\right)\right] \quad ...(5)$$

Data transformed into frequency domain is plotted into Fourier spectrum, containing amplitudes C_K (as shown in equation (6)) as a function of frequency or period (Gvozdic *et al.,* 2011).

$$C_k = \sqrt{A_k^2 + B_k^2} \quad ...(6)$$

Due to ability of Fourier analysis to show cyclic behaviour of time series data, this is used to verify whether variation of time series data is mainly natural or human-induced (Choi *et al.,* 2008). It is assumed that higher amplitudes in seasonal and yearly cycle corresponds to the major effect of natural cycle while higher amplitudes in daily and weekly cycle corresponds to the major effect of anthropogenic activities (Choi *et al.,* 2008).

Results

Unclustered Data

Unclustered data is analysed by inputting all data into PCA. All PCs are tabulated in Table 3, along with explained variation (EV) and cumulative explained variation (CEV). The variables with highest loading factor contribute the most in variation of corresponding principal components, and their values are highlighted in Table 3.

Table 3: PCA of unclustered data

PC	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7	PC_8
Wx	-0.1115	**0.9503**	-0.2540	-0.1411	0.0031	-	-	-
Wy	0.1668	0.2782	**0.9450**	0.0404	-0.0122	0.0005	-	-
Hum	**0.9433**	0.0924	-0.2042	0.2449	0.0010	0.0002	-	-
Temp	-0.2644	0.1045	-0.0249	**0.9583**	0.0132	-0.0012	-0.0003	-
CO	0.0050	-0.0010	0.0129	-0.0120	**0.9998**	0.0061	-0.0077	-0.0006
NO_2	-	-	0.0002	-	0.0083	-0.1009	**0.9939**	-0.0437
O_3	-0.0006	-	-	0.0011	-0.0053	**0.9948**	0.1013	0.0073
SO_2	-	-	-	-	0.0010	-0.0116	0.0427	**0.9990**
EV (%)	83.12	9.15	6.27	1.42	0.04	-	-	-
CEV (%)	83.12	92.27	98.54	99.96	100.00	100.00	100.00	100.00

Note: Values smaller than 0.0001 are not shown

The explained variation is largest in first principal component and gets smaller in successive principal components. The first two principal components are considered as they take account into more than 90% of total variation of data. PC_1 and PC_2 are plotted in factor loading as shown in Figure 2. The most significant variable that contributes to variation in PC_1 is humidity, while x-component wind speed is the most significant in PC_2. This shows that 92.27% of data variation is due to both humidity and wind speed. While other variables are significant in other principal components, they are not as significant because these principal components consider only less than 10% of variation.

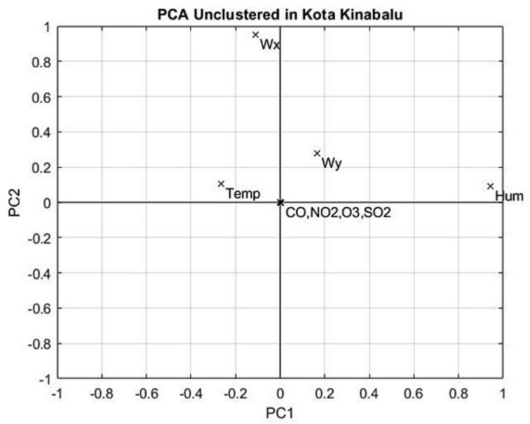

Fig. 2: Factor loading for unclustered data

PC_1 accounts for 83.12% of variation of dataset. At PC_1, humidity has the highest loading factor with the value of 0.9433, followed by temperature (-0.2644) and y-component wind speed (0.1668). As for PC_2 (EV = 9.15%), x-component wind speed has the highest loading factor with the value of 0.9503. Because PC_1 has significantly higher EV compared to PC_2, humidity shows to have the highest significance in variation. Meanwhile, pollutant factors (CO, NO_2, O_3, SO_2) are very close to origin of factor loading plot, which reflects insignificance in variation.

Clustered Data

All monsoonal clusters (NEM, IM_4, SWM, IM_{10}) are analysed using PCA, and the results are tabulated in Table 4. As cumulative explained variable for first two principal components are 92.19 ± 0.09 %, only PC_1 and PC_2 are shown in Table 4. Factor loading for all clusters are plotted as shown in Figure 3.

Table 4: Principal Component Analysis (PCA) for 4 clusters divided based on monsoonal season

Cluster	NEM		IM_4		SWM		IM_{10}	
PC	PC_1	PC_2	PC_1	PC_2	PC_1	PC_2	PC_1	PC_2
Wx	-0.1687	**0.9124**	-0.1475	**0.9678**	-0.0678	**0.9616**	-0.0870	**0.9498**
Wy	0.1499	0.3918	0.2012	0.2109	0.1784	0.2233	0.1526	0.2426
Hum	**0.9386**	0.1120	**0.9303**	0.1247	**0.9454**	0.0673	**0.9414**	0.1004
Temp	-0.2611	0.0383	-0.2688	0.0585	-0.2643	0.1450	-0.2879	0.1699
CO	0.0047	-0.0004	0.0058	0.0013	0.0050	-0.0012	0.0053	-0.0038
NO_2	-	-	-	-	-	-	-	-
O_3	-0.0006	-	-0.0007	-	-0.0006	-	-0.0005	-
SO_2	-	-	-	-	-	-	-	-
EV (%)	83.96	8.35	85.36	6.84	82.37	9.81	81.73	10.35
CEV (%)	83.96	92.31	85.36	92.20	82.37	92.18	81.73	92.08

Note: Values smaller than 0.0001 are not shown

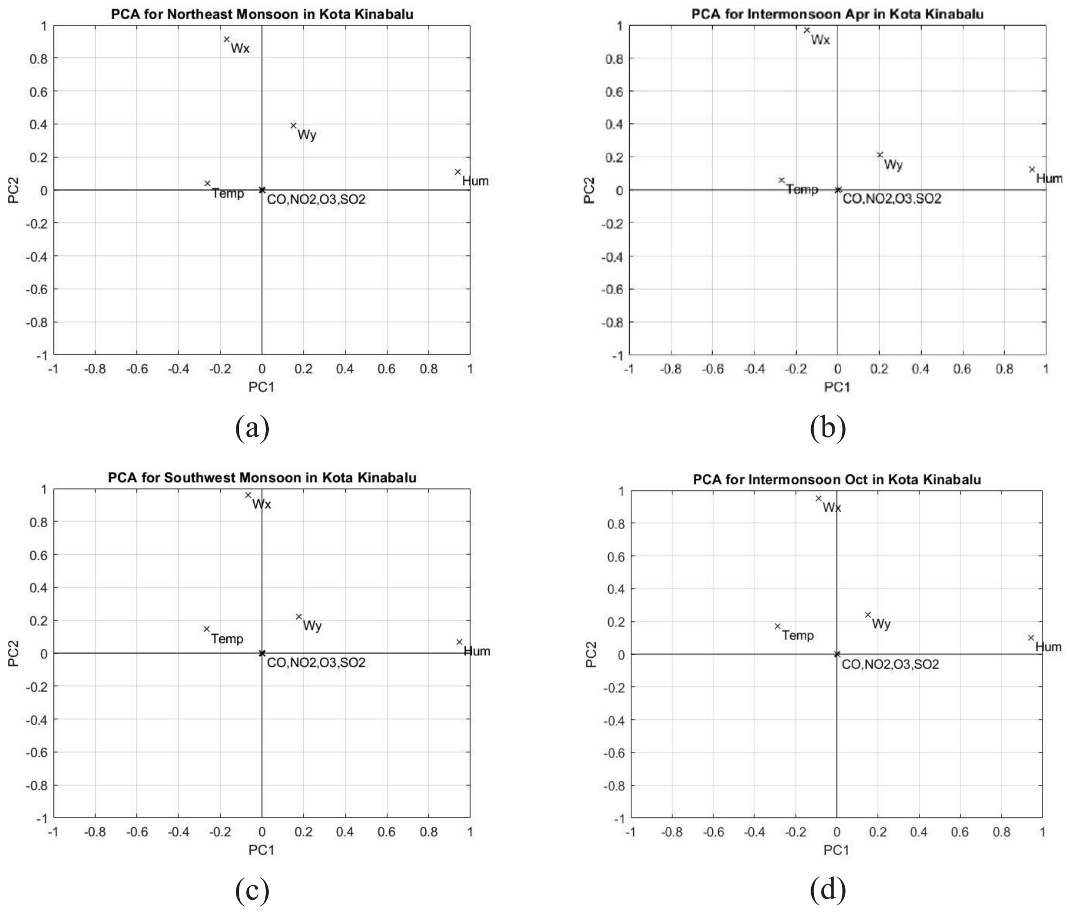

Fig. 3: Factor loading for monsoonal clusters (a) NEM, (b) IM_4, (c) SWM, and (d) IM_{10}

Based on Table 3 and 4, all PC_1 and PC_2 have similar most significant variables. The values are consistent, with small discrepancies. According to EV, PC_1 accounts for 83.35 ± 1.63 % of total variation of data, with humidity having highest factor loading (0.9389 ± 0.0064), followed by ambient temperature (-0.2705 ± 0.0120) and y-component wind speed (0.1705 ± 0.0242). As for PC_2 with EV of 8.84 ± 1.58 %, x-component wind speed has shown to have highest factor loading (0.9479 ± 0.0248). Similar to unclustered data, other variables are not as significant because PC_3 and above consider less than 10% of data variation for all clusters.

Regression Analysis

2-D regression is plotted in Figure 4 to further analyse the variation of each parameter in response to PM_{10} concentration for every cluster. Pollutant factors (CO, NO_2, O_3, SO_2) are not included because their variation is not significant as reflected by factor loading plot in Figure 2 and 3. According to 2-D regression in Figure 4, humidity and temperature generally show moderate to strong correlation with PM_{10} with Pearson coefficient of correlation, ρ of -0.60 ± 0.20 and 0.63 ± 0.11 respectively. However, this is not the case for humidity in IM4 cluster with the value of ρ = -0.37. Furthermore, humidity and temperature show strong negative correlation with each other (ρ = -0.91 ± 0.03) for all clusters.

As for wind speed, both x- and y-components generally show weak to almost no correlation towards PM10 with values of ρ = 0.09 ± 0.14 and ρ = 0.24 ± 0.18 respectively. In addition, both components also exhibit weak correlation towards each other (except during SWM), humidity (except during NEM and IM_{10}) and ambient temperature.

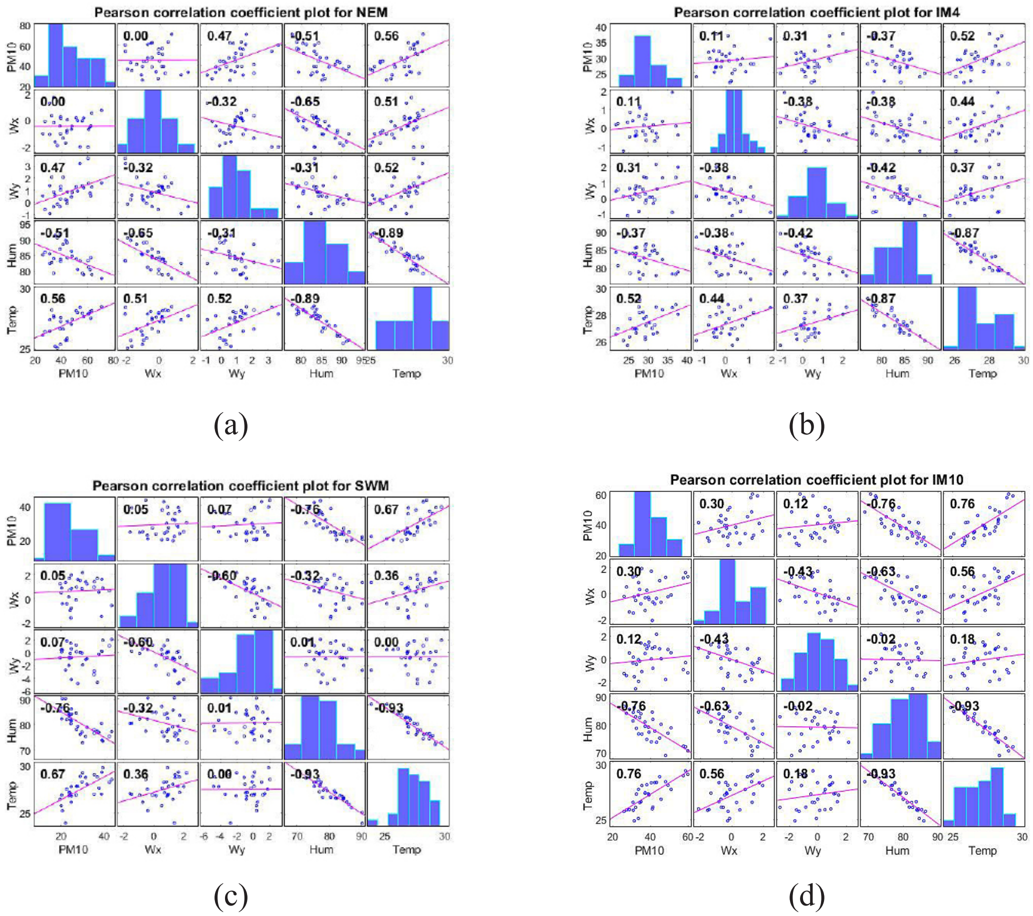

Fig. 4: 2-D Regression plot of PM_{10} concentration with other meteorological factors for (a) NEM, (b) IM4, (c) SWM, and (d) IM_{10} clusters

Fourier Analysis

Fourier spectrum in Figure 5 shows three major peaks corresponding to three major cycles that affect variation of PM_{10} concentration. Seasonal cycle is the strongest for 6-month cycle. This is attributed to monsoonal cycle. However, seasonal cycle is not as strong compared to daily and half-daily cycle. Other cycles such as weekly and monthly cycle does not show strong effect on variation of PM_{10}, as reflected by Fourier spectrum.

Discussion

Based on PCA and factor loading, significant variables contributing to PM_{10} variation for monsoonal cluster does not have much difference when comparing with unclustered dataset. This is reflected by small discrepancies between factor loadings in every cluster as well as unclustered data. As clustered data shows almost similar PCA result with unclustered data, monsoonal clustering is not necessary when it comes to prediction of PM_{10} concentration in Kota Kinabalu. This is further supported by Fourier spectrum as shown in Figure 5. Based on assumption by Choi *et al.,* (2008), PM_{10} concentration cycle is mainly affected by human activities. Daily activities such as traffic congestion, industries and night markets emit PM_{10} particles (Chang *et al.,* 2018), consequently contributing to temporal variation of PM_{10} concentration. High amplitude of daily and half-daily cycle implies that the effect of human-induced activities is dominant over seasonal phenomenon (Choi *et al.,* 2008).

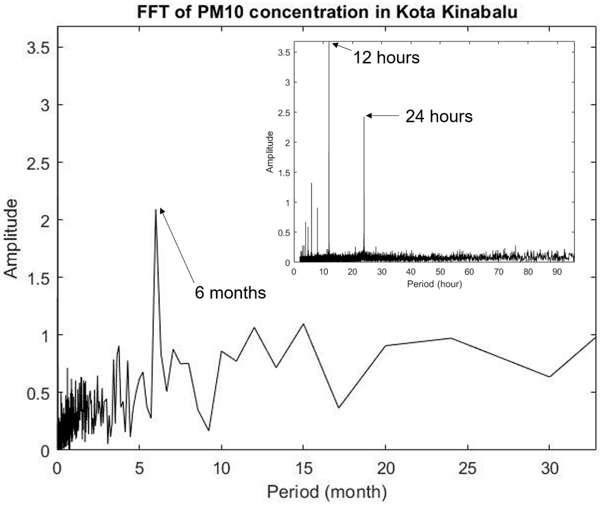

Fig. 5: Fourier spectrum for PM_{10} concentration in Kota Kinabalu

Statistical analysis shows that PM_{10} concentration in Kota Kinabalu decreases as humidity increases. In addition, PM_{10} concentration shows weak negative correlation with humidity as Pearson coefficient of correlation is -0.60 ± 0.20. According to raw data, humidity in Kota Kinabalu almost always exceeds 40%. Also, monthly average humidity in Kota Kinabalu is always above 77% based on Figure 4. At high humidity level, water in air almost reaches saturation. As a result, water becomes more easily condensed and rainfall becomes easier to occur (Lou *et al.,* 2017). This causes washout effect and wet deposition by rain on PM_{10}. At high humidity level, particulate matter absorbs water molecule and becomes heavy enough to be deposited (Munir *et al.,* 2017). At the beginning of rainfall, small raindrop amount and dust emission from the raindrops may raise PM10 concentration until certain extent (Lou *et al.,* 2017). This may result in weak correlation between PM_{10} concentration and humidity.

Moderate to strong correlation is also exhibited between PM_{10} concentration and ambient temperature. This is reflected by Pearson coefficient of correlation of 0.63 ± 0.11. This may be due to atmospheric instability and enhanced kinetic motion of particles (Munir *et al.,* 2017). High ambient temperature allows resuspension of particles into air. Furthermore, ambient temperature is strongly and negatively correlated towards humidity (ρ = -0.91 ± 0.03). The decrease in humidity inhibits deposition of particles, thus further increases PM_{10} concentration in the air.

Both x- and y-components of wind speed are weakly correlated towards PM_{10} concentration. This is observed by values of ρ = 0.09 ± 0.14 for eastern component and ρ = 0.24 ± 0.18 for northern component. It is possible that wind speed facilitates the dispersion of the particles (Munir *et al.,* 2017). However, the dispersion is not fixed and can be both towards and away from Kota Kinabalu, which contributes to weak correlation between wind speed and PM_{10} concentration.

Conclusion

In Kota Kinabalu, clustering method is not necessary when prediction of PM_{10} concentration is made. This is because monsoonal clustering shows small difference with unclustered data. Fourier analysis further confirms this result by showing that seasonal cycle of PM_{10} concentration is not as strong as daily and half-daily cycle. According to regression analysis, humidity and temperature both affect PM_{10} concentration based on respective values of ρ = -0.60 ± 0.20 and ρ = 0.63 ± 0.11. This may be due to high humidity level and strong negative correlation towards each other. On the other hand, components of wind speed show weak correlation towards PM_{10}, probably due to random dispersion of particles towards and away from Kota Kinabalu.

Results from this research suggests that prediction model for PM_{10} concentration in Kota Kinabalu does not require temporal clustering. However, future research requires study to investigate whether this applies for other parts of Sabah. Also, other types of clustering such as humidity level have yet to be studied up until now.

Acknowledgement

The authors would like to thank Universiti Malaysia Sabah for supporting this research by providing grant (SBK0324-2018, SGI0054-2018 and GUG378-2019) and Department of Environment Malaysia for providing meteorological and pollutant data for research purpose.

Funding

The authors received financial support from Universiti Malaysia Sabah via research grants (SBK0324-2018, SGI0054-2018, GUG0378-2019) for research, authorship, and publication of this article.

Conflict of Interest

The authors do not have any conflict of interest.

References

1. Cadelis, G., Tourres, R. & Molinie, J. 2014. Short-Term Effects of the Particulate Pollutants Contained in Saharan Dust on the Visits of Children to the Emergency Department due to Asthmatic Conditions in Guadeloupe (French Archipelago of the Caribbean). *PLOS ONE*. 9(3): 1 – 11. https://doi.org/10.1371/journal.pone.0091136
2. Carugno, M., Dentali, F., Mathieu, G., Fontanella, A., Mariani, J., Bordini, L., Milani, G. P., Consonni, D., Bonzini, M., Bollati, V. & Pesatori, A. C. 2018. PM10 exposure is associated with increased hospitalizations for respiratory syncytial virus bronchiolitis among infants in Lombardy, Italy. *Environmental Research.* 166(2018): 452 – 457. https://doi.org/10.1016/j.envres.2018.06.016
3. Chang, H. W. J., Chee, F. P., Kong, S. K. S. & Sentian, J. 2018. Variability of the PM_{10} concentration in the urban atmosphere of Sabah and its responses to diurnal and weekly changes of CO, NO_2, SO_2 and Ozone. *Asian Journal of Atmospheric Environment.* 12(2): 109 – 126. https://doi.org/10.5572/ajae.2018.12.2.109
4. Choi, Y. S., Ho, C. H., Chen, D., Noh, Y. H. & Song, C. K. 2008. Spectral analysis of weekly variation in PM_{10} mass concentration and meteorological conditions over China. *Atmospheric Environment.* 42(2008): 655 – 666. https://doi.org/10.1016/j.atmosenv.2007.09.075
5. Djamila, H., Ming, C. C. & Kumaresan, S. 2011. Estimation of exterior vertical daylight for the humid tropic of Kota Kinabalu city in East Malaysia. *Renewable energy.* 36(2011): 9 – 15. https://doi.org/10.1016/j.renene.2010.06.040
6. Dominick, D., Juahir, H., Latif, M. T., Zain, S. M., & Aris, A. Z. 2012. Spatial assessment of air quality patterns in Malaysia using multivariate analysis. *Atmospheric Environment*, 60: 172–181. https://doi.org/10.1016/j.atmosenv.2012.06.021
7. Gvozdic, V., Kovac-Andric, E. & Brana, J. 2011. Influence of meteorological factors NO_2, SO_2, CO and PM_{10} on the concentration of O_3 in the Urban Atmosphere of Eastern Croatia. *Environmental Modelling and Assessment*. 16(5): 491 – 501. https://doi.org/ 10.1007/s10666-011-9256-4
8. Ho, D. J., Dayang Siti Maryam, Jafar-Sidik M. & Aung, T. 2013. Influence of weather condition on pelagic fish landings in Kota Kinabalu, Sabah, Malaysia. *Journal of Tropical Biology and Conservation*. 10: 11 – 21. https://doi.org/10.1007/s10666-011-9256-4
9. Kim, C. H. & Son, H. Y. 2011. Measurement and Interpretation of Time Variations of Particulate Matter Observed in the Busan Coastal Area in Korea. *Asian Journal of Atmospheric Environment*. 5(2): 105 – 112. https://doi.org/10.5572/ajae.2011.5.2.105

10. Kim, K. H., Kabir, E. & Kabir, S. 2015. A review on the human health impact of airborne particulate matter. *Environment International*. 74: 136 – 143. https://doi.org/10.1016/j.envint.2014.10.005
11. Li, L. & Liu, D. J. 2014. Study on an Air Quality Evaluation Model for Beijing City Under Haze-Fog Pollution Based on New Ambient Air Quality Standards. *International Joutnal of Environment Research and Public Health*. 11: 8909 – 8923. https://doi.org/10.3390/ijerph110908909
12. Lou, C., Liu, H., Li, Y., Peng, Y., Wang, J. & Dai, L. 2017. Relationships of relative humidity with PM2.5 and PM10 in the Yangtze River Delta, China. *Environmental Monitoring Assessment*. 2017: 1 – 16. https://doi.org/10.1007/s10661-017-6281-z
13. Munir, S., Mohammed, A. M. F., Habeebullah, T. M., Morsy, E. 2017. Analysing PM2.5 and its Association with PM10 and Meteorology in the Arid Climate of Makkah, Saudi Arabia. A*erosol and Air Quality Research.* 17: 453 – 464. https://doi.org/10.1007/s10661-017-6281-z
14. Naing, D. K. S., Anderios, F. & Lin, Z. 2011. Geographic and Ethnic Distribution of P knowlesi infection in Sabah, Malaysia. *International Journal of Collaborative Research on Internal Medicine and Public Health*. 3(5): 391 – 400.
15. Noor, H. M., Nasrudin, N. & Foo, J. 2014. Determinants of Customer Satisfaction of Service Quality: City bus service in Kota Kinabalu, Malaysia. *Procedia – Social and Behavioral Sciences.* 153(2014): 595 – 605. https://doi.org/10.1016/j.sbspro.2014.10.092
16. Ny, M. T. & Lee, B. K. 2010. Size Distribution and Source Identification of Airborne Particulate Matter and Metallic Elements in a Typical Industrial City. *Asian Journal of Atmospheric Environment*. 4(1): 9 – 19. https://doi.org/10.4209/aaqr.2010.10.0090
17. Shaadan, N., Jemain, A. A., Latif, M. T. & Mohd. Deni, S. 2015. Anomaly detection and assessment of PM10 functional data at several locations in the Klang Valley, Malaysia. *Atmospheric Pollution Research*. 6: 365 – 375. https://doi.org/10.5094/APR.2015.040
18. Shahraiyni, H. T. & Sodoudi, S. 2016. Statistical Modeling Approaches for PM10 Prediction in Urban Areas; A Review of 21st-Century Studies. *Atmosphere*. 7: 1 – 24. https://doi.org/10.3390/atmos7020015
19. Teong, K. V., Sukarno, K., Chang, H. W. J., Chee, F. P., Ho, C. M., Dayou, J. 2017. The Monsoon Effect on Rainfall and Solar Radiation in Kota Kinabalu. T*ransactions on Science and Technology.* 4(4): 460 – 465.
20. Zakaria, N. A. & Noor, N. M. 2018. Imputation Methods for Filling Missing Data in Urban Air Pollution Data for Malaysia. *Urbanism*. 9(2): 159 – 166.