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► To cite this version:

Parth Bansal. Spatial dissimilarities in seasonal cycle of PM10 particulate matters in Seoul, Korea. 2019. hal-02193095

HAL Id: hal-02193095

<https://hal.science/hal-02193095>

Preprint submitted on 24 Jul 2019

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Spatial dissimilarities in seasonal cycle of PM₁₀ particulate matters in Seoul, Korea

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Abstract

The increase in spatial and temporal resolution of pollution data has advanced the understanding of trend in pollutant concentration through time and space. However, this has also made inspection of time series and the relation between observations from different monitoring stations difficult to comprehend. In this study, we decompose PM₁₀ concentration time series (2010 - 2018) from 40 Air Quality Monitoring Stations (AQMs) in Seoul and then cluster the seasonal cyclic components using K-Means and K-Shape algorithms. Firstly, the influence of diurnal, weekly and annual cycle on PM₁₀ concentration is shown. Secondly, the clustering results illustrate that both algorithms are useful in determining AQMs with similar cycles, and together provide a comprehensive understanding of spatial differences in pollutant concentration.

Keywords: Air Pollution; Seasonal Cycle; K-Shape; Seoul Korea

1. Introduction

Air pollution has been a cause of concern due to its impact on human health (Kampa and Castanas 2008) and weather and atmospheric conditions (Stern 1977). Among the major air pollutants, the second Seoul air quality improvement plan (ME 2013) identifies PM₁₀, NO_x and SO_x as major contributors to air pollution. While both PM₁₀ (particle diameter < 10 µm) and PM_{2.5} (particle diameter < 2.5 µm) are monitored, Air Quality Index (AQI) deterioration in Seoul is primarily due to high concentration of PM₁₀ matter. Especially during the Asian dust season (Zhang, Gong et al. 2003), air quality frequently fall below unhealthy level on EPA scale.

(Li, Qian et al. 2014) have shown that significant variation exists in pollutant concentrations within a city boundary. However, most of the effort under the air quality improvement plan of Seoul and associated legislations have been spatially and temporally agnostic. Thus, in this study, hourly PM₁₀ dataset from 40 air quality monitoring stations was analyzed for the period of 2010–18. Consequently, we aimed to investigate the effect of time (diurnal, weekly and annual cycle) on PM₁₀ concentration and differences in each of three cycles from 40 AQMs. In doing so, we aim to highlight methods for time series analysis and clustering, which can simplify the analysis of air pollution data.

2. Methods

2.1 Study Area and AQMs

Seoul (37°1'N, 126°58'E) is the largest city of South Korea and fall under humid continental climatic zone under Köppen-Geiger classification. It has a total land area of 605 KM² with an average elevation of 38 M. It is polycentric with high and medium density residential area and about 25.29% of land falls under the regulated green belt where only limited development is allowed. The area has

Figure 1 Location of AQMs in Seoul

four distinct seasons and due to a combination of local climate conditions, internal and foreign anthropogenic emissions and Asian dust, winter usually has poor air quality.

Air pollution is measured hourly as mean of readings at 5 m minute interval by 40 air quality monitoring stations (AQMs) within the boundary of Seoul, shown in figure 1. For PM₁₀, ambient dust monitor using β -ray absorption method is used which has minimum detection limit of $< 1 \mu\text{m}/\text{m}^3$ with the precision of $\pm 2 \mu\text{m}/\text{m}^3$ (Ahmed, Kim et al. 2015).

2.2 Data Processing

2.2.1 Time Series Decomposition

Additive decomposable time series model (Harvey and Peters 1990) is defined as:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (1)$$

Where $g(t)$ is long term trend (non-periodic changes), $s(t)$ is periodic changes and $h(t)$ is holiday effect, i.e. irregularly scheduled events. ε_t is error term contain changes not accounted by the model. Alternatively, time series can also be decomposed multiplicatively, however, based on preliminary inspection using graphs and lower mean absolute percentage error (MAPE) (Armstrong and Collopy 1992) of both models, additive decomposition has been used in this study. For modelling $g(t)$ piecewise linear regression (McZgee and Carleton 1970) with time as regressor is used. Since pollution is also a function of anthropogenic activity which can have multi-period seasonality, Fourier series (Harvey and Shephard 1993) was used to model effect of diurnal, weekly and annual cycle ($s(t)$). Holidays $h(t)$ were not included in the model.

The implementation of model can be found in python library fbprophet (Taylor and Letham 2018).

2.2.2 Time Series Clustering

As the number of AQMs increases along with the temporal frequency of observations, huge amount of detailed air quality data is generated. Different techniques including time series clustering have been developed to identify similar observations and reduce costly human supervision, not only as detached analysis but also as a step for pre-processing.

We use time series clustering to identify similar cycles from 40 AQMs datasets. (Montero and Vilar 2014) described two broad categories for time series similarity (or dissimilarity) investigations: 1) Shape based, where the objective is to compare the geometric profile of the series. 2) Structure based, where the objective is to find the mutual dependency arrangement. In this research, since our objective is to investigate the similarity in PM₁₀ profile across different AQMs, we use algorithms primarily meant for shape based investigations.

2.3.3 Classification Algorithms

K-Means, in general clustering, has been one of the most popular algorithm. To extend it into time series clustering, dissimilarity measures such as Euclidean distance and dynamic time warping (DTW) (Berndt and Clifford 1994) are used. On the other hand, K-Shape (Paparrizos and Gravano 2015) is a relatively new algorithm which uses normalized cross correlation to measure dissimilarity. Further, while K-Means uses an average sequence of all the sequences to derive centroid for clustering, K-Shape compute centroid by minimizing the sum of squared distance to all the sequences. In this study, we used both K-Means based on DTW and K-Shape clustering. The implementation of both algorithms can be found in python library tslearn (Tavenard 2017). The number of clusters while subjective to authors' investigation, were based on the results of Silhouette score (DTW and Euclidean distance as metric) (Rousseeuw 1987), Gap statistic (Tibshirani, Walther et al. 2001) and mean square error (MSE).

3. Results

Hourly PM_{10} data between 2010 – 18, for AQMs located across Seoul was collected and cleaned. 37 of 40 AQMs were active throughout the study period. 2 AQMs started functioning from April 2011, while 1 AQM was retired at the end of 2014. Across all the AQMs, on average, out of 8760 hours in a non-leap year, 8692 observations were recorded. Overall, there are 3,074,436 observations in total across the whole dataset. Figure 1 shows PM_{10} concentration for individual AQMs as well as the arithmetic mean. As with any large dataset, it is difficult to derive any systematic conclusion from simple visualization, but generally, peaks are observed in winter (Nov – Feb) and troughs in summer (July-Sept).

Figure 2 PM_{10} observations for 40 AQM between 2010 - 2018 and their mean.

As per discussion in section 2.2, time series for each AQM was additively decomposed. All three seasonal cyclic components were then clustered separately using K-Means (DTW) and K-Shape algorithm. Annual and weekly cycles were divided into 3 clusters while daily cycles have 4 clusters. The results of decomposition and the subsequent clustering is shown in Figure 2 to 4, along with the mean of each cluster.

Figure 3 Annual seasonal component of PM10. Left A-C, clustering from K-Means (DTW), Left D, mean of K-Means (DTW) clusters. Right A-C clustering from K-Shape, Right D, mean of K-Shape cluster.

Figure 4 Weekly seasonal component of PM10. Left A-C, clustering from K-Means (DTW), Left D, mean of K-Means (DTW) clusters. Right A-C clustering from K-Shape, Right D, mean of K-Shape cluster.

Figure 5 Daily seasonal component of PM₁₀. Left A-C, clustering from K-Means (DTW), Left D, mean of K-Means (DTW) clusters. Right A-C clustering from K-Shape, Right D, mean of K-Shape cluster.

4. Discussion

For studied number of clusters, K-Shape has an average silhouette score of 0.68 and 0.61 vs. 0.61 and 0.55 for K-Means (for DTW and Euclidean distance metric respectively). Hence, while K-Shape performed slightly better as compared to K-Means, the results of two methodologies provide different (but equally important) insights into the variances in PM₁₀ seasonal cycles.

4.1 Annual Seasonal Component Cycle

Annual cycle of all the AQMs indicates that winter (December – January) and spring (March – April – May) has the highest concentration of PM₁₀. Cold air outbreak in southern china sea during winter and Asian dust storm (Kim and Park 2001) are two major causes for the peaks in annual cycles. For

K-Means, AQM in cluster A have marginally lower values in winter and higher value in summer as compared to cluster B. Four AQMs in cluster C are characterized by more extreme values as compared to A & B. On the other hand, for K-Shape, cluster A AQMs are characterized by more consistent change in pattern, as compared to cluster B. Cluster C only has one AQM, which has exceptionally high concentration in Jan – Feb but slightly lower concentration in fall (Sept – Nov), as compared to cluster A and B. These results are in contrast to (Bigi and Harrison 2010) study on London in which they found annual cycle for mean of all AQMs to have no clear pattern for PM₁₀.

4.2 Weekly Seasonal Component Cycle

Among the three seasonal cycles, weekly cycle has very small impact on concentration levels. All but one AQM have a similar weekly cycle, with peaks observed during Tuesday and Saturday. K-Means based cluster A and B are predominantly same and are in fact put together if the number of clusters specified is two. On the other hand, AQMs in K-Shape cluster B has lower concentration for Monday, but higher concentration between Thursdays – Saturday as compared to cluster A. Cluster C has only one observation in both the cases due to its unique peak on Friday.

4.3 Daily Seasonal Component Cycle

As expected, a general trough in PM₁₀ concentration is observed during nighttime (00:00 – 06:00) after which the concentration increases rapidly. From K-Means classifications, cluster A is characterized by relatively smaller slump during nighttime and stable or small increase in concentration after the morning peak. Cluster B has lower concentration in nighttime as compared to A, which increases continuously till 22:00. Cluster C is characterized by very high morning peak and then declines continuously afterwards. Cluster D only has one AQM and shows the same features of cluster C, except that the nighttime low and morning peaks are more extreme. In case of K-Shape classification, cluster A show only small variation throughout the day. Cluster B and C are similar to that K-Means cluster, but are rather more tightly packed. Cluster D on the other hand shows considerably different patterns, indicating that increase in the number of clusters is required.

5. Conclusion

In this study, seasonal decomposition and clustering using K-Means (DTW) and K-Shape is applied to the PM₁₀ concentration time series from 40 AQMs located within the administrative boundary of Seoul. Unlike (Yang, Ning et al. 2017) conclusion that the K-Shape produces superior clustering of building energy usage time series, this work show that both classifications provide a different understanding of patterns in PM₁₀ concentrations. The results from this study will be utilized for developing land use regression model to investigate relationships between urban and traffic characteristics and pollution concentration. This would be based on the methodology utilized by (Kim and Guldman 2015), however, instead of raw data used in the previous study, we expect utilization of only seasonal component would improve the model since such dependent variable would be free of long term trend and noises due to short term fluctuations.

Appendix. Supplementary Information

Raw data associated with this article can be found at airkorea's API (<http://openapi.airkorea.or.kr/>).

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