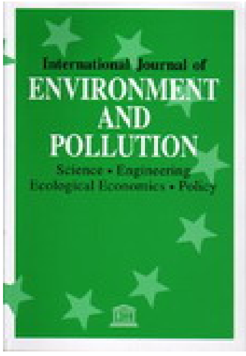

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Spatial and temporal analyses of airborne particulate matter in South Marmara Region of Turkey

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Spatial and temporal analyses of airborne particulate matter in South Marmara Region of Turkey

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Abstract: In the lengthy time period between 2007 and 2019, airborne particulate matter (PM_{10}) levels from real-time intensive measurements were analysed to determine how the long-term PM_{10} may vary from the effects of both meteorological parameters and different emission sources in the South Marmara Region. The main statistical approaches were performed to determine how daily measured long-term PM_{10} varied with the influence of local meteorological parameters in the area. According to the regression models, the significant contributors were ambient temperature and wind speeds. The local sources of PM_{10} may be considered the main contributors to the peak PM_{10} levels in the area. Therefore, spatial analyses were performed to understand the main contributor to the PM_{10} episodes when the highest PM_{10} were observed throughout the years. The cluster and concentration weighted trajectory (CWT) analysis approaches showed that the local sources were mostly associated with the higher PM_{10} levels in the study area.

Keywords: PM_{10}; ANOVA; analysis of variance; regression analysis; HYSPLIT; cluster; CWT; concentration weighted trajectory.

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1 Introduction

Air pollution is still one of the most important environmental risk factors threatening public health worldwide (WHO, 2016). Globally, anthropogenic air pollutants are the primary environmental concern in urban environments. Meteorology, topographic properties, and urban settlements are essential factors of various airborne pollutant levels.

Airborne particulate matter, such as PM_{10}, refers to suspended particles with an aerodynamic diameter up to 10 microns in the atmosphere. Urbanised PM_{10} may occur from industrial applications, such as cement plants, iron and steel plants, coal and mine plants, excavation areas, and from traffic activities, including vehicle exhausts, and roads are also considered residential heating during cold seasons in the urban environment (Bhanarkar et al., 2005; Lothongkum et al., 2008; Abu-Allaban and Abu-Qudais, 2011).

Airborne PM_{10} may adversely affect human respiratory systems, specifically related to upper and lower respiratory diseases (WHO, 2006; Tecer, 2009; Samoli et al., 2013; Stafoggia et al., 2013). Previous studies have shown a relationship between air pollution levels and an increase in respiratory symptoms and mortality (Wordley et al., 1997; Timonen et al., 2002). There is a significant link between air pollution and respiratory-associated hospitalisations and admissions to emergency facilities due to the exacerbation of respiratory complaints or asthma in adults and children (Olcese and Toselli, 1997; Gomzi, 1999; Wong et al., 2000; Brunekreef and Holgate, 2002).

Statistical analysis has been widely used in previous studies to establish a better understanding of PM_{10} levels or to estimate ambient PM_{10} levels by considering meteorological variations (Aldrin and Haff, 2005; Elminir, 2005; Karaca et al., 2005; Vardoulakis and Kassomenos, 2008; Hrust et al., 2009; Munir et al., 2013; Sayegh et al., 2014). Many studies have generally shown that ambient temperature, relative humidity, and wind speed and direction are significant factors affecting local air quality in urban environments (Goyal and Rao, 2007; Giri et al., 2008; Owoade et al., 2012; Galindo et al., 2015; Zhang et al., 2015; Yin et al., 2016; Kayes et al., 2019). Therefore, meteorological parameters are significant factors in the variation in air quality levels in urban environments.

This study aims to draw statistical analyses to investigate the correlation between long-term daily monitored airborne PM_{10} and meteorological parameters, ambient temperature, relative humidity, pressure, wind speed, and direction, to analyse the seasonal variations of airborne PM_{10}, and to generate a regression model to show how meteorological parameters may independently affect airborne PM_{10} levels in the Balikesir province. The present study attempts to provide evidence of any statistical association between the long-term (2007–2018) daily monitored PM_{10} data and hourly measured meteorological data in the same location.

2 Materials and methods

2.1 Study area

The Balikesir province is a medium-sized city located in the northwest part of Turkey and the south of the Marmara region (Figure 1). The city is considered a 1st degree earthquake zone in Turkey, and it has three different climatic zones, including a Mediterranean climate at the coast of the Aegean Sea, a moderate climate at the North sites and a continental climate at the inner sites. In addition, air pollution has gained more importance due to the topographical structure of the Balikesir Province and the decrease in current winds in winters (CAAP, 2019). The factors that negatively affect the air quality levels in the city are the topographic structure of the downtown area, the meteorological conditions, unplanned urbanisation, the poor quality of the fuel used, the industry and traffic activities (CAAP, 2019).

In this study, there is a conventional active air quality monitoring station (AQMS) under the responsibility of the Provincial Environment Directorate in the city. The location of the AQMS, the meteorological station at the local airport, and the downtown area are illustrated in Figure 1 using the Google Earth Digital Image environment.

Figure 1 Aerial 3D-view of downtown Balikesir (see online version for colours)

Source: Google Earth image© (2019)

2.2 Data

In this study, the long-term air quality data, including daily PM_{10}, were measured from the local AQMS in the city. Ambient PM_{10} levels were monitored since June 2007 in the downtown area. Additionally, meteorological parameters, including wind speed (WS), humidity (RH), and pressure (P), were obtained from the meteorological station at the local airbase. Both the locations of the AQMS and the meteorological station are presented in Figure 1.

2.3 Data analysis

In the scope of this study, a series of statistical analyses were performed to describe the long-term variation of ambient PM_{10} with fluctuations in the meteorological parameters. Temporal variations, including frequency histograms and box-plot time series, were generated to evaluate the PM_{10} variations. Spatial variations were made to describe the downtown dispersion of ambient PM_{10} levels. Correlation analyses of PM_{10} with the meteorological variables were performed to define any statistically significant correlations among those variables. Regression analyses, including multiple linear regression (MLR) and quantile linear regression (QLR) models, were performed to gain a better understanding of the effects of meteorological parameters on the variation of ambient PM_{10} in the city. Considering the results obtained from the regression analyses of the datasets, non-parametric correlation analyses, including the Theil-Sen correlation analysis, which is one of the key trend analyses frequently used in air quality studies, were performed and a train analysis showing the long-year changes of air pollutants was performed (Tian and Fernandez, 1999; Elbir et al., 2000; Yolsal, 2016).

In addition to the set of statistical analyses, the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) developed by the US National Oceanic and Atmospheric Administration (NOOA) was performed to determine the major pathways of regional PM_{10} that might affect the observed PM_{10} levels in the study area. In this case, the HYSPLIT model was used to determine the major pathways of the peak PM_{10} levels observed from 2007 to 2019. Additionally, a cluster analysis, including cluster trajectories, for presenting spatial contributions of the highest PM_{10} levels, and concentration weighted trajectory (CWT) analyses were performed using the web-based TrajStat algorithm (Wang et al., 2009) to identify potential source regions. The analysis results are presented in detail in the following section.

3 Results and discussion

3.1 Statistical analysis of PM_{10} with meteorological parameters

The main annual descriptive statistics, such as the mean, confidence intervals for the mean, minimum and maximum levels, and the value at 50% of the distribution of the PM_{10} data, referred to as IQR, are presented in Table 1. The long-term data covered the period from June 2007to 2019.

Table 1 Long-term descriptive statistics for ambient PM_{10} levels

	Descriptive statistics PM_{10}					
		*Confidence interval for mean**				
Years	*Mean*	*Lower bound*	*Upper bound*	*Minimum*	*Maximum*	*Interquartile range*
2007	82(150)[a]	75	88	20	329	45
2008	85(150)	79	91	20	364	51
2009	80(150)	73	86	11	387	48
2010	76(132)	71	81	14	319	47
2011	77(114)	71	82	21	346	46
2012	45(96)	42	48	15	280	20
2013	48(78)	44	51	12	278	30
2014	46(60)	43	49	11	178	23
2015	44(56)	41	48	8	273	27
2016	42(52)	40	45	12	167	22
2017	58(48)	54	63	13	240	32
2018	46(44)	43	49	12	228	21
2019	34(40)	32	36	9	126	20

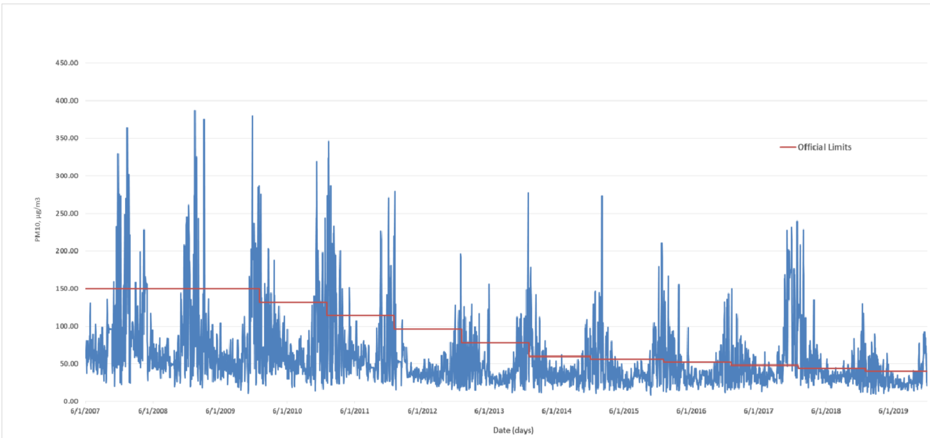
[a]The national PM_{10} limits in parenthesis (RAQAM, 2008).

*at 95% significant level.

The annual mean PM_{10} levels were around 80s μg/m^3 in the first few years, and the PM_{10} levels were relatively lower in the following years. Notably, the annual mean PM_{10} levels declined by about 40s μg/m^3 after 2012. The national limits were repeatedly reduced from 2009 onwards during the adjustment period of the European Union (RAQAM, 2008). Now, the annual ambient PM_{10} limit has been set as 40 μg/m^3 by state officials.

As shown in Figure 2, the time series of the long-term PM_{10} levels indicate that ambient PM_{10} levels are higher especially in winter. Additionally, ambient PM_{10} levels exceed the official limit in winter. The changes in official limits of PM_{10} are identified by the red line in Figure 2. The ambient PM_{10} levels showed a decreasing trend when natural gas was utilised for residential heating in 2010.

Figure 2 Daily variations of PM_{10} levels from 2007 through 2019 (see online version for colours)

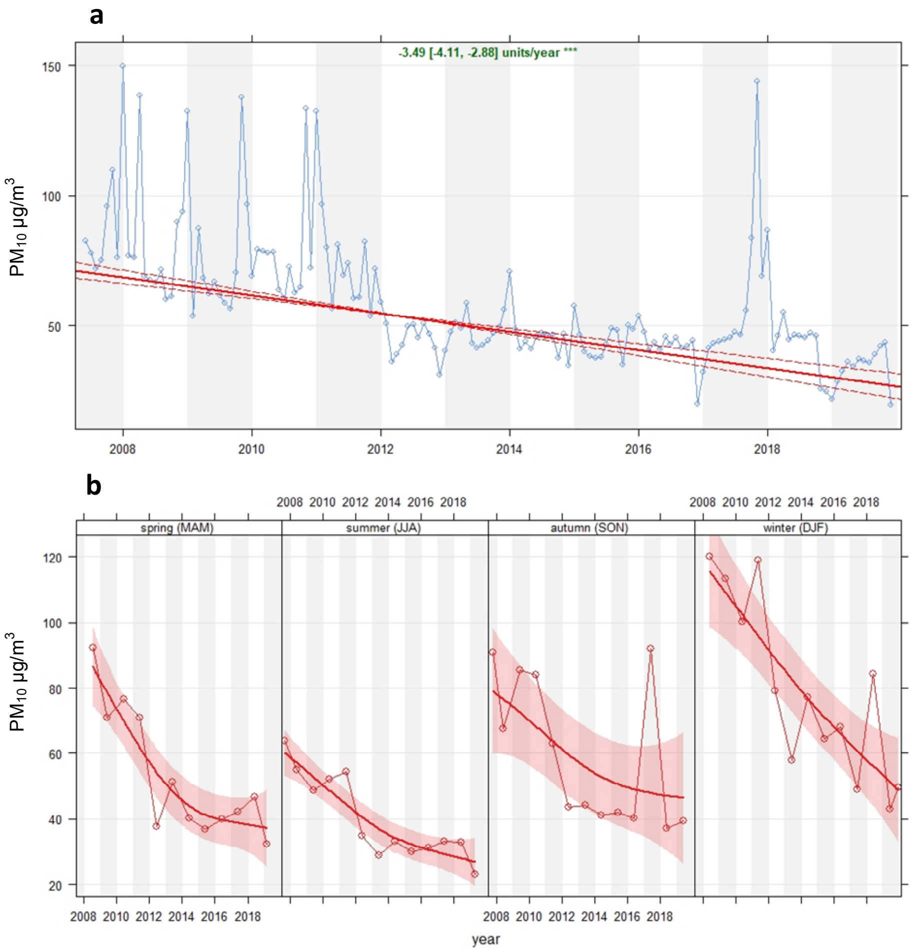


As a result of the Theil-Sen trend analysis, according to the graphs obtained in the R environment using the Carslaw Algorithm (Carslaw, 2019), which facilitates the analysis of daily data, and is presented in Figure 3, the red solid lines represent the PM_{10} forecast averages for all years between 2007 and 2019. The dashed red lines represent the confidence intervals of the forecast values at the 95% confidence level.

According to the Theil-Sen trend analysis results presented in Figure 3(a), the PM_{10} levels show a decreasing trend from around 70s $\mu g/m^3$ to 40s $\mu g/m^3$ in the study period, with an average decrease of 3.5 $\mu g/m^3$ each year. A seasonal trend has also been presented in Figure 3(b) using the Theil-Sen algorithm. The winter season had the highest PM_{10} levels among all seasons and the winter season also showed a decreasing trend for the studied periods.

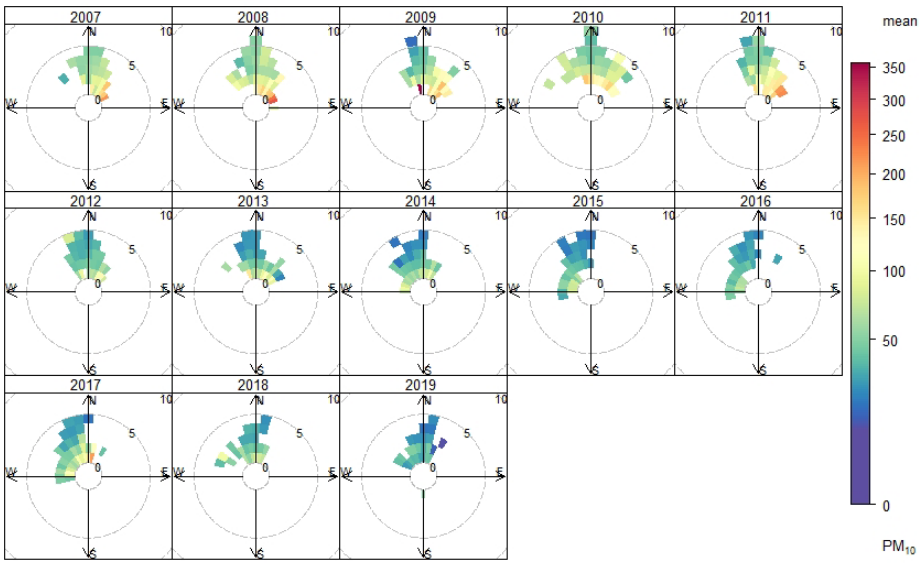
Polar pollution graphs are useful to summarise all available data. In this analysis, a polar means of PM_{10} levels is illustrated using the Carslaw algorithms (Carslaw, 2019), indicating that most of the time, the wind was from a north-westerly or north-easterly direction during the study period. The mean concentration of PM_{10} levels by wind speed and wind direction are shown in Figure 4, which highlights that the PM_{10} concentrations tended to be the highest for northern winds for most of the period, which were at quarries, crushing and screening facilities, briquette houses and marble workshops located in various parts of the city. Although these facilities do not have a direct effect on residential areas, the local PM_{10} levels were affected because the activities of these facilities have negative effects on the air quality of the city (CAAP, 2019).

Figure 3 (a) Overall and (b) seasonal results of Theil-Sen trend analysis for PM_{10} levels (see online version for colours)



The analysis of variance (ANOVA) test was performed to determine whether annual or seasonal PM_{10} levels were identical and to also show any significant difference among the annual or seasonal PM_{10} levels during the study period. The ANOVA test indicated that there was a significant difference among the annual means at the 95% significance level ($p = 0.00$). In other words, the annual means were not equal. Since the annual means were different, the Post-Hoc test (LSD-Least Squared Means) was then performed for more detailed comparisons. According to the LSD, the highest annual means of PM_{10} levels were observed in 2008. However, there was no significant difference between 2008 and the annual means of PM_{10} levels in 2007 ($p = 0.31 > 0.05$) and 2009 ($p = 0.58 > 0.05$). Therefore, 2007, 2008, and 2009 may be considered the years with the highest annual PM_{10} levels observed in the study area. Furthermore, there was no significant difference observed in 2012, 2013, 2014, and 2016. According to the ANOVA test, the lowest annual mean PM_{10} level was measured in 2019 in the study area, with the exception of December. A seasonal basis for an ANOVA test was performed and the winter seasons had the highest mean of PM_{10} levels of 81 µg/m^3 [77–85 µg/m^3 as a 95% confidence interval for the mean]. The fall, spring, and summer seasons were ranked by the seasonal means of PM_{10} levels, respectively.

Figure 4 Polar PM_{10} levels (µg/m^3) by wind speed and wind directions for the study periods (see online version for colours)



Correlation analysis was performed to investigate the possible statistical relationships between the meteorological parameters that play an essential role in PM_{10} variations. Such correlation analyses are widely used in environmental and air pollution studies (Olcese and Toselli, 1997; Elminir, 2005; Celik and Kadi, 2007; Liu et al., 2015; Cakır and Abdullah, 2017; Ismail et al., 2018). The correlation analysis results are presented in Table 2.

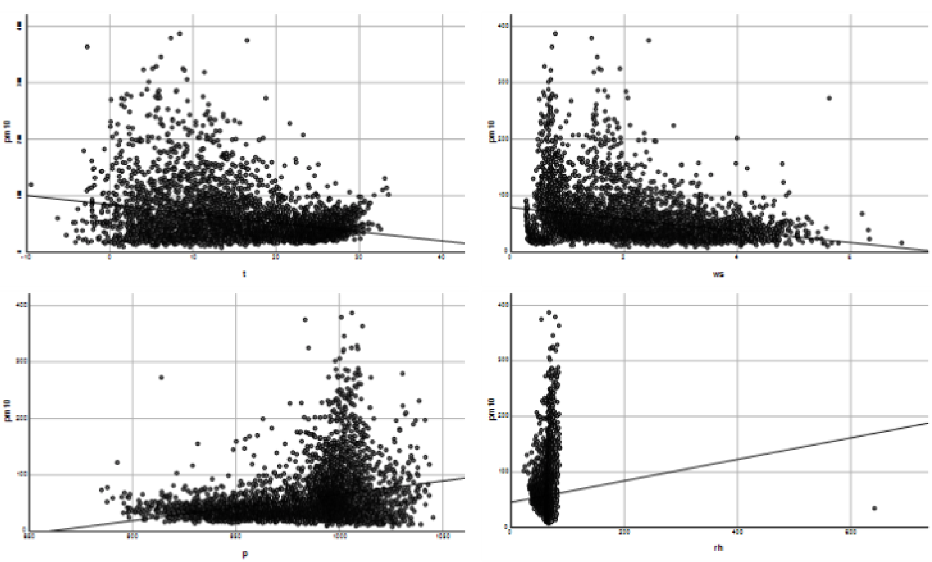
According to the Pearson correlation analysis, changes in the PM_{10} levels in downtown Balikesir could be correlated with local meteorological parameters, such as temperature (T), wind speed (WS) and pressure (P). The highest correlation coefficients were found to be temperature (–0.297), with a tendency towards decreasing PM_{10} levels in the case of both increasing ambient temperature and wind speed during the observation period. The correlation coefficient between relative humidity and PM_{10} was not high. Thus, the correlations between relative humidity and PM_{10} levels were weak in this study. Elminir (2005) stated that the correlation between air pollutants and relative humidity was not significant. Graphical representations of the correlations of the observed meteorological parameters with the measured PM_{10} levels are displayed in Figure 5.

Table 2 Results of Pearson correlation analysis

		PM_{10}	*rh*	*p*	*t*	*ws*
PM_{10}	Pearson Correlation	**1**	0.049^{**}	0.287^{**}	-0.297^{**}	-0.268^{**}
	Sig. (p-value)		0.001	0.000	0.000	0.000
	N	4566	4566	4566	4566	4566
Rh	Pearson Correlation	0.049^{**}	**1**	–0.024	-0.321^{**}	-0.120^{**}
	Sig. (p-value)	0.001		0.107	0.000	0.000
	N	4566	4566	4566	4566	4566
P	Pearson Correlation	0.287^{**}	–0.024	**1**	-0.521^{**}	0.027
	Sig. (p-value)	0.000	0.107		0.000	0.067
	N	4566	4566	4566	4566	4566
T	Pearson Correlation	-0.297^{**}	-0.321^{**}	-0.521^{**}	**1**	0.136^{**}
	Sig. (p-value)	0.000	0.000	0.000		0.000
	N	4566	4566	4566	4566	4566
ws	Pearson Correlation	-0.268^{**}	-0.120^{**}	0.027	0.136^{**}	**1**
	Sig. (p-value)	0.000	0.000	0.067	0.000	
	N	4566	4566	4566	4566	4566

**Correlation is significant at the 0.01 level.

Figure 5 Correlations of the observed meteorological parameters with the measured PM_{10} levels



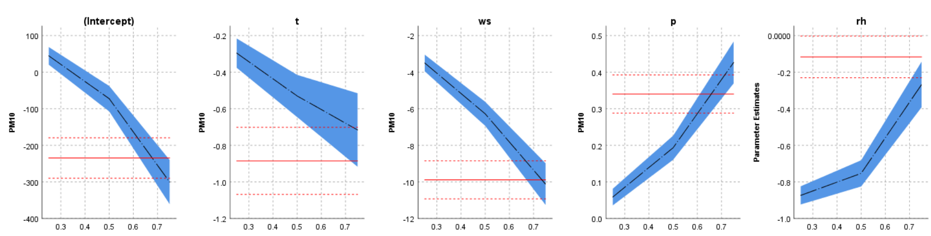
After evaluating the individual correlations, the hierarchical multiple linear regression (HLMR) model was applied using a statistical software package (IBM-SPSS, Version 20, USA) to predict PM_{10} variation by adding the meteorological parameters as a predictor. In the HLMR model, PM_{10} was defined as the dependent variable and all meteorological parameters were defined as independent predictor variables. The model consists of four independent models, which have been generated by individually adding the independent variables into the model. Within the model, the model with the highest R^2 value was selected as the most appropriate model to explain the dependent variable.

It is noticeable that the level of predicting PM_{10} did not significantly change when the all-meteorological parameters were added to the model, so the relative humidity (RH) did not substantially affect predicting PM_{10} levels ($p = 0.045 \sim 0.05$). According to the HLMR model, the significant contributors were found to be T (–0.164), WS (–0.255), and P (0.208) in the analysis. These findings confirmed the results of previous studies that PM_{10} concentrations showed an increasing trend when the temperature, wind speed, and humidity had inversely increased trends (Olcese and Toselli, 1997; Elminir, 2005; Celik and Kadi, 2007; Ismail et al., 2018). A similar analysis was performed by Ismail et al. (2018), who concluded that MLR performed better than principal component regression in Malaysia's industrial areas. Sayegh et al. (2014) also employed both MLR and quantile regression models (QRM) on PM_{10} levels in Makkah, Saudi Arabia. They concluded that QRM performed much better than MLR in their study. The authors showed that QRM had significantly better results, with minimal errors compared to the other models regarding the prediction of ambient PM_{10} levels. Therefore, QRM was also performed in this study to further determine how meteorological parameters may influence the PM_{10} levels in the study area. According to Sayegh et al. (2014), it was stated that the QEM had the best model performance based on several factors, such as the mean absolute error (MAE).

In this study, quantiles were set as 0.25, 0.5, and 0.75 in QRM. Therefore, the MAE calculated for the first quantile (0.25) was 27.94, the MAE for the second quantile (0.50) was 24.65, and the MAE for the third quantile (0.75) was 30.77 in the model. Based on the MAE values, the second quantile (0.5) was selected as the best representative model.

According to QRM results, the wind speed was the most influential parameter on ambient PM_{10} levels in the study area. Also, the other meteorological parameters were significantly important ($p < 0.05$) parameters based on the QRM analysis. A graphical view of the QEM is displayed in Figure 6.

Figure 6 The QRM results at a 0.5 quantile level (see online version for colours)



In Figure 6, the blue shaded area represents confidence intervals of the parameter estimates at the 0.5 quantile. The solid line indicates the parameter estimates, the red line shows the parameter estimates for the MLR with the same predictors, and the dashed red lines denotes the upper and lower intervals for the linear regression with the same predictors. In the QRM, temperature (T) and wind speed (WS) had an inverse correlation with the PM_{10} levels, while pressure (P) and relative humidity (RH) had a positive correlation.

3.2 Spatial analysis of PM_{10} episodes

The highest daily airborne PM_{10} levels were observed during the study years. The highest PM_{10} levels are presented in Table 1 by the descriptive statistics. The highest PM_{10} levels are increased by a combination of natural and anthropogenic activities that occur under major meteorological conditions. The HYSPLIT model was developed by the US National Oceanic and Atmospheric Administration (NOOA) and Australia's Bureau of Meteorology (Stein et al., 2015; Rolph et al., 2017). The HYPSLIT model is a unique modelling tool that can track down either backward or forward movement of air parcels within the described times and zones.

The HYSPLIT model is also a useful tool to better understand the source of local airborne pollutants when they reach their peak values. The peak values of the observed PM_{10} levels with related meteorological data are presented in Table 3.

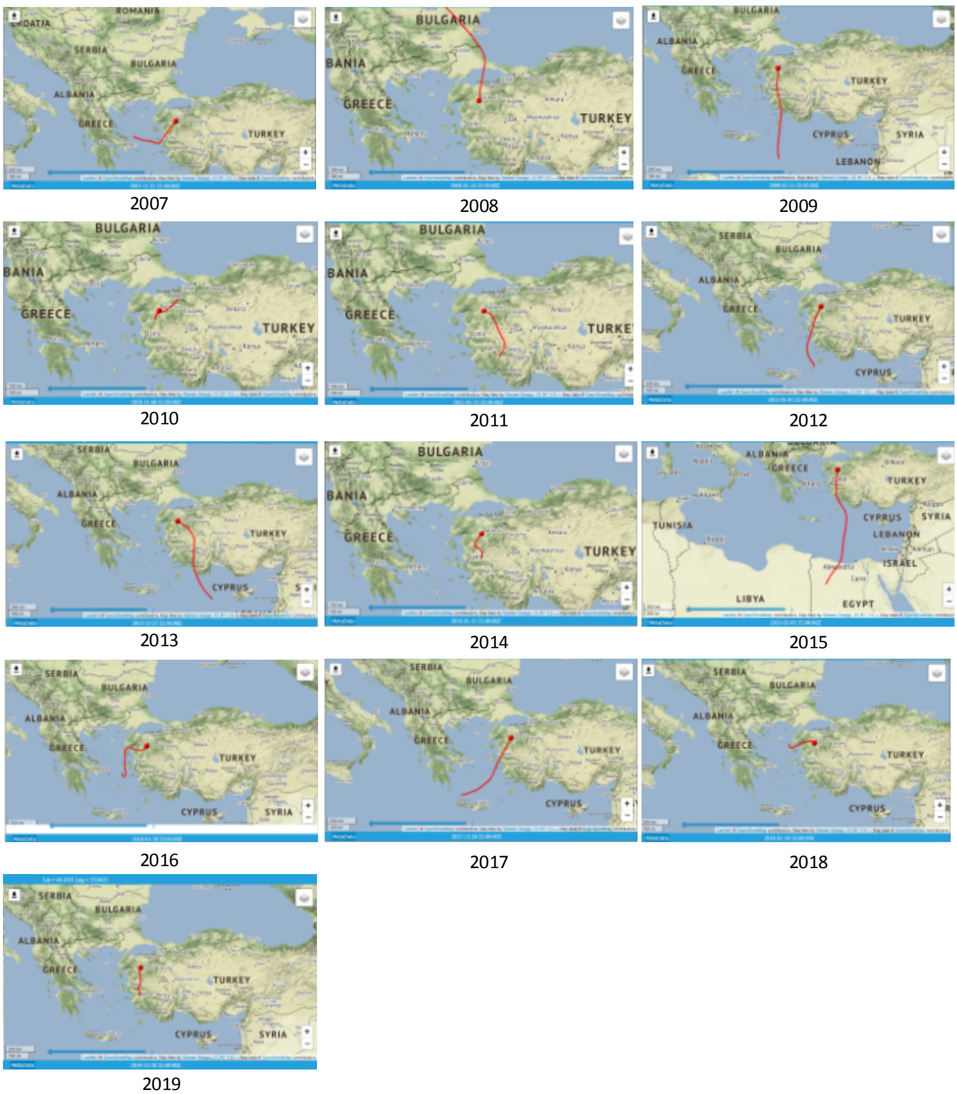
Table 3 The peak PM_{10} levels with dates and related meteorological data

Peak dates	PM_{10}	*rh*	*p*	*t*	*Wind speed*
11/25/2007	329.02	81.60	1008.54	5.56	0.59
1/14/2008	363.71	84.37	1011.17	–2.73	0.72
1/15/2009	387.18	66.88	1006.07	8.40	0.78
11/6/2010	318.82	78.88	1001.84	11.37	1.46
1/12/2011	345.89	73.81	1002.30	6.12	1.52
1/5/2012	279.57	66.09	1030.58	2.05	0.72
12/27/2013	277.52	66.87	1009.99	5.89	0.59
1/11/2014	178.09	68.83	1001.65	5.92	0.57
2/1/2015	272.70	60.74	913.87	18.75	5.62
1/28/2016	166.50	70.91	1006.14	3.21	0.59
12/26/2017	239.58	69.04	1007.83	5.47	0.57
1/30/2018	228.20	69.16	991.51	6.07	0.60
12/18/2019	125.87	70.45	1017.87	6.2	0.27

The HYSPLIT analysis was performed for each peak date presented in Table 3, and the modelling outputs are illustrated in Figure 7, including annual peaks from 2007 to 2019. The peak PM_{10} levels occurred in the cold seasons, more likely in November, December, commonly in January, and for one-case in February. Based on the modelling outputs, the majority of the peak PM_{10} levels may have occurred from local originating sources, such as traffic, residential-heating purposes, and also from sea salts from the Aegean Sea in the cold seasons. However, there are some cases that are significantly crucial regarding regional PM_{10} transportation that originates from the other sources. For example, in 2008, the peak PM_{10} levels may have occurred due to the high regional transportation of PM_{10} originating in South-East Bulgaria, where the intense coal-burning plants are currently located in the vicinity. The air parcel movement from Bulgaria may predominantly affect the peak PM_{10} levels in the study area and are presented by a red dot in Figure 7. Another significant regional PM_{10} transportation can be seen in Figure 5, which reflects a substantial desert effect over Egypt during the local PM_{10} peak in 2015.

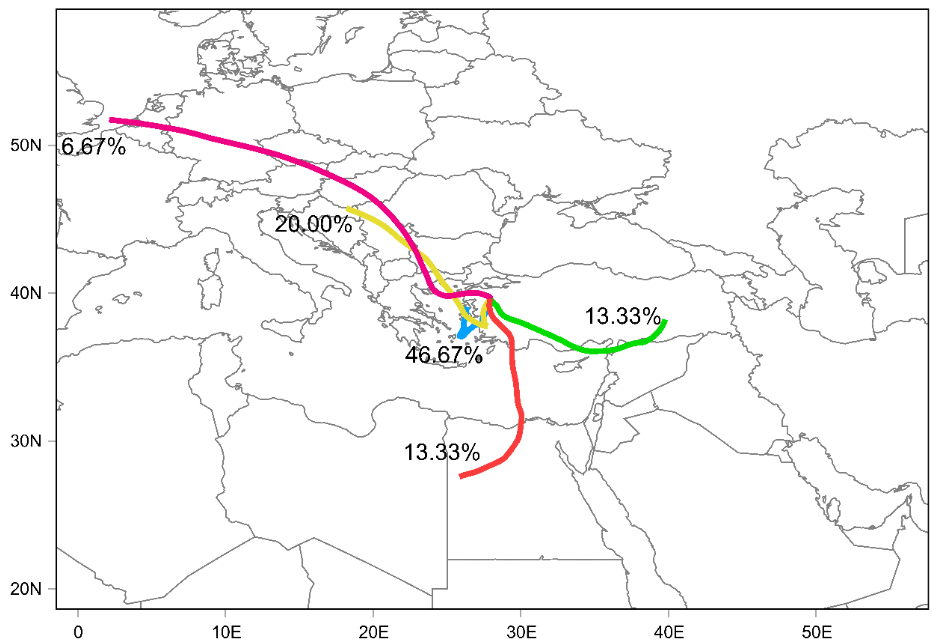
In this study, the HYSPLIT model was used to determine major pathways of the peak PM_{10} levels at 500 m above sea level from 2007 to 2019 (Figure 7).

Figure 7 Analysis of HYPSLIT backward trajectories for PM_{10} episodes during the observation period (see online version for colours)



In general, the long-term PM_{10} levels may have occurred due to local activities, except for a few cases of regional PM_{10} transportation from outside of the study area. The HYSPLIT models also indicate long-distance sources that may have contributed to the high PM_{10} levels in local areas. Cluster analysis, as described by Wang et al. (2009), was performed to determine the PM_{10} pathways that were associated with the high-level clusters for local sources vs. regional sources in the study area. Figure 8 illustrates the trajectory of PM_{10} clusters in a map view.

Figure 8 Results of trajectory cluster analysis during the observation period (see online version for colours)

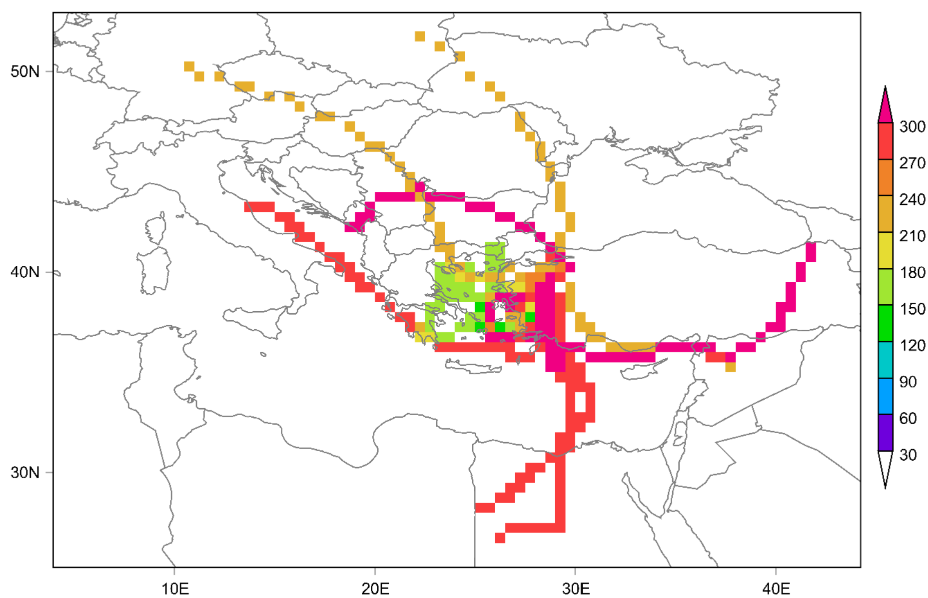


As presented in Figure 8, the blue-coloured cluster shows the highest PM_{10} contribution and indicates that local sources were highly effective at a rate of approximately 47%. The next significant cluster is shown in yellow and represents regional PM_{10} pathways from South-East Europe with a rate of 20%. The other clusters showed that deserts were affected in North Africa and also in the Northern part of the Arabian Peninsula with low rates of 13%.

Concentration weighted analysis also indicated computed ambient PM_{10} concentration fields to identify source areas of PM_{10} in the study location. In the CWT analyses, each grid cell represents the mean concentration of PM_{10} on the back trajectory based on the arrival time concentration using long-term data between 2007 and 2019. The CWT results are presented in Figure 9.

Figure 9 is useful for identifying major sources of PM_{10} concentrations for the area. The CWT analysis showed that the local sources were mainly associated with higher PM_{10} levels. The significant PM_{10} pathways may be described as local, the South-East of continental Europe and the Northern parts of Africa and the Arabian Peninsula, respectively.

Figure 9 Results of the CWT analysis for PM_{10} pathways during the observation period (see online version for colours)



4 Conclusion

The following considerations are made after performing statistical analysis to determine the overall effects of local meteorological parameters on the variations of PM_{10} levels the downtown. The annual mean PM_{10} levels were about 80 $\mu g/m^3$ between 2007 and 2009, and the PM_{10} levels were relatively lower in the following years. The annual mean PM_{10} levels declined to 45 $\mu g/m^3$ in 2012. The national limits were repeatedly reduced from 2009 onwards during the adjustment period by the European Union (EU). The set limit of the EU was violated until 2018.

The time series of the long-term PM_{10} levels identify that ambient PM_{10} levels were significantly higher in winter seasons. There are some cases where ambient PM_{10} levels exceeded the official limit in winter. Therefore, Winter is the main concern for the temporal PM_{10} levels in the city. Furthermore, the Theil-Sen trend analysis showed that PM_{10} levels tended to decrease in both overall and seasonal times during the study period.

According to the ANOVA Post-Hoc test (LSD), the highest annual means of PM_{10} levels were observed in 2008. However, there was no significant difference between 2008 and the annual means of PM_{10} levels in 2007 ($p = 0.31 > 0.05$) and 2009 ($p = 0.58 > 0.05$). Therefore, 2007, 2008, and 2009 may be considered the years with the highest annual PM_{10} levels observed in the study area.

According to the correlation analysis, the highest correlation coefficients were determined to be temperature (–0.297), with a tendency towards decreasing PM_{10} levels in case of increasing ambient temperature, wind speed and pressure during the observation period.

If all meteorological parameters are used, the PM_{10} level can only be estimated or explained as 16%.An HLMR model was used to predict PM_{10} variation by individually adding meteorological parameters as predictors to the model. The highest R^2 was obtained when the temperature (T), wind speed (WS) and pressure (P) meteorological parameters were included in the model as independent variables so that the relative humidity (RH) did not significantly affect predicting PM_{10} levels ($p = 0.045 \sim 0.05$) during the long-term study.

In addition to the statistical analyses, spatial analyses were performed on the study area. Cluster analysis and the CWT approach indicated that local sources were mostly associated with the higher PM_{10} levels during the long-term observation of the study area. As the effects of local meteorological parameters remain low in exposing long-term PM_{10} levels, the number of representative active AQMSs should be increased in the city center. Furthermore, long-range continental dust transport mechanisms should be evaluated in detail in further studies.

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