ISSN: 2148-9173 Vol: 5 Issue:1 March 2018

International Journal of Environment and Geoinformatics (IJEGEO) is an international, multidisciplinary, peer reviewed, open access journal.

Spatial Modelling of Air Pollution from PM_{10} and SO_2 concentrations during Winter Season in Marmara Region (2013-2014)

Ozan Arslan and Özer Akyürek

Abstracting and Indexing: DOAJ, Index Copernicus, OAJI, Scientific Indexing Services, JF, Google Scholar, Open Access

IJEGEO International Journal of Environment and Geoinformatics 5(1): 1--16 (2018)

Spatial Modelling of Air Pollution from PM_{10} and SO_2 concentrations during Winter Season in Marmara Region:2013-2014

Ozan Arslan*, Özer Akyürek

Kocaeli University, Engineering Faculty, Department of Geomatics

Corresponding author*
Tel :+90 262 303 3244
E-mail : ozan601@yahoo.com

Received 10 Nov 2017
Accepted 04 Feb 2018

Abstract

It was aimed to characterize spatial variations of air pollutants in Marmara region, Turkey for determining contribution to air pollution status in this study. We used spatial data analysis for measured sulfur dioxide (SO_2) and particulate matter (PM_{10}) concentrations recorded in Marmara, which is the most industrialized region of Turkey. GIS technique was used for monitoring air pollution and spatial analyses of these pollutants measured with the period during between October 1, 2013 and March 31, 2014 known as winter (heating) season obtained from 61 air quality monitoring stations located in this region. Spatial distribution maps for these pollutants were generated to determine emission patterns for the study area with the aid of geostatistical techniques. Additionally standard and spatial regression models were employed on the measured emissions to reveal possible factors of air quality in the region using standard ordinary least squares (OLS) and spatially autoregressive (SAR) regression models. The two regression models revealed that all the four explanatory meteorological variables (i.e. temperature, wind speed, humidity and atmospheric pressure) used to depict the pollution levels in relation to air quality. After the definition of the final model parameters, the model was fit to the entire data set and the residuals were examined for the presence of spatial autocorrelation with Moran's I. Compared to the OLS technique, SAR is found to be more appropriate when dependent variables exhibit spatial autocorrelation resulting in a valid model.

Keywords: Air Pollution, Geostatistical Analysis, OLS, SAR, Spatial Analysis

Introduction

Air pollution has emerged as a major health, environmental, economic and social problem all over the world. Aside from its adverse effects on the health of all living organisms, urban air pollution has profound regional and global impacts (Jacob and Winner, 2009; Alcamo et al., 2002; Brunekreef and Holgate, 2002; Jenkin and Clemitshaw, 2000; Güven et al., 2000; Kinney, 2008; Lee et al., 2007; Vautard and Hauglustaine, 2007; Lepeule et al., 2012). Concern on air pollution in the rapidly growing urban regions is receiving increasing emphasis all over the world, especially pollution by gaseous and particulate trace metals (Begüm et al., 2004; Salam et al., 2003). The sources of air pollution are classified as natural and anthropogenic. Anthropogenic primary pollutants such as carbon monoxide (CO), particulate matter (PM), nitrogen oxides (NO, NO_2, NO_x) and lead are harmful to health as well as environment. Sulfur dioxide (SO_2) and nitrogen oxides get transformed as sulfuric acid and nitric acid in the atmosphere due to chemical reactions and may fall as acid rain. During the past few decades, the atmosphere has been subjected to a large amount of contaminants via anthropogenic pollutants produced by both stationary (power plants, industrial and residential heating) and diffuse sources (road and marine traffic) (Azimi et al. 2005; Burak et al., 2004; 2009; Demir, 2018, Kural et al., 2018). Coal burning is the main man-made source of sulfur dioxide. Particulate matter consists of both organic and inorganic substances, mainly from dust, fly ash, soot,

DOI: 10.30897/ijegeo.

smoke, aerosols, fumes, mists and condensing vapors. Ozone is a colorless, pungent, highly reactive gas and is the principal component of smog, which is caused primarily by automobile emissions, heavily in urban areas (Yerramilli et al., 2011). In the literature there are many studies in which air pollution has been examined and analyzed with geospatial methods (Elbir, 2004; Fedra and Haurie, 1999; Lin and Lin, 2002; David et al., 1997; Briggs et al., 2003; Chen et al., 2015; Hee-Jae and Myung-Jin, 2014; Xiao et al., 2014; Rohde and Muller, 2015; Matejicek, 2005; Song, 2008). In order to improve the air quality, geographical information system (GIS) based decision support systems have also been developed for urban areas (Guerrero et al., 2008; Lim et al., 2005; Puliafito et al., 2003; Schmidt and Schafer, 1998; Jensen et al., 2001). Air quality modeling and quality mapping by GIS, preparation of emission inventory and scenario analysis for air pollution reduction are the main components of this spatio-temporal urban air quality management system.

Air quality in Turkey is generally a big concern, measurements show that all over the country increased pollution levels have becoming a threat to human health. Monitoring air pollution is the key issue for deciding policy measures and technological interventions to reduce air pollution levels. So typical pollutants have been monitored routinely at most official air-quality stations. Air pollution in Marmara region is also one of the important problems of daily life due to rapid population growth, intensive immigration, industrial facilities, utilization of old combustion technologies in industry, usage of poor quality fuels and traffic emissions. Scientific researches have thus been increased for air quality management and air pollution assessment related to the study region (i.e. Marmara region) (Pekey and Özaslan, 2012; Tayanç, 2000; Tayanç and Berçin, 2007; Akyürek et al., 2013; Gümrükçüoğlu and Soylu, 2011; Karaca, 2012a).

In this study it was aimed to characterize spatial variations of air pollutants such as SO_2 and PM_{10} for determining pollution status in Marmara region. No systematic air pollution monitoring study with GIS approach was reported in the region so far. PM_{10} and SO_2 air pollution values that have recorded as hourly averages were used as dataset in this study between the dates October 1, 2013 and March 31, 2014 which is referred to as the winter (heating) season in Air Quality Evaluation and Management Regulation (AQEMR). Marmara Region was chosen to be the area of study and daily averages from the hourly average data are obtained from the 61 air quality monitoring stations available in the region. Spatial analyses for the pollutant parameters have been carried out within GIS environment and pollution distribution maps created with the aid of kriging method which is one of the geostatistical techniques. In order to examine the contribution of different meteorological parameters on the levels of air pollution regression models were employed. The observed SO_2 concentrations are regressed using humidity, temperature, atmospheric pressure and wind speed variables. In the first instance of regression modeling, we apply ordinary least-squares (OLS) regression model. Since the estimation results obtained from the OLS model may have led to biased parameter estimation, the spatiality of the factors studied should be taken into account. In order to avoid model error and to improve the fitting precision, spatially autoregressive modeling (SAR) was applied. SAR modeling is, in fact, a general extension to OLS regression models and solves the issue of spatial autocorrelation in model residuals. The two regression model results of the observed SO_2 concentrations were quantitatively analyzed.

Materials and Methods

Today, the urbanization is one of the most important factors affecting the air quality profile of Turkey. Significant efforts in recent years, such as the fuel shift from coal to natural gas, have aimed at reducing the air pollution levels in Turkey. Most of the metropolitan cities have built natural gas pipeline systems for use in residential heating and in industries. Significant improvements in the air quality have thus been observed in some cities, and the air pollution profile of Turkey has begun to change. However, some regions of Turkey still suffer from air pollution, as in the Marmara region. Low-quality fuel usage, dominating meteorological factors, land use characteristics and industrial sources influence local and regional air quality parameters in the region (Deniz and Durmusoglu, 2008; Karaca, 2012b).

Study region is the Marmara Region situated between 26^0 and 31^0 Eastern longitudes and 38^0 and 42^0 Northern latitudes with a population of 23,202,727 people. In 2012 - 2013, 779,434 people have been immigrated to, and 654.171 people have been immigrated from the Marmara Region which shelters the provinces equipped with intense industrial facilities (Bursa, İstanbul, Kocaeli, Tekirdağ) within its body, and has a population in proportion to the intensity thereof (http://www.tuik.gov.tr). Due to the improving industrialization and rapid growth of the regional population, increased pollution levels have becoming a threat to human health in the region. Monitoring air pollutants in the region are gaining more importance due to harmful effects. For this reason pollution levels should be monitored in the region attentively. It is thus required to observe and monitor the major pollutant parameters, such as PM_{10} and SO_2, since these pollutants are emitted from the industrial facilities and originated from the solid fuels generally used for the residential heating purposes.

National Air Quality Monitoring Network of Turkey has been established, introducing air quality monitoring stations in 81 provinces within the body of the Ministry of Environment and Urban Planning in 2005-2007, in order to monitor air quality and take required measures in a timely manner. There are 125 air quality monitoring stations, three of them are mobile in Turkey as of the year 2014. SO_2, PM_{10}, nitrogen oxides, CO and O_3 parameters are measured in a fully automatically manner in all of the air quality monitoring stations established. Some of the stations are also capable of measuring some meteorological data additionally. Measurement data accumulated in the monitoring stations are transferred to the Data Processing Center of Environmental Reference Laboratory belonging to the Ministry of Environment and Urban Planning. In addition, 39 air quality monitoring stations have been founded in the region by the Directorate of Marmara Clean Air Center (MCAC) within the body of the relevant ministry. We used all possible data belonging to the specified period as daily average values of PM_{10} and SO_2 measurements belonging to those stations after a data treatment and validation process. These two pollutant parameters are commonly monitored at the stations connected to the system network.

In many countries, the limit values set forth by the European Union (EU) and the World Health Organization (WHO) are used locally in order to keep air pollution under control. Long-term exposure limit values, short-term limit values, winter season average values and warning thresholds for PM_{10} and SO_2 are specified in the AQEMR published in the year 2008 in Turkey. Average limit values for PM_{10} and SO_2 pollutants specified in AQEMR and international regulations are given in Table 1.

Table 1 PM_{10} and SO_2 pollutants with the national and international limits

Pollutant	**Turkish Limit Values (AQEMR) (µg/m^3)**	**EU regulations (µg/m^3)**	**WHO guidelines (µg/m^3)**
PM_{10}	90 (24h) 56 (ann.)	50 (24h) 40 (ann.)	50 (24h) 20 (ann.)
SO_2	470 (1h) 225 (24h) 20 (ann.)	350 (1h) 125 (24h) 20 (ann.)	20 (24h) 500 (10 min)

PM_{10} and SO_2 air pollution emissions that have been recorded as hourly averages between the dates October 1 and March 31 which is referred to as the winter season in AQEMR, were used as dataset in this study. Marmara Region was chosen to be the study area as previously explained and daily averages have been calculated from the hourly average data obtained from the 61 air quality monitoring stations available in the region are given in Fig. 1, and monthly air pollution values are obtained from these daily averages. GIS have been used as a platform for spatio-temporal analysis of urban air quality. Air pollution values have been stored in the form of dbf tables which are a database format and transferred to the geodatabase environment.

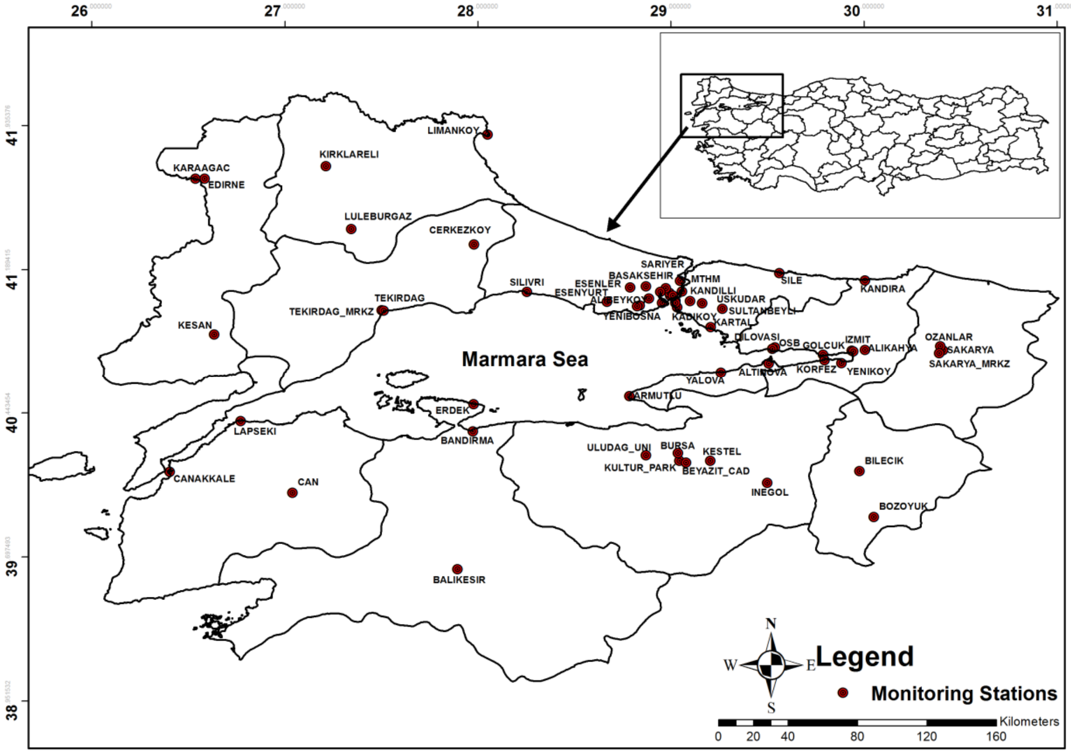

Fig. 1. 61 Air quality monitoring stations available in the Marmara region

Because of its unique spatial and temporal analysis functions, GIS has been widely used in pollution monitoring and evaluation of air quality. In the study it was benefited from ArcGIS 10.1 software for the operations related to database formation, querying, and analysis of air pollution. It was aimed to map spatial distributions of the measured pollutant parameters using geostatistical method in the study region. With the aid of geostatistical analysis module available in the ArcGIS software, PM_{10} and SO_2 air pollution parameters belonging to the winter season have been analyzed according to the kriging method and spatial pollution distribution maps have been generated for the region.

The distributions of five pollutant parameters obtained from the GIS environment are given in Fig. 2. Higher PM10 concentrations generally have been observed in the industrial territories and at places where solid fuels were used for residential heating purposes. During the course of winter season, higher concentration values as monthly averages have been measured in the cities such as Kocaeli, Sakarya, Bursa, Tekirdağ and İstanbul where the industrial facilities are rather intensive. As seen from the Fig. 2 higher PM_{10} concentration values were obtained from Sakarya and Bursa provinces. Measured pollutants are still high in Edirne, Kocaeli, İstanbul, Bilecik and Tekirdağ cities. Minimum concentrations were observed in Yalova city. It should be noted that SO_2 concentration values measured in Edirne and Çanakkale provinces are especially higher than the others (Fig. 2). That is why solid fuels (i.e. coal, etc.) have been used for residential heating in Keşan district (in Edirne) and its surroundings. The other hand there is a thermal power plant located in Çan district (in Çanakkale) within its borders which uses lignite coal to generate electric power. Measured NO and NO_2 concentrations are higher in İstanbul than the other cities in region. Monthly average O_3 concentrations have high values in Balıkesir and Kırklareli cities.

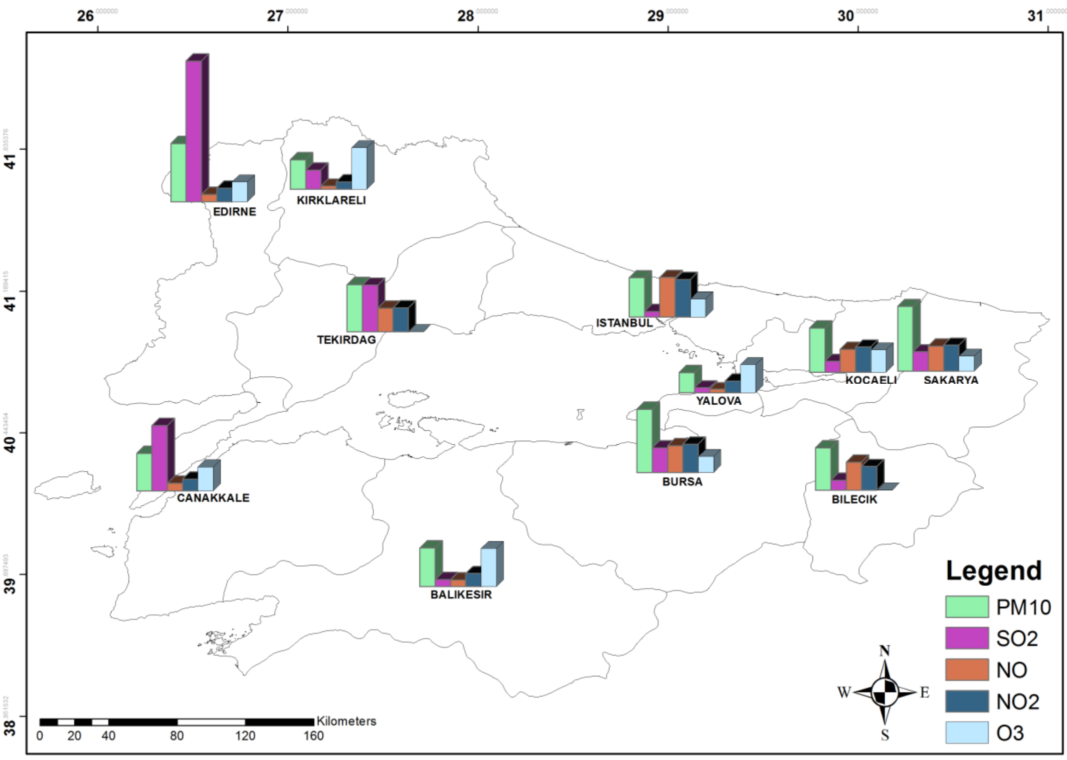

Fig. 2. Distribution of pollutant parameters of winter season for the provinces in GIS environment

Results and Discussion

It is observed that monthly averages for the measured PM_{10} pollutant obtained from the Marmara region exceeded the international limits (i.e. EU and WHO). Investigating hourly concentrations it can be seen that measurement values of the pollutant have exceeded the adopted limits for many times. Monthly averages for the SO_2 pollutant obtained from the region have found to be higher than the limits adopted in WHO regulation and conversely found to be lower than limits of EU. In addition to this hourly measurement values of the pollutant have exceeded the adopted limits for many times. These results indicate that the region has been facing increasing urban air pollution. Descriptive statistics for the measured PM_{10} parameter as monthly averages are shown in the Table 2 for winter season. Limit value is also given for the pollutant parameter for comparing the measurement concentrations. Concentrations as monthly averages are higher than limit values for all the months in the season except October.

Table 2 Descriptive statistics for PM_{10} parameter by month during winter (heating) season in 2013-2014

	Minimum ($\mu g/m^3$)	Maximum ($\mu g/m^3$)	Average ($\mu g/m^3$)	Standard Deviation	Limit Value (annually)
October	9	104	54.53	22.13	
November	8	125	58.07	24.87	
December	10	173	72.57	33.28	56 $\mu g/m^3$
January	8	153	72.31	29.55	
February	8	159	65.76	29.76	
March	10	127	57.59	24.65	

Descriptive statistics for the measured SO_2 parameter as monthly averages are shown in the Table 3 for winter season. Limit value is also given for the pollutant parameter for comparing the measurement concentrations. Concentrations exceeded the limit value for all the months in the season except October particularly. The measured concentration has risen to two times the limit value in December and January.

Table 3 Statistical data for SO_2 parameter by month during winter (heating) season in 2013-2014

	Minimum ($\mu g/m^3$)	Maximum ($\mu g/m^3$)	Average ($\mu g/m^3$)	Standard Deviation	Limit Value (annually)
October	3	308	17.49	42.67	
November	2	554	30.68	81.18	
December	5	893	51.09	133.41	20 $\mu g/m^3$
January	1	700	41.15	107.07	
February	2	590	35.49	88.77	
March	3	553	33.61	79.76	

Figure 3 demonstrates, PM_{10} and SO_2 pollution parameter concentrations respectively generated by the calculation of monthly averages from daily averages obtained from MHTM for Keşan and Çan districts in 2014, and limit values (denoted as dotted lines) specified in AQEMR belonging to these parameters. SO_2 parameter, in particular, has been measured quite above the limit value during the winter months in both districts. SO_2 concentrations measured in Keşan were greater than the national limit value of 150 $\mu g/m^3$ approximately by a factor of five (i.e. five times) in the months January and November and by a factor of four in February. It is clear that such air pollution was resulting from the domestic heating since the values measured during summer months dropped down to zero. In particular, when hourly averages related to SO_2 pollutant parameter are taken into consideration in Keşan, throughout the whole winter season, it is observed that pollutant concentration shows exceptional rises at certain hours of a day. These hours correspond to the hours of operating the heaters and lighting the stoves during morning and evening hours for the heating purposes. The measured values of PM_{10} pollutant emissions reach the same high value as proportional to the SO_2 peak hours. These concentration values for both pollutants continue to keep their high levels throughout the whole winter season at the specified hours of the day (when the heaters and stoves are fired up in the morning and evening).

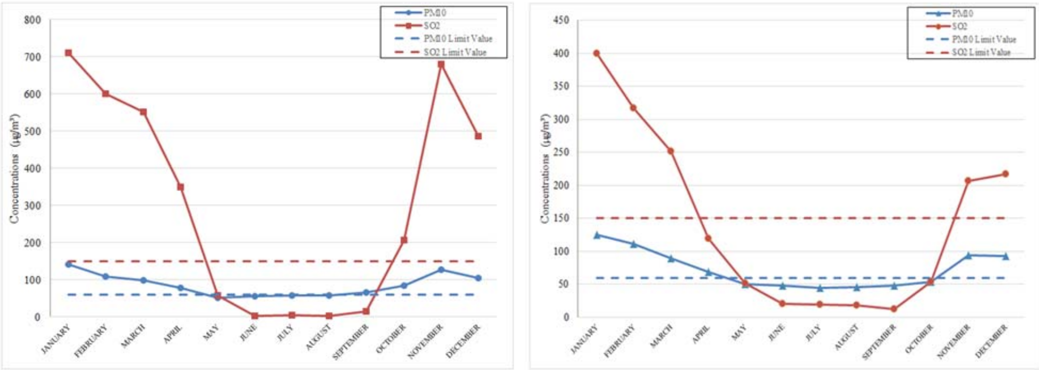

Fig. 3. PM_{10} and SO_2 concentrations and limit values of Keşan (left) and Çan (right) in the year 2014.

Spatial variability with spatial-dependence relations of air pollutants can be examined by determining spatial patterns related to air pollution parameters and generating spatial distribution maps of air pollution with the aid of GIS. Spatial distribution maps are generated by obtaining dependences and probabilities determined from the semivariograms with the support of classical (ordinary) kriging method, which is one of the spatial analysis techniques. The pollution distribution maps presented in Fig. 4 show monthly variations of the PM_{10} concentrations. The particulate matter concentration measured by months, December and January which are literally the middle of this time period became the maximum. As seen from the Fig. 4a PM_{10} concentrations did not exceed limit values of AQEMR (national standard) across in the Marmara region on October. As seen from the figure higher measured concentration values are observed in Dilovası, Kocaeli where intensive industrial plants and organized industrial zones are located, and in Bursa province and also in Sakarya province where solid fuel is used (Gümrükçüoğlu and Soylu, 2011).

PM_{10} concentrations have slightly increased in the same region on November as shown in Fig. 4b. It is clearly be seen from the distribution map belonging to the December in Fig. 4c, PM_{10} levels are generally high throughout the region. Air pollution seem to be high in the districts where industrial facilities (Bursa, Kocaeli and Sakarya, Tekirdağ provinces) and solid fuel is still used for residential heating in Edirne and Çanakkale provinces. Relatively high pollution levels can generally be seen in the region from the distribution map for January in Fig. 4d but air pollution is decreased to a certain extent in Istanbul and Kocaeli provinces. Higher pollution levels can be seen in industrial zones and the districts where solid fuel is widely used as the beginning of the winter season in the distribution map created for February month in Fig. 4e. There seems to be a declining tendency of pollution in the other provinces. Pollutant values are very close to the limit values throughout the region in the map for March in Fig. 4f.

Major source of SO_2 are the solid fuels used for the residential heating purposes. For this reason, as it is seen in the distribution maps (Fig. 5), throughout the whole heating season, much higher pollution values than other stations have been measured in Keşan and its surroundings where solid fuels are used in the houses for heating purposes and Çan where there is a thermal power plant within its borders using lignite coal in order to produce electricity. In addition, high SO_2 values have been recorded in the air quality monitoring stations located in the provinces such as Kocaeli, Sakarya, Bursa and Tekirdağ where the industrial facilities are rather concentrated.

Since direct proportion was observed between the two measured pollutants in this district, interactions of the pollutants are also evaluated to reveal the relationships between the measured concentrations in different districts of the whole region. Fig. 6 shows correlations between the measured SO_2 and PM_{10} pollutants obtained from the different stations in Marmara region. It is clearly be seen that there is a linear relationship between the pollutants. This result is, in fact, typical since sources of these two pollutants are nearly the same as stated in the literature (Tayanç, 2000). Maximum correlation value (R^2=0.97) is observed in Kandıra district on December as shown in Fig. 6c. Minimum correlation coefficient is observed (R^2=0.73) in Keşan district as illustrated in Fig. 6a. Evaluating relationship between SO_2 and PM_{10} concentrations in the other parts of the region direct proportion was seen similarly.

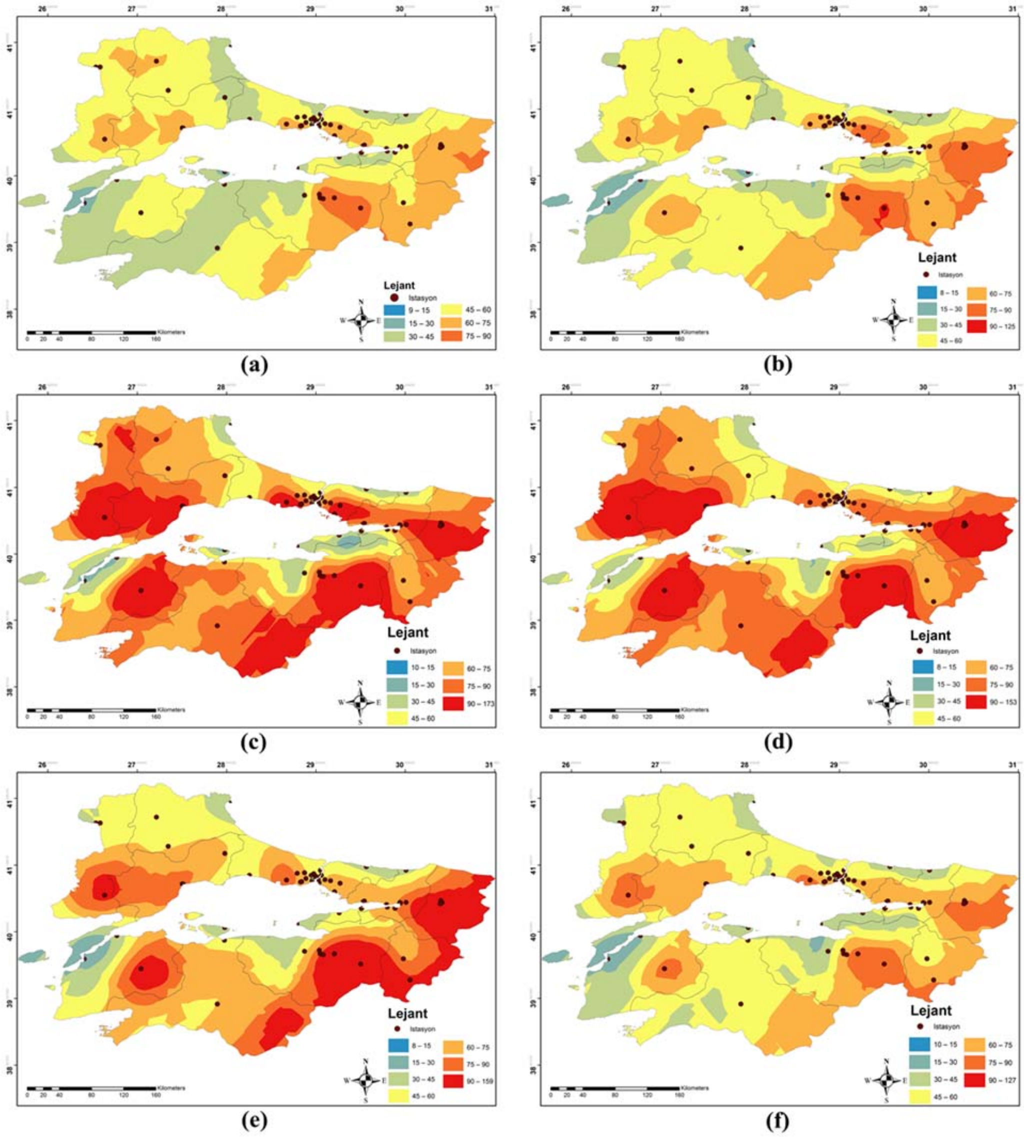

Fig. 4. PM_{10} pollutant distribution maps for winter season in the Marmara region; (a) October (b) November (c) December (d) January (e) February (f) March

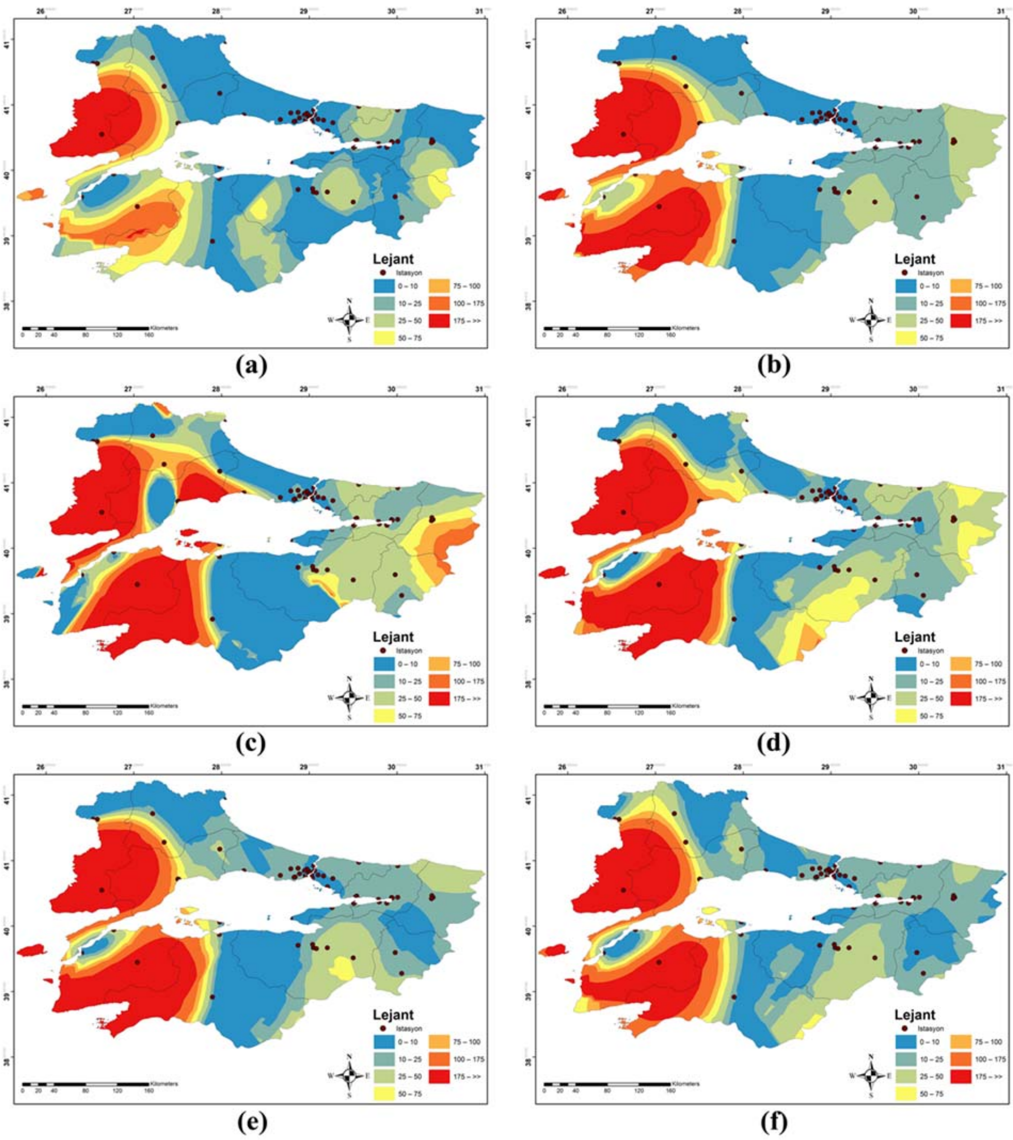

Fig. 5. SO_2 pollutant distribution maps for winter season in the Marmara region; (a) October (b) November (c) December (d) January (e) February (f) March

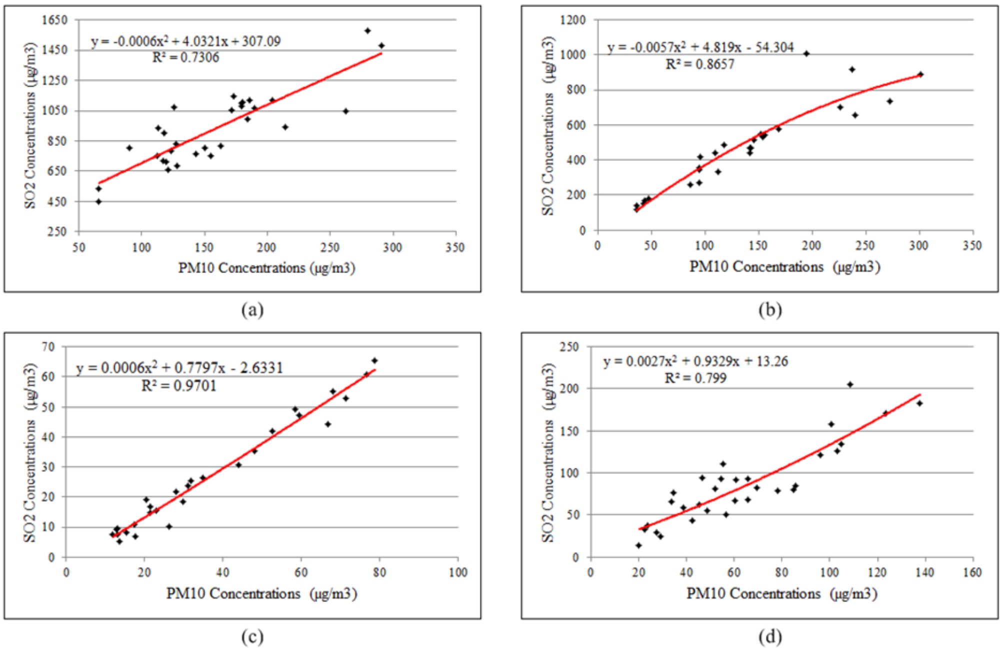

Fig. 6. Relationship between SO_2 and PM_{10} concentrations for districts; (a) Keşan (b) Çan (c) Kandıra (d) Lüleburgaz

In addition, we know from existing experience that air pollution has a strongly trans-regional character; it inevitably affects neighboring regions (i.e. spatial autocorrelation). This characteristic breaks with the basic precondition for classical regression analysis that is if we undertake OLS estimation under this circumstance, the results are in fact likely to be biased. If spatial autocorrelation exists in the spatial units being addressed, an appropriate spatial regression model must be chosen. Spatial regression models allow researchers to account for dependence among their observations, which often arises when observations are collected from points or regions located in space. The spatial lag model (SAR) is spatially constant coefficient model that can be used to produce a spatial extension of OLS, thereby correcting certain spatial dependence problems. Use of the SAR model is appropriate when spatial dependence is suspected in the values of the dependent variable, an occurrence that can give rise to auto-regressive problems. It is widely recognized that description of spatial patterns using variograms is sometimes prone to errors and incorporating the autocorrelation structure into modeling may be an important task. Spatial autocorrelation measures the similarity or strength of correlation between samples for a given variable as a function of spatial distance. For quantitative variables, such as pollutant parameters, the Moran's I coefficient is the most commonly used coefficient in univariate autocorrelation analyses. Spatial data are known to exhibit spatial non-stationarity, inconstant spatial variability, and can imply inconstant relationships among variables over space. This property leads to spatial instability of regression coefficients and can be associated with autocorrelated regression residuals (Fotheringham et al., 1998). Spatial autocorrelation is commonly addressed by spatially autoregressive modeling and different forms of autoregressive models have been recently applied in environmental ecology (Lichstein et al., 2002; Tognelli and Kelt, 2004; Fortin and Dale, 2005). These models have been mainly used as a way to take the spatial structure into account in data and, at the same time, to evaluate how different environmental predictors are related to spatial variations in concentration values.

A spatially autoregressive model (SAR) was calculated to produce a valid model when spatial structure occurs in the error terms of ordinary least squares regression models. The SAR model contains an autoregressive term (qyi), multiplied by a spatial weights matrix (W), which selects spatially autocorrelated units (Getis and Aldstadt, 2004).

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \rho W y_i + \varepsilon_i \quad (1)$$

where the response variable at location *i*, i.e., y_i, (e.g., observed SO_2 values), is expressed as a function of *k* meteorological predictors, i.e., x_{i1} through x_{ik} . The β_0 through βk regression coefficients were estimated using the SAR model. Note that if the autoregressive term is ignored in this equation, standard regression model form is obtained. Both standart regression and spatial autoregressive models were employed to examine the contribution of different sources of air pollution on the levels of pollutants observed in study region. Pollution concentrations (i.e. SO_2, PM_{10}) were modelled as a function of the selected predictors which included to temperature, wind speed, humidity and atmospheric pressure. Hence, standard estimation method, i.e. OLS regression, was used to investigate the influence factors for SO_2 emissions. Through the OLS estimation, the R^2 (goodness of fit) of the model was found to be 0.977, the adjusted R^2 was 0.94 and the *F*-value was 10.784 are shown in the Table 4. The four meteorological variables account for 97.7% of the variation in SO_2 (for January). The global regression model is obtained from the estimation as in the following.

$$y(SO_2) = -68.097 - 4.85_{temperature} + 4.37_{windspeed} - 0.41_{humidity} + 0.14_{pressure} + e \quad (2)$$

The significance tests of the coefficients showed that the regression coefficients to have different signs—that is to say, the selected explanatory variables were shown to have both positive and negative effects in relation to pollutant values. The most important explanatory variable is humidity according to the standardized regression coefficient (-0.835). All the variables passed the significance test at the 1% level. Wind speed was found to have less influence in relation to SO_2 concentrations. Akaike information criterion (AIC) was also used to select the best model. This AIC criterion of the OLS model was -46.8. The diagnostic tests (*i.e.*, Moran's *I*, $p < 0.01$) indicate a possibility of problems with autocorrelation.

Table 4 OLS modelling Results for January SO_2 as a response variable and 4 predictor variables

Variable	Coeff.	Std Coeff.	VIF	Std Error	t	P Value
Constant	-68.097	0	0	97.061	-0.702	< 0.01
Temperature	-4.85	-0.484	2.008	2.136	-2.271	< 0.01
Wind Speed	4.37	0.207	2.653	5.174	0.845	< 0.01
Humidity	-0.41	-0.835	1.157	0.079	-5.159	< 0.01
Pressure	0.14	0.36	3.802	0.114	1.226	< 0.01

n: 6 r: 0.989 r^2: 0.977 r^2adj: 0.943 F: 10.784 P: 0.008
Akaike's Information Criterion (AIC): -46.8

To compare to ordinary linear regression, we set up SAR regression model. SAR regression model for SO_2 concentration data yielded 96.6% R^2 value. The *F*-value was 8.613 and AIC was -12.662 are shown in the Table 5. In this model humidity is the most important variable again according to the standardized regression coefficient. The difference between R2 values suggest that the autoregressive term accounts for a slightly small portion of the model fit. This comparison might be evaluated to be suggest some model stability however by comparing AIC values of the OLS and SAR models, the SAR regression model was considered the more appropriate model. Thus, the results suggest that the chosen model is adequate for modeling the spatial structure in the residuals. Table 5 provides the detailed results of the SAR estimation. The SAR regression model is obtained from the estimation as in the following.

$$y(SO_2) = -78.267 - 5.16_{temperature} + 3.26_{windspeed} - 0.38_{humidity} + 0.15_{pressure} + e \quad (3)$$

On the whole, the value of the parameters estimated using SAR were higher than those obtained using OLS. As a result for predictive purposes, using any model is better than assuming that no spatial autocorrelation exists, especially considering the relative high R^2 values of all autoregressive models.

Table 5 SAR modelling results for January SO_2 as a response variable and 4 predictor variables

Variable	OLS Coeff.	SAR Coeff.	Std Coeff.	Std Error	t	P Value
Constant	-68.097	-78.267	0	37.041	-2.113	< 0.01
Temperature	-4.85	-5.16	-0.515	0.848	-6.088	< 0.01
Wind Speed	4.37	3.263	0.155	2.132	1.531	< 0.01
Humidity	-0.41	-0.387	-0.788	0.032	-12.053	< 0.01
Pressure	0.14	0.153	0.394	0.044	3.515	< 0.01

n: 6 F: 8.613 P: 0.012
Total Explained (Predictor + Space): r: 0.981 r^2:0.962 AIC: -12.662
Spatial autoregressive parameter (rho): -0.772
Alpha: 1.0

It is also plausible to explore spatial patterns in the model, especially in model residuals (Fig. 7 and Fig. 8). There is relatively high Moran's I values in the first distance class, indicating error terms are biased. Additionally there is a lack of explanation of concentration values at these short distances. As it is known Moran's I usually varies between –1.0 and 1.0, for maximum negative and positive autocorrelation, respectively. Non-zero values of Moran's I indicate that SO_2 pollutant values at a given spatial distance are more similar or less similar. From these figures it can be concluded that there is a spatial structure on residuals to a some extent degree. Relatively high values of Moran's I (i.e., I > 0.1) remain in the residuals of the two (OLS and SAR) models.

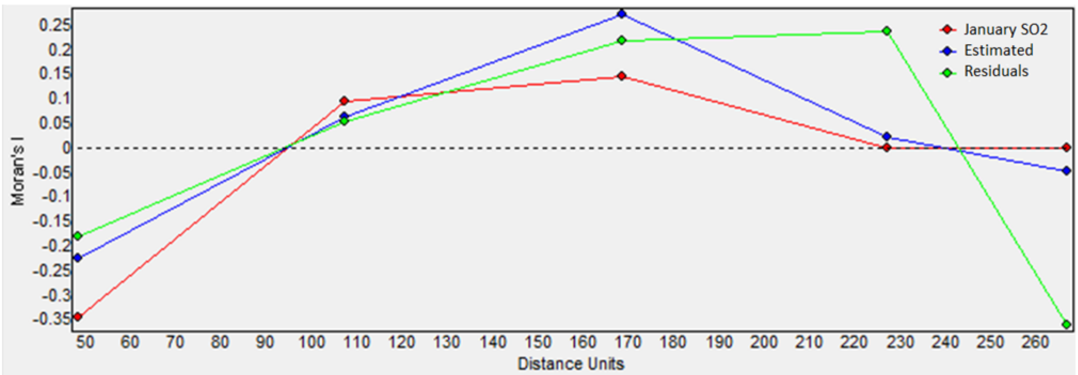

Fig. 7. OLS regression model residual analysis

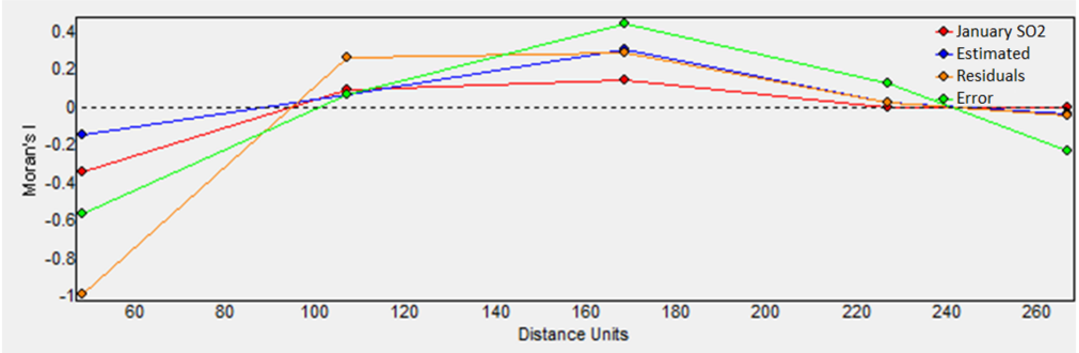

Fig. 8. SAR regression model residual analysis

The residuals from the linear regression model were spatially correlated (i.e. according to Moran's I values), which indicates that the model was not meeting the independence of errors assumption. Briefly, the use of the spatial autoregressive model was effective to remove the spatial autocorrelation that occurred in the residuals of the ordinary least squares regression model.

Conclusion

This study conducted a spatial analysis on the emission patterns of two major air pollutants named PM_{10} and SO_2 for winter period from 2013 through 2014 in Marmara region. One of the main contributions of the study is to show that GIS based spatial analysis can be a powerful tool for air quality management. The technique is effectively used for monitoring and analyzing air pollution in large areas like the study region. Pollution distribution patterns were identified by means of generated pollution distribution maps made by geostatistical interpolation technique for the determination of high concentrations of air pollution sources. It should be noted that considerable increases have been obtained in the measured concentrations of SO_2 and PM_{10} during the winter season forming a serious air pollution in the region. The results indicate that industry and residential heating seem to be responsible for pollution in the study area. The values of PM_{10} measured especially in Bursa, Kocaeli, Sakarya and Tekirdağ provinces where industrial facilities are abundant, were high, and such a trend has been also observed in the pollution distribution maps. In addition, PM_{10} values were observedly high in the surroundings of Keşan and Çan districts as well where solid fuels are used for the residential heating purposes. Considering the fact that SO_2 is generated from the solid fuels used for the heating purposes, in places where natural gas is available for the heating purposes, SO_2 pollution value was measured below the limit values. However, pollution concentrations measured in such places where solid fuels are used for the residential heating purposes as, in particular, Keşan and Çan districts were above the hourly, daily and monthly threshold values in the records.

This study then analyzed the measured emissions to reveal possible factors (predictors) of air quality in the region using standard OLS and SAR regression models. SAR model has been mainly used as a way to take the spatial structure into account in data. The two regression models revealed that all the four explanatory meteorological variables used to depict the pollution levels in relation to air quality. Among the variables, temperature, wind speed, humidity and atmospheric pressure were all found to have had a significant influence over air quality. The humidity variable had the highest univariate R^2 value for all the univariate regressions, which highlights the importance of humidity into the models. After the specification of the final model parameters, the model was fit to the entire data set and the residuals were examined for the presence of spatial autocorrelation with Moran's I. Compared to the OLS technique, SAR is more appropriate when dependent variables exhibit spatial autocorrelation.

References

Akyürek, Ö., Arslan, O. and Karademir, A. (2013). SO_2 ve PM_{10} Hava Kirliliği Parametrelerinin CBS ile Konumsal Analizi: Kocaeli Örneği. TMMOB Coğrafi Bilgi Sistemleri Kongresi, November 11-13, 2013, Ankara, Turkey (in Turkish).

Alcamo, J., Mayerhofer, P., Guardans, R., Harmelen, T., Minnen, J., Onigkeit, J., Posch, M. and Vries, B. (2002). An integrated assessment of regional air pollution and climate change in Europe: findings of the AIR-CLIM project. Environmental Science Policy, 4: 257-272.

Azimi, V. Rocher, M. Muller, R. Moilleron, D.R. and Thévenot (2005). Sources, distribution and variability of hydrocarbons and metals in atmospheric deposition in an urban area (Paris, France) Sci. Total Environ.,337: 223-239.

Begüm, B. A., Kim, E., Biswas, S. K. and Hoopke, P. K. (2004). Investigation of Sources of Atmospheric Aerosol at Urban and Semi Urban Areas in Bangladesh. Atmospheric Environment, 38(19): 3025-3038.

Briggs, D., Beale, L., de Hoogh, C., Gulliver, J. and Mitchell, J. F. (2003). Beyond the buffers: advancing the use of GIS to model exposures to environmental pollution: Isee-478. Epidemiology, 14(5): 95.

Brunekreef, B. and Holgate, S. T. (2002). Air pollution and health. Lancet, 360(9341), 1233-1242.

Burak, S., Doğan, E., and Gazioğlu, C. (2004). Impact of urbanization and tourism on coastal environment. Ocean & Coastal Management 47 (9):, 515-527.

Burak, S., Ünlü, S. and Gazioğlu, C. (2009). Environmental stress created by chemical pollution in the Marmara Sea (Turkey). Asian Journal of Chemistry, Vol. 21(4): 3166-3174.

Chen, W., Yan, L. and Zhao, H. (2015). Seasonal Variations of Atmospheric Pollution and Air Quality in Beijing. Atmosphere, 6: 1753-1770.

David, J. B., Collins, S., Elliott, P., Fischer, P., Kingham, S., Lebret, E., Pryl, K., Van Reeuwijk, H., Smallbone, K. and Andre, V. (1997). Mapping urban air pollution using GIS: a regression-based approach. International Journal of Geographical Information Science, 11: 699-718.

Demir, K.A. (2018). Assessment of Exhaust Emissions from the Local Marine Survey of the Bosphorus, IU, Institute of Marine Sciences and Management Msc. Thesis.

Deniz, C. and Durmuşoğlu, Y. (2008). Estimating shipping emissions in the region of the Sea of Marmara, Turkey. Science of the Total Environment, 390: 255–261.

Elbir, T. (2004). A GIS based decision support system for estimation, visualization and analysis of air pollution for large Turkish cities. Atmospheric Environment, 38, 4509-4517.

Fedra, K. and Haur:e, A. (1999). A decision support system for air quality management combining GIS and optimization techniques. International Journal of Environment Pollution, 12: 125-146.

Fortin, M. J. and Dale, M. (2005). Spatial analysis: a guide for ecologists. Cambridge: Cambridge University Press.

Fotheringham, A., Charlton, M. E. and Brundson, C. (1998). Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. Environment and Planning A, 30(11): 1905–1927.

Getis, A. and Aldstadt, J. (2004). Constructing the spatial weights matrix using a local statistic. Geographical Analysis, 40: 297–309.

Guerrero, P. J., Jorba, O., Baldasano, J. M. and Gasso, S. (2008). The use of a modeling system as a tool for air quality management: annual high-resolution simulations and evaluation. Science of the Total Environment, 390: 323-340.

Gümrükçüoğlu, M. and Soylu, S. (2011). Adapazarı'nda Isınma Kaynaklı Hava Kirliliğinin İncelenmesi. TMMOB Coğrafi Bilgi Sistemleri Kongresi, 31 October – 04 November, 2011, Antalya, Turkey (in Turkish).

Güven, KC., Sur, Hİ., Okuş, E., Yüksek, A., Uysal, A., Balkıs, N., Kıratlı, N., Ünlü,SV., Altıok, H., Taş, S., Aslan, A., Yılmaz, İN., Müftüoğlu, AE., Gazioğlu, C. and Cebeci, M. (2000). Oceanography of the Izmit Bay Following 1999 Earthquake, Turkish Ministry of Environment Report.

Hee-Jae, K. and Myung-Jin, J. (2014). Analysis on Relationship Between Urban Development Characteristics and Air Pollution Level – A Case of Seoul Metropolitan Region. Korea Planners' Association, 49(7): 151-167.

Jacob, D. J. and Winner, D. A. (2009). Effect of climate change on air quality. Atmospheric Environment, 43: 51-63.

Jenkin, M. E. and Clemitshaw, K. C. (2000). Ozone and other secondary photochemical pollutants: chemical processes governing their formation in the planetary boundary layer. Atmospheric Environment, 34: 2499-2527.

Jensen, S. S., Berkowicz, R., Hansen, H. S. and Hertel, O. (2001). A Danish decision-support GIS tool for management of urban air quality and human exposures. Transportation Research Part: D-Transport and Environment, 6: 229-241.

Karaca, F. (2012a). İstanbul'un Tarihi Yarımadası'nda BTEK Yüzey Yayılım Profilinin Araştırılması. Hava Kirliliği Araştırmaları Dergisi, 12(1): 53-65.

Karaca, F. (2012b). Determination of air quality zones in Turkey. Journal of the Air & Waste Management Association, 62(4): 408-419.

Kinney, P. L. (2008). Climate change, air quality, and human health. American Journal of Preventive Medicine, 35: 459-467.

Kural, G., Çağlar Balkıs, N. and Aksu, A. (2018). Source identification of Polycyclic Aromatic Hydrocarbons (PAHs) in the urban environment of İstanbul, International Journal of Environment and Geoinformatics (IJEGEO), Vol.5(1):1-16.

Lee, J., Son, J. and Cho, Y. (2007). The adverse effects of fine particle air pollution on respiratory function in the elderly. Science Total Environment, 385: 28-36.

Lepeule, J., Laden, F., Dockery, D. and Schwartz, J. (2012). Chronic exposure to fine particles and mortality: an extended follow-up of the Harvard six cities study from 1974 to 2009. Environmental Health Perspectives, 120(7): 965-970.

Lichstein, J. W., Simons, T. R., Shriner, S. A. and Franzreb, K. E. (2002). Spatial autocorrelation and autoregressive models in ecology. Ecological Monographs, 72(3): 445-463.

Lim, L. L., Hughes, S. J. and Hellawell, E. E. (2005). Integrated decision support system for urban air quality assessment. Environmental Modelling & Software, 20: 947-954.

Lin, M. D. and Lin, Y. C. (2002). The application of GIS to air quality analysis in Taichung city, Taiwan, ROC. Environmental Modelling & Software, 17: 11-19.

Matejicek, L. (2005). Spatial Modeling of Air Pollution in Urban Areas with GIS: A Case Study on Integrated Database Development. Advances in Geosciences, 4: 63-68.

Pekey, B. and Özaslan, Ü. (2012). Spatial Distribution of SO_2, NO_2, and O_3 Concentrations in an Industrial City of Turkey Using a Passive Sampling Method. Clean – Soil Air Water, 41(5): 423-428.

Puliafito, E., Guevara, M. and Puliafito, C. (2003). Characterization of urban air quality using GIS as a management system. Environmental Pollution, 122: 105-117.

Rohde, R. A. and Muller, R. A. (2015). Air Pollution in China: Mapping of Concentrations and Sources. PLOS ONE, 10(8).

Salam, A., Bauer, H., Kassin, K., Ullah, S. M. and Puxbaum, H. (2003). Aerosol Chemical Characteristics of a Mega-City in southeast Asia (Dhaka, Bangladesh). Atmospheric Environment, 37(18): 2517-2528.

Schmidt, M. and Schafer, R. P. (1998). An integrated simulation system for traffic induced air pollution. Environmental Modelling & Software, 13: 295-303.

Song, S. J. (2008). A GIS Based Approach to Spatio-Temporal Analysis of Urban Air Quality in Chengdu Plain. The International Achieves of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37(B7), Beijing.

and temporal variation of sulfur dioxide levels over Istanbul, Turkey. Environmental Pollution, 107(1): 61-69.

Tayanç, M. and Berçin, A. (2007). SO_2 modeling in İzmit Gulf, Turkey during winter of 1997: 3 cases. Environmental Modelling & Assessment, 12(2): 119-129.

Tognelli, M. F. and Kelt, D. A. (2004). Analysis of determinants of mammalian species richness in South America using spatial autoregressive models. Ecography, 27(4): 427-436.

Vautard, R. and Hauglustaine, D. (2007). Impact of global climate change on regional air quality: introduction to the thematic issue. Comptes Rendus Geoscience, 339: 703-708.

Xiao, F., Qi, L., Yajie, Z., Jingje, W., Heming, L. and Ruofeng, X. (2014). Formation and Dominant Factors of Haze Pollution Over Beijing and Its Peripheral Areas in Winter. Atmospheric Pollution Research, 5(3): 528-538.

Yerramilli, A., Dodla, V. B. R. and Yerramilli, S. (2011). Air Pollution, Modelling and GIS based Decision Support Systems for Air Quality Risk Assessment. In: Nejadkoorki F (Eds), Advanced Air Pollution, InTech Press, Rijeka, 295-324.