Environmental Science and Pollution Research (2019) 26:24331–24345
https://doi.org/10.1007/s11356-018-1277-y

ENVIRONMENTAL PLANNING AND MANAGEMENT

Impact assessment of meteorological and environmental parameters on $PM_{2.5}$ concentrations using remote sensing data and GWR analysis (case study of Tehran)

Fakhreddin Hajiloo[1] · Saeid Hamzeh[1] · Mahsa Gheysari[1]

Received: 24 August 2017 / Accepted: 11 January 2018 / Published online: 1 March 2018

Abstract

The $PM_{2.5}$ as one of the main pollutants in Tehran city has a devastating effect on human health. Knowing the key parameters associated with $PM_{2.5}$ concentration is essential to take effective actions to reduce the concentration of these particles. This study assesses the relationship between meteorological (humidity, pressure, temperature, precipitation, and wind speed) and environmental parameters (normalize difference vegetation index and land surface temperature of MODIS satellite data) on $PM_{2.5}$ concentration in Tehran city. The Geographically Weighted Regression (GWR) was employed to assess the impact of key parameters on $PM_{2.5}$ concentrations in winter and summer. For this purpose, first the seasonal average of meteorological data were extracted and synchronized to satellite data. Then, using the ordinary least square model, the important parameters related to $PM_{2.5}$ concentration were determined and evaluated. Finally, using the GWR model, the relationships between parameters related to $PM_{2.5}$ concentration were analyzed. The results of this study indicate that meteorological and environmental parameters in winter season (71%) have a much higher ability to explain $PM_{2.5}$ concentration than summer season (40%). In winter, $PM_{2.5}$ concentration has a negative correlation with vegetation at most parts of the study area, a negative correlation with LST in the western and a positive correlation in the eastern part of the study area, a positive correlation with temperature, and a negative correlation with wind speed in the northeastern part of the study area. Precipitation has a positive correlation with $PM_{2.5}$ concentration in most parts of the study area in both seasons. But, it was investigated in case of higher precipitation (more than 2 mm), $PM_{2.5}$ concentration decreases. But, there is no negative relationship in any of the dependent parameters with $PM_{2.5}$ concentration in summer. In this season, the air temperature parameter showed a high correlation with $PM_{2.5}$ concentration. Also, spatial variations of the local coefficients for all parameters are higher in winter than in summer.

Keywords Air pollution · Meteorological parameters · NDVI · MODIS · $PM_{2.5}$ · Geographically weighted regression

Introduction

These days, air pollution is known as one of the main problems in urban areas. Outdoor air pollution is mainly derived from urban growth, expansion of industrial activities, and uncontrolled consumption of fossil fuels (Johansson et al. 2008; Shi et al. 2014; WHO 2008). At the first stage, this leads to impact on citizens' respiratory illness and to increase intensity of heart and lung diseases (Fan et al. 2016; Hwang et al. 2017; Yang et al. 2017) and, at the second stage, this plays an important role as a parameter in aggravation of climate changes, climatic fluctuations, and environmental impact (Ren et al. 2007). Hence, air pollution always has been as a major environmental issue by/for the experts and urban planners (White and Engelen 2000). Tehran is among the cities which are subject to severe air pollution and facing unhealthy days more than a third of the year (Rowshan et al. 2009).

In recent years, one of the greatest threats for Tehran has been particulate matters less than 2.5 microns, which causes most unhealthy days (Brajer et al. 2012). High concentration of $PM_{2.5}$ is a serious threat to the environment and human health (Luo et al. 2015; Miri et al. 2017; WHO

Responsible editor: Gerhard Lammel

✉ Saeid Hamzeh
saeid.hamzeh@ut.ac.ir

[1] Department of Remote Sensing and GIS, Faculty of Geography, University of Tehran, Tehran 141556465, Iran

2016) Therefore, the ability of understanding the relevant parameters on $PM_{2.5}$ concentration becomes an increasing key prerequisite to take effective steps to reduction and prevention of aerosol pollution. Parameters like traffic, industries, and land use have a relationship with air pollution in a constant form during the year. Climate and vegetation cover have changing relationship with air pollution (Fisher 2002; Makra et al. 2011; Pcu and Bosiacka 2011). The climate system is a complex, dynamic system, and the elements of this system are mutually influenced by $PM_{2.5}$ concentration (Chen et al. 2015; Kaufman et al. 2002). Therefore, exact analysis of various air pollutants and evaluation of environmental and meteorological parameters such as wind speed, wind direction, relative humidity, and air temperature are essential (Khokhar et al. 2017). As shown by previous studies, meteorological conditions can largely diffuse, dilute, and accumulate pollutants (Pohjola et al. 2002); thus, $PM_{2.5}$ mass concentration is mainly due to meteorological condition (Tai et al. 2010). Yang et al. (2011) concluded that meteorological conditions can, at least, make a contribution of 16% to the reduction of $PM_{2.5}$ mass concentration.

Since the access to ground measurements of related parameters to air pollution faced many limitations, satellite data can be used in areas where ground measurements are not available (Gupta et al. 2006). Potentials definitely exist in using remote sensing information for the validation of emission inventories and for a better understanding of the atmospheric processes controlling air pollution episodes. In addition, remote sensing can complement ground monitoring data when performing assessments of air pollution levels (Veefkind et al. 2007). The idea of using satellite imagery and use of analyst space of different sciences such as geographic information system (GIS) on various topics related to air pollution has spread in recent years. Impacts of different parameters differs basis on the spatial changes (Wu et al. 2017). In recent years, a relatively simple, but effective, new technique for exploring spatially varying relationships, called Geographically Weighted Regression (GWR), has been developed (Brunsdon et al. 2001; Fotheringham et al. 2001). Definitely, for analysis of spatial relationships of meteorological and environmental parameters with air pollution, GWR is more efficient than previous methods such as OLS (one of global spatial models).

In the field of particulate matters, especially $PM_{2.5}$, many studies predicted and estimated the $PM_{2.5}$ concentration using different models and methods. Up to date, some previous studies predicted surface $PM_{2.5}$ concentration by establishing the direct relationship between $PM_{2.5}$ and aerosol optical depth (Hu 2009; Schaap et al. 2009), while others estimated ground-level $PM_{2.5}$ concentrations using satellite aerosol optical depth in conjunction with diverse variables and fields (Liu et al. 2009; Parkinson 2003). In general, the aims of these studies were to recognize the meteorological and land use variables as effective predators of $PM_{2.5}$ and improve the model predictability using those variables (Lin et al. 2015; Liu et al. 2007; Liu et al. 2005; Tian and Chen 2010). The result of Chen et al. (2017a) proved that the higher $PM_{2.5}$ concentration, the stronger influences meteorological factors exert on $PM_{2.5}$ concentration. In another study of Chen et al. (2017b), at the national scale, temperature, humidity, wind, and air pressure exert stronger influences on $PM_{2.5}$ concentrations than other meteorological factors.

In recent years, the application of satellite remote sensing to air quality research, especially the application of aerosol optical depth (AOD) has been greatly promoted (Hoff and Christopher 2009; Martin 2008). But, little researches have been done on the use of another products of remote sensing like NDVI and LST and evaluated them as effective parameters on $PM_{2.5}$ concentration. So far, many models have developed in researches related to $PM_{2.5}$ concentration, but a few studies have used geographically weighted regression to estimate or investigate the effective variables on it (Hu et al. 2013; Lin et al. 2013; Lin et al. 2015; Luo et al. 2017). This study is aimed to investigate the impact of meteorological and environmental parameters on $PM_{2.5}$ concentration in winter and summer seasons using GWR method. For this purpose, for the first time, satellite-derived products (NDVI and LST products of MODIS sensor) as related parameters with air pollution and meteorological parameters were used. To the best of our knowledge, so far, limited attention was paid to explore the seasonal impacts of the parameters on $PM_{2.5}$ concentration, and in this research, we have used the GWR model to compare seasonal impacts of meteorological–environmental parameters on $PM_{2.5}$ concentration using satellite-derived products (LST, NDVI) for the first time.

Material and methods

Study area

The present study was conducted in Tehran, the capital city of Iran, which is located in the north of the central plateau of Iran within the longitudes of 51° to 51° 40′ E and the latitudes of 35° 30′ to 35° 51′ N. Tehran is a mountainside city with an altitude of 900 to 1700 m above sea level. Its urban area spreads entirely over the Iranian plateau, on the southern slopes of a very high and dense mountain barrier, with a peak of 3933 m, which is 2200 m higher than the city's residential areas. According to the latest Iranian Population and Housing Census in 2011 by the Statistical Center of Iran, Tehran, with a population of 8.1 Million people, is still ranked as most populous city in Iran with a very distinct demographic difference than other cities (Statistical Center of Iran, 2011, https://www.amar.org.ir/Portals/1/Iran/Atlas_Census_2011.pdf). Tehran is rated as one of the world's most polluted cities and suffers from severe air pollution. Tehran is divided into 22 urban districts, and based on the availability of meteorological and $PM_{2.5}$ concentration stations, this study was conducted in district nos. 2, 3, 5, 6, 7, 9, 10, 11, and 12. The location of study area is shown in Fig. 1.

Data and methodology

In the present study, different environmental data from meteorological and air quality stations and satellite imagery were used. The summary of these data is given as follows:

- The seasonal average of meteorological parameters (humidity, pressure, precipitation, wind speed, and air temperature calculated from daily data of Meteorological Organization for both winter (2014–2015) and summer (2015) separately.
- Ground-based $PM_{2.5}$ concentration data from seasonal average of daily $PM_{2.5}$ concentration data derived from the air quality station network of environmental protection organization and air quality control center of Tehran.
- Satellite images from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on board the Terra and Aqua satellites (Parkinson 2003): (a) in 36 spectral bands ranging in wavelength from 0.4 μm to 14.4 as 16-day normalized difference vegetation index (NDVI, MOD13A1) to represent the vegetation coverage and (b) land surface temperature (LST, MOD11A1) both achieved at NASA (available at https://ladsweb.modaps.eosdis.nasa.gov), with both being level-1A MODIS/Terra(EOS AM-1) products with spatial resolution of 1 km. the times coinciding the station datasets.

As mentioned above, only the ground measurements which had closed times to the over pass of the MODIS/Terra satellite were used in this study. A summary of variable used in modeling is given in Table 1.

Due to the low number of stations with enough information and lack of adequate coverage by stations in the whole city, and on the other hand because its data collection system is data point, it is necessary to construct new data points within the range of a discrete set of known data points. Generally, interpolation can be used to predict unknown values for any geographic point data, and it predicts values for cells in a raster from a limited number of sample data points. So, the seasonal average of ground measurements was extended to the whole city using IDW interpolation, one of the weighted average methods which estimates cell values by averaging the values

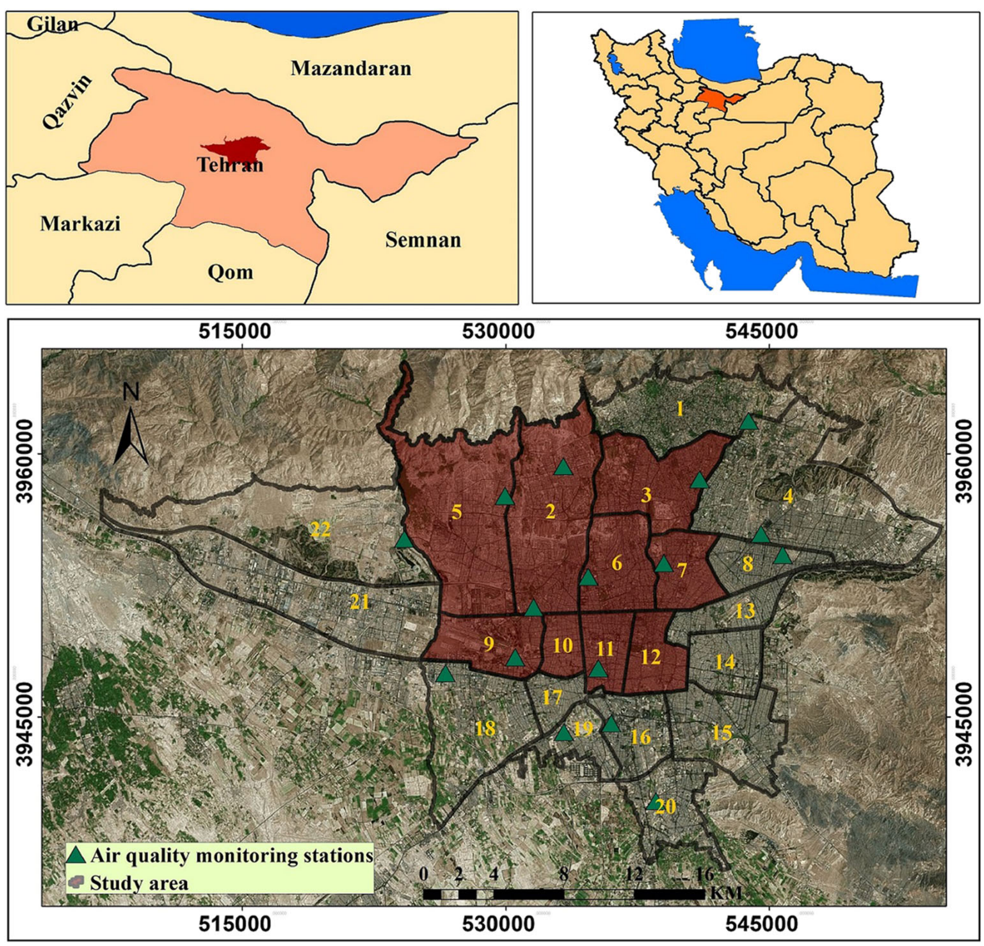

Fig. 1 The location of study area and air quality stations

Table 1 Summary of variables used in modeling analysis

		Winter				Summer			
Variables	Unit	Min	Max	Average	SD	Min	Max	Average	SD
Dependent variable									
$PM_{2.5}$	ug/m3	22.8	45.9	32.2	4.00	20.4	37.6	26.8	3.09
Independent variable									
NDVI	[− 1.1]	0.04	0.29	0.12	0.04	0.07	0.30	0.16	0.05
LST	K	296	304	301	1.55	312	320	316	2.37
Humidity	g/m^3	44.0	51.5	45.8	1.23	22.27	25.5	23.4	0.64
Pressure	hPa	845	882	865	8.43	850	876	861	5.66
Temperature	°C	9.54	11.24	10.1	0.42	31.7	33.3	32.1	0.39
Wind speed	m/s	1.12	2.89	2.05	0.40	1.69	2.83	2.07	0.28
Precipitation	mm	0.49	1.40	0.67	0.14	0.13	0.28	0.18	0.02

of sample data points in the neighborhood of each processing cell and, unlike, e.g., the kriging method, it does not follow the assumptions about the relationship between the spatial data. It only relies on the assumption that the closer a point is to the center of the cell being estimated, the more influence or weight it has in the averaging process.

Satellite images were georeferenced and averaged for both winter (2014–2015) and summer (2015) seasons. Spatial distributions of $PM_{2.5}$ and the chosen independent variables are shown in Figs. 2 and 3.

To assess the impact of meteorological and environmental parameters on $PM_{2.5}$ concentration, firstly with the help of OLS, multivariate correlation analysis was carried out between latent meteorological and environmental parameters and $PM_{2.5}$ concentrations to identify the decisive parameters of $PM_{2.5}$ concentrations before GWR. Actually, variables that had a significant relationship with the $PM_{2.5}$ were defined. For this purpose, all variables were entered into the model by using ArcGIS 10.4.1. Non-significant variables were removed step by step. For example, in the first performance of the model for winter season, pressure and then moisture variables were removed from the model. So, this procedure was continued until all remaining variables were statistically significant. Then, using geographically weighting regression model, the relationship between meteorological and environmental variables with particulate matter less than 2.5 μm were evaluated. Eventually, comparison was done between seasons. The methodology is summarized in the following flowchart (Fig. 4).

OLS model

OLS is a global regression method that it can be implemented in ARC GIS and is described using Eq. (1):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon \quad (1)$$

where Y is the dependent variable, X explanatory variables, β the coefficients of independent variables in describing the dependent variable and the random error with expectation 0 and variance σ^2 (Stone and Brooks 1990). One of the most important parameters in this model, the variance inflation factor value of regression variables (VIF), should be no more than 7.5, which ensures there is no multicollinearity and redundant independent variables in the regression model. If the VIF value is greater than 7.5, it means that two or more variables are similar to each other. VIF can measure how much the estimated variance of a coefficient is increased by local collinearity (Wheeler and Páez 2010; Wheeler and Tiefelsdorf 2005). In addition to VIF, there are some statistical definitions in OLS model such as multiple R-squared and adjusted R-squared values that both are measures of model performance. Possible values range from 0.0 to 1.0. Both the joint F statistic and joint Wald statistic are measures of overall model statistical significance. The Koenker (BP) statistic (Koenker's studentized Breusch-Pagan statistic) is a test to determine if the explanatory variables in the model have a consistent relationship to the dependent variable (what you are trying to predict/understand) both in geographic space and in data space. The Jarque-Bera statistic indicates whether or not the residuals (the observed/known dependent variable values minus the predicted/estimated values) are normally distributed.

GWR model

To constrain the spatial variability, the GWR model has been adopted to examine the relationship between meteorological and environmental parameters and $PM_{2.5}$ concentration on the different parts of the study area. The GWR model proposed by Brunsdon et al. (1996) can be used to estimate the parameters. The GWR is an extension of traditional standard regression techniques such as OLS because it allows local rather than

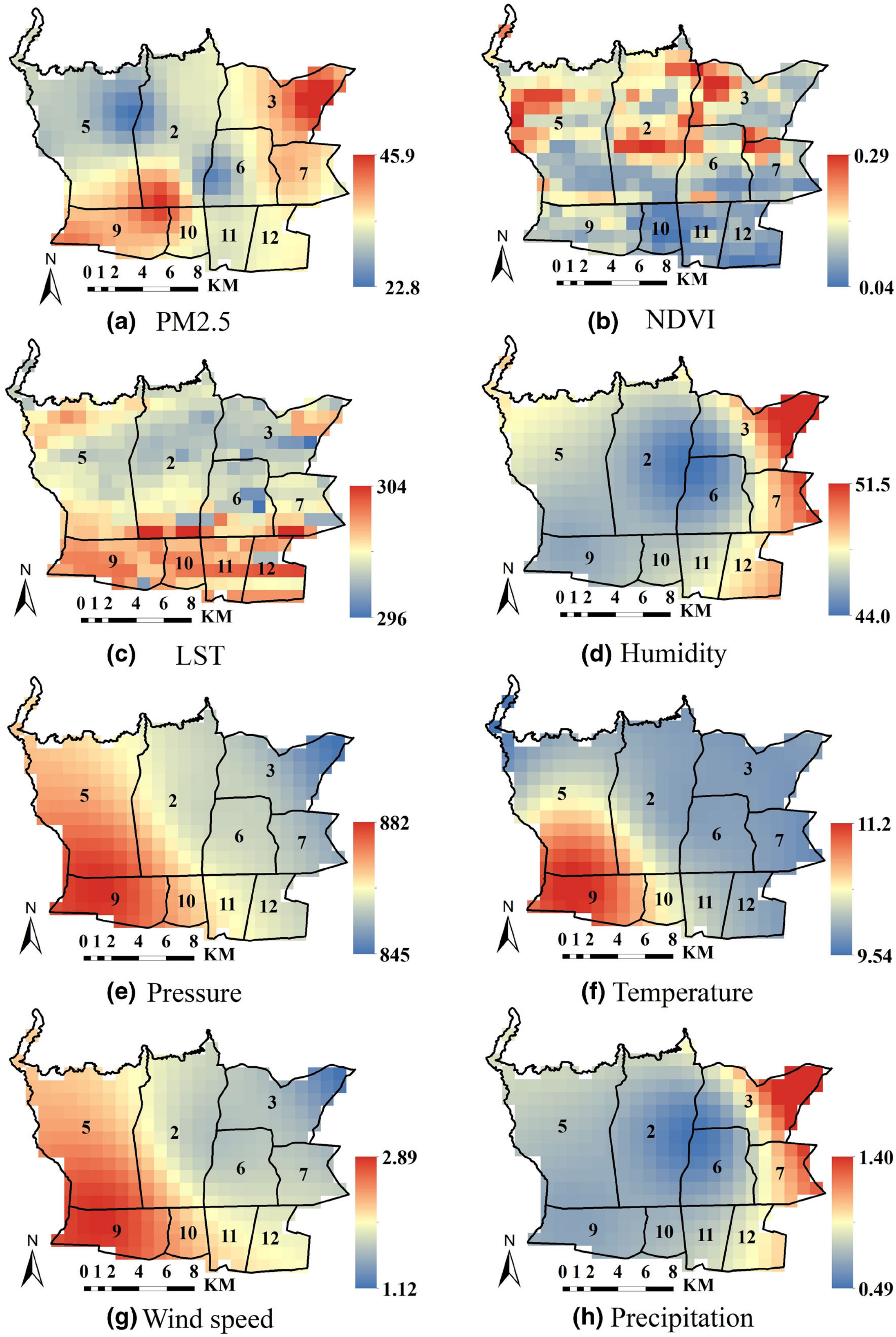

Fig. 2 Spatial distributions of variables in winter

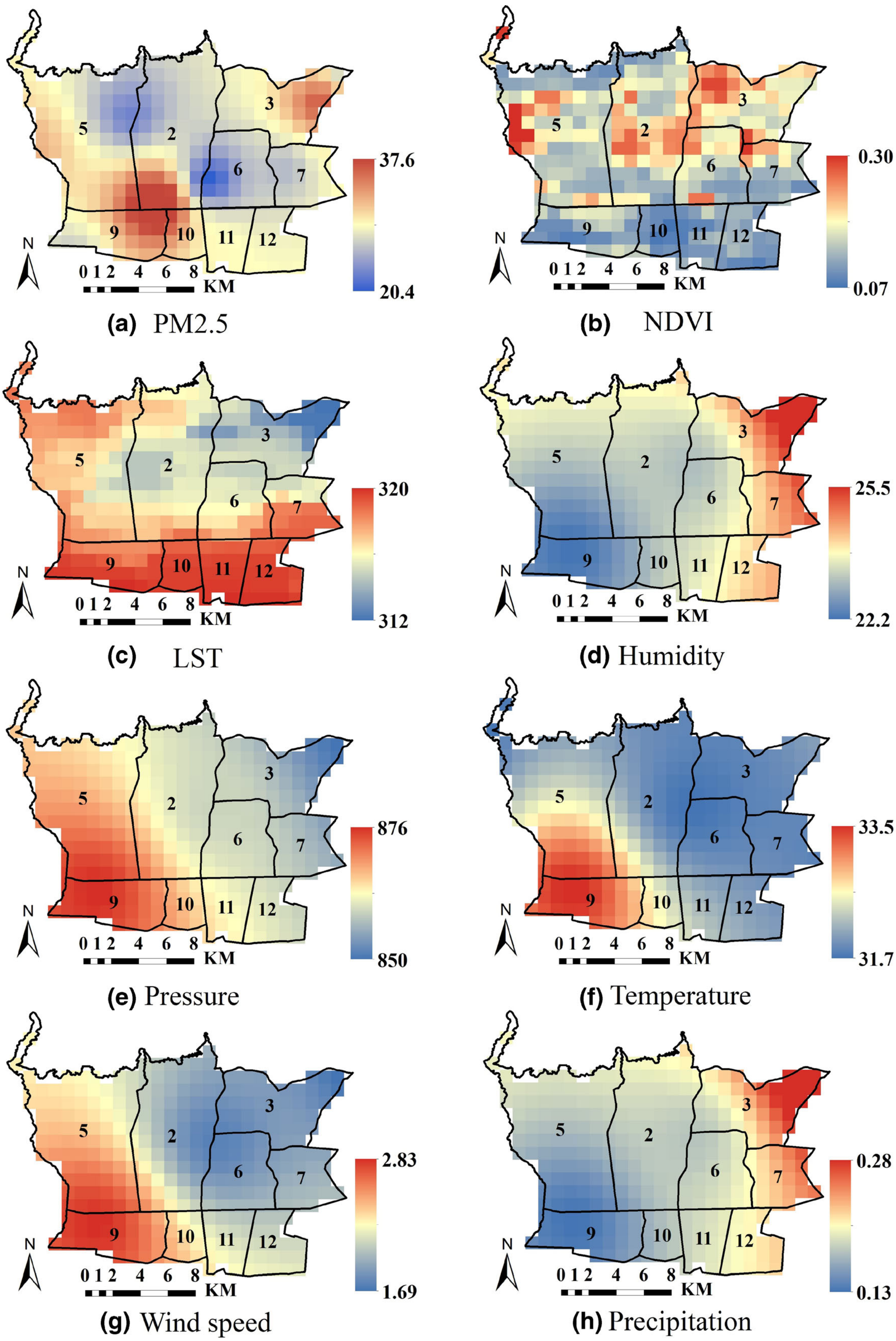

Fig. 3 Spatial distributions of variables in summer

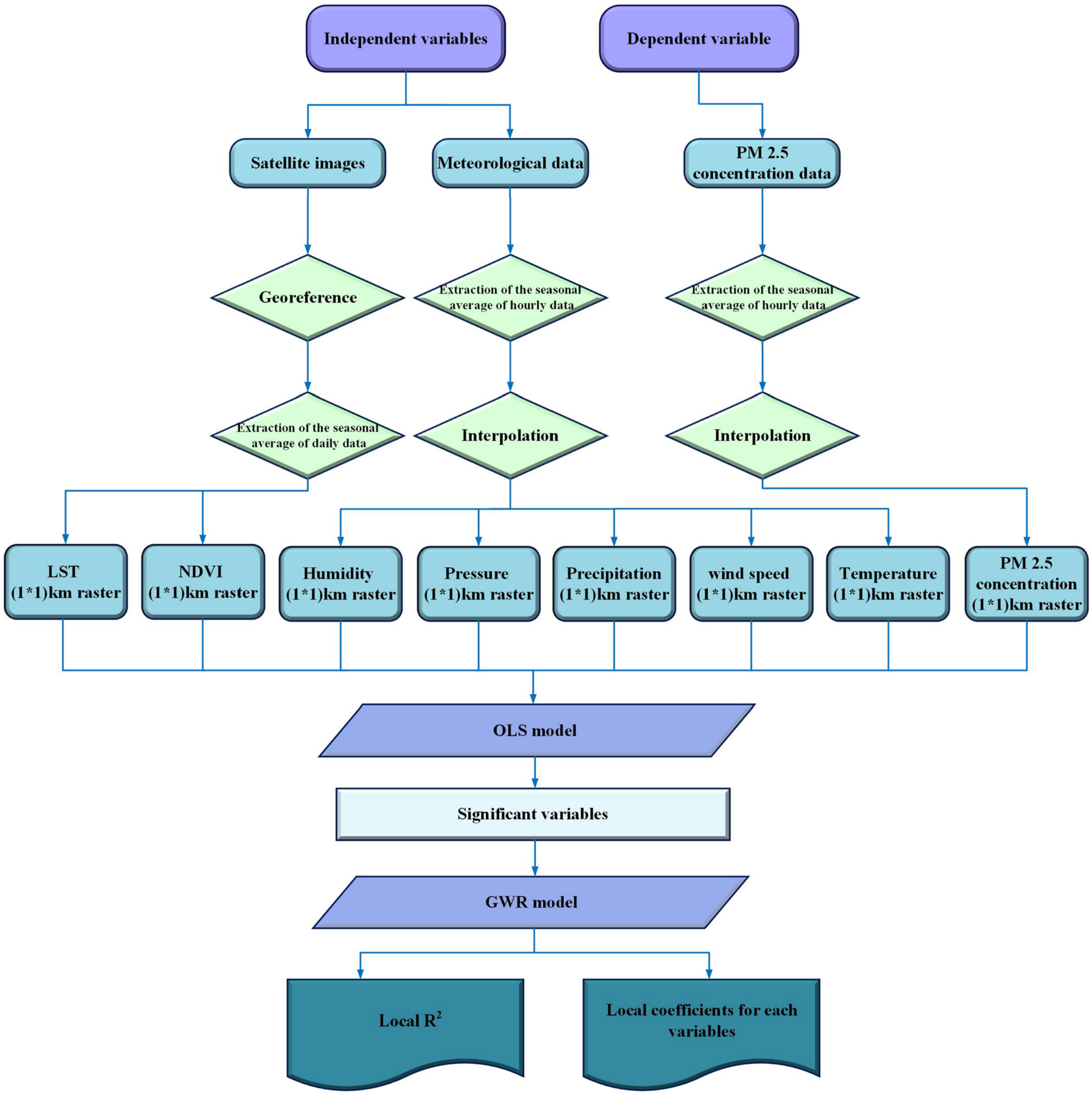

Fig. 4 The flowchart of methodology

global parameter estimates (Fotheringham et al. 2001). Different from global models like OLS, the GWR model stands on local statistic, and it considers the effects from spatial variations of meteorological and geographical variables on the estimation of $PM_{2.5}$ concentration. This method estimates model parameters at each geographical location by using the weighting function of exponential distance decay. The weighting function, called the kernel function, can be stated using the exponential distance decay form:

$$w_{ij} = \exp\left(\frac{d_{ij}^2}{b^2}\right) \tag{2}$$

where W_{ij} represents the weight of observation j for location i, d_{ij} expresses the Euclidean distance between points i and j, and b is the kernel bandwidth. In addition, the observations are weighted by distance, so those closer to the studied location have more influence on the parameter estimates. These estimates are showing how a relationship varies over space. This procedure can help to examine the spatial pattern of the local estimates and to get some understanding of hidden possible causes of the respective patterns (Fotheringham et al. 2003). The basic GWR equation is:

$$y(u, v) = b_0(u, v) + b_1(u, v)x_1 + e(u, v) \tag{3}$$

where y is the dependent variable with a Gaussian distribution; x is the independent variable; u and v are the coordinates of the data; b_0 is the intercept term; b_1 is the coefficient being estimated; and e is the random error term (See et al. 2015). The point is that GWR can not only test the spatial non-stationarity of the input variable, but it can also be used to estimate the outcome variable (Wheeler 2014).

In GWR model bandwidth is the number of neighbors used for each local estimation. Residual squares is the some of the squared residuals in the model. Residual squares is the sum of the squared residuals in the model (the residual being the difference between an observed y value and its estimated value returned by the GWR model). AICc is a measure of model performance and is helpful for comparing different regression models. Taking into account model complexity, the model with the lower AICc value provides a better fit to the observed data.

Results and discussion

Results of OLS model

The first performance of the OLS model showed that some variables do not have a significant relationship with the dependent variable in less than 0.01 significance level. Non-significant variables were removed step by step. Results of the OLS method after removing meaningless variables are shown in Table 2.

VIF was used to detect whether collinearity problems existed among the variables. By checking the amount of VIF, it was found that some variables have redundancy. Data redundancy was deleted by removing humidity variable. This point indicates that humidity and precipitation are very similar to each other. Also, in summer, first pressure and then LST were dropped from the model. Output results of VIF showed that data redundancy is due to precipitation and humidity variables. Therefore, in order to resolve data redundancy, one of the variables was eliminated. The negative relationship between NDVI index and wind speed with the dependent variable ($PM_{2.5}$ concentration) indicates that these two variables play an important role in reducing air pollution in Tehran. The results of OLS model also confirm that NDVI and LST have an inverse correlation with each other. This issue is more pronounced in summer due to the NDVI and LST levels. Amount of adjusted R-squared indicated that 0.41 (winter) and 0.39 (summer) of the variation in $PM_{2.5}$ can be explained by meteorological and environmental parameters. The significant joint F-statistic and joint Wald statistic both indicated that there is a significant linear relationship between the dependent variable and the independent variables. Because the Jarque-Bera statistic was not significant, the model is considered unbiased, and all the key variables were included in the model.

Both the multiple R-squared and adjusted R-squared values are measures of model performance. Possible values range from 0.0 to 1.0. Both the joint F-statistic and joint Wald statistic are measures of overall model statistical significance. The Koenker (BP) statistic (Koenker's studentized Breusch-Pagan statistic) is a test to determine if the explanatory variables in the model have a consistent relationship to the dependent variable (what you are trying to predict/understand) both in geographic space and in data space. The Jarque-Bera statistic indicates whether or not the residuals (the observed/known dependent variable values minus the predicted/estimated values) are normally distributed. The variance

Table 2 Summary of global OLS linear regression model results

	Winter					Summer				
Variables	Coefficient	Std. error	Probability	Robust std. error	VIF	Coefficient	Std. error	Probability	Robust std. error	VIF
Intercept	− 3.39	0.37	0.00*	0.66	…	0.53	0.76	0.00*	0.69	…
NDVI	− 0.16	0.09	0.08*	0.08	1.19	0.13	0.04	0.00*	0.03	1.15
LST	0.06	0.04	0.07*	0.05	1.45	Removed				
Humidity	Removed					0.43	0.24	0.07*	0.21	23**
Pressure	Removed					Removed				
Temperature	1.68	0.14	0.00*	0.13	5.13	0.73	0.13	0.00*	0.12	7.72
Wind speed	− 0.80	0.09	0.00*	0.08	5.48	0.27	0.08	0.00*	0.07	7.50
Precipitation	0.57	0.06	0.00*	0.05	1.27	1.04	0.23	0.00*	0.20	24**
R^2	0.43					0.40				
Adjusted-R^2	0.41					0.39				
AICc	1234					1202				
Joint F-statistic	48.3		0.0000*			44.6		0.0000*		
Joint Wald statistic	326		0.0000*			336.4		0.0000*		
Koenker (BP)	21.4		0.0008*			33.9		0.0001*		
Jarque-Bera	4.25		0.0090			1.55		0.2684		

*indicates a statistically significant p value ($p < 0.01$). **Indicates redundancy among explanatory variables inflation factor (VIF) measures redundancy among explanatory variables. As a rule of thumb, explanatory variables associated with VIF values larger than about 7.5 should be removed (one by one) from the regression model.

Results of GWR model

According to the OLS model, meaningless variables were removed and data redundancy was eliminated. Finally, LST, NDVI, precipitation, air temperature, and wind speed variables for winter and NDVI, temperature, precipitation, and wind speed variables for summer entered into GWR model. A list of explanatory variables considered for inclusion in GWR with their descriptive statistics is given in Table 3.

The GWR model is a significant improvement of the OLS model which is more conspicuous in winter (adjusted R^2 = 0.71) compared to summer (adjusted R^2 = 0.41). Also, AICc value suggests that the local model was a significant improvement. In general, both the OLS and GWR methods show that meteorological and environmental variables in winter have a much stronger relationship with $PM_{2.5}$ concentration than in summer. The summary of GWR model output is shown in Table 4. Also, Figs. 3 and 4 indicate the local coefficients for each of the meteorological and environmental variables for two hot and cold seasons in GWR model.

According to the result of various measurement campaigns (Chen et al. 2017a; Hu et al. 2013; Jiang and Weiwei 2016), local methods like GWR estimates $PM_{2.5}$ concentration much better and more accurate than the global methods, which is confirmed by our results. In agreement with the result of an investigation done in China (Chen et al. 2017b), we found that the influence of meteorological–environmental parameters in the cold season is much stronger than the warm season. The results of the GWR method also show that local variations of coefficients for all parameters and R^2 are very low in summer, which probably is due to larger spatial variations in the cold season caused by more stable atmospheric stratifications, lower mixing layer heights, and lower wind speeds prevailing in winter.

Actually, the local coefficient indicates the degree of correlation between the dependent and independent variable, which can be positive or negative. Figures 5a and 6b show local coefficients for air temperature in winter and summer, respectively. By surveying this parameter, it can be concluded that air temperature has a positive correlation with $PM_{2.5}$ concentration in both seasons. But, the pattern of local coefficient is different in two seasons. Also, in comparison with winter, spatial variations are low and the area is almost uniform. As it can be seen, the correlation between $PM_{2.5}$ and air temperature is much stronger in summer. This is because air temperature can affect the formation of particles; thus, the high air temperature can promote the photochemical reaction between precursors (Wang and Ogawa 2015). In big and crowded cities like Tehran, solar radiation affect the spatial variations in air temperature less than intra-urban human activities like industrial activities, traffic, and population density, as a result we can say although the increase in air temperature leads to an increase in albedo, it cannot have a significant impact on spatial air temperature variations. Actually, the spatial distribution of air temperatures in urban areas is quite complex, and most of the factors that modify energy balance and air temperature conditions in cities arise out of the highly different thermal properties of the urban environment relative to its natural surroundings (Dobrovolný and Krahula 2015; Haddad and Aouachria 2015).

According to Fig. 5b, LST has a positive correlation in the western part of the region, and there is a negative correlation with $PM_{2.5}$ concentration in the east of the region in winter. In fact, by moving from west to east, the positive correlation becomes non-correlation and then negative correlation. Since the air temperature has a positive effect on $PM_{2.5}$ concentration and LST is influenced by many parameters such as air temperature (Khandelwal et al. 2017), the necessary condition for a positive

Table 4 Summary of GWR model output

GWR	Winter	Summer
Bandwidth	0.05	0.21
Residual squares	374	715
Sigma	1.11	1.49
AICc	1007	1195
R^2	0.73	0.41
Adjusted R^2	0.71	0.40

Table 3 Results of GWR model output

	Winter				Summer			
Variables	Min	Max	Average	SD	Min	Max	Average	SD
NDVI	− 0.43	0.32	0.13	0.18	0.12	0.13	0.12	0.003
LST	− 0.43	0.39	0.009	0.22				
Temperature	0.19	0.83	0.58	0.14	0.70	0.90	0.81	0.05
Wind speed	− 0.72	0.72	0.24	0.31	0.17	0.26	0.21	0.02
Precipitation	− 1.81	0.73	0.01	0.70	0.58	0.65	0.62	0.01

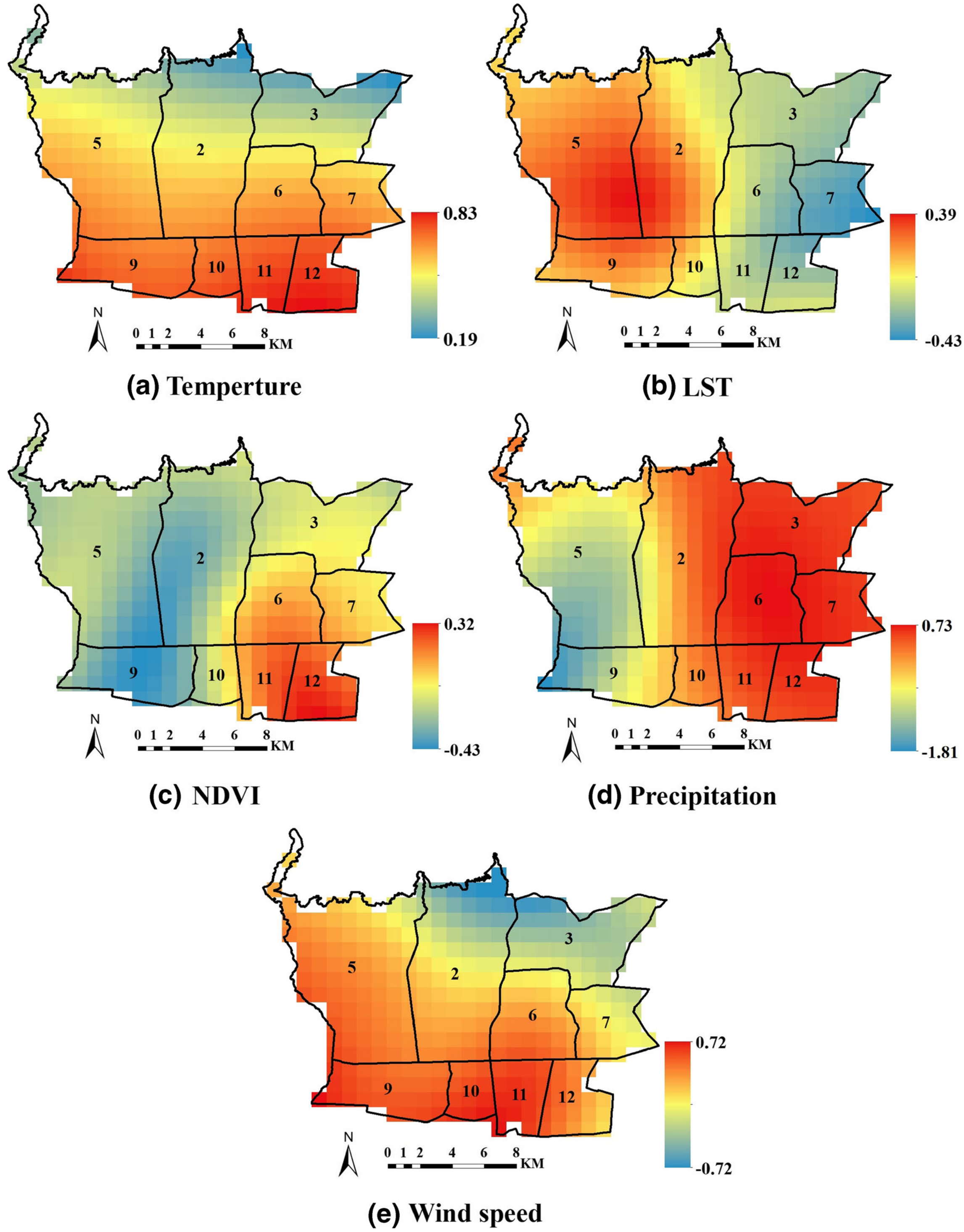

Fig. 5 Spatial distribution of local coefficients in GWR model (winter)

relationship between LST and $PM_{2.5}$ is a positive correlation between LST and air temperature. But, unlike the western part, the relation between LST and air temperature is not positive; the reason could be that the vegetation cover is weak, so generally, for slight vegetated areas, the day LST is higher than air temperature (Chan et al. 2017).

The vegetation coverage described as normalized difference vegetation index (NDVI) is known to have some impact on the spatial patterns of $PM_{2.5}$ (Jiang and Weiwei 2016). Although the effect of vegetation on urban air quality is not yet fully understood (Escobedo et al. 2011; Tiwary et al. 2009), Fig. 5c shows that in most of the study area, there is

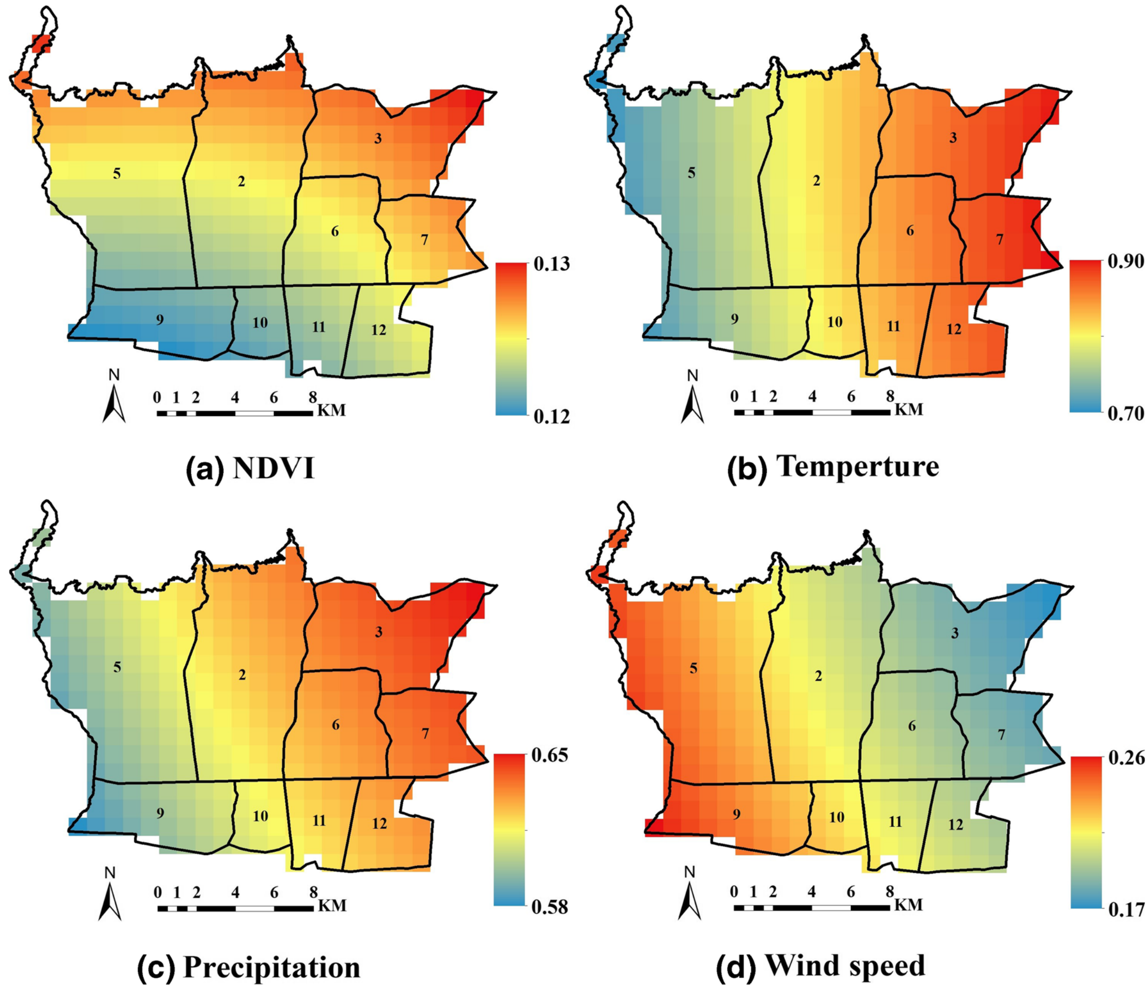

Fig. 6 Spatial distribution of local coefficients in GWR model (summer)

a negative relationship between NDVI parameter and $PM_{2.5}$ concentration in winter. Only a very small part of the south-eastern of the study area has a positive correlation. In general, by moving away from the city center, as for the geography of the urban heat island that generally increases from the urban outskirts towards the city center, the relation between NDVI and $PM_{2.5}$ becomes negative. This correlation indicates that this parameter has a controlling effect on Tehran air pollution. Considering that the highest air pollution in Tehran is observed in winter, improvement of urban vegetation can be a viable strategy to help reduce urban air pollution. Previous studies have shown that vegetation can mitigate particulate air pollution through a number of mechanisms, such as intercepting and accumulating atmospheric particles through leaf pubescence and stomata (Chen et al. 2016; Irga et al. 2015). But, as it can be seen in Fig. 6a, NDVI and $PM_{2.5}$ behave differently in summer, and they have a weak positive correlation with low spatial variations in the whole Tehran city. The weak positive relationship between NDVI and $PM_{2.5}$ in summer can be attributed to the inverse relationship between NDVI and LST. Hence, LST is influenced by the air temperature and both have higher values in summer than in winter, so NDVI has less important role in describing $PM_{2.5}$ in summer. Actually, the impact of NDVI is overcome by the influence of land surface temperature and air temperature. It has shown that air temperature, precipitation, and other meteorological parameters can preferably explain the relationship between concentrations of particulate matter and meteorological parameters (Tai et al. 2010).

As seen in Fig. 5e, there is a negative correlation between the wind speed and $PM_{2.5}$ concentration in the north-eastern part of the case study, which increases up positive correlations in the south-western part. According to Fig. 6d, unlike winter, variations in local coefficients are really low for wind speed in summer with slightly decreasing but always positive local coefficients from the west to the east. Also, the correlation is low and positive. According to the result of wind speed, various impact of wind speed on $PM_{2.5}$ concentration was observed in both seasons as well. It is noticeable that wind speed has a negative effect on $PM_{2.5}$ concentration in winter; it means that higher wind speed is conducive to the diffusion of $PM_{2.5}$, which results in lower concentrations of $PM_{2.5}$ (Luo et al. 2017). The point is that the influence of wind speed on $PM_{2.5}$ concentrations in winter is more obvious than in summer, because the correlation is positive with low spatial variation in summer. These results may be attributed to the local pollution sources in Tehran urban area as dominant source for $PM_{2.5}$ pollution and less external sources, as the actual pollutant concentration is the integrated effect of external and local sources (Pu et al. 2011). Results of GWR model output about precipitation and $PM_{2.5}$ concentration in winter and summer are shown in Figs. 5(c) and 6(d). Precipitation has a positive correlation with $PM_{2.5}$ concentration in most parts of the study area. This result contradicts previous researches. Previous studies show that precipitation can effectively remove atmospheric particulate matter (Li et al. 2015; Lin et al. 2015; Luo et al. 2017; Tai et al. 2010; Wang and Ogawa 2015). Hence, further, precipitation data was investigated to find out complementary explanation. The relationship between $PM_{2.5}$ concentration and precipitation more than 2 mm is shown in Fig. 7. For further analysis, in addition to days with precipitation more than 2 mm, 1 day before each precipitation is also considered.

It was found that the precipitation parameter has special condition in Tehran. The number of rainy days, especially in summer, is low and most precipitations are moderate. When classifying the precipitation data into several classes with regard to the amount of the precipitation and analyzing the impact of each class on the $PM_{2.5}$ concentration, it was found that the days with low precipitation (less than 2 mm) not only affect the decrease of $PM_{2.5}$ concentration, but also increase air pollution due to increasing traffic, while in case of higher precipitation (more than 2 mm), $PM_{2.5}$ concentration decreases.

The local R^2 from the GWR ranges between 0.05 and 0.73 for winter and between 0.37 and 0.43 for summer (Fig. 8a, b). The highest R^2 in winter can be seen in the northeast and the lowest in the central part. In comparison with winter, we see fewer changes in the local distribution of local R^2. The standard residual values show quite the same pattern in both seasons (Fig. 9). The lowest and the highest of standard residual values are seen in the northwest, some parts of the southwest, and northeast, respectively.

However, there exist data gaps in both $PM_{2.5}$ measurements and meteorological parameters that certainly make some limitations for researches. More accurate parameters and variables should be identified to improve new models and methods to gain more accurate examinations and results. Also, the important point in the study of urban problems such as air pollution, use of various data over the years to examine changes over time, and identification of effective and influential parameters also plays an important role.

Conclusion

In the presented study, the impact assessment of meteorological and environmental parameters on $PM_{2.5}$ concentrations in winter and summer was studied. For this purpose, the geographically weighted regression (GWR) model was adopted to explore the impact of environmental parameters on $PM_{2.5}$ concentrations in Tehran city. In comparison with the OLS

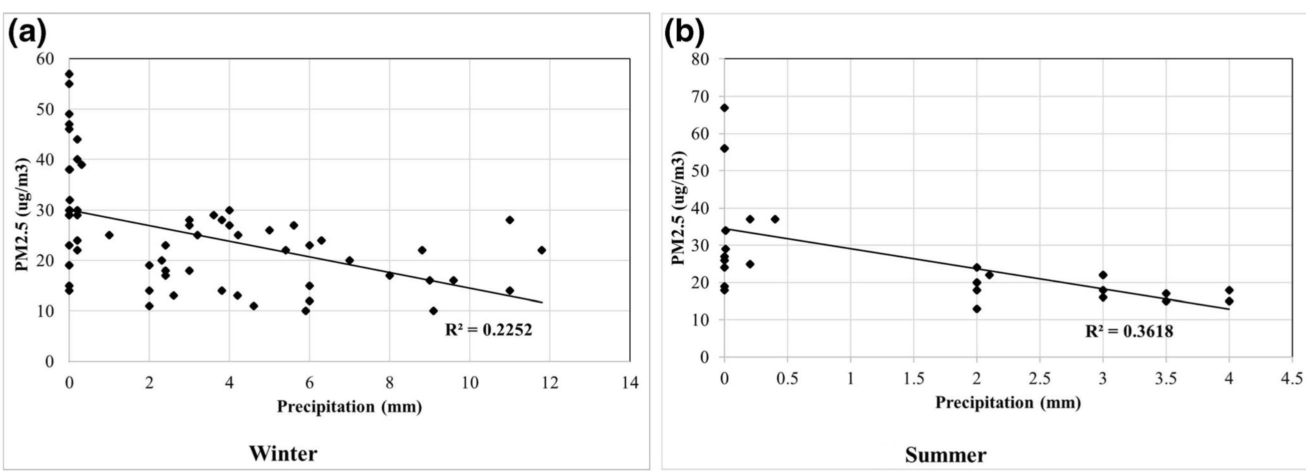

Fig. 7 The relationship between $PM_{2.5}$ concentration and precipitation more than 2 mm (considering the data of 1 day before precipitation)

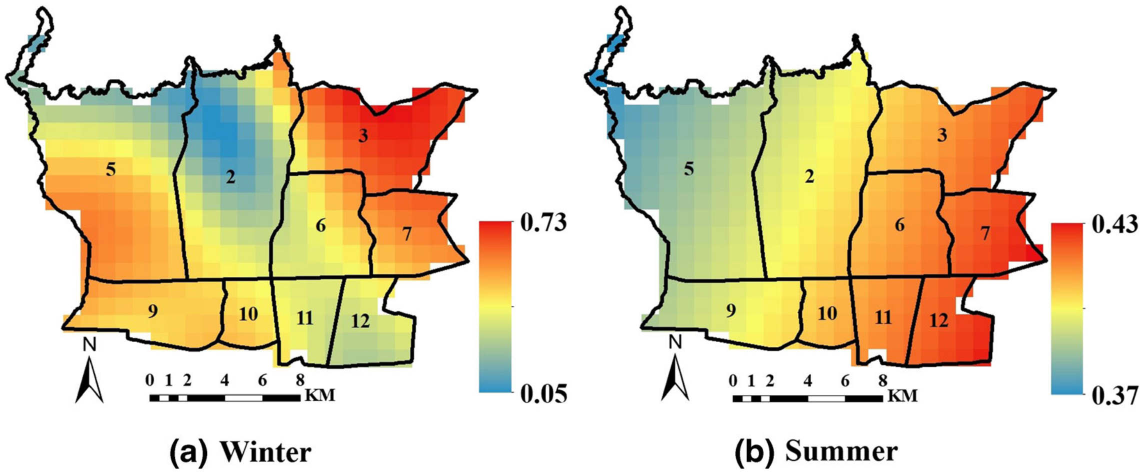

Fig. 8 Spatial distribution of local R^2

method, the GWR model showed a higher ability to analyze the relationships between independent and dependent variables. The study indicated that meteorological and environmental parameters in winter have a much higher ability than in summer to describe $PM_{2.5}$ concentration. Compared to winter season, spatial variation of the local coefficients was lower. Considering the negative correlation between NDVI and $PM_{2.5}$ concentration in winter, it is recommended to increase urban vegetation in order to reduce Tehran's air pollution and especially $PM_{2.5}$ concentration. Air temperature showed the highest correlation with $PM_{2.5}$ concentration in summer. Positive correlation of air temperature in both seasons as well as LST parameter in some areas shows the need for more attention to source-related air pollution control such as reduction of emissions from traffic or air conditioning in summer. However, there is no other way to reduce air pollution without severe control especially at hot season since air temperature cannot be modified. Also, there is an urgent need of an extensive investigation on the emission sources and that very certainly most effective will be the replacement of fossil energy sources by electric power from sustainable sources especially in transportation. We would suggest some directions for future research: (1) more air pollutants such as PM_{10} and ozone should be evaluated and be applied to the potential of remote sensing technology to get a more extensive picture of source-receptor relationships in highly polluted areas like in and around the City of Tehran. (2) Evaluating the capability of different satellite imagery in association with the topics related to air pollution and air quality. (3) Impact assessment of various meteorological and environmental parameters on primary and secondary pollutants. It also needs a larger time span and higher data density in the further research of the next step.

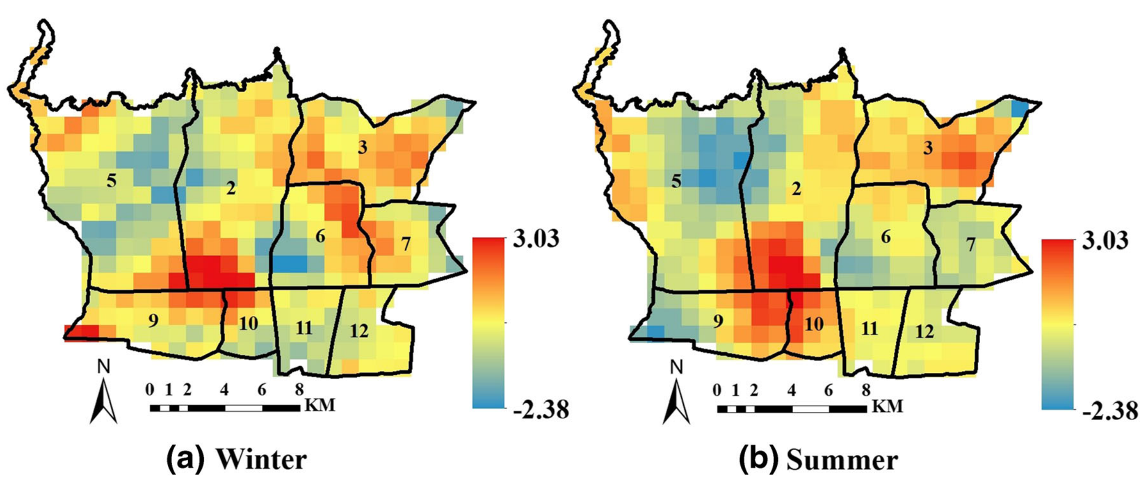

Fig. 9 Spatial distribution of standard residuals of the GWR model

Acknowledgments Authors of this paper would like to acknowledge the Meteorological Organization of Iran for providing us necessary ground data.

References

Brajer V, Hall J, Rahmatian M (2012) Air pollution, its mortality risk, and economic impacts in Tehran, Iran. Iran J Public Health 41:31

Brunsdon C, Fotheringham AS, Charlton ME (1996) Geographically weighted regression: a method for exploring spatial nonstationarity. Geogr Anal 28:281–298

Brunsdon C, McClatchey J, Unwin D (2001) Spatial variations in the average rainfall–altitude relationship in Great Britain: an approach using geographically weighted regression. Int J Climatol 21:455–466

Chan H-P, Chang C-P, Dao PD (2017) Geothermal anomaly mapping using landsat ETM+ data in Ilan Plain, Northeastern Taiwan. Pure Appl Geophys 175:303–323. https://doi.org/10.1007/s00024-017-1690-z

Chen Y, Liu J, Li Y, Sadiq R, Deng Y (2015) RM-DEMATEL: a new methodology to identify the key factors in PM2.5. Environ Sci Pollut Res Int 22(8):6372–6380. https://doi.org/10.1007/s11356-015-4229-9

Chen L, Liu C, Zou R, Yang M, Zhang Z (2016) Experimental examination of effectiveness of vegetation as bio-filter of particulate matters in the urban environment. Environ Pollut 208:198–208

Chen Z, Cai J, Gao B, Xu B, Dai S, He B, Xie X (2017a) Detecting the causality influence of individual meteorological factors on local PM2.5 concentration in the Jing-Jin-Ji region. Sci Rep 7:40735. https://doi.org/10.1038/srep40735

Chen Z, Xie X, Cai J, Chen D, Gao B, He B, Cheng N, Xu B (2017b) Understanding meteorological influences on PM2.5 concentrations across China: a temporal and spatial perspective. Atmos Chem Phys Discuss: 1–30. https://doi.org/10.5194/acp-2017-376

Dobrovolný P, Krahula L (2015) The spatial variability of air temperature and nocturnal urban heat island intensity in the city of Brno, Czech Republic. Morav Geogr Rep 23:8–16

Escobedo FJ, Kroeger T, Wagner JE (2011) Urban forests and pollution mitigation: analyzing ecosystem services and disservices. Environ Pollut 159:2078–2087

Fan J, Li S, Fan C, Bai Z, Yang K (2016) The impact of PM2.5 on asthma emergency department visits: a systematic review and meta-analysis. Environ Sci Pollut Res Int 23(1):843–850. https://doi.org/10.1007/s11356-015-5321-x

Fisher B (2002) Meteorological factors influencing the occurrence of air pollution episodes involving chimney plumes. Meteorol Appl 9(2): 199–210. https://doi.org/10.1017/s1350482702002050

Fotheringham AS, Charlton ME, Brunsdon C (2001) Spatial variations in school performance: a local analysis using geographically weighted regression. Geogr Environ Model 5(1):43–66. https://doi.org/10.1080/13615930120032617

Fotheringham AS, Brunsdon C, Charlton M (2003) Geographically weighted regression: the analysis of spatially varying relationships. John Wiley and Sons, Hoboken

Gupta P, Christophera SA, Wangb J, Gehrigc R, Leed Y, Kumare N (2006) Satellite remote sensing of particulate matter and air quality assessment over global cities. Atmos Environ 40(30):5880–5892. https://doi.org/10.1016/j.atmosenv.2006.03.016

Haddad L, Aouachria Z (2015) Impact of the transport on the Urban Heat Island World Academy of Science, Engineering and Technology. Int J Environ Chem Ecol Geol Geophys Eng 9:968–973

Hoff RM, Christopher SA (2009) Remote sensing of particulate pollution from space: have we reached the promised land? J Air Waste Manage Assoc 59:645–675

Hu Z (2009) Spatial analysis of MODIS aerosol optical depth, PM 2.5, and chronic coronary heart disease. Int J Health Geogr 8(1):27. https://doi.org/10.1186/1476-072X-8-27

Hu X, Waller LA, al-Hamdan MZ, Crosson WL, Estes MG Jr, Estes SM, Quattrochi DA, Sarnat JA, Liu Y (2013) Estimating ground-level PM(2.5) concentrations in the southeastern U.S. using geographically weighted regression. Environ Res 121:1–10. https://doi.org/10.1016/j.envres.2012.11.003

Hwang SL, Lin YC, Lin CM, Hsiao KY (2017) Effects of fine particulate matter and its constituents on emergency room visits for asthma in southern Taiwan during 2008-2010: a population-based study. Environ Sci Pollut Res Int 24(17):15012–15021. https://doi.org/10.1007/s11356-017-9121-3

Irga P, Burchett M, Torpy F (2015) Does urban forestry have a quantitative effect on ambient air quality in an urban environment? Atmos Environ 120:173–181

Jiang M, Weiwei S (2016) Investigating metrological and geographical effect in remote sensing retrival of PM2. 5 concentration in Yangtze River Delta. In: Geoscience and Remote Sensing Symposium (IGARSS), 2016 I.E. International. IEEE, pp 4108–4111

Johansson M, Galle B, Yu T, Tang L, Chen D, Li H, Li JX, Zhang Y (2008) Quantification of total emission of air pollutants from Beijing using mobile mini-DOAS. Atmos Environ 42(29):6926–6933. https://doi.org/10.1016/j.atmosenv.2008.05.025

Kaufman YJ, Tanre D, Boucher O (2002) A satellite view of aerosols in the climate system. Nature 419:215–223

Khandelwal S, Goyal R, Kaul N, Mathew A (2017) Assessment of land surface temperature variation due to change in elevation of area surrounding Jaipur, India. Egypt J Remote Sens Space Sci. https://doi.org/10.1016/j.ejrs.2017.01.005

Khokhar MF, Nisar M, Noreen A, Khan WR, Hakeem KR (2017) Investigating the nitrogen dioxide concentrations in the boundary layer by using multi-axis spectroscopic measurements and comparison with satellite observations. Environ Sci Pollut Res Int 24(3): 2827–2839. https://doi.org/10.1007/s11356-016-7907-3

Li H, Guo B, Han M, Tian M, Zhang J (2015) Particulate matters pollution characteristic and the correlation between PM (PM2.5, PM10) and meteorological factors during the summer in Shijiazhuang. J Environ Prot 6(05):457–463

Lin G, Fu J, Jiang D, Hu W, Dong D, Huang Y, Zhao M (2013) Spatio-temporal variation of PM2.5 concentrations and their relationship with geographic and socioeconomic factors in China. Int J Environ Res Public Health 11(1):173–186. https://doi.org/10.3390/ijerph110100173

Lin G, Fu J, Jiang D, Wang J, Wang Q, Dong D (2015) Spatial variation of the relationship between PM2.5 concentrations and meteorological parameters in China. Biomed Res Int 2015:15. https://doi.org/10.1155/2015/684618

Liu Y, Sarnat JA, Kilaru V, Jacob DJ, Koutrakis P (2005) Estimating ground-level PM2.5 in the eastern United States using satellite remote sensing. Environ Sci Technol 39(9):3269–3278. https://doi.org/10.1021/es049352m

Liu Y, Franklin M, Kahn R, Koutrakis P (2007) Using aerosol optical thickness to predict ground-level PM 2.5 concentrations in the St. Louis area: a comparison between MISR and MODIS. Remote Sens Environ 107(1-2):33–44. https://doi.org/10.1016/j.rse.2006.05.022

Liu Y, Paciorek CJ, Koutrakis P (2009) Estimating regional spatial and temporal variability of PM2.5 concentrations using satellite data, meteorology, and land use information. Environ Health Perspect 117(6):886–892. https://doi.org/10.1289/ehp.0800123

Luo C, Zhu X, Yao C, Hou L, Zhang J, Cao J, Wang A (2015) Short-term exposure to particulate air pollution and risk of myocardial infarction: a systematic review and meta-analysis. Environ Sci Pollut Res Int 22(19):14651–14662. https://doi.org/10.1007/s11356-015-5188-x

Luo J, Du P, Samat A, Xia J, Che M, Xue Z (2017) Spatiotemporal pattern of PM2.5 oncentrations in Mainland China and analysis of its

influencing factors using geographically weightedr. Sci Rep 7: 40607
Makra L, Matyasovszky I, Ionel I, Popescu F, Sümeghy Z (2011) Connection between meteorological elements and pollutants concentrations at Szeged, Hungary Acta Climatologica et Chorologica Universitatis Szegediensis:44–45
Martin RV (2008) Satellite remote sensing of surface air quality. Atmos Environ 42(34):7823–7843. https://doi.org/10.1016/j.atmosenv.2008.07.018
Miri M et al. (2017) Human health impact assessment of exposure to particulate matter: an AirQ software modeling. Environ Sci Pollut Res 24:16513–16519. https://doi.org/10.1007/s11356-017-9189-9
Parkinson CL (2003) Aqua: an earth-observing satellite mission to examine water and other climate variables. IEEE Trans Geosci Remote Sens 41(2):173–183. https://doi.org/10.1109/TGRS.2002.808319
Pcu M, Bosiacka B (2011) Effects of meteorological factors and air pollution on urban pollen concentration. Environ Stud 20:611–618
Pohjola M, Kousa A, Kukkonen J, Härkönen J, Karppinen A, Aarnio P, Koskentalo T (2002) The spatial and temporal variation of measured urban PM 10 and PM 2.5 in the Helsinki metropolitan area. Water, Air, Soil Pollut: Focus 2(5/6):189–201. https://doi.org/10.1023/A:1021379116579
Pu W-w, Zhao X-j, Zhang X-l, Ma Z-q (2011) Effect of meteorological factors on PM2.5 during July to September of Beijing. Procedia Earth Planet Sci 2:272–277
Ren W, Tian H, Chen G, Liu M, Zhang C, Chappelka AH, Pan S (2007) Influence of ozone pollution and climate variability on net primary productivity and carbon storage in China's grassland ecosystems from 1961 to 2000. Environ Pollut 149(3):327–335. https://doi.org/10.1016/j.envpol.2007.05.029
Rowshan G, Khosh AF, Negahban S, Mirkatouly J (2009) Impact of air pollution on climate fluctuations in Tehran city. Environ Sci 7:92–173
Schaap M, Apituley A, Timmermans R, Koelemeijer R, Leeuw G (2009) Exploring the relation between aerosol optical depth and PM 2.5 at Cabauw, the Netherlands. Atmos Chem Phys 9(3):909–925. https://doi.org/10.5194/acp-9-909-2009
See L, Schepaschenko D, Lesiv M, McCallum I, Fritz S, Comber A, Perger C, Schill C, Zhao Y, Maus V, Siraj MA, Albrecht F, Cipriani A, Vakolyuk M, Garcia A, Rabia AH, Singha K, Marcarini AA, Kattenborn T, Hazarika R, Schepaschenko M, van der Velde M, Kraxner F, Obersteiner M (2015) Building a hybrid land cover map with crowdsourcing and geographically weighted regression. ISPRS J Photogramm Remote Sens 103:48–56. https://doi.org/10.1016/j.isprsjprs.2014.06.016
Shi M, Wu H, Zhang S, Li H, Yang T, Liu W, Liu H (2014) Weekly cycle of magnetic characteristics of the daily PM2.5 and PM2.5–10 in Beijing, China. Atmos Environ 98:357–367. https://doi.org/10.1016/j.atmosenv.2014.08.079
Stone M, Brooks RJ (1990) Continuum regression: cross-validated sequentially constructed prediction embracing ordinary least squares, partial least squares and principal components regression. J R Stat Soc Ser B Methodol 52(2):237–269. JSTOR, www.jstor.org/stable/2345437
Tai AP, Mickley LJ, Jacob DJ (2010) Correlations between fine particulate matter (PM 2.5) and meteorological variables in the United States: implications for the sensitivity of PM 2.5 to climate change. Atmos Environ 44(32):3976–3984. https://doi.org/10.1016/j.atmosenv.2010.06.060
Tian J, Chen D (2010) A semi-empirical model for predicting hourly ground-level fine particulate matter (PM 2.5) concentration in southern Ontario from satellite remote sensing and ground-based meteorological measurements. Remote Sens Environ 114(2):221–229. https://doi.org/10.1016/j.rse.2009.09.011
Tiwary A, Sinnett D, Peachey C, Chalabi Z, Vardoulakis S, Fletcher T, Leonardi G, Grundy C, Azapagic A, Hutchings TR (2009) An integrated tool to assess the role of new planting in PM 10 capture and the human health benefits: a case study in London. Environ Pollut 157(10):2645–2653. https://doi.org/10.1016/j.envpol.2009.05.005
Veefkind P, Van Oss R, Eskes H, Borowiak A, Dentner F, Wilson J (2007) The applicability of remote sensing in the field of air pollution. Institute for Environment and Sustainability, Italy, p 59
Wang J, Ogawa S (2015) Effects of meteorological conditions on PM2.5 concentrations in Nagasaki, Japan. Int J Environ Res Public Health 12(8):9089–9101. https://doi.org/10.3390/ijerph120809089
Wheeler DC (2014) Geographically weighted regression. In: Fischer M, Nijkamp P (eds) Handbook of regional science. Springer, Berlin, Heidelberg, pp 1435–1459. https://doi.org/10.1007/978-3-642-23430-9_77
Wheeler D, Páez A (2010) Geographically Weighted Regression. In: Fischer MM, Getis A (eds) Handbook of applied spatial analysis software tools, methods and applications. Springer-Verlag, Berlin
Wheeler D, Tiefelsdorf M (2005) Multicollinearity and correlation among local regression coefficients in geographically weighted regression. J Geogr Syst 7(2):161–187. https://doi.org/10.1007/s10109-005-0155-6
White R, Engelen G (2000) High-resolution integrated modelling of the spatial dynamics of urban and regional systems. Comput Environ Urban Syst 24(5):383–400. https://doi.org/10.1016/S0198-9715(00)00012-0
WHO (2008) Outdoor air pollution: children's health and the environment
WHO (2016) Ambient air pollution: a global assessment of exposure and burden of disease. Geneva
Wu J, Zhu J, Li W, Xu D, Liu J (2017) Estimation of the PM2.5 health effects in China during 2000-2011. Environ Sci Pollut Res Int 24(11):10695–10707. https://doi.org/10.1007/s11356-017-8673-6
Yang L, Wu Y, Davis JM, Hao J (2011) Estimating the effects of meteorology on PM2.5 reduction during the 2008 Summer Olympic Games in Beijing, China. Front Environ Sci Eng China 5(3):331–341. https://doi.org/10.1007/s11783-011-0307-5
Yang C, Zhao W, Deng K, Zhou V, Zhou X, Hou Y (2017) The association between air pollutants and autism spectrum disorders. Environ Sci Pollut Res Int 24(19):15949–15958. https://doi.org/10.1007/s11356-017-8928-2