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Analysis and zoning of air pollution in urban landscape using different models of spatial analysis (Case study: Tehran)

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ABSTRACT

In this study, spatial zoning models were compared to evaluate the concentrations of PM 2.5 on a large scale in the urban landscape of Tehran. The spatial analysis of PM 2.5 concentration was conducted based on the data from twenty-four stations that measure and monitor the air in Tehran. Three interpolation models were used to assess the air pollution status via Arc GIS 10.6.1 software: universal kriging (UK), ordinary kriging (OK), and inverse distance weighted (IDW). The root mean square error (RMSE) and correlation coefficient (R2) were applied to compare the spatial models and select the best model. Standardized *root-mean-square error* (RMSE) was used to select the best conditions for running the OK and UK models. The results showed that the southern and central regions of Tehran had high concentrations of PM 2.5, and the annual mean of all the stations exceeded the EPA standard (15 μ/m^3). According to the annual average, station 16 had the highest concentration of PM2.5 (112.75 μ/m^3). The results of RMSE showed that the OK model was more suitable than the others for the spatial zoning of air pollution in the urban landscape (RMSE=9.322).

1. Introduction

Currently, air pollution is an important issue in many parts of the world. Air pollution is responsible for 4% of all deaths globally [1,5]. Fine particulate matter is an air pollutant with a diameter between 0.00002 and 500 micrometers [1]. Particles with a diameter of fewer than 10 micrometers (PM 10) and 2.5 micrometers (PM 2.5) penetrate deeply into the lungs and have adverse effects on people's health [2]. New research indicates that PM 2.5 is more harmful than PM 10 [3-4]. PM 2.5 particles pose serious risks to lung function and cause cardiovascular problems [6]. New studies show that PM 2.5 particles cause 3.5 million deaths per year from cardiovascular disease and 220,000 deaths from lung cancer [7-8]. A number of studies have linked long-term exposure to PM 2.5 particles with mortality in Europe [9-11] and America [12-13]. Studies in Asian countries were conducted at relatively high exposures [14-16]. Ansari and Ehrampoush [17] concluded that long-term exposure to PM2.5 increases the risk of cardiorespiratory and lung cancer mortality in Tehran, Iran. There are several ways to estimate air pollution. One of the spatial analysis models is inverse distance weighted (IDW), in which weights are proportional to the inverse of the distance [18]. In the IDW method, it is not necessary to determine the pattern of spatial changes [19]. This method calculates an average value for unsampled points using values from nearby weighted points [18-19]. The kriging model is another interpolation method for spatial analysis based on regression [20]. In this method, the determination of weight is based on the distance between the surrounding points and correlation among the measured points [21]. Sampson et al. [22] used the universal kriging (UK) model for estimating the annual PM 2.5 concentrations in ambient air quality across the U.S; it demonstrated a very high level of cross-validated accuracy of prediction and well-calibrated predictive intervals. The results of the ordinary kriging (OK) method for predicting long-term particulate matter concentrations in seven major Korean cities showed that it produced a higher cross-

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validated R2 than the city-specific models [23]. The IDW method was used to assess the spatial distribution of PM 2.5 in Tehran [23-25] and ascertained a high clustering level of pollutants in the study area. Given the importance of particulate matter concentrations, especially PM 2.5 particles, cities are at high risk. Therefore, the PM 2.5 concentration levels in Tehran, as the first metropolis of Iran, were studied in 2019. Different methods of spatial analysis (UK, OK, and IDW) were used to select the best method for zoning the PM2.5 concentration in Tehran. The results of this study could help policymakers to design an integrated air quality system and plan for the effects of this phenomenon. The purpose of this study was to compare three interpolation models, namely universal kriging, ordinary kriging, and inverse distance weighted, for assessing air pollution in Tehran.

2. Materials and methods

2.1. Case study

This research was conducted in the urban landscape of Tehran (Figure 1). Tehran is one of the most polluted areas in the world [17]. It is the most populous city in Iran and Western Asia with a population of around 8.7 million and has the third-largest metropolitan area in the Middle East. The case study spreads from a longitude 51° 25′ 17″ E and a latitude 35° 41′ 48″ N. Tehran is surrounded by the Alborz Mountains on the northern and eastern sides. The average elevation of Tehran is 1200 m above sea level. Many fixed and moving resources affect the increase of air pollutants. The number of these pollutants in the urban landscape increases due to population growth, traffic, and the presence of various industries.

2.2. Data collection

In the study, the spatial analysis of PM 2.5 concentration was conducted based on data from twenty-four stations that measure and monitor the air in Tehran. The Arc GIS 10.6.1 software released by ESRI was used for spatial analysis, and Excel 2019 was used to draw the diagram and other data analyses. Three interpolation models were used to assess the air pollution status of the metropolis of Tehran: universal kriging (UK), ordinary kriging (OK), and inverse distance weighted (IDW). Finally, the best model for zoning the air pollution in Tehran was selected by comparing the three models.

2.3. Models

2.3.1. Ordinary kriging (OK)

The ordinary kriging is a geostatistical method based on the weighted moving average to estimate a value at a point of region [26]. The OK method is the best linear unbiased estimator and is defined as follows (Eq. 1):

$$Z*(x_i) = \sum_{i=1}^{n} \lambda_i z(x_i) \quad (1)$$

where $Z^*(X_i)$ is the estimated factor, λ_i is weight or value of quantity depending on sample i, and z is the value of the variable. This type of kriging is called a linear kriging because of a linear combination of n, and it searches the neighborhood of x_i [27].

2.3.2. Universal kriging (UK)

In the UK method, it assumes the component of spatial correlation between points and a drift or trend in z values. In this case, the kriging combines with the mathematical models of one or two variables [28]. For example, mathematical models with one and two variables are added as follow [Eq. 2 and Eq. 3]:

$$M = b_1 x_i + b_2 y_i \quad (2)$$

$$M = b_1 x_i + b_2 y_i + b_3 x_i^2 + b_4 x_i y_i + b_5 y_i^2 \quad (3)$$

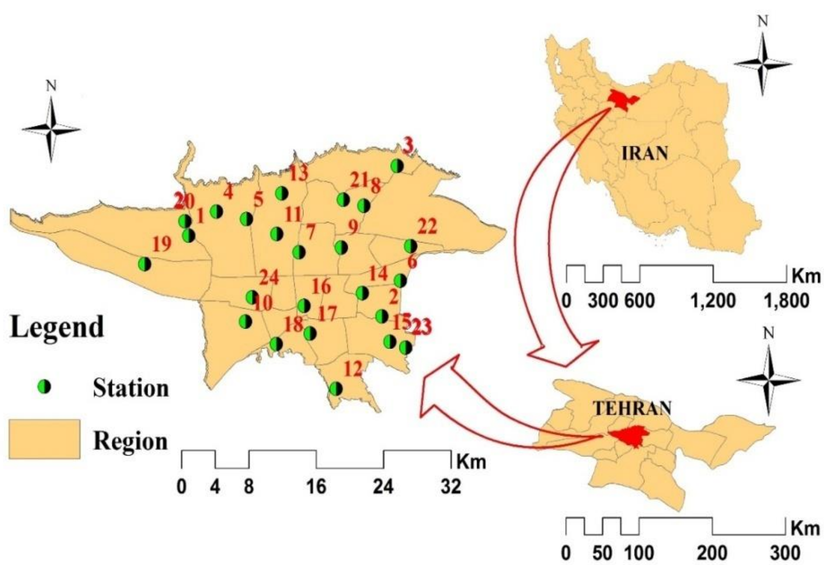

Fig. 1. Location of Tehran and the air quality monitoring stations.

where M is the trend of x_i and y_i that are the coordinates of the points for sample i and b_i is the coefficients of the trend. This model is known as a spatial model with a trend or model in the presence of drift. The locating trend or drift indicates any detectable tendency for the values to change as a function of the coordinate variables [29]. Also, the map of the "standard prediction error" is produced for the two kriging models in GIS.

2.3.3. Inverse distance weighted (IDW)

The IDW is the determined values of unknown points assigned with a weighted average of the values of known points [30]. These weights are calculated by the mathematical power of weights. The larger powers reduce the effect of points farther from the estimated point, and the smaller powers distribute the weights more evenly between the adjacent points [29]. This method considers their distance, regardless of the position and arrangement of the points. In other words, points that have the same distance from the estimated point also have the same weight. The value of the weighting factor is calculated by using the following equation (Eq. 4):

$$\lambda_i = (D_i - \alpha) / \sum_{i=1}^{n} D_i - \alpha \quad (4)$$

where λ_i is the weight of station i, D_i is distance between station i and an unknown point, and α is the weighting power. The root mean square error (RMSE) is used to compare the models and select the best one. The RMSE method is as follows (Eq. 5) [19]:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(q_i - q_i)^2} \quad (5)$$

The standardized RMSE is used to select the most optimal conditions for performing the OK and UK models. The standardized RMSE formula is as follows (Eq. 6):

$$\text{Standardized RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{q_i - q_i}{\sigma_i}\right)^2} \quad (6)$$

where n is value of data, qi is value of measurement, and σi is the standard prediction error [29].

3. Results and discussion

Figure 2 presents the collected data on the air pollution situations in Tehran for PM 2.5, according to the 2019 seasonal average. Based on these results, the highest seasonal average of PM 2.5 concentration occurs in the autumn in Station 16 (142 μ/m^3). Station 13 has the lowest average seasonal pollution in the spring (51 μ/m^3). According to the annual average, Station 16 has the highest concentration of PM2.5 (112.75 μ/m^3). The statistical summary of the air pollution situations in Tehran for PM 2.5 is showed in Table 1. The total seasonal average of the stations was 96.375 μ/m^3, 97.083 μ/m^3, 87.166 μ/m^3, and 72.291 μ/m^3 for winter, autumn, spring, and summer, respectively. The data showed that the highest average concentration occurred in the autumn (97.083 μ/m^3).

Table 1. Statistical summary of air pollution situations in Tehran for PM 2.5 in 2019.

Parameter		PM 2.5
Annual average		88.229
Standard deviation		13.703
Min		60.751
Max		112.752
Seasonal average	Winter	96.375
	Autumn	97.083
	Summer	87.166
	Spring	72.291

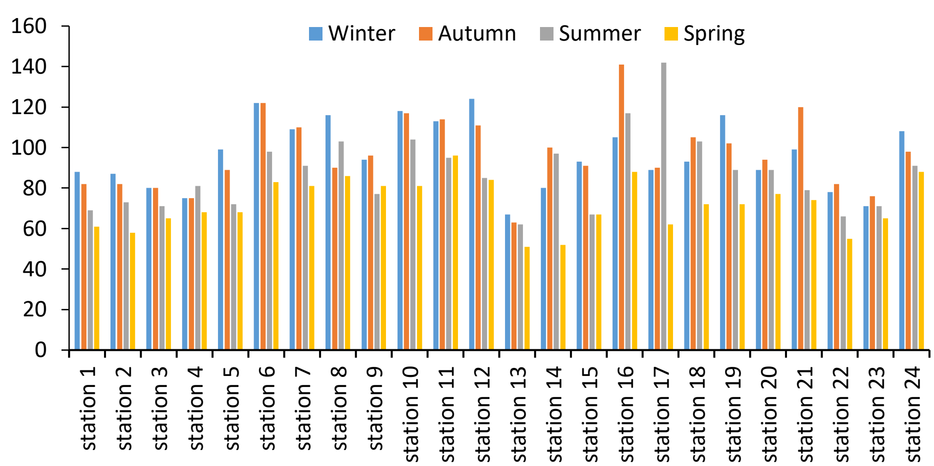

Fig. 2. Seasonal average of air pollution situations in Tehran for PM 2.5 in 2019.

The results of using the UK, OK and IDW methods in the Arc GIS environment are presented in Figures 3, 4, and 5, respectively. The two parameters RMSE and Std. RMSE were used to select the semivariogram type for data normalization in the two kriging models. In this study, the spherical semivariogram and Cox-Box with a power parameter equal to one were used as the best options for running the OK and UK models. Variograms were applied to determine and describe the spatial structure of the data. Variography is the first step in modeling a spatial structure to use in kriging. The spherical variogram model starts from the coordinate origin and has a linear behavior near the origin. As the value increases in the direction of the X-axis, the curve rises rapidly toward higher values of the Y-axis. Then, it gradually decreases its slope and reaches its highest limit at a certain distance, which is called impact range, and stops at the same value. According to the zoning maps, the central and southern regions of the city showed a high concentration of PM 2.5 with undesirable situations compared to the northern and eastern regions of Tehran; so, there are more concerns in these areas.

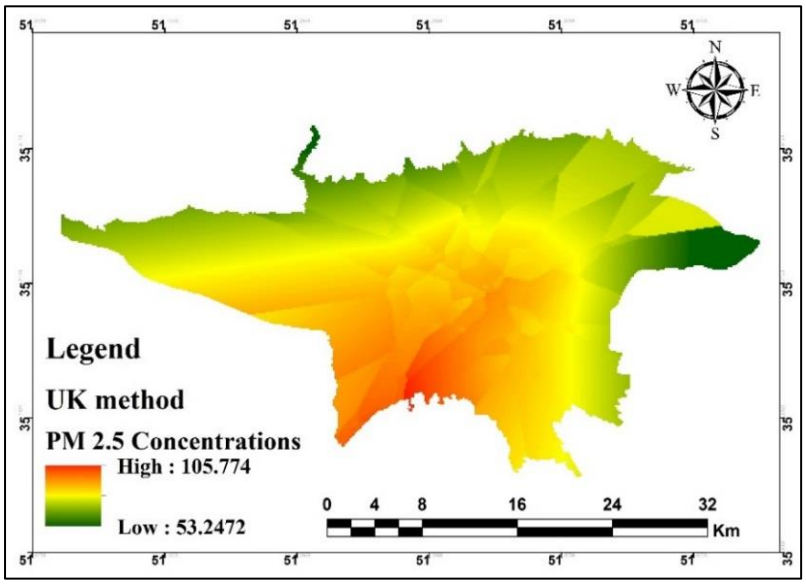

Fig. 3. The result of UK method for spatial zoning in Tehran.

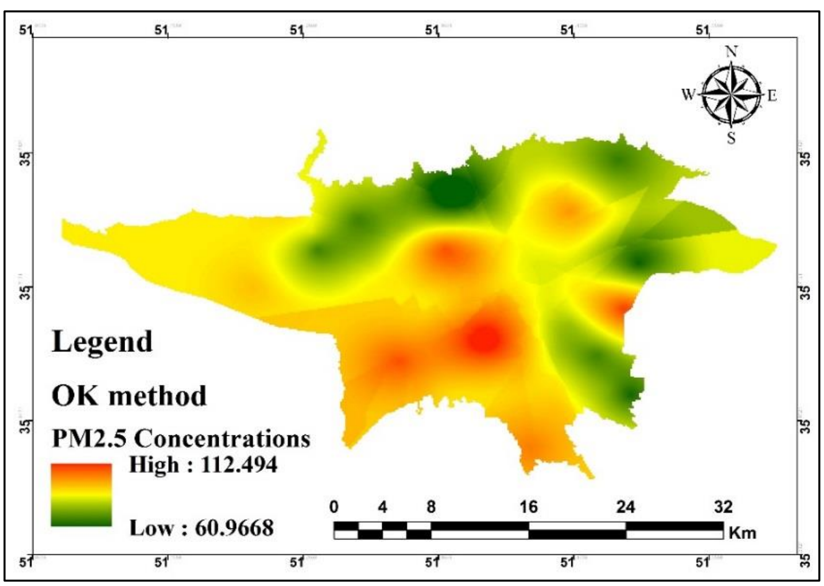

Fig. 4. The result of OK method for spatial zoning in Tehran.

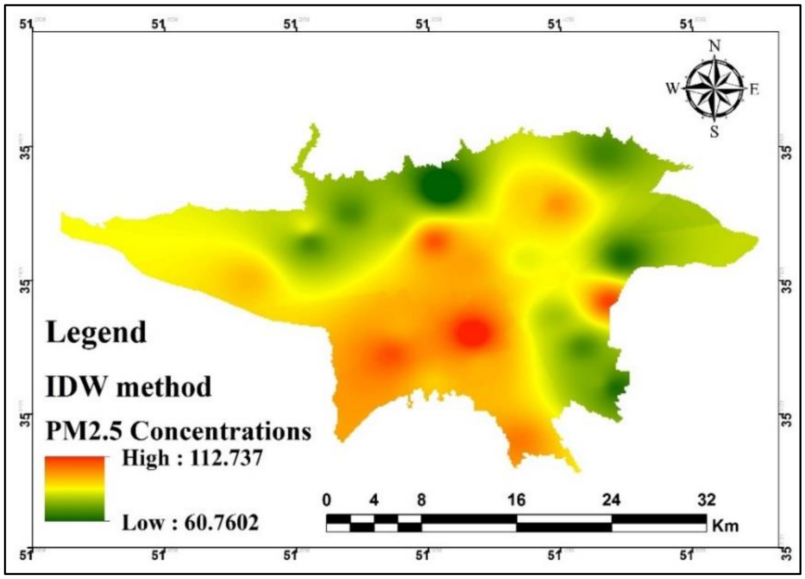

Fig. 5. The result of the IDW method for spatial zoning in Tehran.

RMSE and R^2 indices were used to compare the IDW, OK, and UK models and to select the optimal model in the PM 2.5 air pollution zoning in Tehran. The results of the indices are given in Table 2.

Table 2. Comparison of three interpolation models.

Model	RMSE	Std. RMSE	R^2
Ordinary Kriging (OK)	9.322	1.325	0.798
Universal Kriging (UK)	11.251	1.132	0.712
Inverse Distance Weighted (IDW)	12.247	-	0.663

According to the results of Table 2, the values of RMSE are 9.322, 11.251, and 12.247 for OK, UK, and IDW, respectively. The OK model has better conditions for modeling (RMSE=9.322). Also, the results showed that the OK model had the highest correlation coefficient (R^2=0.798) compared to the other two models. These findings are supported by previous studies as they document that the OK model is more suitable than the other methods [22,29] and make the best RMSE and R^2 in spatial zoning of air pollution [29]. Another study by Norpoor and Feyzi [31] regarding Tehran found that the OK model estimated sampled points without bias and had the lowest RMSE for modeling air pollutants. A study in America [32] showed that the values of R^2 and RMSE were (0.74,8.163), (0.79,6.983) and (0.78, 7.23) for IDW, OK, and UK models, respectively. These results showed higher efficiency of the OK model, which confirms the results of the present study. The study revealed that stations in the southern and central regions in Tehran have high concentrations of PM 2.5 and the annual average of all the stations exceeded the EPA standard (15 μ/m^3). This finding is similar to the results of studies conducted by Halek and Kavousi-Rahim [33], Habibi et al. [23], Haghparast et al. [25], and Pardakhti and Ebrahimi [24] indicating that the above-mentioned air pollution situation was undesirable in these stations.

4. Conclusions

Three interpolation models, namely universal kriging, ordinary kriging, and inverse distance weighted, were used to evaluate and compare the air pollution status in the urban landscape of Tehran. The results showed that the stations of the southern and central regions in Tehran have high concentrations of PM 2.5, and the annual average of all the stations exceeded the EPA standard (15 μ/m^3). The comparison of the three models based on the RMSE index showed that the OK model is more suitable than the other methods for the spatial zoning of air pollution in the urban landscape (RMSE=9.322). According to the average annual concentration of PM 2.5 in the air pollution monitoring stations in Tehran, the concentration exceeds the international standards annual mean (EPA=15 μ/m^3, WHO=10 μ/m^3). It should be noted that this could result in major health risks and adverse effects on the population of Tehran. Therefore, it is possible to reduce the level of air pollution in Tehran by increasing public transportation and green space, replacing aging vehicles, and improving the quality of fuel. Finally, it should be noted that the use of geographical maps allows for the rapid spatial analysis of air pollution and a better understanding of the situation in spatial zoning.

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