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Determining the optimal route with GIS, based on the lowest amount of $PM_{2.5}$ pollutant

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Abstract

Air pollution in Tehran is one of the most important problems of this metropolis. One of the most important pollutants in the air of Tehran is the $PM_{2.5}$ pollutant, which has various effects on people, especially the elderly and children, and can cause all kinds of diseases, including cardiac, respiratory, and even death. In this study, the first goal is to prepare a distribution map of air pollutant p pollution in Tehran city with the help of data related to 15 pollution measurement stations and interpolate the data using the IDW method, and secondly, optimal routing based on the cost layer of $PM_{2.5}$ pollution. This work has been done for two different days that had different levels of pollution. In order to prepare the desired map, ARC software has been used, as well as NET tool for routing. The routing output from the origin to the destination, for the two days of December 4 and December 26, shows the different routes obtained, which mainly passed through the blue and yellow areas of the pollution map, which had less pollution. This means that with the help of routing based on the pollution cost layer, the optimal route with the least amount of pollution can be determined, which can be very effective in determining the route for sick people, the elderly, and children who are most affected by pollution.

Keywords: Optimal route, GIS, air pollution, IDW, $PM_{2.5}$

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1. Introduction

Ambient air pollution poses a serious threat to human health (Boulanger et al., 2017). One of the most important secondary pollutants is particulate matter (PM) (WHO, 2005; Li et al., 2018). particulates matter are divided into two categories based on aerodynamic diameter. Coarse particles are those particles whose dynamic diameter is more than 10 µm (PM_{10}) and are often deposited at the beginning of the respiratory tract (Guarnieri & Balmes, 2014). $PM_{2.5}$, formally defined as particulate matter with diameter less than 2.5 µm, is one of the most harmful air pollutants threatening human health (Liu et al, 2017). $PM_{2.5}$ pollution has become one of the most serious environmental pollution problems in built-up cities (Liu et al., 2023). Fine particulate matter ($PM_{2.5}$) is a serious concern for human health (Ouyang et al., 2015; Di et al., 2016), and a wide variety of public health effects are related to long-term and short-term exposure to $PM_{2.5}$ (Honda et al., 2017; Zanobetti and Schwartz, 2009). $PM_{2.5}$ exposure can cause unfavourable effects such as cardiovascular disease, morbidity, mortality, and respiratory disease (Di et al., 2016; Ouyang et al, 2018). Numerous epidemiological studies have shown that both short-term and long-term exposures to particulate matter with diameter less than 2.5 µm ($PM_{2.5}$) are strongly linked with human respiratory disease, heart disease, lung cancer, and so on (Gamble, 1998, Vallejo et al., 2006). In addition, these particles directly wear the breathing tubes and block the air passages (Kermani et al, 2011). The results of recent 25-year studies show that deaths caused by $PM_{2.5}$ pollutant have increased greatly (Cohen et al., 2017).

Also, studies show that the number of people visiting hospitals due to lung infections due to the increase in the concentration of $PM_{2.5}$ compounds has increased significantly (Zhang et a., 2019). The results of various researches show a direct relationship between the deaths caused by lung cancer and gastrointestinal cancer with the concentration of $PM_{2.5}$ in the air (Hamra et al., 2014; Rahmani et al. 2019). Among the most populated cities in the world, Tehran is one of the most polluted capitals in the world in terms of air pollution. The height of Tehran above the sea level and the presence of Alborz mountains in the north and east, which have blocked the western winds as an obstacle, cause all the pollutants to remain in the city due to the incomplete combustion of fuels (Safavi & Alijani, 2007). The limitation of Tehran by mountains has caused it to not have an effective filtering property and meteorological factors such as temperature inversion, the continuation of high pressure systems with stable air in cold seasons and local winds such as mountains to the plains have intered pollutants into the city center and intensifies the pollution (Karimi et al., 2020). During the last few years, particulate pollution, especially particulate matter with a diameter of less than 2.5 microns, has been proposed as an indicator pollutant of Tehran. The city of Tehran has had the most unhealthy days in recent years in terms of the level of particulate matter pollution, especially $PM_{2.5}$ pollution (Bahari et al., 2016).

According to the provided statistics, 70% of particlulates matter in the air of Tehran city are estimated to be caused by vehicle traffic and some kind of mobile sources (Rafieetoroghi et al., 2017). Therefore, it can be said that the pollution caused by the traffic of vehicles in Tehran is one of the most important factors of air pollution. These cases have caused various researches to be carried out regarding the effects of air pollutants in Tehran, each of which can be effective in order to plan and make decisions in order to reduce air pollution and its effects. Based on this, the purpose of this research is to use GIS as a spatial data analysis tool to model $PM_{2.5}$ pollution and determine the most suitable and best path based on the lowest amount of pollution from the origin to the destination. Geographic Information Systems (GIS) methods have been increasingly used in environment and health research (Xu et al., 2022). GIS-based models are developed to produce maps that are used for the assessments of air quality, health impact assessment and the development of air quality policy (Stedman et al., 2009). Using GIS, it is possible to analyze spatial and temporal changes and patterns of air pollution dispersion at low cost and time. GIS can provide interpolation methods to study the spatial distribution of pollutants, manage spatial data and consider the impact of effective modeling parameters (Shogrkhodaei et al., 2021). Accordingly, in this article, by using GIS spatial processing, $PM_{2.5}$ dispersion map is prepared by interpolation and based on the data of air pollution measuring stations, and then by spatial and topological linking of the linear data of the streets of Tehran and using the network analysis tool in the GIS software, the most optimal path was determined based on the lowest amount of $PM_{2.5}$ pollution, which is defined here as the cost layer. In other words, the challenge of this research is to use GIS in order to value the desired path from the origin to the destination based on the amount of $PM_{2.5}$ pollution.

According to the reviews, most of the researches that have been done so far in the field of pollutant modeling can be divided into two formats: quantitative and qualitative. Quantitative methods rely on numerical measurements and are mostly used to prepare pollution zoning and statistical analysis of data, while qualitative methods rely on measurements based on categories and classifications and They are mostly used to evaluate the effects of air pollution. Quantitative methods are numerical measurements expressed in terms of numbers. The list of this method includes: air monitoring by proximity, interpolation, land use regression model (LUR), dispersion model, random forest (RF), remote sensing (RS) and Geographic Information Systems (GIS) (Susymary & Deepalakshmi, 2020; Gariazzo et al., 2021). In Air Monitoring by proximity, Mean concentration of pollutants monitored in one or more fixed site stations in a region will assign to each of the individuals within that region by calculating the average concentration from all the stations in the region (Pope III et al., 2002). The best method emphasis assigning concentration of pollutants from the nearest monitoring station to the individuals (Ostro et al., 2010). Interpolation endures an option that spatially distributed components are spatially correlated. In other words, substances that are adjacent to each other have identical characteristics. Interpolation eliminates the limitation of air monitoring by proximity if the area is large and not enough monitoring stations are set. There exist two interpolation techniques: deterministic interpolation, and geostatistical interpolation. One of the deterministic interpolation methods that widely used in air pollution exposure is inverse distance weighting in geo statistics (Susymary & Deepalakshmi, 2020). By combining interpolation and GIS, it is possible to analyze spatial data and produce spatial maps and zoning.

One of the works done regarding pollution modeling using interpolation is the work of Masroor et al. (2020) who estimated $PM_{2.5}$ pollution in areas where there is no measurement in the city of Tehran. The hourly concentrations of $PM_{2.5}$ during 2017-2018 period were acquired from the Department of Environment (DOE) and Air Quality Control Company of Tehran (AQCC). The hourly concentrations were validated and 24-h concentrations were calculated. Inverse distance weighting (IDW), Universal Kriging, and Ordinary Kriging were used to spatially model the $PM_{2.5}$ over Tehran metropolis area. The results of this study showed that RMSE value in Kriging method was less than the IDW method. In another article, Ismain et al. (2023) are using spatial interpolation techniques of inverse distance weighted (IDW) to assess $PM_{2.5}$ distribution and predict their concentrations at distinct unmonitored locations. Land Use Regression (LUR) is an empirical model that combines the air pollution monitoring data at countable stations and gather parameters through GIS. Regression models were developed using either stepwise forward regression or through machine learning algorithms. Then they have been applied to many stations in the study area where no measurements are available to predict the concentration of air pollutants. LUR model use traffic representations, population or address density, land use, and altitudes as predictor variables (Susymary & Deepalakshmi, 2020). Dons et al. (2014) used the LUR method to estimate the effects of black carbon (BC) and NO2 pollution on a long-term and daily basis for children living in the Antwerp area. Estimates and spatial-temporal separations in this study were adjusted according to the needs of the epidemiologists involved in this research.

Dispersion models are deterministic model which uses tangible and chemical knowledge to model the dispersions and transformations of the emitted pollutants from sources. Significant development has occurred in the field of dispersion modelling to estimate fine particle concentration (Kukkonen et al., 2016). Another statistical method used for spatial analysis and modeling of pollutants is the random forest (RF) method. The random forest algorithm was first proposed by Breiman (2001), and since that, it has been extremely successful as a general-purpose classification and regression method. The method, which combines several randomized decision trees and averages their predictions, has shown excellent performance in settings with a large number of variables compared to the number of observations. Furthermore, it is versatile enough to be applied to large-scale problems, adaptable to a variety of ad hoc learning tasks, and returns information on each variable importance (Mamic et al., 2023). It has been found that there is a substantial increase in the use of satellite observations for assessing air pollution exposure in epidemiological studies (Susymary & Deepalakshmi, 2020). Furthermore, Satellite remote sensing provides a possibility to monitor continuously spatial coverage of atmospheric particulate matters (Zhang & Li, 2015). By using remote sensing, it is possible to monitor changes in pollution level and analyze the obtained results with the help of different models and in GIS environment. Accordingly, it can be said that the use of remote sensing data in the GIS software environment for analysis and modeling is inevitable.

Xu et al. (2022) used a seasonal spatial-temporal method of modeling $PM_{2.5}$ distribution characteristics based on remote sensing data and GIS. The results indicated that the $PM_{2.5}$ concentration could be simulated by MODIS images and GIS method and could provide high spatial resolution data sources for exposure risk assessment. the last decade, in order to model pollutants and their effects, various researches have been conducted, the common point of which is the use of GIS to model pollutants and their effects. In other words, the use of GIS in studies and research related to pollution modeling and its integration with other modeling methods has increased rapidly. In general, GIS is a suitable method for displaying the inputs and outputs of a spatial model (Vahidnia et al., 2019). As mentioned before, GIS is an important and powerful tool to estimate and visualize different natural or artificial phenomena (Liu et al, 2017). GIS have been widely utilized as a means to store, retrieve, analyze, and visually present spatial data (Mohammadi et al., 2024). As an example, if we want to refer to a number of articles done with the help of GIS, we can refer to the work of Lee and Bae (2021) that in their study, an integrated air quality observation and modeling system with a geographical information system (GIS) was developed to characterize the air pollution caused by local primary emission sources. The results of this study suggest that the proposed method can be useful for understanding adverse air quality conditions and estimating the emissions of air pollutants from primary sources for local environmental and public health authorities.

In another study, Davarpanah and Vahidnia (2022) used multi-criteria decision making, and raster-based shortest path algorithm to solve the problem of determining the optimal route of water pipelines from Ardak to Mashhad. For this purpose, the effective parameters in determining the route were detected and after weighting processes, overlaid in the form of criteria maps in the GIS environment in order to generate cost map. According to the presented materials, it can be said that in recent years, in various spatial investigations and analyzes in the field of air pollution, GIS has played a very important role in combination with other methods and tools and the statistical accuracy of the obtained results has increased. In this research, the aim is to use GIS as a suitable platform for modeling $PM_{2.5}$ pollution in the city of Tehran using the most appropriate interpolation method based on the location of pollution measurement stations and then classifying and determining the most optimal path based on the lowest amount of $PM_{2.5}$ pollution. In this study, in order to perform optimal routing using network analysis in the GIS environment, the parameter of pollution concentration has been considered as a cost layer, While in many other studies conducted in this field, the parameters of route length and time traveled are used as the cost layer to implement the model. Therefore, using the amount of PM pollutant concentration in order to determine the optimal route can be considered as one of the innovations of this research.

2. Materials and Methods

In this section, the steps of doing the work in this study are presented in three sections. In the first part, the data required for the implementation of the modeling process related to the studied area is presented, and in the second part, the general work process is presented in the form of a conceptual model, and then in the third part, the interpolation method used in this research is explained in detail and the reasons for using the method are presented.

2.1. Required Data

In order to prepare a pollution distribution map and also to determine the optimal route with the least amount of pollution, it is necessary to determine the required relevant data. In this study, the city of Tehran has been considered in order to prepare a pollution interpolation map, and various data have been used to implement the relevant model, which are as follows:

- A spatial layer indicating the locations of air pollution monitoring stations in Tehran.
- Descriptive data specifying $PM_{2.5}$ concentrations for each monitoring station based on air quality control company (AQCC) information.
- Polygonal layers representing different areas within Tehran.
- Linear layers outlining the road network and squares within Tehran.

In order to implement the desired model and prepare the appropriate output, the latest data related to the concentration of $PM_{2.5}$ pollutant and also the latest division of the areas of Tehran were used.

2.2. Conceptual model and methodology

As mentioned before, the purpose of this study is to determine the optimal route from the origin to the destination based on the lowest amount of $PM_{2.5}$ pollution. It was prepared for two different days last year that had different $PM_{2.5}$ concentration values, and then this information was attached to the point layer related to the location of the stations and the corresponding layer was called in the GIS software environment. It should be noted that all the work implementation steps were done in ArcGIS 10.8.2 software. In order to create a continuous map of pollution values and to determine the level of pollution concentration for all parts of the city of Tehran, the interpolation method was used. IDW interpolation was used and the corresponding map was prepared for the two days. After preparing the interpolation map, in order to assign a certain amount of pollution to each of the created ranges and classes, the interpolated map was reclassified using the reclassify tool. As regards the input raster can have any cell size and must be a valid raster dataset Therefore, raster to polygon tool was used in ArcGIS software and this conversion was done. The important feature of the raster to polygon tool is that the conversion is done based on the field parameter determined from the descriptive information of the input raster layer, which here is the amount of $PM_{2.5}$ pollution. Of course, if a field is not specified, the cell values of the input raster will become a column with the heading Gridcode in the attribute table of the output feature class. After performing the raster to polygon process, it was necessary to quantify all the streets of Tehran based on the attribute of pollution amount according to the classified map of pollution. To do this, the spatial join tool was used in the ArcGIS software environment.

Spatial join tool, in general, joins attributes from one feature to another based on the spatial relationship. The target features and the joined attributes from the join features are written to the output feature class. By creating the pollution amount field for the linear layer of the streets, the network dataset was made to perform the network analysis tool. The network analysis has been implemented using ArcGIS Network Analyst Extension. Generally, it is a powerful extension of ArcGIS that provides network-based spatial analysis, including route analysis, travel directions, closest facility analysis, and service area analysis. It enables users to dynamically model realistic roads network factors, such as turn restrictions, speed limits, and traffic conditions at different times of the day (Sayed et al., 2017). In order to determine the optimal route with the least amount of pollution, first in the network analyst extension settings related to the built network dataset, the $PM_{2.5}$ pollution amount column was selected as the cost layer and other related settings were also made. After adjusting the best route analysis settings, the starting location and the ending location were selected and then the best route between these two locations was generated using the best route solver tool. A conceptual model illustrating the study process is provided in Figure 1.

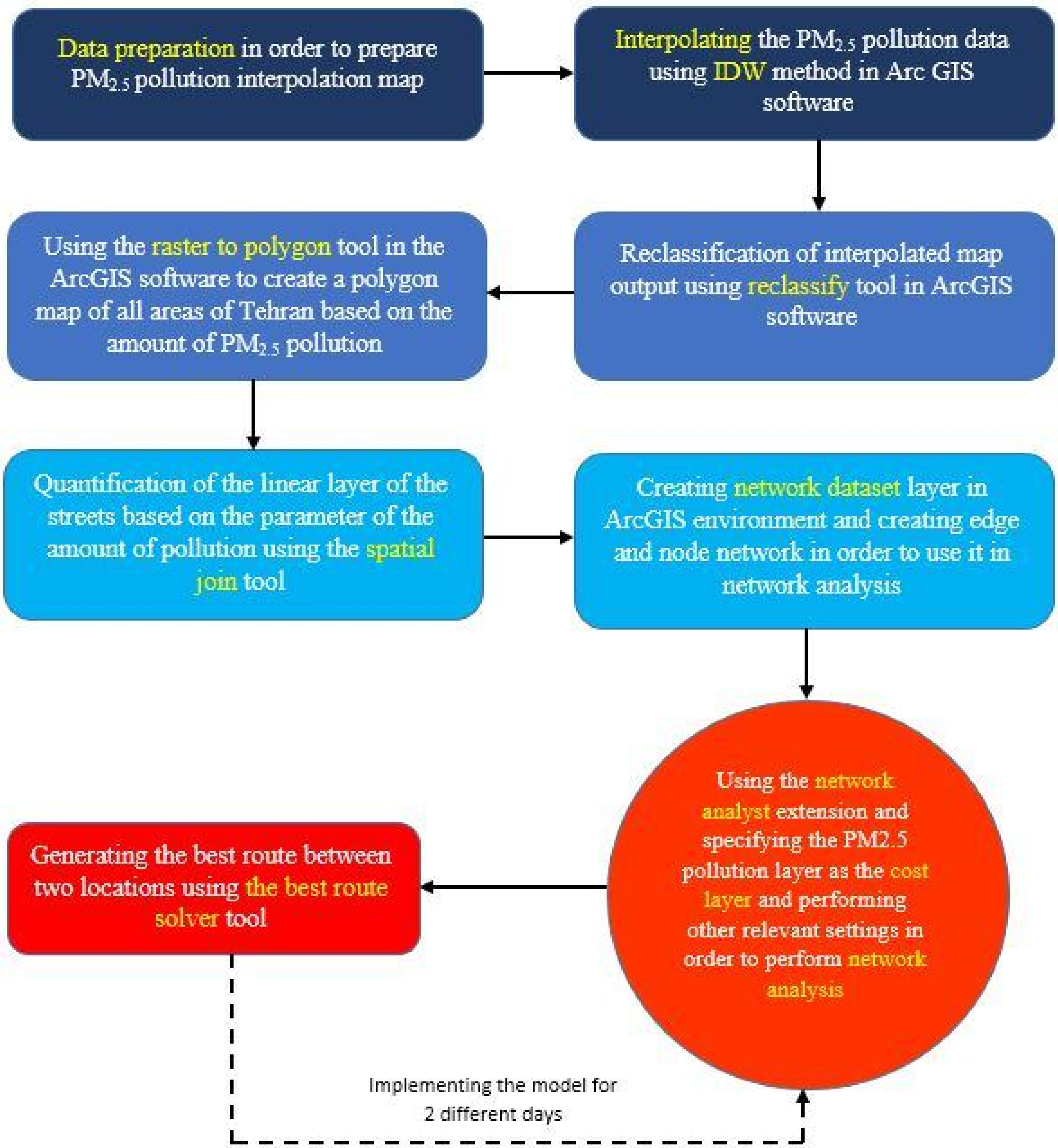

Figure1. Flowchart of the model process in this article

2.3. Interpolation method

As mentioned before, in order to prepare the interpolation map of $PM_{2.5}$ pollution in this study, the IDW method has been used. Considering the location of the pollution dispersion measurement stations and their asymmetric distance to each other, the use of the IDW method provides higher accuracy compared to other interpolation methods. In general, the IDW interpolation method is based on the idea that the effect of the desired phenomenon decreases via increasing the distance (Jalali et al., 2019). The advantage of the mentioned method is that it uses the distance as the weight of the known variable in predicting the unmeasured points because the role of the continuous variable in influencing the distance from the location of the unknown point is reduced. In other words, the performance of the IDW method in interpolation is such that the measurement of the distance between the interpolation point and the sample point was weighted using this method. The weight increases with the proximity of the interpolation point. The distance has an inversely proportional relationship with the weight contribution (Ismain et al., 2023). The details can be expressed as follows:

$$Z = \frac{\sum_{i=1}^{n} \frac{1}{(D_i)P} z_i}{\sum \frac{1}{(D_i)P}} \qquad (1)$$

Based on the Eq. (1), Z is the interpolation point's estimated value, Zi(i = 1 + n) is the measured sample value, n denotes the number of measured samples used in the computation, and Di represent the distance between the interpolation point and the station. P is the power of distance, which has a big impact on the interpolation result. More significant influence is granted by higher P values to values closest to the interpolation point. Power parameter values between 0.5 and 3 yield the best IDW interpolation results, with 2 being the most popular. In order to make sure that the projections don't depart significantly from the measured values, the accuracy of interpolation forecasts was verified by computing root-mean-square error (RMSE) (Ismain et al., 2023). In the next section, the outputs obtained from the implementation of the model are given.

3. Results and Discussion

In order to prepare the $PM_{2.5}$ pollutant interpolation map of the city of Tehran and then determine the optimal route in terms of the least amount of pollution, the data of two different days, including days December 4, 2023 and December 26, 2023 were selected as samples. Based on this, the data of 15 air pollution stations have been used for these two days, which are given in the following table of the station location and the amount of pollution for each station.

Table 1. An example of a table.

Station name	Longitude	latitude	December 4, 2023 (µg/m^3)	December 26, 2023 (µg/m^3)
Aghdasieh	51°29’ 6.114”	35°48’ 0.214”	64.79	13.71
Poonak	51°18’ 51.611”	35°45’ 46.418”	64.66	17.93
Mantagheh 2	51°22’ 5.43”	35 °46’ 37.52”	83.62	16.44
Mantagheh 4	51°29’ 32.95”	35°44’ 30.54”	89.84	19.02
Golbarg	51°30’ 22.073”	35 °43’ 51.692”	55.78	9.1
Setad Bohran	51°25’ 52.31”	35°43’ 37.5”	95.31	16.32
Tarbiat Modarres	51°23’ 1.30”	35°43’ 12.72”	102.43	17.44
Piroozi	51°29’ 37.545”	35°41’ 45.581”	103.46	19.37
Sanati Sharif	51°20’ 44.861”	35°42’ 21.391”	105.21	16.86
Mantagheh 11	51°23’ 23.04”	35°40’ 22.72”	102.11	11.04
Shadabad	51°17’ 36.559”	35°40’ 14.619”	100.53	16.01
Mantagheh 19	51°21’ 45.08”	35°38’ 06.76”	113.66	26.62
Masoudieh	51°29’ 56.48”	35°37’ 48.099”	44.65	14.45
Shahrray	51°25’ 32.08”	35 °36’ 16.475”	66.86	7.52
Mantagheh 21	51°12’ 52.152”	35°42’ 46.673”	93.98	20.82

For day December 4, in order to interpolate data using the IDW method, according to the lowest and highest $PM_{2.5}$ pollutant value of the stations, the interpolation process was carried out in 9 classes and in an equal interval method, in which the lowest value was 44.65 and the highest value was 113.66. For day December 26, interpolation was done as before in 9 classes, where the lowest value is 7.52 and the highest value is 26.62. After interpolation by IDW method, the RMSE value of interpolation on day December 4, was equal to 1.44 and for day December 26, was equal to 1.65. The results obtained from the accuracy of interpolation compared to other methods showed that, as stated before, according to the position of the stations relative to each other and their dispersion as well as their distance, the IDW method has the highest accuracy. After preparing the interpolation map in order to determine the correct numerical value of pollution to each cell, the ranges of the interpolation map were reclassified in 9 classes based on the initial and final values of each range. In the following, the interpolation map as well as the reclassify map of the data for the two days are presented.

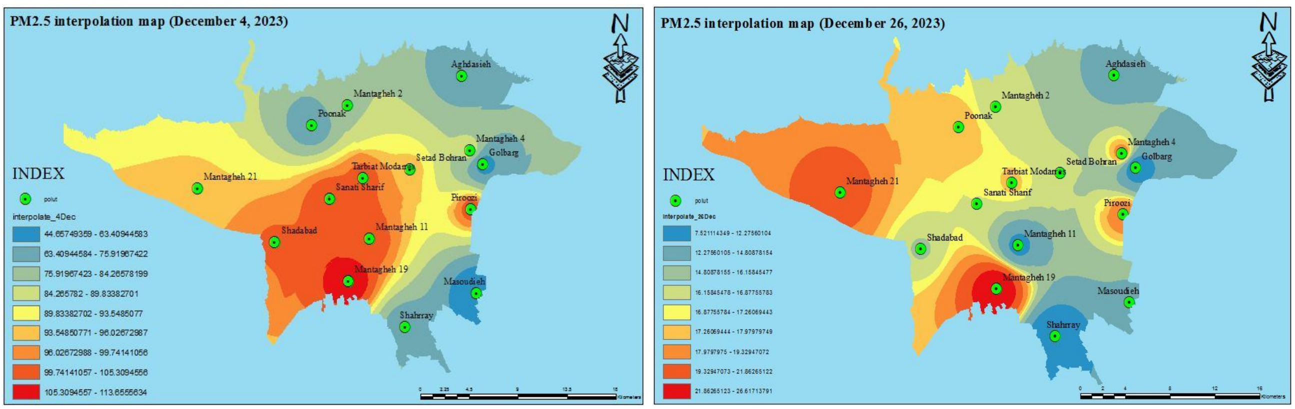

Figure2. (a) first picture of the interpolation map of the day December 4, (b) second picture of the day December 26.

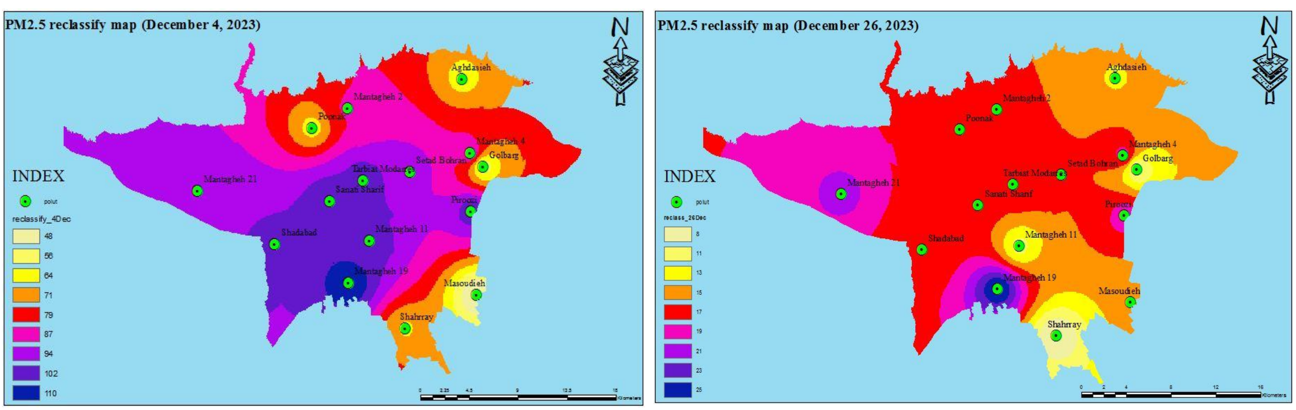

Figure3. (a) first picture of the reclassify map of the day December 4, (b) second picture of the day December 26.

After creating the reclassify map of the desired two days, using the raster to polygon tool in ArcGIS software and based on the stations' $PM_{2.5}$ pollutant values field, the cell values of the input raster became a column with the heading Gridcode in the attribute table and they were vectorized when it is converted to a polygon feature output. By creating the desired field in the attribute table, the vector layer of the streets of Tehran is called in the software environment, and by using the spatial join tool, all attributes of the join features, which are the pollution values of the polygons, are appended to attributes of the target features, which are streets layer and copied over to the output feature class. Therefore, the column of pollution values was added to the layer of streets and each of the streets had a numerical value of pollution. Figures 4 and 5 present the outputs obtained from the two mentioned steps.

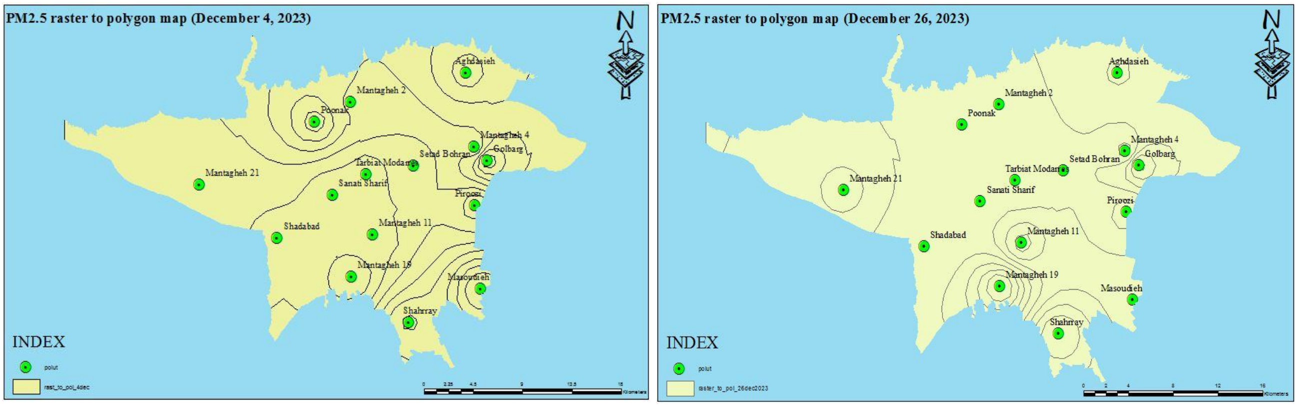

Figure4. (a) first picture of the raster to polygon map of the day December 4, (b) second picture of the day December 26.

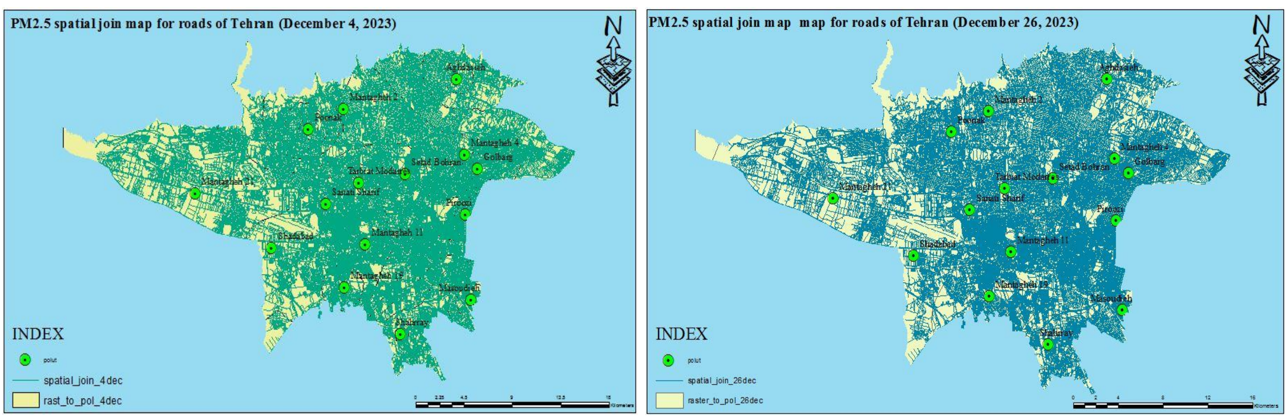

Figure5. (a) first picture of spatial join map of the roads of Tehran for day December 4, (b) second picture of the day December 26.

As mentioned before, the network analyst tool in ArcGIS software was used to determine the optimal route in terms of the least amount of pollution. The network analyst tool is considered one of the most important analytical tools in ArcGIS, which allows more detailed analysis of routes. With this tool, we can make smarter decisions by developing routing plans and Saves time and money by creating and implementing daily route plans to solve routing problems. To analyze the routes, a network dataset had to be built first, which was done in the ArcCatalog environment. The purpose of creating a network dataset is to determine a set of network elements such as edges, junctions and turns and establish topological connections between them. Each network element is associated with a collection of network attributes. Network datasets are typically used to model undirected flow systems. After building the network dataset by calling the maps and routes and determining the amount of pollution as a cost layer, the origin and destination of the routes for the two days were determined and the optimal route was determined using the solve option in network analyst tool, which are presented in the following maps.

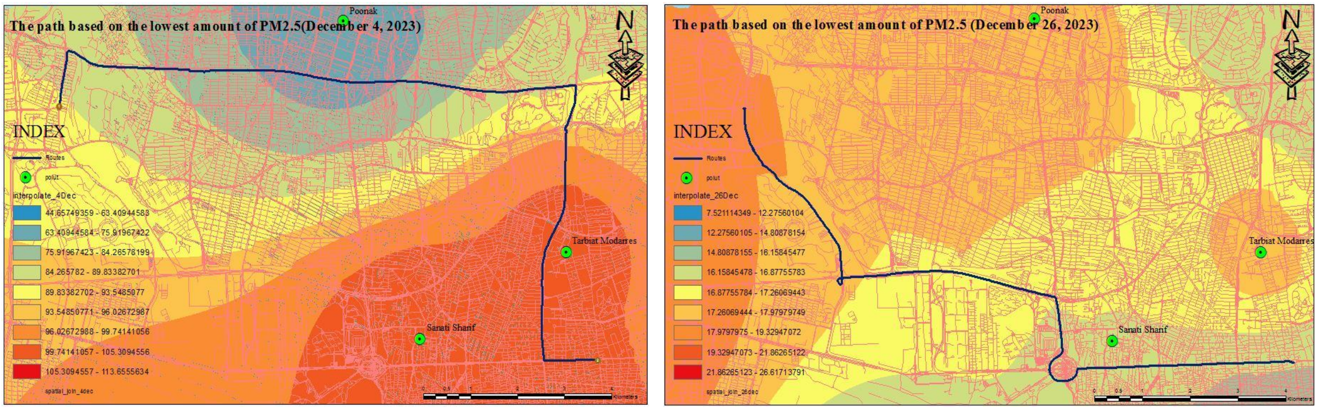

Figure6. (a) first picture of network analyst map of the roads of Tehran for day December 4, (b) second picture of the day December 26.

4. Conclusion

As mentioned before, according to the investigations carried out in many studies in the field of routing, the time layer and route length have been considered as the cost layer. While, in this study, the layer with the lowest amount of $PM_{2.5}$ pollution has been considered as the cost layer, which is considered as an innovation of this research. The outputs of the model show that determining the optimal route based on the lowest amount of pollution can provide us with different suggested routes. In other words, the main initiative of the presented model is to use the amount of $PM_{2.5}$ pollutant as a cost layer to determine the most suitable path to face the least amount of pollution. Determining the route with the least amount of pollution can greatly help the elderly, children and patients whose health is adversely affected by air pollution. As it is clear from the output obtained for December 4, the route obtained from the model is different from the route obtained for December 26. Considering that the amount of pollution was less in the northern part of Tehran on December 4 and most of the northern areas of Tehran in this day were blue, so the route proposed by the model passed through this part and only the end of the route passed through the orange areas.

This is while the route obtained from the model passed through the central part on December 26, which was also due to less pollution and the presence of yellow and blue areas in the central part of the city. In addition to the output of the models based on the pollution layer, the shortest path between the origin and the destination was determined with the help of the Network tool in the ArcGIS software, and by comparing the output of the obtained models with the shortest path obtained, it was determined that the path obtained from the model related to the day December 26 is very close to the shortest path model output. In other words, the route related to the model on December 26 is the most suitable route in terms of the least amount of $PM_{2.5}$ pollution and the shortest path between the origin and the destination. What has been done in this article is the use of interpolation to prepare the $PM_{2.5}$ pollutant distribution map for two different days and the use of the Network analyst tool to determine the optimal route between the origin and destination, which has led to the determination of two different routes for the two days in question. In future research, it is possible to optimize routing by considering the pollution layer as the cost layer and combining it with new methods such as artificial neural network (ANN) or agent-based modeling (ABM).

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