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Evaluation of PM2.5 Emissions in Tehran by Means of Remote Sensing and Regression Models

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ABSTRACT: Defined as any substance in the air that may harm humans, animals, vegetation, and materials, air pollution poses a great danger to human health. It has turned into a worldwide problem as well as a huge environmental risk. Recent years have witnessed the increase of air pollution in many cities around the world. Similarly, it has become a big problem in Iran. Although ground-level monitoring can provide accurate PM2.5 measurements, it has limited spatial coverage and resolution. As a result, Satellite Remote Sensing (RS) has emerged as an approach to estimate ground-level ambient air pollution, making it possible to monitor atmospheric particulate matters continuously and have a spatial coverage of them. Recent studies show a high correlation between ground level PM2.5, estimated by RS on the one hand, and measurements, collected at regulatory monitoring sites on the other. As such, the present study addresses the relation between air pollution and satellite images. For so doing, it derives RS estimates, using satellite measurements from Landsat satellite images. Monitoring data is the daily concentration of PM2.5 contaminants, obtained from air pollution stations. The relation between the concentration of pollutants and the values of various bands of Landsat satellite images is examined through 19 regression models. Among them, the Ensembles Bagged Trees has the lowest Root-Mean-Square Error (RMSE), equal to 21.88. Results show that this model can be used to estimate PM2.5 contaminants, based on Landsat satellite images.

Keywords: Air Pollution, Particulate matter, GIS, Modelling.

INTRODUCTION

Air pollution is one of the most serious environmental issues in many developing countries (Kanada et al., 2013). Economic development, industrial growth, and climate change work hand in hand to increase the level of outdoor pollution in the developing countries. On the contrary, the composition and sources of air pollution vary from region to region (Bourdrel et al., 2017). In recent years, some evidence has been collected from human epidemiological and animal studies, showing that air pollution can hurt the central nervous system (CNS) and cause CNS diseases (Block et al., 2012). According to Pope et al. (2002) and Nafstad et al. (2003), air pollution is one of the factors affecting cardiovascular and pulmonary diseases in many countries. A growing number of studies have all proved a positive relation between air pollution and mortality, including infant mortality (Arceo et al., 2016; Greenstone & Hanna, 2014; and Knittel et al., 2011) and life expectancy (Ebenstein et al., 2017). Some particulate matters (PM) such as PM2.5 and PM10 along with gaseous pollutants are the main contributors to haze formation (Guo et al., 2014), with many studies showing the effect

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of different factors on PM concentration. In 2010, Lelieveld and colleagues reported that about 3.15 million deaths were attributable to atmospheric fine particulate matter (PM2.5) around the globe (Lelieveld et al., 2015). This number represented about 6% of total worldwide mortality. The latest Global Burden of Disease (GBD) study has found out that PM2.5 is the most frequent cause of environment-related deaths worldwide, having caused approximately 2.9 million premature deaths in 2013 around the globe (Brauer et al., 2016).

To understand the effects of PM on the earth's climate system and human health, it is necessary to monitor PM2.5 on a global basis routinely. This is a challenging task as these submicron aerosols are vary a lot in space and time. Typically, ground-based instruments help measuring PM2.5 mass concentration of ambient particles widely in both urban and rural areas of Europe, the United States, Australia, and Asia. However, these ground-based observations represent point measurements and do not provide the necessary coverage for mapping the distribution of regional to global aerosols (Gupta et al., 2006). Ground-level regulatory monitoring networks in developed countries are often used to assess awareness in health studies (Kelly et al., 2011; Miller et al., 2007). However, since fixed-site monitors are monitored primarily, they are often limited to evaluation of greenhouse gas emissions from specific industrial sources and regional background levels in populated areas. This leads to inadequate coverage in many rural areas of developed countries. Developing countries do not have the least coverage. As a result, fixed-site monitors have a limited means of assessing the health effects of rural or developing areas (Prud'homme et al., 2013). Over the past two decades, there has been considerable progress in detection of air pollution from space. Satellite-based advances to surface monitoring networks are significant because air quality assessment is essential, concerning more polluting quantities and multiple spatial scales. One of the reasons for this predicted dependence on satellites is to increase the role of air quality models to determine complicated and extensive environmental features, which cannot be achieved solely through surface observations (Hidy et al., 2009). Our analysis indicates that satellite data is a useful tool to monitor particulate matter air quality, especially in regions in which ground measurements are not available (Gupta & Christopher, 2008). Since ground measurements of PM2.5 are sparse in many areas of the world, satellite data can be used in substitution to monitoring particulate matter air quality (Gupta et al., 2006). Satellite remote sensing reduces uncertainty in the spatial distribution of these deleterious species as well as the processes, affecting them (Martin, 2008).

Hamraz et al. (2014) developed a dynamic model to cope with the complexities of urban air pollution problem of Tehran. It included some subsystems. Another study on air pollution of cement industries was done by Ansari and Seifi (2013). Shahgholian and Hajihosseini in 2009 proposed a dynamic model to evaluate the effects of air pollution in Tehran for the coming decade. They only assumed the population changes as the primary source of air pollution instead, investigating the impact of urban air pollution on health and populations. Sohrabinia and Khorshiddoust in 2007 explored the capabilities of MODIS satellite data to study air pollutants and extract air pollution maps. Their study will used both satellite and ground stations' data. Also, Nabavi et al. (2019) evaluated the applicability of high-resolution Multi-Angle Implementation of Atmospheric Correction (MAIAC) AOD for PM2.5 estimation and Yousefi Kebria et al. (2013) created a model to estimate air pollution by modelling PM10, CO, and O3 in the streets according to the regression method. In 2016, Asghari and Nematzadeh tried to assess and predict air pollution of Tehran with two approaches: In the first one, they used basic ANN with randomly-generated weights, whereas in the second, they applied GA to create the initial weights of ANN.

As it can be seen, different models and methods have been used to model air pollution so far. The current research, however, evaluates and compares different models to select the best one. The paper examines the use of satellite data along with ground data about particulate matter (PM) release. Its main objective is to evaluate Landsat satellite's ability to determine PM2.5 concentration in Tehran, for which it should use and compare different regression methods to estimate PM2.5 concentration. Definition of a relation between satellite pixel values and PM concentrations is also another objective of this paper. Here, satellite estimates are compared with the values obtained by ground stations; afterwards, the accuracy of satellite estimation is calculated. Tehran is considered as the case study due to the sufficient number of its ground stations, which can record PM concentrations as well as the high population, exposed to PM emissions.

MATERIALS AND METHODS

The study has been conducted in Tehran, the capital of Iran, which according to the latest census, has a population of about 8.7 million. Tehran is located along a 51° eastern latitude and 35° north latitude (Behzadi & Alesheikh, 2013). Tehran Province is located between the central Alborz Mountain and the western margin of the Kavir Desert (Alizadeh-Choobari et al., 2016). Its climate is mostly affected by altitude (Figure 1), characterized by cold and dry winters but warm and dusty summers. Tehran has about 40% of the country's industrial units. The fact that the city of Tehran has a particular geographic location (high altitude, elevation difference in the north and south), makes it quite inadequate in terms of urban texture. Many cars travel throughout the day. Adding insult to injury, west winds bring the smoke from factories as well as other contaminating agents into the city of Tehran during the whole year. In general, Tehran has disasterous environmental conditions, with its air pollution being associated with toxic gas content in recent years.

The city has 23 air quality monitoring stations (AQM), the characteristics of which can be seen in Table 1. These stations monitor the concentration of pollutants under the supervision of the Air Quality Control Company (AQCC). Figure 1 shows the distribution of AQM stations in Tehran. These stations perform hourly measurements of various contaminants such as CO, O3, NO2, SO2, PM10, and PM2.5. The present study focuses on the concentrations of PM 2.5, downloaded from the Air Quality Control Center. Meanwhile, these values date between January 2017 and March 2018.

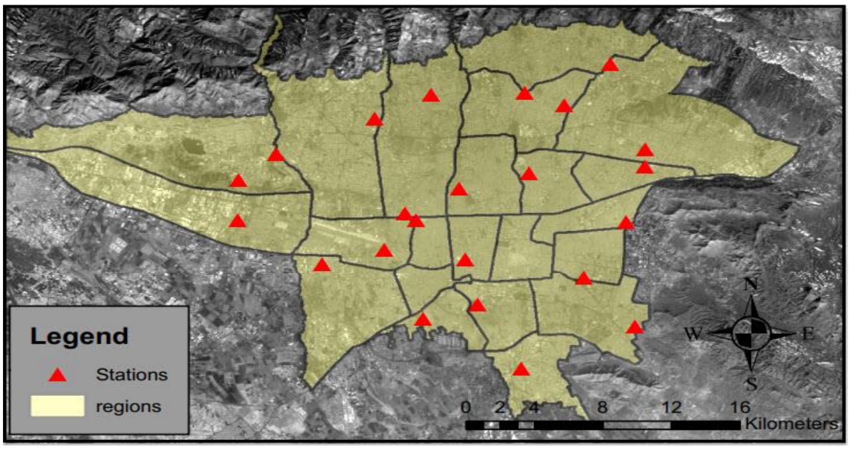

Fig. 1. The study area of Tehran, showing the locations of the Air Quality Control Company (AQCC) in 2018

Table 1. A summary of the characteristics of the stations of Tehran Air Quality Control Company

No	Station Name	Longitude	latitude
1	Rose Park	51.267886	35.739888
2	Mahallati	51.46636	35.661083
3	Aqdasiyeh	51.48414	35.79587
4	Punak	51.33168	35.7623
5	Piroozi	51.49376	35.69599
6	Tarbiat Modares	51.385909	35.71751
7	Darrus	51.45416	35.77
8	Setad Bohran	51.4312	35.72708
9	Shad Abad	51.29735	35.67005
10	Sharif	51.35094	35.70227
11	Shar-e-Rey	51.42571	35.60363
12	Tehran Municipality of District 2	51.368175	35.777089
13	Tehran Municipality of District 4	51.50643	35.74182
14	Tehran Municipality of District 10	51.35803	35.69748
15	Tehran Municipality of District 11	51.38973	35.67298
16	Tehran Municipality of District 16	51.397657	35.644584
17	Tehran Municipality of District 19	51.36252	35.63521
18	Tehran Municipality of District 21	51.24311	35.697773
19	Tehran Municipality of District 22	51.24364	35.723398
20	Sadr	51.428623	35.778232
21	Golbarg	51.50613	35.73103
22	Masoodieh	51.49902	35.63003
23	Fath Square	51.33753	35.67882

All Landsat 8 satellite imagery was downloaded from the United States Geological Survey (USGS). The Landsat 8 satellite payload involved two scientific instruments, namely the Operational Land Imager (OLI) and the Thermal InfraRed Sensor (TIRS). Both of them provided seasonal coverage of the global landmass at a spatial resolution of 30 meters (visible, NIR, SWIR), 100 meters (thermal), and 15 meters (panchromatic). The Landsat Program provides repetitive acquisition of high-resolution multispectral data of the earth's surface on a global basis. The Landsat 8 scene size is 185-km-cross-track-by-180-km-along-track. The study made use of Landsat 8 satellite imagery between January 2017 and March 2018.

The learner regression model is a model of monitored machine learning, describing the relation between a response variable (output), and one or more predictor variables (inputs) (Behzadi & Alesheikh, 2014). To put it more precisely, regression explicitly refers to the estimation of the response variable in comparison with the discrete response variable, used in the classification. Regression is necessary for estimation and forecasting in almost every field, such as engineering, physics, economics, management, etc. Regression analysis helps understanding how a dependent variable changes when one of the independent variables is changed, while other independent variables are constant.

The sample collection section was consisted of two steps. At first, Landsat 8 satellite imagery was collected from January 2017 to May 2018. Tehran has 23 air quality control stations; the characteristics of which can be seen in Table 1. In each satellite image, the radiance of each band was collected for each station. PM2.5 contaminants are also obtained based on the passing time of satellite for every station. The bands' values, along with the amount of PM2.5 contaminants formed a matrix with 12 columns. Eleven columns belonged to the band's values, while the remaining one belonged to the PM2.5 pollutant. The pixel value was related to all objects within that pixel. In the next step, in order to avoid the objects' impact on pixel value, the difference between pixel values in two different times was calculated for each band. Finally, a matrix was provided, which included the difference between the pixel values of the bands and the difference in the amount of pollutants.

The present study employed 19 regression models, which got classified into five groups. The first group was linear regression. It contained Linear, Interactions, Robust, and Stepwise. The linearity in a linear regression model refered to the linearity of the predictor coefficients (Mousavi & Behzadi, 2019b). The second group was a regression tree that included Complex, Medium, and Simple. An object of class Regression Tree can predict responses for new data with the predict method (Mousavi & Behzadi, 2019a). The object contains the data used for training so that it can compute re-substitution predictions. The third was the Support Vector Machine (SVM) regression model, including Linear, Quadratic, Cubic, Fine Gaussian, Medium Gaussian, and Coarse Gaussian. Regression SVM models store data, parameter values, support vectors, and algorithmic implementation information. The fourth group, the Regression Ensemble, contained Boosted Trees, and Bagged Trees. Regression Ensemble combined a set of trained weak learner models and data on which these learners were trained. It was capable of predicting ensemble responses for new data by aggregating predictions from its vulnerable learners. The last group was the Gaussian Process Regression (GPR) model, and included Squared Exponential GPR, Matern 5/2 GPR, Exponential GPR, and Rational Quadratic GPR. Gaussian process regression (GPR) models are nonparametric kernel-based probabilistic ones.

RESULTS AND DISCUSSION

To assess the mentioned regression models, the difference matrix of pixel values in different bands and the difference in pollutants were used in regression models. Eleven columns, associated with bands 1 to 11, formed the inputs, while the PM2.5 pollutant column was regarded as the models' output. After modelling, the RMSE and correlation values were calculated for each model, represented in Table 2 below. Among the 19 regression models, used in this study, the Ensembles Bagged Trees model had the lowest RMSE, being 21.88. It was chosen as the final model to generate an output map. The calculated correlation between the actual PM2.5 data and the predicted values by the regression model was 0.7899.

Table 2. Regression models and their specifications

No	Model name	RMSE	Correlation
1	Linear Regression	23.58	0.2258
2	Interactions Linear Regression	41.54	0.3220
3	Robust Linear Regression	23.52	0.2106
4	Stepwise Linear Regression	22.80	0.2116
5	Complex Tree	25.18	0.7926
6	Medium Tree	24.35	0.6230
7	Simple Tree	23.10	0.4305
8	Linear Support Vector Machine (SVM)	23.59	0.1756
9	Quadratic Support Vector Machine (SVM)	38.05	0.2842
10	Cubic Support Vector Machine (SVM)	771.27	0.3609
11	Fine Gaussian Support Vector Machine (SVM)	22.53	0.5632
12	Medium Gaussian Support Vector Machine (SVM)	22.81	0.3916
13	Coarse Gaussian Support Vector Machine (SVM)	23.71	0.1904
14	Ensemble Boosted Trees	22.06	0.6559
15	Ensemble Bagged Trees	21.88	0.7899
16	Squared Exponential Gaussian Process Regression (GPR)	22.78	0.4035
17	Matern 5/2 Gaussian Process Regression (GPR)	22.18	0.4229
18	Exponential Gaussian Process Regression (GPR)	22.11	0.5749
19	Rational Quadratic Gaussian Process Regression (GPR)	22.79	0.4067

As aforementioned, the Ensembles Bagged Trees model turned out to be the optimal one. Input and Output were the difference between the pixel values in the bands and the difference in pollutants, respectively. Therefore, two satellite images had to be selected. The image with minimum emission of pm2.5 was considered as the base one, whereas the second one became the image in which pollution must be calculated.

In order to calculate the amount of pollution in the second satellite image, the pixel values of the two images got extracted in the eleventh bands. Then, the difference between the pixel's values was obtained and was considered as the values of a matrix. The resultant matrix was entered as an input of the optimal model. The first image (based image) was selected with the least pollution (a clean image). The model's output matrix expressed the difference in pollutant amount of pm2.5 in both images. As the first image was considered clean, the amount of obtained contaminants indicated the amount of pollutant pm2.5 in the second image.

The current study made an attempt to predict PM2.5 contaminant quantities via regression model and satellite imagery for all areas of Tehran. One limitation of this research was the low number of air quality control stations and other possible restrictions of missing PM2.5 pollutant data in different stations and at different times. Finally, using the Ensembles Bagged Trees regression model, PM2.5 contaminants got mapped and contaminated, as shown in Fig. 2. Adding satellite images for more than a year and testing the model showed that by increasing the number of satellite images, the RMSE value of the regression model did not change at all. Thus, it can be concluded that one-year satellite images are enough to create a regression model.

One of the merits of this research was the use of Remote Sensing. Another notable point was that the changes in pollution were not uniform, which was consistent with reality. Four parts of Figure 2 got selected as examples for checking the contamination. Part 1 pertained to Chitgar Lake in eastern Tehran. Although the lake, itself, was clean in terms of PM2.5 contamination, the surrounding areas were contaminated. Section 2 depicted the image of Azadi Square, a bright spot, which expressed the considerable contamination of this field while covering the field of grass. Still, because of the high traffic of vehicles, this area suffered from high pollution. Section 3, the Lavizan Forest Park, showed that the area was clean in terms of vegetation, correctly illustrated in the figure. Section 4 also showed the City Park, which, despite the busy streets surrounding the area, was a clean place for PM2.5 contaminants.

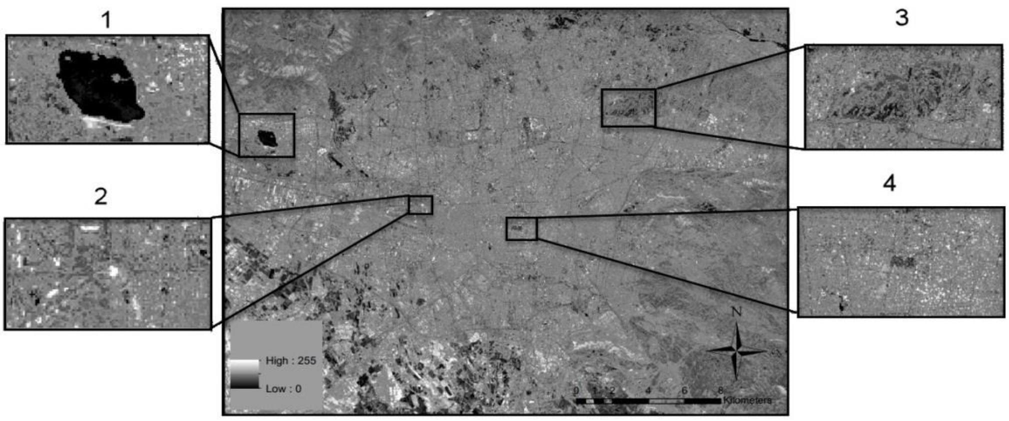

Fig. 2. Estimated PM2.5 concentrations from the final regression models

CONCLUSION

Air pollution in urban areas is one of the consequences of industrialization, and it still increasing in developing countries on a daily basis. Due to the expansion of metropolitan regions as well as increase of the pollutants and damages caused by air pollution, it is necessary to create rapid, comprehensive, and low-cost air pollution maps so that better decisions could be made for metropolitan areas such as Tehran. This study was carried out to find a fast and inexpensive method to produce a PM2.5-contaminant map for Tehran. The PM2.5 pollutant values were collected from 23 monitoring stations in Tehran between the years 2017 and 2018. Using Landsat satellite imagery and multiple regression methods, it was found that there is satellite images and PM4 contaminants are correleated. Afterwards, all models were evaluated, and the PM2.5-contamination map for Tehran was prepared, using the least RMSE model. The lack of such a model to produce a comprehensive map in Tehran has so far caused numerous urban management problems. The results of this study show that satellite imagery can be used very accurately to model air pollution. The use of satellite imagery has many benefits. First, satellite imagery monitors the area altogether. In ground-based methods, air pollution data is collected from a limited number of air pollution stations, and interpolation models generate a pollution map. This makes it hard to trust the interpolated values. In contrast, satellite images are continuous, displaying the information in a pixel-to-pixel manner. Another advantage of the proposed model is that the production of air pollution maps is no longer costly. This means that there is no more need to build a ground-based air pollution station to map the pollution, which would save the costs of building and maintaining a station.

Another point is that the proposed model is applicable to all parts of the country. So if an area lacks a ground station to detect air pollution, satellite imagery and the proposed model could produce a contamination map of that area. Finally, the present study provides a better insight into the contamination situation by presenting the PM-contamination map in all areas of Tehran, and may help urban authorities of Tehran municipality to adopt more efficient managemental strategies.

GRANT SUPPORT DETAILS

The present research did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy has been thoroughly observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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