

Determining Effective Factors Regarding Weather and Some Types of Air Pollutants in Seasonal Changes of PM₁₀ Concentration Using Tree-Based Algorithms in Yazd City

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ARTICLE INFO

ORIGINAL ARTICLE

Article History:

Received: 13 November 2023

Accepted: 20 January 2024

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Keywords:

Air Pollution,

Particulate Matter,

Dust,

Machine Learning,

Random Forest.

ABSTRACT

Introduction: This study was carried out with the aim of determining weather parameters and air pollutants affecting seasonal changes of particulate matter of less than 10 microns (PM₁₀) in Yazd city using Random Forest (RF) and extreme gradient boosting (Xgboost) models.

Materials and Methods: The required data was obtained from 2018 to 2022. Levene's test was applied to investigate the significant difference in the variance of PM₁₀ values in 4 different seasons, and Boruta algorithm was used to select the best predictive variables. RF and Xgboost models were trained using two-thirds of the input data and were tested using the remaining data set. Their performance was evaluated based on R², Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Nash–Sutcliffe Model Efficiency Coefficient (NSE).

Results: The RF showed a higher performance in predicting PM₁₀ in all the study seasons (R² > 0.85; RMSE < 22). The contribution of dust concentration and relative humidity in spring PM₁₀ changes was more than other variables. For summer, wind direction and ozone were identified as the most important variables affecting PM₁₀ concentration. In the autumn and winter, air pollutants and dust concentration had the greatest effect on PM₁₀, respectively.

Conclusion: RF model could explain more than 85% of PM₁₀ seasonal variability in Yazd city. It is recommended to use the model to predict the changes of this air pollutant in other regions with similar climatic and environmental conditions. The results can also be useful for providing suitable solutions to reduce PM₁₀ pollution hazards in Yazd city.

Citation: Ebrahimi-Khusfi Z, Ebrahimi-Khusfi M, Nafarzadegan AR, et al. *Determining Effective Factors Regarding Weather and Some Types of Air Pollutants in Seasonal Changes of PM₁₀ Concentration Using Tree-Based Algorithms in Yazd City*. J Environ Health Sustain Dev. 2024; 9(1): 2180-94.

Introduction

Particulate matter with a diameter of less than 10 μm (PM₁₀) is composed of a variety of solid and liquid compounds originating from crustal matter and anthropogenic activities^{1, 2}. PM₁₀, as one of the most important air pollutants, has adverse

effects on public health and the environment^{3, 4}. Increasing the incidence of cardiovascular and respiratory diseases and mortality rate are among the adverse consequences of degraded air quality due to the increase of PM₁₀ in urban areas⁵⁻⁸.

Complex interactions between different

parameters have a great impact on spatial and temporal variations of PM₁₀ concentrations. Although anthropogenic activities play an important role in particular matters variations^{9, 10}, several studies have linked these variations to changes in meteorological conditions and some other air pollutants¹¹⁻¹⁴. Therefore, it is important to conduct a comprehensive investigation to recognize the contribution of PM₁₀ drivers to the control and management of pollution caused by this air pollutant.

Previous studies focused on exploring the correlations between some climatic parameters and PM₁₀^{15, 16}, and some other stressed the spatial prediction of PM₁₀ based on different models of machine learning (ML)¹⁷⁻¹⁹. However, predicting the seasonal changes of PM₁₀ and determining the share of factors affecting it in different seasons has not been extensively studied; however, it has received more attention in the present study.

According to the previous works, temperature, rainfall, wind speed, wind direction, air pressure, sunshine duration, and relative humidity have been identified as the most important meteorological drivers controlling PM₁₀ concentrations which can be used to model and estimate PM₁₀ in urban environments^{14, 20, 21}.

In addition to climatic drivers, dust events also affect changes in particular matters concentration especially in desert environments²²⁻²⁴. Therefore, dust-related indicators such as dust events frequency can be used to estimate and model PM₁₀. Dust concentration (DC) changes from one place to another place, especially over cities located in arid regions and adjacent to dust-prone areas^{25, 26}. Therefore, it can play an important role in changing the concentration of particular matters and can be considered as another dust-related indicator to predict temporal and spatial variation of PM₁₀; but, so far it has not been used in air pollutants modeling studies. Hence, in this study, along with climatic variables mentioned above, DC and total dust event frequency (TDF) was also used to estimate daily changes in PM₁₀ concentration in Yazd city, and to determine its relative importance in estimating PM₁₀ in different seasons. The city is

located near Yazd-Ardakan plain, which is one of the most sensitive dust-prone areas in Central Iran, and the dust entering it, has endangered the health of the inhabitants of this region²⁷.

In modeling and predicting PM₁₀ concentration, some models of ML have shown better performance than others. The least absolute shrinkage and selection operator (LASSO), support vector regression (SVR), random forest (RF), K-Nearest Neighbour (KNN), extreme gradient boosting (Xgboost), and artificial neural network (ANN) were evaluated for spatial prediction of PM₁₀ concentrations in Ankara, and the best performance was obtained from ANN model¹⁷. Among the RF, Xgboost, and artificial neural networks (ANN), the RF and Xgboost models had the best performance in predicting PMs²⁸, and between the Gradient boosted regression (GBR) and RF, the second model²⁹ has been successfully applied to predict PM₁₀. The high capacity of the RF model compared to Naïve Bayes (NB) and KNN for spatial prediction of PM₁₀ in Italy has been proven in another study¹⁹. The RF, bagged classification, and regression trees (Bagged CART) models showed the same and higher performance compared with the mixture discriminate analysis (MDA) in estimating PM₁₀ in Barcelona Province¹⁸. In general, based on recent works, the RF, Xgboost, ANN, and Bagged CART models are optimal models for estimating PM₁₀ concentrations. In this study, tree-based models (RF and Xgboost) were used to estimate daily PM₁₀ concentrations across Yazd city.

It is worth noting that in studies on PM₁₀ estimation and prediction, the selection of the most appropriate estimators is very important because the existence of a collinearity effect between them can lead to a decrease in estimation accuracy. This issue has not been considered in most of the recent studies^{17, 19, 29}, while the authors have tried to choose the best estimators to predict the target variable (PM₁₀) using various techniques such as removing variables with minimum variance and Boruta algorithm³⁰. Generally, the main objectives of this study were (i) to identify optimal variables among the air pollutants, meteorological factors,

TDF, and DC for predicting daily PM₁₀ concentration in different seasons, (ii) to evaluate the performance of RF and Xgboost models in modeling and estimating PM₁₀, and (iii) to determine the relative importance of best PM₁₀ predictors in different seasons in Yazd city.

Materials and Methods

Study city

The study area of the current research is Yazd city located in the center of Iran. The area of the city is about 1629 square kilometers, and it is located in the path of dusty winds originating from Yazd-Ardakan plain, one of the critical centers of

dust production in central Iran. There are three air pollutants measurement stations in Yazd city. After checking the statistics of these stations, it was found that the station located in Sanat Square has many statistical deficiencies. To investigate the objectives of this research, the information related to the other two stations, which have a common statistical period from 2018 to 2022, as well as their geographical location, was used as shown in Figure 1.

The methodology of the present research is shown in Figure 2, and more details are provided in the following sections.

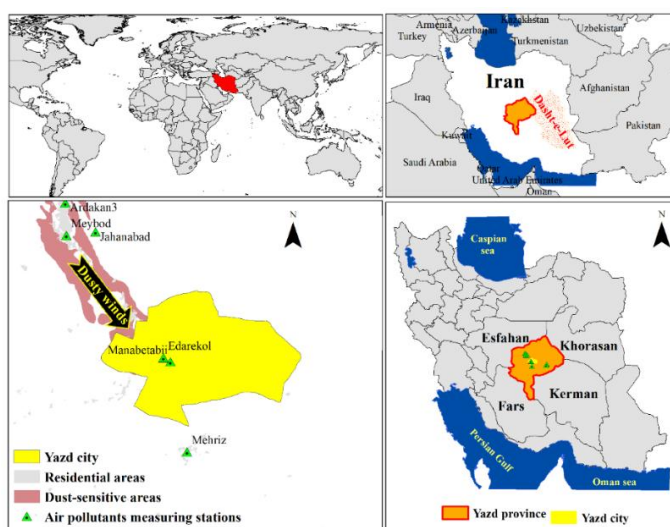


Figure 1: The geographical location of the study area and air pollutants measuring stations in Yazd province

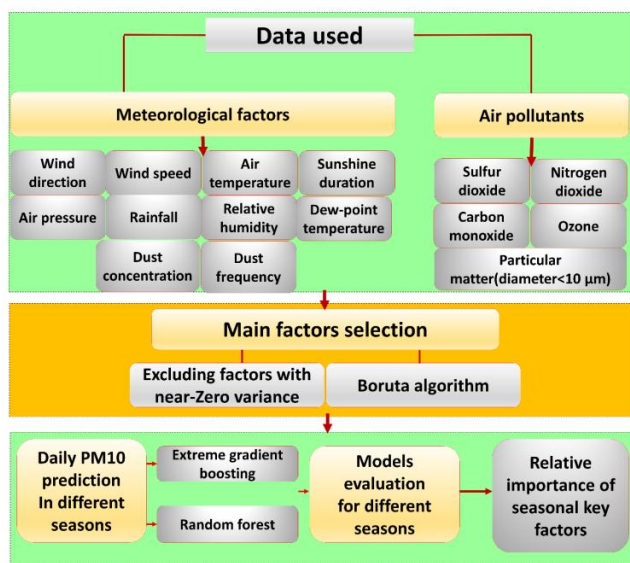


Figure 2: Schematic diagram of estimating process of daily PM₁₀ concentration and determining key factors in different seasons

Data used

In this study, the data related to some air pollutants (SO₂, NO₂, O₃, and CO) as well as weather parameters mentioned in Table 1 were used. Meteorological and air pollutants data were respectively obtained from meteorological and environmental protection organizations of Yazd Province.

Meteorological data including air temperature, rainfall, relative humidity, wind speed, wind direction, sunshine duration, dew-point temperature, and air pressure were collected on a daily scale. Data on horizontal visibility (HV), internal dust-event codes, and external dust-event codes were recorded in synoptic stations. Internal events are recorded with codes 07 to 09, 30 to 35, and 98 while external events are recorded with code 06 in the synoptic stations³¹. In this study, the data recorded at the Yazd synoptic were acquired from the Meteorological Organization of Yazd Province for the same statistical period as air pollutants data. They were utilized to calculate TDF (Equation 1), and DC³² as expressed by Equations (1-3):

$$TDF = IDF + EDF \tag{1}$$

where, TDF is total dust frequency, and IDF and EDF refer to internal dust-event frequency and external dust-event frequency, respectively.

$$DC(\mu\text{g}/\text{m}^3) = \frac{3802.29}{\text{visibility}^{0.84}} \text{ visibility (km)} < 3.5 \tag{2}$$

$$DC(\mu\text{g}/\text{m}^3) = \exp(-0.11 \times \text{visibility} + 7.62) \text{ visibility (km)} \geq 3.5 \tag{3}$$

DC was calculated in the 3-hourly scales from 2018 to 2022, and daily DC was then calculated by averaging 3-hourly DC for all the dusty days of the study period. For days without dust occurrence, the DC value was considered zero. In general, according to the study background and the researchers' understanding of the factors affecting the PM₁₀ concentration, data on sixteen factors were initially collected (Table 1), and based on the techniques described below, the main factors affecting PM₁₀ concentrations were then selected to predict daily PM₁₀ concentrations during different seasons and analyze the relative importance of the dominant factors affecting them in the Yazd city.

Table 1: Collected variables to predict daily changes of PM₁₀ in Yazd city

No.	Description	Abbreviation	Unit
1	Sulfur dioxide	SO ₂	ppb
2	Nitrogen dioxide	NO ₂	ppb
3	Ozone	O ₃	ppb
4	Carbon monoxide	CO	ppm
5	Mean wind speed	WSmean	m/s
6	Air temperature	T _{min}	°C
7	Air pressure	Pr	hpa
8	Rainfall	Rain	mm
9	Relative humidity	RH	%
10	Sunshine duration	SSD	hours
11	Dew-point temperature	Td	°C
12	Horizontal visibility	HV	m
13	Wind direction	WD	°
14	Dust concentration	DC	μg/m ³
15	Total dust frequency	TDF	

Statistical analysis and selection of main predictors

In this stage, at first, the significant difference in the variance of the target variable values (PM₁₀) between the four seasons was investigated using

Levene's test.

The existence of near-zero variance (NZV) predictors and the strong correlation between predictor variables can lead to increased errors in modeling and decrease its accuracy (Kuhn 2008

³³). For this reason, it is necessary to identify such variables before modeling. Predictors with NZV can be detected based on the fraction of unique values of less than 10% ³⁴ which was used in the present work. The Boruta is also a useful tool for determining the multicollinearity of predictors and selecting the main factors affecting the target variables (PM₁₀, in this study). This algorithm has a 7-step process as follows ³⁵:

- i. A copy of all the variables is added to develop system information with at least five shadows.
- ii. The correlation of the added variables with the response variable is removed.
- iii. A random forest classification is performed on the extended information system, and the calculated Z-scores are collected.
- iv. The maximum Z score is explored among the shadow variables.
- v. A two-way equality test is performed for variables whose importance is not determined in the previous step.
- vi. Variables with very low importance and shadow variables are removed.
- vii. This process is repeated until the importance of all the variables is determined, or the algorithm reaches the predetermined range of RFS.

After completing the mentioned steps, some variables are confirmed for modeling, and others are rejected, and the confirmed variables can be used for modeling and forecasting.

Prediction of daily PM₁₀ concentration in different seasons

The models used to predict seasonal PM₁₀ changes in Yazd city were RF and Xgboost. The RF trains multiple decision trees in parallel with bootstrap data samples and results in an individual prediction (Breiman, 2001). Bootstrapping guarantees that each tree in the RF is unique and plays an effective role in reducing the overall variance of the classification. This method also has the ability to rank predictor variables based on

their role in decreasing regression prediction error. In this method, instead of searching for the most important attributes while dividing a node, the best attributes are searched among a random subset of attributes, leading to a wide diversity and a better model. In general, RF is widely used in various sciences for modeling and forecasting purposes ³⁶⁻³⁸ due to its simplicity, high diversity, and application in both classification and regression ³⁹, which are suitable capacities. In addition, this model provides a good and strong estimate of the importance of variables using sensitivity analysis, and accordingly ⁴⁰, there is no need to perform sensitivity analysis. The number of trees (ntree) and the number of randomly selected predictors (mtry) are the optimized hyper-parameters of this model.

Xgboost was another model used in this study. Boosting is a progressive method in which a subset of data is randomly selected to reduce the loss function by creating new tree models ⁴¹. The two models of RF and Xgboost differ in how the trees are made. The Xgboost works better than RF if the data between classes is relatively moderated, there is not much noise in the data, and the parameters are fine-tuned ²⁸. Using the Xgboost model, a forecasting model in the form of a reinforcement set of weakly gradient descending trees generates that optimizes the loss function ⁴². In this model, the major tunable hyper-parameters were a booster, max-depth, min-child-weight, colsample-bytree, subsample, and etc.

In the present work, both models were trained based on two-thirds of the daily data related to PM₁₀ and the variables confirmed in the previous step, which were tested based on one-third of the remaining data in the spring, summer, autumn, and winter seasons. The technique used to train the models was 10-cross-correlation with 5 repeats.

Schematic diagram of the RF and Xgboost models are presented in Figure 3.

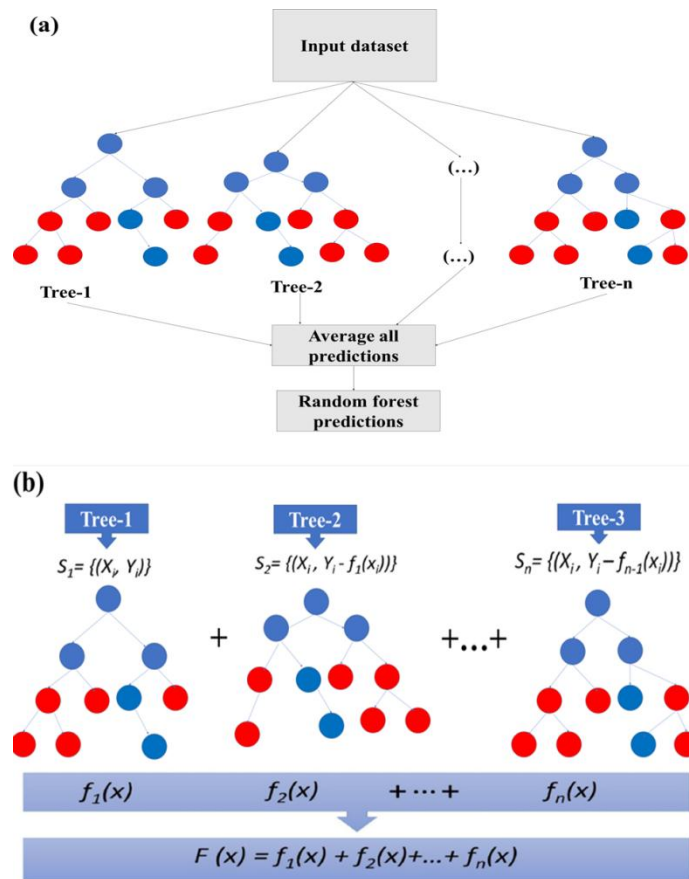


Figure 3: Schematic diagram of RF (a)⁴³ and Xgboost models (b)⁴³.

Accuracy assessment of RF and Xgboost models

The performance of the models used to predict seasonal changes in PM₁₀ was evaluated using the accuracy metrics presented in Equations 4 to 7:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [PM_{10,obs} - PM_{10,est}]^2}, (0 \leq RMSE < +\infty) \tag{4}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |PM_{10,obs} - PM_{10,est}|, (0 \leq MAE < +\infty) \tag{5}$$

$$R = \left[\frac{\frac{1}{n} \sum_{i=1}^n (PM_{10,obs} - \overline{PM_{10,obs}})(PM_{10,est} - \overline{PM_{10,est}})}{\sqrt{\frac{1}{n} \sum_{i=1}^n (PM_{10,obs} - \overline{PM_{10,obs}})^2} \sqrt{\frac{1}{n} \sum_{i=1}^n (PM_{10,est} - \overline{PM_{10,est}})^2}} \right], (-1 < R \leq +1) \tag{6}$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^n [PM_{10,obs} - PM_{10,est}]^2}{\sum_{i=1}^n [PPM_{10,obs} - \overline{PM_{10,obs}}]^2} \right], (-\infty < NSE \leq 1) \tag{7}$$

where, n is the total number of observations. (PM_{10,obs})_i and PM_{10,est} (PM_{10,est})_i refers to the observed and estimated daily PM₁₀, respectively. Also, $\overline{PM_{10,obs}}$ is the averaged observed PM₁₀, and $\overline{PM_{10,est}}$ is the averaged estimated PM₁₀.

Results

Main predictors of daily PM₁₀ changes in different seasons

The results obtained from Levene’s test indicated that there was a significant difference between the variance of target variable (PM₁₀) seasonal values in the air of Yazd city (Levene Statistic = 2.98 (Sig < 0.05); Table 2). Therefore, the selection of predictive variables and modeling was done separately for each season.

After excluding the variables with NZV, the most important PM₁₀ predictors for each season were selected based on Boruta algorithm. The results are presented in Figures 4 and 5, respectively.

Table 2: Homogeneity of variance for PM₁₀ values in all seasons based on Levene’s test

Test of homogeneity of variance				
Target variable	Levene statistic	df ₁	df ₂	Sig.
PM ₁₀	2.984	3	1172	0.030

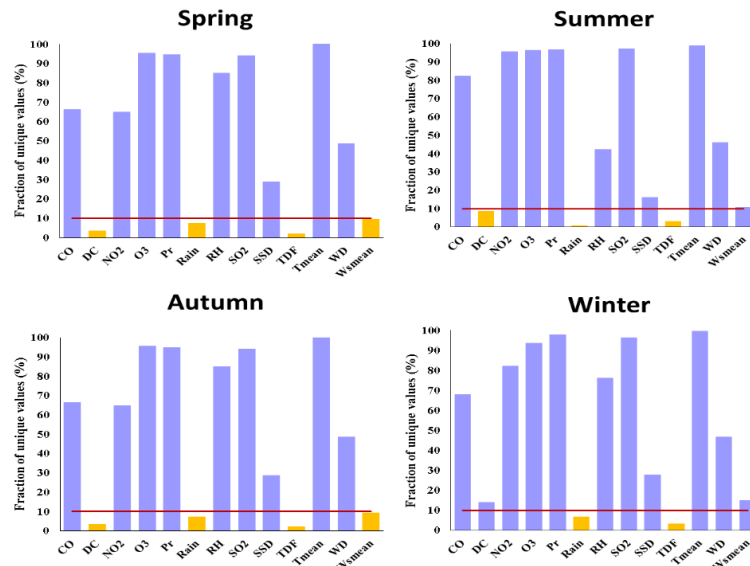


Figure 4: Fraction of unique values related to all the variables used to predict PM₁₀ concentrations in different seasons

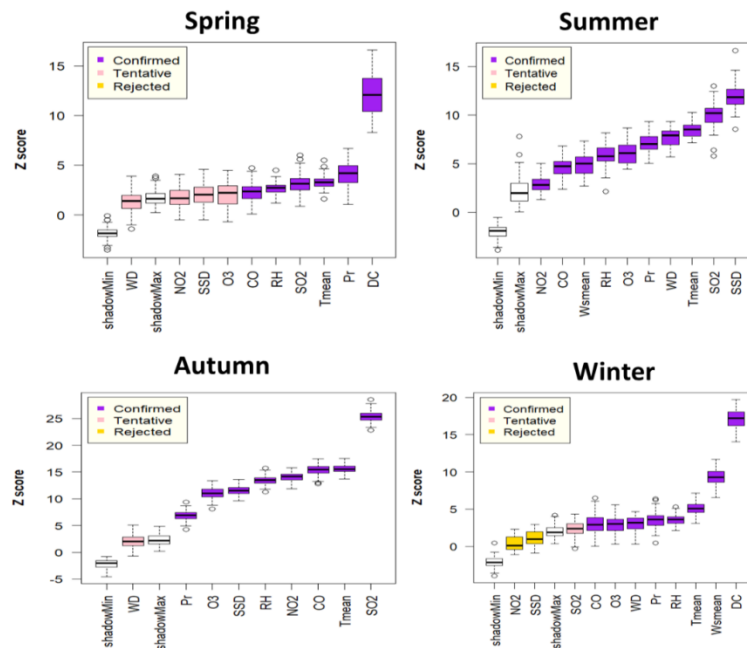


Figure 5: Selected variables by Boruta algorithm for predicting daily PM₁₀ concentrations in different seasons

Performance of RF and Xgboost tree models in predicting daily PM₁₀ concentrations in different seasons

In this study, in order to predict the

concentration of target variable, the data related to the days in which information was recorded for all the confirmed variables in Figure 5 were used. The total number of these days for spring, summer,

autumn, and winter were 301, 306, 288, and 281 days respectively. The capacity of the two different machine learning models, namely RF and Xgboost, to predict daily PM₁₀ concentration in different seasons across the urban environment of Yazd City, was tested using a ten-fold CV with 5 replications. The results are summarized in Table 3. As observed, the values of R² and Nash–Sutcliffe Model Efficiency Coefficient (NSE) obtained from RF model for both test and training data sets in all study seasons were higher than the

values obtained from the Xgboost model. In contrast, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values obtained from RF model were lower than those obtained from the Xgboost model. Accordingly, RF was chosen as the most effective model for predicting daily PM₁₀ concentration in all the seasons in Yazd city. The observed and predicted PM₁₀ values in testing data set for each season based on the best model (RF) were shown in Figure 6.

Table 3: Performance of RF and Xgboost models for predicting daily PM₁₀ concentration in different seasons

Evaluation metrics		RF model							
		R ²		RMSE		MAE		NSE	
Datasets		Train	Test	Train	Test	Train	Test	Train	Test
Spring		0.92	0.87	29.6	15.1	13.7	10.2	0.84	0.85
Summer		0.91	0.92	19.6	18.4	11	12.4	0.83	0.85
Autumn		0.94	0.94	11.9	12.9	8.5	9.3	0.93	0.92
Winter		0.93	0.88	28.9	21.6	14.3	12.2	0.88	0.87

Evaluation metrics		Xgboost model							
		R ²		RMSE		MAE		NSE	
Datasets		Train	Test	Train	Test	Train	Test	Train	Test
Spring		0.49	0.47	49.8	28.5	26.1	21.5	0.46	0.45
Summer		0.65	0.64	29.7	31	18.4	21.9	0.63	0.59
Autumn		0.95	0.95	9.3	10.8	7.1	7.8	0.95	0.94
Winter		0.91	0.80	26.9	27	18.7	16.9	0.90	0.80

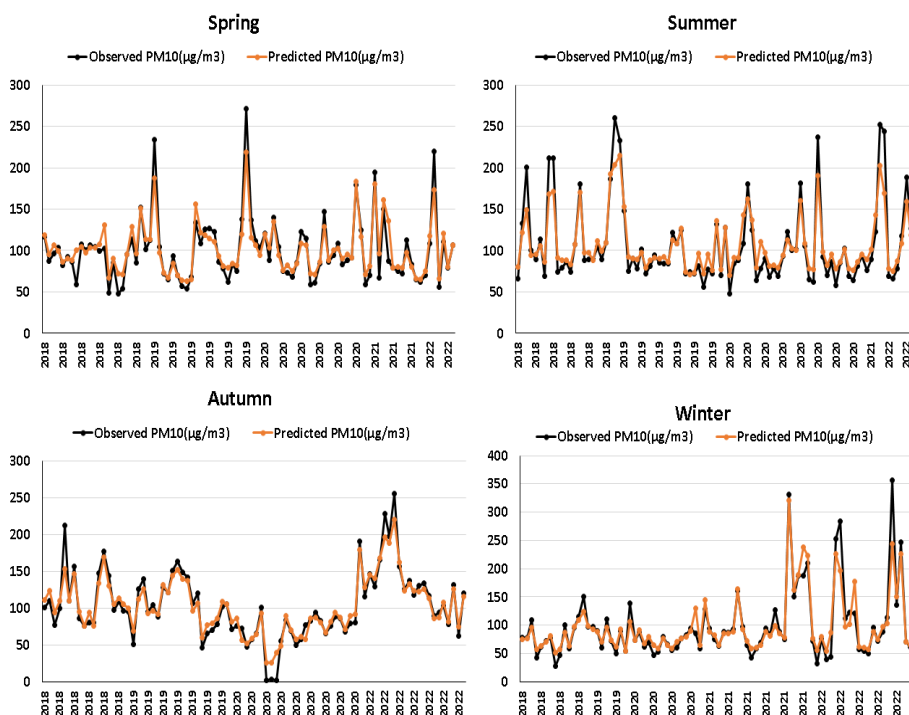


Figure 6: Observed and predicted PM₁₀ concentrations based on the best model in testing data sets for different seasons

The relative importance of factors affecting daily PM₁₀ concentrations in different seasons

Relative importance of factors influencing PM₁₀ in different seasons was reported using RF

model because it was selected as a more efficient model in the previous step. The values were normalized between 0-1 and were presented in Figure 7.

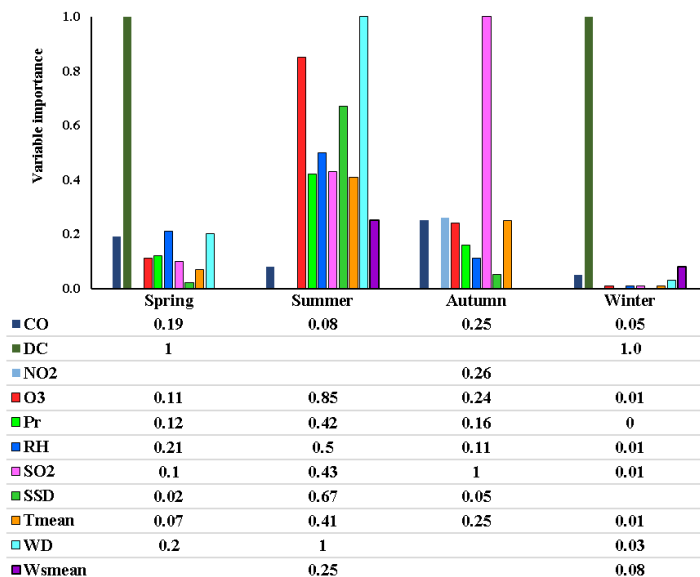


Figure 7: Relative importance of main factors affecting daily PM₁₀ concentration in different seasons in Yazd city

The results showed that for predicting daily PM₁₀ concentration in the spring, DC, RH, WD, CO, and O₃ were the most important factors, respectively. The WD followed by O₃, SSD, and RH had a greater role in predicting daily PM₁₀ in the summer. The most important predictor variables of daily PM₁₀ in the autumn were SO₂, NO₂, T, CO, and O₃, respectively. DC had played the most important part in predicting daily PM₁₀ in the winter, while other variables made a much smaller contribution. In general, the variable of DC in spring and winter, SO₂ in autumn, and WD in summer had a greater impact in predicting the daily PM₁₀, compared to other parameters.

Discussion

Particulate matter ≤ 10 μm (PM₁₀), as one of the most important air pollutants, have adverse effects on public health and the environment. Therefore, it is of great importance to predict and identify the factors affecting their concentration changes in different regions. In this study, after removing the variables with low variance, Boruta algorithm was used to select the best predictive variables of PM₁₀ seasonal changes in weather. According to the

results of this study, in spring and autumn, the fraction of unique values was less than 10% for 4 variables of DC, Rain, TDF, and Wsmean, and a higher percentage for other variables. In summer, the lowest values of variance were observed in DC, Rain, and TDF variables, and in the winter season, it was only observed for the last two variables. Therefore, they were excluded, and other variables were used to introduce Boruta algorithm in each season separately. According to Boruta algorithm results, some variables were not confirmed to model and predict daily PM₁₀ concentrations in the study seasons. Unconfirmed and tentative variables for predicting PM₁₀ in spring were WD, NO₂, SSD, and O₃ while in autumn; the only variable was NO₂ variable. For winter, NO₂, SSD, and SO₂ were not confirmed for predicting daily PM₁₀, while for summer, all the variables were confirmed. Finally, the remaining parameters (marked in blue in Figure 4) were confirmed and used to predict the target variable in different seasons. In one study, T_{max}, T_{min}, WS_{max}, WD_{max}, evaporation, and rainfall were selected as independent variables for PM₁₀ prediction in all the seasons in Isfahan⁴⁴. In addition to these parameters, maximum and

minimum values of relative humidity and sunshine hours were chosen to predict seasonal PM₁₀ in Ahvaz city⁴⁵. Most of the climate variables selected in the previous studies were confirmed in the current study and were largely consistent with the findings of this stage in the present study. Kliengchuay W, et al., found that some air pollutants such as NO₂ and CO also had an effect on the daily concentration of PM₁₀, and in the context of choosing these variables, it could be concluded that the findings of this study were consistent with the reports of these researchers¹⁴. One of the reasons regarding the similarity of the selected parameters for predicting the PM₁₀ in Isfahan and Ahvaz in all the seasons was that all the climatic variables entered the modeling process without performing collinear analysis. This was while this important issue was taken into account in the present study. For this purpose, Boruta algorithm was used separately to select predictor variables in each season.

In this study, the performance of RF and Xgboost models was evaluated based on R², RMSE, MAE, and NSE. Compared to Xgboost model, RF showed a higher performance in predicting PM₁₀ in all the seasons and was selected as the best predictive model. The adjusted R² value in this model was almost 0.9 for all the seasons, indicating that confirmed variables using Boruta algorithm could explain almost 90 % variability of daily PM₁₀ in different seasons. The successful application of the RF model for predicting PM₁₀ was also proved by Mallet²⁹ and Tella Balogun¹⁹, which confirmed the findings obtained from this study. The higher accuracy of RF for PM₁₀ prediction could be due to the following strengths. This model was highly iterative in nature, which made bootstrap data points for robust and stable forecasts. There were user-friendly OpenSource R libraries, some of which were designed to handle large numbers of input variables. Furthermore, the model had an inherent high capacity to handle nonlinear and high-order interactions between predictors⁴⁶. In addition, RF approach had less restrictive assumptions and was more flexible⁴⁷.

In general, some variables such as CO, O₃, RH,

SO₂, and T_{mean} had been selected to predict seasonal PM₁₀ changes in Yazd city. This suggested that the changes in all the mentioned variables had an impact on pollution changes caused by PM₁₀ in the weather during all the seasons. In addition to these parameters, the changes of some variables such as spring and winter DC, summer and winter WS mean, and autumn NO₂ had influenced the changes of PM₁₀ in the weather of Yazd city. These results showed the complex relationship between climatic parameters and PM₁₀ in different seasons. Such behaviors had also been reported in some of the previous studies regarding PM₁₀ and other air pollutants in different parts of the world. The production and destruction of O₃ in Baghdad city was affected by different levels of solar radiation in different seasons⁴⁸, and seasonal changes of air dust had different effects on surface solar radiation in Taklamakan desert⁴⁹.⁵⁰ Soil moisture followed by air pollution hours, soil heat flux, air pressure, vegetation cover, wind direction, and evaporation were identified as the most important environmental factors affecting PM₁₀ changes in Isfahan⁵¹. Although Isfahan is located in the vicinity of Yazd city, the relative importance of environmental factors affecting PM₁₀ changes in these cities was different. Difference in the study period selected for Isfahan (2013 to 2019) and Yazd (2018 to 2022), as well as the study scale selected, which was annual for Isfahan and seasonal for Yazd, were the main reasons for the difference in the selection of some predictor variables of PM₁₀ in these cities.

In general, the high contribution of DC in predicting PM₁₀ concentrations in the spring and winter indicated the local origin of dust particles in these seasons in Yazd. One of these sources was the Yazd-Ardakan plain, where a large amount of soil particles is separated from the soil surface every year due to the phenomenon of wind erosion⁵², and because the direction of the prevailing winds is from the side of this plain towards the city of Yazd⁵³, a large part these particles are transferred to this city. Considering that the increase in DC was caused by the increase in the frequency of dust events and dusty days, and the fact that there was a significant

relationship between seasonal changes in PM₁₀ and dusty days in Birjand city⁵⁴, with relatively similar climatic conditions to Yazd, the findings of another researcher confirmed the findings of the present research. Probably, the cold weather and increase in the traffic of automobiles, followed by the increase in the consumption of fossil fuels in the autumn, were the reasons for the increase in sulfur dioxide gas and the greater contribution of this factor in predicting the PM₁₀ in this season. The significant contribution of WD in predicting PM₁₀ concentrations in summer indicated that regional sources had a great impact on PM concentration in the dusty city of Yazd in this season. Guerra and Lane⁵⁵ pointed out a significant relationship between the wind direction and the concentration of PMs, which to some extent confirmed findings of this study. Although the mentioned variables were influential in predicting the concentration of PM₁₀ in the study area, the influence of other climatic parameters and air pollutants should not be ignored. For example, in winter, one of the reasons for increasing air pollution was air temperature inversions⁵⁶, and this might be the reason why this variable appeared in the list of the main variables predicting winter PM₁₀ concentration. The effect of temperature fluctuations on PM₁₀ concentration variations had been proven in a study conducted by Plocoste and Calif¹⁵. Wind speed affected PM₁₀ concentration by affecting the horizontal dissemination⁵⁷. Moreover, on warm days, the wind can increase the concentration of particular matters by removing soil particles and road dust⁵⁸. In several studies, sunshine duration had been identified as a key factor affecting the concentration of PM₁₀, which was consistent with the findings of this research. Solar radiation was also identified as another major factor affecting the change in PM₁₀ concentration in different seasons because its changes were a function of changes in the concentration of airborne particles, cloud covers, and anthropogenic pollutions in the urban areas^{59, 60}. In agreement with the findings of this study, the important role of some drivers such as wind speed, wind direction, air pressure, relative humidity, air temperature, rainfall, and O₃ in PMs changes had

also been reported by Duarte and Schneider⁶¹ for urban environments. Most of these variables were successfully used to predict PM₁₀ concentration in previous studies^{18, 29} and confirmed outcomes of this study.

Conclusion

Analysis of daily changes in air pollutants concentrations and determining the factors influencing these changes can help to better manage air quality in urban environments. In this work, the efficiency of RF and Xgboost models for predicting daily PM₁₀ concentrations in different seasons was evaluated, and the most important factors affecting it were identified by the best fitted model. The major findings of this study are as follows:

- According to the accuracy metrics, the RF model is better than the Xgboost model for predicting the daily PM₁₀ concentration in all seasons.
- DC has the greatest relative importance in predicting daily PM₁₀ concentrations in spring and winter.
- WD and SO₂ are identified as the most important factors affecting the daily changes of PM₁₀ concentration in summer and autumn, respectively.

One of the limitations of this study was the lack of access to information on air pollutants in all the stations of Yazd city in a similar and long-term period. Furthermore, the incompleteness of PM₁₀ information in other air pollution monitoring stations in Yazd province was one of the limitations of this study regarding the analysis of spatial variations of PM₁₀ at a larger scale. Having such information provides a broader insight into areas with a higher risk of pollution in the province. Therefore, it is suggested that if PM₁₀ information is recorded in the coming years for all the air pollution measuring stations in Yazd province, they should be used for spatial analysis of PM₁₀ changes at the provincial scale.

Acknowledgments

This research was supported by the University of Jiroft under grant NO: 4812-01-1. The authors would like to thank the vice-chancellor of

education and research in the university for his support and the department of environment and the meteorological organization of Yazd province for providing the required information on air pollutants and meteorological parameters.

Conflict of Interest

The authors declared no conflict of interest.

Funding

This research was supported by the University of Jiroft under grant NO: 4812-01-1.

Ethical considerations

The authors fully addressed ethical issues including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publishing and/or submission, redundancy, etc.

Code of ethics

This study was carried out with the aim of determining weather parameters and air pollutants affecting seasonal changes of particulate matter of less than 10 microns using meteorological data and air pollutants measures. The ethics code is not applicable for this research.

Authors' contributions

Zohre Ebrahimi-Khusfi and Ali Reza Nafarzadegan contributed to the study's conception and design. Data collection, statistical analysis and data processing were performed by Zohre Ebrahimi-Khusfi, Mohsen Ebrahimi-Khusfi, and Ali Reza Nafarzadegan. The first draft of the manuscript was written by Zohre Ebrahimi-Khusfi and Mojtaba Soleimani Sardoo. Zohre Ebrahimi-Khusfi and Ali Reza Nafarzadegan were responsible for reviewing and revising the manuscript and supervising the project. All the authors read and approved the final manuscript.

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