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Principal Component Regression Modeling and Analysis of PM_{10} and Meteorological Parameters in Sarajevo with and without Temperature Inversion

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Abstract: The specific geographic location of Sarajevo, which is located in a valley surrounded by mountains, provides the opportunity to analyze the relation between the concentration of PM_{10} and meteorological parameters with and without temperature inversion. The main aim of this paper was to develop forecasting models of the hourly average of PM_{10} values in the Sarajevo urban area based on meteorological parameters measured in Sarajevo and on the Bjelasnica mountain with and without temperature inversion by using principal component regression (PCR). Also, this research explored and analyzed the differences in the values of the meteorological parameters and PM_{10} in Sarajevo with and without temperature inversion, and the difference in temperatures between Sarajevo and Bjelasnica with temperature inversion using statistical hypothesis testing with a total of 240 hypothesis tests performed. The measurements of meteorological parameters were taken from 2020 to 2022 for both Sarajevo (630 m) and the Bjelasnica mountain (2067 m), which allowed for the identification of time periods with and without temperature inversion, while measurements of PM_{10} were taken only in Sarajevo. Data were collected during the heating season (November, December, January, February and March). Since analyses have shown that only January and November had time periods with and without temperature inversion during each hour of the day, a total of seven cases were identified: two cases with and five cases without temperature inversion. For each case, three PCR models were developed using all principal components, backward elimination and eigenvalue principal component elimination criteria ($\lambda < 1$). A total of 21 models were developed. The performance of the models were evaluated based on the coefficient of determination R^2 and the standard error SE. The backward elimination models were shown to have high performances with the highest value of $R^2 = 97.19$ and the lowest value of $SE = 1.32$. The study showed that some principal components with eigenvalues $\lambda < 1$ were significantly related to the independent variable PM_{10} and thus were retained in the PCR models. In the study, it was shown that backward elimination PCR was an adequate tool to develop PM_{10} forecasting models with high performances and that it could be useful for authorities for early warnings or other action to protect citizens from very harmful pollution. Hypothesis tests showed different relations of meteorological parameters and PM_{10} with and without temperature inversion.

Keywords: principal component regression; environmental and spatiotemporal statistics; temperature inversion; air quality and pollution; PM_{10}; meteorological parameters

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1. Introduction

Temperature inversion, as a natural phenomenon, occurs when temperatures at higher altitudes are higher than temperatures at lower altitudes, causing pollutants to be stuck and leading to higher pollutant concentrations in the air. The problem of air pollution is one of the major problems in the city of Sarajevo, where the citizens often face excessive levels of air pollutants [1,2]. The problem of air pollution is particularly present in the winter period and the heating season in the months of November, December, January, February and March. In addition to the increased emission of pollutants in the winter and heating season, the air quality is also affected by the reduced air flow in winter, the occurrence of temperature inversion, turbulent diffusion and the presence of heat islands. Sarajevo has a specific geographical location because it is surrounded by mountains, which makes air ventilation difficult. Due to its position in the heart of the Dinaric Alps and its remoteness from the Mediterranean belt, Sarajevo is subject to a continental and alpine climate, which is mainly characterized by long and cold winters; hot summers with fleeting in-between periods of spring and autumn; strong temperature inversions; frequent presence of dense fog, especially during winter months; very low wind speeds and weak winds potential caused by Sarajevo's valley-like topography.

The relation between temperature inversion during the winter and visits to the emergency department due to asthma was investigated in [3]. Single and multiple linear regression was used to assess the effects of temperature inversion on the PM_{10} concentration in the air. It was concluded that elevated temperature inversions mostly determined an unfavorable PM_{10} concentration in the lower troposphere [4]. Hua [5] investigated the relationship between temperature inversion and the concentration of polluting air particles, such as SO_2, CO, NO_2, $PM_{2.5}$ and PM_{10}, and found that the temperature inversion level is positively correlated with the concentration of most polluting particles in Beijing. In [6], a rapid increase in PM_{10} and $PM_{2.5}$ was highlighted during temperature inversions in the winter season in Tehran, causing health problems due to air pollution. In Hanoi City, Vietnam, Trinh et al. [7] investigated the impact of temperature inversions on acute respiratory and cardiovascular diseases commonly associated with air pollution. The relationship between temperature inversion and the concentration of polluting air particles (SO_2, NO_2, $PM_{2.5}$ and PM_{10}) was positively correlated.

The WHO identified particulate matter (PM), ozone (O_3), nitrogen dioxide (NO_2) and sulfur dioxide (SO_2) as the main components of the air that are harmful to human health. Measurements of the concentrations of solid particles and ozone show concentrations that represent a health hazard in many cities, including cities in developed countries [8]. Particulate matter (PM) is a complex mixture of particles of mainly an inhomogeneous chemical composition of different sizes, shapes, chemical, physical and thermodynamic properties, usually solid carbon material, unburned hydrocarbons and inorganic compounds. Particulate matter contains the fraction of grains below 10 µm (PM_{10}). Fine particulate matter is defined as particles that are 2.5 microns or less in diameter ($PM_{2.5}$) [9]. The air quality in Poland exceeded the norms for particulate matter, especially in the winter season, which mainly influences the comfort of living of the population of inner-city areas of big cities and agglomerations. In 2013, PM_{10} amounted to 12.6%, and $PM_{2.5}$ to 10.9% of the total emissions [10].

In most research studies, the levels of nitrogen dioxide are correlated with the levels of particulate matter and ozone in the air, and the harmful pollutants are examined together in the case of three pollutants. Traffic, and the residential heating industry and systems are the most significant sources of particulate matter [11–13]. Many earlier works have pointed out the harmfulness of air pollutants for human health, which was especially manifest in urban areas [11,14,15].

Neural network models were developed in [16,17] to predict the concentrations of air pollutants of SO_2, PM_{10}, NO_2, O_3 and CO based on meteorological parameters, air humidity, pressure and temperature, wind speed and direction. It was concluded that the optimal models had very good performances and could be used to predict the concentration of air pollutants in Sarajevo with high performance. In these research studies, temperature inversion and its specific interaction with air pollutants was not separately analyzed. In [18], a hybrid model consisting of feed-forward neural networks, convolution neural network and long short-term neural networks showed the best performance in prediction of PM in Ankara. It was concluded that the most important variables in the prediction of PM were its own lagged values, other air pollutants, the earth skin temperature and wind speed. A hybrid model that combines the k-means clustering technique and the long short-term memory (LSTM) was developed in [19] for the prediction of the daily average concentration of PM_{10}.

The comparison of air quality in Sarajevo during March 2019 and March 2020 presented a unique opportunity, as both months shared similar causes of air pollution for one portion of the month, but differed in terms of the causes of air pollution during the lockdown period that was imposed due to the outbreak of SARS-CoV-2. It was determined that there was statistical evidence to conclude that the mean PM_{10} and O_3 values during the lockdown period in March 2020 are greater than the mean PM_{10} and O_3 values before the lockdown in March 2020. Also, it was shown that there was insufficient evidence to conclude that the mean PM_{10} value in March 2019 is greater than the mean PM_{10} in March 2020 before the lockdown measures. The conclusions in this paper addressed the issue of the sources of air pollution since there were no cars on the streets during the lockdown, and people spent the majority of the time in houses and flats that were heated [20], which is in contrast to some other areas in the world where pollution declined due to much lower global economic and transport activities [21].

Depending on the size and characteristics of inhalable particles, the health risks are varied. Short-term exposure to PM_{10} and $PM_{2.5}$ particles can lead to lung diseases, triggering asthma attacks or acute bronchitis. Long-term exposure to these particles is connected with problems such as impaired lung function, cardiovascular disease, and the development of chronic bronchitis [22]. According to EU Directive 2008/50/EC, the mean annual and daily PM_{10} limit may not exceed 40 $\mu g/m^3$ and 50 $\mu g/m^3$, respectively [23]. The concentration of particulate matter is not only influenced by the source of emission but also by different diffusion conditions, whereas the diffusion of particulate matter in the air is influenced by the geographic location and meteorological parameters. Some of the key meteorological parameters affecting the concentration of particulate matter in the air are temperature, precipitation, wind, and relative humidity [15,24,25].

According to research, there is a negative correlation between air temperature and the concentration of particulate matter, the lower the air temperature the higher the concentration of particular matter [26,27]. A positive correlation is observed between relative air humidity and the concentration of particulate matter, which is visible up to a threshold value, above which it ceases to exist. Specifically, particulate matter accumulates humidity, and so humidity and the concentration of particulate matter move up in tandem until they reach the point of the so-called dry deposition [28,29].

Wind direction and wind velocity affect the direction in which particulate matter spreads in the air as well as the airborne concentration of particulate matter. From the perspective of air pollution, poor wind potential, especially when coupled with low wind speeds in the winter, is conducive to the build-up of pollutants in the thin layer of the atmosphere, which, depending on the level of emissions, can hit peak concentrations [30]. Precipitation has a different effect on the concentration of air pollution by eliminating gases and depositing particles through chemical processes [31,32].

In combination with an anticyclone and the absence of wind, low temperatures led to the build-up and formation of a thick layer of smog. Approximately 4000 people died in just seven days of December 1952 as a consequence of the Great Smog of London [33,34]. The relationships between meteorological parameters were examined in [35], and it was found that atmospheric pressure and relative humidity were positively correlated with PM_{10}, while the correlation between solar radiation and temperature was negative. Data on PM_{10} concentrations and their connection with other pollutants (NO_x, CO, O_3 and SO_2) and meteorological parameters were analyzed in [36], and a positive correlation was observed between PM_{10} and NO_x, and CO and solar radiation at selected monitoring sites during the winter period. The concentration of PM_{10} and O_3, wind speed and precipitation are negatively correlated.

In [37], the maximum wind velocity for the period from 2001 to 2010 analyzed, which ranged from 8.3 to 25.9 m/s, while the average wind velocity ranged from 0 to 2.6 m/s. Figure 2 shows average wind velocities and directions for the Sarajevo measuring station. As for air pollution, such poor wind potential, particularly in the winter with low wind speed conditions, is advantageous for the build-up of pollutants in the very thin layer of the atmosphere, which, depending on the level of the emission, can reach peak concentrations.

The maximum wind velocity was analyzed with reference to the period from the year 2000 through to 2010, which during November and December ranged from 36 to 52 m/s at the Bjelasnica Meteorological Station. During other months, the maximum wind velocity oscillated from 24 to 45 m/s, while the mean wind velocity ranged from 5.5 to 19.4 m/s. Figure 1 shows prevailing wind directions to be north (N), south (S), and southwest (SW)—more specifically, south-southwest (SSW) [38].

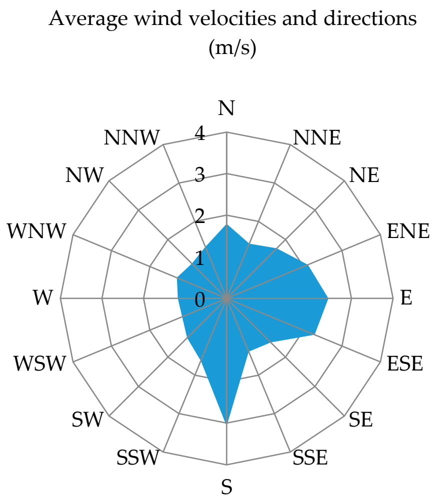

Figure 1. Average wind velocities and directions for the Bjelasnica region for the period 2000–2010 [30,38].

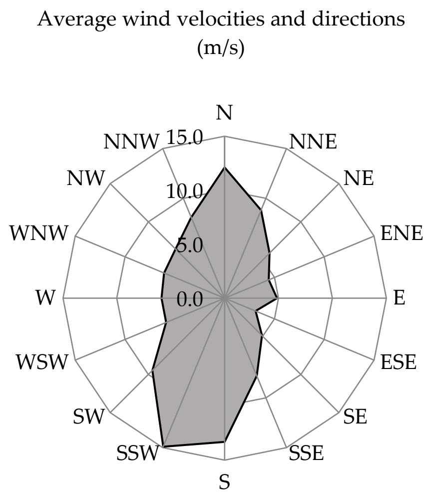

Figure 2. Average wind velocities and directions for the Sarajevo measuring station for the period 2001–2010 [37].

If accompanied by high emissions of harmful elements into the atmosphere, such climatic conditions are conducive to their concentration, especially in the winter season. Sarajevo is situated along the erosion-affected Miljacka River at an average altitude of 542 m. It is towered by mountain massifs: Ozren (1532 m), Romanija (1649 m), Trebevic (1629 m), Jahorina (1913 m), Treskavica (2088 m), Igman (1502 m), Bjelasnica (2067 m) and Ivan mountain (1542 m). The Sarajevo Meteorological Station (Bjelave) is placed at an altitude of 630 m above sea level at 43°52′21″ N 18°25′59″ E, while the Bjelasnica Meteorological

Station, also known as the Bjelasnica Observatory, is located at an altitude of 2067 m above sea level at 43°42′21″ N and 18°15′15″ E (Figure 3).

A big problem for the city of Sarajevo is the appearance of the phenomenon of temperature inversion. With the presence of temperature inversion, fog appears and interacts with the pollutants in the air to form smog, which is a big problem during the winter in Sarajevo. In the winter period spanning November through March, as radiation fog starts to form, the air temperature in Sarajevo, instead of decreasing, begins to increase with altitude, i.e., the altitude-induced change in temperature is positive, and thus the so-called temperature inversion must be discussed. Depending on weather conditions, temperature inversion occurs in the lower and upper layers of air. The atmosphere is then extremely stable, which creates the worst possible situation from the point of view of air pollution as pollutants become substantially dispersed. The period during the months of November, December, January, February, and March is the heating season in Sarajevo.

Figure 3. Locations of Bjelasnica Meteorological Station (red dot) and Sarajevo Meteorological Station (orange dot). Adapted from [39].

With the aim of analyzing this problem of the interaction between temperature inversion and air pollution, values of the PM_{10} concentration, temperature, humidity, pressure, and wind speed in Sarajevo, as well as data on temperature, pressure, and humidity on the mountain Bjelasnica were collected. The data were collected at the Federal Meteorological Institute of BiH and contain consecutive hourly values of the meteorological parameters and the concentration of PM_{10} air pollutant. The data were collected in the winter period and the heating season in Sarajevo for the months of November, December, January, February, and March in the period from 2020 to 2022. Since the heating season in Sarajevo begins mid-October and ends mid-April, the months from April until October were not taken into consideration.

In this research, time periods with and without temperature inversion were identified, meteorological parameters and the PM_{10} concentration were analyzed, and principal component regression PM_{10} forecasting models were developed. The temperature, humidity, pressure and wind speed for Sarajevo, and temperature, humidity and pressure for Bjelasnica were used as inputs, while the output was the PM_{10} concentration for Sarajevo. Models were created for seven cases: November and January with and without inversion; and November, December, January, February, and March without inversion. For each case, three principal component regression models were developed using all principal components, backward elimination, and eigenvalue principal component elimination criteria ($\lambda < 1$). Also, 240 statistical hypothesis tests were performed to examine the significance of the difference of values of the meteorological parameters and PM_{10} in Sarajevo with and without temperature inversion, and the difference of temperatures between Sarajevo and Bjelasnica with temperature inversion.

2. Materials and Methods

2.1. Study Area and Data Collection

Data for this research were collected from the Federal Hydrometeorological Institute of BiH. The place where the foundations of the first meteorological station in Bosnia and Herzegovina were laid 122 years ago today is the place of the Federal Hydrometeorological Institute of BiH, where all weather phenomena are monitored, as shown in Figure 4. In 1894, a meteorological observatory was erected at the highest point of the Bjelasnica Mountain, at an altitude of 2067 m as depicted in Figure 5.

So, for the collection of data two meteorological stations were used: one at low altitude in the Sarajevo urban area and one at high altitude on the Bjelasnica mountain. The Sarajevo Meteorological Station is located in the part of the city called Bjelave at an altitude of 630 m, while the Bjelasnica Meteorological Station is located on the top of the mountain at an altitude of 2067 m. Data collected at the low and the high altitudes allowed for the identification of time periods with and without temperature inversion. Data collected at the Sarajevo Meteorological Station included the concentration of air pollutant PM_{10} $[\mu g/m^3]$, temperature [°C], relative humidity [%], pressure [hPa], and wind speed [m/s], while data collected at the Bjelasnica Meteorological Station included temperature [°C], pressure [hPa] and relative humidity [%]. Data were collected on hourly basis.

Figure 4. Sarajevo Meteorological Station (Bjelave).

Figure 5. Bjelasnica Meteorological Station.

2.2. Principal Component Regression

The presence of multicollinearity between the regressor (predictor or independent) variables in multiple linear regression (MLR) variances of the estimated regression coefficients can become large. This means that the estimates of the coefficients become less precise and can make it difficult to interpret the significance of individual variables in the model, and can lead to unstable and potentially misleading estimates of the regression coefficients and the regression equation as a whole. One of the methods to avoid the multicollinearity problem in regression analysis is to perform principal component regression (PCR). The difference between MLR is that PCR uses the principal components as the predictor variables for regression analysis instead of the original variables. In other words, the first step is to perform principal component analysis (PCA) on the original independent variables, and then to use the obtained principal components (PC) as the independent variables in MLR with the original dependent variable.

Since independent variables in this research were correlated, PCR is performed to create a prediction regression model of the average of PM_{10} and to avoid the problem of multicollinearity.

Each principal component represents the linear combination of the original regressor variables with respect to maximum variability in the data. After the eigenvectors, also known as loadings or weights, and eigenvalues are computed, it is possible to calculate the values of principal components for each sample by multiplying the matrix of independent variables with the matrix of eigenvectors, as given by Equation (1):

$$P = XA \tag{1}$$

where:

$$X = \begin{bmatrix} X_1 & X_2 & \cdots & X_k \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}$$

$$A = \begin{bmatrix} A_1 & A_2 & \cdots & A_k \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ a_{k1} & a_{k2} & \cdots & a_{kk} \end{bmatrix}$$

$$P = \begin{bmatrix} P_1 & P_2 & \cdots & P_k \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1k} \\ p_{21} & p_{22} & \cdots & p_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nk} \end{bmatrix}$$

where:

$k =$ number of independent variables;
$n =$ number of samples (observations);
$X =$ matrix of independent variables;
$A =$ matrix of eigenvectors;
$P =$ matrix of principal components.

As it can be seen from Equation (1) and the P matrix, the number of calculated principal components is the same as the number of independent variables. Computed principal components are then used in the developing regression model instead of the original regressors for the prediction of the average hourly PM_{10} concentration with and without temperature inversion, as shown by Equation (2):

$$\hat{y} = b_0 + \sum_{j=1}^{m} b_j PC_j \tag{2}$$

where:

m = number of principal components;
$\hat{y}$ = predicted value of average hourly PM_{10};
b_j = principal component regression coefficients;
b_0 = intercept;
PC_j = principal components.

There are different strategies and suggestions on how many principal components to retain in the model. The decision on the best number m of how many principal components to retain is not clear-cut [40]. If all principal components were preserved, then the resulting model would be the same as that obtained by ordinary least square (OLS). However, as indicated in [41], the calculation may be numerically more stable than direct calculation. A simple but arbitrary rule of thumb, which proved to be practical, was to only consider principal components with eigenvalues of 1 or higher [42]. Typically, a principal component was considered statistically significant if its eigenvalue was $\lambda \geq 1$ [43]. However, as stated in [44], all relations should be thoroughly analyzed since it has always possible that a PC with a small variance could be related to the dependent variable in a regression model, which could be important in explaining the dependent variable as PCs with large variances, and should not be discarded without careful consideration. The cautionary note regarding the selection of principal components was written in [45], stating that it was possible that the first $(k-1)$ PCs, which might include all of the variances cumulatively, had no contribution to the regression fit and that the dependent variable might be better related and explained by the last PC with the smallest variance, which was typically ignored in traditional PCR methodology. The method chosen in [46,47] for the selection of PCs was the forward selection procedure, while in this research, the backward selection procedure was applied.

Since principal components are used as predictor variables in principal component regression, computed regression coefficients are not related to original independent variables and thus their interpretation is very complicated, which is considered as a drawback of principal component regression. PC scores are obtained by multiplying the values of the original independent variables and eigenvectors of each PC. Thus, individual elements of eigenvectors signify the weight of the corresponding independent variable x_i $(i = 1, \ldots, k)$. In this research, the interpretation of PCs is based on the computation of correlation coefficients between the original variables, PCs, and the findings in which the original variables have strong correlation with each principal component.

In this research study, three strategies were used for the development of regression models: (1) full PCR models with all PCs included, (2) backward elimination regression and (3) eigenvalue PCs elimination criteria. The evaluation of the performances of the developed models was done based on the coefficient of determination $\left(R^2\right)$ and the standard error (SE).

The number of developed models was as follows: 3 PCR models for November with temperature inversion, 3 PCR models for January with temperature inversion as well as 3 PCR models individually for November, December, January, February, and March without temperature inversion. It is important to note that data collected showed that temperature inversion was present during the months of November and January, while during December, February and March, there were only a few hours detected or none at all with temperature inversion. That is why the analysis was performed for November and January for both cases, i.e., with and without temperature inversion, while analysis for December, February, and March was done for the case without temperature inversion. In total 21 PCR models were developed, out of which 6 PCR models with temperature inversion and 15 PCR models without temperature inversion.

In this research study, a total of seven meteorological parameters were taken into consideration as regressor variables. Values of pressure, temperature, relative humidity, and wind speed were measured in Sarajevo, while the values of relative humidity, temperature, and pressure were measured on the Bjelasnica mountain.

3. Results and Discussion

3.1. Analysis of PM_{10} and Meteorological Parameters

The average January hourly values of PM_{10} $[\mu g/m^3]$, pressure [hPa], temperature [°C], and relative humidity [%] in Sarajevo, with temperature inversion (TI) and without temperature inversion, are presented in Figures 6–9, respectively, while the average hourly temperatures [°C] in Sarajevo and on the Bjelasnica mountain with temperature inversion are depicted in Figure 10. Figures 6–10 include 95% confidence intervals. In January, only one case of temperature inversion was detected at 14:00 and 15:00 h, so there are no confidence intervals for these two hours in January, while at 13:00, there were only three cases of temperature inversion. The average PM_{10} values in Sarajevo with and without temperature inversion in January are shown by box and whisker plot in Figure 11. In Figure 11, five-number summary values are depicted, which are minimum and maximum values, median value as well as the first quartile and third quartile values.

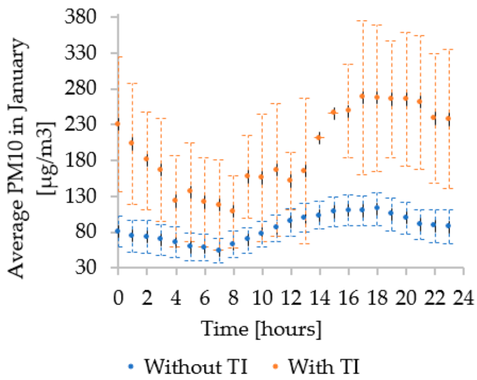

Figure 6. Average PM_{10} in January in Sarajevo with and without TI.

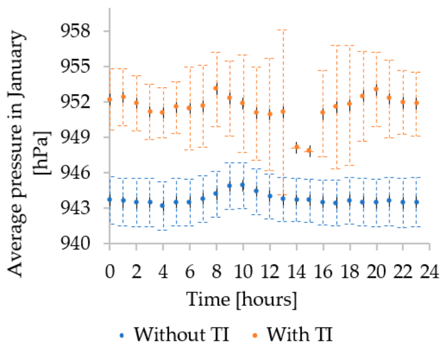

Figure 7. Average pressure in January in Sarajevo with and without TI.

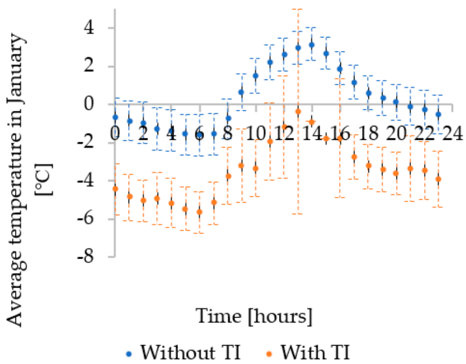

Figure 8. Average temperature in January in Sarajevo with and without TI.

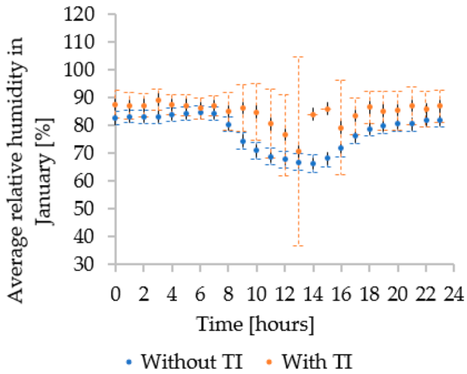

Figure 9. Average relative humidity in January in Sarajevo with and without TI.

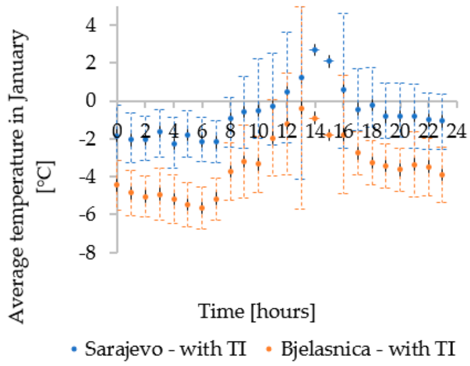

Figure 10. Average temperature in January in Sarajevo and Bjelasnica with TI.

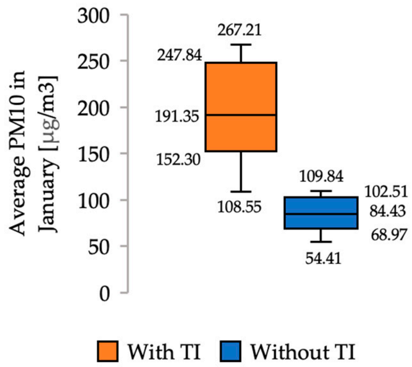

Figure 11. Average PM_{10} in January in Sarajevo with and without TI.

It can be seen that with temperature inversion, average hourly values of pressure and relative humidity in Sarajevo are higher than when there is no temperature inversion. The concentration of PM_{10} is always higher in the presence of temperature inversion compared to values when there is no temperature inversion. Both average hourly PM_{10} concentration values show almost the same distribution patterns in a way that the values start to decline in the late afternoon hours until the following morning hours. The values start to rise in the morning hours until late afternoon. This distribution pattern can be explained by the intensity of activities of the people during the day as well as the by the daily heating pattern. The box and whisker plot shows that the concentration of PM_{10} goes up to the maximum value of 267.21 µg/m^3, while the minimum value of the concentration of PM_{10} with temperature inversion is 108.55 µg/m^3. The maximum PM_{10} value without temperature inversion is 109.84 µg/m^3, while the minimum value is 54.41 µg/m^3.

The concentration of PM_{10} [µg/m^3], pressure [hPa], temperature [°C], and relative humidity [%] both with and without temperature inversion in November are depicted in Figures 12–15, respectively. It can be seen that during November, the average hourly temperatures both in Sarajevo and on the Bjelasnica mountain are positive, as depicted in Figure 16. Figures 12–16 include 95% confidence intervals. As in January, it can be seen that with the presence of temperature inversion, average hourly values of pressure and relative humidity in Sarajevo are higher than when there is no temperature inversion. The concentration of PM_{10} is higher in the presence of temperature inversion compared to values when there is no temperature inversion, except at 3 a.m., 4 a.m., 1 p.m. and 2 p.m., when it follows almost the same pattern as in January, except that there is a certain decline of values from 11 a.m. until 2 p.m. The average PM_{10} values in Sarajevo with and without temperature inversion in January are shown by box and whisker plot in Figure 17. In Figure 17, five-number summary values are depicted, which are minimum and maximum values, median value as well as the first quartile and third quartile values.

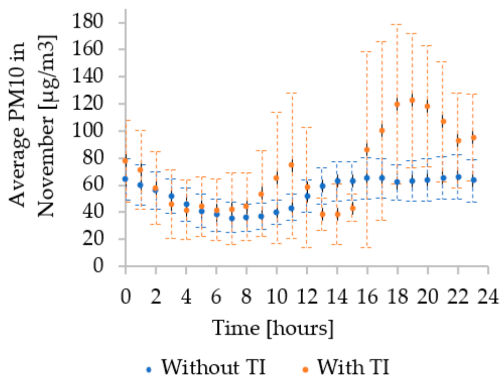

Figure 12. Average PM_{10} in November in Sarajevo with and without TI.

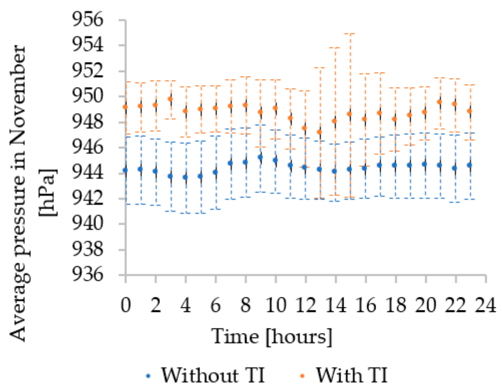

Figure 13. Average pressure in November in Sarajevo with and without TI.

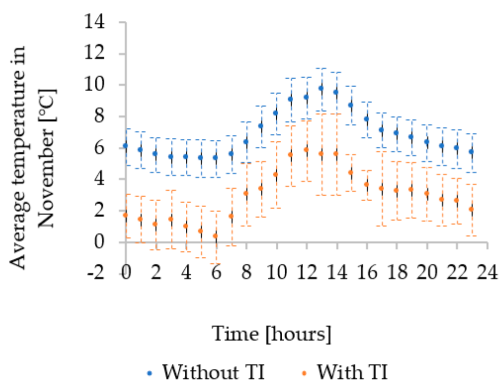

Figure 14. Average temperature in November in Sarajevo with and without TI.

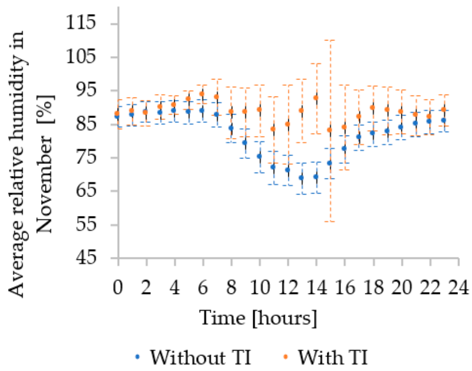

Figure 15. Average relative humidity in November in Sarajevo with and without TI.

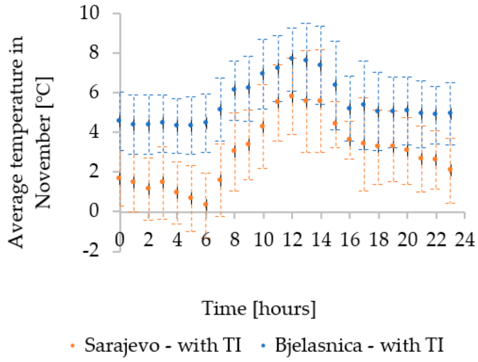

Figure 16. Average temperature in November in Sarajevo and Bjelasnica with TI.

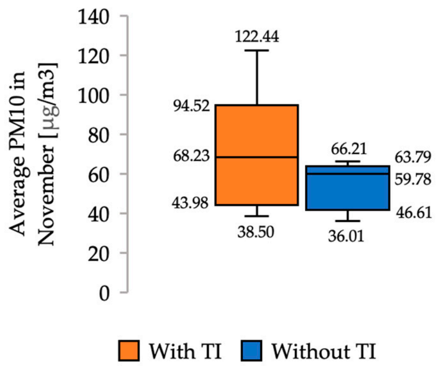

Figure 17. Average PM_{10} in November in Sarajevo with and without TI.

The box and whisker plot shows that with the temperature inversion in November, the average concentration of PM_{10} goes up to the maximum value of 122.44 µg/m^3, while the minimum value is 38.50 µg/m^3. The maximum value of the concentration of PM_{10} without temperature inversion in November is 66.21 µg/m^3, while the minimum value is 36.01 µg/m^3.

Table 1 depicts the results of the hypothesis tests for the differences in the means of the PM_{10} values, meteorological parameters with and without TI in Sarajevo as well as mean temperatures in Sarajevo and Bjelasnica in January and November with temperature inversion. The hypothesis tests were performed with a significance level of $\alpha = 0.05$. For this research study, lower-tailed test was performed. The null (H_0) and the alternative hypothesis (H_1) for this research were:

$$H_0 : \mu_1 - \mu_2 \geq 0$$

$$H_1 : \mu_1 - \mu_2 < 0$$

where:

μ_1 represents the average hourly values of humidity in Sarajevo (HS), pressure in Sarajevo (PS), temperature in Sarajevo (TS) without temperature inversion in January and November;

μ_2 represents the average hourly values of humidity in Sarajevo (HS), pressure in Sarajevo (PS), temperature in Sarajevo (TS) with temperature inversion in January and November.

Also, the last columns for the months of January and November of Table 1 depict the p-values of the hypothesis tests for the differences in the two means between the average temperatures in Sarajevo and Bjelasnica in January and November with temperature inversion.

All results with a p-value < 0.05 were considered statistically significant, meaning that there was statistical evidence that the claim stated in the research hypothesis H_1 was true. If the null hypothesis were rejected, the conclusion would be that there was evidence that $\mu_1 < \mu_2$. If the null hypothesis were not rejected the conclusion would be that there was insufficient evidence that $\mu_1 < \mu_2$. Regarding the hypothesis tests for the differences in the two means between the average temperatures in Sarajevo and Bjelasnica in January and November, if the p-value < 0.05, the null hypothesis would be rejected with the conclusion that there was statistical evidence that with temperature inversion average temperature in Sarajevo was statistically lower than the average temperature on Bjelasnica.

From Table 1 it can be seen that during January, except at 13:00, the values of PM_{10} in Sarajevo were significantly lower without temperature inversion, while this cannot be said for November, where there was no significant difference in PM_{10} in Sarajevo with and without temperature inversion. The pressure in Sarajevo in January and temperature in Sarajevo in November were significantly lower without temperature inversion for each hour of the day. The temperature in Sarajevo in January and pressure in Sarajevo in November were significantly lower without temperature inversion, except for some afternoon hours. At certain hours of the day, the humidity in Sarajevo without temperature inversion was significantly lower than with temperature inversion, and sometimes, it was the opposite, without a visible pattern. In January and November with temperature inversion, during the morning and evening hours, the temperatures in Sarajevo were significantly lower than temperatures on Bjelasnica for both January and November. In January only one case of temperature inversion was detected at 14:00 and 15:00 h, so the hypothesis testing could not be performed.

Table 1. Hypothesis tests for differences in PM_{10} and meteorological parameters in Sarajevo with and without TI, and differences of temperatures in Sarajevo and Bjelasnica with TI in January and November.

	January					**November**				
	***PM*₁₀**	***HS***	***PS***	***TS***	***TS/TB***	***PM*₁₀**	***HS***	***PS***	***TS***	***TS/TB***
Time	***p*-Value**									
00:00	0.002	0.033	0.000	0.000	0.000	0.200	0.000	0.002	0.000	0.002
01:00	0.003	0.072	0.000	0.000	0.002	0.248	0.324	0.002	0.000	0.003
02:00	0.003	0.045	0.000	0.000	0.000	0.455	0.547	0.001	0.000	0.002
03:00	0.006	0.005	0.000	0.000	0.000	0.663	0.234	0.000	0.000	0.005
04:00	0.044	0.059	0.000	0.000	0.001	0.629	0.184	0.001	0.000	0.001
05:00	0.018	0.098	0.000	0.000	0.000	0.400	0.042	0.001	0.000	0.001
06:00	0.027	0.249	0.000	0.000	0.000	0.375	0.010	0.002	0.000	0.000
07:00	0.027	0.100	0.000	0.000	0.000	0.314	0.045	0.004	0.000	0.002
08:00	0.043	0.086	0.000	0.001	0.002	0.270	0.131	0.005	0.003	0.006
09:00	0.004	0.006	0.000	0.001	0.019	0.142	0.014	0.026	0.000	0.009
10:00	0.041	0.009	0.002	0.000	0.026	0.135	0.020	0.007	0.002	0.020
11:00	0.041	0.030	0.003	0.001	0.126	0.113	0.019	0.013	0.002	0.069
12:00	0.006	0.090	0.006	0.008	0.151	0.376	0.017	0.043	0.002	0.048
13:00	0.064	0.340	0.015	0.063	0.236	0.992	0.010	0.100	0.003	0.063
14:00	N/A	N/A	N/A	N/A	N/A	0.978	0.001	0.072	0.004	0.085

Table 1. *Cont.*

	January					November				
	PM_{10}	*HS*	*PS*	*TS*	*TS/TB*	PM_{10}	*HS*	*PS*	*TS*	*TS/TB*
Time	***p*-Value**									
15:00	N/A	N/A	N/A	N/A	N/A	0.993	0.175	0.060	0.000	0.034
16:00	0.002	0.137	0.001	0.013	0.096	0.251	0.135	0.028	0.000	0.035
17:00	0.006	0.020	0.004	0.000	0.022	0.122	0.069	0.014	0.004	0.079
18:00	0.006	0.010	0.004	0.000	0.006	0.028	0.021	0.016	0.001	0.074
19:00	0.001	0.063	0.000	0.000	0.008	0.013	0.049	0.009	0.001	0.069
20:00	0.002	0.085	0.000	0.000	0.004	0.012	0.099	0.006	0.001	0.038
21:00	0.001	0.034	0.000	0.001	0.015	0.036	0.210	0.001	0.001	0.024
22:00	0.002	0.110	0.000	0.000	0.009	0.078	0.332	0.002	0.000	0.012
23:00	0.003	0.053	0.000	0.000	0.003	0.036	0.132	0.006	0.000	0.006

3.2. Principal Component Regression Models

As explained above, 21 PCR models were developed. The evaluation of the performances of 21 developed PCR models was done by examining the coefficient of determination R^2 and the standard error (SE) of the residuals.

The coefficients of determination are depicted in Table 2. The evaluation of performances of the developed PCR models based on the coefficients of determination R^2 shows that all models using all seven PCs and using backward regression can explain the high percentage of variability of the independent variable compared to the low values of R^2 using the eigenvalue PC elimination criterion ($\lambda < 1$). The highest value of R^2 was 97.58% for January without temperature inversion using the full PCR model. The lowest value was $R^2 = 14.20\%$, which was calculated by the model developed for December without temperature inversion using the eigenvalue PC elimination criterion ($\lambda < 1$). According to the evaluation of the performances based on R^2, it can be concluded that the models developed using the eigenvalue PC elimination criterion are less appropriate for the prediction of the independent variable compared to full PCR models using all seven PCs and PCR models developed using backward regression.

Table 2. Evaluation of performances of PCR models.

Model	Month	TI	Full Model		Backward Regression		Eigenvalue Criterion ($\lambda \geq 1$)	
			R^2 (%)	SE	R^2 (%)	SE	R^2 (%)	SE
1	November	Yes	85.91	12.71	81.10	13.51	34.65	24.48
			PC: 1, 2, 3, 4, 5, 6, 7		PC: 1, 2, 4, 6		PC: 1, 2, 3	
2	January	Yes	85.46	25.33	83.30	24.91	74.30	30.12
			PC: 1, 2, 3, 4, 5, 6, 7		PC: 1, 2, 3, 7		PC: 1, 2, 3	
3	November	No	90.02	4.27	87.54	4.38	60.59	7.41
			PC: 1, 2, 3, 4, 5, 6, 7		PC: 2, 3, 4, 5		PC: 1, 2	
4	December	No	81.23	5.01	69.63	5.70	14.20	9.14
			PC: 1, 2, 3, 4, 5, 6, 7		PC: 1, 2, 3		PC: 1	
5	January	No	97.58	3.35	97.19	3.24	36.48	14.67
			PC: 1, 2, 3, 4, 5, 6, 7		PC: 1, 2, 4		PC: 1	
6	February	No	91.32	3.33	86.33	3.74	74.79	4.84
			PC: 1, 2, 3, 4, 5, 6, 7		PC: 1, 2, 3		PC: 1	
7	March	No	91.99	1.33	90.08	1.32	75.98	2.01
			PC: 1, 2, 3, 4, 5, 6, 7		PC: 1, 3, 4		PC: 1, 2	

Another measure of model performance is the standard error. Standard error as a measure of the variability of dependent variable values from predicted values represents an estimate of the standard deviation of the actual dependent values from the predicted values. In other words, standard error of the estimate is the square root of the sum of the squared errors divided by corresponding degrees of freedom and thus can be viewed as the standard deviation of the prediction error. As it can be seen from Table 2, the full PCR models using all seven PCs and PCR models developed using backward regression have smaller standard errors compared to the eigenvalue PC elimination criterion ($\lambda < 1$). The highest standard error was computed by the model developed using the eigenvalue PC elimination criterion for January with temperature inversion, with a value of 30.12. The lowest value of standard error was 1.32 computed by the model developed for March without temperature inversion using backward regression. According to the evaluation of the performances based on standard error, it can be concluded that the models developed using the eigenvalue PC elimination criterion are less appropriate for the prediction of the independent variable because of higher values of standard error compared to the full PCR models using all seven PCs and PCR models developed using backward regression. Finally, for all models, all regression assumptions were examined and were satisfied. In this research study, PCR was used to avoid the problem of severe multicollinearity between the original independent variables and to retain all variables in the regression model. Both aims were achieved since the PCs were orthogonal and multicollinearity disappeared completely, and since each PC was a linear combination of original independent variables, no matter how many PCs were retained in the model, the regression equation always contained all independent variables.

From Table 2, it can be seen that the models developed using the eigenvalue PC elimination criteria when the PCs with $\lambda < 1$ were discarded showed poor performance. The models developed with regression that retained all seven PCs and models developed using backward elimination PCR showed very high values of R^2 and low values of SE. Since the regression models that retained all PCs and backward elimination regression models have similar performances, the backward elimination regression models were recommended for PM_{10} forecasting because non-significant PCs were eliminated from these models. The models developed using backward regression showed that some PCs with small variances, which would be discarded from the PCR models based on the eigenvalue PC elimination criteria ($\lambda < 1$), were significantly related to the dependent variable in the regression model and contributed to the regression fit, while in some cases, PCs with higher variances were discarded from the model.

Table 3 shows the chosen forecasting models for each case.

Table 3. PCR models developed using backward elimination regression.

Model	Month	TI	PCR Models
1	November	Yes	$PM_{10} = -1885 - 4.77{\cdot}PC1 + 2.23{\cdot}PC2 + 18.96{\cdot}PC4 - 60.87{\cdot}PC6$
2	January	Yes	$PM_{10} = -20,487 - 3.78{\cdot}PC1 + 9.18{\cdot}PC2 + 15.58{\cdot}PC3 - 92.60{\cdot}PC7$
3	November	No	$PM_{10} = 1280 - 7.10{\cdot}PC2 + 10.62{\cdot}PC3 + 17.17{\cdot}PC4 + 14.38{\cdot}PC5$
4	December	No	$PM_{10} = 16,312 + 0.78{\cdot}PC1 + 6.94{\cdot}PC2 - 21.42{\cdot}PC3$
5	January	No	$PM_{10} = -868 + 1.59{\cdot}PC1 + 24.68{\cdot}PC2 - 23.32{\cdot}PC4$
6	February	No	$PM_{10} = -5001 - 0.78{\cdot}PC1 + 4.97{\cdot}PC2 + 5.57{\cdot}PC3$
7	March	No	$PM_{10} = -4747 - 0.28{\cdot}PC1 + 2.14{\cdot}PC3 + 4.89{\cdot}PC4$

The standard errors of the regression coefficients are depicted in Table 4.

Table 4. Standard errors of the regression coefficients.

		Standard Error						
		PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**
With TI	November	0.89	0.96	-	6.35	-	9.76	-
	January	0.66	1.54	3.88	-	-	-	28.9
Without TI	November	-	0.76	2.43	4.06	5.16	-	-
	December	0.25	2.14	4.2	-	-	-	-
	January	0.1	1.28	-	2.99	-	-	-
	February	0.07	1.46	2.44	-	-	-	-
	March	0.02	-	0.53	1.27	-	-	-

To interpret the principal components in each final model developed using backward elimination regression, all coefficients of correlation were computed between each principal component and the original variables: humidity in Sarajevo (HS), humidity on Bjelasnica (HB), pressure in Sarajevo (PS), pressure on Bjelasnica (PB), temperature in Sarajevo (TS), temperature on Bjelasnica (TB), and wind speed in Sarajevo (WS). All computed correlation coefficients between each principal component and the original variables for all seven models are depicted in Table 5. The interpretation of the principal components is based on detecting strong correlations between the original variables and principal components. In this research study, correlations ≥ 0.5 are considered as strong.

From Table 5, it can be seen that for Model 1, $PC1$ has a strong positive correlation with humidity in Sarajevo (HS) and humidity on Bjelasnica (HB), which means that $PC1$ increases with increasing humidity in Sarajevo and humidity on Bjelasnica. $PC2$ has a strong negative correlation with humidity on Bjelasnica (HB) and strong positive correlations with pressure in Sarajevo (PS), temperature in Sarajevo (TS) and temperature on Bjelasnica (TB). This means that $PC2$ increases with decreasing humidity on Bjelasnica and increasing pressure in Sarajevo, temperature in Sarajevo and temperature on Bjelasnica. For $PC4$, strong positive correlations are detected with pressure in Sarajevo (PS) and pressure on Bjelasnica (PB), which means that $PC4$ increases with increasing pressure in Sarajevo and pressure on Bjelasnica. Finally, for Model 1, it can be seen that $PC6$ is not strongly correlated with any of the original independent variables. Based on the values of coefficients of correlation depicted in Table 5 and on the findings, in which the original variables are strongly correlated with each component, a similar analysis can be done for all other models.

Table 5. Correlation coefficients between original variables and principal components for each model.

	PC	***HS***	***HB***	***PS***	***PB***	***TS***	***TB***	***WS***
Model 1	1	0.91	0.54	0.18	−0.29	−0.47	−0.31	0.46
	2	0.35	−0.83	0.69	−0.08	−0.66	−0.63	0.22
	4	0.01	−0.01	−0.50	−0.75	0.03	−0.12	−0.11
	6	−0.01	0	−0.04	−0.30	−0.08	0.17	0.30
Model 2	1	0.67	0.98	0.46	−0.62	−0.91	−0.88	0.03
	2	0.74	−0.18	−0.16	−0.11	−0.24	0.02	0.35
	3	0	−0.03	0.86	0.69	−0.16	−0.39	−0.27
	7	0.01	0.01	0.07	−0.14	−0.06	0.06	−0.08
Model 3	2	−0.05	0.48	−0.26	−0.28	0.07	−0.17	−0.17
	3	0.01	−0.01	−0.91	−0.24	0.01	0.08	0.21
	4	0	0	−0.02	0.20	0.08	0.29	0.48
	5	−0.01	0	−0.18	0.26	−0.01	−0.13	−0.19
Model 4	1	−1	−0.30	−0.28	0.41	0.99	0.84	0.05
	2	0	−0.93	0.78	0.47	0.01	0.13	0.03
	3	0	0.20	0.49	0.61	0.15	0.38	0.10

Table 5. *Cont.*

	PC	*HS*	*HB*	*PS*	*PB*	*TS*	*TB*	*WS*
Model 5	1	−1	−0.94	0.48	0.95	0.98	0.96	0.25
	2	0.02	−0.25	−0.62	−0.02	0.17	0.25	−0.04
	4	0.01	−0.08	−0.10	−0.17	−0.10	−0.11	0
Model 6	1	1	0.65	0.47	−0.57	−1	−0.95	0.09
	2	−0.01	−0.12	0.84	0.75	0	0.17	0.14
	3	0.01	−0.72	−0.21	0.23	−0.03	0.21	0.16
Model 7	1	1	0.97	0.68	−0.67	−1	−0.84	0.13
	3	0.01	−0.01	0.67	0.61	−0.03	−0.27	−0.19
	4	−0.02	−0.01	0.01	0.33	0.05	0.29	0.31

Figures 18 and 19 depict the observed and forecasted values of the hourly average for PM_{10} in November and January, respectively, with temperature inversion (TI). Figures 18 and 19 include 95% confidence intervals. The forecasted values were calculated using the regression equation for Model 1 for November and the regression equation for Model 2 for January from Table 3. From Figures 18 and 19, it can be seen that both Model 1 and Model 2 forecast hourly average PM_{10} with high performances.

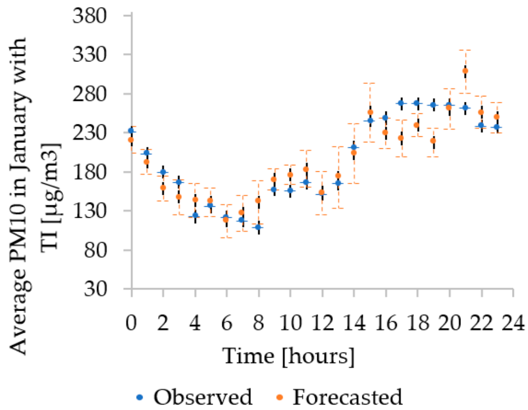

Figure 18. Observed and forecasted PM_{10} values in November with temperature inversion in Sarajevo.

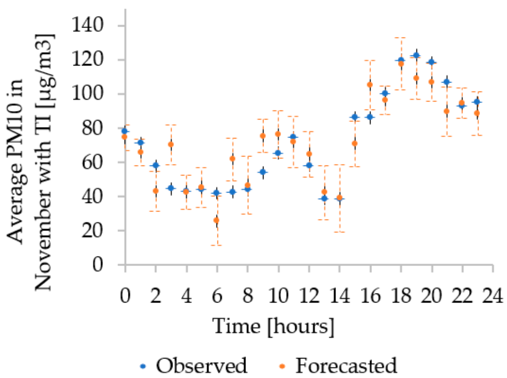

Figure 19. Observed and forecasted PM_{10} values in January with temperature inversion in Sarajevo.

Figures 20–24 show the observed and forecasted values of hourly average for PM_{10} in November, December, January, February, and March without temperature inversion (TI).

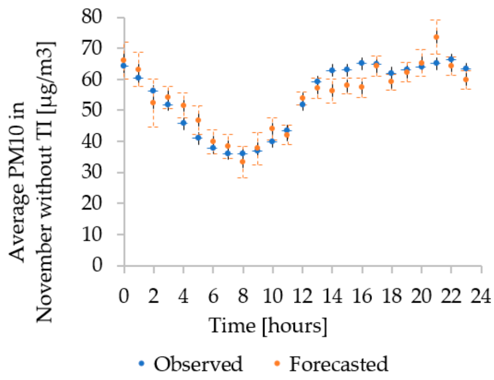

Figure 20. Observed and forecasted PM_{10} values in November without temperature inversion in Sarajevo.

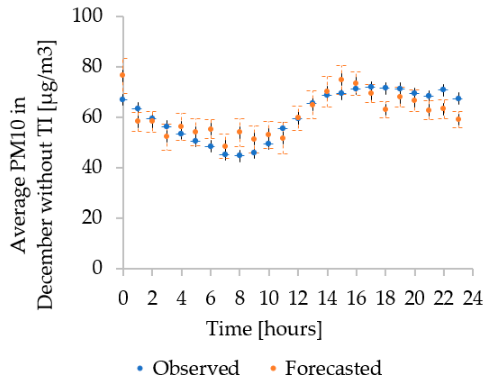

Figure 21. Observed and forecasted PM_{10} values in December without temperature inversion in Sarajevo.

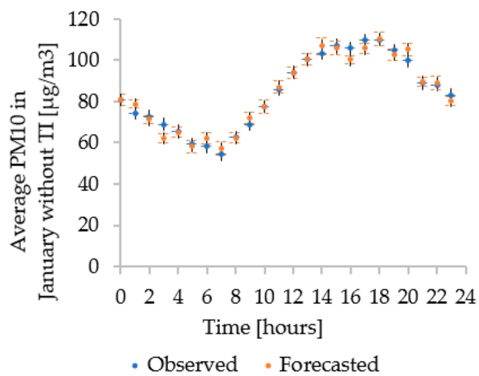

Figure 22. Observed and forecasted PM_{10} values in January without temperature inversion in Sarajevo.

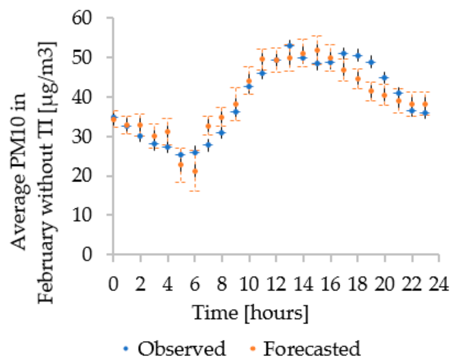

Figure 23. Observed and forecasted PM_{10} values in February without temperature inversion in Sarajevo.

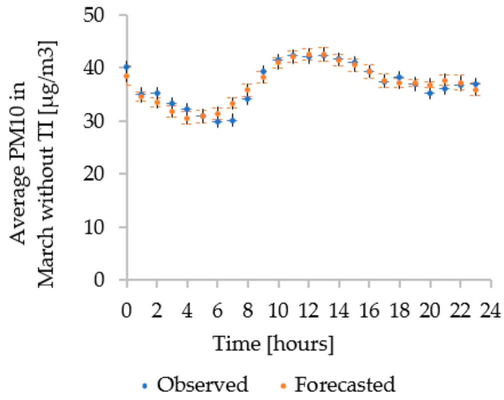

Figure 24. Observed and forecasted PM_{10} values in March without temperature inversion in Sarajevo.

The regression equations of Models 2, 3, 4, 5, 6 and 7 from Table 3 are used to calculate forecasted hourly average for PM_{10} for November, December, January, February and March, respectively. From Figures 20–24, it can be seen that all models forecast hourly average for PM_{10} with high performances.

4. Conclusions

In this study, forecasting models of hourly average PM_{10} values in the Sarajevo urban area based on meteorological parameters measured in Sarajevo and on the Bjelasnica mountain with and without temperature inversion by using principal component regression (PCR) were developed. Also, 240 hypothesis tests were performed to analyze differences in the values of the meteorological parameters and PM_{10} in Sarajevo with and without temperature inversion, and the difference of temperatures between Sarajevo and Bjelasnica with temperature inversion.

Hourly values of meteorological parameters (temperature, humidity, pressure, and wind speed) and PM_{10} were measured for Sarajevo at the meteorological station in Bjelave located at 630 m altitude. Also, hourly values for temperature, humidity, and pressure were measured at the meteorological station on Bjelasnica mountain located at 2067 m altitude. These data were collected for months during the heating season—from November to March during the period of 2020–2022.

Data for each month were sorted by hours with and without temperature inversion. The criterion to detect a month with temperature inversion was the existence of temperature inversion at each hour of the day for that month during the period of those three years. November and January were the only months that met this criterion.

For forecasting PM_{10} values, seven different cases were analyzed: November, December, January, February, and March without temperature inversion, and November and January with temperature inversion. For each case, three PCR models were created using all principal components, backward elimination and eigenvalue principal component elimination criteria ($\lambda < 1$). A total of 21 models were created. The evaluation of the performances of developed the PCR models was done using the coefficient of determination R^2 and the standard error SE.

The models developed using the eigenvalue PC elimination criteria, in which PCs with $\lambda < 1$ were discarded, showed poor performances with R^2 values between 14.20% and 75.98%, and SE values between 2.01 and 30.12. The models developed with regression that retained all seven PCs and models developed using backward elimination PCR showed very high performances with high values of R^2 and low values of SE. The regression models that retained all PCs had values of R^2 between 81.23% and 97.58% and SE between 1.33 and 25.33. Backward elimination models had values of R^2 between 69.63% and 97.19%, and SE between 1.32 and 24.91.

Since regression models that retained all PCs and backward elimination regression models have similar performances, backward elimination regression models were recommended for PM_{10} forecasting because non-significant PCs were eliminated from these models. The models developed using backward regression showed that some PCs with small variances, which would have been discarded from the PCR models based on the eigenvalue PC elimination criteria ($\lambda < 1$), were significantly related to the dependent variable in the regression model and contributed to the regression fit, while in some cases, PCs with higher variances were discarded from the model.

The average concentration of PM_{10} with temperature inversion in January was between the minimum value of 108.55 $\mu g/m^3$ and the maximum value of 267.21 $\mu g/m^3$, while without the temperature inversion, those values were between 54.41 $\mu g/m^3$ and 109.84 $\mu g/m^3$. The average concentration of PM_{10} with the temperature inversion in November was between the minimum value of 38.50 $\mu g/m^3$ and the maximum value of 122.44 $\mu g/m^3$, while those values without the temperature inversion in November were between 36.01 $\mu g/m^3$ and 66.21 $\mu g/m^3$.

The hypothesis tests showed that in January, except at 13:00, the values of PM_{10} in Sarajevo were significantly lower without temperature inversion, while this is not the case for November, during which there was no significant difference in PM_{10} in Sarajevo with and without temperature inversion. The pressure in Sarajevo in January was significantly lower without temperature inversion for each hour of the day, while in November it was significantly lower as well, except for the time period from 15:00 until 17:00. The temperature in Sarajevo in November was significantly lower without temperature inversion, while in January it was significantly lower as well, except at 13:00. The humidity in Sarajevo without temperature inversion at certain hours of the day was significantly lower than with temperature inversion, and sometimes it was opposite, without a clear pattern. In the morning and evening hours, temperatures in Sarajevo were significantly lower than temperatures on Bjelasnica for both January and November with temperature inversion.

Developed models can be used for PM_{10} forecasting by relevant authorities in Sarajevo to issue early warnings based on weather forecast as well as to undertake preventive actions to lower the PM_{10} concentration in the air and protect citizens from the harmful effects of air pollution. Although the concentration of PM_{10} showed high values throughout the heating season, special focus should be placed on periods with temperature inversion, especially in January where there is a significant difference between the mean values of PM_{10} with and without temperature inversion.

For future research, we recommend increasing the number of meteorological stations in Sarajevo and Bjelasnica and also on the other mountains around Sarajevo to analyze the different effects of meteorological parameters on air pollution. Also, other pollutants could be measured and included.

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References

1. Hasanovic, M.; Cetkovic, T.; Pourrut, B.; Caluk Klacar, L.; Hadzic Omanovic, M.; Durmic-Pasic, A.; Haveric, S.; Haveric, A. Air pollution in Sarajevo, Bosnia and Herzegovina, assessed by plant comet assay. *Mutagenesis* **2023**, *38*, 43–50. [CrossRef]
2. Cetkovic, T.; Haveric, A.; Behmen, S.; Hadzic Omanovic, M.; Caluk Klacar, L.; Dzaferspahic, A.; Durmisevic, I.; Mehanovic, M.; Haveric, S. A pilot biomonitoring study of air pollution in the urban area of Sarajevo, Bosnia and Herzegovina: Genotoxicity assessment in buccal cells. *Mutagenesis* **2023**, *38*, 33–42. [CrossRef]
3. Beard, J.D.; Beck, C.; Graham, R.; Packham, S.C.; Traphagan, M.; Giles, R.T.; Morgan, J.G. Winter temperature inversions and emergency department visits for asthma in Salt Lake County, Utah, 2003–2008. *Environ. Health Perspect.* **2012**, *120*, 1385–1390. [CrossRef]
4. Czarnecka, M.; Nidzgorska-Lencewicz, J. The impact of thermal inversion on the variability of PM_{10} concentration in winter seasons in Tricity. *Environ. Prot. Eng.* **2017**, *43*, 157–172. [CrossRef]
5. Hua, S. The Correlation between Temperature Inversion and Atmosphere Pollution in Beijing. Highlights in Science. *Eng. Technol.* **2022**, *25*, 87–93. [CrossRef]
6. Hosseini, V.; Shahbazi, H. Urban Air Pollution in Iran. *Iran. Stud.* **2016**, *49*, 1029–1046. [CrossRef]
7. Trinh, T.T.; Trinh, T.T.; Le, T.T.; Nguyen, T.D.H.; Tu, B.M. Temperature inversion and air pollution relationship, and its effects on human health in Hanoi City, Vietnam. *Environ. Geochem. Health* **2019**, *41*, 929–937. [CrossRef]
8. World Health Organization. *Regional Office for Europe. Air Quality Guidelines: Global Update 2005: Particulate Matter, Ozone, Nitrogen Dioxide and Sulfur Dioxide*; WHO Regional Office for Europe: Copenhagen, Denmark, 2006. Available online: https://apps.who.int/iris/handle/10665/107823 (accessed on 19 May 2023).
9. World Health Organization. *Regional Office for Europe. WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*; World Health Organization: Geneva, Switzerland, 2021. Available online: https://apps.who.int/iris/handle/10665/345329 (accessed on 18 May 2023).
10. Nidzgorska-Lencewicz, J.; Czarnecka, M. Thermal Inversion and Particulate Matter Concentration in Wrocław in Winter Season. *Atmosphere* **2020**, *11*, 1351. [CrossRef]
11. Brook, R.D.; Rajagopalan, S.; Pope, C.A., III; Brook, J.R.; Bhatnagar, A.; Diez-Roux, A.V.; Holguin, F.; Hong, Y.; Luepker, R.V.; Mittleman, M.A.; et al. Particulate matter air pollution and cardiovascular disease: An update to the scientific statement from the American Heart Association. *Circulation* **2010**, *121*, 2331–2378. [CrossRef]
12. Manisalidis, I.; Stavropoulou, E.; Stavropoulos, A.; Bezirtzoglou, E. Environmental and Health Impacts of Air Pollution: A Review. *Front. Public Health* **2020**, *8*, 14. [CrossRef]
13. Manju, A.; Kalaiselvi, K.; Dhananjayan, V.; Palanivel, M.; Banupriya, G.S.; Vidhya, M.H.; Panjakumar, K.; Ravichandran, B. Spatio-seasonal variation in ambient air pollutants and influence of meteorological factors in Coimbatore, Southern India. *Air Qual. Atmos. Health* **2018**, *11*, 1179–1189. [CrossRef]
14. Boubel, R.W.; Fox, D.L.; Turner, D.B.; Stern, A.C. *Fundamentals of Air Pollution*, 3rd ed.; Academic Press, Inc.: San Diego, CA, USA, 1994; pp. 149–152.
15. Rajagopalan, S.; Al-Kindi, S.G.; Brook, R.D. Air pollution and cardiovascular disease: JACC state-of-the-art review. *J. Am. Coll. Cardiol.* **2018**, *72*, 2054–2070. [CrossRef]
16. Pasic, M.; Bijelonja, I. NARX-SP Neural Network Models for Air Quality Prediction for the 24th and 48th Hour Ahead. *Int. J. Qual. Res.* **2020**, *14*, 577–592. [CrossRef]
17. Pasic, M.; Bijelonja, I.; Kadric, E.; Bajric, H. Modeling of Nonlinear Autoregressive Neural Network for Multi-Step Ahead Air Quality Prediction. *TEM J.* **2020**, *9*, 884–892. [CrossRef]
18. Akbal, Y.; Ünlü, K.D. A deep learning approach to model daily particular matter of Ankara: Key features and forecasting. *Int. J. Environ. Sci. Technol.* **2022**, *19*, 5911–5927. [CrossRef]
19. Ariff, N.M.; Bakar, M.A.A.; Lim, H.Y. Prediction of PM10 Concentration in Malaysia Using K-Means Clustering and LSTM Hybrid Model. *Atmosphere* **2023**, *14*, 853. [CrossRef]
20. Pasic, M.; Bijelonja, I.; Pasic, M. Air quality during SARS-CoV-2 (COVID-19) lockdown in Sarajevo. *Period. Eng. Nat. Sci.* **2020**, *8*, 884–892. [CrossRef]
21. Venter, Z.S.; Aunan, K.; Chowdhury; Lelievel, J. COVID-19 lockdowns cause global airpollution declines. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 18984–18990. [CrossRef]
22. Seaton, A.; MacNee, N.; Donaldson, K.; Godden, D. Particulate air pollution and acute health effects. *Lancet* **1995**, *345*, 176–178. [CrossRef]
23. European Environment Agency. EU Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on ambient air quality and cleaner air for Europe. *Off. J. Eur. Union* **2008**, *L152*, 1–44.
24. Barmpadimos, I.; Keller, J.; Oderbolz, D.; Hueglin, C.; Prévôt, A.S.H. One decade of parallel fine ($PM_{2.5}$) and coarse (PM_{10}–$PM_{2.5}$) particulate matter measurements in Europe: Trends and variability. *Atmos. Chem. Phys.* **2012**, *12*, 3189–3203. [CrossRef]
25. Zhang, H.; Wang, Y.; Hu, J.; Ying, Q.; Hu, X.M. Relationships between meteorological parameters and criteria air pollutants in three megacities in China. *Environ. Res.* **2015**, *140*, 242–254. [CrossRef]
26. Hernandez, G.; Berry, T.-A.; Wallis, S.L.; Poyner, D. Temperature and Humidity Effects on Particulate Matter Concentrations in a Sub-Tropical Climate during Winter. In Proceedings of the International Conference of the Environment, Chemistry and Biology, Queensland, Australia, 20–22 November 2017. [CrossRef]

27. Kassomenos, P.; Kelessis, A.; Petrakakis, M.; Zoumakis, N.; Christides, T.; Paschalidou, A.K. Air Quality assessment in a heavily-polluted urban Mediterranean environment through Air Quality indices. *Ecol. Indic.* **2012**, *18*, 259–268. [CrossRef]
28. Dockery, D.W.; Pope, C.A., 3rd; Xu, X.; Spengler, J.D.; Ware, J.H.; Fay, M.E.; Ferris, B.G., Jr.; Speizer, F.E. An association between air pollution and mortality in six U.S. cities. *N. Engl. J. Med.* **1993**, *329*, 1753–1759. [CrossRef]
29. Zhang, X.; Li, Z.; Wang, F.; Song, M.; Zhou, X.; Ming, J. Carbonaceous Aerosols in PM_1, $PM_{2.5}$, and PM_{10} Size Fractions over the Lanzhou City, Northwest China. *Atmosphere* **2020**, *11*, 1368. [CrossRef]
30. Blažević, R.; Hadžiahmetović, H.; Ahmović, I. Statistical Analysis and Assessment of Wind Energy Potential in Sarajevo, Bosnia and Herzegovina. *Teh. Vjesn.* **2021**, *28*, 1511–1518. [CrossRef]
31. Fisher, B.E.A. The transport and removal of sulfur dioxide in a rain system. *Atmos. Environ.* **1982**, *16*, 775–783. [CrossRef]
32. Shukla, J.B.; Misra, A.K.; Sundar, S.; Naresh, R. Effect of rain on removal of a gaseous pollutant and two different particulate matters from the atmosphere of a city. *Math. Comput. Model.* **2008**, *48*, 832–844. [CrossRef]
33. Bell, M.L.; Davis, D.L. Reassessment of the Lethal London Fog of 1952: Novel Indicators of Acute and Chronic Consequences of Acute Exposure to Air Pollution. *Environ. Health Perspect.* **2001**, *109*, 389–394. [CrossRef]
34. Brimblecombe, P. *The Big Smoke: A History of Air Pollution in London since Medieval Times*; Methuen & Co.: London, UK, 1987.
35. Dunea, D.; Iordache, S.; Ianache, C. Relationship between airborne particulate matter and weather conditions in Târgoviște urban area during cold months. *Rev. Roum. Chim.* **2015**, *60*, 595–601.
36. Vardoulakis, S.; Kassomenos, P. Sources and factors affecting PM_{10} levels in two European cities: Implications for local air quality management. *Atmos. Environ.* **2008**, *42*, 3949–3963. [CrossRef]
37. Hadziahmetovic, H.; Dzaferovic, E.; Ahmovic, I.; Blazevic, R. Analysis of Wind Velocity Data in the Area of the City of Sarajevo in Period from 2001–2010. In Proceedings of the 29th International DAAAM Symposium, Zadar, Croatia, 24–27 October 2018. [CrossRef]
38. Hadziahmetovic, H.; Ahmovic, I.; Blazevic, R. Analysis of wind velocity data in the area of Bjelasnica in period from 2000–2010. In Proceedings of the 30th International DAAAM Symposium, Zadar, Croatia, 23–26 October 2019. [CrossRef]
39. Sarajevo-Google Maps. Available online: https://www.google.com/maps/@43.7871214.18.2224241.62868m/data=!3m1!1e3 (accessed on 19 May 2023).
40. Jolliffe, I.T. *Principal Component Analysis*, 2nd ed.; Springer: New York, NY, USA, 2002.
41. Flury, B. *Common Principal Components and Related Models*; John Wiley & Sons: New York, NY, USA, 1988.
42. Jeffers, J.N.R. Two Case Studies in the Application of Principal Component Analysist. *J. R. Stat. Soc. Ser. C* **1967**, *16*, 225–236. [CrossRef]
43. Abdul-Wahab, S.A.; Bakheitb, C.S.; Al-Alawi, S.M. Principal component and multiple regression analysis in modelling of ground-level ozone and factors affecting its concentrations. *Environ. Model. Softw.* **2005**, *20*, 1263–1271. [CrossRef]
44. Jolliffe, I.T. A Note on the Use of Principal Components in Regression. *J. R. Stat. Soc. Ser. C* **1982**, *31*, 300–303. [CrossRef]
45. Hadi, A.S.; Ling, R.F. Some Cautionary Notes on the Use of Principal Components Regression. *Am. Stat.* **1998**, *52*, 15–19. [CrossRef]
46. Xie, Y.L.; Kalivas, J.H. Evaluation of principal component selection methods to form a global prediction model by principal component regression. *Anal. Chim. Acta* **1997**, *348*, 19–27. [CrossRef]
47. Jouan-Rimbaud, D.; Walczak, B.; Massart, D.L.; Last, I.R.; Prebble, K.A. Comparison of multivariate methods based on latent vectors and methods based on wavelength selection for the analysis of near-infrared spectroscopic data. *Anal. Chim. Acta* **1995**, *304*, 285–295. [CrossRef]