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The Influence of Climatological Variables on Particulate Matter and Sulphur Dioxide

Mine Tülin ZATEROĞLU*[1] ORCID *0000-0002-1050-6174*

[1]*Cukurova University, Vocational School of Adana Organized Industrial Region Technical Sciences, Electrical and Energy Department, Adana, Türkiye*

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Abstract

The prediction of air pollutants has become an important issue because of the increasing effects on human health and environmental problems. This paper intends to build up predicting model for estimating air pollutants concentrations through a statistical approach based on the Multiple Linear Regression method. The analysis contains the daily concentration values of air pollutants and climatological variables such as cloudiness, wind speed, precipitation, relative humidity and air temperature at the monitoring station located in Kırıkkale. The influence of climate elements on air pollutants was defined using the regression analysis method as statistically significant (significance level smaller than 5%). Among the assessed climatological variables, cloudiness, precipitation and relative humidity were the most frequently chosen variables in stepwise regression models for particulate matter whereas relative humidity and minimum air temperature were the most for sulphur dioxide.

Keywords: Particulate matter, Climatological variables, Sulphur dioxide, Linear regression model

İklimsel Değişkenlerin Partikül Madde ve Kükürt Dioksit Üzerindeki Etkisi

Öz

Hava kirleticilerin tahmin edilmesi, insan sağlığı üzerindeki etkilerinin artması ve çevre sorunları nedeniyle önemli bir konu haline gelmiştir. Bu makale, Çoklu Doğrusal Regresyon yöntemine dayalı istatistiksel yaklaşım yoluyla hava kirletici konsantrasyonlarını tahmin etmek için bir tahmin modeli oluşturmayı amaçlamaktadır. Analiz, Kırıkkale'de bulunan izleme istasyonunda hava kirleticilerin günlük konsantrasyon değerlerini ve bulutluluk, rüzgar hızı, yağış, bağıl nem ve hava sıcaklığı gibi iklimsel değişkenleri içermektedir. İklim elemanlarının hava kirleticileri üzerindeki etkisi, regresyon analizi yöntemi kullanılarak istatistiksel açıdan önemli olarak tanımlanmıştır (%5'ten küçük önem düzeyi). Değerlendirilen iklimsel değişkenler arasında, partikül madde için adımsal regresyon modellerinde en sık seçilen değişkenler bulutluluk, yağış ve bağıl nem olurken, kükürt dioksit için en çok bağıl nem ve minimum hava sıcaklığı seçilmiştir.

Anahtar Kelimeler: Partikül madde, İklimsel değişkenler, Kükürt dioksit, Doğrusal regresyon modeli

*Corresponding author (Sorumlu yazar): Mine Tülin ZATEROĞLU, *mtzateroglu@cu.edu.tr*

1. INTRODUCTION

Rapid industrialization, increase in energy usage and demand, and population growth led to environmental deterioration such as air pollution in urban areas. Air pollutant-related problems have attracted attention and enhanced awareness all over the world [1-2]. Some of the biggest effects of air pollutant exposure on humans are evident in urban settings [3]. Air pollution adversely affects human health and the environment [4-6]. Studies show that there is a connection between air pollution and diseases such as cancer [7] and cardiovascular disease [8]. The high concentrations of air pollutants may cause some health problems such as dizziness, headache and asthma. Furthermore, they may be concluded in a heart attack [9]. Therefore, many authorities recommend measuring and predicting air pollutants in the atmosphere. The prediction of pollutants in the air is made through some dispersion models such as Gaussian, and Lagrangian which need detailed information for the sources and the other parameters for air pollutants. So, it is more convenient to utilize statistical models that simplify the prediction of air pollutant concentration [10-12].

Sulfur dioxide (SO_2), a kind of air pollutant, is a suffocating, colourless and acidic gas formed by the release of sulfur compounds in the natural structure of fuels during combustion. SO_2 is regarded to be one of the major air pollutants which contributed to respiratory diseases and premature deaths over the World [13]. It also forms sulphuric acid which causes the degradation of ecological systems such as plants, soil, and water [14]. SO_2 is a kind of sulphate aerosol and has an impact on the radiation budget by inducing a cooling influence [15]. SO_2 is a short-lived (i.e. on the order of days) atmospheric element in the troposphere and has a high variability as temporal and spatial [15]. When SO_2 emission diffuses into the troposphere, it undergoes gas, and liquid phase oxidation by the OH, and H_2O_2 molecules, respectively. Then it creates sulphate aerosols and goes inside cloud droplets [16-17]. Particulate matter is formed by the chemical conversion of gaseous emissions and their bulk formation. The main components of particulate matter are black carbon, sulfate, ammonia, nitrates, sodium chloride, mineral dust and water [18]. Particles with a diameter of 5-10 micrometres are defined as suspended particles. It generally contains homogeneous mixtures and its characteristics vary considerably from place to place. Particulate matter less than 10 micrometres in diameter are called PM_{10}. Some researchers have examined the characteristics, dispersion, and modelling of air pollutants, PM_{10} and SO_2, in recent years [19-25]. Climatological parameters are in interact both with air pollutants and with each other in the atmospheric environment [26-30]. The occurrence of physical-chemical interactions in the atmospheric environment influences air quality. Climatological conditions can obstruct or support the air pollutants’ dispersion in the atmosphere through dilution, diffusion, and deposition [31-33]. If the conditions such as low wind speed, orography, etc., obstruct the dispersion, in this case, there will be an increment in air pollutant concentration unrelated to the increment in emissions [34-36]. Similarly, air pollutant concentration is influenced by climate elements such as relative humidity, air temperature, wind speed and precipitation [37]. There have been many studies about the influence of climate variables on air pollutants i.e. particulate matter and sulphur dioxide [38-47]. In another research, a relationship was found between sulphur dioxide and some climate elements [48]. In general, an increment in wind speed provides a decrement in air pollutant concentration [49-50]. The results of these attempts have demonstrated that the concentration of sulphur dioxide is associated with wind speed, relative humidity and air temperature. The high value of relative humidity and low value of wind speed and air temperature causes the low concentration of sulphur dioxide. Furthermore, most precipitation among meteorological variables has effects on the concentration of particulate matter via reduction [51].

Modelling of air pollutant data is very complex due to fundamental interrelationships between a large number of variables of different types that provide a complex combination of relationships. Purposing the facilitation of the statistical complication, some methods have been used to model and overcome those interrelationships. There are many models and techniques to predict the concentration of air pollutants such as principle component analysis and principal component regression [52-55], feed-forward backpropagation method [55-56], machine learning algorithms in artificial intelligence technologies [57]. Also, multiple linear regression [52,54,59], probabilistic modelling [60], and the various models [61-65]. In addition, the researchers, Nejadkoorki and Baroutian [66], and Chaloulakou et al. [67] operated an artificial neural network method whereas Chen et al. [68] used stepwise regression and wavelet analysis in prediction. Furthermore, Ramli et al. used the Bayesian Model Averaging method to estimate the concentration of particulate matter in Malaysia [46]. They used some air pollutants, i.e., NO_2, SO_2, CO, O_3 and climate variables i.e., air temperature, wind speed and relative humidity. According to prediction models, wind speed and relative humidity were determined as crucial parameters. Furthermore, the multiple linear regression method has been operated by some researchers [69-70]. The estimation models are a significant tool because they are improved to minimize the error or autocorrelation in the model. In the present study, linear regression analysis which is one of the simplification methods has been applied to air pollutant and climate datasets. This method has been preferred and operated for many years by researchers [71-78]. Furthermore, there have been some studies about the relationship between air pollutants and climate variables [28-30,76-81].

The main purpose of this study is to develop predicting models for estimating the daily air pollutants such as particulate matter and sulphur dioxide which have interactions with meteorological variables in the atmospheric environment.

2. MATERIAL AND METHOD

2.1. Study Area and Data

Kırıkkale Province is located between 33^o 20'-34^o 25' east meridians and 39^o 20'-40^o 20' north parallels in the northern hemisphere. It is in the temperate climate zone at an altitude of 747 meters from the sea. However, the climate becomes continental since the area where it is located is far from the sea, and the daily temperature difference changes due to the steppe. According to Thornthwaite climate classification, the climate class of the city is D, B^{I}2, s, b^{I}3 (means semi-arid, second-degree mesothermal, water surplus in winter and moderate, summer evaporation rate 55.6%). Due to this semi-arid climate, summers are hot and dry and winters are cold in the province. Precipitation is generally in the form of rain and snow. The wind blows from a North-East direction.

The province is among the provinces with air pollution in Turkey. The most important reason for this event is the use of poor-quality coal in domestic heating and industrial activities, wrong and irregular urbanization, insufficient thermal insulation in buildings and meteorological conditions. The increase in the number of vehicles is also a factor in the increase in pollution caused by exhaust emissions. Industrial activities are concentrated in the manufacturing industry, especially petro-chemistry and metal, feed and food industry, agricultural machinery, wood and furniture works, soil, and textile.

The daily average air pollution data as particulate matter (PM_{10}) and sulphur dioxide (SO_2) measured in the air quality monitoring station; climate data as cloudiness (C), wind speed (WS), precipitation (P), relative humidity (H), maximum air temperature (Tmax), minimum air temperature (Tmin) measured in ground-based meteorological station located in central Kırıkkale were obtained from Ministry of Environment and Urbanisation, and Turkish State Meteorological Service respectively for 5 years period of 2012-2016.

2.2. Method

The Multiple Linear Regression method depends on one response (dependent) variable to be estimated and two or more explanatory (independent) variables. The relationship between response and explanatory variables is expressed in the general formula shown below as (Equation 1):

$$Y = b_1 + b_2X_2 + \cdots + b_pX_p + \varepsilon \quad (1)$$

where p is the number of independent variables. Y determines the air pollutant concentration (dependent variable); X_1, X_2, ……, X_p are climate variables (independent variables); b_1, b_2, b_3, ……., b_p define the parameters of regression. Ɛ is the forecasted error parameter that is provided from explanatory indiscriminate illustration with constant variance and means zero (normal distribution). To forecast the values of coefficient matrix b, the least square error parameter method is operated in regression analysis.

Equation 1 may be rewritten in matrix form shown in Equation 2:

$$Y = Xb + \varepsilon \quad (2)$$

where n is the number of observations, Y is a matrix in n x 1, X is a matrix in n x p, b is a p x 1 matrix and ε is a matrix in n x 1 size. At the end of the least square method, the result is provided as the parameters of matrix b through b = $(X^TX)^{-1}(X^TY)$ where X^T denotes the transpose of matrix X. Furthermore, the *t*-test and F test are utilized to find out the significance grades of the coefficient parameters. After operating the regression analysis, the forecasting models are built in a confidence interval of 95% (statistically significant value).

To evaluate the performance of the predicted models, some statistical measures are used in the analysis. One of the commonly used criteria is the multiple determination coefficient (R^2) which describes the percentage of variance in the dependent variable expressed through the prediction models. It is defined as the square of the correlation coefficient (R). A correlation coefficient is a measure between the measured and estimated values. It changes between 0 (denotes no correlation) and 1 (-1 means perfect negative correlation whereas +1 is a perfect positive correlation). The R-value is calculated with the following formula [26,82]:

$$R = \frac{\overline{(C_o-\overline{C_o})(C_p-\overline{C_p})}}{\sigma_{C_p}\sigma_{C_o}} \quad (3)$$

where C_o define the observed values, C_p identifies the estimated values, $\overline{C_o}$ and $\overline{C_p}$ denote the mean values of the datasets, σ_{C_p} and σ_{C_o} are the standard deviations of the predicted and observed datasets.

Standard Error of Estimation (SEE) is defined as the quantity of the difference between the predicted and observed values. The value of SEE should be as small as possible or close to zero (0 is ideal) and is computed by the formula shown below:

$$SEE = \sqrt{\frac{\sum(C_o-C_p)^2}{n-2}} \quad (4)$$

where n is the number of observations.

3. RESULTS AND DISCUSSION

3.1. The Results of Regression Analysis for PM_{10} and SO_2 with Climate Variables

Daily mean values of air pollutant concentrations and climatological variables were analyzed from 2012-2016. The data for all months of the year i.e. January (JAN) to December (DEC) have been used to establish the mathematical expressions in predicting the particulate matter and sulphur dioxide through climate elements as shown in Table 1 and Table 2 respectively. Additionally, the performance indices, i.e. R, R^2, SEE and significance findings (statistically significance level which is lower than 5%) have been presented in the tables.

Table 1. Regression models for PM_{10} with climate variables

Period	Mathematical expression	Significance	R	R^2	SEE
JAN	-40.451+18.984*C-0.723*P	0.026	0.839	0.704	10.685
FEB	71.434+3.133*Tmin	0.035	0.586	0.343	17.532
MAR	28.901+29.769*WS	0.036	0.455	0.207	25.330
APR	88.976-17.888*C+0.343*P	0.011	0.851	0.724	11.659
MAY	87.317-18.052*C	0.023	0.705	0.497	14.680
JUN	-28.796+5.326*Tmin	0.030	0.625	0.390	14.041
JUL	110.639-1.899*H	0.005	0.773	0.598	11.238
AUG	46.408-16.487*C	0.038	0.600	0.360	16.548
SEP	159.046-2.512*H	0.003	0.837	0.701	11.412
OCT	13.605+0.418*P	0.040	0.582	0.339	21.257
NOV	174.138-28.665*C	0.047	0.713	0.508	38.280
DEC	109.211-30.822*WS	0.031	0.507	0.257	23.292

According to Table 1, the concentration of particulate matter was generally defined by a single parameter except for January and April. In both months, cloudiness and precipitation affected the particulate matter together explaining its variance nearly in the same grade as 70.4% and 72.4%. The lowest value of the multiple determination coefficient and the correlation coefficient was obtained in March for wind speed than in December while the highest value was in April for cloudiness and precipitation than in January. Tmax was not selected as an important parameter in the regression model by the stepwise regression method to forecast PM_{10}. Particulate matter is related to low precipitation in JAN, high minimum air temperature in FEB, high wind speed in MAR, low cloudiness and high precipitation in APR. Also, low cloudiness in MAY, high minimum air temperature in JUN, low relative humidity in JUL, low cloudiness in AUG, low relative humidity in SEP, high precipitation in OCT, low cloudiness in NOV, and low wind speed in DEC. In a similar study, relative humidity and wind speed were found as important parameters affecting particulate matter concentration [50].

Table 2. Regression models for SO_2 with climate variables

Period	Mathematical expression	Significance	R	R^2	SEE
JAN	43.481+19.077*C-1.252*P	0.047	0.771	0.594	18.289
FEB	123.808-0.83*P	0.029	0.653	0.427	26.732
MAR	53.266-4.069*Tmin	0.025	0.444	0.197	21.450
APR	-18.795+12.781*C	0.041	0.600	0.36	14.023
MAY	-111.850+48.011*Tmin-1.830*P	0.009	0.833	0.694	58.440
JUN	284.919-25.783*Tmin	0.004	0.768	0.589	45.413
JUL	-356.755-34.597*Tmin+23.451*Tmax	0.017	0.799	0.638	50.143
AUG	148.643-8.808.Tmin	0.010	0.795	0.632	17.174
SEP	-173.657+3.801*H	0.013	0.717	0.515	26.447
OCT	-257.248-51.853*C+5.025*H+86.801*WS	0.042	0.788	0.622	30.841
NOV	548.775-6.771*H-9.216*Tmin	0.004	0.943	0.890	18.250
DEC	826.348-9.154*H	0.0003	0.946	0.896	20.413

All variables have been obtained as effective regressors in predicting SO_2. In JAN, MAY, JUL, OCT and NOV, the concentration of sulphur dioxide was determined by two climate variables, while in the rest months one variable i.e. precipitation, minimum air temperature, cloudiness and relative humidity. The value of the determination coefficient varied from 0.197 to

0.896 which means weak to a high level. Relative humidity and minimum air temperature provided better results in models than the other variables. Sulphur dioxide is associated with high cloudiness and low precipitation in JAN, low precipitation in FEB, low minimum air temperature in MAR, and high cloudiness in APR. Also, high minimum air temperature and low precipitation in MAY, a low minimum air temperature in JUN, a low minimum air temperature and high maximum air temperature in JUL, and a low minimum air temperature in AUG. Also, high relative humidity in SEP, low cloudiness, high relative humidity and wind speed in OCT, low relative humidity and minimum air temperature in NOV and low relative humidity in DEC. In some studies, the air temperature was obtained as a significant variable impacting sulphur dioxide concentration [41-42,44]. In another study, the coefficient of regression between sulphur dioxide and the temperature was obtained as 73% [77]. Additionally, there has been a relation between sulphur dioxide and low wind speed in high grade while relative humidity in low grade [43]. Cuhadaroglu and Demirci [38] found a relationship between air pollutants, such as particulate matter and sulphur dioxide, and climate variables i.e. relative humidity, wind speed and air temperature in weak and moderate levels. Similar results were obtained in another study [40].

3.2. The Results of Regression Analysis for PM_{10} With SO_2

Air pollutants are related to each other. To determine the relationships between particulate matter and sulphur dioxide, four regression methods i.e. linear, logarithmic, quadratic and cubic have been operated on pollutant data via the SPSS package program.

Table 3. Regression models for PM_{10} related to SO_2 for JAN-JUN

Period	Model	Mathematical expression	R	R^2	SEE
JAN	Linear	$-7.023+0.531*SO_2$	0.566	0.321	24.147
	Logarithmic	$-232.614+60.806*\ln(SO_2)$	0.557	0.310	24.334
	Quadratic	$6.007+0.310*SO_2+0.001**[SO_2]^2$	0.567	0.322	25.298
	Cubic	$-240.028+6.822*SO_2-0.053**[SO_2]^2+0.000143*[SO_2]^3$	0.597	0.356	25.987
FEB	Linear	$58.539-0.125*SO_2$	0.177	0.031	24.060
	Logarithmic	106.192-13.292*ln(SO2)	0.247	0.061	23.687
	Quadratic	$86.213-0.772*SO_2+0.003**[SO_2]^2$	0.315	0.099	24.234
	Cubic	$54.824+0.618*SO_2-0.013**[SO_2]^2+0.000056**[SO_2]^3$	0.340	0.116	25.178
MAR	Linear	$65.076-0.373*SO_2$	0.354	0.125	25.38
	Logarithmic	$171.169-31.489*\ln(SO_2)$	0.431	0.185	24.493
	Quadratic	$176.683-3.667*SO_2+0.022**[SO_2]^2$	0.601	0.361	22.573
	Cubic	$319.735-10.072*SO_2+0.11*[SO_2]^2-0.000379*[SO_2]^3$	0.627	0.393	22.984
APR	Linear	$31.836-0.213*SO_2$	0.269	0.073	17.412
	Logarithmic	$78.357-15.142*\ln(SO_2)$	0.404	0.163	16.538
	Quadratic	$69.904-1.875*SO_2+0.015**[SO_2]^2$	0.534	0.285	16.032
	Cubic	$207.066-11.212*SO_2+0.199**[SO_2]^2-0.001*[SO_2]^3$	0.789	0.623	12.275
MAY	Linear	$19.439-0.028*SO_2$	0.139	0.019	17.692
	Logarithmic	$46.692-8.605*\ln(SO_2)$	0.456	0.208	15.899
	Quadratic	$40.535-0.949*SO_2+0.003*[SO_2]^2$	0.550	0.302	15.653
	Cubic	$40.535-0.949*SO_2+0.003*[SO_2]^2$	0.550	0.302	15.653
JUN	Linear	$22.979-0.105*SO_2$	0.409	0.168	14.827
	Logarithmic	$57.551-11.613*\ln(SO_2)$	0.771	0.594	10.348
	Quadratic	$35.040-0.585*SO_2+0.002*[SO_2]^2$	0.674	0.455	12.487
	Cubic	$49.701-1.553*SO_2+0.015*[SO_2]^2-0.00003668*[SO_2]^3$	0.834	0.695	9.760

Table 4. Regression models for PM_{10} related to SO_2 for JUL-DEC

Period	Model	Mathematical Expression	R	R^2	SEE
JUL	Linear	$21.999-0.084*SO_2$	0.401	0.161	14.884
	Logarithmic	$51.388-10.055*\ln(SO_2)$	0.793	0.629	9.898
	Quadratic	$33.521-0.545*SO_2+0.002*[SO_2]^2$	0.698	0.487	12.157
	Cubic	$43.649-1.186*SO_2+0.009*[SO_2]^2-0.000019*[SO_2]^3$	0.839	0.703	9.699
AUG	Linear	$33.092-0.450*SO_2$	0.518	0.268	18.642
	Logarithmic	$79.930-19.176*\ln(SO_2)$	0.805	0.648	12.924
	Quadratic	$67.506-2.716*SO_2+0.025*[SO_2]^2$	0.856	0.733	11.809
	Cubic	$87.532-5.769*SO_2+0.128*[SO_2]^2-0.00084*[SO_2]^3$	0.935	0.874	8.560
SEP	Linear	$24.776-0.215*SO_2$	0.408	0.166	16.034
	Logarithmic	$62.170-13.470*\ln(SO_2)$	0.635	0.403	13.571
	Quadratic	$44.809-1.313*SO_2+0.009*[SO_2]^2$	0.637	0.406	14.132
	Cubic	$72.209-3.838*SO_2+0.066*[SO_2]^2-0.0003369*[SO_2]^3$	0.794	0.631	11.690
OCT	Linear	$44.039-0.319*SO_2$	0.480	0.231	22.727
	Logarithmic	$122.974-25.868*\ln(SO_2)$	0.747	0.558	17.230
	Quadratic	$75.451-1.462*SO_2+0.007*[SO_2]^2$	0.727	0.528	18.530
	Cubic	$138.360-6.528*SO_2+0.099*[SO_2]^2 -0.000388*[SO_2]^3$	0.919	0.844	11.120
NOV	Linear	$116.864-0.586*SO_2$	0.600	0.360	37.155
	Logarithmic	$279.246-49.462*\ln(SO_2)$	0.646	0.418	35.421
	Quadratic	$153.505-1.558*SO_2+0.005*[SO_2]^2$	0.648	0.420	37.074
	Cubic	$176.994-2.569*SO_2+0.017*[SO_2]^2-0.0000385*[SO_2]^3$	0.652	0.425	38.923
DEC	Linear	$59.422-0.011*SO_2$	0.025	0.001	26.400
	Logarithmic	$79.388-4.730*\ln(SO_2)$	0.111	0.012	26.245
	Quadratic	$78.313-0.387*SO_2+0.001*[SO_2]^2$	0.251	0.063	26.610
	Cubic	$97.908-1.110*SO_2+0.008*[SO_2]^2-0.0000173*[SO_2]^3$	0.291	0.085	27.465

In all models for Tables 3 and 4, the cubic prediction models are more successful than the others. The lowest correlation coefficient and multiple determination coefficient have been observed in December, then in February.

In general, the high levels of particulate matter and sulphur dioxide are related to the low levels of wind speed and air temperature, and high levels of relative humidity [83]. Anyway, these relations could change for different periods and also locations with various effective parameters such as other meteorological conditions, topography, inversion, and street canyons.

4. CONCLUSION

This research demonstrates that daily mean concentration values of particulate matter and sulphur dioxide could be estimated using climatological parameters. The estimated models have been established as statistically significant through the stepwise regression method which allowed the most crucial climate parameters to be included in the models. These models indicate that cloudiness, precipitation and relative humidity are the most frequently elected variables in models to estimate particulate matter while relative humidity and minimum air temperature are the most for sulphur dioxide. Furthermore, the computed values of the correlation coefficient and multiple determination coefficient for the judgement of model performance indicate that the established models are commonly in acceptable weak, moderate and high grades. The highest level of model performance has been obtained in April with parameters cloudiness and precipitation for particulate matter whereas in December with a parameter relative humidity for sulphur dioxide.

Air pollutant data were modelled with climate variables using the multiple linear regression method. Moreover, to reveal the relationships between particulate matter and sulphur dioxide, various regression methods, such as linear, logarithmic, quadratic and cubic were applied to the air pollution dataset. As the result of that analysis, among all methods, the cubic estimated models which have bigger determination coefficients were much more successful than the rest models for air pollutants.

The usage of poor-quality coal that contains high sulphur and ash, population growth, and traffic density contribute to air pollution in Kırıkkale. Additionally, the topography of the province, the settlements of the building block the wind and also the turbulence created by the blowing wind in the city cause the pollutants not to be dispersed and remained in the environment.

Since the concentrations of air pollution parameters are commonly significantly associated with climatological variables, the findings from the present research could ensure some beneficial information for studies on air pollution management and planning.

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