Water Air Soil Pollut (2023) 234:259
https://doi.org/10.1007/s11270-023-06265-0

The Influence of Meteorological Factors on Air Quality in the Province of Van, Turkey

Erdinc Aladag

Received: 17 November 2022 / Accepted: 23 March 2023

Abstract Van, the most crowded province in the east of Turkey, is afflicted by intense air pollution especially in winter. Permanence and transport of air pollutants are closely associated with the region's meteorological features. Hourly and annual variations in PM_{10} and SO_2 air pollutants and temperature, wind, pressure, and humidity atmospheric variables were investigated in Van city center for 2015–2020. A multiple non-linear regression (MLNR) model was used to research the effect of meteorological parameters on air quality. Stepwise and best-subset statistical methods were applied to optimize estimators in the MNLR model. In the winter months, increases above limit values were observed for PM_{10} and SO_2 linked to increases in low-quality fuel consumption due to reducing temperatures in the evenings. Spearman analysis showed there were moderate inverse correlations with temperature (R^2=-0.42) and wind speed (R^2=-0.42) and weak positive correlations with pressure (R^2=0.35) and humidity (R^2=0.22) for the air quality index. The MNLR model using minimum temperature (T_{min}), average wind speed (W_s), the maximum pressure (P_{max}), and average humidity (H_{avg}) was the most successful (R = 0.53, RMSE = 0.24) air quality model. The reduction in air quality was associated with colder temperatures, lower wind speed, higher atmospheric pressure and higher humidity. In conclusion, policymakers and implementors should pay attention to local climate features to effectively minimize urban air pollution.

Keywords Air pollution · Meteorological effects · Van · Correlation · Stepwise regression

1 Introduction

Each year, it is predicted that seven million people die due to diseases linked to exposure to air pollution, shown to be the main environmental health threat (Pandey et al., 2021; WHO, 2022). The total cost to the global economy of early deaths caused by low air quality is more than five trillion US dollars (Roy & Braathen, 2017; World Bank, 2016). Currently, nine out of every ten people live in dense urban centers where atmospheric pollutants exceed the guideline values determined by the World Health Organization (WHO, 2022). Brønnum-Hansen et al., (2018) stated that minimizing atmospheric pollutant levels in cities to the levels of rural areas will extend life expectancy by two years. Urban inhabitants in low- and moderate-income countries, where heavy industry, motorized traffic, rapid population increases, and unplanned urbanization occur, are faced with even higher levels of air pollutants (Aksoy et al., 2021; Babatola, 2018; Brønnum-Hansen et al., 2018; Hajat et al., 2015;

E. Aladag (✉)
Department of Environmental Engineering, Faculty of Engineering, Van Yuzuncu Yil University, 65080 Van, Turkey
e-mail: erdincaladag@gmail.com

Published online: 05 April 2023

Tran et al., 2021; Zhou et al., 2020). Environmental pollution is not only airborne, but may enter the food chain through other receiving environments like aqueous media and soil and may negatively affect human health as a result (Abigail et al., 2016; Disli et al., 2021; Samuel et al., 2018; Zeng et al., 2019). Led by Bangladesh, currently, all of the most polluted countries are located in Africa and Asia (AQI, 2022). The dense populations in cities in these countries lead to the increased mortality rate from high pollution and there are findings showing a negative impact on life expectancy (Fuller et al., 2022; Rahman et al., 2022; Sarkodie et al., 2019). Considering the global urbanization rate will reach 68% by 2050 from 55% at present, more people in cities on these continents are expected to be impacted by air pollution (Tran et al., 2021; United Nations, 2018). Research assessing air quality in urban areas is an important guide for the adoption of sustainable environmental policies by national and local authorities for the development and preservation of livable cities.

Urban air pollution is closely related to the climate features, as much as the geographical, demographic, and socioeconomic structure of the region (Zhang et al., 2016). Many studies observed that meteorological conditions affect the formation and distribution of air pollution (He et al., 2017; Qi et al., 2021). Atmospheric changes on a seasonal and daily basis shape anthropogenic air pollution in urban centers by impacting human activities. A study in China concluded that the use of coal-powered heating systems with falling temperatures reduced the weekly air quality by 36% and increased deaths linked to air pollution by 14% (M. Fan et al., 2020). In Erzurum city center in the northeast of Turkey, with similar continental climate features to the present study area, a notable increase in the amount of atmospheric aerosols was identified with the effect of residential heating in the winter season (Aladağ, 2021). Much research reported that there are severe falls in air quality linked to the use of coal and increased vehicle traffic in crowded cities with hard winters and low-income levels (Barrington-Leigh et al., 2019; Kerimray et al., 2017; Liu et al., 2019; Mazzeo et al., 2018). In fact, atmospheric components like wind, rainfall, humidity, and pressure are important determinants of the distribution and permanence of air pollution (Zhan et al., 2018; Zhang, 2019). Wen et al., (2020) reported that low wind speed and high humidity increased particulate matter (PM) accumulation in the winter months. Ramsey et al., (2014) concluded that relative humidity was not as effective as wind and rainfall. Studies investigating the impacts of atmospheric conditions on urban air quality indicated there were strong inverse correlations between air pollutants with temperature and wind, while there were significant positive correlations with pressure and humidity (Bai et al., 2016; Cakir & Sita, 2020; Kayes et al., 2019). Correlation analysis investigates the one-to-one relationship between air quality and a single environmental factor. However, most of the time, meteorological parameters have a combined effect on outdoor air pollution. Multiple regression models created by bringing together a variety of atmospheric components may be more effective in explaining these complicated relationships.

Air pollution observations in Turkey date back to the 1960s. Air quality monitoring stations were first operated in the capital Ankara and in other large cities a short duration afterwards. Since 2020, Turkey has performed hourly measurements of PM, SO_2, CO, NO_2, and O_3 air pollutants at a total of 355 monitoring stations. High levels of outdoor air pollution were observed in crowded cities, which are the industrial centers of the country, like İstanbul, Ankara, and İzmir in the past century, while at present it has become a serious environmental problem threatening human life expectancy and quality of life even in provinces without developed industry. One of these provinces is Van, which is the province with the sixth-highest SO_2 measured in 2020 and with an annual PM_{10} concentration equivalent to nearly two times the guideline value recommended by the WHO (Right to Clean Air Platform, 2022; WHO, 2022). SO_2 pollution occurs as a result of the combustion of fossil fuels containing sulfur during domestic heating and some industrial processes. Particulate matter pollution is mostly due to industry and partly due to fossil fuels used in urban heating (Menteşe & Tağıl, 2012). In provinces like Van with a hard winter season and without developed industry, the use of dusty and low-calorie coal containing high sulfur instead of natural gas for heating purposes is very common (Çay & Yildiz, 2011; Öztürk & Bayram, 2019). In cities unprepared for the rapid increase in population, palliative solutions aiming to resolve housing needs without paying attention to the morphologic structure, topography, and microclimate features of the region may also lead to many environmental problems like air pollution (Khalaf, 2019; Yilmaz et al., 2021). Research investigating the relationship between air quality in Van city center, one of the provinces receiving the most migration in the region, with meteorological factors is limited in the literature. For example, air quality modeling research was performed using estimators like rainfall and wind speed (Kong & Tian, 2020; Yang et al., 2017; H. Zhang & Zhao, 2019).

Many studies accepted a multiple linear relationship between air pollutants and estimators. However, this method generally does not reflect the true relationship between variables (Weichenthal et al., 2016; L. Zhang et al., 2021). For air quality modeling, it is necessary to reveal complicated non-linear correlations in real-world processes (Raga & Le Moyne, 1996; Valverde et al., 2015). For this, a variety of non-linear regression methods were developed like an artificial neural network, random forest, and support vector machine (Araki et al., 2018; J. Fan et al., 2018; Meng et al., 2018; Srivastava et al., 2018). However, though most of these methods were successful for the estimation of air quality, they are not adequate to understand the single or synergistic effects of meteorological parameters on air pollution as they are removed from linear correlation assumptions (Ren et al., 2020; L. Zhang et al., 2021). In this study, the best subset and stepwise multiple non-linear regression methods are proposed to be able to determine the significance level for connections between air quality and meteorological factors. Though using linear regression approaches for these methods, limited numbers of studies were not able to determine non-linear effects between variables (Arain et al., 2007; Cuhadaroglu & Demirci, 1997; Ilten & Selici, 2008). There is no other study in the literature dealing with the hierarchic pattern of multiple non-linear relationships between air quality with meteorological estimators using both methods together.

This article reveals the variations on different time scales of air quality and meteorological factors and the correlations between them for the years 2015–2020 in Van city center. The research comprises three sections, with the first section investigating the daily and yearly variations in meteorological parameters of temperature, wind, humidity, and pressure with the air pollutants of particulate matter and sulfur dioxide. Later, the amounts, directions, and significance of correlations between the air quality index with meteorological factors are determined. In the final section, the combined effect of meteorological parameters is investigated with air quality estimation models developed using atmospheric components with different features. Additionally, the target is to ensure urban inhabitants in Van are impacted less by low outdoor air quality due to this research, which offers a range of preventive precautions about protecting public health against air pollution.

2 Materials and Methods

2.1 Study Area

The study area was identified as Van province and is located in the Eastern Anatolia region of Turkey. In 2020, the population of Van was 1,149,342 people and it was the most crowded province in the region, with 54.4% of this population living in Tuşba, İpekyolu and Edremit central counties. With an elevation of 1730 m, the city center is surrounded by Şahbağı Hill to the north (1968 m), Musakent hill to the northeast (2407 m), Mount Erek to the east (3204 m), and Lake Van to the west. The province is 79th out of 81 for per capita GDP and has so little industry as to be non-existent (Turkish Statistical Institute, 2020). For this reason, the main causes of air pollution in the city are heating and transport. The city is dominated by a continental climate, and it is covered in snow during the winter months. In spite of the arrival of natural gas in 2007, nearly 40% of heating requirements in 2016 were still met by coal (Öztürk & Bayram, 2019). The other important source of pollution of traffic is dense during the day and nearly reaches the stopping point during rush hours (Yakın & Behçet, 2019). The lack of a ring road leads to heavy vehicles being directed through the main arteries of the city center, and this situation further increases the traffic load along the Tuşba-Edremit line. There is one air quality monitoring station (AQMS) (38°30′14.4"N, 43°22′16.3"E) and one meteorological observation station (MOS) (38°28′08.4"N, 43°20′13.2"E) present within Van provincial boundary operated by the Ministry of Environment, Urbanization and Climate Change. Figure 1 shows the map of Van city center and the locations of the AQMS and MOS. With air pollution due to heating and transport largely reflected due to

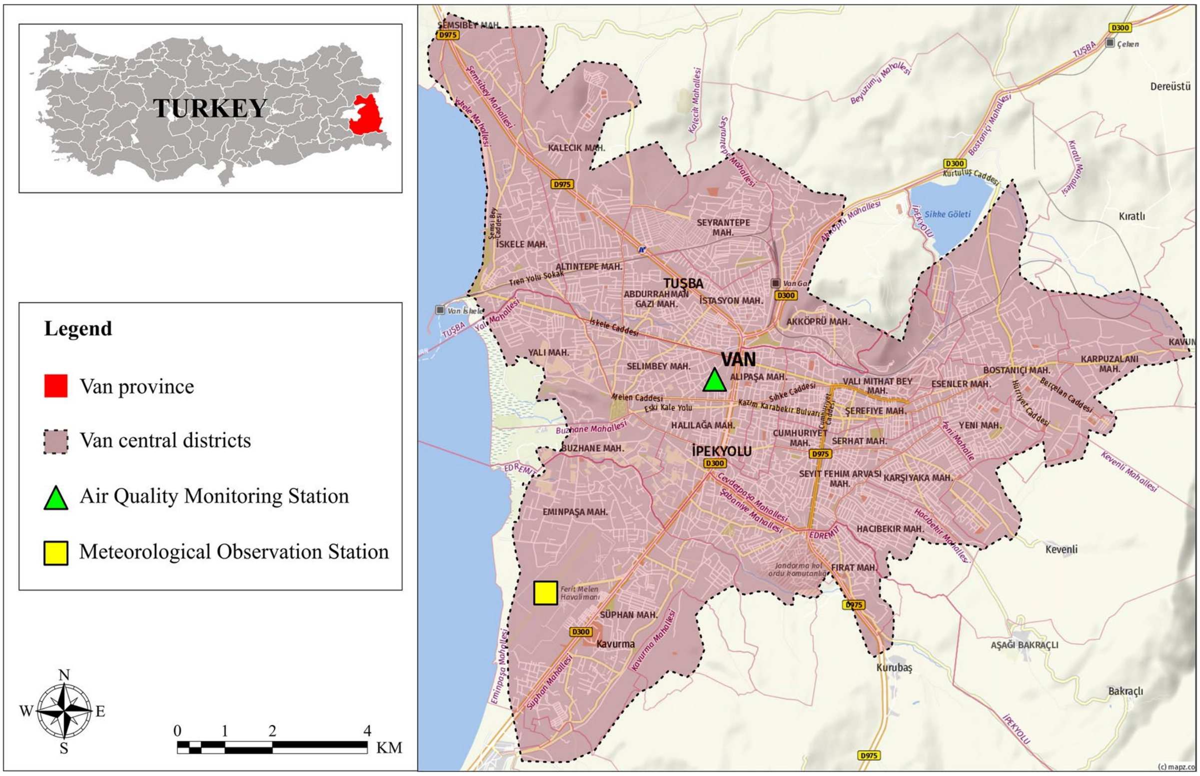


Fig. 1 Location map of the air quality monitoring and meteorology stations in Van city

its location within the settlement area and close to the main road, the AQMS measures concentrations of particulate matter with a diameter smaller than 10 μm (PM_{10}, μg/m^3) and sulfur dioxide (SO_2, μg/m^3). The MOS, located at the airport (LTCI) nearly 5 km south of the AQMS, measures temperature (T, °C), atmospheric pressure (P, hPa), relative humidity (H, %), wind direction (W_D, °deg) and wind speed (W_s, m/s).

2.2 Data Collection

The study used hourly data obtained from these stations between 1 January 2015 and 31 December 2020. Air pollution data were obtained from the National Air Quality Observation Network (http://www.havaizleme.gov.tr/) and meteorological data were obtained from the Turkish State Meteorological Service (http://www.mgm.gov.tr/). The 6-year data set included a total of 315,648 data points. The missing data rate was less than 5% for each parameter, and deficient data were removed from the data set without any correction. To be able to investigate extraordinary meteorological situations occurring during the day, a data set was created containing daily averages calculated from the hourly data, in addition to minimum and maximum values within the day for temperature, relative humidity, and pressure parameters.

Using the arithmetic mean of wind speed, with vectoral magnitude, is not an acceptable approach alone most of the time. For this reason, hourly wind speed (Ws) and direction (W_D) were decomposed with W_X for the x-axis and W_Y for the y-axis as shown in Eqs. 1 and 2 and the average was taken (Feng et al., 2015). In this way, the distributions of the daily mean wind speed were determined on the east–west and north–south axes.

$$W_X = W_S \times \cos(W_D) \quad (1)$$

$$W_Y = W_S \times \sin(W_D) \quad (2)$$

2.3 Calculation of Air Quality Index

To be able to determine air quality at a certain location, the air quality index (AQI) is an environmental quality marker calculated by noting the hourly and daily measurements of gas or particulate pollutants in the atmosphere (U.S. Environmental Protection Agency, 2022). Every level of the AQI, classified in six levels, is symbolized by a different color and has different break points for the six main pollutants (PM_{10}, $PM_{2.5}$, SO_2, CO, NO_2, and O_3). Table 1 shows the break point values and level colors for PM_{10} and SO_2 air pollutants in the air quality index (U.S. Environmental Protection Agency, 2016). Firstly, with the aid of Eq. 3, the daily air quality index ($IAQI_P$) was determined for each air pollutant. Here, the daily mean value was used for determining air quality for PM_{10}, while the daily SO_2 value was used if the hourly maximum value was above 305 ppb; otherwise, the hourly SO_2 value was used for SO_2. Later, the largest value among the $IAQI_P$ values (Eq. 4) was determined as the daily AQI value. Additionally, the air pollutant with the maximum value among $IAQI_P$ values was the atmospheric pollutant responsible for that day's air quality.

$$IAQI_P = \frac{I_{Hi} - I_{Lo}}{BP_{Hi} - BP_{Lo}}\left(C_P - BP_{Lo}\right) + I_{Lo} \tag{3}$$

$$\mathrm{AQI} = \max\left(IAQI_1, IAQI_2, \ldots, IAQI_n\right) \tag{4}$$

Here, $IAQI_P$ is the air quality index for pollutant P; C_P is the concentration of pollutant P; BP_{Hi} is the upper break point for C_P; BP_{Lo} is the lower break point for C_P; I_{Hi} is the AQI belonging to BP_{Hi}; and I_{Lo} is the AQI value belonging to BP_{Lo}.

As the AQI value increases, the outdoor air quality falls. The possible effects of AQI level on human health and recommended precautions are given in Table 2 (U.S. Environmental Protection Agency, 2022). As can be seen here, on days when the AQI value is above 50, it may cause health problems in certain sections of society at risk from exposure to air pollutants. Being outside when the AQI is above the fourth level (> 150) is not recommended even for healthy individuals in the general population.

2.4 Non-Linear Regression Model

The data set without normal distribution according to the Jarque-Berra test, frequently used for time series, had non-parametric Spearman's rank correlation analysis applied (Aladağ, 2021). Environmental factors generally have a synergistic effect on air pollution. Single correlations of independent variables are limited in identifying these complicated relationships. For this reason, the multiple non-linear regression (MNLR) model used in the study may be more explanatory for the relationship between air quality and meteorological variables. When creating this model, only the impact of the atmospheric conditions on air quality for that day was investigated, without any prospective estimations expected, so past and offset values for air pollutants and meteorological measurements were not included in the calculations.

The multiple linear regression model may be defined as follows (Turalıoğlu et al., 2005).

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_M x_{Mi} + \varepsilon_i \tag{5}$$

In the linear equation (Eq. 5) above, y is the AQI value for observation i and x shows the meteorological variable.

Table 1 Levels and break points of the air quality index

AQI categories	AQI values	PM_{10} (μg/m^3)	SO_2 (ppb)
Good	0–50	0–54 (24-hr)	0–35 (1-hr)
Moderate	51–100	55–154 (24-hr)	36–75 (1-hr)
Unhealthy for sensitive groups	101–150	155–254 (24-hr)	76–185 (1-hr)
Unhealthy	151–200	255–354 (24-hr)	186–304 (1-hr)
Very unhealthy	201–300	355–424 (24-hr)	305–604 (24-hr)
Hazardous	301–500	425–604 (24-hr)	605–1004 (24-hr)

Table 2 Health effects and recommended precautions for air quality levels

AQI levels	Health impacts	Recommended precautions
I. (Good)	No health effects observed.	Outdoor activities may continue.
II. (Moderate)	Aerosols may mildly affect hypersensitive individuals.	Exceptionally sensitive people should consider reducing prolonged outdoor activities.
III. (Unhealthy for sensitive groups)	May affect children and the elderly, as well as those with respiratory and heart disease.	These people should reduce continuous and high intensity outdoor activities.
IV. (Unhealthy)	May cause serious health effects in sensitive individuals. May affect the heart and respiratory system of healthy people.	Children, the elderly, and those with heart or lung disease should avoid prolonged and intense outdoor exercise. The public should avoid outdoor activities.
IV. (Very unhealthy)	A variety of symptoms may be observed in healthy individuals. May cause serious effects in persons with respiratory disease.	Children, the elderly and those with heart or lung disease should stay indoors and avoid going outdoors if possible. The public should reduce outdoor activities.
IV. (Hazardous)	Hazardous for everyone. May cause severe effects in sensitive persons, children, the elderly, and persons with respiratory or cardiac disease.	All outdoor physical activity should be minimized by everyone.

β_0 is the intercept term, β_M is the regression coefficient for meteorological factor M, and ε is the error term.

The general appearance of non-linear regression is assumed to be as follows (Eq. 6):

$$y_i = \beta_0 \times \left(x_{1i}^{\beta_1}\right) \times \left(x_{2i}^{\beta_2}\right) \times \cdots \times \left(x_{Mi}^{\beta_M}\right) + \varepsilon_i \tag{6}$$

Here β_0, β_1, β_2, and β_M are non-linear model coefficients. Conversion of the non-linear equation to linear form allows the possibility for an easier solution. For this reason, it is linearized in Eq. 7 with the aid of a logarithm (Yasar et al., 2012).

$$\log\left(y_i\right) = \log\left(\beta_0\right) + \beta_1 \log\left(x_{1i}\right) + \beta_2 \log\left(x_{2i}\right) + \cdots + \beta_M \log\left(x_{Mi}\right) + \varepsilon_i \tag{7}$$

For parameters with the highest correlation among meteorological factors with different types and features, the combined effect of different combinations of generally independent variables is ignored in air quality models created by combining estimators. Sometimes, a model created without using a parameter with a high correlation may provide more sensitive estimations. For this reason, different algorithms like stepwise and best subsets are used for the selection of more effective estimators for estimation by the model. Stepwise regression is a process operating prospectively and retrospectively in the selection of the independent variables (Cuhadaroglu & Demirci, 1997). Decisions are not just made by only adding variables; at the same time, decisions are made about whether it is necessary to remove variables according to model criteria. Estimator selection ends when the significance level does not meet the criteria for adding (α=0.05) or removing (α=0.1) more variables (Ilten & Selici, 2008). The general model using all variables is called the enter model (Yasar et al., 2012). Another systematic approach for determining variables included in regression is the best subsets method, which chooses the subcluster with the best model success among 2^k estimator clusters created with different combinations of k variables (Saithanu & Mekparyup, 2014). Data visualization and modeling were completed in the R Studio (2021.09.1) environment.

2.5 Performance Evaluation

The performance of the models was measured with the commonly used correlation coefficient (R), root mean square error (RMSE), and the sum of squared error (SSE). These are defined according to Eqs. 8–10 below.

$$R = \frac{\frac{1}{N}\sum_{i=1}^{N}(P_i - \overline{P})(O_i - \overline{O})}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - \overline{P})^2}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - \overline{O})^2}} \tag{8}$$

$$RMSE = \sum_{i=1}^{N}\frac{1}{N}\sqrt{(P_i - O_i)^2} \tag{9}$$

$$SSE = \sum_{i=1}^{N}(P_i - O_i)^2 \tag{10}$$

Here, P and O are the estimated and observed values of AQI at the time i; while $\overline{P}$ and $\overline{O}$ represent the estimated and observed mean values for the N number of AQI, respectively. Models with low RMSE and SSE and high R values are accepted as having a relatively better fit.

3 Results and Discussion

One of the meteorological parameters accepted as being important with a direct connection to air pollution is temperature. Figure 2 shows the climate radial chart according to month for the years 2015 to 2020. Here, the color fill represents the daily mean temperature, while the internal diameter of the radial is the minimum and the external diameter of the radial is the maximum temperature. A climate radial with a relatively more red color and larger size shows a warmer year, while a color radial that is smaller and has blue-purple tones indicates a relatively colder year. Accordingly, 2017 was the coldest year with the average value of 9.7 °C, while 2018 was the warmest year with a mean 11.3 °C. Additionally, 2017 was observed to have a mean minimum temperature of 4.0 °C, while 2018 was observed to have a mean maximum temperature of 16.1 °C. The period from December to March had mean lowest temperatures below zero (mean: -3.8 °C), while June–July had mean highest temperatures above 24 °C (mean: 26.0 °C). The excessive temperature differences during the year (±29.8 °C), high elevation, aridity, and steppe vegetation show that continental climate conditions are dominant in Van city center.

The distribution and movement of air pollutants in the atmosphere are affected by the direction and strength of the wind. At low wind speeds, the transport of aerosols and gases from the source becomes more difficult and urban air pollution becomes more permanent. Contrary to this, strong wind flows move anthropogenic pollution away from urban centers, while it may bring regional dust and sand storms into the city. Figure 3 shows the wind rose diagrams according to month. As seen in the figure, the period from October–February is the time when the strongest winds are experienced during the year. In this period, the dominant wind direction is clearly east and northeast. In the period from March to August, the strength of the wind reduces and it comes from west and northwest directions. The city center, located on the shore of Lake Van, is affected by winds from the mountains to the east in the winter months and the effect of the warming lake is felt due to winds from the west in the summer months.

Atmospheric pressure and relative humidity are other meteorological factors affecting air pollution. Figure 4 and 5 show the hourly and monthly changes in air pressure and humidity, respectively. The periodic movements and daily variability of these parameters affect air quality so the hourly trends in 95% confidence intervals and monthly boxplots were

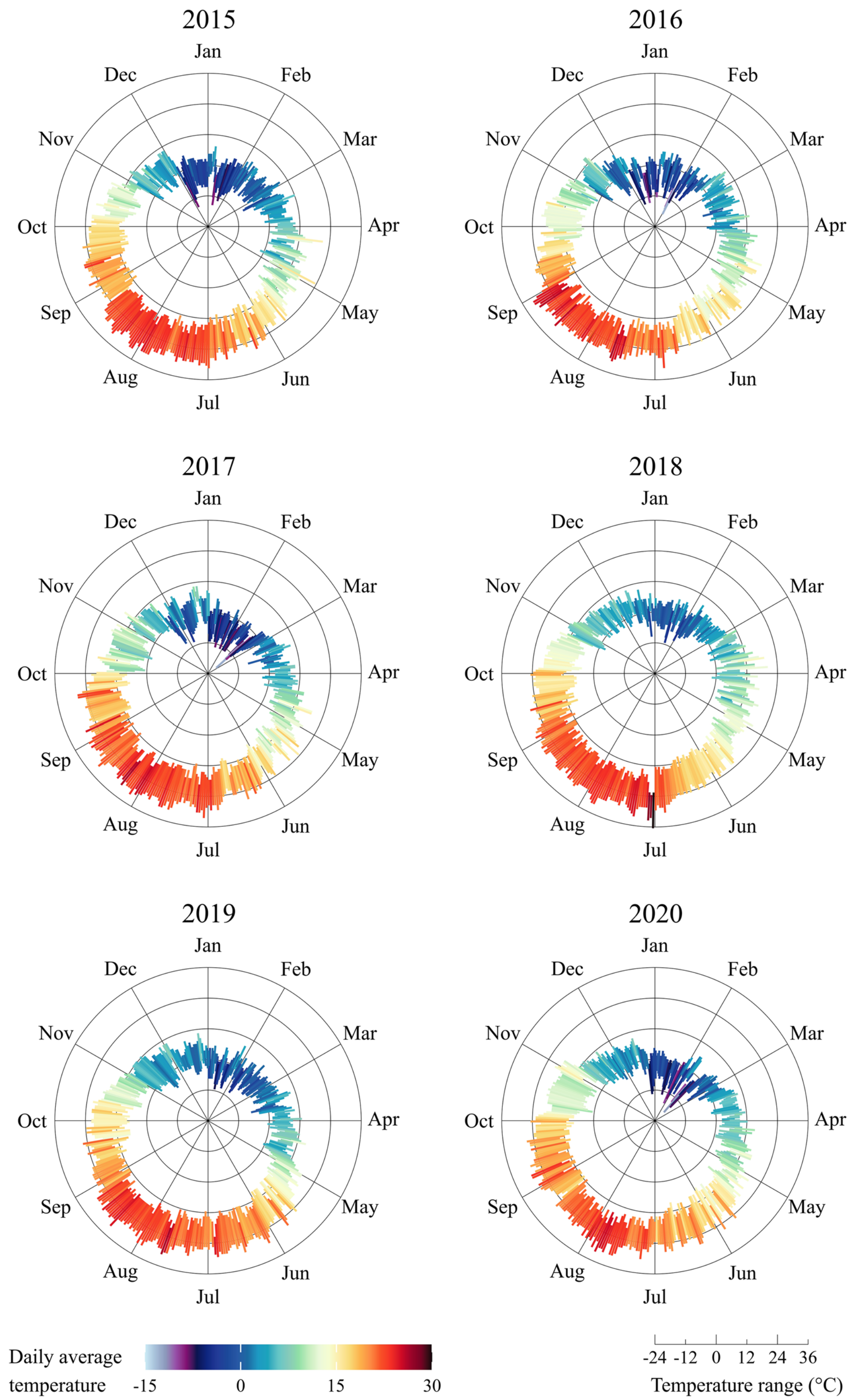


Fig. 2 Climate radials between 2015 and 2020

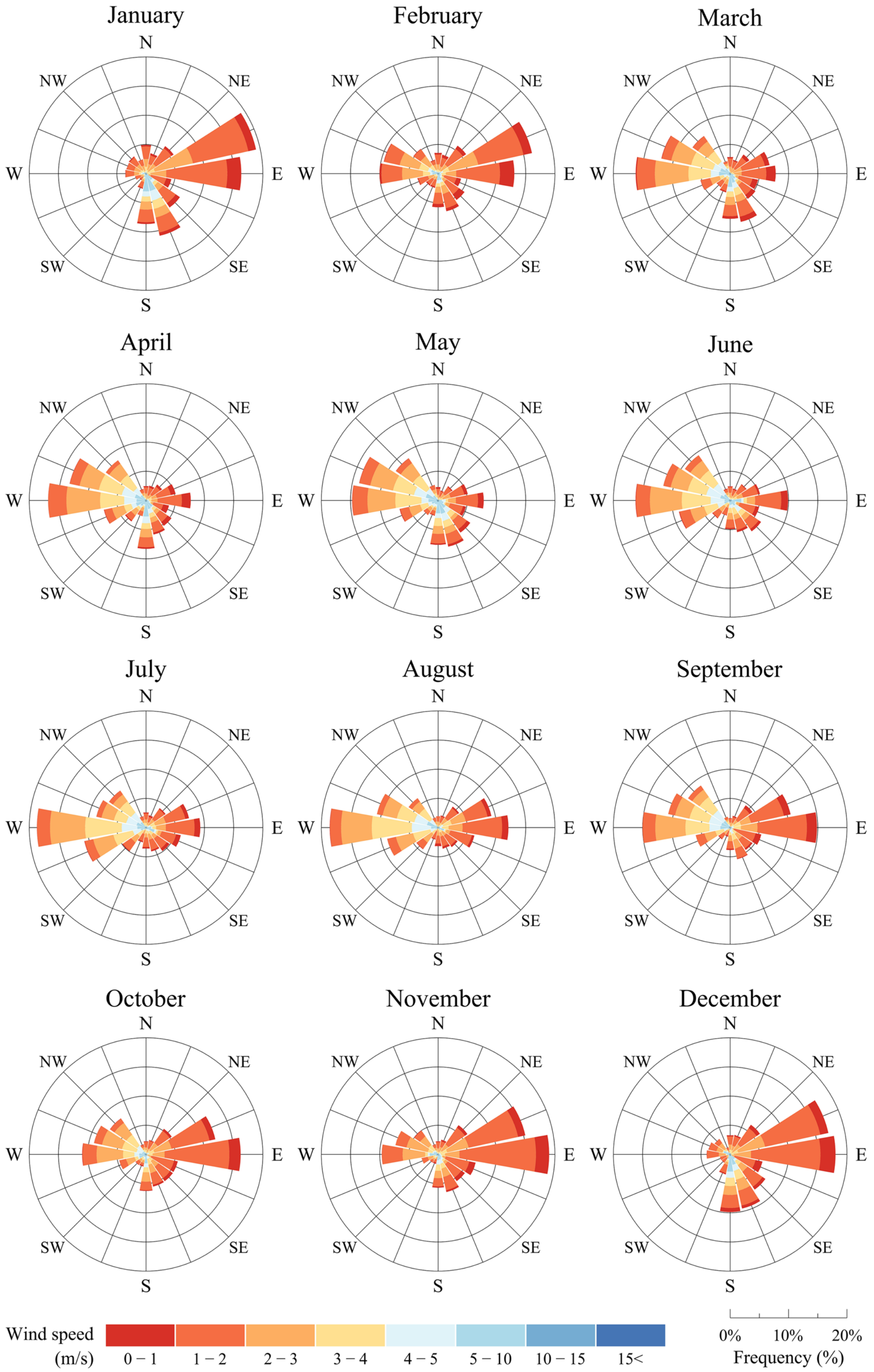


Fig. 3 Monthly wind rose diagrams

used. As can be seen in Fig. 4a, the hourly air pressure displays cyclical variation which increases from 04:00–09:00, reduces from 10:00 to 16:00, increases from 17:00 to 21:00 and reduces from 22:00 to 03:00. When investigated on a monthly basis in Fig. 4b, the air pressure reaches highest levels from October–February. In the period from June–August, there are lower levels compared to other months. The highest variability is observed in the months of February and December. On Fig. 5a, the humidity reaches up to 70% from 05:00, rapidly reduces with the sunrise and falls below 55% by 14:00. In the evening when the effect of the sun is lost, it increases again. As understood from the monthly boxplots shown in Fig. 5b, the humidity measured in the city center begins to reduce in March. It reaches lowest levels in July, August, and September. These months are the period with the least rainfall in the city center. With the effect of increasing rainfall in the fall months, humidity begins to rise again in October and relatively higher humidity rates are observed between December–February in the winter period.

The amount of outdoor air pollutants displays extreme differences within the day and year linked to meteorological factors and human activity. To be able to investigate variations in PM_{10} and SO_2 together on an hourly and monthly basis, the radar graphs given in Fig. 6 and Fig. 7 were used. These graphs show the mean amount of air pollutants between 00:00 and 23:00 with PM_{10} shown in orange and SO_2 in purple. The thick red dashed line in both figures shows the mean hourly amounts for 2015–2020 and the green circle indicates the limit value recommended by WHO (50 μg/m^3 for PM_{10} and 20 μg/m^3 for SO_2). The lower right of the figures shows the pollution scale. On Fig. 6, PM_{10} remains below the limit values between 03:00 and 18:00 during the year. However, in the fall and winter seasons, especially in the evening hours (19:00 to 00:00), high particulate matter pollution is experienced in the city. In the period from January to March, the particulate matter pollution continues until late in the night. According to the results, the main reason for pollution at night when human activity is relatively reduced is considered to be fuel use for heating purposes. Additionally, the small increase from 08:00 to 10:00 in the morning may be associated with traffic. The cleanest period in terms of atmospheric particles is the months from April–June, with aerosol amounts remaining below limit values at all hours of the day.

Figure 7 displays the monthly and hourly SO_2 variations in the Van city center. Here, from November–February when air pollution is at highest levels, the SO_2 amount is nearly 3 times the limit value recommended by the WHO from 18:00 in the evening until 02:00 at night. In January, measurements were above the limit value of 20 μg/m^3 during the whole day. With the effect of increasing rain and low temperatures in the winter months, the increased use of coal for the purpose of domestic heating is thought to play an important role in sulfur dioxide pollution. Additionally, the sudden drop in SO_2 amounts from April–October supports this finding. In this period, the mean sulfur dioxide concentration measured in every hour was below the limit value. In the winter months, individuals sensitive to changes in air quality should not spend time outside in the evening hours as much as possible and if they must, it is recommended they use masks for aerosols in addition to air pollutants in gas form.

In order to assess the effects of exposure to atmospheric pollutants with different types and levels on humans, the air quality index, a combination of these pollutants, was calculated. Figure 8 gives the air quality calendar colored according to Table 1 for daily AQI values in Van city center for the years 2015–2020. Here, the separate columns are years, while rows display weeks. Months are denoted by the thick frames. According to the calendar, nearly every day from November–February had moderate-low levels of air quality. From April–June, the days with the best air quality are experienced.

To be able to better understand the variations in air quality, Fig. 9 shows the monthly distribution and averages for air quality level. Here, the colored bars on the left axis show the percentage AQI, while the small black boxes on the right rate indicate the mean AQI values. Additionally, the fine light–dark gray lines to the right of the colored bars (light gray: SO_2 and dark gray: PM_{10}) represent the proportion of air pollutants determining the air quality for that month. Air quality was higher from April–October. In this period, the monthly mean air quality was below the first level ($AQI < 50$). May was the cleanest month. Additionally, the atmospheric pollutants determining air quality in the summer were the high rates of particulate matter. Since November–March, air quality reduces by severe rates. In this period, the main culprit behind the low air quality is sulfur dioxide. On winter days with low air quality observed, individuals with respiratory tract problems are recommended not to go outside unless absolutely necessary. Especially in February, the first-level air quality rate falls below 30% and the mean air quality is about 83. As can be seen on the graph, variation is higher in the winter and fall seasons compared to other periods; for this reason, the probability of sudden changes in air quality is higher compared to the summer.

Table 3 shows the annual distribution and averages for the daily air quality index for the years 2015–2020. 2015 and 2017, in that order, were the years with the highest air quality. The year 2016 was the year with the most days when first-level air quality was experienced (257 days). The year 2020 was the year with the worst mean air quality index. Additionally, it was the most polluted year with second level and above air quality observed at 43.17%. According to the annual mean AQI values, Van city center was observed to have air quality that is progressively reducing. Linear regression analysis results support this finding ($y = 2.69\mathrm{x} + 46.26$, $R^2 = 0.78$). Additionally, unhealthy and hazardous levels of air pollution were identified on 5 days in 2016, 6 days in 2019 and 5 days in 2020. These levels show that air pollution is a general threat in terms of public health.

Table 4 assesses the air quality index according to the days of the week. Accordingly, Sundays and Saturdays were the cleanest days in Van city center. Tuesdays and Fridays, in that order, were the days with the worst air quality in the week. If the general average is examined, the weekend had more cleaner days compared to weekdays. At the weekend—especially Sunday—public institutions and banks are all closed along with most private workplaces. This situation may cause a fall in traffic by reducing human mobility and industrial-derived emissions.

Table 5 provides important descriptive statistical features like the minimum, maximum, interval, average., and standard deviation for air quality and meteorological parameters. Figure 10 shows the correlation results between meteorological factors and the air quality index. According to the results, the daily average wind speed (W_s) and minimum temperature experienced during the day (T_{min}) were meteorological variables with the highest correlation to air quality (-0.42). The inverse correlation indicates the minimum temperature during the day causes an increase in pollutant emissions by triggering coal and natural gas consumption for residential heating. Similarly, the daily average and maximum temperatures ($T_{min} > T_{avg} > T_{max}$) had an inverse proportion to air quality. For this reason, the reduction in temperatures may be said to lower the air quality in the city center. Additionally, the reduction in air movements on calm and wind-free days is thought to increase cumulative air pollution by making it more difficult to transport air pollutants away from the city center. Wind direction was only significant on the horizontal axis (east–west); however, there was a very weak correlation. Humidity and air pressure were directly proportional to the air quality index. Daily mean humidity had a greater correlation than the minimum and maximum humidity recorded during the day ($H_{avg} > H_{min} > H_{max}$). The highest air pressure experienced during the day had a higher correlation than the average and minimum pressures ($P_{max} > P_{avg} > P_{min}$).

According to the correlation test, temperature, wind speed, air pressure, and humidity, in that order, were concluded to have significant correlations with air quality. Inferences made by considering only single correlation results remain inadequate most of the time to explain the mobility of matter in the dynamic environment of the atmosphere. For this reason, air quality models were created using the multiple non-linear regression method by combining a variety of meteorological factors as independent variables. To determine the predictors in these models, firstly enter and stepwise regression analysis was performed. Table 6 shows the variance analysis of the models created for air quality estimation. Regression models SR1-SR5 involve predictors being added or removed in a stepwise fashion, while enter shows the regression model using all predictors. According to the results, all models were significant ($p < 0.001$).

Table 7 includes the correlation coefficients and error amounts for MNLR models. As can be seen, the enter model had the highest correlation and lowest error. The stepwise regression models approaching this model most closely were SR5 and SR4, in that order.

Table 8 shows the regression coefficients related to the stepwise and enter MNLR models. The enter

Fig. 4 Hourly average (**a**) and monthly notched boxplots (**b**) for air pressure in Van City

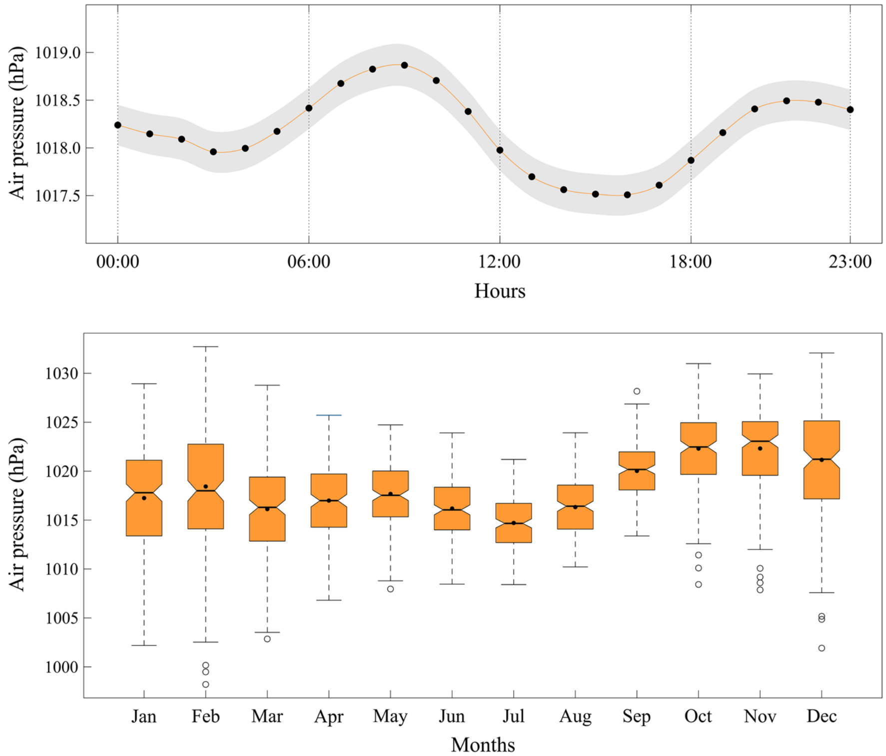
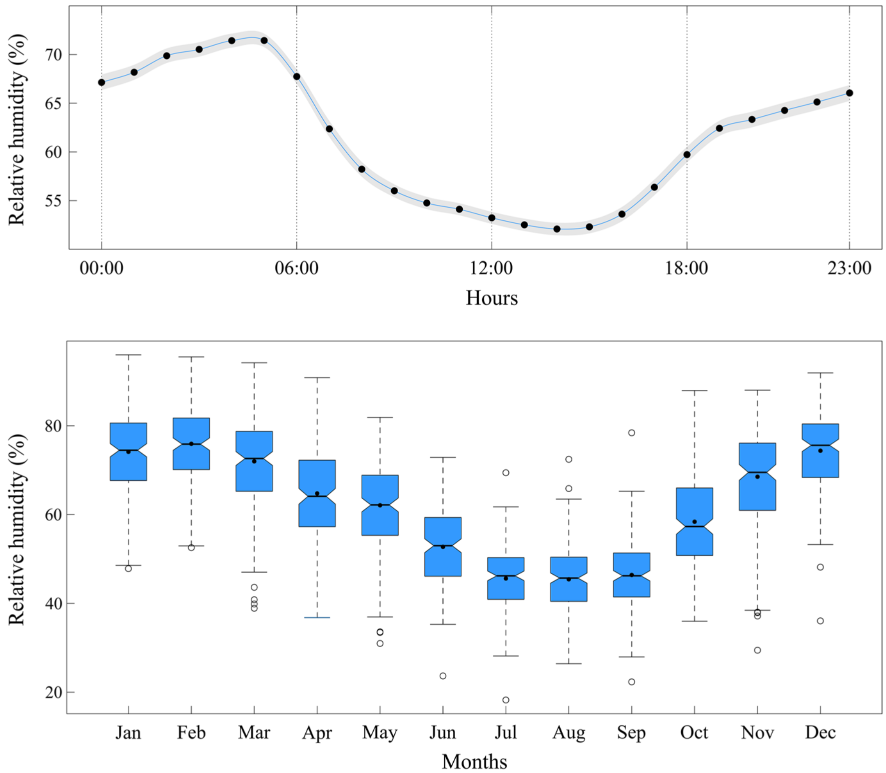


Fig. 5 Hourly average (**a**) and monthly notched boxplots (**b**) for humidity in Van City



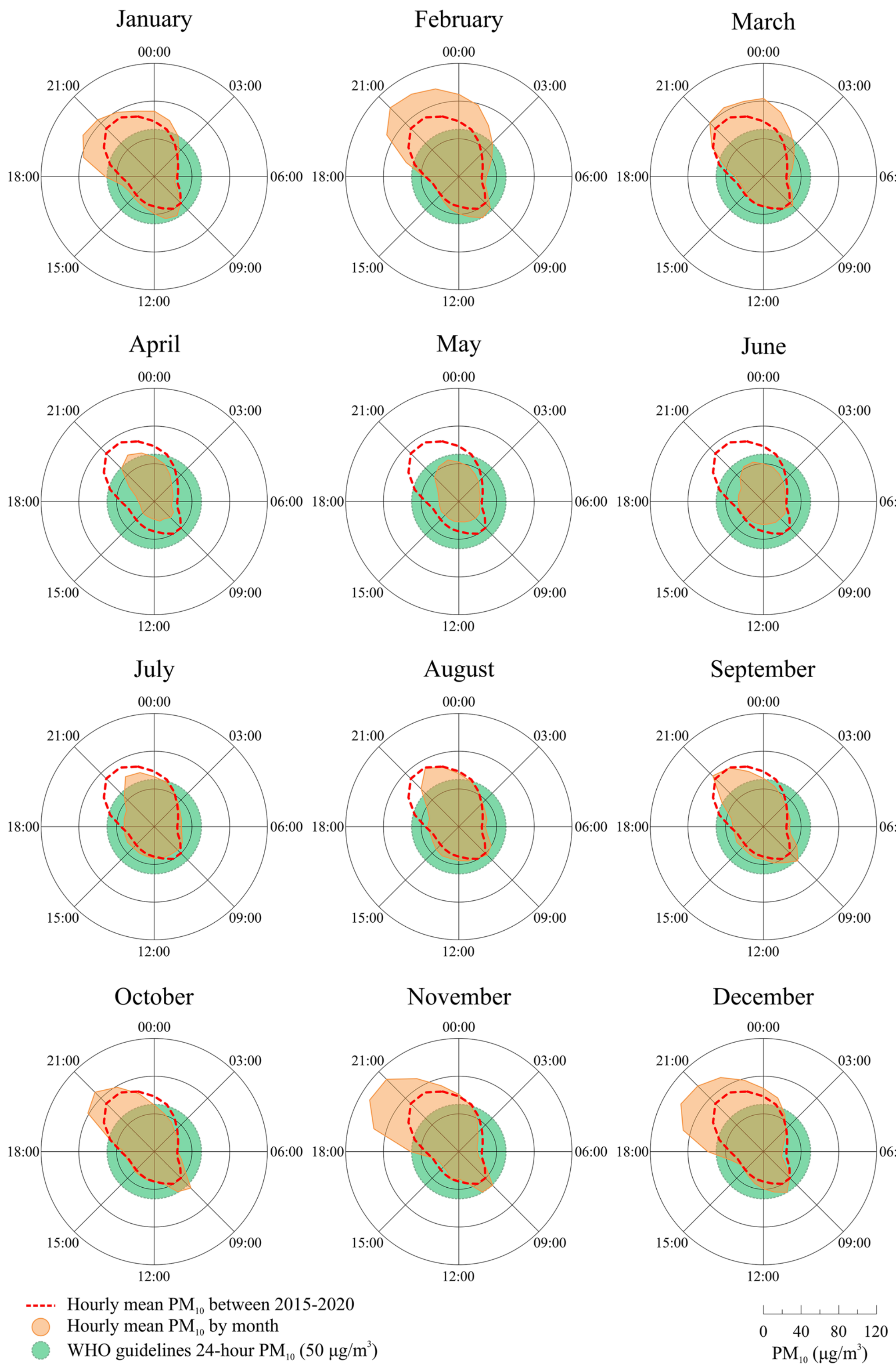


Fig. 6 Hourly PM_{10} radar graphs by month

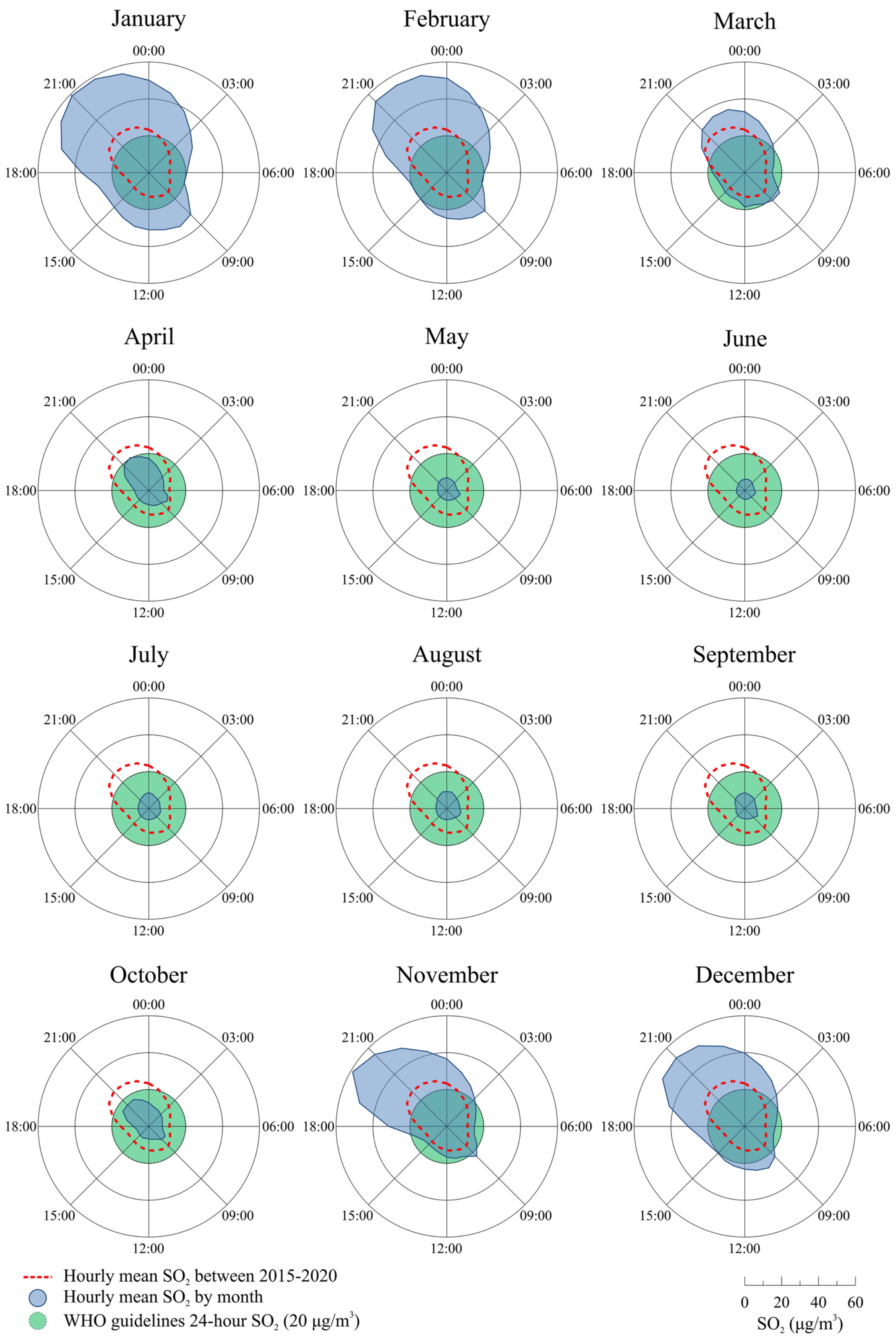


Fig. 7 Hourly SO_2 radar graphs by month

Fig. 8 Air quality calendar for Van city center between 2015 and 2020

model had a significance level (p) larger than 0.001 for all components, apart from P_{max}, T_{min} and W_s, so this model was rejected. For the SR5 model, the same situation was valid for P_{max}. In this situation, the valid stepwise regression model was SR4. The empirical equation for the SR4 model including the T_{min},

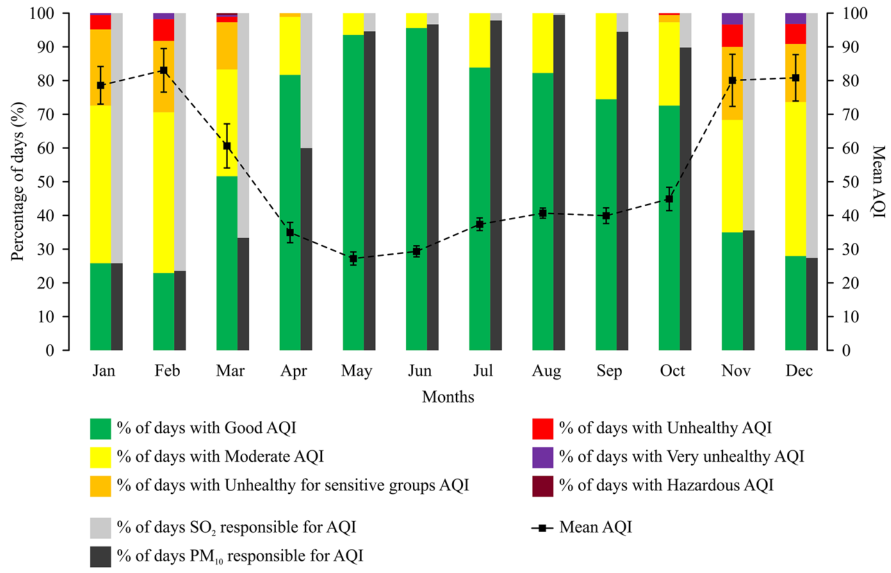


Fig. 9 Daily air quality index percent and average by month

Table 3 Annual distribution and mean values for air quality index

Years	I	II	III	IV	V	VI	AQI_{mean}
2015	241	99	23	2	0	0	46.58
2016	257	72	23	9	5	0	49.71
2017	232	105	24	3	1	0	48.17
2018	205	106	41	12	1	0	58.38
2019	226	98	30	5	6	0	54.66
2020	208	98	40	15	4	1	60.37

Table 4 Weekly distribution of air quality index values

Days of week	I	II	III	IV	V	VI	AQI_{mean}
Monday	199	78	26	4	6	0	54.01
Tuesday	192	87	21	9	3	1	55.19
Wednesday	188	89	29	5	2	0	52.61
Thursday	196	87	21	6	4	0	53.25
Friday	192	80	26	14	1	0	54.25
Saturday	197	78	34	4	0	0	51.75
Sunday	205	79	24	4	1	0	49.80

W_s, H_{avg}, and P_{max} meteorologic parameters is given below (Eq. 11).

$$AQI = 797.995 \times T_{min}^{-0.704} \times W_s^{-0.578} \times H_{avg}^{-0.262} \times P_{max}^{0.328} \tag{11}$$

Another approach used to determine predictors in multiple non-linear regression models is the best subsets. The regression coefficients and error amounts for MNLR models created with the best subsets model using different meteorological components are shown in Table 9. When the results are investigated, the performance for two models using four predictors was at a satisfactory level. The T_{min}, W_s, and P_{max} parameters were common to the two models and generally were the most frequently chosen variables in other models. The model created

Table 5 Descriptive statistics

	Mean	Std. dev	Minimum	Maximum	Range	Skewness	Kurtosis
AQI	52.97	38.04	6.35	387.20	380.85	2.03	6.21
H_{avg}	61.34	14.63	18.25	95.92	77.67	−0.04	−0.92
H_{max}	80.23	14.10	31.00	100.00	69.00	−0.55	−0.70
H_{min}	42.10	14.67	8.00	87.00	79.00	0.30	−0.42
P_{avg}	1018.20	4.94	998.20	1032.70	34.50	−0.11	0.10
P_{max}	1020.00	4.75	1000.10	1034.90	34.80	−0.03	−0.07
P_{min}	1016.40	5.27	996.00	1031.20	35.20	−0.23	0.31
T_{avg}	10.23	9.04	−12.90	29.96	42.86	−0.09	−1.13
T_{max}	15.04	9.61	−9.00	36.00	45.00	−0.01	−1.24
T_{min}	4.72	8.09	−20.00	23.00	43.00	−0.21	−0.82
W_s	2.74	1.10	0.42	9.75	9.33	1.66	4.22
W_x	0.22	0.68	−3.06	8.25	11.31	0.57	10.66
W_y	−0.05	0.55	−3.76	6.89	10.66	0.32	14.17

Fig. 10 Correlations of AQI and meteorological variables

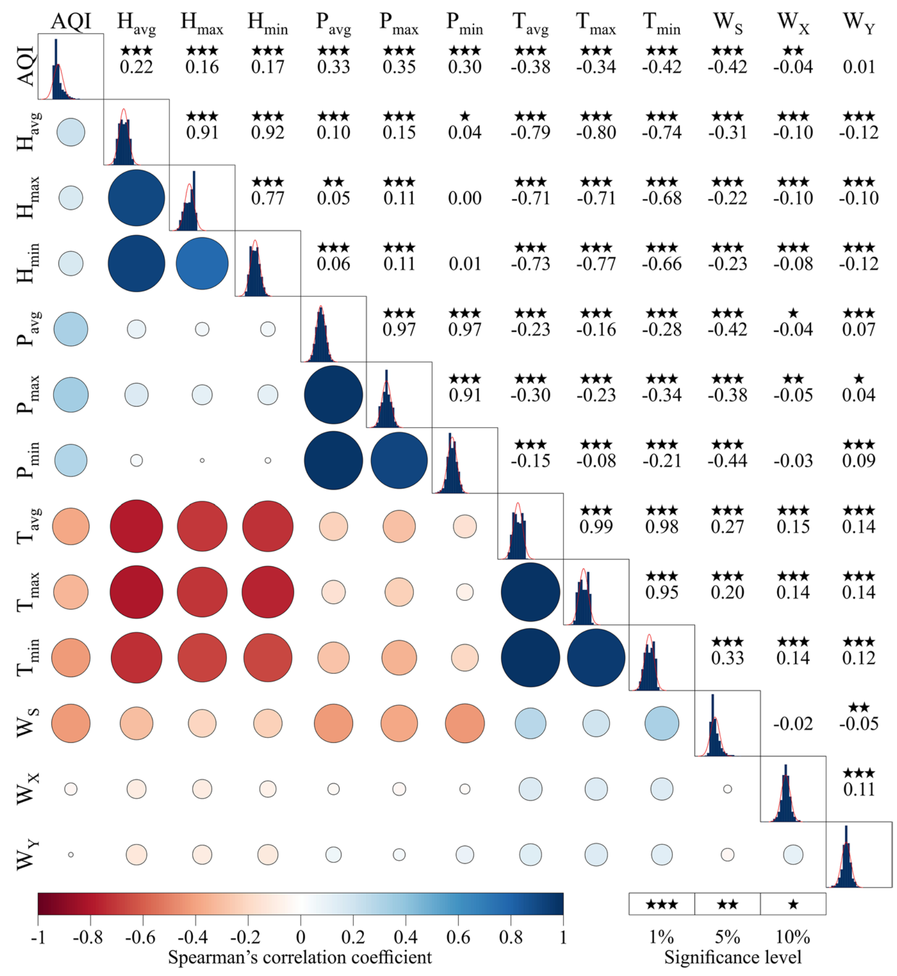


Table 6 ANOVA results for stepwise and enter MNLR models

Model	Predictors		Sum of squares	Df	Mean square	F	*p*-value
SR1	T_{min}	Regression	30.284	1	30.284	472.080	0.000
		Residual	140.489	2190	0.064		
		Total	170.773	2191			
SR2	$T_{min,}$ W_s	Regression	43.335	2	21.667	372.180	0.000
		Residual	127.438	2189	0.058		
		Total	170.773	2191			
SR3	T_{min}, W_s, H_{avg}	Regression	46.573	3	15.524	273.490	0.000
		Residual	124.200	2188	0.057		
		Total	170.773	2191			
SR4	T_{min}, W_s, H_{avg}, P_{max}	Regression	48.942	4	12.235	219.640	0.000
		Residual	121.831	2187	0.056		
		Total	170.773	2191			
SR5	T_{min}, W_s, H_{avg}, P_{max}, P_{avg}	Regression	49.246	5	9.849	177.170	0.000
		Residual	121.527	2186	0.056		
		Total	170.773	2191			
Enter	H_{avg}, H_{max}, H_{min}, P_{avg}, P_{max}, P_{min}, T_{avg}, T_{max}, T_{min}, W_s	Regression	49.833	10	4.983	89.867	0.000
		Residual	120.940	2181	0.055		
		Total	170.773	2191			

Table 7 Summary of MNLR models

Model	R	R^2	RMSE
SR1	0.421	0.177	0.25328
SR2	0.504	0.254	0.24128
SR3	0.522	0.273	0.23825
SR4	0.535	0.287	0.23602
SR5	0.537	0.288	0.23578
Enter	0.540	0.292	0.23548

with H_{avg} was better with a very close difference compared to the model created with H_{max}. Both the best subsets and stepwise regression methods confirmed the same meteorological parameters were model predictors. Additionally, the parameters chosen in both regression methods were compatible with the regression results.

According to findings obtained from correlation analysis and regression models, T_{min}, W_s, H_{avg}, and P_{max} are meteorological elements with a significant effect on air quality. With the effect of low temperatures experienced in the winter months in the northern hemisphere, it appears that particulate matter and sulfur dioxide emissions due to the common use of coal in rural areas with continental climate features, especially in undeveloped countries, are the main causes of air pollution (Liu et al., 2019; Z. Zhang et al., 2017). In Van city center, with large temperature differences hourly and seasonally, the winter season is much harder compared to other provinces in the eastern section of the country. For this reason, the minimum temperatures experienced during the day have more impact on air pollution compared to average and maximum temperatures. Wind speed has an important role in the permanence of pollutants in the air. On calm days without wind, pollution cannot be transported away from the area of origin and it becomes more permanent (Li et al., 2019). Here, air quality increases on days with more air movement. Humidity has a milder effect on air quality. According to meteorological theory, high air humidity creates a productive environment for the adherence of atmospheric particulate matter to water vapor, and aerosols cause fog by remaining suspended in the air. This situation causes the accumulation of air pollutants and a reduction in air quality (Y. Zhang, 2019). However, over longer periods, when humidity in the air increases to create effective rainfall, air pollutants reduce with precipitation and it has a cleaning effect on the air (Xu et al., 2017). Low air pressure leads to wind and rain (Gao et al.,

Table 8 Coefficients for MNLR models

Model	Variables	Unstandardized coefficients (β)	Std. error	Standardized coefficients (β)	t	*p*-value
SR1	(Constant)	440.555	0.046		57.047	0.000
	T_{min}	−0.723	0.033	−0.421	−21.727	0.000
SR2	(Constant)	584.790	0.045		61.615	0.000
	T_{min}	−0.587	0.033	−0.342	−17.813	0.000
	W_s	−0.622	0.042	−0.288	−14.972	0.000
SR3	(Constant)	3235.937	0.108		32.541	0.000
	T_{min}	−0.761	0.040	−0.443	−19.086	0.000
	W_s	−0.670	0.041	−0.310	−16.146	0.000
	H_{avg}	−0.295	0.039	−0.176	−7.553	0.000
SR4	(Constant)	797.995	0.142		20.472	0.000
	T_{min}	−0.704	0.040	−0.410	−17.402	0.000
	W_s	−0.578	0.043	−0.267	−13.299	0.000
	H_{avg}	−0.262	0.039	−0.156	−6.706	0.000
	P_{max}	0.328	0.050	0.129	6.521	0.000
SR5	(Constant)	816.582	0.142		20.554	0.000
	T_{min}	−0.686	0.041	−0.400	−16.673	0.000
	W_s	−0.616	0.046	−0.285	−13.287	0.000
	H_{avg}	−0.277	0.040	−0.165	−7.005	0.000
	P_{max}	0.755	0.189	0.297	3.989	0.000
	P_{avg}	−0.420	0.180	−0.177	−2.34	0.019
Enter	(Constant)	1020.939	0.152		19.834	0.000
	H_{avg}	−0.055	0.125	−0.033	−0.44	0.660
	H_{max}	−0.188	0.094	−0.101	−1.993	0.046
	H_{min}	−0.083	0.055	−0.064	−1.505	0.132
	P_{avg}	−1.043	0.420	−0.440	−2.485	0.013
	P_{max}	1.052	0.263	0.414	3.992	0.000
	P_{min}	0.363	0.204	0.168	1.782	0.075
	T_{avg}	0.306	0.230	0.215	1.329	0.184
	T_{max}	−0.278	0.144	−0.193	−1.924	0.054
	T_{min}	−0.762	0.178	−0.444	−4.285	0.000
	W_s	−0.606	0.049	−0.280	−12.466	0.000

2019). The increase in air pressure ensures a stagnant situation by suppressing the movements of the air (Li et al., 2019; Lin et al., 2019). For this reason, high air pressure suppresses the transport of pollutants and is expected to reduce air quality.

4 Conclusion

Air pollution is one of the most serious environmental problems in Van provincial center in the east of Turkey, especially during the winter months. In this study, variations in observed air pollutants and meteorological parameters on different time scales and the association with air quality in the city were investigated for the years 2015–2020. Urbanization, traffic, and the use of low-quality fuel cause air pollution just as much as the unproductive topography of the city and continental climate conditions. November to February is the period when the highest PM_{10} and SO_2 pollution are observed. Air pollution rapidly increases with falling temperatures in the evening hours. The air quality index on most days in the winter months reached levels accepted as unhealthy. In this period, it is recommended that groups at risk from the main determinant of air

Table 9 Results for best subsets MNLR models

Vars	H_{avg}	H_{max}	H_{min}	P_{avg}	P_{max}	P_{min}	T_{avg}	T_{max}	T_{min}	W_s	R^2	RMSE
1									•		0.176	0.25334
1							•				0.150	0.25732
2									•	•	0.253	0.24132
2							•			•	0.241	0.24328
3	•								•	•	0.272	0.23834
3					•				•	•	0.271	0.23840
4		•			•				•	•	0.286	0.23606
4	•				•				•	•	0.286	0.23608
5		•		•	•				•	•	0.288	0.23584
5	•			•	•				•	•	0.288	0.23585
6		•	•	•	•				•	•	0.289	0.23566
6	•	•		•	•				•	•	0.289	0.23573
7		•	•	•	•			•	•	•	0.290	0.23562
7		•	•	•	•	•			•	•	0.289	0.23563
8		•	•	•	•	•		•	•	•	0.290	0.23557
8		•	•	•	•		•	•	•	•	0.290	0.23562
9		•	•	•	•	•	•	•	•	•	0.291	0.23556
9	•	•	•	•	•	•		•	•	•	0.290	0.23561
10	•	•	•	•	•	•	•	•	•	•	0.291	0.23561

quality of SO_2 should not go outside unless necessary and the public in general should use masks. Additionally, significant findings were not encountered indicating that the air quality will improve in future years and the distributions were similar through the years. To increase urban air quality the use of natural gas, with lower pollutant emissions, should be encouraged more for indoor heating. Additionally, it is recommended that households regularly clean chimney and heating systems in the fall and use dust-free, high-calorie, and quality fuel. Additionally, the popularization of chimney gas purification methods will contribute to the development of urban air quality. Another important source of pollution in the city is the intense daytime traffic. To overcome this problem, the use of fossil fuel vehicles in the city center may be limited, regular exhaust emission measurements may be performed and most importantly, the use of public transport may be encouraged.

The results show that there is a statistically significant correlation between the air quality index and meteorological factors in Van city center. There was a strong inverse relationship identified between temperature and air quality. This situation is consistent with the high fuel consumption causing more SO_2 emissions in the winter period when low temperatures are observed. Another parameter with a strong inverse correlation was wind speed. High wind speed increases air quality due to diluting pollutants in the atmosphere. Additionally, high air pressure had a significant positive correlation with the air quality index. The humidity had a relatively weaker correlation. According to the stepwise regression and best subsets methods applied for predictive parameter selection in multiple non-linear regression models, the minimum temperature during the day, average wind speed, maximum air pressure and average humidity were the main meteorological determinants of air quality. Fuel consumption for domestic heating purposes and stable air conditions in cold, calm and dry weather may cause an increase in the amount and permanence of air pollution. Urban planners should include wind flows in addition to green space and population density when deciding on the placement of buildings and living areas. Residential and industrial buildings should be designed with plans and heights that do not prevent wind flow. Additionally, legislators and implementors are expected to adopt more effective strategies to improve air quality in city centers.

Like many cities in the eastern region of the country, Van has inadequate numbers (only 1) of air pollution monitoring stations. For this reason, the air quality experienced by people in low-income groups living on the periphery of the city is a topic of curiosity. Additionally, the atmospheric pollutants monitored at the station located right in the heart of the city are limited to coarse particulate matter amounts and sulfur dioxide. To be able to more comprehensively analyze spatial and temporal variations in air quality, the number of monitoring stations and parameters measured should be increased. There is a need for future studies to involve broader, more comprehensive research considering factors like building density, socioeconomic structure, aging, and life expectancy, in addition to including more air pollutants and meteorological factors to be able to better understand air pollution in urban centers.

Author Contribution Erdinc Aladag: conceptualization, visualization, investigation, editing, validation, writing—original draft.

Data Availability Not applicable.

Declarations

Ethics Approval and Consent to Participate Not applicable.

Consent for Publication Not applicable.

Competing Interests The authors declare no competing interests.

References

Abigail, M. E. A., Samuel, S. M., & Chidambaram, R. (2016). Application of rice husk nanosorbents containing 2,4-dichlorophenoxyacetic acid herbicide to control weeds and reduce leaching from soil. *Journal of the Taiwan Institute of Chemical Engineers, 63*, 318–326. https://doi.org/10.1016/j.jtice.2016.03.024

Aksoy, S. A., Kiziltan, A., Kiziltan, M., Köksal, M. A., Öztürk, F., Tekeli, ŞE., Aslanoğlu, S. Y., Im, U., Duran, N., & Ünal, A. (2021). Mortality and morbidity costs of road traffic-based air pollution in Turkey. *Journal of Transport & Health, 22*, 101142.

Aladağ, E. (2021). Forecasting of particulate matter with a hybrid ARIMA model based on wavelet transformation and seasonal adjustment. *Urban Climate, 39*, 100930. https://doi.org/10.1016/j.uclim.2021.100930

AQI. (2022). Top 10 most polluted cities in the world (2022 Data). https://www.aqi.in/blog/top10-most-polluted-cities-in-the-world/. Accessed 5 March 2023.

Arain, M., Blair, R., Finkelstein, N., Brook, J., Sahsuvaroglu, T., Beckerman, B., Zhang, L., & Jerrett, M. (2007). The use of wind fields in a land use regression model to predict air pollution concentrations for health exposure studies. *Atmospheric Environment, 41*(16), 3453–3464.

Araki, S., Shima, M., & Yamamoto, K. (2018). Spatiotemporal land use random forest model for estimating metropolitan NO2 exposure in Japan. *Science of the Total Environment, 634*, 1269–1277.

Babatola, S. S. (2018). Global burden of diseases attributable to air pollution. *Journal of Public Health in Africa, 9*(3), 813.

Bai, Y., Li, Y., Wang, X., Xie, J., & Li, C. (2016). Air pollutants concentrations forecasting using back propagation neural network based on wavelet decomposition with meteorological conditions. *Atmospheric Pollution Research, 7*(3), 557–566.

Barrington-Leigh, C., Baumgartner, J., Carter, E., Robinson, B. E., Tao, S., & Zhang, Y. (2019). An evaluation of air quality, home heating and well-being under Beijing's programme to eliminate household coal use. *Nature Energy, 4*(5), 416–423.

Brønnum-Hansen, H., Bender, A. M., Andersen, Z. J., Sørensen, J., Bønløkke, J. H., Boshuizen, H., Becker, T., Diderichsen, F., & Loft, S. (2018). Assessment of impact of traffic-related air pollution on morbidity and mortality in Copenhagen Municipality and the health gain of reduced exposure. *Environment International, 121*, 973–980.

Cakir, S., & Sita, M. (2020). Evaluating the performance of ANN in predicting the concentrations of ambient air pollutants in Nicosia. *Atmospheric Pollution Research, 11*(12), 2327–2334.

Çay, Y., & Yildiz, A. (2011). Fosil kaynaklı yakıtların neden olduğu hava kirliliğinin doğal gaz kullanımı ile değişimi, Van ili örneği. *Makine Teknolojileri Elektronik Dergisi (elektronik), 8*(4), 45–52.

Cuhadaroglu, B., & Demirci, E. (1997). Influence of some meteorological factors on air pollution in Trabzon city. *Energy and Buildings, 25*(3), 179–184.

Disli, E., Ozturk, D., & Aladağ, E. (2021). Utilizing mining dam bottom sludge as a novel adsorbent for AuO removal from wastewaters: Batch and column studies. *Journal of Molecular Liquids, 338*, 116644.

Fan, J., Wu, L., Zhang, F., Cai, H., Wang, X., Lu, X., & Xiang, Y. (2018). Evaluating the effect of air pollution on global and diffuse solar radiation prediction using support vector machine modeling based on sunshine duration and air temperature. *Renewable and Sustainable Energy Reviews, 94*, 732–747.

Fan, M., He, G., & Zhou, M. (2020). The winter choke: Coal-fired heating, air pollution, and mortality in China. *Journal of Health Economics, 71*, 102316.

Feng, X., Li, Q., Zhu, Y., Hou, J., Jin, L., & Wang, J. (2015). Artificial neural networks forecasting of PM2. 5 pollution using air mass trajectory based geographic model and wavelet transformation. *Atmospheric Environment, 107*, 118–128.

Fuller, R., Landrigan, P. J., Balakrishnan, K., Bathan, G., Bose-O'Reilly, S., Brauer, M., Caravanos, J., Chiles, T., Cohen, A., & Corra, L. (2022). Pollution and health:

A progress update. *The Lancet Planetary Health*, 6(6), 535–547.
Gao, Y., Wang, Z., Liu, C., & Peng, Z.-R. (2019). Assessing neighborhood air pollution exposure and its relationship with the urban form. *Building and Environment, 155*, 15–24.
Hajat, A., Hsia, C., & O'Neill, M. S. (2015). Socioeconomic disparities and air pollution exposure: A global review. *Current Environmental Health Reports, 2*(4), 440–450.
He, J., Gong, S., Yu, Y., Yu, L., Wu, L., Mao, H., Song, C., Zhao, S., Liu, H., & Li, X. (2017). Air pollution characteristics and their relation to meteorological conditions during 2014–2015 in major Chinese cities. *Environmental Pollution, 223*, 484–496.
Ilten, N., & Selici, A. T. (2008). Investigating the impacts of some meteorological parameters on air pollution in Balikesir, Turkey. *Environmental Monitoring and Assessment, 140*, 267–277.
Kayes, I., Shahriar, S. A., Hasan, K., Akhter, M., Kabir, M., & Salam, M. (2019). The relationships between meteorological parameters and air pollutants in an urban environment. *Global Journal of Environmental Science and Management, 5*(3), 265–278.
Kerimray, A., Rojas-Solórzano, L., Torkmahalleh, M. A., Hopke, P. K., & Gallachóir, B. P. Ó. (2017). Coal use for residential heating: Patterns, health implications and lessons learned. *Energy for Sustainable Development, 40*, 19–30.
Khalaf, S. (2019). Doğu Anadolu Bölgesi'nde nüfus gelişimi. *Avrasya Sosyal Ve Ekonomi Araştırmaları Dergisi, 6*(2), 241–262.
Kong, L., & Tian, G. (2020). Assessment of the spatio-temporal pattern of PM 2.5 and its driving factors using a land use regression model in Beijing, China. *Environmental Monitoring and Assessment, 192*, 1–19.
Li, R., Wang, Z., Cui, L., Fu, H., Zhang, L., Kong, L., Chen, W., & Chen, J. (2019). Air pollution characteristics in China during 2015–2016: Spatiotemporal variations and key meteorological factors. *Science of the Total Environment, 648*, 902–915.
Lin, X., Chen, J., Lu, T., Huang, D., & Zhang, J. (2019). Air pollution characteristics and meteorological correlates in Lin'an, Hangzhou. *China. Aerosol and Air Quality Research, 19*(12), 2770–2780.
Liu, G., Xin, J., Wang, X., Si, R., Ma, Y., Wen, T., Zhao, L., Zhao, D., Wang, Y., & Gao, W. (2019). Impact of the coal banning zone on visibility in the Beijing-Tianjin-Hebei region. *Science of the Total Environment, 692*, 402–410.
Mazzeo, A., Huneeus, N., Ordoñez, C., Orfanoz-Cheuquelaf, A., Menut, L., Mailler, S., Valari, M., van der Gon, H. D., Gallardo, L., & Muñoz, R. (2018). Impact of residential combustion and transport emissions on air pollution in Santiago during winter. *Atmospheric Environment, 190*, 195–208.
Meng, X., Hand, J. L., Schichtel, B. A., & Liu, Y. (2018). Space-time trends of PM2. 5 constituents in the conterminous United States estimated by a machine learning approach, 2005–2015. *Environment International, 121*, 1137–1147.
Menteşe, S., & Tağıl, Ş. (2012). Bilecik'te iklim elemanlarının hava kirliliği üzerine etkisi. *Balıkesir Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 15*(28), 3–16.
Öztürk, D., & Bayram, T. (2019). Van İli Kent Merkezinde Hava Kirliliği. *Bitlis Eren Üniversitesi Fen Bilimleri Dergisi, 8*(3), 1142–1153. https://doi.org/10.17798/bitlisfen.529099
Pandey, A., Brauer, M., Cropper, M. L., Balakrishnan, K., Mathur, P., Dey, S., Turkgulu, B., Kumar, G. A., Khare, M., & Beig, G. (2021). Health and economic impact of air pollution in the states of India: The global burden of disease study 2019. *The Lancet Planetary Health, 5*(1), e25–e38.
Qi, X., Mei, G., Cuomo, S., Liu, C., & Xu, N. (2021). Data analysis and mining of the correlations between meteorological conditions and air quality: A case study in Beijing. *Internet of Things, 14*, 100127.
Raga, G., & Le Moyne, L. (1996). On the nature of air pollution dynamics in Mexico City—I. *Nonlinear Analysis Atmospheric Environment, 30*(23), 3987–3993.
Rahman, M. M., Rana, R., & Khanam, R. (2022). Determinants of life expectancy in most polluted countries: Exploring the effect of environmental degradation. *PLoS ONE, 17*(1), e0262802.
Ramsey, N. R., Klein, P. M., & Moore, B., III. (2014). The impact of meteorological parameters on urban air quality. *Atmospheric Environment, 86*, 58–67.
Ren, X., Mi, Z., & Georgopoulos, P. G. (2020). Comparison of machine learning and land use regression for fine scale spatiotemporal estimation of ambient air pollution: Modeling ozone concentrations across the contiguous United States. *Environment International, 142*, 105827.
Right to Clean Air Platform. (2022). Dark report 2021: Air pollution and health effects. https://www.temizhavahakki.com/kara-rapor/. Accessed 22 July 2022.
Roy, R., & Braathen, N. A. (2017). *The rising cost of ambient air pollution thus far in the 21st century: Results from the BRIICS and the OECD countries*. OECD Environment Working Papers, No. 124. OECD Publishing.
Saithanu, K., & Mekparyup, J. (2014). Using multiple linear regression to predict PM10 concentration in Chonburi, Thailand. *Global Journal of Pure and Applied Mathematics, 10*(6), 835–839.
Samuel, M. S., Subramaniyan, V., Bhattacharya, J., Parthiban, C., Chand, S., & Singh, N. P. (2018). A GO-CS@ MOF [Zn (BDC)(DMF)] material for the adsorption of chromium (VI) ions from aqueous solution. *Composites Part b: Engineering, 152*, 116–125.
Sarkodie, S. A., Strezov, V., Jiang, Y., & Evans, T. (2019). Proximate determinants of particulate matter (PM2. 5) emission, mortality and life expectancy in Europe, Central Asia, Australia, Canada and the US. *Science of the Total Environment, 683*, 489–497.
Srivastava, C., Singh, S., & Singh, A. P. (2018). Estimation of air pollution in Delhi using machine learning techniques. In *2018 International Conference on Computing, Power and Communication Technologies (GUCON)* (pp. 304–309).

Tran, P. T., Adam, M. G., Tham, K. W., Schiavon, S., Pantelic, J., Linden, P. F., Sofianopoulou, E., Sekhar, S. C., Cheong, D. K. W., & Balasubramanian, R. (2021). Assessment and mitigation of personal exposure to particulate air pollution in cities: An exploratory study. *Sustainable Cities and Society, 72*, 103052.

Turalıoğlu, F. S., Nuhoğlu, A., & Bayraktar, H. (2005). Impacts of some meteorological parameters on SO2 and TSP concentrations in Erzurum, Turkey. *Chemosphere, 59*(11), 1633–1642.

Turkish Statistical Institute. (2020). *Provincial gross domestic product in Turkey*. https://data.tuik.gov.tr/Bulten/Index?p=Il-Bazinda-Gayrisafi-Yurt-Ici-Hasila-2020-37188. Accessed 24 July 2022.

U.S. Environmental Protection Agency. (2016). *Technical assistance document for the reporting of daily air quality—the air quality index (AQI) (EPA-454/B-16-002)*. Publication No.

U.S. Environmental Protection Agency. (2022). *Air quality index (AQI) basics*. https://airnow.gov/index.cfm?action=aqibasics.aqi. Accessed 30 July 2022.

United Nations. (2018). *Revision of world urbanization prospects. New York: United Nations Department of Economic and Social Affairs*. https://www.un.org/development/desa/publications/2018-revision-of-world-urbanization-prospects.html. Accessed 27 July 2022.

Valverde, V., Pay, M. T., & Baldasano, J. M. (2015). Circulation-type classification derived on a climatic basis to study air quality dynamics over the Iberian Peninsula. *International Journal of Climatology, 35*(10), 2877–2897.

Weichenthal, S., Van Ryswyk, K., Goldstein, A., Bagg, S., Shekkarizfard, M., & Hatzopoulou, M. (2016). A land use regression model for ambient ultrafine particles in Montreal, Canada: A comparison of linear regression and a machine learning approach. *Environmental Research, 146*, 65–72.

Wen, W., Ma, X., Tang, Y., Wei, P., Wang, J., & Guo, C. (2020). The impacts of meteorology on source contributions of air pollution in winter in Beijing, 2015–2017 changes. *Atmospheric Pollution Research, 11*(11), 1953–1962.

WHO. (2022). *Air pollution*. https://www.who.int/health-topics/air-pollution. Accessed 22 July 2022.

World Bank. (2016). *The cost of air pollution: strengthening the economic case for action*.

Xu, L., Zhou, J., Guo, Y., Wu, T., Chen, T., Zhong, Q., Yuan, D., Chen, P., & Ou, C. (2017). Spatiotemporal pattern of air quality index and its associated factors in 31 Chinese provincial capital cities. *Air Quality, Atmosphere & Health, 10*(5), 601–609.

Yakın, A., & Behçet, R. (2019). Van ili trafik kaynaklı hava kirleticilerinin emisyon envanteri. *Journal of the Institute of Science and Technology, 9*(3), 1567–1573.

Yang, H., Chen, W., & Liang, Z. (2017). Impact of land use on PM2. 5 pollution in a representative city of middle China. *International Journal of Environmental Research and Public Health, 14*(5), 462.

Yasar, A., Bilgili, M., & Simsek, E. (2012). Water demand forecasting based on stepwise multiple nonlinear regression analysis. *Arabian Journal for Science and Engineering, 37*, 2333–2341.

Yilmaz, S., Sezen, I., & Sari, E. N. (2021). The relationships between ecological urbanization, green areas, and air pollution in Erzurum/Turkey. *Environmental and Ecological Statistics, 28*(4), 733–759.

Zeng, S., Ma, J., Yang, Y., Zhang, S., Liu, G.-J., & Chen, F. (2019). Spatial assessment of farmland soil pollution and its potential human health risks in China. *Science of the Total Environment, 687*, 642–653.

Zhan, D., Kwan, M.-P., Zhang, W., Yu, X., Meng, B., & Liu, Q. (2018). The driving factors of air quality index in China. *Journal of Cleaner Production, 197*, 1342–1351.

Zhang, Y. (2019). Dynamic effect analysis of meteorological conditions on air pollution: A case study from Beijing. *Science of the Total Environment, 684*, 178–185.

Zhang, H., & Zhao, Y. (2019). Land use regression for spatial distribution of urban particulate matter (PM 10) and sulfur dioxide (SO 2) in a heavily polluted city in Northeast China. *Environmental Monitoring and Assessment, 191*, 1–14.

Zhang, H., Wang, Z., & Zhang, W. (2016). Exploring spatiotemporal patterns of PM2. 5 in China based on ground-level observations for 190 cities. *Environmental Pollution, 216*, 559–567.

Zhang, Z., Wang, W., Cheng, M., Liu, S., Xu, J., He, Y., & Meng, F. (2017). The contribution of residential coal combustion to PM2. 5 pollution over China's Beijing-Tianjin-Hebei region in winter. *Atmospheric Environment, 159*, 147–161.

Zhang, L., Tian, X., Zhao, Y., Liu, L., Li, Z., Tao, L., Wang, X., Guo, X., & Luo, Y. (2021). Application of nonlinear land use regression models for ambient air pollutants and air quality index. *Atmospheric Pollution Research, 12*(10), 101186.

Zhou, W., Yu, W., & Fu, B. (2020). Urbanisation and its environmental effects in six emerging mega-city regions, China. In *Mega-City Region Development in China* 175–203. Routledge.