published by

EQA - International Journal of Environmental Quality
ISSN 2281-4485 - Vol. 72 (2026): 125 - 135
Journal homepage: https://eqa.unibo.it/

The effect of air pollution on respiratory diseases in the era of global warming: research from Türkiye

Şenay Çetin Doğruparmak[1], Kazım Onur Demirarslan[2*], Gülşen Aydın Keskin[3], Kadriye Ergün[3]

[1] Kocaeli University Faculty of Engineering, Department of Environmental Engineering, Kocaeli, Türkiye
[2] Artvin Coruh University Faculty of Engineering, Department of Environmental Engineering, Artvin, Türkiye
[3] Balikesir University, Faculty of Engineering, Department of Industrial Engineering, Balikesir, Türkiye

* Corresponding author E.mail: onurdemirarslan@artvin.edu.tr

Article info
Received 24/11/2025; received in revised form 19/1/2026; accepted 5/2/2026
DOI: 10.60923/issn.2281-4485/23350

Abstract
Air pollution and climate change are interconnected, posing significant health risks. This study assesses air pollution levels in Türkiye, their link to respiratory disorders, and regional variations. Findings show that Istanbul, Türkiye's most populous city, has the highest patient count (mean ± SD: 387 ± 302). Positive correlations were found between air pollutants and patient numbers, except for ozone; sulfur dioxide showed the strongest correlation ($r = 0.7$). Multivariate regression indicated adjusted $R^2 > 0.5$ in four regions. K-means++ clustering categorized regions by population density, with the largest cluster covering 28.3% of the dataset. These results underscore the impact of air pollution on respiratory health, highlighting the need for targeted interventions to reduce environmental risks and disease prevalence

Keywords: *Global Warming, Air Pollution, Respiratory Disease, Statistical Analysis, Clustering, Epidemiological Study.*

Introduction

Global warming, air pollution, and health are interrelated challenges. Climate change, characterized by rising global temperatures, exacerbates air pollution through increased heatwaves, storms, and wildfires, elevating pollutant levels (Tran et al., 2023). Higher temperatures also enhance emissions of pollutants like ground-level ozone, while meteorological shifts influence pollutant formation, transport, and dispersion, posing severe environmental and health risks (HEAL, 2021). Additionally, declining air quality and increased pollen concentrations further impact respiratory health. Without effective mitigation strategies, these interconnected issues will continue to amplify global health risks, contributing to the disease burden, particularly under projected temperature increases of 1.5–4.8°C by the end of the century (Tran et al., 2023). The adverse effects of air pollution on health are substantial. According to the World Health Organization (WHO, 2021), air pollution is responsible for approximately 7 million deaths annually, with 4.2 million linked to ambient air pollution and 3.8 million to indoor air pollution. Global studies attribute 19% of cardiovascular disease deaths to poor air quality (Collaborators, 2016). By 2050, the Organization for Economic Cooperation and Development (OECD, 2012) predicts ambient air pollution will be the leading environmental cause of death. Even in regions with declining early death rates, such as Europe, air pollution continues to cause nearly 400,000 premature deaths annually (EEA, 2021). Notably, an OpenAQ survey shows that half of the world's nations fail to meet standards for outdoor air quality (RCAP, 2020). Prolonged air pollution exposure increases susceptibility to viral infections and chronic diseases (RCAP, 2020). Pollutants impair lung function, raising the risk of respiratory infections, asthma, and COPD (Domingo and Rovira, 2020; Zhang et al., 2020). PM10 is linked to Obstructive Sleep Apnea Syndrome (Yıldız Gülhan et al., 2020), while MS prevalence is higher in industrial zones (Türk Börü et al., 2020). PM2.5 exposure has caused over 44,000 early deaths in Türkiye

DOI: 10.60923/issn.2281-4485/23350

(Pala et al., 2021), with air pollution-related health costs exceeding $9 million annually in cities like Niğde (Kara et al., 2021). Recent developments, such as the Covid-19 pandemic, have highlighted the interplay between environmental factors and health outcomes. While measures against the pandemic temporarily reduced air pollution, elevated pollution levels have been linked to increased Covid-19 cases and deaths (RCAP, 2020). Numerous studies confirm that exposure to pollutants worsens respiratory diseases and amplifies risks of hospitalization and mortality (Mele and Magazzino, 2021; Zhang et al., 2020; Brandt et al., 2020; Wu et al., 2020; Travaglio et al., 2021; Angelis et al., 2021). These findings underscore the urgency of addressing air quality to safeguard public health. Türkiye combats air pollution through regulations, international agreements, and civil society initiatives. However, industrialization and urbanization continue to drive pollution, increasing air pollution-related deaths (RCAP, 2020). Identifying problems and solutions is crucial. This study assesses the regional distribution of air pollution, its link to respiratory diseases, and regional variations. Using SPSS, QGIS, and machine learning algorithms, it offers a comprehensive analysis of pollution dynamics and health impacts. Unlike previous studies in Türkiye focusing on specific pollutants or stations, this study analyzes comprehensive air pollution data from 355 stations across all 81 provinces. The findings aim to fill a gap in the literature and highlight the need for effective strategies to reduce air pollution and its health impacts.

Material method

This study analyzed air pollution data (PM10, PM2.5, SO_2, NO_2, NO_X, CO, and O_3) from 355 stations across 81 regions in Türkiye and respiratory disease data from the Ministry of Health's Covid-19 Situation Reports. Air quality data was downloaded from the air monitoring site (www.havaizleme.gov.tr) and categorized into 12 regions (RTMEU, 2020). In determining the regions, Covid-19 Status Reports published by the Ministry of Health were used. The reports presented Covid-19 Patient Numbers broken down by regions in accordance with the "Statistical Regional Units Türkiye Classification-1 (Türkiye SRE-1)", based on the following regions: Aegean (1st region), Western Marmara (2nd region), Istanbul (3rd region), Eastern Marmara (4th region), Western Anatolia (5th region), Mediterranean (6th region), Central Anatolia (7th region), Western Black Sea (8th region), Eastern Black Sea (9th region), North-Eastern Anatolia (10th region), Central-Eastern Anatolia (11th region), South-Eastern Anatolia (12 th region) (Fig. 1). In this study, the analysis was made from June 29th, 2020 to November 23rd, 2020. The analysis showed that some stations had long measurement gaps. Data sets with at least 75% completeness were included, while those missing measurements for an entire month were excluded. Patient data were obtained from the Ministry of Health's Covid-19 Information Platform via Regular Situation Reports, which were publicly available for a limited time (RTMH, 2020). Figure 2 presents daily patient numbers from these reports. The study used the KMO (Kaiser-Meyer-Olkin) and Bartlett's test to assess data suitability and the One-Sample Kolmogorov-Smirnov (K-S) test to check for normal distribution. KMO values range from 0 to 1, with ≥0.5 and $p < 0.05$ indicating data suitability for analysis. A very small p- value (e.g., $p = 0.000$) in Bartlett's test confirms significant variable

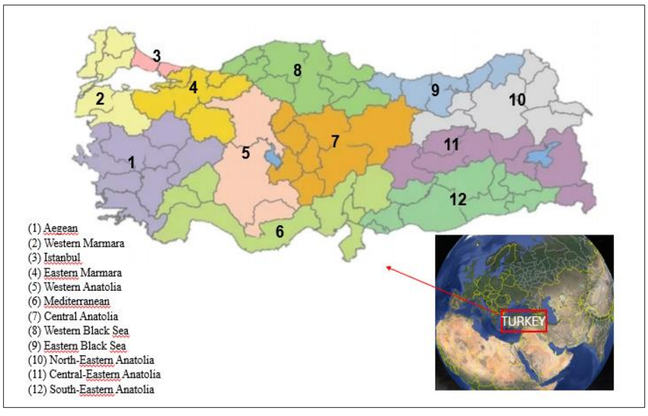

Figure 1. *Regions of patient numbers by NUTS-1, Türkiye (RTMH, 2020)*

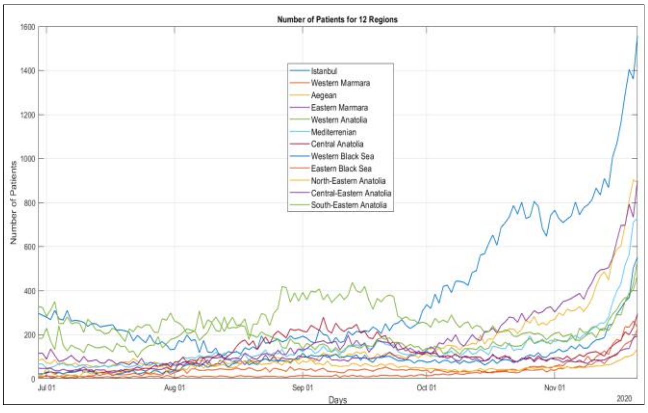

Figure 2. *Number of daily patients between 29.06.2020 and 21.11.2020 (RTMH, 2020)*

DOI: 10.60923/issn.2281-4485/23350

relationships (Napitupulu et al., 2017). After these tests, descriptive statistics were conducted for data interpret-tation. QGIS software was used to visualize the geographic distribution of air pollution and patient numbers. Correlation analysis examined their relationship across regions, while multiple linear regression (MLR) models estimated the impact of air pollutants on patient numbers. MLR, a statistical method, uses multiple explanatory variables to predict a response variable (Peter et al., 2019; Özbay et al., 2011). Clustering analysis classified locations into subgroups based on air pollutant type and concentration. This widely used data mining technique identifies similar data structures. The k-means++ method, preferred for large datasets, is an unsupervised learning approach used in data science and machine learning (Ikotun et al., 2023). Although the pandemic has officially ended, Covid-19 persists in various forms. Given the shorter transmission time of new variants, patient numbers and pollutant data were offset by two days for analysis. Assessments were conducted over 146 days. Due to the unavailability of pollutant parameter values for PM2.5, NO_2, NO_X, CO, and O_3 in the Central Eastern Anatolia region and SO_2, NO_2, NO_X, CO, and O_3 in the Southeastern Anatolia region within the given date range, the clustering analysis was applied to a total of 10 regions. The dataset comprises 146 daily emission characteristics for seven pollutants across ten regions and a single dependent variable representing the number of patients. During the clustering process, two alternatives were evaluated: one in which the number of patients was included as an independent variable, and another where it was excluded entirely. Based on the Silhouette coefficients, the optimal number of clusters for both alternatives was determined to be two. However, to align the analysis with the regions identified by the Ministry of Health during the early stages of the Covid-19 outbreak, a cluster count of k=10 was chosen instead of the optimal number of clusters. This decision was based on the assumption that factors such as air temperature and wind, in addition to the selected parameters, could influence disease prevalence. The clustering processes were performed using the Orange Data Mining Program.

Results

Air pollutant concentrations and patient numbers

The KMO-Bartlett's test and the One-Sample Kolmogorov-Smirnov (K-S) test were conducted on the patient dataset and separately on the 12-region emissions data group. Due to the unavailability of pollutant parameter measurements for PM2.5, NO_2, NO_X, CO, and O_3 in the Central-Eastern Anatolia region, and for SO_2, NO_2, NO_X, CO, and O_3 in the Southeastern Anatolia region within the specified dates, these pollutants were not evaluated for these regions. The dataset was deemed suitable for analysis across 10 regions, as the KMO values ranged from 0.531 to 0.850, exceeding the threshold of 0.5 in all regions except for the Aegean and North-Eastern Anatolia regions, at a significance level of p=0.000. It was determined that there was a significant relationship between the variables because the p value obtained for the Bartlett test was very small (p=0.000). The sample data did not follow a normal distribution because The test statistic from the One-Sample Kolmogorov-Smirnov (K-S) test and the corresponding significance values (p-value) were also determined less than 0.05. Descriptive statistics were conducted on concentrations of air pollutants (PM10, PM2.5, SO_2, NO_2, NO_X, CO, and O_3) at all monitoring stations. The results, along with the number of patients, are presented in Table 1. As shown in the table, Istanbul had the highest maximum, mean, and standard deviation values for the number of patients, with a mean ± standard deviation of 387 ±302. According to 2020 statistics, Istanbul had a population of 15,462,452, significantly larger than other regions. The population density in Istanbul was 2910 people/km², compared to other regions: 1851 in the Mediterranean, 1682 in Eastern Marmara, 1077 in Southeastern Anatolia, 951 in the Aegean, 730 in Western Black Sea, 501 in Eastern Black Sea, 436 in Western Marmara, 391 in Central Anatolia, 358 in Central-Eastern Anatolia, 307 in Western Anatolia, and 220 in North-Eastern Anatolia. Regarding pollution levels, the table indicates that NO_X, NO_2, and CO emissions were particularly high in Istanbul. These elevated levels are likely attributable to the widespread use of natural gas for heating and high traffic density. However, other pollutants, such as PM10 and PM2.5, were not as elevated in Istanbul compared to other regions. The highest standard deviations for PM10 and PM2.5 were observed in Southeastern Anatolia. While the highest standard deviation for SO_2 was in Central Anatolia, it was also notably high in Southeastern Anatolia, likely due to the extensive use of fossil fuels for home heating. The highest standard deviations for O_3 were recorded in Central Anatolia, which can be attributed to ozone's tendency to accumulate in rural areas. Within the scope of the study, mapping was performed using Quantum GIS (QGIS) geographic information

DOI: 10.60923/issn.2281-4485/23350

Table 1. *Descriptive statistics for each region*

Region/Pollutant	PM10	PM2,5	SO_2	NO_2	NO_X	CO	O_3	Patient Count	PM10	PM2,5	SO_2	NO_2	NO_X	CO	O_3	Patient Count
	Mean								Std. Dev							
Istanbul	28	12	4	32	50	629	35	387	17	8	1	14	44	183	11	302
Western Marmara	32	10	5	11	19	620	66	31	13	6	2	5	12	183	18	47
Aegean	41	12	8	16	21	387	20	160	12	6	1	4	6	173	7	157
Eastern Marmara	33	14	5	22	35	549	58	175	15	7	2	9	23	207	18	162
Western Anatolia	38	13	5	38	53	428	40	248	15	7	2	15	39	193	10	87
Mediterrenian	34	18	5	28	35	474	62	135	9	7	2	10	17	170	16	103
Central Anatolia	43	13	5	30	40	372	59	117	20	7	4	12	21	179	19	66
Western Black Sea	39	15	7	23	33	485	22	90	14	7	2	7	17	178	8	78
Eastern Black Sea	34	15	5	21	30	485	48	40	11	7	2	7	12	92	11	30
North-Eastern Anatolia	40	21	4	25	31	391	60	52	18	13	2	8	16	211	18	21
Central-Eastern Anatolia	44	29	8					94	14	9	4					42
South-Eastern Anatolia	51	34	9					202	26	16	3					65
	Min								Max							
Istanbul	12	5	3	15	11	420	5	99	97	54	7	89	212	1516	61	1557
Western Marmara	17	4	3	5	8	393	21	4	84	41	20	26	64	1273	90	262
Aegean	21	5	5	5	10	148	3	45	92	44	13	31	44	773	40	902
Eastern Marmara	16	5	3	10	18	315	16	55	94	45	12	52	117	1661	83	899
Western Anatolia	15	6	2	14	17	253	20	96	92	43	12	79	186	1125	68	533
Mediterrenian	13	11	2	5	8	304	22	48	61	53	16	59	111	1270	83	728
Central Anatolia	20	6	2	12	16	176	21	22	107	43	19	54	96	1114	89	294
Western Black Sea	21	8	4	11	15	221	9	14	92	44	15	46	83	1046	41	551
Eastern Black Sea	13	8	3	12	15	369	17	6	76	39	11	46	74	933	70	226
North-Eastern Anatolia	15	7	2	10	12	289	23	9	106	61	12	43	83	1234	96	137
Central-Eastern Anatolia	19	13	5					27	87	58	23					197
South-Eastern Anatolia	21	13	5					110	170	102	24					468

system software to understand the spatial distribution of both pollution levels and patient numbers, as shown in Figure 3. This method was used to draw attention to the differences across Turkey's regions. The results obtained for these differences by region are given below:

- significant disparities were observed in the prevalence of patient numbers across twelve distinct regions in Türkiye. Istanbul stood out as the region with the highest patient numbers. This is attributed to its high population density and its elevated levels of economic and social activity compared to other cities. It has been observed that health problems have increased in parallel with environmental problems brought on by urbanization;
- conversely, in the Southeastern Anatolia Region, with a population density of 1,134 people/km², the patient numbers reached 29,910, underscoring the region's vulnerability to the pandemic. The considerable population density and substantial patient volume significantly strained the healthcare system. Pollution maps revealed high levels of all emissions except for O_3, which was not measured. Air pollution in this region was notably more severe than in other regions;
- in the Western Anatolia Region, despite a comparatively lower population density of 392 people/km² and the presence of three metropolitan centers, the patient numbers reached 36,657, highlighting the severity of the pandemic and the rapidity of its spread. This outcome can be attributed to Ankara, Türkiye's capital, which is located within this region. The high concentration of government entities in Ankara, surpassing private firms, necessitated the continued attendance of government employees during the pandemic to maintain public services. This increased the likelihood of virus transmission. Regarding pollution, Western Anatolia recorded higher average levels of NO_X and NO_2 emissions, primarily due to vehicular congestion;
- the Marmara Region, including Eastern and Western Marmara, saw a high patient influx due to its strategic position between Türkiye's economic and cultural hubs. With a population density of 1,830 people/km²

DOI: 10.60923/issn.2281-4485/23350

and five major cities, it was heavily impacted by the pandemic. In contrast, interior regions like Central Anatolia, Central-Eastern Anatolia, and North-Eastern Anatolia, with a lower density (984 people/km²) and four major cities, recorded fewer cases. The weaker influence of urban centers likely helped control the virus's spread, despite similar pollution levels to Marmara;

. the Aegean Region, with five metropolitan cities and a population density of 978 people/km², reported 23,652

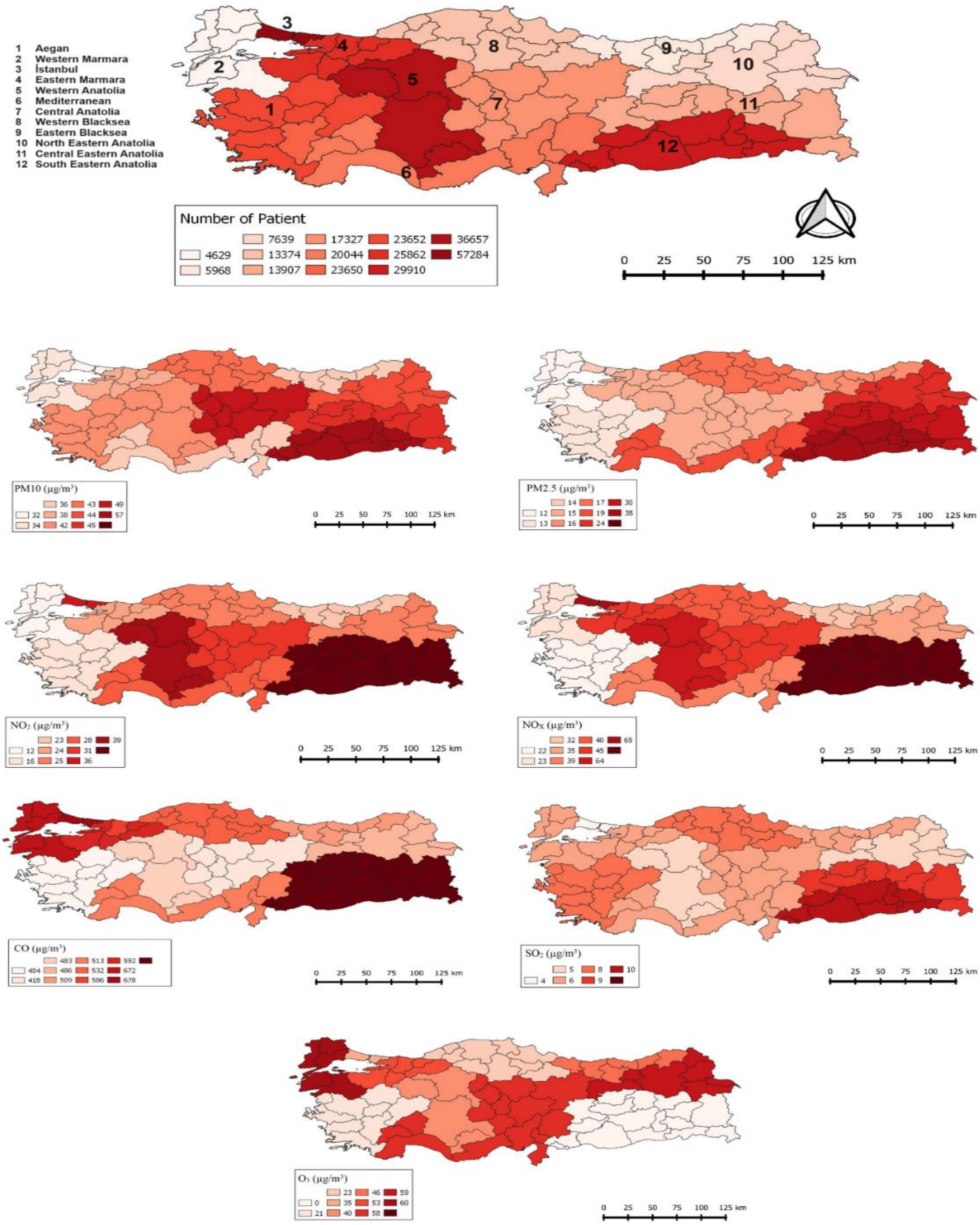

Figure 3. *Maps of patient numbers and pollution levels*

DOI: 10.60923/issn.2281-4485/23350

- patients, while the Mediterranean Region, with a slightly higher density (1,035 people/km²) and also five metropolitan cities, had 20,044 patients. Despite its lower population density, the Aegean Region's higher PM10 and SO_2 levels may have contributed to increased patient numbers. Additionally, greater interpersonal interaction in the region could be a factor in the higher case count;

- in the Black Sea Region, comprising the Eastern and Western Black Sea areas, the population density is 1,262 people/km². Despite this, pollution levels in the Black Sea Region were not at the lowest levels. Other factors, such as the region's physical nature, can explain why the number of patients has not increased significantly.

The analysis found that patient numbers increased in regions with high air pollution, consistent with studies in the USA and Europe linking long-term exposure to PM2.5, NO_2, SO_2, and O_3 to Covid-19 mortality (Coker et al., 2020; Mele and Magazzino, 2020; Yılmaz and Şimşek, 2020; Wu et al., 2020; Zoran et al., 2020; Dettori et al., 2021; Hu et al., 2021; Konstantinoudis et al., 2021; Liu et al., 2021; Naqvi et al., 2021; Khorsandi et al., 2021; Laxmipriya and Narayanan, 2021; Singh, 2021; Li and Managi, 2022). These findings emphasize the need to integrate air quality improvements into national policies, as reducing pollution would enhance public health, lower healthcare costs, boost the economy, and promote environmental sustainability. An analysis of patient numbers and population density across Türkiye revealed significant regional differences, influenced by factors beyond environmental conditions. Healthcare infrastructure and individual traits, including genetics, age, obesity, chronic illnesses, social distancing, hygiene, and nutrition, also play a role. Based on patient percentage relative to population density, regions can be categorized into three distinct groups. This regional grouping facilitates the implementation of targeted measures:

-regions where patient numbers align with population density: Aegean (9% - 9%);

- regions with higher patient numbers than population density: Western Anatolia (14.31% - 3.69%), Central Anatolia (6.76% - 3.83%), Central Eastern Anatolia (5.43% - 3.58%), North Eastern Anatolia (2.98% - 1.84%), Southeastern Anatolia (11.67% - 10.67%).

-regions with lower patient numbers than population density: Istanbul (22.35% - 28.35%), Eastern Marmara (10.09% - 12.88%), Western Marmara (1.81% - 4.34%), Eastern Black Sea (2.33% - 4.81%), Western Black Sea (5.22% - 7.07%), Mediterranean (7.82% - 9.78%).

Correlation and regression analyses of air pollutants and patient numbers

Correlation analysis examined the relationship between patient numbers and pollutant concentrations across regions (Table 2). Given the disease's incubation period, an infectious period of two days was assumed, comparing pollutant levels with patient numbers recorded two days post-exposure. The review of the correlation coefficients in Table 2 indicates that the number of patients in all regions is positively correlated with NO_2, NO_X, and CO levels. PM10 and PM2.5 levels also exhibited positive correlations in all regions except one, whereas SO_2 showed positive correlations in all regions except two. In contrast, O_3 levels demonstrated a negative correlation with patient numbers in all regions except one. Correlation coefficients (r) indicate relationship strength: very weak (0.00–0.25), weak (0.26–0.49), moderate (0.50–0.69), strong (0.70–0.89), and very strong (0.90–1.0) (Akoglu, 2018).

Table 2. *Correlation between patient numbers and pollutant parameters for all regions*

Region-Patient Number	CO	NO_2	NO_X	O_3	PM10	PM2.5	SO_2
Aegean	0.03	0.23	0.15	-0.17	0.12	0.32	0.27
Central Anatolia	0.15	0.28	0.19	0.12	0.19	0.25	-0.07
Central-Eastern Anatolia					0.08		0.01
Eastern Black Sea	0.23	0.42	0.48	-0.34	0.04	0.11	0.01
Eastern Marmara	0.59	0.45	0.58	-0.72	0.33	0.38	0.07
Istanbul	0.13	0.25	0.42	-0.66	0.11	0.21	0.31
Mediterrenian	0.52	0.43	0.46	-0.58	0.17	0.49	0.64
North-Eastern Anatolia	0.19	0.29	0.23	-0.28	0.14	0.23	0.35
South-Eastern Anatolia					-0.36	-0.21	-0.01
Western Anatolia	0.12	0.42	0.23	-0.13	0.2	0.18	0.37
Western Black Sea	0.59	0.36	0.49	-0.14	0.24	0.53	0.7
Western Marmara	0.34	0.25	0.31	-0.57	0.07	0.3	0.278
All Region	0.23	0.42	0.48	-0.34	0.04	0.11	0.01

EQA 72 (2026): 125 - 135

DOI: 10.60923/issn.2281-4485/23350

Moderate positive correlations between pollutants and patient numbers were found in the Western Black Sea (CO: 0.59, PM2.5: 0.53, SO2: 0.70), Mediterranean (CO: 0.52, SO2: 0.64), and Eastern Marmara (NOX: 0.58). High negative correlations were found in Eastern Marmara, Istanbul, Mediterranean, and Western Marmara (O3: -0.57 to -0.72). While this does not imply direct causality, the relationship is notable. Experimental studies also suggest that air pollution exposure increases susceptibility to respiratory infections through various mechanisms (Poniedziałek et al., 2024). Air pollution may weaken the body's defenses against airborne viruses, increasing susceptibility to viral diseases. This study's patient data (RCAP, 2020) support this hypothesis, consistent with previous research (Frontera et al., 2020; Martelletti and Martelletti, 2020; Zhu et al., 2020). The impact of air pollutants on patient numbers was estimated using multivariate linear regression. This analysis examined their relationship across regions, generating corresponding equations (Table 3). The analysis was included significant air pollutants - PM10, PM2.5, SO_2, NO_2, NO_X, CO, and O_3 - as independent variables. The adjusted R^2 values of the regression equations were presented in Table 3. It can be observed that R^2values exceed 0.5 in four regions, indicating a good fit of the regression model in these cases. In contrast, the adjusted R^2 values for the remaining eight regions range from 0 to 0.46, suggesting a weaker model fit in these areas.

Table 3. *Regression equations and R² values for all regions*

	intercept	PM10	PM2.5	SO_2	NO_2	NO_X	CO	O_3	Adjusted R^2	p-value
Aegean	-77	-6.3	12.7	41.0	19.7	-9.2	0.1	-6.9	0.3	8.3e-9
Central Anatolia	-8	-0.5	5.0	-9.0	4.2	-1.8	0.1	0.6	0.3	1.5e-8
Central-Eastern Anatolia	85	0.2		-0.1					0.0	0.64
Eastern Black Sea	-36	-1.5	0.7	3.0	1.6	-0.6	0.2	-0.3	0.6	1.2e-25
Eastern Marmara	359	-4.2	1.7	-16.1	3.1	1.4	0.2	-4.3	0.6	1.6e-23
Istanbul	944	-7.3	11.3	128.4	-9.1	4.5	-0.7	-13.2	0.5	2.1e-21
Mediterrenian	98	-2.1	3.0	18.5	3.1	-1.7	0.0	-1.4	0.5	1.8e-17
North-Eastern Anatolia	57	-0.1	-0.4	11.5	1.5	-0.5	-0.1	-0.3	0.3	3.3e-10
South-Eastern Anatolia	202	-2.4	2.2	5.5					0.2	1.3e-8
Western Anatolia	175	-0.7	-0.8	26.4	5.3	-0.8	-0.3	-1.4	0.4	2.8e-13
Western Black Sea	-54	-2.3	6.3	18.8	-3.7	1.5	0.0	1.6	0.6	1.1e-23
Western Marmara	176	-1.5	3.6	3.5	-2.8	-0.2	0.0	-1.8	0.4	3.6e-15
All Region	277	-3.2	0.3	-7.3	0.9	3.2	0.0	-2.3	0.4	1.5e-133

Clustering of all regions with k means++

The k-means algorithm identified similar regions based on air pollutant types, concentrations, and patient numbers (Table 4). Silhouette coefficients and data counts are presented for two clustering scenarios: Case A (including patient numbers) and Case B (excluding them). In Case A, cluster C5 had the most data points (413, 28.3%). It included data from nine regions, with over 50% from Eastern Black Sea (55%) and Mediterranean (51%). Regions with more than 20% in this cluster included Western Black Sea (46%), North Eastern Anatolia (38%), and Eastern Marmara (36%). A comparison of population, population density, GDP (gross domestic product), and patient numbers between the Mediterranean and Eastern Black Sea showed significant differences. The Mediterranean region had a population of 10,461,626, a density of 1,851 people/km², and a GDP of 320,325, while the Eastern Black Sea had 2,677,584 people, a density of 501 people/km², and a GDP of 219,438 (TÜİK, 2020a; TÜİK, 2020b). Despite these differences, both regions showed similar pollutant concentrations and patient numbers in k-means clustering. In Case B, cluster C1 was the largest, with 283 data points (19.4% of the total). In this scenario, data distribution among the four clusters was balanced. Cluster C1 included data from all regions, with over 20% from Eastern Black Sea (45.2%), Mediterranean (26%), Western Black Sea (24%), and Western Anatolia (21%). Regions contributing 10–20% included Aegean, Eastern Marmara, Istanbul, Central Anatolia, and Western Marmara. Cluster C8 (90 data points) had the highest representation from Istanbul and Western Marmara, indicating similar pollutant concentration patterns. Given time, budget, and personnel constraints, clustering techniques can help group similar regions for more focused analysis.

DOI: 10.60923/issn.2281-4485/23350

Table 4
Clustering of all regions with k means++

Including number of patients (Case A)		Excluding number of patients (Case B)	
Silhouette Scores		Silhouette Scores	
2	0.510	2	0.557
3	0.445	3	0.485
4	0.370	4	0.444
5	0.378	5	0.434
6	0.359	6	0.402
7	0.342	7	0.394
8	0.345	8	0.367
9	0.315	9	0.362
10	0.330	10	0.338

Clustering including patient numbers, data numbers and percentage falling into clusters (A)			Clustering excluding patients numbers, data numbers and percentage falling into clusters (B)		
C5	413	28.3%	C1	283	19.4%
C1	296	20.3%	C3	280	19.2%
C7	196	13.4%	C8	236	16.2%
C6	160	11.0%	C10	228	15.6%
C2	121	8.3%	C4	153	10.5%
C8	118	8.1%	C7	102	7.0%
C3	83	5.7%	C6	80	5.5%
C4	51	3.5%	C2	57	3.9%
C9	15	1.0%	C5	38	2.6%
C10	7	0.5%	C9	3	0.2%

Conclusions

This study assessed air pollution in Türkiye, its link to respiratory disorders, and regional variations in its impact. Findings indicate that respiratory diseases are sensitive to air pollutants, though prevalence varies by region. Istanbul had the highest mean patient count (387 ±302) and significantly higher NO_X, NO_2, and CO emissions. This suggests that urbanization exacer-bates both environmental and health issues. Comparing patient numbers with population density revealed one region where they were equal, five where patient numbers exceeded population density, and six where they were lower. These variations highlight the need to consider additional factors, such as healthcare infrastructure and individual characteristics, alongside environmental influences on patient numbers. A positive correlation was found between patient numbers and all pollutants except O_3. Based on this, a regression model was developed, but it showed a good fit in only four regions, indicating its limited applicability across all regions. The k-means++ algorithm identified the Eastern Black Sea, Mediterranean, Western Black Sea, and Western Anatolia as similar in pollutant levels, while the Eastern Black Sea and Mediterranean also showed similarities in both pollutants and patient numbers. This method is useful when resource constraints limit detailed regional assessments. The findings emphasize the need to reduce environmental factors to prevent respiratory diseases. In Türkiye, air pollution is highest in urban areas with heavy traffic and coal use. Without precautions, these regions will be most vulnerable in a future pandemic, underscoring the importance of regional pandemic action plans. Since air pollution, health, and climate change are interconnected, reducing pollution and improving public health should be integral to climate policy, requiring a collaborative approach. This study has several limitations. Emissions and patient numbers are influenced by factors such as emission sources, removal methods, meteorological conditions, and topography. Patient-related variables, including genetics, exposure duration, and treatment, also affect outcomes but could not be fully accounted for due to data constraints. Additionally, the study focused only on outdoor pollution, excluding indoor

DOI: 10.60923/issn.2281-4485/23350

pollution, which can impact respiratory health. Moreover, while individual air pollutants were analyzed, potential synergistic effects from simultaneous exposure were not considered. Future research incorporating these factors will yield more comprehensive results.

Author contribution declaration

Şenay Çetin Doğruparmak: Investigation, data editing, SPSS software usage, writing original draft, writing-review and editing. Kazım Onur Demirarslan: SPSS software usage, Quantum GIS (QGIS) geographic information system software usage, writing original draft. Gülşen Aydın Keskin: Investigation, methodology, SPSS software usage, writing-original draft. Kadriye Ergün: Orange data mining program usage.

Statements and Declarations

Funding. The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Competing interests. The authors have no relevant financial or non-financial interests to disclose.

Ethical approval. The regions used in the study were defined on the basis of the Covid-19 Status Reports published by Republic of Türkiye Ministry of Health on the website https://covid19.saglik.gov.tr/. Covid-19 patient numbers were also downloaded from this website. During the pandemic, daily patient numbers were published on this site and presented as a report. The data was publicly accessible data. For this, it does not have a "Clinical Trial Number". Daily air quality data were downloaded from the website https://www.havaizleme.gov.tr of Republic of Türkiye Ministry of Environment, Urbanization and Climate Change. Everyone can access to the data. This study does not present any ethical concern.

Ethical responsibility. All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

Data Availability Statement. The data supporting this study's findings are available from the corresponding author upon reasonable request.

Consent to Participate. Not applicable.

Consent to Publish. Not applicable.

References

AKOGLU H, (2018) User's guide to correlation coefficients. Türkiye Journal Emergency Medicine, 18 (3): 91-93. https://doi.org/10.1016/j.tjem.2018.08.001

ANGELIS D.E., RENZETTI S., VOLTA M., DONATO F., CALZA S., PLACIDI D., LUCCHINI G.R., ROTA M., (2021) Covid-19 incidence and mortality in Lombardy, Italy: An ecological study on the role of air pollution, meteorological factors, demographic and socioeconomic variables. Environmental Research, 195:110777. https://doi.org/10.1016/j.envres.2021.110777

BRANDT E.B., BECK A.F., MERSHA T.B. (2020) Air pollution, racial disparities, and Covid-19 mortality. The Journal of Allergy and Clinical Immunology, 146 (1):61–63. https://doi.org/10.1016/j.jaci.2020.04.035

COKER E.S., CAVALLI L., FABRIZI E., GUASTELLA G., LIPPO E., PARISI ML, PONTAROLLO N, RIZZATI M, VARACCA A., VERGALLI S., (2020) The effects of air pollution on Covid-19 related mortality in northern Italy. Environmental Research Economics, 76: 611–634. https://doi.org/10.1007/s10640-020-00486-1

COLLABORATORS G.D.B. (2016) Risk Factors Collaborators. Global, regional, and national comparative risk assessment of 84 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016. Global Health Metrics. 390(10100):1345-1422. https://doi.org/10.1016/S0140-6736(17)32366-8

DETTORI M., DEIANA G., BALLETTO G., BORRUSO G., MURGANTE B., ARGHITTU A., AZARA A., CASTIGLIA P. (2021) Air pollutants and risk of death due to Covid-19 in Italy. Environmental Research, 192:110459. https://doi.org/10.1016/j.envres.2020.110459

DOMINGO L.J., ROVIRA J. (2020) Effects of air pollutants on the transmission and severity of respiratory viral infections. Environmemtal Research, 187:109650. https://doi.org/10.1016/j.envres.2020.109650

EEA (2021) Air Pollution. Europen Environmental Agency. https://www.eea.europa.eu/tr/themes/air

FRONTERA A., CIANFANELLI L., VLACHOS K., LANDONI G., CREMONA G. (2020) Severe air pollution links to higher mortality in Covid-19 patients. Journal Infection, 81(2):255–259. https://doi.org/10.1016/j.jinf.2020.05.031

HEAL, The Health and Environment Alliance (2021) EU's Clean Air for Health Transition 2021-2030 HEAL 10 demands. Brussels-Belgium. https://www.env-health.org/wp-content/uploads/2021/09/HEAL_10-demands_-air-quality_September21.pdf

DOI: 10.60923/issn.2281-4485/23350

HU H., ZHENG Y., WEN X., SMITH S.S., NIZOMOV J., FISHE J., HOGAN W.R., SHENKMAN E.A., BIAN J. (2021) An external exposome-wide association study of Covid-19 mortality in the United States. Science Total Environmental, 768: 144832. https://doi.org/10.1016/j.scitotenv.2020.144832

IKOTUN A.M,, EZUGWU A.E., ABUALIGAH L., ABUHAIJA B., HEMING J., (2023) K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. Information Science, 622: 178-210. https://doi.org/10.1016/j.ins.2022.11.139

KARA E, ÖZDILEK HG, KARA EE, BALCANDI F, MESTAV B, (2021) Ambient Air Quality and General Health Outcomes in Nigde (Turkey) between 2011 and 2017. Iran Journal Public Health, 50(10):1963-1972. https://doi: 10.18502/ijph.v50i10.7496

KONSTANTINOUDIS G, PADELLINI T, BENNETT JE, DAVIES B, EZZATI M, BLANGIARDO M, (2021) Long-term exposure to air pollution and Covid-19 mortality in England: a hierarchical spatial analysis. Environmental International, 146: 106316. https://doi.org/10.1016/j.envint.2020.106316

KHORSANDI B, FARZAD K, TAHRIRI H, MAKNOON R, (2021) Association between short-term exposure to air pollution and Covid-19 hospital admission/mortality during warm seasons. Environmental Monitoring Assessment, 193: 426. https://doi.org/10.1007/s10661-021-09210-y

LAXMIPRIYA S, NARAYANAN RM, (2021) Covid-19 and its relationship to particulate matter pollution – Case study from part of greater Chennai, India. Materials Today: Proceedings, 43:1634–1639. https://doi.org/10.1016/j.matpr.2020.09.768

LI C, MANAGI S, (2022) Impacts of air pollution on Covid-19 case fatality rate: a global analysis. Environmental Science and Pollution Research International , 29(18):27496-27509. https://doi.org/10.1007/s11356-021-18442-x

LIU Q., XU S., LU X. (2021) Association between air pollution and Covid-19 infection: evidence from data at national and municipal levels. Environmental Science and Pollution Research International, 28:37231–37243. https://doi.org/10.1007/s11356-021-13319-5

MARTELLETTI L., MARTELLETTI P. (2020) Air pollution and the novel Covid-19 disease: a putative disease risk factor. SN Comprehensive Clinical Medicine, 15, 1–5. https://doi.org/10.1007/s42399-020-00274-4

MELE M., MAGAZZINO C. (2020) Pollution, economic growth, and Covid-19 deaths in India: machine learning evidence. Environmental Science Pollution Research, 28, 2669–2677. https://doi.org/10.1007/s11356-020-10689-0

NAPITUPULU D., ABDEL KADAR J., KARTIKA JATI R. (2017) Validity testing of technology acceptance model based on factor analysis approach, Indonesian Journal of Electrical Engineering and Computer Science, 5(3):697-704. http://doi.org/10.11591/ijeecs.v5.i3.pp697-704

NAQVI H.R., MUTREJA G., SHAKEEL A., SIDDIQUI M.A., (2021) Spatio-temporal analysis of air quality and its relationship with major Covid-19 hotspot places in India. Remote Sensing Applications: Soc Environ, 22:100473. https://doi.org/10.1016/j.rsase.2021.100473

OECD, (2012) OECD Environmental outlook to 2050. OECD Publishing. http://dx.doi.org/10.1787/9789264122246-en

ÖZBAY B., AYDIN KESKİN G., ÇETİN DOĞRUPARMAK Ş., AYBERK S. (2011) Multivariate methods for ground-level ozone modeling. Atmospheric Resarch, 102(1-2):57–65. http://doi.org/10.1016/j.atmosres.2011.06.005

PALA K., AYKAC N., YASIN Y., (2021) Premature deaths attributable to long-term exposure to PM2.5 in Turkey. Environmental Science Pollution Research, 28(37):51940-51947. https://doi.org/10.1007/s11356-021-13923-5

PETER S.C., DHANJAL J.K., MALİK V., RADHA-KRİSHNAN N., JAYAKANTHAN M., SUNDAR D. (2019) Quantitative Structure-Activity Relationship (QSAR): Modeling Approaches to Biological Applications. Enc Bioinformatics Computational Biology, 2:661-676. https://doi.org/10.1016/B978-0-12-809633-8.20197-0.

PONİEDZİAŁEK B., RZYMSKİ P., ZARĘBSKA-MİCHALUK D., FLİSİAK R. (2024) Viral respiratory infections and air pollution: A review focused on research in Poland. Chemosphere, 359:142256. https://doi.org/10.1016/j.chemosphere.2024.142256

RCAP (2020) Right to Clean Air Platform, Black Report, 2020. https://www.temizhavahakki.org/wp-content/uploads/ 2020/09/Kara-Rapor-2020-Son27082020.pdf

RTMEU (2020) Air Quality Monitoring. Database. Republic of Türkiye Ministry of Environment, Urbanization and Climate Change publications, Ankara, Türkiye. https://sim.csb.gov.tr

RTMH (2020) Republic of Türkiye Ministry of Health. Covid-19 Information Platform. https://covid19.s aglik.gov.tr/TR-66935/genel-koronavirus-tablosu.html

SINGH A, (2021) Ambient air pollution and Covid-19 in Delhi, India: time-series evidence. International Journal of Environmental Health Research, 32(11):2575-2588. https://doi.org/10.1080/09603123.2021.1977258

TRAN H.M., TSAI F.J., LEE Y.L., CHANG J.H., CHANG L.T., CHANG T.Y., CHUNG K.F., KUO H.P., LEE K.Y.,

DOI: 10.60923/issn.2281-4485/23350

CHUANG K.J., CHUANG H.C. (2023) The impact of air pollution on respiratory diseases in an era of climate change: A review of the current evidence. Science of the Total Environment, 898: 166340. https://doi.org/10.1016/j.scitotenv.2023.166340

TRAVAGLIO M., YU Y-, POPOVIC R., SELLEY L., LEAL N.S., MARTINS L.M. (2021) Links between air pol-lu-tion and Covid-19 in England. Environmental Pollution, 268:115859. https://doi.org/10.1016/j.envpol.2020.115859

TÜİK (2020a) Gross domestic product. Turkish Statistical Institute. https://data.tuik.gov.tr/Bulten/Index?p=Donemsel-Gayrisafi-Yurt-Ici-Hasila-IV.-Ceyrek:-Ekim---Aralik,-2020-37180

TÜİK (2020b) Address-Based Population Registration System Results. Turkish Statistical Institute. https://data.tuik.gov.tr/Bulten/Index?p=Adrese-Dayali-Nufus-Kayit-Sistemi-Sonuclari-2020-37210

TÜRK BÖRÜ Ü., BÖLÜK C., TAŞDEMIR M-, GEZER T., SERIM V.A. (2020) Air pollution, a possible risk factor for multiple sclerosis. Acta Neurologica Scandinavica. 141(5):431-437. https://doi.org/10.1111/ane.13223

WU X., NETHERY R., SABATH M., BRAUN D., DOMINICI F. (2020) Air pollution and Covid-19 mortality in the United States: Strengths and limitations of an ecological regression analysis. Science Advances, 6(45). http://doi.org/10.1126/sciadv.abd4049

WHO, (2021) Air Pollution. World Health Organization. https://www.who.int/health-topics/air-pollution#tab=tab1

YILDIZ GÜLHAN P, GÜLEÇ BALBAY E, ELVERIŞLI MF, ERÇELIK M, ARBAK P, (2020) Do the levels of particulate matters less than 10 µm and seasons affect sleep? Aging Male, 23(1):36-41. https://doi.org/10.1080/13685538.2019.1655637

YILMAZ V, ŞIMŞEK T, (2020) The relationship between air quality and Covid-19: An application on G-7 countries. Turkish Studies, 15(4): 1353-1366. http://doi.org/10.7827/TurkishStudies.43883

ZHANG Z, XUE T, JIN X, (2020) Effects of meteorological conditions and air pollution on Covid-19 transmission: Evidence from 219 Chinese cities. Science of the Total Environment, 741:140244. https://doi.org/10.1016/j.scitotenv.2020.140244

ZHU Y, XIE J, HUANG F, & CAO L, (2020) Association between short-term exposure to air pollution and Covid-19 infection: Evidence from China. Science of the Total Environment, 727:138704. https://doi.org/10.1016/j.scitotenv.2020.138704

ZORAN MA, SAVASTRU RS, SAVASTRU DM, TAUTAN MN, (2020) Assessing the relationship between surface levels of PM2.5 and PM10 particulate matter impact on Covid-19 in Milan, Italy. Science of the Total Environment, 738:139825. https://doi.org/10.1016/j.scitotenv.2020.139825