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Investigating the Relationship Between Air Quality, Meteorological Parameters, and the Transmission Dynamics of COVID-19: A Case Study for Türkiye

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Abstract
Understanding the influence of air quality parameters and meteorological factors on SARS-CoV-2 transmission remains a critical concern in the science world. This study investigates the effects of air quality and meteorological parameters on the occurrence of SARS-CoV-2 cases in the cities of Türkiye. Air quality data including $PM_{2.5}$, PM_{10}, O_3, SO_2, CO, along with meteorological data such as temperature and humidity, were analyzed across 41 cities in Türkiye using Geographic Information Systems and spatial regression models. This regional case study contributes to existing research by emphasizing the importance of localized investigations, acknowledging that the unique characteristics of cities in Türkiye demand a region-specific approach. Differences in climate, air quality, and urbanization patterns across regions can significantly influence disease transmission, making localized studies essential for a comprehensive understanding of virus spread. Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) methods were employed to assess both global and localized associations. While the OLS analysis did not reveal statistically significant relationships at the national scale, the GWR approach uncovered notable spatial variability in the strength of associations, particularly for $PM_{2.5}$ and PM_{10}. Certain cities, such as Aksaray and Konya, exhibited stronger correlations between particulate matter concentrations and COVID-19 incidence, suggesting the influence of localized environmental and urban characteristics. The findings of this study aim to enhance global efforts to improve resilience against emerging infectious diseases and promote sustainable, healthier urban environments through tailored regional strategies. Additionally, the results provide valuable insights to local policymakers, aiding in the implementation of strategies to improve air quality in high-risk regions and mitigate the adverse effects of future pandemics on public health and the economy.
Keywords: air quality, SARS-CoV-2, meteorological factors, COVID-19

I. INTRODUCTION

Since the World Health Organization officially declared the COVID-19 pandemic in March 2020 [1], environmental factors, particularly air quality, have emerged as significant components in understanding the dynamics of SARS-CoV-2 transmission. The virus spreads primarily through human-to-human contact, especially via respiratory droplets that are expelled when an infected individual coughs, sneezes, or exhales near others [2]. Urban centers such as New York City in the United States, Madrid, Barcelona, and Milan in Italy have experienced particularly severe effects of the pandemic due to their high population densities and urban pollution levels [3]. Many studies have examined the variations in COVID-19 prevalence and fatality rates in these areas, establishing connections between air pollutants such as particulate matter (PM), nitrogen dioxide (NO_2), and ozone (O_3). Initial research indicates that exposure to particulate matter (PM) could play a key role in the transmission of the virus, with inhalation of these particles serving as a potential vector for SARS-CoV-2 [4].

Additional studies have presented conflicting evidence on the impact of environmental factors like temperature and particulate matter levels. For instance, while some research suggests that lower temperatures and increased PM_{10} levels may reduce COVID-19 incidence, other studies highlight the greater risk posed by $PM_{2.5}$ and high humidity levels [5]. As the pandemic progressed, researchers worldwide began investigating the spatial relationships between air pollution, meteorological conditions, and COVID-19 transmission. In Bangladesh, for example, Hassan et al. [6] found a significant correlation between infection rates and $PM_{2.5}$, carbon monoxide (CO), and ozone (O_3) levels. Similarly, in Canada, a study by Stieb et al. [7] explored the relationship between long-term $PM_{2.5}$ exposure, temperature, and public health, revealing a positive, but statistically insignificant, link between COVID-19 cases and air pollution. The study shows the importance of regions with severe health impacts and minimal variations in pollutant exposure, which likely influenced these findings.

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Research in Chile further emphasized the role of air pollution and meteorological factors in shaping COVID-19 mortality rates. Dales et al. [8] observed a strong correlation between elevated levels of CO, NO_2, $PM_{2.5}$, and increased COVID-19 deaths, with fluctuations in temperature and humidity playing a significant role in these outcomes. In metropolitan centers where ozone (O_3) and PM_{10} frequently exceeded safety limits, researchers suggested that SARS-CoV-2 could potentially attach to PM_{10} particles, prolonging its persistence in the atmosphere, particularly in stable atmospheric conditions with high concentrations of particulate matter.

This trend was also observed in Spain, another country severely affected by the pandemic. Researchers there focused on measuring PM_{10}, NO_2, O_3, and CO levels, uncovering positive associations between these pollutants and COVID-19 transmission [3]. In addition, studies from the Middle East, characterized by warmer climates, revealed significant environmental changes that could influence viral transmission. For instance, Meo et al. [9] highlighted the role of sandstorms in dispersing $PM_{2.5}$, CO, and O_3, which increased the risk of COVID-19 transmission. Sulfur dioxide (SO_2), however, was found to decrease the incidence of confirmed cases in Iran, suggesting a complex interaction between various pollutants and viral transmission [10]. Further research examined the daily exposure to $PM_{2.5}$, PM_{10}, and ozone, finding strong correlations between short-term exposure and increased COVID-19 incidence, particularly in warmer regions.

The earlier studies in Türkiye analyzed the temporal relationship between parameters and COVID-19 cases [11]. The later studies investigated the spatial analysis in different regions of the country [12]. Building upon this global body of research, the present study investigates the relationship between air quality, meteorological factors, and COVID-19 transmission in Türkiye. Using geographic analysis tools within ArcMap [13], the study employs both Geographically Weighted Regression (GWR) and Ordinary Least Squares (OLS) analyses to explore these relationships. While OLS regression identifies the best-fitting line by minimizing the difference between observed and predicted values, GWR accounts for geographic variability in the correlation between independent and dependent variables. GWR provided more insightful results by capturing regional variations and underlying mechanisms. Although its predictive power remains subject to debate, GWR offers a better understanding of non-linear relationships between air pollution, meteorological conditions, and COVID-19 transmission. This comprehensive analysis shows the importance of regional variability and environmental factors in understanding the dynamics of the pandemic in Türkiye.

II. MATERIALS and METHODS

Data Collection

The COVID-19 infection case numbers were obtained from the Ministry of Health's official website, covering eight weeks from February 14, 2021, to April 2, 2021 [14]. This data encompassed 41 cities in Türkiye, specifically selected due to the limited availability of information on PM_{10}, $PM_{2.5}$, SO_2, O_3, and CO concentrations in other cities. The air quality parameters were obtained from the Ministry of Environment, Urbanization, and Climate Change [15], while meteorological data was provided by the General Directorate of Meteorology within the Ministry [16].

Study Area

The study area covers 41 cities across Türkiye, selected based on the availability of consistent and comprehensive data on air quality parameters and meteorological conditions. The selected cities are Adana, Aksaray, Amasya, Antalya, Artvin, Balıkesir, Çanakkale, Iğdır, Karabük, Kayseri, Kırklareli, Kırşehir, Konya, Kütahya, Malatya, Manisa, Mersin, Muş, Nevşehir, Niğde, Ordu, Rize, Sakarya, Samsun, Sivas, Tekirdağ, Tokat, Trabzon, Tunceli, Uşak, Van, Yalova, Yozgat, Zonguldak, Elazığ, Erzurum, Erzincan, Afyonkarahisar, Aydın, Bolu, and Denizli. Türkiye's geographical diversity, covers various climate zones and urbanization patterns, provides a valuable context for exploring environmental influences on public health. The cities included in the analysis represent a range of geographic regions, including coastal, inland, urban, and semi-rural areas, ensuring that the study captures spatial variation in environmental and atmospheric conditions. This regional distribution supports a robust spatial analysis framework to investigate the relationships between environmental factors and COVID-19 transmission using GIS-based statistical modeling techniques.

Statistical Methods

A range of data visualization techniques and regression models were employed to explore the influence of air quality and meteorological factors on the transmission of SARS-CoV-2 in Türkiye. The methodology was designed to account for both linear and non-linear relationships between variables. To analyze linear associations, the OLS regression model was used. For geospatial analysis, the GWR technique was implemented, utilizing ArcMap software [12]. Within ArcMap, data layers were used to create heat maps, and the software generated raster surfaces that displayed the concentration of point data in specific regions.

OLS regression was applied to model the relationships between the independent variables (PM_{10}, $PM_{2.5}$, SO_2, O_3, NO_2, temperature, wind direction, and wind speed) and the dependent variable (number of COVID-19 cases). ArcMap's spatial statistics tools were utilized to perform the OLS regression and analyze spatial relationships within the dataset.

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki} + \varepsilon_i \quad \textbf{(1)}$$

Where:

- y_i is the dependent variable (COVID-19 cases in city i),

- x_{1i}, x_{2i}, ..., x_{ki} are the independent variables (e.g., PM_{10}, $PM_{2.5}$, SO_2, etc.),

- β_0 is the intercept,

- β_1, β_2, ..., β_k are the coefficients to be estimated,

- ε_i is the error term. [12]

To further investigate potential non-linear associations, GWR analysis was conducted using ArcMap's Toolbox. GWR, as a local regression method, accounts for spatial heterogeneity, making it distinct from OLS, which assumes uniformity across the study area.

$$y_i = \beta_0(u_i, v_i) + \Sigma\, [\beta_k(u_i, v_i) * x_{ki}] + \varepsilon_i \quad \textbf{(2)}$$

Where:

- (u_i, v_i) are the coordinates of location i,

- $\beta_k(u_i, v_i)$ represents the location-specific coefficient for variable k,

- Other terms are as defined in the OLS equation. [12]

The dependent variable in the GWR analysis was the number of COVID-19 cases, and the independent variables included PM_{10}, $PM_{2.5}$, SO_2, O_3, NO_2, temperature, wind direction, and wind speed. Several key parameters were considered during the GWR analysis, including bandwidth, residual sum of squares, effective number of parameters, sigma, Akaike Information Criterion corrected for small sample size (AICc) [17], and R-squared. Detailed explanations of these parameters are provided in the results and discussion sections of this paper.

III. RESULTS and DISCUSSION

Exploratory Data Analysis

The heat maps show the visualization of the dispersion of average COVID-19 cases per 100,000 people over an eight-week period across various cities. As shown in Figure 1, the color white signifies the absence of officially shared data, thereby leading to the exclusion of cities falling under this category from our study. Conversely, cities denoted by a distinctive orange, such as Samsun, Ordu, and Trabzon cities are indicative of a notable prevalence of COVID-19 cases. Upon initial inspection, it becomes apparent that larger urban centers and those with a substantial presence in the tourism sector exhibit a higher incidence of cases, while smaller cities exhibit a comparatively lower density of such occurrences. A comprehensive statistical summary encompassing all the parameters referenced within the specified time interval can be found in Table 1.

Temperature constituted one of the meteorological parameters subjected to our analysis. In Figure 2, the depiction of elevated temperatures is denoted by a deeper shade of green. Notably, cities such as Antalya, Adana, and Trabzon emerged as possessing higher temperature levels when compared to the remaining cities showcased in the illustration. The distribution of humidity follows a pattern similar to temperature in some cities, whereas in others, it differs significantly.

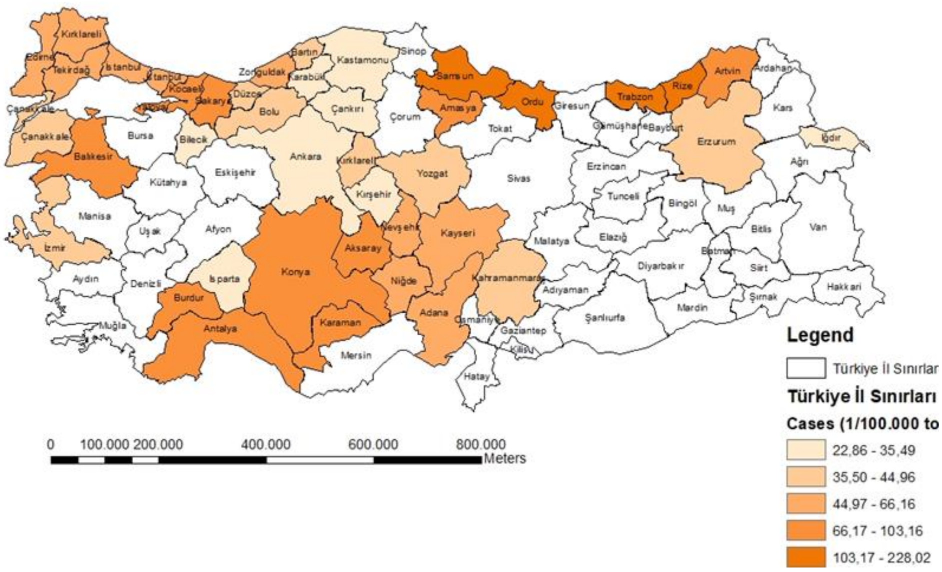

Figure 1. Heat map illustrating the variation in COVID-19 cases across different cities of Türkiye.

Table 1. Statistical summary table, concentrations of the parameters (µg/m^3)

City	No	Avg. PM_{10}	Avg. SO_2	Avg. NO_2	Avg. O_3	Avg. $PM_{2.5}$
Adana	8	16.75	4.39	13.36	51.64	6.67
Aksaray	8	41.62	18.57	21.73	45.02	20.38
Amasya	8	56.07	0.00	27.70	38.07	30.92
Ankara	8	55.68	3.07	44.75	23.32	18.82
Antalya	8	39.19	4.78	34.28	50.11	18.25
Artvin	8	21.5.	8.97	18.23	57.44	0.00
Balıkesir	8	72.32	27.07	32.40	39.48	26.02
Bartın	8	58.21	12.54	31.74	45.40	24.98
Bilecik	8	43.48	11.89	21.55	78.68	19.30
Bolu	8	45.34	20.81	30.77	32.05	19.18
Burdur	8	42.38	16.91	25.99	49.92	27.30
Çanakkale	8	34.36	13.72	20.51	50.06	15.86
Çankırı	8	31.98	22.38	31.87	44.17	9.65
Düzce	8	43.54	10.22	15.62	11.26	29.27
Edirne	8	70.21	68.70	11.24	35.51	33.34
Erzurum	8	61.4	0.00	54.82	0.00	36.97
Iğdır	8	67.38	5.09	14.49	67.64	34.55
Isparta	8	39.95	20.25	29.12	51.54	25.12
İstanbul	8	41.40	18.48	56.07	64.81	22.42
İzmir	8	36.60	8.85	0.00	0.00	21.58
Kahramanmaraş	8	87.30	21.89	34.34	8.35	24.51
Karabük	8	71.33	3.38	28.09	0.00	25.21
Karaman	8	26.74	5.77	21.16	55.68	16.42
Kastamonu	8	30.28	17.8	27.43	24.34	9.26
Kayseri	8	50.89	7.96	54.85	0.00	41.64
Kırıkkale	8	0.00	17.85	23.83	3.44	14.09
Kırklareli	8	50.37	22.10	17.37	55.17	17.66
Kırşehir	8	23.23	13.26	68.63	55.94	8.59
Kocaeli	8	31.48	12.46	16.71	54.68	18.78
Konya	8	57.11	8.98	47.23	25.78	32.60
Nevşehir	8	34.16	10.98	24.25	48.56	12.13
Niğde	8	34.78	5.82	26.12	57.00	18.34
Ordu	8	34.29	15.75	62.26	0.00	17.72
Rize	8	27.76	4.98	6.52	76.37	12.35
Sakarya	8	39.16	29.83	25.70	35.16	32.17
Samsun	8	33.15	10.25	66.43	7.64	9.53
Tekirdağ	8	44.65	28.63	28.02	39.79	23.64
Trabzon	8	61.74	8	41.65	0.00	23.88
Yalova	8	46.99	57.59	44.16	49.24	20.38
Yozgat	8	41.80	38.52	27.38	5.54	10.53
Zonguldak	8	61.42	24.01	21.20	35.99	33.96

The proximity of cities to bodies of water plays a crucial role in influencing local humidity levels. However, for a more in-depth understanding, comprehensive meteorological analyses would be necessary.

$PM_{2.5}$ has emerged as a key parameter in this study, given its considerable impact on the results. As demonstrated in Figure 3, cities such as Konya, Amasya, Kayseri, Trabzon, and Iğdır are marked by the darkest shades of pink, indicating high concentrations of $PM_{2.5}$. Konya's economy is largely based on agriculture and livestock farming. Although specific emission data for Konya is limited, studies from other regions have shown that such activities contribute substantially to particulate matter concentrations [18,19]. The elevated $PM_{2.5}$ levels in Konya can thus be attributed to these practices. Similarly, Amasya, Kayseri, Trabzon, and Iğdır exhibit high $PM_{2.5}$ concentrations, which can be explained by comparable economic activities.

In contrast, cities like Kırklareli, Çanakkale, Balıkesir, and Rize are represented by lighter shades of pink, signifying lower $PM_{2.5}$ concentrations. The sources of particulate matter in these urban centers are more diverse, stemming from a broader range of activities. It is essential to recognize that the origins of particulate matter in these regions are highly complex, influenced not only by industrial or agricultural practices but also by factors such as daily human behaviors and local pollution control measures. These diverse factors contribute to the varying levels of particulate matter observed across different regions. The highest concentrations of PM_{10} were observed in four cities: Karabük, Trabzon, Kahramanmaraş, and Iğdır. Identifying the exact sources of PM_{10} in these regions is challenging due to the nature of particulate emissions. However, one contributing factor in these cities is the use of wood burning for heating during the winter months, which significantly adds to particulate matter levels. On the other hand, cities such as Kırşehir and others have lower PM_{10} levels, which could arise from a variety of sources. These cities do not share a common primary cause for PM_{10} generation. Geographically, they are not close enough to exhibit similar weather-related patterns, making it difficult to draw direct correlations between PM_{10} concentrations and meteorological parameters like temperature or conditions related to SARS-CoV-2. As such, understanding the interplay of these factors requires a more nuanced approach.

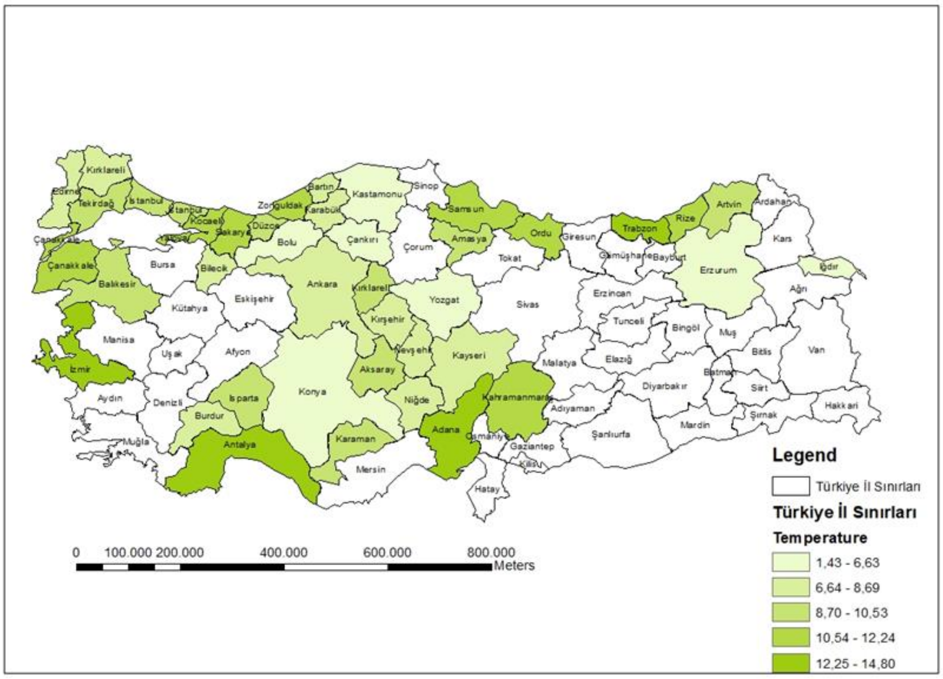

Figure 2. Heat map illustrating the variation in temperature across different cities of Türkiye.

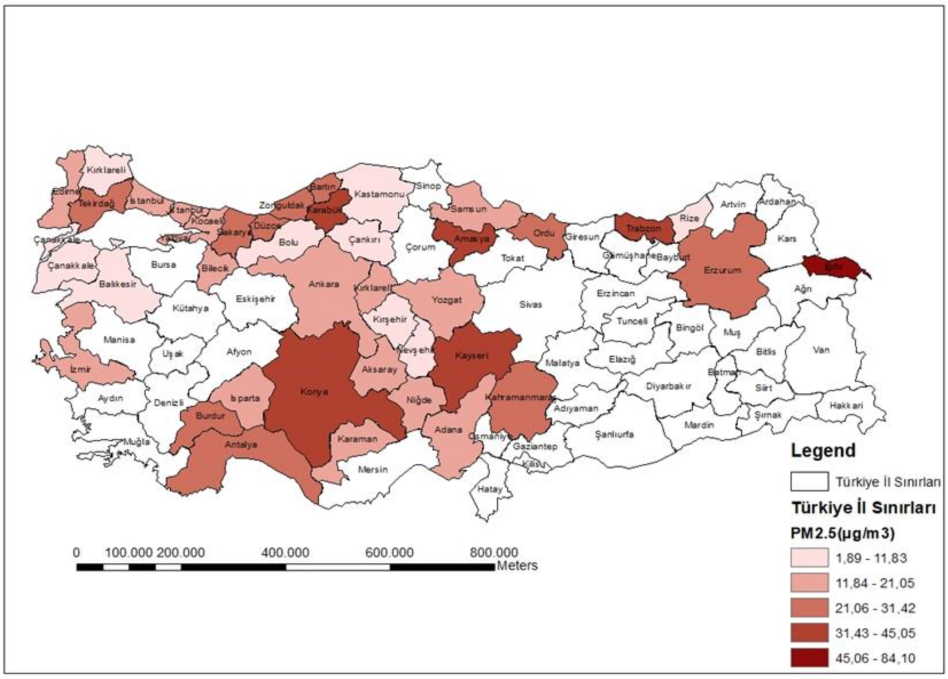

Figure 3. Heat map illustrating the variation in $PM_{2.5}$ concentrations across different cities of Türkiye.

The Ordinary Least Squares Analysis

The spatial dataset was analyzed using OLS regression, a commonly used method due to its simplicity and effectiveness in providing a global perspective on variable relationships. OLS was selected to serve as a baseline model, offering insights into potential explanatory factors and laying the groundwork for comparisons with more advanced spatial regression techniques. The results of the OLS analysis are displayed in Table 2.

Table 2. Summary of OLS Results - Model Variables

Variable	Intercept	PM_{10}	SO_2	NO_2	$PM_{2.5}$
Coefficient [a]	73.85	-0.44	0.19	0.18	0.52
StdError	22.25	0.51	0.66	0.40	0.88
t-Statistic	3.32	-0.87	0.29	0.44	0.59
Probability [b]	0.002071*	0.39	0.78	0.66	0.56
Robust_SE	13.87	0.34	0.58	0.36	0.64
Robust_t	5.33	-1.30	0.33	0.49	0.81
Robust_Pr [b]	0.000005*	0.20	0.75	0.63	0.42
VIF [c]	---------	2.61	1.04	1.05	2.64

The OLS model did not provide sufficient evidence to conclusively link the independent variables to COVID-19 case numbers. The analysis was unable to determine whether air pollution directly contributes to an increase in COVID-19 cases or merely exacerbates the impact of the virus on the population. However, the analysis suggests that certain pollutants' intensity may be correlated with case levels, as shown in the heat maps. The OLS model does not robustly support a direct association between the independent variables and COVID-19 cases. This is evident because the probability values for each independent variable are higher than 0.001, and even when using Robust Probability to test for significance, no meaningful results were obtained. While some positive coefficients were observed, they lacked statistical significance. This indicates that the relationship between air pollutants and COVID-19 cases might be more complex than what a linear regression model can capture, or that other variables may play a stronger role in driving COVID-19 case numbers. In this context, more flexible models, such as nonlinear regression, machine learning algorithms (e.g., random forest or gradient boosting), or spatial-temporal models, may offer better performance by capturing potential interactions, nonlinear effects, or spatial dependencies that a simple linear model cannot account for.

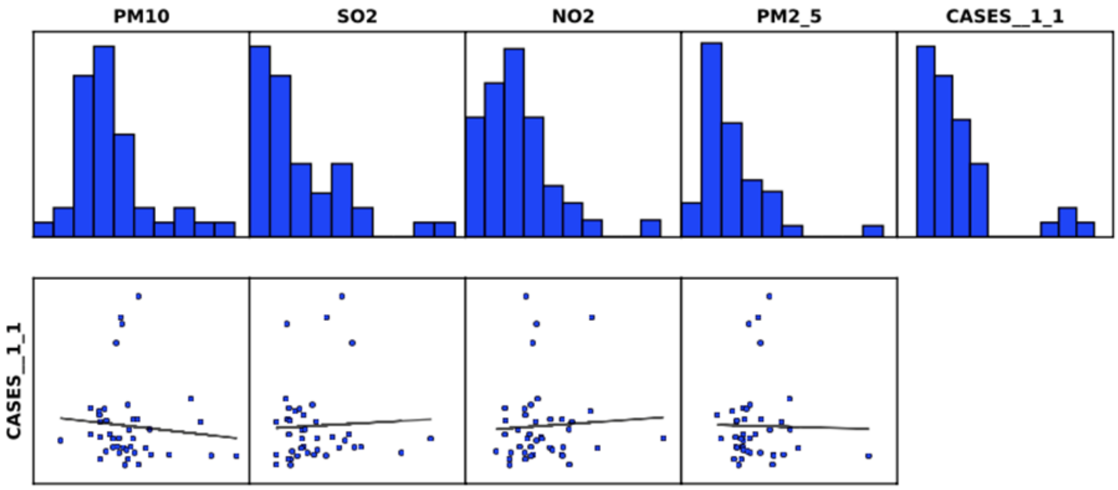

Figure 4. Variable distributions and relationships.

Figure 4 presents the relationships between the dependent and explanatory variables. The histograms display the distribution of each variable, providing a visual overview of their patterns and central tendencies. Meanwhile, the scatterplots illustrate the relationship between each explanatory variable and the dependent variable, offering a clear representation of their associations. These graphical representations collectively provide valuable insights into the distribution of the variables and the nature of their interconnections, enhancing our understanding of their underlying relationships.

It is important to recognize the limitations of OLS, particularly its assumption of constant relationships across the dataset and its inability to account for spatial dependencies. These limitations can result in an incomplete analysis, especially when dealing with spatially distributed data. To address these shortcomings and better capture the complexities inherent in spatial data, GWR offers a more nuanced approach by considering spatial variations and localized relationships.

The Geographically Weighted Regression Analysis

The GWR technique was employed in this study to account for the spatial heterogeneity present within the dataset. While the initial analysis using OLS regression provided useful insights into the overall relationships between variables, it failed to capture the potential spatial variations and non-stationarity inherent in the data. GWR was used to investigate and better understand the localized relationships between the dependent and explanatory variables. This method enables the estimation of spatially varying coefficients, revealing how these relationships differ across various cities.

Through the application of GWR, a more detailed understanding of the spatial patterns emerged, addressing the spatial non-stationarity within the study area. The results obtained from GWR provide a clearer picture of the spatially varying associations, offering valuable insights into the localized dynamics of the variables under investigation. In this study, both single-variable and multivariable GWR analyses were conducted. The single-variable analysis aimed to explore the spatial variations and localized impacts of specific independent variables on COVID-19 cases. For example, as shown in Figure 3, $PM_{2.5}$ concentrations were analyzed using GWR, revealing notable localized impacts. The province of Aksaray, in particular, was highlighted as having the highest concentrations of $PM_{2.5}$, demonstrating the power of GWR in pinpointing regional variations.

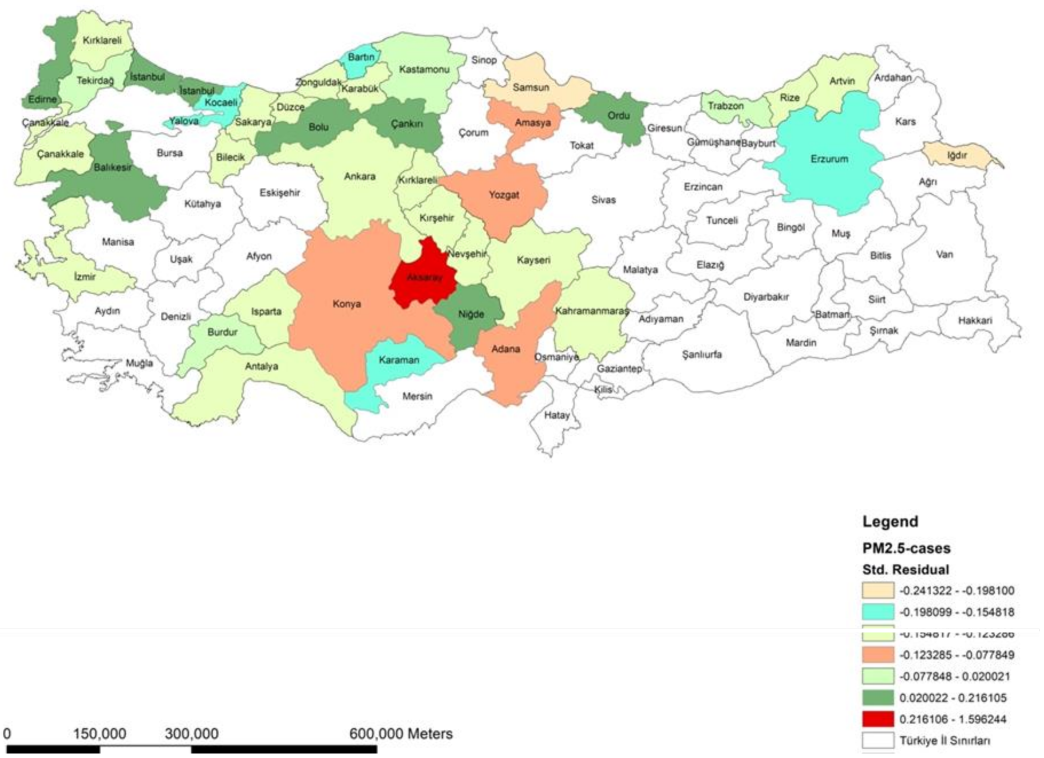

Figure 5. Single variable Geographically Weighted Regression heat map depicting the spatial distribution of $PM_{2.5}$ concentrations.

Figure 5 presents the spatial relationships between multiple air quality parameters and COVID-19 cases. This multivariable approach allows for a more comprehensive assessment of the spatially varying effects of several predictors simultaneously. By accounting for multiple variables, the analysis provides deeper insights into the factors contributing to the observed patterns or variations in the dependent variable across different locations. The multivariable GWR analysis helps to identify how the interaction between various air quality indicators influences the spread of COVID-19, offering a more detailed understanding of the drivers behind these spatial patterns.

The GWR results for the model variables suggests that the model does not provide strong evidence linking the independent variables to COVID-19 cases. It remains unclear whether air pollution directly contributes to the increase in COVID-19 infections or simply exacerbates the virus's impact on more vulnerable populations. Nonetheless, the analysis indicates a potential correlation between the intensity of certain pollutants and the severity of COVID-19 cases, as demonstrated in Figure 6. The heat map generated from the GWR analysis reveals the standard deviations for $PM_{2.5}$, PM_{10}, SO_2, and NO_2, shedding light on the spatial distribution of these air pollution parameters.

The further details of the GWR results, offering key insights into the relationships between variables. The R-squared value indicates that approximately 69% of the variability in COVID-19 cases can be explained by the independent variables included in the GWR model. The AICc measures model fit while balancing complexity and accuracy. A lower AICc value represents a better trade-off, and in this case, the AICc value is 5297.5, suggesting a reasonable fit of the GWR model. The bandwidth parameter in GWR defines the spatial extent over which relationships between variables are estimated, with neighboring data points considered within this distance. In this model, the bandwidth value is 34,256, which indicates the spatial range taken into account for each location. The residual sum of squares represents the goodness of fit of the model, where a lower value suggests a better alignment of the model with the data. Finally, the sigma value, representing the standard deviation of the residuals, is 4187, indicating the typical deviation between observed and predicted values in the model.

IV. CONCLUSION

This study investigated the association between SARS-CoV-2 and various meteorological and air pollution factors. The research employed ArcMap for conducting Ordinary Least Squares and Geographically Weighted Regression analyses. These two approaches yielded distinct results, with GWR proving effective with geographic variations and localized influences, while OLS was more suitable for situations where interactions remained consistent across different cities. GWR, being more intricate, provided a comprehensive examination by identifying spatial variations. Nonetheless, it is important noting that GWR can be computationally intensive and necessitates careful consideration of geographic scales, making local model interpretation more challenging. In the OLS analysis, the data characteristics did not reveal a significant link between COVID-19 cases and meteorological and air pollution factors. This suggests that the relationship may be more complex than what can be captured by a linear model. Additionally, it hints at the possibility of other independent variables that should be considered to obtain more accurate results.

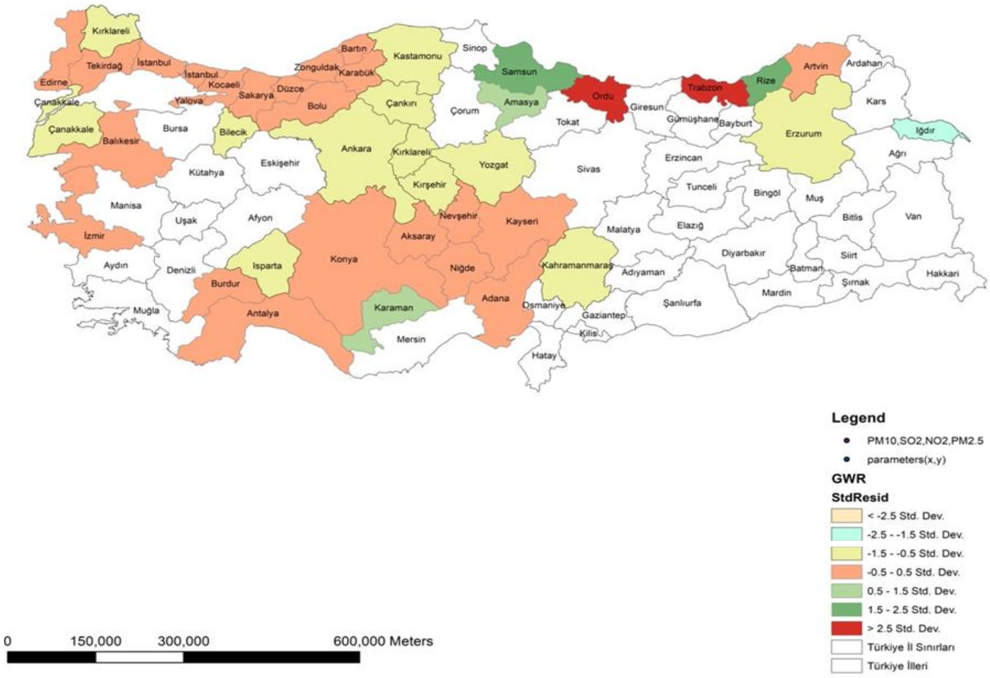

Figure 6. Multivariable Geographically Weighted Regression heat map depicting the spatial distribution of air quality parameters.

Conversely, in the GWR analysis, the dataset displayed a non-linear relationship between COVID-19 cases and meteorological and air pollution parameters. Notably, certain cities, such as Samsun, Rize, and Artvin, exhibited contrasting results in both methods, as indicated by different standard deviations. On the other hand, Trabzon and Ordu demonstrated a greater degree of consistency in terms of data variability. To arrive at a more precise interpretation, it is essential to delve deeper into the specifics of the GWR study, including the variables utilized and the source of these results. Furthermore, to strike a better balance between model accuracy and complexity, it may be beneficial to reduce the number of parameters in the dataset.

Several limitations of the current study should be acknowledged. First, the analysis was limited by the spatial resolution and temporal granularity of the COVID-19 case data and air quality data. Daily or weekly case counts, if available, would allow for more dynamic temporal modeling. Second, the set of environmental predictors was limited; additional variables such as population mobility, socioeconomic indicators, healthcare access, or vaccination rates might improve explanatory power. Third, the GWR model, although effective in capturing spatial variations, is computationally intensive and may be sensitive to the choice of kernel and bandwidth, which could affect result interpretation.

To enhance the robustness of future studies, more comprehensive datasets with higher spatial and temporal resolution should be used. Including a broader array of predictor variables and employing ensemble or hybrid modeling approaches could also improve predictive accuracy. Finally, cross-validation or out-of-sample testing should be applied to compare model performance objectively and ensure generalizability.

In conclusion, while GWR demonstrated its strength in capturing spatial heterogeneity, the study underlines the need for more flexible and data-rich modeling strategies to fully understand the environmental determinants of COVID-19 spread.

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