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Spatio-temporal analysis of impact of environmental parameters on air pollution in districts of Tabriz Metropolis: A seasonal perspective

Mir Ali Seyed Mosaffayi[1], Sajjad Moshiril[2], Bohadir Abdumuminov[3], Khalil Valizadeh Kamran*[2] Bakhtiar Feizizadeh[2]

[1] *University of Tabriz, Faculty of Planning and Environmental Sciences, Department of Urban and Regional Planning, Tabriz, Iran;* alimossafa1998@gmail.com

[2] *University of Tabriz, Faculty of Planning and Environmental Sciences, Department of Remote Sensing and GIS, Tabriz, Iran;* sajjad.moshiri@tabrizu.ac.ir; valizadeh@tabrizu.ac.ir; Bakhtiar.feizizadeh@gmail.com

[3] *Termez State University Faculty of Natural Sciences, Department of Geography, Termez, Uzbekistan; abdumuminovb@tersu.uz*

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Abstract: Air pollution has become a significant challenge in Tabriz over the years, prompting this study to investigate the spatio-temporal relationships between environmental parameters - sum of vegetation cover area (SVCA) and mean land surface temperature (MLST) and air pollutants (CO, SO_2, NO_2) across the ten districts of Tabriz metropolitan area on a seasonal basis. The data used in this research were derived from satellite images on the Google Earth Engine (GEE) platform, with SVCA data obtained from Sentinel-2, MLST from Landsat-8, and air pollutants from Sentinel-5 images. The Modified Geographically Weighted Regression (MGWR) model was employed to analyze the relationships between environmental parameters and air pollutants, with environmental parameters as independent variables and air pollutants as dependent variables. Data analysis reveals a significant and strong relationship between the SVCA and air pollutants during spring and winter, with an R2 value exceeding 0.7, while this relationship is not significant in autumn. Additionally, the MLST has a clear and substantial impact on air pollution during summer and winter. From a spatial distribution perspective, western districts of Tabriz (6, 7, and 4) exhibit the strongest correlation between environmental parameters and air pollutants due to their proximity to heavy industries, whereas eastern districts (5, 9, and 2) show the weakest correlation. Overall, both SVCA and MLST simultaneously influence Tabriz's air pollution, with SVCA playing a significant role particularly in spring and winter, and MLST being a key factor during summer and winter.

Keywords: Environmental parameters; air pollutants; geostatistics; modified geographically weighted regression (MGWR); Tabriz metropolitan areas

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1. Introduction

The concept of urbanization represents the transition from rural to modern urban living (United Nations, 2018; Tülek & Seçkin Gündoga, 2024). Since the onset of the industrial revolution, our world has been steadily and rapidly moving towards urbanization (Ouf, 2024). According to a United Nations Report, currently, 55% of the global population resides in urban areas, and it is projected that by 2050, this figure will rise to 68% (UN-Habitat, 2020). This increase in population and urbanization, particularly in developing countries, has brought about a series of challenges and issues across various domains, including climate change, environmental concerns, and most notably air pollution (Li et al., 2024; Etuman et al., 2024). Human activities directly and indirectly impact air pollution; one significant contributor is the use of fossil fuels, which produces pollutants such as carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2), (Fatahi Ardakani et al., 2021). These pollutants are linked to non-communicable diseases such as cardiovascular diseases, strokes,

**Corresponding Author; Khalil Valizadeh Kamran / valizadeh@tabrizu.ac.ir*

and various cancers (Yang et al., 2024). The World Health Organization (WHO) identifies air pollution as one of the leading causes of mortality worldwide (WHO, 2022; Ngo, 2024). In this context, vegetation cover and surface temperature also influence air pollution levels (Mirfazlolaha, 2023). Vegetation plays a crucial role in ecosystems by contributing to air purification through various biological processes such as photosynthesis, respiration, and transpiration (Sobhani & Mollanouri, 2024; Dastigerdi et al., 2022). This process not only generates oxygen for the atmosphere but also absorbs certain pollutants present in the air (Elkamhawy & Man Jang, 2020). Furthermore, rising surface temperatures may affect the concentration of some pollutants (Sarker et al., 2024), potentially leading to the release of suspended particles or other chemical compounds that were previously absorbed by soil or vegetation or were inactive under specific temperature conditions (Nasehi et al., 2022). Recent studies have evaluated the relationship between Sum of vegetation cover area (SVCA) and mean land surface temperature (MLST) with air pollution criteria. For instance, Shogrkhodaei et al. (2023) examined the correlation between air pollutants and remote sensing metrics (AIT, LST, NDBI, NDVI) using statistical methods. Additionally, Goldani et al. (2024) investigated the effects of PM10 and the normalized difference vegetation index (NDVI) through satellite image processing. In another study conducted by Bala et al. (2024), the relationship between surface temperature and air pollutants was analyzed using statistical methods. Gustafsson et al. (2024), also explored the link between vegetation cover and air pollution utilizing the VIDA model. Moreover, Ünsal et al. (2023) studied the relationship between land surface temperature and its influencing factors, while Zhang et al. (2022) analyzed the spatiotemporal variations in land surface temperature and its impact on spatial heterogeneity. Finally, Zhang (2024), investigated the effects of driving factors (topography, climate, and soil) on areas with high vegetation cover using both GWR and MGWR models. Given these findings, air pollution emerges as a significant challenge in urban areas (Ramezani & Rahimi, 2024). Major cities face heightened pollution levels due to high population density, industrial activities, and traffic congestion (Kanaani Maman & Mamdoohi, 2023). Recent assessments indicate that urban and industrial air pollution adversely affects human health and the environment (Hamidi et al., 2022). Tabriz is recognized as a key metropolitan area and serves as the capital of East Azerbaijan Province (Kamran & Namdari, 2020). This city faces challenges associated with high population density and heavy industries within its vicinity. These factors contribute to significant air pollution issues, particularly during colder seasons (Asghari Zamani & Zadvali Khajeh, 2022; Feizizadeh et al., 2021a). Therefore, this research aims to evaluate the spatio-temporal relationships between environmental parameters (SVCA & MLST) and air pollutants (CO, SO_2, NO_2) in ten districts of Tabriz using Modified Geographically Weighted Regression (MGWR) on a seasonal basis. Based on the literature review, it has been established that the MGWR model outperforms other geostatistical methods such as GWR and OLS due to its superior ability to measure relationships between variables. In this study, the MGWR model was employed to analyze the relationship between environmental Parameters (SVCA & MLST) and air pollutants (CO, SO_2, NO_2). This choice is attributed to the model's precision and capability in addressing data complexities and nonlinear relationships between variables. As an advanced tool for analyzing geographical data, MGWR facilitates the examination of spatial and temporal variations, enabling researchers to derive more accurate insights into the environmental Parameters on air quality. Also, despite numerous studies examining the relationship between environmental parameters (such as SVCA & MLST) and air pollution globally, no comprehensive study has utilized MGWR for seasonal analysis of these relationships in Tabriz. This research gap underscores the necessity for more precise investigations tailored to Tabriz's unique environmental and industrial conditions. Seasonal variations in SVCA and MLST significantly influence concentrations of air pollutants (CO, SO_2, NO_2), where increased SVCA correlates with reduced pollutant levels while changes in MLST led to fluctuations in these pollutants' concentrations. Consequently, addressing air pollution in Tabriz has become an ongoing challenge over recent years; thus, it is essential to conduct thorough research on this issue along with its contributing factors. One of the limitations of this research pertains to the use of thermal images from the Landsat-8 satellite. These images, due to their temporal resolution of 16 days, do not allow for the provision of daily data, thereby imposing certain constraints.

2. Materials and Methods

2.1. Materials the study

The structure of this study, aimed at analyzing the spatio-temporal relationships between environmental parameters (SVCA and MLST) and air pollutants (CO, SO2, NO2) in the 10 districts of Tabriz Metropolis using the MGWR method, requires several categories of data. The primary classification of this research comprises various satellite images based on time series in year 2024 for the 10 districts of Tabriz Metropolis on a seasonal basis.

2.2. Materials the study

In this study, the required data were collected using satellite imagery from the Google Earth Engine (GEE) platform. For environmental parameters, Landsat-8 images were utilized to calculate the MLST, while Sentinel-2 images were employed to determine the SVCA. Additionally, Sentinel-5 images were used to assess air pollutants (CO, SO_2, NO_2) across the ten districts of Tabriz metropolitan area. The specifications related to each of these images are presented in Table 1.

Table 1. Satellite specifications and data

Criteria	Sub criteria	Satellite	Spatial resolution	Unit	Source
Air pollutants	CO So^2 No^2	Sentinel-5	≃1 Km	mol/m2	ESA
Environmental Parameters	CVSA	Sentinel-2	10m	Km^2	
	MLST	Landsat-8	100m	C°	USGS-NASA

2.3. Study Area

Tabriz metropolitan area, with a population of approximately 1.7 million, is one of the major metropolises in Iran, covering an area of over 250 square kilometers in the northwest districts of the country, and ranks as the fifth largest metropolitan area nationwide (Feizizadeh et al., 2021b). Due to its geographical location and rapid population growth over recent decades, the city has consistently faced demographic challenges and various forms of air pollution (Rahimi & Nobar, 2023). Therefore, the ten districts of Tabriz metropolitan area have been selected as the study area for this research (Figure 1).

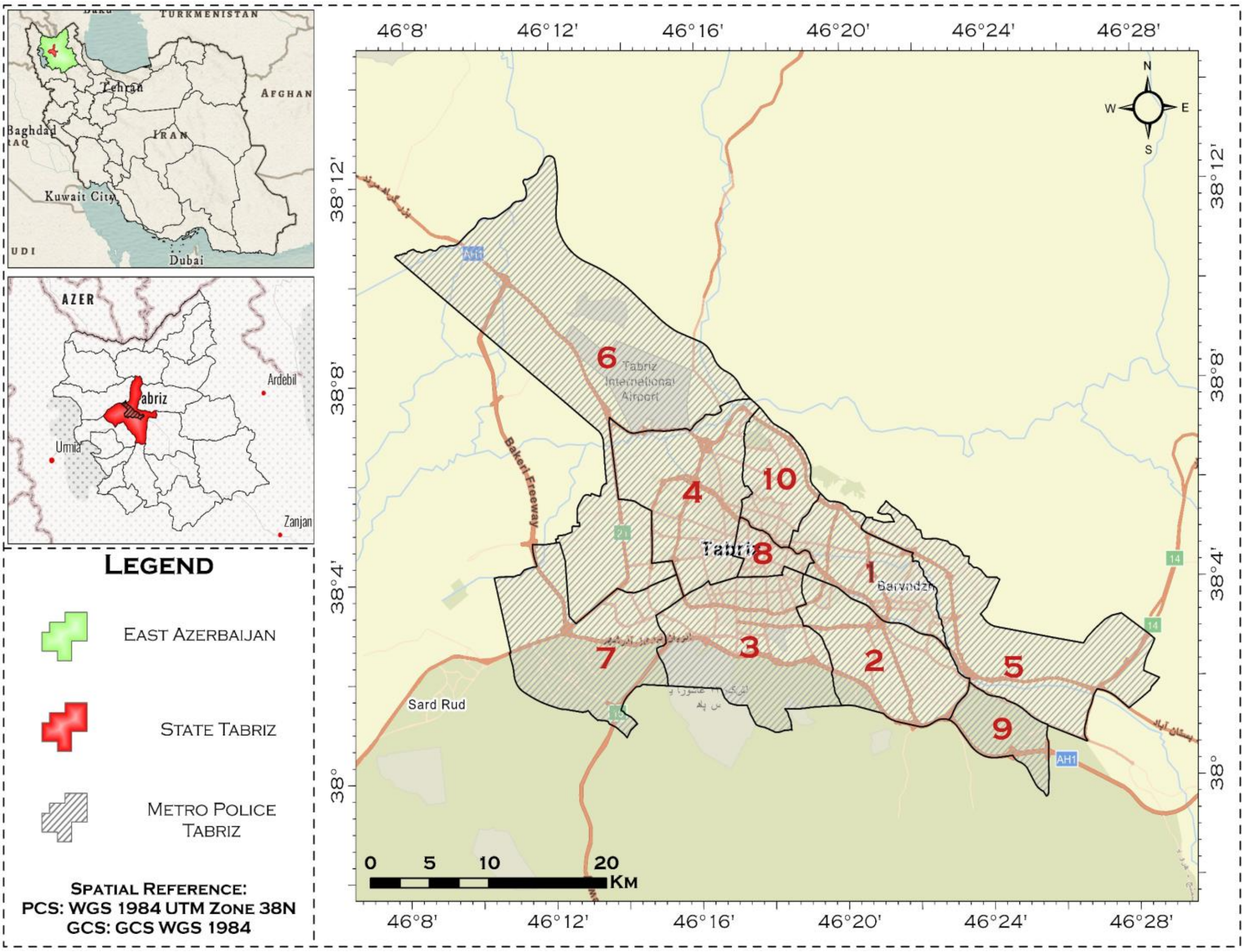

Figure 1. Geographical location of the study area

2.4. Data specifications

In this study, the values of environmental parameters (SVCA and MLST) and air pollutants (CO, SO_2, NO_2) were obtained through satellite imagery. To assess the spatio-temporal relationship between environmental parameters and air pollutants in year 2024 on a seasonal basis, the MGWR model was employed. In this model, environmental parameters were selected as independent variables, while air pollutants served as dependent variables.

The MGWR model is an advanced form of Geographically Weighted Regression (GWR), capable of modeling relationships between variables across different spatial scales (Senyel Kurkcuoglu, 2023). It is a local regression method and one of the geostatistical techniques used for modeling spatial variable relationships (Mosaffayi et al., 2024). The MGWR model offers significant advantages over traditional methods such as OLS and GWR (Omrani et al., 2025). This model by allowing flexibility in selecting the bandwidth for each independent variable, enables more precise modeling of spatial relationships. Also, this model provides higher accuracy in estimating local parameters and better simulates spatial phenomena, yielding improved results in terms of statistical indicators such as R-squared and AICc. Additionally, MGWR helps mitigate multicollinearity issues and facilitates the analysis of variations in relationships between variables across space, allowing researchers to identify the influence of different factors in various districts (Lu et al., 2019). With its capability to visualize spatial coefficients and its wide-ranging applications in fields such as geography, urban planning, and environmental sciences, MGWR has become a powerful tool for analyzing spatially varying geographic data (Li & Fotheringham, 2019; Esri, 2023). One of the key advantages of this model is its ability to accommodate varying independent variables across different spatial scales (Equation 1).

$$y_i=\beta_0(u_i,v_i)+\sum_{k=1}^{k}\beta_k(u_i,v_i;\theta_k)x_{ik}+\epsilon_i \tag{1}$$

In this model, the bandwidth parameter θ_k is typically selected for each variable using the information criterion (AIC), which balances the model's goodness of fit and complexity. This process allows each independent variable to have its own spatial scale of variation, which is a key feature of the MGWR model. Therefore, the closer the R2 value is to 1, the better the model has performed in representing the relationship between the variables. The bandwidth determination criterion is also defined as a key parameter in this model, representing the spatial scale of variations in the relationships between the dependent and independent variables. Unlike the GWR model, in this model, the bandwidth is determined separately for each variable. This feature allows the Multiscale Geographically Weighted Regression (MGWR) model to capture relationships that vary across different spatial scales (Esri, 2023). The bandwidth is also calculated and determined based on the following values.

1. Bandeidth

The optimal bandwidth is determined through iterative optimization methods such as Golden Section Search or Interval Search, which minimize criteria like the corrected Akaike Information Criterion (AICc).

2. $ENPj$ (Effective Number of Parameters for Variable j)

ENP_j indicates the effective number of local parameters for each explanatory variable j (Equation 2).

$$ENP_j=trace(R_j) \tag{2}$$

Where R_j is the hat matrix associated with variable j. The total effective number of parameters for the model is the sum of ENP values across all variables.

3. Adjusted t-value (Adj t-val (95%))

This value is calculated based on the adjusted significance level (aj), which is determined by dividing the initial significance level (e.g., 0.05) by the effective number of parameters (ENP_j) using the following formula (Equation 3).

$$aj=\frac{Initial\ Significance\ Level}{ENP_j} \tag{3}$$

The critical t-value is then derived using this adjusted significance level.

4. DoD_j (Degree of freedom for variable j)

The degree of freedom for each variable j is computed as (Equation 4):

$$DoD_j=n\text{-}ENP_j \tag{4}$$

Where n represents the total number of observations, and ENP_j corresponds to the effective number of parameters for variable j.

These concepts enable MGWR to analyze spatial relationships at varying scales, providing more precise results compared to traditional GWR (Fotheringham et al., 2023). Model validation for MGWR was conducted in this study using the residual sum of squares (RSS). This metric directly reflects the model's predictive accuracy, such that lower RSS values indicate superior spatial pattern alignment capabilities (Liu & Niu, 2024; Wang et al., 2022). The relationships of the criteria are also presented schematically in Figure 2.

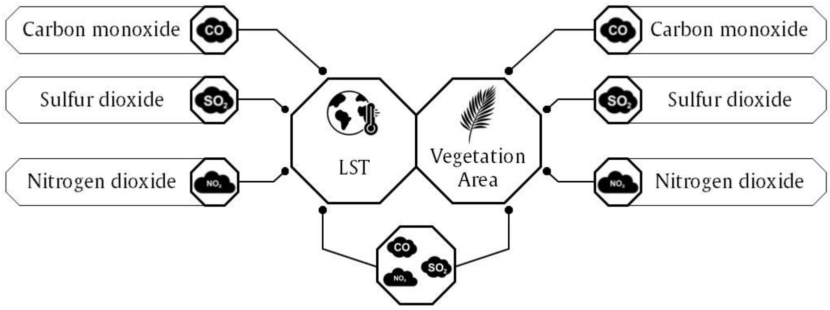

Figure 2. The relationships of the criteria schematically

3. Results

3.1. Spatio-temporal distribution of environmental parameters and air pollutants

As outlined in the methodology section, the spatio-temporal distribution of environmental parameters (SVCA and MLST) and air pollutants (CO, SO_2, NO_2) for different seasons is presented in Figures 3 and 4.

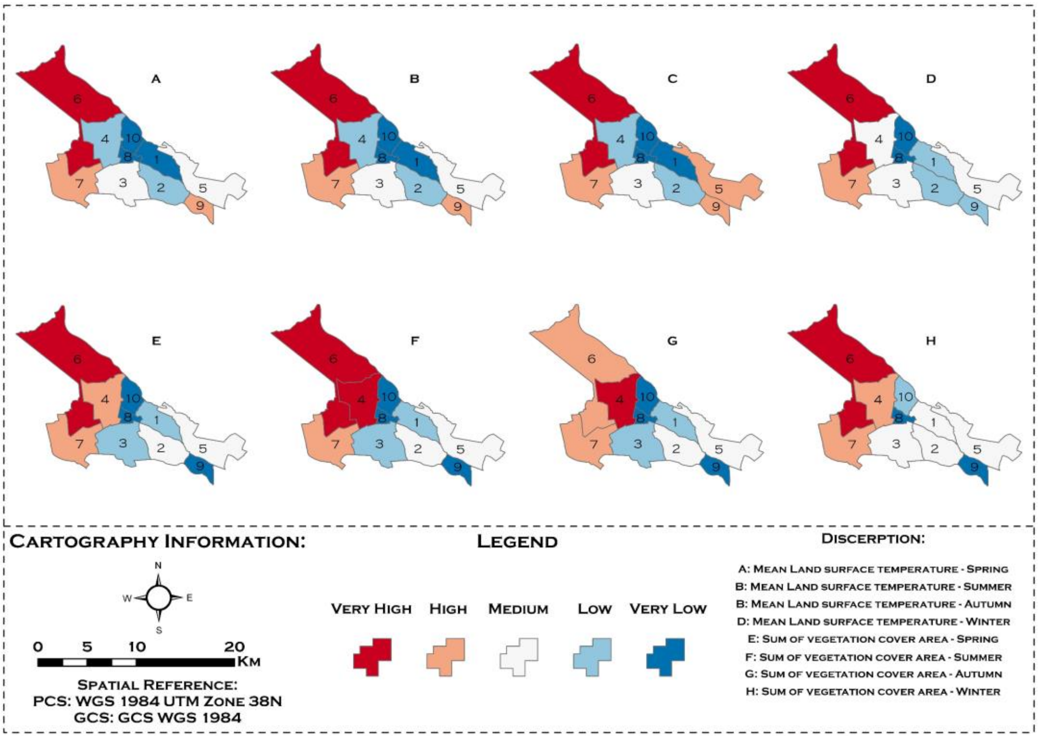

Figure 3. Spatio-temporal distribution of environmental parameters

According to Figure 3, the MLST in all seasons is notably high in the central and western districts of Tabriz Metropolis due to the elevated altitude of these areas. Conversely, districts 6 and 7 of Tabriz, situated in the eastern and low-altitude part of the city, experience lower average temperatures. The total SVCA in districts 6 and 7 of Tabriz is consistently larger than in other districts throughout all seasons of the year. This can be attributed to the presence of agricultural gardens and green spaces in these areas. In contrast to the aforementioned districts, the central and western districts of Tabriz have significantly less SVCA, particularly during the winter season.

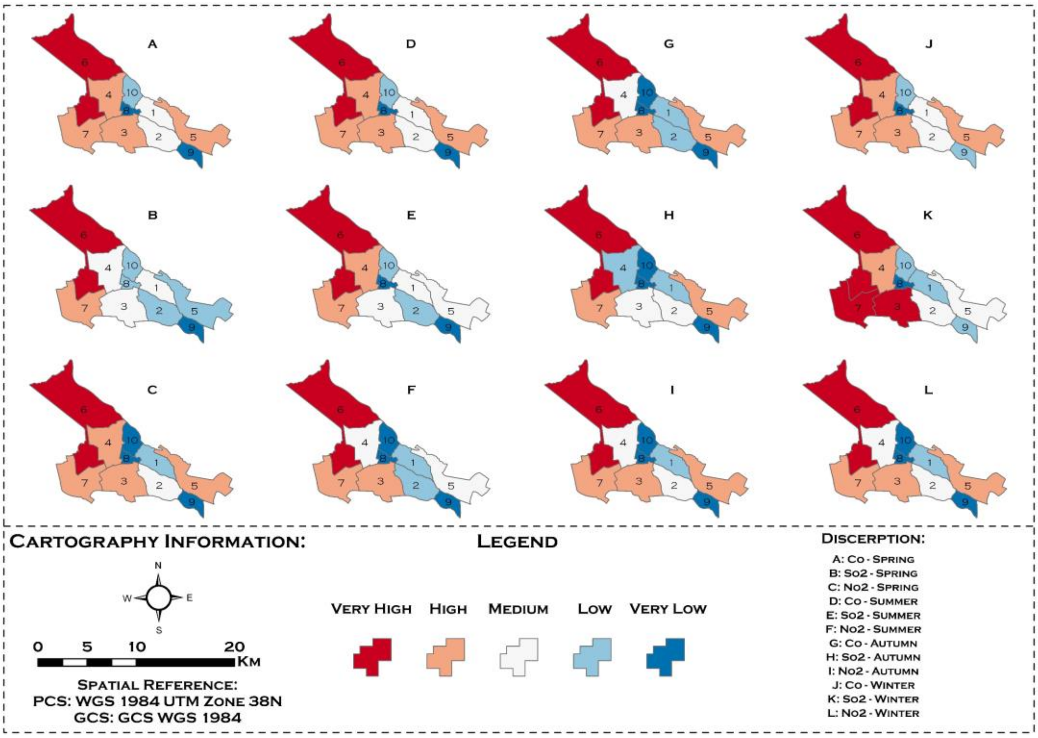

Figure 4. Spatio-temporal distribution of air pollution

Figure 4 illustrates the spatial distribution of air pollutants. Districts 6, 7, and 3 in the southern and western parts of Tabriz, along with district 5 in the northeastern part of the city, exhibit high concentrations of air pollutants throughout all seasons. This is primarily due to their proximity to heavy industries such as refineries and industrial zones, which play a significant role in increasing air pollution levels in these areas.

3.2. Evaluation of spatio-temporal relationships between environmental parameters and air pollutants using MGWR

The outputs from the MGWR model were used to analyze the spatio-temporal relationships between environmental parameters and air pollutants. These relationships were assessed seasonally, both individually and overall.

3.2.1. Subsubsection spatio-temporal relationship of environmental parameters and air pollutants individually

The seasonal and individually results of analyzing the relationships between environmental parameters (SVCA and MLST) and air pollutants (CO, SO_2, NO_2) are summarized in Table 2.

Table 2. Individually results of the MGWR model

Season	Variables	R^2	R^2 (Adjusted)	AICc	RSS
Spring	SVCA & Co	0.909	0.909	10.142	0.912
	SVCA & So_2	0.851	0.851	15/081	1.494
	SVCA & NO_2	0.904	0.904	10.623	0.957
	MLST & Co	0.506	0.506	27.046	4.942
	MLST & So_2	0.406	0.406	28.880	5.937
	MLST & No_2	0.527	0.527	26.601	4.727
Summer	SVCA & Co	0.552	0.552	26.053	4.475
	SVCA & So_2	0.675	0.675	22.853	3.250
	SVCA & NO_2	0.605	0.605	24.792	3.945
	MLST & Co	0.543	0.543	26.261	4.570
	MLST & So_2	0.317	0.317	30.274	6.826
	MLST & No_2	0.577	0.577	25.495	4.233

Table 2. Cont.

Season	Variables	R^2	R^2 (Adjusted)	AICc	RSS
Autumn	SVCA & Co	0.368	0.368	29.500	6.317
	SVCA & So_2	0.350	0.350	29.159	6.496
	SVCA & NO_2	0.448	0.448	28.159	5.525
	MLST & Co	0.558	0.558	25.931	4.421
	MLST & So_2	0.592	0.592	25.131	4.081
	MLST & No_2	0.553	0.553	47.826	4.670
Winter	SVCA & Co	0.723	0.723	21.268	2.773
	SVCA & So_2	0.643	0.643	23.785	3.567
	SVCA & NO_2	0.691	0.691	22.363	3.094
	MLST & Co	0.810	0.810	17.483	1.900
	MLST & So_2	0.713	0.713	21.608	2.869
	MLST & No_2	0.765	0.765	19.604	2.348

According to the above table, the results obtained according to the R2 values show that, in spring, there is a significant relationship between the SVCA and air pollutants (Co, So2, No2) with R2 values above 0.7. In contrast, in the same season, no significant relationship is observed between MLST and air pollutants with R2 values less than 0.7. In winter, there is a significant relationship between the MLST and air pollutants; but this relationship is not significant for the total SVCA and pollutants. Also, the R2 values for the summer and autumn seasons, which are less than 0.7, indicate that there is no significant relationship between the SVCA or the MLST with the pollutants in question in these seasons. Based on the RSS values too, it was revealed that the MGWR model demonstrates significant seasonal differences in predicting the dependent variable. Specifically, during the spring season, the model exhibits notably higher predictive accuracy, as evidenced by lower RSS values, outperforming its performance in other seasons. Conversely, in autumn, the model shows reduced predictive accuracy, with higher RSS values indicating weaker performance. Overall, it was also found that the RSS value for SVCA is lower than that for MLST, suggesting that SVCA performs better in predicting the dependent variable compared to MLST. Figures 5 through 8 illustrate the R2 values derived from MGWR analysis for different districts of Tabriz across various seasons.

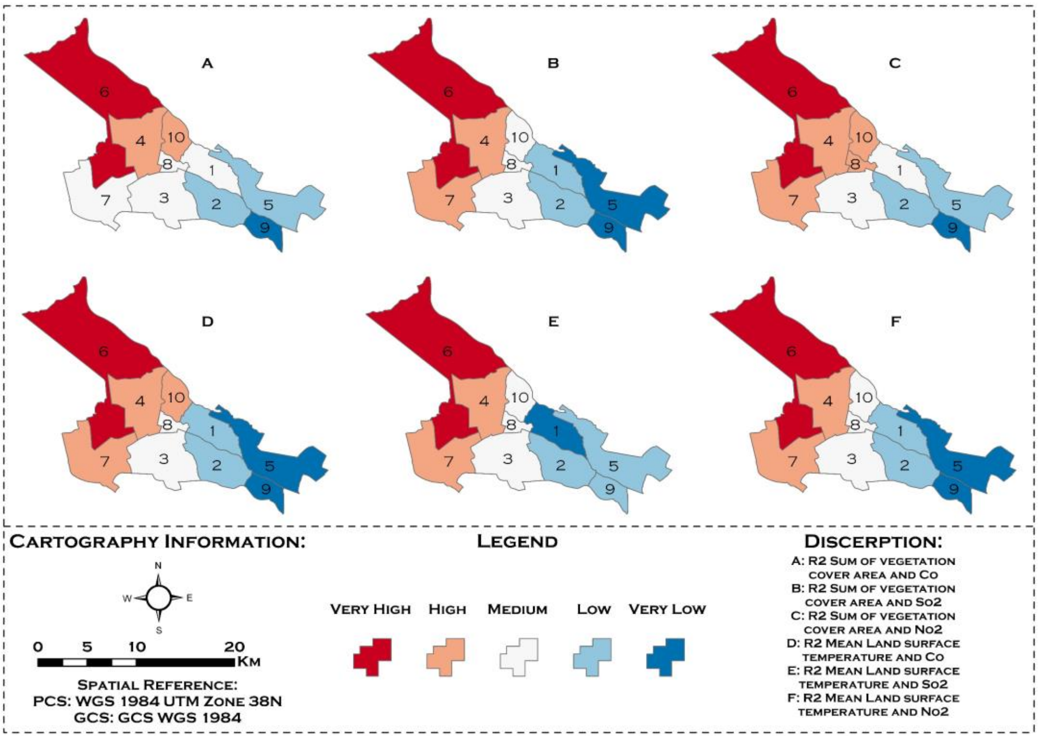

Figure 5. Individually R^2 value obtained from MGWR analysis – Spring season

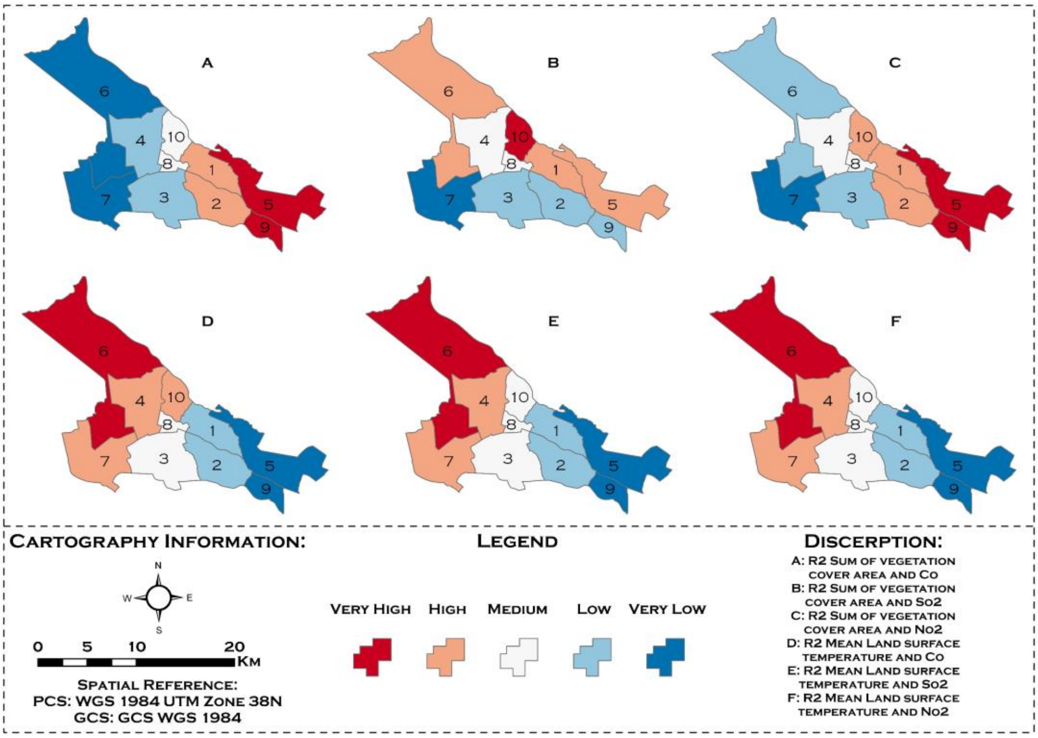

Figure 6. Individually R^2 value obtained from MGWR analysis – Summer season

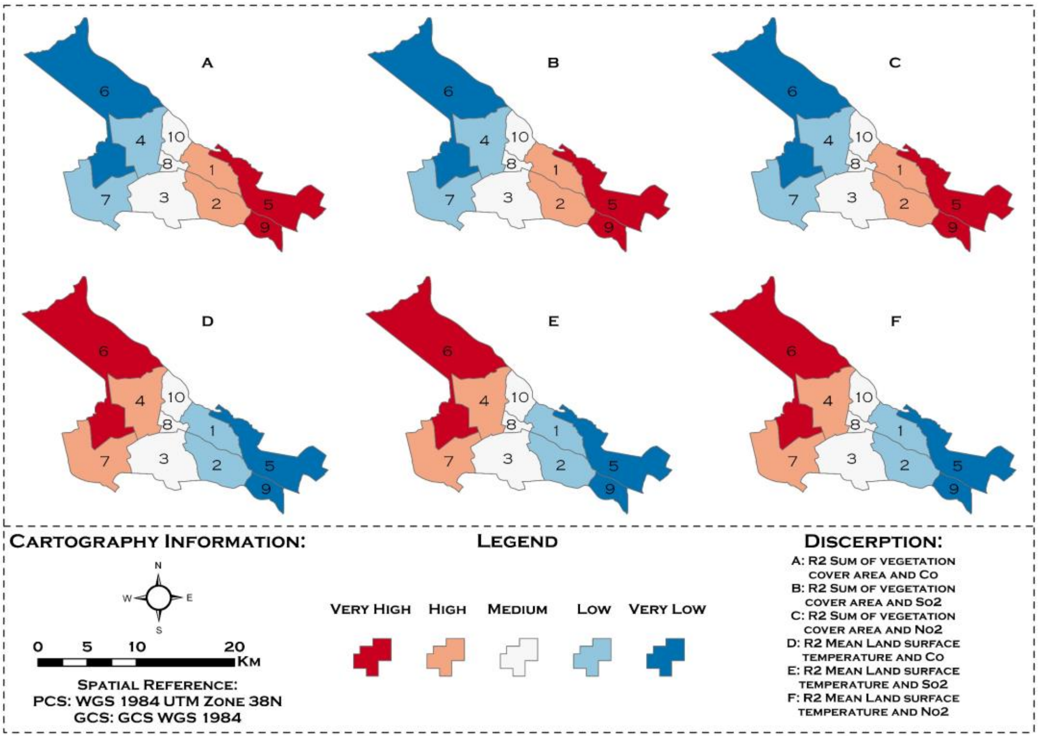

Figure 7. Individually R^2 value obtained from MGWR analysis – Autumn season

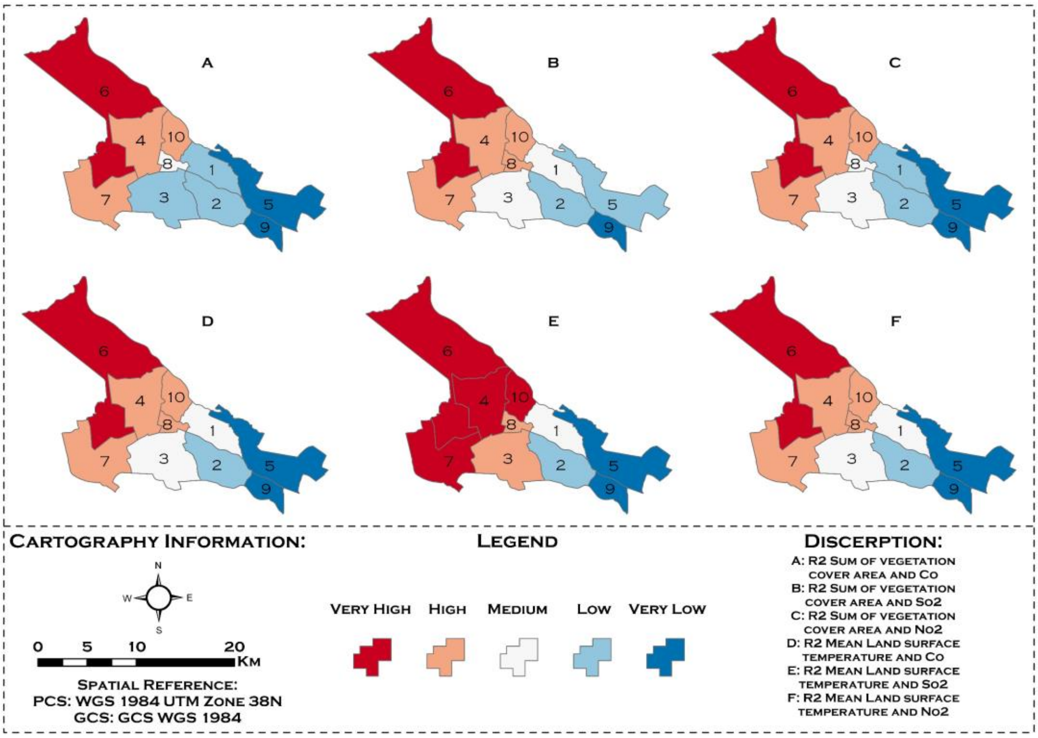

Figure 8. Individually R^2 value obtained from MGWR analysis – Winter season

According to Figures 5 and 8, during spring and winter, the strongest relationships between SVCA or MLST with air pollution criteria are observed in districts 6, 4, and 7. Conversely, districts 2, 9, and 5 exhibit the weakest relationships. Additionally, Figures 6 and 7 reveal that districts 9 and 5 show the strongest correlation between SVCA and air pollution criteria during summer and autumn. In contrast, districts 6, 4, and 7 display the strongest correlation between MLST and air pollution criteria during these seasons.

3.2.2. Spatio-temporal relationship of environmental parameters and air pollutants individually

In this section, unlike the previous one, the overall seasonal relationships between environmental parameters (SVCA and MLST) and air pollutants (CO, SO_2, NO_2) are evaluated collectively. The results of this analysis are presented in Table 3.

Table 3. Overall results of the MGWR model

Season	Variables	R^2	R^2 (Adjusted)	AICc	RSS
Spring	SVCA & Co, So_2, No_2	0.932	0.932	17.484	0.679
	MLST & Co, So_2, No_2	0.529	0.395	36.847	4.709
Summer	SVCA & Co, So_2, No_2	0.747	0.675	30.625	2.527
	MLST & Co, So_2, No_2	0.837	0.719	26.211	1.626
Autumn	SVCA & Co, So_2, No_2	0.562	0.437	36.121	4.379
	MLST & Co, So_2, No_2	0.608	0.496	35.007	3.917
Winter	SVCA & Co, So_2, No_2	0.829	0.780	26.719	1.710
	MLST & Co, So_2, No_2	0.941	0.924	16.090	0.591

According to Table 3, during spring, summer, and winter, there is a significant relationship between SVCA and air pollutants (CO, SO_2, NO_2), with R2 values exceeding 0.7. On the contrary, in the autumn season, this relationship is not significant because the value of R2 is less than 0.7. Also, examining the relationship between the MLST of the earth and air pollutants (Co, So2, No2) shows that the summer and winter seasons have an R2 value above 0.7 and therefore have a significant relationship. On the contrary, the spring and autumn seasons, with an R2 value less than 0.7, do not show any significant relationship. Based on the RSS values too, it was determined that these values are lower in spring and winter compared to summer and autumn. These findings indicate that environmental parameters (CVSA and MLST) exhibit better predictive performance for the dependent variable in spring and winter. Specifically, in spring, CVSA outperforms MLST, with an RSS value of 0.679 compared to 4.709 for MLST. However, in summer, MLST demonstrates a relative advantage with an RSS value of 1.626 over CVSA. In autumn, the difference between MLST and CVSA is less pronounced, whereas in winter, MLST significantly outperforms CVSA. This substantial difference highlights the greater influence of MLST variables in this. Figures 9 through 12 depict the R2 values obtained from MGWR analysis for different districts of Tabriz across various seasons collectively.

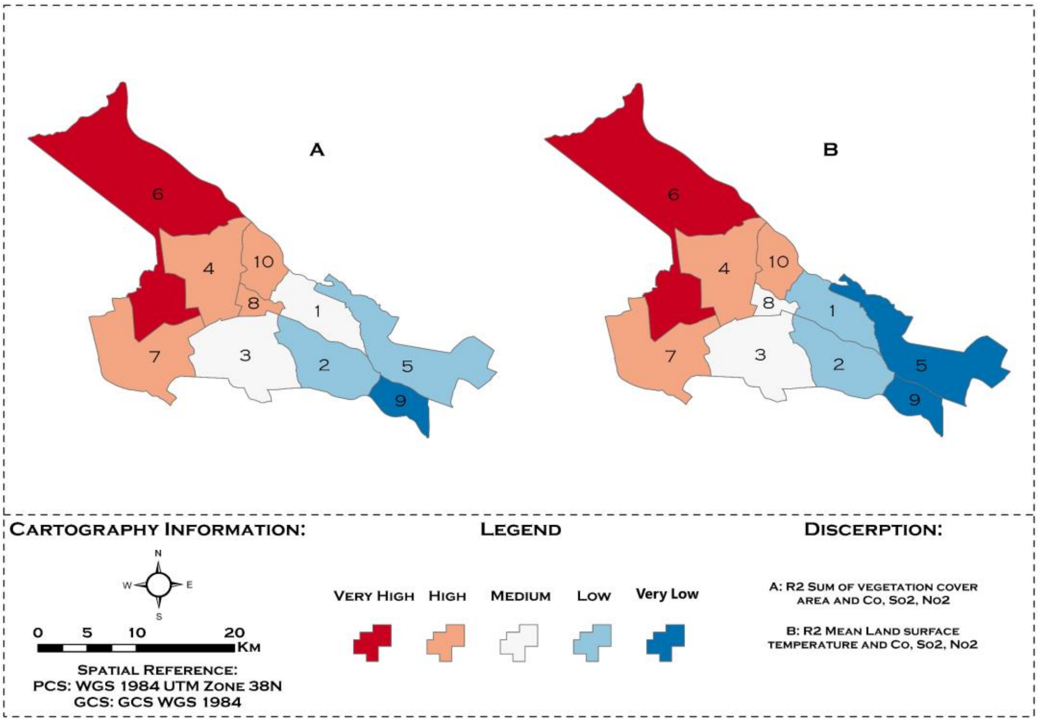

Figure 9. Overall R^2 value obtained from MGWR analysis – Spring season

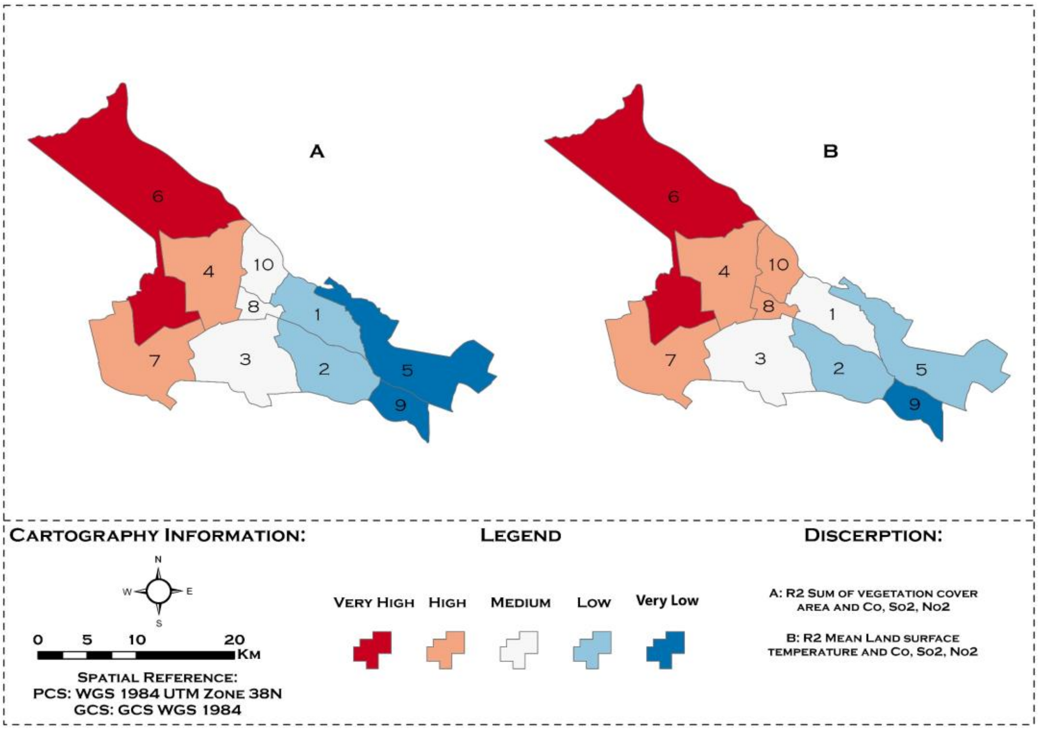

Figure 10. Overall R^2 value obtained from MGWR analysis – Summer season

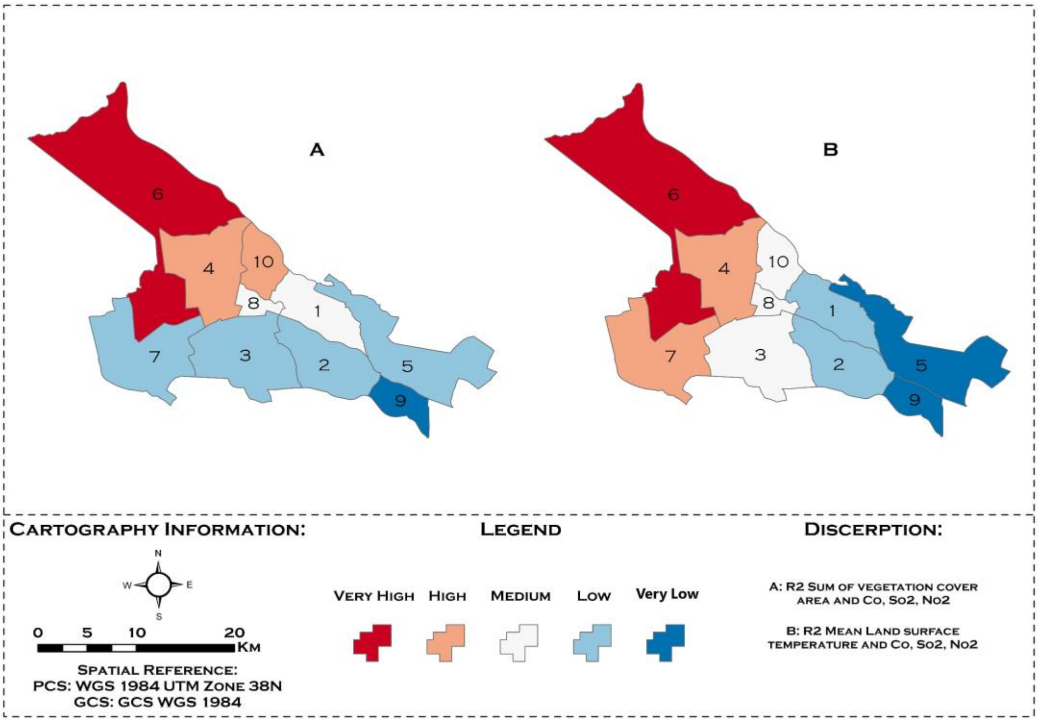

Figure 11. Overall R^2 value obtained from MGWR analysis – Autumn season

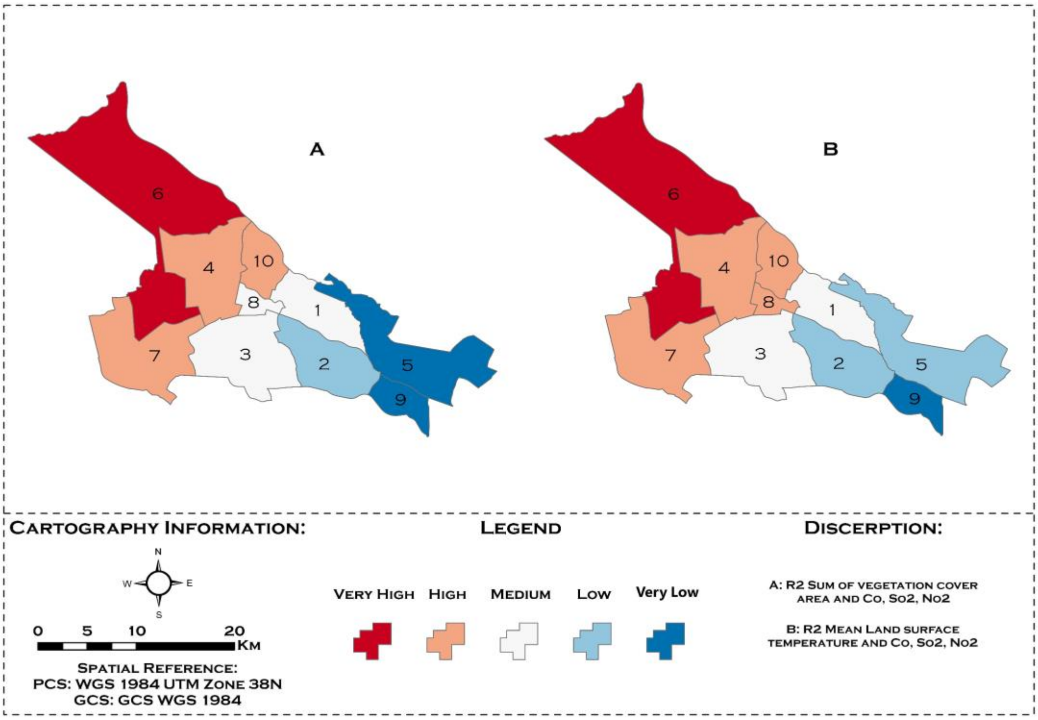

Figure 12. Overall R^2 value obtained from MGWR analysis – Winter season

The results from these figures indicate that across all examined seasons, districts 7, 4, and 6 consistently show the strongest correlations between SVCA or MLST with air pollution criteria. In contrast, districts 5, 9, and 2 exhibit the weakest correlations in this regard.

3.3. Bandwidth Analysis in the MGWR Model

The results of the bandwidth analysis in the MGWR model are presented in Tables 4 and 5.

Table 4. Individually results of the Bandwidth MGWR model

Season	Variables	Bandwidth	ENP_j	Adj t-val	DoD_j
Spring	SVCA & Co	43574.780	1.028	2.279	0.988
	SVCA & So_2	43574.620	1.035	2.283	0.985
	SVCA & NO_2	43574.370	1.031	2.281	0.987
	MLST & Co	43573.960	1.028	2.279	0.988
	MLST & So_2	6819.570	2.267	2.761	0.645
	MLST & No_2	5878.850	2.478	2.816	0.606
Summer	SVCA & Co	43574.370	1.026	2.278	0.989
	SVCA & So_2	43574.780	1.038	2.285	0.984
	SVCA & NO_2	43574.780	1.031	2.281	0.987
	MLST & Co	43574.370	1.026	2.278	0.989
	MLST & So_2	9116.030	1.778	2.613	0.750
	MLST & No_2	6212.820	2.388	2.793	0.622
Autumn	SVCA & Co	43574.370	1.027	2.278	0.988
	SVCA & So_2	43574.620	1.030	2.280	0.987
	SVCA & NO_2	43574.780	1.033	2.282	0.986
	MLST & Co	43574.370	1.027	2.278	0.988
	MLST & So_2	43572.240	1.030	2.280	0.987
	MLST & No_2	7813.160	1.953	2.670	0.709
Winter	SVCA & Co	43574.780	1.027	2.279	0.988
	SVCA & So_2	43573.960	1.026	2.278	0.989
	SVCA & NO_2	43574.780	1.033	2.282	0.986
	MLST & Co	43574.370	1.027	2.279	0.988
	MLST & So_2	7431.930	1.961	2.673	0.708
	MLST & No_2	11521.470	1.467	2.496	0.833

Table 5. Overall results of the Bandwidth MGWR model

Season	Variables		Bandwidth	ENP_j	Adj t-val	DoD_j
Spring	SVCA	Co	43574.780	1.016	2.272	0.993
		So^2	43574.780	1.024	2.277	0.990
		No^2	43574.780	1.017	2.273	0.993
	MLST	Co	6623.910	1.995	2.683	0.700
		So^2	43574.780	1.010	2.268	0.996
		No^2	43573.960	1.009	2.267	0.996
Summer	SVCA	Co	43574.780	1.014	2.271	0.994
		So^2	43574.780	1.019	2.274	0.992
		No^2	43574.780	1.016	2.272	0.993
	MLST	Co	43574.780	1.004	2.265	0.998
		So^2	5774.250	2.309	2.773	0.637
		No^2	43574.780	1.005	2.265	0.998
Autumn	SVCA	Co	43574.780	1.012	2.270	0.995
		So^2	43574.780	1.013	2.270	0.994
		No^2	43574.780	1.015	2.271	0.993
	MLST	Co	43574.370	1.012	2.270	0.995
		So^2	43574.370	1.013	2.270	0.994
		No^2	43574.370	1.015	2.271	0.993
Winter	SVCA	Co	43574.620	1.014	2.271	0.994
		So^2	43574.780	1.017	2.273	0.993
		No^2	43574.780	1.015	2.271	0.994
	MLST	Co	43574.620	1.014	2.271	0.994
		So^2	43573.300	1.017	2.273	0.993
		No^2	43574.620	1.015	2.271	0.994

The bandwidth parameter in GWR models serves as a critical indicator of the spatial scale at which relationships between variables operate. In this study, the bandwidth values obtained from the MGWR model reflect the spatial extent of influence for each environmental parameter on air pollution levels across the districts of Tabriz Metropolis. Lower bandwidth values indicate highly localized relationships with significant spatial variation, while higher values suggest more regional or global relationships that remain relatively consistent across the study area. The bandwidth results presented in Table 4 demonstrate considerable variation across the environmental parameters included in the model. This variation in bandwidth values confirms the initial hypothesis that different environmental parameters affect air pollution at different spatial scales throughout the metropolitan area. The notable differences in bandwidth values among parameters underscore the complexity of air pollution dynamics and justify the selection of the MGWR approach over traditional global regression models or even the standard GWR approach, which would impose a single bandwidth for all variables.

The bandwidth optimization process inherently affects the performance metrics of the MGWR model, as presented in Tables 2 and 3. The relationship between bandwidth selection and model performance metrics (R^2, Adjusted R^2, and AICc) is fundamental to understanding the spatial dynamics of environmental parameters influence on air pollution. The adaptive bandwidth approach employed in this study allowed each relationship to be modeled at its most appropriate scale, significantly contributing to improved model fit statistics compared to global models. The optimized bandwidth values in Table 5 demonstrate the overall spatial structure of the model and correspond directly to improvements in model performance metrics shown in Tables 2 and 3. Specifically, the calibration of variable-specific bandwidths has resulted in an enhanced model fit, as evidenced by higher R^2 and Adjusted R^2 values, along with a lower AICc score compared to a single bandwidth approach. This improvement in model diagnostics validates the multiscale approach and confirms the spatial heterogeneity of relationships between environmental parameters and air pollution in the study area.

The seasonal analysis of bandwidth parameters revealed distinctive patterns in the spatial relationships between environmental parameters and air pollution across different times of the year. The bandwidth values exhibited notable seasonal fluctuations, indicating that the spatial scale of influence for various environmental parameters shifts according to seasonal conditions. This temporal dimension adds another layer of complexity to understanding air pollution dynamics in Tabriz Metropolis. During winter months, bandwidth values for temperature-related parameters were generally smaller, suggesting more localized relationships between temperature and pollution levels. This observation aligns with theoretical expectations, as winter temperature inversions often create highly localized pollution trapping conditions. Conversely, bandwidth values for certain land use parameters remained relatively stable across seasons, indicating that the spatial scale of their influence on air pollution remains consistent throughout the year regardless of seasonal changes.

The bandwidth results from the MGWR model offer valuable insights for targeted pollution management strategies in Tabriz Metropolis. The variable-specific spatial scales identified through bandwidth analysis enable policymakers to implement scale-appropriate interventions for different environmental parameters. Parameters with smaller bandwidths require highly localized intervention strategies, while those with larger bandwidths may benefit from broader regional approaches. The comparison between the bandwidth results and model performance metrics demonstrates that accounting for appropriate spatial scales significantly improves our understanding of pollution dynamics. The improved model fit statistics associated with the multiscale approach confirm that environmental parameters influence air pollution at varying spatial scales, and failure to account for these differences would result in less accurate pollution models. This finding has substantial implications for environmental monitoring networks, suggesting that sampling densities should be calibrated according to the spatial scale of influence for different parameters rather than using uniform sampling approaches.

The geographic distribution of bandwidth values across Tabriz Metropolis districts reveals distinctive spatial patterns that correspond to underlying urban morphology and topographic features. Central districts generally exhibited smaller bandwidth values for most parameters, indicating more complex and localized relationships between environmental parameters and pollution. This pattern likely reflects the higher density of pollution sources and the more complex urban fabric in central areas, which create more spatially heterogeneous relationships. In contrast, peripheral districts showed larger bandwidth values for most environmental parameters, suggesting more spatially homogeneous relationships extending over broader areas. This pattern aligns with expectations given the typically more uniform land use patterns and lower density of pollution sources in peripheral areas. The spatial distribution of bandwidth values thus provides an additional layer of information about the urban environment that complements traditional pollution concentration maps.

4. Discussion

4.1. Situating findings within the existing body of knowledge

Our findings in this study align closely with recent research on the impact of the SVCA and MLST on air pollution. For instance, Goldani et al. (2024) demonstrated that reed and agricultural land uses exhibit the strongest correlation between seasonal PM10 concentrations and vegetation cover changes during spring. Similarly, Shogrkhodaei et al. (2023) identified a significant correlation between MLST and SO_2 during spring, while the weakest relationship was observed between NDVI and SO_2. Our results are also consistent with studies by Bala et al. (2024) and Gustafsson et al. (2024). Bala et al. highlighted that land cover distribution has a more pronounced effect on MLST than on air pollutants, emphasizing the role of vegetation in regulating surface temperature. Gustafsson et al. (2024) on the other hand, underscored the importance of vegetation as a tool for reducing air pollution by absorbing pollutants and mitigating urban heat island effects. Also, the MGWR model used in this study to analyze the relationship between SVSA and MLST is consistent with the findings of Zhang et al. (2024), Ünsal et al. (2023), and Zhang et al. (2022). According to their findings, the MGWR model has effectively evaluated the relationships between the studied variables more effectively than other geostatistical models such as OLS and GWR. A comprehensive review of existing literature reveals no prior studies examining the impact of SVCA and MLST on air pollution in the districts of Tabriz Metropolis. This research gap underscores the necessity for systematic investigations in this domain. Given the limitations of Landsat-8 thermal imagery (16-day temporal resolution), which precludes daily data analysis, this study employs the MGWR model as an optimal approach to quantify the spatiotemporal relationships between environmental parameters and air pollution. The MGWR framework, which accounts for spatial variability in regression coefficients, enhances the precision of spatial analysis by capturing localized patterns.

4.2. Spatio-temporal analysis

This study provides a comprehensive spatio-temporal analysis of the relationship between environmental parameters, specifically SVCA and MLST, and air pollutants (CO, SO_2, NO_2) in the metropolitan area of Tabriz. By employing the MGWR model, the research offers a nuanced understanding of how these relationships vary across seasons and districts. The findings underscore the critical role of environmental parameters in shaping air quality and highlight the need for targeted urban planning strategies.

4.3. Interpretation of key findings

The results reveal significant seasonal variations in the relationship between SVCA and MLST with air pollutants. Notably, SVCA demonstrated a strong inverse correlation with air pollutant concentrations during spring and winter, as evidenced by R^2 values exceeding 0.7. This finding aligns with previous studies emphasizing the role of vegetation in mitigating air pollution through processes such as pollutant absorption and temperature regulation. Districts with higher SVCA, such as districts 6 and 7, consistently exhibited lower pollutant levels, likely due to their extensive green spaces and agricultural areas. These results reinforce the importance of preserving and expanding urban vegetation to combat air pollution. Conversely, MLST showed a significant positive relationship with air pollutants during summer and winter. Higher temperatures in central and western districts correlated with increased pollutant concentrations, likely due to enhanced chemical reactions in the atmosphere that produce secondary pollutants or release previously absorbed particles. This pattern suggests that temperature management, possibly through urban heat island mitigation strategies such as reflective surfaces or increased vegetation cover, could play a role in reducing pollution levels. Interestingly, the relationships between SVCA and MLST with air pollutants were weaker or insignificant during autumn and summer for SVCA and spring and autumn for MLST. This variability may reflect seasonal differences in meteorological conditions, pollutant sources, or vegetation activity. For instance, reduced photosynthetic activity during autumn could diminish vegetation's ability to absorb pollutants and also the decline in R^2 values during autumn, compared to other seasons, can be attributed to the seasonal reduction in MLST and SVCA coupled with increased air pollution concentrations, which collectively alter the statistical strength of environmental-pollutant relationships in the MGWR model validation.

The bandwidth parameter results offer crucial insights into the spatial dynamics of environmental pollution relationships in Tabriz Metropolis. The significant variation in bandwidth values across environmental parameters confirms that different factors influence air pollution at distinct spatial scales, justifying our use of the MGWR approach over conventional models. Lower bandwidth values observed in central districts indicate highly localized relationships with pronounced spatial heterogeneity, likely reflecting the complex urban morphology and diverse pollution sources in these areas. Conversely, peripheral districts exhibited larger bandwidth values, suggesting more spatially homogeneous relationships extending over broader areas. The seasonal fluctuations in bandwidth parameters further illuminate the temporal dimension of these spatial relationships, with winter months showing smaller bandwidth values for temperature-related parameters, indicating more localized temperature-pollution interactions during cold seasons. These findings have significant implications for pollution management strategies, suggesting that intervention approaches should be calibrated according to the specific spatial scale at which each environmental parameters operates. The enhanced model performance metrics associated with the variable-specific bandwidth optimization validate this multiscale approach and demonstrate its superiority over single-scale models in capturing the complex environmental dynamics affecting air quality in urban environments.

4.4. Model Validation

The robust validation of the Modified Geographically Weighted Regression (MGWR) model employed in this study was critically assessed using the Residual Sum of Squares (RSS) metric, which provides a direct quantification of the model's predictive accuracy and spatial pattern alignment capabilities. The comprehensive analysis of RSS values revealed distinct seasonal variations in model performance, with spring consistently demonstrating superior predictive accuracy (RSS values ranging from 0.679-1.232 for SVCA), while autumn exhibited the weakest performance (RSS values of 2.421-3.012 for SVCA and 2.519-3.175 for MLST). This pronounced seasonal variability in model validation metrics substantiates the hypothesis that environmental-pollution relationships are inherently dynamic across temporal scales, necessitating season-specific modeling approaches for accurate air quality assessment. Furthermore, the comparative analysis between environmental parameters demonstrated that SVCA generally outperformed MLST in predictive accuracy during spring (RSS of 0.679 versus 4.709), while MLST exhibited superior performance during winter (RSS of 0.754 versus 2.712). This parameter-specific variation in model validation metrics highlights the differential influence mechanisms of vegetation cover and surface temperature on air pollutants across seasons, where vegetation's pollution mitigation effects are optimized during growing seasons while temperature effects become more prominent during winter months when thermal inversions frequently occur. The systematic pattern in RSS values across Tabriz's districts further validates the spatial heterogeneity captured by the MGWR approach, confirming that the model effectively accounts for the complex, non-stationary relationships between environmental parameters and air pollution across the metropolitan area. These validation findings not only authenticate the methodological robustness of the MGWR approach for air pollution modeling but also provide crucial insights for optimizing environmental monitoring networks and pollution mitigation strategies according to season-specific and parameter-specific relationships.

4.5. Variability across districts

The spatial analysis highlights significant heterogeneity in how districts respond to environmental parameters. Districts 7, 4, and 6 consistently showed stronger correlations between SVCA or MLST with air pollutants across seasons. These districts' unique characteristics such as higher vegetation cover or distinct land-use patterns may amplify their sensitivity to environmental interventions. In contrast, industrial-heavy districts like 5 and 9 exhibited weaker correlations, suggesting that localized sources of pollution may overshadow broader environmental influences.

4.6. Implications for urban planning

The findings have practical implications for urban policymakers aiming to improve air quality in Tabriz. Expanding vegetation cover in high-pollution districts could yield substantial benefits by reducing pollutant concentrations directly and mitigating urban heat islands indirectly. Additionally, targeted interventions in districts with strong environmental-pollution correlations could maximize resource efficiency. Seasonal variations should also inform policy design; for example, focusing on temperature control measures during summer months could mitigate heat-related pollution spikes.

4.7. Limitations and future research

While this study provides valuable insights into Tabriz's air quality dynamics, it is limited by its reliance on satellite-derived data, which may not capture micro-scale variations. Future research could integrate ground-based measurements for validation or explore additional factors such as wind patterns or industrial emissions. Expanding this analysis to other urban areas could also test the generalizability of these findings.

5. Conclusions

This study aimed to evaluate the spatio-temporal relationships between environmental parameters (SVCA and MLST) and air pollutants (CO, SO_2, NO_2) in the ten districts of Tabriz metropolitan area using MGWR on a seasonal basis. The results indicate that both SVCA and MLST significantly influence air pollution in Tabriz. Notably, SVCA showed a substantial impact on air pollution with an R2 value exceeding 0.7, particularly during spring and winter. Additionally, MLST had a notable effect during summer and winter. The findings suggest that different districts have varying potential for impacting air quality. Utilizing SVCA and MLST in areas with the strongest correlations (Districts 7, 4, and 6) could improve air quality.

Moreover, considering the unique conditions of each region is crucial for reducing air pollution. Vegetation not only absorbs pollutants like carbon dioxide but also reduces temperature, highlighting the importance of land-use planning for enhancing air quality. These findings can serve as valuable guidance for urban policymakers to implement more effective environmental strategies and improve residents' quality of life.

Author Contributions:
M.A.S. Mosaffayi: Investigation, Collected the datasets, Methodology, Writing—original draft preparation.
S. Moshiri: Designed the research, analyzed the data, Validation, review and editing.
B. Abdumuminov: Validation, review and editing
K.V. Kamran: Conceptualization, Supervisor, Writing—review and editing.
B. Feizizadeh: Conceptualization, Supervisor, Writing—review and editing, Commented on the manuscript.

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