

تقييم العلاقات بين عمق المظهر الهوائي والعوامل البيئية بناءً على نموذج الانحدار الموزون جغرافياً وزمنياً
(دراسة حالة: محافظة السليمانية، العراق (2025/2020)

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الكلمات المفتاحية: الغبار، رطوبة التربة، NDVI، التباين المكاني الزمني، السليمانية

كيفية اقتباس البحث

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Evaluation of the Relationships Between Aerosol Optical Depth and Environmental Factors Based on Geographic and Temporal Weighted Regression Model (Case Study: Sulaymaniyah Province, Iraq) (2020-2025).

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ملخص

عمق البصريات الهوائية (AOD) هو أحد المؤشرات المهمة لتقييم حمل الهباء الجوي وظروف الغبار في المناطق الجافة ونصف الجافة. وبالنظر إلى التباين الطبوغرافي والمناخي والبيئي لمحافظة السليمانية في العراق، وتعرضها لنقل الغبار، كان هدف الدراسة الحالية تقدير AOD ودراسة التغير المكاني والزمني لتأثير العوامل البيئية باستخدام نموذج الانحدار الموزون جغرافياً وزمانياً (GTWR). في هذه الدراسة، تم نمذجة AOD باستخدام خمسة متغيرات تفسيرية تشمل رطوبة التربة وسرعة الرياح ومؤشر الغطاء النباتي المختلف المعياري (NDVI) ودرجة حرارة سطح الأرض (LST) وهطول الأمطار خلال فترة ست سنوات (2020-2025). تم تقييم أداء طريقة المربعات الصغرى العادية (OLS) والانحدار الموزون جغرافياً (GWR) والانحدار الموزون زمنياً (TWR) وتمت مقارنة نماذج GTWR باستخدام مؤشرات إحصائية. كما تم تحليل

المعاملات المكانية والزمانية لنموذج GTWR لتحديد أنماط غير متجانسة لتأثيرات المتغيرات. عند مقارنة النماذج، أظهر GTWR أفضل أداء مع R^2 (0.912)، RMSE (0.078)، و AICc (-15376.3) وكان له قدرة أعلى على تفسير تغييرات AOD مقارنة بالنماذج الأخرى. أظهر تحليل المعاملات المكانية والزمانية أن رطوبة التربة و NDVI هما العامل الأكثر استقراراً في تقليل AOD، بينما كان LST هو العامل الأكثر أهمية في زيادة AOD. كما أظهر سرعة الرياح والهطول تأثيرات مكانية وزمنية متغيرة، مما يشير إلى اعتمادها على الظروف المحلية والزمنية. يمكن اعتبار هذا النمط نتيجة لتفاعل ظروف الرطوبة والنباتات السطحية، والاحتباس الحراري، ووعورة زاغروس، وعملية نقل الغبار. بشكل عام، تُظهر النتائج أن نموذج GTWR، بالإضافة إلى تحسين دقة التقدير، يوفر إمكانية تحديد العوامل المسيطرة والمناطق الحساسة للغبار، ويمكن أن يكون أساساً علمياً لمراقبة الهواء الجوي وإدارة جودة الهواء في محافظة السليمانية والمناطق المماثلة.

Abstract

Aerosol optical depth (AOD) is one of the important indicators for assessing aerosol load and dust conditions in arid and semi-arid regions. Considering the topographic, climatic, and environmental heterogeneity of Sulaymaniyah Province, Iraq, and its exposure to dust transport, the aim of the present study was to estimate AOD and investigate the spatiotemporal variability of the effect of environmental factors using the geographical and temporal weighted regression (GTWR) model. In this study, AOD was modeled using five explanatory variables including soil moisture, wind speed, normalized difference vegetation index (NDVI), land surface temperature (LST), and precipitation over a six-year period (2020-2025). The performance of ordinary least squares (OLS), geographical weighted regression (GWR), temporally weighted regression (TWR), and GTWR models was compared using statistical indices. Also, the spatial and temporal coefficients of GTWR were analyzed to identify heterogeneous patterns of variable effects. In comparing the models, GTWR showed the best performance with R^2 (0.912), RMSE (0.078), and AICc (-15376.3) and had a higher power in explaining AOD changes than other models. Spatial and temporal coefficient analysis showed that soil moisture and NDVI were the most stable factors reducing AOD, while LST was the most important factor increasing AOD. Wind speed and precipitation also showed variable spatiotemporal effects, indicating their dependence on local and temporal conditions. This pattern can be considered the result of the interaction of moisture conditions and surface vegetation, global warming, Zagros





ruggedness, and dust transport processes. Overall, the findings show that GTWR, in addition to improving the accuracy of the estimation, provides the possibility of identifying controlling factors and dust-sensitive areas, and can be a scientific basis for aerosol monitoring and air quality management in Sulaymaniyah province and similar areas.

Introduction

Aerosols are complex multiphase systems consisting of very fine solid or liquid particles suspended in the atmosphere and surrounding gaseous medium, with particle sizes typically ranging from 0.001 to 100 μm . These particles are of particular importance due to their significant role in environmental processes, human health, and climate change at regional and global scales (Yuan et al., 2023). Atmospheric aerosols originate from a variety of sources, including mineral dust, sulfates, sea salt, organic compounds, and black carbon, and due to differences in emission sources, meteorological conditions, and atmospheric transport processes, they have complex chemical compositions and significant spatiotemporal variations (Yao et al., 2026). Aerosol optical depth (AOD) is one of the most important optical properties of aerosols, which indicates the degree of attenuation and extinction of solar radiation due to scattering and absorption by aerosol particles in the entire atmospheric column. This index is used as an important physical parameter to assess the level of air pollution and to investigate changes in aerosol load in the atmosphere (Deng et al., 2012). Various studies have shown that several factors contribute to AOD variations. These factors include meteorological variables such as precipitation, relative humidity, temperature and wind speed, topographic and land surface factors such as digital elevation model (DEM) and normalized difference vegetation index (NDVI), as well as socio-economic factors related to human activities (Padimala and Matli, 2024; Ding et al., 2020; He et al., 2019). Understanding the relationship between these factors and AOD changes is essential for air quality management, dust event prediction, and environmental impact assessment. With the development of remote sensing technologies, satellite data have become one of the most important sources of information for studying aerosol characteristics and monitoring atmospheric pollution due to their wide spatial coverage, high temporal continuity, and ability to monitor areas without ground stations (Wei et al., 2020). AOD has been measured and estimated by various satellite sensors, including the multiangle imaging spectroradiometer (MISR), the moderate resolution imaging spectroradiometer (MODIS), the sea-viewing wide field-of-view sensor (SeaWiFS), the zone mapping imaging (OMI), the visible infrared imaging radiometer (VIIRS), and the

polarization and directionality of the Earth's reflectances (POLDER) instrument (Li et al., 2020). In recent years, the use of weighted regression models has been considered as an advanced approach to analyze the complex relationships between AOD and environmental factors, because these models allow for the examination of spatial and temporal variations in the relationships between variables (Rahman et al., 2024). The ordinary least squares (OLS) regression model is based on the assumption that the regression coefficients are constant over the entire study area, while many environmental phenomena have spatial heterogeneity (Shi et al., 2018). To overcome the limitations of classical models, Brunsdon et al. (1996) introduced the geographical weighted regression (GWR) model, which is able to examine the spatial variations in the relationships between variables at different locations. The temporally weighted regression (TWR) model also allows for the study of temporal changes in the relationships between variables by introducing the time component into the weighting matrix (Bai et al., 2016). Subsequently, Huang et al. (2010) developed the geographically and temporally weighted regression (GTWR) model by combining spatial and temporal distance. This model is able to consider spatial heterogeneity in the relationships between variables and model the temporal dependencies in the data (He and Huang, 2018). In recent years, the GTWR model has become one of the most widely used methods in modeling spatiotemporal phenomena and has been used in various fields such as heavy metal studies (Wang et al., 2024), energy efficiency (Zhang et al., 2020), and PM_{2.5} concentrations (Chu and Bilal, 2019). Sulaymaniyah Province in northeastern Iraq faces significant challenges in assessing the spatiotemporal changes of aerosols due to its location on the Middle East dust transport route, rapid urbanization, increasing human activities, and limited ground-based monitoring networks (Al-Taie et al., 2020; Halos et al., 2017). Although several studies have investigated AOD changes in Iraq, the use of advanced models such as GTWR to estimate AOD in Sulaymaniyah Province remains limited. Therefore, it is necessary to investigate the mechanisms controlling AOD and determine the relative contributions of factors affecting its changes in this region. This study investigates the spatiotemporal heterogeneity of the relationships between AOD and environmental factors over a six-year period (2020-2025) using the GTWR model. The results of this research can provide valuable information for air quality management, urban planning, monitoring atmospheric pollution, and reducing the consequences of dust storms in the region.



Materials and Methods

Study Area

Sulaymaniyah Province is located in the northeastern part of Iraq and in the Kurdistan Regional Government. The province borders Iran to the east, Erbil Province to the north, Kirkuk Province to the west, and Diyala Province to the south. The geographical area of the province is between $44^{\circ}32'$ to $46^{\circ}20'$ east longitude and $32^{\circ}34'$ to $36^{\circ}31'$ north latitude, covering an area of $20,235 \text{ km}^2$ (Figure 1). Sulaymaniyah has a continental and subtropical climate with arid to semi-arid variations, characterized by hot and dry summers and mild winters (Tao et al., 2022). The annual temperature range is between 8.5 and 49°C . Summer temperatures range from 16 to 51°C and winter temperatures range from 8.5 to 14°C . The average annual rainfall in different regions of the province varies between 300 and 700 mm , with the highest amount of precipitation usually occurring between November and April, while the summer season is almost devoid of significant rainfall (Ali et al., 2023). Sulaymaniyah is an excellent case study for assessing atmospheric aerosols and their relationship with environmental factors due to its arid environment, delicate soil composition, and increasing anthropogenic pressures.

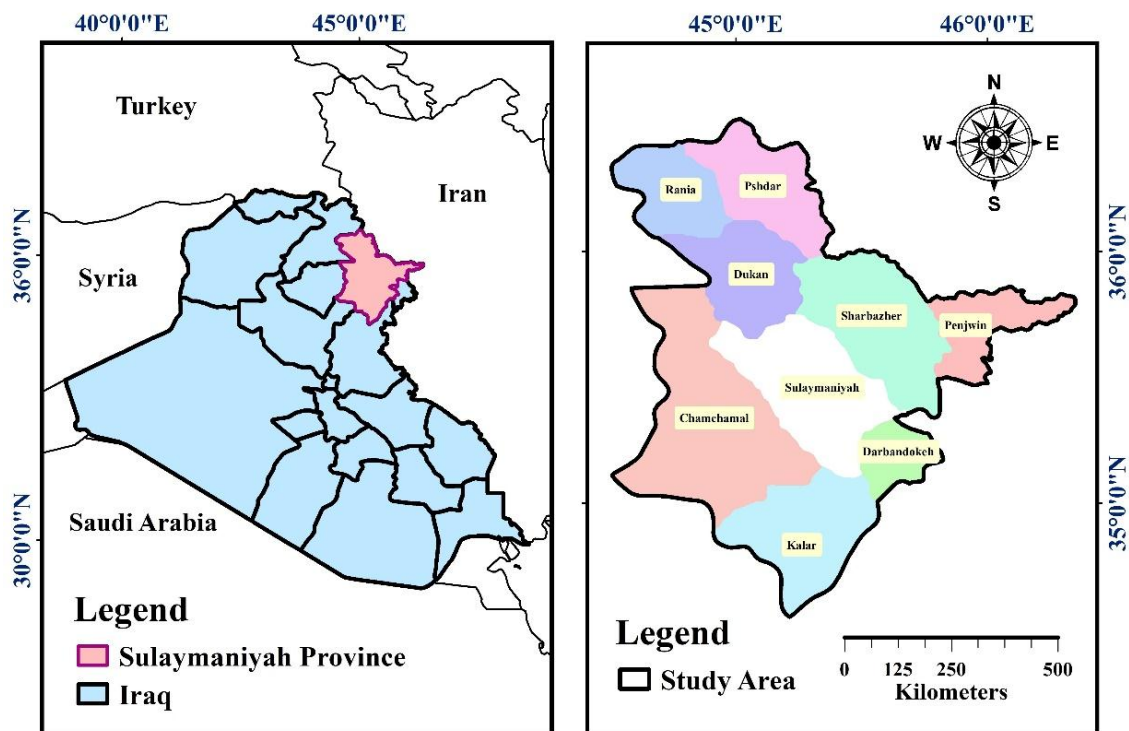


Figure 1. Location of the study area

Data collection

The MCD19A2 product is a MODIS sensor product based on the multi-angle implementation of atmospheric correction (MAIAC) algorithm. This product has a spatial resolution of 1 km and a daily temporal resolution (Lyapustin et al., 2018). Unlike traditional AOD extraction algorithms, the MAIAC algorithm is developed based on satellite image processing and time series analysis and has a higher ability to estimate AOD in areas with different reflectance levels, including areas with dense vegetation and arid and desert areas (Lyapustin et al., 2012). The AOD data used in this study were extracted from the MCD19A2 product at a wavelength of 0.47 μm for the period 2020 to 2025 via the google earth engine (GEE) platform. In order to reduce short-term fluctuations and examine long-term changes in AOD, the annual average AOD values were calculated for each year using programming codes in the GEE environment and used as the dependent variable in subsequent analyses. In order to examine the factors affecting the spatial and temporal changes in AOD, five explanatory variables including soil moisture, wind speed, NDVI, land surface temperature (LST), and precipitation were selected based on their roles in the processes of emission, transport, dispersion, and removal of aerosol particles from the atmosphere. All data used were extracted through the GEE platform and prepared for modeling analyses after the coordinate system and spatial resolution were standardized. The complete specifications of the explanatory variables (environmental factors) are presented in Table 1.

Table 1. Characteristics of explanatory variables used in the models

Data Type	Dataset/Product	Unit	Data Source
Soil Moisture	SMAP Soil Moisture Active Passive (SMAP)	m^3/m^3	NASA SMAP
Wind Speed	ERA5 Reanalysis	m/s	European Center for Medium-Range Weather Forecasts (ECMWF)
NDVI	MOD13A2	-	MODIS Terra (NASA)
LST	MOD11A2	$^{\circ}\text{C}$ (converted from Kelvin)	MODIS Terra (NASA)
Rainfall	Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS)	mm	Climate Hazards Center (UCSB)



Research Method

To conduct spatial analyses, a regular network was created using the Create Fishnet tool in ArcGIS10.8.2 software. This network was used as a spatial sampling frame and the values of the studied variables were extracted from the relevant raster layers. For this purpose, the Extract Multi Values to Points tool was used. Before running the regression models, to examine the collinearity between the explanatory variables (environmental factors), the variance inflation factor (VIF) was calculated using SPSS22 software. To investigate the relationships between AOD and environmental factors, four models including OLS, GWR, TWR and GTWR were considered. The GTWR model was implemented using the GTWR-Addins plugin developed by Huang et al. (2010) in ArcGIS 10.8.2. Since the variables used had different numerical ranges, all variables were converted to the range of zero to one using the minimum-maximum standardization method before entering the model (Jolliffe and Cadima, 2016). In the final stage, the coefficients obtained from the GTWR model were extracted to examine the spatial and temporal changes in the effect of each environmental factor on AOD. In order to spatially display these coefficients, the inverse distance weighted (IDW) interpolation method was used in ArcGIS. This analysis allowed examining the spatial heterogeneity of the relationships between AOD and effective environmental factors in Sulaymaniyah province. The general process of conducting the research is presented in Figure 2.

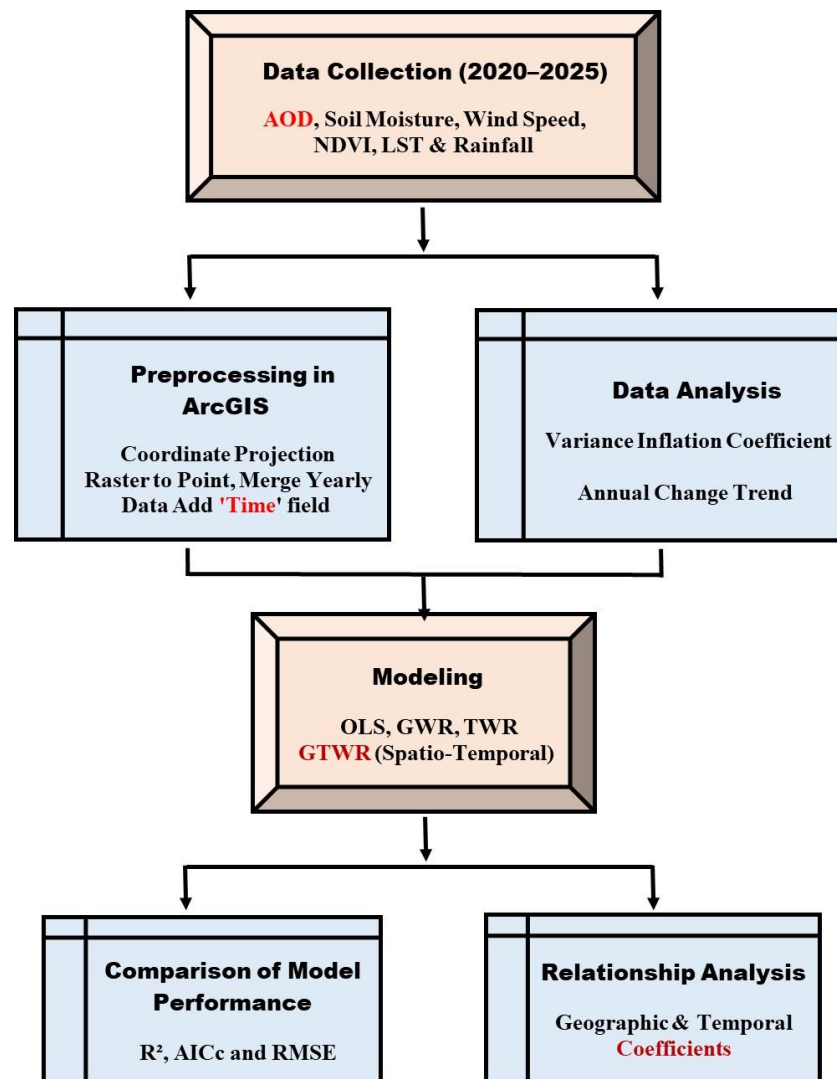


Figure 2. Method adopted in the research

Geographic and temporal weighted regression model

The GTWR model is an extended version of the GWR model that, in addition to spatial heterogeneity, also considers temporal changes in the relationships between variables (Huang et al., 2010). The general structure of the GTWR model is according to equation (1):

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^K \beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \quad (1)$$

Where Y_i is the AOD value, X_{ik} is the k th explanatory variable, (u_i, v_i, t_i) is the spatiotemporal coordinates of observation i , $\beta_0(u_i, v_i, t_i)$ and $\beta_k(u_i, v_i, t_i)$ are the latitude values from the origin and the local regression coefficient, respectively. Based on the weighted least squares



method, the estimation of the variables $\beta_k(u_i, v_i, t_i)$ can be given as equation (2):

$$\hat{\beta}_k(u_i, v_i, t_i) = [X^T W(u_i, v_i, t_i)]^{-1} X^T W(u_i, v_i, t_i) Y \quad (2)$$

where $W(u_i, v_i, t_i)$ is the spatiotemporal weight matrix and its diagonal elements $w_{ij(1 \leq j \leq n)}$ represent the weight assigned to each observation. Determining the weight matrix is considered the most important step in implementing the GTWR model, because more weight is assigned to observations that are closer to the desired point in terms of space and time (Huang et al., 2010). In this study, the Gaussian kernel function was used to calculate the weight of observations, which is expressed as equation (3).

$$w_{ij} = \exp(-(d_{ij}^{ST})^2 / h^2) \quad (3)$$

where h is the model bandwidth and controls the influence of adjacent observations on the coefficient estimation process. d_{ij}^{ST} represents the combined spatiotemporal distance between two observations i and j , which is obtained by combining the spatial distance (d^S) and the temporal distance (d^T). Choosing the appropriate bandwidth plays a decisive role in the performance of the model, such that choosing a large bandwidth will increase smoothing and reduce the sensitivity of the model to local variations, and choosing a small bandwidth will cause overfitting (Dong et al., 2019). Therefore, in the present study, the optimal bandwidth was determined using the Akaike-corrected criterion (AICc). The spatiotemporal distance used in the GTWR model is calculated according to equation (4).

$$d_{ij}^{ST} = \sqrt{\lambda[(u_i - u_j)^2 + (v_i - v_j)^2] + \mu(t_i - t_j)^2} \quad (4)$$

where λ and μ are scale parameters to balance spatial and temporal effects, respectively.

Evaluation of the accuracy of the models' performance

To evaluate and compare the performance of the studied models, the statistical indices of the coefficient of determination (R^2), the akaike information corrected criterion (AICc), and the root mean square error

(RMSE) were used. R^2 indicates the ability of the model to explain the changes in the target variable, with larger values indicating better model fit. In contrast, lower values of AICc and RMSE indicate better model performance and greater accuracy in estimating AOD (Zhao et al., 2020). The R^2 , RMSE, and AICc indices were obtained using equations (5), (6), and (7), respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (6)$$

$$AICc = 2n \log_e(\hat{\sigma}) + n \log_e(2\pi) + n\{n + \text{tr}(S)/n - 2 - \text{tr}(S)\} \quad (7)$$

Where y_i and $\hat{y}_i$ represent the actual and predicted AOD, respectively, $\bar{y}$ is the mean of the actual AOD, n is the sample size, $\hat{\sigma}$ is the estimated standard deviation of the error term, and $\text{tr}(S)$ represents the effect of the hat matrix S .

Results and Discussion

Annual AOD trends and environmental factors

Figure 3 shows the annual AOD trends and explanatory variables (environmental factors) including soil moisture, wind speed, NDVI, LST, and precipitation during the years 2020 to 2025. AOD showed a distinct fluctuation pattern during the study period; its average decreased from 0.205 in 2020 to 0.175 in 2021, then reached the highest value of the study period, 0.290, in 2022. After this peak, AOD decreased in 2023 and experienced a slight increasing trend during 2024 and 2025 (Figure 3a). The significant increase in AOD in 2022 could be related to the increase in surface access to erodible materials, the decrease in vegetation cover,



and the change in the transport conditions and persistence of aerosols in the atmosphere. Soil moisture had a mainly decreasing trend throughout the study period, from higher values at the beginning of the period to a minimum of $0.091 \text{ m}^3/\text{m}^3$ in 2025 (Figure 3b). A decrease in surface moisture can be associated with a decrease in soil particle adhesion and an increase in the surface susceptibility to wind erosion; therefore, the potential for particle emission to the atmosphere increases if wind energy is available and there is insufficient vegetation cover (AlNasser et al., 2025). Wind speed also showed interannual variability; its highest value was recorded in 2021 (1.969 m/s), then decreased to 1.827 m/s by 2023 and increased again in 2025 (Figure 3c). The minimum NDVI in 2022 (0.214) coincided with the maximum AOD, while the increase in NDVI in 2023 and 2024 was accompanied by a decrease in AOD (Figure 3d). LST reached a maximum value (33.379°C) in 2021 and then showed a decreasing trend (Figure 3e). Precipitation also showed significant variability; the highest annual amount was recorded in 2020 (676.356 mm) and the lowest in 2021 (476.401 mm), while after an increase in precipitation in 2023 and 2024, its amount slightly decreased in 2025 (Figure 3f). Overall, the comparison of the variables' trends shows that none of the environmental factors alone is able to fully explain the AOD changes in Sulaymaniyah. The peak of AOD in 2022 coincided with the minimum of NDVI and the decrease in surface moisture conditions, while the maximum of wind speed and LST were recorded in 2021. This non-synchrony suggests the existence of complex and non-stationary spatio-temporal interactions between the factors affecting AOD.

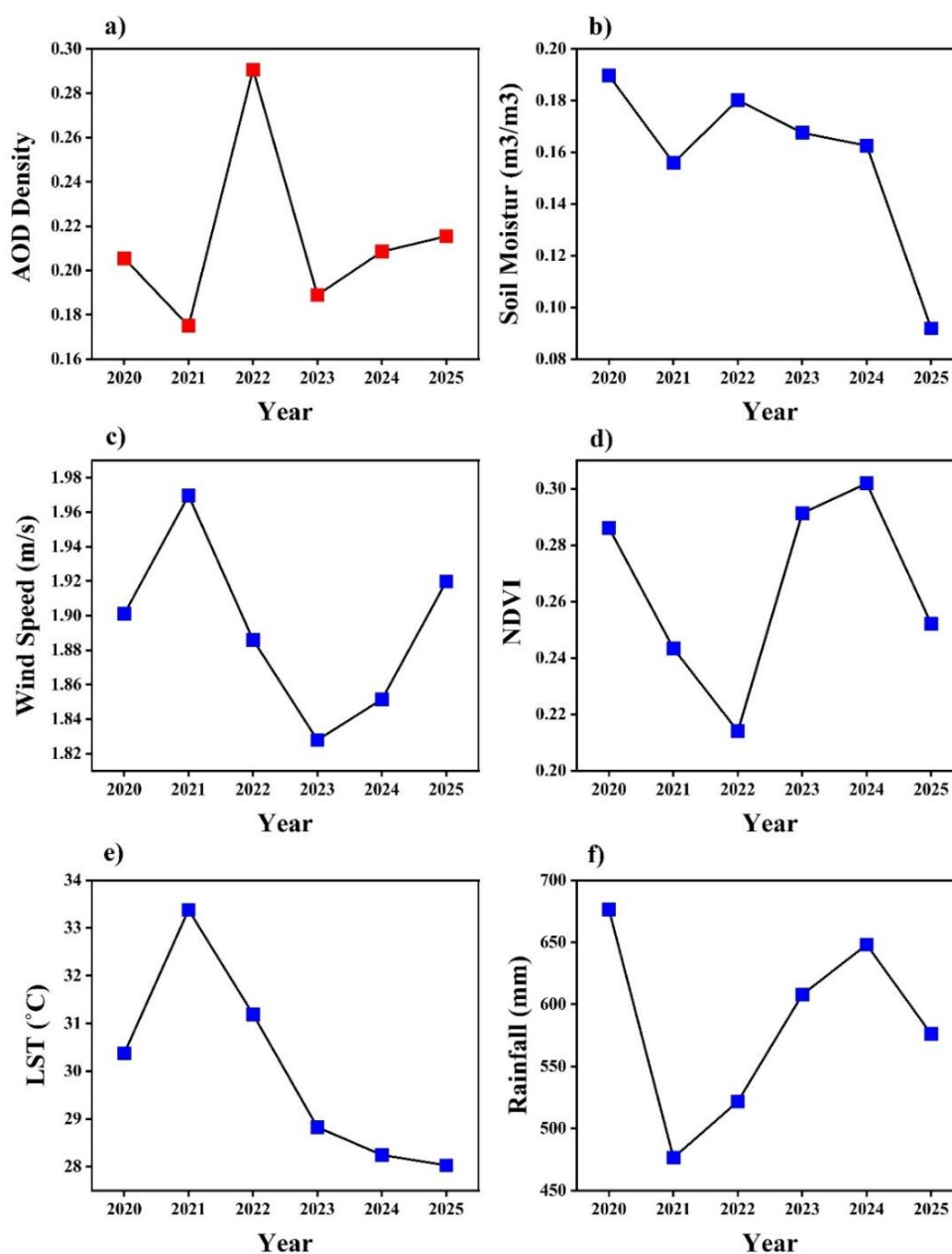


Figure 3. Changes in annual mean AOD (a), soil moisture (b), wind speed (c), NDVI (d), LST (e) and rainfall (f) in Sulaymaniyah Province (2020-2025)

Comparison of model performance

Variance inflation factor (VIF) was calculated for explanatory variables (environmental factors) (Table 2). Higher VIF values indicate greater intensity of collinearity among variables and based on previous studies, values between 5 and 10 are considered as multiple collinearity warning range (Shrestha, 2020). Examination of VIF values showed that all variables have values less than 5 throughout the study period. The highest



VIF value is related to wind speed in 2020 with a value of 4.249 and soil moisture in 2022 with a value of 4.014. Although these values are higher than other variables, they are still below the critical threshold (5) and indicate that the correlation of these variables with other environmental factors is moderate and acceptable. In contrast, the NDVI variable showed the lowest VIF values (1.419-1.823) in all years. Therefore, the spatial-temporal coefficients estimated by GTWR will have good stability and interpretability.

Table 2. VIF values of explanatory variables (environmental factors)

Year	VIF				
	Soil Moisture	Wind Speed	NDVI	LST	Rainfall
2020	3.418	4.249	1.419	2.111	2.070
2021	3.463	4.079	1.786	2.326	2.380
2022	4.014	3.721	1.823	2.634	1.726
2023	1.811	2.527	1.456	1.989	1.257
2024	2.187	2.905	1.432	1.874	1.990
2025	1.114	2.280	1.678	2.026	1.707

In order to evaluate the performance of OLS, GWR, TWR and GTWR models in estimating AOD, three indices R^2 , AICc and RMSE were compared (Table 3). OLS showed the weakest performance among the models studied. This model could only explain 13% of the AOD variations ($R^2=0.133$), while the relatively high RMSE (0.421) and AICc value (236.549) indicate the poor fit of the model and its inability to describe AOD variations. Considering spatial heterogeneity, GWR showed a significant improvement over OLS. The R^2 value increased from 0.133 to 0.511. Also, the RMSE and AICc value decreased significantly. These results indicate that the relationships between AOD and environmental factors are not uniform at the regional level and modeling the spatial variations of the coefficients increases the prediction accuracy. TWR, which only considers the temporal variations of the coefficients, performed better than GWR. The R^2 value of 0.894 indicates that about 89% of the AOD variations were explained by this model. In addition, the RMSE decreased to 0.085 and the AICc value reached -14183.9. These results indicate that the temporal variations of the relationships between AOD and environmental factors during the study period played a very important role in improving the model performance. Among the four models, GTWR showed the best performance. This model, with an R^2 of 0.912, was able to explain more than 91% of the AOD variations. The simultaneous decrease in RMSE (0.078) and AICc

(-15376.3) along with the increase in R^2 indicates that the simultaneous consideration of spatial and temporal dependencies in the regression coefficients has been able to model the complex structure of AOD variations with more accuracy. The superiority of GTWR in the present study is consistent with recent studies in the field of modeling particulate matter and aerosols. In a study in southwest China, GTWR was used to estimate $PM_{2.5}$ using AOD and environmental variables, and the values of OLS, GWR, and GTWR models were 0.554, 0.713, and 0.801, respectively, which showed the obvious superiority of GTWR in representing $PM_{2.5}$ changes (Liu et al., 2024). Also, Huang et al. (2025) combined AOD, ground-based $PM_{2.5}$ data, and meteorological variables in the dry region of Xinjiang, and achieved $R^2=0.920$ for GTWR, which had a higher performance than GWR. Furthermore, a large-scale study in China showed that simultaneously considering spatial and temporal dependence in GTWR improved the model performance in analyzing atmospheric pollutants ($PM_{2.5}$, PM_{10} , SO_2 , NO_2 , CO and O_3) and that local heterogeneity should be considered in air pollution modeling (Yang et al., 2024). These results confirm the importance of GTWR in dust-prone areas with strong environmental heterogeneity.

Table 3. Performance evaluation indicators of the studied models

Model	R^2	AICc	RMSE
OLS	0.133	236.549	0.421
GWR	0.511	-1228.2	0.126
TWR	0.894	-	0.085
GTWR	0.912	-	0.078

Study of spatial and temporal coefficients derived from the GTWR model

Figure 4 shows the spatial distribution of coefficients derived from the GTWR model for environmental factors in Sulaymaniyah province. The results indicate significant spatial instability of the relationships between AOD and environmental factors; such that the intensity and, in some areas, the direction of the effect of the variables change. This pattern indicates that the relationship between AOD and land surface conditions and meteorological factors cannot be described by a fixed coefficient across the province. Soil moisture had negative coefficients in most parts



of the province, and the strongest negative values (1.435) were observed mainly in the southern and southwestern parts. This pattern suggests that in these areas, increasing soil moisture is associated with decreasing AOD. In contrast, the weakness of this relationship in parts of the north and northeast can be partly attributed to the wetter conditions, higher altitudes, and denser vegetation in these areas. This is of greater importance in Iraq and the Zagros region, where changes in water availability and drying of wetlands can expand surfaces susceptible to dust generation (Nassif et al., 2024; Ismail et al., 2024). The role of soil moisture in controlling dust emission has also been demonstrated in studies by Shao (2008) and Ginoux et al. (2012). Wind speed coefficients were mostly negative, but positive in some central and northern parts. This change in sign is of particular importance, because wind speed can simultaneously play two different roles in the dust system: in conditions where the surface is susceptible to erosion, increased wind can cause the removal and resuspension of particles; However, after particles enter the atmosphere, increased mixing and horizontal transport can dilute local aerosol concentrations. Therefore, the negative wind coefficient in parts of Sulaymaniyah does not necessarily mean that wind does not play a role in dust transport, but rather that the effect of dispersion and ventilation dominates over local production in those locations. This interpretation is especially important in a region with complex topography such as the Zagros, because the roughness can change the effective direction and speed of air flow at a local scale (Hussien et al., 2024). Therefore, the different signs of wind coefficients in the GTWR map can be considered a reflection of the difference in the role of wind as a factor in aerosol production, transport, or dispersion. NDVI coefficients were negative almost throughout the province, indicating a decreasing relationship between vegetation cover and AOD. The greater magnitude of the negative coefficients (1.166) in the sparsely vegetated southern and southwestern regions suggests that vegetation changes in these areas are likely to be more important in controlling dust emissions, while in the higher, more densely vegetated northern and northeastern regions, AOD sensitivity to NDVI changes is less. Regional studies on Syria and Iraq have also shown that reduced vegetation cover and increased bare areas can contribute to increased dust emissions and their transport downwind (Rocha-Lima et al., 2024). Therefore, the spatial pattern of NDVI in the present study supports the protective role of vegetation in reducing dust potential. LST had positive coefficients in most parts of the province, with stronger values (0.486) observed mainly in the central and eastern regions. This pattern suggests that in these regions, the increase in LST

was associated with the increase in AOD. In contrast, weaker or negative coefficients in parts of the northern highlands can be associated with cooler conditions, higher altitudes, and denser vegetation in these regions (Alam et al., 2014). Therefore, the positive effect of LST in Sulaymaniyah province is likely to reflect the simultaneous warming, surface dryness, and greater susceptibility of bare lands to erosion, rather than the increase in temperature alone directly causing the increase in AOD. The rainfall pattern was more complex than the other variables, with negative coefficients mainly observed in the northern parts and positive coefficients in some central and southern regions. The negativity of these coefficients in the north of the province is consistent with two known mechanisms: first, wet washing of aerosols from the atmosphere and second, increased soil moisture and enhanced vegetation cover that can limit the re-dispersion of particles (Muter et al., 2025). In contrast, positive coefficients in some drier areas should not be interpreted as evidence of “dust production by rainfall”; rather, they could be due to the temporal difference between rainfall and surface response, short-term rainfall, the coincidence of rainfall with the arrival of dust plumes, or the effect of omitted variables. Therefore, the change in sign of rainfall coefficients is one of the important evidences of spatial instability of the AOD–precipitation relationship in the province.

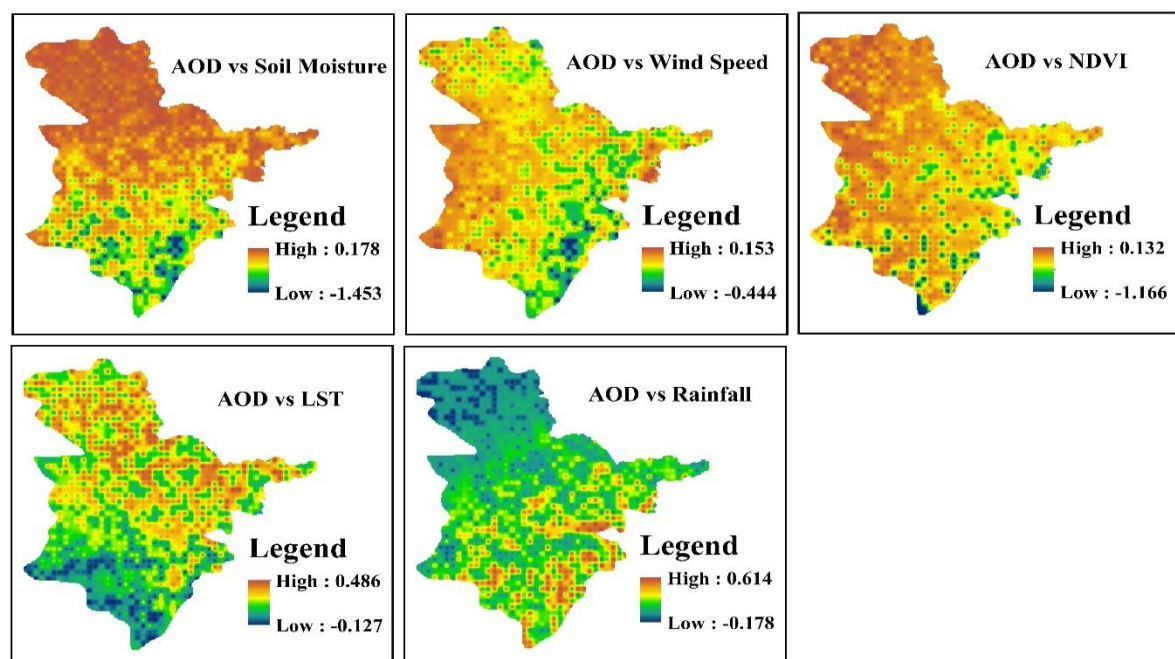


Figure 4. Spatial coefficients derived from the GTWR model in the 2020-2025 time period



Table 4 shows the average time coefficients of the explanatory variables (environmental factors) affecting AOD during the years 2020-2025. The change in sign and amplitude of the coefficients during the study period indicates that the relationship between AOD and environmental factors is not static in time and the intensity of the effect of the variables changes in different years. Soil moisture had a negative coefficient in all the years of the study, and its value increased from -0.026 in 2020 to -0.654 in 2024. The increase in the absolute value of the coefficient indicates that the decreasing relationship between soil moisture and AOD has become stronger in the final years of the period. Al Zubi et al. (2024) used MODIS satellite data and spatiotemporal analysis of dust emission sources in Iraq, Syria, and Jordan to show that the majority of dust sources are concentrated in the Tigris-Euphrates basin, with barren lands and dried wetlands being the most important sources of particle emission; this finding highlights the importance of land surface conditions, drought, and reduced surface cover in controlling dust emission in the region and its transport to adjacent areas, including northern Iraq. Wind speed also had a negative coefficient in all years, increasing from -0.034 in 2020 to -0.228 in 2024. At first glance, this result may be different from the physical expectation of increased dust emission due to increased wind speed; because increased wind speed, if it crosses the erosion threshold, can increase surface shear stress and cause particle detachment and resuspension. However, wind speed after particles enter the atmosphere can also cause horizontal transport, mixing, and regional ventilation (Xia et al., 2025). NDVI had negative coefficients in all years, and the largest absolute value of its coefficient was obtained in 2022, about 0.622. This result indicates that vegetation cover was mainly associated with the decrease in AOD during the entire study period, and its reducing effect was more prominent in 2022. Wang et al. (2026) showed that the increase in vegetation cover in arid regions was associated with the decrease in dust storm activity, and a significant negative correlation (0.616) was observed between NDVI and dust activity. In contrast, LST had a positive coefficient in all years, increasing from 0.005 in 2020 to 0.322 in 2024. This trend indicates that the positive relationship between LST and AOD has been strengthened during the study period. Zhang (2024) reported a positive relationship between AOD and LST in a study of spatiotemporal changes in AOD in the arid region of northwest China, such that an increase in LST was accompanied by an increase in aerosol load, which can be attributed to the role of warm and dry land surface conditions in increasing the readiness for particle diffusion and resuspension. Unlike other variables, precipitation did not have a uniform temporal behavior;

its coefficients were negative in 2020 and 2023 and positive in other years, and the highest positive value was observed in 2022, about 0.331. The change in the sign of the coefficient indicates that the relationship between precipitation and AOD in Sulaymaniyah is strongly dependent on temporal conditions. The positive coefficient of precipitation in some years should not be interpreted as a direct effect of precipitation on the increase in AOD; rather, it could reflect the synchrony of precipitation with other atmospheric processes, a delayed surface response, or the effect of uncontrolled factors. This also highlights the importance of using GTWR, as the model allows for the detection of changes in the sign and strength of this relationship over time.

Table 4. Mean time coefficients obtained from the GTWR model in the period 2020-2025

Year	Soil Moisture	Wind Speed	NDVI	LST	Rainfall
2020	-0.026	-0.034	-0.040	0.005	-0.016
2021	-0.029	-0.065	-0.207	0.004	0.069
2022	-0.055	-0.047	-0.622	0.269	0.331
2023	-0.326	-0.156	-0.048	0.294	-0.028
2024	-0.654	-0.228	-0.136	0.322	0.284
2025	-0.373	-0.121	-0.119	0.223	0.184

Conclusion

The results of this study showed that AOD in Sulaymaniyah province follows a non-stationary spatial and temporal pattern and the intensity and direction of the effect of environmental factors are different at different locations and times. Comparison of models showed that GTWR with R^2 (0.912), RMSE (0.078) and AICc (-15376.3) performs better than OLS, GWR and TWR, thus providing a more suitable framework for estimating AOD in the study area. Based on the spatial and temporal coefficients obtained from the GTWR model, soil moisture and NDVI were the most important factors reducing AOD and LST was the most important factor increasing it; while the effect of wind speed and precipitation was strongly dependent on space and time. The results indicate that AOD



changes in Sulaymaniyah are the result of a complex interaction of land surface conditions, climate, vegetation, and dust transport processes. The GTWR model can be used as an effective tool to identify areas sensitive to increased aerosol load, monitor dust, and support air quality management in arid and semi-arid regions.

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Conflict of interest

The author declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

Life science reporting

No life science threat was practiced in this research.

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