The University of Tehran Press

Pollution

Print ISSN: 2383-451X
Online ISSN: 2383-4501

https://jpoll.ut.ac.ir/

Analyzing the Relationships Between Aerosol Optical Depth and Environmental Variables Using Geographically and Temporally Weighted Regression Model

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Article Info

Article type:
Research Article

Article history:
Received: 15 February 2026
Revised: 10 April 2026
Accepted: 15 April 2026

Keywords:
Aerosol Optical Depth,
Soil Moisture,
Spatio-temporal Heterogeneity,
Rainfall,
Wind Speed

ABSTRACT

This study aimed to investigate the effect of environmental variables on the distribution of Aerosol Optical Depth (AOD) in Sanandaj County over a six-year period from 2019 to 2024 using a Geographically and Temporally Weighted Regression (GTWR) Model. In order to analyze the relationships between AOD and the factors affecting it, five environmental variables including soil moisture, wind speed, NDVI, LST and rainfall were selected. The GTWR model was implemented using GTWR-Addins, a software package in ArcGIS software. To improve its performance, GTWR was compared with OLS, GWR and TWR in terms of goodness of fit and other statistical measures. The GTWR model was able to identify spatial and temporal heterogeneities simultaneously and had higher explanatory power (R^2=0.80) than other models. The spatial and temporal coefficients obtained from this model showed that wind speed and LST have a positive and stable effect on AOD and are considered the most important increasing factors. Soil moisture and NDVI have variable spatio-temporal behavior and in most cases have a reducing effect on AOD. Rainfall has a small-scale and nonlinear effect that varies depending on the spatial pattern and intensity of precipitation. These findings demonstrate the high importance of environmental variables in controlling AOD dynamics and the necessity of simultaneously considering spatial and temporal dimensions in environmental modeling. For future studies, the GTWR model can be used to analyze the AOD impact coefficients at multiple spatial scales and add significant factors such as population, Gross Domestic Product (GDP) and road density.

Cite this article: Saedpanah, M, & Souri, B. (2026). Analyzing the Relationships Between Aerosol Optical Depth and Environmental Variables Using Geographically and Temporally Weighted Regression Model. *Pollution*, 12(2), 655-667. https://doi.org/10.22059/poll.2026.411243.3295

DOI: https://doi.org/10.22059/poll.2026.411243.3295

INTRODUCTION

Aerosols significantly affect the environment, human health, and regional and global weather patterns (Yuan et al., 2023). Also, from an economic point of view, they may cause a decrease in the efficiency of solar energy production, defects in the performance of machinery, and an increase in cleaning costs (AlNasser et al., 2025). One of the main factors of aerosol formation is strong winds and barren lands. In addition, variables such as temperature and precipitation indirectly affect aerosols by affecting vegetation and soil moisture (Zhou et al., 2024; Liu et al., 2020). Aerosol Optical Depth (AOD) is very important for understanding the aerosol load and spatial and temporal changes, and with its help, the amount of air pollution (dust, smoke and industrial pollution) can be measured on a large scale. Unlike ground-based monitoring stations, remote sensing can provide an effective tool to assess air pollutants and their changes (Bai et al., 2016). Currently, MCD19A2 from the Moderate Resolution Imaging Spectroradiometer (MODIS) series of aerosol products are the most widely used AOD data products (Zhang et al., 2021).

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Studying AOD and determining the factors affecting it by using weighted regression models is one of the new approaches in the analysis of environmental phenomena, which provides the possibility of better understanding and localization of spatial and temporal changes (Rahman et al., 2024). One of the most well-known of them is the Geographically Weighted Regression (GWR) model introduced by Brunsdon et al. (1996). Unlike classical regression models such as Ordinary Least Squares (OLS), which assume the same coefficients throughout the study area, GWR determines regression coefficients locally and depending on geographic coordinates, and this improves the accuracy and interpretability of the model in heterogeneous spatial data (Shi et al., 2018). One of the limitations of the GWR model is that it cannot cope well with time changes due to ignoring time information. Therefore, Geographically and Temporally Weighted Regression (GTWR) was proposed by Huang et al. (2010). The simultaneous weighting GTWR based on spatial and temporal distance analyzes the inconsistent and dynamic changes in the data, which is very suitable for phenomena such as AOD that are influenced by environmental and temporal factors. GWR ignores temporal instability and Temporally Weighted Regression (TWR) ignores spatial instability, thus integrating GTWR, GWR and TWR into a single framework (Wei et al., 2019). Due to the importance of dust, extensive studies have been conducted on the evaluation of AOD and factors affecting it. Rahman et al. (2024) investigated AOD trends and its relationship with climate factors from 2001 to 2023 over Saudi Arabia by adopting the GWR model. The values of GWR coefficient showed that the higher degree of relationship is with temperature and pressure, followed by wind speed, solar radiation, humidity and rainfall. Quan et al. (2023) evaluated PM2.5 concentration based on GTWR model and MCD19A2 data from 2015 to 2020 in Xinjiang, China. The findings showed that the GTWR model performs better than the Simple Linear Regression (SLR) and GWR models in terms of accuracy and feasibility in retrieving PM2.5 concentrations. At the same time, by combining the GTWR model and MCD19A2 data, a spatial distribution map of PM2.5 with better spatial resolution can be obtained. Many studies have proven the superiority of GTWR for modeling spatial and temporal heterogeneity in the fields of housing price forecasting (Wu et al., 2019), PM2.5 concentrations (He and Huang, 2018), and public transportation passengers (Ma et al., 2018). However, limited researches have used this approach in order to model the effect of environmental variables on AOD from a spatial and temporal perspective. Due to its special geographical location, mountainous topography, proximity to dust sources in the west of the country, and influence of regional atmospheric currents, Sanandaj County is one of the areas prone to significant changes in the amount and distribution of aerosols. Therefore, accurate assessment of spatial and temporal changes of AOD in this region can be effective in better understanding of atmospheric processes, air pollution monitoring and environmental planning. This research was conducted with the aim of investigating how environmental variables affected AOD distribution in Sanandaj County during a six-year period (2019-2024) using the GTWR model. The findings of the study can provide valuable theoretical resources for local managers in formulating strategies for the comprehensive improvement of the environment, ecological management and protection.

MATERIAL AND METHODS

Study Area

Sanandaj County with an area of 2936.29 km^2 lies between latitudes 35°N to 36°N and longitudes 46°E to 48°E with a fluctuating altitude range between 1450 to 1538 meters above the sea level located in in western Iran (Figure 1). The study area has a temperate, cold, semi-arid climate with an average rainfall of 480 mm. The absolute maximum and minimum temperature reach +40°C and -31°C, respectively. The climatic conditions, geographical diversity, and topography have resulted in the emergence of various land forms, including deep valleys,

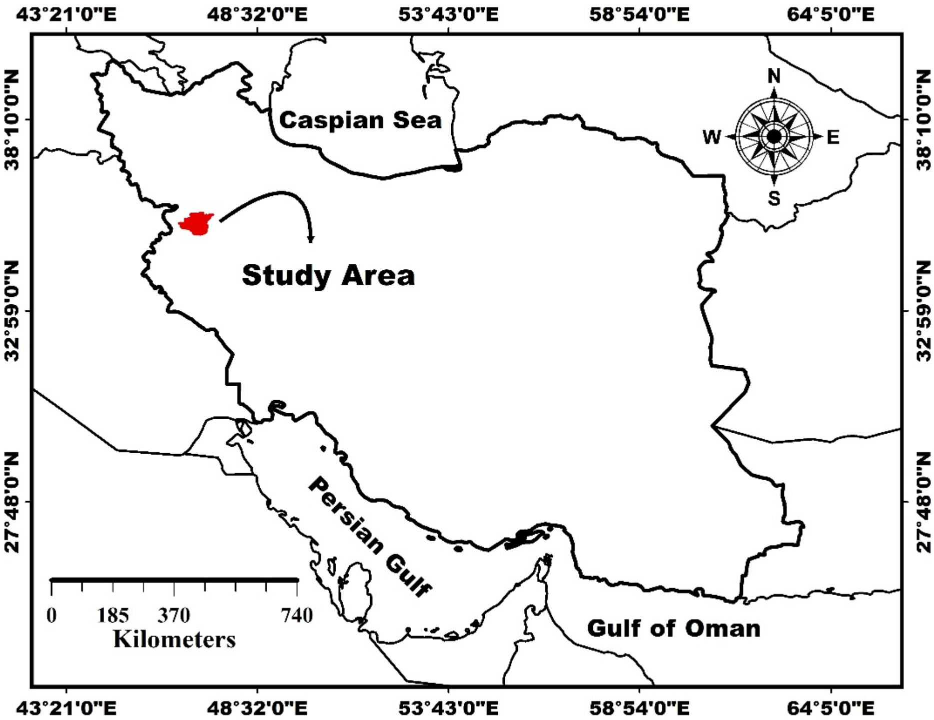

Fig. 1. Location of the study area in western Iran

pastures, agriculture and various forest communities (Azami et al., 2015).

Data Collection

The data used in this research was obtained from the Google Earth Engine (GEE) system, which enables efficient analysis. This system uses Google's cloud computing infrastructure (https://code.earthengine.google.com) in order to significantly reduce analysis time (Zurqani, 2024). The processed satellite data of MCD19A2 were prepared in the period of 2019 to 2024 in terms of micrograms per cubic meter. The band used in this research is the blue band (0.47 µm). MCD19A2 is actually the daily land AOD with the Multi-Angle Implementation of Atmospheric Correction (MAIAC). This daily 1 km resolution product combines data from both MODIS instruments to provide information on atmospheric properties and visibility geometry (Zhu et al., 2023). The accuracy of these data has been confirmed by many researchers (Filonchyk and Hurynovich, 2020; Bilal et al., 2019).

Environmental Variables

In order to analyze the relationships between AOD and the factors affecting it, five environmental variables (soil moisture, wind speed, vegetation, Land Surface Temperature (LST) and rainfall) were selected in the period from 2019 to 2024. Soil moisture data were obtained from the Soil Moisture Active Passive (SMAP) in cubic meters of water per cubic meter of soil (Oneill et al., 2023). SMAP was launched in 2015 and has an L-band radiometer, which is ideal for detecting soil moisture through vegetation layers (Sehler et al., 2019). In the present study, morning data (level 3) was used. These data are preferable to evening data due to the adverse effect of sunlight on data quality (West, 2014). Wind speed data were collected from the European Center for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis dataset in m/s. ERA5 uses the latest modeling and data assimilation approaches and offers improvements over other reanalysis datasets (Jourdier, 2020). The Normalized Difference Vegetation Index

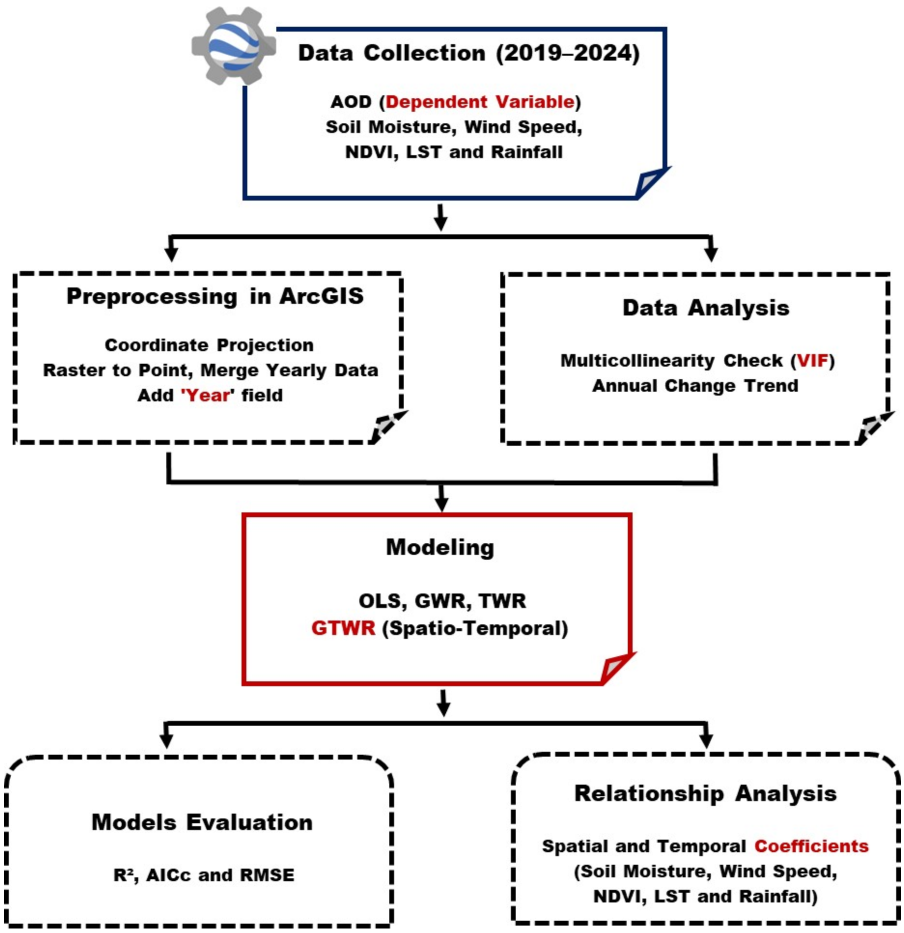

Fig. 2. Diagram of the method adopted in the research

(NDVI) is widely used to distinguish areas with vegetation from areas without vegetation. In the current research, the MOD13A2 product of data combined at 16-day intervals with a resolution of 1 km was used. This combined distance smooths atmospheric variations and errors (Waring et al., 2006). The MOD11A2 data is a level 3 product from Terra that provides 8-day average LST at 1 km spatial resolution derived from the MOD11A1 product (Barben et al., 2024). LST are shown in degrees Kelvin with a minimum scale of 7500 and a maximum of 65535, and the values of these data were converted to degrees Celsius. Precipitation data calculated by the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) were considered in millimeters. The CHIRP/S algorithm combines three main data sources (Climate Hazards Group precipitation climatology: CHPclim; TIR-based satellite precipitation estimates: IRP; and in situ rain gauge measurements) (Dinku et al., 2018). The process of producing maps and diagrams is presented in figure 2.

Methodology

With the help of Create Fishnet tool in ArcGIS10.8.2 software, a regular network of square cells was created to perform spatial analysis. Extract Multi Values to Points tool was used to extract spatial variable values from raster layers for sampling points. Before modeling, Multicollinearity between environmental variables was tested in SPSS22 software to ensure that all selected environmental variables (independent variable) were statistically significant in relation to AOD (dependent variable) and not collinear. The GTWR model was implemented using GTWR-Addins, a software package developed by Huang et al. (2010) in ArcGIS10.8.2

software. Since the range of values of the variables used is different, all of them should be normalized before modeling so that the range of numbers is between 0 and 1 (Jolliffe and Cadima, 2016).

Geographically and Temporally Weighted Regression (GTWR)

It is a spatial statistical model that expands GWR by including the temporal dimension and better explains the spatial and temporal relationships between independent and dependent variables (Pan et al., 2025). GTWR is expressed as equation (1):

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

where Y_i is the dependent variable, X_{ik} is the kth explanatory variable, (u_i, v_i, t_i) coordinates of the location and time of observation i, $\beta_0(u_i, v_i, t_i)$ and $\beta_k(u_i, v_i, t_i)$ represent the values of width from the origin and regression coefficient, respectively. Based on local weighted least squares, the estimation of $\beta_k(u_i, v_i, t_i)$ variables can be presented as equation (2):

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

where $W(u_i, v_i, t_i)$ is the weight matrix of space and time and its diagonal elements $w_{ij(1 \le j \le n)}$ are the weight given to observation point j in the vicinity of observation point i. Determining w_{ij} is the key to calculating the weight matrix. The GTWR model defines w_{ij} as a function of decreasing spatial and temporal distance that results in higher weighting of data points closer to observation i (Huang et al., 2010). The most common weighting functions are Gaussian kernel functions (Equation 3):

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

where h is a parameter called bandwidth to control the range of radial influence, d_{ij}^{ST} is the spatial and temporal distance that calculates the proximity between observations i and j. In the GTWR model, the spatial and temporal distance is defined as equation (4):

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

where ë and ì are scale parameters to balance spatial and temporal effects, respectively. If the mentioned parameters are equal to zero, the spatial and temporal distance is reduced to GWR or TWR distance. In order to investigate the relationship between the dependent variable (AOD) and environmental variables, four regression models with different levels of complexity including OLS, GWR, TWR and GTWR were used. These models were compared based on statistical indices including coefficient of determination (R^2), Akaike Information Corrected Criterion (AICc) and Root Mean Square Error (RMSE). Higher values of R^2 and lower values of AICc indicate improved accuracy of the model (Zhao et al., 2020).

RESULTS & DISCUSSIONS

Annual Trend of AOD and Environmental Variables

A study of the time trend of AOD and environmental variables during the years 2019 to 2024 shows that each of the factors affecting AOD changes had certain fluctuations in the studied period (Figure 3). The highest (211.03 μg/m^3) and lowest (153.49 μg/m^3) AOD were observed

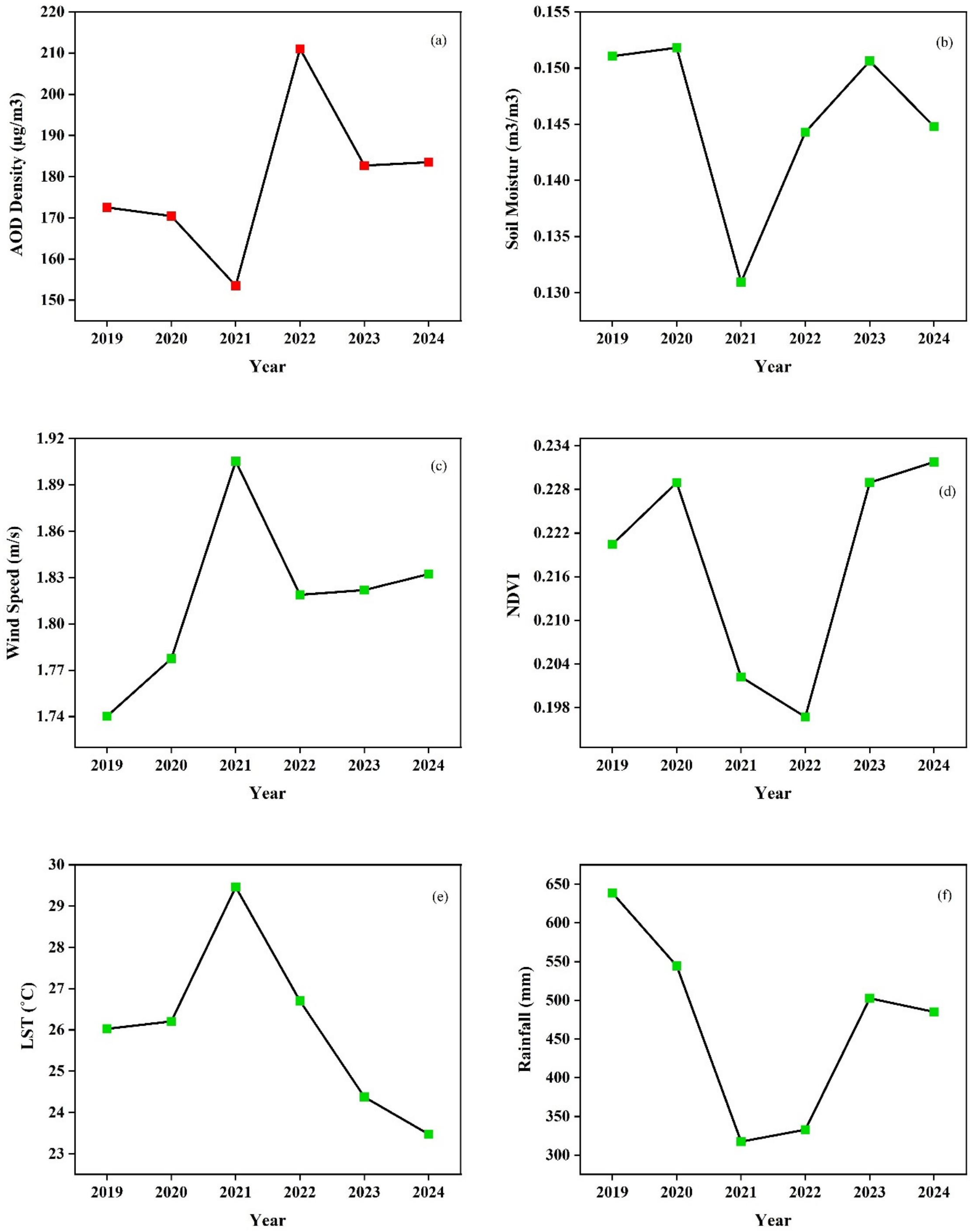

Fig. 3. Changes in annual mean AOD (a), soil moisture (b), wind speed (c), NDVI (d), LST (e) and rainfall (f) in Sanandaj County (2019-2024)

in 2022 and 2021, respectively. Soil moisture changes show that there was a sharp decrease in 2021 (0.13 m^3/m^3) and then it gradually increased. A gradual increase in wind speed was observed in the first years and reached its highest value in 2021 (1.90 m/s). NDVI decreased significantly in 2021 and 2022 and then increased again. Its maximum value was achieved in 2024 (0.23). LST reached its highest value in 2021 (29.46°C) and its lowest value in 2024 (23.47°C). The annual rainfall trend shows that it experienced the highest value in 2019 (638.55 mm) and the lowest value in 2021 (317.25 mm).

Detection of Multicollinearity

In order to examine Multicollinearity between environmental variables in regression models, the Variance Inflation Factor (VIF) index was calculated during the years 2019 to 2024 (Table 1). The results show that the VIF values for all variables are in the range between 1.06 and 1.68. Given that a VIF value of less than 5 indicates significant multiple noncollinearity between variables, it can be concluded that the necessary conditions exist for building regression models with high statistical stability and accuracy.

Evaluating the Power of Models in Explaining Spatial and Temporal Heterogeneity

The evaluation indices of each model are presented in Table 2. The results show that the OLS model is only able to explain about 46 percent of the AOD changes and has low accuracy. This model assumes that the relationships between variables are constant at all points and times, so it has limited effectiveness for data with spatial and temporal heterogeneity. Adding a time dimension to the model improved R^2 to 0.60 and reduced RMSE from 0.10 to 0.07, indicating a significant role of time in AOD changes. However, the GWR model which only considers spatial heterogeneity, has achieved higher accuracy. This superiority indicates that AOD changes in the study area are more affected by spatial heterogeneity than by temporal variations. Finally, the GTWR model, which simultaneously incorporates spatial and temporal heterogeneities, has shown the best performance, with an R^2 value of 0.80 and an RMSE of 0.05. Also, the AICc value in this model is the lowest among the four models (-22952.9), which indicates the best balance between accuracy and complexity of the model.

Identifying Regions and Periods with High Correlation between AOD and Environmental Variables

The GTWR model provides various geographical coefficients, each of which is correlated

Table 1. VIF values of environmental variables

Year	VIF				
	Soil Moisture	**Wind Speed**	**NDVI**	**LST**	**Rainfall**
2019	1.26	1.46	1.38	1.68	1.27
2020	1.32	1.31	1.16	1.47	1.27
2021	1.33	1.46	1.06	1.47	1.32
2022	1.33	1.41	1.06	1.39	1.32
2023	1.32	1.37	1.06	1.33	1.40
2024	1.32	1.31	1.08	1.36	1.33

Table 2. Power evaluation indices of regression models

Model	**R^2**	**AICc**	**RMSE**
OLS	0.46	-17656.4	0.10
TWR	0.60	-19910.5	0.07
GWR	0.65	-20895.3	0.06
GTWR	0.80	-22952.9	0.05

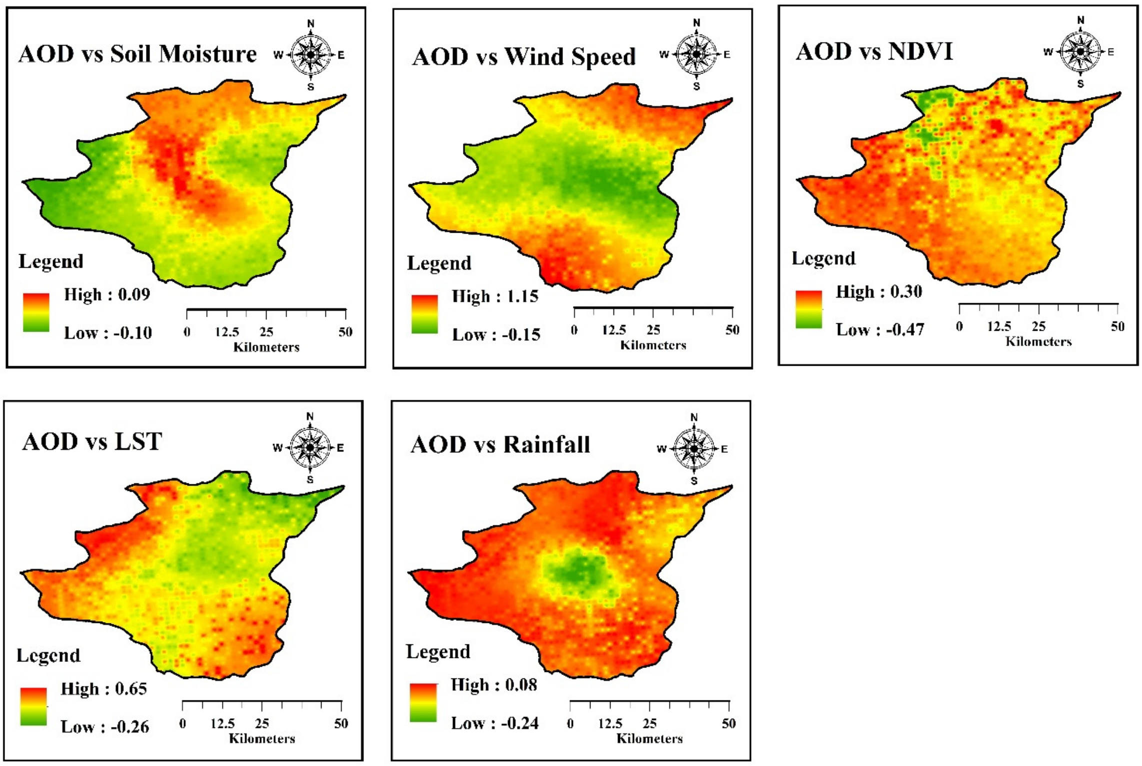

Fig. 4. Spatial distribution of estimated coefficients obtained from the GTWR model in the period 2019-2024

with a weighted value. Using the output of the GTWR model, the spatial distribution of these coefficients was mapped using Inverse Distance Weighted (IDW) interpolation with the aim of explaining the relationship between AOD and environmental variables in Sanandaj County during the period 2019-2024 (Figure 4). The spatial pattern of the coefficient between AOD and soil moisture produced a positive correlation with a maximum value of 0.09 per year per unit increase in soil moisture (m^3/m^3). The effect of soil moisture in the center of the study area is significantly positive. However, in other areas a negative coefficient with a maximum value of 0.10 was observed. Wind speed shows a negative correlation with AOD in most of the study area, meaning that AOD decreases by a maximum of 0.15 per year for each unit increase in wind speed (m/s). While in the north and south of Sanandaj County, AOD is positively correlated with wind speed. The correlation between NDVI and AOD in the center and northwest of the study area was negative, indicating the inhibitory role of vegetation in the occurrence of AOD. In the south and southwest areas, a positive correlation with a maximum value of 0.30 was observed. The estimated coefficient for AOD and LST shows an inverse relationship in the north and northeast of the study area. The highest negative correlation value is 0.26, meaning that AOD can decrease by 0.26 per year for every unit increase in temperature (°C). Rainfall in most of the study area has a positive correlation with AOD with a maximum value of 0.08 per year. However, in the center of the study area, a negative coefficient was observed, meaning that AOD decreases with a maximum value of 0.24 per year for each unit increase in precipitation (mm).

Temporal changes in the estimated coefficients obtained from the GTWR model indicate significant changes in the impact of environmental variables on AOD during the period 2019 to 2024 (Table 3). Soil moisture coefficients in the early years (2019-2020) have a positive value and are close to zero. However, from 2021 onwards they are negative and maintain their downward trend until 2024. This change indicates that in the early years, the increase in soil

Table 3. Average time changes of estimated coefficients obtained from the GTWR model in the period 2019-2024

Year	Soil Moisture	Wind Speed	NDVI	LST	Rainfall
2019	0.003	0.405	-0.053	0.294	0.004
2020	0.003	0.408	0.007	0.238	0.016
2021	-0.012	0.411	0.157	0.194	0.015
2022	-0.017	0.371	0.122	0.368	-0.018
2023	-0.016	0.528	0.035	0.288	0.0005
2024	-0.016	0.544	0.003	0.245	0.020

moisture was accompanied by a slight increase in AOD, while in recent years, the increase in soil moisture has led to a decrease in AOD. The wind speed coefficients are positive and relatively high in all years (0.37 to 0.54), indicating a direct and strong relationship between wind speed and AOD increase. The increase in coefficients in the final years (2023-2024) indicates that the contribution of wind to the transport and redistribution of AOD has increased in recent years. The negative coefficient of NDVI in 2019 indicates that the increase in NDVI has led to a decrease in AOD. The positive coefficients (2020-2022) indicate that NDVI in this period may have a different effect on the AOD distribution along with other variables. The decrease in the coefficient value in the period 2023-2024 indicates that the effect of NDVI on AOD has decreased again and has approached a more stable state. The LST coefficients have also been positive in all years. This indicates that increasing temperature causes AOD to increase. The highest coefficient is observed in 2022 (0.36), which probably coincided with drier periods and more intense heat. Rainfall coefficients show more fluctuations. In most years, the coefficient value is positive and small, but in 2022, a negative coefficient was recorded. These changes imply that the effect of precipitation on AOD is non-uniform and depends on the intensity and spatial pattern of precipitation.

Overall, the analysis of time trends showed that 2022 is a critical period in terms of increasing AOD, and these changes occurred mainly under the combined influence of decreased rainfall and soil moisture, increased LST, decreased NDVI and increased wind speed. Annual changes (2019-2024) of environmental variables indicate the significant role of dry and unstable atmospheric conditions in increasing AOD in Sanandaj County. The results of the GTWR model showed that the model's power in explaining spatial and temporal variations of AOD has increased significantly compared to the OLS, GWR and TWR models. The value of the coefficient of determination (R^2=0.80) and the reduction of the error index (RMSE=0.05) indicate that considering spatial-temporal heterogeneity has led to a significant improvement in the model's performance. This indicates that the behavior of factors affecting AOD has considerable dynamics not only in space but also over time. Quan et al. (2023) found that the GTWR model with R^2=0.72 performed better than the GWR model (R^2=0.64) in terms of accuracy and feasibility in retrieving PM2.5 concentrations. In the study of Chu et al. (2015), the R^2 values of the GWR and GTWR models in modeling the spatio-temporal heterogeneity of PM10-PM2.5 were reported to be 0.90 and 0.94, respectively. In Huang et al. (2010) study, GTWR performed better (R^2=0.92) than GWR (R^2=0.88) and TWR (R^2=0.77) models. The difference in model power across studies could be related to the selection of predictors (Zhao et al., 2020). Spatial and temporal variations of AOD reflect the complex interactions of dust emission sources and environmental variables. Soil moisture had negative coefficients with a relatively stable trend during the six-year period (2019-2024), indicating its inhibitory effect on the increase of AOD. Higher soil moisture appears to have reduced AOD emissions through increased surface adhesion and reduced wind erosion. Bao et al. (2021) investigated the spatio-temporal changes in dust emissions in Xilingol League during the period 2005 to 2018. The results showed that dust abundance was negatively correlated with NDVI and soil moisture. Wind speed had positive and relatively large coefficients in all years (2019-2024), indicating a stable and increasing effect of wind speed on AOD. Increasing wind speed causes horizontal transport and dust ascent from the ground surface to the atmosphere, and thus contributes significantly to its increase. The stability of this relationship over the studied period emphasizes that wind is one of the most important controlling factors in spatial and temporal changes in AOD. Li et al. (2020) analyzed the effects of climatic factors on dust emission levels in Kuwait from 2001 to 2017. The results indicated a positive relationship between wind speed and dust levels. In the present study, NDVI showed a different temporal pattern. In 2019, its relationship with AOD was negative, while from 2020 onwards, positive coefficients were observed, reaching its highest value (0.157) in 2021. This change in direction could indicate the effect of vegetation on land surface processes under different atmospheric conditions. In 2019, due to the possibility of denser vegetation and higher rainfall, the role of vegetation in reducing AOD was prominent, but in subsequent years, with the occurrence of drought and a decrease in plant density, the controlling effect of plants on dust was weakened and appeared as a positive relationship. Yao et al. (2021) showed that the reduction of dust in East Asia was associated with increased NDVI, soil moisture, rainfall and reduced wind speed. The results of Li and Wang (2014) study in Guangdong Province, China showed that AOD was strongly negatively correlated with NDVI during 2010–2012. However, He et al. (2016) reported a weak correlation between AOD and NDVI at the national level between 2002–2015. In the present study, LST coefficients were positive in all years. This indicates that increasing temperature causes increasing AOD. From a physical perspective, increasing temperature causes greater dryness of the soil surface, decreases relative humidity and intensifies atmospheric instabilities, ultimately increasing the dispersion and persistence of dust in the atmosphere. In a study by Rahman et al. (2024), a negative correlation between AOD and temperature (0.0173) and solar radiation (0.0006) was reported in Saudi Arabia. The interaction between AOD and temperature is complex. Aerosols from natural sources show that smaller particles are more common at colder temperatures, while larger particles are more common at warmer temperatures (Price et al., 2016). The effect of precipitation on AOD changes is spatially and temporally dynamic and dependent on annual climatic conditions. In drier periods or with irregular rainfall distribution, the correlation between precipitation and AOD reduction is weakened or even reversed, especially in 2022, while in wetter years the clearing effect of precipitation is strengthened. In the study by Jin and Wang (2018), increased rainfall, vegetation cover and soil moisture led to a significant reduction in dust in the northwestern Indian subcontinent. In addition, with increased rainfall in this area, vegetation cover increased and AOD decreased. These results indicate that the factors affecting AOD changes are highly dependent on spatial and temporal conditions and a comprehensive understanding of their dynamics requires the use of advanced models such as GTWR.

CONCLUSION

In this study, the relationship between AOD and five environmental variables in Sanandaj County in western Iran from 2019 to 2024 was investigated by adopting the GTWR model. This model was able to identify spatial and temporal heterogeneities simultaneously and had higher explanatory power (R^2=0.80) than other models. The spatial and temporal coefficients obtained from the GTWR model showed that wind speed and LST have a positive and stable effect on AOD and are considered the most important increasing factors. Soil moisture and NDVI have a variable spatial-temporal behavior and in most cases have a decreasing effect on AOD. Rainfall has a small-scale and nonlinear effect that varies depending on the spatial pattern and precipitation intensity. These findings demonstrate the high importance of environmental variables in controlling AOD dynamics and the necessity of simultaneously considering spatial and temporal dimensions in environmental modeling. For future studies, the GTWR model can be used to analyze the AOD impact coefficients at multiple spatial scales and add significant factors such as population, Gross Domestic Product (GDP) and road density to it.

GRANT SUPPORT DETAILS

The present research did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this manuscript.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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