

Article

Spatiotemporal Variations and Driving Factor Analysis of Aerosol Optical Depth in Terrestrial Ecosystems in Northern Xinjiang from 2001 to 2023

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Abstract: Investigating the spatiotemporal variations in Aerosol Optical Depth (AOD) in terrestrial ecosystems and their driving factors is significant for deepening our understanding of the relationship between ecosystem types and aerosols. This study utilized 1 km resolution AOD data from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Mann–Kendall (M-K) trend test to analyze the spatiotemporal variations in AOD in seven ecosystems in Northern Xinjiang from 2001 to 2023. The geographic detector model was employed to investigate the effects of driving factors, including gross domestic product, population density, specific humidity, precipitation, temperature, wind speed, soil moisture, and elevation, on the distribution of AOD in the ecosystems. The results indicate that over the past 23 years, wetlands had the highest annual average AOD values, followed by settlements, farmlands, deserts, grasslands, others, and forests, respectively. Furthermore, the AOD values decrease with increasing ecosystem elevation. The annual mean of AOD in Northern Xinjiang generally shows a fluctuating upward trend. The M-K test shows that the proportion of area with an increasing trend in AOD in the settlement ecosystems is the highest (92.17%), while the proportion of area with a decreasing trend in the forest ecosystem is the highest (21.78%). On a seasonal scale, grassland, settlement, farmland, forest, and wetland ecosystems exhibit peak values in spring and winter, whereas desert and other ecosystems only show peaks in spring. Different types of ecosystems show different sensitivities to driving factors. Grassland and forest ecosystems are primarily influenced by temperature and altitude, while desert and settlement ecosystems are most affected by wind speed and humidity. Farmlands are mainly influenced by wind speed and altitude, wetlands are significantly impacted by population density and humidity, and other ecosystems are predominantly affected by humidity and altitude. This paper serves as a reference for targeted air pollution prevention and regional ecological environmental protection.

Keywords: AOD; terrestrial ecosystems; spatiotemporal variations; Mann–Kendall trend test; geographic detector; driving factors



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1. Introduction

Aerosols are liquid or solid particles suspended in the atmosphere with diameters ranging from 0.001 to 100 μm , which can be categorized into natural and anthropogenic sources [1,2]. Natural sources include dust, sea salt, volcanic ash, and biogenic aerosols, while anthropogenic sources encompass sulfates, nitrates, and organic aerosols, which play essential roles in atmospheric pollution [3–5]. Aerosols can induce direct climate effects by scattering and absorbing solar radiation [6–8] and provide condensation surfaces for water

vapor, influencing cloud formation and precipitation patterns, thus causing indirect climate effects [9,10]. Additionally, the chemical substances in aerosols can enter the human body through respiration, posing health risks [11,12].

AOD, which measures the aerosol extinction coefficient from the Earth's surface to the top of the atmosphere, is an important optical parameter for estimating aerosol concentration and assessing air pollution [13–15]. At present, multiple satellite remote sensing platforms have conducted large-scale, long-term monitoring of AOD at different spatial and temporal scales, with representative ones including MODIS sensors from Terra and Aqua satellites [16–18], the AHI sensor from Himawari-8/9 satellites [19,20], and the CALIOP sensor from the CALIPSO satellite [21], providing critical data support for global and regional aerosol pollution research [22–24].

The formation and spatial distribution of aerosols are complex, involving multiple factors such as gas-phase chemical reactions, physical processes, diverse sources, and varying environmental conditions.

Regarding anthropogenic aerosol sources, Sun et al. [25] found that industrial activities, transportation, energy consumption, and biomass burning are China's primary sources of urban aerosols. According to de Leeuw et al. [26], the reduction in AOD in China is primarily controlled by human-induced pollution emissions, with human activities contributing 75–94% to AOD reduction. At the same time, meteorological conditions account for a relatively minor impact, within $\pm 10\%$. Yuan et al. [27] analyzed the drivers of AOD across ten national urban clusters in China, noting significant influences from socio-economic factors and PM_{2.5} emissions, with varying impacts across cities at different development levels. Zhen et al. [28] observed that the spatial pattern of AOD in the Yellow River Basin cities is driven collectively by meteorological, topographical, and socio-economic factors. In this region, meteorological factors play a more crucial role, although their impact varies significantly among urban clusters.

Regarding natural aerosols, wind speed, soil conditions, vegetation coverage, and thermal instability are vital factors influencing dust aerosol emissions. [29,30]. Dust storms typically occur in arid and semi-arid regions. Wind speed and soil moisture are closely related to the probability of dust storms, with higher soil moisture at different wind speeds suppressing dust aerosol emissions [31]. Zhou et al. [32] believe that relative humidity and precipitation significantly impact the distribution of AOD in Central Asia. However, the combined effect of temperature and relative humidity acts as a two-factor enhancement. Wang et al. [33] showed that the influence of the same driving factors on dust aerosols varies by region. In East Asia, the Taklamakan Desert is primarily influenced by relative humidity, precipitation, temperature, and wind speed. In contrast, the Gobi Desert is mainly affected by temperature, relative humidity, and soil temperature. In a separate study on AOD drivers in arid regions, Ma et al. [34] found that meteorological conditions are the primary driver of AOD in Xinjiang. In contrast, precipitation and population increasingly impact the eastern region year by year, with human activity factors having the most significant influence in the northern region.

Notably, the atmospheric boundary layer is in direct contact with the Earth's surface, and different underlying surface structures and land use/cover change (LUCC) types influence aerosols' transmission, distribution, and variation by altering local climate conditions and their feedback mechanisms. Yu et al. [35] found in their study on the impact of urbanization on AOD in Beijing that AOD showed a positive correlation with regional surface temperature, which was also positively correlated with land use. Xu et al. [36] discovered through their research in the Yangtze River Delta that the growth rate of AOD in urban areas with high human activity levels is more significant than that in rural areas. Wei et al. [37], through a comparative study of different cities in Shandong Province, discovered that atmospheric pollution responds differently to various land cover types, with a negative correlation for forest areas and a positive correlation for urban areas. Zhao et al. [38] found that PM_{2.5} variations in the Yangtze River Delta region are influenced differently by vegetation, with coniferous forests, broadleaf forests, and shrubs being more effective in

reducing atmospheric particulate matter than grasslands. Through their investigation of the relationship between forest structure and PM_{2.5} concentration, Liu et al. [39] demonstrated that tree canopies can effectively reduce the diffusion rate of PM_{2.5} and play a significant role in the absorption and deposition of particulate matter. A study by Wang et al. [40] on the Heihe River Basin in the arid region of northwest China indicated that dust emissions from dry lakebeds and degraded grasslands in spring are 10–16 times higher than dust emissions from other landscapes. Similarly, in Xinjiang, China, Liu et al. [41], using MODIS AOD and land use data to estimate natural and anthropogenic dust emissions, found that natural dust emissions account for 92% of total dust emissions, significantly higher than the 8% attributable to anthropogenic sources. Another study on arid regions by Liu et al. [42] quantitatively analyzed the contribution of different land use types in Central Asia to aerosols, revealing that deserts contribute positively to AOD. At the same time, grasslands showed a significant reduction in AOD.

Topography can influence the height of the planetary boundary layer, atmospheric stability, temperature, and wind speed, impacting aerosol emissions and vertical mixing. Juan M. Casañas et al. [43] conducted a geostatistical analysis of the relationship between topography, land cover, and AOD in the Tulum Valley and surrounding areas in Argentina, demonstrating a direct link between AOD-related parameters and both topography and land cover types. Zhou et al. [44] found that the topography of the Tibetan Plateau affects the distribution of dust aerosols in the Tarim Basin, with dust concentrations in the atmosphere showing a pattern of decreasing in the upper layers and increasing in the lower layers as the elevation of the Tibetan Plateau decreases. Dai et al. [45], in a comparative study of aerosol concentrations across various mountainous and urban areas in eastern China, noted that the aerosol concentrations of Total Suspended Particles (TSP) and PM₁₀ in high mountain areas are generally lower than those in plain cities. In a recent study, Ana del Águila et al. [46] found through a 20-year monitoring of the vertical zonal distribution of different ecosystems in the Sierra Nevada Mountains that AOD in pine forest ecosystems at elevations of 1200–1700 m was 18.4% lower than in the 700–1200 m range. Compared to ecosystems with bare soil and low vegetation, forest ecosystems exhibit lower AOD levels.

These studies demonstrate that changes in local surface conditions, such as to land cover/ecosystem type and altitude, can impact aerosol emissions. These changes will further affect climate conditions such as temperature, cloud cover, precipitation, and solar reflectance, changing the environment [47]. For example, in the Aral Sea [48], Urmia Lake [49], and Ebinur Lake [50], the gradual drying up of lakes has led to ecological degradation and has gradually developed into a new aerosol pollution source in Central Asia.

Northern Xinjiang, China, is a typical arid and semi-arid region with diverse landforms, including basins, plains, and high mountains, resulting in a complex surface environment and diverse ecosystems [51]. It has long been affected by drought, desertification, salinization, and intense human activities, leading to a fragile ecological environment [52,53]. Over the past 20 years, rapid socio-economic development has increased anthropogenic pollution, vegetation degradation, and frequent dusty weather, exacerbating atmospheric aerosol pollution in the region. According to the 2023 Ecological Environment Bulletin of Xinjiang, three out of seven national urban air quality monitoring sites in Northern Xinjiang are experiencing exceedances. The complex topography and diverse ecosystems make it a natural laboratory for studying surface structure and aerosol behavior.

Currently, most studies examine the spatiotemporal distribution of AOD and its influencing factors on a regional scale. However, this approach is limited when interpreting AOD characteristics under different surface structures. Therefore, this study utilizes the 550 nm AOD data from the MODIS Multi-Angle Implementation of Atmospheric Correction algorithm (MAIAC) version 6.1 (MCD19A2.061) to analyze the spatiotemporal variation characteristics and driving factors of AOD in seven terrestrial ecosystems in Northern Xinjiang from 2001 to 2023. The main contents include the following: (1) exploring the spatial distribution characteristics of AOD in different ecosystems and its distribution pattern with altitude changes; (2) revealing the temporal variation law of AOD in different

ecosystems; and (3) clarifying the driving factors of AOD and their differences among various ecosystem types. This study can provide a reference for understanding the differences in aerosol behavior in complex geographical regions and for decision-makers to consider the order of priority in environmental governance.

2. Study Area

The study area is located in the Northern Xinjiang Uygur Autonomous Region, China (42.2° to 49.2° N, 79.8° to 91.6° E) (Figure 1). The region predominantly exhibits characteristics of a temperate continental arid climate [54,55]. Northern Xinjiang has complex and diverse landforms, including the Altay Mountains, the Junggar Basin, the western Junggar Mountains, the Tianshan Mountains, and their intermountain basins, with elevations ranging from 105 m to 6955 m. The alternating distribution of humid mountains and arid basins results in diverse landscape features of the ecosystems [56,57]. Northern Xinjiang has experienced rapid industrialization and urbanization in recent years, making it Central Asia's most economically developed and fastest-growing region. However, this has also resulted in an increase in air pollution emissions [58]. Additionally, the Gurbantunggut Desert within the region is a significant source of dust in Central Asia [59]. Both anthropogenic and natural aerosols have posed severe threats to the environmental safety of the arid region.

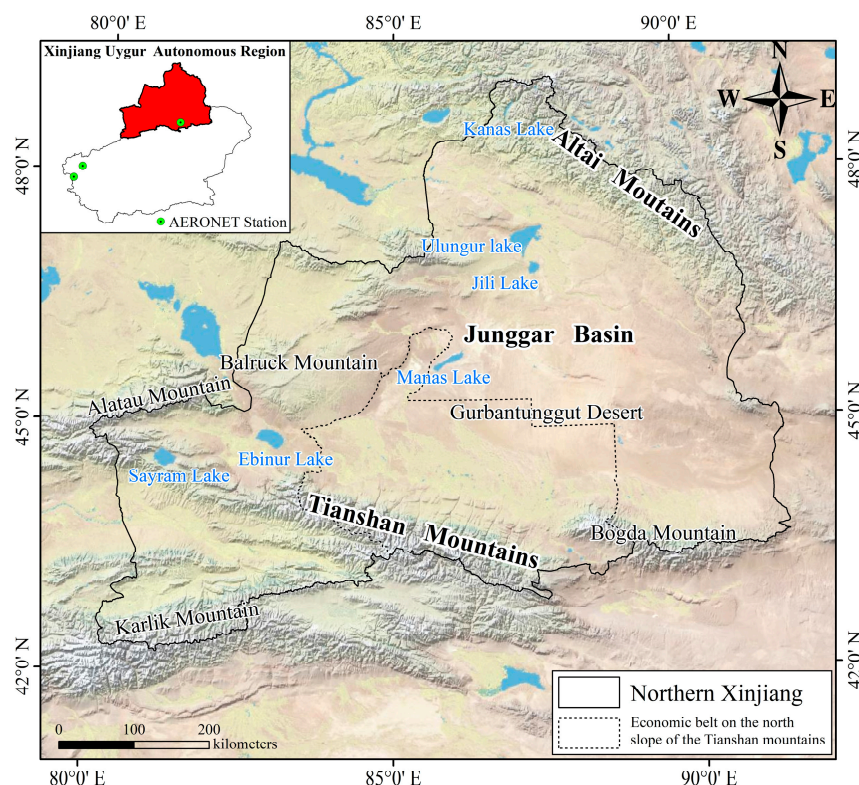


Figure 1. A schematic map of the location of the study area.

3. Dataset

3.1. AOD Data

The AOD satellite remote sensing data come from the MCD19A2.061 dataset, an AOD product with a $1\text{ km} \times 1\text{ km}$ spatial resolution generated by the MODIS MAIAC onboard the Terra and Aqua satellites. This dataset provides data from February 2000 to the present [60,61]. The MAIAC ensures data quality by performing cloud detection and atmospheric effect correction, incorporating bidirectional surface reflectance effects through temporal series and spatial analysis to enhance cloud and snow detection quality [62,63]. We developed a data collection algorithm using the web code editor of the Google Earth

Engine platform (earthengine.google.com) [64] to process daily 550 nm AOD from 2001 to 2023 and obtain monthly and annual averages for different periods [32]. The AOD data were batch-converted to the CGCS2000 Lambert projection using ArcGIS Desktop 10.8 (ESRI, Redlands, CA, USA) and clipped according to the study area mask.

AOD ground measurement data were sourced from the Aerosol Robotic Network (AERONET) [65,66]. All 2.0 level (completed cloud masking and quality inspection) available data from 2001 to 2023 were obtained from three different stations in Kashi (Kashgar), Muztagh_Ata (Aktao), and Asia1 (Urumqi) within Xinjiang Uygur Autonomous Region. The MAIAC 550nm AOD data were subjected to spatiotemporal matching and accuracy verification. The information of these stations is shown in Table 1.

Table 1. Information of AERONET ground observation stations.

Station	Latitude/Longitude	Altitude	Operational Time
Asia1	43.783° N/87.650° E	935 m	13 August 2007 to 15 August 2007
Muztagh_Ata	38.408° N/75.039° E	3674 m	6 June 2011 to 20 December 2011
Kashi	39.504° N/75.930° E	1320 m	21 March 2019 to 29 April 2019

3.2. Terrestrial Ecosystem Data

Multi-temporal ecosystem distribution data were obtained from the Resource and Environment Science Data Center of the Chinese Academy of Sciences (www.resdc.cn, accessed on 15 June 2024) (Figure 2). This dataset identifies and classifies various ecosystem types based on land use data obtained through human–computer interactive visual interpretation relying on Landsat remote sensing images. The division criteria [67,68] are shown in Table 2.

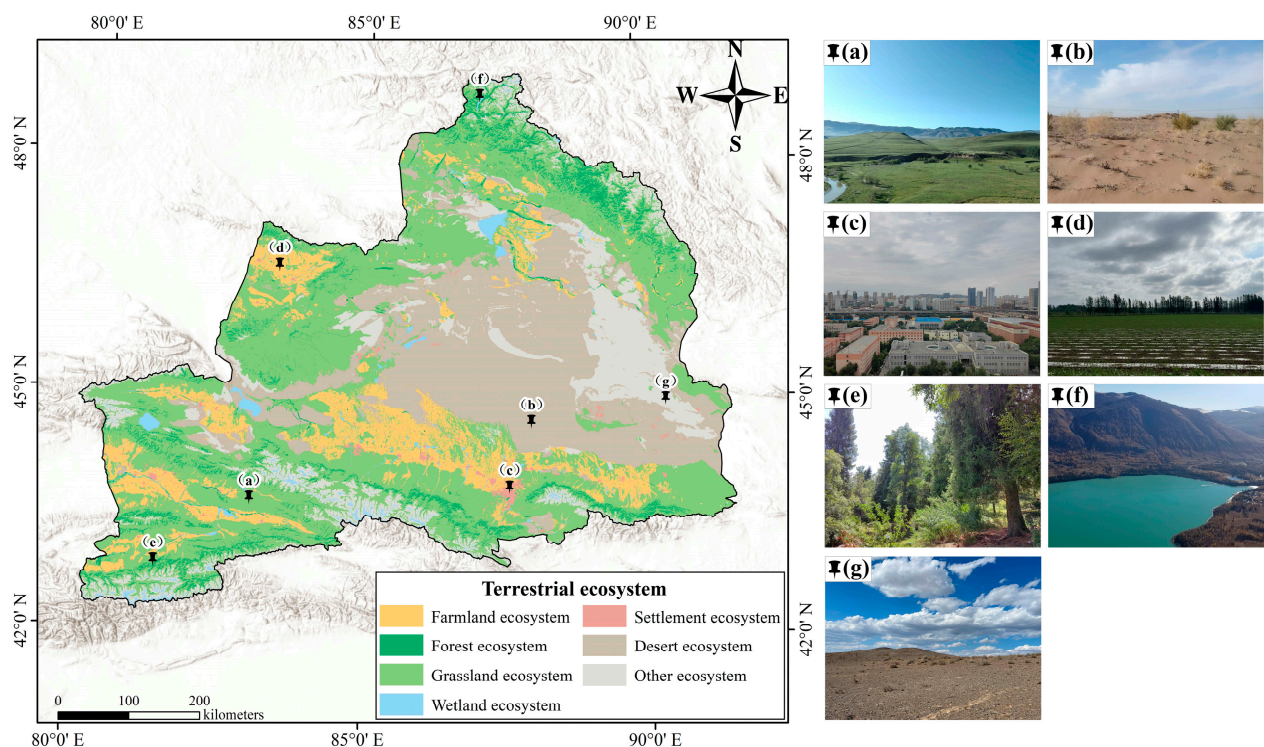


Figure 2. Ecosystem distribution and typical landscape images.

Table 2. Classification criteria for ecosystems.

Ecosystem	Land Use Type	Description
Farmland ecosystem	Paddy land, dry land	An ecosystem mainly comprises cultivated land, such as mature, cultivated land, newly reclaimed land, rotational fallow land, and grassland-crop rotation land for growing crops.
Forest ecosystem	Wooded land, shrubland, open woodland, other woodland	An ecosystem mainly comprises cultivated land, such as mature, cultivated land, newly reclaimed land, rotational fallow land, and grassland-crop rotation land for growing crops.
Grassland ecosystem	High-cover grassland, medium-cover grassland, low-cover grassland	An ecosystem composed of various grasslands mainly growing herbaceous plants with a coverage of more than 5%, including shrub grasslands and sparse forest grasslands with a canopy density of less than 10%.
Wetland ecosystem	River channels, lakes, reservoirs, permanent glaciers and snowfields, mudflats, swamps	An ecosystem includes natural terrestrial waters and water conservancy facilities.
Settlement ecosystem	Urban, rural, and other construction land	An ecosystem comprises artificial facilities such as urban and rural settlements and industrial, mining, and transportation facilities outside them.
Desert ecosystem	Sandy land, Gobi desert, saline land, alpine desert, tundra	An ecosystem that is currently unused or difficult to use.
Other ecosystem	Bare land, bare rocky land	An ecosystem with soil cover on the surface and less than 5% vegetation coverage or an ecosystem with a gravel coverage area greater than 5%.

3.3. Driving Factor Data

We selected representative driving factors related to human activity, climate, and surface conditions to investigate their influence on the distribution of AOD (Aerosol Optical Depth) across different ecosystems. These factors include Gross Domestic Product (GDP), Population Density (POP), Specific Humidity (SH), Precipitation (Pre), Temperature (T), Wind Speed (Wind), Soil Moisture (SoilMoi), and Digital Elevation Model (DEM). Driving factor data with a spatial resolution lower than MAIAC AOD is resampled to 1×1 km through cubic convolution interpolation to match AOD data. The sources and specific information of these data are shown in Table 3.

Table 3. Information on driving factors.

Driving Factor	Variable	Spatial Resolution	Unit	Data Source
Human activity	Gross Domestic Product	1 km	Million dollar	Scientific Data [69] and Statistical Yearbook of Xinjiang Uygur Autonomous Region [70]. Oak Ridge National Laboratory Land Scan [71]. and Statistical Yearbook of Xinjiang Uygur Autonomous Region [70].
	Population Density	1 km	Person	
Meteorological condition	Specific Humidity	0.25°	kg/kg	NASA Global Land Data Assimilation System [72].
	Precipitation	0.1°	m	The fifth generation ECMWF atmospheric reanalysis of the global climate [73].
	Temperature	1 km	°C	National Qinghai Tibet Plateau Data Center [74].
	Wind Speed	0.25°	m/s	NASA Global Land Data Assimilation System [72].
Surface condition	Soil Moisture	0.1°	m ³ /m ³	The fifth generation ECMWF atmospheric reanalysis of the global climate [73].
	Digital Elevation Model	30 m	m	

4. Research Methodology

In this study, we first validated the usability of MODIS AOD data in Xinjiang through spatial and temporal matching with ground-based measurements. Subsequently, 296,736 sampling points were set up at a density of 1×1 km across the study area to analyze the distribution characteristics of AOD across ecosystem types at various elevations. Additionally, based on the M-K trend test and linear fitting, we explored the interannual variation characteristics of ecosystem type AOD and discussed its seasonal variation patterns. Finally, we applied the Geographic Detector to examine the impact of meteorological, surface condition, and human activity factors on the interannual spatial variability of AOD from 2001 to 2023.

4.1. Data Matching and Validation

To compare the alignment of satellite remote sensing AOD with ground-based AOD measurements in the study area, the Ångström wavelength exponent equation (Equation (1)) [76,77] was used to interpolate AERONET AOD at 500 nm and 675 nm to estimate AOD at 550 nm (Equation (2)). Subsequently, a spatiotemporal matching approach was employed to perform linear regression analysis, comparing the AERONET AOD averaged over ± 30 min of satellite overpass time with the MAIAC AOD averaged over a 3×3 pixel area surrounding the site location. Accuracy was validated using the Pearson's r and Root Mean Square Error (RMSE) to assess the suitability of MAIAC AOD in the study area.

$$\alpha = -\frac{\log(\tau_1/\tau_2)}{\log(\lambda_1/\lambda_2)} \quad (1)$$

$$\tau_\lambda = \beta \lambda^{-\alpha} \quad (2)$$

where λ_1 and λ_2 denote two different wavelengths, τ_1 and τ_2 denote the AOD values at the corresponding wavelengths, and α denotes the Ångström wavelength exponent. τ_λ is the optical thickness of the aerosol corresponding to a wavelength of λ . β is the atmospheric turbidity coefficient.

4.2. Mann–Kendall Trend Test

The M-K trend test is a non-parametric method used to assess the significance of trends in time series data [78,79]. It is suitable for detecting trends in long-term time series data. The process is as follows:

For the time series $\{AOD_n\}$, where $n = 2001, 2002, 2003, 2004, \dots, 2023$, define S as the test statistic, and the calculation formula is Equation (3).

$$S = \sum_{i=1}^{n-1} \sum_{j=n+1}^n \text{sgn}(AOD_i - AOD_j) \quad (3)$$

AOD_i and AOD_j represent the annual average pixel values of AOD in year i and year j , respectively. sgn is the sign function. The calculation formula is as shown in Equation (4).

$$\text{sgn}(AOD_i - AOD_j) = \begin{cases} 1, AOD_i - AOD_j > 0 \\ 0, AOD_i - AOD_j = 0 \\ -1, AOD_i - AOD_j < 0 \end{cases} \quad (4)$$

The calculation methods of the Z statistic (Equation (5)) and variance (Var) of S (Equation (6)) are as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, (S > 0) \\ 0, (S = 0) \\ \frac{S+1}{\sqrt{Var(S)}}, (S < 0) \end{cases} \quad (5)$$

$$Var(S) = \frac{n(n-1)(2n+5)}{18} \quad (6)$$

The Z statistic conforms to the standard normal distribution. A positive value indicates an upward trend, and a negative value indicates a downward trend [80]. In this study, we chose $\alpha = 0.05$ and 0.1 to test the significance of the trend in AOD on the pixel scale from 2001 to 2023.

4.3. Geographic Detector

Geographic Detector, with its factor, interaction, risk, and ecological detection capabilities, is a crucial statistical tool for identifying the spatial heterogeneity and driving factors of geographical elements [81]. This study utilizes factor, interaction, and risk detectors to analyze the driving factors of AOD.

The factor detector quantitatively describes the explanatory power of factors on AOD. The results are represented by the q value (Equation (7)), where $q \in [0, 1]$. When the q value is close to 1, it indicates that the factor has a strong explanatory power for the spatial heterogeneity of AOD. When q is close to 0, it indicates a weak explanatory power.

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (7)$$

where L is the number of levels after the factors are classified, this study sets L to 8. $h = 1, 2, 3, \dots, 8$. N_h and N represent the number of sample points at level h and all levels. σ^2 and σ_h^2 represent the variances of AOD at level h and all levels.

The interaction detector can evaluate the impact and explanatory power of the interaction between factors on AOD. The results of these interactions are categorized into five types, as shown in Table 4.

Table 4. Interaction patterns between factors.

Criterion	Interaction Pattern
$q(X_n \cap X_i) < \min(q(X_n), q(X_i))$	Nonlinearity attenuation
$\min(q(X_n), q(X_i)) < q(X_n \cap X_i) < \max(q(X_n), q(X_i))$	Single-factor nonlinearity decreases
$q(X_n \cap X_i) > \max(q(X_n), q(X_i))$	Two-factor enhancement
$q(X_n \cap X_i) = q(X_n) + q(X_i)$	Independent
$q(X_n \cap X_i) > q(X_n) + q(X_i)$	Nonlinear enhancement

The risk detector calculates the mean AOD in different hierarchical partitions of factors and determines whether there is a significant difference between the mean of these subregions at different levels, further identifying the regions where AOD increases or decreases.

Since the independent variables used in the Geographic Detector are the number of types, different factors must be graded. In this study, all factors are divided into eight levels. We use natural breaks (Jenks) for division for meteorological and surface condition factors, while we use geometrical intervals for human activity factors. We established a $1 \text{ km} \times 1 \text{ km}$ grid to match the MODIS AOD data, using the grid center points as sampling locations. A total of 296,736 sampling points were set up within the study area. The driving factors and the annual mean MODIS AOD values were extracted using the Extract Multi Values to Points tool in ArcGIS 10.8 and imported into the spatial database of the sampling points. These data were then used as input variables for the Geographic Detector model.

5. Results and Analysis

5.1. Spatial Distribution Pattern of AOD

Figure 3 presents the comparative validation results of MAIAC AOD and AERONET AOD. The Pearson's r value is 0.7776, and the RMSE is 0.05638. The results indicate

that the MAIAC AOD products from Terra and Aqua, which have a spatial resolution of 1 km, generally align with the overall trend in AERONET ground-based observations, demonstrating a high accuracy and applicability in the Xinjiang region.

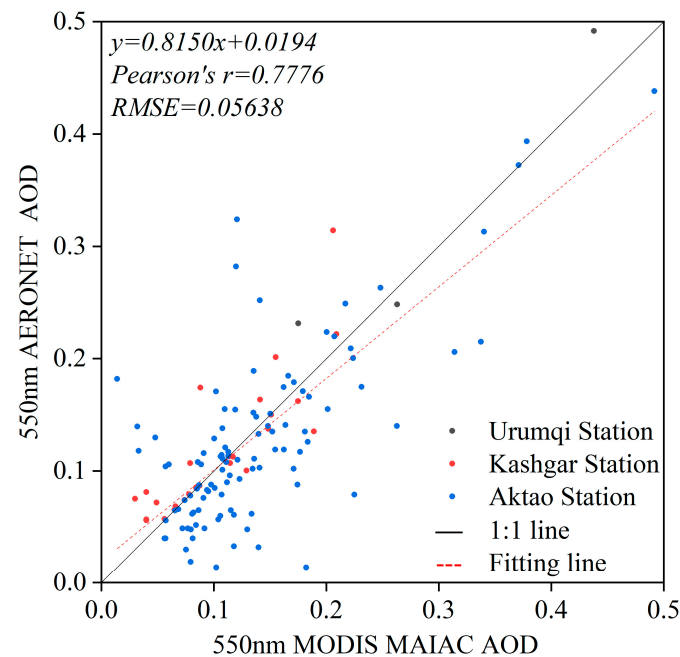


Figure 3. Scatter plot of AERONET AOD and MODIS MAIAC AOD from 2001 to 2023.

The spatial distribution of the interannual mean of MAIAC AOD in Northern Xinjiang from 2001 to 2023 is shown in Figure 4. The distribution of AOD shows significant regional differences. High-value areas are mainly concentrated in the economically developed and densely populated economic belt on the north slope of the Tianshan mountains, Yili River Valley Oasis, Tacheng Oasis, Irtysh River Oasis, and the relatively arid Gurbantunggut Desert. Ebinur Lake and Manas Lake are two extremely high-value areas of AOD in Northern Xinjiang. Low-value regions are mainly distributed in mountainous areas such as the Tianshan and Altai Mountains.

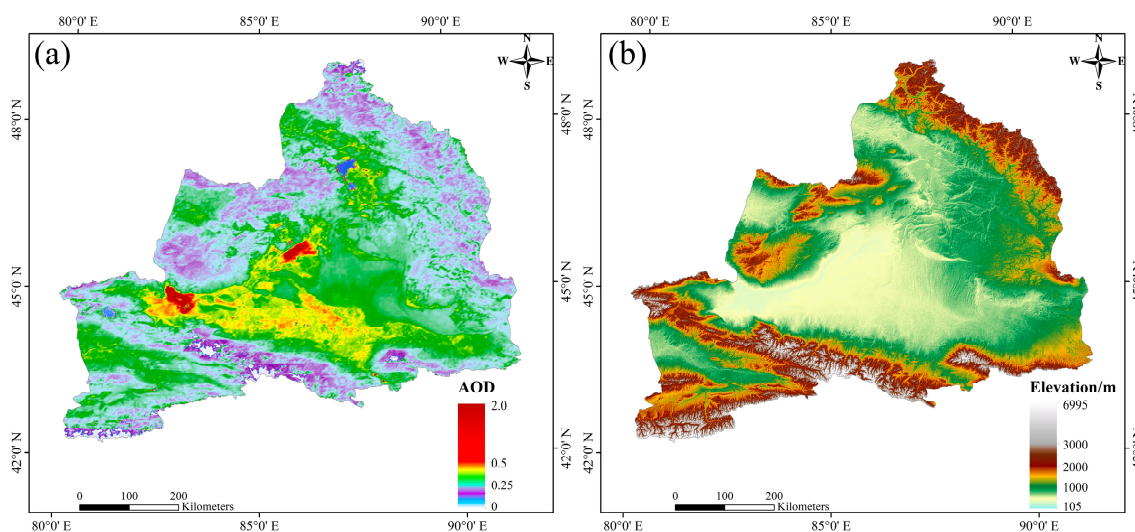


Figure 4. (a) Spatial distribution of annual mean AOD averaged from 2001 to 2023 over Northern Xinjiang. (b) Elevation of Northern Xinjiang.

We observed that the distribution of AOD in Northern Xinjiang is significantly influenced by the topography, with a clear distinction between the plains and mountainous regions. Therefore, we conducted a visualization and zonal statistical analysis of AOD in ecosystems at different elevations to reveal the spatial heterogeneity resulting from vertical zonation. Since the MAIAC algorithm may be affected by high reflectivity over continuous time periods and generate uncertainties, areas with long-term snow cover will be filled with null data [62]. Therefore, higher areas above 6000 m above sea level are not analyzed in this study.

Figure 5 shows the distribution of the interannual mean of AOD of different ecosystems varying with altitude. Figure 5a shows that the area below 4000 m above sea level is the leading distribution area of aerosols. The land area above 4000 m only accounts for 0.53% of the study area. There is almost no human activity here, and at the same time, there are fewer natural dust sources. Regarding ecosystem types, grasslands are widely distributed below 3500 m above sea level. Deserts are mainly concentrated in the 500–1200 m area, and a small amount is distributed between 1200 and 2000 m. Settlements and farmlands appear within 500–2000 m, mainly concentrated in the plain at 500–1000 m. Forests are distributed between 500 and 3000 m; their main distribution area is the mountainous area at 2000–3000 m. Wetlands are concentrated in two altitude areas. The 500–1500 m area is mainly plain lake water systems, while the 3500–5000 m area is the leading distribution area of alpine lake water systems. Other ecosystems are primarily concentrated in the high-altitude area of 3000–4500 m, with a small sporadic distribution below 3000 m.

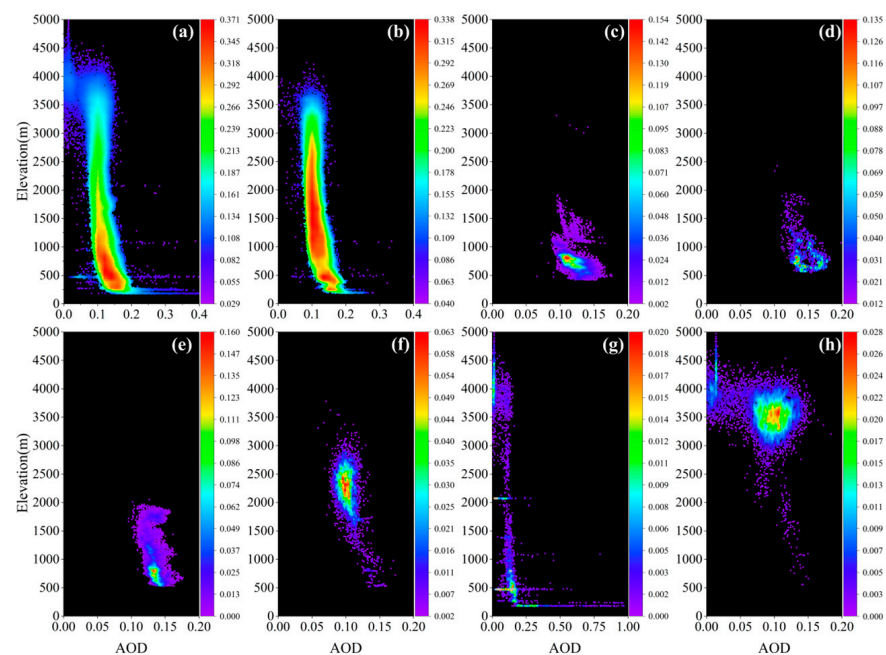


Figure 5. The distribution of the annual mean AOD averaged from 2001 to 2023 in ecosystems at different elevations. (a) Entire study area; (b) grasslands; (c) deserts; (d) settlements; (e) farmlands; (f) forests; (g) wetlands; (h) others.

Due to the large altitude span, we divided it into three main intervals: (0, 1000] m, (1000, 2000] m, and (2000, 6000] m, for detailed analysis (Figure 6).

The area below 1000 m above sea level accounts for 56.29% of the total study area. Here, the terrain is flat and open. In total, 85.3% of the farmland and 93.5% of the desert are distributed in Northern Xinjiang. The median AOD levels of ecosystem types in this area are in the following order: settlements (0.153) > farmlands (0.151) > wetlands (0.141) > forests (0.138) > grasslands (0.136) > deserts (0.126) > others (0.115). In the past two decades, the construction of land and cultivated land in the urban agglomeration of the economic belt on the north slope of the Tianshan mountains has shown a drastic double-expansion

trend. Industrial and traffic pollution emissions in settlements have significantly increased aerosol particles in the air in a local range. In farmland, during the farming process, the soil is disturbed, dust is generated, and agricultural chemicals are sprayed, keeping AOD in the region at a relatively high level.

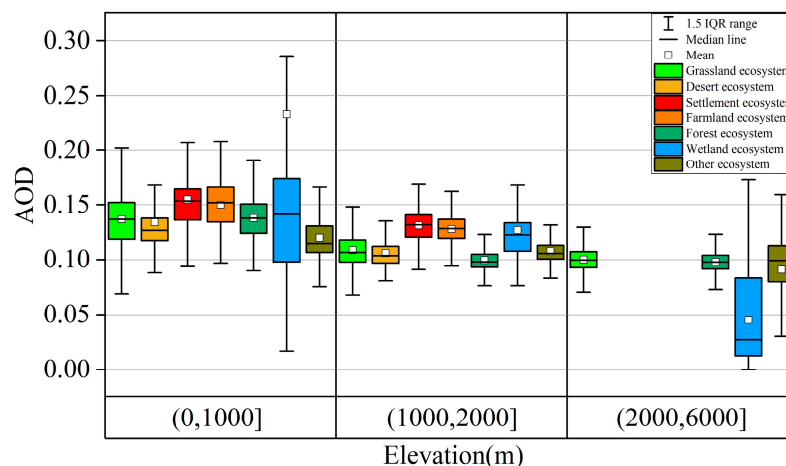


Figure 6. A box plot of the interannual mean AOD values for different ecosystem types across elevation intervals from 2001 to 2023.

It is worth noting that the AOD of wetlands is the highest in terms of the mean, which is mainly affected by extreme values. As mentioned, Manas Lake and Ebinur Lake are two areas of an exceptionally high AOD distribution in Northern Xinjiang, with average lake surface elevations of 257 m and 189 m, respectively. These lakes are all saltwater lakes. Affected by agricultural water use and human expansion activities, the lake bodies are shrinking [82–84]. After the lake bottoms dry up, a large amount of exposed dust and salt sediment spread under the action of wind, which is the main reason for keeping AOD in this area at the highest level. While Jili Lake (482 m) and Ulungur Lake (468 m) are abundant in water, the surrounding surface conditions are good, the vegetation coverage is high, and there is a lack of loose and easily spread dust and salt dust substances. In the wetlands within this altitude interval, the AOD of these two lakes is always maintained at a relatively low level.

In forests, the complex structure of the tree canopy, characterized by variations in leaf density and tree height, leads to changes in airflow velocity at different heights. This variability enhances air convection within the forest and generates turbulence within the canopy [85]. Additionally, temperatures at the top of the canopy are typically higher than those at the bottom, creating a vertical temperature gradient that further promotes air convection. Turbulent and convective motions allow for higher peak velocities of vertical airflow, especially in canopy gaps or open areas [86,87]. This airflow benefits the forest's ability to intercept and filter particulate matter, thereby maintaining lower levels of AOD [46]. In addition, the grassland vegetation in this interval is relatively low, and its ability to adsorb and retain atmospheric particulate matter is relatively weak. There are relatively few aerosols generated by biological activities and soil processes. The AOD is lower than that of the forests. The deserts correspond to the main body of the Gurbantunggut Desert and are mainly composed of fixed and semi-fixed dunes. It has a relatively high stability. Compared with the desertified grassland in the region, it is not quickly carried into the atmosphere by the wind to form dust aerosols [88]. The other ecosystems dominated by exposed rocks have a hard surface. The content of dust particulate matter is lower than that in deserts and is the area with the lowest AOD level among all ecosystems.

The 1000–2000 m altitude is mainly the transition zone between mountains and oases, accounting for 29.82% of the total study area. The ecosystems are mainly grasslands, forests,

and exposed rocks. Only a tiny amount of farmland and settlements are on the northern slope of the Tianshan Mountains and in the Yili River Valley. The median AOD levels are in the following order: settlements (0.131) > farmlands (0.128) > wetlands (0.122) > grasslands (0.106) > others (0.105) > deserts (0.103) > forests (0.098). As the altitude rises above 3000 m, the alpine area mainly comprises the Tianshan and Altai Mountains. It primarily includes rocks, alpine meadows, deciduous broad-leaved forests, and mountain coniferous forests. The median AOD of forest, grassland, and other ecosystems is around 0.11. The wetland ecosystems, mainly composed of alpine lakes and other water systems, have the lowest AOD above 3000 m, with a median of 0.027.

Significant differences exist in the spatial distribution of AOD across different elevation levels among various ecosystems in Northern Xinjiang. Low-elevation farmlands and settlements typically exhibit higher AOD levels, whereas grasslands, forests, and rocky areas in mountainous regions generally display lower AOD levels. Overall, AOD decreases gradually with increasing ecosystem elevation, and this pattern remains consistent across seasonal variations (Figure 7). This suggests that regardless of the elevation at which an ecosystem is situated, it plays an essential role in evaluating AOD.

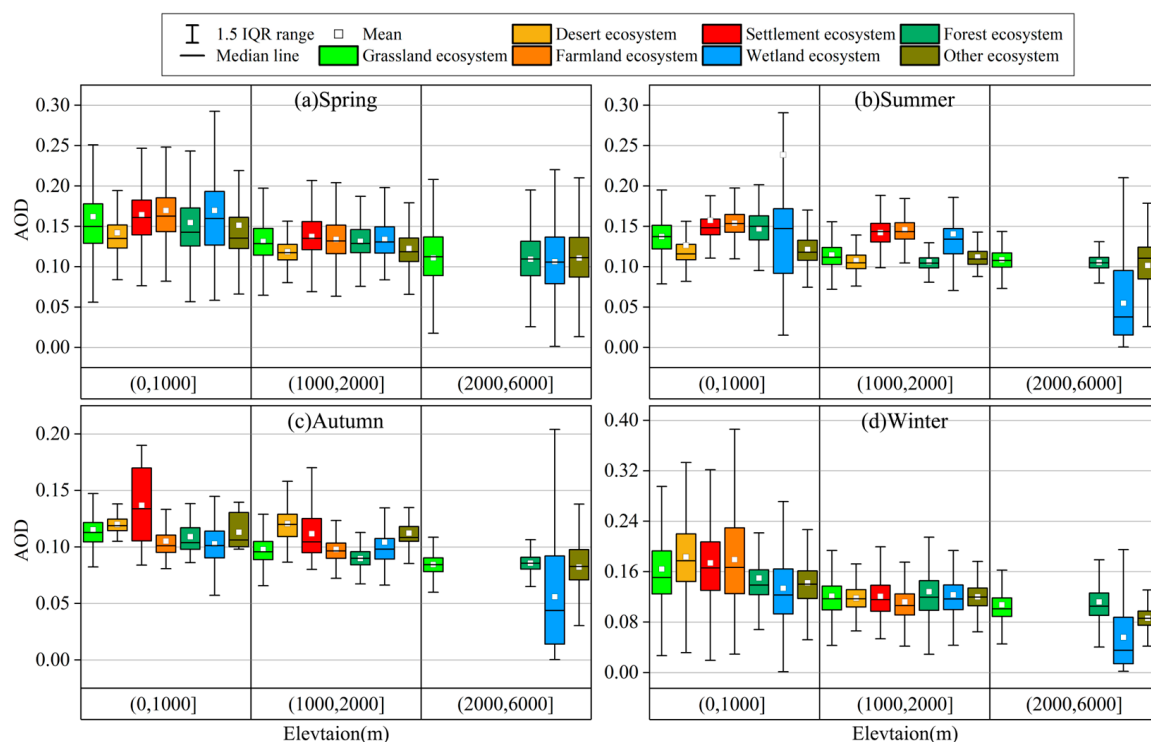


Figure 7. A box plot of the interannual seasonal mean AOD values for different ecosystem types across elevation intervals from 2001 to 2023: (a) spring, March to May; (b) summer, June to August; (c) autumn, September to October; (d) winter, November to February.

5.2. Temporal Variation Characteristics of AOD

To explore the spatial distribution pattern of the interannual variation trend in AOD, we conduct the M-K trend test and divide it into five levels at the pixel scale, namely a significant increase ($Z > 1.96$), a slight increase ($1.65 < Z \leq 1.96$), no significant change ($-1.65 \leq Z \leq 1.65$), a slight decrease ($-1.96 \leq Z < -1.65$), and a significant decrease ($Z < -1.96$). The visualization results are shown in Figure 8, and the area statistical results are shown in Figure 9.

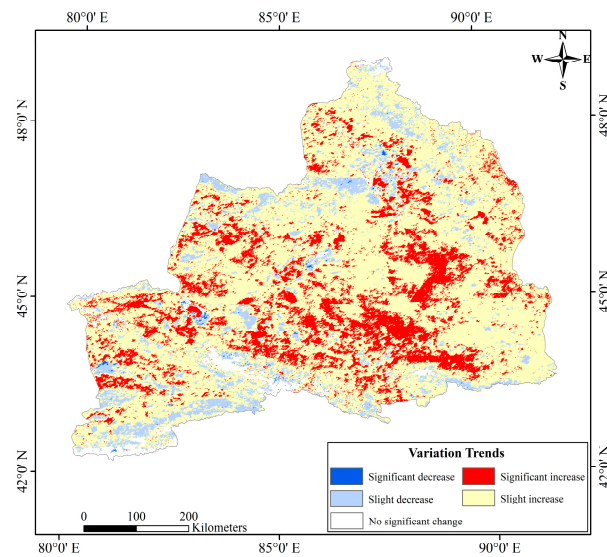


Figure 8. Spatial distribution of AOD change trend.

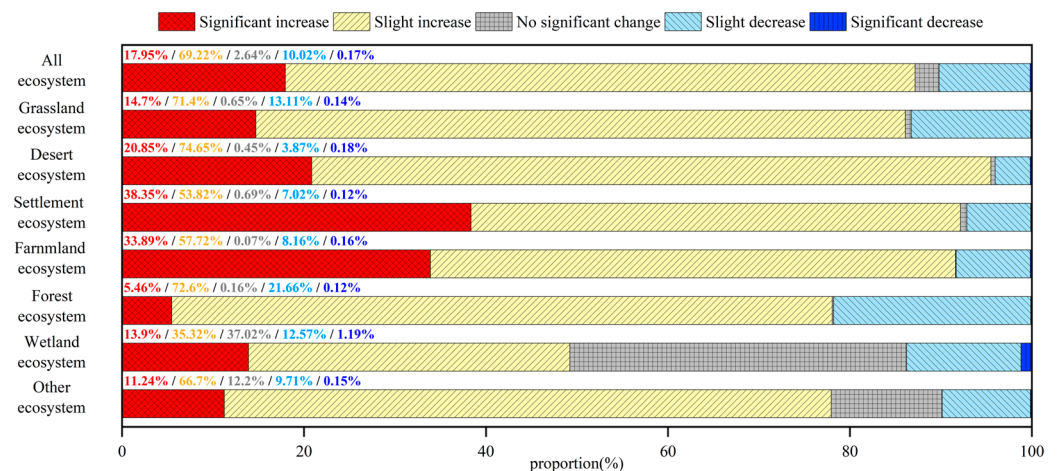


Figure 9. Proportion of pixel area of change trend by ecosystem types.

In Northern Xinjiang, the area with a significant decrease has a value of 0.17%, and the pixels are scattered in a dotted manner. There is an area which showed a slight decrease of 10.02%, showing a characteristic distribution along the mountains. The pixels with a significant increase account for 17.95% and are mainly distributed in various oasis areas and the Gurbantunggut Desert and its surroundings. The pixels with the most significant area proportion are those with a slight increase, accounting for 69.22%, and are evenly distributed throughout Northern Xinjiang. Only 2.64% of the pixels have no significant change and are distributed in the high-altitude mountain areas of the Tianshan Mountains and Bogda Peak. The differences within ecosystem types are also significant. On the whole, a slight increase is the primary trend. The proportion of pixels with a significant increase within different ecosystems is as follows: settlements (38.35%) > farmlands (33.89%) > deserts (20.85%) > grasslands (14.7%) > wetlands (13.9%) > others (11.24%) > forests (5.46%). Regarding the decreasing trend, 21.78% of the pixels in the forest show a significant and slight decrease, which has to do with the ecosystems showing the highest proportion of AOD decrease. This is followed by wetlands (13.25%), grasslands (13.25%), others (9.86%), farmlands (8.32%), settlements (7.14%), and deserts (4.05%).

The annual average change in AOD in different ecosystems is shown in Figure 10. In general, the AOD in Northern Xinjiang shows a fluctuating upward trend. During the period from 2001 to 2023, the linear growth rates of each ecosystem are as follows: wetlands

$(1.46 \times 10^{-2} \text{ year}^{-1}) > \text{settlements } (8.1 \times 10^{-3} \text{ year}^{-1}) > \text{farmlands } (7.8 \times 10^{-3} \text{ year}^{-1}) > \text{deserts } (5.9 \times 10^{-3} \text{ year}^{-1}) > \text{others } (4.5 \times 10^{-3} \text{ year}^{-1}) > \text{grasslands } (3.7 \times 10^{-3} \text{ year}^{-1}) > \text{forests } (2.3 \times 10^{-3} \text{ year}^{-1})$. The average AOD levels are in the following order: wetlands (0.154) > settlements (0.151) > farmlands (0.147) > deserts (0.132) > grasslands (0.114) > others (0.106) > forests (0.102).



Figure 10. Annual average AOD changes of ecosystem types from 2001 to 2023.

We analyze it in five stages: 2001–2005, 2005–2010, 2010–2015, 2015–2020, and 2020–2023. Before 2005, the settlement, farmland, forest, and wetland ecosystems showed a growth trend, while the grassland, desert, and other ecosystems with AOD values relatively far from towns showed a downward trend. All ecosystems except the wetlands had the lowest value in 2003. From 2005 to 2020, the economic development of Northern Xinjiang was the fastest. Apart from how the forests showed a downward trend ($-2.6 \times 10^{-4} \text{ year}^{-1}$) from 2005 to 2010, the AOD of all ecosystems increased at different rates. Among them, the rapid increase in settlements and farmlands from 2010 to 2020 may be related to the rapid development model of an extensive economy. Taking Urumqi, the largest city in Northern Xinjiang, as an example, GDP increased by about 493% from 2005 to 2020. The anthropogenic aerosol emissions experienced a substantial growth stage. However, during the same period, the wetlands showed the fastest rate of growth ($-6.74 \times 10^{-3} \text{ year}^{-1}$) from 2010 to 2015. This is closely related to the severe and rapid degradation of the ecological environment of Ebinur Lake and Manas Lake and the severe natural aerosol pollution.

From 2005 to 2015, the upward trend in AOD in Northern Xinjiang sharply contrasted with the improvement in air quality in metropolitan areas such as Beijing, Shanghai, and Guangzhou [89]. This phenomenon is related to the implementation of the Western Development Strategy, which has intensified the emission of anthropogenic aerosols in Northwest China [90]. However, some positive pollution control actions have caused changes in the annual average level of AOD in the short term. The downward trend from 2013 to 2017 is closely related to implementing the 2013–2017 Clean Air Action Plan [91]. Subsequently, the Chinese government launched the Three-Year Action Plan for Defending the Blue Sky in 2018 [92]. We found that from 2018 to 2021, there was a failure to sustain the declining trend in AOD observed since 2013. Instead, it began to rise in 2018 and reached the highest annual level in nearly 20 years in 2019. This phenomenon completely differs from the rapid decline in AOD in eastern China from 2013 to 2021 [93]. We believe the

Three-Year Action Plan for Defending the Blue Sky is less effective in Northern Xinjiang than the 2013–2017 Clean Air Action Plan.

After 2021, due to the slowdown in economic growth and the government's stricter environmental protection efforts, the emissions of anthropogenic and natural aerosols have been controlled to a certain extent. Different ecosystems in Northern Xinjiang have shown a relatively apparent downward trend and reached another historic low in 2022.

Figure 11 shows the variation in the interannual monthly mean of AOD. On a seasonal scale, the AOD in Northern Xinjiang presents a bimodal variation curve. It decreases from January to February and May to September, while it increases from March to April and October to December. The peak months of AOD in different ecosystems are different. The peaks of grasslands, deserts, and forests appear in March, while those of settlements, wetlands, and others appear in April, and that of farmlands in May.

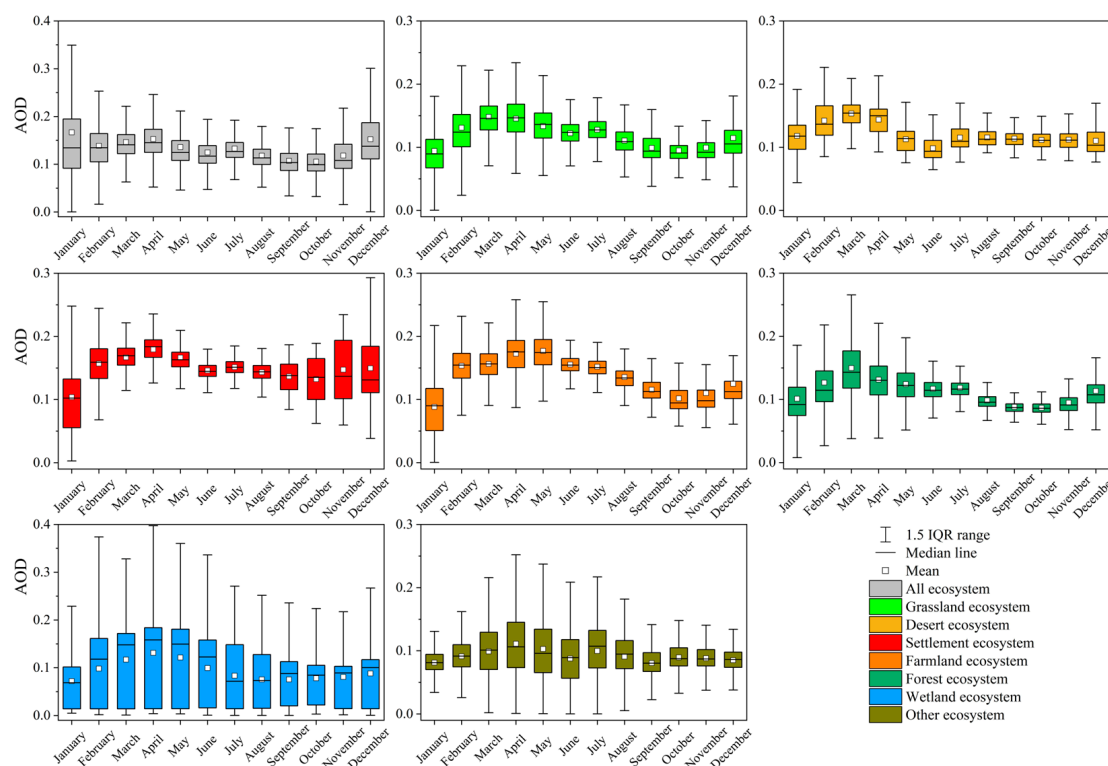


Figure 11. Interannual monthly mean changes in AOD in different ecosystems from 2001 to 2023.

In spring (March to May), Northern Xinjiang is often affected by the dry, cold air brought by the westerlies [94]. This dry and stable weather condition brought by the cold air is conducive to accumulating aerosols, leading to frequent dust weather. Strong winds carry a large amount of dust and soil particles, increasing the concentration of particulate matter in the atmosphere. Therefore, high AOD values are detected in all ecosystems in March and April. The AOD of farmlands gradually increases from March and reaches its peak in May, closely related to the large-scale agricultural activities during the same period.

In summer (June to August), the AOD of all ecosystems begins to decline. Spatially, along the economic belt on the north slope of the Tianshan mountains, it still maintains a relatively high level (Figure 12f–h). Although Northern Xinjiang experiences increased precipitation in summer, high vegetation coverage, and favorable atmospheric dispersion conditions, deserts in arid and semi-arid regions remain natural sources of particulate emissions. Consequently, a slight increase in AOD was observed in the desert areas in June.

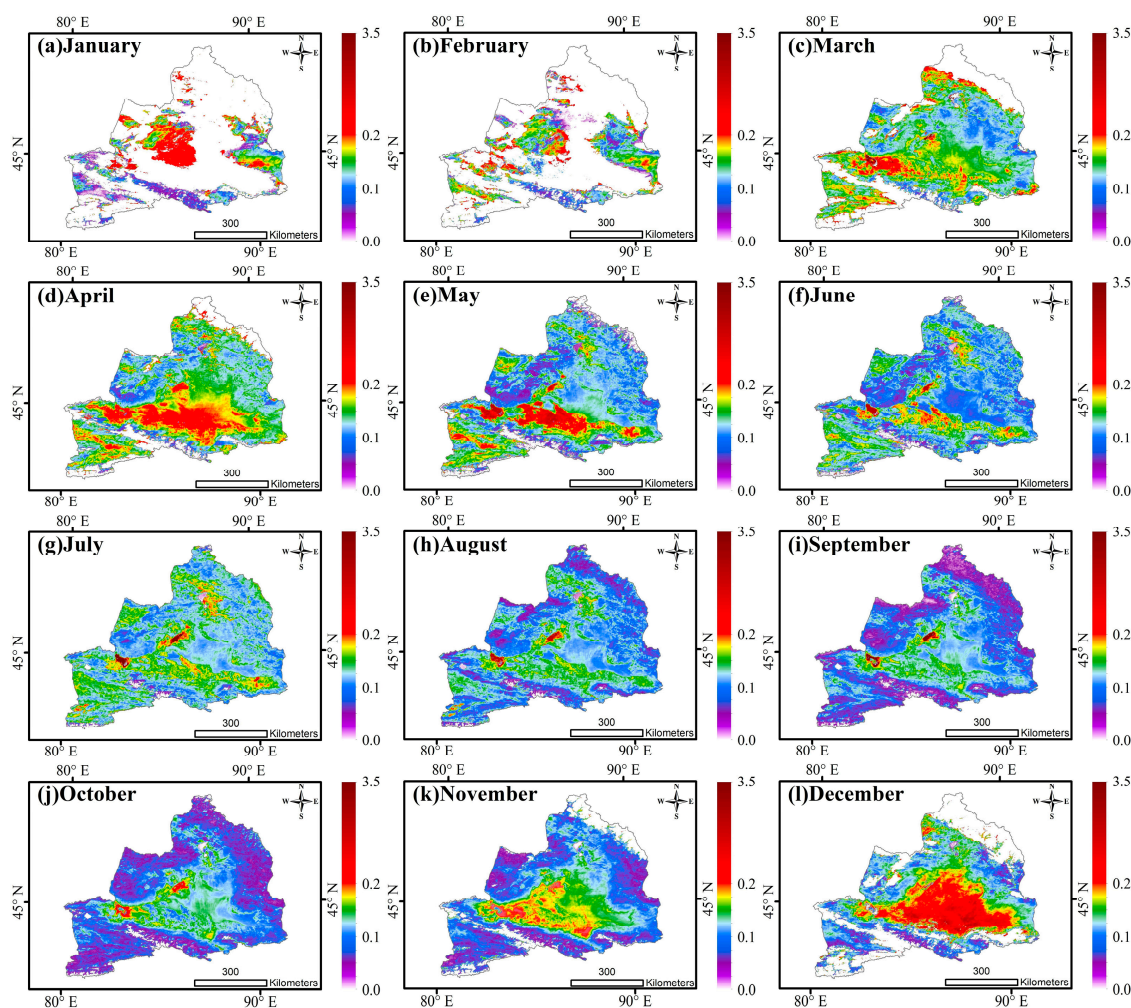


Figure 12. Spatial distribution of interannual monthly mean of AOD in Northern Xinjiang.

In autumn (September to October), the AOD variations across different ecosystems tend to stabilize at a relatively low overall level. This is significantly associated with the reduced frequency of dust storm events during autumn.

As winter sets in (November to February), temperatures drop rapidly, and urban areas gradually enter the heating season. During this phase, low wind speeds and high relative humidity, combined with the concentrated use of fossil fuels, lead to a significant increase in particulate emissions and a notable decline in air quality. The lower planetary boundary layer facilitates the accumulation of aerosols near the surface in winter, further contributing to the rise in AOD.

The economic belt along the northern slope of the Tianshan Mountains is a region with frequent human activities characterized by contiguous agricultural lands and urban areas, with various ecosystems interspersed. In winter, areas near towns experience varying air quality pollution (Figure 12k,i). As a result, the AOD for settlement, agricultural, grassland, forest, and wetland ecosystems begins a new upward trend starting in November, exhibiting a bimodal variation throughout the year. In contrast, desert and other ecosystems far from human activity show an unimodal variation pattern over the year.

It is important to note that from January to February, blank pixels were observed in most areas of the Tianshan and Altai Mountains and the Junggar Basin (Figure 12a,b). This is due to prolonged snow cover, which increases surface reflectance, thereby affecting the MAIAC algorithm's retrieval of AOD and resulting in incomplete AOD data. In areas where data are available, the increase in AOD is closely linked to large-scale population activities around the Chinese New Year and the rise in heating demands [95].

5.3. Analysis of Driving Factors

We selected eight driving factors from human activities, meteorological conditions, and surface conditions as the independent variables (X) of the geographical detector. The dependent variable Y is the interannual mean of AOD. Table 5 shows the results of the factor detector.

Table 5. Results of factor detector.

Driving Factors		Human Activity		Meteorological Condition			Surface Condition		
		X1 GDP	X2 POP	X3 SH	X4 Pre	X5 T	X6 Wind	X7 SoilMoi	X8 DEM
Grassland ecosystem	q value	0.102	0.109	0.238	0.216	0.435	0.035	0.195	0.528
	p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Desert ecosystem	q value	0.001	0.001	0.118	0.002	0.056	0.042	0.006	0.080
	p value	1.00	1.00	0.00	1.00	0.00	0.00	0.85	0.00
Settlement ecosystem	q value	0.010	0.019	0.042	0.032	0.032	0.021	0.025	0.047
	p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Farmland ecosystem	q value	0.039	0.011	0.079	0.268	0.164	0.112	0.210	0.425
	p value	0.00	0.79	0.00	0.00	0.00	0.00	0.00	0.00
Forest ecosystem	q value	0.113	0.208	0.168	0.353	0.501	0.134	0.319	0.539
	p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wetland ecosystem	q value	0.001	0.001	0.202	0.148	0.280	0.106	0.115	0.129
	p value	0.83	0.67	0.00	0.00	0.00	0.00	0.00	0.00
Other ecosystem	q value	0.016	0.023	0.250	0.171	0.253	0.050	0.179	0.334
	p value	1.00	0.98	0.00	0.00	0.00	0.00	0.00	0.00

For grasslands, the factors with the highest explanatory power for AOD are DEM, T, and SH, with q values of 0.528, 0.435, and 0.238, respectively. Others are secondary factors. In deserts, only SH has an explanatory power of 0.118, and the explanatory power of other factors is relatively weak. The explanatory power of all single factors in settlements is not prominent, and the q value is below 0.1. Surface condition factors DEM and SoilMoi have high explanatory power for farmlands, with q values of 0.425 and 0.21, respectively. In addition, the meteorological condition Pre also has a significant influence, with a q value of 0.268. The factors that have the highest impact on forests are DEM and T, and the q values are both greater than 0.5. In wetlands, T and SH have relatively high explanatory power for AOD among all factors, which are 0.28 and 0.202, respectively. Other ecosystems are mainly affected by DEM, T, and SH, with explanatory powers of 0.334, 0.253, and 0.25, respectively.

These results indicate that the same driving factors significantly differ in the degree of influence on AOD in different ecosystems. However, in a natural state, the spatial distribution of AOD is jointly affected by multiple factors. A single factor usually cannot fully explain this phenomenon, so it is necessary to consider the combined effects of natural and human factors comprehensively.

Figure 13 shows the results of the interaction detector. The interaction between factors has a greater impact on AOD than the individual effect of a single factor, with two-factor enhancement and nonlinear enhancement as the main interaction patterns.

For grassland and forest areas, the interaction between T and DEM ($X5 \cap X8$) has the most significant impact on the spatial differentiation of AOD, with q values of 0.601 (grassland) and 0.632 (forest), respectively. It is worth noting that when DEM interacts with any other environmental factor, the q value is above 0.5, which has a relatively high influence. Grasslands and forests are widely distributed below 3500 m. As altitude increases, air density and atmospheric pressure gradually decrease, and higher elevations are often associated with more substantial wind speeds and lower humidity. These factors facilitate the dispersion and dilution of aerosols, reducing their accumulation in the atmosphere.

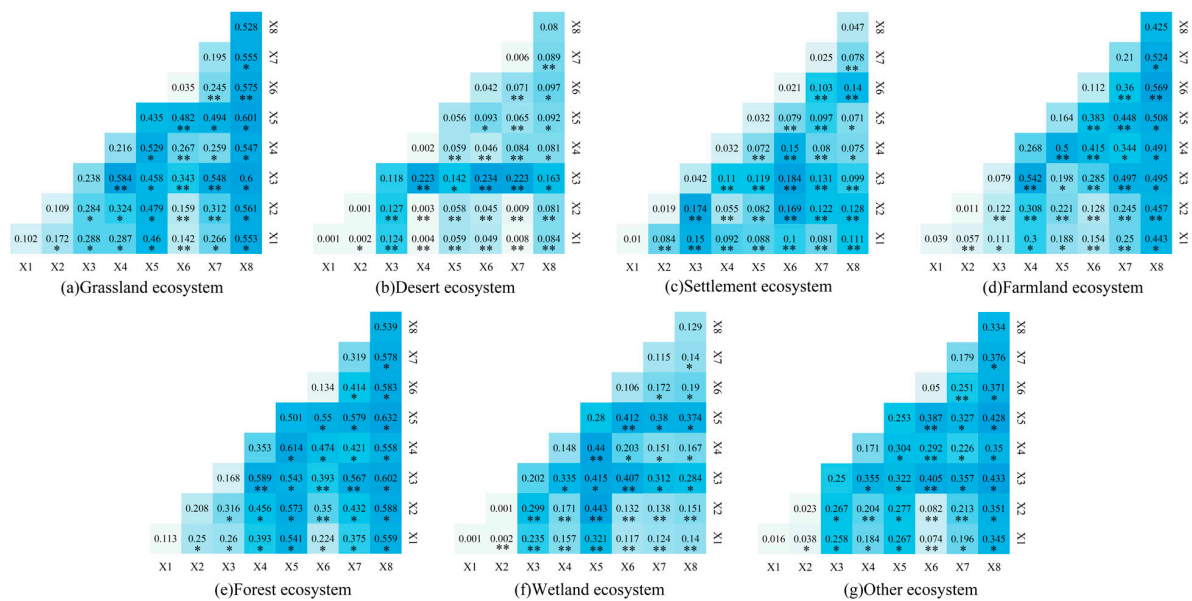


Figure 13. Results of interaction detector. (a–g) The numbers represent the explanatory power of the interaction of driving factors. * represents two-factor enhancement, and ** represents nonlinear enhancement.

In desert areas, the combined effect of SH and Wind ($X3 \cap X6$) is the greatest, with a q value of 0.234. In the Gurbantunggut Desert area, moist air can increase the cohesion between soil particles and better fix the ground. In addition, high humidity can directly affect the vegetation coverage in the desert. Some ephemeral plants usually grow, flower, and reproduce rapidly after a short rainy season, fix the sand and soil through roots, prevent the movement of dunes, and reduce the frequency and intensity of sandstorms. On the contrary, in drier areas of the desert, more particulate matter can be lifted into the air under strong winds. The stronger the wind speed, the easier it is to form dust weather and increase the AOD level. The interaction combinations of other factors have a relatively weak impact on the desert, and the q values are all less than 0.1. In settlement areas, SH and Wind ($X3 \cap X6$), SH and POP ($X3 \cap X2$), and POP and Wind ($X2 \cap X6$) show relatively significant effects, with q values of 0.184, 0.174, and 0.169, respectively. Higher population density in urban areas usually means a higher possibility of anthropogenic aerosol pollution, while wind speed and humidity directly affect the aggregation and diffusion of aerosols.

For farmland, the interaction between wind speed and elevation ($X6 \cap X8$) significantly influences AOD, with a q -value of 0.569. Farmland is primarily distributed between elevations of 500 and 2000 m, with a sharp decrease in area above 2000 m. The primary sources of aerosols in these areas are soil particles raised during cultivation and pesticide spraying, dispersed by the wind. However, below 1200 m, farmland and settlements are interspersed, meaning that lower-elevation regions are more susceptible to long-range industrial pollution transport from surrounding areas. This influence gradually diminishes with increasing elevation.

In wetland ecosystems, the interaction between POP and T ($X2 \cap X5$) has an explanatory power of 0.443. This sufficiently explains the phenomenon of a lake drying up due to human activities in Manas Lake and Ebinur Lake, exposing a large amount of salt substances and causing the diffusion of surface particulate matter with the increase in temperature. In other ecosystems, the q value under the interaction of SH and DEM ($X3 \cap X8$) is 0.428, indicating that in the main rock area distributed at an altitude of 3500 m, the coupling of terrain and humidity conditions has the most significant impact on the spatial differentiation of AOD.

Notably, wind speed and elevation are two critical driving factors influencing the spatial variation in the AOD of ecosystems, often closely linked to long-range aerosol transport and the height of the atmospheric boundary layer. Generally, the uplift of particles from the surface requires convection or stronger updrafts. However, topography and

monsoon effects also influence surface wind speed and direction. Additionally, the height of the planetary boundary layer, which varies seasonally, determines the extent to which pollutants can be mixed and diluted in the air. In some high-altitude ecosystems, where human activities are limited, elevation helps block the horizontal diffusion of pollutants, and meteorological conditions are more favorable for aerosol dispersion as these areas are closer to or in direct contact with the free atmosphere. Therefore, coupling various meteorological conditions, surface characteristics, and human activities is crucial in influencing the spatial variability of the AOD in terrestrial ecosystems.

The risk detector reflects the changes in the mean of the AOD from driving factors under different classifications (Figure 14). For all ecosystems, when the T is in the range of 8.55–11.94 °C (Level 8), AOD reaches its peak. Low-altitude (DEM) and low-precipitation (Pre) areas are also risk intervals with high AOD values, and AOD shows a decrease with the increase in altitude and precipitation. The AOD in settlement and wetland ecosystems shows the characteristics of increase-decrease-increase with the increase in SH. In contrast, the rest of the ecosystems show an increase with the increase in SH. In a highly humid environment, the higher water vapor content in the air can condense on tiny particles and promote the formation of aerosols such as haze. SoilMoi is not sensitive to the change in AOD in settlements, which is caused by the high surface-hardening rate in towns. However, in other ecosystems, the lower the water content of the surface soil, the higher the risk of AOD increases.



Figure 14. The results of the risk detector. The horizontal axis represents the mean of the AOD, and the vertical axis represents the driving factors in different classifications. Red and green represent the highest and lowest AOD values, respectively.

Wind speed primarily affects AOD by suspending and dispersing surface particles. In forested areas, aerosols mainly originate from biogenic particles emitted by vegetation, while long-range transported dust particles contribute only a tiny portion [96–98]. AOD in forest ecosystems exhibits a linear increase with rising wind speeds, reaching a maximum value of 0.125 when wind speed is between 4.45 and 5.29 m/s (Level 8). In contrast, in the rest of the ecosystems, the relationship between wind speed and AOD follows a nonlinear pattern, either increasing and then decreasing or showing a rise-decline-rise trend. Higher wind speeds enhance horizontal and vertical atmospheric mixing, rapidly dispersing aerosol particles over a larger area, thereby reducing local AOD. This phenomenon is consistent with the findings of Zhou et al. [32] and Liu et al. [42] in Central Asia.

Except for the settlement ecosystems, the AOD of all ecosystems increases with the increase in GDP and POP. Settlements are the main areas for human habitation and activities such as industrial production. Due to the relatively high GDP and POP levels and small spatial variability, the impact of human activity factors on AOD in this area has showed the same pattern.

6. Discussion

At present, many scholars have used AOD data with different spatial resolutions to study the spatial variation characteristics of aerosols, including $0.1^\circ \times 0.1^\circ$ (AERDB L2 VIIRS_SNPP) [99], $0.5^\circ \times 0.625^\circ$ (MERRA-2) [100], $10 \text{ km} \times 10 \text{ km}$ (MYD04/MOD04) [101], and $3 \text{ km} \times 3 \text{ km}$ (MYD04_3k/MOD04_3k) dimensions [102]. However, these data with lower resolutions make it difficult to capture the local changes in aerosols accurately. In contrast, MAIAC AOD, with a high resolution of $1 \times 1 \text{ km}$, can more accurately depict the spatial distribution of aerosols and performs better in complex terrain areas, consistent with previous studies' viewpoints [46].

We have observed that since the 21st century, the AOD of different ecosystems has exhibited significant variability, indicating that there may be the influence of abrupt change factors. For example, changes in the frequency of human activities in the region and short-term special environmental governance measures may impact this phenomenon [26]. A typical case is that of 2022, where the average AOD of various ecosystems in Northern Xinjiang decreased by 17% to 22% compared to 2021, reaching the lowest level in nearly a decade. This significant drop is closely related to the large-scale lockdown measures during the COVID-19 pandemic. Multiple studies have shown that the significant reduction in industrial production activities, transportation, and human activities during the pandemic significantly reduced the emission of aerosol pollutants [103]. This further indicates that human behavior or policy changes can immediately and significantly affect air pollution levels, echoing previous studies [104,105].

At the seasonal level, for the MAIAC AOD data used in this study, there are blank pixels in most areas of Northern Xinjiang as well as in the Tianshan Mountains and Altai Mountains from January to February. Therefore, the AOD data during this period often only partially reflect the actual air pollution situation, which is consistent with other research results in this region [106]. In the future, data-deficient areas can be supplemented and updated by combining ground monitoring data and spatial interpolation methods to more comprehensively analyze the AOD change situation in areas with high snow cover.

Different ecosystems have different influences on aerosols' generation, transmission, and deposition due to differences in vegetation coverage, soil structure, and water circulation [42,46,107], and there are also significant differences in the degree of response to driving factors. In this study, for grassland, farmland, forest, and other ecosystems with noticeable distribution differences with altitude changes, the AOD distribution is most affected by the combined action of surface and meteorological conditions. Desert and settlement ecosystems are mainly concentrated in low-altitude areas. The influence of meteorological conditions on AOD is greater than the difference in surface conditions within the decomposition area. In addition, we found that the interaction between population density and humidity has a high explanatory power for changes in AOD levels in

wetland ecosystems. This helps to clarify the formation reasons for the spatial differences in high AOD levels in places such as Manas Lake and Ebinur Lake and low AOD levels in areas such as Ulungur Lake, Jili Lake, Sayram Lake, and Kanas Lake, which have not been involved in previous studies.

This study further highlights the complexity of AOD changes in ecosystem types and the regional differences in air pollution. This necessitates that governance measures cannot be generalized. Systematic thinking should be carried out according to the actual situation of the region, including factors such as land use types, geographical environment, climatic conditions, industrial structure, and population density, to formulate targeted governance plans. Reasonable control of anthropogenic pollution emissions in urban areas, the setting of emission reduction targets, and the implementation of more effective environmental governance measures for shrinking water areas, deserts, and desertified grasslands with fragile ecological environments should be undertaken.

7. Conclusions

In this study, using MODIS MAIAC AOD data, we analyzed the spatiotemporal variation characteristics of AOD in grassland, desert, settlement, farmland, forest, wetland, and other ecosystems from 2001 to 2023. We also applied the geographical detector model to explore the influence of eight driving factors, including GDP, population density, specific humidity, precipitation, temperature, wind speed, soil moisture, and DEM, on the spatial differentiation of AOD in different ecosystems. The following conclusions can be drawn:

- (1) In the Northern Xinjiang region, the interannual average high-value areas of AOD are mainly concentrated in the economic belt on the north slope of the Tianshan mountains, the Gurbantunggut Desert, and other oasis areas. Low-value regions are mainly distributed in the Altai Mountains and Tianshan Mountains, showing a distribution pattern related to topographic features. The interannual average levels of the AOD of various ecosystems are in the order of wetlands > settlements > farmlands > deserts > grasslands > others > forests. Due to the ecological degradation of Manas Lake and Ebinur Lake and the frequent occurrence of dust activities, the average AOD level in wetland ecosystems is higher than in settlement ecosystems, where anthropogenic aerosol emissions are the primary source. Additionally, AOD shows a decreasing trend with the increasing elevation of the ecosystems.
- (2) Over the past 23 years, the AOD of different ecosystems has shown a fluctuating upward trend. The linear growth rates are in the following order: wetlands > settlements > farmlands > deserts > others > grasslands > forests. The Mann–Kendall trend test shows that the proportion of pixels with an increasing trend in the AOD of the settlement ecosystem is the highest, at 92.17%; the proportion of pixels with a decreasing trend in the AOD of the forest ecosystem is the highest, at 21.78%. On the interannual seasonal scale, the AOD of grassland, settlement, farmland, forest, and wetland ecosystems shows a bimodal curve, with peaks appearing in spring and winter, respectively; desert and other ecosystems show a unimodal curve, with the peak appearing in spring.
- (3) The sensitivity of driving factors to the interannual spatial variability of AOD across ecosystems varies. Grasslands and forests are mainly affected by temperature and altitude; deserts and settlements are most affected by wind speed and humidity; farmlands are mainly affected by wind speed and altitude; wetlands are greatly affected by population density and humidity; other ecosystems are mainly affected by humidity and altitude.

Long-term meteorological changes directly affect the processes of aerosol generation, transport, and removal, which in turn shape the AOD distribution patterns across different ecosystems. Rising temperatures accelerate photochemical reactions in the atmosphere, promoting the formation of secondary aerosols such as sulfates and nitrates [108]. Precipitation effectively reduces aerosol particles in the atmosphere through wet deposition [109], while long-term changes in wind speed are crucial for aerosol dispersion and long-range

transport [110]. Increased humidity also contributes to the formation of secondary organic aerosols [108]. These meteorological changes and the structural characteristics of ecosystems jointly determine the spatiotemporal distribution of AOD. Changes in AOD reflect the physical and chemical processes of aerosols and the complex interactions between ecosystems and climate. Therefore, in addressing future climate change and regional air pollution control, it is essential to consider the synergies between meteorological conditions, aerosols, and ecosystems to optimize management strategies and promote sustainable environmental and ecological development.

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