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# Analysis of Vegetation Coverage Changes and Influencing Factors in Aksu, Xinjiang, China (2000–2020): A Comparative Study of Climate Factors and Urban Development

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**Abstract:** The ecological environment is fundamental to human survival and development, and China has seen a historical shift from localized to widespread improvements in its ecological conditions. Aksu, a typical ecologically sensitive region in Xinjiang, China, is significant for the study of vegetation dynamics and their driving factors, which is crucial for ecological conservation. This study evaluates the spatiotemporal changes in vegetation coverage in Aksu from 2000 to 2020 using long-term Normalized Difference Vegetation Index (NDVI) data and trend analysis. Additionally, this study explores key factors influencing vegetation changes through correlation analysis with temperature, precipitation, and nighttime light data. The results indicate the following: (1) vegetation coverage in Aksu exhibits significant spatial heterogeneity, with annual NDVI increasing at a rate of 0.83% per year ($p < 0.05$); (2) the influence of temperature and precipitation on NDVI was weakly correlated from 2000 to 2020; and (3) a strong positive correlation was found between nighttime light intensity and NDVI, suggesting that urban development plays a dominant role in vegetation change, while temperature and precipitation have comparatively minor impacts. The findings provide a scientific basis for ecological conservation and sustainable development in the region.

**Keywords:** vegetation change; NDVI; urbanization; remote sensing; Aksu; Xinjiang

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## 1. Introduction

Vegetation is a core component of terrestrial ecosystems, playing a crucial regulatory role in processes such as the water and carbon cycle and energy flows [1]. The spatiotemporal dynamics of vegetation cover not only affect landscape structure and function but are also closely related to biodiversity and ecosystem processes [2–4]. As global climate change and human activities intensify, understanding and monitoring vegetation dynamics has become a central task in ecological and environmental research [1,5,6].This is especially critical in ecologically sensitive areas and arid and semi-arid regions, where precise monitoring and analysis are essential [7–11].

In studies of global vegetation change drivers, climate factors such as temperature and precipitation are typically regarded as dominant influences [12,13]. However, recent advancements in remote sensing technology have enabled long-term monitoring of vegetation through satellite data, with the Normalized Difference Vegetation Index (NDVI) being widely used to represent vegetation growth status and coverage characteristics [14–16]. NDVI is highly sensitive to seasonal and interannual changes, making it effective for reflecting the influence of climatic factors on vegetation dynamics [1,17–19]. Nonetheless, while research on climate influences is relatively mature, attention to the role of human

activities is comparatively limited. In arid regions, particularly in China's Xinjiang region, the impact of human-driven factors may be more pronounced than that of climate change, making it scientifically significant and practically valuable to study the effects of human activities on vegetation dynamics [20,21].

In recent years, nighttime light data (such as Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) and Visible Infrared Imaging Radiometer Suite (VIIRS)) have been widely used in ecological and environmental research because they effectively reflect human activity intensity and urbanization processes [22–24]. Nighttime light data have proven to be an effective tool for quantifying the impacts of human activities such as urban expansion and agricultural development, providing a new perspective for environmental analysis [25–28]. For example, in many arid and semi-arid regions, the growth of urban areas and agricultural irrigation may have significant positive or negative impacts on vegetation cover, often creating changes that diverge from traditional climate-driven patterns [29,30]. In the Aksu region of Xinjiang (China), complex terrain, arid climate conditions, and a fragile ecological environment make vegetation particularly sensitive to human activities [31,32]. The combined mechanisms of human and climate impacts need to be further explored [33,34].

To address these research gaps, this study utilizes long-term NDVI data from 2000 to 2020 from the Moderate Resolution Imaging Spectroradiometer (MODIS, which has the advantages of rich spectral bands, high time resolution, wide coverage, free access, and so on) and systematically investigates the drivers of vegetation change in the Aksu region through correlation analyses with temperature, precipitation, and nighttime light data. Specifically, this study employs nighttime light data as an indicator of urbanization and human activity intensity, along with climate factors, to reveal the impacts of urban expansion and ecological engineering on vegetation cover. Unlike traditional studies focused solely on climatic factors, this study considers the dynamic role of human activities such as urban expansion and agricultural development and examines their spatial–temporal interactions with climate factors. The methods and results presented in this study will provide new scientific insights into the complex drivers of vegetation dynamics in arid regions and offer decision support for ecological conservation and sustainable development policies in Aksu.

The findings from this study will contribute to understanding vegetation response patterns in arid areas under rapid urbanization and climate change, providing a reference for sustainable ecological management in other ecologically vulnerable regions.

## 2. Study Area, Dataset, and Methodology

### 2.1. Study Area

The research area of this paper includes Aksu region and the scope of Alar City, which are referred to as Aksu. Aksu is situated in southern Xinjiang of China, between the Tianshan Mountains to the north and the Tarim Basin to the south, in the mid-southern part of Xinjiang. It is geographically located between 78°03′ E and 84°07′ E and 39°30′ N and 42°41′ N, as shown in Figure 1a. The area is bounded by the Ili Kazakh Autonomous Prefecture of Xinjiang, China, and to the north and borders Hotan, Kashgar, and Kezhou to the south of Xinjiang, China. Covering approximately 132,500 $km^2$, the terrain includes mountains (29.4%), plains (39.8%), and deserts (32.58%). Major rivers in Aksu include the Tarim River, the Aksu River, and the Dolang River. The region is characterized by abundant solar energy and heat, with an average annual temperature of 11.6 °C and annual precipitation of about 112 mm (Figure 1b,c). The primary oases are the Aksu Oasis and the Weiku Oasis.

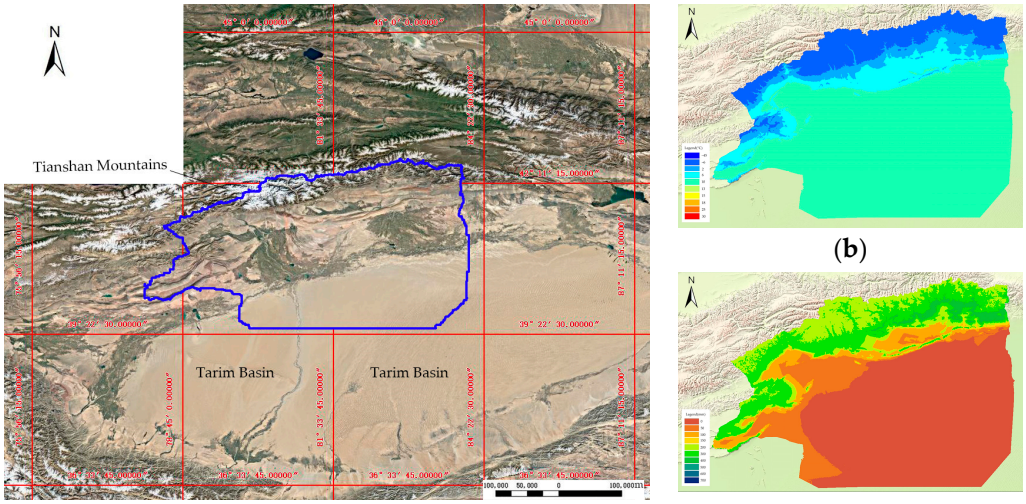



**Figure 1.** Comprehensive map of the study area: (**a**) geographical location of the study area (the area indicated by the blue line), (**b**) temperature map for 2020, and (**c**) precipitation map for 2020.

### *2.2. Vegetation Data Sources and Preprocessing*

This study utilizes MODIS NDVI data (One specific data product of the Moderate Resolution Imaging Spectroradiometer: a space remote sensing instrument developed and built by NASA) to represent vegetation growth status and coverage in Aksu, with a spatial resolution of 1 km [35,36]. NDVI is widely chosen for its sensitivity to green vegetation cover, simplicity, and ability to effectively represent vegetation health, especially in arid and semi-arid regions like Aksu. Although alternative indices such as the Enhanced Vegetation Index (EVI) and Soil-Adjusted Vegetation Index (SAVI) offer specific advantages—such as improved performance in high-biomass areas or reduced soil influence—NDVI remains the most suitable choice for Aksu's sparse and low-contrast vegetation landscape. Comparative tests showed NDVI's greater consistency and interpretability under Aksu's conditions, reinforcing its selection for this study.

Data were downloaded at monthly intervals from 2000 to 2020 via the Google Earth Engine platform (GEE), using a maximum value composite method to minimize cloud and aerosol interference [37,38]. To further smooth the data and eliminate short-term fluctuations, Savitzky–Golay (S-G) filtering was applied, focusing on seasonal (1 May–30 September) NDVI to capture the growing season.

To enhance data transparency, Table 1 summarizes the primary datasets used in this study, including data sources, spatial resolution, temporal range, and preprocessing steps, facilitating a clear understanding and replication of the study's methodology.

### *2.3. Meteorological and Human Activity Data Sources and Preprocessing*

To comprehensively analyze the driving factors of vegetation change, this study integrates temperature, precipitation, and nighttime light data, aligning these with NDVI data by resampling all datasets to a common spatial resolution and temporal scale. Specifically, NDVI data were derived from MODIS at a 1 km spatial resolution and aggregated monthly, while temperature and precipitation data from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5-Land) dataset were interpolated to match the same spatial grid and time intervals using bilinear resampling. Nighttime light data, which included both the Defense Meteorological Satellite Program-Operational Line-scan System (DMSP-OLS) and the National Polar-orbiting Operational Environmental Satellite System Preparatory Project/Visible Infrared Imaging Radiometer Suite (NPP/VIIRS), were calibrated for intersensor consistency and subsequently aligned temporally through annual averaging. These steps ensure that all datasets are temporally synchronized and spatially

consistent, thereby minimizing biases and enhancing the reliability of correlation and trend analyses.

**Table 1.** Summary of Image Data and Basic Information Used in This Study.

| Data Type | Data Source | Product Code | Spatial Resolution | Temporal Range | Preprocessing Steps | Coordinate System |
|---|---|---|---|---|---|---|
| NDVI | MODIS | MOD13A3 | 1 km | 2000–2020 | Maximum value composite, S-G filtering | WGS84 [3] |
| Temperature and precipitation | ECMWF ERA5-Land [1] | - | 0.1° | 2000–2020 | Calculation of annual mean temperature and total precipitation | WGS84 |
| Nighttime light | DMSP-OLS/VIIRS [2] | - | 1 km | 2000–2020 | Data calibration and consistency processing | WGS84 |

[1] European Centre for Medium-Range Weather Forecasts, ERA5-Land: ECMWF Reanalysis v5, a state-of-the-art global reanalysis dataset for land applications. [2] Defense Meteorological Satellite Program-Operational Line-scan System/Visible Infrared Imaging Radiometer Suite. [3] World Geodetic System 1984.

#### 2.3.1. Temperature and Precipitation Data

Meteorological data were obtained from the ERA5-Land dataset, covering the period from 2000 to 2020, with a spatial resolution of 0.1°. Monthly temperature and precipitation data were used to calculate annual mean temperature and total precipitation, aligning with the interannual variability of NDVI [39]. These meteorological datasets were spatially matched with NDVI data using grid interpolation methods to ensure spatial consistency across all datasets.

#### 2.3.2. Nighttime Light Data

Nighttime light data were sourced from a combination of DMSP-OLS (2000–2013) and NPP/VIIRS (2012–2020) datasets, with a spatial resolution of 1 km, to represent urbanization and human activity intensity [40,41]. Consistency adjustments were applied to DMSP-OLS data using a pseudo-invariant pixel calibration method to ensure comparability across years. For data after 2012, NPP/VIIRS annual average values replaced DMSP-OLS, with brightness values standardized between the two datasets. This process resulted in a continuous nighttime light dataset from 2000 to 2020, reflecting the spatiotemporal dynamics of human activities.

The improved DMSP-OLS-like data typically retains the dimensionless digital number (DN) format for compatibility with the original DMSP-OLS data. Although consistency adjustments, such as pseudo-invariant pixel calibration, are applied to make the data comparable across years, these calibrated values do not have direct physical units. Instead, they represent relative brightness intensity.

For improved DMSP-OLS-like data, standardization or calibration methods are used to align the brightness values between DMSP-OLS and VIIRS data, ensuring consistency in brightness values across datasets. However, the final data are still expressed as DN, typically within the original range of 0 to 63, allowing for long-term temporal analysis.

### *2.4. Methodology and Workflow*

To provide a structured overview of the methodology, Figure 2 presents a flowchart outlining the workflow used in this study, detailing the main stages.

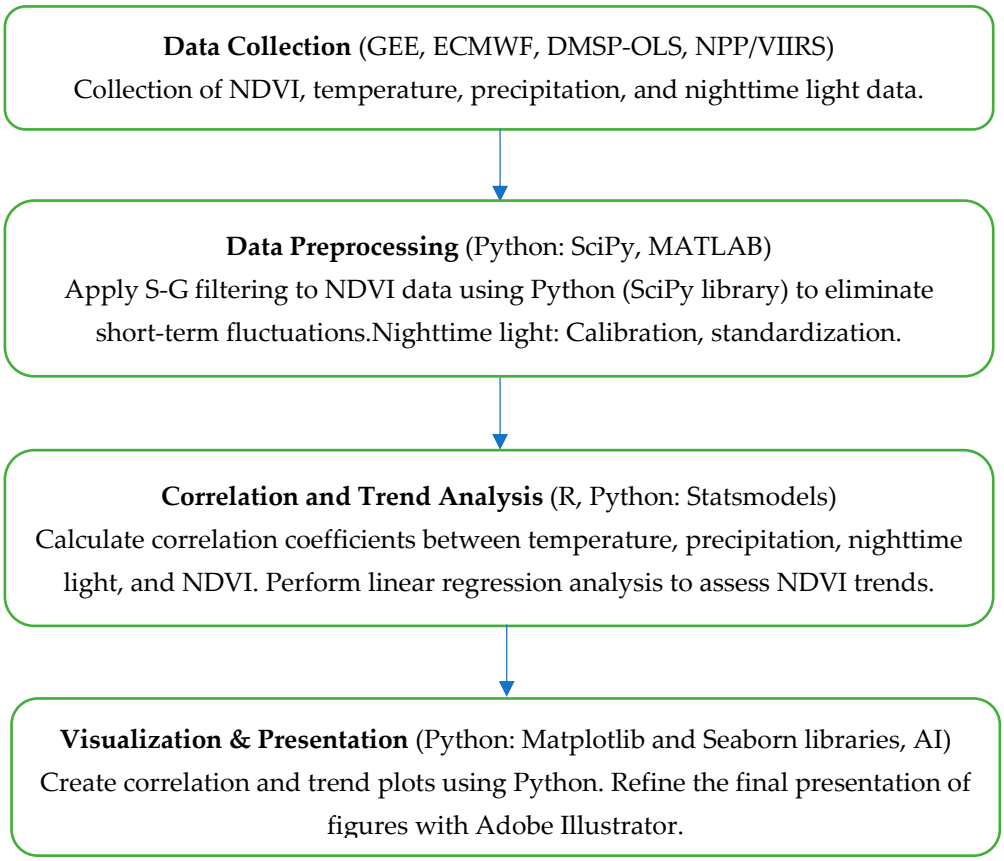



**Figure 2.** Workflow diagram.

### *2.5. Correlation Analysis and Trend Analysis*

#### 2.5.1. Correlation Analysis

Correlation analysis is a commonly used statistical method for evaluating the degree of linear association between variables [42,43]. By calculating correlation coefficients, this method reveals the strength and direction of associations between variables. Correlation analysis was conducted to examine the degree of linear association between NDVI and the other factors. The formula used to calculate the correlation coefficient *r* between NDVI and each variable (temperature, precipitation, and nighttime light) is given in Formula (1) as follows:

$$r(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var[X]Var[Y]}} \quad (1)$$

where Cov(X,Y) represents the covariance between X and Y, and Var[X] and Var[Y] denote their variances. This analysis aimed to uncover interactions between climate, human activities, and vegetation in Aksu.

#### 2.5.2. Trend Analysis

To identify long-term changes in NDVI, a linear trend analysis was applied to calculate the rate of NDVI change over time [44,45] using Formula (2). The regression coefficient a of the trend represents the rate of change in NDVI over time x.

$$a = \frac{\sum_{i=1}^{n} i \times NDVI - \frac{(\sum_{i=1}^{n} i)(\sum_{i=1}^{n} NDVI_i)}{n}}{\sum_{i=1}^{n} i^2 - \frac{(\sum_{i=1}^{n} NDVI_i)^2}{n}} \quad (2)$$

where n is the study period duration, and $NDVI_i$ represents the NDVI value in year i. Positive values of a indicate an increasing trend, while negative values indicate a decreasing trend.

In the trend analysis, the changes in NDVI over time can be categorized into the following five classes: Significant Decrease, Moderate Decrease, No Significant Change, Moderate Increase, and Significant Increase [46]. Classification is based on the value of the trend coefficient a and its corresponding $p$-value. The criteria for each category are provided in Table 2.

**Table 2.** Classification of change trends.

| Category | Condition | Description |
| --- | --- | --- |
| Significant Decrease | a < 0 and $p \leq 0.01$ | NDVI shows a significant decreasing trend (high significance level, $p \leq 0.01$). |
| Moderate Decrease | a < 0 and $0.01 < p \leq 0.05$ | NDVI shows a decreasing trend with moderate significance ($0.01 < p \leq 0.05$). |
| No Significant Change | $p > 0.05$ | NDVI change is not significant, with no clear trend observed. |
| Moderate Increase | a > 0 and $0.01 < p \leq 0.05$ | NDVI shows an increasing trend with moderate significance ($0.01 < p \leq 0.05$). |
| Significant Increase | a > 0 and $p \leq 0.01$ | NDVI shows a significant increasing trend (high significance level, $p \leq 0.01$). |

This classification facilitates the quantitative analysis of both the spatial and temporal trends of vegetation in Aksu and helps elucidate the extent to which climate factors and human activities influence changes in NDVI.

### *2.6. Methodological Steps to Address Biases and Uncertainties*

To enhance the accuracy of trend detection, this study undertook specific steps to minimize biases and uncertainties in NDVI and nighttime light data processing. For NDVI data, the S-G filtering method was applied to reduce noise without distorting the data trends [47]. This filter was selected for its effectiveness in preserving the temporal structure of NDVI signals while removing short-term fluctuations. Parameters for the S-G filter were optimized based on prior studies and data characteristics to ensure the smoothest representation of NDVI changes across seasons. For nighttime light data, consistency adjustments, including pseudo-invariant pixel calibration, were applied to align the DMSP-OLS and VIIRS datasets and achieve comparability across different years. This calibration process ensured that trends observed in nighttime light intensity accurately reflected real changes in urbanization levels rather than sensor discrepancies. These data processing methods improve the reliability of the results, enhancing transparency and reproducibility.

## 3. Results

### *3.1. Characteristics of NDVI Distribution and Change*

The analysis of the average NDVI from 2000 to 2020 in the Aksu region reveals significant spatial heterogeneity in vegetation coverage (Figure 3). Vegetation is primarily concentrated in Aral City and Aksu City, where the average NDVI reaches 0.48. Following these are Baicheng County, Wensu County, Awati County, Wushi County, and Kuqa County, with an average NDVI of approximately 0.4. The lowest is in Shaya County, where the average NDVI is only 0.23, mainly due to the presence of desert and bare land in the southern part of the county, resulting in low vegetation coverage.

Based on trend analysis and slope changes, NDVI trends were categorized into five classes (as shown in Figure 4). The phase-wise analysis is described below.

From 2000 to 2005, a significant increase in NDVI was observed, with 65% of the area showing an increasing trend and 30% showing a decreasing trend.

Between 2006 and 2010, the increasing trend accounted for 62% of the area, while the decreasing trend accounted for 34%, indicating a continued rise in NDVI during this period.

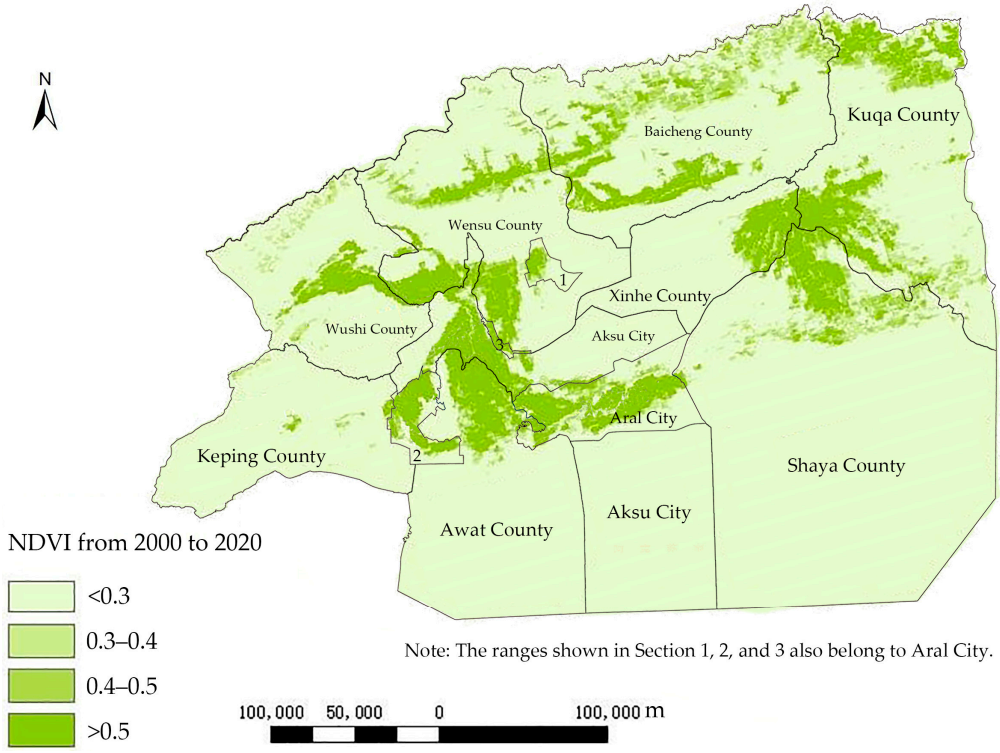



**Figure 3.** Spatial distribution map of average NDVI in the Aksu region from 2000 to 2020.

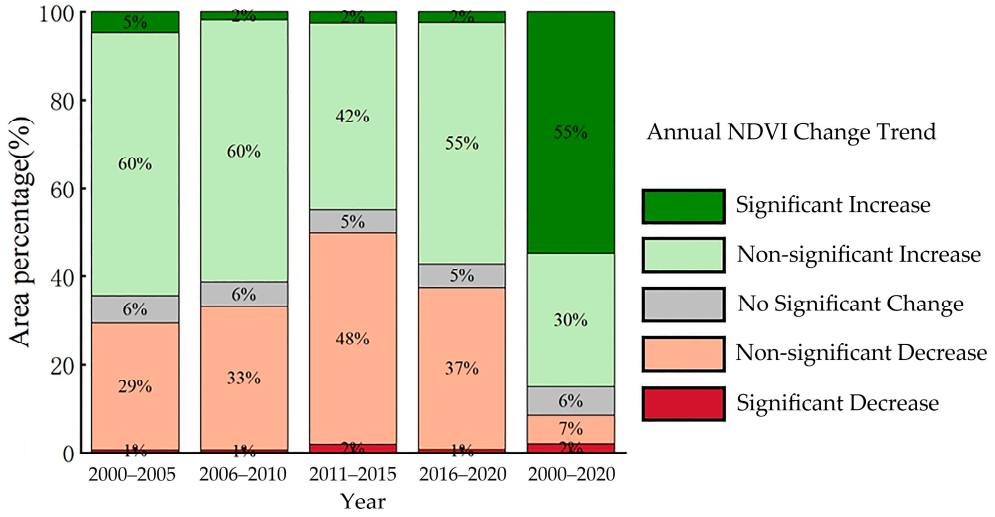



**Figure 4.** NDVI change trends in Aksu from 2000 to 2020.

From 2011 to 2015, the decreasing trend (50%) exceeded the increasing trend (44%), indicating a decline in vegetation coverage.

Between 2016 and 2020, NDVI rebounded, with the increasing trend covering 57% of the area and the decreasing trend covering 38%.

Overall, from 2000 to 2020, NDVI in Aksu showed a significant increasing trend, with 85% of the area experiencing an increase and only 9% showing a decreasing trend, suggesting an improvement in regional vegetation coverage.

The analysis indicates that vegetation coverage in Aksu experienced varying degrees of fluctuation across different phases, particularly with a downward trend between 2011 and 2015, followed by a recovery from 2016 to 2020. These findings align with the economic development, urban expansion, and ecological engineering projects implemented in different counties of Aksu, providing insights into vegetation change in the region.

The interannual variation of NDVI in Aksu from 2000 to 2020 is shown in Figure 5. During this period, NDVI displayed a significant increasing trend, with an annual growth rate of 0.83% ($p < 0.05$). The growth rate peaked between 2010 and 2012 at 3.05% per year ($p < 0.05$), while a slight decline was observed from 2018 to 2020 at 0.33% per year ($p < 0.05$). Overall, the trend indicates a notable improvement in vegetation coverage in Aksu over the study period.

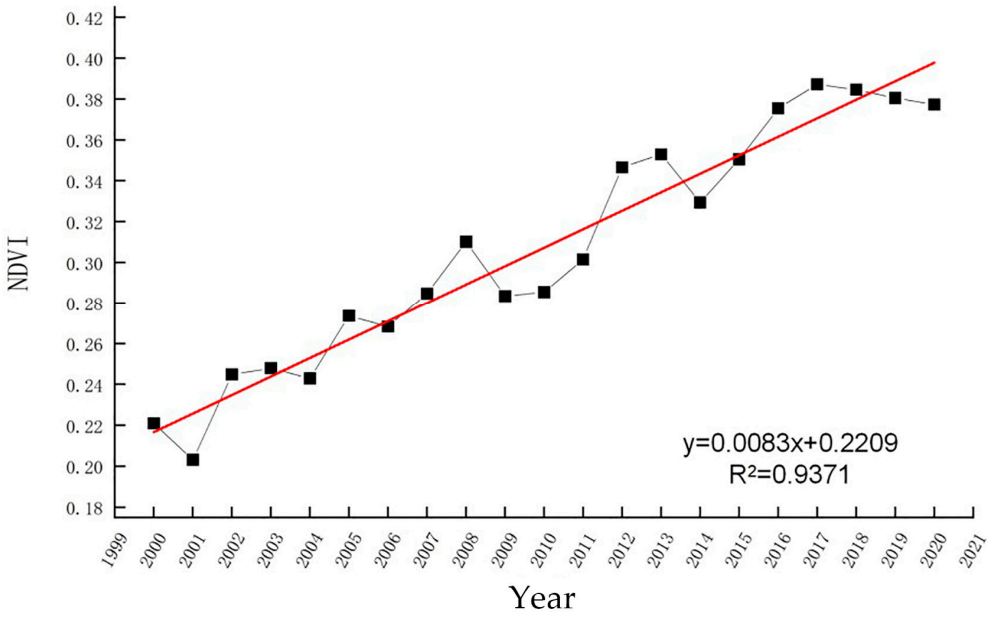



**Figure 5.** Annual average NDVI change trends in Aksu from 2000 to 2020.

### *3.2. Factors Influencing Changes in Vegetation NDVI*

To investigate the factors affecting vegetation changes, this study analyzes the impact of temperature, precipitation, and human activities (urbanization) on NDVI.

#### 3.2.1. Relationship Between Temperature and NDVI

From 2000 to 2020, the annual average temperature in Aksu fluctuated significantly (Figure 6), with a minimum of 9.92 °C in 2012 and a maximum of 11.98 °C in 2020. NDVI exhibited a positive correlation with temperature, with a correlation coefficient of 0.34 ($R^2 = 0.1157$). Although this correlation coefficient is relatively low, it reflects the unique characteristics of the arid environment in Aksu, where vegetation growth is less sensitive to temperature changes due to the dominance of drought-resistant species such as Haloxylon and Tamarix. These plants are well-adapted to high-temperature conditions, relying more on water availability than on temperature for growth.

Moreover, the weak correlation can be attributed to the significant influence of non-climatic factors, such as irrigation and land management practices, which play a dominant role in sustaining vegetation in this region. For instance, the widespread use of irrigation systems decouples vegetation growth from natural temperature fluctuations. Additionally, the spatial heterogeneity of temperature changes and the limited seasonal growth periods in this region further reduce the direct impact of temperature on NDVI.

This result underscores the importance of considering additional variables, such as water resource management and soil conditions, in future analyses to better capture the driving factors of vegetation dynamics in arid and semi-arid regions like Aksu.

#### 3.2.2. Relationship Between Precipitation and NDVI

As shown in Figure 7, the annual precipitation in Aksu varied considerably, with the lowest level recorded at 72 mm in 2007 and the highest at 217 mm in 2010. NDVI also showed a positive correlation with precipitation, with a correlation coefficient of 0.39

($R^2$ = 0.1523). This weak correlation likely reflects the low and highly variable precipitation levels in Aksu, where annual rainfall is insufficient to sustain vegetation growth without supplementary irrigation. Furthermore, the region's vegetation primarily relies on groundwater and irrigation from rivers, rather than direct rainfall, as a water source. This decoupling between precipitation and vegetation growth reduces the strength of the observed relationship. Additionally, the spatiotemporal heterogeneity of precipitation patterns, coupled with anthropogenic interventions such as controlled water allocation for agriculture, further complicates the direct link between precipitation and NDVI.

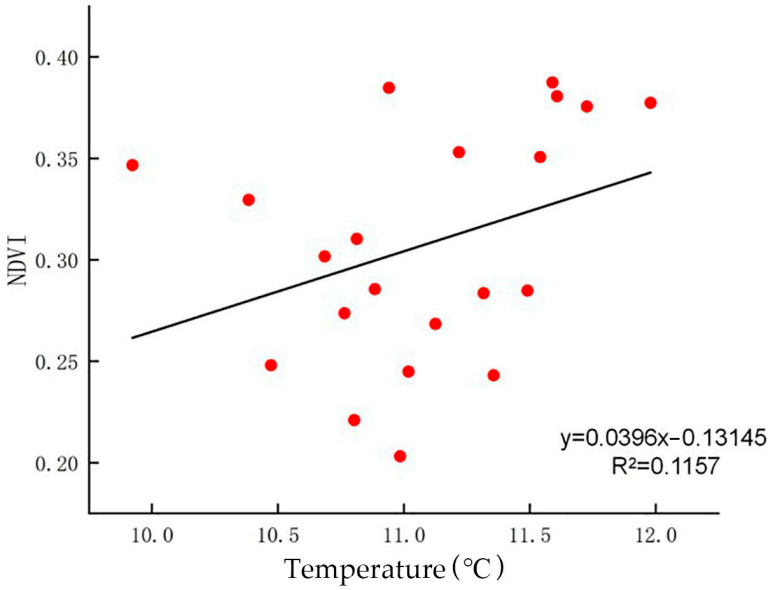



**Figure 6.** Correlation between NDVI and temperature in Aksu from 2000 to 2020.

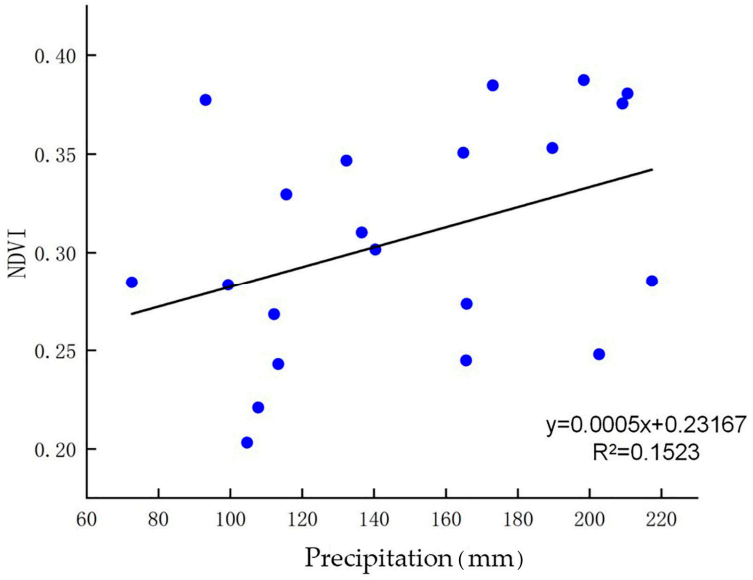



**Figure 7.** Correlation between NDVI and precipitation in Aksu from 2000 to 2020.

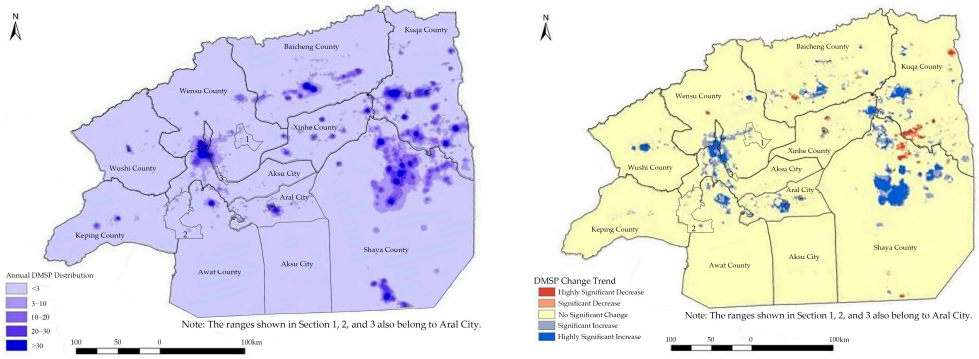
### 3.2.3. Impact of Urbanization on NDVI

Urbanization in Aksu has significantly influenced vegetation change. Analysis of nighttime light data from 2000 to 2020 reveals a marked increase in nighttime light intensity in urban development areas, reflecting the intensification of human activities. Nighttime light and NDVI displayed a significant positive correlation, with a correlation coefficient of 0.83 and $R^2$ = 0.6872, suggesting a strong association between urbanization and vegetation

change. Nighttime light data, as a proxy for human activity intensity, demonstrates its reliability and practicality in reflecting vegetation changes.

Rapid urbanization in Aksu has brought dual impacts on the regional ecological environment: on the one hand, it has exacerbated the consumption of natural resources and increased ecological pressure; on the other hand, economic and agricultural developments have promoted improvements in vegetation coverage, particularly in areas surrounding urban centers. Therefore, studying the impact of urbanization on vegetation changes is crucial for balancing economic development and ecological conservation.

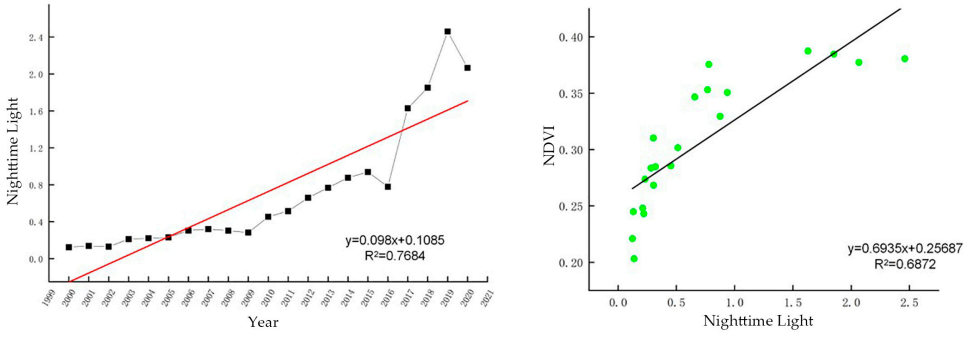
The analysis of the spatial distribution and trend of the annual average nighttime light in the Aksu region reveals that the areas with the highest brightness are concentrated in Aksu City, Aral City, and the county towns of Shaya, Baicheng, Wushi, and Kuqa, reflecting significant levels of urbanization in these areas (Figure 8a). Notably, the desert oil field area in southern Shaya County has the highest nighttime brightness, reaching 61. The nighttime lights in urban areas such as Aral City, Aksu City, and Shaya County show an increasing trend, while the area at the border between Shaya County and Kuqa County exhibits a decreasing trend (Figure 8b).




(**a**) (**b**)

**Figure 8.** Distribution and change trend of the average annual night light in the Aksu region from 2000 to 2020: (**a**) light distribution and (**b**) lighting trend.

In addition, Figure 9a shows that the annual average nighttime light values in Aksu consistently increased over the study period, with an annual growth rate of 9.8%, particularly notable between 2016 and 2017. The correlation analysis between nighttime light and NDVI (Figure 9b) further confirms this observation. The positive correlation between nighttime light changes and NDVI ($R^2$ = 0.6872, correlation coefficient = 0.83) indicates that nighttime light effectively reflects the dynamic changes in vegetation coverage. The accelerated urbanization process in Aksu has facilitated the improvement of vegetation coverage, and the impact of human activities on vegetation far exceeds that of climatic factors.




(**a**) (**b**)

**Figure 9.** Correlation analysis between nighttime light and NDVI in Aksu from 2000 to 2020: (**a**) annual average nighttime light change and (**b**) correlation between nighttime light and NDVI.

## 4. Discussion

The Aksu region, situated in the arid northwest of China, experiences a warm, temperate, arid climate, which makes it particularly sensitive to climate change and vulnerable to vegetation degradation [48,49]. Vegetation dynamics in Aksu are influenced by a complex interplay between climate variability and human activities, with anthropogenic factors playing a particularly prominent role. Previous studies have demonstrated the utility of combining NDVI and nighttime light data to assess human impacts on ecological systems [50–52]. For instance, Li Qiang et al. explored the influence of ecological restoration efforts on economic development across China using nighttime light and NDVI data [51], while Zou Yanhong et al. employed time-series nighttime light data and MODIS NDVI to monitor urban expansion in the Yangtze River Delta from 2000 to 2020, validating the use of nighttime light as an effective indicator of human activity changes [53]. These studies support the methodology of our research by underscoring the effectiveness of nighttime light as a proxy for urbanization and human impact, particularly in regions where direct observational data are limited. By integrating NDVI and nighttime light data over a two-decade period, this study provides a comprehensive analysis of the drivers of vegetation change in Aksu, contributing valuable insights into the region's ecological dynamics under both natural and anthropogenic influences.

### *4.1. Change Trends of Vegetation NDVI*

From 2000 to 2020, the annual mean NDVI in the Aksu region generally showed an increasing trend, particularly in Aksu City, Shaya County, Xinhe County, and Kuqa County. The significant vegetation growth in these areas is primarily attributed to the expansion of cultivated land due to population growth and urban expansion. Additionally, advancements in agricultural technology, such as water-saving irrigation, have substantially improved the efficiency of water resource use, reducing limitations on vegetation growth and subsequently promoting increases in vegetation cover. Furthermore, a series of ecological conservation and restoration projects initiated in 2000, such as the Tarim River Comprehensive Management Project and the Aksu River Basin Ecological Management Project, have provided strong support for vegetation improvement [48,54–58]. These projects have played a critical role in enhancing the local environment, improving water resource utilization, and combating desertification. However, the slowed NDVI growth from 2011 to 2015 might indicate a reduced effectiveness of these ecological restoration projects, as well as a slowdown in urban expansion and infrastructure development.

### *4.2. The Impact of Human Activities on Vegetation Change*

The results indicate that the overall NDVI trend in the Aksu region has increased significantly, consistent with previous research that highlights the focus on ecological conservation and agricultural development in Xinjiang. Particularly, the "Kekeya Greening Project [59,60]," recognized by the United Nations as one of the "Global 500 Best Practices", exemplifies Aksu's active exploration of paths for ecological civilization construction and economic development under the guidance of the "Two Mountains" theory. This model provides valuable insights for green development in other ecologically fragile regions.

To isolate the effects of artificial projects from global warming and increased $CO_2$ concentrations, this study employs a proxy analysis using nighttime light intensity as an indicator of human activity. Regions with significant nighttime light intensity changes, indicative of urbanization and infrastructure development, were compared to areas with minimal human intervention. While the impact of climate factors such as temperature and precipitation was included in the correlation analysis, the dominance of human-driven projects is inferred from the spatial correspondence between increased nighttime light and NDVI trends. Future studies could enhance this approach by incorporating land-use data and higher-resolution remote sensing imagery to quantitatively separate these effects.

### 4.3. The Influence of Climatic Factors on Vegetation

Although temperature and precipitation are positively correlated with NDVI, the correlation is relatively weak. This suggests that the role of climate factors in vegetation change in the Aksu region plays a small role. The area's drought-resistant and heat-tolerant vegetation, such as Haloxylon, Calligonum, and Tamarix, have low sensitivity to climate fluctuations and are well adapted to the region's arid conditions [61]. Thus, climate change has a minimal impact on NDVI, as these drought-tolerant vegetation types provide some resilience against adverse climate variations.

### 4.4. The Role of Urbanization in Vegetation Change

Expanded analysis revealed a strong correlation ($R^2$ = 0.6872) between nighttime light intensity and NDVI, indicating urbanization as a major driver of greening. Statistical results are supported by scatter plots illustrating this relationship. Additionally, a threshold effect was observed: beyond a certain urbanization level, NDVI gains stabilized or declined, highlighting the limits of greening in highly urbanized areas. Strategic urban planning integrating green spaces is critical for sustainable vegetation growth.

The relationship between NDVI and nighttime light in our study does not follow a simple linear trend; instead, it presents a curved or two-step linear trend, suggesting the presence of a potential threshold effect. This pattern indicates that as nighttime light intensity—a proxy for urbanization—increases, vegetation (indicated by NDVI) initially shows a positive correlation with urban expansion, likely due to enhanced greening efforts, such as urban landscaping and the establishment of green spaces. However, beyond a certain threshold of urbanization intensity, the growth in NDVI levels begins to stabilize or even diminish.

This trend could reflect a stage of urban development where further greening efforts become secondary to the demands for construction and infrastructure expansion, which reduce available space for vegetation. In highly urbanized areas, vegetation cover may reach an upper limit, after which additional nighttime light intensity primarily indicates dense urban infrastructure rather than increased vegetation. This finding aligns with observations in other regions where early urban growth is associated with urban greening, but excessive urbanization reduces the relative importance of green spaces [62].

These insights reveal that there may be a limit to urban greening under intense urbanization pressures. This threshold effect underscores the importance of strategic urban planning that prioritizes sustainable green space integration to maintain ecological balance in rapidly urbanizing areas. Future studies could explore this phenomenon further by examining detailed land-use data to better understand how different stages of urbanization impact vegetation dynamics.

### 4.5. Broader Ecological, Agricultural, and Socio-Economic Implications of Vegetation Changes in Aksu

The observed increase in NDVI across Aksu, largely driven by urban expansion and agricultural activities, holds significant ecological, agricultural, and socio-economic implications. Ecologically, the expansion of vegetation contributes to improved soil stability and increased carbon sequestration potential, which are crucial for mitigating desertification and promoting ecological resilience in arid environments. From an agricultural perspective, enhanced vegetation cover supports the productivity of economically important crops such as cotton and jujube, reinforcing local livelihoods and contributing to regional economic stability. However, this agricultural expansion places greater pressure on water resources, posing socio-economic challenges. Given Aksu's limited water supply, the growing irrigation demands may risk depleting local aquifers and straining regional water resources [63]. Addressing these concerns calls for implementing advanced irrigation techniques and developing water management policies that balance agricultural growth with ecological sustainability.

### 4.6. Comparison with Similar Regions Facing Urbanization and Climate Impacts

Comparing Aksu's vegetation changes with those in other arid or semi-arid regions undergoing similar urbanization and climate pressures, such as the Central Asian steppes and parts of the Middle East [64–67], offers valuable insights. In these regions, urbanization and agricultural intensification often lead to significant vegetation cover changes, as observed in Aksu. However, unique factors in Aksu, such as specific ecological restoration projects and water-saving irrigation techniques, may yield distinct vegetation responses compared to other regions. For instance, the vegetation improvement in Aksu linked with projects like the Tarim River Comprehensive Management Project underscores the role of targeted ecological interventions in mitigating adverse urbanization impacts [68,69]. This comparative perspective highlights both common patterns of urbanization effects on vegetation across arid zones and the particular advantages of local ecological policies in enhancing vegetation resilience.

### 4.7. Study Limitations and Future Prospects

This study utilizes NDVI, temperature, precipitation, and nighttime light data to systematically analyze vegetation dynamics and their driving factors in the Aksu region. However, there are certain limitations that future research could build upon to expand this analysis.

First, although MODIS NDVI and other remote sensing data provide valuable large-scale, long-term monitoring, they are relatively low in spatial resolution and can be influenced by atmospheric interference and sensor calibration issues. Integrating higher-resolution remote sensing data, such as Landsat, could offer more detailed spatial insights in future studies. Additionally, this study employs nighttime light data as an indicator of human activity intensity, which effectively captures urbanization trends. However, nighttime light data alone cannot fully reflect finer land-use changes. Incorporating detailed land-use datasets would allow for a more comprehensive analysis of human impacts.

In terms of climate factors, temperature and precipitation are critical variables affecting vegetation dynamics, but other factors, such as soil moisture, wind, and evapotranspiration, may also play significant roles. These climate factors may impact vegetation types differently, and future studies that incorporate a wider range of climate variables could deepen our understanding of vegetation response mechanisms.

Moreover, this study primarily uses correlation and trend analysis to reveal relationships between NDVI and climate and human activity. While this approach effectively captures general trends, multivariate methods such as multiple regression or machine learning algorithms could reveal more complex interdependencies. These advanced methods, however, require higher-dimensional data and refined model tuning. With advances in data availability and analytical techniques, future research could employ these methods to explore the complex drivers of vegetation dynamics in greater depth. Furthermore, comparative studies in areas with similar urbanization and climate impacts could enhance the generalizability of the findings.

Lastly, due to the remote location of Aksu, field data collection poses practical challenges. This study's conclusions are primarily based on analyses of remote sensing and meteorological data. Future research that integrates field observations and high-resolution imagery from multiple sources would provide a more robust foundation for ecological management and sustainable development in the region.

### 4.8. Novelty and Innovation in Research Methods and Data Processing

This study introduces several innovative aspects in its approach to analyzing vegetation dynamics in Aksu, particularly through its use of data integration and tailored processing techniques. First, by combining MODIS NDVI data with nighttime light data as a proxy for human activity, this study uniquely captures the combined impacts of urbanization and climate on vegetation trends in an arid region.

Furthermore, the methodology incorporates an S-G filtering process for NDVI data smoothing, specifically optimized for Aksu's unique arid climate and vegetation characteristics. This tailored filtering technique minimizes short-term data noise without compromising the temporal trend integrity, ensuring that subtle vegetation responses to seasonal and annual changes are accurately detected. This study also applies a pseudo-invariant pixel calibration to align DMSP-OLS and VIIRS nighttime light datasets, achieving temporal consistency in human activity measures—a critical factor given the long study period.

These methodological refinements not only improve data accuracy but also introduce a replicable framework for other arid regions where urbanization, climate variability, and vegetation dynamics intersect. By integrating these innovative techniques, this study provides a valuable contribution to remote sensing methodologies for ecological monitoring in challenging environments like Aksu.

## 5. Conclusions

Based on long-term NDVI data from 2000 to 2020, combined with trend change and correlation analysis methods, this study investigated the spatiotemporal variation of vegetation cover in Aksu, Xinjiang, China, and explored the impact of temperature, precipitation, and nighttime light on vegetation change. The main conclusions are as follows:

### *5.1. Spatial Heterogeneity of Vegetation Cover*

Vegetation cover in Aksu exhibits significant spatial heterogeneity (as shown in Figure 3). Alar City and Aksu City have relatively high NDVI values, with an average of 0.48, much higher than other counties (Keping, Wushi, Awat, Wensu, Xinhe, Shaya, Baicheng, and Kuqa). Overall, the annual mean NDVI shows a general upward trend from 2000 to 2020. This change is closely related to agricultural development, especially the cultivation of economic crops such as cotton and jujube, which have contributed to improved vegetation cover in plain areas. The analysis indicates that the annual mean NDVI increased significantly at a rate of 0.83% per year ($p < 0.05$), suggesting a continuous improvement in vegetation cover.

### *5.2. Influence of Temperature and Precipitation*

While this study finds that the influence of temperature and precipitation on NDVI changes in Aksu appears limited, further analysis suggests several underlying reasons for this outcome. One potential reason is the inherent resilience of Aksu's vegetation types to climatic fluctuations, given the arid conditions and relatively stable, drought-adapted plant communities in the region. Vegetation in arid environments like Aksu has often evolved to withstand variability in temperature and precipitation, relying on deep root systems and other adaptive mechanisms to maintain stability despite external climate changes.

Additionally, Aksu's vegetation dynamics may be more significantly impacted by non-climatic factors, such as human-driven activities (e.g., urban expansion, agricultural practices) that directly influence vegetation cover and health. For instance, nighttime light data as a proxy for urbanization revealed that human activities play a prominent role in shaping vegetation patterns, potentially overshadowing the effects of temperature and precipitation changes.

To deepen the understanding of this limited climatic influence, future research should examine other climate variables—such as soil moisture, wind, and evapotranspiration—that may play a more direct role in influencing vegetation in arid regions. Furthermore, distinguishing the responses of specific vegetation types (e.g., shrubland vs. grassland) to these factors could yield a more nuanced perspective, as different plant communities may exhibit varying sensitivities to environmental changes. Expanding the analysis to consider these additional factors would provide a more comprehensive picture of the climatic and non-climatic drivers of vegetation dynamics in Aksu and similar arid regions.

### *5.3. Significant Impact of Urban Development on Vegetation Change*

This study found that nighttime light values have continued to increase in Aksu, indicating rapid urbanization. The strong positive correlation between nighttime lights and NDVI ($R^2$ = 0.6872, correlation coefficient = 0.83) reflects the dominant role of human activities in driving vegetation change in this region. The land-use changes and advancements in agricultural technology brought about by urban development have significantly contributed to improvements in vegetation cover. Therefore, urban development has a more significant influence on vegetation change in Aksu, while temperature and precipitation play secondary roles.

In summary, this study indicates that the spatiotemporal changes in vegetation cover in Aksu are significantly influenced by human activities and ecological protection measures, with climate factors playing a minor role. Future research could further incorporate high-resolution remote sensing data and analyze the long-term impact of human activities and ecological projects on vegetation dynamics, providing more precise support for ecological management and sustainable development in the Aksu region.

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