

MODELING PROCESS OF THE SPATIAL-TEMPORAL CHANGES OF VEGETATION COVER AND ITS RELATIONSHIP WITH DRIVERS IN DRYLANDS AND WETLANDS IN XIANJIANG (CHINA)

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ABSTRACT

Findings reveal that the majority of studied areas are classified as bare lands, while the lowest amount is covered by lichens and mosses. Grassland and cropland occupy major areas of the region, with highest normalized difference vegetation index (NDVI) value saw in 2020, showing dense vegetation in the western, northwestern and northern regions. Afforestation efforts shown positive results, with a 4% increase in forested area between 2000 and 2022.

RÉSUMÉ: Processus de modélisation des changements spatio-temporels de la couverture végétale et de sa relation avec les facteurs de changement dans les zones arides et humides du Xianjiang (Chine).

Les résultats révèlent que la majorité des zones étudiées sont classées comme des terres nues, tandis que la plus petite partie est couverte de lichens et de mousses. Les prairies et les terres cultivées occupent une grande partie de la région, la valeur la plus élevée de l'indice de végétation par différence normalisée (NDVI) étant observée en 2020, ce qui indique une végétation dense dans les régions de l'ouest, du nord-ouest et du nord. Les efforts de reboisement ont donné des résultats positifs, avec une augmentation de 4% de la superficie forestière entre 2000 et 2022.

REZUMAT: Procesul de modelare a schimbărilor spațio-temporale ale acoperirii vegetale și relația acesteia cu factori ai zonelor uscate și zonelor umede din Xianjiang (China).

Rezultatele arată că majoritatea ariilor studiate sunt clasificate ca terenuri goale, cea mai mică proporție este acoperită de licheni și mușchi. Pajiștile și terenurile cultivate ocupă arii mari ale regiunii, cu o valoare mare a indicelui de vegetație (NDVI) în 2020, indicând vegetație densă în regiunile de vest, nord-vest și nord. Eforturile de împădurire au arătat rezultate pozitive, cu o creștere cu 4% a suprafeței împădurite între 2000 și 2022.

INTRODUCTION

Vegetation plays a key role in Earth's biosphere, influencing biogeochemical cycles, carbon balance regulation, and climate stability (He et al., 2023; Zhuang et al., 2019; Jiang et al., 2017). It also provides environmental protection, defence of soil from erosion, wind and sand damage, and preventing desertification (Wang et al., 2023; Zhuang et al., 2019). Additionally, vegetation contributes to the energy cycle by reducing greenhouse gas, supporting global carbon balance, and ensuring climate stability (Zhuang et al., 2019). Thus, it is vital to monitor changes in vegetation over time and understand the underlying mechanisms to effectively manage ecological processes and protect the environment (Li et al., 2021).

Many studies conducted worldwide saw significant changes in vegetation across various scales (Gadiga, 2015). These studies have highlighted the influence of both natural and human factors, such as climate change, land use modifications, and ecological interventions on the dynamics of vegetation patterns (Wang et al., 2023; Wang et al., 2022; Gadiga, 2015). Natural factors exert long-term control, for instance, weather conditions determine the type of vegetation, and alterations in rainfall deeply impact vegetation growth and health. On the other hand, social factors play a significant role in short-term scales. Growth of urban economies and rise in urban population contribute to the expansion of urban areas (Hu and Hu, 2019).

When a large-scale change in vegetation occurs in an area, it affects the energy balance of the surface, which may cause heating or cooling effects (Han et al., 2022), land use change is one of the main challenges that affects natural landscapes and has raised concerns about sustainable development and food security (Hu and Nacun, 2018; Li et al., 2015). That is why, countries and organizations around the world have accepted the risks of reducing vegetation cover and considered measures for protection (Wang et al., 2023). IGBP (International Geosphere-Biosphere Program) and IHDP (Global Change Human Factors Program) proposed the research program "land use/change of cover" (LULC) in 1995 (Liu et al., 2022). As one of the most active economies in the world, China has undergone many changes in land use over the past decades, increasingly contributing to environmental crises (Zhu et al., 2022; Yin et al., 2018). In the last fifty years, China has implemented some measures to protect the Loess plateau, aiming to mitigate soil erosion and enhance ecological conditions. Among these initiatives, the "project of restoring cultivated land to forests and grasses" has emerged as a prominent ecological revitalization scheme. This project, initiated in 1999, has yielded ample improvements in vegetation quantity and quality on the Loess plateau (Zhang et al., 2020). However previous studies have shown that between 1700 and 1950 there was an increasing trend in arable land in China, although they show diverse magnitudes and rates (Miao et al., 2016). Consequently, vegetation is a comprehensive indicator of environmental change, and therefore, spatial and temporal changes in vegetation and its response to climate change have become key issues in global change research (Xianfeng et al., 2014). Xiao and Weng (2007) examined land use changes in southern China from 1991 to 2001, showing that agricultural land decreased and forest land increased slightly. In the study of spatial-temporal dynamic changes in vegetation, the plant Normalized Difference index (NDVI), is an important factor for assessing plant growth status and vegetation distribution pattern (Duan et al., 2021). Gadiga (2015) studied the state and dynamics of vegetation in the Mubi Region in Nigeria using the NDVI index, and the vegetation in the region has suffered record degradation due to the growth of urbanization. Zhuang et al. (2020) conducted a study investigating vegetation dynamics in China's Xinjiang province from 1981 to 2018 using the normalized vegetation difference index (NDVI). Their findings revealed that multiple factors,

including precipitation, influenced vegetation changes in the region. Areas with notable vegetation dynamics were primarily concentrated on the northern and southern slopes of the Tianshan Mountains, the Ely River Valley, and the Altai region. Meng et al. (2020) assessed the temporal and spatial variations in the NDVI index in Mongolia and examined natural and human factors influencing these changes. The results indicated major degradation in desert steppe and the Gobi Desert within arid regions, while grassland steppe and Alpine steppe exhibited significant upward trends. The researchers also observed that climatic parameters, such as precipitation, had a positive impact on vegetation distribution. Overall, these studies highlight the influence of factors such as precipitation on vegetation dynamics and underscore the specific regions affected by these changes in China's Xinjiang province and Mongolia.

Xinjiang Province, in northwestern China, has been susceptible to the effects of climate change, experiencing warming over the last four decades. The region has witnessed notable transformations in vegetation patterns during last years (Han et al., 2022; Zhuang et al., 2019). Understanding the changes in vegetation cover is crucial in realising the temporal and spatial dynamics of this region and the feedback between vegetation and the atmosphere.

This study aimed to analyze and model the detection of vegetation cover changes in various areas of Xinjiang Province over a 23-year period. By harnessing the connectivity of sensor datasets from remote sensing platforms, time series data was utilized to track these changes. Examining the relationship between vegetation dynamics and climate and environmental stimuli is vital in the context of global warming and climate change research, as it provides insights into the dynamic responses of terrestrial ecosystems to these phenomena. The study employed the ArcGIS platform to predict the impact of climate and environmental factors on plant indicators, leveraging open-source data and coding techniques.

MATERIAL AND METHODS

Study area

Xinjiang Province is situated in northwestern China, spanning from 73°20'E to 96°25'E and 34°15'N to 49°10'N (Jiapaer et al., 2015). With a total land area of 1.66 million km², it accounts for approximately one-sixth of China's land area (Yu et al., 2020). The province encompasses a delicate ecological zone characterized by a complex arid environment, with mountainous areas comprising 51.4% and plain areas comprising 48.6% of the total land area (Luo et al., 2019; Jiapaer et al., 2015). Xinjiang exhibits diverse landforms, including the Altai Mountains in the north, the Kunlun Mountains and A-erh-chin Mountains in the south, and the Tian Shan Mountains spanning the central part of the province. These major mountain ranges encircle the Junggar Basin and the Tarim Basin (Zhao et al., 2022), which serve as the sources of numerous rivers (Luo et al., 2019). The Tian Shan Mountains, Altai Mountains, and Kunlun Mountains harbor extensive forest and grassland vegetation, while oases and cities are located in the valley plains. As of 2018, forest land and grassland accounted for 31.29% of the land area, with grassland being the predominant vegetation type (Zhuang et al., 2020). The Junggar and Tarim Basins are characterized by typical temperate desert vegetation. Despite belonging to a temperate continental climate, Xinjiang exhibits distinct differences between its northern and southern regions due to its extensive north-south span. The annual precipitation in northern Xinjiang ranges from 100 to 500 mm, with average temperatures ranging from 4 to 8°C. In southern Xinjiang, annual precipitation ranges from 20 to 100 mm, while average temperatures range from 10 to 13°C (Cao and Gao, 2022). Figure 1 provides a visual representation of Xinjiang Province's geographical location and its ecoregions.

Preparation of vegetation data from 2000 to 2023

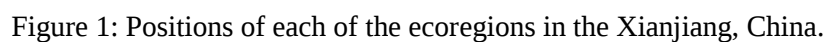
Modeling the study is based on calculating satellite data. Calculations were completed with the help of the Google Earth Engine (GEE) platform and catalogs of raster files on the platform. Other open sources of data were used such as MODIS/061/myd13a1-NDVI (16 daily-2000 to 2023 – with a spatial resolution of 250 meters – global scale, and data sets of drivers such as daily LST (Kelvin), precipitation (mm/d), global land cover extracted from Sentinel-1 and 2 data and Global 30 Arc-Second Elevation to extract DEM and slope. Data through ArcGIS platform was extracted to track vegetation cover changes, areas, and calculation of the drivers affecting the vegetation. The main sources and characteristics of the data collected are displayed in table 1.

Table 1: Main sources of data with the satellite products specifications.

Sattelite/ Model	Product name	Date name	Unit	Spatial resolution	Temporal resolution	Time extent
Modis/ Terra	MOD11A1.061 Terra Land Surface Temperature and Emissivity Daily Global 1 km	LST_Day 1 km LST_Night 1 km	Kelvin	1,000 m	Daily	2000-02-24
Modis/ Terra	Vegetation Indices	NDVI	–	500 m	Daily	2000-02-18
Modis/ Terra	Vegetation Indices	NDVI	–	500 m	Daily	2000-02-18
CHIRPS	CSB- CHG/CHIRPS/ DAILY	Precipitation	mm/d	–	Daily	1981-01- 01T00:00:00 Z–2023-06- 30T00:00:00
Sentinel-1 and 2 data	ESA World Cover 2020	Global Land cover product	–	10 m	Annually	2020-2021
GTOPO30	Global 30 Arc- Second Elevation	DEM	m	1 km	NaN	1996

Ecoregion data

Ecoregions, defined as regions with similar ecosystems, have become increasingly significant in the evaluation and administration of environmental matters. They offer a comprehensive framework that allows for flexible and comparative analysis of intricate environmental issues (Lovland and Merchant, 2004). We downloaded Ecoregion data from <https://ecoregions.appspot.com> and cropped it for Xinjiang Province. There are 14 terrestrial biomes and 846 ecoregions worldwide. Plant communities within a given biome may exhibit comparable structural characteristics while harboring distinct species compositions. Table 2, list the 17 ecoregions and five biomes in Xinjiang Province. Figure 1 shows the positions of each of the ecoregions of Xianjian Province.



Taklimakan Desert ecoregion with 742,657 km² accounts for 18.1% of the province and Tian Shan montane conifer forests ecoregion with 27,568 km² covers 0.67% of the province, representing the largest and smallest areas among the Xinjiang-Tian Shan ecoregions (Tab. 2).

Table 2: Xinjiang ecoregions, classified by name, area, percentage.

Ecoregions	Area km ²	%
Alashan Plateau semi-desert	674,352	16.498
Altai alpine meadow and tundra	90,434	2.212
Altai montane forest and forest steppe	142,875	3.495
Altai steppe and semi-desert	83,192	2.035
Central Tibetan Plateau alpine steppe	629,190	15.393
Emin Valley steppe	65,135	1.594
Junggar Basin semi-desert	304,938	7.460
Karakoram-West Tibetan Plateau alpine steppe	143,265	3.50
North Tibetan Plateau-Kunlun Mountains alpine desert	374,494	9.162
Pamir alpine desert and tundra	118,072	2.889
Qaidam Basin semi-desert	192,147	4.701
Rock and Ice	34,830	0.852
Taklimakan Desert	742,657	18.169
Tarim Basin deciduous forests and steppe	54,533	1.334
Tian Shan foothill arid steppe	129,231	3.162
Tian Shan montane conifer forests	275,68	0.674
Tian Shan montane steppe and meadows	280,611	6.865

Implementation phases

Tracking and analysis of the models took place in several phases: Identifying the current state of the study border; Calculation and zoning of vegetation at the study boundary (time series 2000 to 2023) and determination of maximum and minimum density; Analysis of spatial-temporal distribution of vegetation since 2000 by classification method; Areas where the value of NDVI is greater than 0.5 and vice versa areas where the value of NDVI is less than 0.5.; Estimation of vegetation density using kernel density and point density: 1) Monitoring and evaluation of vegetation cover from the past 23 years using land surface measurements (Divisions by municipalities), 2) Monitoring and evaluation of vegetation cover from 2000-2023 using land surface measurements (Divisions by ecoregions); Estimation of the area and percentage of afforestation and deforestation at the beginning and end of the desired time period (2000-2022); Identifying the pattern of spatial distribution of vegetation in the study border with spatial autocorrelation with a confidence level above 90%, Average Nearest Neighbor; Estimation of hot spots and cold spots of vegetation in the border of the study with a confidence level above 90% using hot spot analysis, clusters and outliers; Identification of factors affecting the distribution of vegetation in the study border (land use, land surface temperature, rainfall, slope, elevation); Spatial modeling of factors affecting vegetation (OLS).

RESULTS

Identifying the current state of the study border

Figure 2 shows patterns for the digital elevation model (A), slope (B), precipitation parameter (C) and LULC variations calculated. According to the digital elevation model, the area studied has expanded between 152 m and 7,553 m, which will create a wide range of plant species, each plant specific to an elevation surface.

As much as altitude increase, precipitation increase, temperature decrease, dry stress decrease, and the vegetation develops, this trend continues till higher altitudes where low temperatures reduces the vegetation. The gradient variation pattern (Fig. 2B) also represents gradient fluctuations of 0 to 356 degrees in the study area, which is very diverse. There is a question of which slopes in the Xinjiang ecoregions have more vegetation?

For the northern hemisphere of the Earth, including Xinjiang, which is wide and rich in diversity, the slopes facing south receive more sunlight and become drier and warmer, support drought-resistant vegetation and are less favorable for trees, while the slopes facing north retain moisture and are cold and humid and are suitable for humid plants.

The rain pattern is displayed in figure 2C. The highest rainfall was 704 mm and the lowest was 13 mm. Precipitation is one of the most important factors affecting the growth and development of vegetation. According to studies conducted in many Xinjiang ecosystems, especially grasslands and arable land, the growth of seasonal plants occurs entirely within the rainy season. In times of drought, vegetation grows poorly in these ecosystems. If it rains, the sudden growth of vegetable plants actually turns. Unsure what is being communicated.

By manipulating the Sentinel-1 and 2 satellite data sets, tracking land use and land cover changes, for 2020, LULC was considered as one of the drivers that reflected vegetation in the ecoregions of Xinjiang. Figure 2D shows this classification visually, and table 3 examines the classification of LULC and their area and percentage.

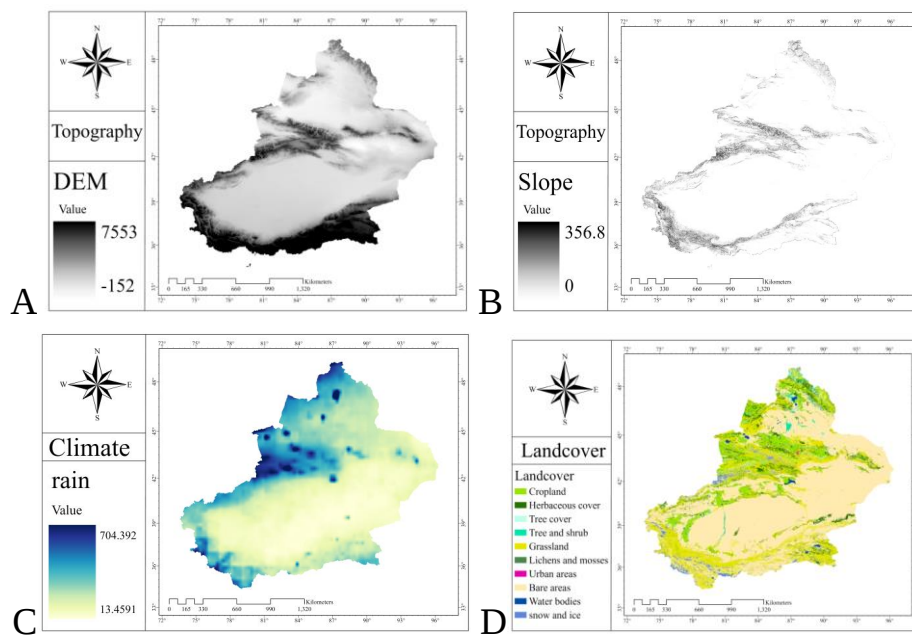


Figure 2: Digital elevation model (A), slope (B), precipitation (C) and LULC (D).

Table 3 shows, the largest area is the Bare area class, (139,433.7 km², or ying 61.49%), and the smallest area is the Lichens and Mosses class (41.8 km², or 0.018%). Bare land refers to areas where dominant vegetation covers under 90%. This category contains areas without artificial cover and includes regions with less than 4% vegetative cover. Examples include bare rock regions, sandy areas, and deserts. Table 3 shows that mosses and lichens has the smallest area, however it is argued that it plays a very important role in study area. Both mosses and lichens have a significant role in maintaining a healthy environment as they contribute to the absorption of carbon dioxide and other air pollutants. Lichens, in particular, possess valuable detoxifying properties that make them highly beneficial to various organisms.

Table 3: Classification of LULC alignments, area and percentage.

LULC	Area km ²	%
Crop land	16,263.74	7.17
Herbaceous cover	13,615.37	6
Tree cover	2,038.06	0.89
Tree and shrub	1,989.67	0.87
Grassland	48,112	21.2
Lichens and mosses	41.8	0.018
Urban areas	261.83	0.11
Bare areas	139,433.7	61.49
Water bodies	1,306.74	0.57
Snow and ice	3,692.84	1.62

Table 3 is divided into valuable LULC classes and their respective area and percent coverage of the study area. These classes together create an incredibly diverse and complex BioCycle and any changes in urban area, cropland and bare area classes will greatly affect the quality and quantity of valuable classes.

Calculation and zoning of vegetation at the study boundary in time series 2000 to 2023 and determination of maximum and minimum density

Satellites carry numerous sensors that measure the reflection of red and near-infrared light waves from land surfaces. By utilizing mathematical algorithms, scientists convert the raw satellite data related to these light waves into vegetation indices. These indices serve as indicators of vegetation greenness, representing the relative density and health of vegetation for each pixel in a satellite image. Among various vegetation indices, the Normalized Difference Vegetation Index (NDVI) is widely employed. NDVI values range from +1.0 to -1.0. Barren areas such as rocks, sand, or snow typically exhibit very low NDVI values, often 0.1 or less. Regions with sparse vegetation like shrubs, grasslands, or aging crops show moderate NDVI values ranging from approximately 0.2 to 0.5. High NDVI values, around 0.6 to 0.9, correspond to dense vegetation found in temperate and tropical forests or crops during their peak growth stage (Tahir et al., 2019; Elsu et al., 2017). Researchers can utilize raw satellite data to convert it into NDVI values, which enables the creation of images and other products that provide a general assessment of vegetation characteristics, quantity, and condition on a global scale. NDVI is particularly valuable for monitoring vegetation at continental to global levels, as it can account for variations in lighting conditions, surface slope, and viewing angles. However, it should be noted that NDVI may become saturated in areas with dense vegetation and is influenced by the color of the underlying soil. By averaging NDVI values over time, researchers can establish a baseline for normal growing conditions in a specific region during a particular time of year. Subsequent analysis can then evaluate the relative health of vegetation compared to this baseline. Over time, NDVI analysis can identify areas where vegetation is flourishing or experiencing stress, as well as detect changes in vegetation patterns resulting from human activities like deforestation, natural disturbances such as wildfires, or shifts in plants' phenological stages (*).

Figure 3 shows the visual patterns of vegetation classification calculated with the average NDVI value for the time series 2000 to 2023. The highest value of NDVI is for 2020 (Fig. 3E), with a value of 0.933 predicted, and according to the classification of NDVI value balances; it represents areas with dense vegetation. The lowest value of -0.199 corresponds to 2010 (Fig. 3C), representing areas with the presence of abundant sand, rocks, and snow.

Based on the NDVI value patterns depicted in figure 3, the western, northwestern, and northern areas of Xinjiang Province exhibit the highest NDVI values. These regions encompass various ecoregions, including the arid steppe of the Tian Shan foothills, conifer forests of the Tian Shan Mountains, steppe and meadows of the Tian Shan montane region, steppe in the Emin Valley, steppe and semi-desert in Altai, forest and forest steppe in Altai Mountains, and alpine meadow and tundra in Altai.

The average value of NDVI is estimated to be approximately between 0.2 and 0.5 which are spread in the central, western and northwestern and southwestern regions, are also broadcasted in the form of spots in the eastern regions of Xinjiang Province, which this type of classification represents scattered vegetation, savanna, shrubs, meadows, and agricultural lands. The classification of certain areas within the Tian Shan montane steppe and meadow ecoregion serves as a notable illustration of this categorization.

Ecoregions like Taklimakan Desert, north Tibetan Plateau-Kunlun mountains alpine desert and junggar basin semi desert positioned in the central, central south, southern and northern regions of Xinjiang Province respectively experienced the lowest value of NDVI, and are covered with very scattered vegetation, sand, barren rock and rarely snow (Fig. 3).

Analysis of spatial-temporal distribution of vegetation 2000-2023 by classification method (Areas with NDVI > 0.5 and NDVI < 0.5).

The temporal and spatial distribution of the average annual NDVI value was examined. This classification specifically identifies regions where the NDVI value exceeds 0.5, and regions where the NDVI value is below 0.5, based on data from 2000 to 2023 (Fig. 5). 2015 had the highest area of the regions, with a NDVI value greater than 0.5 in Xinjiang Province, which has an area of 149,450.6 km² (Tab. 4, Fig. 5D). 2000 also experienced the largest area with a NDVI less than 0.5, this value includes 1,614,503.6 km² (Tab. 4, Fig. 5A). In summary, the range of NDVI values spans from -1.0 to 1.0. Negative values represent clouds and water, values close to zero indicate bare soil, and higher positive values of NDVI correspond to varying levels of vegetation density, ranging from sparse vegetation (0.1-0.5) to dense green vegetation (0.6 and above). 2015 has experienced the highest level of dense vegetation, and 2000 is also covered with a sporadic and vast vegetation community.

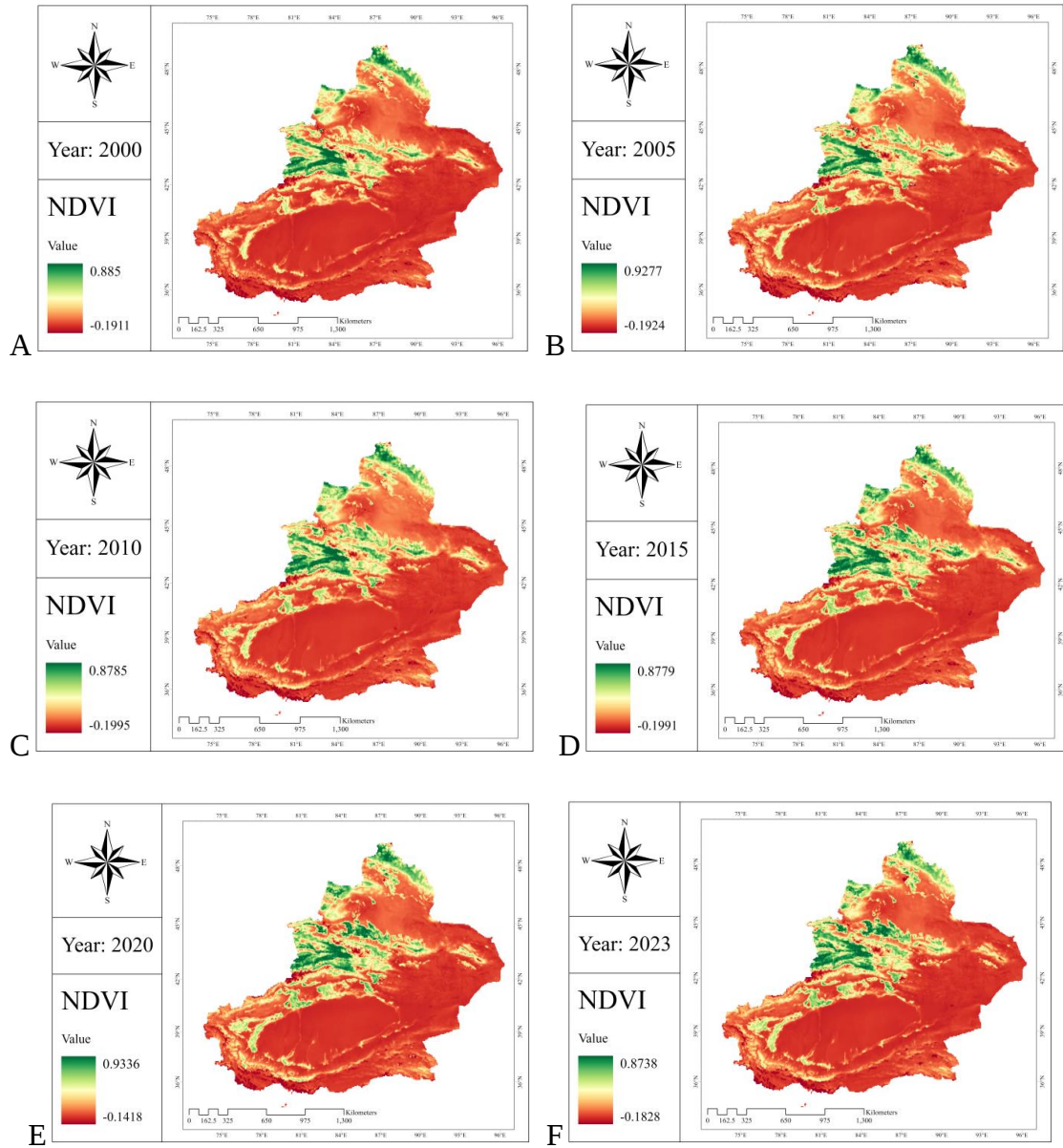


Figure 3: Visual patterns of temporal and spatial changes of vegetation calculated by the mean value of NDVI for the time series 2000 to 2023.

Table 4: Statistics on area in km² from 2000 to 2023.

Year	2000	2005	2010	2015	2020	2023
Area (km ²) of arenas where the value of the NDVI < 0.5	1614503.61	1600279.06	1587131.76	1574324.40	1583306.92	1578566.28
Area (km ²) of arenas where the value of the NDVI > 0.5	109396.39	123345.94	136518.24	149450.60	142168.08	146908.72

Figure 4 describes changes in boundary areas from 2000-2023. Figure 4A clearly shows a decrease in area for arenas with a NDVI of less than 0.5. On the other hand figure 4B shows a unique phenomenon, where area of areas with NDVI more than 0.5 is increasing, indicating the existence of suitable conditions for vegetation development as well as correct management of the arenas. The increasing quantity of positive NDVI values signifies a rise in the presence of green vegetation. What are the factors that affect NDVI? NDVI is an important indicator that reflects the state of the regional climate and the environment, which is affected by precipitation, temperature, the water content of the soil, humans, etc. For instance, Yao et al. (2023) conducted a study utilizing GeoDetector to investigate the impact of various factors on NDVI, such as climate, soil, topography, and human activities. Their findings revealed that the primary contributing factors were night light brightness (51.9%), annual average air temperature (47%), and annual average atmospheric pressure (45.8%). Additional research has demonstrated that NDVI exhibits a stronger correlation with changes in rainfall ($R = 0.75$) compared to temperature and elevation. Generally, NDVI values tend to decrease under extremely high and low temperature conditions. Furthermore, the growth pattern of NDVI varies with altitude, with a more pronounced response observed between 70 m and 1,500 m above sea level. These aspects will be further examined in the subsequent sections of this article, exploring the relationship between NDVI and rainfall, land use and land cover changes, elevation, slope, and LST, as well as modeling the interconnectedness of these factors.

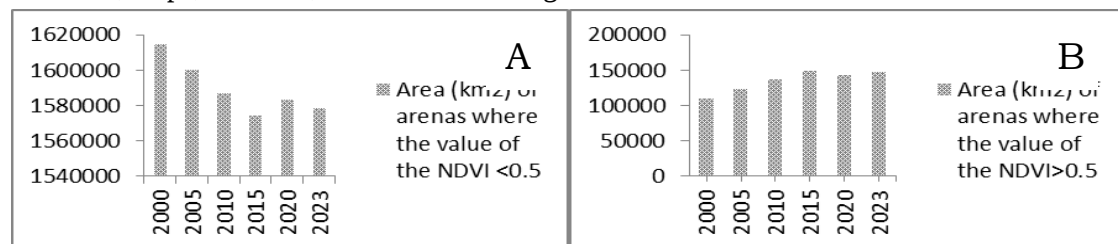


Figure 4: Changes in the area of studied boundaries (km²) where the NDVI value is less than 0.5.(A) and NDVI value is more than 0.5 (B).

Figure 5 reports visual patterns of NDVI value, for the northern regions of Xinjiang such as Altai Mountains forest and forest steppe, Altai alpine meadow and tundra, parts of the Emin Valley steppe and large parts of the Tian Shan ecoregions. Likewise it reports the montane steppe meadows, the montane conifer forest and the foothill arid steppe and the central parts of this province are seen as spots that have experienced NDVI values >5 from 2000 to 2023. This value reached its highest value in 2015 (Tab. 4, Fig. 4B), After a hiatus in 2020, it increased again until 2023. Areas that had NDVI values <5 and have scattered vegetation, bare land, sand and agricultural land (displayed in red), with the exception of 2020, have experienced a downward trend (Fig. 4A). Overall the very positive ecological event is taking shape and every year we see an increase in conservation, restoration, and development of vegetation coverage in all parts of the Xinjiang Province. This constructive process is more prominent in central and western parts such as the Tian Shan Mountains and northern areas such as the Altai Mountains and the Emin Valley (Fig. 5).

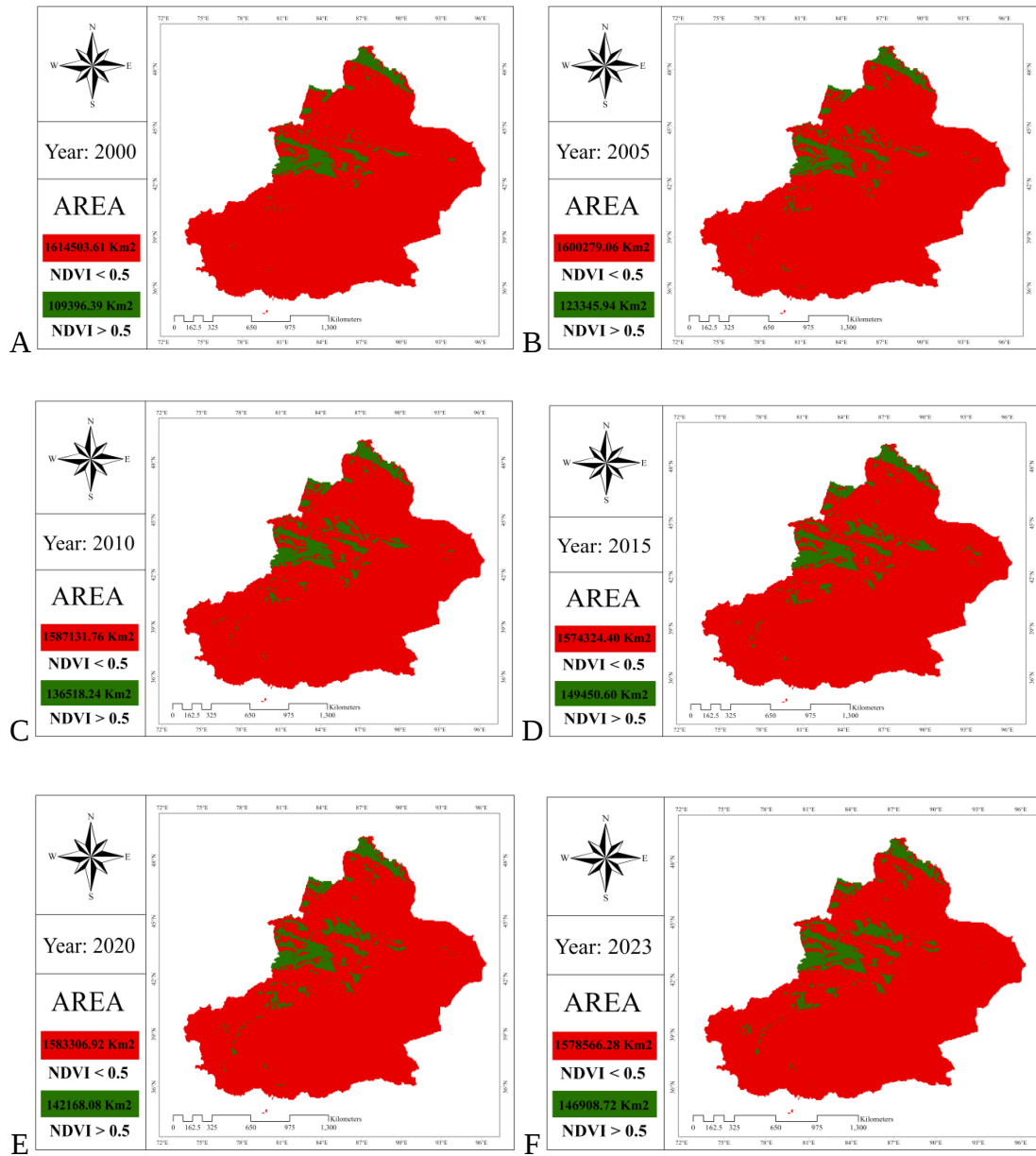


Figure 5: Visual patterns of NDVI temporal and spatial distribution along with area of arenas with a value greater than 0.5 and less than 0.5 for 2000 to 2023.

Estimation of vegetation density using kernel density and point density monitoring and evaluation of vegetation cover from 2000-2023 using land surface measurements (Divisions by municipalities)

Figure 6 shows temporal and spatial patterns of monitoring and evaluating vegetation changes using land surface measurements, which are borders of counties, and have modeled changes since 2000. The NDVI value is an average of the total months of the year. The modeling process relies on assessing vegetation density and leverages the kernel density method. This approach involves calculating the density of point features surrounding each output raster cell. Essentially, a smooth curved surface is fitted over each point in the model. Kernel density estimation, a statistical technique, is utilized for estimating the probability density function of a random variable using kernel smoothing. In this case, the variable of interest is the annual average NDVI value.

Kernel estimator results argue that the maximum values close to NDVI >0.55 with green, and the minimal values are close to NDVI <0.07, highlighted in red. The range between maximum and minimum is aligned with yellow and orange colors (Fig. 6). In general, the northern and western counties of Xinjiang Province have experienced the development of vegetation, in other words the southern and eastern counties have lost the harmony of warm red and orange colors and turned into pale yellow and green colors (Fig. 6).

According to table 5, the highest average NDVI value is related to Ili Kazakh County, which experienced a value of 0.54 in 2000. The lowest average NDVI value of 0.07 also belongs to Khotan County.

According to NASA Earth Observatory website (***), extremely low NDVI values (0.1 and below) indicate barren areas such as rock, sand, or snow. Moderate values (0.2 to 0.3) correspond to shrub and grassland, while high values (0.6 to 0.8) signify temperate and tropical rainforests. Applying this principle, it can be observed that Khotan County predominantly consists of very sparse vegetation, desert, sand, and rock, whereas Ili Kazakh County and Shihezi County exhibited a relatively moderate vegetation situation in 2000, characterized by grasslands, shrubs, as well as broadleaf and coniferous species (Fig. 7).

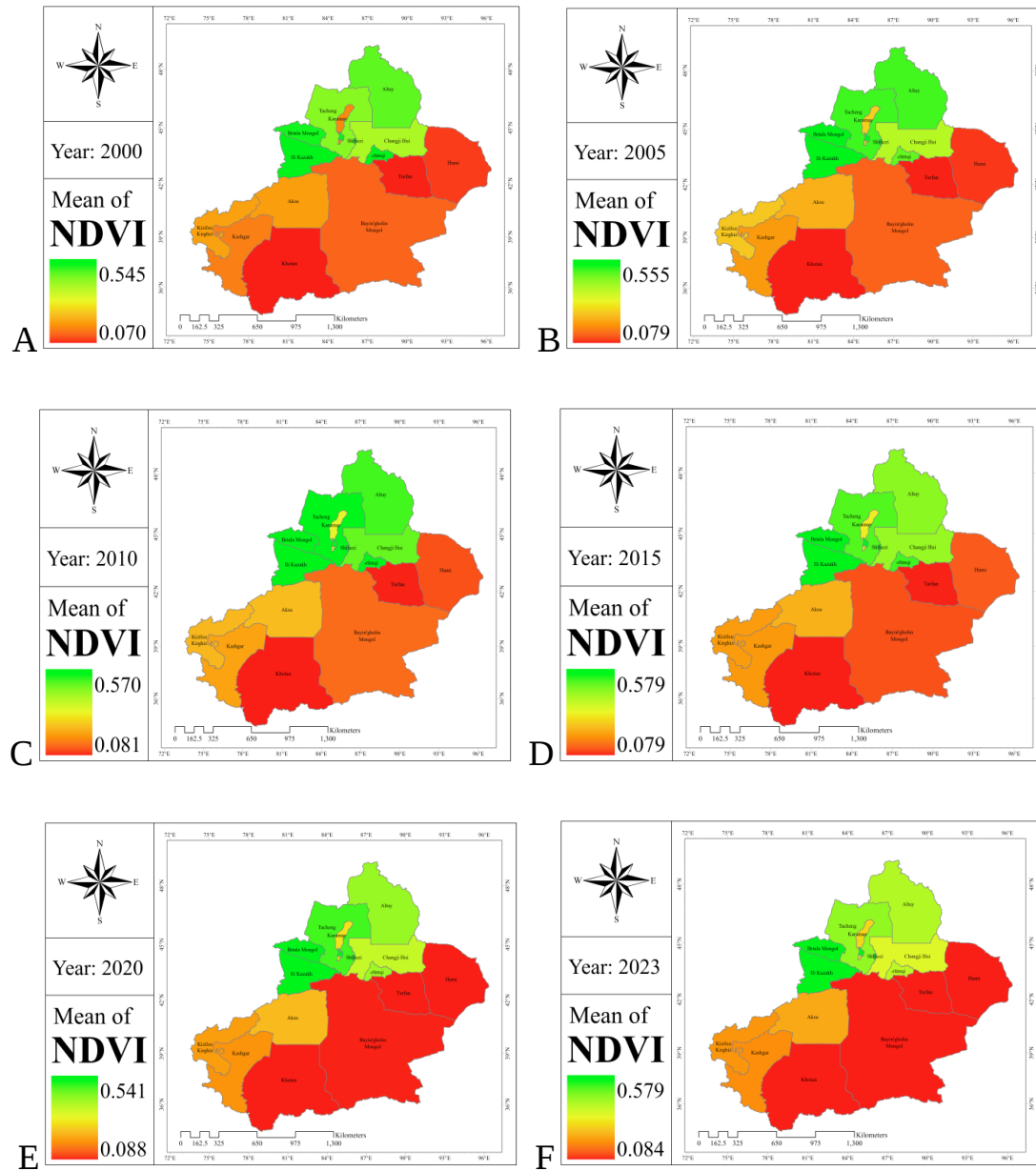


Figure 6: Examination of spatial and temporal patterns of vegetation density using Kernel density estimation.

Table 5: Classification of vegetation cover (NDVI) based on county divisions in two.

No.	Name	Minimum	Maximum	Mean
1	Aksu	-0.052921	0.691787	0.136181
2	Altay	-0.123229	0.859978	0.270487
3	Bayin'gholin	-0.191100	0.878285	0.104023
4	Bortala	-0.171962	0.874815	0.290748
5	Changji Hui	-0.033705	0.803515	0.233974
6	Hami	-0.027253	0.678575	0.088444
7	Ili Kazakh	-0.043728	0.885946	0.54512
8	Karamay	0.03571	0.541906	0.124138
9	Kashgar	-0.075600	0.536531	0.118364
10	Khotan	-0.117503	0.677344	0.070696
11	Kizilsu	-0.054392	0.547	0.137629
12	Shihezi	0.201837	0.640216	0.484435
13	Tacheng	-0.156277	0.819484	0.253239
14	Turfan	-0.038627	0.58874	0.082853
15	Urümqi	-0.038954	0.724495	0.307904

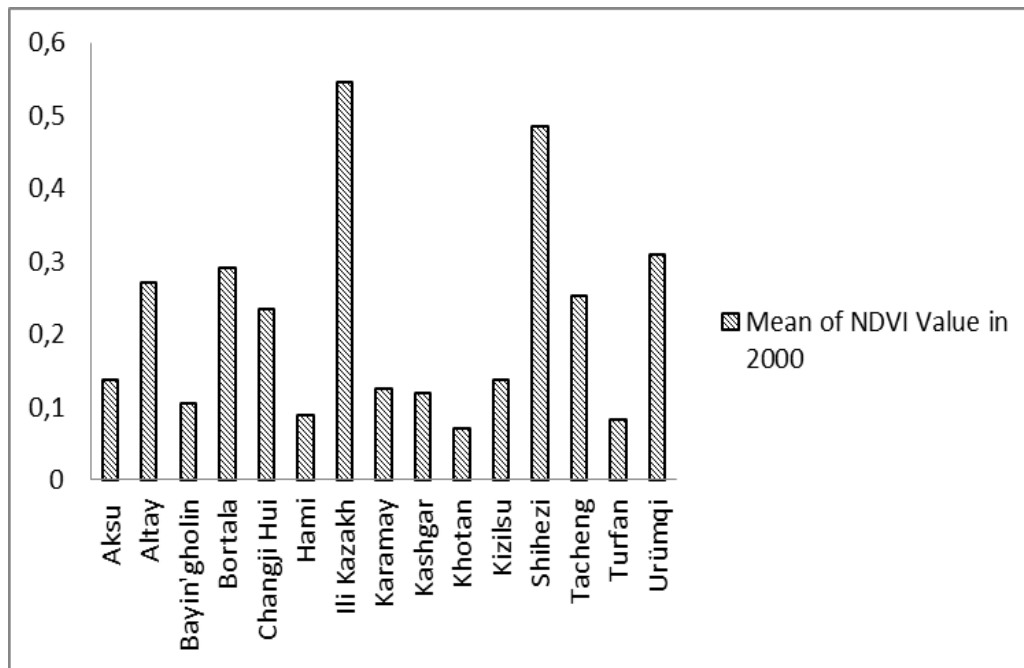


Figure 7: Statistics of average annual NDVI value based on the division of county boundaries in 2000.

Tables 5-10 as well as figures 7-12 show the NDVI values of the cities of Xinjiang Province 2000-2003. The results showed that Ili Kazakh city and then Shihezi city had the highest NDVI value during the period studied. The lowest NDVI value was for Khotan city. Examining the NDVI index values in Ili Kazakh city 2000 to 2023 showed that the amount of vegetation has grown significantly and improved. In this city, the NDVI value in 2000 was 0.54, which gradually increased in 2005, 2010, and 2015 (0.55, 0.57, and 0.57, respectively).

Table 6: Classification of vegetation cover (NDVI) based on county divisions in 2005.

No.	Name	Minimum	Maximum	Mean
1	Aksu	-0.122748	0.742965	0.148695
2	Altay	-0.192430	0.927757	0.279236
3	Bayin'gholin	-0.184302	0.869611	0.10498
4	Bortala	-0.155703	0.875777	0.307521
5	Changji Hui	-0.027991	0.773594	0.229612
6	Hami	-0.073582	0.669499	0.088761
7	Ili Kazakh	-0.046839	0.88735	0.555844
8	Karamay	-0.042529	0.670178	0.169616
9	Kashgar	-0.175655	0.563468	0.135556
10	Khotan	-0.074800	0.60319	0.079338
11	Kizilsu Kirghiz	-0.055451	0.5445	0.1639
12	Shihezi	0.170395	0.704664	0.521317
13	Tacheng	-0.048387	0.808383	0.279653
14	Turfan	0.011559	0.578973	0.084733
15	Urümqi	-0.030313	0.695617	0.269192

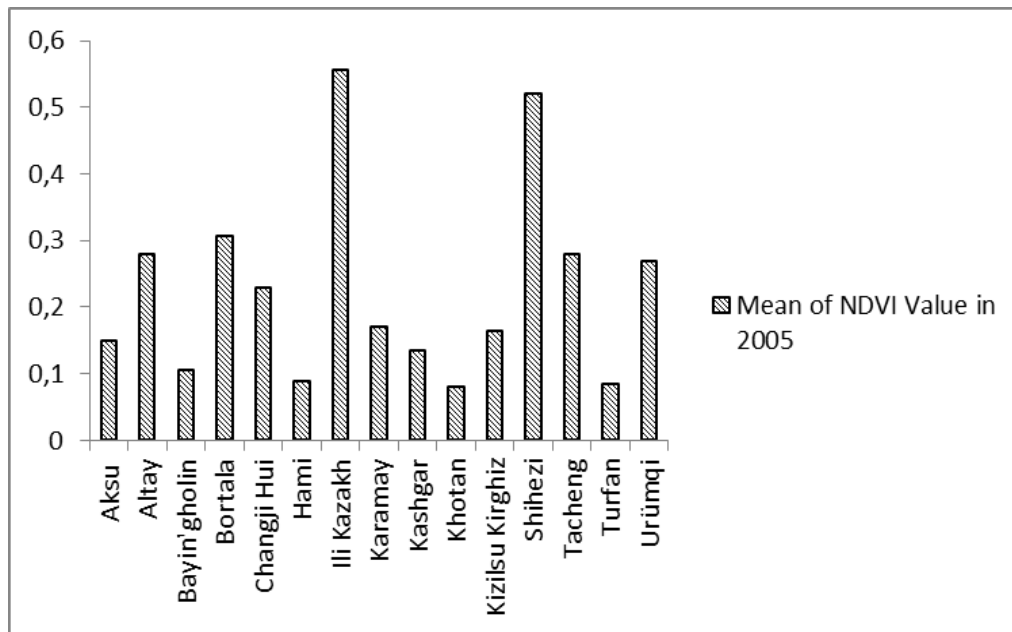


Figure 8: Statistics of average annual NDVI value based on the division of county boundaries in 2005.

Table 7: Classification of vegetation cover (NDVI) based on county divisions in 2010.

No.	Name	Minimum	Maximum	Mean
1	Aksu	-0.065500	0.687213	0.160299
2	Altay	-0.116237	0.864199	0.286228
3	Bayin'gholin Mongol	-0.187300	0.869814	0.111299
4	Bortala Mongol	-0.190533	0.820894	0.315226
5	Changji Hui	-0.023896	0.81202	0.274984
6	Hami	-0.072722	0.68649	0.099629
7	Ili Kazakh	-0.033036	0.878573	0.570325
8	Karamay	-0.025764	0.712739	0.204186
9	Kashgar	-0.080600	0.684593	0.143876
10	Khotan	-0.074623	0.694637	0.081276
11	Kizilsu Kirghiz	-0.064005	0.662137	0.156734
12	Shihezi	0.261811	0.7112	0.56347
13	Tacheng	-0.128363	0.807561	0.305837
14	Turfan	0.011221	0.593036	0.086799
15	Urümqi	-0.033983	0.75133	0.304136

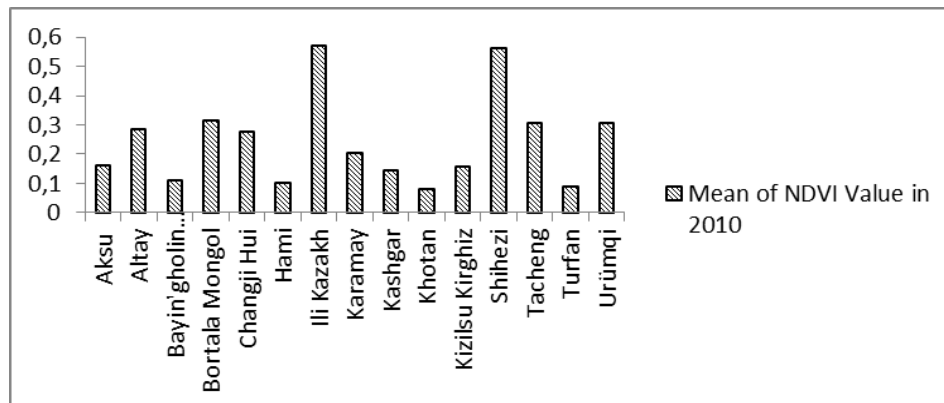


Figure 9: Statistics of average annual NDVI value based on the division of county boundaries in 2010.

Table 8: Classification of vegetation cover (NDVI) based on county divisions in 2015.

No.	Name	Minimum	Maximum	Mean
1	Aksu	-0.060800	0.666599	0.167056
2	Altay	-0.199042	0.866951	0.279071
3	Bayin'gholin Mongol	-0.199100	0.857465	0.111562
4	Bortala Mongol	-0.150868	0.83892	0.337688
5	Changji Hui	-0.038100	0.841333	0.271983
6	Hami	-0.085294	0.737637	0.11500
7	Ili Kazakh	-0.041731	0.877921	0.579145
8	Karamay	0.007897	0.780512	0.210299
9	Kashgar	-0.086180	0.682347	0.151257
10	Khotan	-0.080100	0.592517	0.079768
11	Kizilsu Kirghiz	-0.056029	0.521963	0.152814
12	Shihezi	0.19053	0.760908	0.510827
13	Tacheng	-0.189183	0.830494	0.30230
14	Turfan	0.005873	0.629756	0.096969
15	Urümqi	-0.049939	0.726139	0.30828

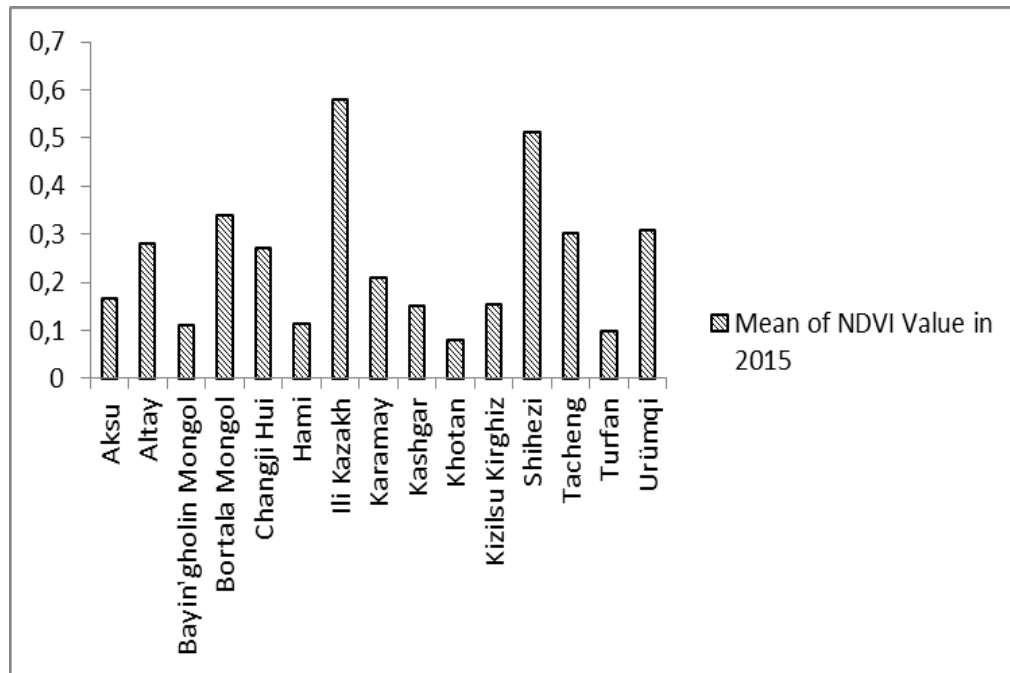


Figure 10: Statistics of average annual NDVI value based on the division of county boundaries in 2015.

Table 9: Classification of vegetation cover (NDVI) based on county divisions in 2020.

No.	Name	Minimum	Maximum	Mean
1	Aksu	-0.069200	0.779886	0.18251
2	Altay	-0.141897	0.848825	0.27150
3	Bayin'gholin Mongol	-0.127306	0.822712	0.115179
4	Bortala Mongol	-0.135692	0.933632	0.330082
5	Changji Hui	-0.019654	0.797883	0.246454
6	Hami	-0.030933	0.652469	0.091052
7	Ili Kazakh	-0.039898	0.865697	0.541766
8	Karamay	0.036021	0.781246	0.211123
9	Kashgar	-0.057445	0.646838	0.160216
10	Khotan	-0.076941	0.614853	0.08908
11	Kizilsu Kirghiz	-0.051024	0.52605	0.166212
12	Shihezi	0.134233	0.817762	0.5278
13	Tacheng	-0.043740	0.825483	0.30307
14	Turfan	0.013841	0.592871	0.0888
15	Urümqi	-0.033376	0.67819	0.267829

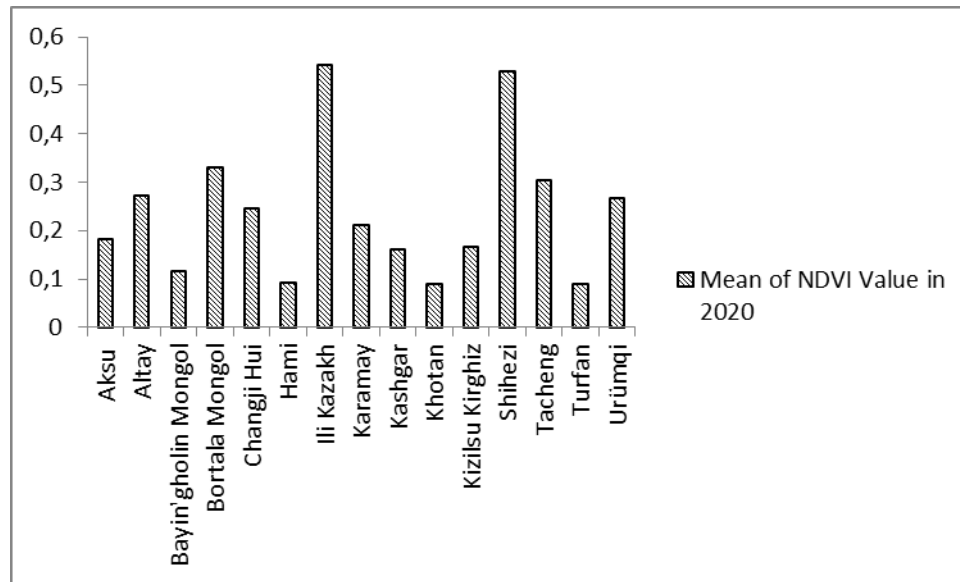


Figure 11: Statistics of average annual NDVI value based on the division of county boundaries in 2020.

Table 10: Classification of vegetation cover (NDVI) based on county divisions in 2023.

No.	Name	Minimum	Maximum	Mean
1	Aksu	-0.060800	0.736774	0.178739
2	Altay	-0.182885	0.83864	0.271577
3	Bayin'gholin Mongol	-0.162868	0.833813	0.113792
4	Bortala Mongol	-0.177081	0.847629	0.3529
5	Changji Hui	-0.009055	0.800372	0.24254
6	Hami	-0.058832	0.640684	0.08512
7	Ili Kazakh	-0.037388	0.87388	0.579248
8	Karamay	0.038863	0.790834	0.210868
9	Kashgar	-0.076800	0.651084	0.16133
10	Khotan	-0.076644	0.558047	0.08468
11	Kizilsu Kirghiz	-0.052250	0.661522	0.166611
12	Shihezi	0.136324	0.814858	0.5312
13	Tacheng	-0.039781	0.841734	0.29065
14	Turfan	0.019744	0.576473	0.088044
15	Urümqi	-0.011569	0.687454	0.264764

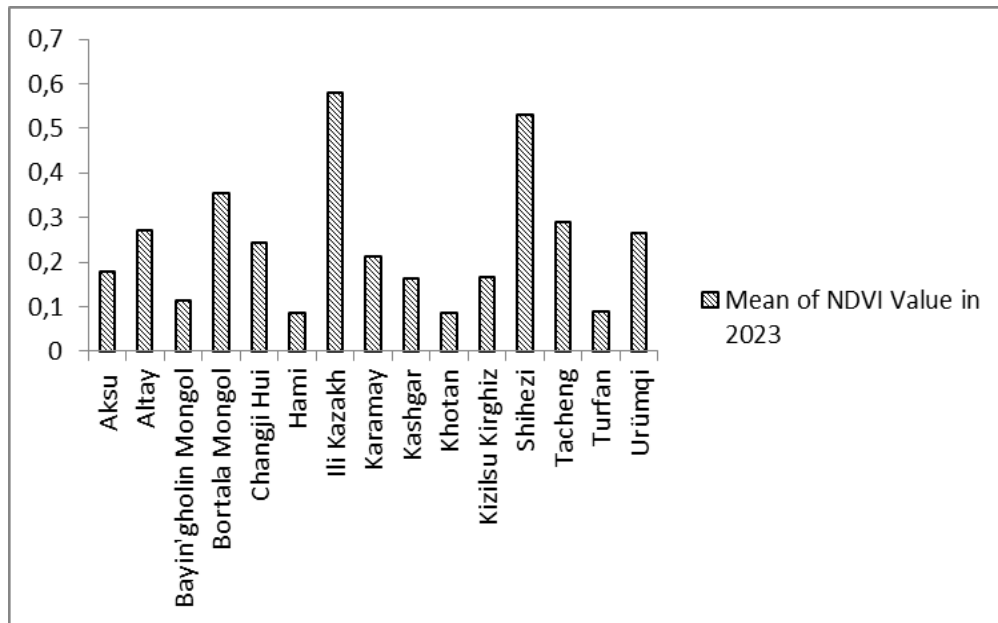


Figure 12: Statistics of average annual NDVI value based on the division of county boundaries in 2023.

However, in 2020, the NDVI value in Ili Kazakh city area decreased slightly (0.54), then increased again in 2023 (0.58). In Shihezi city, this significant trend of vegetation growth was observed, with average NDVI value reaching from 0.48 in 2000 to 0.53 in 2023.

This growth trend was seen NDVI index values for Khotan County, which had the lowest NDVI rate among the different counties of Xinjiang Province. According to tables 5-10, as well as figures 7-12, the NDVI value in Khotan County in 2000 and 2005 averaged 0.07, which gradually reached 0.08 in 2010, 2015, 2020 and 2023.

According to the information provided on the NASA Earth Observatory website (***), it is stated that low NDVI values (0.1 and below) indicate barren areas consisting of rock, sand, or snow. Moderate values (0.2 to 0.3) suggest the presence of shrubs and meadows, while high values (0.6 to 0.8) are associated with temperate and tropical rainforests. Applying this principle, it can be argued that the region of Khotan has minimal vegetation, predominantly comprising desert, sand, and rock. On the other hand, the cities of Ili Kazakh and Shihezi exhibit a relatively moderate level of vegetation, including meadows, shrubs, as well as broadleaf and coniferous species.

Monitoring and evaluation of vegetation cover from 2000-2023 using land surface measurements (Divisions by ecoregions)

Figure 13 shows the pattern of spatial and temporal changes in vegetation cover in the ecoregions of Xinjiang Province during 2000-2023 using the kernel density function.

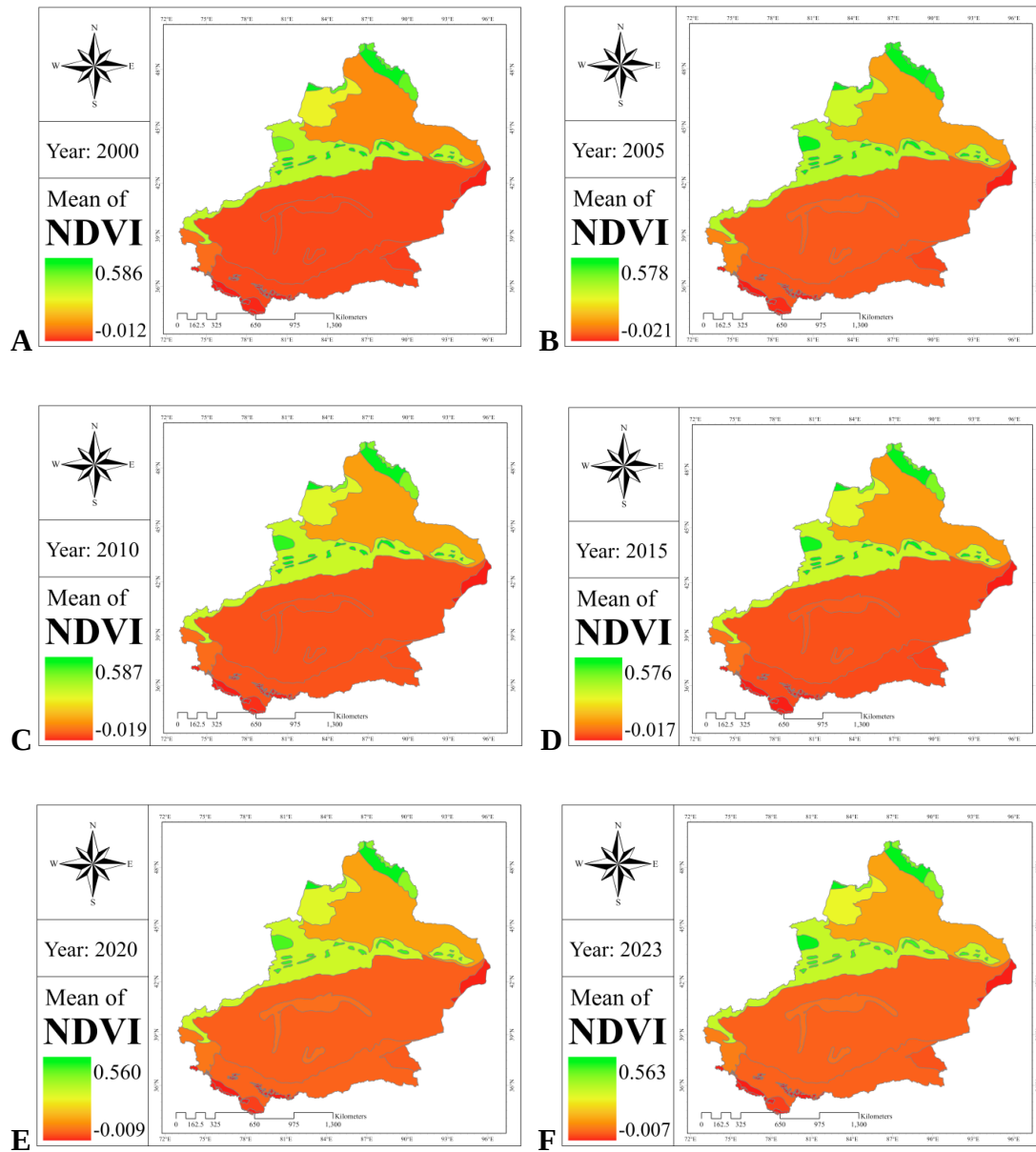


Figure 13: Patterns of temporal and spatial changes in vegetation cover using kernel density estimators in the borders of the ecoregions Xinjiang Province.

Most of the Taklimakan Desert is completely devoid of vegetation, but hardy plants such as Halogeton, Halostachys, and camelthorn grow in its foothills. Although the value of NDVI in this ecoregion is low, it has had a growing trend during the studied years, the value of NDVI increased from 0.08 in 2000 to 0.09 in 2005 and 2010 and gradually increased to 0.1 in 2015, 2020 and 2023 (Tabs. 11-16, Fig. 13).

This growing trend in the amount of vegetation was also observed in other ecoregions that have thin and scattered vegetation. Among them are the ecoregions of North Tibetan Plateau-Kunlun Mountains alpine, Junggar Basin semi-desert, Tarim Basin deciduous forests and steppe, and Pamir alpine desert and tundra, respectively in the southern, northern, central and southwest of Xinjiang Province. Therefore, in these ecoregions, the vegetation is sparse and the NDVI is low. However, in these ecoregions, the amount of vegetation has improved since 2000, with mean NDVI levels going from 0.08, 0.15, 0.08 and 0.11 in 2000 to 0.10, 0.18, 0.12 and 0.13 respectively in 2023.

Table 11: Classification of vegetation cover (NDVI) based on ecoregions divisions in 2000.

Name	Minimum	Maximum	Mean	Area of arenas with NDVI classification (km ²)
Alashan Plateau semi-desert	0.020716	0.167403	0.066595	1.549515
Altai alpine meadow and tundra	-0.041297	0.8356	0.447685	1.847604
Altai montane forest and forest steppe	0.110255	0.859978	0.586297	2.038968
Altai steppe and semi-desert	0.24145	0.799791	0.521414	0.254039
Central Tibetan Plateau alpine steppe	0.0532	0.0789	0.069438	0.015808
Emin Valley steppe	0.055365	0.819484	0.290983	5.343731
Junggar Basin semi-desert	-0.171962	0.874815	0.152806	27.366403
Karakoram-West Tibetan Plateau alpine steppe	-0.062345	0.218932	0.031641	0.779973
North Tibetan Plateau-Kunlun Mountains alpine desert	-0.164422	0.513398	0.086163	19.851451
Pamir alpine desert and tundra	-0.054019	0.424546	0.119441	3.417256
Qaidam Basin semi-desert	-0.191100	0.278864	0.080643	2.209025
Rock and Ice	-0.075600	0.269455	-0.012968	1.099327
Taklimakan Desert	-0.181898	0.793929	0.086815	76.751566
Tarim Basin deciduous forests and steppe	0.016457	0.61935	0.089074	5.763608
Tian Shan foothill arid steppe	0.10338	0.789768	0.439169	0.972174
Tian Shan montane conifer forests	0.086819	0.885946	0.530611	1.425375
Tian Shan montane steppe and meadows	-0.093751	0.875281	0.353765	21.228148

Table 12: Classification of vegetation cover (NDVI) based on ecoregions divisions in 2005.

Name	Minimum	Maximum	Mean	Area of arenas with NDVI classifi- cation (km ²)
Alashan Plateau semi-desert	0.024269	0.137483	0.063685	1.549515
Altai alpine meadow and tundra	-0.035260	0.83096	0.451796	1.847604
Altai montane forest and forest steppe	0.10491	0.863939	0.57805	2.038968
Altai steppe and semi-desert	0.267149	0.808383	0.544267	0.254039
Central Tibetan Plateau alpine steppe	0.0578	0.0776	0.069378	0.015808
Emin Valley steppe	0.064729	0.80623	0.317591	5.343731
Junggar Basin semi-desert	-0.192430	0.927757	0.168551	27.365448
Karakoram-West Tibetan Plateau alpine steppe	-0.064121	0.26982	0.026307	0.779973
North Tibetan Plateau-Kunlun Mountains alpine desert	-0.184302	0.550939	0.094414	19.846451
Pamir alpine desert and tundra	-0.054584	0.422466	0.13886	3.417256
Qaidam Basin semi-desert	0.171300	0.26967	0.082013	2.201525
Rock and Ice	-0.074800	0.344393	-0.021671	1.099327
Taklimakan Desert	-0.175655	0.78328	0.095594	76.756566
Tarim Basin deciduous forests and steppe	-0.122748	0.742965	0.101872	5.763608
Tian Shan foothill arid steppe	0.128404	0.761067	0.499164	0.972174
Tian Shan montane conifer forests	0.042952	0.872852	0.492354	1.425375
Tian Shan montane steppe and meadows	-0.108059	0.88735	0.342893	21.209103

Table 13: Classification of vegetation cover (NDVI) based on ecoregions divisions in 2010.

Name	Minimum	Maximum	Mean	Area of arenas with NDVI classifi- cation (km ²)
Alashan Plateau semi-desert	0.0251	0.156013	0.069917	1.549515
Altai alpine meadow and tundra	-0.030100	0.8483	0.447748	1.847604
Altai montane forest and forest steppe	0.153305	0.864199	0.567695	2.038968
Altai steppe and semi-desert	0.238124	0.807561	0.587318	0.254039
Central Tibetan Plateau alpine steppe	0.066	0.0851	0.077617	0.015808
Emin Valley steppe	0.067906	0.798935	0.335793	5.343731
Junggar Basin semi-desert	-0.128363	0.820894	0.188803	27.378903
Karakoram-West Tibetan Plateau alpine steppe	-0.065062	0.195633	0.025916	0.779973
North Tibetan Plateau-Kunlun Mountains alpine desert	-0.163778	0.537248	0.102822	19.848951
Pamir alpine desert and tundra	-0.064005	0.415137	0.12624	3.417256
Qaidam Basin semi-desert	-0.187300	0.348592	0.098393	2.186525
Rock and Ice	-0.080600	0.261311	-0.019348	1.099327
Taklimakan Desert	-0.125400	0.7671	0.099849	76.726566
Tarim Basin deciduous forests and steppe	-0.011591	0.65088	0.101618	5.763608
Tian Shan foothill arid steppe	0.132332	0.795914	0.516423	0.972174
Tian Shan montane conifer forests	0.075842	0.876967	0.548598	1.425375
Tian Shan montane steppe and meadows	-0.190533	-0.878573	0.365406	21.240648

Table 14: Classification of vegetation cover (NDVI) based on ecoregions divisions in 2015.

Name	Minimum	Maximum	Mean	Area of arenas with NDVI classifi- cation (km ²)
Alashan Plateau semi-desert	0.02805	0.152062	0.073175	1.549515
Altai alpine meadow and tundra	-0.014300	0.849298	0.46039	1.847604
Altai montane forest and forest steppe	0.1477	0.866951	0.571273	2.038968
Altai steppe and semi-desert	0.2203	0.808246	0.576432	0.254039
Central Tibetan Plateau alpine steppe	0.0643	0.0867	0.074508	0.015808
Emin Valley steppe	0.065934	0.830494	0.333953	5.343731
Junggar Basin semi-desert	-0.199042	0.83892	0.187073	27.371403
Karakoram-West Tibetan Plateau alpine steppe	-0.064099	0.218998	0.031506	0.779973
North Tibetan Plateau-Kunlun Mountains alpine desert	-0.199100	0.544989	0.098162	19.856451
Pamir alpine desert and tundra	-0.045398	0.469946	0.137724	3.417256
Qaidam Basin semi-desert	-0.185452	0.296632	0.091435	2.201525
Rock and Ice	-0.086180	0.290036	0.017878	1.099327
Taklimakan Desert	-0.167808	0.7579	0.10416	76.734066
Tarim Basin deciduous forests and steppe	0.030569	0.655555	0.111113	5.763608
Tian Shan foothill arid steppe	0.109939	0.825393	0.53483	0.972174
Tian Shan montane conifer forests	0.04382	0.858642	0.5565	1.425375
Tian Shan montane steppe and meadows	-0.085294	0.877921	0.368744	21.230648

The distinct topographical features found in the Tianshan and Altai mountains have resulted in the presence of abundant grassland and forest vegetation. Consequently, the ecoregions situated in this region, namely Tian Shan foothill arid steppe, Altai montane forest and forest steppe, Altai steppe and semi-desert, Tian Shan montane conifer forests, Altai alpine meadow and tundra, and Emin Valley steppe, exhibit substantial vegetation with high NDVI values. As can be seen, the revitalization and development of vegetation in these ecoregions is more prominent during the period under study. Only in 2020, NDVI decreased in these ecoregions, but it again has an upward trend and normal vegetation has increased. This revitalization and development of vegetation is more prominent in the Tian Shan foothill arid steppe ecoregion, so that its NDVI has increased from 0.48 in 2020 to 0.56 in 2023 (Fig. 13, Tabs. 15 and 16).

Table 15: Vegetation cover classification (NDVI) based on ecoregions divisions (2020).

Name	Minimum	Maximum	Mean	Area of arenas with NDVI classifi- cation (km ²)
Alashan Plateau semi-desert	0.031	0.129193	0.066389	1.549515
Altai alpine meadow and tundra	-0.020200	0.8201	0.425986	1.847604
Altai montane forest and forest steppe	0.11874	0.848825	0.54862	2.038968
Altai steppe and semi-desert	0.20505	0.76781	0.560979	0.254039
Central Tibetan Plateau alpine steppe	0.0695	0.0887	0.080397	0.015808
Emin Valley steppe	0.068533	0.819078	0.324058	5.343731
Junggar Basin semi-desert	-0.141897	0.825483	0.184406	27.421403
Karakoram-West Tibetan Plateau alpine steppe	-0.042049	0.190949	0.036133	0.779973
North Tibetan Plateau-Kunlun Mountains alpine desert	-0.074712	0.614853	0.11043	19.873951
Pamir alpine desert and tundra	-0.051024	0.405781	0.13389	3.417256
Qaidam Basin semi-desert	-0.092845	0.535508	0.102987	2.241525
Rock and Ice	-0.076941	0.259547	-0.009148	1.099327
Taklimakan Desert	-0.127306	0.779886	0.107867	76.786566
Tarim Basin deciduous forests and steppe	0.034547	0.728055	0.124142	5.763608
Tian Shan foothill arid steppe	0.142023	0.859359	0.483168	0.972174
Tian Shan montane conifer forests	0.044904	0.845019	0.488253	1.425375
Tian Shan montane steppe and meadows	-0.102500	0.933632	0.34722	21.240648

Table 16: Vegetation cover classification (NDVI) based on ecoregions divisions (2023).

Name	Minimum	Maximum	Mean	Area of arenas with NDVI classifi- cation (km ²)
Alashan Plateau semi-desert	0.031885	0.112891	0.06282	1.549515
Altai alpine meadow and tundra	-0.017536	0.813509	0.423099	1.847604
Altai montane forest and forest steppe	0.122865	0.83864	0.54210	2.038968
Altai steppe and semi-desert	0.21795	0.778232	0.53419	0.254039
Central Tibetan Plateau alpine steppe	0.0655	0.0856	0.078207	0.015808
Emin Valley steppe	0.060161	0.828862	0.301536	5.343731
Junggar Basin semi-desert	-0.182885	0.841734	0.18347	27.421403
Karakoram-West Tibetan Plateau alpine steppe	-0.047465	0.218858	0.046283	0.779973
North Tibetan Plateau-Kunlun Mountains alpine desert	-0.135032	0.557652	0.106581	19.873951
Pamir alpine desert and tundra	-0.057781	0.411547	0.13789	3.417256
Qaidam Basin semi-desert	-0.162868	0.353611	0.094669	2.241525
Rock and Ice	-0.076800	0.356202	-0.007643	1.099327
Taklimakan Desert	-0.145283	0.760485	0.106296	76.786566
Tarim Basin deciduous forests and steppe	0.031389	0.733905	0.12035	5.763608
Tian Shan foothill arid steppe	0.171138	0.870284	0.563711	0.972174
Tian Shan montane conifer forests	0.049584	0.864204	0.48319	1.425375
Tian Shan montane steppe and meadows	-0.060800	0.87388	0.353977	21.240648

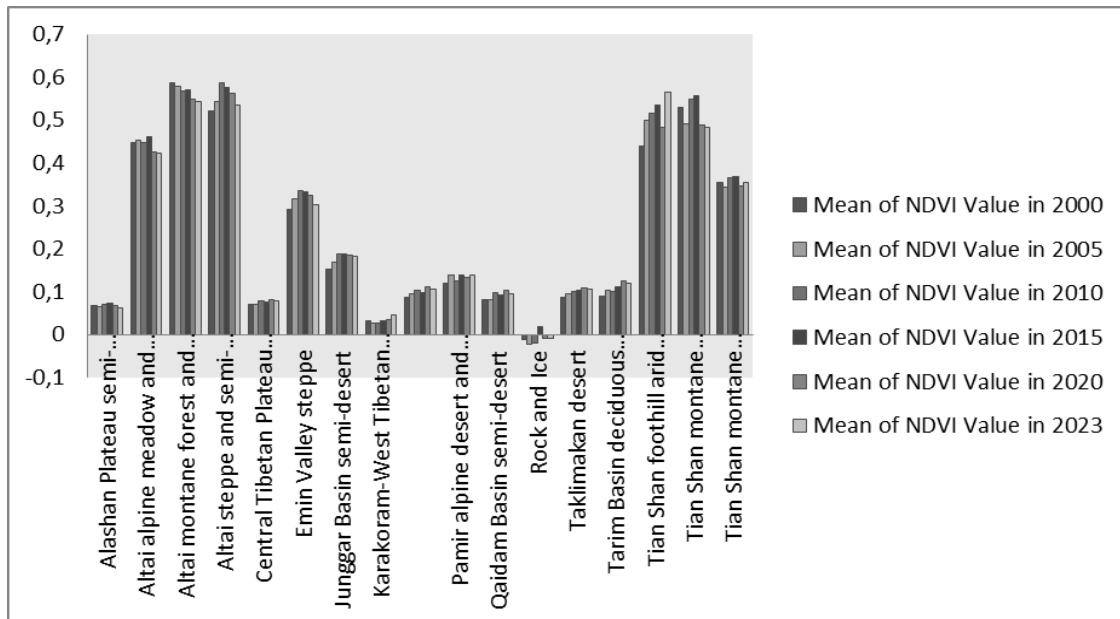


Figure 14: Column chart of average NDVI values (annual)
By ecoregion boundaries from 2000, 2005, 2010, 2015, 2020 and 2023.

Tables 11-16 as well as figure 14 show the NDVI values of different eco-origins during the studied years. As can be seen, the ecoregions located in the range of Tianshan and Altai mountains have the highest NDVI. According to the NDVI values in the mentioned tables, it can be said that there have been many changes in the vegetation of the region during different years. In 2000 and 2005, the Altai montane forest and forest steppe ecoregions had the highest NDVI values of 0.58 and 0.57 among the Xinjiang ecoregions, respectively. The highest NDVI value in 2010, 2015 and 2020 with values of 0.58, 0.57 and 0.56 belonged to Altai steppe and semi-desert ecoregion and in 2023 with value of 0.56 belonged to Tian Shan foothill arid steppe ecoregion.

Estimation of the area and percentage of afforestation and deforestation (2000 to 2022)

Changes in land use and land cover have significant impacts on ecology, the environment, and politics at both global and regional levels. Therefore, land cover monitoring and modeling is important in environmental planning and management. Figure 15 shows the spatial distribution of deforestation and afforestation in Xinjiang Province (Figure 15A), ecoregions (Fig. 15B) and counties of Xinjiang Province (Fig. 15C) from 2000 to 2022.

Additionally, the table show the changes in vegetation cover in Xinjiang Province between 2000 and 2022. Specifically, when examining the vegetation in the northern regions of Xinjiang Province, such as Altai montane forest and forest steppe, Altai steppe and semi-desert, Emin Valley steppe, and Tian Shan montane steppe and meadows ecoregions, no significant alterations have been observed. These regions collectively encompass an average area of approximately 1.665 million km² within Xinjiang Province. According to figure 15 and tables 17-18, most parts of Xinjiang Province lack vegetation (1,403,680.527 km²). In figure 15, the areas without vegetation are highlighted with a yellow color, mainly representing the

southern and central regions of Xinjiang Province. These areas include the Taklimakan Desert, North Tibetan Plateau-Kunlun Mountains alpine desert, Central Tibetan Plateau alpine steppe, Karakoram-West Tibetan Plateau, as well as alpine steppe and Pamir alpine desert and tundra. It is worth noting that there has been no significant change in the vegetation status of these regions. From 2000 to 2022, approximately one percent of the land area in Xinjiang Province has experienced vegetation degradation.

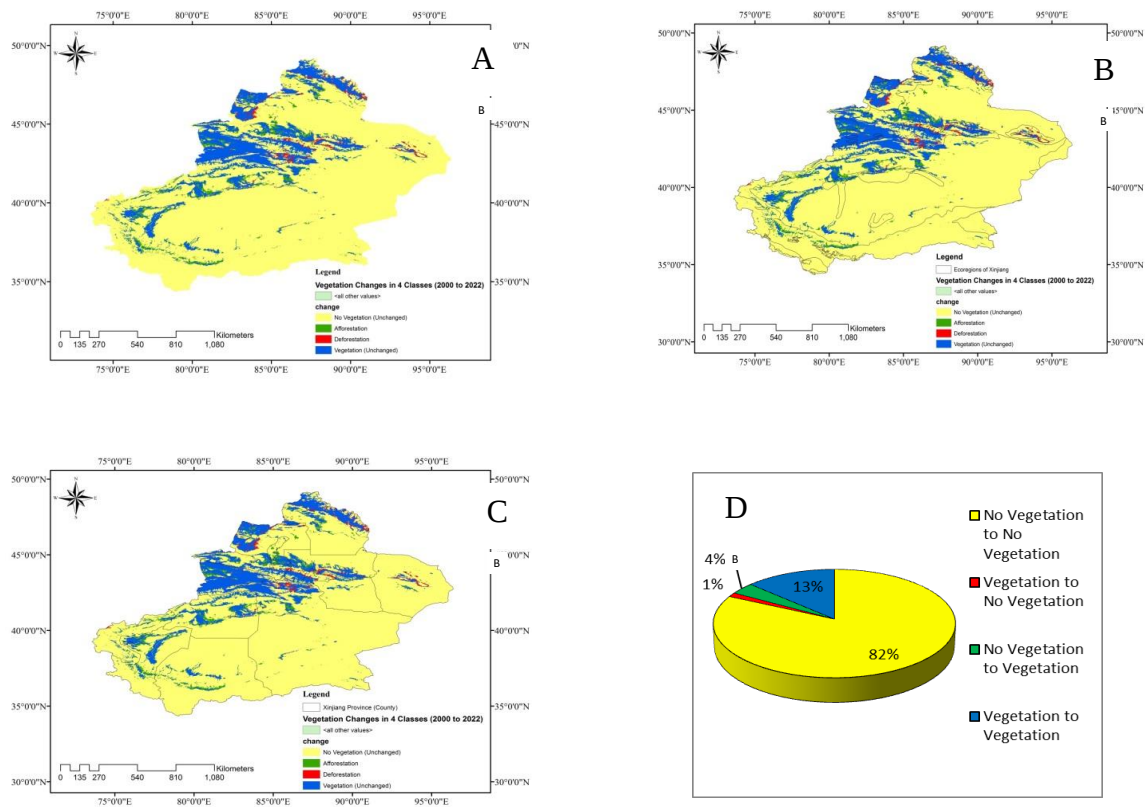


Figure 15: Visual patterns of forestry and deforestation, their area and percentage from 2000 to 2022 (Classification based on border of Xinjiang Province (A), the borders of eco-regions (B), the borders of the counties (C), the pie chart of the percentage changes in the area of afforestation and deforestation activities and other changes (D).

Deforestation and vegetation destruction have primarily occurred within the ecoregions of Tian Shan montane steppe and meadows, Emin Valley steppe, Tian Shan montane conifer forests, and Altai alpine meadow and tundra, covering an area of 21,749.34084 km². However, due to protective measures and efforts towards vegetation revitalization and development, significant positive ecological changes have taken place in various parts of Xinjiang Province. Notably, in an area of 59,743.718885 km², approximately 4% of the total area of Xinjiang Province, predominantly in the Junggar Basin semi-desert, Tian Shan foothill arid steppe, Tian Shan montane steppe and meadows, Taklimakan Desert, and North Tibetan Plateau-Kunlun Mountains ecoregions, there has been substantial restoration of alpine desert vegetation (Fig. 15).

Table 17: Area of revival and development activities and destruction of vegetation coverage in Xinjiang province from 2000 to 2022.

Vegetation changes	Area (km ²)
No Vegetation to No Vegetation	1,403,680.527142
Vegetation to No Vegetation (Deforestation)	21,749.340839
No Vegetation to Vegetation (Afforestation)	59,743.718885
Vegetation to Vegetation	223,681.424438

Figures 16 and 17 as well as table 18 show the changes in vegetation in 2022 compared to 2000. Figure 16 shows the vegetation cover has had a significant growing trend, with, 37988.61 km² of the target areas without vegetation cover being reduced. Also, vegetated areas in 2022 was 283,462.35 km², which has increased by an average of 37,988.467 km² compared to 2000.

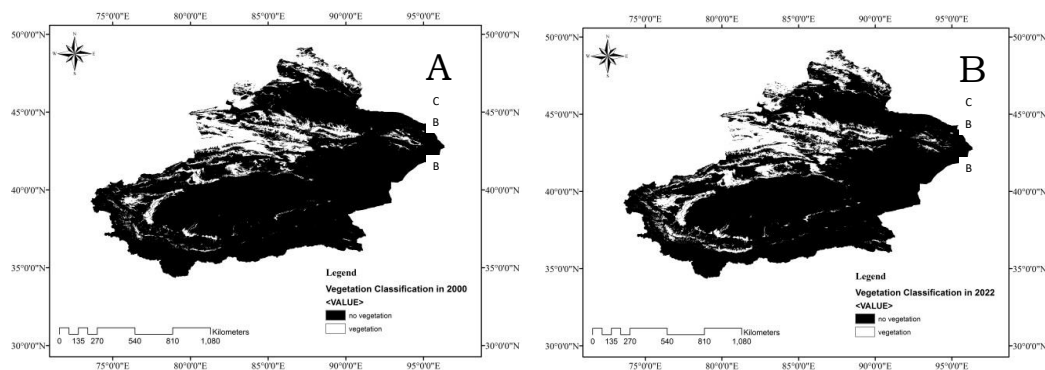


Figure 16: Visual patterns of vegetation changes based on the presence or absence of vegetation from 2000 (A) to 2022 (B).

Table 18: The area of vegetation changes in Xinjiang province from 2000 to 2022.

Vegetation changes in 2000	Area (km ²)
No Vegetation	1,463,463.10104
Vegetation	245,473.884643
Vegetation Changes in 2022	Area (km ²)
No Vegetation	1,425,474.48557
Vegetation	28,3462.351692

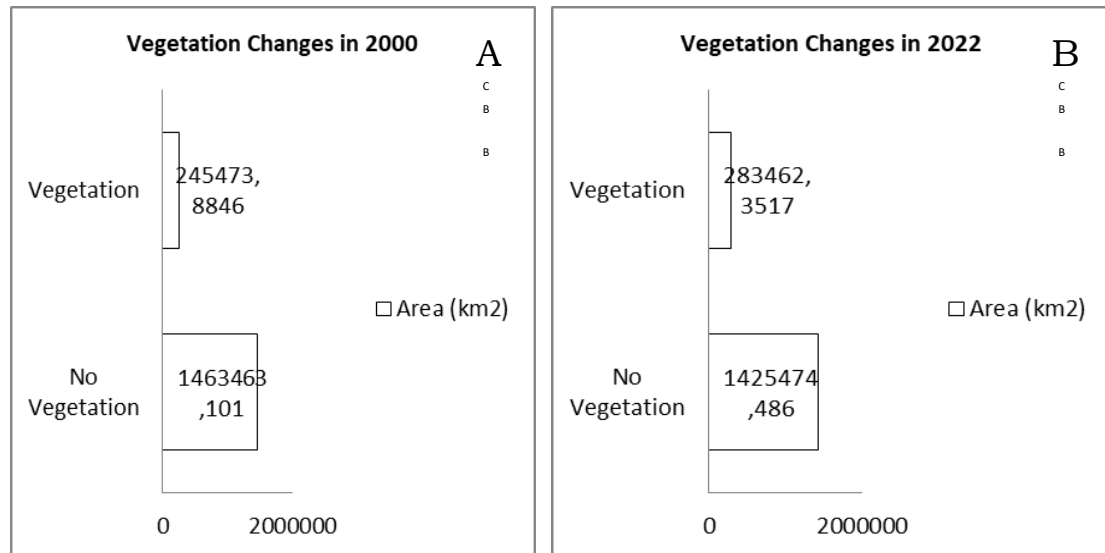


Figure 17: Models of changes in vegetation area based on the presence or absence of vegetation in square kilometers from 2000 (A) to 2022 (B).

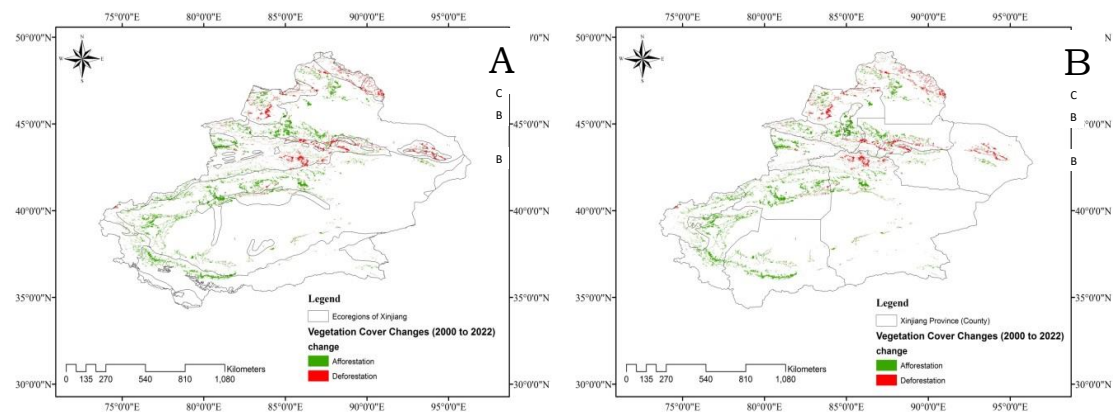


Figure 18: Visual patterns of afforestation and deforestation based on county boundaries and ecoregions in square kilometers from 2000 (A) to 2022 (B).

In contrast, deforestation has been observed in the northern and southeastern parts of Xinjiang Province, which account for only 27% of the total area. These regions correspond to the ecoregions of Altai montane forest and forest steppe, Altai alpine meadow and tundra, Emin Valley steppe, Tian Shan montane steppe and meadows, and Tian Shan montane conifer forests. In general, it can be said that vegetation has grown significantly and environmental protection measures and policies have had positive ecological effects. The area of afforestation and deforestation was 59,743.72 and 21,749.34 km², respectively, which means that the area of restored areas is on average 37,994.38 km² more than the destroyed areas (Tab. 19).

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Table 19: Area of afforestation and deforestation in Xinjiang Province from 2000 to 2022.

Vegetation changes from 2000 to 2022	Area (km ²)
Deforestation	21,749.34084
Afforestation	59,743.71889

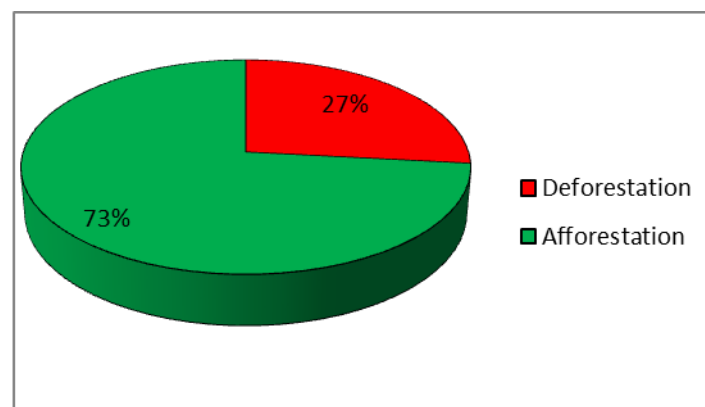


Figure 19. Circular graph percentage of afforestation and deforestation areas by percentage from 2000 to 2022.

Identifying the pattern of spatial distribution of vegetation within the study border using spatial autocorrelation (confidence level above 90% (Spatial) autocorrelation, Average Nearest Neighbor)

Tables 20-25 show clustering of the average distribution of NDVI in the ecoregions of Xinjiang Province during the years 2000-2023 respectively.

All outputs represent the same result. Hence the clusteriness of the mean distribution of NDVI at the border of the ecoregions of Xinjiang Province for 2000 which is as follows: Based on the z-score of 4.125841, it is highly improbable that this clustered pattern is due to random chance, with a probability of less than 1%.

Table 20: Clusteriness of the mean distribution of NDVI of the ecoregions of Xinjiang Province in 2000.

Moran's Index:	0/604016
Expected Index:	-0/062500
Variance:	0/026097
z-score:	4/125841
p-value:	0/000037
Global Moran's I Summary	
Input Feature Class:	Ecoregions of Xinjiang
Input Field:	Export of 2000 (Mean NDVI)
Conceptualization:	Invers Distance
Distance Method:	Euclidean
Row Standardization:	True
Distance Threshold:	628514/2532 m
Weights Matrix File:	None
Selection Set:	False

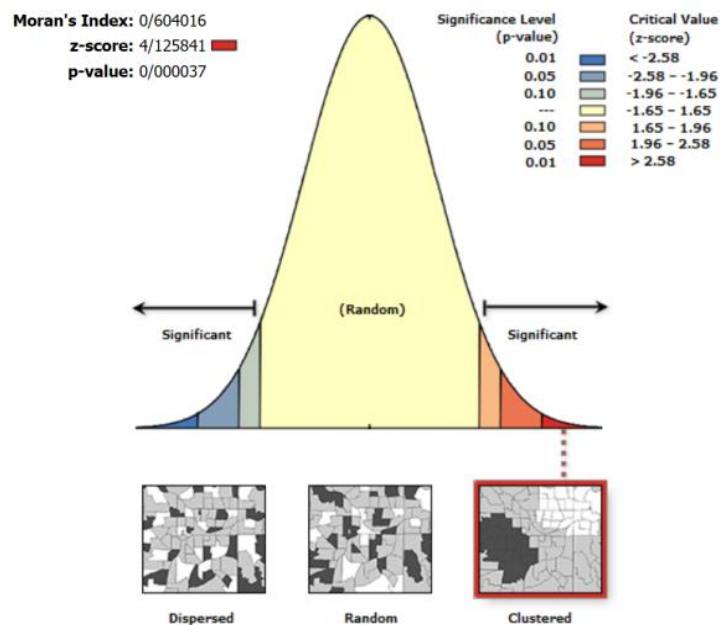


Figure 20. Moran's index for the year 2000 based on the mean NDVI distribution.

How can we interpret Moran's index? When the z-score or p-value indicates statistical significance, a positive value of Moran's I index suggests a tendency towards clustering, while a negative value of Moran's I index suggests a tendency towards dispersion. This tool calculates a z-score and p-value to determine whether the null hypotheses can be rejected. The expected value of Moran's I is $-1/(N-1)$. Values of I that surpass $-1/(N-1)$ indicate positive spatial autocorrelation, meaning that similar values, whether high or low, tend to cluster

together in space. Values of I below $-1/(N-1)$ indicate negative spatial autocorrelation, where neighboring values are dissimilar (Figs. 20-24). Regarding the results in table 21 for the year 2005, the z-score of 4.202093 suggests that there is a less than 1% chance that the observed clustered pattern is due to random chance. Therefore, the result can be considered reliable. (**)

Table 21: Clusteriness of the mean distribution of NDVI of the ecoregions of Xinjiang Province in 2005.

Moran's Index:	0.617828
Expected Index:	-0.062500
Variance:	0.026212
z-score:	4.202093
p-value:	0.000026
Global Moran's I Summary	
Input Feature Class:	Ecoregions of Xinjiang
Input Field:	Export of 2005 (Mean NDVI)
Conceptualization:	Invers distance
Distance Method:	Euclidean
Row Standardization:	True
Distance Threshold:	628514.2532 m
Weights Matrix File:	None
Selection Set:	False

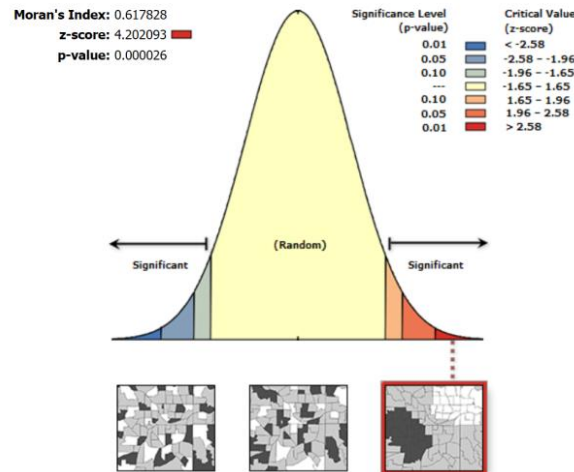


Figure 21: Moran's index for the year 2005 based on the mean NDVI distribution.

Table 22, which presents the clustering analysis of the average NDVI distribution in the ecological regions of Xinjiang Province in 2010, indicate the following: With a z-score of 4.176516, the probability of observing such a clustered pattern by random chance is less than 1%.

Table 22: Clusteriness of the mean distribution of NDVI of the ecoregions of Xinjiang Province in 2010.

Moran's Index:	0.614116
Expected Index:	-0.062500
Variance:	0.026246
z-score:	4.176516
p-value:	0.000030
Global Moran's I Summary	
Input Feature Class:	Ecoregions of Xinjiang
Input Field:	Export of 2010 (Mean NDVI)
Conceptualization:	Invers Distance
Distance Method:	Euclidean
Row Standardization:	True
Distance Threshold:	628514.2532 Meters
Weights Matrix File:	None
Selection Set:	False

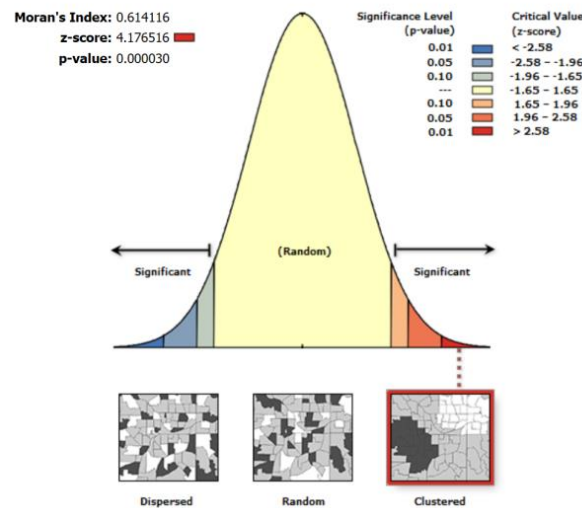


Figure 22: Moran's index for the year 2010 based on the mean NDVI distribution.

Table 23, which depicts the clustering analysis of the average NDVI distribution in the ecological regions of Xinjiang Province in 2015, reveal the following: With a z-score of 4.165062, the probability of this clustered pattern occurring by random chance is less than 1%.

Table 23: Clusteriness of the mean distribution of NDVI of the ecoregions of Xinjiang Province in 2015.

Moran's Index:	0.612921
Expected Index:	-0.062500
Variance:	0.026297
z-score:	4.165062
p-value:	0.000031
Global Moran's I Summary	
Input Feature Class:	Ecoregions of Xinjiang
Input Field:	Export of 2015 (Mean NDVI)
Conceptualization:	Invers Distance
Distance Method:	Euclidean
Row Standardization:	True
Distance Threshold:	628514.2532 Meters
Weights Matrix File:	None
Selection Set:	False

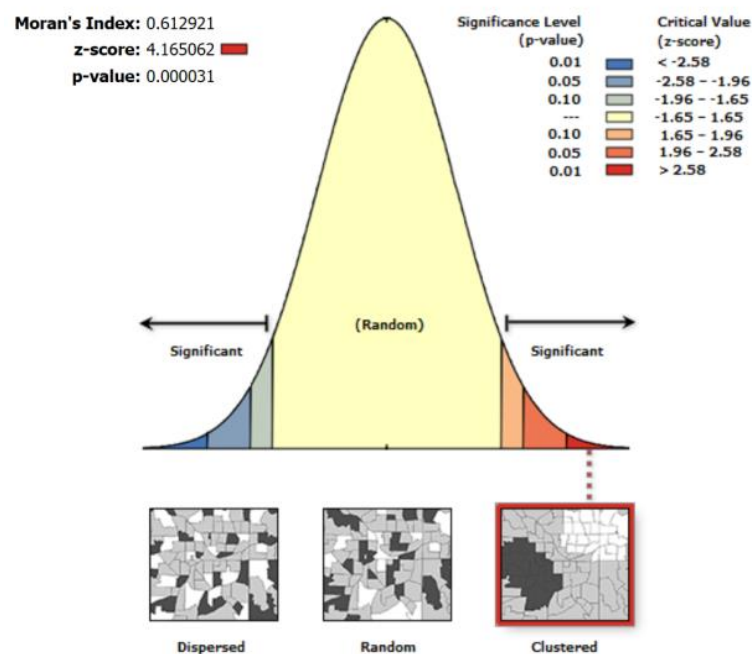


Figure 23: Moran's index for the year 2015 based on the mean NDVI distribution.

Table 24, depicting the clustering analysis of the average NDVI distribution in the ecological regions of Xinjiang Province in 2020, indicate the following: With a z-score of 4.232639, the probability of observing such a clustered pattern by random chance is less than 1%.

Table 24: Clusteriness of the mean distribution of NDVI of the ecoregions of Xinjiang Province in 2020

Moran's Index:	0.622168
Expected Index:	-0.062500
Variance:	0.026166
z-score:	4.232639
p-value:	0.000023
Global Moran's I Summary	
Input Feature Class:	Ecoregions of Xinjiang
Input Field:	Export of 2020 (Mean NDVI)
Conceptualization:	Invers Distance
Distance Method:	Euclidean
Row Standardization:	True
Distance Threshold:	628514.2532 Meters
Weights Matrix File:	None
Selection Set:	False

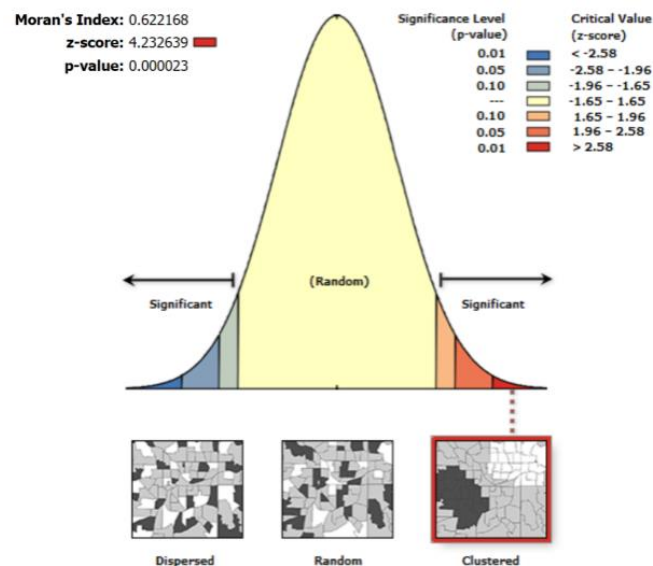


Figure 24: Moran's index for the year 2020 based on the mean NDVI distribution.

Lastly, table 25, illustrating the clustering analysis of the average NDVI distribution in the ecological regions of Xinjiang Province in 2023, suggest the following: With a z-score of 4.001364, the probability of observing such a clustered pattern due to random chance is less than 1%.

Table 25: Clusteriness of the mean distribution of NDVI of the ecoregions of Xinjiang Province in 2023.

Moran's Index:	0.584470
Expected Index:	-0.062500
Variance:	0.026143
z-score:	4.001364
p-value:	0.000063
Global Moran's I Summary	
Input Feature Class:	Ecoregions of Xinjiang
Input Field:	Export of 2023 (Mean NDVI)
Conceptualization:	Invers Distance
Distance Method:	Euclidean
Row Standardization:	True
Distance Threshold:	628514.2532 Meters
Weights Matrix File:	None
Selection Set:	False

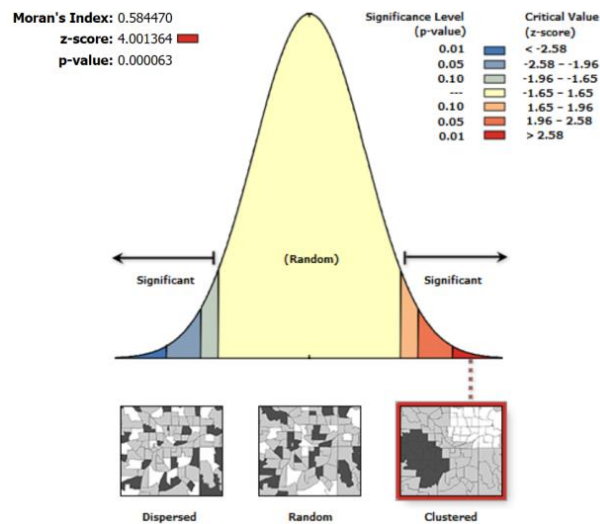


Figure 25: Moran's index for the year 2023 based on the mean NDVI distribution.

We found that z-score or p-value expressed statistical significance, as well as the Moran i-positive index value indicating a clustering tendency, while the Moran I-negative index value indicates a dispersion tendency. The tool utilizes a z-score and p-value to determine the possibility of rejecting null assumptions.

The expected value of Moran's I is $-1/(N-1)$. I values exceeding $-1/(N-1)$ indicate positive spatial correlation, where similar values, whether high or low, tend to cluster together in space. Conversely, I values below $-1/(N-1)$ represent negative spatial correlation, indicating that neighboring values differ from each other (Fig. 25).

Estimation of hot spots and cold spots of vegetation within the border of the study area (confidence level > 90%) using hot spot analysis, clusters and outliers.

According to Moran outputs, for all the years studied 2000 to 2023, NDVI spatial distribution patterns were calculated in clusters (Figs. 26A,B).

One point that has caused this distribution to be clustered is how the ecoregions are distributed. If we look closely, the highest NDVI average is more common in the northern and northwestern parts, and it's actually more concentrated, and that shows the cluster distribution pattern, and it's been going the same way all year. It is the same locally.

Hot spots and cold spots of NDVI, were calculated with confidence percentages of 90, 95 and 99 percent, which certainly increases the percentage of confidence. The following patterns show the north and northwest parts are definitely considered hot spots because there is the highest percentage of average NDVI in these areas (Figs. 26A,B).

Ecoregions include cold spots as well as not significant are also clearly marked which make up the southern and central parts of the ecoregions of Xinjiang Province.

The high high cluster relates to the hot spots that are available in the Tian Shan ecoregions and northwestern Xinjiang Province, and the high low outlier, which is red, and the low low outlier, which are blue, which are described as inconveniences. Low low cluster are clusters that express cold spots that spread in the southern parts, and clusters that have a very low confidence percentage are not significant, which are shown white (Figs. 26A,B).

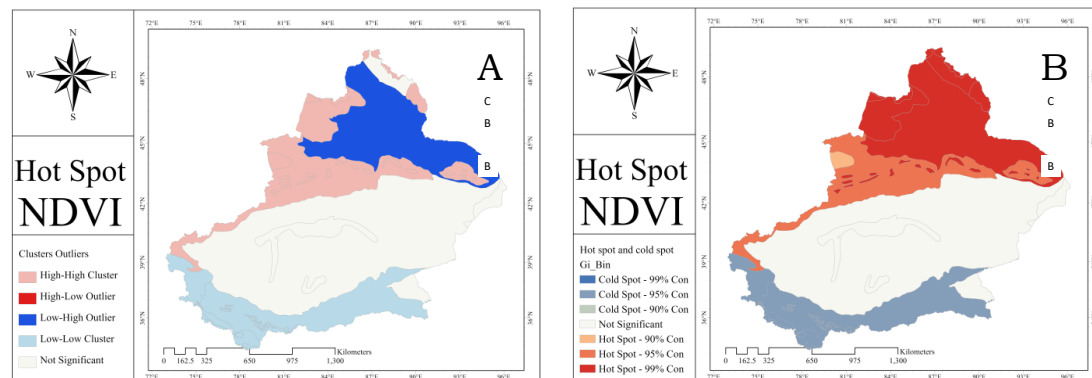


Figure 26: Spatial patterns of hot and cold spots changes in vegetation based on the boundaries of the ecoregions of Xinjiang Province (Clusters outliers is A, Hot Spot and Cold Spot is B).

Identification of factors affecting the distribution of vegetation within the study border (land use land cover, LST, rainfall, slope, elevation) by OLS

Ordinary Least Squares regression (OLS) is a widely used method for estimating the coefficient of linear regression equations. It helps describe the association between a dependent variable and one or more quantitative independent variables, whether it is a simple linear regression or multiple linear regression. In this calculation, NDVI is the dependent variable of the research and LULC, LST, Slope, Rainfall and Elevation are considered independent variables. The results are shown in figure 27.

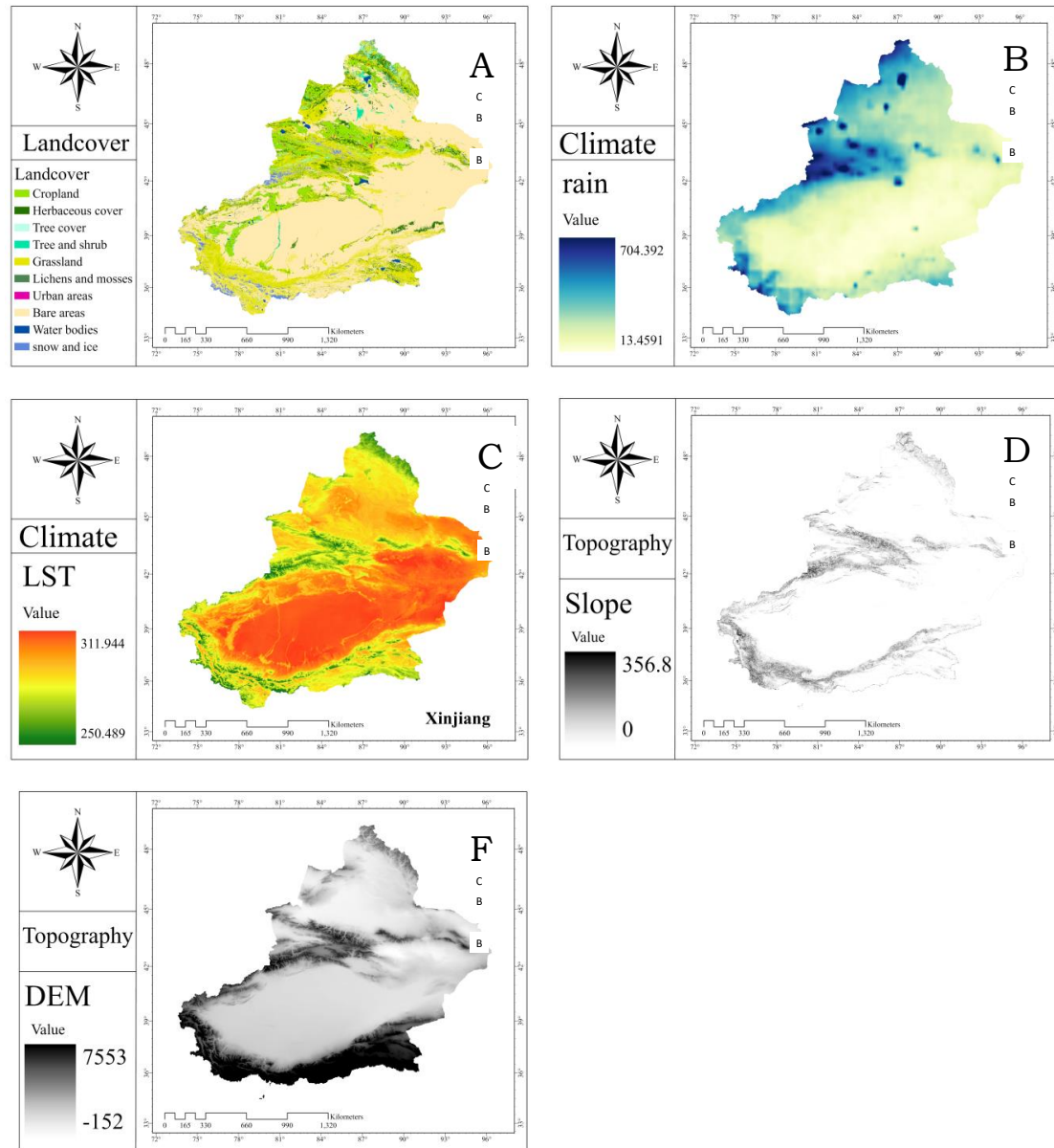


Figure 27: Spatial patterns of effective land use land cover (A), rainfall (B), LST (C), slope (D), elevation (E) drivers on vegetation distribution in Xinjiang Province.

Table 26: Summary of OLS results between NDVI and LULC model.

Variable	Coefficient [A]	Stderror	T-Statistic	Probability [B]	Robust_SE	Robust_T	Robust_Pr [B]
Intercept	−0/613850	0/129693	−4/733110	0/000268*	0/113681	−5/399769	0/000074*
LULC model	0/544243	0/080852	6/731360	0/000007*	0/069100	7/876157	0/000001*

In table 26, the column for Coefficient [a] shows the extent and manner of the relationship between LULC and NDVI. This relationship is strong (0.54) and it should have been predicted like this, and the relationship is also positive. For this connection to be meaningful, refer to the Probability [b] columns and Robust_Pr [b], we see that the numbers are less than 0.03 and are especially starred, the stars of the results indicate the significance of this relationship and we can calculate that LULC is a driver that has a complete impact on NDVI and has a positive relationship.

Table 27: Summary of OLS results between NDVI and LST model.

Variable	Coefficient [A]	Stderror	T-Statistic	Probability [B]	Robust_SE	Robust_T	Robust_Pr [B]
Intercept	1/104029	1/661837	0/664342	0/516554	1/564522	0/705665	0/491210
LST model	-0/003002	0/005791	-0/518356	0/611774	0/005384	-0/557562	0/585370

Table 27 shows the summary of OLS results between NDVI and LST models dedicate that they have a negative relationship with each other (Coefficient [a]) and this value is equal to -0.003002, in fact, areas covered with dense vegetation have low LST values and this relationship also argues this point. Unfortunately, the relationship between LST and NDVI is not very significant according to the Probability column [b] and Robust_Pr [b].

Table 28: Summary of OLS results between NDVI and rainfall model.

Variable	Coefficient [A]	Stderror	T-Statistic	Probability [B]	Robust_SE	Robust_T	Robust_Pr [B]
Intercept	-0/033441	0/107761	-0/310326	0/760585	0/052291	-0/639516	0/532133
Rainfall model	0/001301	0/000470	2/768490	0/014340*	0/000370	3/518273	0/003106*

Table 28 shows there is a statistically significant relationship between NDVI and rainfall. However, the impact of this relationship is not as strong as the influence of the LULC factor.

Table 29: Summary of OLS results between NDVI and elevation model.

Variable	Coefficient [A]	Stderror	T-Statistic	Probability [B]	Robust_SE	Robust_T	Robust_Pr [B]
Intercept	0/414286	0/078734	5/261874	0/000096*	0/085896	4/823133	0/000225*
Elevation model (DEM)	-0/000064	0/000025	-2/561612	0/021689*	0/000019	-3/423192	0/003775*

Focusing on the column Coefficient [a] and Probability [b] in table 29, the results show a meaningful and inverse relationship between NDVI and DEM with confidence level and value of -0.00006, although this relationship is not very strong, but this relationship can be trusted. It is interpreted as having more vegetation in areas where there is less height.

Table 30: Summary of OLS results between NDVI and slope model.

Variable	Coefficient [A]	Stderror	T-Statistic	Probability [B]	Robust_SE	Robust _T	Robust _Pr [B]
Intercept	0/253870	0/083998	3/022338	0/008573*	0/069781	3/638121	0/002430*
Slope model	–0/001246	0/007745	–0/160889	0/874325	0/006483	–0/192223	0/850144

The relationship between NDVI and slope is inverse but not a significant relationship (Tab. 30). Among the results, LULC factor is the most effective factor affecting NDVI and after LULC factor, the LST factor is not very significant, although it has indirect relationship and after LULC it can be the most effective factor on vegetation.

The dominant factor influencing NDVI is land use and land cover (LULC) driver, which has the strongest impact. Following the LULC driver, land surface temperature (LST) factor can also be considered significant, although its influence is not as pronounced. Despite having an indirect relationship, the LST factor becomes the most influential factor in the distribution and growth of vegetation within the counties and boundaries ecoregions of Xinjiang Province after the LULC driver.

DISCUSSION

Many research studies claims that vegetation is an important part of the Earth's ecosystem and biosphere, which, in addition to affecting biogeochemical cycles, carbon balance regulation and maintaining climate stability, water and soil protection, is responsible for an important part of completing the energy cycle as well. On the other hand, monitoring and modeling the time and place changes in vegetation cover and predicting the processes affecting it are considered an integral part of ecological resource and reserve management. Recently, understanding dynamics of vegetation patterns, mainly caused by various natural and human factors such as climate and soil changes, land use changes, wildfires, and mining measures, has become widespread. Therefore, this article attempts to revise a model of changes in vegetation and natural and human drivers affecting the temporal spatial distribution process and dynamics of vegetation at the scale of the counties and ecoregions in Xinjiang Province from 2000 to present. Satellite platforms such as Modis/Terra, CHIRPS, Sentinel 1-2 and GTOPO30 platforms were used to extract the NDVI, LST, precipitation (rainfall), global land cover product and DEM data respectively. NDVI was inserted into the dependent variable and effective drivers were also listed as LULC, LST, precipitation (rainfall), elevation and slope. Methods of calculating and zoning vegetation, predicting mean, minimal and maximum values, temporal and spatial patterns of vegetation, distribution and changes in their area in km², kernel density and point density, estimation of afforestation and deforestation, spatial distribution patterns with confident level, identification of hot and cold spots and prediction of drivers affecting the development and distribution of vegetation were considered the most important methodological elements of the study. Terrain factors, such as altitude, play a role in influencing vegetation coverage. Changes in effective accumulated temperature and soil moisture caused by altitude variations can impact vegetation growth (Liu et al., 2023). The output findings from this research argue that; interpretation of the digital elevation model (DEM) and slope argues the study boundaries have expanded between altitude levels –152 m and 7,553 m and fluctuations of 0 to 356 degrees that, in conjunction with patterns of average annual precipitation 0 to 704 mm and average annual LST 250 to 311 K, have created a wide range of herbaceous plant species, shrubs, and broadleaf and coniferous trees. In a study

conducted by Wang et al. (2022) in Southeast Tibet, it was observed that vegetation patterns exhibit noticeable spatial variations with changes in elevation. The impact of slope and aspect on NDVI change was found to be relatively less significant compared to elevation. Similarly, Xianghong et al. (2015) found in their research in China that elevation plays a crucial role in determining local-scale land use spatial patterns. Areas below 400 m in elevation tend to have higher land use intensity, and it decreases significantly as the elevation increases. LULC driver alignment also assessed that the highest amount of area is related to the bare area class, which is 139,433.7 km², which occupies almost 61.49% of the study area, and the lowest amount of area is related to the lichens and mosses class, which accounts for 41.8 km², or 0.018% of the total studied area. The grassland and crop land occupy 21.2% and 7.17%, and were calibrated in second and third place after bare land respectively.

When studying the spatio-temporal dynamics of vegetation, the Normalized Difference Vegetation Index (NDVI) serves as a vital indicator to assess the state and distribution patterns of plant growth at both global and regional scales. It also enables the observation of long-term vegetation changes over time (Zhuang et al., 2020; Gadiga, 2015). We utilized the NDVI of natural vegetation to track vegetation dynamics. Our analysis revealed that the highest NDVI value, reaching 0.933, was observed in July for 2020, indicating vigorous vegetation growth. This predicted value represents areas with dense vegetation which were occupied western, northwestern and north regions likewise Tian Shan and Altai ecoregions, whereas findings represented the lowest NDVI value of -0.199 corresponded to 2010, which has the presence of abundant sand, rocks such as Taklimakan Desert in the central, east and southern ecoregions in fact.

2015 had the highest area of the regions, with NDVI value of more than 0.5, (149,450.6 km²), and 2000 also experienced the largest area corresponding to areas with a NDVI value of less than 0.5 (161,450.3.6 km²). Therefore, 2015 has experienced the highest level of dense vegetation, and 2000 is also covered with sporadic and vast vegetation community.

Overall, the findings argued that areas where NDVI value has decreased to less than 0.5, their area also declined from 2000 to 2023, or the area NDVI value more than 0.5 increased, which indicates the existence of suitable conditions for the development of vegetation as well as the correct management of the areas studied by humans. The rising number of positive NDVI values indicates a growth in the extent of green vegetation.

Interpretation of visual patterns and robust statistical parameters proved that afforestation activities have increased by 4% from 2000 to 2022 that covers an area of 59,743.71 km² in all the studied boundaries, which is very commendable. Areas that had a diversity of vegetation cover have also benefited from the process of restoration, development and proper management of vegetation cover during the same period, with the area reaching 13%, which occupies approximately 223,681.42 km² of the total studied area in Xinjiang Province.

Countries and international organizations worldwide are slowly but surely acknowledging the threats and risks accompanying the deteriorating and declining vegetation coverage and are implementing various complex measures to safeguard vegetation (Wang et al., 2023). Over the past five decades, the Chinese government has actively promoted the implementation of multiple environmental protection initiatives, resulting in significant positive changes in vegetation cover. Noteworthy projects include the Grain for Green Project, the establishment of the Three-North Shelterbelt Program, and the conservation of natural forest resources.

Amendments and enhancements to the “Forest Law of the People’s Republic of China” have been implemented alongside ecological programs aimed at curbing deforestation and increasing forest area. Since 2000, one such ecological restoration initiative is the “Returning Cultivated Land to Forests and Grasses Project” (Wang et al., 2023; He et al., 2023; Han et al., 2022; Yin et al., 2018). Based on the results of various studies, this set of measures has had an effective role in the growth of vegetation, in this regard, the results of the studies of Zhuang et al. (2020), in Xinjiang and Zhong Bao et al. (2008), Xuemei et al. (2016), Karnieli et al. (2014), Shan et al. (2022), He et al. (2023) in other parts of China, indicates that the vegetation cover has an upward trend.

Also, cluster distribution and hot and cold spot processors calculated at 90, 95 and 99 percent confidence levels that the borders of the ecoregions in the northern and northwestern regions of Xinjiang Province certainly formed the high percentage of the average value of the NDVI. The central and southern ecoregions were found to have minor values of NDVI. The results of the OLS estimate show a strong link between NDVI and LULC valued at 0.54, which is significant. Vegetation is very sensitive to climate change (Wang et al., 2023) hence, it becomes vital to examine the spatio-temporal vegetation changes and how it responds to long-term climate changes. The findings reveal a weak relationship between NDVI and LST, with a value of -0.003 . This lack of significance is evident in both the probability and robust probability analyses. Notably, areas characterized by dense vegetation exhibit lower LST values, which aligns with this relationship. Similarly, a study of Gang et al. (2016) in Central Asia yielded similar results, indicating a weak negative correlation between annual NDVI and temperature. The relationship between precipitation and NDVI was significant with a value of 0.001, although precipitation drivers are not as effective as LULC. In this particular context, various studies conducted by Liu et al. (2006) and Sun et al. (2001) in the Yellow River Basin, China, Zhong Bao et al. (2008) in the Loess Plateau, China, and Xuemei et al. (2016) in the Hexi region of Northwest China have revealed a positive correlation between NDVI and precipitation. Precipitation is identified as the primary driver of vegetation growth, while temperature plays a moderating role in this process (Li et al., 2022). Additionally, it has been observed that there are time lags in the response of NDVI to changes in precipitation (Gang et al., 2016).

There is a meaningful and inverse relationship between NDVI and DEM with confidence level and value of -0.00006 , showing that vegetation is more present at lower altitudes. The OLS model also showed a negative relationship between NDVI and slope with the confidence level -0.0012 which was not very noticeable. Henceforth, the LULC driver is the most effective factor affecting NDVI, and the LST driver can be practically emphasized after the LULC, but it is not strongly meaningful, although it has an indirect relationship, and after the LULC driver, LST can be the most effective driver in the distribution and development of vegetation within the counties and ecoregions boundaries of Xinjiang Province. As a consequence, NDVI is an important vegetation indicator that reflects the state of the regional climate and the environment drivers, which are significantly affected by precipitation, temperature, topographic complications, and human activities.

CONCLUSIONS

Vegetation holds great significance within the ecosystem, and any form of destruction can have detrimental consequences for the environment. Hence, it is crucial to actively monitor, conserve, and sustainably utilize this vital resource. The dynamics of vegetation patterns involve complex processes influenced by a range of biological and human-induced factors, including climate change, changes in land use, and ecological engineering practices. The findings of this study indicate that the dynamics of vegetation cover are impacted by various environmental factors, notably land use and land cover (LULC), land surface temperature (LST), rainfall, elevation, and slope. Moreover, the implementation of diverse vegetation protection policies has proven effective in rejuvenating and fostering vegetation growth. Utilizing the Normalized Difference Vegetation Index (NDVI) to examine vegetation dynamics facilitates a better comprehension of how vegetation responds to different natural and human variables.

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