Multisource Remote Sensing Monitoring and Analysis of the Driving Forces of Vegetation Restoration in the Mu Us Sandy Land

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Abstract: The Mu Us Sandy Land is a key region of man-made desert control and farmland to forest (grass) return in China. Despite global change and the strong influence of human activities, the vegetation in this region has been significantly improved and restored. In this study, multisource remote sensing data and multiple indicators were used to quantitatively monitor and evaluate the vegetation restoration status in this area. The driving factors were also analysed. The results show that in the past 20 years, nearly the entire Mu Us Sandy Land significantly and substantively recovered. The regional fractional vegetation cover increased, with an average annual growth rate of 0.59% and obvious spatial heterogeneity. The nine most important driving factors could comprehensively account for 58.38% of the spatial distribution of the vegetation coverage. Factors such as land use and land cover, the aridity index, and gross domestic product had the most significant impact, followed by precipitation and temperature. The results confirmed that the vegetation was restored and improved in the Mu Us Sandy Land and determined the main driving factors, which is helpful for vegetation restoration and ecological improvement on sandy land similar to the Mu Us Sandy Land.

Keywords: Mu Us Sandy Land; fractional vegetation cover; multisource remote sensing; driving factor; geodetectors; random forest

1. Introduction

Vegetation is the main biological component of terrestrial ecosystems and the primary contributor to terrestrial carbon exchange. It plays an important role in soil and water conservation, regulates the composition of the atmosphere, and slows the rise in greenhouse gas concentrations, while strongly affecting the circulation and flow of matter and energy [1,2]. Sandy land is a typical type of sensitive and fragile land in many ecosystems. The vegetation in sandy land systems can prevent wind and sand erosion, maintain water and soil, and promote a positive succession of the community, thereby curbing or reversing the process of regional desertification and improving the regional ecological environment [3].

As one of the four major sandy areas in China, the Mu Us Sandy Land was once full of yellow sand and its environment was harsh. In recent decades, the Chinese government and its citizens have made great efforts to restore the vegetation and improve the ecology of this area. Several restoration projects have been implemented, including the construction of the Three-North Shelter Forest, the return of farmland to forest and grassland, and the protection of natural forest resources [4]. With the advancement of a series of engineering measures, local residents and the media believe that “moving sand dunes were gradually
fixed, sandstorm disasters were reduced, vegetation was restored, and the ecological environment was improved”. Some people even say that the Mu Us Sandy Land is about to disappear and turn into an oasis.

Satellite remote sensing observation technology provides rich data and technical support for monitoring the dynamic changes in vegetation at different temporal and spatial scales [5,6]. Through the inversion of the original remote sensing image data, a series of indices and indicators representing the vegetation growth state can be obtained. The most common of these indicators are the normalised difference vegetation index (NDVI), enhanced vegetation index (EVI), fractional vegetation cover (FVC), leaf area index (LAI), net primary productivity (NPP), gross primary productivity (GPP), and biomass (BM). The FVC, which has been widely used [7–9], is a quantitative indicator that expresses the coverage of the surface vegetation community and is also an important indicator of changes in the ecological environment [10,11]. The FVC inversion methods by remote sensing mainly include mixed pixel decomposition [12], mixed spectral models, vegetation index models [13,14], and spectral gradient difference models. Among these methods, the pixel binary model [15,16] and the vegetation index [17,18] are widely used due to their accessibility and high degree of accuracy. However, other indicators can reflect the true growth state of vegetation from different perspectives. Multi-indicator and multi-aspect monitoring can better reflect the real dynamic changing trends of vegetation.

Vegetation changes reflect the changes in an ecosystem and the various natural and anthropogenic impacts on the environment. Beyond a simple understanding of the current status of vegetation change, determining which factors lead to and drive vegetation change is important. The succession model, driving mechanism, and forecasting and regulation of regional vegetation have become important subjects of global change research [19–22]. Researchers have applied principal component analysis, trend analysis [23], geodetectors (GD) [24,25], the support vector machine (SVM) algorithm, the random forest (RF) algorithm, and other methods to analyse the contribution of many factors to dynamic vegetation changes. Based on the results of these analyses, people have gradually realised the regionality, diversity, and complexity of the driving factors behind dynamic changes in vegetation.

In summary, the Mu Us Sandy Land is a typical arid and semiarid desert area located in the core of the interlaced agro-pastoral zone in northern China; the vegetation habitat is fragile, sensitive to changes in environmental factors, and subject to strong human interference and influences. Against the backdrop of global climate change and the implementation of a series of ecological protection projects by the Chinese government, the vegetation landscape in this region has been significantly improved. Although previous studies have partially explored the dynamics of these changes, they have not been sufficiently in-depth and detailed. In terms of exploring the driving factors for vegetation restoration in the Mu Us Sandy Land, comprehensive and detailed research is needed. Multisource remote sensing image data from 2000 to 2020 were collected. Based on a number of vegetation status indicators, such as the FVC, LAI, and NPP, the vegetation changes in the Mu Us Sandy Land were monitored. Several natural and human indicators were analysed to determine the driving factors of vegetation change. In this study, we attempted to answer the following questions: (1) Has the vegetation of the Mu Us Sandy Land recovered? If recovery has occurred, in what area, when, and to what extent? (2) Which environmental factors have a relatively important impact on the dynamic changes in the vegetation of the Mu Us Sandy Land? How much do they contribute to vegetation dynamics, individually and in combination? The results of this research will enhance the public understanding of the quantification of vegetation restoration in the Mu Us Sandy Land and provide an in-depth analysis of the driving factors and driving mechanisms of vegetation change.
2. Materials and Methods

2.1. Overview of the Study Area

The Mu Us Sandy Land (107°25′–110°22′ E, 37°31′–39°41′ N) is one of the four major sandy lands in China (Figure 1) and an important part of the ecological security barrier in northern China, with an area of approximately 42,600 km². The annual average temperature is approximately 8.5 to 8.9 °C, the annual temperature range is large, and the annual average rainfall is 340 mm and mostly concentrated from June to September. The altitude in the area is approximately 900 to 1600 m, with the terrain gradually rising from the southeast to the northwest. The landforms are primarily crescent-shaped dunes and dune chains, and the soils are mostly aeolian sandy soil, fluvo-aquic soil, chestnut calcium soil, and brown calcium soil. The shrub community dominates the vegetation cover, and the main species are Salix, Artemisia, thorn bean, and sea buckthorn. The site is located in the windbreak and sand fixation ecological function protection zone and the water and soil conservation ecological function protection zone. The water system in the area is made up of the Yellow River mainstream water system and the Ordos inner water area.

![Figure 1. Overview of the study area.](image)

2.2. Data Source and Preprocessing

From 2016 to 2018, when the vegetation was growing vigorously (from August to October), we conducted several samplings and field investigations of the vegetation to gain a comprehensive understanding of the vegetation growth in the entire Mu Us Sandy Land. The vegetation type, vegetation coverage, local topography, and landscape photos of the sampling site were collected. Survey data from a total of 45 sample points were obtained, with the sample distribution shown in Figure 1.
Landsat-5 TM remote sensing images from 2000 and 2010 and Landsat-8 OLI images from 2020 were obtained from the US Geological Survey (https://earthexplorer.usgs.gov/) (accessed on 16 June 2021), for a total of 12 scenes. Radiometric calibration and atmospheric correction were performed using ENVI 5.3. The Moderate Resolution Imaging Spectroradiometer (MODIS) datasets MOD13Q1 (2000–2020), MCD15A3H (2003–2020), and MOD17A3HGF (2000–2020) were obtained from NASA’s EOS/MODIS data (https://ladsweb.modaps.eosdis.nasa.gov/): the time scales were 16 d, 4 d, and 1 a; the spatial resolutions were 250 m, 500 m, and 1000 m; and the number of images were 480, 1659, and 21, respectively. Using the Google Earth Engine (GEE) platform (https://code.earthengine.google.com/) (accessed on 4 March 2022), the data were converted, cut, and downloaded. To reduce the influence of the atmosphere, the maximum value composite (MVC) method was used to convert the 16-day MODIS-NDVI data into monthly average data. The 4-day MODIS-LAI data were summarised by the monthly maximum value and the annual average LAI was obtained. Various types of data were also collected to determine the driving factors affecting the vegetation distribution. Natural factors included the altitude (ALT), slope (SLO), aspect (ASP), annual average temperature (TEM), annual precipitation (PRE), air humidity (AH), annual average wind speed (WS), annual mean atmospheric pressure (AP), solar radiation intensity (SRI), river buffer distance (RBD), aridity index (AI), and soil type (ST). Human factors included land use and land cover (LULC), kilometre grid gross domestic product (GDP), and population density (PD). The altitude data were downloaded from the Geospatial Data Cloud (http://www.gscloud.cn) (accessed on 14 September 2021) with a spatial resolution of 30 m, while the annual precipitation and annual average temperature raster data were downloaded from the National Earth System Science Data Centre (http://www.geodata.cn) (accessed on 28 July 2021) with a spatial resolution of 1000 m. Other meteorological factors came from the China Meteorological Data Network (http://data.cma.cn) (accessed on 14 July 2021), while the aridity index was downloaded from the Consultative Group for International Agricultural Research (CGIAR) CSI website (https://cgiarcsi.community/) (accessed on 21 October 2021). The river system data, including lakes, reservoirs, rivers, ditches, and river structure lines, came from the 1:250,000 vector map dataset of the National Geographic Information Resource Catalogue Service System (https://www.webmap.cn/) (accessed on 3 April 2022); the land use and land cover data with a resolution of 10 m were downloaded from World Cover (https://esa-worldcover.org/en) (accessed on 17 September 2021); and the population density data were obtained from World Pop (https://hub.worldpop.org/) (accessed on 3 September 2021). The spatial resolution was 100 m, while the GDP spatial distribution kilometre grid and soil type data were downloaded from the Chinese Academy of Sciences Resource and Environmental Science and Data Centre (https://www.resdc.cn/) (accessed on 10 September 2021) with a spatial resolution of 1000 m.

The kriging method was used to interpolate data from 11 meteorological stations in the Mu Us Sandy Land to generate grid layers, with the multiple ring buffer tool used to generate 1 km, 3 km, 7 km, 17 km, and 21 km buffers for the river system vector data with ArcGIS 10.6. The distance from the river was divided into seven categories. The LULC was divided into seven categories, namely, trees, shrubland, grassland, cropland, built-up land, barren vegetation, and open water. Using the optimal spatial discrete function of the “GD” package in R, ALT, TEM, PRE, AH, SRI, AI, and GDP data were divided into seven categories. The spatial resolution of the above data was uniformly resampled to 30 m and the coordinate system was WGS 1984, UTM Zone 49 N. The workflow flow chart is shown in Figure 2.
2.3. Methods

2.3.1. Fractional Vegetation Cover Inversion

The FVC refers to the vertical projected area of vegetation (including leaves, stems, and branches) on the ground as a fraction of the total statistical area. The FVC is usually inverted by vegetation indices. There are many types of vegetation indices, with the NDVI the most widely used [26,27]. In this study, the NDVI was selected to invert the FVC. The formula for the NDVI is:

\[
\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}}
\]  

(1)

The NDVI value ranges from −1 to 1, where \( \rho_{\text{NIR}} \) is the near-infrared band and \( \rho_{\text{RED}} \) is the red band. The NDVI can reflect the basic status of vegetation coverage and growth. The larger its value, the better the vegetation growth. However, the NDVI also has the disadvantages of high vegetation coverage being easily saturated and low vegetation coverage being difficult to distinguish. The basic principle of the pixel binary model is to assume that a surface pixel is composed of vegetation coverage and non-vegetation coverage, with the spectral information also linearly weighted by those two factors. The weight of each factor is the proportion of its area in the pixel [28]. Therefore, in this study, we used the pixel dichotomy model to estimate vegetation coverage of the Mu Us Sandy Land. The calculation formula is:

\[
\text{FVC} = \frac{(\text{NDVI} - \text{NDVI}_{\text{soil}})}{(\text{NDVI}_{\text{veg}} - \text{NDVI}_{\text{soil}})}
\]  

(2)

where \( \text{NDVI}_{\text{veg}} \) is the NDVI value of a pixel with pure vegetation cover and \( \text{NDVI}_{\text{soil}} \) is the NDVI value of no vegetation cover or bare soil. Due to the inevitable existence of noise, \( \text{NDVI}_{\text{veg}} \) and \( \text{NDVI}_{\text{soil}} \) generally present the maximum and minimum values within a certain confidence range. Referring to the application of the pixel binary model, we used empirical values of 0.05 and 0.7 for \( \text{NDVI}_{\text{soil}} \) and \( \text{NDVI}_{\text{veg}} \), respectively [29,30]. According to China’s “Technical Regulations for Land Use Status Survey” and “National Report on Desertification Control”, the vegetation coverage of the Mu Us Sandy Land can be divided into five grades, namely, very low vegetation coverage (0–0.2), low vegetation coverage (0.2 to 0.4), medium vegetation coverage (0.4 to 0.6), medium-to-high vegetation coverage (0.6 to 0.8), and high vegetation coverage (0.8 to 1).

2.3.2. Trend Analysis

The Theil–Sen median method is a robust nonparametric statistical trend calculation method [23,31,32], also known as the Sen slope estimation. This method has a high computational efficiency, is not sensitive to measurement errors or outlier data, and is often used
in trend analyses of long-term series data. The Mann–Kendall test is a nonparametric test method. Unlike parametric test methods, it does not require samples to follow a certain distribution, and it is less disturbed by outliers, so it is more suitable for sequential variables. The Mann–Kendall test has been successfully used to study changes in hydrological and meteorological trends, and to assess the significance of changes in runoff, precipitation, climate, etc. \[33,34\].

\[
\beta = \text{Median} \left( \frac{X_j - X_i}{j - i} \right) \quad \text{for all } i < j
\]  

(3)

where \(X_i\) and \(X_j\) are the continuous data values of the time series for years \(i\) and \(j\), respectively, and \(\beta\) is the estimated value of the trend slope in the data series. \(\beta > 0\) indicates that the time series presents an upward trend; \(\beta < 0\) indicates that the time series presents a downward trend. In this paper, Sen + MK was calculated using the “sen.slope” function in the trend package in R.

2.3.3. Geodetectors

Geodetectors are a set of statistical methods that detect spatial heterogeneity and reveal the driving forces of land surface state variables. The central principle of geodetectors is to detect the degree to which independent variables explain dependent variables through spatial heterogeneity, with the methods including factor detectors, interaction detectors, risk detectors, and ecological detectors \[24,25\].

(1) Factor detector: This detector calculates the spatial heterogeneity of different factors and detects how much a certain factor \(X\) explains the spatial heterogeneity of attribute \(Y\); the stronger the spatial differentiation, the greater the value, and vice versa. The calculation formula is:

\[
q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma^2_h}{N \sigma^2}
\]  

(4)

In this formula, \(h = 1 \ldots , L\) is the layer of \(Y\) or the layer of each factor \(X\); \(N_h\) and \(N\) are the number of units in layers \(h\) and \(Y\), respectively; and \(\sigma^2_h\) and \(\sigma^2\) are the variance of layer \(h\) and the variance of the \(Y\) values for the entire area, respectively.

(2) Interaction detector: This detector indicates the interaction between different influencing factors. It compares one-factor \(q\)-values, two-factor \(q\)-values, and the sum of two-factor interactions, and evaluates whether the explanatory power of factors \(X_1\) and \(X_2\) for the dependent variable increases or decreases, i.e., it mainly compares factors \(q(X), q(X_1) + q(X_2)\), and \(q(X_1 \cap X_2)\).

(3) Risk detector: A statistical significance test is performed by calculating the mean value of the dependent variable in the subregions of the influencing factors. The larger the mean value of the dependent variable in each factor subregion, the more favourable it is for the dependent variable in the subregion to be in a good state, and the suitable range or type of the dependent variable can be judged by each factor subregion.

\[
t_{\gamma_{h=1}} - t_{\gamma_{h=2}} = \frac{Y_{h=1} - Y_{h=2}}{\left[ \frac{\text{Var}(Y_{h=1})}{n_{h=1}} + \frac{\text{Var}(Y_{h=2})}{n_{h=2}} \right]^{1/2}}
\]  

(5)

In the formula, \(Y_h\) represents the attribute mean value in subregion \(h\), \(n_h\) is the number of samples in subregion \(h\), and \(\text{Var}\) represents the variance. In this study, the risk detector was used to calculate and compare the mean value of the dependent variable in the corresponding spatial range of the different value ranges of various driving factors to judge the relationship between the factors and the dependent variable.

2.3.4. Random Forest Factor Importance Analysis

The RF algorithm was proposed by Breiman \[35,36\] and has the advantages of diverse angles, a large allowable sample size, a lack of sensitivity to multivariate linearity, and a
good tolerance of outliers and noise. The comprehensive interpretation rate reflects the accuracy of the training set and test set of the RF model. The method can use the IncNodePurity index as the basis for evaluating the importance of multiple factors. IncNodePurity is the average reduction in the node impurity that is measured by the residual sum of squares, which represents the heterogeneity of each variable based on the observations in each node of the classification tree. Larger values indicate that the comparison variable has a greater importance [37,38]. This method can be easily implemented using the RF toolkit in R.

3. Results

3.1. Spatial and Temporal Variation of the FVC

3.1.1. Spatial Distribution of the FVC

Based on our field investigation, the period of vigorous vegetation growth in the Mu Us Sandy Land is from late-July to mid-August. Therefore, we selected the Landsat data in July and August from 2000, 2010, and 2020 to compare with the MODIS annual maximum synthetic data (Figure 3). The MODIS annual maximum synthetic FVC was slightly larger than the FVC calculated from the Landsat data. The results obtained from these two different data sources were similar. As the years passed, vegetation coverage of the Mu Us Sandy Land was high in the eastern and southern margins and low in the northwest and central regions. Accounting for variability in the image quality of the Landsat data in a specific area and time period due to factors such as cloudiness and time, we analysed the results of the FVC inversion using MODIS and divided it into five stages according to the equal interval method. The area with medium–high or high vegetation coverage (FVC > 0.6) was mainly in Shaanxi Province and accounted for 34% of the total area. The southeastern part of the Mu Us Sandy Land was characterised by a low altitude, mostly low mountain plains, relatively dense water systems, higher precipitation, and suitable hydrological conditions for vegetation growth. The areas with very low or low vegetation coverage (FVC < 0.4) were mainly located in the Inner Mongolia Autonomous Region, accounting for 27% of the total area. This area has a higher altitude, more mobile sand dunes, and an arid climate, and receives less rainfall; thus, it is not conducive to vegetation restoration.

Figure 3. Spatial distribution of the FVC from 2000 to 2020 (a: Landsat, b: MODIS).
Using the spatial distribution data of the FVC from 2000 to 2020, the area transition matrix for different coverages was calculated (Table 1). Over time, vegetation coverage changed from very low to low-to-moderate. The area with a very low vegetation coverage decreased from 10,346.93 km$^2$ in 2000 to 972.27 km$^2$ in 2020, a decrease of 21.96%; the area with a low vegetation coverage decreased from 23,303.28 km$^2$ in 2000 to 10,715.25 km$^2$ in 2020, a decrease of 29.49%. The proportions of medium, medium–high, and high coverage all increased to varying degrees; the most significant increase was for the area with medium coverage, with an increase of 22.56%, followed by medium–high and high coverage, with increases of 19.22% and 9.67%, respectively. A significant decrease was observed in the area with FVC values of 0 to 0.4, with a reduction of 28,167.49 km$^2$; the areas with medium coverage, medium–high coverage, and high coverage increased by 9630.64 km$^2$, 8204.20 km$^2$, and 4127.84 km$^2$, respectively. This finding showed that the vegetation restoration process in the Mu Us area was in the initial stage. Future vegetation restoration in this area will require national policy support to achieve the goal of having people vacation in the sand, enjoying clear waters and lush mountains.

### Table 1. Transfer matrix of FVC in 2000–2020 (unit: km$^2$).

<table>
<thead>
<tr>
<th>FVC</th>
<th>0–0.2 (Very Low)</th>
<th>0.2–0.4 (Low)</th>
<th>0.4–0.6 (Medium)</th>
<th>0.6–0.8 (Medium–High)</th>
<th>0.8–1 (High)</th>
<th>2020 Total</th>
<th>Transfer in</th>
</tr>
</thead>
<tbody>
<tr>
<td>0–0.2</td>
<td>943.44</td>
<td>24.01</td>
<td>2.15</td>
<td>1.61</td>
<td>1.07</td>
<td>972.27</td>
<td>28.84</td>
</tr>
<tr>
<td>0.2–0.4</td>
<td>5860.05</td>
<td>4539.28</td>
<td>304.94</td>
<td>7.74</td>
<td>3.24</td>
<td>10,715.25</td>
<td>6175.97</td>
</tr>
<tr>
<td>0.4–0.6</td>
<td>2769.57</td>
<td>11,705.83</td>
<td>2014.90</td>
<td>78.85</td>
<td>8.66</td>
<td>16,577.82</td>
<td>14,562.91</td>
</tr>
<tr>
<td>0.6–0.8</td>
<td>611.34</td>
<td>5330.60</td>
<td>2903.64</td>
<td>691.67</td>
<td>251.45</td>
<td>9788.70</td>
<td>9097.03</td>
</tr>
<tr>
<td>0.8–1</td>
<td>162.53</td>
<td>1703.55</td>
<td>1721.55</td>
<td>804.62</td>
<td>246.65</td>
<td>4638.91</td>
<td>4392.26</td>
</tr>
<tr>
<td>2000 Total</td>
<td>10,346.93</td>
<td>23,303.28</td>
<td>6947.18</td>
<td>1584.50</td>
<td>511.06</td>
<td>42,692.95</td>
<td>-</td>
</tr>
<tr>
<td>Transfer out</td>
<td>9403.49</td>
<td>18,764.00</td>
<td>4932.28</td>
<td>892.82</td>
<td>264.41</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Change</td>
<td>−9374.66</td>
<td>−12,588.03</td>
<td>9630.64</td>
<td>8204.20</td>
<td>4127.84</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

#### 3.1.2. Interannual Variation in the FVC

The interannual average vegetation coverage of the Mu Us Sandy Land from 2000 to 2020 based on the MODIS data was calculated using a pixel dichotomy model, with a linear regression analysis performed (Figure 6a). From 2000 to 2020, the FVC in the Mu Us Sandy Land exhibited an overall trend that fluctuated upwards, with five peak years in 2003, 2007, 2010, 2013, and 2018. By linear fitting to the mean value of the entire study section, the slope was estimated to be 0.00597. This result indicated that the overall trend of vegetation coverage was increasing and its variation trend was moderately improving. The FVC value ranged from 16% to 29%, the rate of change was 0.59%/a, and the interannual variation trend was relatively weak. Since the implementation of the project of returning farmland to forest and grassland in 1999, the FVC was the smallest in 2000 and showed a rapid growth rate in 2002. The vegetation coverage of the Mu Us Sandy Land reached a maximum in 2018. From a long-term perspective, in the past 20 years, vegetation coverage has experienced a slight fluctuation and an upward trend, increasing by nearly 73%, and generally improving. Some areas have transformed into a “desert oasis”.

#### 3.1.3. Changing Trend of Vegetation Coverage

The vegetation coverage in the study area showed a trend of overall improvement (Table 2 and Figure 4). The areas with obvious improvement in vegetation coverage accounted for 81.1% of the total area and were distributed in the entire region except the northwest and west; the areas with a slight improvement in vegetation coverage accounted for 15.1% of the total area and were mainly concentrated in the west and northwest; stable areas accounted for 1.29% of the total area and were distributed in urban construction areas and lake water system areas; the areas with slightly degraded and severely degraded vegetation coverage accounted for 2.31% and 0.2% of the total area, respectively; the areas
with a degraded vegetation coverage were distributed in surrounding counties and urban areas. The land cover type in these areas changed from grassland and cultivated land to construction land, with vegetation degradation nearly consistent with the urbanisation process. After decades of governance, the ecological environment of the Mu Us Sandy Land has been greatly improved and the vegetation coverage has been effectively restored.

Table 2. Statistics of vegetation change trends in the past 20 years.

<table>
<thead>
<tr>
<th>SFVC</th>
<th>Z Value</th>
<th>Trend of FVC</th>
<th>Percentage/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>≥0.0005</td>
<td>≥1.96</td>
<td>Substantial improvement</td>
<td>81.1</td>
</tr>
<tr>
<td>≥0.0005</td>
<td>−1.96–1.96</td>
<td>Slight improvement</td>
<td>15.1</td>
</tr>
<tr>
<td>−0.0005–0.0005</td>
<td>−1.96–1.96</td>
<td>Stable</td>
<td>1.29</td>
</tr>
<tr>
<td>−0.0005</td>
<td>−1.96–1.96</td>
<td>Slight degradation</td>
<td>2.31</td>
</tr>
<tr>
<td>−0.0005</td>
<td>&lt;−1.96</td>
<td>Serious degradation</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Figure 4. The spatial distribution characteristics of the FVC variation in the Mu Us Sandy Land.

3.1.4. Spatial and Temporal Variation of the LAI and NPP

Using MODIS’s LAI and NPP products for data sources and data preprocessing (Section 2.2), the regional annual average LAI and annual NPP results were obtained. Three typical years (2000, 2010, and 2020) were selected (the LAI data from 2000 were missing, so data from 2003 were selected), and the results of the LAI and NPP were spatially mapped (Figure 5). Over time, both the LAI and NPP in the Mu Us Sandy Land exhibited a significant growth trend. The areas where the LAI and NPP improved were almost the same as those of the FVC, with the eastern and southern edge areas of the region (within Shaanxi Province) experiencing the most obvious growth. Although different degrees of growth were observed in the central area, the growth rate in this area lagged behind that of other areas.
Linear regression analysis was performed on the annual average LAI and annual NPP of the vegetation in the Mu Us Sandy Land (Figure 6b,c), with a fluctuating upward trend observed overall. The peak NPP appeared in 2004, 2010, 2012, 2016, and 2019. The peak LAI occurred in 2003, 2007, 2010, 2012, and 2018, and the year of appearance was basically the same as the peak year of the FVC. Through linear fitting of the NPP in the entire study area, the average annual growth rate of the NPP was 4.719 gC/m², while the average annual growth rate of the LAI was 0.0027. In the past 20 years, the LAI and the NPP have significantly increased in the Mu Us Sandy Land.

Figure 6. The FVC, LAI, and NPP over time in the Mu Us Sandy Land ((a) is the annual mean FVC, (b) is the annual mean LAI, and (c) is the annual accumulated NPP).

Based on these results, we found that the vegetation restoration in the Mu Us Sandy Land was regional, comprehensive, and substantial; in most areas of the region, various vegetation indicators increased and improved significantly. Although the improvement exhibited spatial heterogeneity, it was generally widespread.
3.2. Analysis of the Factors Driving Vegetation Coverage Changes

3.2.1. Factor Detection

The spatial distribution data of the FVC and 15 influencing factors in the Mu Us Sandy Land (in 2020) were run through the “GD” package in R, with the simulation results obtained by the factor detector shown in Table 3. For the 15 influencing factors, the \( p \) values were all less than 0.05 and the results were considered to be valid.

Table 3. Results of factor detector affecting vegetation distribution in Mu Us Sandy Land.

<table>
<thead>
<tr>
<th>Variable</th>
<th>LULC</th>
<th>AI</th>
<th>PRE</th>
<th>GDP</th>
<th>TEM</th>
<th>SRI</th>
<th>AH</th>
<th>ALT</th>
<th>AP</th>
<th>RBD</th>
<th>WS</th>
<th>ST</th>
<th>SLO</th>
<th>PD</th>
<th>ASP</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q ) value (%)</td>
<td>27.29</td>
<td>23.44</td>
<td>20.65</td>
<td>19.88</td>
<td>13.41</td>
<td>12.32</td>
<td>10.77</td>
<td>10.37</td>
<td>9.41</td>
<td>8.79</td>
<td>7.28</td>
<td>3.08</td>
<td>0.95</td>
<td>0.68</td>
<td>0.10</td>
</tr>
</tbody>
</table>

For the convenience of analysis and expression, the first nine factors with \( q \) values greater than 9% were selected for analysis and subsequent interactive detection and risk detection; the spatial distribution of the nine factors is shown in Figure 7.

Figure 7. Potential drivers of vegetation coverage ((a) Annual rainfall. (b) Annual mean temperature. (c) Annual average humidity. (d) Annual average solar radiation intensity. (e) Types of land use and land cover. (f) River buffer distance. (g) GDP of the kilometre grid. (h) Aridity index. (i) Altitude).
Among the nine most important factors, the q value of LULC was the largest (27.29%), followed by AI (23.44%), PRE (20.65%), GDP (19.88%), TEM (13.41%), SRI (12.32%), AH (10.77%), and ALT (10.37%), while RBD was the smallest (8.79%). These results suggest that the vegetation restoration in the Mu Us Sandy Land had a certain relationship with natural and human factors. The harsh natural conditions had a profound impact on human activities and economic development, resulting in differences in the spatial distribution of vegetation coverage in the Mu Us Sandy Land. The vegetation coverage was affected by the synergistic effects of natural conditions and human factors. The most prominent factors were LULC, AI, PRE, and GDP. The differences in the values were small, with RBD having the least effect on the spatial distribution of vegetation coverage in the Mu Us Sandy Land.

3.2.2. Interactive Detection

We applied interaction detection to the different factors and found that the q value for interaction was greater than that of a single factor and less than that of the sum of the two factors. This approach is only one type of two-factor enhancement. All the factor interactions showed dependence. As shown in Figure 8, after the interaction, q(AI) ∩ q(LULC) (0.439), q(PRE) ∩ q(LULC) (0.429), and q(GDP) ∩ q(LULC) (0.419) were the largest among all interaction types, with all q values >0.4. These results indicated an interaction between LULC and other factors, and the explanatory power of vegetation coverage was greatly improved. Similarly, AI, PRE, and GDP exhibited interactions with other factors, and the explanatory power of vegetation coverage was obviously improved. These findings further indicated that LULC, AI, PRE, and GDP were the main driving factors among the various factors. TEM, ALT, SRI, AH, and RBD had relatively weak interactions. Overall, the single factor interaction showed an enhancement effect, with the value of the interaction between human and natural factors greater than that of the sum of two natural factors or two human factors. This result indicated that different types of factors had synergistic effects.

3.2.3. Random Forest Impact Factor Importance Analysis

To ensure the reliability of the factor detection results, we used the RF algorithm and nine factors (relatively important factors selected by the geodetectors) as explanatory independent variables to reassess their importance and their overall contribution to the spatial distribution of vegetation coverage. The sample points were divided into a training set and a test set at a ratio of 7:3. The results showed that the comprehensive explanation rate of the nine factors on vegetation coverage in the Mu Us Sandy Land was 58.38%; LULC and AI were more important to the distribution of vegetation coverage, with the importance of each variable ranked in order (Figure 9). This result was reasonably consistent with the results of the geodetectors. From the perspective of the spatial distribution of the main driving factors, natural and human factors were the main factors affecting vegetation coverage.
changes. Coordinating the relationship between humans and nature can support vegetation restoration and ecological protection.

Figure 9. Importance ranking results of the RF algorithm.

4. Discussion

4.1. Analysis of Vegetation Restoration in the Mu Us Sandy Land

The Mu Us Sandy Land has some unique features. It is a sandy land that is relatively close to the ocean and near an area in eastern China with a high population density and intense economic activity. It is also the core of the interlaced agro-pastoral zone in northern China. It is an ecologically fragile area that is sensitive to global changes and human disturbances. It has also been a key model area for artificial sand control in China over the past 60 years. In recent years, the restoration of vegetation in this area has been widely recognised and followed by scientists, government departments, and the general public. Some people even say that the Mu Us Sandy Land is about to disappear and become an oasis. In this study, from a quantitative perspective, we first confirmed that the vegetation in the Mu Us Sandy Land has improved significantly in recent years (Figures 3–6). In addition, the restoration of the vegetation was reflected by multiple indicators: the FVC, the annual average LAI, and the annual NPP. The results showed that the vegetation restoration in this area has been multifaceted and substantial. Some previous studies have used the NDVI as a single indicator to analyse the dynamic changes in the vegetation of the Mu Us Sandy Land [39–43]. Their conclusion that the vegetation in this area was gradually restored was consistent with this paper. Second, for the entire Mu Us Sandy Land, the vegetation restoration trend showed obvious spatial heterogeneity. Vegetation recovery was most obvious in the eastern and southern fringe areas of the region (in Shaanxi Province). In contrast, in the northwestern fringe and central areas, although vegetation has recovered to varying degrees, the rate of recovery has lagged behind that of other areas. Liu et al. [15] used remote sensing data and the pixel dichotomy model, and inversed the FVC of the Mu Us Sandy Land (eastern half). Their FVC results showed the spatial distribution characteristics of gradually decreasing vegetation from southeast to northwest. Sun et al. [40] analysed the spatial characteristics of vegetation restoration in this area. The results also reflected this trend. Through an in situ investigation, we identified large areas of sand dunes in the northwest edge and central areas of the sandy land (Figure 10). Therefore, although the restoration of vegetation in the Mu Us Sandy Land was apparent and clearly reflected in the quantitative monitoring via remote sensing, the desert has not completely disappeared and turned into an oasis.

Nowadays, with the intensification of global changes and human activities, the dynamic changes of regional vegetation tended to be more obvious. In addition, thanks to the rapid development of remote sensing observation technology, human beings have
the ability and technology to observe this change. Therefore, the research on dynamic monitoring of regional vegetation using remote sensing technology was widely performed. In China, the phenomenon of vegetation restoration has also been widely reported in other areas except the study area of this paper. Nie et al. [44] and Sun et al. [45] studied the dynamic changes of vegetation on the Loess Plateau in recent decades. Tian et al. [43] focused on vegetation dynamic changes in Inner Mongolia from 2000 to 2012. Sun et al. [46] focused on vegetation dynamic changes in North China. Even in other parts of the world, such as Europe [47–49], Africa [50–52], and Australia [53–55], regional vegetation dynamics had been widely concerning. These studies revealed a fact consistent with the conclusion of this paper. Regional environmental conditions can be artificially improved locally, but the efforts should be based on local conditions and require a large amount of investment; changes in large-scale regional landscapes and the restoration of vegetation mainly depend on the long-term shaping of natural conditions.

Figure 10. Photographs of typical sampling points in the Mu Us Sandy Land. (The numbers 1, 10, 17, 28, 36 mean part of sample points numbers same as Figure 1. The numbers (1), (10), (17), (28), (36) is the number of landscape photos of corresponding sample points).

In this paper, multisource remote sensing data, namely, Landsat-5 TM/-8 OLI and MODIS dataset MOD13Q1, were selected as image data to invert the FVC. Both of these time series could reflect the trend of vegetation restoration in Mu Us Sandy Land with good consistency. However, the vegetation coverage calculated by the MODIS dataset was slightly higher than that of the Landsat satellite images. We speculate that the reasons are as follows: First, the spatial resolution of the two data sources was inconsistent. The resolution of the MODIS image is 250 m and that of Landsat is 30 m; there is a more obvious mixed effect for MODIS. Second, considering the effect of error, we used the synthesised maximum value method for MODIS images. The results of multiple indicators were highly consistent in both time and space (Figures 3, 5 and 6).

4.2. Analysis of the Driving Forces of Vegetation Restoration

The significant recovery of the vegetation of the Mu Us Sandy Land was confirmed, but which environmental factors drove this change? In this study, 15 environmental factors were initially selected to analyse the driving forces of dynamic vegetation changes by using the geodetector method. Then, nine relatively important environmental factors were selected for further analysis. To ensure the reliability of the factor detection results, the RF classification algorithm was also used to evaluate multiple factors (nine relatively important selected factors) and the comprehensive interpretation ability and importance ranking of
individual factors. The discrimination results of the two methods for factor importance were highly consistent.

Among the driving factors selected in this study, the land cover type had the strongest explanatory power for the distribution of vegetation coverage, followed by the aridity index and precipitation; the explanatory power of these three indicators exceeded 20%. These results basically reflected the dynamic changes in vegetation in the Mu Us Sandy Land, which were mainly affected by the combined effects of natural and human factors. The type of land cover was a comprehensive reflection of natural, human factors and reflected the land use situation and economic level of the region. At the same time, this fact also reflected the investment potential and success of execution of artificial improvement of the environment. The aridity index was also a composite index that reflected the synergistic effect of two main natural factors, temperature and precipitation, among natural factors. This factor was followed by the GDP factor that reflected the level of economic development, the investment ability. In summary, the dynamic changes in the vegetation of the Mu Us Sandy Land were attributed to the general warming and humidification in northern China due to global climate change, resulting in a general improvement in vegetation coverage in the entire region. However, in the eastern and southern margins of the Mu Us Sandy Land (in Shaanxi Province), 60 years of artificial desert management and the implementation of the project to return farmland to forests and grasslands, coupled with the better natural basic conditions in the southeastern margin, have resulted in a very high vegetation restoration effect in this area. Significantly, the regional landscape transformed from a desert to an oasis. The results of the analysis of the driving factors indicated that regional vegetation restoration was a complex and dynamic process that was affected by the interaction of multiple factors (3.2.2 Conclusion), with no single factor having an absolute effect on the distribution of vegetation based on its explanatory power (the maximum single factor q value did not exceed 30%).

The spatial pattern of the vegetation in the Mu Us Sandy Land was affected by a variety of factors. To further refine the distribution of vegetation coverage within the spatial range corresponding to the specific values (levels) of different factors, we selected different values for each factor in the risk detector results (level) corresponding to the average spatial area of vegetation coverage to analyse the relationship between each factor and vegetation coverage. The results are shown in Figure 11. The effects of various natural, human factors on vegetation coverage in the Mu Us Sandy Land differed. Greater values of factors such as precipitation, air humidity, and aridity index corresponded to a higher vegetation coverage, demonstrating that the precipitation, temperature, humidity, and aridity index were positively correlated with vegetation coverage. However, altitude was negatively correlated with vegetation coverage, while other natural factors showed a certain degree of volatility and complexity in this region.

Among the human factors, vegetation coverage in areas where the LULC was forestland was the highest, followed by cropland and grassland. Water and unused land (bare land and sandy land) were the lowest. The higher the GDP, the higher the vegetation coverage. In conclusion, the relationship between vegetation coverage in the Mu Us Sandy Land and the values of the above factors could well explain the current situation of regional vegetation restoration. Many natural factors were positively correlated with vegetation coverage; due to recent global climate change, northern China has experienced a trend of overall warming and humidification. Therefore, changes in these natural factors drove the recovery of vegetation. Among the human factors, among the LULC types, forestland corresponded to high vegetation coverage, while water bodies and unused land corresponded to low vegetation coverage. In the Mu Us Sandy Land, many years of afforestation, desert control, and returning farmland to forests and grasslands have driven the conversion of unused land to forest, leading to an increase in vegetation coverage. In addition, the GDP factor was positively correlated with vegetation coverage. The increase in GDP reflected the agglomeration of population, economic development, and increase in the human investment capacity and the implementation of environmental improvement. In the study
area, especially the southeastern edge (in Shaanxi Province), with the development of the economy, artificial and continuous sand control has resulted in a significant recovery of the vegetation.

![Graph showing the recovery of vegetation with various factors affecting it.](image)

Figure 11. Risk detector results for each factor.

Some studies have analysed the driving factors of vegetation restoration in the Mu Us Sandy Land. Li, Sun et al. [40,42] showed that precipitation, temperature, and relative humidity were significantly positively correlated with vegetation coverage in the Mu Us region, while the average wind speed and sunshine hours were significantly negatively correlated with vegetation coverage. Gao et al. [39] showed that human activities were the dominant drivers of vegetation changes. Accurate detection of vegetation coverage is helpful for evaluating the development status and future potential of ecosystems. Yan et al. [56] showed that increases in temperature and precipitation were positively correlated with increases in aboveground biomass, while human factors such as population and policies also affected the temporal and spatial patterns of aboveground biomass. Nie, Sun et al. [44,45] evaluated the relationship between vegetation, climate, and human activities in the southern part of the Mu Us Sandy Land. Their results showed that climate change had a positive impact on vegetation coverage; in areas with fewer water shortages, higher temperatures were beneficial to the growth of vegetation, while natural and human factors were the key drivers of vegetation change. GDP, land cover type, slope, and temperature had the greatest impact on vegetation coverage. In addition, in other arid and semiarid regions, temperature and precipitation have been the dominant factors affecting the dynamic changes in vegetation [57], while human activities have had a significant impact on vegetation growth in plains areas [46]. The annual precipitation in the Inner Mongolia Plateau has the strongest inhibitory effect on vegetation growth [40]. In most areas of northwestern China, the sensitivity to changes in the availability of water and heat is relatively high, and climate warming has had a relatively large impact on the vegetation [20,58]. Drought during the growing season and pregrowth period has a large negative impact on vegetation growth [59]. In addition to precipitation, temperature, and human activities, factors such as wind speed, humidity, solar radiation intensity, and other climatic conditions, as well as land use conditions and other factors, also affect vegetation changes to varying degrees [60–63]. The temporal and
spatial changes in vegetation exhibit pronounced spatial heterogeneity. The influencing factors differ for the same vegetation type in different regions, as well as different vegetation types in the same region [64,65]. Wang et al. [66] studied the interaction between vegetation, climate, and human factors in the Hunshandake Sandy Land and concluded that human factors were the main driving factors of the vegetation distribution and precipitation was the most important climate factor. Zhang et al. [67] examined the typical Gobi region in the southern margin of Xinjiang and showed that vegetation coverage was highly negatively correlated with altitude. Zhang and Jin [68] studied the relationship between the vegetation restoration process and human factors in the Three-River Headwaters region of China from 2000 to 2018. Their results indicated that climatic conditions were favourable for vegetation restoration, while human activities were unfavourable for vegetation growth. Anees et al. [69] revealed the change in vegetation coverage in Pakistan from 2003 to 2013 by using MODIS-NDVI and believed that human activities and climate factors were the main driving factors of the dynamic change in vegetation coverage. Based on the previous studies and this paper, the conclusion is that regional vegetation dynamic changes are driven by many complex factors, both natural and human activities. There is obvious interaction, superposition effect, and strong spatiotemporal heterogeneity between them.

4.3. Effectiveness and Limitations

In this study, we selected satellite data from Landsat and MODIS to quantitatively monitor the restoration of vegetation in the Mu Us Sandy Land. The overall spatial distribution and temporal trend of the monitoring results from these two data sources were reasonably consistent. The vegetation coverage results retrieved from the MODIS data were generally slightly higher than those retrieved from Landsat. The results of quantitative monitoring via satellite images have enabled people to gain a more intuitive and accurate understanding of the vegetation restoration in the Mu Us Sandy Land over the past 20 years. In the analysis of the driving factors, the importance of the factors based on the two methods was highly consistent. The geodetector method can quantify the explanatory power of single factor or multifactor interactive effects on the spatial distribution of vegetation coverage; the RF method can be used to determine the comprehensive explanatory power of all detection factors and the relative importance of each factor. Compared with traditional linear regression and correlation analyses, geodetectors can better explain the spatial heterogeneity of dependent variables and reveal the driving factors. However, in the analysis of driving factors, due to the limitations of data collection, only a few human factors were selected; in particular, data related to artificial sand control and returning farmland to forests and grasslands were difficult to obtain, so only the GDP and land cover type were used.

5. Conclusions

In this study, multisource remote sensing data were used, the temporal and spatial changes in the vegetation were quantitatively analysed, and the contributions of natural and human factors to vegetation coverage were examined in the Mu Us Sandy Land from 2000 to 2020. The main findings were as follows:

(1) In the past 20 years in the Mu Us Sandy Land, the effect of vegetation restoration has been obvious, and the spatiotemporal dynamics of vegetation, as determined by multiple vegetation indicators, have tended to be consistent. Vegetation coverage in almost the entire study area increased, with an average annual growth rate of 0.59%; the area with the highest vegetation coverage and the most obvious recovery was located in the eastern and southern margins of the Mu Us Sandy Land (in Shaanxi Province). The dynamic trends determined by multisource remote sensing monitoring of vegetation restoration also tended to be consistent. The MODIS inversion results for vegetation coverage were slightly higher than the Landsat inversion results.

(2) Among the selected factors, the comprehensive explanatory power of natural and human factors for vegetation coverage in the Mu Us Sandy Land was 58.38%. The
land cover type and aridity index had the most significant impact on the vegetation distribution, followed by precipitation, GDP, and other factors; the factor importance rankings for the two methods were highly consistent. Among the natural factors, precipitation, temperature, humidity, and the aridity index were positively correlated with fractional vegetation coverage, while altitude was negatively correlated with fractional vegetation coverage. Among human factors, GDP was positively correlated with fractional vegetation coverage. Among land cover types, forestland had the highest vegetation coverage and water bodies had the lowest vegetation coverage. The growth and restoration of vegetation were affected by natural conditions as well as regional economic development and land use.

Finally, the main conclusions are summarised: (1) The vegetation in Mu Us Sandy Land has indeed recovered significantly in the past 20 years; the degree of vegetation restoration generally decreased from southeast to northwest. (2) The driving factors of vegetation restoration involved many aspects, such as natural and human aspects, and there was obvious interaction and superposition of various factors. Thus, clear and detailed answers have been provided for the questions mentioned in the introduction to this paper.

In fact, vegetation restoration in Mu Us Sandy Land was the result of long-term and multifactor interactions. Against the backdrop of global climate change and increasing temperature and humidity levels in northern China, the trend in the vegetation conditions in the Mu Us Sandy Land has generally been towards recovery and improvement. The eastern and southern margins of the Mu Us Sandy Land (in Shaanxi Province) have been subject to long-term artificial sand control and the implementation of the project to return farmland to forests and grasslands. The vegetation restoration in this region has been particularly remarkable. However, the Mu Us Sandy Land is still far from being characterised as an oasis. Artificial interventions targeting the regional ecological environment could have significant positive effects in local areas, but any approach must be based on relatively suitable natural conditions.

In this study, due to the lack of appropriate data and indicators, the impact of various man-made projects and policies on vegetation restoration was not quantified. Follow-up research should further seek relevant data indicators so that the role of policy factors can be clearly explained. In addition, future research should further quantify natural, human, economic, and policy impacts to provide a more sufficient theoretical basis and practical case studies for vegetation restoration and ecological environment improvement in arid and semiarid areas.

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