Assessment of the Effectiveness of Sand-Control and Desertification in the Mu Us Desert, China

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Abstract: The first successful sand-control was achieved in the Mu Us Desert by local people in the 1950–1960s, and their experience and approach have been extended to the whole Ordos and Northern China since then. The objective of this paper is to assess comprehensively the effectiveness of sand-control in 15 counties in and around Mu Us using multitemporal satellite images and socioeconomic data. After atmospheric correction, Landsat TM and OLI images were harnessed for land cover classification based on the ground-truth data and for derivation of the GDVI (generalized difference vegetation index) to extract the biophysical changes of the managed desert and desertification. Climatic, socioeconomic, environmental and spatial factors were selected for coupling analysis by multiple linear and logistic regression models to reveal the driving forces of desertification and their spatial determinants. The results show that from 1991 to 2020, 8712 km\(^2\) or 63% of the desert has been converted into pastures and shrublands with a greenness increase of 0.3509 in GDVI; the effectiveness of sand-control is favored by the rational agropastoral activities and policies; though desertification occurs locally, it is associated with both climatic and socioeconomic factors, such as wind speed, precipitation, water availability, distance to roads and animal husbandry.

Keywords: post-classification differencing; generalized difference vegetation index (GDVI); multiple linear regression; logistic regression

1. Introduction

Desertification is a phenomenon of land degradation resulting from by human activities and climate variations in arid, semi-arid and partially sub-humid areas [1,2]. With more than about four million km\(^2\) of dryland, China has been suffering from desertification since centuries ago. Though sand-control through afforestation and plantation of shrubs and herbaceous vegetation has been widely effectuated in the dryland areas since the 1950s, there is still large area of desert in China, reaching 739,200 km\(^2\) [3]. This poses a serious threat to the sustainable socioeconomic development in the arid region.

Remote sensing (RS) technology has become an important data source and technical means for desertification monitoring due to its wide detection range and observation periodicity since the 1970s [2,4–10]. It has been successfully applied to distinguish desert encroachment or climate events of the south border movement of the Saharan Desert [5], desertification in Sahel [4], in western Rajasthan in India in 1990s [11], and in Mu Us [2,8]. Remote sensing approaches include, but are not limited to, differencing-and-thresholding technique and supervised classification [7,8,12–14], in which the quantitative evaluation of desertification based on remote sensing indicators is made possible [15,16]. Commonly-used indicators are the normalized difference vegetation index (NDVI), fractional vege-
tation coverage (FVC), vegetation net primary productivity (NPP), rainfall-use efficiency (RUE), etc. [17–20]. Both FVC and NDVI are able to identify land degradation and distinguish the degree of governance of sand land [8,21]. However, it is difficult to discern subtle changes in vegetation when applied to desert areas with sparse vegetation. Recently, Wu (2014) proposed the generalized difference vegetation index (GDVI) for arid areas [22], and Xie et al. (2020) developed a set of monitoring and restoration assessment indicators (MRAIs) for assessing the mining impacts and restoration effectiveness [23]. Since these two indicators were developed for sparse vegetation areas, both of them are promising for land degradation and desertification study. In addition, supervised classification is also widely used in land cover mapping and dynamic monitoring of desertification [5,8,12,24]. With improvement of classification algorithm and technique, land cover mapping including desertification can be achieved with high accuracy and reliability [24]. Therefore, combination of the supervised classification with differencing-and-thresholding technique will allow the advantages of each to complement the other, and hence achieve a comprehensive quantitative evaluation of the effectiveness of sand-control [8].

Actually, for desertification monitoring and assessment, we have to mention the European megaproject, the Mediterranean desertification and land use (MEDALUS) projects I, II and III from 1989 to 1999 [25], which proposed a comprehensive assessment approach using four main quality indices, e.g., climate quality index (CQI), soil quality index (SQI), vegetation quality index (VQI), and the management (human influence) quality index (MQI). These indices were employed to constitute an environmental sensitive area index (ESAI) to identify the vulnerable area of desertification. The DesertWatch projects funded by the European Space Agency (ESA) (2004–2008) followed this and applied Earth Observation (EO)-based information to derive environmental elements to generate a land degradation index and develop the desertification scenarios [26]. Lee et al. (2019), Bouhata and Bensekhria (2021), and Abuzaid and Abdelatif (2022) respectively applied the MEDALUS approach for desertification vulnerability assessment in Mongolia, Algeria and Egypt [27–29].

Analysis on the driving forces of desertification is an indispensable part of desert monitoring and assessment [9]. Most of the driving factors are related to climate and human activities [30], e.g., precipitation, temperature, wind speed, and sunshine hours, and socioeconomic factors such as gross domestic product (GDP), population, and livestock numbers [18,31,32]. At present, the research on the driving force mainly focuses on two aspects: (1) Using correlation analysis, principal component analysis, stepwise linear regression, and other methods to explore the influence of human activity and climate on land cover change and desertification [2,6], and these methods have been proved effective. However, desertification is a complicated process, and simple linear models cannot fully reveal its driving mechanism [33,34]. (2) In recent years, several studies on the driving forces of the spatial variability of desertification have been carried out employing the geographically weighted regression, geographic detectors, logistic regression models, etc., and all of these approaches may lead to promising results [35–38]. With the development in socioeconomic, construction of roads, expansion of settlements, protection of farmland and other human activities have also become important factors for desertification reversal [36,38]. However, currently, the existing research mainly focuses on a fixed time point or single phase, and few studies have incorporated human activity into desertification modeling, and this may fail to rationally uncover the real mechanism and causes of desertification in different periods. Even the MEDALUS and DesertWatch projects focused on prediction of the vulnerable areas of desertification, but not on its driving forces.

Based on the above understanding, the objective of the study is to conduct a comprehensive monitoring and assessment of the desertification progress and the effectiveness of sand-control in space and time, taking the Mu Us Desert in China as an example, so as to provide an extension of or a complement to the MEDALUS and DesertWatch projects and put forward feasible suggestions for decision-makers to manage the remaining active deserts. One specific objective of this study is to build spatially explicit models of desertific-
cation and sand-control activity. Multitemporal Landsat images and socioeconomic data will be employed for achieving these purposes.

2. Materials and Methods  
2.1. The Study Area  

The study area is located at the junction of three provinces, namely Inner Mongolia, Shaanxi and Ningxia, in northern China. The main part is the Mu Us Desert (or Sandy Land) with a geographical extent from 105°20′17″ E to 109°32′41″ E in longitude and 36°49′12″ N to 39°49′31″ N in latitude and covering an area of 73,737 km² (Figure 1). The terrain is relatively flat, with an average elevation of 1380 m. Apart from a few mountains (Mts) in the northwest (e.g., Helan Mts and Zhuozi Mts), most of the study area is sandy land, desert in Mu Us, and farmland in the Yinchuan Plain. It borders the Loess Plateau in the south and southeast.

The average annual rainfall is about 317 mm, mainly concentrated in July–September [2,8], while annual evaporation reaches 2500 mm, much stronger than precipitation. Winds from the northwest blow on average 230 days per year, and those exceeding the speed of 17 m/s (Beaufort Scale-8) may occur during more than 40 days [8]. The mean annual temperature is about 6.0–8.5 °C, but there is a significant difference between summer and winter and between day and night.

The vegetation type is mainly shrubs and herbs in the sandy land, and rice and maize are the main cultivation in the Yinchuan Plain with which the greenness reaches its maximum in July and August. The special terrain and climate conditions, as well as the overgrazing in the early periods, have made the study area largely desertified or susceptible to desertification.

There are rich mineral resources including coal, oil and gas in the study area, and that is why the latter was designated as one of the energy bases of China by the central government in 1999 [8].

Since 1959, local people started to conduct sand-control activities and many large-scale combating desertification campaigns have been successfully undertaken by individual/household companies and national teams since then.

Figure 1. Location of the study area.

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2.2. Data and Processing

To achieve our purposes, a combined method of post-classification differencing and GDVI differencing was proposed to quantitatively evaluate the spatial distribution and degree of sand-control. A set of socioeconomic, climatic and environmental factors were selected to quantitatively analyze the driving forces of the spatial heterogeneity of desert governance in different periods using multiple linear regression and logistic regression models.

2.2.1. Data

Satellite Data

Landsat TM, ETM+ and OLI images from 1987 to 2020 with path/row numbers 128/33-34 and 129/33-34 and 16 tiles of digital elevation model (DEM) data (ASTERV003, 30 m resolution) of the study area were obtained from the USGS data server (glovis.usgs.gov, accessed on 16 June 2020) and NASA (earthdata.nasa.gov, accessed on 16 June 2020). Landsat images were mostly acquired in summer from July to September with cloud cover less than 1% (Table 1) in terms of the phenological features of crops and vegetation in the continental climate zone. Due to frequent cloudy weather in summer, it is difficult to acquire cloud-free images for the adjacent scenes of different paths in the same year. Hence, selection of images depended on the availability of cloud-free images and there was difference in acquisition dates of the adjacent scenes of images. The obtained Landsat images were utilized for the following supervised classification and derivation of different vegetation index, GDVI, and land surface temperature (LST).

| Captors     | Scene Path/Row No | Acquisition Dates | Spatial Resolution | Source                                      |
|-------------|-------------------|-------------------|-------------------|---------------------------------------------|
| Landsat 5 TM| 128/33            | 23 August 1991    | 30 m              | USGS https://glovis.usgs.gov (last accessed on 20 May 2021) |
| Landsat 5 TM| 128/34            | 23 August 1991    | 30 m              |                                             |
| Landsat 5 TM| 129/33            | 30 August 1991    | 30 m              |                                             |
| Landsat 5 TM| 129/34            | 26 August 1999    | 30 m              |                                             |
| Landsat 8 OLI| 129/33           | 30 August 1991    | 30 m              |                                             |
| Landsat 8 OLI| 129/34           | 26 July 2019      | 30 m              |                                             |

Socioeconomic Data

It is difficult to monitor and quantify human activity, and the best way is to use annual socioeconomic data, the finally quantified expression of human activity during a one-year period, for research [2]. For the study area, county-level socioeconomic data are available from the Statistic Yearbooks published by the government. The data include the total sown area, meat product, total number of livestock at the end of year, sheep stock, per capita net income of farmers and herdsmen, gross output of agriculture, forestry, animal husbandry and fishery, gross domestic product (GDP) and total population. For this reason, the Statistic Yearbooks of Inner Mongolia, Ningxia and Shaanxi from 1990 to 2020 were collected. Due to the change of administrative divisions, we combined the data of Xixia,
Xinxing and Jinfeng districts into Yinchuan City; Wuda, Hainan and Haibowan districts were merged into Wuhai City; and Dawukou and Huinong districts were incorporated into Shizuishan City. Finally, socioeconomic data of 15 counties and cities were prepared for analysis.

Meteorological Data

The monthly average temperature, average precipitation, average wind speed, maximum wind speed and sunshine duration of four stations, e.g., Yulin, Etog, Otogqian and Uxin, were obtained from the website of National Meteorological Science Data Center of China (http://data.cma.cn, accessed on 18 June 2021) [39]. Those of Yinchuan, Shizuishan, Pingluo, Huinong, Yongning, Helan, Wuzhen, Lingwu, Yanchi, Qingtongxia and Zhongning were extracted from the Ningxia Statistic Yearbooks.

Field Data

Field survey was conducted in August 2000, June 2002, May 2005, October 2020 and July 2021 to (1) understand land use/cover and its change; (2) coal mining in five coal fields, namely Qipanjing, Zhuozi Mts, Shanghaimiao, Shitanjing and Ruqigou coal fields; (3) oil and gas exploitation in the banners Otog, Otogqian and Uxin; and (4) sand-control achievement by local and national companies in the whole study area. In total, more than 2000 observation points were collected with GPS location. One surprising thing observed is that sandy land has greatly decreased from 2000 to 2021 and converted mostly into shrublands and forests in dunes and grasslands in interdunes thanks to the sand-control activity.

2.2.2. Processing Procedures

Satellite Data Processing

Atmospheric correction of Landsat images was conducted using the COST model developed by Chavez (1996) [40], where the band minimum was employed to remove the haze effect and at-satellite radiance of all bands was converted into surface reflectance.

Land surface temperature (LST) was derived from the thermal band of Landsat TM and OLI data [41,42]. The dryland-tailored vegetation index, GDVI, is shown in Equation (1). When \( n = 1 \), GDVI = NDVI; when \( n = 2 \), it is suitable for characterizing dryland biomes including shrubland, woodland and forest; when \( n = 3 \), it can be used for monitoring the degradation and desertification in sparsely vegetated area [22,23]. Compared with NDVI and other vegetation indices, GDVI has higher sensitivity and dynamic range, and is able to identify more effectively subtle differences in vegetation greenness in low vegetated areas [22]. Therefore, GDVI of \( n = 3 \) was produced for the successive analysis.

\[
GDVI = \frac{\rho_{\text{NIR}}^n - \rho_{\text{R}}^n}{\rho_{\text{NIR}}^n + \rho_{\text{R}}^n} 
\]

where, \( \rho_{\text{NIR}} \) is the spectral reflectance of the near-infrared band, and \( \rho_{\text{R}} \) is that of the red band.

Slope and aspect were produced from the DEM data and used for land cover classification [24] and desertification modeling as a part of the environmental factors.

Land Cover Classification

A dataset of eleven bands, including elevation, slope, aspect, LST, GDVI and six spectral bands (blue, green, red, near infrared, shortwave infrared 1 (SWIR 1) and SWIR 2) through layer-stacking function was composed for each observation year [24].

Based on field survey and knowledge, we defined 30–32 initial classes of ground-truth samples (regions of interest, ROIs) for different scenes and observation years, and half of the samples (about 5–6% of the total scene) were used for training, i.e., training samples (TS), and the remaining half for validation, or rather, validation samples (VS). Sand-control and desertified land (or deserts) were the important classes to be classified out. After classification, all initial classes were merged into 12 classes in terms of the similarity.
namely sandy land, shrublands, grasslands, waters, artificial (built up) areas, bare soil, loess land, woodlands, coal mines, saline land, croplands and fallows. Forests were sporadic and less than several pixels, and merged into woodlands. Finally, the sandy land was extracted as a mask, and all the remaining classes were merged into non-sand land for further analysis.

Supervised classification using maximum likelihood approach was conducted, and the results were validated with VS.

**Processing of the Driving Factors**

The distance from the random points in the managed areas and desertified land to roads, water bodies, residential areas and farmland was obtained by proximity analysis. The change of water bodies and mining area were obtained by the statistics of classified images. Population density was calculated by Equation (2).

\[ Y = \frac{X}{A} \tag{2} \]

where, \( Y \) is the population density, \( X \) is total population, and \( A \) is the area.

**2.3. Effectiveness Assessment of Sand-Control**

**2.3.1. Post-Classification Differencing**

Post-classification differencing is a method for identification of land cover change proposed by Wu [12]. The same type of land cover of the different observation time, deserts and controlled sandy land in this case, was extracted from the classified images and a differencing was applied to obtain the change in space. Equation (3) was used to calculate the difference. Taking desertification as an example, when \( \Delta S = 0 \), it means no change in sandy land during this period; when \( \Delta S = 1 \), the desert or sandy land has expanded; when \( \Delta S = -1 \), the sandy land is reduced and controlled [8,12]. This method can be used to monitor the overall change of sandy land and identify accurately the area and spatial distribution of sandy land, and at the same time, quantify which land cover types have been converted into sandy land or vice versa. This will allow to produce the gain/loss change matrix of land cover of the study area in different observation periods.

\[ \Delta S = S_{T2} - S_{T1} \tag{3} \]

**2.3.2. \( \Delta GDVI \)**

Based on the calculation of GDVI of different time images, a differencing was effectuated under the masks of deserts or sand-control extracted from the classified images:

\[ \Delta GDVI = GDVI_{T2} - GDVI_{T1} \tag{4} \]

When \( \Delta GDVI < 0 \), desertification has occurred as vegetation vigor has decreased; if \( \Delta GDVI > 0 \), indicating a vegetation increase, or rather, sandy land has been controlled and converted into vegetated area such as grasslands and shrublands.

**2.3.3. Multiple Linear Regression Analysis**

Multiple linear stepwise regression is an approach to analyze the relationship between a dependent variable and several independent variables, and to find which independent variable(s) contribute(s) most to the dependent or which factor(s) has(have) played the most important role in the event occurrence (Equation (5)) [2,6,43].

\[ Y_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} + U_i \tag{5} \]

where, \( Y_i \) is the dependent variable, \( X_{1i}, \ldots, X_{ki} \) are the independent variables, and \( \beta_0, \beta_1, \ldots, \beta_k \) are the regression coefficients of their corresponding variables, and \( U_i \) is the random error. The
dependent variable in this case is the desertified land or sand-control area at county-level, and the independent variables are county-level socioeconomic and climatic factors.

2.3.4. Logistic Regression Analysis

Logistic regression model (LRM) is capable of dealing with both categorical and continuous variables and can effectively achieve spatially explicit analysis to reveal the probability of certain change in space (i.e., with probability of 1 indicating event occurred, and 0 indicating it has not occurred) associated with multiple independent variables, i.e., spatial determinants. It was first used in the field of disease diagnosis and has been extended to land change research to reveal the spatial determinants of land cover change in environmental geography and geological disaster prediction in recent decades [2,44–46]. However, it has been rarely used in the quantitative analysis of desertification driving force because of the particularity of its dependent variable. The formula (6) was used to establish the LRM.

\[
P = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i)}}
\]

where, \(P\) is the probability, \(X_1 \ldots, X_i\) are the independent variables, and \(\beta_0, \beta_1 \ldots, \beta_i\) are the regression coefficients of their corresponding variables.

Before logistic regression analysis, it is necessary to undertake the collinearity diagnosis to check whether there is collinearity among the independent variables using either tolerance (TOL) or variable inflation factor (VIF) as an indicator. If VIF < 10 or TOL > 0.1, there is no evident collinearity and the result of the logistic regression analysis shall be reliable.

In order to examine the importance of factors influencing sand-control and desertification, the following preprocessing is required. First, rasterization of the independent variables, e.g., GDP, per capita rural net income, meet product and so on are converted into county-level raster; then, creation of the random points in the controlled and uncontrolled areas of sandy lands, the desertified areas and the unchanged areas in line with the ratio of 1:1. The points in the desertified areas and sand-control areas were assigned a value of 1, and in non-desertification and non-control areas were assigned a value of 0, which were used as dependent variables. At last, the values of independent and dependent variables were both extracted and input into SPSS, a package for statistic analysis, for logistic regression modeling.

The model was tested in two aspects: (1) the Hosmer-Lemeshow (H-L) test was used to evaluate the degree of fit of the model; if H-L > 0.05, the model was considered to have a good fit; and (2) using significance (Sig), e.g., Sig < 0.05, to test whether the independent variable in the model has a significant effect on the dependent variable. Finally, the absolute values of the regression coefficients or odds ratios (OR) were used for judging the influence degree of the independent variables on the dependent variable.

3. Results

3.1. Dynamic Situation of the Desert

As shown in Table 2, the overall accuracy (OA) of the land cover classification vs. the validation samples is about 90.3–92.8% with a kappa coefficient of 0.87–0.90. The desert or sandy land is mainly distributed in the banners Otoq, Otoqqian and Uxin, among which the last has the largest area (Table 3 and Figure 2). In the past 30 years, sandy land has decreased by 8712.23 km\(^2\), accounting for 63.05% of the total sandy land though there were slight fluctuation in some counties in different periods, e.g., from 1991 to 1999, sandy land increased by 291.6 km\(^2\) in Yanchi, and from 1999 to 2010, sandy land in Yinchuan, Otoqqian and Wuzhong had an increase of 32.22 km\(^2\), 65.13 km\(^2\) and 3.59 km\(^2\), respectively, while a decrease appeared in other areas in the whole period.
Table 2. Accuracy of land cover classification.

| Year | Overall Accuracy | Kappa Coefficient |
|------|------------------|-------------------|
| 1991 | 92.35%           | 0.9009            |
| 1999 | 92.87%           | 0.9086            |
| 2010 | 90.33%           | 0.8767            |
| 2020 | 92.59%           | 0.9061            |

Table 3. Area of sandy land.

| City/County or Banner | 1991  | Sandy Land | 2010  | 2020  |
|-----------------------|-------|------------|-------|-------|
|                       | Area (km²) | 1991 | Area (km²) | 1999 | Area (km²) | 2010 | Area (km²) | 2020 |
| Wuhai City            | 232.60 | 114.73 | 43.36 | 5.93 |
| Otogqian              | 3164.50 | 1925.91 | 1991.04 | 1611.14 |
| Otog                  | 3262.41 | 2362.18 | 2118.26 | 1271.96 |
| Uxin                  | 4693.44 | 3861.74 | 2159.62 | 1848.40 |
| Dingbian              | 224.60 | 99.40 | 56.16 | 24.91 |
| Yinchuan              | 172.50 | 33.16 | 65.38 | 4.45 |
| Yongning              | 10.31 | 1.10 | 0.56 | 0.88 |
| Helan                 | 10.15 | 4.79 | 2.29 | 0.07 |
| Lingwu                | 703.12 | 614.50 | 323.03 | 143.80 |
| Shizuishan            | 2.95 | 0.87 | 0.41 | 0.04 |
| Pingluo               | 215.35 | 148.06 | 134.74 | 44.64 |
| Wuzhong               | 20.09 | 5.85 | 9.44 | 0.77 |
| Yanchi                | 740.98 | 1032.56 | 222.99 | 103.33 |
| Qingtongxia           | 5.36 | 9.93 | 3.11 | 2.02 |
| Zhongning             | 130.41 | 79.41 | 38.63 | 11.71 |
| Total                 | 13,818.45 | 10,401.03 | 7173.87 | 5106.22 |

3.2. Effectiveness of the Combating Desertification

Between 1991–2020, a total of 9140.44 km² of sandy land has been managed and converted into pastures, shrublands, and even forests (Table 4). The main sand-control areas are located in the banners (counties) Uxin, Otog and Otogqian, with an area of 3022.76 km², 2090.48 km² and 1637.36 km² respectively. As shown in Figures 3 and 4, the area of sand-control was much larger than the desertified land.
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Table 4. Areas of sand-control and desertification.

| Period         | Sand-Control | Desertification |
|----------------|--------------|-----------------|
|                | 1991–1999   | 1999–2010       | 2010–2020       | 1991–2020       | 1991–1999   | 1999–2010       | 2010–2020       | 1991–2020       |
| Area (km$^2$)  | 5537.61     | 4969.28         | 3420.24         | 9140.44         | 2120.36     | 1742.40         | 1352.53         | 428.13          |
| Proportion (%) | 40.07        | 47.78           | 47.68           | 66.15           | 3.36        | 2.62             | 1.94             | 0.68            |
| ΔGDVI          | 0.1575       | 0.1806          | 0.1456          | 0.3518          | −0.0921     | −0.1237          | −0.0997          | −0.0691         |

Figure 2. Spatial distribution of sandy land in the study area: (a) 1991; (b) 1999; (c) 2010; and (d) 2020.
Figure 3. Area and proportion of the sand-control and desertification at county- and/or city-level: (a) 1991–1999; (b) 1999–2010; (c) 2010–2020; (d) 1991–2020.

Figure 4. Spatial distribution of sand-control and desertification: (a) 1991–1999; (b) 1999–2010; (c) 2010–2020; (d) 1991–2020.
Most of the sand-control was effectuated in the western margin of the desert, i.e., the west part of the banners Otog and Otogqian, followed by the southern area in Dingbian, Lingwu and Yanchi (Figures 3 and 4). The desertification occurred mainly in Yanchi and Lingwu in 1991–1999 (Figure 4a), but it was concentrated in the west of Otogqian and Otog in 1999–2010 (Figure 4b), and it appeared as small dots in the east of the study area in 2010–2020, and a large piece of desertification was not observed in the last period (Figure 4c).

As seen in Table 4, the vegetation greenness represented by $\Delta GDVI$ in the controlled areas in the past 30 years has gained an increase of 0.3518 with a minimum of 0.1456 in 2010–2020, while the greenness had decreased by 0.0691 in the desertified area, and the biggest decrease ($-0.1237$) appeared in 1999–2010.

Presented in Tables 5–8, sandy land was mostly transferred into shrublands and grasslands with an area of 6359.79 km$^2$, accounting for 69.58%, from 1991 to 2020. This conversion took up 4943.51 km$^2$, 4088.33 km$^2$ and 2606.92 km$^2$, accounting for 89.27%, 82.27% and 76.22%, respectively, in the three observed periods 1991–2000, 2000–2010 and 2010–2020. It is obvious that sand-control by planting shrubs such as *Salix cheilophila*, *Tamarix ramosissima*, *Hedysarum mongolicum*, *Caragana korshinskii Kom*, *Hippophae rhamnoides L.* and *Lycium chinense Miller* and herbaceous vegetation including *Medicago sativa L.*, *Artemisia desertorum*, *Artemisia sieversiana*, *Astragalus adsurgens Pall.* has achieved a remarkable output.

Figures 3–5 show that the extent of sand-control was much larger than that of desertification, whereas it was the opposite in Yanchi during 1991–1999. From 1991 to 2020, sand-control seems to have had the best effectiveness in Uxin with an increase of 0.0897 in GDVI, and the lowest effectiveness in Shizuishan, with an increase of 0.0002. Meanwhile, $\Delta GDVI$ of the desertified area was close to 0 (Figure 5).

![Figure 5](image-url)  
**Figure 5.** The mean values of $\Delta GDVI$ of the sand-control and desertification area in each county: (a) 1991–1999; (b) 1999–2010; (c) 2010–2020; (d) 1991–2020.

### 3.3. Determinants of Sand-Control and Desertification

As shown in Table 9, 15 factors from three aspects were used for stepwise linear regression modeling with the area of sand-control and desertification as the dependent variable. Taking $R^2 > 0.60$ as the model testing standard, seven models were finally obtained (Table 10).
Table 5. Land use transfer matrix of the study area from 1991 to 1999 (km²).

|          | 1991          | 1999          |
|----------|---------------|---------------|
| Sandy Land | 8275.67       | 5430.03       |
| Shrub    | 2253.4        | 10223.66      |
| Saline   | 229.32        | 166.91        |
| Cropland | 213.24        | 102.51        |
| Water    | 38.06         | 23.2          |
| Grassland | 2476.09      | 7572.67       |
| Building | 23.39         | 93.29         |
| Woodland | 0.78          | 27.5          |
| Loess    | 101.66        | 157.1         |
| Bare soil | 278.71       | 7572.67       |
| Coal mine | 1.82         | 1885.86       |
| Loss     | 5537.61       | 7793.13       |
| Net Change | -3417.25     | 798.75        |

Table 6. Land use transfer matrix of the study area from 1999 to 2010 (km²).

|          | 1999          | 2010          |
|----------|---------------|---------------|
| Sandy Land | 5430.03       | 590.29        |
| Shrub    | 2202.47       | 460.17        |
| Saline   | 162.9         | 476.33        |
| Cropland | 102.32        | 508.66        |
| Water    | 26.49         | 89.75         |
| Grassland | 1885.86     | 3955.27       |
| Building | 101.66        | 367.1         |
| Woodland | 1.82          | 10.73         |
| Loess    | 157.1         | 168.95        |
| Bare soil | 325.93       | 685.61        |
| Coal mine | 2.73         | 64.05         |
| Loss     | 4969.28       | 6748.84       |
| Net Change | -5006.44     | 7477.59       |
Table 7. Land use transfer matrix of the study area from 2010 to 2020 (km\(^2\)).

|          | Sandy Land | Shrubs | Saline | Cropland | Water | Grassland | Building | Woodland | Loess | Bare Soil | Coal Mine | Gain      |
|----------|------------|--------|--------|----------|-------|------------|----------|----------|-------|-----------|-----------|-----------|
| **2010** | 3753.44    | 643.64 | 36.24  | 27.78    | 6.35  | 598.53     | 14.17    | 0.14     | 4.21  | 21.46     | 0.01      | 1352.53   |
| **2020** | 3753.44    | 643.64 | 36.24  | 27.78    | 6.35  | 598.53     | 14.17    | 0.14     | 4.21  | 21.46     | 0.01      | 1352.53   |

Table 8. Land use transfer matrix of the study area from 1991 to 2020 (km²).

|          | Sandy Land | Shrubs | Saline | Cropland | Water | Grassland | Building | Woodland | Loess | Bare Soil | Coal Mine | Gain      |
|----------|------------|--------|--------|----------|-------|------------|----------|----------|-------|-----------|-----------|-----------|
| **1991** | 4677.05    | 111.58 | 13.69  | 49.05    | 6.45  | 240.85     | 0.41     | 1.02     | 1.08  | 3.99      | 0.01      | 428.13    |
| **2020** | 4677.05    | 111.58 | 13.69  | 49.05    | 6.45  | 240.85     | 0.41     | 1.02     | 1.08  | 3.99      | 0.01      | 428.13    |
Table 9. Socio-environmental factors for multiple linear regression modeling.

| Type                      | Factors                                      | Symbol | Data Preprocessing |
|---------------------------|----------------------------------------------|--------|--------------------|
| Social and Economic Factors | Total Sown Area                               | X₁     |                    |
|                           | Meat Product                                  | X₂     |                    |
|                           | Sheep Number                                  | X₃     |                    |
|                           | Total Number of Livestock at the Year-end     | X₄     |                    |
|                           | Per capita Net Income of Farmers and Herdsmen | X₅     |                    |
|                           | Gross Output of Farming, Forestry, Animal     | X₆     |                    |
|                           | Husbandry and Fishery                         |        |                    |
|                           | Gross Domestic Product (GDP)                  | X₇     |                    |
|                           | Population Density                            | X₈     |                    |
| Meteorological Factors    | Annual Precipitation                          | X₉     |                    |
|                           | Mean Temperature                              | X₁₀    |                    |
|                           | Maximum Wind Speed                            | X₁₁    |                    |
|                           | Average Wind Speed                            | X₁₂    |                    |
|                           | Sunshine Duration                             | X₁₃    |                    |
| Environmental Factors     | Area of Water                                 | X₁₄    |                    |
|                           | Area of Coal Mines                            | X₁₅    |                    |

Table 10. Multiple linear regression models.

| Model (Area)       | Period       | Expression                                                                 | R²  |
|--------------------|--------------|----------------------------------------------------------------------------|-----|
| Sand-Control       | 1991–1999    | Y₁ = −0.370 − 0.679*ΔX₁₀ − 0.420*ΔX₁₅                                        | 0.898 (7) |
|                    | 1999–2010    | Y₂ = −8.009 × 10⁻¹⁷ + 0.855*ΔX₂ − 0.392*ΔX₁₃                                 | 0.764 (8) |
|                    | 2010–2020    | Y₃ = 1.410 × 10⁻¹⁶ + 0.570*ΔX₅ + 0.520*ΔX₃                                   | 0.835 (9) |
|                    | 1991–2020    | Y₄ = −1.03 × 10⁻¹⁵ + 0.801*ΔX₅ + 0.465*ΔX₉                                   | 0.764 (10) |
| Desertification    | 1991–1999    | Y₅ = 0.206 − 1.058*ΔX₅                                                   | 0.600 (11) |
|                    | 2010–2020    | Y₆ = 1.646 × 10⁻¹⁶ + 0.573*ΔX₅ − 0.404*ΔX₁₄                               | 0.638 (12) |
|                    | 1991–2020    | Y₇ = −1.091 × 10⁻¹⁵ + 0.637*ΔX₅ + 0.411*ΔX₁₂                               | 0.628 (13) |

Note: Here Y₁, Y₂, Y₃ and Y₄ are the areas of sand-control in each county in 1991–1999, 1999–2010, 2010–2020 and 1991–2020, respectively, while Y₅, Y₆, Y₇, and Y₈ are the areas of desertification in each county in 1991–1999, 2010–2020 and 1991–2020, respectively. Of the corresponding period, ΔX₈ is the difference in annual mean temperature, ΔX₉ the difference in coal mine area, ΔX₁₀ the difference in meat product, ΔX₁₃ the difference in sunshine duration, ΔX₅ the difference in per capita net income of farmers and herdsmen, ΔX₅ the difference in sheep number, ΔX₉ the difference in annual precipitation, ΔX₁₂ the difference in average wind speed, and ΔX₁₄ the difference in area of water body.

In terms of the multiple linear regression models in Table 10, it is seen that sand-control area is closely associated with the difference in temperature, mining area, meat product, sunshine hours, per capita net income of farmers and herdsmen, sheep number, and precipitation between the two observation years. More concretely, the increases in mining area, temperature and sunshine hours are negatively correlated with the sand-controlled area, while the increase in meat (pork, beef and mutton) product, per capita net income of farmers and herdsmen, sheep number and precipitation are positively correlated with the sand-controlled area.

The desertified area is related to the average wind speed and water. More exactly, the increase in average wind speed is the main driving force of desertification, while the increase in water areas are the favorable factors to reverse desertification, that is, lead to a decrease in desertified area.

3.4. Spatial Variability of Sand-Control

Different from those used for multiple linear regression analysis, here 19 socio-environmental factors shown in Table 11 were used for logistic regression modeling to understand the different spatial distribution of sand-control and desertification in different periods, and the obtained models that have passed the Hosmer–Lemeshow (HL) test are...
presented in Table 12. It is worth mentioning that the spatial factors are the different distances at the start of the observed period, and the socioeconomic and climate factors are the increments of the same period which have been rasterized to county-level as depicted before. The optimal discretization method was used to discretize the meteorological and spatial factors, and Z-Score was applied to normalize the socioeconomic factors, which were all taken as independent variables.

Table 11. Socio-environmental factors for logistic regression (LR) modeling.

| Type               | Factors                                                                 | Data Preprocessing |
|--------------------|-------------------------------------------------------------------------|--------------------|
| Social and Economic Factors | Total Sown Area, Meat Product, Sheep Number, Total Number of Livestock at the End of Year, Per capita Net Income of Farmers and Herdsmen, Gross Output of Farming, Forestry, Animal Husbandry and Fishery, Gross Domestic Product (GDP) | Z-Score            |
| Climatic Factors   | Precipitation, Temperature, Maximum Wind Speed, Average Wind Speed, Sunshine Duration |                   |
| Spatial Factors    | Distance from Road, Distance from City, Distance from Water, Distance from Cropland | The optimal discretization |
| Terrain Factors    | Elevation, Aspect, Slope |                   |

Temperature, meat product, per capita net income of farmers and herdsmen and sheep number, elevation, distance from road and distance from cropland are the important factors driving spatial differentiation of sand-control. In general, low elevation, increases in temperature, and increase in per capita net income of farmers and herdsmen and proximity to roads created a favorable condition for sand-control activity. It is worth mentioning that prior to 1999, increases in meat product and sheep number constrained sand-control, or rather, led to desertification, but after 1999 they have become favorable factors as controlled deserts have served for cropping and forage production. Prior to 2010, the closer to cropland, the higher the possibility of sandy land to be controlled; while it was the opposite after 2010, as combating desertification activity gradually moved into the heart areas of deserts.

Based on the regression coefficients and odds ratio (OR), it is possible to distinguish the importance of the socio-environmental factors (independent variables) in the sand-control or desertification event. As seen in Tables 10 and 12–14 the important factors causing the spatial variability of desertification include temperature, average wind speed, precipitation, per capita net income of farmers and herdsmen, GDP, total sown area and year-end number of big livestock. The areas far from cities and roads with low elevation and slope seem more susceptible to desertification than those close to cities and roads because the latter is easier to be managed and controlled. The increase in GDP, net income of farmers and herdsmen, the year-end number of big livestock and the total sown area for grain production are the driving forces of desertification. Additionally, the decrease in temperatures and reduction in water availability and increase in wind speeds increase the probability of desertification.
Table 12. Logistic regression models.

| Model       | Period         | Expression                                                                 | HL Test |
|-------------|----------------|----------------------------------------------------------------------------|---------|
| Sand-Control | 1991–1999      | $P_1 = \frac{\exp(42.666 - 0.362\Delta X_2 - 0.107\Delta X_3 + \cdots - 0.047\Delta X_{18})}{1 + \exp(42.666 - 0.362\Delta X_2 - 0.107\Delta X_3 + \cdots - 0.047\Delta X_{18})}$ | 0.184 (14) |
|             | 1999–2010      | $P_2 = \frac{\exp(3.464 + 0.34\Delta X_2 - 0.693\Delta X_3 + \cdots - 0.647\Delta X_{16})}{1 + \exp(3.464 + 0.34\Delta X_2 - 0.693\Delta X_3 + \cdots - 0.647\Delta X_{16})}$ | 0.567 (15) |
|             | 2010–2020      | $P_3 = \frac{\exp(3.274 + 0.268\Delta X_2 + 0.522\Delta X_3 + \cdots - 0.326\Delta X_{17})}{1 + \exp(3.274 + 0.268\Delta X_2 + 0.522\Delta X_3 + \cdots - 0.326\Delta X_{17})}$ | 0.723 (16) |
|             | 1991–2020      | $P_4 = \frac{\exp(5.005 + 0.425\Delta X_2 + 1.067\Delta X_3 + \cdots - 0.029\Delta X_{19})}{1 + \exp(5.005 + 0.425\Delta X_2 + 1.067\Delta X_3 + \cdots - 0.029\Delta X_{19})}$ | 0.079 (17) |
| Desertification | 1991–1999      | $P_5 = \frac{\exp(-12.257 + 0.458\Delta X_2 - 0.493\Delta X_3 + \cdots - 0.069\Delta X_{19})}{1 + \exp(-12.257 + 0.458\Delta X_2 - 0.493\Delta X_3 + \cdots - 0.069\Delta X_{19})}$ | 0.277 (18) |
|             | 1999–2010      | $P_6 = \frac{\exp(1.627 - 0.261\Delta X_2 + 0.31\Delta X_3 + \cdots - 2.744\Delta X_{17})}{1 + \exp(1.627 - 0.261\Delta X_2 + 0.31\Delta X_3 + \cdots - 2.744\Delta X_{17})}$ | 0.155 (19) |
|             | 2010–2020      | $P_7 = \frac{\exp(11.825 - 0.23\Delta X_2 + 0.805\Delta X_3 + \cdots - 0.059\Delta X_{19})}{1 + \exp(11.825 - 0.23\Delta X_2 + 0.805\Delta X_3 + \cdots - 0.059\Delta X_{19})}$ | 0.476 (20) |
|             | 1991–2020      | $P_8 = \frac{\exp(-7.632 + 1.755\Delta X_2 + 1.741\Delta X_3 + 0.84\Delta X_{13} - 0.081\Delta X_{19})}{1 + \exp(-7.632 + 1.755\Delta X_2 + 1.741\Delta X_3 + 0.84\Delta X_{13} - 0.081\Delta X_{19})}$ | 0.276 (21) |

Note: $P_1$, $P_2$, $P_3$ and $P_4$ are the probability of sand-control occurrence respectively in 1991–1999, 1999–2010, 2010–2020 and 1991–2020, while $P_5$, $P_6$, $P_7$, and $P_8$ are the probability of desertification appearance respectively in 1991–1999, 1999–2010, 2010–2020, and 1991–2020. Of the corresponding period, $\Delta X_1$ is the difference in total sown area, $\Delta X_2$ the difference in meat product, $\Delta X_3$ the difference in sheep number, $\Delta X_4$ the difference of year-end big livestock, $\Delta X_5$ the difference of per capita net income of farmers and herdsmen, $\Delta X_6$ the difference of gross output of farming, forestry, animal husbandry and fishery, $\Delta X_7$ the difference of gross domestic product (GDP), $\Delta X_8$ the difference of precipitation, $\Delta X_9$ the difference of temperature, $\Delta X_{10}$ the difference of maximum wind speed, $\Delta X_{11}$ the difference of average wind speed, $\Delta X_{12}$ the difference of sunshine duration, $\Delta X_{13}$ the distance from road, $\Delta X_{14}$ the distance from city, $\Delta X_{15}$ the distance from water resource, $\Delta X_{16}$ the distance from cropland, $\Delta X_{17}$ the elevation, $\Delta X_{18}$ the aspect, and $\Delta X_{19}$ the slope.
| Factor | β    | SE  | 1991–1999 Wals | 1999–2010 Wals | 2010–2020 Wals | 1991–2020 Wals | OR  | SE  | 1991–1999 Sig | 1999–2010 Sig | 2010–2020 Sig | 1991–2020 Sig | OR  | SE  |
|-------|------|-----|----------------|----------------|----------------|----------------|------|-----|---------------|---------------|---------------|---------------|------|-----|
| \(X_1\) | 0.425 | 0.141 | 9.113 | 0.003 | 1.530 |
| \(X_2\) | 0.268 | 0.077 | 12.091 | 0.001 | 1.307 | -1.067 | 0.173 | 38.104 | 0.000 | 0.344 |
| \(X_3\) | 0.522 | 0.061 | 73.807 | 0.000 | 1.686 | 0.750 | 0.105 | 50.774 | 0.000 | 2.117 |
| \(X_4\) | -0.693 | 0.089 | 61.035 | 0.000 | 0.500 |
| \(X_5\) | -0.268 | 0.065 | 19.267 | 0.000 | 0.752 |
| \(X_6\) | 0.151 | 0.074 | 4.182 | 0.041 | 1.163 | 0.210 | 0.071 | 8.675 | 0.003 | 1.234 | 0.268 | 0.094 | 8.095 | 0.004 | 1.308 |
| \(X_7\) | 0.801 | 0.209 | 14.761 | 0.000 | 2.228 | -1.014 | 0.169 | 36.107 | 0.000 | 0.363 |
| \(X_8\) | -0.711 | 0.136 | 27.178 | 0.000 | 0.491 | 0.400 | 0.145 | 7.577 | 0.006 | 1.492 | 0.532 | 0.138 | 14.970 | 0.000 | 1.703 | 0.270 | 0.115 | 5.070 | 0.019 | 1.310 |
| \(X_9\) | -0.658 | 0.194 | 11.563 | 0.001 | 0.518 |
| \(X_{10}\) | 0.235 | 0.135 | 3.033 | 0.082 | 1.265 |
| \(X_{11}\) | -0.206 | 0.110 | 3.530 | 0.060 | 0.814 |
| \(X_{12}\) | -19.515 | 7842.123 | 0.000 | 0.998 | 0.000 |
| \(X_{13}\) | -0.294 | 0.096 | 9.447 | 0.002 | 0.745 | -0.776 | 0.093 | 69.097 | 0.000 | 0.460 | -0.687 | 0.128 | 28.944 | 0.000 | 0.503 | -0.527 | 0.067 | 61.855 | 0.000 | 0.590 |
| \(X_{14}\) | -0.385 | 0.140 | 7.524 | 0.006 | 0.681 | -0.637 | 0.157 | 16.395 | 0.000 | 0.529 | -0.246 | 0.110 | 4.942 | 0.026 | 0.782 |
| \(X_{15}\) | -0.333 | 0.077 | 18.564 | 0.000 | 0.717 |
| \(X_{16}\) | -0.376 | 0.077 | 23.601 | 0.000 | 0.686 | -0.647 | 0.119 | 29.633 | 0.000 | 0.523 | 0.356 | 0.093 | 14.697 | 0.000 | 1.428 | -0.597 | 0.061 | 94.860 | 0.000 | 0.551 |
| \(X_{17}\) | -0.566 | 0.105 | 29.117 | 0.000 | 0.568 | -0.326 | 0.075 | 18.896 | 0.000 | 0.722 | -0.723 | 0.078 | 85.185 | 0.000 | 0.485 |
| \(X_{18}\) | -0.047 | 0.017 | 7.510 | 0.006 | 0.954 |
| \(X_{19}\) | -0.029 | 0.013 | 5.349 | 0.021 | 0.971 |
| Const | 42.666 | 15684.246 | 0.000 | 0.998 | 3.386E18 | 3.464 | 0.705 | 24.143 | 0.000 | 31.955 | 3.274 | 0.536 | 37.246 | 0.000 | 26.419 | 5.005 | 0.585 | 73.242 | 0.000 | 149.184 |

Note: (1) \(\beta\) denotes the regression coefficient and SE standard error; Wals means Wald test, and Sig significance; OR is odds ratio. (2) Factors or variables whose variable inflation factor (VIF) was largely less than 2.5 were used for logistic regression modeling, and those with VIF > 10 were removed prior to modeling.
Table 14. Logistic regression models for desertification.

| Factor | β     | SE    | Wals | Sig | OR    | β     | SE    | Wals | Sig | OR    | β     | SE    | Wals | Sig | OR    | β     | SE    | Wals | Sig | OR    | β     | SE    | Wals | Sig | OR    |
|--------|-------|-------|------|-----|-------|-------|-------|------|-----|-------|-------|-------|------|-----|-------|-------|-------|------|-----|-------|-------|-------|------|-----|-------|
| X1     | 0.458 | 0.106 | 18.831 | 0.000 | 1.581 | -0.261 | 0.124 | 4.397 | 0.036 | 0.770 | -0.805 | 0.222 | 13.105 | 0.000 | 0.447 |
| X2     | -0.0493 | 0.108 | 20.845 | 0.000 | 0.611 | 0.310 | 0.119 | 6.806 | 0.009 | 1.363 |
| X3     | -0.688 | 0.126 | 29.675 | 0.000 | 0.503 | 0.310 | 0.119 | 6.806 | 0.009 | 1.363 |
| X4     | 0.368 | 0.122 | 9.077 | 0.003 | 1.444 | 0.260 | 0.124 | 4.424 | 0.035 | 1.297 | 0.346 | 0.125 | 7.689 | 0.006 | 1.414 |
| X5     | 0.449 | 0.121 | 13.635 | 0.000 | 1.566 | -0.1052 | 0.197 | 28.409 | 0.000 | 0.349 | 2.157 | 0.378 | 32.625 | 0.000 | 0.450 |
| X6     | 3.410 | 0.603 | 31.954 | 0.000 | 30.255 | -0.491 | 0.203 | 5.876 | 0.015 | 0.612 | -18.066 | 6138.015 | 0.000 | 0.998 |
| X7     | 0.391 | 0.127 | 9.530 | 0.002 | 1.479 | 0.746 | 0.207 | 12.923 | 0.000 | 2.108 | 1.741 | 0.228 | 58.118 | 0.000 | 5.703 |
| X8     | 0.741 | 0.189 | 15.350 | 0.000 | 0.477 | -0.524 | 0.153 | 11.641 | 0.000 | 0.592 |
| X9     | 0.930 | 0.164 | 32.229 | 0.000 | 2.535 | 0.387 | 0.172 | 5.064 | 0.024 | 1.472 | 0.705 | 0.214 | 10.875 | 0.001 | 2.025 |
| X10    | 1.327 | 0.415 | 10.228 | 0.001 | 3.769 | 1.153 | 0.156 | 54.779 | 0.000 | 3.169 |
| X11    | 0.232 | 0.138 | 2.832 | 0.092 | 1.261 | -2.744 | 0.624 | 19.349 | 0.000 | 0.064 | -0.903 | 0.323 | 7.809 | 0.005 | 0.405 |
| X12    | 0.069 | 0.020 | 12.197 | 0.000 | 0.934 | -0.059 | 0.026 | 5.160 | 0.023 | 0.943 | -0.081 | 0.034 | 5.720 | 0.017 | 0.922 |
| X13    | -12.257 | 1.887 | 59.674 | 0.000 | 0.000 | 1.627 | 1.066 | 2.331 | 0.127 | 5.090 | 11.825 | 6138.015 | 0.000 | 0.998 |

Note: (1) β denotes the regression coefficient and SE standard error; Wald means Wald test, and Sig significance; OR is odds ratio. (2) Factors or variables whose VIF was largely less than 2.5 were used for logistic regression modeling, and those with VIF > 10 were removed prior to modeling.
4. Discussion

4.1. Spatiotemporal Variability of the Sand-Control Effectiveness

As demonstrated above, the sand-control exhibits obvious spatiotemporal variability. This is probably because of the difference in regional implementation of the ecological restoration projects or environmental protection policies [8,33,47,48]. In 1999, the Grain for Green Program (GGP), or the Conversion of Cropland to Forest and Grassland Program, was promulgated by the Central Government and first implemented in Shaanxi, Ningxia and Inner Mongolia while the third phase of the Three-North Shelter Forest Program (TNSFP) was reaching its end. In addition, the local governments, e.g., the banners Otogqian and Otog, issued the “Grazing ban and rotation policy with a subsidy system” in 2001 [8]. At the same time, a large number of families or household companies started to devote themselves to the sand-control activities. The fourth and fifth phase of the TNSFP, which were focused on desertification prevention and control, was achieved respectively in 2010 and 2020. Moreover, the Central Government invested another 13.6 billion yuan in 2011 to eight main pastoral areas in Northern China for implementation of a protection policy with subsidy and incentive mechanisms, including subsidies for the grazing ban, incentives for balancing forage productivity and livestock, and for good performance of herdsmen (http://www.moa.gov.cn, accessed on 8 June 2021) [49]. These programs, policies and spontaneous sand-control activities have played a positive role in desertification reversal since the 1990s, but with a spatial variability in space as there was a difference in implementation progress of these initiatives. For this reason, the proportion of sand-control has increased significantly, despite of its spatial variability. Actually, a large piece of the degraded grassland in the banners Uxin, Otog and Otogqian has been restored.

4.2. Driving Forces for Desertification and Sand-Control

Some authors consider that climate is the main driving force of desertification [50], while others believe that human activities exert more impact on the latter [18]. Our research indicates that both human activities and climate condition including animal husbandry (i.e., increase in big livestock and, in particular, sheep number), GDP growth, variation in wind speed and temperature (Tables 10, 12 and 14) have played an important role in this process. More concretely, linear regression analysis reveals that desertification is positively correlated with the maximum and average wind speed and negatively correlated with the area of water (Table 10).

These analyses demonstrate that variation in strong wind speed, coal mining, grazing and reduction in water availability may have driven the occurrence of desertification.

As demonstrated in Table 14, logistic regression modeling uncovers that in different periods, the probability of desertification in space is different and the roles of the socio-environmental factors are also different. However, in the past 30 years, the contribution of $\Delta X_9$, local reduction in precipitation, $\Delta X_{11}$, increase in wind speed, and $X_{13}$, distance to roads, have played a positive role, while $X_{19}$, slope, takes a negative part in the desertification process, meaning that steep slope does not favor desertification. Therefore, desertification is associated with both climate condition and human activity, and this finding confirms the correctness of the definition of “desertification” by UNCCD in 1994.

Increase in precipitation is conducive to vegetation growth, thus promoting sand-control and vegetation recovery. It is worth mentioning that previous studies have shown that over-reclamation and over-stock will inevitably exacerbate desertification [2,8,30], whereas our study reveals that since 1999, the increase in meat product including pork, beef and mutton is a favorable sand-control indicator, and since 2010, the increase of per capita income of farmers and herdsmen has been also conducive for combating desertification. This is because in the frame of the TNSFP, GGP (1999), the Ecological Grassland Protection Project (2011) and other national ecological projects, sand-control has not only promoted vegetation recovery to reverse desertification, but also produced economic value as forages such as Medicago sativa and Astragalus adsurgens pall for dry-lot feeding [8], and plantations.
of *Elaeagnus angustifolia* Linn., *Lycium barbarum* L., *Ephedra sinica* Stapf [2], etc., have brought a significant improvement in net rural income. Hence, sand-control favors both agricultural and pastoral activities.

4.3. Spatially Explicit Probability of Sand-Control and Desertification

Logistic regression modeling discovers that the area with flat terrain and low elevation is convenient for transportation and irrigation of planted trees, shrubs and herbage, and thus shows high probability of sand-control events. This is consistent with our field survey (Figure 6). Owing to the developed transportation, high accessibility and convenience for management, the areas close to cities, roads and farmland have a high probability of being managed. Meanwhile, those far from cities, roads and farmland are prone to desertification due to less human management and costly transport; this is similar to the results of Feng et al. (2021) [33]. Water source is essential for vegetation growth, and the closer to water, the lower the cost for irrigation and the higher the possibility of being controlled. The areas with irrational agricultural activity and animal husbandry had a high probability of desertification before 1999 because profit-seeking did not go with environmental protection. As Wu et al. (2013) revealed [8], reclamation for cropping and abandonment after 2–3 years of cultivation, land was left with erosion by both wind and water, and herdsmen preferred to breed the maximum possible number of sheep and big livestock to compete for the public grassland resource to maximize their economic profit, which had been discussed by Hardin in his article “The Tragedy of the Commons” [51]. However, since the large-scale implementation of policies, such as rotational grazing and the grazing-ban policy with a subsidy mechanism in 2001, the probability of successful sand-control in these areas has been significantly increased, in particular after 2010. This is in agreement with our field survey in July 2021 (Figure 7), which shows the difference between the rotational grazing areas and the grazing-ban area.

![Figure 6. Landscape of interdune (grassland and pasture) and sand dune. (Photo was taken on 15 July 2021).](image-url)
5. Conclusions

This paper presents an integrated remote sensing-based study on the effectiveness of sand-control and desertification in the Mu Us Desert, and spatially explicit models aiding to explain spatial determinants of sand-control and desertification were developed. We found that a total of 8712.23 km² of sandy land (63.05% of the study area) has been controlled and converted into shrublands and grasslands with different greenness, where GDVI has increased by 0.3509 on average from 1991 to 2020. This activity has brought not only recovery of vegetation cover, but also growth in rural income and meat products, allowing an improvement of the livelihood of herdsmen, and thus created a win–win situation. This is a great success of combating desertification by local people and the Chinese governments, and this experience deserves to be extended to other desert control in Northern China and even to other dryland countries across the world. However, despite the decrease in desert area, desertification is still taking place locally and more than 5000 km² of deserts remain unmanaged in the study area.

Multiple linear regression models illustrate that the rural per capita income, wind speed and water source play a role in desertification process, and logistic regression models reveal that the local reduction in precipitation, increase in wind speed and the distance to roads are the key factors influencing the desertification in the past three decades. Anyway, desertification is associated with both climate and human activity, such as wind speed, precipitation, water availability, distance to roads, rural per capita income and animal husbandry. The climatic part, such as variation in wind speed and precipitation, can be hardly managed, but it is possible to control animal husbandry (e.g., rational sheep number and livestock), and to make relatively remote areas accessible by road construction and available water. In this way, existing desertification may be reversed and future desertification could be avoided. The findings of this study may provide advice for local decision-makers in taking measures to conduct sand-control of the next step in Mu Us or elsewhere.

Different from the existing MEDALUS and DesertWatch projects, which were aimed at desertification vulnerability assessment and scenario modeling, this study attempted to reveal the desertification mechanism by two kinds of regression modeling, and achieved a quantitative desertification assessment with a deepened understanding on its driving forces. We can say that this study is an extension or a complement of the two mentioned projects in the continental climate dryland environment. Probably, a combination of these two approaches may lead to a more comprehensive research on desertification. This will be the topic of our next research in the Ordos region.
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