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Spatiotemporal change and drivers analysis of desertification in the arid region of northwest China based on Geographic Detector

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Highlights

1. Remote sensing monitoring of desertification was successfully realized.

2. Human activities are the main drivers of desertification changes.

3. Ecological water conveyance projects can effectively prevent desertification.

Spatiotemporal change and drivers analysis of desertification in the arid region of northwest China based on Geographic Detector

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Abstract：

The arid region of Northwest China is a hotspot for global desertification research, because it is affected by the combined effects of climate change and human activities, and it has had a huge impact on human society in recent years. Based on multiple meteorological and spatial attribute data sets, NDVI-Albedo feature space principle and geographic detectors were used to analyze the main drivers to the spatiotemporal changes of desertification in the arid region of northwest China from 2003 to 2018. The results are shown that: (1) The area of severe desertification in the arid region of northwestern China shows a downward trend, and the area of high desertification and non-desertification regions increases correspondingly，the area of medium and low desertification remains basically unchanged. The desertification divided index (DDI) is the highest in the mid-altitude region. The DDI of middle and lower reaches of the Tarim River has the fastest rising rate, due to the impact of human agricultural activities and ecological water conveyance. (2) According to the analysis results of the geographic detector model, precipitation is the main factor driving the spatial distribution of desertification, especially the interpretive ability of the interaction between land use and precipitation is more than 50% for the spatial distribution of DDI. Land use change and its interaction with other factors have the highest degree of explanation for desertification changes. Therefore, human activities, especially land use and ecological water conservancy projects, are the most important factors to improve desertification in the arid area of Northwest China. This study provides a scientific basis for agricultural management and ecological engineering construction in arid region.

Keywords： Desertification; Attribution analysis; Ecological Water Conveyance; Geographic detector; Arid region.

1. Introduction

Desertification is a complex phenomenon resulting from the interaction of natural (biophysical) and anthropogenic factors with different temporal and spatial variability (Gao et al., 2012). Over 40% area of global land surface is suffering this major environmental issue (Do et al., 2013), and two thirds of the countries and nearly one billion people are affected by it (Ver et al., 2006), this social-economic-environmental problem has resulted in huge economics losses every year (Armahol et al., 2011; Reynolds et al., 2011). This issue is also serious in northern China of the past 50 years (Wang, 2004; Wang et al., 2004). As society develops and climate changes (shoba, 2016), the problem of desertification becomes more and more serious (Ajaj et al., 2017; Xu et al., 2018), although 194 countries have ratified the United Nations convention on combating Desertification (wessel et al., 2012), and highlighted the desertification as one of the obstacles to the global sustainable development (UNCCD, 2017).

Some studies have pointed out that: the regional climate of northwest China had shown the trend of climate change from the warm dry pattern to the warm wet pattern, and this warm wet pattern phenomenon would become wet in the whole area of northwest China to 2050 (Shi et al., 2003). But, because the precipitation base is too small, the increased precipitation is much less than the strong evaporation capacity, the warm wet pattern phenomenon cannot fundamentally change the landscape pattern of the northwest of China (Chen et al., 2015). With the development of the agricultural economy in arid areas, irrigation water consumes a large amount of ecological water, the river cut-off point moves upward, the river cut-off time is lengthened, and the degradation of downstream vegetation further intensifies the expansion of desertification area(Li et al., 2020). Fortunately, the government implemented the water delivery project in time to restore the downstream ecological environment to a certain extent (Liu et al., 2012). According to the results of the Fifth China Desertification Monitoring, by 2014, the total area of desertification in China reached 2.61×10^7 km^2, accounting for 27.20% of the total area of the country (http://www.forestry.gov.cn/portal/main/s/195/content-457769.html), which is slightly lower than the fourth monitoring result. Whether the main driving force of this trend comes from climate change or human activities needs to be further studied.

However, traditional methods of desertification monitoring require a great deal of human and financial resources. At the same time, the lack of a scientific method for monitoring and a unified assessment system leads to very different research results (Safriel et al., 2007; Vogt et al., 2011). With the development of remote sensing, the international study of remote sensing monitoring of desertification began in the 1970s (Basso et al., 2000). Initially, researchers used vegetation indices to reflect land degradation and indicate desertification (Wessels et al., 2012). In the 1980's, studies found that land surface albedo is one of the most important parameters of the ground radiant energy balance, which determine the radiant energy absorbed by the underlying surface (Liang et al., 2011). At present, the application of remote sensing in desertification assessment has developed from empirical visual interpretation, vegetation single index evaluation to multi-remote index comprehensive evaluation, and desertification remote sensing evaluation technology is becoming more and more mature (Wei et al., 2018). Using the change vector analysis (CVA) technique and Landsat thematic mapper (TM) satellite images combined normalized difference vegetation index (NDVI)-albedo, NDVI-bare soil index (BI) and tasselled cap greenness (TCG)-tasselled cap brightness (TCB) etc. Results showed that the combination NDVI-albedo feature space has the highest monitoring accuracy (Vorovencii, I., 2017). These methods have greatly promoted the development of remote sensing monitoring of desertification.

Desertification is usually promoted by a variety of causal factors (Qi et al., 2013), which can be mainly classified as natural and human factors. The main natural factors that promote desertification are changes in climate factors such as Temperature, Precipitation, Wind (Shoba et al., 2015), and the human activity factors that affect it are mainly through agricultural reclamation and overgrazing (Yu et al., 2018; Feng et al., 2015). When it occurs in arid, semi-arid and sub-humid dry areas, it is mainly derived from the human impact (Renold et al., 2007). Changes in land use directly change the form of surface vegetation, and even change the rate of soil erosion (Ota and Eyasu,2020). Existing studies mostly analyzed dynamic correlation between desertification and main driving factors, and most research on the factors influencing spatiotemporal variation in desertification is conducted by trend regression and correlation analyzes. As a sensitive area of climate change, the research on the change of desertification in the arid region of northwest China is a reference to the world. So, the main drivers and their contribution rates need further quantitative research. The geographical detector is a new spatial statistical method that is used to identify driving factors by detecting spatial heterogeneity, independent of any linear hypothesis (Wang and Xu, 2017; Wang and Bai et al., 2017). It uses spatial variance to quantify the relative importance of single factors and their implicit interaction with response variables (wang and xu, 2017), which provides a new idea for a quantitative description of the drivers of desertification.

Thus, our study attempted to: (1) Analysis the spatiotemporal changes of desertification in Arid Areas of Northwest China in Recent Years; (2) Identify the main driving factors and their contribution rate to the desertification change.

2. Data and methods

2.1. Study area

The arid region of northwest China located in the hinterland of the Eurasian continent. The geographic coordinates are between 73°–106°E and 35°–50°N, and the area is about 2.5×10^6 km^2, which accounting for about a quarter of China's land area (Fig1). This region with a perennial dry climate and less than 400 mm of precipitation is one of the major desertification regions of the world. The study area mainly consists of plateaus and mountains. The largest desert of China, Taklamakan Desert, is also located there. The vegetation coverage in the arid region of northwest China is very low, so the species are rare and the community structure is simple too, and the main plants here generally are cold-resistant and salt-tolerant shrubs or small subshrubs. In recent years, with the development of agriculture and animal husbandry, more frequent human activities and poor land management pose a higher challenge to desertification control in arid and semi-arid areas. Since 1972, the Tarim River has been dry-out for 34 consecutive years, until the implementation of the ecological water delivery project. China loses 128.1 billion yuan each year due to land desertification, which is 3.6 times the fiscal revenue of provinces (Xinjiang, Gansu, Inner Mongolia, Qinghai, Shaanxi, Ningxia) in desertification areas (Liu., 2006).

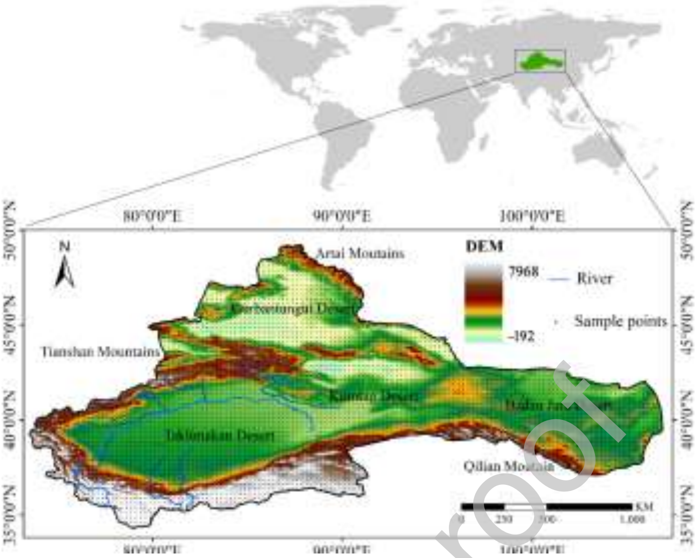

Figure 1. Study Area

2.2. Data sources and preprocessing

The Moderate-resolution Imaging Spectroradiometer data NDVI and Albedo for this study are all download from https://search.earthdata.nasa.gov/search/order/1, Both data are semimonthly syntheses with a spatial resolution of 500 m. In order to remove noise, this study selects the maximum relative pixel value of four NDVI images from July to August each year to synthesize a single image. The surface albedo product MCD43A3 has the same spatial and temporal resolution as the NDVI image, it mainly including White sky albedo and local Black sky albedo at noon sun angle. This study chooses the black sky short wave radiation due to the shortwave radiation of black sky reflects the albedo of direct sunlight on the surface at noon time.

Natural factors include altitude (ASL), precipitation (P), temperature (T), wind speed (WS), potential evapotranspiration (PET), and human factors include land use are the main driving factors for the desertification change. The altitude is obtained by DEM extraction provided by Geospatial Data Cloud. All meteorological data were downloaded from the China Meteorological Data Service Centre website. Each meteorological factor is divided into seven levels by natural breakpoint method. The soil data was selected from the Harmonized World Soil Database (HWSD) and roughly divided into seven types according to the FAO90 standard. The land use (LU) data comes from the China Land Survey. In this study, land use was divided into two categories: natural vegetation and agricultural land when analyzing the driving factors of spatial differentiation. When analyzing the driving factors of change trends, land use was divided into four categories, they are natural vegetation, agricultural land, natural vegetation transformed into agricultural land, agricultural land transformed into natural vegetation area.

The vegetation survey data comes from the field survey of the lower Tarim River, where the vegetation coverage degree is calculated by the ratio of the vegetation coverage area to the quadrat area.

Table 1. Drivers and their classification

Factors	Grade							Unit
	1	2	3	4	5	6	7	
Asl	<0	0～1	1～2	2～3	3～4	4～5	>5	kilometer
P	<94	94～175	175～240	240～301	301～370	370～450	>450	mm/y
T	<-6.6	-6.6～-3.5	-3.5～0	0～3.6	3.6～7.2	7.2～10.7	>10.7	℃/y
WS	<1.9	1.9～3.0	3.0～4.0	4.0～5.1	5.1～6.2	6.2～7.3	>7.3	m/s
PET	<296	296～433	433～570	570～707	707～858	858～1036	>1036	Mm/y
LU*	Natural vegetation	Farming land	Farming land to Natural vegetation	Natural vegetation to Farming land	\	\	\	\
Soil	Calcic Chernozems	Mollic Solonchaks	Eutric Leptosols	Humic Cambisols	Glaciers	Haplic Solonchaks	Mollic Leptosols	\

*Note: When analyzing the spatial differentiation of desertification,The land use types are divided into two categories: agricultural land and natural vegetation. When conducting trend change analysis, it is divided into four categories, all meteorological factors are reclassified according to the rate of change from 2003 to 2017.

2.3. Method

2.3.1. Principles of feature space

Numerous studies have proved that NDVI can be effectively used for vegetation monitoring, and the estimation of vegetation coverage and vegetation leaf area index is an important biophysical parameter reflecting the state of surface vegetation (Wei et al., 2018). Generally, with the increase of desertification degree, the surface vegetation is seriously damaged, which result the decrease of surface vegetation cover and biomass, and the vegetation index decreases correspondingly in remote sensing image. Therefore, the vegetation index (NDVI) can be used to characterize the degree of desert. Albedo of surface albedo retrieved from remote sensing data is a physical parameter reflecting the reflection characteristics of surface to solar shortwave radiation. the change of surface albedo is affected by soil moisture, vegetation cover, snow cover and other abnormal land conditions. Similarly, with the increase of desertification degree, the surface conditions will change obviously, including the decrease of vegetation coverage, surface water content and surface roughness, which lead to the corresponding increase of surface albedo. Thus, surface albedo was also another important indicator of desertification. In the figure of Albedo-NDVI feature space (Fig. 2), the point A represents arid bare soil, the change of surface albedo in bare land is highly related to the surface water content, and the B point represents the water-rich bare soil. The point in the figure represents the high vegetation cover area. because the soil water content is low, the albedo is relatively high, and the D point corresponds to the high vegetation cover and sufficient soil water content, the albedo of the point is relatively low.

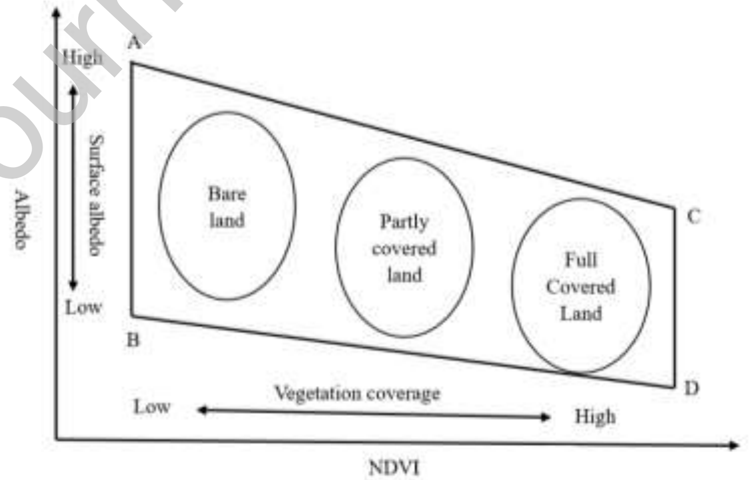

Figure 2. Albedo-NDVI feature space

There is a significant linear relationship between albedo and NDVI, which can be expressed as:

$$Albedo = a * NDVI_{max} + b \quad (1)$$

Where a is the slope of the regression equation, b is the intercept of the regression equation on the ordinate. According to Verstraete and Pinty research conclusion (Verstraete et al., 1996), if the characteristic space is divided in the vertical direction representing Albedo-NDVI changing trend of desertification, the different desertification land can be effectively distinguished. Desertification can be expressed through DDI (Desertification Divided Index) indicators.

$$DDI = K * NDVI - Albedo \quad (2)$$

Where K was determined by the slope of the straight line fitted in the feature space, is the minus count backwards of "a".

2.3.2. Classification of desertification and accuracy assessment

The "Natural Breaks Classification" (Jenks) is based on the natural grouping inherent in the data. The classification interval will be identified, similar values can be grouped most appropriately, and the differences between the classes can be maximized with the smallest variance within the group. Features will be divided into multiple classes, and for these classes, boundaries will be set where the differences in data values are relatively large. This study divided the DDI values into five different levels by Jenks classification. These five desertification levels are severe desertification, high desertification, medium desertification, low desertification, and non-desertification.

In order to verify the remote sensing monitoring accuracy of desertification, this study uses the measured data from the vegetation quadrat method survey in the Tarim River Basin from 2003 to 2019 for verification. The verification sample site mainly includes the sample data of 50m*50m along the river channel in the sections of Yingsu, Aragan, Abu Dale.

2.3.3. Trend analysis and geographical detector

The trend line simulated by the univariate linear regression equation is not a simple line between the first year and the last year, but represents the overall change trend by the slope of the change in the desertification index (Stow, et al., 2003).

$$Slope = \frac{n \times \sum_{i=1}^{n}(i \times DDI_i) - \sum_{i=1}^{n} i \sum_{i=1}^{n} DDI_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2} \quad (3)$$

Where i is the ordinal number for 2003-2018, DDI_i is the DDI value for the i year. Slope>0 indicates an increasing trend in the value of DDI in 2003-2018, whereas Slope<0 indicates a decreasing trend. At the same time, this research conducted a significant test on the results in the process of trend analysis.

Geographic detectors are a set of statistical methods to detect spatial heterogeneity and reveal the driving force behind them. The core idea is based on the assumption that if an independent variable(X) has an important influence on an dependent variable(Y), the spatial distribution of the independent variable and the dependent variable should be similar. Geographical detectors mainly include differentiation and factor detection, risk detection, interaction detection and ecological detection. Factor detection and interaction detection are mainly selected in this study, which can be represented by q values.

$$q = 1 - \frac{SSW}{SST} = 1 - \frac{\sum_{h=1}^{L} N_H \sigma_h^2}{N\sigma^2} \quad (4)$$

Where h and L are the stratification of variable Y or factor X; The N_h and N are the number of units in the stratification h and the whole area, respectively;$\sigma_h^2$and $\sigma^2$are the variance of the Y values of the h stratification and the whole region, respectively; SSW is the sum of the in-stratification variance, SST the region total variance. The value range of q is [0, 1].The larger the q value, the stronger the explanatory power of the independent variable X to the attribute Y and vice versa. In this study, 3589 samples with a grid point resolution of 0.25 degrees were generated in the study area to make up sample size.

3. Result

3.1. Temporal and spatial distribution of desertification

The degree of desertification is divided into five levels by using the natural breakpoint method (Jenk), severe desertification (<0.42); high desertification (0.42-1.18), medium desertification (1.18-2.33); low desertification (2.33-3.59); and non-desertification (>3.59). The arid region of northwest China is the most concentrated desert area in China, including the Taklamakan Desert, Gulbantongut

Desert, and so on, where accounts for about 80% of the total desert area of the country. On a spatial scale, severe desertification is mainly concentrated in areas of these deserts, such as the northern part of the Gurbantungut desert and the northwest of the Badan Jara desert. Medium and low desertification are mainly concentrated in the transitional zone between desert and mountain areas as well as in the river coastal areas. Non-desertification is all distributed in high-altitude mountain areas (Fig.3).

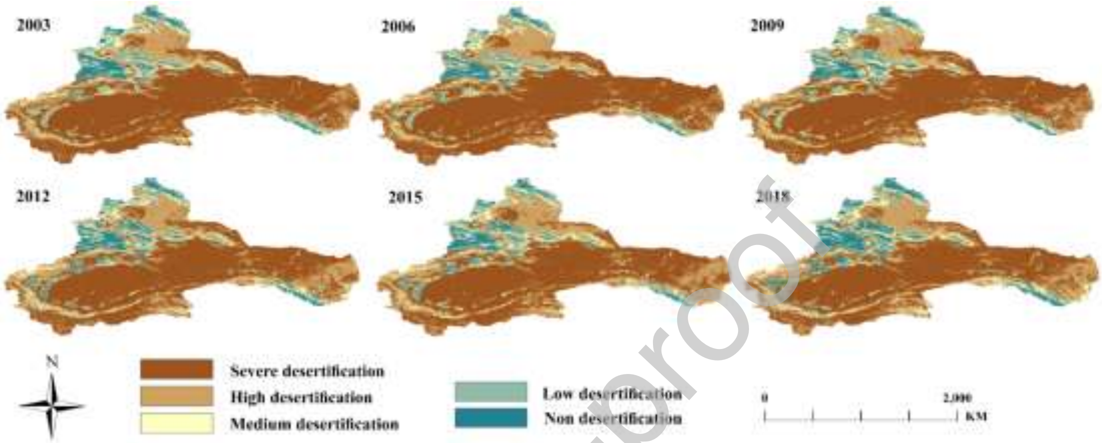

Figure 3. Desertification grade classification based on the desertification difference index

In the statistical process of the desertification area over the years, we found that the area of different degrees of desertification changed differently (Fig4a). We can see that the area of severe desertification dropped fluctuating from 52.7% to 40.5% in 2003-2018. While the area of high desertification has increased from 24.7% to 30.7%, and its area change is obviously symmetrical with the curve of severe desertification. There has been no significant change in medium and low desertification, but it is worth noting that the area of non-desertification has increased significantly, area proportion rose from 6.4% to 10.6% in this period. In order to further analyze the spatial change of the desertification degree in the arid area of Northwest China, we calculated the slope based on the grid-scale and conducted a significant analysis. We found that significant changes occurred in 9.1% of the study area, and more than 90% of the areas not change significantly or even not changed (Fig4b). The grid with a significant increase in DDI index is mainly concentrated in the transitional zone along Rivers and the lower reaches of the Tarim River, accounting for 8.3% of the study area. The main reason may be the ecological water conveyance project that began in

2000 to deliver water to the lower reaches of the Tarim River through Bosten Lake and Daxihaizi Reservoir. Which has improved the ecological environment of the lower reaches of the Tarim River. Comparing the different degrees of desertification and the amount of ecological water conveyance over the years (Figure4a), we found that the two do have a strong correlation. The extreme desertification area will have a minimum value within one to two years after one year of ecological water conveyance years, while the high desertification and non-desertification area will reach the maximum value. The opposite is also true. The area where DDI decreased significantly and the degree of desertification intensified accounted for only 0.08%, mainly concentrated in the middle reaches of the Tarim River (Figure4b). Human agricultural activities may be the main reason for the significant increase or decrease of the DDI in the middle reaches of the Tarim River.

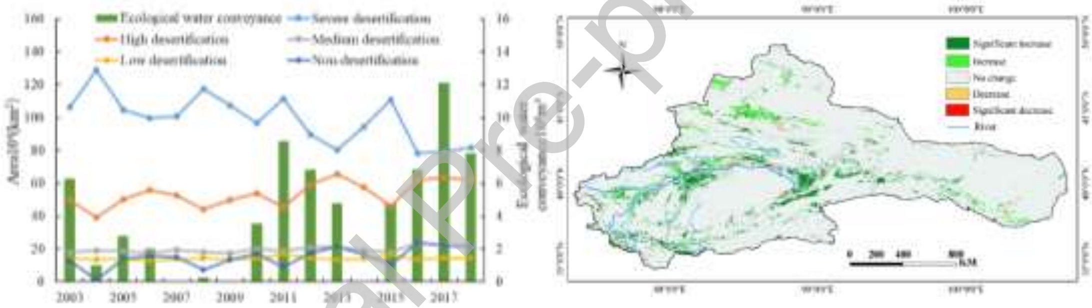

Figure 4. Spatio-temporal changes of desertification in the arid region of Northwest China (a)Changes of different desertification levels area and ecological water conveyance from 2003-2018 ,(b)desertification divided index spatial change map.

3.2. Drivers of desertification

Attribution analysis of spatial differentiation and change trend of Desertification Divided Index (DDI) in the arid area of northwest China was carried out by using the geographical detector, the results are shown in Figure5. The order of interpretive ability for desertification by different factors are: Precipitation>Soil type>Land use>Temperature>Potential evapotranspiration>Altitude>Wind speed. The distribution of desertification is mainly limited by water factors, soil types, and land use, because of the arid area of northwest China located deep in Eurasia. Combined the results of risk detector for desertification spatial differentiation (figure5b). Precipitation, as the most powerful explanatory factor for the distribution of desertification, and the desertification divided index continues to increase with its increase because the amount of water resources determines the degree of vegetation coverage. The temperature itself has little effect on the desertification divided index, the q value is only 0.175, but the effect of temperature interacted with other factors are greater than the former. The effect of altitude on the desertification distribution is similar to temperature, the desertification divided index increases first and then decreases as the altitude increases, which is mainly affected by the interaction between altitude and precipitation, temperature, and soil type. In low altitude areas, affected by the interaction between altitude and soil type and precipitation, as the altitude increases, the soil type changes, and precipitation increases, so the desertification classification index is increasing. Different land use types in arid areas also have a great different impact on the desertification divided index. The DDI of agricultural land is much higher than that of natural vegetation areas. In a word, the interaction between land use and precipitation has the strongest ability to interpret the desertification divided index in the arid region of Northwest China, exceeding 0.5.

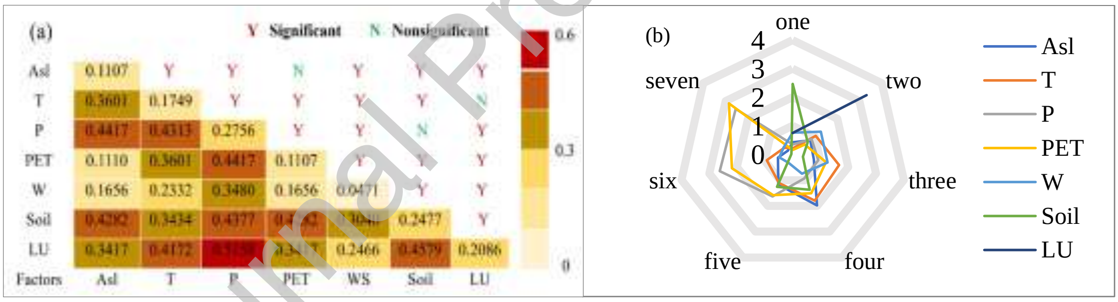

Figure 5. Map of drivers of the Spatial Distribution of Desertification Based on Geographic Detectors. (a) factors detection and interactive detection matrix, (b) radar map of risk detection for desertification spatial differentiation.

Factor detection and interactive detection for the rate of change in the desertification divided index based on geographical detectors are shown in figure 6. Land use change has the strongest interpretive ability for the rate of change of the desertification divided index, q statistics is 0.327, significantly higher than any other factors. The interpretive ability of the interaction between land use change and other factors is greater than the land use itself, among them, the q statistic of the interaction between land use and potential evapotranspiration is bigger than others. However, changes in natural factors such as temperature and precipitation have little impact on desertification changes. Combined with the results of risk detectors (Figure 6), we found that it was mainly due to changes in human activities in the middle reaches of the Tarim River and the ecological water transportation project that changed the underlying surface conditions along and downstream of the Tarim River. From the perspective of altitude, the largest desertification change rate is mainly concentrated in 2000 m to3000 m. Judging from the land use change with the highest q-statistics, the change of the desertification grading index is the smallest in areas with natural vegetation, while the slope is the largest in areas where farmland and natural vegetation are converted to farmland. These aspects support the conclusion that in the arid area of the northwest, the main factors driving desertification changes are land use changes and water conservancy project construction.

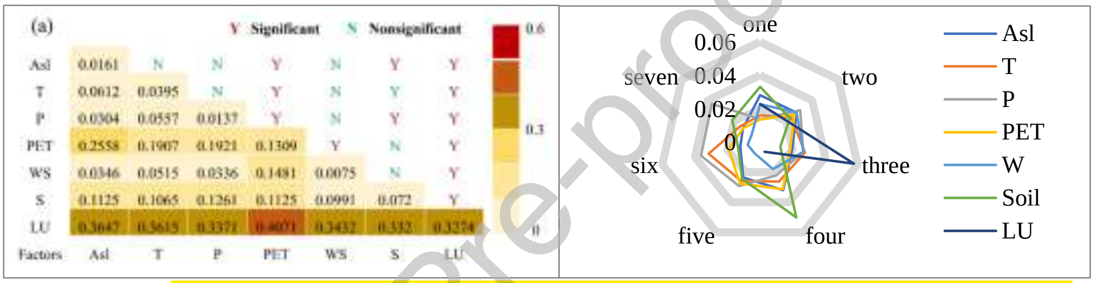

Figure 6. Map of drivers of the spatial change of desertification Based on Geographic Detectors. (a) factors detection and interactive detection matrix, (b) radar map of risk detection for desertification spatial change.

4. Discussion

4.1. Accuracy assessment and verification

This study extracted the NDVI and Albedo values in the arid region of northwest China from 2003 to 2018. According to the feature space principle of NDVI and Albedo, with the step size of 0.01, $Albedo_{max}$ and $Albedo_{min}$ corresponding to different NDVI values are read through programming. The result shows that the NDVI-Albedo characteristic space is triangular or trapezoidal, and the $Albedo_{max}$ shows a significant negative correlation with the NDVI, and all the R^2 is above 0.79.

To realize the remote sensing monitoring of desertification, its accuracy needs to be evaluated and verified. Existing research is mainly verified by soil moisture or Landsat true color images (Wei, 2018), verification through field survey data can guarantee the credibility of the results (Qi, 2019). This study verifies the accuracy of monitoring desertification with the DDI index by using vegetation coverage data of the field vegetation survey plot in the lower reaches of the Tarim River. The correlation analysis results of the desertification divided index and the sample vegetation cover are shown in Figure7 below. According to the scatterplot, the vegetation coverage and DDI index have a very significant positive correlation, correlation coefficient R^2 reaches above 0.8. Therefore, it is reasonable to use DDI to monitor desertification in the arid region of the Northwest. At the same time, modified soil adjusted vegetation index and topsoil grain size index were introduced to replace NDVI to build different models in some studies (Wei, 2018). There are some differences in the results of each model under different landform types. Presently, the Albedo-NDVI model is a widely accepted model and can be used to accurately acquire desertification information.

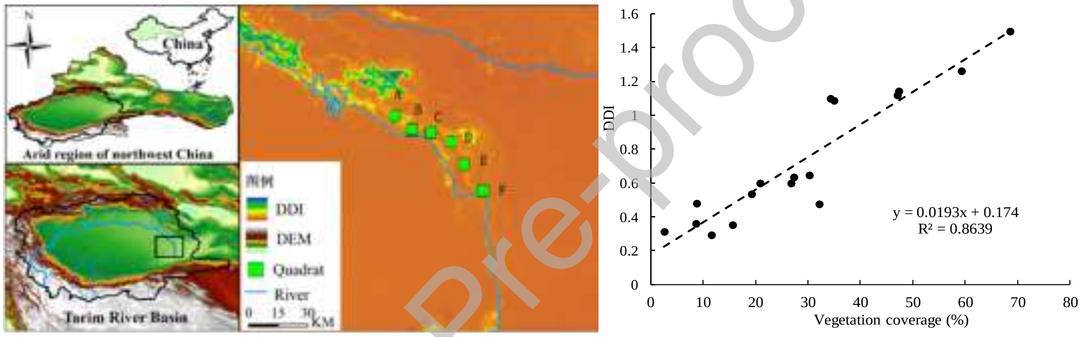

Figure7. Vegetation survey sample distribution map and scatter plot of correlation between vegetation coverage and DDI index. A: Akhmahan, B: Yingsu, C: Abu dal, D: Kardai, E: Tugmailai, F: Arakan.

4.2. Other applications of NDVI-albedo spatial feature principle

The spatial feature principle of NDVI-Albedo can also be used to calculate vegetation condition albedo drought index (VCADI), the specific principle refers to the citation (Abudu,2007). VCADI is basically consistent with regional precipitation dynamics, which has a significant correlation with soil moisture. This index can realize drought remote sensing monitoring without surface ancillary data. The remote sensing monitoring results of drought in the northwest China arid region from 2003 to 2018 based on VCADI is shown in figure 8.According to the natural breakpoint method, the drought is divided into five grades， severe wet(<0.28); wet (0.28-0.47); normal (0.47-0.63); drought (0.63-0.79); severe drought (0.79-1). The overall drought situation is severe in the study area, mainly concentrated in desert areas, and only the mountain and valley areas are relatively wet.

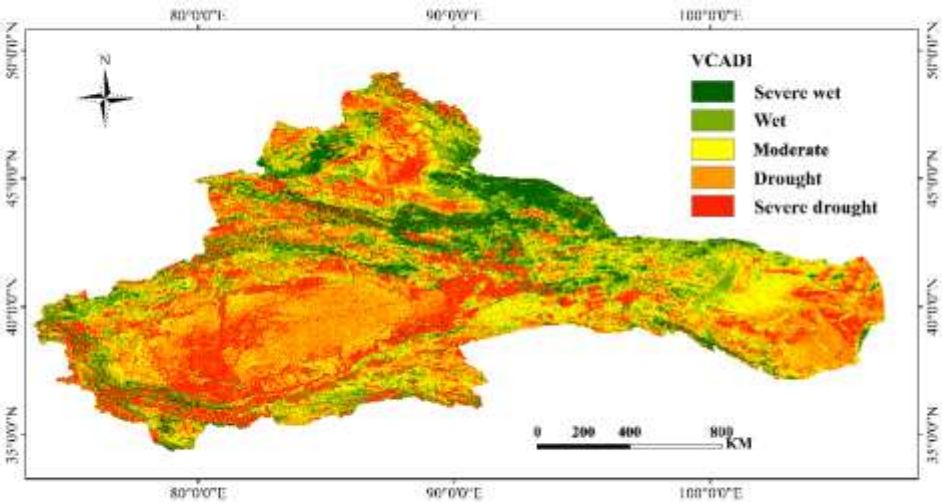

Figure 8. Distribution map of drought in the arid region of Northwest China

Compared with previous studies on the analysis of driving factors for desertification, this study used geographic detectors to quantitatively describe the contribution rates of various factors driving desertification. Most of the existing research is still left in the stage of qualitative description such as related analysis(Do,2012)， although it is possible to roughly find out what the main driving factors are and it is difficult to quantitatively describe the interpretive ability of those factors. The results of those study show that the spatial distribution of desertification in the arid region of Northwest China is mainly affected by the interaction of precipitation and land use, interpretive ability is more than 50%. In recent years, the change in the degree of desertification has little to do with climate change, human activities are the main driver (Huang, 2019). Agricultural reclamation activities and the construction of ecological water delivery projects have certainly improved desertification in the middle and lower reaches of the Tarim River. This study provides theoretical basis and technical support to grasp the dynamic development trend of desertification in the region, and provides reference for ecological environment construction and economic development.

4.3. The effect of anthropogenic factors to the desertification

The results are often negative when assessing the impact of human activities on desertification in existing studies (Hu et al., 2015; Wang et al., 2012). Overgrazing, drainage of water systems, land reclamation for agriculture are the main ways to increase the degree of desertification. However, with the development of society and the formulation of relevant government management policies, the situation has been reversed. In the Xinjiang region of the study area, the government implements reclamation of sandy land and soil amelioration that converted desertification area into farmland from the 1990s (Wang et al., 2012); Some experts believe that the expansion of arable land in the Tarim River Basin has occupied part of the desert-oase ecotone (Sun et al., 2020), which is likely to have a negative impact on desertification control. But, more reasonable agricultural planning and more advanced irrigation technology will gradually reduce the total agricultural water demand (Zhang et al., 2009); Three North Shelter Forest project planted shrubs and trees to fix sand dunes and increased the vegetation cover (Zhao et al., 2009; Wang et al., 2010); Years of ecological water conveyance projects have gradually improved the ecological environment in the lower reaches of the Tarim River(Hao and Li, 2014; Yu et al., 2012; Chen et al., 2010). Human factors are the most effective way to curb and reverse desertification. In Central Asia, the desertification process in forests and areas of sparse vegetation was extremely sensitive to climatic variations, while that in croplands and grasslands was vulnerable to human activities (Jiang et al., 2019). Therefore, reasonable planning and construction of engineering facilities, the vigorous development of water-saving agriculture, and the popularization of optimized irrigation methods require the implementation and promotion of local governments. In particular, the ecological water delivery project is a new measure to ensure the supply of ecological water and curb the desertification of vegetation degraded land, which has important reference significance for desertification control in other arid regions in the world.

5. Conclusion

It is feasible to extract desertification information based on the feature space models of NDVI- Albedo. From 2003 to 2018, the area of severe desertification in the arid region of northwest China was shrinking and changing to high desertification, and the area of non-desertification is also increasing. In addition, the areas with the most significant increase in the desertification divided index are mainly concentrated in the areas along and lower reaches of the Tarim River.

According to the research of geographic detector, precipitation, soil type, and land use are the three main factors that dominate the desertification distribution in the arid area of northwest China, especially the interaction between precipitation and land use. According to the analysis of the factors driving the change of the desertification divided index, the impact of land use is the most significant. Human activities and ecological water conveyance are the main factors affecting desertification changes in the arid region of Northwest China in recent years. The local government should continue to optimize agricultural management policies, rationally arrange ecological water conveyance, and further effectively curb the development of desertification. This also has a strong reference value for desertification control in other arid regions

However, the geographic detector method can only analyze based on regions, and cannot distinguish the main drivers of desertification in different geographic units on a spatial scale. Dividing the study area according to different geographic units will directly affect the contribution rate of the main drivers, so choosing an appropriate dividing basis and conducting desertification control targeted for the main factors is also one of the ways to improve efficiency.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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