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Remote Sensing Monitoring of Soil Salinization Based on SI-Brightness Feature Space and Drivers Analysis: A Case Study of Surface Mining Areas in Semi-Arid Steppe

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ABSTRACT The real-time monitoring and driving force research of soil salinization in semi-arid grassland are of great significance for regional and local ecological environment protection, management, and sustainable development. We selected a typical ''mine-town-agriculture-pastureland-industry'' interlaced ecologically fragile area as the study area. Based on the method of SI (Salinization Index)-Brightness feature space, we constructed a new spectral index named Semi-Arid Steppe Salinization Index (SASSI), which is more suitable for soil salinization remote sensing monitoring in semi-arid steppe. The geodetector method was used to analyze the driving forces of the temporal-spatial changes of soil salinization. The results indicated that: (1) SASSI presented a high correlation with soil surface salt content ($R^2 = 0.7698$), and made full use of multi-dimensional remote sensing information. SASSI can reflect the salinization status of surface soil. The indicator calculation was simple and easy to obtain, which was conducive to the quantitative analysis and monitoring of salinization. (2) The driving factors affecting the spatial distribution and change of soil salinization were water, surface mines, town, agriculture, industry, road network, and elevation. The salinized areas were mainly distributed around the wetlands of the Xilin River Basin, mining landscapes, and town landscapes. (3) The total area of salinized soil in the study area increased from 32.03 km^2 in 2002 to 150.46 km^2 in 2017. The area of salinized soil increased rapidly from 2005 to 2014, but the growth rate slowed down after 2014. The salinized soil was mainly located in the salt marsh wetland in 2002, however had spread to the whole study area in 2017. This study provides references for remote sensing monitoring of soil salinization and the impact of land use, topography and other natural factors on soil salinization in the semi-arid steppe.

INDEX TERMS SI-Brightness feature space, semi-arid steppe, soil salinization, remote sensing monitoring, drivers analysis.

I. INTRODUCTION

Soil salinization is a phenomenon of land degradation caused by the interaction of many factors, such as the unreasonable development and utilization of natural resources, the fragile ecological environment, and the aggravation of climate change. It is an increasingly serious global problem. According to the mapping of global soil salinization by Ivushkin *et al.* [1] (Figure 1), the total area of land affected by salt in more than 100 countries and regions of the

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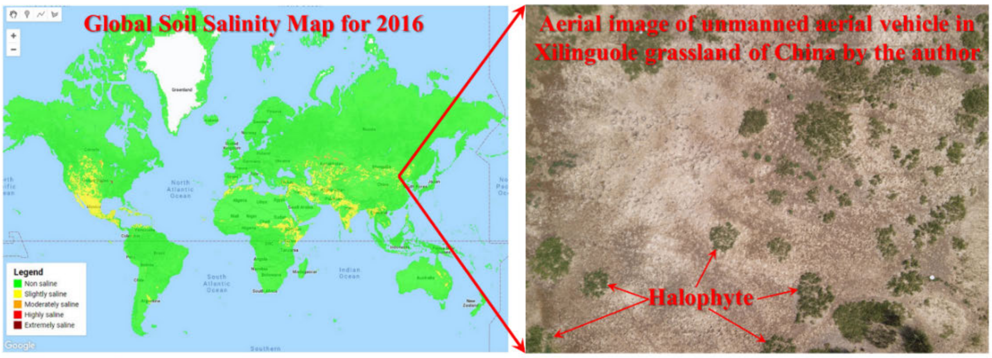


FIGURE 1. Global soil salinity map for 2016[1] and a UAV aerial image in Xilinguole grassland of China by the author for 2017.

world was about 1 billion hectares, and the average annual increase rate of soil salinization was about 200 Mha from 1986 to 2016 [2]. More and more previously unaffected areas begin to suffer from soil salinization. In arid and semi-arid regions (more than 75% of the world's residents), soil salinization is particularly serious due to the lack of rainfall, high intensity of water evaporation, high groundwater level, and high water-soluble salt content [3]. About 30% of the land in arid and semi-arid regions is affected by soil salinization. An effective prediction showed that by 2050, more than 50% of the world's arable land will become saline soil [4]. The total area of salinized soil in China is about 3.6×10^7 hectares, accounting for 4.88% of the total available land and 15% of the irrigated land in the country. Due to the seriousness of the problem, countries all over the world have incorporated soil salinization into their future development plans, which has become an important part of the global climate change research framework [5].

Soil salinity has high temporal-spatial variability. Therefore, it is very important to monitor and study the driving factors in large-scale and real-time in order to avoid the serious social and economic consequences of extreme environment, especially in semi-arid grasslands with large areas and sparsely population [6], [7]. Traditional soil salinization monitoring adopts fixed-point field survey, which is not only time-consuming and laborious but also highly destructive, with few measuring points and poor representativeness. It cannot meet the requirements of quickly, inexpensively, and dynamically obtaining large-area salinized soil salinity information. At present, remote sensing is the only way to monitor soil salinization in large-scale and long-term [8]. The quantitative inversion of remote sensing data is based on the relationship between the spectral information of remote sensing image pixels and the corresponding ground target information [9]. It is an advanced method of quantitative remote sensing monitoring research to use all kinds of indicators extracted from multispectral remote sensing images to construct feature space for surface information extraction and dynamic monitoring [10]. Selecting suitable feature parameters to establish feature space so as to improve the accuracy of quantitative remote sensing monitoring is an innovative hot topic in current research [11]. The feature space method has been widely used in remote sensing quantitative monitoring due to its advantages of simplicity, convenience, and high precision. Not only soil salinization remote sensing monitoring [12], feature space method has been widely used in desertification remote sensing monitoring [13], [14], drought remote sensing monitoring [15], [16], remote sensing monitoring of soil dryness and wetness [17], heavy metal stress [18], crop moisture [19], cultivated land fertility [20], surface evapotranspiration [21], soil moisture retrieval [22], [23] and many other remote sensing quantitative monitoring fields.

Semi-arid grassland areas are short of water resources, low environmental carrying capacity, and ecologically fragile. Driven by both natural and human factors, semi-arid grassland areas continue to degrade. The research on the driving forces of soil salinization in semi-arid grassland areas aims to reveal the real motivation behind soil salinization and its mechanism from a typical regional perspective. Strengthen the research on the driving force and driving mechanism of soil salinization, accurately identify the driving factors that lead to soil salinization, and understanding the internal relationship among factors are of practical significance for the rational management of salinized land, the adjustment of land use structure, the protection of grassland, the formulation of regulatory policies and measures, the rational layout of economic development, and the promotion of sustainable utilization of grassland resources. Eswar *et al.* [24] mainly studied the impact of climate change on the driving force of soil salinity. Masoud *et al.* [25] taking the desert oasis in Egypt as an example, presented that soil salinity was greatly affected by slope, surface temperature, top layer thickness, groundwater depth, and elevation. Su *et al.* [26] took a coastal city of China as an example, and concluded that groundwater depth and salt concentration are the main factors driving soil salinization in the study area. Zhang *et al.* [27] took Xinjiang, China as an example, and the research showed that the change of soil salt was mainly affected by human factors on a small scale, such as irrigation and land use, while natural factors including groundwater, topography and climate mainly affect the change of soil salt on a large

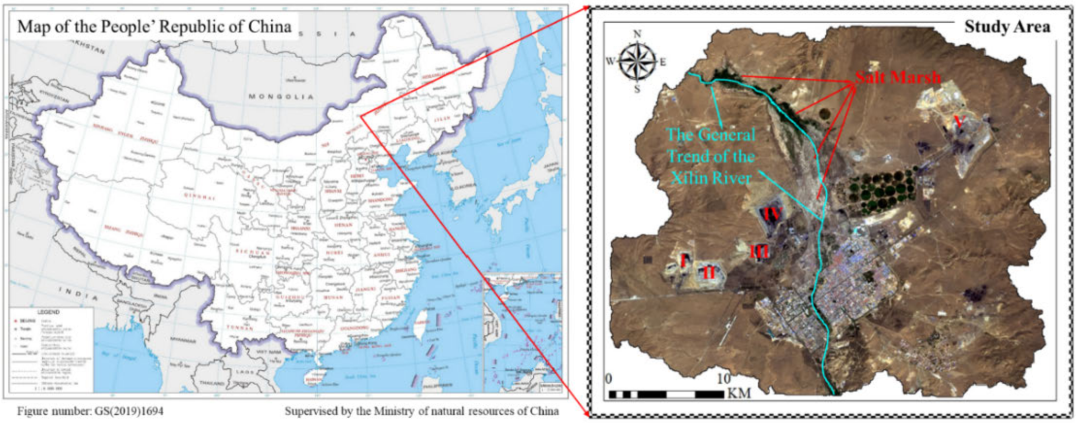


FIGURE 2. Location of the Research Area. I: Surface Germanium Mine; II: West No. 2 Surface Mine; III: West No. 3 Surface Mine; IV: No. 1 Surface Mine; and V: East No. 2 Surface Mine.

temporal-spatial scale. However, the driving theory of soil salinization is complex, and difficult to be accurately and quantitatively identified [26], especially in ''mine-town-agriculture-pastureland-industry (It means that mining, town, agriculture, pastureland and industry coexist.)'' interlaced ecologically fragile area. Geodetector is an effective method to quantitatively analyze the driving forces and influencing factors of various phenomena and the interaction of multiple factors. It does not need too many assumptions and overcomes the limitations of traditional methods in dealing with category traversal [28]. As a sensitive area of climate change and an increasingly active area of human disturbance, it is of great significance to study remote sensing monitoring and driving force of soil salinization in semi-arid grassland [29]. Thus, this paper aims to: (1) construct remote sensing monitoring model of soil salinization based on SI-Brightness feature space; (2) analyze the driving forces of soil salinization in semi-arid grasslands based on the geodetector.

II. MATERIALS AND METHODS

A. STUDY AREA

The study area is located in Xilinhot City (county-level city), Xilinguole League, Inner Mongolia Autonomous Region, China (Figure 2), which is the core area of the northern sand control belt of two screens and three belts of China's ecological security. According to the ''National sustainable development plan for resource-based cities (2013-2020) of China'', Xilinhot is a growing resource-based city. The altitude is 970∼1202 m. The total area of the study area is 1021.38km^2. It is located in the westerly flow belt of mid-latitude and belongs to the semi-arid continental climate of the mid-temperate zone. The extreme maximum temperature over the years is 38.3 °C, the minimum temperature is −42.4 °C, and the average temperature is 1.7 °C. The annual average rainfall is 294.74 mm, the annual average potential evaporation is 1794.64 mm, the potential evaporation is far more than the precipitation, and the soil salinization is serious. The Xilin River, the only river in the study area, has now become a seasonal river [14]. A large number of salt marshes are distributed in Xilin River Basin.

B. DATA AND PREPROCESSING

Six Landsat images (2002/07/08, 2005/08/17, 2008/07/08, 2011/08/02, 2014/07/25, 2017/07/17) were used. The data type before 2013 is Landsat TM, and the data type after 2013 is Landsat OLI (Operational Land Imager). The row number is 124/029. With the help of ENVI software, radiometric correction, FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) atmospheric correction, image registration, and clipping were carried out. The NDVI (Normalized Difference Vegetation Index) [30], Albedo [31], MSAVI (Modified Soil Adjusted Vegetation Index) [32], SI (Salinity Index) [33], SMI (Salinization Monitoring Index) [34], and BCI (Biophysical Composition Index) [35] were calculated by using bands of Landsat. Three indicators of Brightness (BI), Greenness (GVI), and Wetness (WI) in the tasseled cap transformation [36] were calculated. The landscape classification map adopted existing results [37].

C. SI-BRIGHTNESS FEATURE SPACE ANALYSIS

Khan and Sato [33] found that the red band of the Landsat image has sensitive response characteristics to soil salinity. By comparing the spectral characteristics of typical ground objects and band mixing test analysis, it is found that the SI determined by the red and blue bands of remote sensing images can better reflect the soil salinization. The Brightness component in tassel cap transform [36] reflects the difference in soil salinization degree. The more serious the soil salinization degree is, the higher the reflectivity is, and the greater the brightness is.

The one-dimensional space of SI and Brightness has a good correlation with salinization. In order to further study the distribution of different land types in the SI-Brightness two-dimensional space, this paper divides the SI-Brightness two-dimensional space into four parts: high vegetation coverage area, impervious surface, salinization area, and other types.

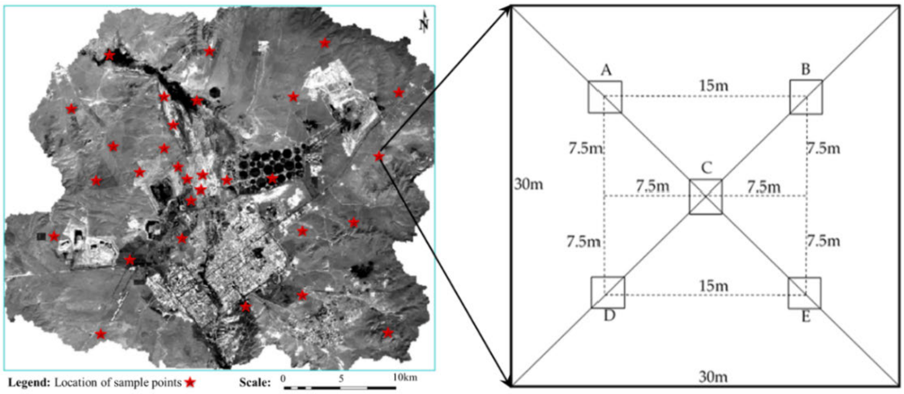


FIGURE 3. Spatial distribution of sample plots and layout of quadrat.

SMI was used to extract salinized soil. BCI combined with visual interpretation was used to extract impervious surface. NDVI was used to extract high vegetation coverage areas.

D. COLLECTION OF SOIL SAMPLES

In order to verify the authenticity and reliability of the remote sensing monitoring model of semi-arid steppe soil salinization, soil samples were collected in July and August 2017. The distribution of sample points is shown in Figure 3 (a). There were 30 sample points. The galaxy-1 RTK measurement system was used for positioning during sampling. The sampling depth was 0∼20 cm with a soil drill. Considering the matching with Landsat image, the sample square size was 30 m∗30 m [Figure 3 (b)]. Each sample was composed of the center sample and the surrounding four sub-samples.

E. GEODETECTOR

Soil salinization is mainly affected by natural and human factors. Since the study area is relatively small, the differences in natural driving factors such as climate change are small. At the same time, the study area is located on the border of northern China, which is a typical Mongolian settlement area. The population growth is extremely slow, cultural concepts are very similar, and changes in many aspects such as technology and economy are relatively slow. Therefore, according to the characteristics of the study area and the conclusions of the previous study [27], this study chose elevation, slope, aspect, and distance to the nearest water landscape as natural driving factors, and chose the distance to the nearest mining landscape, the distance to the nearest town landscape, the distance to the nearest industrial landscape, the distance to the nearest agricultural landscape, and the distance to the nearest road network landscape as humanistic driving factors [37]. The drivers were analyzed by the geodetector method [38].

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{1}$$

where $h = 1, \ldots,$ L represents the stratification of variable Y or factor X; N_h and N represent the unit numbers of layer h and the whole region, respectively; σ_h^2 and σ^2 represents the variances of Y values of layer h and the whole region, respectively; q represents the size of the drivers, and the range of q is [0,1].

III. RESULTS

A. REMOTE SENSING MONITORING OF SOIL SALINIZATION BASED ON SI-BRIGHTNESS FEATURE SPACE ANALYSIS

1) SI-BRIGHTNESS TWO-DIMENSIONAL FEATURE SPACE DISTRIBUTION

In this study, SI was used as abscissa to represent the change of surface salinity, and Brightness was used as ordinate to represent the change of surface Albedo. SI-Brightness two-dimensional spatial scatter diagrams were constructed (Figure 4). As can be seen from Figure 4, the correlations between SI and Brightness over the years were higher than 0.77, and the scatter diagrams showed a typical trapezoidal strip distribution. From the results of SI-Brightness two-dimensional spatial classification (Figure 5), it can be seen that the distribution of different surface cover types in SI-Brightness two-dimensional space showed distinct variation patterns. SI-Brightness two-dimensional space can distinguish different types of surface cover very well. Figure 5 (a) can be visualized as Figure 5 (b). The classification accuracy and kappa coefficient were 93.36% and 0.92, respectively.

2) THE CONSTRUCTION OF A REMOTE SENSING MONITORING MODEL FOR SOIL SALINIZATION

It can be seen from the SI-Brightness feature space that as the Brightness and the SI value increase, the surface vegetation coverage decreased, the surface energy and water balance changed, resulting in the decrease of soil moisture, the increase of surface albedo, and soil salinity, and the surface gradually developed into a bare soil type with no vegetation coverage and heavy salinization degree (Figure 1). The line A-B in Figure 4 and Figure 5 (b) was the slope of SI-Brightness two-dimensional space. Through the spatial statistical characteristics, the expression of slope A-B

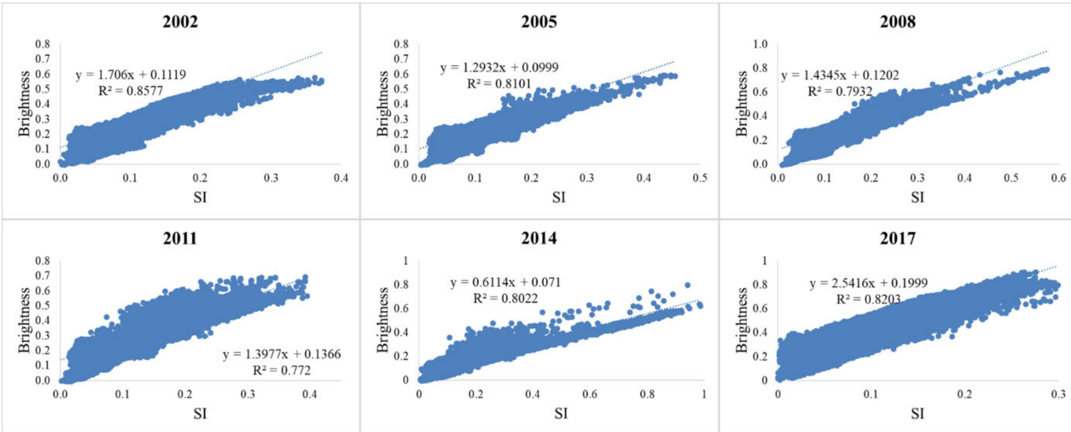
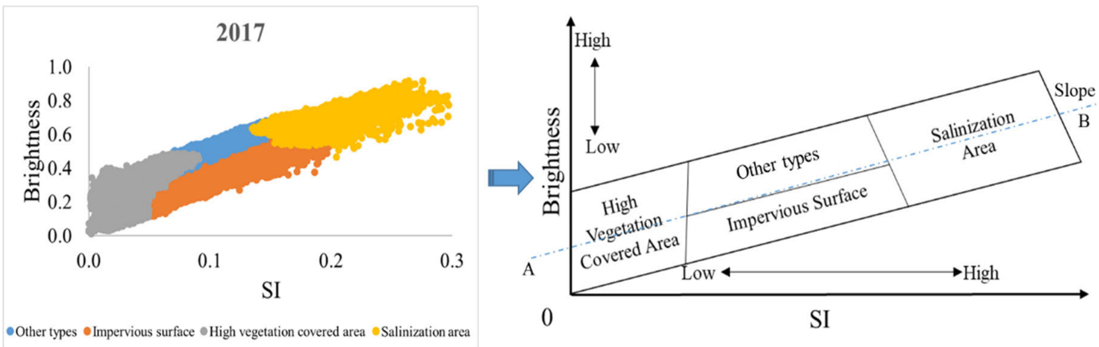


FIGURE 4. SI-Brightness two-dimensional spatial scatter diagrams.



(a) (b)

FIGURE 5. Distribution of different land types in SI-Brightness two-dimensional space.

(equation 2) can be obtained, and the degree of soil salinization gradually increases from A to B (Figure 5). For remote sensing monitoring of soil salinization, it is more convenient to use a comprehensive spectral index than two separate variables. In other words, in order to realize the quantitative monitoring and investigation of the temporal-spatial distribution and dynamic changes of salinization, the feature space constructed by combining the information of salinity index and brightness index can be used as a reasonable index to reflect the degree of salinization and can distinguish different degrees of salinized land [39]. According to the research conclusion of Verstraete and Pinty [40], employing the vertical line of A-B line to segment SI-Brightness feature space can effectively separate non-salinized land, salinized land, and salinized land of different degrees, so as to construct the Semi-Arid Steppe Salinization Index (SASSI) (Equation 3). SASSI was a new index constructed in this study. According to formula 3, the spatial distribution maps of remote sensing monitoring of semi-arid grassland salinization in 2002, 2005, 2008, 2011, 2014, and 2017 were calculated (Figure 6).

$$Brightness = a \times SI + b \tag{2}$$

$$SASSI = SI + a \times Brightness \tag{3}$$

where *SASSI* is the Semi-Arid Steppe Salinization Index. *Brightness* is the brightness value in tassel cap transformation. *SI* is the salt index. *a* is the slope of the SI-Brightness two-dimensional space. *b* is the intercept of the slope of SI-Brightness two-dimensional space on the ordinate.

3) VALIDATION OF REMOTE SENSING MONITORING MODEL FOR SOIL SALINIZATION

In order to verify the effectiveness of SASSI, field soil samples were collected, tested, and analyzed in late July 2017. The results were compared with the SASSI extracted from Landsat data in 2017. The results showed that the SASSI model had a high correlation with soil surface salt content ($R^2 = 0.7698$). SASSI had good applicability in this study area and had a strict positive correlation with soil salinity (Figure 7).

B. DRIVING FORCE ANALYSIS OF SOIL SALINIZATION BASED ON GEODETECTOR

It can be seen from Table 1 that the *q* values of the distance to the nearest water landscape, the distance to the nearest mining landscape, the distance to the nearest town landscape, the distance to the nearest agricultural landscape, and the distance to the nearest industrial landscape in six years all

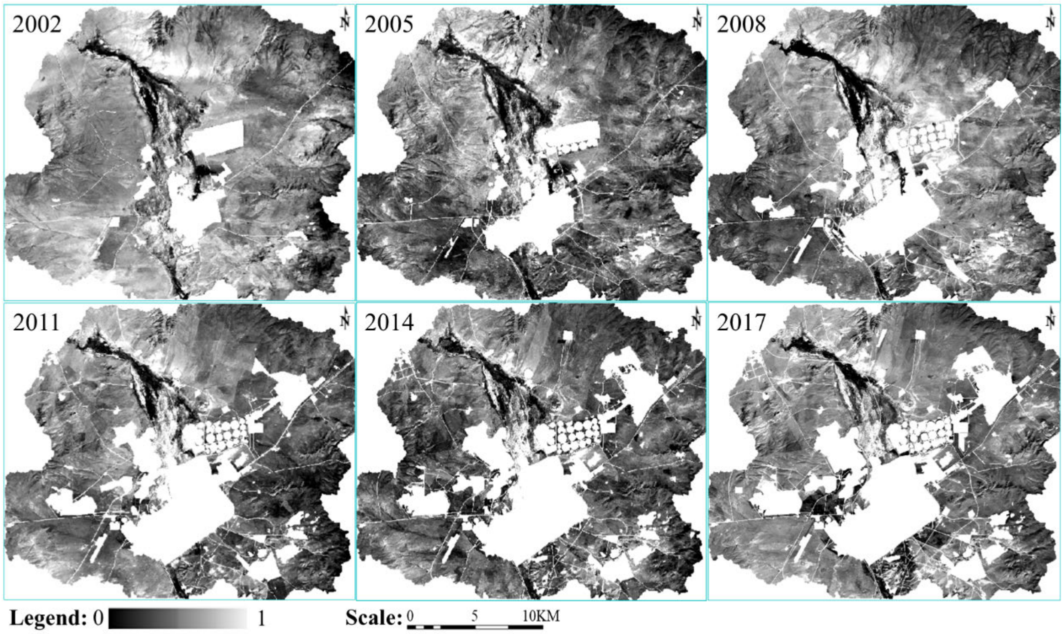


FIGURE 6. Soil salinization remote sensing monitoring spatial distribution map of grassland.

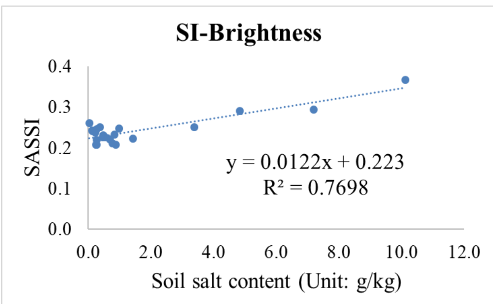


FIGURE 7. Analysis of correlation between SASSI and soil salinity in 2017.

exceeded 0.7, indicating that these five factors had a strong driving effect on the spatial distribution and change of soil salinization. Combined with Figures 6 and 9, it can be found that salinization areas were mainly distributed in the wetland of Xilin River Basin and the surrounding areas of mining landscape and urban landscape. The q values of the distance to the nearest road network landscape were between 0.7722 and 0.4124, which indicated that the driving effect of the distance to the nearest road network landscape on the spatial distribution and change of soil salinization in the study area was also obvious. The q values of elevation over the years were between 0.1739 and 0.2669, which indicated that the driving effect of elevation on the spatial distribution and change of soil salinization in the study area was light, but there was also a certain driving effect. Through field investigation, we found that the soil salinization in wetlands and other catchment areas were relatively serious, and a large area of salt marsh wetland has been formed (Figures 1 and 2). The q values of slope and aspect over the years were less than 0.012, indicating that these two driving factors had no significant driving effect on the spatial distribution and change of soil salinization in the study area. In summary, from the average q values over the years, the driving factors affecting the spatial distribution and changes of grassland soil salinization in the study area were water, surface mines, town, agriculture, industry, road network, and elevation.

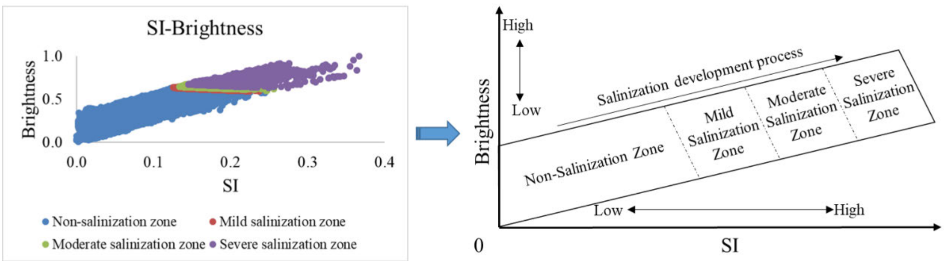
IV. DISCUSSION

A. DEVELOPMENT PROCESS OF SOIL SALINIZATION

In order to further study the relationship between SASSI, SI-brightness two-dimensional space, and the development process of salinization, according to SASSI value from high to low, SI-brightness two-dimensional space was divided into four parts: severe salinization zone, moderate salinization zone, mild salinization zone, and non-salinization zone. According to the national standard of the People's Republic of China ''Classification standard for degradation, desertification, and salinization of natural grassland (GB 19377-2003)'', combined with SI-Brightness feature space, the SASSI values of different salinized soils were determined: non-salinization (<0.4), mild salinization (0.4∼0.44), moderate salinization (0.44∼0.51), and severe salinization (0.51). It can be seen from Figure 8 (a) that the development process of salinization can be directly reflected in the two-dimensional space of SI-Brightness. With the increase of SASSI value, the degree of salinization became more and more serious, and the two-dimensional space of SI-Brightness was closer to point B in its slope A-B. The distribution of severe salinization zone was more dispersed, and the distribution of moderate salinization zone and mild

TABLE 1. ***q*** **values of driving factors of soil salinization in the study area over the years.**

Type	WATER	MINE	TOWN	AGRI	INDU	ROAD	ELEV	Aspect	Slope
2002	0.9806	0.9610	0.9306	0.8963	0.9398	0.7722	0.2669	0.0042	0.0040
2005	0.9678	0.9544	0.9212	0.9164	0.9631	0.7398	0.1747	0.0096	0.0070
2008	0.9651	0.9174	0.9169	0.9164	0.8572	0.7288	0.2378	0.0049	0.0071
2011	0.9702	0.9252	0.9082	0.8849	0.8105	0.4896	0.2384	0.0116	0.0090
2014	0.9147	0.8968	0.8933	0.8832	0.7891	0.4569	0.2060	0.0050	0.0090
2017	0.9483	0.9053	0.8617	0.8853	0.7072	0.4124	0.1739	0.0079	0.0066
Mean	0.9578	0.9267	0.9053	0.8971	0.8445	0.6000	0.2163	0.0072	0.0071



(a) (b)

FIGURE 8. **Schematic diagram of the salinization development process of SI-Brightness feature space based on SASSI.**

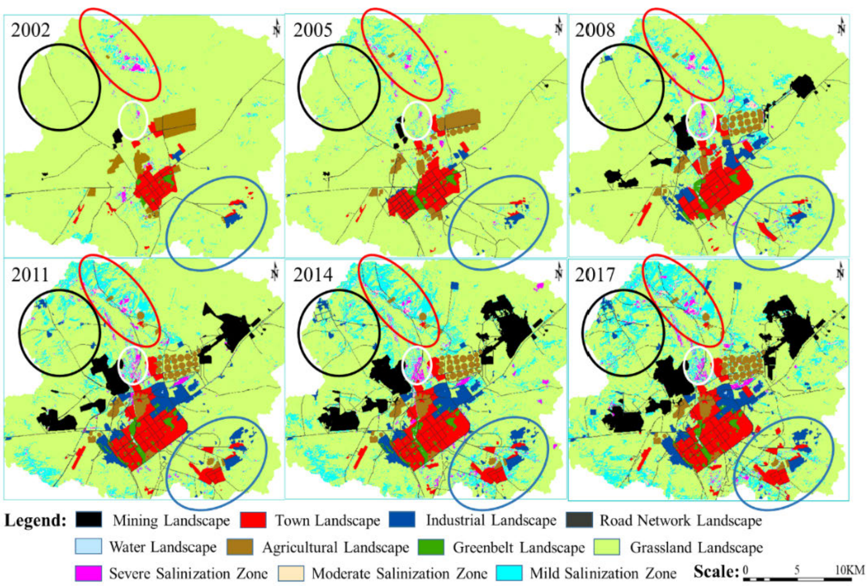


FIGURE 9. **Schematic diagram of the salinization development process of SI-Brightness feature space based on SASSI.**

salinization zone were closer. Figure 8 (a) can be visualized as Figure 8 (b). Therefore, the SASSI model constructed in this study can reflect the development process of salinization in the semi-arid steppe. This model is defined as the Semi-Arid Steppe Salinization Index (SASSI).

According to the development process of soil salinization, combined with landscape ecological classification map [37] and Figure 6, we made the spatiotemporal evolution map of soil salinization (Figure 9) and calculated the area of soil salinization of each grade from 2002 to 2017 (Figure 10). It can be seen from Figure 9 and Figure 10 that the total area of soil salinization increased year by year from 32.03 km^2 in 2002 to 150.46 km^2 in 2017. From 2005 to 2014, the area of salinized soil increased rapidly, and the growth rate

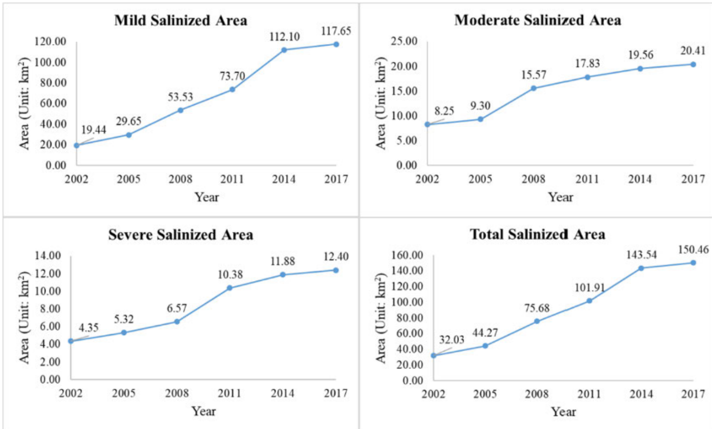


FIGURE 10. Schematic diagram of the salinization development process of SI-Brightness feature space based on SASSI.

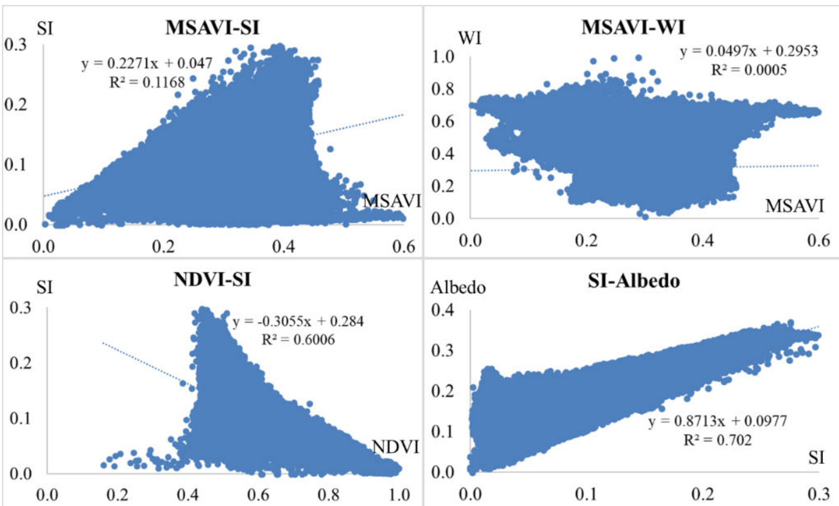


FIGURE 11. Two-dimensional spatial scatter plots of four commonly used salinization indices.

slowed down after 2014. At the same time, from 2005 to 2014, urban expansion, coal development, and road construction were also strengthened. From the perspective of the spatial distribution of soil salinization, the salinized soil in 2002 was mainly located in the salt marsh wetland (red circle), and in 2017, the salinized soil has spread to the whole study area. The soil salinization around the wetland of the Xilin River Basin (red circle) in the north of the study area has been the most serious over the years, and it has become more serious year by year. In the northwest corner (black circle) and southeast corner (blue circle) of the study area, under the influence of human disturbance such as industrial development, the salinized soil has never developed to exist, and it has gradually become more serious. Under the influence of coal and oil exploitation, the area of salinized soil in the central area of the study area (white circle) increased year by year. Severe and moderate salinization was mainly distributed in salt marsh wetland, while mild salinization was mainly distributed around urban landscape, mining landscape, industrial landscape, and road landscape.

B. COMPARISON BETWEEN SASSI AND OTHER SALINIZATION INDEXES

Wang *et al.* [41] proposed the concept of NDVI-SI feature space and established the Salinization Detection Index model [42]. Ding *et al.* [11] proposed the concept of MSAVI-WI feature space and established a soil salinity monitoring index MWI. Zhang *et al.* [43] proposed the concept of MSAVI-SI feature space and established a soil salinity monitoring model MSI. Ha *et al.* [34] proposed the concept of SI-Albedo feature space and established the Salinization Monitoring Index (SMI) model. In order to further verify the good applicability of the SASSI model in semi-arid grassland salinization remote sensing monitoring, four commonly used salinization remote sensing monitoring indexes were selected and compared with SASSI. It can be seen from Figure 11 that the correlation between MSAVI-WI and MSAVI-SI was extremely low, and the applicability in this study area is poor. R^2 of NDVI-SI and R^2 of SI-Albedo were 0.6 and 0.702, respectively, indicating that SDI and SMI can be used in this study area. It can be seen from Figure 12 that

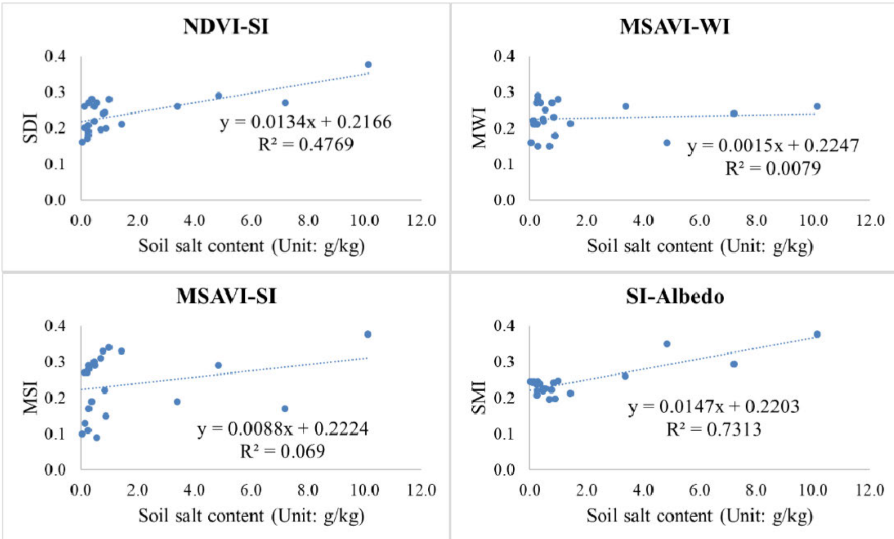


FIGURE 12. Correlation analysis between four commonly used salinization indexes and soil salinization.

the correlation between soil salt content and MWI and MSI extracted from Landsat data was lower than 0.1, which further confirms the conclusion of Figure 11. The correlation of soil salt content with SDI and SMI extracted from Landsat data were 0.4769 and 0.7313, respectively. According to the conclusion in Figure 6, SMI has good applicability in this study area. Combined with Figures 4, 5, 7, 11, and 12, the SASSI model constructed in this study is more suitable for remote sensing monitoring of salinization in this study area. The Brightness used in the SASSI model and the Albedo used in the SMI model both represent the surface albedo. Therefore, the two-dimensional feature space constructed by the surface albedo and the salinity index is very suitable for remote sensing monitoring of salinization in semi-arid grasslands.

C. DRIVING FORCE ANALYSIS OF SURFACE MINING ON SOIL SALINIZATION

Soil salinization is a complex natural phenomenon under the impact of a large number of natural and human factors [7], [44]. In terms of natural factors, Xilinguole grassland is one of the four natural grasslands in China. It is a typical semi-arid grassland with a continental climate. The precipitation is small and the potential evaporation is large. The salt dissolved in water is very easy to accumulate on the surface. In spring, the soil surface water evaporates violently, and the capillary water rises, which makes the salt in groundwater collect on the surface. In summer, it is the rainy season in the study area, the rainfall is very concentrated, and a large number of soluble salt seeps into the ground or flows away with the water. The terrain causes the water to carry water-soluble salts from high to low and collect in low-lying areas. Therefore, it is easy to form salt marsh wetlands in semi-arid grasslands (Figures 1, 2, and 9).

In terms of human factors, land use type (or landscape type) directly reflects the way and intensity of human use of land. Numerous studies have shown that land use has different relationships with soil salinization [26], [45], [46]. The unreasonable irrigation of the agricultural landscape will destroy the original water-salt balance. If the irrigation water is greater than the discharge water, the groundwater level will rise to the critical depth, and the secondary salinization of soil may be severe. The unreasonable use of groundwater and wastewater discharge in urban life and industrial production are also driving factors that cause the soil salinization around town landscapes and industrial landscapes. This study focused on the analysis of the driving force of surface mining on soil salinization.

Xilinhot City is located in the hinterland of Xilinguole grassland. It is a typical mining city where many kinds of mineral resources such as coal, oil, and heavy metals are developed at the same time. The contradiction among human, land, and the ecological environment is serious. The Shengli Coalfield in Xilinhot City is close to the northern suburb of the city. It is the lignite coalfield with the thickest coal seam and the largest reserves in China. Among them, the germanium-containing lignite contains 3226 tons of germanium metal reserves, accounting for 65% of the domestic proven germanium metal reserves, and 38% of the world's proven germanium metal reserves. It is one of China's 14 large-scale coal bases and 16 large-scale coal power bases.

The original landform of semi-arid grassland is flat, and a large number of open-pits and dumps are formed after surface mining. The change of terrain is the most direct and serious impact of surface mining on semi-arid grassland, and further affects the transmission of ecological flow. Surface coal mining drains groundwater, causing the phreatic aquifer in the grassland mining area and surrounding areas to be gradually drained. Groundwater replenishment, runoff, and drainage conditions have also changed, and the groundwater level has dropped, resulting in a decrease in surface river runoff, surface water loss, water conservation, and regulation capabilities, wetlands gradually shrinking, biomass declines, and grasslands gradually degradation in semi-arid grasslands. The critical water level (The critical water level is the groundwater level that can cause soil salinization and damage to the root system of vegetation) of the soil will gradually decrease, and the height difference between the critical water level and the phreatic level will gradually decrease. When the groundwater level is equal to or higher than the critical water level of surface soil, soil salinization will occur.

Most of the accumulated soil in the dump is mudstone, parent material, and other mixed-layer loose materials. The roughness of the ground is large, the corrosion resistance is small, and the vegetation recovery is slow. As a result, the soil and water loss of the dump slope and platform are serious [47]. Salts containing Ca, Mg, K, Na, etc. are leached out, dissolved in surface and underground runoff, and then collected in plains and low-lying areas, and finally, through evaporation, the soil is salinized. According to the survey, the closer to the dump, the higher the salt content, up to more than 0.7%, and the salt composition is mainly bicarbonate. Besides, the accumulation pressure of the dump increases the groundwater level and the mineralization of groundwater [48].

Large-scale coal power bases will produce a large amount of fly ash. Because fly ash has a high Ca^{2+} supply capacity, it is an amendment for reclaiming sodium salt soil [49]. Mishra *et al.* [50] research showed that when fly ash is used in combination with gypsum and green manure, it has the effect of reclaiming saline soil. This method is adapted to local conditions, can not only solve the problem of soil salinization but also help to deal with the waste fly ash, which can be considered to be popularized in the coal power base of soil salinization.

D. LIMITATIONS AND UNCERTAINTIES

1) REMOTE SENSING MONITORING OF SOIL SALINIZATION

There are great differences in soil salinization among countries and regions in the world. The generation mechanism, manifestation, and type of soil salinization are also different. The applicability of the SASSI model in various countries and regions and the applicability of different research scales also require a large amount of data for empirical research. Through comparative experiments, some scholars found that the Landsat remote sensing index model constructed by three-dimensional feature space has higher quantitative information extraction accuracy than two-dimensional feature space [10], [51]. However, there is no comprehensive analysis from the perspective of theoretical principles. Therefore, the authors think that it will be an important development direction of quantitative remote sensing to build a remote sensing quantitative monitoring model based on multi-dimensional feature space and deeply analyze the theory of multi-dimensional feature space. At the same time, due to the different composition and content of soluble salt in salinized soil, in order to carry out more in-depth remote sensing monitoring research on soil salinization, a spectral database of salinized soil should be established [51]. Through theoretical research and field investigation, it is found that all kinds of salinization monitoring indexes constructed by multispectral remote sensing images are only suitable for the extraction of soil salinization information in bare land or low vegetation coverage areas, but not suitable for the areas with dense halophytes. In the future, this problem should be further studied.

2) DRIVING FORCES OF SOIL SALINIZATION

Existing studies show that there are many factors affecting soil salinization, including rainfall, temperature, humidity, pH, evaporation, vegetation cover, groundwater, soil properties (physical, chemical, and biological), agricultural irrigation, grazing, economic development, policy-making, and so on [5]. This study mainly calculated the driving force of landscape types (or land-use types) and topography on soil salinization and focused on the analysis of the impact of surface mining on soil salinization. Future research should combine a variety of remote sensing monitoring methods, ground surveys and sampling to conduct in-depth research on the driving force of soil salinization.

3) SCALE AND VERIFICATION

In this paper, we mainly focused on the single scale, however, the scale effect will lead to the change of system characteristics when the spatial-temporal scale changes. Therefore, we need to carry out multi-scale remote sensing monitoring research and drivers analysis of soil salinization in the future.

The authors' vision is that the soil salinization remote sensing monitoring method proposed by this research has a wide range of applicability. Although the Shengli Coalfield in Xilinhot City is typical in semi-arid grassland areas, the geographical and ecological conditions of the world are very different. Therefore, the theories and methods in this study need more cases to verify. At the same time, a large number of case studies can make the theory and method more perfect.

V. CONCLUSION

Based on the theory of feature space, using Landsat image and field survey data, studying spectral characteristics and many spectral indices of Landsat image in depth, constructing SI-Brightness feature space by selecting SI and cap transform Brightness index, this paper proposed a new spectral index, Semi-Arid Steppe Salinization Index (SASSI), which is simple, accurate and more suitable for semi-arid steppe. The results showed that there was a significant correlation between SI and Brightness, and the two-dimensional scatter plots showed a typical trapezoidal strip distribution. The comprehensive information of SI-Brightness feature space can be applied to salinization monitoring and analysis. The SASSI model constructed in this study can reflect the development process of salinization in the semi-arid steppe.

The SASSI model has a high correlation ($R^2 = 0.7698$) with the salt content on the soil surface and makes full use of multi-dimensional remote sensing information. Based on the method of geodetector, this study chose elevation, slope, aspect, and distance to the nearest water landscape as natural driving factors, and chose the distance to the nearest mining landscape, the distance to the nearest town landscape, the distance to the nearest industrial landscape, the distance to the nearest agricultural landscape, and the distance to the nearest road network landscape as humanistic driving factors. The results showed that the driving factors affecting the spatial distribution and changes of grassland soil salinization in the study area were water, surface mines, town, agriculture, industry, road network, and elevation. Salinization areas mainly distributed in the wetland of Xilin River Basin and the surrounding areas of mining landscape and urban landscape. The total area of saline soil in the study area increased from 32.03 km^2 in 2002 to 150.46 km^2 in 2017. From 2005 to 2014, the area of salinized soil increased rapidly, and the growth rate slowed down after 2014. In 2002, the salinized soil was mainly located in the salt marsh wetland. In 2017, the salinized soil has spread to the whole study area.

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