Detection model of soil salinization information in the Yellow River Delta based on feature space models with typical surface parameters derived from Landsat8 OLI image

Bing Guo, Wenqian Zang, Wei Luo, Ye Wen, Fei Yang, Baomin Han, Yewen Fan, Xi Chen, Zhen Qi, Zhen Wang, Shuting Chen & Xiao Yang

To cite this article: Bing Guo, Wenqian Zang, Wei Luo, Ye Wen, Fei Yang, Baomin Han, Yewen Fan, Xi Chen, Zhen Qi, Zhen Wang, Shuting Chen & Xiao Yang (2020) Detection model of soil salinization information in the Yellow River Delta based on feature space models with typical surface parameters derived from Landsat8 OLI image, Geomatics, Natural Hazards and Risk, 11:1, 288-300, DOI: 10.1080/19475705.2020.1721573

To link to this article: https://doi.org/10.1080/19475705.2020.1721573

© 2020 The Author(s). Published by Informa UK, Limited trading as Taylor & Francis Group

Published online: 06 Feb 2020.

Submit your article to this journal

View related articles

Citing articles: 1 View citing articles

Article views: 111

View Crossmark data
Detection model of soil salinization information in the Yellow River Delta based on feature space models with typical surface parameters derived from Landsat8 OLI image

Bing Guo^a,b,c,d, Wenqian Zang^e, Wei Luo^f, Ye Wen^g, Fei Yang^h, Baomin Han^a, Yewen Fan^c, Xi Chen^a, Zhen Qi^a, Zhen Wang^a, Shuting Chen^a and Xiao Yang^a

^aSchool of Civil Architectural Engineering, Shandong University of Technology, Zibo, China; ^bKey Laboratory of Geomatics and Digital Technology of Shandong Province, Qingdao, China; ^cState Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China; ^dKey Laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China; ^eAerospace Information Research Institute, Chinese Academy of Sciences, Beijing, China; ^fNorth China Institute of Aerospace Engineering, LangFang Hebei Province, China; ^gCollege of Land and Environment, Shenyang Agricultural University, Shenyang, China; ^hState Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research of Chinese Academy of Sciences, Beijing, China

ABSTRACT
The Yellow River Delta, with the most typical new wetland system in warm temperate zone of China, is suffering from increasingly serious salinization. The purpose of this study is to utilize five typical surface parameters, including Albedo (the surface Albedo), NDVI (vegetation index), SI (salinity index), WI (humidity index), and \( I_{Fe_2O_3} \) (iron oxide index), to construct 10 different feature spaces and, then, propose two different kinds of monitoring models (point-to-point model and point to line model) of soil salinization. The results showed that the inversion accuracy of the \( I_{Fe_2O_3} \) feature space detection index based on the point-to-point model was the highest with \( R^2 = 0.86 \). However, the inversion accuracy of Albedo-NDVI feature space detection index based on the point-to-point model is the lowest with \( R^2 = 0.72 \). This is due to the fact that NDVI is not sensitive enough to indicate the status of vegetation grown in the region with low (disturbance of soil background) and high (influenced by the saturation effect) vegetation coverage. The chemical weathering is also a primary cause of soil salinization, during which \( Fe_2O_3 \) is formed by the reaction of oxygen present in the atmosphere with primary \( Fe^{2+} \) minerals in the soil. Therefore, the Albedo–\( I_{Fe_2O_3} \) feature space detection index based on the point-to-point model has a stronger applicability to monitor the information of soil salinization in the Yellow River Delta. This above point-to-point detection model can be utilized as a better approach to provide data and decision support for the development of agriculture, construction of reservoirs, and protection of natural ecological system in the Yellow River Delta.

CONTACT Wenqian Zang 154520807@qq.com
© 2020 The Author(s). Published by Informa UK Limited trading as Taylor & Francis Group.
This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.
1. Introduction

At present times, soil salinization has emerged as a global environmental problem that critically threatens the ecological environment and damages the limited soil resources (Metternicht and Zinck 2003). Soil salinization often occurs in the zones with arid climate, strong evaporation, higher groundwater level, and salt content, or in the coastal areas that are affected by seawater erosion (Tajgardan et al. 2010; Wang et al. 2010; Ruhollah et al. 2016). Climate, topography, geomorphology, groundwater, halophytes, etc., are some of the factors that affect soil salinization. Soil salinization not only affects agricultural stability and sustainable development, but also is not conducive to land construction activities. So, it is necessary to dynamically monitor and analyze the information of it. Generally, human activities (the usage of poor quality irrigation water, intense application of fertilizers, and unreasonable cultivation methods) and natural factors (climate change, frequent agricultural drought events) are the two main driving factors affecting soil salinization (Bouaziz et al. 2011; Allbed and Kumar 2013). Therefore, scientific management and utilization of saline soil resources, improvement of land productivity, and enhancement of ecological protection, together, hold a considerable amount of significance to the environment (Wang et al. 2019).

Traditional soil salinization detection methods are suitable for field point observations or small-scale research works. However, it is difficult to dynamically obtain large-scale information about salinization. Since the 1960s, remote sensing technology has been widely used in the assessment of soil salinity due to its advantages such as high spatial-temporal resolution, fast data acquisition, large amount of information, low costs, and less restrictions by ground conditions (Solvia et al. 2007; Wang et al. 2010; Fallah Shamsi et al. 2013; Gorji et al. 2017). At present, there are two main methods to obtain salinization information based on remote sensing images, namely visual interpretation and automatic classification by considering auxiliary factors such as soil salinity and groundwater (Khan et al. 2005; Wu et al. 2006; Zeng et al. 2006; Alejandro and Kenji 2007; Allbed and Kumar 2013). During the past years, scholars at home and abroad have conducted quantitative research works on soil salinization utilizing different surface indices derived from the remote sensing images (Wang et al. 2002; ; Zhang et al. 2011; Yahiaoui et al. 2015; Zhang et al. 2006). The models of the feature space have been widely used in the detection of soil salinity, surface evapotranspiration, soil moisture, crop moisture content, desertification, and other information, and have obtained better results (Allbed and Kumar 2013). However, most research works are just based on the single feature space or only consider the linear relationship among surface parameters, which has ignored the applicability of feature space models.

Based on the above concerns, after the complete consideration of the vegetation coverage and types, the authors have utilized five typical surface parameters to construct 10 feature space detection indices based on two categories of models and, then, proposed the optimal soil salinization monitoring model for the Yellow River Delta.
2. Study areas and methods

2.1. Study areas

The Yellow River Delta is located in the estuary area of the Yellow River in Dongying, Shandong province, China, and it covers more than 6000 km² (Figure 1). The study area is dominated by the continental monsoon climate characterized by an average annual temperature of 12.1 °C and a ≥ 10 °C accumulated temperature of 4200 °C (Liu et al. 2016). In addition, the average annual precipitation is 500–600 mm, most of which occurs in the summer. However, due to the significant characteristics of seasonal dry and wet alternating, evaporation is far greater than rainfall, thereby leading to severe soil salinization (Guo et al. 2019a). The groundwater level is high and the degree of mineralization is 32.4 g/L. The salinized land accounts for more than 70% of the total area. Due to the low and flat terrains, the seawater erosion is critical for the environment. The groundwater table and soluble salt content are high, and the soil surface salt content is between 0.4% and 1.5% (Guo et al. 2019b). The mechanical composition of the soil is mainly composed of silt or muddy silt with interbedded sand and clay. The vegetation types mainly consist of Salix matsudana, Fraxinus chinensis, Phragmites australis, Imperata cylindrical, and Aeluropus littoralis.

2.2. Data collection and preprocessing

The path/row of Landsat8 OLI images (26 August 2016) is 121/34. The image quality is high with the total cloud cover of greater than 10% and the spatial resolution is
30 m. In order to remove the geometric distortion and the influence of atmospheric interference on the image quality, geometric and atmospheric corrections were carried out on the images through geometric correction and FLAASH models, respectively. In this study, 32 sampling sites were set and for each sampling site, five soil samples were taken from the corners and the mid-point of a 30-m square and then were mixed into one sample. All the soil samples were first air dried, and then crushed passed through a 2-mm mesh. The large debris, plant roots, and stones were removed by hand. The salt content of all soil samples was analyzed using the suspensions of 1:5 soils: water ratio. Finally, the soil salt content was measured following the method of Bao (2000).

2.3. Index selection of the remote sensing monitoring model

Surface albedo is the ratio of the solar radiation flux reflected from the land surface to the incoming solar radiation flux (Alejandro and Kenji 2007). With the aggravation of soil salinization, the coverage of non-saline-resistant vegetation on the soil surface decreases along with the decrease in moisture. The salinity in the soil will precipitate out of the soil surface, and the soil surface will have the apparent changes that will affect the albedo of the surface (Guo et al. 2019a). Vegetation index and surface reflectance, which can affect the vegetation growth and surface albedo, respectively, can be used as indirect indicators to measure the soil salinity (Gorji et al. 2017).

Humidity index is the third component of Landsat8 OLI images after Hat Transformation, which can reflects the humidity of soil in the study region (Hu et al. 2019). The Yellow River Delta is located in the coastal area, and there is a significant difference in humidity between the coastal and inland areas (Guo et al. 2019b). Salt in seawater is one of the primary sources of soil salinity. Soil humidity can be significantly affected by seawater, so there are higher chances for soil salinization to occur in the study area (Ha et al. 2009). Humidity index and salinity index determined by red reflectance and blue reflectance, respectively, can be used as important indices to monitor soil salinization (Khan et al. 2005). The process of soil salinization will not only affect the growth and types of vegetation in the salinized area, but also affect the composition and change of chemical substances contained in the soil. Iron oxide is the present in soil, and it is a crucial factor that affects the hyperspectral characteristics of the soil. Many absorption characteristics of soil in the visible band are caused by iron oxides, and the presence of iron oxides will lead to a decrease of the reflectivity of soil in the whole band range (Peng et al. 2013). Therefore, the iron oxide index of soil can be selected as an index to evaluate the degree of soil salinization.

The surface can be monitored by the imaging process of satellite remote sensing, in which the electromagnetic energy reflected by the target is used to obtain the information of soil salinization and also by combining the surface ecological environment of the Yellow River Delta and the relevant research works (Zeng et al. 2006; Ha et al. 2009; Guo et al. 2019b; Hu et al. 2019). The five typical remote sensing monitoring indices are calculated as follows:
Albedo = 0.356 × B + 0.130 × R + 0.373 × NIR + 0.085 × SWIR₁ + 0.072 × SWIR₂−0.0018

\[ \text{NDVI} = \frac{\text{NIR}−R}{\text{NIR}+R} \] (2)

\[ \text{SI} = \sqrt{B \times R} \] (3)

\[ \text{WI} = 0.1446 \times B + 0.1761 \times G + 0.3322 \times R + 0.3396 \times \text{NIR}−0.6210 \times \text{SWIR₁}−0.4186 \times \text{SWIR₂} \] (4)

\[ IFe₂O₃ = \frac{R}{\text{NIR}} \] (5)

where \( B, G, R, \) NIR, SWIR₁, and SWIR₂ refer to blue band, green band, red band, mid-infrared band, and near-infrared band, respectively.

2.4. Index standardization

In order to remove the difference of five typical surface parameters, the standardization of different indicators was conducted and calculated as follows:

\[ V_i = \frac{F_i−F_{i,\text{min}}}{F_{i,\text{max}}−F_{i,\text{min}}} \] (6)

where \( V_i \) is the normalized index \( i \); \( F_i \) is the indicator \( i \); \( F_{i,\text{min}} \) is the minimum value of indicator \( i \); and \( F_{i,\text{max}} \) is the maximum value of humidity index.

2.5. Models derived from feature space

Two categories of model based on the trajectory of soil salinization in the feature space have been proposed, including point-to-point model and point to the line model. The point-to-point model was constructed based on the distance formula that any point to a specific point in feature space. Then, the point to line model was developed according to the distance formula that any point to a specific line in feature space.

3. Experimental results and analysis

3.1. Construction of feature spaces

In order to reduce the effects of water and impervious surfaces on the extraction of soil salinization information, the regions with rivers, lakes, and artificial building were removed to improve the inversion accuracy of feature space model for soil salinization. Then, 10 feature spaces were constructed by utilizing five indexes including
surface albedo (Albedo), vegetation index (NDVI), salinity index (SI), humidity index (WI), and iron oxide index $I_{\text{Fe}_2\text{O}_3}$: As shown in Figure 2, the feature spaces derived from different surface parameters can be divided into two categories according to the shapes of the feature spaces and the spatial patterns of salinized soil at different levels in the feature space. The first category (point-to-point model) includes Figure 2(a, b, e–i) and the second category (point-to-line model) includes Figure 2(c, d, j). In this paper, Albedo-$I_{\text{Fe}_2\text{O}_3}$ and Albedo-SI feature spaces were selected to analyze the spatial distribution characteristics of each kind of feature space model, respectively.

### 3.2. Construction of the remote sensing detection model of salinization

Figure 3 shows that there are significant differences in the spatial distribution of soil salinization in the Albedo-$I_{\text{Fe}_2\text{O}_3}$ feature space. According to the distance to the point (0.8, 0), four-point clusters distributed in different regions in the study area were selected. The relationship between different levels of soil salinization and four-point clusters was obtained by analyzing 25 field measured samples of each point cluster. As shown in Figure 3, the red point clusters were mainly distributed in the zone of non-soil salinization, while the blue, yellow, and pink point clusters were mostly concentrated in zones of mild, moderate, and severe salinization, respectively. Therefore, different levels of soil salinization (non-soil salinization ($<1.0 \, \text{g} \times \text{kg}^{-1}$, Figure 3(a)),

![Figure 2. Ten feature spaces constructed by five typical surfaces](image)
mild-soil salinization (1.0–2.0 g kg\(^{-1}\), Figure 3(b)), moderate soil salinization (2.0–4.0 g kg\(^{-1}\), Figure 3(c)), and severe soil salinization (4.0 g kg\(^{-1}\), Figure 3(d)) were distributed in the different zones of the Albedo–\(I_{\text{Fe}_2\text{O}_3}\) feature space. Soil salinization can be well identified and distinguished, which is consistent with the results of field investigation.

Figure 4 shows that there are also significant spatial distribution differences for different levels of soil salinization in the Albedo-SI feature space. The distance from any point in the feature space to the L-line that perpendicular to the soil line can be used to indicate the process of soil salinization. As we move further away from the L-line, the salinization will become more severe. According to the distance to the L-line, four-point groups distributed in different positions in the study area are also selected. In order to further study the relationship between different levels of soil salinization and four-point clusters, 25 field samples from each point cluster were analyzed. The results showed that different levels of soil salinization (non-salinization, mild salinization, moderate salinization, and severe salinization) were correspondingly distributed in different levels of the Albedo-SI feature space.

Figure 5(a) shows that there is an obvious nonlinear relationship between Albedo and \(I_{\text{Fe}_2\text{O}_3}\), which is consistent with the trajectory of soil salinization in the feature space. The straight line perpendicular to the E-F line can better distinguish the different levels of soil salinization. The distance from any point in the feature space to D (0.8, 0) can be used to explain the degree of soil salinization, that is, as we move further away from point D, there will be more salt content in the soil and the degree of soil salinization will be more severe. According to the distance formula between the two points, the distance from C (any point in the Albedo–\(I_{\text{Fe}_2\text{O}_3}\) feature space) to the point D can be obtained as follows:
The remote sensing detection model (SDI1) of soil salinization is established, and its expression is as follows:

$$L_1 = \sqrt{(\text{Albedo} - 0.8)^2 + IFe_2O_3^2}$$  \hspace{1cm} (7)$$

There is also an obvious nonlinear relationship between Albedo and SI, which is similar to the trajectory (L0) of soil salinization in the feature space. As shown in Figure 6, the distance from any point in the feature space to L can be used to explain the degree of soil salinization, that is, we move further away from the L-line, the
degree of soil salinization will be more severe. In the Albedo-SI feature space, the distance \( L_2 \) from \( P \) to the straight line \( L \) can be obtained according to the distance formula between point and line which is as follows (Guo et al. 2019a):

\[
L_2 = \frac{|1 + M \times \text{Albedo} - \text{SI}|}{\sqrt{1 + M^2}}
\]  

Then, a remote sensing monitoring model of soil salinization (SDI_2) was established, in which \( M \) was the slope of soil line and the expression is as follows:

\[
SDI_2 = \frac{|1 + M \times \text{Albedo} - \text{SI}|}{\sqrt{1 + M^2}}
\]

4. Results and discussions

Based on the above two categories of model, 10 feature space salinization detection indices have been calculated. The spatial distributions of soil salinization information are shown in Figure 7. The zones of soil salinization were mainly distributed in the northern Hekou district, eastern Kenli and Dongying district, which was consistent with the results of Liu et al. (2016).

In order to analyze and compare the inversion accuracies of the above 10 salinization detection indices, 32 field observation samples were used to calculate the correlation coefficients between the field observed value and inversed value, then to determine the optimal remote sensing monitoring model of soil salinization for the Yellow River Delta. The results (Table 1) showed that the inversion accuracy of the Albedo–\( \text{I}_{\text{Fe}_2\text{O}_3} \) feature space detection index based on the point-to-point model was the highest with \( R^2 = 0.86 \), while the inversion accuracy of the Albedo-NDVI feature space detection index based on the point-to-point model was the lowest with \( R^2 = 0.72 \). The average inversion accuracy of feature space detection indices that comprised \( \text{I}_{\text{Fe}_2\text{O}_3} \) was the largest with \( R^2 = 0.81 \), followed by that of Albedo (\( R^2 = 0.80 \)) and SI (\( R^2 = 0.80 \)). However, the average inversion accuracy of feature space...
detection index that comprised NDVI was the smallest with $R^2 = 0.77$, which was consistent with our previous studies (Guo et al. 2019a, 2019b). NDVI is a better indicator of the vegetation grown and coverage, however, it is not sensitive enough to reflect the status of vegetation grown in the regions with low and high coverage of vegetation (Aldabaa et al. 2015; Cao et al. 2016; Bannari et al. 2018). The reflectance of red band will be saturated, when the vegetation coverage reaches a certain degree. Moreover, the vegetation index is exaggerated in the low vegetation area, while vegetation index is compressed in the high vegetation area with the continuously increasing reflectance of near-infrared band (Yu et al. 2018; Guo et al. 2019b). Additionally, there are many salt-tolerant plants, so that the NDVI is not smaller in some areas with more severe salinization in the Yellow River Delta (Weng et al. 2010; Guo et al. 2019b).

Table 1. Comparisons of inversion accuracy of different monitoring models.

| Category of model     | Feature space       | $R^2$ |
|-----------------------|---------------------|-------|
| Point-to-point model  | Albedo-$I_{Fe_2O_3}$ | 0.86  |
|                       | Albedo-NDVI         | 0.72  |
|                       | NDVI-$I_{Fe_2O_3}$  | 0.78  |
|                       | SI-$I_{Fe_2O_3}$    | 0.85  |
|                       | WI-$I_{Fe_2O_3}$    | 0.8   |
|                       | SI-NDVI             | 0.78  |
|                       | WI-NDVI             | 0.82  |
| Point to line model   | Albedo-SI           | 0.83  |
|                       | Albedo-WI           | 0.79  |
|                       | SI-WI               | 0.72  |

Figure 7. Spatial distributions of the soil salinization information of 10 feature space models (a) Albedo-$I_{Fe_2O_3}$; (b) Albedo, NDVI; (C) Albedo-SI; (d) Albedo-WI; (e) NDVI-$I_{Fe_2O_3}$; (f) SI-$I_{Fe_2O_3}$; (g) WI-$I_{Fe_2O_3}$; (h) SI-NDVI; (e) WI-NDVI; (j) SI-WI.
Ferric oxide is a primary dyeing material in the soil that can greatly affect the spectral characteristics of the soil (Bai et al. 2018; Yu et al. 2018). Many absorption characteristics of salinized soil in the visible light band are caused by iron oxides, and the presence of iron oxides will lead to a decrease in reflectivity of soil in the whole visible band range (Douaoui et al. 2006; Peng et al. 2013). Additionally, the chemical weathering is also a primary cause of soil salinization, during which Fe₂O₃ is formed by the reaction of oxygen present in the atmosphere with primary Fe²⁺ minerals in the soil. Moreover, the mass percentage would increase with the aggravation of weathering (Hu et al. 2019). With the aggravation of soil salinization, the coverage of non-saline-resistant vegetation and surface soil moisture would decrease. Then, the salinity in the soil will precipitate out of the soil surface, affecting the albedo of the surface (Ruhollah et al. 2016; Masoud et al. 2019). Based on the above analysis, the surface parameter of I_{Fe₂O₃} is a better index to indicate the salinization information and the Albedo–I_{Fe₂O₃} feature space detection index based on the point-to-point model has the best applicability to monitor the salinization process in the Yellow River Delta.

5. Conclusion

After the complete consideration of the vegetation landscape of the Yellow River Delta, the authors utilized five typical surface parameters, such as Albedo, NDVI, SI, WI, and I_{Fe₂O₃}, to construct 10 feature spaces and, then, established two categories of soil salinization detection model. The feature space model is an effective approach to monitor and distinguish the different levels of soil salinization in the Yellow River Delta with an average inversion accuracy of 0.794. In addition, I_{Fe₂O₃} is a better surface parameter to indicate the salinization information and the Albedo–I_{Fe₂O₃} feature space detection index based on the point-to-point model has the best applicability to monitor the salinization process in the Yellow River Delta. The research results further elucidated the mechanism and law of soil salinization and provided a scientific basis for the prevention and control of soil salinization. However, due to the involvement of complex mechanisms among different surface parameters in the natural environment, further research is needed to clarify the mechanism of soil salinization process and improve the inversion accuracy.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the Open Research Fund of Key Laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences (Grant No. 2019LDE006); the Strategic Priority Research Program of Chinese Academy of Sciences (Grant No. XDA2002040203); Natural Science Foundation of Shandong Province (Grant No. ZR2018BD001); Open Fund of State Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University (Grant No. 17104); Project of Shandong Province Higher Educational Science and Technology Program (Grant No. J18KA181); Open
Aldabaa AAA, Weindorf DC, Chakraborty S, Akriti S, Bin L. 2015. Combination of proximal and remote sensing methods for rapid soil salinity quantification. Geoerma. 239–240:34–46.

Alejandro MA, Kenji O. 2007. Estimation of vegetation parameter for modeling soil erosion using linear Spectral Mixture Analysis of Landsat ETM data. ISPRS J Photogramm. 62(4):309–324.

Allbed A, Kumar L. 2013. Soil salinity mapping and monitoring in arid and semi-Arid regions using remote sensing technology: a review. ARS. 2(4):373–385.

Bai L, Wang C, Zang S, Zang SY, Wu CS, Luo JM, Wu YX. 2018. Mapping soil alkalinity and salinity in Northern Songnen Plain, China with the HJ-1 hyperspectral imager data and partial least squares regression. Sensors-Basel. 18(11):3855.

Bannari A, El-Battay A, Bannari R, Rhinane H. 2018. Sentinel-MSI VNIR and SWIR bands sensitivity analysis for soil salinity discrimination in an arid landscape. Remote Sens-Basel. 10(6):855.

Bao SD. 2000. Soil and agricultural chemistry analysis. Beijing, China: Chinese Agricultural Press; p. 178–198.

Bouaziz M, Matschullat J, Gloaguen R. 2011. Improved remote sensing detection of soil salinity from a semi-arid climate in Northeast Brazil. Cr Geosci. 343(11–12):795–803.

Cao L, Ding J, Halik Ü, Su W, Ning J, Miu C, Li H. 2016. Extraction and modeling of regional soil salinization based on data from GF-1 satellite. Acta Pedol Sin. 53(6):1399–1409.

Douaoui AERK, Nicolas H, Walter C. 2006. Detecting salinity hazards within a semiarid context by means of combining soil and remote-sensing data. Geoderma. 134(1–2):217–223.

Fallah Shamsi SR, Zare S, Abtahi SA. 2013. Soil salinity characteristics using moderate resolution imaging spectroradiometer (MODIS) images and statistical analysis. Arch Agron Soil Sci. 59(4):471–489.

Gorji T, Sertel E, Tanik A. 2017. Monitoring soil salinity via remote sensing technology under data scarce conditions: a case study from Turkey. Ecol Induc. 74:384–391.

Guo B, Yang F, Han BM, Fan YW, Chen ST, Yang WN, Jiang L. 2019b. A model for the rapid monitoring of soil salinization in the Yellow River Delta using Landsat 8 OLI imagery based on VI-SI feature space. Remote Sens Lett. 10(8):796–805.

Guo B, Yang F, Fan Y, Han B, Chen S, Yang W. 2019a. Dynamic monitoring of soil salinization in Yellow River Delta utilizing MSAVI–SI feature space models with Landsat images. Environ Earth Sci. 78(10):308.

Ha XP, Ding JL, Puxifulati T, Luo JY, Zhang F. 2009. Research on extraction of salinized soil information in arid areas based on si-albedo characteristic space-taking the Keriya river basin oasis as an example. Acta Pedologica Sin. 46(3):381–390.

Hu J, Peng J, Zhou Y, Xu D, Zhao R, Jiang Q, Fu T, Wang F, Shi Z. 2019. Quantitative estimation of soil salinity using UAV-borne hyperspectral and satellite multispectral images. Remote Sens. 11(7):736.

Khan NM, Rastoskuev VV, Sato Y, Shiozawa S. 2005. Assessment of hydrosaline land degradation by using a simple approach of remote sensing indicators. Agr Water Manage. 77(1–3):96–109.

Liu GM, Li JB, Zhang XC, Wang XP, Lv ZZ, Yang JS, Shao HB, Yu SP. 2016. GIS-mapping spatial distribution of soil salinity for Eco-restoring the Yellow River Delta in combination with Electromagnetic Induction. Ecol Eng. 94:306–331.

Masoud AA, Koike K, Mohamed GA, Mohamed MEH, Khaled SG. 2019. Mapping soil salinity using spectral mixture analysis of landsat 8 OLI images to identify factors influencing salinization in an arid region. Int J Appl Earth Obs. 83:101944.
Metternicht G, Zinck J. 2003. Remote sensing of soil salinity: potentials and constraints. Remote Sens Environ. 85(1):1–20.

Peng J, Xiang HY, Zhou Q, Zhang YZ, Wang JQ, Peng XA. 2013. Hyperspectral response of soil iron oxide. Spectrosc Spect Anal. 33(02):502–506.

Ruhollah TM, Ayoubi S, Namazi Z, Malone BP, Zolfaghari AA, Sadrabadi FR. 2016. Prediction of soil surface salinity in arid region of central Iran using auxiliary variables and genetic programming. Arid Land Res Manage. 30:49–64.

Solvia F, Steven A F, Stefania M, Luca B, Arduino MD, Claudio R. 2007. Satellite-based indices in the analysis of land cover for municipalities in Siena province, Italy. J Environ Manage. 86(2):383–389.

Taijgardan T, Ayoubi S, Shataee S. 2010. Soil surface salinity prediction using ASTER data: comparing statistical and geostatistical models. Aust J Basic Appl Sci. 4(3):457–467.

Wang F, Ding JL, Wu MC. 2010. Remote sensing model of soil salinization based on NDVI-SI characteristic space. Trans CSAE. 26(8):168–173.

Wang JZ, Ding JL, Yu DL, Ma XK, Zhang ZP, Ge XY, Teng DX, Li XH, Liang J, Lizaga I, Chen XY, et al. 2019. Capability of Sentinel-2 MSI data for monitoring and mapping of soil salinity in dry and wet seasons in the Ebinur Lake region, Xinjiang, China. Geoderma. 353:172–187.

Wang D, Wilson C, Shannon M. 2002. Interpretation of salinity and irrigation effects on soybean canopy reflectance in visible and near-infrared spectrum domain. Int J Remote Sens. 23(5):811–824.

Weng YL, Gong P, Zhu ZL. 2010. A spectral index for estimating soil salinity in the Yellow River Delta Region of China Using EO-1 hyperion data. Pedosphere. 20(3):378–388.

Wu J, He T, Cheng PG. 2006. Study on land degradation mapping by using hyperion data in HengShan Region of China. Prog Geogr. 25(2):131–139.

Yahiaoui I, Douaoui A, Zhang Q, Ziane A. 2015. Soil salinity prediction in the Lower Cheliff plain (Algeria) based on remote sensing and topographic feature analysis. J Arid Land. 7(6):794–805.

Yu H, Liu M, Du B, Wang Z, Hu L, Zhang B. 2018. Mapping soil Salinity/Sodicity by using landsat OLI imagery and PLSR algorithm over Semiarid West Jilin Province, China. Sensors (Basel). 18(4):pii:E1048.

Zeng YN, Xiang ZHD, Xu H. 2006. Albedo-NDVI space and remote sensing synthesis index models for desertification monitoring. Sci Geogr Sin. 26(1):75–82.

Zhang TT, Zeng SL, Gao Y, Ouyang ZT, Li B, Fang CM, Zhao B. 2011. Using hyperspectral vegetation indices as a proxy to monitor soil salinity. Ecol Indic. 11(6):1552–1562.

Zhang PM, Zhang ZHD, Li XQ, Wang Y, Yu JK, Huang YF. 2006. Desertification remote sensing information extraction from Qinghai-Tibet Plateau and evolution analysis. Arid Land Geogr. 29(5):710–717.