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Assessment of Desertification in Settlements of Qazvin Plain Using Sentinel-2 Images, Spectral Indices and Desertification Divided Index

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Abstract: In this study, Sentinel-2 images have been used for the quantitative assessment of desertification in Qazvin Plain. First, topsoil grain size index (*TGSI*), albedo, *normalized difference vegetation index* (*NDVI*) and *modified* soil adjusted vegetation index (MSAVI) were extracted. Next, for linear regression, different combinations of indices were considered and Pearson correlation was established between NDVI and albedo, MSAVI and albedo, TGSI and albedo, TGSI and MSAVI. Then, using the NDVI-albedo and MSAVI-albedo regression, Desertification Divided Index (DDI) was estimated. Finally, the map of desertification was drawn for the study area in five classes of very severe, severe, moderate, low and very low. The study found that albedo was negatively correlated with MSAVI and NDVI indices but positively correlated with TGSI. The strongest correlation was between MSAVI and albedo (-0.417), while the weakest was between albedo and TGSI (0.33). According to DDI, the desertification situation in the region has been in the alarming range. In fact, by testing albedo with MSAVI in 2018, 2.4% of the region was classified with very severe desertification, while 21.7% had very low desertification. According to albedo-NDVI, 18.51% of the region had very severe desertification. In 2023, the first value increased to 10.3% and the second decreased to 5% indication remarkable rise in desertification in five years.

Key words: NDVI, albedo, TGSI, desertification, Qazvin Plain.

Globally, desertification is one of the most complex environmental issues that affects the social and economic status of millions of people in different regions (Kosmas *et al*., 2014). Desertification occurs mainly in arid, semi-arid and sub-humid regions due to various climatic and human factors such as climate change and excess exploitation of natural resources (Yu *et al*., 2018; Darouiche *et al*., 2015). By changing biogeochemical, ecological and hydrological processes, this phenomenon can lead to severe land degradation, loss of biodiversity, loss of habitats, endangerment of species and loss of land productivity (Hu *et al*., 2020). According to the report of the United Nations Convention to Combat Desertification (UNCCD, 2015), 25% of the earth's surface is degraded or prone to degradation.

The proportion of degraded land is likely to increase by 30-40% and could affect almost three billion people who are mostly below the poverty line (Hu *et al.*, 2020). Desertification has been a major challenge for different regions of the world, especially the Mediterranean coast, Africa and other developing regions of the World and also China (Dregne, 2002). Monitoring the spatial and temporal pattern of desertification is necessary to limit the adverse effects of this phenomenon (Guang *et al.*, 2017). Various methods have been proposed to investigate the process of desertification. These methods include the use of mathematical algorithms (Afrasinei *et al.*, 2018) and remote sensing technologies (Zhao *et al.*, 2013). During the last three decades, remote sensing has been used as an effective tool for spatial and temporal monitoring of desertification (Pan and Li, 2013; Das *et al.*, 2024). Remote sensing, combined with geographic information system (GIS), is a cost-effective approach that allows rapid assessment of various land features in space and time due to the availability of high-resolution multi-temporal satellite images (Wang *et al.*, 2012). Various studies offer a range of remote sensing techniques for monitoring desertification, like spectral composition analysis (Sun *et al.*, 2017) and spectral indices (Lamchin *et al.*, 2016). Approaches based on different indices are widely used to investigate land degradation (Zhao *et al.*, 2013). For example, NDVI and MSAVI are used to monitor vegetation conditions for desertification assessment (Wu *et al.*, 2019). Indices such as albedo and TGSI can detect the spatial heterogeneity of soil texture (Liu *et al.*, 2018). In fact, many researchers around the world have successfully used these indices to assess desertification (Jiang and Lin, 2018; Wei *et al.*, 2018).

In some studies, albedo-NDVI and albedo-MSAVI models have been proposed for desertification analysis (Zeng *et al.*, 2006; Feng *et al.*, 2018). Other researchers also used albedo-TGSI-based model (Guo *et al.*, 2020). However, among these indices, albedo-NDVI has been widely considered. This index shows a strong negative correlation and reflects the state of desertification (Citation needed).

In Iran, several studies have been conducted on DDI. The trend of desertification in the surroundings of the Lake Urmia was investigated during 2000-2018 (Khodaei *et al.*, 2020). Using remote sensing time series data, the desertification process in the Khuzestan Province was investigated. The results showed that none of the series, except for the high desertification time series, showed a significant trend at the level of 5% (Geloogerdi *et al.*, 2021). This study is based on TGSI, NDVI, albedo and MSAVI. The combination of these indices was tested through Pearson correlation. The objective of this study was to map changes in desertification classes in Qazvin Plain (2018, 2023) using Sentinel-2 images. It integrated remote sensing indices (MSAVI, albedo, NDVI, and TGSI) to identify desertification-affected areas, analyze their correlations, and develop a linear regression model to calculate the DDI.

Materials and Methods

Study area

Qazvin Plain is located in the southern part of Qazvin and on the southern slopes of Alborz Mountain range. The study area is located in the geographical coordinates of 35°42′ to 36°08′ N latitude and 49°09′ to 50°38′ E longitude. The region has dry and semi-arid climate, and the annual rainfall is less than 380 mm yr^{-1}. In spring and autumn, this region is affected by Mediterranean cyclones, and in summer, it is affected by high-pressure subtropical anticyclones. Geologically, the southern part of the Alborz Mountain range has also been affected by the Laramide *orogeny* to the Pasadenian *orogeny*. This area has been severely affected by the desertification trend.

The study uses, Sentinel-2 images of 2018 and 2023 to assess DDI. for the entire region of the Qazvin Plain. The spatial resolution of the images provides the opportunity to observe the ground accurately. The Sentinel-2′ multispectral images consist of 13 spectral bands with a resolution of 10 m (4 bands), 20 m (6 bands) and 60 m (3 bands). These 13 bands cover a wide range of wavelengths from 440 to 2200 nm. In this study, red, infrared, blue, green, SWIR1 and SWIR2 bands were used. The satellite image of July 11, 2023 and July 27, 2018 for a day without cloud cover was used to perform the analysis. The July images help distinguish agricultural land from natural vegetation, as crops are typically harvested before this month. These images were downloaded from http://schiub.copernicus.eu.

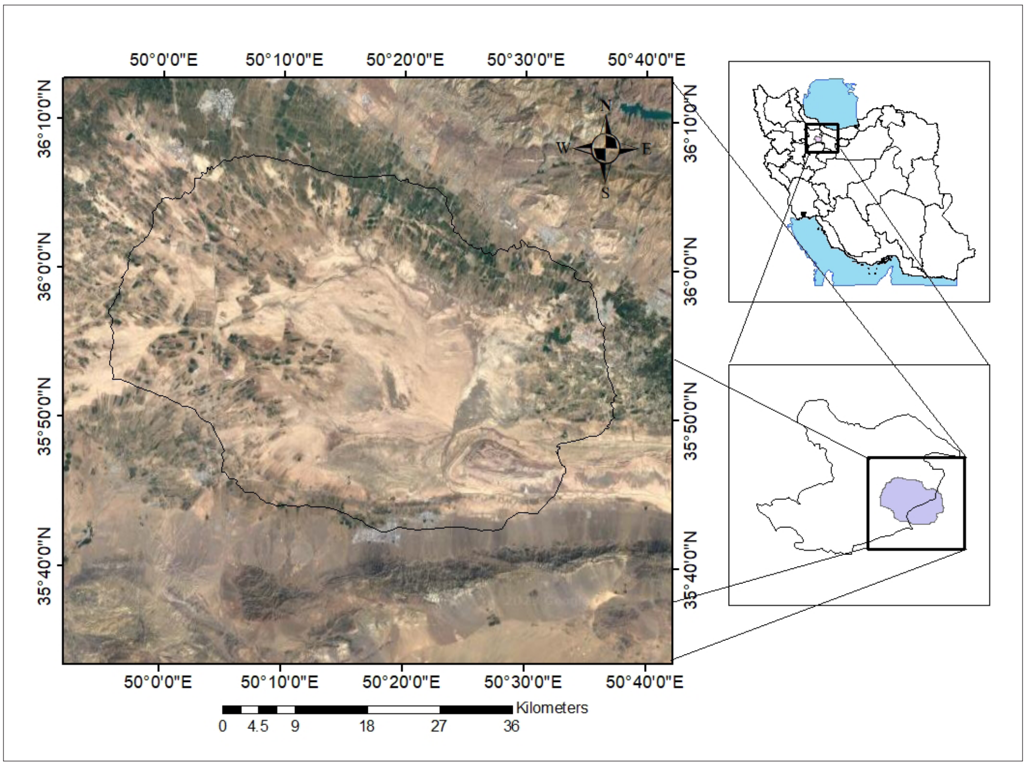

Fig. 1. Location of the study area in Qazvin Plain (Sentinel 2) (https://dataspace.copernicus.eu)

The method adopted in this study was based on the extraction of NDVI, TGSI, albedo and MSAVI, which provides the possibility to assess and monitor desertification. This study included acquiring satellite images, calculating spectral indices, analyzing the correlation between spectral indices, calculating DDI and analyzing regression.

Four indices of NDVI, albedo, MSAVI and TGSI were estimated using Sentinel-2 image. NDVI is a dimensionless radiometric measurement index. Due to its high sensitivity to the presence, density, and state of vegetation, NDVI has been widely used to investigate desertification in arid and semi-arid regions (Lamchin *et al.*, 2016). This index combines the infrared and red bands of the Sentinel-2 image using the following equation.

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad ...1$$

where, Red and NIR refer to infrared and near infrared bands.

The albedo of the earth's surface determines the balance of radiant energy on the earth and shows the amount of energy absorbed by the underlying surfaces. Also, this index shows the amount of solar radiation reflected by the surface in the short-wave spectral range. Albedo values can be affected by soil moisture, vegetation, snow cover and other soil surface conditions. An increase in surface albedo can show evidence of desertification. Albedo has an inverse relationship with NDVI and is estimated using the following equation (Liang *et al.*, 2003).

$$Albedo = \frac{[(0.35*BLUE)+(0.13*RED)+(0.373*NIR)+(0.085*SWIR1)+(0.072*SWIR2)-0.018]}{1.016} \qquad ...2$$

Although NDVI effectively assesses the vegetation conditions, this index has limitations in detecting areas with low vegetation and is affected by the soil background. For this purpose, MSAVI was used to minimize external effects. This index is usually used in areas where NDVI does not reflect the actual state of vegetation due to lack of chlorophyll or poor vegetation. Also, this index provides information about the state of vegetation in these areas and separates the effects of other factors from it. MSAVI values are estimated using the following equation (Qi *et al.*, 1994).

$$MSAVI = \frac{2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8(NIR - RED)}}{2} \qquad ...3$$

To identify areas with low vegetation cover and barren lands, TGSI was proposed (Wang *et al.*, 2012). A larger particle size indicates a higher probability of desertification. TGSI is based on the measurement of spectral reflectance and laboratory analysis of the composition of particles in the surface layer of the soil. Positive values indicate coarse soil particles and negative values indicate vegetation and / or water. The higher the TGSI, the rougher the ground surface. TGSI values are estimated using the following equation:

$$TGSI = \frac{RED - BLUE}{RED + BLUE + GREEN} \quad ...4$$

To remove dimensional differences between different indices, the values of spectral indices were normalized. The normalization process is described by the following equations.

$$albedo = \frac{albedo - albedo_{min}}{albedo_{max} - albedo_{min}} \times 100 \quad ...5$$

$$MSAVI = \frac{MSAVI - MSAVI_{min}}{MSAVI_{max} - MSAVI_{min}} \times 100 \quad ...6$$

$$TGSI = \frac{TGSI - TGSI_{min}}{TGSI_{max} - TGSI_{min}} \times 100 \quad ...7$$

$$NDVI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100 \quad ...8$$

The extraction of different DDI is based on the analysis of several combinations of spectral indices in order to select a combination that shows the best classes of desertification. For this purpose, pixels were selected for the points corresponding to each index. To extract the intensity of desertification and determine the best correlation, four combinations of albedo-NDVI, albedo-TGSI, albedo-MSAVI and TGSI-MSAVI were considered. A linear regression relationship was established between these indices. To draw the intensity of desertification, regression relationships between the above indices were used.

Desertification Divided Index (DDI) is a model used by researchers to map the sensitivity to desertification in arid and semi-arid regions (Becerril *et al.*, 2016). DDI is based on feature-space classification (Citation needed). According to various studies, different areas of desertification can be effectively obtained from dividing the albedo-NDVI feature space in the vertical direction, which represents the desertification trend (Verstraete and Pinty, 1996). DDI is calculated as follows:

$$DDI = K \times NDVI - albedo \quad ...9$$

where DDI is the desertification divided index for two feature space models and K is the slope of the line. Then, the calculated desertification intensity values are divided into five categories. These five classes represent very severe, severe, moderate, low and very low desertification.

Results and Discussion

The findings presented in Table 1 and Fig. 2 shows calculation results of four spectral indices of NDVI, albedo, MSAVI and TGSI. NDVI values vary between -0.39 and 0.72. Low NDVI values correspond to desert areas. In contrast, high values reflect soils with significant vegetation cover. The surface albedo values are consistent with the study results of NDVI. Low albedo values indicate dense vegetation. High albedo values reflect areas with little vegetation such as steppe regions. TGSI provides information on the size of surface soil particles. The values of this index fluctuate between -0.28 and 0.47. High values of this index indicate coarse particles in surface soil and show degraded areas. MSAVI values are between -1 and 0.84 and low values indicate barren soil and high values indicate dense vegetation. In fact, MSAVI achieves better results in areas with poor vegetation cover. Albedo highlights barren soil areas while TGSI focuses on areas with coarse soil particles. These areas show areas of desertification. Comparison of albedo

Table 1. Correlation values and linear regression between indices

Index	2018				2023			
	Pearson correlation	R^2	Slope	Regression equation	Pearson correlation	R^2	Slope	Regression equation
albedo-MSAVI	-0.48	0.23	-6.71	y= -6.71x+18.2	-0.417	0.165	-0.44	y=-0.44x+51.57
albedo-NDVI	-0.48	0.18	-0.34	y= -0.34x+19.6	-0.37	0.14	-0.19	y=-0.19x+24.8
albedo-TGSI	-0.13	0.01	-0.23	y= -0.23x+3.67	0.33	0.11	0.36	y=-0.36x+5.42
MSAVI- TGSI	-0.17	0.03	-0.02	y= -0.02x+66.9	-0.412	0.161	-0.42	y=-0.4x+90.2

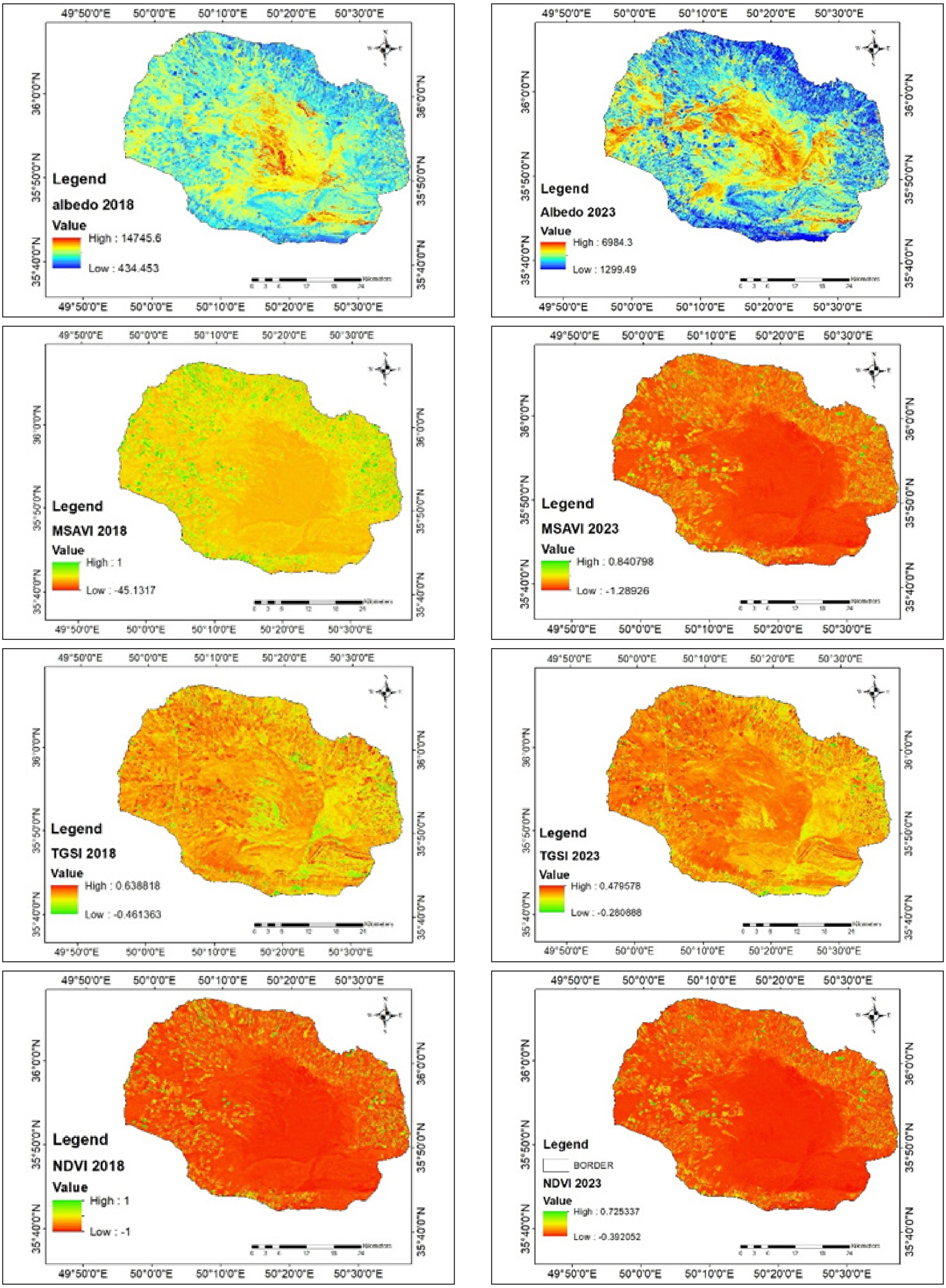

Fig. 2. Map of (a) albedo; (b) MSAVI; (c) TGSI and (d) NDVI in Qazvin Plain (2018, 2023).

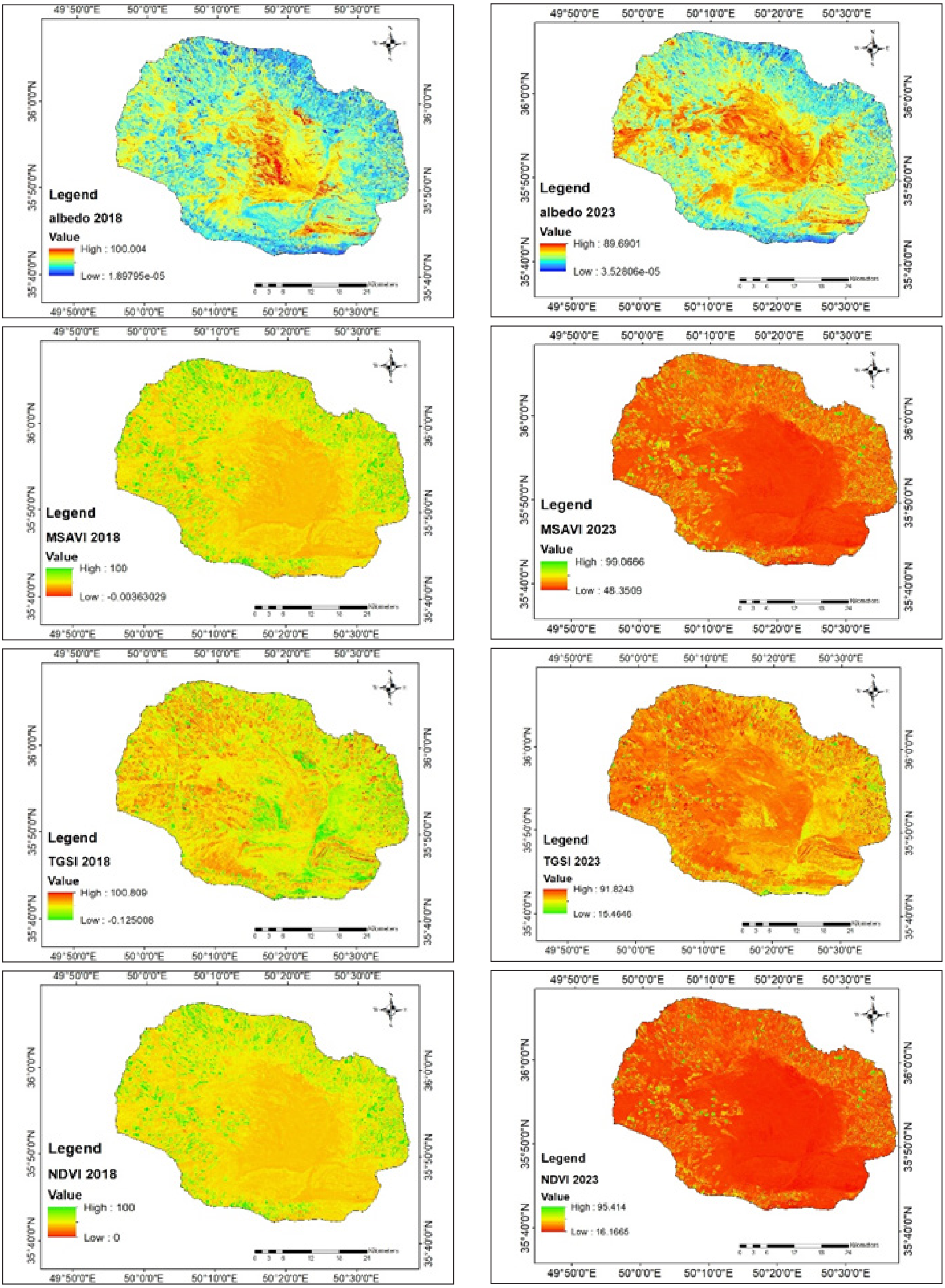

*Fig. 3. Normalized maps of (a) albedo; (b) MSAVI; (c) TGSI and (d) NDVI in 2018, 2023.(**reference missing**)*

Table 2. Summary of desertification classification based on DDI

Desertification	DDI (albedo- MSAVI)	DDI (albedo- NDVI)
Very severe	31.8-16.43	32.8-23.39
Severe	16.43-15.7	23.39-22.24
Moderate	15.7-14.42	22.24-20.02
Low	14.42-12.04	20.3-16.2
Very low	<12.04	< 16.2

Table 3. Area resulting from DDI based on two albedo-NDVI and albedo-MSAVI models (2018, 2023)

Desertification	2018				2023			
	albedo- MSAVI		albedo- NDVI		albedo- MSAVI		albedo- NDVI	
	Area (km^2)	percent	Area (km^2)	percent	Area (km^2)	percent	Area (km^2)	percent
Very severe	50.68	2.4	386.1	18.51	215.9	10.3	713.63	34.2
Severe	301.1	14.4	815.1	30.1	575.5	27.6	830.18	39.8
Moderate	613.5	29.42	664.8	31.88	713.9	34.2	413.3	19.8
Low	665.6	31.9	155.7	7.46	474.1	22.7	92.1	4.41
Very low	453.3	21.7	62.6	3	104.7	5	35.1	1.68

values between 2018 and 2023 shows that areas with high albedo have significantly increased in 2023. In terms of the NDVI index, it has been observed that the maximum NDVI values have decreased from 1 in 2018 to 0.72 in 2023. In terms of the TGCI index, the maximum value has also decreased, from 0.63 in 2018 to 0.47 in 2023. Finally, the maximum values of the MSAVI index also decreased, from 1 in 2018 to 0.84 in 2023.

To calculate the linear regression, four combinations of desertification indices were tested. In three of these combinations, albedo was considered as a dependent variable and TGSI, NDVI, and MSAVI were considered as independent variables. In the fourth combination, TGSI was considered as a dependent variable and MSAVI was considered as an independent variable. A significant negative correlation was observed between albedo and MSAVI (-0.417) and albedo and NDVI (-0.37). There is a weak correlation between Albedo-TGSI (0.33) and MSAVI-TGSI (-0.412). The coefficient of determination (R^2) between albedo-NDVI and albedo-MSAVI was 0.14 and 0.165, respectively. The resulting values make it possible to extract the intensity of desertification.

Several studies have shown the effectiveness of using the albedo-NDVI relationship to distinguish between different classes of desertification. In fact, areas with high albedo and low NDVI values have poor vegetation cover and high desertification. Albedo-NDVI scatter plot of these indices was drawn based on the data of NDVI and albedo indices.

DDI is a model used by various researchers to accurately map desertification sensitivity in arid to semi-arid regions (Pan and Li, 2013). In this study, proposing albedo-NDVI and albedo-MSAVI models makes it possible to extract different DDI. Different areas of desertification can be distinguished by dividing two combinations of albedo-NDVI and albedo-MSAVI in the vertical direction, which shows the desertification trend. Based on linear relationships, the area perpendicular to albedo-MSAVI and albedo-NDVI relationships can be estimated by a simple linear polynomial. Therefore, DDI values can be obtained from the following equations:

$$DDI = K \times NDVI - albedo \quad ...10$$

$$DDI = K \times MSAVI - albedo \quad ...11$$

where, DDI is the desertification divided index of the models and k is determined by the slope of the straight line. k values for NDVI-albedo equal to 1.51 and 1.05 for MSAVI-albedo. Then, the calculated values of DDI were divided into five categories: very severe, severe, moderate, low and very low. Table 2 shows DDI values.

After extracting the degree of desertification using DDI, the DDI map was drawn based on albedo-NDVI and albedo-MSAVI models. Table 3 shows the calculation results of both models. According to the results of the albedo-NDVI model in 2018, 31.88% of the region has

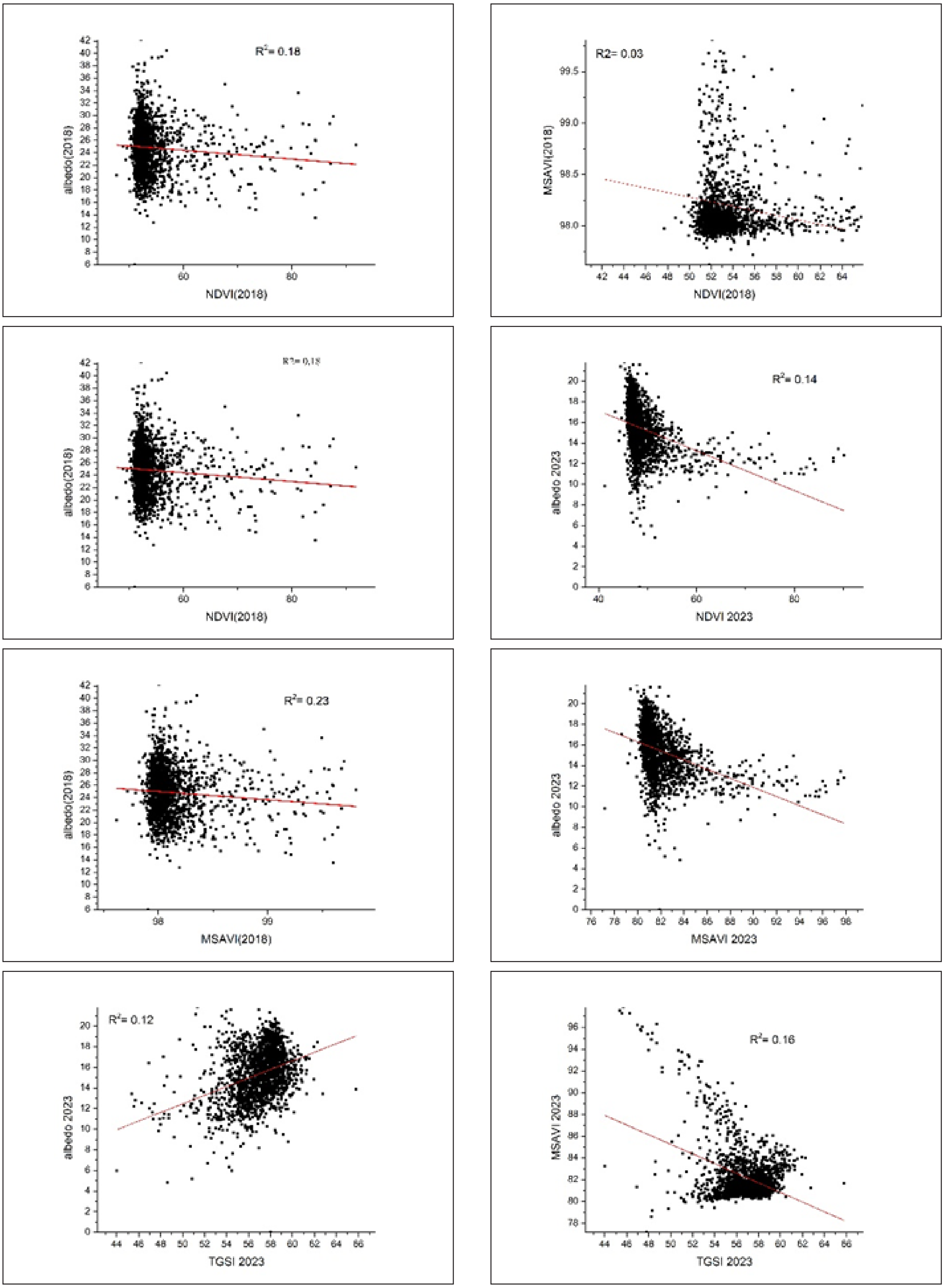

Fig. 4. Scatter plot between indices to establish linear regression relationship.

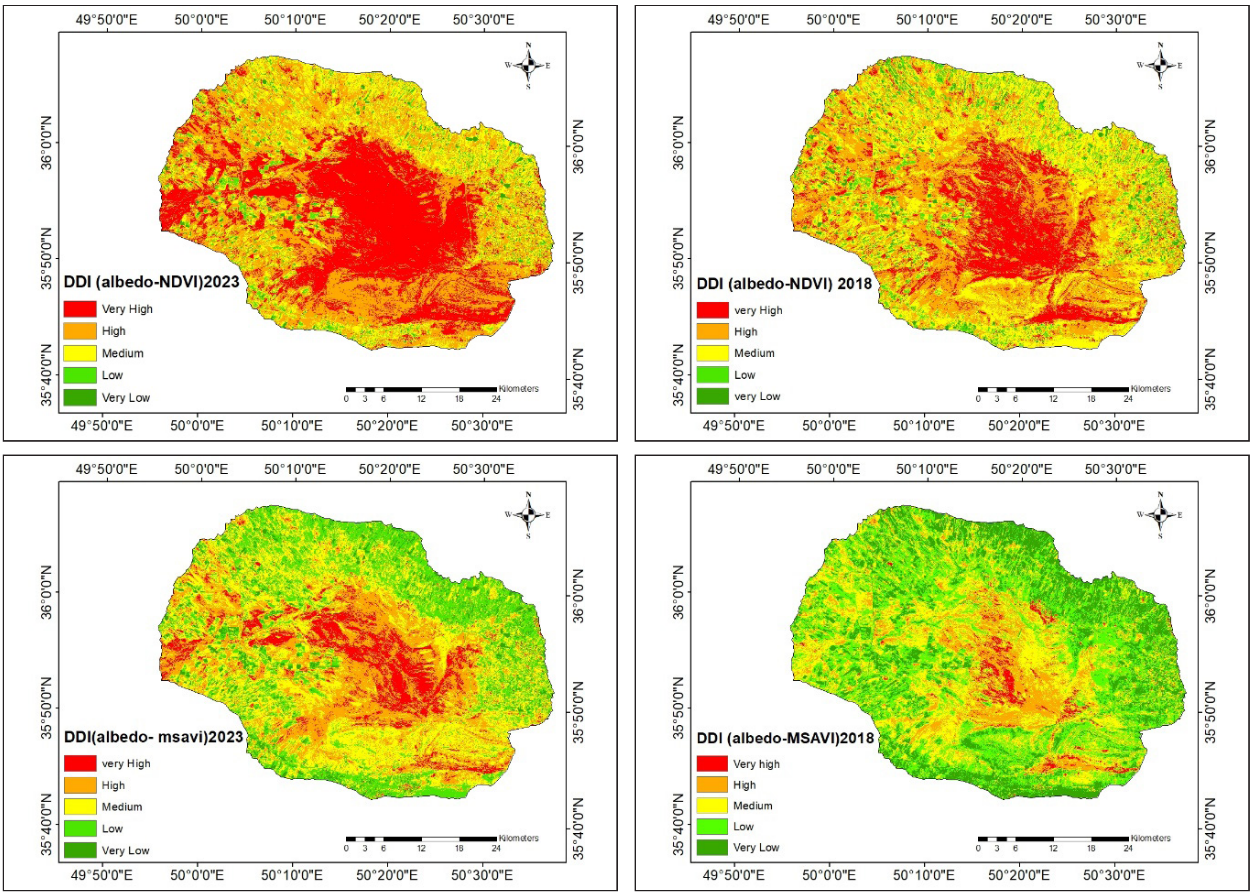

Fig. 5. DDI map based on albedo-MSAVI and albedo-NDVI regression.

experienced moderate desertification, 30.1% severe desertification and 18.51% very severe desertification. The areas affected by low desertification and very low desertification are 7.46% and 3% of the study area, respectively. These values for the albedo-MSAVI model and for the very severe, severe, moderate, low and very low classes were 2.4, 14.4, 29.42, 31.9 and 21.7, respectively. In 2023, a significant increase in desertification for albedo-MSAVI model in the classes of very high, high, medium, low and very low equivalent to 10.3, 27.6, 34.2, 22.7 and 5 respectively. This indicates that the intensity of desertification is expanding rapidly (Fig. 3, Fig. 4, Fig. 5, Table 2 and Table 3)

Conclusion

In this study, desertification was analyzed by proposing two albedo-NDVI and albedo-MSAVI models for 2018 and 2023. The models achieved better results than the traditional models based on vegetation. Among these two models, the albedo-MSAVI model can be the most suitable for the study area, which is mainly composed of areas with low vegetation. The albedo-NDVI model achieved better results for areas with dense vegetation. However, these areas include only a small part of the study area. Considering the effectiveness of albedo-MSAVI and albedo-NDVI models in the study area, these models can be used as a reference for decision makers for natural resource management. According to the study results, special operational plans should be implemented to overcome the desertification and reduce land degradation.

Reference

Afrasinei, G.M., Melis, M.T. and Arras, C. 2018. Spatiotemporal and spectral analysis of sand encroachment dynamics in southern Tunisia. *European Journal of Remote Sensing* 51: 352-374

Becerril-Piña, R., Díaz-Delgado, C., Mastachi-Loza, C.A. and González-Sosa, E. 2016. Integration of remote sensing techniques for monitoring desertification in Mexico. *Human and Ecological Risk Assessment: An International Journal* 22: 1323-1340

Darouiche, F.Z., Assaoud, S. and Ouarhache, D. 2015. La dynamique de la désertification dans le Nord-Est du Maroc au cours des deux dernières décennies: Etat des lieux et précision des zones d'intérêt. *Mots du Com d'organisation*, p 228

Das, S., Ningrechon, A. and Chakraborty, E. 2024. Unveiling the vulnerability: Mapping Desertification and Land Degradation in the Eastern fringes of the Thar Desert, *Annals of Arid Zone* 63(4): 33- 52.

Dregne, H.E. 2002. Land degradation in the drylands. *Arid Land Research and Management* 16:99-132

Feng, J., Ding, J.L. and Wei, W.Y. 2018. A Study of soil salinization in Weigan and Kuqa rivers oasis based on Albedo-MSAVI feature space. *China Rural Water Hydropower* 2: 147-152

Geloogerdi, S., Vali, A. and Sharifi, M. 2021. Investigation of Desertification Trend in the Center of Khuzestan province Using Remote Sensing Time Series Data. *Iranian Journal of Soil and Water Research* 52(11): 2843-2857.

Guang, Y., Dong, C. and Xinlin, H.2017. Land use change characteristics affected by water saving practices in Manas River Basin, China using Landsat satellite images. *International Journal of Agricultural and Biological Engineering* 10: 123-33.

Guo, B., Zang, W. and Han, B. 2020. Dynamic monitoring of desertification in Naiman Banner based on feature space models with typical surface parameters derived from LANDSAT images. *Land Degradation and Development* 31(12): 1573-1592.

Hu, Y., Han, Y. and Zhang, Y. 2020. Land desertification and its influencing factors in Kazakhstan. *Journal of Arid Environment* 180: 104203.

Jiang, M. and Lin, Y. 2018. Desertification in the south Junggar Basin, 2000-2009: Part I. Spatial analysis and indicator retrieval. *Advances in Space Research* 62: 1-15

Khodaei Geshlag, F., Roostaei, S. and Mokhtari, D. 2020. Monitoring the Desertification Trend in the Areas Surrounding Lake Urmia (2000-2018), *Geography and Environmental Planning* 31(3): 21-40.

Kosmas, C., Kairis, O. and Karavitis, C. 2014. Evaluation and selection of indicators for land degradation and desertification monitoring: Methodological approach. *Environmental Management* 54: 951-970.

Lamchin, M., Lee, J-Y. and Lee, W-K.2016. Assessment of land cover change and desertification using remote sensing technology in a local region of Mongolia. *Advances in Space Research* 57: 64-77.

Liang, S., Shuey, CJ. and Russ, AL. 2003. Narrowband to broadband conversions of land surface albedo: II Validation. *Remote Sensing of Environment* 84: 25-41.

Liu, Q., Zhao, Y. and Zhang, X. 2018. Spatiotemporal patterns of desertification dynamics and desertification effects on ecosystem Services in the Mu Us Desert in China. *Sustainability* 10: 589.

Pan, J. and Li, T. 2013. Extracting desertification from Landsat TM imagery based on spectral mixture analysis and Albedo-Vegetation feature space. *Natural Hazards* 68: 915-927.

Qi, J., Chehbouni, A. and Huete, AR.1994. A modified soil adjusted vegetation index. Remote Sens Environ 48: 119-126.

Sun, G., Chen, X. and Ren, J. 2017. Stratified spectral mixture analysis of medium resolution imagery for impervious surface mapping. *International Journal of Applied Earth Observation and Geoinformation* 60: 38-48.

UNCCD UNC to CD 2015. *Climate change and land degradation*: Bridging Knowledge and Stakeholders

Verstraete, M.M. and Pinty, B. 1996. Designing optimal spectral indexes for remote sensing applications. *IEEE Transactions on Geoscience and Remote Sensing* 34: 1254-1265.

Wang, T., Yan, C.Z., Song, X. and Xie, J.L. 2012. Monitoring recent trends in the area of aeolian desertified land using Landsat images in China's Xinjiang region. *ISPRS Journal of Photogrammetry and Remote Sensing* 68: 184-190.

Wei, H., Wang, J. and Cheng, K.2018. Desertification information extraction based on feature space combinations on the Mongolian plateau. *Remote Sensing* 10: 1614.

Wu, Z., Lei, S. and Bian, Z.2019. Study of the desertification index based on the albedo-MSAVI feature space for semi-arid steppe region. *Environmental Earth Sciences* 78: 232.

Yu, P., Han, D. and Liu, S. 2018. Soil quality assessment under different land uses in an alpine grassland. *CATENA* 171: 280-287.

Zhao, H., Liu, R. and Zhou, R.2013. Properties and mechanisms of change of soil macro-fauna communities in the desertification process of Horqin sandy grassland. *Acta Prataculturae Sinica* 22: 70.

Zeng, Y., Feng, Z. and Xiang, N. 2006. Albedo-NDVI space and remote sensing synthesis index models for desertification monitoring. *Scientia Geographica Sinica* 26: 75.

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