Italian Journal of Engineering Geology and Environment
www.ijege.uniroma1.it

STUDY ON LAND DEGRADATION MONITORING IN SHANXI BY USING REMOTE SENSING IMAGES

Xiaorong ZHANG

Shanxi Conservancy Technical Institute, Yuncheng, Shanxi 044000, China
Corresponding author: r356762@163.com

EXTENDED ABSTRACT

Il degrado del suolo e del territorio è un fenomeno complesso su cui incidono molti fattori interdipendenti quali le attività antropiche e gli eventi naturali, con conseguenti squilibri negli ecosistemi con impatto negativo sulla società umana oltre che sull'ambiente naturale.

Come affrontare questo problema ambientale è ormai un obiettivo globale: oltre a risanare i terreni degradati, è ancora più cruciale monitorare come misura preventiva i terreni esistenti non degradati.

A questo scopo, fondamentale è la tecnica del telerilevamento, ampiamente applicata nel monitoraggio del degrado del territorio, che può fornire un valido supporto tecnico nell' affrontare questo problema.

Il telerilevamento è una tecnica avanzata che utilizza piattaforme satellitari o aeree per acquisire informazioni sulla superficie. Analizzando ed elaborando immagini di telerilevamento, è possibile estrarre dati preziosi come i tipi di uso del suolo, la copertura vegetale e la topografia, cruciali per il monitoraggio del degrado del suolo. Il degrado del suolo si riferisce al declino della sua qualità e dell'equilibrio ecologico, causato dalle attività umane e da fattori naturali, fino ad una diminuzione della copertura vegetale, all'erosione e alla scarsità d'acqua, causando gravi impatti sulla produzione agricola, sull'ambiente e sulla vita umana.

La procedura fondamentale per il monitoraggio del degrado del suolo comprende diverse fasi: acquisizione di immagini di telerilevamento, identificazione delle categorie di terreno, calcolo della produttività primaria netta (NPP) e analisi delle tendenze temporali del degrado del suolo. In primo luogo, le informazioni sulla superficie vengono ottenute tramite piattaforme di telerilevamento, quindi, vengono utilizzate tecniche di elaborazione delle immagini e di visione artificiale per ottenere informazioni come i tipi di utilizzo del territorio e la copertura vegetale.

Al fine di convalidare l'efficacia dell'applicazione pratica della tecnologia di telerilevamento nel monitoraggio del degrado del territorio, questo studio ha condotto un'analisi sulla provincia dello Shanxi, una delle aree più importanti della Cina per la produzione di energia che negli ultimi anni è stata alle prese con gravi problemi di degrado del territorio.

Analizzando ed elaborando immagini di telerilevamento dal 2016 al 2021, questa ricerca ha studiato i cambiamenti nei tipi di copertura del suolo nella provincia dello Shanxi durante questo periodo. I risultati hanno indicato un aumento annuale costante della proporzione di terreni forestali, pascoli e terreni edificabili nella provincia dello Shanxi, accompagnato da un graduale declino dei terreni coltivabili. Nel complesso, si è osservata una tendenza al rialzo di NPP in tutta la regione, con aumenti rilevanti nella maggior parte delle aree, e solo in una piccola parte della regione si è registrato una diminuzione significative del NPP.

La ragione principale di questo fenomeno è legato a politiche di restituzione dei terreni agricoli a foreste e praterie, attraverso il ripristino della vegetazione ed una attenta governance ecologica: fattori che hanno portato collettivamente a cambiamenti nelle tipologie di utilizzo del territorio nella provincia dello Shanxi, promuovendo al tempo stesso il recupero e lo sviluppo dell'ecosistema locale.

In conclusione, la tecnologia del telerilevamento ha ampie prospettive di applicazionenel monitoraggio del degrado del territorio.

Attraverso l'analisi e l'elaborazione di immagini telerilevate, è possibile ottenere informazioni tempestive sul degrado del territorio e sui suoi modelli, fornendo basi scientifiche e supporto tecnico per la formulazione di corrispondenti misure di controllo oltre a fornire un importante supporto dati e una base decisionale per settori quali la conservazione ecologica, la produzione agricola e la pianificazione urbana.

Tuttavia, la tecnologia di telerilevamento presenta anche alcune limitazioni, come restrizioni sulla qualità dei dati, sulla risoluzione spaziale e sulla sequenza temporale. Pertanto, nella ricerca futura è necessaria un'ulteriore ottimizzazione della tecnologia del telerilevamento per migliorarne l'accuratezza e l'affidabilità per un sempre più attento monitoraggio del degrado del territorio e della protezione ambientale.

IJEGE, 2 (2023): 33-38, DOI: 10.4408/IJEGE.2023-02.O-04
E-ISSN 2035-5688 | ISSN 1825-6635 / ©Author(s)

ABSTRACT

Land degradation is a serious environmental problem. This paper briefly introduces the concept of remote sensing image technology and land degradation, and describes the basic process of using remote sensing image to monitor land degradation. Then, Shanxi Province was taken as an example to analyze the land cover type change and net primary productivity (NPP) change during 2016-2021. The annual average precipitation showed an increasing trend, and there was a significant positive correlation between the area of land types such as forest lands, grasslands, and water areas and the annual average precipitation. Moreover, the proportion of forest land, grassland, and construction land increased while the proportion of cultivated land gradually decreased; however, the proportion of water area remained basically unchanged. The local NPP showed an overall upward trend; NPP increased significantly or extremely significantly in most regions, while NPP decreased significantly or extremely significantly in a small part of regions.

Keywords: *remote sensing image, land degradation, monitoring, net primary productivity*

INTRODUCTION

Land degradation poses a significant challenge to the global environment, which has brought great impact on the ecological environment and human social and economic development (Selvaraj & Nagarajan, 2021). With the rise in population, the rapid pace of urbanization, and the transformation of agricultural production techniques, the problem of land degradation is becoming more and more prominent in many areas (Zuo *et alii*, 2022). Remote sensing image technology, as a non-contact information acquisition method, has great advantages for land degradation monitoring (Liang *et alii*, 2019). It can provide large-scale land cover information with high spatial and temporal resolution, and provide an effective means for the identification and analysis of land degradation. Remote sensing image technology is a technology to obtain information about the Earth's surface through satellites, aircraft or other remote sensing platforms. It captures and records electromagnetic radiation on the earth's surface, and then converts these radiation into visual images or data for people to observe and analyze the earth's surface (Easdale *et alii*, 2019). Remote sensing image technology does not require actual contact with the surface, avoiding the trouble of field investigation. The multi-spectral information collected by the technology can reflect more surface information. A large enough coverage area can provide more comprehensive information. Periodically observing the same area enables analysis of dynamic changes in the earth's surface (Venter *et alii*, 2020). The manifestations of land degradation mainly include soil and water loss caused by wind erosion, water erosion or freeze-thaw, land salinization caused by excessive accumulation of salt in soil, land desertification caused by wind erosion due to loss of vegetation cover, and land pollution caused by industrial waste water, pesticides, and other harmful substances (Lorenz *et alii*, 2019).

Some relevant studies are as follows. Herrmann *et alii* (2019) proposed that in addition to remote sensing images, evaluations by local land users can also be used as indicators of land degradation. They used participatory photo collection method at three sites in Fero, Senegal, to elicit the views of local herdsmen on land degradation and determine the indicators they used to describe pasture quality. The results verified the validity of these indicators. Giuliani *et alii* (2020) used Landsat observational data cubes to monitor land degradation at the national scale according to SDG15.3.1 indicators. Using geographic information system (GIS)-based spatial analysis and a critical overview of current forestry management models, Bassan *et alii* (2020) examined the limits of conservation and successful monitoring/assessment of woodlands in central Togo. Their main finding is that land classification based on a small number of inventory parameters is no substitute for 'what a forest is'. However, when these inventory parameters are properly determined, they can serve as a means of promoting sound forest management and conservation. Taheri Dehkordi *et alii* (2022) proposed a training sample generation method based on an iterative k-means refinement process, which was used for water body mapping. The results demonstrated the satisfactory performance of this method. Liu *et alii* (2022) adopted the Carnegie-Ames-Stanford approach (CASA) model to calculate the photosynthetic radiation absorption fraction and maximum light use efficiency suitable for major vegetation types in China, based on more finely resolved observations and monitoring-global land cover classification products. Kang *et alii* (2021) utilized the Euclidean distance approach to integrate the normalized difference vegetation index (NDVI) and net primary productivity (NPP) to introduce the land degradation and development index (LDDI). This index was employed for detecting the process of land degradation and development (LDD) in China from 1985 to 2015. They also explored its quantitative relationship with climate change and human activities. The results indicated that significant land development occurred in China during the study period, accounting for approximately 45% of China's mainland. Moreover, temperature and precipitation had limited impact on affected LDD areas, while human activities emerged as the main driving force. This paper briefly introduces the remote sensing image technology and the concept of land degradation, describes the basic flow of land degradation monitoring by remote sensing image, and analyzes Shanxi Province. The contribution of this article lies in the analysis of the trend of land cover change using remote sensing technology, providing valuable references for preventing land degradation.

MATERIALS AND METHODS

Study area

This paper took Shanxi Province as the research subject of example analysis, and its geographical location is shown in Figure 1. Shanxi has a diverse geographical environment, including loess plateau, mountains, hills, basins, and other landforms, and rich natural landscapes, as shown in Figure 2. The Yellow River runs through Shanxi from west to east, forming many unique valley landforms.

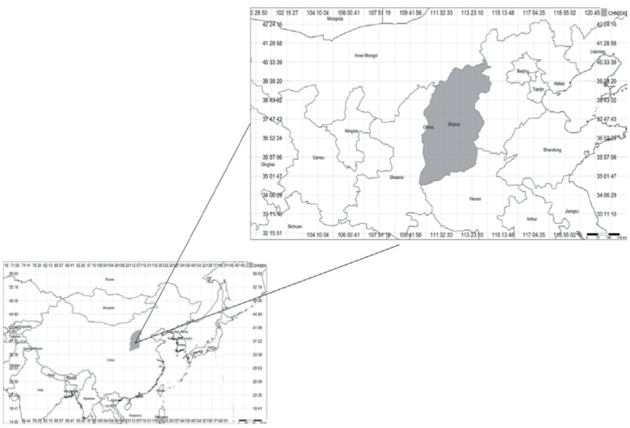

Fig. 1 - Study area location

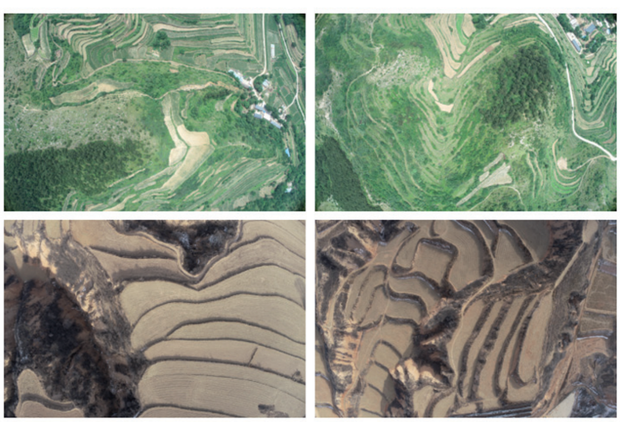

Fig. 2 - Remote sensing map of Shanxi Province

Dataset and preprocessing

In this paper, the land degradation monitoring research in Shanxi Province mainly relied on remote sensing image data and related meteorological data. Among them, the remote sensing image is from https://www.gscloud.cn/. The monthly NDVI synthesized MYDND1M data with a spatial resolution of 500 m was selected. Meteorological data are from the Central Meteorological Network (nmc.gov.cn/index.html). The data covered the period from 2016 to 2021.

Methods

The traditional land degradation monitoring generally adopts the form of manual monitoring. Because it is a field survey of the land, the data obtained is of high accuracy. However, the scope of manual monitoring is limited due to limited manpower. With the emergence and development of remote sensing image technology, land degradation monitoring with a larger scope and longer time span has been realized (Pravalie *et alii*, 2020). The basic process of land degradation monitoring using remote sensing image technology is displayed in Figure 3.

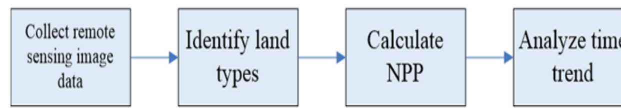

Fig. 3 - Basic flow of land degradation monitoring based on remote sensing images

1. Remote sensing image data of the area to be monitored is collected. Remote sensing image data includes images of multiple bands, each with a different wavelength range, which can highlight specific coverage information on the surface (Lu *et alii*, 2020). For example, the band with a wavelength range of 0.45-0.52 appears blue, which is sensitive to plant chlorophyll response and easier to penetrate water. It can be used to detect the distribution of underwater plants with chlorophyll.
2. The classification algorithm is used to identify and classify the land types in the remote sensing images, so as to preliminarily analyze the distribution of land types in the monitoring area and realize the preliminary monitoring of land degradation. The available classification algorithms include support vector machine, maximum likelihood classification, back-propagation neural network (BPNN), and convolutional neural network (CNN) (Omuto *et alii*, 2022).
3. The distribution of *NPP* in the monitoring area is calculated by using remote sensing images (Guo & Yang, 2022). The calculation method is:

$$
\begin{cases}
NPP_{x,t} = APAR_{x,t} \times \varepsilon_{x,t} \\
APAR_{x,t} = SOL_{x,t} \times FPAR_{x,t} \times c \\
FPAR_{x,t} = \dfrac{NDVI_{x,t} - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \times (FPAR_{\max} - FPAR_{\min}) + FPAR_{\min} \\
\varepsilon_{x,t} = T_{\varepsilon 1,x,t} \times T_{\varepsilon 2,x,t} \times W_{\varepsilon,x,t} \times \varepsilon_{\max} \\
T_{\varepsilon 1,x,t} = 0.8 + 0.02 \cdot T_{opt,x} - 0.0005 \cdot T_{opt,c}^{2} \\
T_{\varepsilon 2,x,t} = \begin{cases} \dfrac{1.184^{2}}{(1+e^{0.2\cdot(T_{opt,x}-10-T_{x,t})})\cdot(1+e^{0.3\cdot(-T_{opt,x}-10+T_{x,t})})} & -13℃ < T_{x,t} < 10℃ \\ \dfrac{T_{\varepsilon 2,x,T_{opt,x}}}{2} & others \end{cases} \\
W_{\varepsilon,x,t} = 0.5 + 0.5 \cdot \dfrac{EET_{x,t}}{PET_{x,t}}
\end{cases}
$$

where $NPP_{x,t}$ represents the net primary productivity of image grid x in time period t, $APAR_{x,t}$ represents the actual effective light radiation absorbed by image grid x in time period t, $\varepsilon_{x,t}$ represents the actual light energy utilization rate, $SOL_{x,t}$ denotes the total solar radiation, $FPAR_{x,t}$ denotes the absorption ratio of effective photosynthetic radiation, c is the proportion of radiation energy that is actually utilized, $NDVI_{x,t}$ is the $NDVI$, $T_{\varepsilon 1x,t}$ and $T_{\varepsilon 1x,t}$ are disturbance factors caused by temperature (Rajbanshi & Das, 2021), $W_{\varepsilon,x,t}$ is the disturbance factor caused by precipitation, ε_{max} is the maximum utilization rate of light energy, $T_{opt,x}$ is the average temperature during the period, $T_{x,t}$ is the ambient temperature of image grid x in time period t, $EET_{x,t}$ is the actual evaporation amount, and $PET_{x,t}$ is the potential evaporation.

4. After NPP of different time periods is calculated, time trend analysis can be carried out on the monitoring area. In this paper, unary linear regression analysis is adopted. Monitoring time is taken as the independent variable, and NPP is taken as the dependent variable. The slope of the regression equation (Tiwari *et alii*, 2021) is calculated:

$$\theta = \frac{n \cdot \sum_{i=1}^{n} i \cdot C_i - \sum_{i=1}^{n} i \cdot \sum_{i=1}^{n} C_i}{n \cdot \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where θ is the slope of the regression equation, n is the number of monitoring periods, and C_i is the NPP in time period i.

RESULTS

The average annual precipitation amount in Shanxi Province from 2016 to 2021 is shown in Figure 4, ranged from a minimum of 512.0 mm to a maximum of 712.2 mm. Based on the fitted linear trend line, there was an upward trend in the average annual precipitation amount in Shanxi Province during the period of 2016-2021.

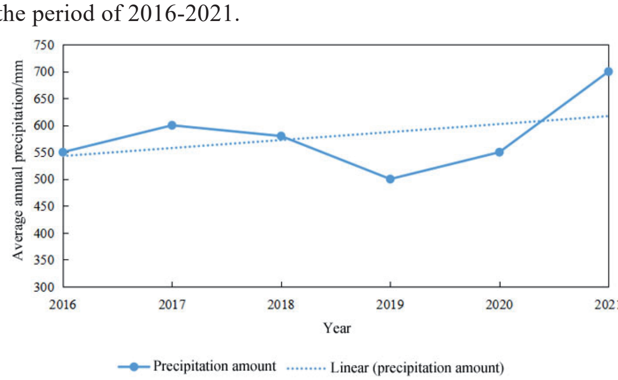

Fig. 4 - Average annual precipitation amount in Shanxi Province from 2016 to 2021

The results of a correlation analysis on different land types and precipitation amount in Shanxi Province are shown in Table 1. It can be observed that the P values of the correlation coefficients between land types such as forests, grasslands, and water areas and the annual average precipitation amount were all less than 0.05, indicating statistical significance.

The changes of land use proportion and average NPP in Shanxi Province from 2016 to 2021 are shown in Figure 5. It can be seen from Figure 5 that the proportion of different land use types in Shanxi Province changed with the passage of years. The proportion of forest land, grassland, and construction land increased, while the proportion of cultivated land decreased gradually. The proportion of water area was basically unchanged. In addition, the proportion of cultivated land was the largest in 2016 and 2017, and was second only to that of forest land after 2018. The average NPP of Shanxi Province also increased gradually with the passage of years.

	Forest land	Cultivated land	Grassland	Construction land	Water area
Coefficient of correlation with precipitation amount	1.236	0.897	1.332	0.542	1.311
P value	0.021	0.058	0.032	0.098	0.012

Tab. 1 - Results of correlation analysis of different land types and precipitation amount in Shanxi Province

Fig. 5 - Changes of land use proportions and average NPP in Shanxi Province from 2016 to 2021

The proportion of land degradation area in Shanxi Province during 2016-2021 is shown in Table 2. As can be seen from Table 2, the land degradation phenomena in Shanxi Province mainly included soil erosion, salinization, and grassland degradation.

Land degradation phenomenon	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021
Soil erosion	1.56%	1.13%	1.06%	0.87%	0.90%
Salinization	1.42%	1.02%	0.81%	0.69%	0.42%
Grassland degradation	0.12%	0.13%	0.12%	0.11%	0.13%

Tab. 2 - The proportion of land degradation area in Shanxi Province from 2016 to 2021

In general, the proportion of local land area where land degradation occurred showed a decreasing trend. In the same period of time, soil erosion accounted for the largest proportion, followed by salinization, and grassland degradation was the least.

The distribution of NPP in Shanxi Province from 2016 to 2021 is shown in Figure 6, and its changing trend is shown in Table 3. As can be seen from Figure 6, the areas with medium and low NPP in Shanxi Province gradually decreased over time, while the areas with high NPP gradually increased. As can be seen from the NPP change trend shown in Table 3, with the passage of time, NPP in most regions increased significantly or extremely significantly. NPP in only a small part of regions decreased significantly or extremely significantly, while NPP in the remaining regions did not change significantly.

Time period	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021
The proportion of area with extremely significant reduction of NPP/%	0.12	0.13	0.12	0.11	0.13
The proportion of area with significant reduction of NPP /%	2.98	2.15	1.87	1.56	1.32
The proportion of area with no significant change of NPP/%	30.35	29.87	28.73	27.89	27.74
The proportion of area with significant increase of NPP/%	24.15	24.18	25.32	25.69	26.34
The proportion of area with extremely significant increase of NPP/%	42.40	43.67	43.96	44.75	44.47

Tab. 3 - NPP trends in Shanxi Province from 2016 to 2021

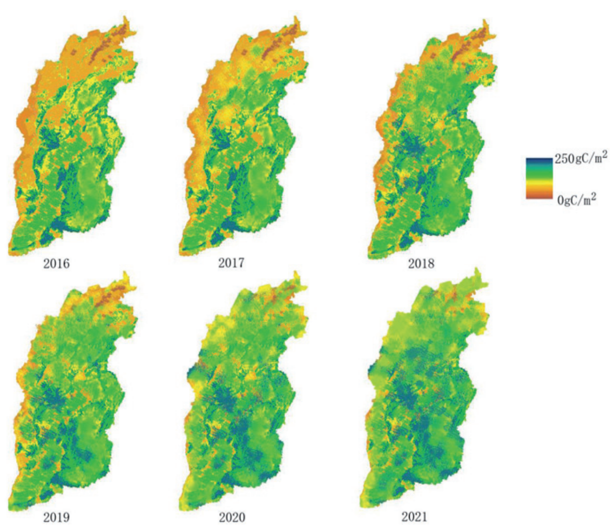

Fig. 6 - NPP distribution in Shanxi Province from 2016 to 2021

DISCUSSION

With population growth, rapid urbanization, and changes in agricultural production methods, land degradation in many areas has become an increasingly serious problem. The land degradation in Shanxi is mainly manifested in soil erosion, salinization, grassland degradation, etc. These negative changes will not only affect local agriculture, but also destroy the local ecological diversity. Therefore, it is necessary to monitor the local land degradation situation in order to make corresponding countermeasures. Remote sensing image technology is a non-contact information acquisition method, which uses satellite to obtain high-resolution image data and then identifies the land surface information according to the spectral data in the image data. This paper took Shanxi Province as an subject to conduct a case study of land degradation monitoring. In the analysis process, the land cover type of Shanxi Province was first identified. Then, NDVI data in remote sensing image information and meteorological data were used to invert the NPP of Shanxi Province. Finally, the spatial-temporal trend of NPP of Shanxi Province was analyzed, and the specific results are shown above.

From 2016 to 2021, the water area in Shanxi Province has not changed significantly, the cultivated land area has gradually decreased, and the woodland, grassland, and construction land have gradually increased, which is due to the local implementation of the policy of returning farmland to forest and grassland. Due to the increase of population and the promotion of urbanization, the construction land also increased. The NPP of Shanxi Province is increasing year by year on the whole, which is also because the area of forest and grassland is increasing year by year under the policy of returning farmland to forest and grassland. The change trend of NPP in Shanxi Province from 2016 to 2021 can further prove this point. During this period, NPP in most local areas has a significant or extremely significant increase, while NPP in only a small part of local areas has a significant decrease. Therefore, on the whole, local NPP shows an increasing trend.

CONCLUSIONS

This paper briefly introduces the concepts of remote sensing image technology and land degradation, and describes the basic process of using remote sensing image to monitor land degradation. Then, Shanxi Province was taken as a case to analyze the changes of land cover type and NPP in 2016-2021. The results are summarized as follows.

- During this period, the average annual precipitation amount showed an increasing trend in Shanxi Province, and there was a significant positive correlation between the area of land types such as forest lands, grasslands, and water areas and the average annual precipitation amount.
- The proportion of forest land, grassland, and construction land increased, the proportion of cultivated land gradually decreased, and the proportion of water area remained basically unchanged.
- The total NPP of Shanxi Province gradually increased with the passage of years, in which the area with middle and low NPP gradually decreased, and the area with high NPP gradually increased.

- Soil erosion, salinization, and grassland degradation were the main manifestations of land degradation in Shanxi Province.
- With the passage of time, NPP increased significantly or extremely significantly in most regions, while NPP decreased significantly or extremely significantly in a small part of regions.

REFERENCES

Bassan K.A., Kokou K. & Sills E.O. (2020) - *Constraints to Tropical Forest Conservation and Successful Monitoring and Assessment of Land Uses Cover and Change: Do the Forest Definition and Administration Really Matter?* Natural Resources, **11**: 1-19.

Easdale M.H., Faria C., Hara S., Perez Leon N., Umana F., Tittonell P. & Bruzzone O. (2019) - *Trend-cycles of vegetation dynamics as a tool for land degradation assessment and monitoring*. Ecological Indicators: Integrating, Monitoring, Assessment and Management, **107**: 105545.1-105545.10.

Giuliani G., Chatenoux B., Benvenuti A., Lacroix P., Santoro M. & Mazzetti P. (2020) - *Monitoring land degradation at national level using satellite Earth Observation time-series data to support SDG15 – exploring the potential of data cube.* Big Earth Data, **4**: 3-22.

Guo B. & Yang F. (2022) - *A novel feature space monitoring index of salinisation in the Yellow River Delta based on SENTINEL-2B MSI images.* Land Degradation and Development, **33**: 2303-2316.

Herrmann S., Diouf A.A. & Sall I. (2019) - *Beyond bioproductivity: Engaging local perspectives in land degradation monitoring and assessment.* Journal of Arid Environments, **173**: 1-5.

Kang J., Zhang Y. & Biswas A. (2021) - *Land Degradation and Development Processes and Their Response to Climate Change and Human Activity in China from 1982 to 2015.* Remote Sensing, **13**: 1-13.

Liang Z., Wu Z., Yao W., Noori M., Yang C., Xiao P. & Deng L. (2019) - *Pisha sandstone: Causes, processes and erosion options for its control and prospects.* International Research on Soil and Water Conservation, **7**: 1-8.

Liu Y., Han X., Weng F., Xu Y., Zhang Y. & Tang S. (2022) - *Estimation of Terrestrial Net Primary Productivity in China from Fengyun-3D Satellite Data*. Journal of Meteorological Research, **36**: 401-416.

Lorenz K., Lal R. & Ehlers K. (2019) - *Soil organic carbon stock as an indicator for monitoring land and soil degradation in relation to United Nations' Sustainable Development Goals.* Land Degradation & Development, **30**: 824-838.

Lu H., Liu G., Zhang C. & Okuda T. (2020) - *Approaches to quantifying carbon emissions from degradation in pan-tropic forests-Implications for effective REDD monitoring.* Land Degradation and Development, **31**: 1-16.

Omuto C.T., Vargas R.R., Elmobarak A.A., Mapeshoane B.E., Koetlisi K.A., Ahmadzai H. & Mohamed N. (2022) - *Digital soil assessment in support of a soil information system for monitoring salinization and sodification in agricultural areas*. Land Degradation and Development, **33**: 1204-1218.

Pravalie R., Patriche C., Tiscovschi A., Dumitrascu M., Savulescu I., Sirodoev I. & Bandoc G. (2020) - *Recent spatio-temporal changes of land sensitivity to degradation in Romania due to climate change and human activities: An approach based on multiple environmental quality indicators*. Ecological Indicators: Integrating, Monitoring, Assessment and Management, **118**: 1-16.

Rajbanshi J. & Das S. (2021) - *Monitoring Land Sensitivity to Desertification using ESAI Approach and Evaluation of the Responsible Indicators – A Spatio-temporal Study in India*. Land Degradation and Development, **32**: 3045-3061.

Selvaraj R. & Nagarajan S.K. (2021) - *Land Cover Change Detection from Remotely Sensed IoT Data for Assessment of Land Degradation: A Survey.* Journal of Information & Knowledge Management, **20**: 1-10.

Taheri Dehkordi A., Valadan Zoej M.J., Ghasemi H., Ghaderpour E. & Hassan Q.K. (2022) - *A New Clustering Method to Generate Training Samples for Supervised Monitoring of Long-Term Water Surface Dynamics Using Landsat Data through Google Earth Engine.* Sustainability, 14: 1-24.

Tiwari A., Tomar S.S., Katare V., Vyas S.P. & Dhinwa P.S. (2021) - *Long-term monitoring of land-use/land-cover change in Morena district, Madhya Pradesh, India, using EO satellite data. Current Science: A Fortnightly* Journal of Research, **121**: 1584-1593.

Venter Z.S., Scott S.L., Desmet P.G. & Hoffman M.T. (2020) - *Application of Landsat-derived vegetation trends over South Africa: Potential for monitoring Land Degradation And Restoration*. Ecological Indicators, **113**: 1-9.

Zuo L., Wu B., You L., Huang W., Meng R., Dong Y., Pan T. & Wang Y. (2022) - *Big Earth Data Supports Sustainable Food Production: Practices and Prospects*. Bulletin of Chinese Academy of Sciences, **36**: 885-895.

Received November 2023 - Accepted December 2023