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Applications of the Land Degradation Index (LDI) in remote sensing-based land degradation studies: an analytical review (Review article)

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تطبيقات مؤشر تدهور الأراضي (LDI) في دراسات تدهور الأراضي القائمة على الاستشعار عن بعد: مراجعة تحليلية (مقال مراجعة)

المدرس المساعد هنادي طالب إسماعيل القيسي
جامعة بغداد/ كلية علوم الهندسة الزراعية/ قسم مكافحة التصحر

ملخص:

يُعد تدهور الأراضي تحديًا بيئيًا عالميًا يتطلب حلولاً فعالة لضمان الاكتفاء الذاتي الغذائي للأجيال الحالية والمقبلة. ولمعالجة هذه القضايا، ظهر مؤشر تدهور الأراضي (LDI) في بداية الألفية الثالثة كأسلوب فعال لرصد وقياس تدهور الأراضي وتدهور صحة النظم الإيكولوجية من خلال استخدام الاستشعار عن بعد. يعرض هذا المقال آخر المستجدات المنهجية والتطبيقات العملية لمؤشر تدهور الأراضي (LDI) على مدى السنوات الخمس الماضية (٢٠٢٠–٢٠٢٥)، مع التركيز على منهجيات شاملة تدمج مؤشرات طيفية متعددة، وتقنيات التعلم الآلي، والبنية التحتية الافتراضية. وتُظهر النتائج أن النماذج التي تم تطويرها لمؤشر تدهور الأراضي (LDI) حققت دقة تصل إلى ٩٧٪ في تقدير مستوى تدهور الأراضي، مما يوفر أساسًا علميًا متينًا لصانعي القرار من أجل تحسين استراتيجيات الإدارة المستدامة.

الكلمات المفتاحية: مؤشر تدهور الأراضي، الاستشعار عن بُعد، LDI، الألبيدو، التعلم الآلي.

Abstract:

Land degradation is a global environmental challenge that requires effective solutions to ensure food self-sufficiency for current and future generations. To address such issues, the Land Degradation Index (LDI) emerged at the start of the third millennium as an effective technique for monitoring and measuring land degradation and the decline in ecosystem health through the use of remote sensing. This article presents methodological updates and practical applications of the LDI over the past five years (2020–2025), highlighting comprehensive methodologies that integrate multiple spectral indices, machine learning techniques and virtual infrastructure. The results show that the models developed for the LDI achieved an accuracy of up to 97% in estimating the level of land degradation, providing a robust scientific basis for decision-makers to improve sustainable management strategies.

Keywords: Land Degradation Index, remote sensing, LDI, albedo, machine learning.

١. Introduction:

Land degradation can be described as a gradual reduction in the productive capacity of land, resulting from interconnected processes such as soil erosion, ecological imbalance, and vegetation loss. , as revealed by a study by Amin (2025) revealed that over 40% of the world' land area is degraded, which is considered one of the most pressing challenges to food security

١,١. The Iraqi Context:

Iraq faces significant challenges in the areas of land degradation and desertification. According to a report by the Central Organisation for Iraqi Statistics (2024), degraded land has expanded to cover 96.5 million dunams, whilst over 40 million dunams have become desert. A study by Zwain (2021) showed that Basra Governorate in southern Iraq is experiencing severe degradation; remote sensing analyses using Landsat data for the period 1973–2013 revealed a significant reduction in vegetation cover alongside an expansion of the area of land affected by desertification . To address these challenges, the Iraqi Ministry of Agriculture has prepared a national report setting out objectives for 'neutralizing the effects of land degradation' in line with the international framework for tackling desertification (UNCCD). The boundaries of degraded areas were delineated using three key biophysical indicators, including: soil fertility, soil texture, and soil organic matter, as well as indicators relating to (salinisation, erosion and sandstorms). .

٢. Theoretical and methodological principles of the Land Degradation Index (LDI)

٢,١ Key components of the LDI:

The Land Degradation Index (LDI) is developed through the integration of multiple spectral and environmental indicators. Zhang et al. (2024) An in-depth study was carried out of the Ebinur Lake basin in China covering the period 2002–2022, in which they integrated the Soil-Adjusted Vegetation Index (SAVI), the Thermal-Vegetation Drought Index (TVDI) and the Salinity Index (SDI) using the Analytic Hierarchy Process (AHP) and the entropy method. The results indicated an increase in the proportion of degraded land of approximately 17% over the study period, with these areas concentrated in the north-western part of the desert plain.

٢,١,١Normalised Difference Vegetation Index (NDVI):

٢,١,١ Normalised Difference Vegetation Index (NDVI):

This is the key component in most LDI models, indicating the density and health of vegetation cover. In Iraq, Dhamin (2023) used the NDVI to assess the level of agricultural land degradation in the southern part of Baghdad for the period 2010–2019, utilising imagery (Landsat-5TM and Landsat-8OLI) and incorporating climate statistics obtained from the European Institute for Sensory Weather Forecasting (ECMWF). The study concluded that climate change is the main factor behind the decline in agricultural productivity.

٢,١,٢Surface albedo:

This is an important physical parameter that characterises soil and land cover. A study by Ebrahimi (2024) showed that the linear relationship between reflectivity of surfaces and spectral indices is effectively used in deriving degradation severity indices. The study also assessed Reliability of spectral data extracted from Sentinel-2 imagery using 100 ground control points. The results showed that the MSAVI-Albedo demonstrated superior predictive performance and high efficiency in calibration and validation.

٢,١,٣Land Surface Temperature (LST):

This is used as an indicator of thermal stress and drought. In an Iraqi study, Singh (2024) demonstrated that LST has a positive correlation with land degradation in semi-arid areas.

٢,١,٤ Soil salinity indices :

Soil salinity in Iraq is a key factor in land degradation. Aksoy (2024) conducted a comparative study to assess the potential of the LDI index for mapping soil salinity using Landsat-8 OLI and Sentinel-2 MSI data in a semi-arid region of Morocco, The high-resolution data yielded an R^2 of 0.83 and an RMSE of 0.87 ds/m, compared to an R^2 of 0.83 and an RMSE of 1.24 ds/m for Landsat-8.The results of these studies are highly significant for the Iraqi environment, as salinity affects 75% of the irrigated land in central and southern Iraq.

.٣Practical application in various environments:

٣,١Monitoring desertification in arid and semi-arid areas:

Globally, Sohrabizadeh (2024) conducted an advanced study to diagnose land degradation in the Iranian Sistan Plain during the period 1990–2020 and to forecast conditions for the year 2030. The study utilised the Random Forest algorithm to compile several indices, including (NDVI, EVI, VCI, TCI). The model achieved very high accuracy with a correlation coefficient of $R^2 = 0.97$ and RMSE = 0.089, and predicted a sustained decline in desertification until 2030 . In Iraq, and specifically in the Euphrates Plain, researchers conducted a comprehensive study using remote sensing technology to monitor soil degradation over the period 1976–2020, utilising a number of Landsat images (Landsat 1–5 MSS, Landsat 4–5 TM, Landsat 7, Landsat 8). The study highlighted the delineation of degraded areas in the Silver Plain. Unoriented classification was used for images from 1976 to 1996, and oriented classification for images from 2014 to 2021. The results showed the expansion of sand dune areas and the degradation of agricultural land . In Wasit Governorate, researchers conducted a study of the district for the period 2014–2022 using (Landsat 8) Land cover was classified into six categories. The results showed that the proportion of arid land in reached 69% of the total area of 1,515.50 km², whilst the proportion of agricultural land was only 16% (351.41 km²) and the proportion of land affected by salinisation was 5% (116.38 km²). This time period was selected due to severe drought, high salinity levels and variations in irrigation practices . In Dhi Qar Governorate, Hassan (2023) used the NDVI index to study changes in vegetation cover over the period 1990–2022. The findings concluded that there has been a reduction in green space, caused by drought and unsustainable practices . An analytical study of time series for vegetation cover indices was also carried out in Dhi Qar Governorate, using 40 Landsat images and applying the Mann-Kendall test to determine the trend over time . Gaznayee (2021) also applied time modeling analysis of the (NDVI and NDEI) and the standardised precipitation index to assess the level of drought in Sulaymaniyah Governorate for the period 1998–2017. Forty Landsat images were used to analyse the dynamics of the vegetation and hydrological environment; the results indicated that drought has become a persistent and highly dangerous phenomenon in the study area . In the Shiklawa region of Iraqi Kurdistan, a study was conducted to assess the potential for land degradation using advanced techniques. The study utilised several machine learning algorithms (Random Forest, Naive Bayes, Logistic Regression); of these, the Random Forest model demonstrated the highest level of accuracy, as indicated by the area under the curve (AUC) of 0.882. .

٣,٢Monitoring national and regional land degradation:

٣,٢Monitoring national and regional land degradation:

Shao (2024) developed sophisticated evaluation methodology based on two integrated thresholds to establish priority management approaches for achieving Land Degradation Neutrality (LDN) in Inner Asia. The study combined the improved indicators of declining land productivity (LDI) model for desert regions with critical thresholds and ecosystem service (ES) indicators, linking them to the Sustainable Development Goals (SDGs). The study found an increase in the LDI for the period 2000–2022, a decline in ecosystem services, and a slowdown in SDG progress in the most affected regions . In recent Iraqi studies, a comprehensive analysis was conducted to assess the consequences of global warming on the health of plant cover and degradation of land across Iraq's various climatic environments for the period 1981–2020. The study utilised 252 images from the MODIS Vegetation Indices (MOD13) for the period 2000–2020. The results showed a sharp decline in vegetation cover and a rise in the area of degraded land, particularly during the summer . In an advanced study conducted in the provinces of Al-Qadisiyah and Babil in central Iraq covering the period 2000–2023, an integrated approach comprising Fractional Vegetation Cover, the Mann–Kendall test and Sen's slope was used to identify trends in greening and degradation (2) LandTrendr was used to determine the timing and extent of disturbances, and annual LULC maps were generated using Random Forest and the XGBoost model, which was employed to map degradation impacts and identify climate indicators affecting human populations. The results indicated that 51.5% of the land underwent recovery, whilst 2.5% suffered severe degradation. The XGBoost model identified drought and agricultural cover density as the most significant factors contributing to degradation . In the province of Erbil in northern of Iraq, researchers used high-resolution MODIS and Pleiades imagery to conduct a spatiotemporal assessment of vegetation cover in the urban environment. The study found that vegetation cover had declined as a result of urban sprawl and signs of environmental degradation.

.٤Integration of intelligent algorithms with the Land Degradation Index (LDI):

٤,١Machine learning algorithms used:

There has recently been significant progress in the application of intelligent algorithms to assess the level of degradation of land, as These algorithms have proven their effectiveness in processing big data and analysing the changing relationships between various environmental factors..

٤,١,١Random Forest (RF):

This algorithm has become the most widely used in studies addressing land degradation due to its advantages, such as a high level of competence in dealing with changing relationships and resistance to overfitting, as well as providing an assessment of the extent of each factor's influence. Yousefi et al. (2021) applied the RF model in a comprehensive study to assess pasture degradation in the Alborz Mountains in Iran, where the model performed exceptionally well with an ROC-AUC coefficient of 0.96, outperforming traditional algorithms such as Supervised machine learning algorithm (SVM).

٤,١,٢XGBoost (Extreme Gradient Boosting)

This algorithm has recently come to the fore due to its power and sophistication, as it is characterised by its significant predictive capabilities and its ability to handle big data. In a recent study published in Earth in 2025, which addressed forest degradation and deforestation along the Iraqi-Turkish border in Dohuk Governorate over the period (2015–2024). The researchers utilised seven machine learning algorithms, amongst which XGBoost stood out for its consistently outstanding performance, with a predictive accuracy (R^2) which reached (0.903) in 2015, (0.910) in 2019 and (0.950) in 2024, with a significant reduction in the root mean square error ($RMSE \leq 0.035$). The SHAP (SHapley Additive exPlanations) technique was also used to enhance the model's interpretability, This reveals a structural shift in the factors contributing to forest degradation, from climatic factors (rainfall and temperature) in 2015 to human activities (such as fires, the construction of transport routes, and the reduction of vegetation cover) in 2024. The results showed a 12% decline in forest area, which fell from 630 square kilometres in 2015 to 577 square kilometres in 2024, demonstrating the effectiveness of the XGBoost algorithm in the dynamic monitoring of forest cover in regions with geopolitical complexity . The XGBoost algorithm was also used in the Iraqi study in the provinces of Al-Qadisiyah and Babil, as mentioned earlier, to map risks and degradation and to assign climate and human-related indicators; The area under the curve (AUC) was 0.884 and identified 9.7% of the area as being subject to a high level of degradation.

٤,١,٣Support Vector Machine (SVM):

SVM is used to classify degraded areas into categories and define the boundaries separating them by identifying the decision boundary, which maximises the separation between different classes. Recent comparative studies have shown that SVM typically achieves lower accuracy than RF and XGBoost in land cover and land degradation classification applications, particularly when dealing with large datasets. In a comprehensive study by Adugna et al (2022) , the efficiency of RF and SVM was compared when mapping land cover at a large regional scale across the African continent using 1 km resolution FY-3C imagery. The results showed that the RF algorithm outperformed the SVM algorithm, achieving an overall accuracy (OA) of 0.86 and a Kappa coefficient (k) of 0.83, thereby outperforming the SVM algorithm by 1–2% in overall accuracy and 3% in the Kappa coefficient. Furthermore, RF performed best when classifying mixed categories, Whereas performance was similar when classifying non-mixed groups with clear spectral variation.. The study also demonstrated that RF has the capacity to handle large datasets where SVM fails . Jayasinghe and Withanage (2024) also compared the performance of SVM, RF and ANN in monitoring changes in land use in cities; the results showed that the SVM model achieved an overall accuracy ranging from 77% and 94% for the years 1995 to 2023, whilst RF achieved the highest accuracy of 96% with R-squared values ranging from 0.92 to 0.97, thereby outperforming SVM and ANN.

٤,١,٤Long Short-Term Memory (LSTM):

LSTM networks represent one of the most significant advancements in the application of deep neural networks to land degradation and the prediction of soil water content, as they are designed to overcome the problem of gradient vanishing in traditional Recurrent Neural Networks (RNNs), enabling them to store and utilise data across long time series. In a comprehensive study conducted by Wang et al (2024), ten different network architectures were evaluated for predicting soil moisture, including LSTM, CNN, Transformer and six other hybrid architectures. The results showed that the GAN-LSTM model, which combines LSTM with generative adversarial networks, outperforms the standard LSTM in most cases, particularly in 3–7-day forecasting tasks. The study utilised SHAP (SHapley Additive Explanations) analysis to analyse how the models work and identify the variables with the greatest influence on soil moisture prediction. The results demonstrated that the ability of LSTM to model time series makes it highly suitable for predicting soil moisture, as it achieved superior correlation coefficients (R^2), RMSE and MAE values compared to other models . In an advanced application of smart farming, researchers used the Advanced LSTM model to predict the levels of nitrogen (N), phosphorus (P) and potassium (K) present in the soil, as these are essential elements for determining the correct amount of fertiliser the soil requires. The results showed that LSTM significantly outperformed traditional machine learning algorithms (Random Forest, KNN, SVR, Gradient Boosting) in processing soil time-series data, whilst the classical models achieved only moderate accuracy.

LSTM has also been successfully used for early warning of long-term agricultural drought, with researchers utilising 21 years of training data to predict four climatic variables, including (precipitation, temperature, soil moisture and NDVI) to calculate the Enhanced Drought Index (ECDI) for the next 12 months in the US state of Texas. The results demonstrated that LSTM has great potential for predicting land degradation and long-term drought.

All these studies have confirmed that LSTM represents a significant advance in the ability to predict soil and land degradation over the long term, as it enables the modelling of time series and the identification of the cumulative impact of agricultural practices and climate change.

٤،٢The comprehensive approach:

Salmi et al. (2025) conducted an in-depth study of land degradation in the Egyptian governorate of Damietta, using six key indicators, including the Wind Erosion Quality Index (WEQI) and the Geological Index (GI), the Topographic Quality Index (TQI), the Chemical Quality Index (CQI), the Physical Quality Index (PQI) and the Vegetation Quality Index (VQI)). The results indicated that 31.83% of the study area is subject to significant degradation, and 51.5% of the land has a reduced level of vegetation cover.

.٥The capabilities of Google Earth Engine cloud computing platforms:

٥،١Capabilities of Google Earth Engine:

These platforms have brought about a major advancement in the field of land degradation studies by providing direct access to the entire Landsat archive dating back to 1972 and satellite data (Sentinel-1, Sentinel-2, MODIS), with the ability to process massive time-series datasets in a matter of minutes.

٥،٢Practical Applications:

Chen et al. (2021) adapted the methodology (Spectral Mixture Analysis - Continuous Change Detection and Classification) on GEE to identify severe and advanced forest degradation in temperate regions. The study found that high accuracy in detecting both gradual and abrupt degradation is achieved by combining SMA and CCDC to isolate seasonal variations from actual degradation. . In a latest study, Berra et al. (2024) developed a comprehensive workflow using GEE to generate harmonised surface reflectance statistics (HLS) from satellite imagery (Landsat-7/8 – Sentinel-2), thereby enabling near-daily time series with a spatial resolution of 30 metres and continuous statistics from 1972 to the present.

.٦Spatial accuracy of the LDI index:

In a comprehensive study conducted by Ebrahimi, A., et al. (2024) to verify the accuracy of the LDI index, the results showed that the indices (MSAVI-Albedo, SAVI-Albedo and NDVI-Albedo) exhibited statistically significant differences ($P > 0.05$) from field statistics, whilst (TGSI-Albedo and BSI-Albedo) showed significant differences ($P \leq 0.001$). The study concluded that MSAVI is optimal for mapping the severity of degradation. .

.٧Challenges:

Iraq's national report on LDN indicated that dust storms have increased significantly from an average of no more than 24 days a year during the period 1951–1990 to 283 days in 2012;consequently, remote sensing monitoring operations have become complex and this has an impact on the accuracy of the statistics produced.

.٨Conclusions:

Following a comprehensive review of studies and research published between 2020 and 2025, the following conclusions can be drawn:

Firstly: Methodological developments of the LDI:

Studies have shown that the Land Degradation Index (LDI) has evolved from a simple combination of the NDVI and albedo indices to a comprehensive methodology incorporating several indices (SAVI, TVDI, SDI, LST) and utilising advanced analytical techniques such as AHP and the entropy method. These developments have significantly improved the accuracy of the assessment, with correlation coefficients reaching 0.97 in some studies.

Secondly: Accuracy and reliability:

The results of the field verification indicated that soil-corrected indices (MSAVI), when combined with albedo, provide a high degree of accuracy in assessing the level of degradation, whereas conventional indices (BSI, TGSI) require significant improvement. The accuracy achieved in salinity mapping using Sentinel-2 ($R^2 = 0.89$) is clearly superior to that of Landsat-8 ($R^2 = 0.83$), demonstrating the significant importance of spatial accuracy in assessing the severity of land degradation.

Thirdly: Machine learning

We have found that machine learning algorithms, particularly Random Forest and XGBoost, are highly effective in combining multiple indicators and identifying the factors causing land degradation. Furthermore, the ability of these models to scientifically address these non-linear patterns in correlations and long-term predictions has made them indispensable tools in modern land degradation studies. Moreover, advances in LSTM for time-series modelling open up promising avenues for predicting land degradation over many years.

Fourth: The importance of cloud computing platforms

The Google Earth Engine platform has brought about a quantum leap in the ability to analyse vast areas at national and regional levels, thereby facilitating the monitoring of land degradation with high efficiency. Furthermore, the ability to process massive amounts of spatial data in a short time has paved the way for comprehensive studies that were previously difficult to conduct.

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Fifth: The Situation in Iraq:

Iraq faces serious problems, the effects of which are exacerbated by land degradation; according to the latest statistics, more than 40 million dunams have become desert. Local Iraqi studies have also shown a significant decline in vegetation cover in most Iraqi governorates and a sharp rise in soil salinity in irrigated agricultural land in central and southern Iraq, as well as widespread drought in the Kurdistan Region, In addition, the area of barren land has expanded by 69% in some areas, such as Wasit Governorate.

Sixth: Spatial and temporal variation

Studies have highlighted a marked difference in the patterns and levels of degradation across a wide range of regions. Whilst some regions have shown signs of recovery, reaching a rate of 51.5% in the study of Babylon and Qadisiyah, other regions continue to suffer from significant and ongoing degradation. This variation underscores the importance of analyzing local conditions and the need to adopt specific local management strategies.

Seventh: Factors influencing degradation:

The studies identified relevant factors, including climate change (drought, rising temperatures), resource-depleting agricultural practices, poor water resource management, unsustainable agriculture and unplanned urban expansion.

Eighth: Research gaps:

Despite the tremendous progress in this field, there is a scarcity of studies covering timeframes spanning decades in the Iraqi environment, a lack of comprehensive field surveys, a neglect of socio-economic factors, and a scarcity of studies evaluating the effectiveness of strategies adopted for recovery and rehabilitation.Seventh: Factors influencing degradation:

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.٩Recommendations:

Based on the findings, it is recommended that:

-١A comprehensive national monitoring system be established in Iraq to monitor land degradation using the GEE.
-٢Improving standardised protocols for calculating and applying the LDI index.
-٣Strengthening field survey and in-situ monitoring programmes.
-٤Building the capacity of Iraqi national institutions in remote sensing technology.
-٥Conducting integrated longitudinal studies over an extended period.
-٦Improving LDI models specifically for the Iraqi context.
-٧Combining radar data with optical data to overcome the issue of dust storms.
-٨Applying deep learning techniques to predict future land degradation.
-٩Utilising monitoring results and linking them to decision-making and sustainable land-use planning.
-١٠Improving strategies for urgent intervention based on early warning systems.
-١١Strengthening regional cooperation in the exchange of data and expertise.
-١٢Supporting local projects in the field of conservation agriculture and sustainable development .