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

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Abstract
Land degradation is one of the world's most pressing environmental issues and has become a major threat to food security and sustainable development. The Land Degradation Index (LDI) has emerged as a key tool for monitoring and assessing the extent of land degradation using remote sensing technology. 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.

1. Introduction

Land degradation is defined as the continuous decline in a land's productive capacity, as evidenced by a number of interrelated processes such as soil erosion, ecological imbalance and the loss of vegetation cover, as revealed by a study by Amin (2025) revealed that over 40% of the world's land area is degraded, which is considered one of the most pressing challenges to food security.

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 developed a national report to set Land Degradation Neutrality (LDN) targets in collaboration with the United Nations Convention to Combat Desertification (UNCCD). The boundaries of degraded areas were delineated using three key biophysical indicators, including: land productivity, land cover, and soil organic carbon, as well as indicators relating to salinisation, erosion and sandstorms.

2. Theoretical and Methodological Principles of the Land Degradation Index (LDI)

2.1. Key Components of the LDI

The Land Degradation Index (LDI) is derived from a combination of spectral and environmental indices. Zhang et al. (2024) conducted a comprehensive study 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.

2.1.1. 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 images (Landsat-5TM and Landsat-8OLI) and incorporating climate data obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). The results indicated a strong correlation between climate change and the degradation of agricultural land.

2.1.2. Surface Albedo

This is an important physical parameter that characterises soil and land cover. A study by Ebrahimi (2024) showed that the linear relationship between albedo and spectral indices is effectively used in deriving degradation severity indices. The study also assessed the accuracy of spectral indices extracted from Sentinel-2 imagery using 100 ground control points. The results showed that the MSAVI-Albedo index achieved the lowest root mean square error (RMSE) and the highest correlation.

2.1.3. Land 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.

2.1.4. 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.

3. Practical Application in Various Environments

3.1. Monitoring Desertification in Arid and Semi-Arid Areas

Globally, Sohrabizadeh (2024) conducted an advanced study to monitor and predict desertification 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 km^2, whilst the proportion of agricultural land was only 16% (351.41 km^2) and the proportion of land affected by salinisation was 5% (116.38 km^2). 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 results indicated a significant decline in the area of vegetation cover, 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-series 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 changes in vegetation cover and water bodies; 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 collected 22 variables, including the NDVI index, rock characteristics, soil type and slope. The study utilised several machine learning algorithms (Random Forest, Naive Bayes, Logistic Regression); of these, the Random Forest model achieved the highest accuracy, with an area under the curve (AUC) of 0.882.

3.2. Monitoring National and Regional Land Degradation

Shao (2024) developed an innovative dual-threshold assessment method to establish priority management approaches for achieving Land Degradation Neutrality (LDN) in Central Asia. The study combined the improved Land Degradation Index (LDI) model for arid 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 impact of climate change on the health of vegetation cover and land degradation 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 significant decrease in vegetation cover and an increase 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 the Kurdistan Region 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.

4. Integration of Machine Learning Techniques with the Land Degradation Index (LDI)

4.1. Machine Learning Algorithms

There has recently been significant progress in the application of machine learning algorithms to assess the level of land degradation, as these algorithms have demonstrated their ability to process complex data and non-linear relationships between various environmental factors.

4.1.1. Random Forest (RF)

This algorithm has become the most widely used in studies addressing land degradation due to its advantages, such as the ability to handle non-linear 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 Support Vector Machines (SVM).

4.1.2. XGBoost (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 ≤ 0.035). The SHAP (SHapley Additive exPlanations) technique was also used to enhance the model's interpretability, revealing a clear temporal shift in the drivers of forest degradation from climatic factors (rainfall – temperature) in 2015 to human misuse (fires – road construction – land clearing) in 2024. The results indicated a 12% decline in forest area, from 630 km^2 in 2015 to 577 km^2 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 model achieved an AUC of 0.884 and identified 9.7% of the area as being subject to a high level of degradation.

4.1.3. Support Vector Machine (SVM)

SVM is used to classify degraded areas into categories and define the boundaries separating them by finding the hyperplane , 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 performance 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 RF outperformed SVM with an overall accuracy (OA) of 0.86 and a Kappa coefficient (k) of 0.83, which is 1–2% and 3%) than the best SVM model, respectively. Furthermore, RF performed best when classifying mixed categories, whilst performance was similar when classifying pure categories with distinct 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.

4.1.4. Long 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.

4.2. The Comprehensive Approach

Selmy et al. (2025) conducted a comprehensive assessment of land degradation in the Egyptian governorate of Damietta, combining six key indices, including the Wind Erosion Quality Index (WEQI), 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.

5. The Capabilities of Google Earth Engine Cloud Computing Platforms

5.1. Capabilities 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.

5.2. Practical Applications

Chen et al. (2021) developed an approach (Continuous Change Detection and Classification – Spectral Mixture Analysis) based on GEE to monitor acute and gradual forest degradation in temperate forests. The study concluded that high accuracy in detecting both gradual and sudden degradation is achieved by combining SMA and CCDC to isolate seasonal variations from actual degradation. In a recent 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.

6. Spatial Accuracy of the LDI Index

In a comprehensive study conducted by Ebrahimi 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 statistically significant differences ($P \leq 0.001$). The study concluded that MSAVI is the most suitable for mapping the severity of degradation.

Iraq's national report on LDN indicated that dust storms increased significantly from an average of 24 days per 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.

7. Conclusion

In conclusion, studies published between 2020 and 2025 show that the Land Degradation Index (LDI) has developed significantly from a simple integration of NDVI and albedo into a more comprehensive approach that combines several remote sensing indices, such as SAVI, TVDI, SDI, LST, and MSAVI, supported by advanced analytical techniques including AHP, entropy methods, cloud computing, and machine learning. These developments have improved the accuracy and reliability of land degradation assessment, particularly when soil-corrected indices and high-resolution satellite data such as Sentinel-2 are used. Machine learning algorithms, especially Random Forest, XGBoost, and LSTM, have also become important tools for integrating multiple indicators, identifying degradation drivers, and predicting future trends. In addition, Google Earth Engine has greatly enhanced the ability to monitor land degradation over large areas efficiently and rapidly. In the Iraqi context, land degradation remains a serious environmental problem, marked by desertification, declining vegetation cover, increasing soil salinity, drought, and the expansion of barren land in several regions. The reviewed studies also reveal clear spatial and temporal variations, indicating that degradation patterns differ from one area to another and therefore require locally specific management strategies. The main factors influencing degradation include climate change, drought, rising temperatures, poor water management, unsustainable agricultural practices, and unplanned urban expansion. Despite these advances, important research gaps remain, particularly the limited availability of long-term studies in Iraq, the lack of comprehensive field validation, the limited consideration of socio-economic factors, and the scarcity of studies evaluating the effectiveness of land rehabilitation and recovery strategies.

Based on the findings, several recommendations can be proposed to strengthen land degradation assessment and management in Iraq. A comprehensive national monitoring system should be established using Google Earth Engine to support continuous and large-scale observation of land degradation. In addition, standardized protocols for calculating and applying the Land Degradation Index should be improved, together with stronger field survey and in-situ monitoring programs to increase the accuracy and reliability of assessment results. It is also important to build the capacity of Iraqi national institutions in remote sensing technology and to conduct integrated longitudinal studies over extended periods. Furthermore, LDI models should be improved and adapted specifically to the Iraqi environmental context, including the integration of radar and optical data to overcome limitations caused by dust storms. The application of deep learning techniques is also recommended to predict future land degradation trends more accurately. Finally, monitoring results should be directly linked to decision-making and sustainable land-use planning, supported by early warning systems, regional cooperation in data and expertise exchange, and local projects in conservation agriculture and sustainable development.

Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

All authors in this publication declare no conflict of interest regarding the title, data, location, and results of the research.

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Supplementary Materials

This study does not include any supplementary materials.

Declaration on AI Use

The authors declare that no artificial intelligence (AI) or AI-assisted tools were used in the preparation of this manuscript. AI were used only to improve readability and language under strict human oversight; no content, ideas, analyses, or conclusions were generated by AI.

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