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Bi-temporal assessment of vegetation-cover change using Landsat modified soil adjusted vegetation index (1984–2022): The Oued Rdat Basin, Morocco

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ABSTRACT

Vegetation cover is an important indicator of ecosystem condition and environmental sustainability, particularly in semi-arid regions affected by climatic variability and anthropogenic pressures. This study assesses vegetation-cover differences in the Oued Rdat Basin, northwestern Morocco, between 1984 and 2022 using Landsat imagery, the modified soil adjusted vegetation index (MSAVI), and Geographic Information Systems. Two Landsat scenes acquired in July 1984 and July 2022 were processed and compared using a post-classification approach to identify net spatial changes in vegetation conditions. The 2022 MSAVI classification was independently evaluated using 100 validation points derived from high-resolution Google Earth Pro imagery, yielding an overall accuracy of 85.0% and a Kappa coefficient of 0.80. The results indicate that vegetated surfaces decreased from approximately 62% of the basin area in 1984 to 40% in 2022, representing a net reduction of 22 percentage points. Conversely, bare or sparsely vegetated surfaces increased from approximately 38% to 60%. Vegetation loss was concentrated mainly in the central and downstream sectors, whereas localized recovery and persistent vegetation were observed in some upstream and mountainous areas. These patterns may reflect the combined influence of climatic variability, land-use change, and other anthropogenic pressures; however, their relative contributions were not quantitatively assessed. Because the analysis is based on two observation dates, the results represent net bi-temporal differences rather than a continuous vegetation trajectory. The findings demonstrate the usefulness of combining MSAVI and GIS for identifying vegetation-loss areas and supporting watershed management, ecosystem restoration, and environmental planning in semi-arid environments.

Keywords: MSAVI, vegetation cover change, remote sensing, GIS, Oued Rdat Basin, Morocco.

INTRODUCTION

Vegetation cover is a key indicator of environmental quality and ecosystem stability, particularly in Mediterranean and semi-arid regions where natural resources are highly sensitive to climatic variability and human pressures. Vegetation plays a fundamental role in regulating hydrological processes, reducing soil erosion, maintaining biodiversity, and supporting agricultural productivity. Changes in vegetation cover therefore provide valuable information about land degradation processes and environmental transformations occurring over time (Pettorelli et al., 2005; Xue and Su, 2017).

Monitoring vegetation-cover changes has become increasingly important in the context of global environmental change. Population growth, agricultural expansion, urbanization, deforestation, and climate variability have significantly altered land-cover patterns in many regions of the world. These transformations are particularly important in semi-arid environments, where vegetation conditions are highly sensitive to rainfall variability, recurrent drought, and increasing land-use pressures (Bijaber et al., 2018; Measho et al., 2019).

Recent advances in remote sensing technologies have greatly improved the capacity to assess vegetation conditions over large spatial scales and long observation periods. Satellite imagery provides cost-effective and spatially consistent information on land-surface characteristics, enabling researchers to evaluate vegetation distribution and detect land-cover changes over time. The Landsat program, with its long-term archive extending back to the 1970s, represents one of the most valuable data sources for environmental monitoring and land-cover change assessment (Wulder et al., 2019).

Vegetation indices derived from multispectral satellite imagery have been widely applied to quantify vegetation conditions and evaluate environmental changes. Among these indices, the normalized difference vegetation index (NDVI) has been extensively used in ecological and geographical studies. However, in semi-arid environments characterized by low density vegetation and exposed soils, NDVI values may be affected by soil background reflectance, which can reduce its performance. To overcome this limitation, Qi et al. (1994) developed the modified soil adjusted vegetation index (MSAVI), which reduces soil influence and improves vegetation detection in areas with low-vegetation density. Consequently, MSAVI has been successfully applied in arid and semi-arid environments.

The integration of remote sensing and geographic information systems (GIS) has further enhanced vegetation-cover assessment by allowing spatial visualization, classification, and quantification of environmental changes. Numerous studies have demonstrated the effectiveness of combining Landsat imagery with GIS techniques for evaluating land-cover transformations and supporting sustainable natural resource management (Lu et al., 2004).

In Morocco, Mediterranean and semi-arid landscapes are exposed to substantial environmental pressures associated with rainfall variability, recurrent drought, agricultural activity, land-use transformation, and demographic change. Remote-sensing observations have increasingly been used to characterize these processes and their impacts on vegetation and land-surface conditions. At the national scale, satellite-based drought monitoring has demonstrated the importance of integrating precipitation, vegetation, evapotranspiration, and land-surface temperature indicators to characterize drought conditions in Morocco (Bijaber et al., 2018). At the watershed scale, studies have also highlighted the importance of land-use and vegetation conditions in environmental degradation processes.

Previous research conducted in the Oued Rdat Basin has mainly focused on land-use/land-cover dynamics and erosion-related environmental processes. Aouragh et al. (2023), for example, assessed gully-erosion susceptibility and demonstrated the important role of land use/cover in controlling erosion-prone areas, particularly in downstream agricultural and bare-land sectors. More recently, Belhak et al. (2026) analyzed multi-decadal land-use and land-cover changes between 1990 and 2020 and documented substantial transformations in forest, agricultural, bare, and built-up surfaces.

Despite these contributions, vegetation-density changes in the Oued Rdat Basin have not been specifically examined using a soil-adjusted vegetation index designed for landscapes characterized by low-density vegetation and substantial soil exposure. The scientific contribution of the present study therefore lies not in proposing a new remote-sensing methodology, but in providing a complementary vegetation-focused assessment of the basin using the MSAVI. Unlike conventional land-use/land-cover classifications, MSAVI enables the spatial variation of vegetation density to be examined while reducing the influence of soil background reflectance, which is particularly relevant in semi-arid environments.

In addition, the study extends the observation window back to 1984, thereby providing a 38-year bi-temporal comparison of vegetation conditions between 1984 and 2022. The combined use of fixed MSAVI thresholds and post-classification spatial comparison makes it possible to distinguish vegetation loss, recovery, persistence, and persistent sparsely vegetated surfaces. This vegetation-density perspective complements previous LULC and erosion studies in the basin and provides additional spatial information relevant to the identification of areas potentially affected by vegetation degradation.

Against this background, the present study provides a complementary vegetation-density perspective on environmental change in the Oued Rdat Basin by applying MSAVI to Landsat observations acquired in 1984 and 2022. The study is designed to complement previous land-use/land-cover and erosion assessments by specifically examining spatial differences in vegetation density while reducing the influence of exposed-soil reflectance. The specific objectives are to: (i) map vegetation-density patterns for the two selected dates, (ii) quantify differences in vegetation cover between 1984 and 2022, and (iii) identify areas characterized by vegetation loss, recovery, or relative stability. Because the analysis is based on two observation dates, the study evaluates net spatial differences between the selected years rather than the complete temporal trajectory of vegetation change during the intervening period.

STUDY AREA

The Oued Rdat Basin is located in northwestern Morocco, between approximately 5°20′ and 5°55′ W longitude and 34°28′ and 34°49′ N latitude. It forms part of the northern sector of the lower Sebou Basin and covers approximately 1.165 km². The basin is bordered by the Mda Basin to the west, the Ouergha Basin to the east, and the Loukkos Basin to the north, while Oued Rdat constitutes a tributary of the Sebou River (Belhak et al., 2026) (Figure 1).

Administratively, the basin extends across parts of the provinces of Sidi Kacem, Ouezzane, and Kenitra. Settlement is predominantly rural, with more than 200 villages distributed throughout the watershed (Belhak et al., 2026). Agricultural activities represent an important component of land use, while previous studies have also identified bare and agricultural surfaces, particularly in downstream sectors, as environmentally sensitive areas with elevated susceptibility to gully erosion (Aouragh et al., 2023).

MATERIAL AND METHODS

Satellite data

This study used two Landsat images acquired from the United States Geological Survey. The images represent two observation points at the beginning and end of the study period and were selected from the same summer season to improve seasonal comparability. The analysis should

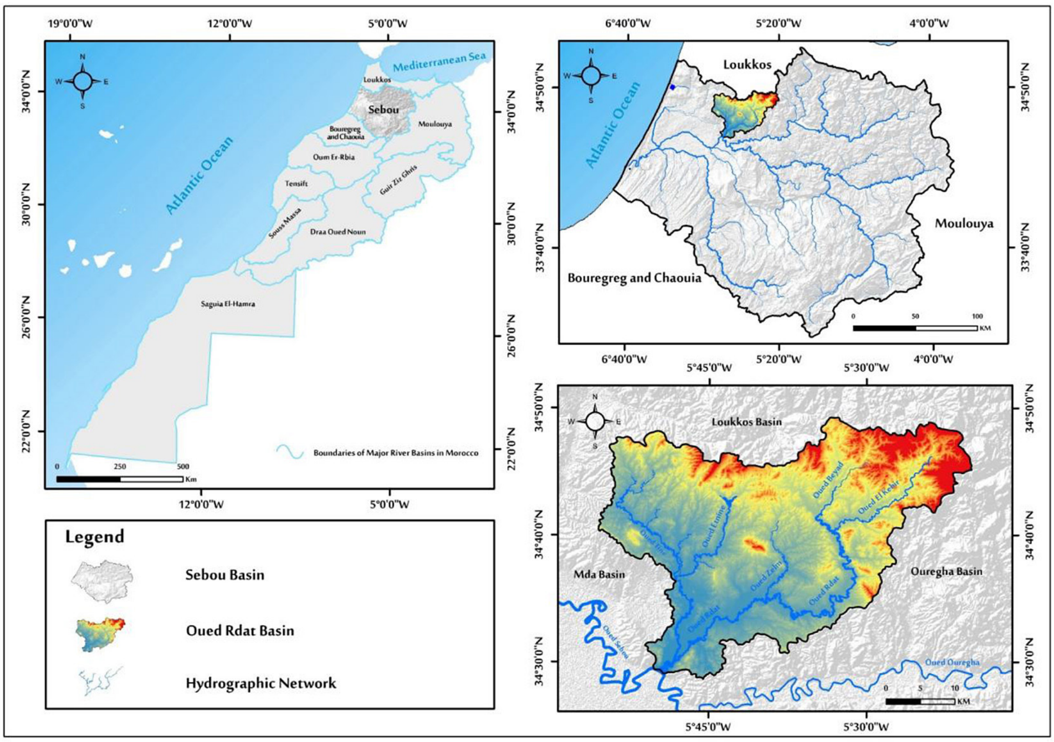

Figure 1. Geographical location of the Oued Rdat Basin

Table 1. Landsat imagery used in the study

Satellite	Sensor	Acquisition date	Spatial resolution
Landsat 5	TM	1984-07-17	30 m
Landsat 8	OLI	2022-07-26	30 m

Note: Source United States Geological Survey (USGS).

therefore be interpreted as a bi-temporal comparison of vegetation conditions in July 1984 and July 2022, rather than as a continuous time-series assessment. Both images had minimal cloud contamination over the study area (Table 1).

Image pre-processing

Landsat Collection 2 Level-2 Surface Reflectance products were obtained from the USGS and processed in ArcGIS Pro. Cloud and cloud-shadow contamination was evaluated using the quality-assurance bands, and scenes with minimal contamination over the basin were selected. Surface-reflectance scaling parameters supplied with the products were applied. Both images were reprojected to WGS 84/UTM Zone 30N, aligned at 30 m resolution, and clipped to the Oued Rdat Basin boundary using the same spatial extent and processing procedure to ensure comparability between 1984 and 2022.

Vegetation index: Modified soil adjusted vegetation index

Vegetation cover was assessed using the modified soil adjusted vegetation index (MSAVI), developed by Qi et al. (1994). This index was selected because it reduces the influence of soil background reflectance, which is particularly important in semi-arid environments characterized by low-density vegetation cover. The MSAVI was calculated using the following equation:

$$MSAVI = \frac{2Nir + 1 - \sqrt{(2Nir + 1)^2 - 8(Nir - Red)}}{2} \quad (1)$$

where: *NIR* represents near-infrared reflectance and *Red* represents red reflectance. For Landsat 5 TM, bands 4 and 3 were used for *NIR* and *Red*, respectively, while Landsat 8 OLI bands 5 and 4 were used.

MSAVI values range between -1 and +1, with higher values generally indicating denser vegetation cover and lower values corresponding to bare soil or low-density vegetation conditions.

MSAVI classification

Following MSAVI calculation, the resulting values were classified into four vegetation-density categories using fixed thresholds applied consistently to both observation dates. MSAVI values equal to or below 0.20 were classified as bare or sparsely vegetated surfaces, values greater than 0.20 and up to 0.40 as low-density vegetation, values greater than 0.40 and up to 0.60 as moderate-density vegetation, and values above 0.60 as high-density vegetation. These thresholds were adopted as operational classes to distinguish progressively increasing vegetation density and were evaluated against the distribution of MSAVI values within the study area. The same classification thresholds were applied to both the 1984 and 2022 datasets to ensure temporal comparability and to prevent detected differences from being influenced by date-specific classification boundaries.

Change detection analysis

Vegetation-cover changes between July 1984 and July 2022 were assessed through post-classification comparison of the MSAVI-derived vegetation maps. The classified rasters from the two observation dates were spatially overlaid within a GIS environment, and pixel-level transitions were identified by comparing the vegetation status of each pixel between the two dates.

For the vegetation/non-vegetation comparison, four principal transition categories were distinguished: vegetation degradation, representing pixels classified as vegetated in 1984 and bare or sparsely vegetated in 2022; vegetation recovery, representing pixels classified as bare or sparsely vegetated in 1984 and vegetated in 2022; stable vegetation, representing pixels classified as vegetated at both observation dates; and bare or sparsely vegetated surfaces, representing pixels remaining within the non-vegetated category at both dates. The area and percentage occupied by each transition category were subsequently calculated to quantify the magnitude and spatial distribution of net vegetation-cover changes within the basin.

Because this approach compares two discrete observation dates, the resulting transition categories represent net differences between July 1984 and July 2022 and should not be interpreted as evidence of continuous vegetation degradation or recovery throughout the intervening period.

GIS analysis and data availability

All spatial analyses were performed in ArcGIS Pro using the same processing workflow for both Landsat datasets. The 1984 and 2022 images were prepared, aligned, and clipped to the Oued Rdat Basin boundary, and the resulting MSAVI rasters were reclassified using identical thresholds at a 30 m spatial resolution in the WGS 84/UTM Zone 30N coordinate system. Pixel-level transitions were mapped and quantified as vegetation degradation, vegetation recovery, stable vegetation, or persistent bare and sparsely vegetated surfaces, and the area of each category was calculated. Landsat Collection 2 Level-2 Surface Reflectance data are publicly available from the USGS.

Accuracy assessment

A quantitative accuracy assessment was carried out for the 2022 MSAVI-derived vegetation classification using 100 independent validation points. Reference information was obtained primarily from high-resolution Google Earth Pro imagery acquired as close as possible to the Landsat observation date in 2022. Each validation point was visually interpreted from the reference imagery and compared with the corresponding vegetation class assigned by the MSAVI-based classification.

Classification accuracy was evaluated through a confusion matrix comparing the mapped classes with the independently interpreted reference classes. Overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and the Kappa coefficient were calculated from the confusion matrix following established remote-sensing accuracy-assessment procedures (Congalton, 1991; Foody, 2002; Olofsson et al., 2014).

Overall accuracy was calculated as:

$$OA = \frac{\sum D}{N} \times 100 \tag{2}$$

$$PA = \frac{D}{R} \times 100 \tag{3}$$

$$UA = \frac{D}{C} \times 100 \tag{4}$$

where: ΣD represents the total number of validation points correctly classified, N is the total number of validation points, D corresponds to the number of correctly classified samples within a given vegetation class, R represents the total number of reference samples belonging to that class, and C represents the total number of samples assigned to that class by the MSAVI classification.

In addition, the Kappa coefficient was calculated to evaluate the level of agreement between the MSAVI-derived classification and the reference data while accounting for agreement that may occur by chance (Cohen, 1960; Congalton, 1991).

Quantitative validation was limited to the 2022 classification because suitable high-resolution reference imagery was unavailable for 1984, which remains a limitation of the study.

RESULTS

Differences in vegetation-cover distribution between 1984 and 2022

The MSAVI analysis revealed marked differences in vegetation-cover distribution between the two selected observation dates. In July 1984, vegetated classes occupied approximately 62% of the basin, whereas bare or sparsely vegetated surfaces accounted for approximately 38%. In July 2022, the proportion of vegetated classes decreased to approximately 40%, while bare or sparsely vegetated surfaces increased to approximately 60%. These values indicate a net difference of about 22 percentage points between the two selected dates. However, because the analysis is based on two Landsat observations, the results do not describe the annual or continuous trajectory of vegetation change during the period from 1984 to 2022.

In 2022, the spatial distribution of vegetation cover showed considerable changes compared with 1984. Vegetated areas decreased to approximately 40% of the basin area, while bare or sparsely vegetated surfaces increased to approximately 60%. This corresponds to a net reduction of approximately 22 percentage points over the study period (Figure 2).

The comparison of vegetation-density classes indicates that low-density vegetation experienced

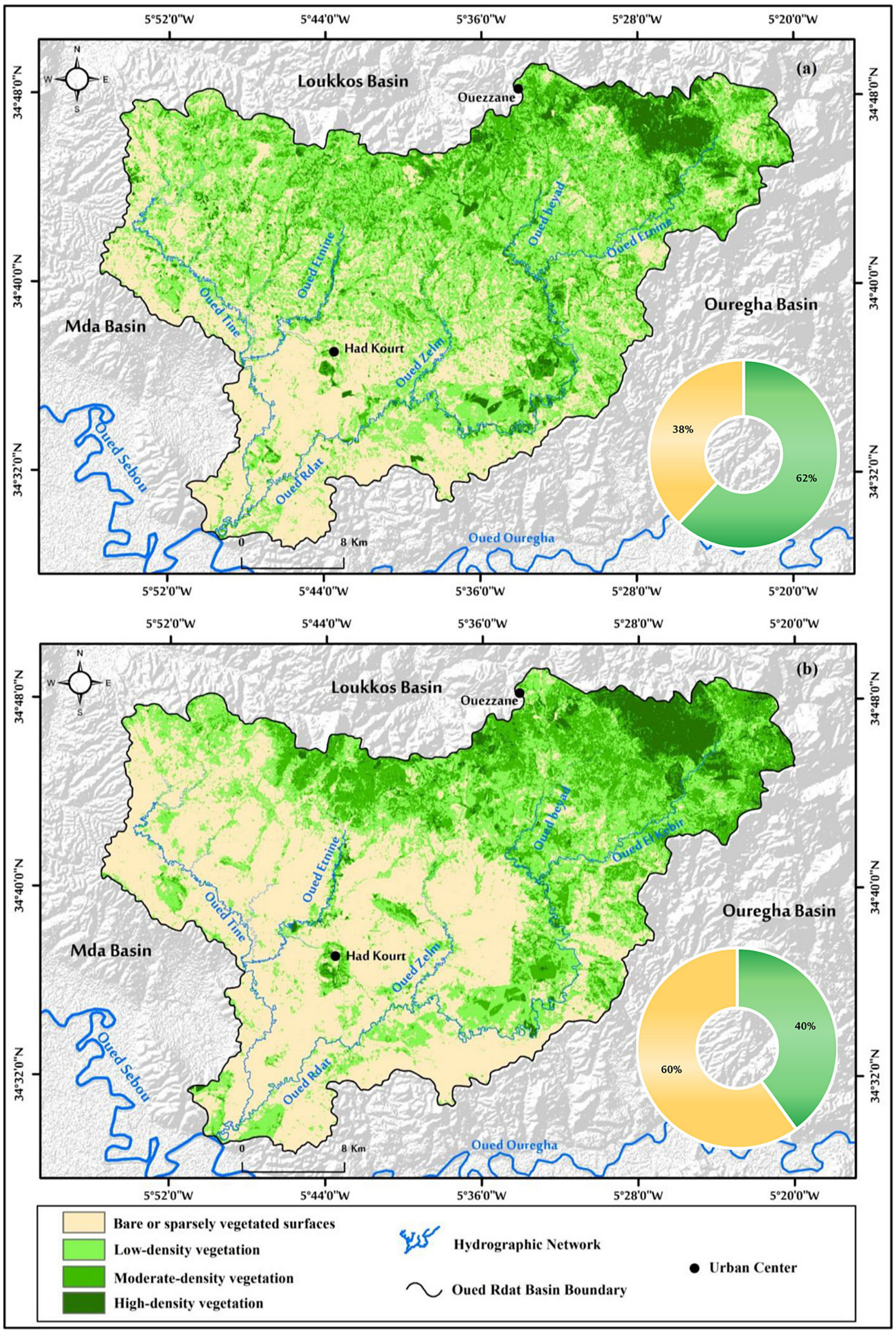

Figure 2. Spatial distribution of vegetation cover based on MSAVI classification in the Oued Rdat Basin: (a) 1984, (b) 2022

the largest decline, decreasing by approximately 18%, followed by moderate-density vegetation, which decreased by 4%. In contrast, high-density vegetation showed a slight increase from 4% in 1984 to 5% in 2022. This increase was spatially limited and occurred mainly in localized upstream areas.

Overall, the results indicate substantially lower vegetation cover in July 2022 than in July 1984 across large parts of the Oued Rdat Basin. Because intermediate observation dates were not analyzed, this difference should be interpreted as a net bi-temporal change rather than as evidence of a continuous decline throughout the 1984–2022 period (Figure 3).

Bi-temporal vegetation-cover change detection

The post-classification comparison of MSAVI-derived vegetation maps allowed the identification of four main categories of land-cover

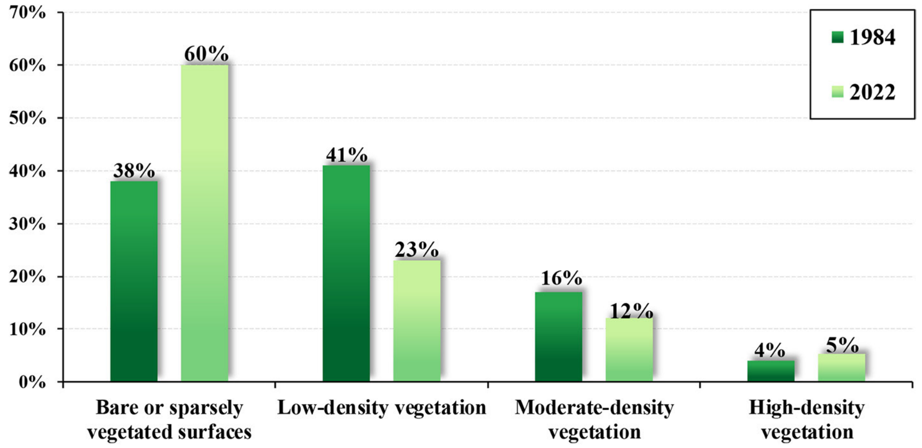

Figure 3. MSAVI classification between 1984 and 2022

change: vegetation degradation, vegetation recovery, stable vegetation cover, and bare or sparsely vegetated surfaces (Figure 4).

The analysis indicates that vegetation degradation was the dominant change category between 1984 and 2022, representing approximately 22% of the basin area. Vegetation recovery accounted for about 11%, while stable vegetation cover represented 39% of the study area. Persistent bare land or sparsely vegetated surfaces occupied approximately 28% of the basin (Figure 5).

Spatially, vegetation degradation was mainly concentrated in the central sectors of the watershed, whereas vegetation recovery occurred in localized upstream areas. Stable vegetation was primarily distributed in forested and mountainous zones, while bare or sparsely vegetated surfaces dominated downstream sectors.

Overall, vegetation degradation exceeded vegetation recovery, indicating a net decline in vegetation cover across the Oued Rdat Basin during the study period.

Accuracy assessment of the 2022 MSAVI classification

The quantitative accuracy assessment of the 2022 MSAVI-derived vegetation classification was based on 100 independent validation points

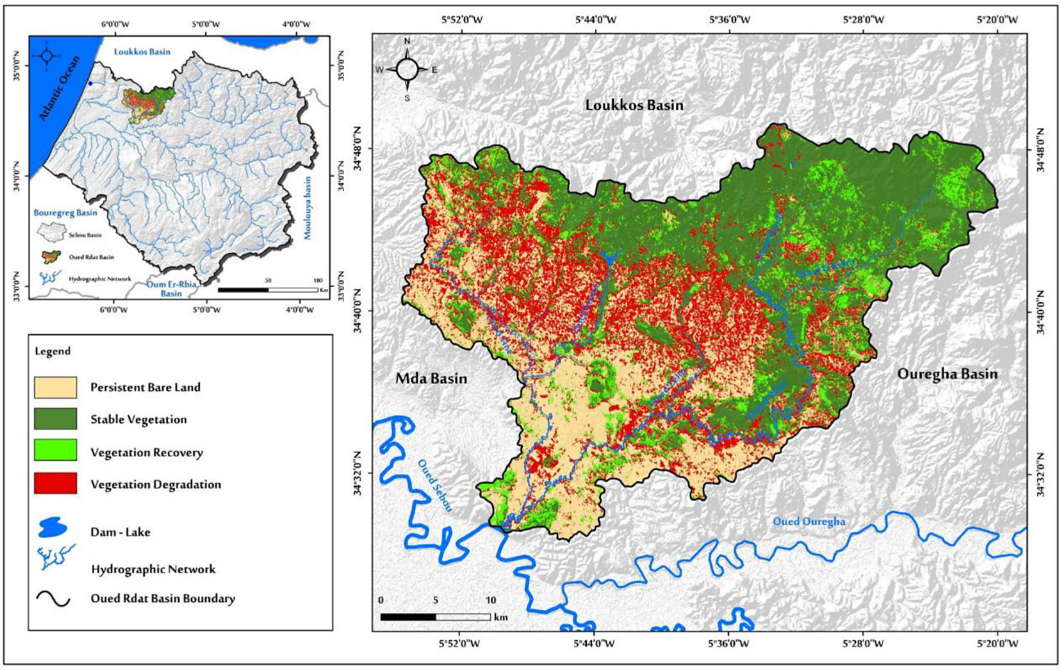

Figure 4. Vegetation-cover change map (1984–2022)

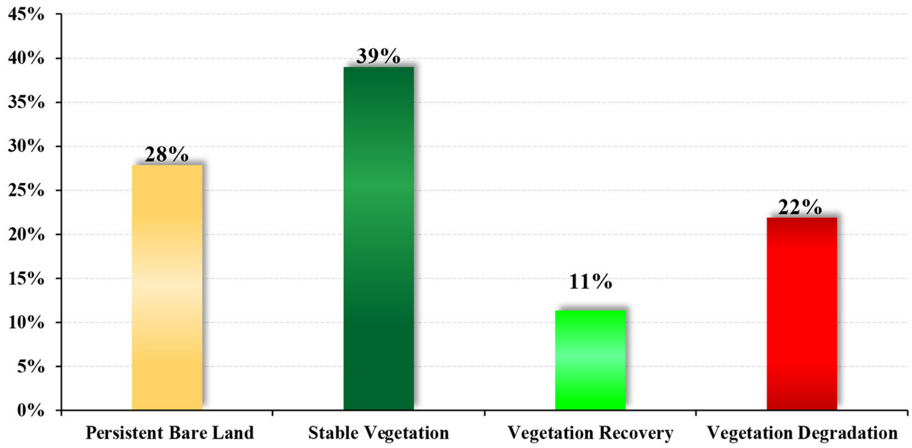

Figure 5. Vegetation-cover change categories (1984–2022)

(Table 2). The confusion matrix produced an Overall Accuracy of 85.0% and a Kappa coefficient of 0.80, indicating strong agreement between the classified map and the reference data.

The highest classification performance was obtained for high-density vegetation, with a Producer's Accuracy of 96.0% and a User's Accuracy of 92.31%. Bare or sparsely vegetated surfaces also showed high classification accuracy, with Producer's and User's accuracies of 88.0% and 91.67%, respectively. Lower accuracies were observed for low-density and moderate-density vegetation, mainly because of confusion between adjacent vegetation density classes with similar MSAVI values. Detailed class-based accuracy results are presented in Table 3.

DISCUSSION

Potential factors influencing vegetation cover changes in the Oued Rdat Basin

The comparison of the 1984 and 2022 Landsat images indicates a substantial difference in vegetation-cover conditions between the two selected dates. The lower extent of vegetated classes in 2022 may reflect the combined influence of climatic variability, agricultural practices, land-use transformation, and other anthropogenic pressures. Nevertheless, the bi-temporal design does not allow the observed difference to be interpreted as a continuous or linear degradation trend throughout the entire 1984–2022 period.

Table 2. Confusion matrix for the 2022 MSAVI-derived vegetation classification

Classified	Bare or sparsely vegetated	Low-density	Moderate-density	High-density	Total reference
Bare or sparsely vegetated	22	2	1	0	25
Low-density	2	19	4	0	25
Moderate-density	0	3	20	2	25
High-density	0	0	1	24	25
Total classified	24	24	26	26	100

Table 3. Accuracy metrics for the 2022 MSAVI-derived vegetation classification

Vegetation class	Producer accuracy (%)	User accuracy (%)
Bare or sparsely vegetated surfaces	88.00	91.67
Low-density vegetation	76.00	79.17
Moderate-density vegetation	80.00	76.92
High-density vegetation	96.00	92.31

Climatic influence

Climatic variability may represent an important background factor influencing vegetation conditions in the Oued Rdat Basin. Morocco is characterized by pronounced spatial and temporal variability in precipitation, and recurrent drought constitutes an important component of environmental variability at the national scale. Satellite-based drought-monitoring studies have demonstrated the close relevance of precipitation anomalies, vegetation conditions, evapotranspiration, and land-surface temperature for characterizing drought impacts in Morocco (Bijaber et al., 2018). Under semi-arid and Mediterranean conditions, prolonged rainfall deficits can reduce soil-water availability, constrain vegetation growth and regeneration, and increase the exposure of sparsely vegetated surfaces.

The lower proportion of vegetation detected in July 2022 relative to July 1984 is broadly consistent with observations from other semi-arid environments in which vegetation greenness responds strongly to rainfall variability and recurrent drought (Measho et al., 2019). Nevertheless, the present study did not quantitatively analyze precipitation, drought indices, or soil-moisture conditions during the two observation periods. Climatic variability should therefore be considered a plausible explanatory factor rather than a directly demonstrated cause of the vegetation-cover differences identified in the basin.

Anthropogenic pressure

Anthropogenic activities may also contribute to vegetation-cover transformations within the Oued Rdat Basin. Potential pressures include agricultural land-use change, grazing, fuelwood extraction, forest fires, and settlement expansion. These activities can affect vegetation density through biomass removal, disturbance of natural regeneration, conversion of natural vegetation, and increased pressure on soil and water resources. However, because these drivers were not individually quantified in the present study, their effects should be interpreted as potential explanatory mechanisms rather than directly established causes.

Previous research provides local evidence that land-use pressures are relevant to environmental degradation in the basin. Aouragh et al. (2023) identified land use/cover as an important factor controlling gully-erosion susceptibility in the Rdat watershed and showed that downstream areas characterized by bare and agricultural surfaces were particularly susceptible to erosion. In addition, the multi-decadal analysis of Belhak et al. (2026) documented substantial land-cover transformations between 1990 and 2020, including declining forest cover, temporal expansion of bare or sparsely vegetated surfaces, fluctuations in agricultural land, and gradual growth of built-up surfaces. These findings provide a broader land-use context within which the vegetation-cover differences detected by MSAVI may be interpreted.

Forest fires represent an additional disturbance potentially affecting local vegetation conditions. According to unpublished administrative records provided by the Provincial Directorate of Water and Forests of Ouezzane, approximately 3,094 ha of the Izarene Forest were affected by fire between 1980 and 2023. Fire can produce immediate vegetation loss and, where disturbances are repeated or severe, may influence subsequent regeneration and vegetation structure. Nevertheless, determining the specific contribution of fire to the spatial patterns detected in this study would require the integration of historical burned-area datasets and post-fire vegetation trajectories.

Comparison with previous studies

The vegetation-cover differences identified in the present study are broadly consistent with previous evidence of environmental transformation within the Wadi Rdat Basin. Using Landsat imagery for 1990, 2000, 2010, and 2020, Belhak et al. (2026) documented a persistent decline in forest cover from 16.74% of the basin area in 1990 to 7.73% in 2020, together with substantial fluctuations in agricultural land and bare surfaces. Bare or sparsely vegetated areas expanded markedly between 2000 and 2010 before partially decreasing by 2020, indicating that the basin has experienced considerable landscape reorganization over recent decades.

The present MSAVI-based assessment complements these findings by focusing on vegetation density rather than discrete land-use and land-cover categories. The percentages obtained in the two studies should therefore not be interpreted as directly comparable or contradictory. Agricultural land, rangeland, and other LULC categories may display different vegetation-density conditions according to crop cycles, land-management practices, rainfall variability, and satellite-acquisition dates. The reduction detected between July 1984 and July 2022 consequently represents a net difference in vegetation conditions between the two selected observations. The concentration of vegetation loss in the central and downstream sectors is also relevant to Aouragh et al. (2023), who identified downstream agricultural and bare areas as highly susceptible to gully erosion. This spatial correspondence may have important implications for soil vulnerability and watershed management, although the relationship between vegetation loss and erosion was not directly tested in the present study.

Similar vegetation and land-cover transformations have been reported in other semi-arid areas of North Africa. In northern Algeria, Benhizia et al. (2024) documented pronounced spatial and temporal variability in drought and vegetation conditions between 2011 and 2022, emphasizing the influence of rainfall and temperature on vegetation responses in Mediterranean drylands. In semi-arid Tunisia, Kadri et al. (2023) reported extensive land-use changes between 1980 and 2021, including a fourfold expansion of rainfed olive cultivation, an increase in irrigated agriculture, and substantial reductions in rangelands and rainfed annual crops. These transformations were related to interacting climatic, hydrological, demographic, agricultural, and socio-economic pressures. Although such drivers were not quantified in the present analysis, the studies from Algeria and Tunisia indicate that vegetation change in North African drylands commonly occurs within a broader context of climatic variability and increasing land-use pressure.

Evidence from southern Spain further shows that Mediterranean vegetation dynamics are spatially heterogeneous and do not always follow a uniform degradation trajectory. Galacho-Jiménez et al. (2023) found that more than 70% of the studied natural landscapes retained their original characteristics between 1997 and 2021. This relative stability contrasts with the overall reduction detected in the Oued Rdat Basin, but it is consistent with the localized areas of stable vegetation and recovery observed in upstream and mountainous sectors. These comparisons suggest that degradation, persistence, and recovery may occur simultaneously within semi-arid Mediterranean landscapes, depending on local environmental conditions and management histories.

Studies from the Middle East also emphasize the role of water availability and temporal context in vegetation dynamics. Badarneh et al. (2024) used Landsat and MODIS imagery to examine agricultural drought in northern Jordan and highlighted the value of integrating vegetation and climatic indicators when interpreting vegetation stress. In the hyper-arid Arava Valley, Meroz et al. (2025) showed that vegetation responses to wet and dry periods may be delayed by approximately two to four years. This finding is relevant to the present bi-temporal analysis because vegetation conditions observed on a single date may partly reflect climatic conditions accumulated during preceding seasons or years. The difference between July 1984 and July 2022 in the Oued Rdat Basin may therefore incorporate both long-term landscape transformation and delayed or date-specific climatic effects.

Comparable patterns have been reported in East African drylands. Measho et al. (2021) found that vegetation dynamics across the Horn of Africa were positively associated with precipitation and negatively associated with land-surface temperature, confirming the strong climatic sensitivity of vegetation in water-limited environments. In Djibouti, Wardle and Phillips (2025) documented vegetation loss between 1990 and 2010 followed by recovery between 2010 and 2020. These results demonstrate that vegetation dynamics in arid and semi-arid regions may involve alternating phases of decline and recovery rather than a continuous linear trend. This supports the cautious interpretation adopted in the present study, in which the differences between 1984 and 2022 are considered net bi-temporal changes rather than evidence of uninterrupted degradation over the entire 38-year period.

Overall, comparisons with studies from North Africa, the Mediterranean region, the Middle East, and East Africa indicate that vegetation-cover change in dry environments is spatially heterogeneous, temporally non-linear, and influenced by interacting climatic and anthropogenic processes. The lower vegetation extent observed in the Oued Rdat Basin in 2022 is broadly consistent with vegetation vulnerability, drought stress, and land-use transformation reported elsewhere, while localized persistence and recovery reflect the contrasting responses documented in other semi-arid regions. Nevertheless, differences in observation periods, sensors, vegetation indices, classification procedures, and environmental settings prevent direct numerical comparison. A denser Landsat time series combined with precipitation, drought, fire, land-use, and socio-economic data would be necessary to reconstruct the full temporal trajectory of vegetation change and identify the relative contribution of its potential drivers.

Limitations and future perspectives

This study provides a bi-temporal assessment of vegetation-cover conditions in the Oued Rdat Basin using Landsat imagery, MSAVI, and GIS techniques. The reliability and interpretation of the results should nevertheless be considered in light of several methodological limitations. First, the use of two observation dates allows the identification of net spatial differences between July 1984 and July 2022 but does not capture interannual variability, short-term fluctuations, disturbance-recovery cycles, or the temporal trajectory of vegetation change during the intervening 38 years. Consequently, the identified differences represent the conditions observed on the two selected dates and should not be interpreted as evidence of a continuous or linear degradation process throughout the entire study period.

Second, the percentages of vegetation loss, recovery, and persistence are dependent on the MSAVI classification framework and the fixed thresholds adopted in this study. Although identical thresholds were applied to both dates to maintain temporal consistency, uncertainty associated with threshold-based classification and differences between Landsat sensors may influence the estimated extent of individual vegetation classes.

Third, extensive field-based reference data are not available for both observation dates, particularly for the historical 1984 image. Consequently, independent validation of all MSAVI-derived classes could not be performed consistently for both dates. The results should therefore be interpreted primarily as a comparative remote-sensing assessment of spatial differences in vegetation conditions rather than as an absolute reconstruction of vegetation cover over the entire 1984–2022 period.

Finally, although climatic variability and anthropogenic pressures provide plausible explanations for the observed spatial patterns, their relative contributions were not quantitatively evaluated in the present study. These factors are therefore discussed as potential drivers rather than demonstrated causal mechanisms.

CONCLUSIONS

This study assessed vegetation-cover differences in the Oued Rdat Basin, northwestern Morocco, between July 1984 and July 2022 using Landsat satellite imagery, the Modified Soil Adjusted Vegetation Index (MSAVI), and Geographic Information Systems. The bi-temporal approach provided a spatially explicit assessment of net vegetation-cover differences between the two selected observation dates and enabled the identification of areas characterized by vegetation loss, recovery, and relative stability. The 2022 classification achieved an Overall Accuracy of 85.0% and a Kappa coefficient of 0.80, supporting the reliability of the recent vegetation map.

The results indicate a substantial net reduction in vegetation cover at the basin scale, from approximately 62% in 1984 to 40% in 2022, accompanied by an increase in bare or sparsely vegetated surfaces from approximately 38% to 60%. Vegetation loss was spatially concentrated mainly in central and downstream sectors, whereas localized recovery occurred in some upstream areas. These findings indicate that vegetation conditions differed substantially between the two observation dates but do not imply that vegetation degradation occurred continuously throughout the entire 1984-2022 period.

The observed spatial patterns occur within a basin that previous research has shown to be undergoing important land-use and environmental transformations. Climatic variability, drought, agricultural land-use change, fire, resource use, and settlement expansion represent potential factors that may influence vegetation conditions; however, their individual contributions cannot be established from the present bi-temporal analysis. Further research integrating multi-temporal satellite observations with climatic, land-use, fire, socio-economic, and field-based datasets is therefore required to distinguish the mechanisms responsible for vegetation change.

Overall, MSAVI provided a useful indicator for examining vegetation-cover conditions in a landscape characterized by substantial soil exposure and variable vegetation density. Its integration with GIS offers a practical framework for locating areas of vegetation loss and supporting future watershed-management, ecosystem-restoration, and soil-conservation strategies in the Oued Rdat Basin.

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