Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

The Green Dam in Algeria: From an Ambitious Project in 1971 to an Environmental Rehabilitation Strategy in 2023, Djelfa Province as a Model

Orabi Salem Mohamed[1, *], Setti M'hammed [2], Alouat Mohamed[1], Chinoune Saad[3]
[1] *Laboratory of History, Civilization and Applied Geography, Department of History and Geography, Higher Normal School of Bouzareah, Algeria*
[2] *Faculty of Earth Sciences, Geography and territorial Planning, University of Science and Technology Houari Boumediene (USTHB), BP 32 Bab Ezzouar, 16111 Algiers, Algeria*
[3] *Department of Earth and Space Sciences, Faculty of Natural and Life Sciences, university of Djelfa, Algeria*
**Corresponding author: m.orabisalem@yahoo.com*

ARTICLE INFO

Received: 12 Nov 2024

Revised: 24 Dec 2024

Accepted: 27 Jan 2025

ABSTRACT

The Algerian government has launched a project to rehabilitate the Green Dam, which was established in 1971 to protect ecosystems and combat desertification. It extends over 1500 kilometers (from east to west) and 20 kilometers (from north to south) across 13 provinces. With the aim of economically exploiting, it through the cultivation of fruit trees, enhancing agriculture and livestock, and improving infrastructure. The research paper aims to track the course of this great project since 1985 and monitor its developments every 10 years, including the government's new decision to rehabilitate the Green Wall in 2023. We used both old and new remote sensing data. Two sources of satellite images were used: (1) GLC_FCS30D, the Global Land Cover product for the years 1985, 1995, 2005, and 2015, and (2) satellite imagery for the year 2025 from the Sentinel-2 multispectral satellite. The NGCC GLC_FCS30D database (Global Land Cover Maps) was produced with a resolution of 30 meters derived from temporal Landsat images and advanced classification methods. Given the diversity of land cover types displayed, especially forests, the dynamics of vegetation can be measured over the long term. GLC_FCS30D mapping data was processed to extract and measure the amounts of forested areas for 24 municipalities across the study area. After an extensive study over the monitored periods, we reached a series of results, particularly characterized by forest instability, fragility of the forest cover, and forest degradation. This is due to several factors, including climate change and human activities such as illegal logging.

Keywords: Green Dam, Desertification, Reforestation, Environmental Rehabilitation, Sustainable Development, Djelfa Province.

INTRODUCTION

The Green Dam, is one of the largest strategic environmental projects, which was initiated by the Algerian government in 1971. This project sought to combat desertification, safeguard ecosystems, and promote sustainable development (Boumediene et al., 2023; Khaouani et al., 2019; Saifi et al., 2014). Its purpose was establishing a tree cordon that would extend some 1,500 km from the Moroccan border in the west to the Tunisian border in the east, and would be in average 20 km wide. Spanning across 13 provinces, the area covers around 3 million hectares and was established to halt the northward movement of the Algerian desert, protect cultivated lands and steppes, and mitigate desertification and soil degradation within the semi-arid high plateaus of Algeria (Khaouani et al., 2019; Mihi et al., 2024; Boumediene et al., 2023; Saifi et al., 2014; Merdas et al., 2017)

Pinus pinea (Aleppo pine), to be planted to naturally-regenerating native tree and fruiting species, was anticipated to stabilize soil, reduce wind erosion, enhance biodiversity and alleviate poverty of local peoples by enabling agriculture and livestock activities (Boumediene et al., 2023; Khaouani et al., 2019; Merdas et al., 2017; Saifi et al., 2014; Zehraoui, 2021).

The project first originated as a national level initiative, which drew from inputs from national service and the Algerian army (Saifi et al., 2014). Through the Green Dam, the first 400 model villages were created and agricultural productivity

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

increased in the country's north (Boumediene et al., 2023). However, by the 1990s the project had become ineffective, due to overgrazing and poor planning, lack of community involvement, and a combination of environmental factors such as drought and invasiveness of pine caterpillars" (Boumediene et al. 2023; Khaouani et al. 2019; Mihi et al.2024; Saifi et al. 2014; Zehraoui 2021).

On 29 October 2023, Algeria revived its plans to rehabilitate the Green Dam in its initial step towards sustainable development and combat climate change by expanding its coverage from 3.7 million hectares to 4.7 million hectares in the steppe areas, targeting 13 provinces, 183 municipalities and 1,200 sectors till 2026. 24 municipalities are situated in Djelfa alone, which constitutes about 13.11% of the overall municipalities that would be involved in the project (Boumediene et al., 2023; Khaouani et al., 2019; Mihi et al., 2024).

The first part includes afforestation of 400,000 ha, higher tree diversity (over crops like olive, almond, prickly pear) and adding economic aspects (fruit tree, agro-industries and infrastructure) (Boumediene et al., 2023; Merdas et al., 2017). The project then focused on a budget of 75 billion Algerian dinars (approximately 562 million dollars) allocated from 2023 to 2030, towards public mobilization for good pastoral practices and respect for international obligations such as the UN convention to combat desertification (UNCCD) and the African great green wall initiative (Boumediene et al., 2023; Saifi et al., 2014).

These refurbishment measures expand upon the Green Dam concept so that it can cope with modern challenges such as climate change, freshwater scarcity, and rural exodus by linking households to water via the digging of water wells, investment in rural infrastructures, and local employment creation (Boumediene et al., 2023; Merdas et al., 2017). Currently, in 2023, the project remains active, with 45 nurseries established to grow 120 million seedlings and efforts to introduce drought-resistant species to increase resilience are ongoing (Boumediene et al., 2023; Khaouani et al., 2019; Zehraoui, 2021).

Funded by the Green Climate Fund (GCF) and the Food and Agriculture Organization (FAO), the project reaffirms the dedication of the country to the promotion of sustainable land management and the safeguarding of the environment (Boumediene et al., 2023; Hezil et al., 2024; Saifi et al., 2014). However, some major challenges such as public awareness, technical capacity, and rigorous monitoring are still needed for long-term sustainability of the project (Boumediene et al., 2023; Khaouani et al., 2019; Mihi et al., 2024; Zehraoui, 2021).

UTILIZED DATA

Historical and recent remote sensing data were combined to monitor spatial and temporal variations in forest cover within the Green Dam area, located in the province of Djelfa (see Figure 1). We used two primary sources of satellite imagery: (1) the GLC_FCS30D global land cover product for 1985, 1995, 2005, and 2015, and (2) 2025 Sentinel-2 multispectral images.

The GLC_FCS30D map was generated by the National Geomatics Center of China (NGCC) at a spatial resolution of 30 m using time-series Landsat images and advanced classification algorithms (Zhang et al., 2020). The dataset provides fine grained land cover classes such as forest types, which is suitable for long term follow-up of vegetation changes. GLC_FCS30D maps were reclassified to delineate and analyses "forest cover" at the level of the 24 municipality of the study area.

The most recent image used for this particular analysis was a Sentinel-2 Level-1C image from 31st March 2025. Sentinel-2 operated by the European Space Agency (ESA) delivers high resolution multispectral data with spatial resolution between 10 and 20 m that is well suited to the monitoring of vegetation (Drusch et al., 2012). To be consistent with historical data, the image was atmospherically corrected to Level-2A with the Sen2Cor processor.

The 2025 imagery was classified through a supervised classification, and for the same a Maximum Likelihood Classification (MLC) was used. MLC is a powerful parametric technique and is widely applied in remote sensing for the vegetation and forest mapping (Richards, 2022). It computes the likelihood of each pixel to belong to a class according to a training set and a normal distribution of pixels.

The uniform projection for all data sets (37) used is WGS84/ UTMZone31N. The preprocessing involved in cloud masking, resampling, and forest classes extraction. Such data organization allows a trustworthy ground to obtain insights of the evolution, degradation and potential recovery of forest areas in the Green Dam over the four last decades, that is what appears to us in Table 1 and the flowchart script in Figure 2.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Table 1 Datasets and Sources Used for Land Cover Change Analysis in Djelfa Province (Source: Authors, 2025)

Dataset	Source	Resolution	Projection	Date	Classes	Band Combinations
GLC_FCS30D	Google Earth Engine	30m	WGS 1984	1985, 1995, 2005, 2015	*Impervious Surfaces* and other grouped land use categories	36 classes simplified and regrouped into broader categories
Sentinel-2B	Copernicus (ESA)	10m	WGS 1984 Zone 31 North	31/03/2025 (Cloud Cover: less than 10%)	MLC Classification trained on supervised samples	(Bands 11, 8, 4) (Bands 12, 11, 4)
Planned Reforestation Works	Forest conservation in Djelfa Province	Vector	WGS 1984 Zone 31 North	2021	/	/
Study area	PBMD	Vector	WGS 1984 Zone 31 North	1984	/	/

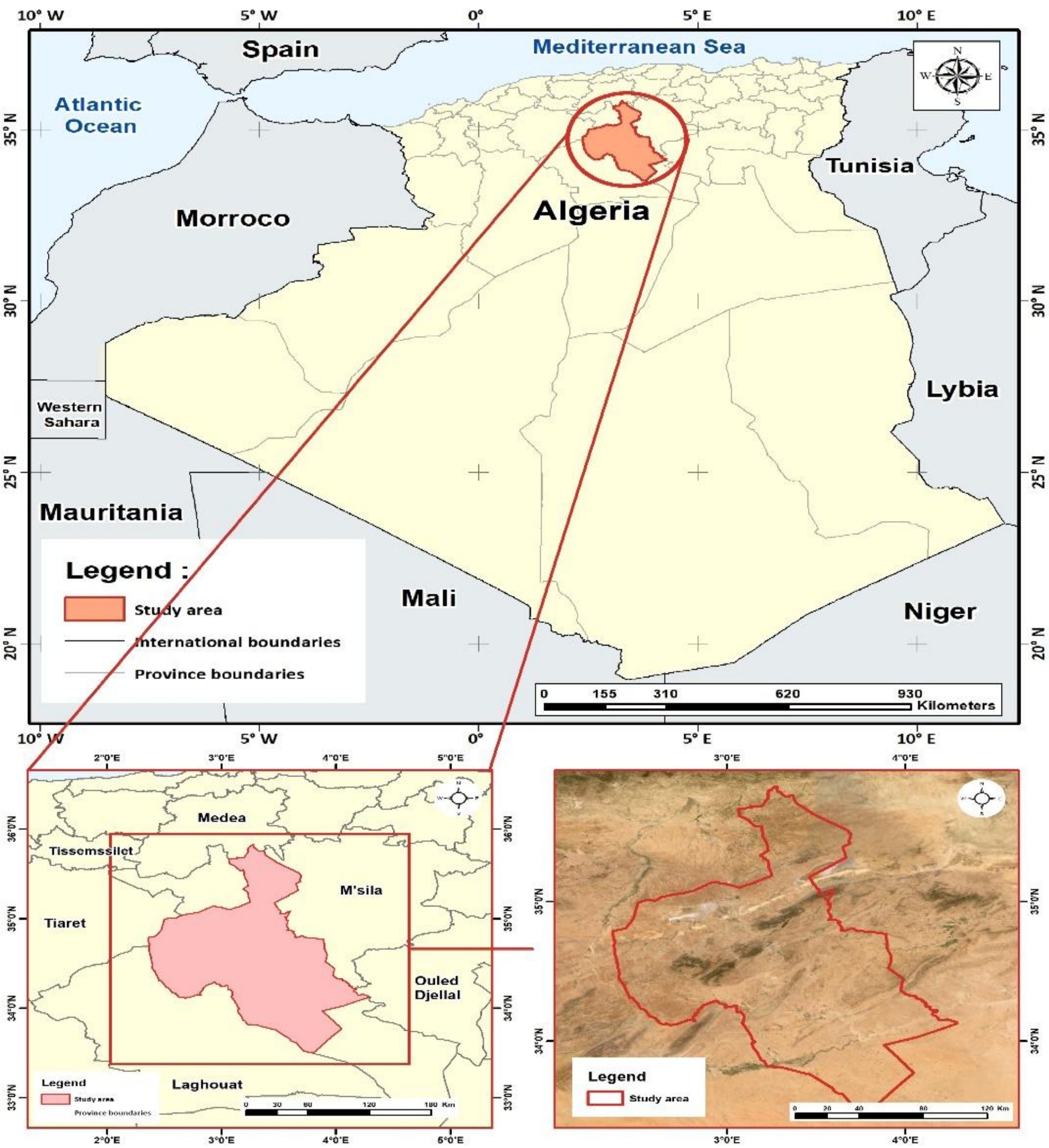

Figure 1. Map of the province of Djelfa (study area) (Source: Authors, 2025)

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

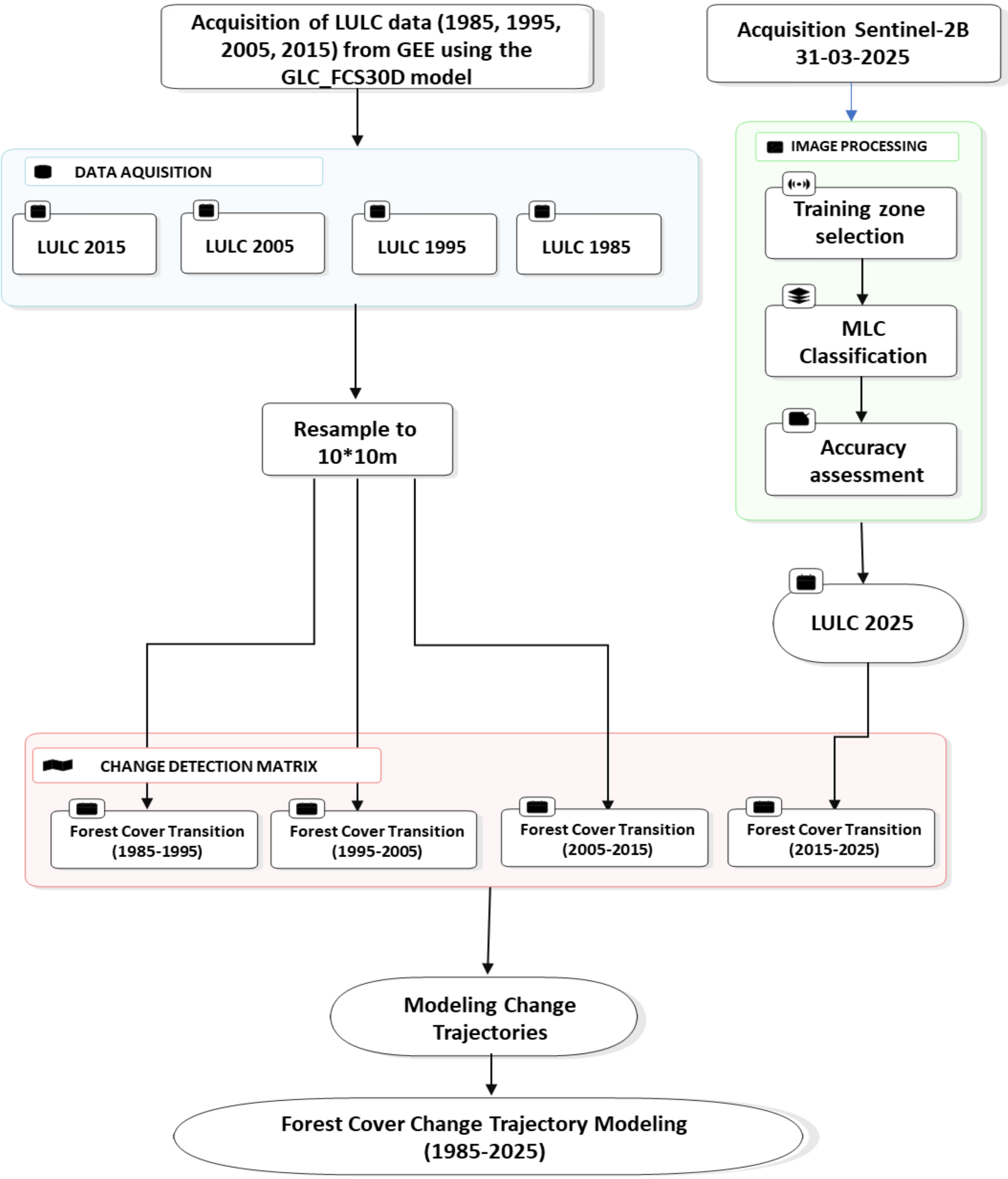

Figure 2. Flowchart of analysis process (Source: Authors, 2025)

METHODOLOGY

1. Pre-processing of GLC_FCS30D products

The GLC_FCS30D data set was pre-processed so as to obtain an image album that better represents changes in the land cover, in forested areas, over time. Data were managed and manipulated using a customized script developed in Google Earth Engine (GEE). Namely, land cover data from 1985, 1995, 2005 and 2015 were collected and harmonized in order to allow comparison between years.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

There are two major steps in the preprocessing:

Recoding of classes:

The 36-land cover classes of the source GLC_FCS30D data were aggregated and reclassified to fit the interest in woody vegetation of this study. The "Forest" and "Shrubland" types were combined into one "Woody Vegetation" group, based on the ecological rationale that semi-arid woodlands are a part of forest ecosystems (Maestre et al., 2011).

Resampling:

For consistency in spatial domain with the 2025 Sentinel-2 imagery (10-meter resolution), the GLC_FCS30D was then resampled (native resolution of 30 meters in 10x10 meters) using the nearest neighbor approach. This strategy maintains the discrete organizational characteristics of the land cover form without generating mixed pixels, thus better for the thematic mapping of vegetation patterns (Chen et al., 2017; Wei, H et al., 2023). In contrast to interpolation techniques (e.g., bilinear or cubic resampling), nearest neighbor resampling preserves distinct class boundaries, which is especially important for detecting changes in forest extent and fragmentation (Fayyad, U, et al., 1996).

The GLC_FCS30D data set has become popular in a number of environmental and ecological studies, especially for studying the dynamics and degradation of forests. For example, (Zhang et al. (2020) introduced the first global 30-meter resolution annual land cover change monitoring data product, GLC_FCS30D, established on dense time-series Landsat images and a continuous change detection algorithm, providing a detailed classification system from 1985 to 2022. This data set has been essential to tracking forest loss, fragmentation, and regrowth on both a global and regional level.

While the GLC_FCS30D product goes till 2022, this work is limited to the period 1985—2015 to follow an underlying decadal approach. This method ensures regular time intervals, is helpful for interpretation in comparison to flow measures, and red uses the error introduced by non-it me restriction of data.

Moreover had used the GLC_FCS30D for monitoring the effects of climate change and change in land use on the wind erosion process, with special emphasis on its use for mapping trends in vegetation cover, which are vital to achieve the land degradation neutrality aspects. Its use in generating high temporal resolution forest cover products (Li, J et al., 2020) also confirms its power in representing fine variations of forest ecosystems in semi-arid and transitional areas.

These applications demonstrate the importance that the GLC_FCS30D classification has for analyzing long-term forest changes, which would correspondingly make the GLC_FCS30D an excellent dataset for monitoring vegetation dynamics in the Green Dam area, where identification of slow evolution of forest and shrubland degradation and recovery is necessary for ecological monitoring and restoration.

2 Sentinel-2 Image Classification

Training samples for the 2025 dataset were chosen through field observations and extensive visual interpretation of a March 31 2025 Sentinel-2B image. Training samples totaling 1000 were distributed across six land cover classes, especially to discriminate forest from cropland in line with the objectives of the study on forestation dynamics.

Landcover products resulting from the Sentinel-2 sensor were pre-processed following guidelines provided in (ESA, 2021) for high-resolution imagery by way of resampling and subletting in the Sentinel Application Platform (SNAP) environment. To enable comparison between temporal layers, resampling was performed to a constant 10 m spatial resolution to be consistent with the GLC_FCS30D dataset.

Certain band combinations were utilized such as Bands 8 (NIR), 4 (Red), and 3 (Green) to better detect vegetation cover— considering to assess forest degradation; and bands11 (SWIR1) and 8A (narrow NIR). It was found that this combination was particularly effective for reliable classification of forested areas (Immitzer et al., 2016; Drusch et al., 2012).

The classification process used the Maximum Likelihood Classification (MLC) algorithm, which has been shown to be effective for images with nearly normally distributed data as the algorithm of choice for processing multispectral remote sensing data. The classification was performed in QGIS using the Semi-Automatic Classification Plugin (SCP) which

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

provides powerful supervised classification capabilities and has been extensively validated for land cover applications in semi-arid (Congedo, 2016) and forested environments respectively.

This methodological approach guarantees that the approached spatial complexity of the forest cover of the Green Dam region was respected when generating the classification results, as recommended in the consideration of methods and the best practices for remote sensing studies based on monitoring forest ecosystems in arid and semi-arid zones.

3. Accuracy Assessment

An independent validation dataset of 1000 random points was used to assess the accuracy of the Sentinel-2-based classification. The evaluation returned a Kappa value of 0.89 and an overall classification accuracy of 89%, indicating a very good reliability in accordance with land cover mapping standards (Foody, 2002).

Data Processing and Analysis

3.1. Preprocessing and Classification

Multi-temporal satellite imagery was used to extract land cover changes in the study site from 1985 up to 2025. The GLC_FCS30D global dataset, which provides consistent land cover maps over time, was used to extract forest and non-forest classes. To allow for comparison with high spatial resolution Sentinel-2 data for the year 2025, these were resampled to a spatial resolution of 10 m. For the 2025 map, land cover classes were created using maximum likelihood classification (MLC) in QGIS, and training data were selected based on a visual interpretation of 2015 high-resolution imagery, cross-validated against high-resolution imagery from 2019 to 2023.

3.2. METHOD: Change Detection Using transition-matrices

Based on these, four land cover transition matrices were produced for the years from 1985 to 1995, 1995 to 2005, 2005 to 2015 and 2015 to 2025, and used to classified from both space to time change. Land cover transitions were classified using this approach into:

Non-forest → non-forest and forest → forest: stable areas

Comeback → non forest → forest (Reforestation)

Loss of forests →non-forest (deforestation)

This commonly used matrix-based approach, well known in land change science for its application in capturing both stable and changed areas through time (Pontius et al., 2004; Singh, 1989),

We further performed a change detection analysis with land cover transition matrices to quantify spatiotemporal variations in forest extent in the study area. It enables an accurate quantification of the conversions between forest and non-forest classes during different time intervals (Reynolds, J. F et al. 2007) The classification land cover maps generated from the GLC_FCS30D product and the Sentinel-2 imagery were accordingly harmonized to reclassify the land cover categories into two major classes: Forest and Non-Forest. Land cover maps with time series were prepared for periods of 1985–1995, 1995–2005, 2005–2015 and 2015–2025. To ensure spatial consistency, each map was projected into a common coordinate system, and needed to be clipped to the study boundary.

Transition matrices were generated for each decade using cross-tabulation algorithms in GIS (QGIS and Google Earth Engine). These matrices that indicate the area (km^2) of stable pixels (forest → forest or non-forest → non-forest), and land cover transitions (forest → non-forest, or non-forest → forest). This allows us to detect not only deforestation but also reforestation events through time, consistent with standard methods in land change science (Singh, 1989).

The trends in land dynamics revealed by the analysis are:

- Persistent land cover is represented by stable classes.
- Non-forest to forest gains indicate reforestation or afforestation
- Forest to non-forest losses imply deforestation or degradation.
- These transitions are also employed to estimate net forest change and calculate generally stable landscape50 indicators (Zhu et al.2012).

This matrix-based method offers an open-access, reproducible process for assessing land cover change and further insights in the effectiveness of reforestation programs like the rehabilitation of the Green Dam in arid and semi-arid regions.

The transition matrices were subsequently used within a change trajectory modelling framework to determine the persistence and directional trend of forest cover change across four decades.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

3.3. Change Trajectory Modeling

As a first step to understand long-term forest dynamic we applied a change trajectory analysis with the QGIS. Forest cover maps classified as a binary outcome (1 = forest, 0 = non-forest, bin) were then generated for each year. Each pixel was given a unique trajectory code based on the following formula:

*Trajectory Code=(F1985*10000) +(F1995*1000) +(F2005*100) +(F2015*10) +(F2025*1)*

For every observation year within the area of study, each pixel was assigned a binary class code; "1"(class-forest) and "0"(class-non-forest). The code was used to build up multi-temporal binary trajectories (e.g. "11111" means forest in every year between 1985 and 2025, and "10000" means deforestation only early on). The resulting change trajectories were examined, resulting in the identification of six transformational change categories:

a) Stable non-Forest
b) Toward Reforestation, but with Unstable Change
c) Call-To-Action Unstable Change for Deforestation
d) Continuous Reforestation
e) Continuous Deforestation
f) Stable Forest

The unstable changes categories (10010, 10100, 01010) identify zones that alternately changed forest and non-forest and then terminated with a permanent change. If the end-state was non-forest they were classified as "unstable deforestation" and if the final state was forest, they were classified as "unstable reforestation"(Kennedy et al. 2007; Coppin et al. 2004).

Table 2 Classification of Land Cover Change Trajectories Based on Forest Dynamics (1985–2025)

No.	Trajectory Class	Description	Example Binary Sequences (1985–2025)
1	Stable Forest	Areas that remained forested throughout the entire period	11111
2	Stable non-Forest	Areas that remained non-forested throughout the entire period	00000
3	Continuous Deforestation	Areas that were forested in 1985 and gradually became non-forest	10000, 11000, 11100, 11110
4	Continuous Reforestation	Areas that gradually transitioned to forest over time	00001, 00011, 00111, 01111
5	Unstable Change Toward Deforestation	Areas that fluctuated but ended as non-forest	10100, 10010, 11010, 10110
6	Unstable Change Toward Reforestation	Areas that fluctuated but ended as forest	10001, 10101, 10011, 10111

- Each binary sequence represents the state of a pixel across **five dates**: 1985, 1995, 2005, 2015, and 2025.
- 1 = forest, 0 = non-forest.

The classification strategy is thus geared to portraying not only the stability of forest change but also directly about directionality and relates particularly well to recent suggestions in land change literature. Thus, a literature review informs that intermittent or oscillatory transitions are usually due to environmental stress or anthropogenic pressures or land use conflicts and need to be differentiated from adaptive and transformative transitions (Bell, J. & Stockdale, A. 2015; Brown et al. 2013). Thus, trajectory-based analyses must also consider permanent conversion vs temporary transitions with important implications for forest management and restoration policies.

These are categorized according to their smoothness on a per trajectory basis, which allows researchers to find transitional dynamics that cannot be detected using a simple binary change detection approach. Such information is not only indispensable for the analysis of land cover change that includes the temporal permanence of transitions, their reversibility and their direction (Zhu et al., 2012; Huang et al., 2010). This framework of analysis is the most appropriate particularly in dryland and semi-arid ecosystems, which like the Algerian steppe realize a potentially unstable pattern, driven by anthropogenic pressures (grazing, fuelwood harvesting) but also overlaid with climatic variations (Belhadj, A., 2023).

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

4. Result

4.1. Accuracy Assessment of Land Cover Classification

Study design and assessment of classified land cover mapping reliability using Sentinel-2B dataset A stratified random sampling method such as Equalized Stratified Random Sampling mitigates the sampling bias and gets a better accuracy assessment. In this method all land cover classes were represented in proportion in the validation dataset. The favorable and unfavorable aspect were taken in opposite balance (contrary) for each class, which led to the following special methodology.

Summary of the results of the accuracy assessment (Table 3, overall accuracy of 2025 classification was 89% referring to as a great correlation between classification and reference data). The Kappa coefficient adjusted for chance agreement was 0.87(95% Cohen's Kappa CI 0.73 to 1.00) consistent with high reliability of the classification. Values for user accuracy and producer accuracy were relatively consistent between classes, varying from 85% to 92%, supporting the suitability of the classification approach (Table 2).

Table 3 Accuracy Assessment Results for Sentinel-2B Classification (2025).

Dataset	Year	Validation Points	Overall Accuracy (%)	Kappa Coefficient	User Accuracy (%)	Producer Accuracy (%)
Sentinel-2B	2025	500	89	0.87	90	88

The classification accuracy was assessed using 500 random validation points following the Equalized Stratified Random Sampling approach (Jensen, 2005) and resulted in an overall accuracy of 89% and a Kappa coefficient of 0.87 for the 2025 Sentinel-2B classification. These values ensure a very high reliability and classification quality, especially in the distinction of forested against non-forest area. The user and producer accuracies vary from 85% to 92%, which represents a substantial level of agreement with reference data (Foody, 2002).

To evaluate the trustworthiness of the accuracy assessment an Equalized Stratified Random Sampling strategy was used. This guaranteed a proportionate representation of land cover classes in the validation set regarding area, minimized the potential sampling bias and increased the representativity of the results. Such methodological precision is indispensable for urban studies because it preserves valid inferences on spatial dynamics alongside their actionable use as input data for land use planning.

4.2. LAND COVER CHANGE ANALYSES

The land cover datasets for 1985, 1995, 2005, 2015 and 2025 were compared after preprocessing and classification to characterize forest cover change and dynamics of the study area. This analysis examined only change detection and change tracking on forested areas as shown on figure 3

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

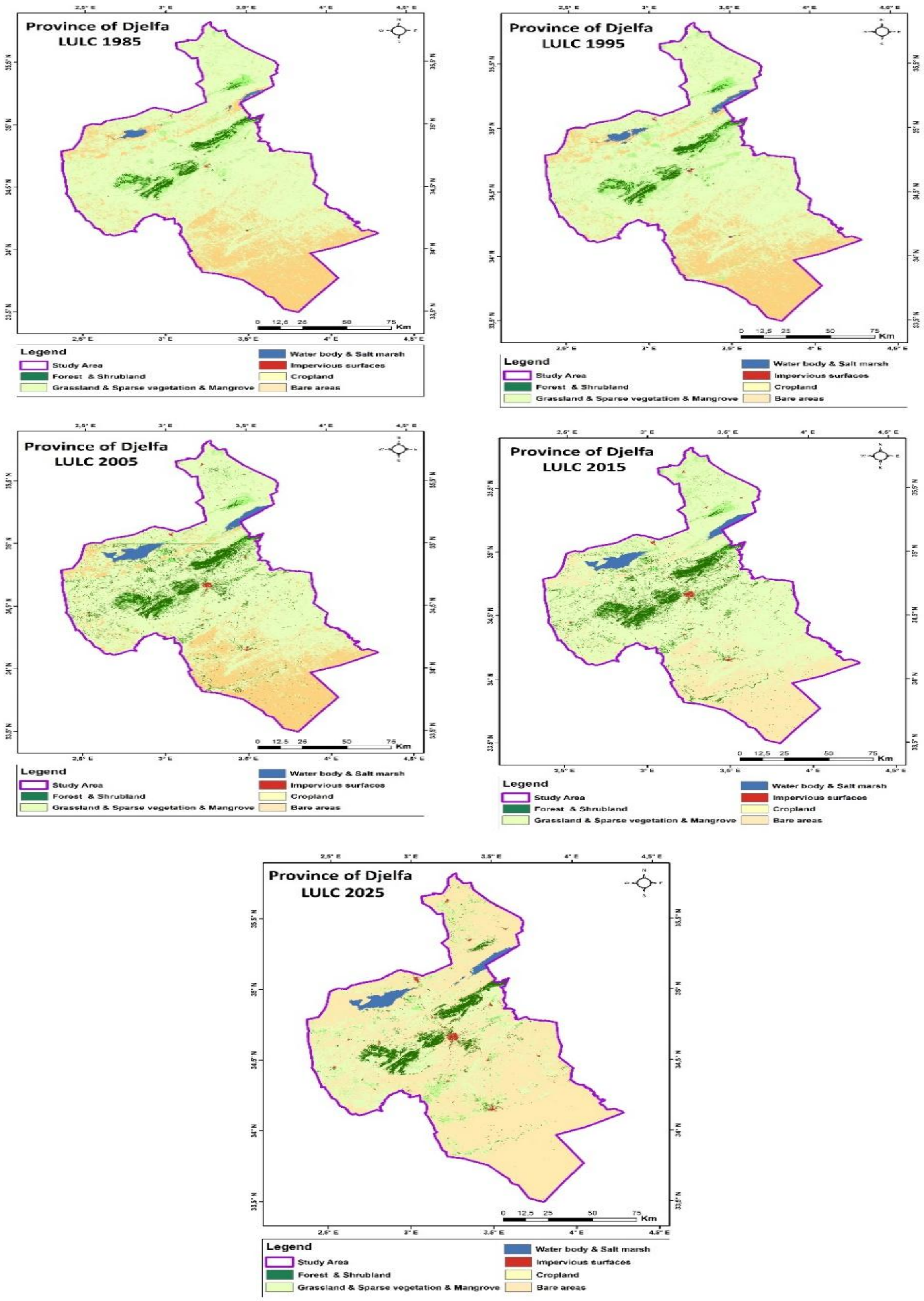

Figure 3. Maps of Land Cover Change Analyses in the province of Djelfa (1885-2025) (study area)

(Source: Authors, 2025)

4.3. FOREST COVER CHANGE ANALYSIS BASED ON TRANSITION MATRIX (1985–2025)

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

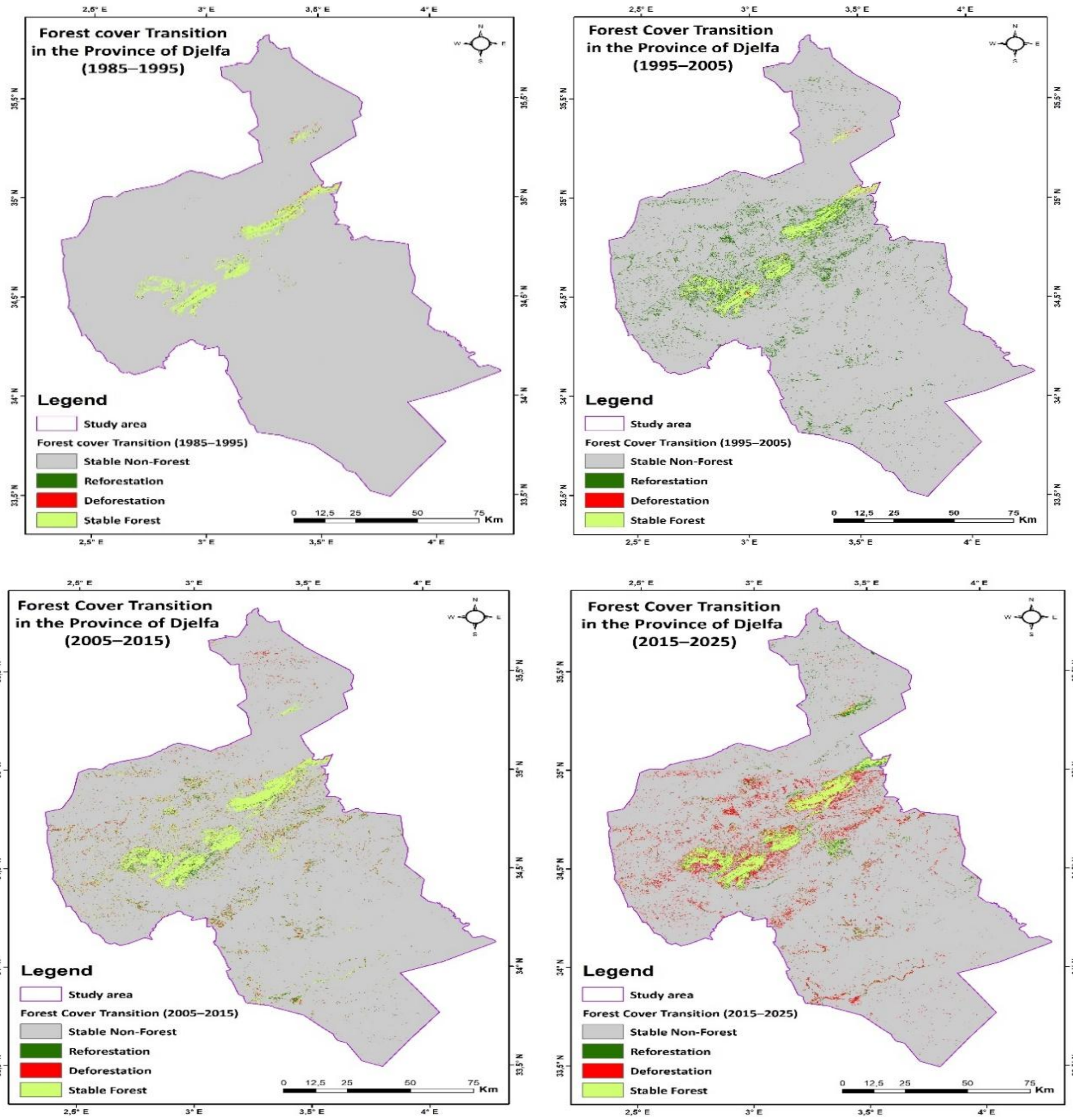

Figure 4. Maps of forest cover change analysis based on transition matrix (1985–2025) the province of Djelfa (study area) (Source: Authors, 2025)

As seen in (Figure 4 and table 4), the forest cover of the study area has been changed massively during the study period 1985–2025. Although reforestation grew during the period from 1995 to 2015, the period of 2015–2025 is characterized by general deforestation. In all, the trend underlies intensifying forest cover depletion and persistent need for sustainable land resources management

Table 4 Forest Cover Change Analysis Based on Transition Matrix (1985–2025) (Source: Authors, 2025)

	Non-Forest -non-Forest (Km²)	forest - forest	non-forest -forest	forest - non-forest
1985-1995	19146,92	444,04	21,46	16,15
1995-2005	18296,52	448,93	866,55	16,58
2005-2015	17993,06	1081,57	320,04	233,91
2015-2025	17943,77	639,01	284,40	761,40

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

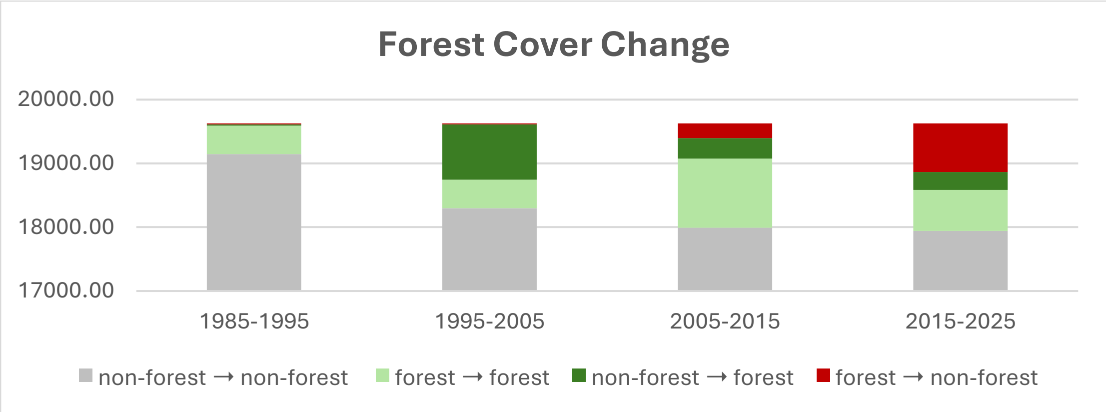

Figure 5. Curve Forest Cover Change (1985–2025) the province of Djelfa (study area) (Source: Authors, 2025)

Data from the transition matrices (in km²) showing the temporal dynamics of forest and non-forest cover over four decades in the study area. Between 1985 and 1995 not much changed, with the vast majority of the area remaining as nothing but non-forest land cover (19 146.92 km²), producing nearly no instances of forest gain (21.46 km²) or forest loss (16.15 km²). This indicates a more stable land-use dynamic, perhaps due to a slight human pressure or limited reforestations at this time (Figure 5).

Afforestation is particularly high between 1995 and 2005, when 866.55 km² change from non-forest to forest. This may reflect the influence of national or regional reforestation policies like the Green Dam rehabilitation programs. Only 16.58 km² of forest loss took place over the same period, showing a net gain in forest cover this decade.

There is a decline in forest gain (320.04 km²) and a significant change in forest to non-forest (i.e., deforestation (233.91 km²) between 2005 to 2015. This time could indicate increasing pressures for environmental degradation (reliable basis, overgrazing, and climate stress).

But from 2015 to 2025, it is an opposite trend; the forest loss amounts greatly increased to 761.40 km², which is more than two times of the afforestation value (284.40 km²). The transition suggests a change from forest to the non-forest (906.03 km²) with an increase of stable forest areas (639.01 km²). That means deforestation pressures likely from agricultural encroachment or lack of maintenance of reforested areas have increased in recent times.

Main Observations:

- High levels of stable non-forest areas dominate the all periods, indicating a major barrier to land reclamation.
- The afforestation peaked during the period from 1995–2005, likely to be a result of public afforestation policies.
- In the last decade, the rise in deforestation has greatly outstripped the progress of earlier decades.

4.4. Overview of Change Trajectory Modeling: Forest Dynamics:

Table 5 and Figures 6 and 7 highlights that the vast majority of the area remains non-forested, with relatively small but notable trends in both reforestation and deforestation, indicating ongoing but limited forest dynamics. Use of the (Forest Cover Change Trajectory Modeling (1985–2025)).

Table 5 Forest Cover Change Trajectory (Source: Authors, 2025)

Forest Dynamics	**Area (km²)**
Stable non-Forest	17726,30
Unstable Change Toward Reforestation	43,53
Unstable Change Toward Deforestation	944,69
Continuous Reforestation	476,16
Continuous Deforestation	34,18
Stable Forest	403,72

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

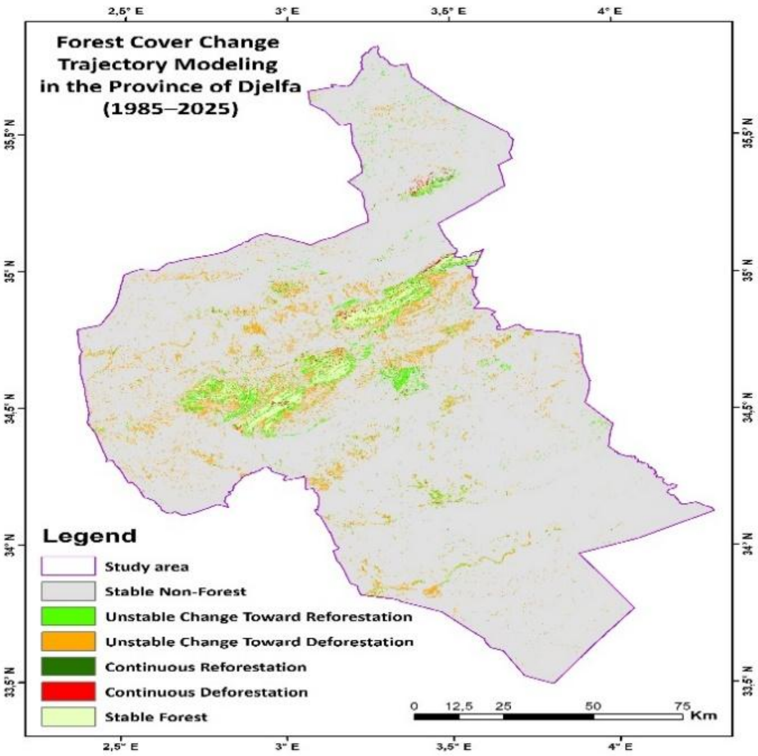

Figure 6. Maps of Overview of Change Trajectory Modeling: Forest Dynamics (1985–2025) the province of Djelfa (study area) (Source: Authors, 2025)

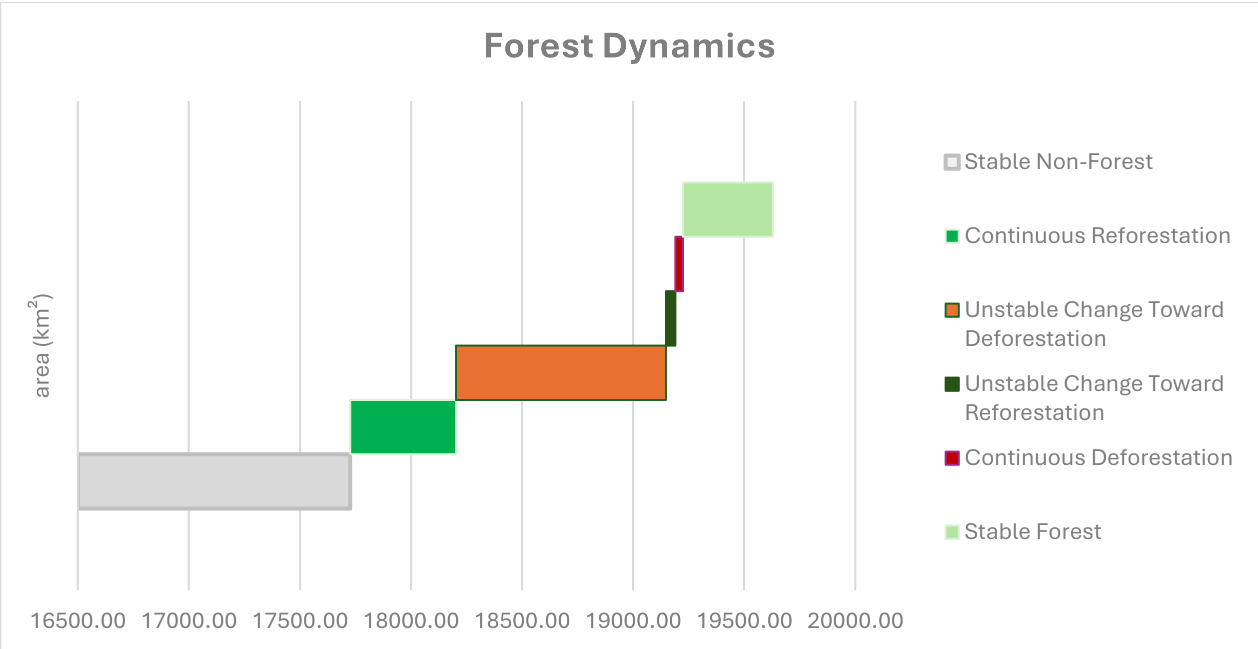

Figure 7. Curve Overview of Change Trajectory Modeling: Forest Dynamics (1985–2025) the province of Djelfa (study area) (Source: Authors, 2025)

Forest cover evolution based on trajectory sequences from 1985 to 2025: A spatiotemporal analysis the findings reveal more subtle transformations in land cover that cannot be captured using traditional binary transition matrices:

- The landscape is dominated by stable non-Forest (17,726.30 km²), which corresponds to the transition matrix suggesting that forest remained the most stable land.
- The largest of these dynamic categories, Unstable Change Toward Deforestation, carpets 944.69 km² of the land. Forest states also showed cyclical changes (e.g., forest gain, followed by forest loss), but concluded in a

non-forest state. Such instability can be linked to temporary recovery of forest followed by human-induced damage and climatic stress (Kamusoko & Aniya, 2009).

- Continuous Reforestation (CR) – Where there are areas of complete recovery on tree cover for at least three consecutive monitoring events (and, in the case of satellite-based remote sensing, locations consistently classified as forest across three consecutive measurement periods) covering a total of 476.16 km². The afforestation peaks during 1995–2005 in the transition matrix corresponds with figure 7.
- On the other hand, Continuous Deforestation is low (34.18 km²), indicating that the occurrence of extensive and one-directional forest loss is less likely to occur as opposed to temporary and dynamic patterns.
- Unstable Change Toward Reforestation was limited to 43.53 km² and indicates more spatially restricted or patchy approaches to reforestation that were unstable throughout the years.
- At last, Stable Forests account for a mere 403.72 km², showing the low resilience or the short-lived presence of Forests in the area. This is also consistent with the transition matrix results were also the areas of transition to/from forest were always smaller than those of non-forest transition.

Main Insights:

- Comparison of trajectory groupings of land cover dynamics reveals more complexity and realism, producing instability not captured by traditional transition matrices.
- Instability in deforestation arises as the main risk, mimicking how patches of forest are threatened and often more susceptible than others.
- The difference between continuous and discontinuous transitions indicate that forest protection policies have had either a short-lived success or met competing land uses.

4.5 Proposed Reforestation Operations and Forest Preservation Strategy

In Algeria, a number of reforestation and afforestation programs have been projected within the Green Dam area as well as in the surrounding semi-arid regions, as part of the national strategy for forest conservation and desertification control. The land planned works encompasses a total of ~6,212.51 km², broken out as follows;

Table 6 Planned Reforestation Works (Source: Authors, 2025)

Planned Reforestation Works	Area (Km²)
Green Dam Rehabilitation	485,10
Green Dam Forest Expansion	850,37
Agropastoral Expansion	4818,83
Roadside Reforestation Expansion	58,21

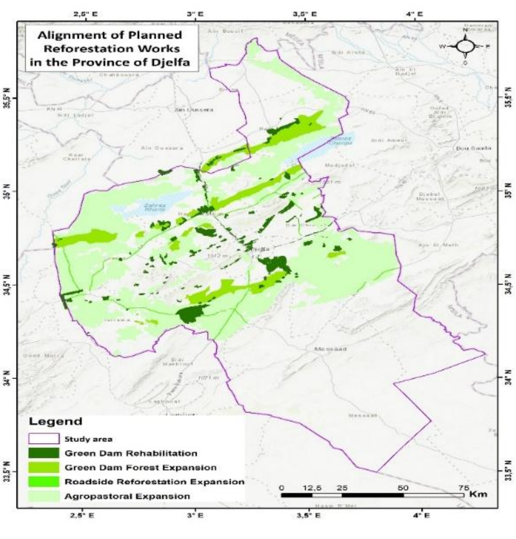

Figure 8. map Proposed Reforestation Operations and Forest Preservation Strategy the province of Djelfa (study area) (Source: Authors, 2025)

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

As described in (Table 6 and Figure 8) These actions come within the framework of the National Strategy to Combat Land Degradation, and correspond to Algeria's commitments within the framework of the UN Convention to Combat Desertification (UNCCD). The Green Dam first start out in the 1970s and it has been in the same line with FAO definition that the Green Dam is a strategic action to protect the gain in ground and built a threshold against Sahara encroachment, with the goal of enabling soil to accumulate avoid, vegetation will get over, and sustain agropastoral systems in the local (FAO, 2000).

The program has developed from installing a barrier of Aleppo pine (Pinus pinea) just to slow sand movement, to integrating landscape management activities such as reforestation, agropastoral land rehabilitation and biodiversity conservation. They are critical to cushioning fragile steppe ecosystems from the pressure and impacts of climate variability and land degradation

Discussion

From 1985 to 1995, stable forest dynamics were observed, with a small forest gain (21.46 km2) and token forest loss (16.15 km2). There will be little intervention and little large-scale implementation of reforestation projects in this time frame.

Afforestation increased between 1995 and 2005, with 866.55 km² changing from non–forest to forest. This would result from the national reforestation policies including the urgent rehabilitation of the Green Dam which aimed to address desertification and stabilize the steppe ecosystem (Boumediene, et al, 2019; World Bank, 2023). On the flip side, forest loss was also very low (16.58 km²) reflecting a clear forest gain in this era.

Forest gain reduced (320.04 km 2) whilst forest loss accelerated during the 2005–2015-decade (233.91 km 2). Such a trend could be the result of anthropogenic stressors, urban and agricultural development as well as climate variations, potentially eroding past restoration success (FAO, 2022).

It is a more complex relationship during the years 2015 to 2025. Reforestation achieved 284.40 km² and deforestation was at 761.40 km² i.e. The remained net forest cover loss This might suggest that a recent past of challenging conservation has not done enough to compensate new damaging force. These sub sections including the newly launched forest restoration programmed and Green Dam restoration (485.10 km²), forest expansion (850.37 km²), agropastoral expansion (4818.83 km²) and roadside afforestation work (58.21 km²) are a reflection of emerging political will also to restore degraded lands and also curtail further degradation caused by ecosystem services (World Bank, 2023; APS, 2024)

CONCLUSION AND RECOMMENDATIONS

Improve Coordination among Institutions

The coherence of sectoral policies and their long-term sustainability require an overarching governance framework that is clear and involves all relevant stakeholders, such as the environmental (i.e. Ministry of Environmental Protection or similar), agricultural, and local development agencies.

Enhance Local Participation

Involving local communities, particularly pastoralists and farmers, in the planning, planting and monitoring stages will result in better ownership of the project and a reduced risk of human-induced degradation.

Utilize Climate Adapted Species

Planting native and drought-resilient plant species that are more in tune with the semi-arid and arid realities of the steppe landscapes is a better solution as opposed to the aforementioned reforestation efforts.

Combine Geospatial and Monitoring Technologies

The use of remote sensing, GIS tools, and satellite imagery can also enhance tracking of the changes in vegetative cover, soil health, and efficaciousness of intervention zones.

Support Research and Training

Urge academic and scientific institutions to carry out long-term monitoring studies of soil quality, biodiversity, and socio-economic effects of the Green Dam, and promote capacity-building programs for technical personnel and local stakeholders.

Secure Sustainable Funding

National budgets, international cooperation, and climate finance can establish sustainable fiscal mechanisms that will ensure continuing assistance.

Raise Awareness and Environmental Education

Educational campaigns directed at youth, schools and rural communities will raise environmental awareness and help embed a culture of sustainable land management.

Initiated in the early 1970s, the Green Dam, is one of Algeria's most ambitious ecological projects with the primary purpose of combating desertification and, and stabilizing fragile ecosystems lining the southern edge of the steppe. The project was originally planned as a greenbelt that would span the entire country, but it faced management challenges, lack of local buy-in, budget constraints, and environmental problems such as overgrazing and climate change over the decades.

The revival of the so-called Green Dam project over the past few years, in the context of national and global sustainability agendas, though from the problems he received previously, represents another effort, political and ecological, to confront land degradation and construct ecological resilience. By combining new science, community involvement and sustainable land-use planning, it is possible, however, that the Green Dam could be turned into a (strategically) large advantage for environmental protection and rural development.

REFRENCES

[1] APS – Algérie Presse Service. (2024). Green Dam Rehabilitation: A model of sustainable development and climate resilience.https://www.aps.dz/en/economy/53598-green-dam-rehabilitation-model-of-sustainable-development-climate-resilience

[2] Belhadj, A., Allache, F. D., Boulghobra, N., & Mebrek, N. (2023). Botanical diversity of arid steppe in South East of Algeria (Biskra). Journal of Ecological Engineering, 24(1), 120-134.

[3] Bell, J., & Stockdale, A. (2015). Evolving national park models: The emergence of an economic imperative and its effect on the contested nature of the 'national 'park concept in Northern Ireland. Land Use Policy, 49, 213-226.

[4] Boumediene, K., Edine, B. D., Said, B., & Ilyes, H. (2023). A diachronic study of the green dam dynamics by space teledetection: semi-arid zone of Djelfa, Algeria. Natural Resources and Sustainable Development, 13(1), 137–146. https://doi.org/10.31924/nrsd.v13i1.123

[5] Brown, D. G., Verburg, P. H., Pontius Jr, R. G., & Lange, M. D. (2013). Opportunities to improve impact, integration, and evaluation of land change models. Current Opinion in Environmental Sustainability, 5(5), 452-457. https://doi.org/10.1016/j.cosust.2013.07.012

[6] Chen, G., Weng, Q., Hay, G. J., & He, Y. (2018). Geographic object-based image analysis (GEOBIA): Emerging trends and future opportunities. GIScience & Remote Sensing, 55(2), 159-182. https://doi.org/10.1080/15481603.2018.1426092

[7] Congedo, L. (2016). Semi-Automatic Classification Plugin Documentation.

[8] Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: a review. International Journal of Remote Sensing, 25(9), 1565–1596. https://doi.org/10.1080/0143116031000101675

[9] Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., ... & Bargellini, P. (2012). Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. Remote Sensing of Environment, 120, 25-36. https://doi.org/10.1016/j.rse.2011.11.026

[10] ESA (2021). Sentinel Application Platform (SNAP) User Manual. European Space Agency.

[11] FAO. (2011). State of the World's Forests 2011. Food and Agriculture Organization of the United Nations.

[12] FAO. (2022). The State of the World's Forests 2022. Food and Agriculture Organization of the United Nations. https://doi.org/10.4060/cb9360

[13] Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). The KDD process for extracting useful knowledge from volumes of data. Communications of the ACM, 39(11), 27-34. https://doi.org/10.1145/240455.240464

[14] Foody, G. M. (2002). Status of land cover classification accuracy assessment. Remote Sensing of Environment, 80(1), 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4

[15] Hezil, S., Aouadj, S. A., Degaichia, H., Ouinten, Y., Lafri, I., Bounab, S., & Chakali, G. (2024). The role of rehabilitating and restoration the green dam in managing the impact of invasive forest pests in Algeria. Brazilian

Journal of Animal and Environmental Research, 7(4), e75010-e75010. https://doi.org/10.34188/bjaerv7n4-081

[16] Huang, C., Goward, S. N., Masek, J. G., Thomas, N., Zhu, Z., & Vogelmann, J. E. (2010). An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks. Remote Sensing of Environment, 114(1), 183-198. https://doi.org/10.1016/j.rse.2009.08.017

[17] Immitzer, M., Vuolo, F., & Atzberger, C. (2016). First experience with Sentinel-2 data for crop and tree species classifications in central Europe. Remote Sensing, 8(3), 166. https://doi.org/10.3390/rs8030166

[18] Jensen, J. R. Introductory digital image processing: a remote sensing perspective. 3rded.: Prentice Hall; 2005

[19] Kamusoko, C., & Aniya, M. (2009). Hybrid classification of Landsat data and GIS for land use/cover change analysis of the Bindura district, Zimbabwe. International Journal of Remote Sensing, 30(1),97-115. https://doi.org/10.1080/01431160802244268

[20] Kennedy, R. E., Cohen, W. B., & Schroeder, T. A. (2007). Trajectory-based change detection for automated characterization of forest disturbance dynamics. Remote sensing of environment, 110(3), 370-386. https://doi.org/10.1016/j.rse.2007.03.010

[21] Khaouani, B., Hirche, A., & Salamani, M. (2019). Ecological dynamics of the green dam by remote sensing: The case of Moudjbara (Djelfa, Central Algeria). PONTE International Journal of Science and Research, 75(4), Article 8. https://doi.org/10.21506/j.ponte.2019.4.8

[22] Li, J., Pei, Y., Zhao, S., Xiao, R., Sang, X., & Zhang, C. (2020). A review of remote sensing for environmental monitoring in China. Remote Sensing, 12(7), 1130. https://doi.org/10.3390/rs12071130

[23] Maestre, F. T., Bowker, M. A., Cantón, Y., Castillo-Monroy, A. P., Cortina, J., Escolar, C., ... & Martínez, I. (2011). Ecology and functional roles of biological soil crusts in semi-arid ecosystems of Spain. Journal of arid environments, 75(12), 1282-1291. https://doi.org/10.1016/j.jaridenv.2010.12.008

[24] Merdas, S., Mostephaoui, T., & Belhamra, M. (2017). Reforestation in Algeria: History, current practice and future perspectives. Reforesta, 3, 116–124. https://doi.org/10.21750/REFOR.3.10.34

[25] Mihi, A., Zerroug, K., Kouachi, M. E., & Benarfa, N. (2024). Spatiotemporal changes of desertification degree in the Algerian green barrier over the last four decades (1984–2020). Arid Land Research and Management, 38(3), 362–381. https://doi.org/10.1080/15324982.2024.2316657

[26] Pontius, R. G., Jr., Huffaker, D., & Denman, K. (2004). Useful techniques of validation for spatially explicit land-change models. Ecological Modelling, 179(4), 445–461. https://doi.org/10.1016/j.ecolmodel.2004.05.010

[27] Reynolds, J. F., Smith, D. M. S., Lambin, E. F., Turner, B. L., Mortimore, M., Batterbury, S. P., ... & Walker, B. (2007). Global desertification: building a science for dryland development. science, 316(5826), 847-851. https://doi.org/10.1126/science.1131634

[28] Richards, J. A., & Richards, J. A. (2022). Remote sensing digital image analysis (Vol. 5, pp. 256-258). Berlin/Heidelberg, Germany: springer. https://doi.org/10.1007/978-3-642-30062-2

[29] Saifi, M., Boulghobra, N., & Fattoum, L. (2014). The Green Dam in Algeria as a tool to combat desertification. GRF Davos Planet@Risk, 3(1), 1–4. https://www.researchgate.net/publication/273286423

[30] Singh, A. (1989). Review article digital change detection techniques using remotely-sensed data. International journal of remote sensing, 10(6), 989-1003. https://doi.org/10.1080/01431168908903939

[31] Wei, H., Jia, K., Wang, Q., Cao, B., Qi, J., Zhao, W., & Yang, J. (2023). Real-time remote sensing detection framework of the earth's surface anomalies based on a priori knowledge base. International Journal of Applied Earth Observation and Geoinformation, 122, 103429. https://doi.org/10.1016/j.jag.2023.103429

[32] World Bank. (2023). Strengthening the sustainability and climate resilience of Algeria's forests. World Bank Press Release. https://www.worldbank.org/en/news/press-release/2023/11/13/strengthening-the-sustainability-and-climate-resilience-of-algeria-forests

[33] Zehraoui, R. (2021). Étude phytoécologique et impacts des reboisements du barrage sur la biodiversité floristique: Cas de la région de Djelfa (Algérie). Agrobiologia, 10(2), 2062–2075

[34] Zhang, X., Liu, L., Chen, X., Gao, Y., Xie, S., & Mi, J. (2020). GLC_FCS30: Global land-cover product with fine classification system at 30 m using time-series Landsat imagery. Earth System Science Data Discussions, 2020, 1-31. https://doi.org/10.5194/essd-13-2753-2021

[35] Zhu, Z., Woodcock, C. E., & Olofsson, P. (2012). Continuous monitoring of forest disturbance using all available Landsat imagery. Remote sensing of environment, 122, 75-91. https://doi.org/10.1016/j.rse.2011.10.030