



Detection of Deforestation Utilizing GIS, Remote Sensing, and Artificial Intelligence: A Case Study of the Acacia Forest, Khartoum State, Sudan

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Abstract: This study analyzes changes in forest cover in the Acacia forest of Khartoum (2021–2026) using GIS, remote sensing, Sentinel-2 imagery, and an artificial intelligence-based Random Forest classification model. Random Forest is often an appropriate baseline for tabular data and for traditional pixel-based change detection (e.g., comparing multi-temporal bands, NDVI, or SAVI), and it is used in this study.

Spectral indices (NDVI and SAVI) derived from bands B2, B3, B4, and B8 were used as model inputs. The classifier was trained on 2023 baseline data, using NDVI thresholding to distinguish forest from non-forest areas. The results indicate substantial forest degradation over the five-year monitoring period, primarily caused by unauthorized logging. According to the NDVI values used to assess deforestation in the forest, the NDVI values for Year 2021 (0.4151), Year 2022 (0.5480), Year 2023 (0.5962), Year 2024 (0.5864), Year 2025 (0.56226), and Year 2026 (0.35181) indicate deforestation across the study years.

Keywords: Earth Observation (EO), Earth Observing System (EOS), Machine Learning (ML), Artificial Intelligence (AI), Normalized Difference Vegetation Index (NDVI), The Soil-Adjusted Vegetation Index (SAVI), Random Forest (RF), Change Detection (CD), Near Infra-Red (NIR).

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1. INTRODUCTION

The Acacia Forest, one of Khartoum State's oldest and largest reserves, was added to the national reserve system in 1939. It mainly features acacia trees that withstand autumn floodwaters. The forest hosts a variety of bird species, including resident and migratory birds such as geese, egrets, terns, ibises, ducks, gulls, herons, sparrows, and other savanna birds. It covers 1,500 hectares on the White Nile's eastern bank near the Nile's confluence.

War in Sudan and indiscriminate logging for cooking and other uses are among the main causes of deforestation and forest damage. The Acacia Forest was not the only forest in

Khartoum to be destroyed; according to official statistics, Khartoum has 19 forests, most of which are located along the banks of the Nile. These forests were also damaged by human activity during the armed conflict [1].

1.1 Importance of The Acacia Forest:

This forest has major educational value. The Forestry Experts School was established there in 1946 to train forestry personnel in techniques, management, and cultivation, reflecting the growing need for formal forestry education in Sudan. It produced the first generation of forestry technicians, who played a major role in forestry across Sudan.

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The forest also abounds with reptiles, insects, and small wild animals, enriching the natural environment and enhancing its vitality. All this has made the Acacia Forest a natural retreat for Khartoum residents and visitors. It is a vital link in the region's ecological balance, helping moderate the climate and absorbing gases and toxins from vehicle emissions and factory waste [1].

1.2 Forests in Sudan

Worldwide, forest types vary with climate, geography, and dominant species, including tropical rainforests, boreal forests, and temperate deciduous forests. Furthermore, forests can be classified based on administrative boundaries, land cover (including trees and ground vegetation), or land use, such as timber production, conservation efforts, or recreational activities.

Sudan, the largest Arab country by forest area, with about 183,595 sq km (10–11%), has diverse forests, including dense Nilotic forests along the Nile, Dahra forests in arid regions, and limited irrigated forests. The acacia forest at the Nile's confluence faces encroachment and development plans, some of which have been blocked by local opposition.

UN and FAO data show that deforestation in Sudan causes over 9.3 million tons of CO₂ emissions annually, with forest degradation adding 1.6 million tons. Protecting forests is vital to fight climate change and sustain environmental health[1].

1.3 Deforestation

A forest is a substantial area densely populated with trees and undergrowth, encompassing both untouched virgin forests with intricate canopies and high biodiversity and secondary forests influenced by human activity.

Deforestation refers to the irreversible removal of trees and forest cover, primarily instigated by human activities such as agriculture, logging, and infrastructure development. This process converts diverse forest ecosystems into land designated for other purposes, thereby exerting substantial influence on global climate and biodiversity [2, 3].

Population growth, conflict, and the demand for timber to produce food are among the primary drivers of deforestation and changes in land use for agriculture, industry, and urban development. Inadequate forest management practices are also a significant contributor to the increasing rate of forest degradation [4].

They are responsible for approximately 15% of all greenhouse gas emissions, thereby contributing to rising global temperatures, altered weather patterns, and more frequent extreme weather events. [4].

Deforestation refers to the removal, felling, or clearing of forests or other vegetative areas, including tree plantations, to facilitate agricultural, industrial, urban, or rural

development. It is also associated with modifications to forestry practices, such as slash-and-burn techniques, which are integral to shifting cultivation agricultural systems. [5].

The figure below shows ALT detection results in a deforested area in the municipality of Apuí, Amazonas state (Brazil).[6]

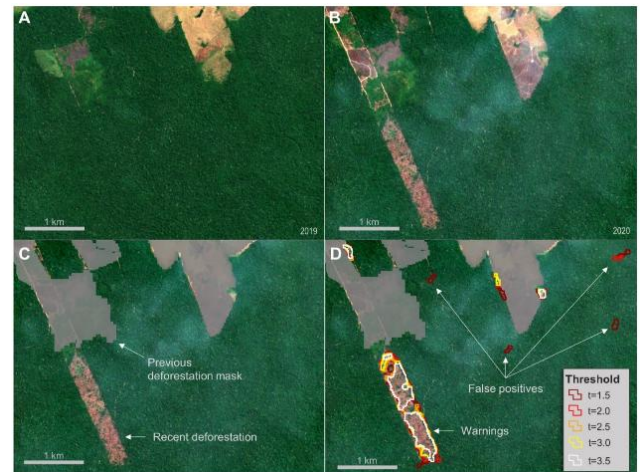


Figure Error! No text of specified style in document.-1
Figure 15. ALT detection results in a deforested area in Apuí municipality, Amazonas state (Brazil).

According to the United Nations Food and Agriculture Organization, deforestation is "the conversion of forest to other land use, independently of whether human-induced or not," and constitutes a significant environmental challenge. Since 1990, more than 420 million hectares of forest have been lost. Furthermore, since 2000, approximately 47 million hectares of ecologically invaluable primary forests have been lost. [7].

1.4 Deforestation in Sudan

From 2001 to 2025, Sudan lost 1.2 kha of tree cover, equivalent to 2.0% of the 2000 tree cover area, and emitted 420 kt of CO_{2e}. This loss indicates a modest but meaningful source of carbon emissions and underscores the need for stronger land management to protect the remaining tree cover and limit future climate impacts. This loss figure excludes tree cover gains over the same period and therefore does not represent net change. [8].

From 2021 to 2025, 100% of tree cover loss in Sudan occurred in natural forests. The total loss in natural forests was 2.9 kha, equivalent to 690 kt of CO_{2e} emissions. [8].

In 2025, it lost 1.1 thousand hectares (kha) of natural forest, equivalent to 250 kilotons (kt) of carbon dioxide (CO₂) emissions. [8].

1.5 The Main Causes of Deforestation

Understanding the dynamics of land use and land cover has increasingly been recognized as a key priority in global environmental change research[9].

The primary concern is that deforestation is challenging to define, quantify, and elucidate due to the absence of a single, precise definition or a reliable method of measurement. It is equally difficult to ascertain the extent of deforestation or its causes, as it varies across regions.

Instead of a single predominant cause, deforestation generally results from an amalgamation of economic, social, and environmental factors, complicating the identification of a sole driving force[10, 11].

- Agricultural expansion serves as the primary catalyst for global deforestation.
- Commercial and industrial logging operations result in the removal of extensive forested areas, leading to land degradation and facilitating the conversion of previously inaccessible regions.
- Mining activities significantly contribute to forest depletion, both directly and via the development of associated infrastructure.
- Urbanization and settlement expansion necessitate the clearing of forests to accommodate growing human populations and infrastructural development.
- Climate change exacerbates forest destruction through extreme weather phenomena such as wildfires and droughts, thereby intensifying rates of deforestation pressure[7].

1.6 The Impact of Pollution and Carbon Emissions

Carbon dioxide (CO_2) and methane (CH_4) are important greenhouse gases in the atmosphere and have significant impacts on Earth's radiative forcing and climate. Carbon greenhouse gas emissions include compounds such as CO_2 and CH_4 that trap heat in the atmosphere, contributing to global warming. These are often referred to as "carbon emissions" because they are measured in CO_2 equivalents (CO_2e). Since the Industrial Revolution, fossil fuel burning has increased, raising CO_2 levels and accelerating global warming[12].

The carbon cycle is the process that moves carbon among plants, animals, microbes, Earth's minerals, and the atmosphere. Carbon is the fourth most abundant element in the universe. With its ability to form complex molecules such as DNA and proteins, carbon makes life on Earth possible. Carbon in the form of carbon dioxide (CO_2) is also an important part of our atmosphere, where it helps to control the Earth's temperature[13].



Figure Error! No text of specified style in document.-2
Al-Sunt Forest 2023



Figure Error! No text of specified style in document.-3
Al-Sunt Forest 2026

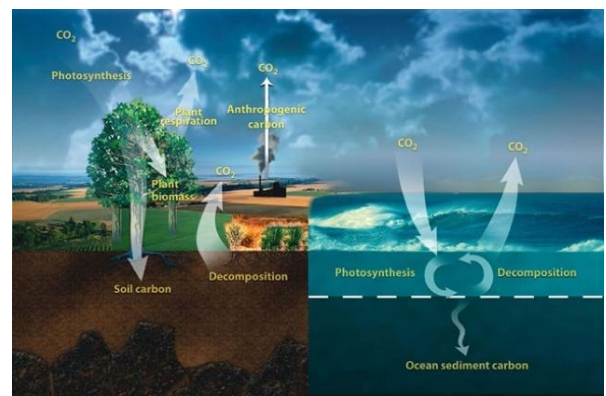


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The carbon cycle describes how carbon moves among the atmosphere, soils, living organisms, the ocean, and human activities

1.7 Remote Sensing

The term 'remote sensing' has various definitions; however, the United States Geological Survey (USGS) defines it as the "process of detecting and monitoring an area's physical characteristics by measuring its reflected and emitted radiation from a distance," typically carried out using satellites or aircraft. Specialized cameras are used to capture these images, thereby helping researchers gain a more comprehensive understanding of Earth. [14]Gathering information about Earth's surface and interior has become a priority for many researchers. Remote sensing and GIS have evolved from technologies such as surveying, photogrammetry, mapping, mathematics, and statistics. Satellite remote sensing is crucial for observing Earth's surface at various scales, enabling rapid monitoring of atmospheric, surface, and oceanic conditions to support hazard assessment. Satellite data supplement limited field measurements, which are essential for modeling. In the 1970s, sensors such as Landsat, AVHRR, TOMS, and HIRS served specific purposes, such as monitoring land, clouds, ozone, and weather. These missions provided valuable data and were extended and improved over time.[15].

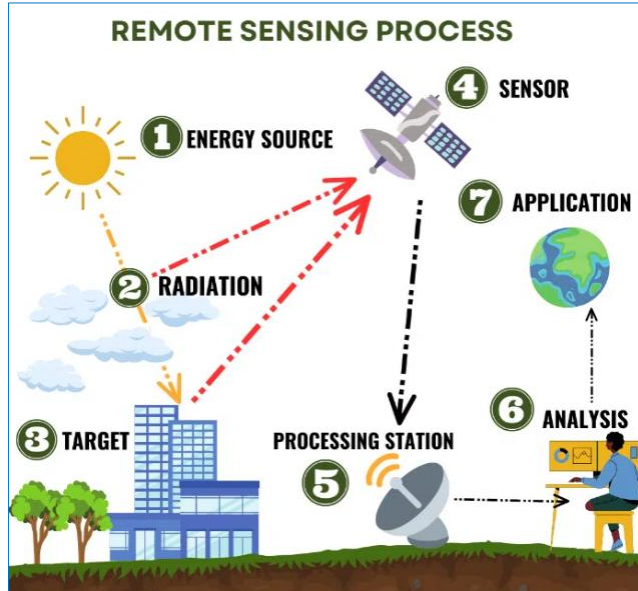


Figure Error! No text of specified style in document.-5
Remote Sensing Process[16]

The two main types of remote sensors are active and passive, both of which measure reflected or emitted energy within specific electromagnetic regions.

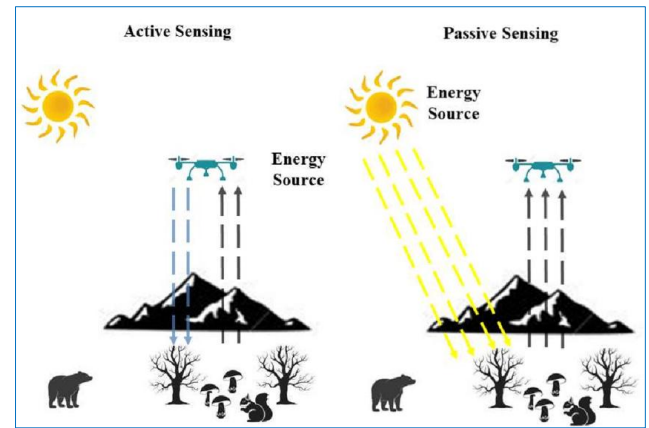


Figure Error! No text of specified style in document.-6
Remote Sensing types[17]

1.7.1 Remote Sensing Image Change Detection

Change detection in remote sensing compares images over time to identify surface changes. Traditional pixel-based methods like differencing, change vector analysis, and PCA rely on spectral differences. Object-based techniques segment images into meaningful units using context and geometry. Machine learning classifiers trained on handcrafted features and deep learning models using CNNs, Siamese networks, and transformers leverage spatiotemporal dependencies and self-attention to improve robustness against variations. Large datasets and high-resolution sensors have advanced applications in areas such as deforestation, urban growth, and disaster assessment. Challenges include co-registration errors, limited labeled data, and scalability for large archives. [18, 19].

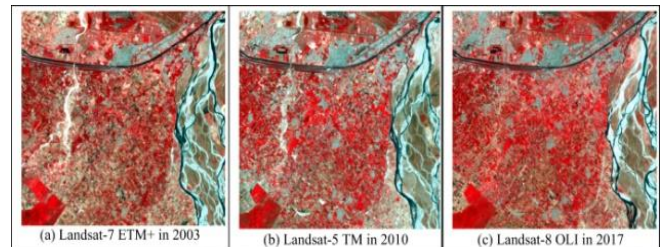


Figure Error! No text of specified style in document.-7
Change detection techniques for land cover[20]

Remote sensing image change detection (CD) is used to identify significant changes between bitemporal images. Given two co-registered images acquired at different times, illumination variations and misregistration errors can obscure the actual object changes. Exploring the relationships among different spatiotemporal pixels may improve the performance of CD methods [19].

Modern change detection (CD) has achieved remarkable success thanks to the strong discriminative power of deep convolutional networks. However, high-resolution remote sensing CD remains challenging due to the complexity of scene objects. Objects with the same semantic concept may show different spectral characteristics at different times and

locations. Most recent CD pipelines that rely solely on convolutions still struggle to capture long-range dependencies across space and time[21].

1.8 Artificial Intelligence (AI)

Artificial intelligence (AI) has been recognized as a vital contemporary technology with demonstrated effectiveness across multiple domains, including satellite image classification [22]. AI is an important and rapidly evolving field within computer science that focuses on developing machines and systems capable of performing tasks that typically require human intelligence[23]such as problem-solving, learning, and decision-making [14]. Researchers are making significant progress in developing technologies that can simulate human cognitive processes. Although computers excel in many areas, the human brain continues to surpass them in common sense, inspiration, and imagination[24, 25]. In recent years, machine learning has expanded rapidly and found numerous applications. It concerns the automatic identification of meaningful patterns in data and aims to enhance the adaptability and learning capacity of software applications [26] Artificial intelligence also encompasses the integration of computer science, physiology, and philosophy. Replicating the complex behavior of the human brain, composed of billions of neurons, remains one of the most challenging problems in artificial intelligence. AI logic is grounded in concepts developed by philosophers and mathematicians and later applied in AI systems [22, 27].

In recent years, deep learning algorithms have been widely recognized as the preferred approach for remote sensing image analysis and have been successfully applied to change detection. However, only a limited number of comprehensive review papers on deep learning-based remote sensing image change detection methods are currently available[28].

1.9 Remote sensing mapping

Remote sensing mapping helps update forest cover, monitor depletion, and measure the biophysical properties of forest stands. These applications include collecting harvest information, updating timber supply inventory data, and assessing broad forest type, vegetation density, and biomass. It is also used for environmental monitoring, including the quantity, health, and diversity of the Earth's forests.

1.10 Spectral indices

Spectral indices are mathematical equations that combine reflectance values from two or more spectral bands to highlight specific physical, chemical, or biological features of the Earth's surface.

Satellites and sensors capture light across bands such as visible (red, green, and blue), near-infrared (NIR), and shortwave infrared (SWIR). Because materials like vegetation, water, soil, and urban structures absorb and reflect light differently across these wavelengths, spectral indices isolate these signals while reducing background noise, such as atmospheric interference and topographic effects.

1.10.1 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI), one of the earliest remote sensing products used to simplify multispectral imagery, is now the most widely used index for vegetation assessment. Its popularity stems from the fact that NDVI can be calculated using any multispectral sensor with visible and near-IR bands. The low cost and weight of multispectral sensors mean they can be mounted on satellites, aircraft, and increasingly Unmanned Aerial Systems (UAS). While studies have found NDVI effective for expressing vegetation status and quantifying vegetation attributes, its widespread use, especially in UAS applications, carries inherent risks of misuse by end users with little to no remote sensing education[29].

The formula for the Normalized Difference Vegetation Index (NDVI) is

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

where NIR is near-infrared light, and Red is visible red light.

1.10.2 The Soil-Adjusted Vegetation Index (SAVI)

The Soil-Adjusted Vegetation Index (SAVI) is a vegetation index that minimizes the influence of soil brightness by applying a soil-brightness correction factor. It is often used in arid regions where vegetative cover is low.

$$SAVI = \left(\frac{(NIR - Red)}{(NIR + Red + L)} \right) * (1 + L)$$

NIR = pixel values from the near-infrared band

Red = pixel values from the near-red band

L = amount of green vegetation cover, A constant value is added to the numerator and denominator of the NDVI equation to account for differential red and near-infrared extinction through a vegetation canopy over a soil background. Typically set to [0.5] as the default baseline for intermediate or moderate green vegetation cover (30%–40% density). Range: Values vary from [0] to [1], depending on the canopy density of the observed area.

2. EARTH OBSERVATION SATELLITES

2.1 Orbits of Earth Observation Satellites

An orbit is the path that satellites, such as Earth observers, follow around the planet, chosen based on their goals. Earth observation satellites mainly use a sun-synchronous orbit, a polar orbit that passes over the poles, which is ideal for consistent data collection. This orbit combines a sun-synchronous orbit, maintaining a constant angle with the Sun for same-area observation, with a sub-recurrent orbit, revisiting the same location at the same time daily after a fixed interval. This enables efficient environmental monitoring and data collection.

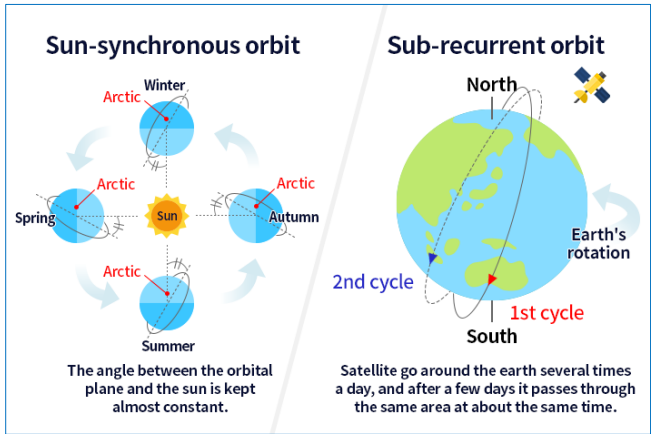


Figure Error! No text of specified style in document.-8 Orbits of Earth observation satellites[30]

Earth observation satellites fall into two main categories: those operated by government agencies (public domain) and

those built and maintained by private companies (private domain).

This study focuses on the Sentinel-2 satellite.

2.2 Sentinel- 2 images

Sentinel-2 is a constellation of optical imaging satellites in the European Union's Copernicus Earth observation program.

It currently includes three identical satellites: Sentinel-2A (launched in 2015), Sentinel-2B (launched in 2017), and Sentinel-2C (scheduled for 2024). Their orbits are coordinated to optimize coverage and revisit times [31]. This polar-orbiting, multispectral imaging mission is designed for land monitoring, providing imagery of vegetation, soil, water cover, and coastal areas. Accurate data after events such as floods or earthquakes. [32].

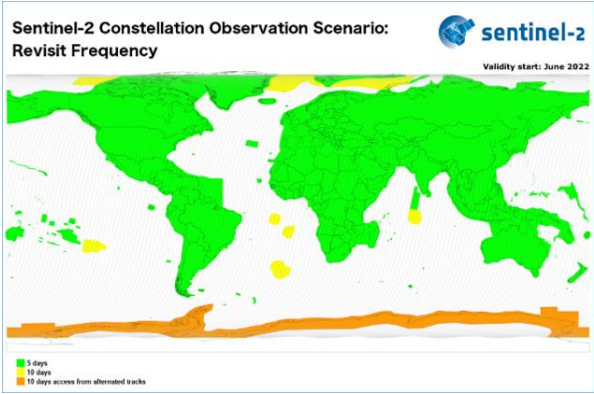


Figure Error! No text of specified style in document.-9 Revisit time for Sentinel-2 [33]

Table Error! No text of specified style in document.-1 Highlights the key band combinations used in Earth observations and other applications.[33]

Application	Layers Band combination									Product Type	
	True Color	False color	NDVI	False color (urban)	Moisture index	SWIR	NDWI	NDSI	Scene classification (L2A only)	L1C	L2A
	B4, B3, B2	B8, B4, B3		B12, B11, B4							
Geophysical			✓	✓	✓	✓	✓		✓	✓	✓
Land Monitoring	✓	✓	✓	✓					✓	✓	✓
Maritime Monitoring	✓			✓	✓		✓			✓	✓
Emergency Management	✓	✓	✓	✓	✓	✓		✓		✓	✓
Security	✓			✓	✓		✓	✓		✓	✓

3. PREVIOUS Study

3.1 Tech-Driven Forest Conservation: Combating Deforestation with Internet of Things, Artificial Intelligence, and Remote Sensing

Deforestation poses a major global challenge affecting biodiversity, climate, and livelihoods. Using technologies such as IoT, AI, and remote sensing holds great promise. This review examines their roles in monitoring, detecting, predicting, and preventing deforestation through real-time data and early detection, addressing illegal logging, diseases, and fires. It discusses advantages, limitations, current status, and future potential of IoT, satellite imagery, drones, and AI, highlighting their importance in forest and species conservation. The findings aim to inform debates and support future research, guiding effective policies for forest preservation [34].

3.2 Leveraging the Internet of Things, Remote Sensing, and Artificial Intelligence for Sustainable Forest Management

Sustainable forest management is vital for addressing climate change, biodiversity loss, and deforestation. Human pressure on forest ecosystems requires innovative approaches to ensure long-term health and productivity. This study examines how the Internet of Things (IoT), remote sensing, and artificial intelligence (AI) improve sustainable forest management. Researchers reviewed 196 studies published from 2021 to 2024 across IEEE Xplore Digital Library, MDPI, Taylor & Francis, ScienceDirect, Frontiers, Springer, SAGE, Hindawi, Nature, Wiley Online Library, and Google Scholar. Findings show that IoT devices, including drones, enable real-time data collection on temperature, humidity, soil moisture, and tree growth, supporting continuous forest monitoring. Remote sensing, using satellite imagery and aerial surveys, provides high-resolution data for large-scale assessments, including forest cover change, biomass estimation, and early detection of illegal logging. Integrated with AI, these tools improve predictive modeling, data analysis, and decision-making, leading to more effective forest management. The study also notes challenges such as data security concerns, bandwidth limits, interoperability issues, and high costs. Despite these barriers, IoT, remote sensing, and AI offer transformative potential to improve forest resilience, carbon sequestration, and biodiversity conservation. These technologies are essential for preserving forest ecosystems and mitigating climate change through real-time monitoring, optimized resource allocation, and data-driven decision-making[35].

3.3 Change Detection of Deforestation in the Brazilian Amazon Using Landsat Data and Convolutional Neural Networks

Mapping deforestation is essential for satellite imagery and deep learning applications. for managing tropical rainforests and understanding their implications for climate change through greenhouse gas emissions. Methods: This study evaluated the use of deep learning (DL) algorithms, particularly convolutional neural networks (CNNs), to improve deforestation mapping from satellite imagery.

Deforestation was mapped between image pairs acquired approximately one year apart, covering 2017–2018 and 2018–2019. Three CNN architectures from the literature-SharpMask, U-Net, and ResUnet-were used to classify change between years and were compared with two classic machine learning (ML) algorithms, random forest (RF) and multilayer perceptron (MLP), as reference methods. Results: Following validation, the DL models outperformed the ML models on most metrics, including the Kappa index, F1 score, and mean intersection over union (mIoU). ResUnet achieved the best overall performance, obtaining 0.94 on all three measures in both time sequences. In addition, the DL models produced more clearly defined deforestation patches and did not require post-processing to remove noise, unlike the ML models. Conclusion: These results indicate that DL approaches are more effective than traditional ML methods for deforestation mapping from satellite imagery[36].

4. DATA & METHOD

4.1 Data

The initial data source is multi-temporal satellite imagery from the Copernicus and USGS websites, covering the same season across six different years.

Several types of geospatial data were used in this study: Sentinel-2 satellite imagery for multi-temporal analysis and vector data. (Table Error! No text of specified style in document.-2, Table Error! No text of specified style in document.-3) showing the imagery data obtained from the Copernicus and USGS websites. All data are in the metric unit system's Universal Transverse Mercator (UTM) zone 36N projection [37].

Table Error! No text of specified style in document.-2
Raster Data Used in the Study

Name	Date
S2A_MSIL2A_2021_03_28 R078_T36PVC	28-03-2021

S2A_MSIL2A_2022_03_28 R078_T36PVC	28-03-2022
S2A_MSIL2A_2023_03_28 R078_T36PVC	28-03-2023
S2A_MSIL2A_2024_03_28 R078_T36PVC	27-03-2024
S2A_MSIL2A_2025_03_29 R078_T36PVC	29-03-2025
S2A_MSIL2A_2026_03_27 R078_T36PVC	27-03-2026

Table Error! No text of specified style in document.-3
Vector Data of Study Area

Name of layers	Type Of Data
Target Area Boundary	Vector Data
Study Area (Boundary of AL-Sunt Forest)	Vector Data

4.2 Study Area

The study was conducted in Khartoum City, within the Khartoum Locality on the eastern bank of the White Nile, covering approximately 22.623 square kilometers. The latitude range is [15° 37' 7.135" N to 15° 34' 14.191" N], and the longitude range is [32° 29' 10.472"E to 32° 31' 33.584"E]. The coordinates of the study area use the Projected Coordinate System: WGS_1984_UTM_Zone_36N.

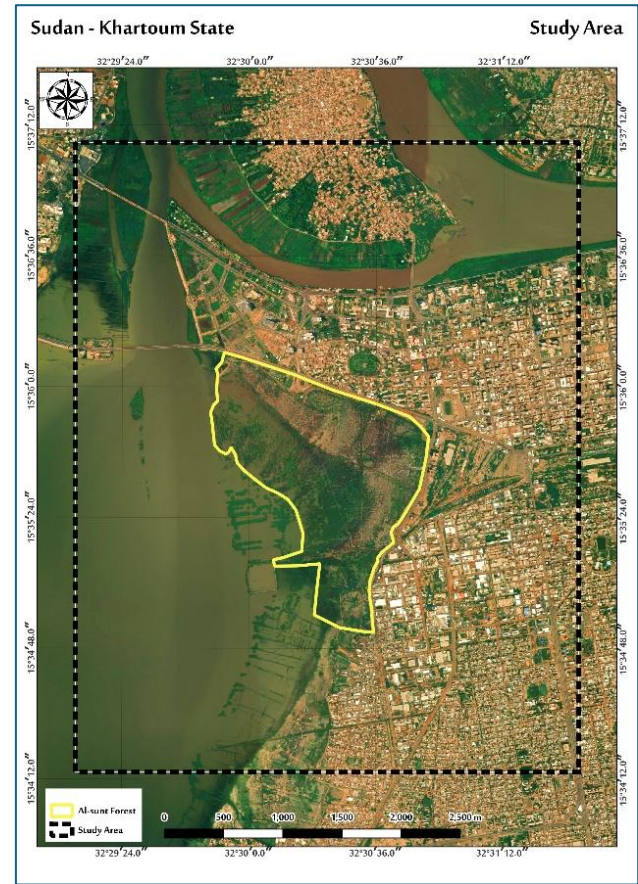


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Study Area

4.3 Methods

The study employs analytical and comparative methods to examine imagery of the study area and assess deforestation in Al-Sunt Forest between 2021 and 2026, attributed to the war and tree cutting during the conflict in Khartoum. It uses machine learning and artificial intelligence, along with a random forest classifier and Sentinel-2 bands, to calculate NDVI and SAVI and compare these indices across years.

5. RESULTS AND DISCUSSION

Insufficient forest management practices significantly contribute to the escalating rate of forest degradation. An analysis using the Random Forest model to classify and monitor deforestation has identified both forest degradation and disappearance.



Figure Error! No text of specified style in document.-11
Forest - 2022



Figure Error! No text of specified style in document.-12
Forest – 2023



Figure Error! No text of specified style in document.-13
Forest – 2023



Figure Error! No text of specified style in document.-16
Forest – 2026



Figure Error! No text of specified style in document.-14
Forest – 2024



Figure Error! No text of specified style in document.-15
Forest – 2025

5.1 Forest Area During Years:

Year	Forest Area HA	Area Change HA
2021	0.000000	0.000000
2022	0.209955	0.209955
2023	1.079767	0.869812
2024	1.519672	0.439905
2025	0.679853	-0.839819
2026	0.000000	-0.679853

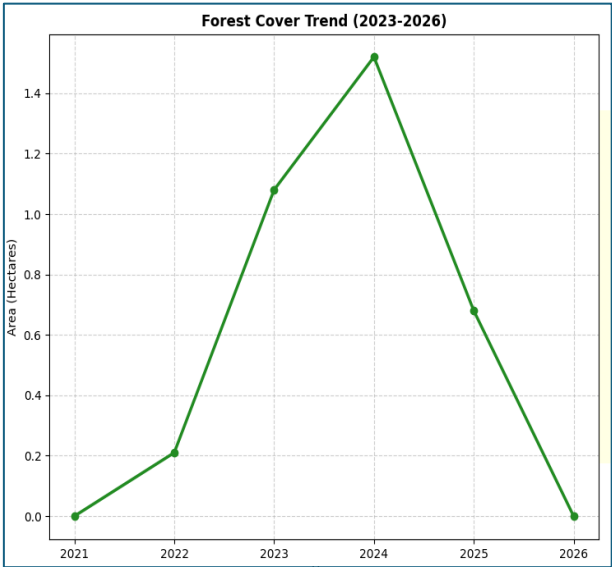


Figure Error! No text of specified style in document.-17
Forest Coverages During Target years

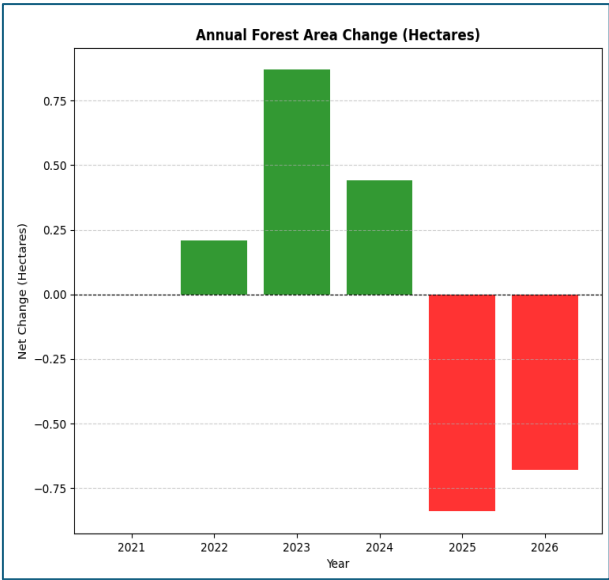


Figure Error! No text of specified style in document.-18
Annual Changes in the Forest

5.2 NDVI Results:

5.2.1 Processing NDVI for the year 2021 within the forest boundary.

Year 2021 NDVI Statistics	
Mean NDVI	0.1346
Min NDVI	-0.0210
Max NDVI	0.4151

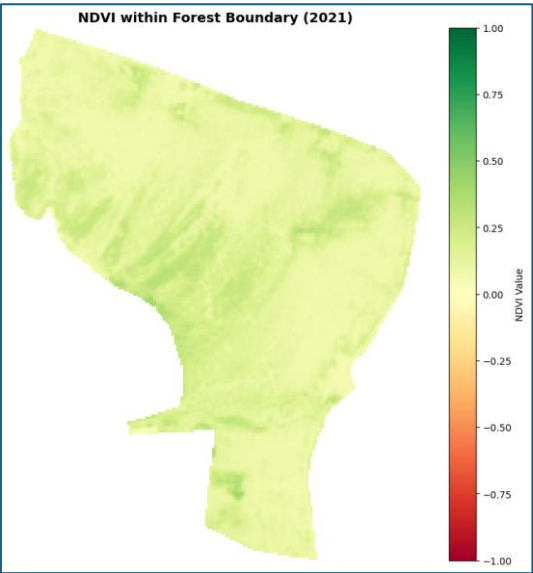


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NDVI for year 2021

5.2.2 Processing NDVI for year 2022 within the forest boundary

Year 2022 NDVI Statistics	
Mean NDVI	0.1481
Min NDVI	-0.1162
Max NDVI	0.5480

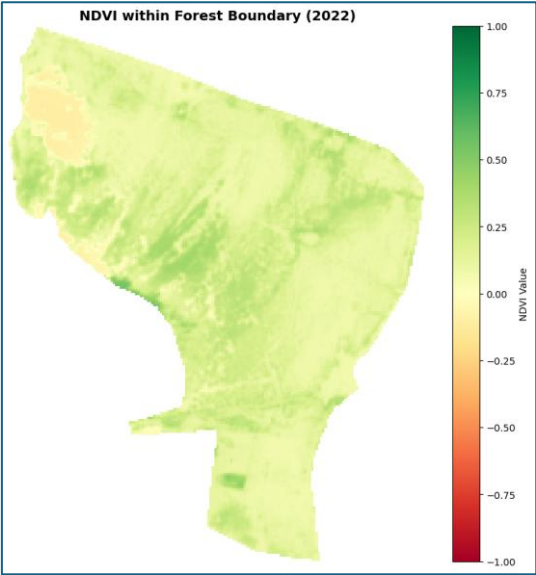


Figure Error! No text of specified style in document.-20
NDVI for year 2022

5.2.3 Processing NDVI for year 2023 within the forest boundary

Year 2023 NDVI Statistics	
Mean NDVI	0.1223
Min NDVI	-0.1925
Max NDVI	0.5962

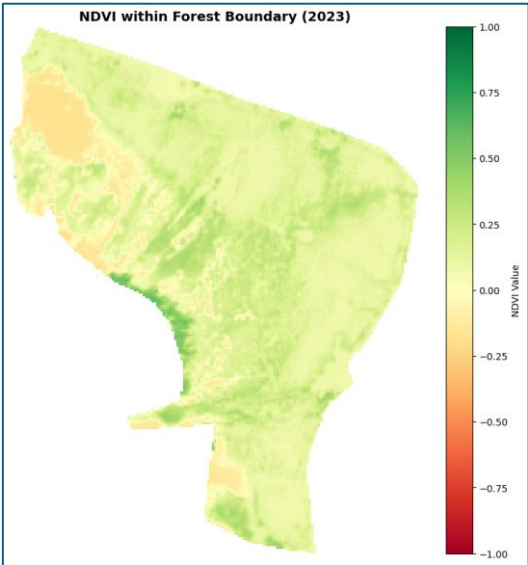


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NDVI for year 2023

5.2.4 Processing NDVI for year 2024 within the forest boundary

Year 2024 NDVI Statistics	
Mean NDVI	0.1861
Min NDVI	-0.1233
Max NDVI	0.5864

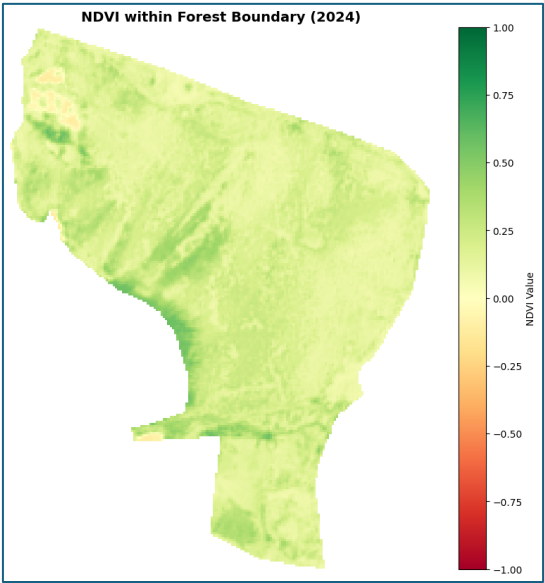


Figure Error! No text of specified style in document.-22NDVI for year 2024

5.2.5 Processing NDVI for year 2025 within the forest boundary

Year 2025 NDVI Statistics	
Mean NDVI	0.1850
Min NDVI	-0.1494
Max NDVI	0.5623

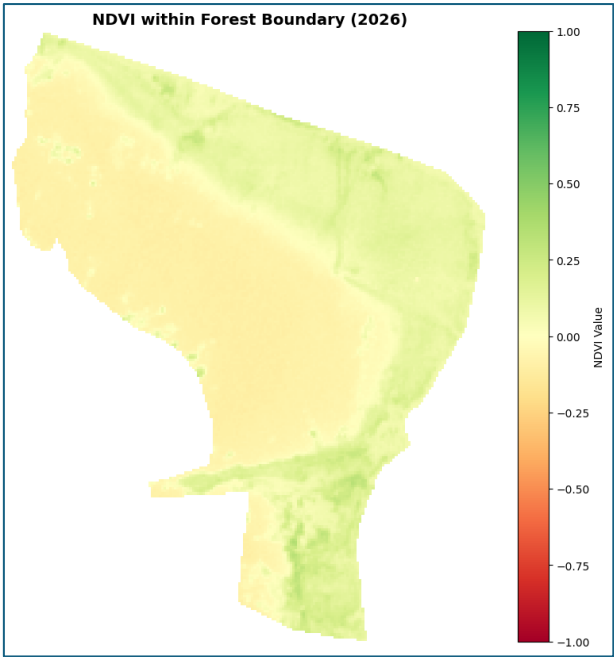
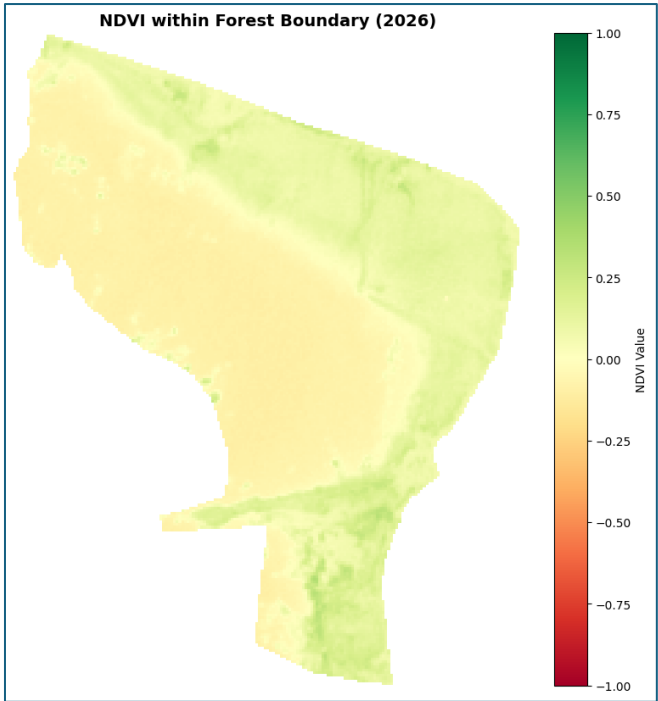


Figure Error! No text of specified style in document.-23
NDVI for year 2025

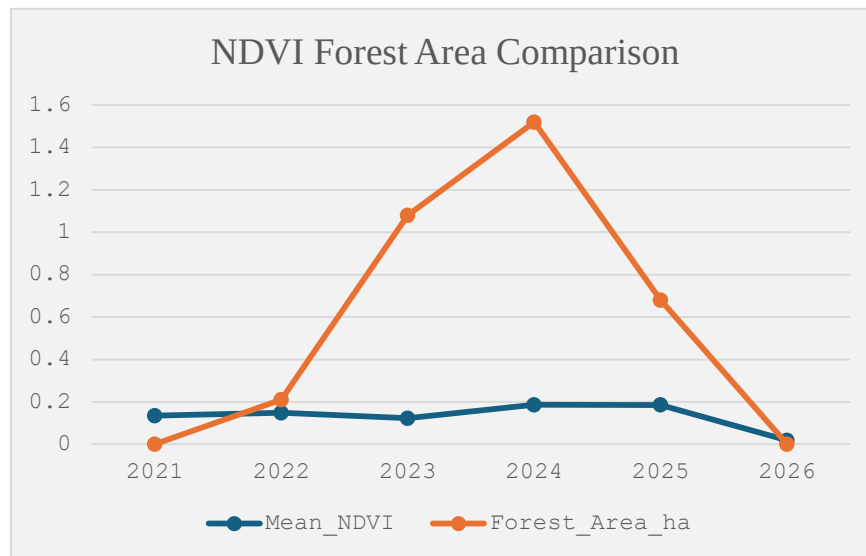
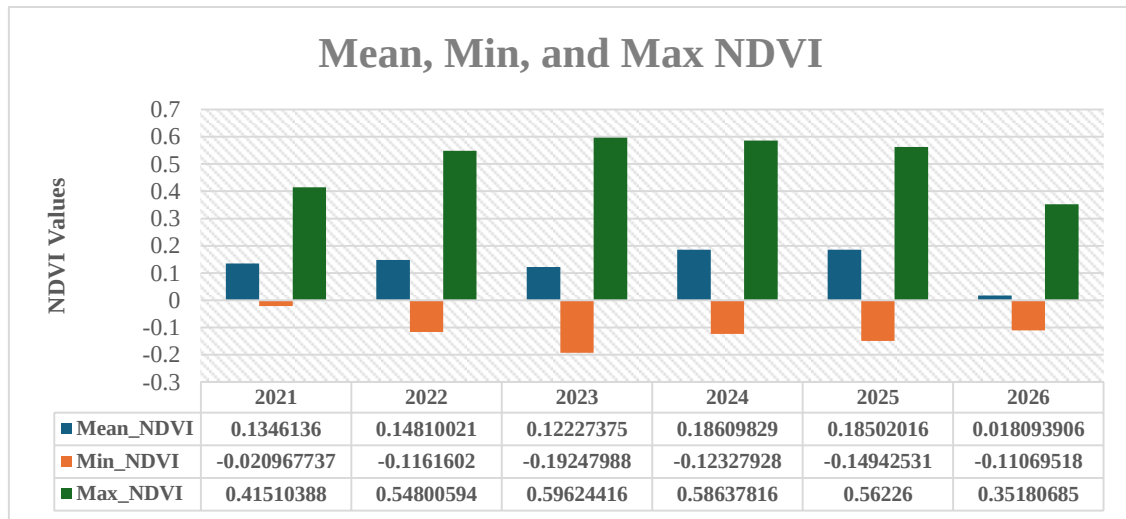
5.2.6 Processing NDVI for year 2026 within the forest boundary



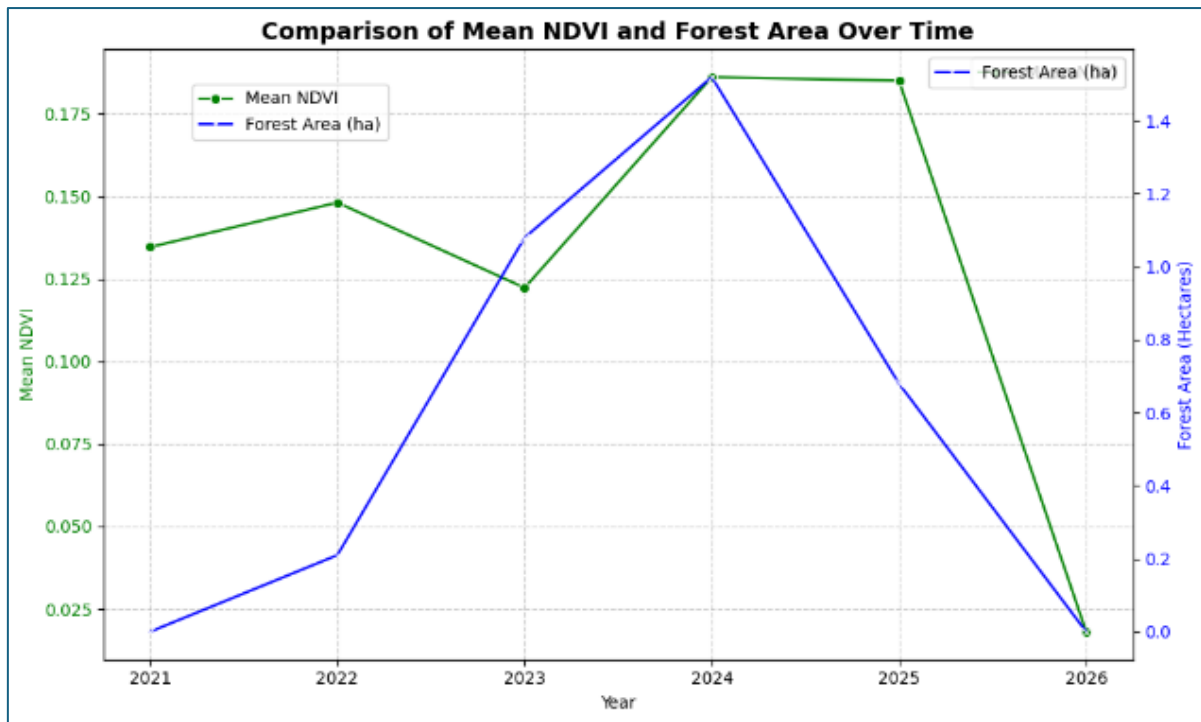
Year 2026 NDVI Statistics	
Mean NDVI	0.0181
Min NDVI	-0.1107
Max NDVI	0.3518

5.2.7 Mean, Min, and Max NDVI

Year	Mean_NDVI	Min_NDVI	Max_NDVI
2021	0.1346136	-0.020967737	0.41510388
2022	0.14810021	-0.1161602	0.54800594
2023	0.12227375	-0.19247988	0.59624416
2024	0.18609829	-0.12327928	0.58637816
2025	0.18502016	-0.14942531	0.56226
2026	0.018093906	-0.11069518	0.35180685



5.2.8 Comparison of Mean NDVI Cross Years



5.2.9 Spectral Indices NDVI & SAVI Cross Study Years

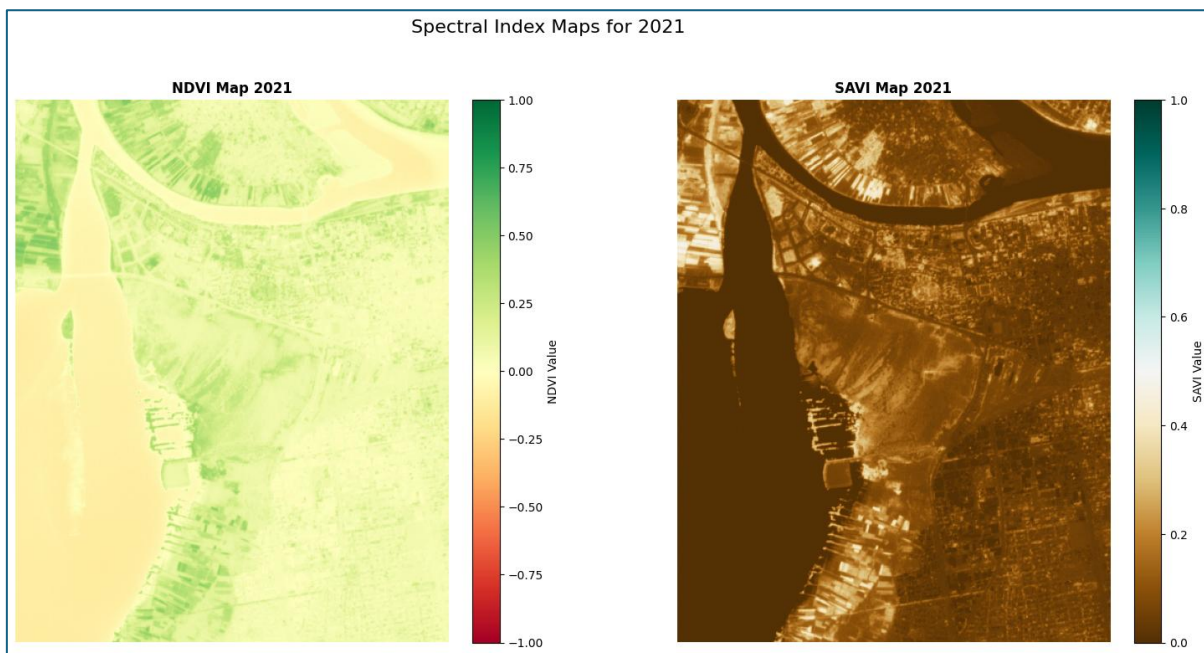


Figure Error! No text of specified style in document.-24 NDVI and SAVI 2021

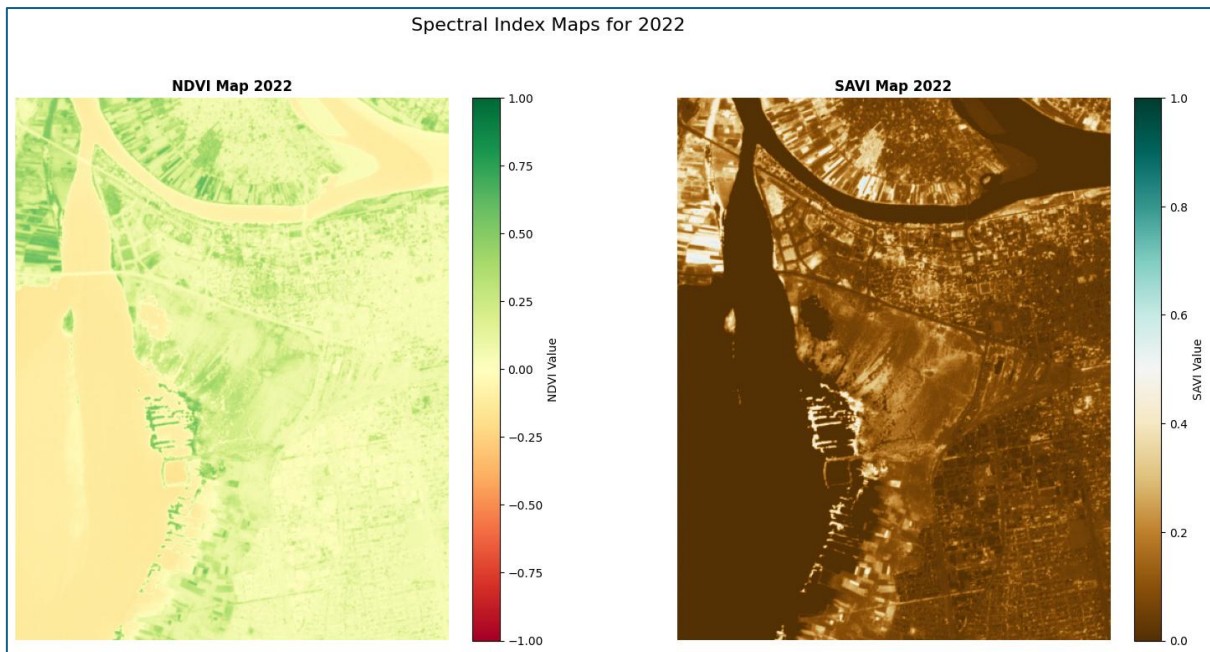


Figure Error! No text of specified style in document.-25 NDVI and SAVI 2022

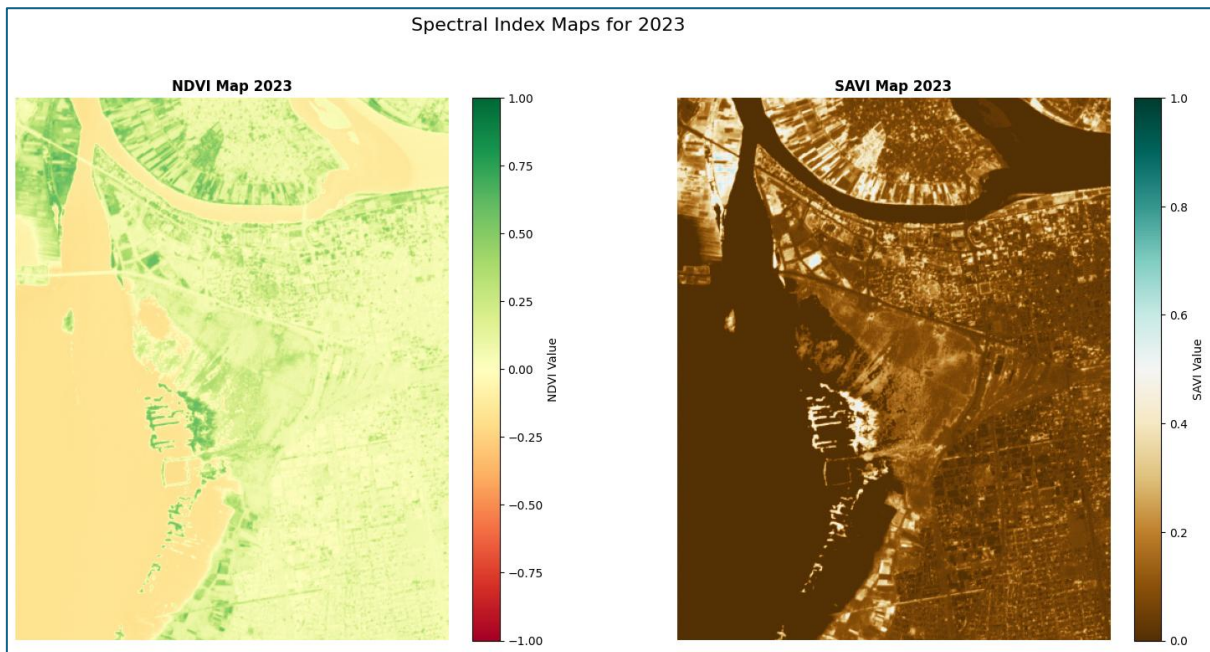


Figure Error! No text of specified style in document.-26 NDVI and SAVI 2023

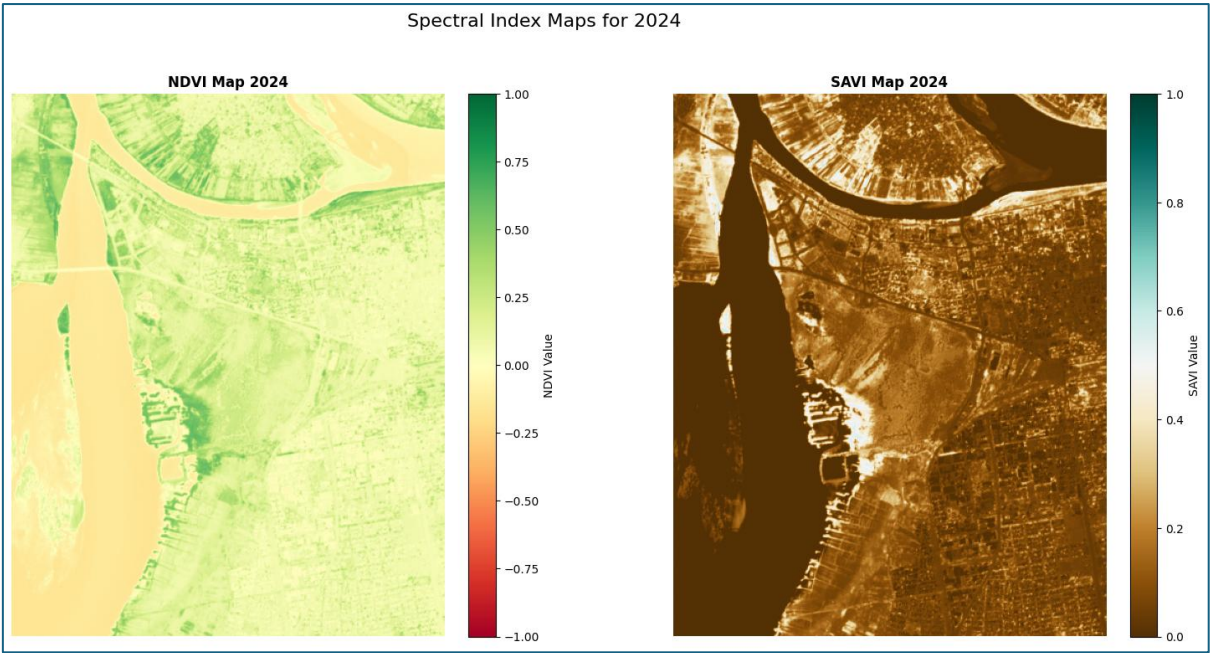


Figure Error! No text of specified style in document.-27 NDVI and SAVI 2024

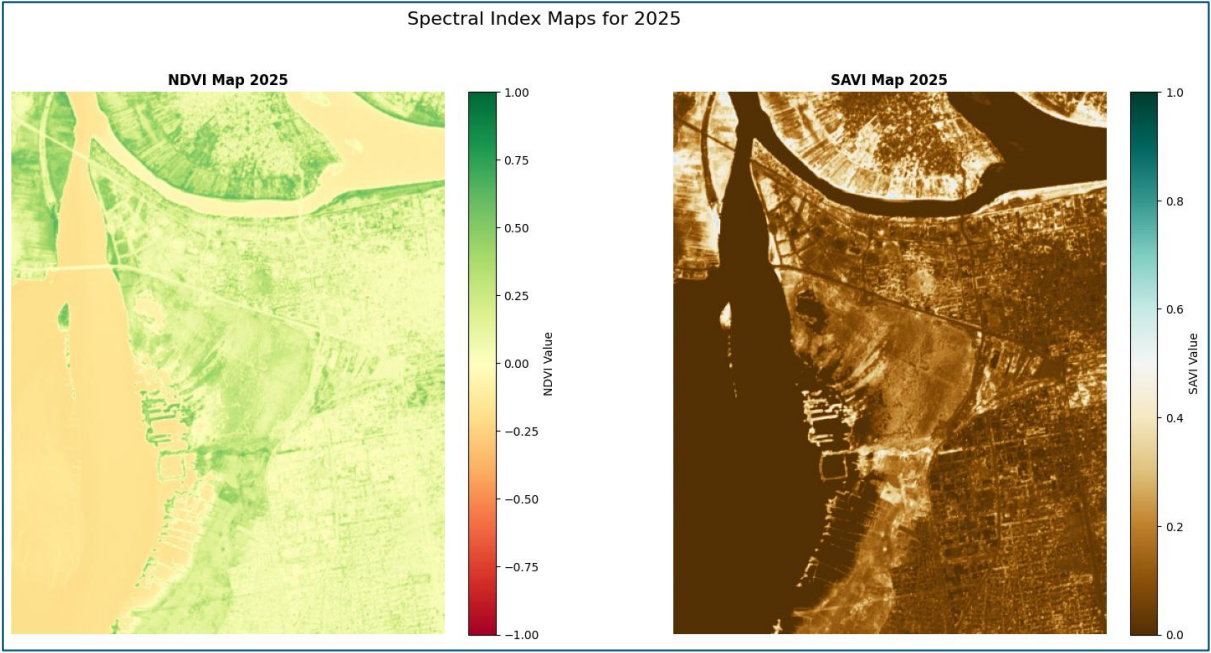


Figure Error! No text of specified style in document.-28 NDVI and SAVI 2025

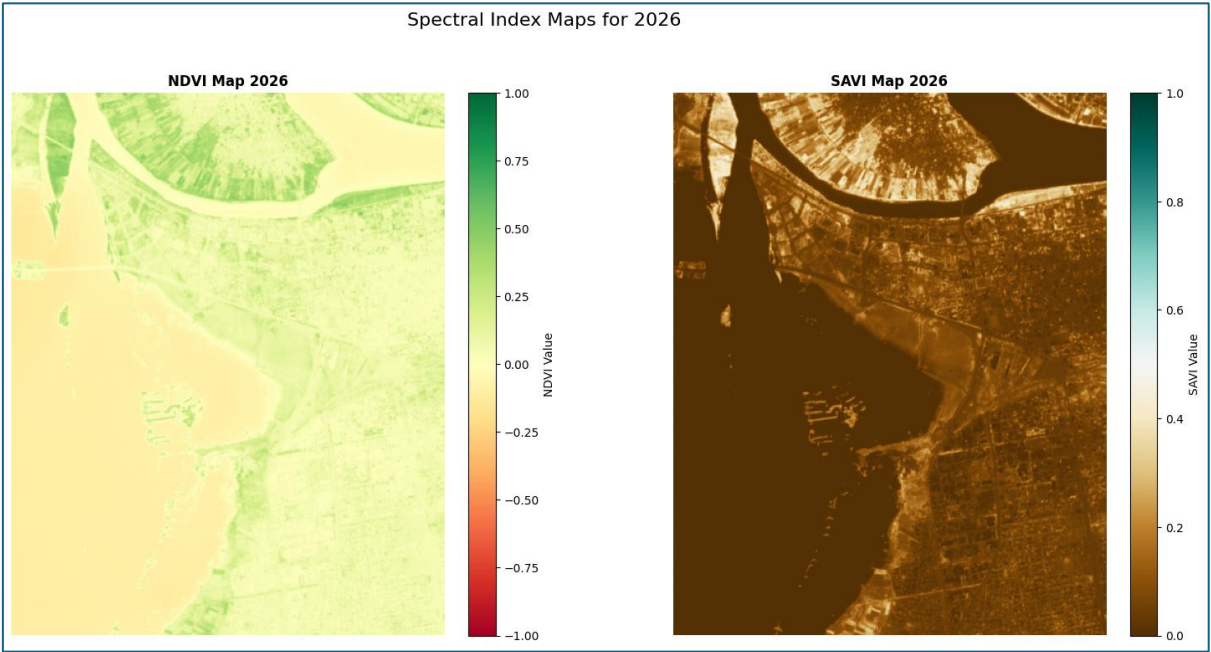


Figure Error! No text of specified style in document.-29 NDVI and SAVI 2026

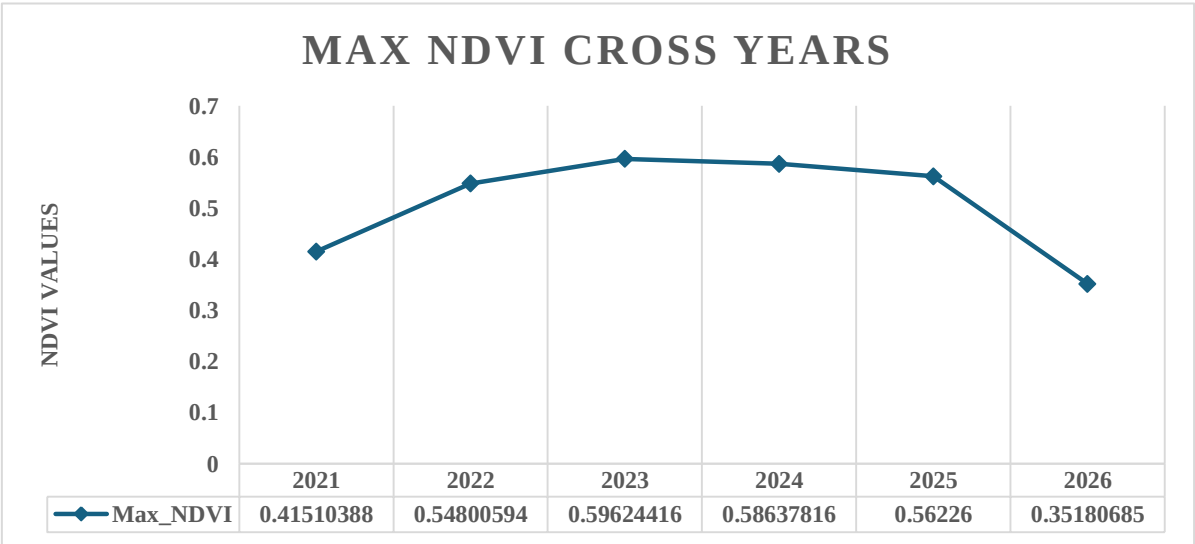


Figure Error! No text of specified style in document.-30 The Max NDVI Cross Years

Conclusion

Assessing deforestation and canopy loss with both the Normalized Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI) provides a more robust spatial analysis than using a single index.

Spatiotemporal monitoring of the Acacia forest (AL-Sunt) in Khartoum (2021–2026) used Earth observation data, GIS, and machine learning. Sentinel-2 bands (B2, B3, B4, B8) were preprocessed by cloud masking, spatial subsetting to the study area, and year-specific compositing before deriving NDVI and SAVI.

NDVI can misread bright bare soil as vegetation change or sparse regrowth. SAVI reduces the effects of soil moisture and type, enabling consistent multitemporal monitoring across seasons and years. Deforestation begins with narrow access roads, small clearings, and fragmented forest edges. Because 10 m Sentinel-2 pixels often mix canopy and exposed earth, SAVI stabilizes mixed-pixel values and helps delineate roads and small disturbance patches.

A Random Forest model was calibrated using 2023 baseline training data, along with NDVI thresholding for binary land-cover classification (forest vs. non-forest). Results showed severe canopy loss and spatial fragmentation throughout the study period, driven primarily by illegal deforestation.

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