

Faculté des bioingénieurs

Leveraging Remote Sensing and Machine Learning to Detect Cocoa-Driven Deforestation in Landscape-Specific Contexts

**Study area: Western and Western North
Regions, Ghana**

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List of Abbreviations

ANN	Artificial Neural Network
CFI	Cocoa and Forest Initiative
CNN	Convolutional Neural Networks
EPA	Environment Protection Agency
ESA	European Space Agency
EUDR	European Union Deforestation Regulation
FAO	Food and Agriculture Organization
GCFRP	Ghana Cocoa Forest REDD+ Programme
GEE	Google Earth Engine
GFW	Global Forest Watch
GDP	Gross Domestic Product
GLM	Generalized Linear Model
HIA	Hotspot Intervention Area
HFZ	High Forest Zone
LIDAR	Light Detection and Ranging
MSI	Multi-Spectral Instrument
NICFI	Norway's International Climate & Forests Initiative
RADD	Radar for Detecting Deforestation
RADAR	Radio Detection and Ranging
RF	Random Forest
RMSC	Resource Management Support Centre
RS	Remote Sensing
S1	Sentinel-1
S2	Sentinel-2
SZ	Savanna Zone
SVM	Support Vector Machines
TMF	Tropical Moist Forest
UAV	Unmanned Aerial Vehicles
UDM	Usable Data Masks
WRI	World Resource Institute

1. Introduction

Deforestation, the alarming loss of forests, has become a global issue, with millions of hectares of forest lost each year, which has implications for ecosystems, biodiversity, and climate change (Hansen, 2013). In this era of environmental issues, several countries struggle to balance development for economic growth and the conservation of natural resources (Vancutsem et al., 2021). Ghana, a country in West Africa, is no exception, contributing to high rates of global deforestation (Kyere-Boateng & Marek, 2021). According to the GFW Ghana lost 118,000 hectares of natural forest in 2022, equivalent to 78 million tons of CO₂ emissions. There was a 60% increase in forest loss from 2018, making Ghana the country with the highest relative increase in deforestation among other tropical countries.

The major drivers of deforestation in Ghana include agriculture expansion, with over a quarter of cocoa expansion driven by the high demand for chocolate. Cocoa serves as a primary raw material for chocolate production, making its cultivation a central factor in the environmental impact of the chocolate industry in Ghana. Mining is also driven by the global demand for minerals such as gold and diamond, logging and timber extraction for charcoal and fuelwood, tree crop plantation expansion, and infrastructure development such as roads and highways (Ashiagbor et al., 2022; Panwar et al., 2022). Rapid urbanization, caused by population growth, is another significant contributor to deforestation (Koranteng & Zawila-niedzwiecki, 2015). These drivers are intrinsically tied to particular landscapes, each presenting unique challenges (Wolff et al., 2020). In the Western Region of Ghana, agricultural expansion for cocoa production is the main driver of deforestation as dense forests and croplands give way to cocoa plantations (Ashiagbor et al., 2022). In parts of the Ashanti Region of Ghana, urbanization and food crop production contribute to deforestation (Nyamekye et al., 2020; Wolff et al., 2020). Meanwhile, in parts of the Eastern Region, mining activities and tree crop plantation expansion, such as rubber, citrus, cocoa, and oil palm, play a prominent role.

Considering the complex interplay of the various drivers of deforestation in different parts of Ghana, there is a need to adopt a landscape-specific approach to monitor and address issues of deforestation effectively (Wolff et al., 2020). An effective approach for monitoring deforestation in landscape-specific contexts involves fusing remote sensing technologies with cutting-edge machine learning techniques (Mitchell et al., 2017). Studies have shown that remote-sensing technologies can detect changes in forest cover over an extended timeframe, while machine-learning techniques are used to analyze large volumes of remotely sensed data

to derive valuable insights from it (Daiyoub et al., 2023; Tariq et al., 2023). Remote sensing technologies used for forest monitoring encompass satellite and aerial imagery, Light Detection and Ranging (LiDAR), and Unmanned Aerial Vehicles (UAVs). In contrast, machine learning techniques include Random Forests, Support Vector machines (SVMs), and Deep Learning techniques such as Convolutional Neural Networks (CNNs) (Brovelli et al., 2020; Kumar et al., 2010). Among these technologies and techniques, each of them possesses a unique set of strengths and weaknesses (Gao et al., 2020).

Although previous studies have investigated various machine learning algorithms and their effectiveness for forest monitoring in Ghana, there is a pressing need for a comparative analysis that evaluates the performance of these approaches in landscape-specific contexts (Ashiagbor et al., 2022; Dacosta et al., 2019; Nyamekye et al., 2020). Thus, this research seeks to bridge this crucial gap by thoroughly exploring remote sensing and machine learning algorithms to detect and analyze deforestation dynamics in Ghana's cocoa-driven deforestation context. Overall, the results will shed light on the performance and the most suitable approach for detecting cocoa-driven deforestation in specific Ghana landscapes. This will be pivotal in enabling precise and timely deforestation monitoring for strategies and policies such as the European Union Deforestation Regulation (EUDR).

2. Literature Review

This chapter provides an overview of the current knowledge of mapping deforestation in different landscapes. Section 2.1 highlights the regional context of Ghana's forest resources, deforestation, drivers, and landscape-specific deforestation dynamics. Section 2.2 talks about remote sensing for monitoring deforestation. Sections 2.3 and 2.4 explore the potential of Sentinel 2 and planet imagery for forest monitoring. Section 2.5 highlights in-depth machine-learning techniques used for forest monitoring.

2.1 Regional Context

2.1.1 Forest Resources in Ghana

Ghana has rich natural resources and various forest ecosystems that contribute to its ecological, economic, and cultural heritage. Forested lands cover about 7.9 million hectares, constituting 35% of the total land area of 22.8 million hectares (FAO, 2020). About 7.6 million hectares are considered primary forests; the remaining are considered planted forests. These ecosystems fall under two main ecological zones, each with distinct characteristics and forest types. The High Forest Zone (HFZ) is situated in the country's southwestern part and consists of 34% of forests. The Savanna Zone (SZ) is in the northern part and comprises 66% of forests (MLNR, 2012). Forests are classified as on-reserve (mainly for production or protection) and off-reserve (open for agriculture).

There are 282 protected zones (Figure 1) covering 715000 hectares, 216 of which are located in the HFZ (Oduro et al.,2012). There are two types of forest reserves: Production reserves exploited for timber, which cover about 80%, and Protection reserves for conservation purposes, which cover 20%. National parks and wildlife reserves constitute other types of forest reserves that are categorized as Protected areas. Ghana has various forest types, including tropical rainforests, moist semideciduous forests, mangroves, and savanna woodlands. They provide timber and non-timber forest products (NTFPs), ecosystem services for livelihoods, habitats for fauna and flora, and climate regulation. However, over time, forests in Ghana have faced high rates of deforestation and degradation due to several factors.

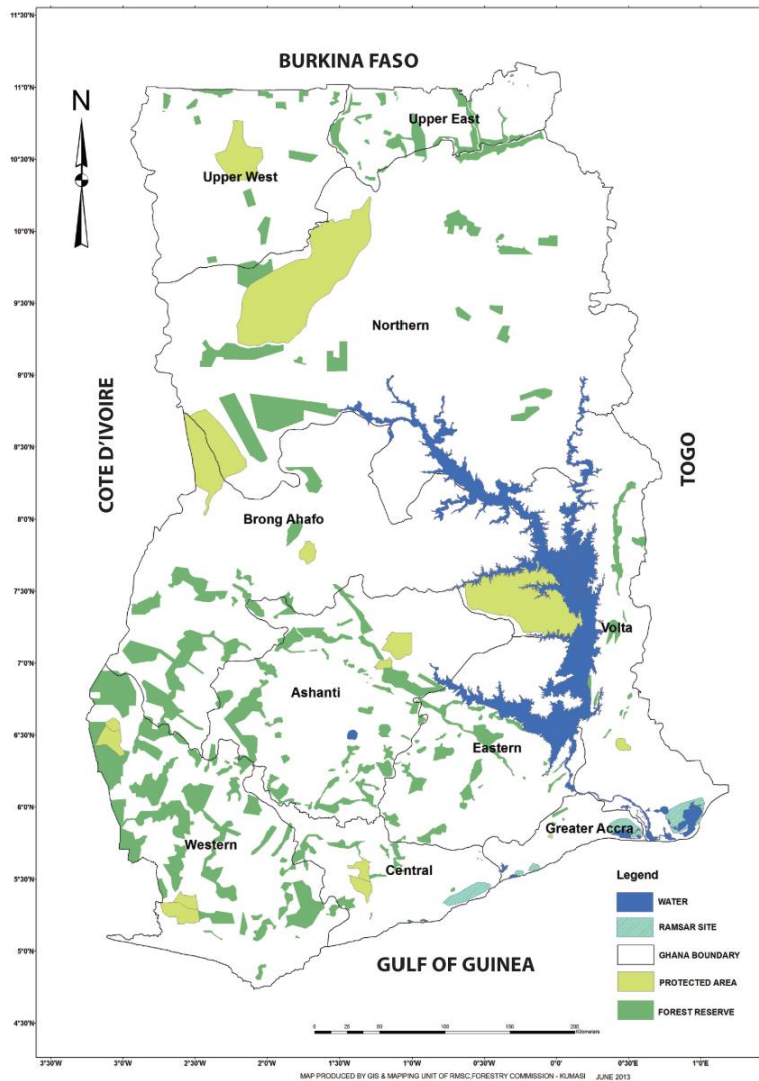


Figure 1. Forest Reserves in Ghana, Source: MLNR, 2012

2.1.2 Deforestation in Ghana: Trends and Implications

Deforestation in Ghana has become a major concern in recent decades, with significant implications for biodiversity, soil degradation, water pollution, and climate change (Kyere-Boateng & Marek, 2021). It has wide-reaching consequences beyond its environmental impact. Notably, forest resources play a vital role in the livelihoods of Ghana's forest-dependent communities, contributing as much as 38% to their income and a substantial 6% to the country's annual Gross Domestic Product (GDP) (Appiah et al., 2009). Thus, a decline in forests largely affects the livelihood of these individuals who depend directly on them and the country's economy (Acheampong et al., 2019).

Ghana's forests had average annual deforestation rates of 0.7%, 0.5%, 0.4%, and 0.6% respectively for the periods 1990–2000, 2000–20005, 2005–2010, and 2010–2015, respectively (Acheampong et al., 2019). Overall, Ghana has lost over 33.7% of its actual extent, equivalent to 25000 km² from 1990 to 2010 (Amoah et al., 2023). The main drivers of deforestation include agricultural expansion (mainly cocoa), unsustainable farming practices (usually because of insecure land tenure), illegal logging, urban expansion, mining activities, uncontrolled bushfires, and the expansion of tree crop plantations such as citrus, oil palm, and rubber (Ashiagbor et al., 2022; Damnyag et al., 2012; Nyamekye et al., 2020). Other factors contributing to deforestation include land tenure arrangements and traditional land use practices such as shifting cultivation and slash-and-burn agriculture (Damnyag et al., 2012).

Ghana's deforestation releases significant amounts of carbon dioxide into the atmosphere, contributing to climate change (Wolff et al., 2020). The rate of deforestation in Ghana was estimated at 2.19% per annum, the sixth-highest deforestation rate globally (Dacosta et al., 2019). This alarming trend has far-reaching implications for global climate change, underscoring the need for effective strategies to combat deforestation (Amoah et al., 2023). Ghana's efforts to combat deforestation are crucial for both the nation's environmental well-being and its commitment to acting on climate change worldwide (Ashiagbor et al., 2022).

2.1.3 Multi-Driver Deforestation in Ghana

Multi-driver deforestation is a complex process of forest loss caused by several interconnected drivers simultaneously in a landscape. Deforestation in Ghana is caused by several factors, which include mining activities for gold, bauxite, diamond, and manganese, lumber extraction, population growth, urbanization, the demand for housing and industrial development, encroached forest lands, unsustainable agricultural expansion, illegal logging/chain saw operations (Afele et al., 2022). Other drivers include fluctuations in staple crop prices, causing farmers to intensify agriculture or expand agricultural lands in forests to make more returns and the lack of economic opportunities encouraging individuals to engage in illegal mining/logging activities.

Although there are policies and government agencies, such as the Environment Protection Agency (EPA), Minerals Commission, and Forestry Commission, to regulate the usage of these limited resources, individuals still engage in activities leading to uncontrolled forest loss (Damnyag et al., 2012). These interconnected drivers of forest loss underscore the need to develop data-driven strategies to address deforestation to better inform policy and decision-

making. The country's agriculture industry primarily focuses on subsistence and commercial farming, thus necessitating the conversion of forests into farmlands to cultivate cash crops such as oil palm, rubber, and food crops (Ajagun et al., 2021).

Additionally, the global demand for minerals such as gold, bauxite, and diamond largely influences the establishment of mining concessions, contributing to high rates of deforestation in Ghana (Amoah et al., 2023). This mining industry serves as a source of livelihood for impoverished communities where individuals are involved in illegal small-scale mining, known as "galamsey", and large-scale exploration companies at the expense of forest ecosystems and biodiversity (Afele et al., 2022). The Government of Ghana has implemented regulatory measures to ensure that mining activities are done sustainably so that no harm is caused (Obodai et al., 2019). These measures include reclaiming lands, reforestation, and afforestation projects after mining (Bansah et al., 2016).

2.1.4 Cocoa-Driven Deforestation in Ghana

Ghana's economy primarily centers on cocoa production, an agricultural sector that boosts the country's GDP and provides livelihood to over 800000 rural Ghanaian families (Nasser et al., 2020). It is the major cash crop that contributes 25% of foreign exchange earnings (Kyere-Boateng & Marek, 2021). However, this economic boon comes at an environmental cost, which poses a threat to the country as it thrives well in forest landscapes (Damnyag et al., 2013). Although cocoa plays a pivotal role as the leading agricultural export crop, the negative environmental effects, such as deforestation, are becoming increasingly apparent (Ajagun et al., 2021; Kyere-Boateng & Marek, 2021).

Global cocoa demand drives cocoa expansion, mainly for chocolate production and economic incentives (Gockowski & Sonwa, 2011). The need to balance economic gains from cocoa and ecological loss from forests highlights the urgency of addressing cocoa-driven deforestation in Ghana (Ashiagbor et al., 2022). Ghana is the second largest global cocoa producer, following the Ivory Coast, which is the leading cocoa producer (Brobbe et al., 2020). Cocoa production is responsible for a 54.6% loss of closed forests and 77.8% of open forests (Kyere-Boateng & Marek, 2021). Currently, cocoa farming has shifted from high shade to low/no shade monoculture, which necessitates large land areas, leading to widespread forest clearance (Ajagun et al., 2021). Farmers tend to cut the shade trees from their cocoa farms so that their cocoa can attract a good amount of sunlight for increased yield.

To increase cocoa yield to meet the rising global demand, farmers tend to convert forests to accommodate the expansion (Ashiagbor et al., 2022). This practice has resulted in the loss of approximately 1.45 million hectares of forest land. Several initiatives, such as reforestation programs, land tenure reforms, technological advancements, and international cocoa sustainability partnerships involving governments, NGOs, and the private sector, have been implemented to manage cocoa-driven deforestation (Nasser et al., 2020). The Cocoa and Forests Initiative (CFI) is an active commitment implemented in Ghana through collaborative efforts between chocolate and cocoa companies, the government, and other stakeholders to end deforestation and restore forest areas through no further conversion of any forest land for cocoa production.

2.1.5 Landscape-Specific Dynamics of Deforestation in Ghana

A landscape is a heterogeneous area consisting of different ecosystems, such as vegetation and water bodies, interacting in a geographical unit (Darvishi et al., 2024). Most landscapes in Ghana have different ecosystems coexisting in a given area, yet often characterized by a predominant land cover type. Over time, forest landscapes have undergone fragmentation due to the high rates of deforestation, which have significantly affected the ecosystem. Deforestation dynamics are complicated, with different drivers interacting to make landscapes unique (Wolff et al., 2020). The various drivers encompassing mining, logging, agriculture expansion, and urbanization occur within specific geographical contexts influenced by environmental, social, and economic factors in the landscape (Acheampong et al., 2019).

Mining activities occur in landscapes with mineral deposits; the popular mining area in Ghana is the Ashanti Region, which is known for gold and has high mining rates to eliminate poverty (Forkuor et al., 2020). The Eastern Region also has deposits of minerals such as gold and bauxite, and high rates of illegal mining lead to forest loss. Agriculture expansion typically occurs in the Western Region of Ghana largely due to fertile soils and better climatic conditions. Cocoa is rapidly cultivated in those parts of Ghana as they survive better in such landscapes (Kyere-Boateng & Marek, 2021). Also, in some parts of the Eastern Region of Ghana, some cocoa farms thrive together with other tree crops such as oil palm, rubber, citrus, and food crops, making it a diverse landscape.

2.2 Remote Sensing for Forest Monitoring

In forest monitoring, remote sensing has emerged as a key technology that allows comprehensive monitoring of forests and an effective way to analyze and track changes occurring on a larger scale over time (Lechner et al., 2020). This technology provides insights into the spatial extent of forest cover, forest type, and forests' biophysical and biochemical properties. Researchers and land managers have acquired insights into forest dynamics, such as afforestation, deforestation, land use, and land cover changes (Juniyanti & Situmorang, 2023; Smith et al., 2024). Different remote sensing techniques are used for forest monitoring, and they include satellite imagery (such as Planet, Landsat, and Sentinel), aerial photography, Light Detection and Ranging (LIDAR), and RADAR-based sensors such as Sentinel 1 (Lee et al., 2020).

Each of these techniques has strengths and weaknesses, and their suitability depends on the goal of forest monitoring. Generally, satellite imagery provides wide coverage for monitoring large forest areas and frequent revisits for analysis that are done over time (Bochenek et al., 2018). Additionally, satellite data is often free and offers a variety of spectral bands that are essential in different application areas. Landsat consists of at least seven bands that cover a wide range of the electromagnetic spectrum and have a 30-meter resolution. Sentinel 2 also consists of thirteen bands with a 10-meter resolution. A major limitation of satellite imagery is cloud cover, which obstructs the satellite's view, resulting in inconsistencies and gaps in the data (Banskota et al., 2014). That aside, in some cases, spatial resolution is low and limits the level of details obtained about an area.

Comparatively, aerial photography provides a higher spatial resolution than satellite imagery, essential for detailed mapping and analysis (Szatmári et al., 2016). However, using this technology can be expensive regarding time and cost, especially for larger scale coverage, has less frequency in data acquisition, requires specific expertise to operate, and depends on flight regulations in an area and the weather (Fraser & Congalton, 2018). Radar has all-weather imaging properties unaffected by clouds or weather conditions and operates without solar illumination (Thiel et al., 2006). The revisit time is frequent, and this provides consistency in data. A constraint of radar is its inability to accurately differentiate between vegetation types, which could be attributed to sensor limitations (Nguyen et al., 2021).

2.2.1 Forest Monitoring Systems

2.2.1.1 Global Forest Watch (GFW)

GFW is an open-access interactive online forest monitoring and alert system that provides data, technology, and tools to better manage and protect forest landscapes (Hansen et al., 2013). This was launched by the World Resource Institute (WRI) in 1997 to create transparency and accountability in decision-making on how forests are managed and for whom. Leveraging satellite data, advanced computer algorithms, and cloud computing power, GFW offers an open-access platform that allows the creation of custom maps and analysis of forest trends to make informed decisions for sustainable forest management. This platform enables users to subscribe to alerts, download data at the regional and national level regarding illegal deforestation and fires to report unsustainable activities, protect land and resources, sustainably source commodities, and conduct research at the forefront of conservation.

The platform provides data from Planet, Landsat, Sentinel, and Google satellite imagery with different levels of resolution. GFW also provides a 30m x 30m West Africa Cocoa Plot Heat Map for Côte d'Ivoire and Ghana, representing the various existing cocoa farms. This dataset is obtained from the World Resources Institute and presents the plot polygons in the direct supply chains of 19 cocoa and chocolate companies. It does not show the exact polygons or capture the entire cocoa extent of these countries; it only shows the areas the companies have mapped.

2.2.1.2 Tropical Moist Forest (TMF)

The European Commission's Joint Research Centre developed this dataset to monitor forest change in TMF areas (Vancutsem et al., 2021). The product's temporal resolution ranges from 1990 to 2022, with a spatial resolution of 30m x 30m utilizing Landsat images. The TMF explorer, a web-mapping tool, provides information on undisturbed and degraded TMF. It also provides information on the annual change collection, highlighting the TMF extent and related disturbances (deforestation and degradation) and post-disturbances for each year between 1990 and 2020. There are classes on undisturbed TMF, degraded TMF, deforested land, forest regrowth, permanent and seasonal water, and other land cover types. Additional data is provided on the deforestation and degradation years that changes occurred. The TMF maps have been updated up to 2022 with additional improvements and corrections. The recent update includes integrating the Sentinel 2 data at 10m for 2022 as a transition map. The transition map

shows the sequential dynamics of changes by providing transition stages from the first year of the monitoring period to the end of 2022.

2.2.1.3 RADD Forest Disturbance Alert

Radar for Detecting Deforestation (RADD) alert is a remote sensing-based platform that detects and monitors forest disturbance in near real-time. This platform was developed by the GFW initiative in collaboration with WRI, Wageningen University, Google Earth Engine (GEE), the University of Maryland, the European Space Agency (ESA), and Deltares in 2020. This system leverages Sentinel 1 and advanced algorithms to detect deforestation, wildfires, illegal logging, and land use land cover changes, intending to provide timely information for forest management. Sentinel 1 is a cloud-penetrating radar which provides consistent data every 6 to 12 days. In cloudy tropical areas, radar is an advantage for detecting forest disturbances caused by agriculture and logging at a higher resolution with a mapping unit of 0.1 ha.

RADD alert is openly available via GEE and GFW. It has coverage for the primary humid tropical forest of South America (13 countries), Central America (6 countries), Africa (25 countries), Southeast Asia (5 countries), and the Pacific (1 country). An observation from the Sentinel 1C band triggers a forest disturbance alert. Subsequently, observations are used to iteratively update forest disturbance probability, increase confidence, and confirm or reject the alert. In most cases, alerts are confirmed within a maximum 90-day period if the probability is above 97.5, and at forest disturbance probabilities above 85%, unconfirmed alerts are generated. Confirmed alerts were validated in the Congo Basin, and there was a high level of accuracy for disturbances larger than 0.2 ha.

This dataset defines forest disturbance as the complete or partial removal of tree cover within a 10 m Sentinel-1 pixel. This complete tree cover removal is associated with a stand-replacement disturbance at the Sentinel-1 pixel scale, while partial removal is related to disturbances associated with boundary pixels and selective logging. A limitation of RADD is its inability to separate human-induced disturbances, such as agriculture expansion and mining, from natural forest disturbances, such as landslides. Also, small-scale changes are detected promptly, whereas large-scale changes take longer to reach a high probability of being flagged as alert. In swamp forests, false detections may occur due to the high sensitivity of short-wavelength C-band radar to moisture.

2.2.1.4 Ecometrica Forest Monitoring System

Forest 2020 is a major investment by the UK Space Agency to protect and restore up to 300 million ha of forests by monitoring national forest monitoring systems in six partner countries through better satellite data applications. Ecometrica led this to deliver up-to-date deforestation data for Brazil, Colombia, Mexico, Indonesia, Kenya, and Ghana. This system aims to improve forest change detection, especially in challenging land use systems, improve the mapping of risk and priority areas, and serve as a digital structure to manage and distribute earth observation data for end users.

Under this project, the Resource Management Support Centre (RMSC) of the Forestry Commission, collaborating with scientists from the Kwame Nkrumah University of Science and Technology and the University of Leicester, UK, launched a National Map of Forests and Land Use. This map uses satellite data from the Copernicus Sentinel, field samples, and machine-learning techniques to provide land use and cover data. An advantage of this platform is the existence of forests and cocoa segregated as separate land cover classes, which is important for informing decisions on sustainable agriculture. A national land use land cover map exists for 2019, and a draft has been submitted for 2021. Although this national-level portal exists, the data provided is not up to date, and efforts should be made to make it more current as it is beneficial.

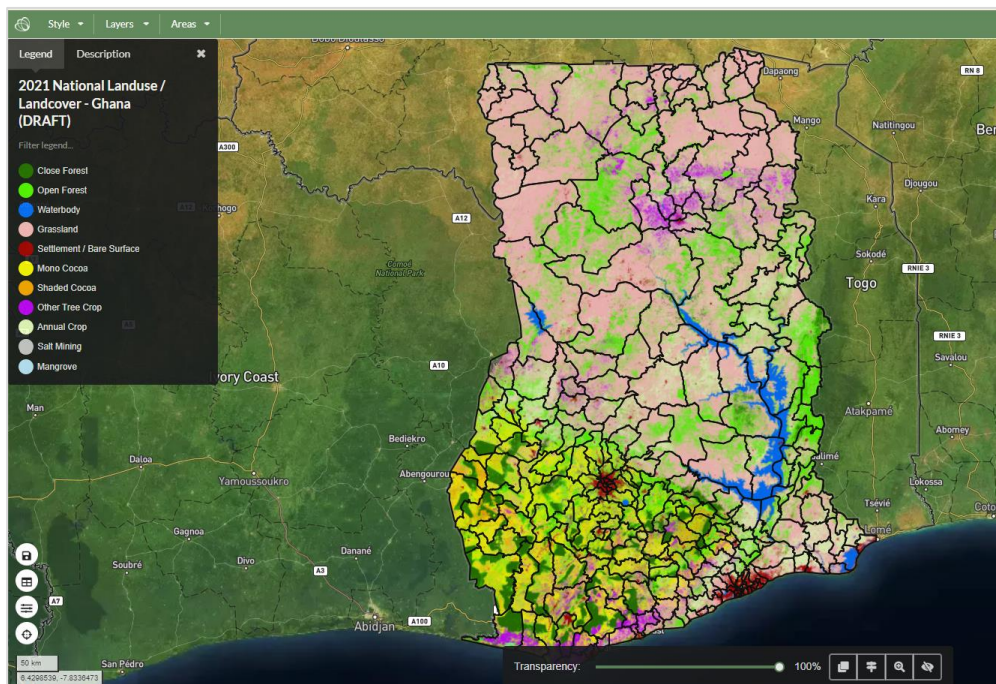


Figure 2. National Landuse / Landcover - Ghana (DRAFT)

2.2.1.5 Cocoa Map for Côte d'Ivoire and Ghana

Côte d'Ivoire and Ghana, the world's major cocoa producers, account for two-thirds of global cocoa production, contributing significantly to the GDP. Although cocoa is the primary perennial commodity that provides income, there was no precise map of the total extent of cocoa production in these countries. Kalischek et al. (2022) identified this research gap and combined cocoa plantation data with satellite data in a deep-learning framework to create high-resolution maps for 2021. The study used Sentinel 2 images of 10m resolution, a vegetation height map with over 100,000 GPS-tracked cocoa farms, and manually labeled over 10,000 polygons representing other classes for both countries. A binary cocoa and probability map was produced, with cocoa classified as all values greater than a 65% threshold and the rest as non-cocoa (Figure 3). The F1 score for cocoa was 87.3%, and non-cocoa was 84.1%. The accuracy of this map produced was 85.9%.

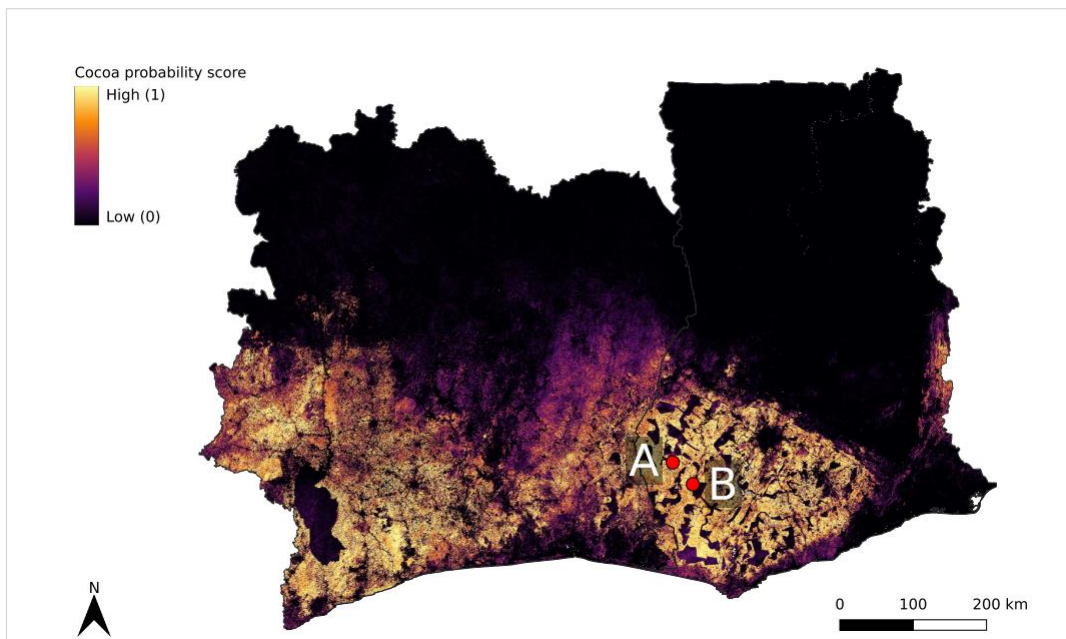


Figure 3. Cocoa map for Côte d'Ivoire and Ghana, Source: Kalischek et al. (2022)

A critical assessment of cocoa classification with limited reference data for Côte d'Ivoire and Ghana exists (Moraiti et al., 2024). Considering the limited access to cocoa data, this study used Sentinel 2 imagery from 2018 to 2021 and the random forest model to produce reliable maps. A total of 93 cocoa polygons were collected from the field for this study, and they were used as a guide to create additional calibration data for the classification. Overall, 11 vegetation indices and 14 textural features were used with the S2 median composite image to create a binary cocoa map. Different input datasets were created using these features to compare which

features gave the best results. Of all the input datasets, the highest F1 score for cocoa was 84.6%, with an overall accuracy of 85.1%. This result was from integrating the four most important features that influenced the model: the S2 composites, the vegetation indices, and textural features. This study detected most cocoa trees and delineated them from forest trees. However, there were some misclassifications, with sparse shade trees and grassland in between, which were also classified as cocoa.

2.3 Sentinel 2 for Forest Monitoring

This mission is based on the constellation of two twin satellites, S2A, launched on 23rd June 2015, and S2B, launched on 7th March 2017, with a third S2C undergoing testing in the same orbit but phased at 180°. S2 carries a multi-spectral imager with 13 bands (Figure 5) in the visible, near-infrared, and shortwave infrared as part of the spectrum (Drusch et al., 2012). The spatial resolution ranges from 10m to 60m, four bands at 10m, six bands at 20m, and 3 bands at 60m. Sentinel 2 has an orbital swath width of 290 km and a revisit time of 5 days. It is used in application areas, including land management, agriculture, disaster control, humanitarian disease operations, risk mapping, security concerns, and forestry.

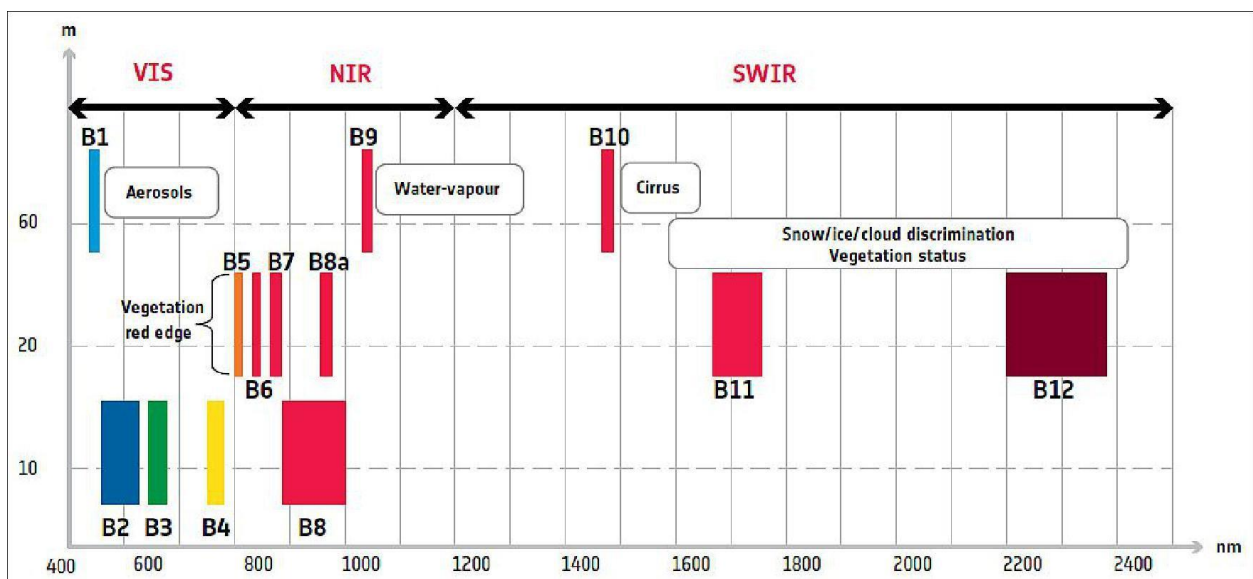


Figure 4. Spectral resolution of Sentinel 2, Source: ESA, 2023

Sentinel 2 has two types of data products: user, which has a systemic generation and is distributed online, or pilot products made available on demand. For user products, there are Level 1B, 2A, and 1C. Level 1B has Top-of-Atmosphere radiances in sensor geometry and is available for expert users. Level 1C has Top-of-Atmosphere radiances in cartographic geometry and Level 2A is made up of atmospherically surface reflectance in cartographic

geometry available for all users. Pilot products are either Level 2H, which consists of Harmonized SENTINEL 2 and Landsat-8/9 surface reflectance in cartographic geometry, or Level 2F, which consists of Fused S2 + Landsat-8/9 surface reflectance in cartographic geometry.

Previous studies have successfully investigated the use of Sentinel 2 for forest monitoring (Grabska et al., 2019; Lastovicka et al., 2020; Phiri et al., 2019; Puletti et al., 2018; Waldeland et al., 2022). For instance, a study on using S2 for rainforest mapping in Gabon resulted in high accuracies; the overall accuracy ranged between 92.6% and 98.5%, indicating the effectiveness of this satellite for forest monitoring (Wasniewski et al., 2020). This accuracy is comparable to a study that used S2 to map successional forest stages in a subtropical forest in Southern Brazil, giving an overall accuracy between 92.6 and 97.4% (Sothe et al., 2017). Although S2 is effective in forest monitoring, clouds largely affect it. Thus, areas with high cloud cover have some limitations concerning its usage. Also, accuracies are relatively lower in situations where a wide range of vegetation types need to be segregated. This was confirmed in a study that used S1 and S2 to segregate cocoa from forests in Ghana. In that study, S2 and vegetation indices alone could not segregate cocoa from forests and required data fusion with S1 (Ashiagbor et al., 2020). The integration of S1 and S2 can complement each other for forest monitoring since S1 is not influenced by cloud cover.

2.4 Planet Imagery for Forest Monitoring

Planet imagery is a satellite imagery captured by a private earth observation company known as Planet Labs. They provide high-resolution images taken daily from a constellation of small satellites. There are three distinct constellations of satellites: Dove (PlanetScope) with a 3-5m resolution, SkySat with a 50cm resolution, and RapidEye with a 5m resolution that retired in 2020. Planet imagery dates back to 2009 and is accessible through Planet's API, web applications, and GIS integrations. It has been used in application areas, which include forestry, agriculture, urban planning, disaster response, climate change, and infrastructure monitoring. Planet's satellite imagery is a paid product, but through initiatives like Norway's International Climate & Forests Initiative (NICFI) partnership, users can access analysis ready mosaics of tropical areas.

Several studies have explored the use of the high resolution planet imagery for forest monitoring (Csillik et al., 2019, 2020; Francini et al., 2020; Masolele et al., 2024; Pascual et al., 2022; Wagner et al., 2023). Pickering et al. (2021) explored PlanetScope imagery for

cropland and tree-cover loss area estimation in Pakistan and Peru. This study was compared with Landsat imagery, and the conclusion was that planet data could capture small cropland and tree-cover loss events. Additionally, even in Peru’s relatively cloudy tropical forests, the time series of PlanetScope was more consistent and sufficient due to the daily images taken. Another study looked into the use of Planet NICFI to map the diversity of land uses following deforestation across Africa with an F1 score of 84% (Masolele et al., 2024). The different land use types following deforestation include cocoa, cashew, rubber, oil palm, settlement, plantation forest, mining, and large-scale cropland.

2.5 Machine Learning Techniques for Forest Monitoring

Several machine-learning techniques exist and have been used for forest monitoring (Ashiagbor et al., 2023; Brovelli et al., 2020; Luan&Tsai, 2021). They include Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), k-Nearest Neighbour (kNN), Generalized Linear Model (GLM). In most cases, these machine learning classifiers are selected for forest mapping based on which one gives the highest accuracy from an extensive literature review, considering they all have their strengths and weaknesses. A study by Ashiagbor et al. (2023) presents an assessment of machine learning classifiers in mapping the cocoa-forest mosaic landscape of Ghana using S2. RF, SVM, ANN, and kNN were used in this study to compare the classification output and make recommendations for their use in certain landscapes. In the study, there were significant differences in the maps produced by the different classifiers in terms of class area and the distribution of the classes (Figure 5).

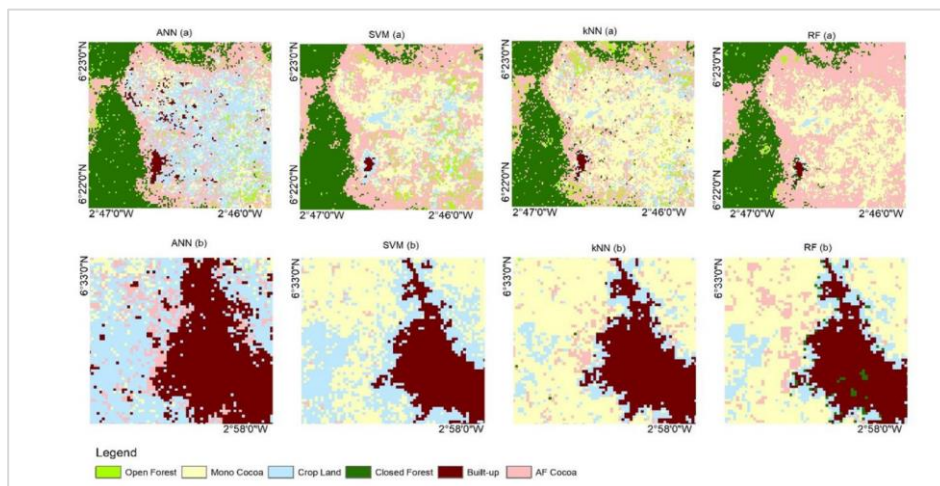


Figure 5. Disparities in the class area and class distribution of machine learning classifiers,

Source: Ashiagbor et al., 2023

RF recorded the highest overall accuracy of 84.77%, confirmed in related studies (Brovelli et al., 2020). The overall accuracy for kNN was 84.11%, 81.45% for SVM, and the lowest accuracy was 76.17% using ANN. The classification output of RF and kNN did not vary much and accurately represented the study landscape. Most other classes, such as built-up, were classified correctly with relatively low confidence in agroforestry cocoa and open forest due to the similarities in their spectral signatures. This usually occurs when classifying highly heterogeneous landscapes compared to less heterogeneous ones. Although there are disparities in the classifiers, all four had an accuracy above the satisfactory agreement and can be considered a representation of the landscape to an extent. Nevertheless, a study by Shao et al. (2019) indicated that concluding that the best classifier gives the highest accuracy may produce a misleading map that does not reflect the landscape. Thus, the choice of classifier should not be solely based on overall accuracy and kappa, and other factors should be included.

Kalischek et al. (2022) developed a deep learning framework using S2 to map cocoa in Ivory Coast and Ghana to improve accuracy and increase confidence in mapping these cocoa landscapes. The main classes used were cocoa and non-cocoa, and the overall accuracy obtained was 85.9%. Although the accuracy is a bit higher than that of RF, it could have been much better since the study used binary classification, unlike studies that investigated other classes and not just cocoa. Machine learning classifiers seem to perform better in less heterogeneous landscapes compared to highly heterogeneous landscapes where all classes have been segregated (Ashiagbor et al., 2023; Oduro et al., 2021). It would be necessary to have a comparative study of the same classifier tested at different landscapes to draw these conclusions. Further studies can also investigate the use of RF and deep learning to map deforestation in the cocoa forest mosaic landscape using a binary approach with less class segregation for accuracy comparison. Additionally, RF and deep learning methods can be compared in mapping forest loss with a high level of heterogeneity in the cocoa mosaic landscape so that the performances can be evaluated.

3. Objectives

This master thesis aims to evaluate the performance of remote sensing approaches and machine learning techniques in detecting cocoa-driven deforestation in landscape-specific contexts in Ghana. In an attempt to achieve this aim, three specific objectives were taken into consideration.

The first objective is to compare the effectiveness of different satellite products in mapping the Tonton Forest Reserve and its surrounding areas in 2023. This objective involves the comparison of Sentinel 2, Planet imagery, and a Pan-sharpened Sentinel 2 dataset. These datasets are integrated with a Random Forest model to understand land use patterns.

The second objective of the study is to conduct a change detection analysis to identify patterns of cocoa-driven deforestation from 2022 to 2023 in the Tonton Forest Reserve and its surrounding areas. This objective focuses on the satellite product and model that best maps the landscape to predict the land use patterns of the previous year. A transition map highlighting the areas where cocoa contributes to deforestation will be produced.

The third objective of this study is to validate the model's effectiveness in a different landscape by testing it in the Bia Protected Area and its surroundings. This validation process aims to evaluate the performance and applicability of the developed model in a different landscape with varying land use patterns. This evaluation will provide insights into whether a landscape-specific model is necessary, thus guiding future monitoring and conservation efforts in Ghana's diverse ecosystems.

This study is relevant as it will inform decisions on the methodology that works best for detecting cocoa-driven deforestation, particularly for the EUDR.

4. Materials and Methods

This chapter outlines the methodology used in this study. Section 4.1 describes the materials used in 2 sections: the study area and the data sources. Section 4.2 describes the methodology for evaluating the performance of remote sensing approaches and machine learning techniques to detect cocoa-driven deforestation in Ghana.

4.1 Materials

4.1.1 Study Area

The study areas selected surround the Tonton Forest Reserve (TFR) and the Bia Protected Area (BPA) in the Western and Western North Regions, respectively (Figure 6).

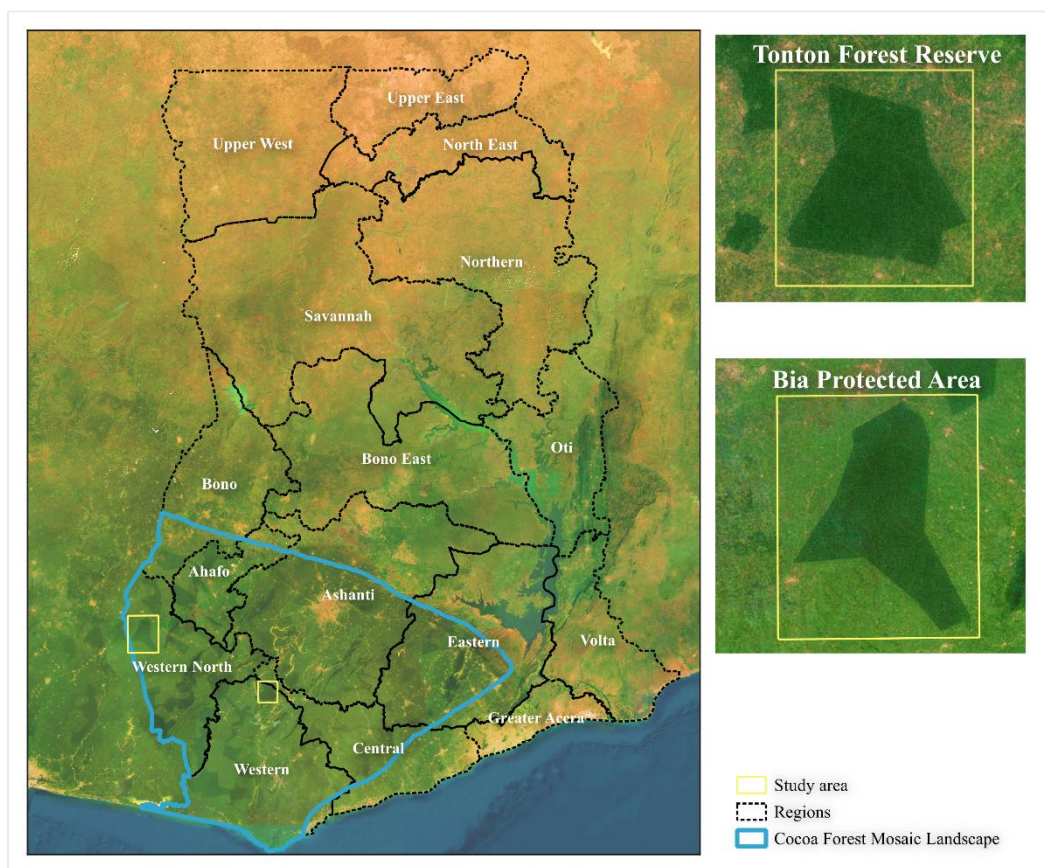


Figure 6. Study area map

The study areas for this research are defined by two distinct boundaries in the cocoa forest mosaic landscape. The first is a 20km² by 20km² boundary encompassing the Tonton Forest Reserve and its surroundings. The second area is a 25km² by 25km² boundary around the Bia Protected area and its surroundings. The TFR has an area coverage of 32,000 ha and an elevation of about 221 meters above sea level. This reserve experiences two distinct seasons:

the dry season, usually from December to March, and the rainy season from April to October. It plays a role in conserving forest resources and providing habitat for various fauna and flora. It comprises on-reserves (closed forests) under strict restrictions for conservation purposes and off reserves (open forests) with fewer restrictions. Over the past years, the reserve has been exposed to agricultural expansion, particularly cocoa, illegal logging, illegal mining, urbanisation, and other land uses that threaten forest resources. In this reserve, local farmers have been allowed to establish admitted farms in the reserve. These admitted farms are designated areas within the forest where local farmers can follow a Modified Taungya System, an agroforestry system that plants food crops and restores degraded forests. Efforts such as the Ghana Cocoa Forest REDD+ Programme (GCFRP) are being made to reduce deforestation, especially cocoa-driven in this area, to ensure long-term benefits that can be obtained from the reserve.

The Bia Protected Area covers 30,600 ha and is divided into two areas: the Bia National Park in the north, covering 7,770 ha, and the Bia Resource Reserve in the south, which covers 22,790 ha. The Bia National Park hosts African forest elephants, chimpanzees, White-nosed sooty Mangabey, Olive Colobus, Bongo, and Bushbuck, as well as 130 bird species and 404 butterfly species. It is the first UNESCO recognized Biosphere Reserve in Ghana. It is found in the Juaboso-Bia districts, considered hotspot intervention areas (HIA) for the GCFRP.

4.1.2 Data Sources

For this study, the dataset used were existing cocoa data for creating training data, and satellite imagery for image classification.

4.1.2.1 Existing Cocoa Data

The existing cocoa data used were the cocoa map for Côte d'Ivoire and Ghana produced by Kalischek et al. (2022) and polygons representing the boundaries of cocoa farms in Ghana. These datasets were used to guide training data for cocoa areas. The map segregates cocoa and non-cocoa areas in Ghana's cocoa forest mosaic landscape. Additionally, the data obtained from the Ghana Forestry Commission provides information on the farmers, their respective cocoa farm boundaries, area coverage, and yield (Figure 7).

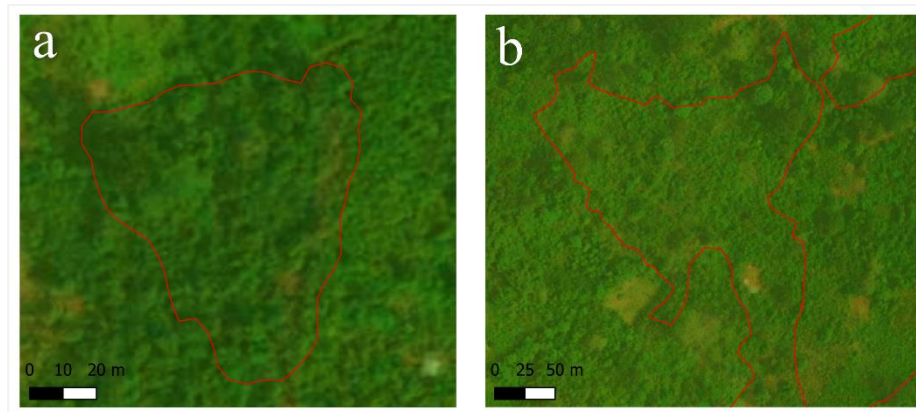


Figure 7. Cocoa farm boundaries in Ghana

4.1.2.2 Satellite Imagery

This study used two optical satellite images: Sentinel 2 and Planet NICFI. Sentinel 2 under the Copernicus program has a 10 m spatial resolution and 13 spectral bands capturing visible, near-infrared, and shortwave infrared wavelengths. It provides data from 2015 till date with a revisit time of 3-5 days. This is useful for environmental monitoring and is applicable in agriculture, forestry, urban planning, and disaster management.

High resolution Planet imagery made available through the NICFI program was also used in this study. The NICFI Satellite Data Program Basemaps for Tropical Forest Monitoring-Africa provides bi-annual mosaics between December 2015 and August 2020 and monthly mosaics from September 2020 onwards. These Planet NICFI mosaics are high-resolution images primarily used to monitor tropical forests. They are analysis ready mosaics that have undergone initial pre-processing steps, including atmospheric corrections based on seasonal Landsat data models by applying normalization and harmonization of Top of Atmosphere Reflectance scene data to surface reflectance corrected Landsat data. Cloud masks using Usable Data Masks (UDM) have been applied to these basemaps to remove clouds, heavy haze and cloud shadow. The basemaps have been normalized with historical Landsat data and optimized for deforestation detection.

4.2 Methods

To evaluate the performance of remote sensing approaches and machine learning techniques to detect cocoa-driven deforestation in landscape specific contexts, a comparative analysis of different satellite products was conducted, change detection analysis, and a model evaluation in a different landscape (Figure 8).

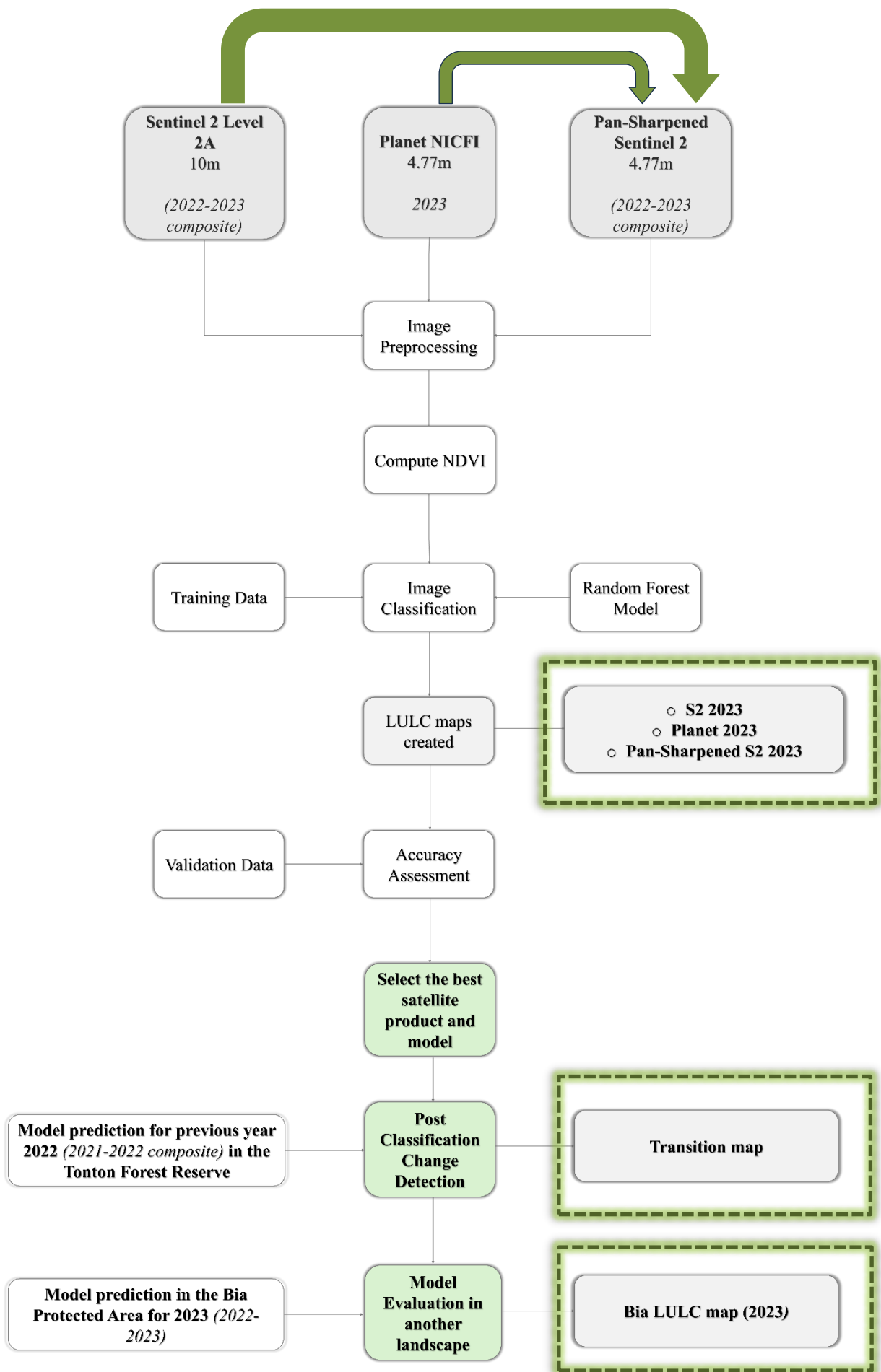


Figure 8. Overview of the methodology used for this study

4.2.1 Image Acquisition and Pre-processing

Harmonized Sentinel 2 images from the “Sentinel 2 Multi-spectral Instrument, Level 2A” image collection. Images were acquired from Google Earth Engine (GEE) for 2022 and 2023 using a two-year composite of 2021-2022 and 2022-2023 due to high cloud cover. This Sentinel 2 level 2 data has been pre-processed and computed by running the sen2cor algorithm. The image collection has 23 bands with 13 spectral bands and other bands such as the Scene Classification Map for cloud masking, Aerosol Optical Thickness (AOT), Water Vapour Pressure (WVP), QA60, etc. The S2 images were filtered using the Tonton Forest Reserve and Bia Protected Area shapefiles and the years of interest. The images downloaded were based on the availability of cloud free images with a cloud cover percentage of less than 2%. Median composites were obtained, and the SCL cloud mask was used to remove existing clouds from the composite further. The Normalized Difference Vegetation Index (NDVI) was calculated using the near-infrared (NIR) (band 8) and red band (band 4) to better highlight vegetation in the landscape.

Planet NICFI images were obtained in GEE from the image collection “Planet & NICFI Basemaps for Tropical Forest Monitoring-Tropical Africa.” Images were acquired for December 2022 and December 2023 only due to the availability of cloud-free images around that period. There are four spectral bands, i.e. Blue, Green, Red, and Near-Infrared. The main pre-processing steps were filtering by the study area and date. NDVI was computed for 2022 and 2023 and added as a feature for image classification.

Pan-sharpening was performed on the Sentinel 2 image to increase its spatial resolution, which was used as an additional dataset. This process was done using the “pansharpening” tool in QGIS. Pan-sharpening creates a new dataset by resampling the lower-resolution Sentinel 2 based on the high-resolution planet image. This process enhances the spatial detail of the image while maintaining the spectral features. This was used without the NDVI for the classification.

4.2.2 Image Classification

For the comparative study, all three datasets were classified separately using training data collected for the various classes. The polygon training data was collected using Google satellite imagery as a guide to identify the different LULC classes. The existing cocoa map by Kalisheck et al., 2022 was clipped to the study areas and used to create training data, particularly for cocoa (Figure 9). Additionally, the cocoa polygons obtained from the Ghana Forestry Commission

were used to understand better how cocoa farms look on the satellite image for easy identification. These training datasets created were pre-processed to remove unwanted samples and ensure that well represented classes are used for the image classification.



Figure 9. Cocoa map of the Tonton Forest Reserve (Kalisheck et al., 2022)

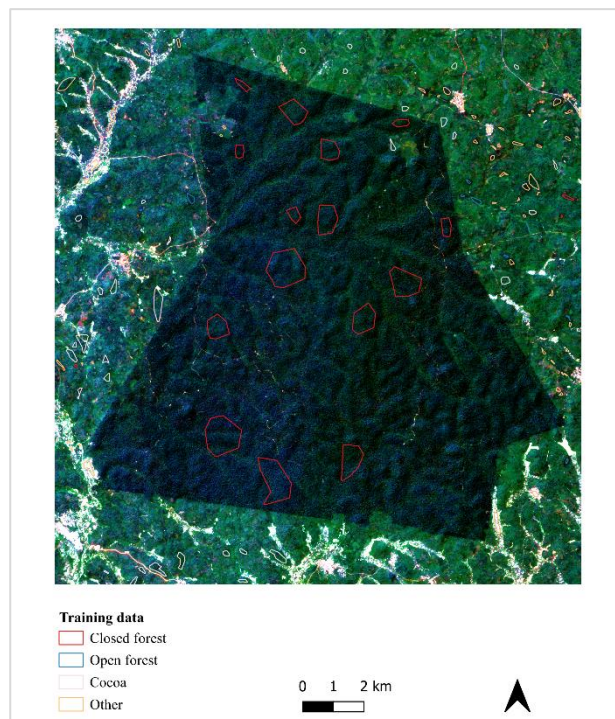


Figure 10. Training datasets created for Sentinel 2 in the Tonton Forest Reserve

Four land use types were defined in the study area: Closed forest, Open forest, Cocoa, and Other.

Table 1. Definition of land use land cover classes used in the study

Code	LULC	Description
1	Closed forest	These are forests with over 60% canopy cover and 5m in height. They are found within the forest reserves and protected areas with limited access.
2	Open forest	They represent degraded forests, usually with crown cover between 15% and 60%. They are found outside the forest reserve and protected area with fewer restrictions, unlike the forest reserves.
3	Cocoa	These are full sun/monoculture and agroforestry cocoa farms in the landscape.
4	Other	This comprises croplands, grassland, bareland, urban areas, mining ponds, and other tree plantations such as oil palm.

Image classification was performed using the three different training datasets, where 177 were well-represented polygons of Sentinel 2 image were used to calibrate the RF model. There were 19 classes for closed forest, 29 for open forest, 43 for cocoa and 81 for other classes. A total of 192 well-represented polygons were used to calibrate the RF model for the Planet NICFI image. For the Pan-sharpened S2 image, 123 polygons were created to calibrate the model.

4.2.3 Accuracy Assessment

Accuracy assessment was performed to determine the quality of all LULC maps produced to inform the decision on the dataset that best classifies the cocoa-forest mosaic landscape. A stratified random sampling was done, 50 points per class for the four classes as reference data using planet data and google satellite and compared with the classification results. A confusion matrix was computed, and the comparison was carried out using statistical errors, including the overall accuracy, producer's accuracy, user's accuracy, and kappa coefficient.

The overall accuracy measures the proportion of correctly classified classes out of the total for an understanding of the model's performance. It is calculated by dividing the total number of correctly classified classes by the total number of classes. The producer's accuracy indicates the map accuracy from the producer's view to highlight how well features on the ground are shown on the map. It is calculated by dividing the number of correctly classified classes of a particular class by its total number of classes. The user's accuracy is the accuracy from the point of view of the map user. This is calculated by taking the total number of a correctly classified class and dividing by the row total. The kappa coefficient is the probability of observed agreement minus the probability of expected agreement divided by one minus the probability of expected agreement.



Figure 11. The validation dataset created for the accuracy assessment of the Sentinel 2 map

4.2.4 Post-Classification Change Detection

A post-classification change detection technique was used in the study to detect the location, nature, and rate of land use and land cover changes in the landscape. LULC predictions of the Tonton Forest Reserve were made based on the highest-performing dataset and model used. The overlay procedure was used to obtain the changes in LULC over time (Jayakumar & Arockiasamy, 2003). A new thematic layer was produced from the two four-class maps with combinations of 'from– to' change classes. The changes, particularly from all other classes, i.e., closed forest, open forest, and other to cocoa, were highlighted to address the concern of

quantifying how cocoa expansion is taking over other land use types, especially forests. The transitions were validated using to confirm that these changes have occurred in 2023.

4.2.5 Model Evaluation in a Different Landscape

The evaluation of the model in a different landscape was done to test the robustness of the model and its applicability in other areas with similar or different characteristics. No additional training datasets were created for this purpose. The major concern was to ensure that the image for the area of interest had pre-processing steps similar to those on which the model was trained. The already trained model was used to make LULC predictions for the four classes in the Bia Protected Area in 2023.

5. Results

This chapter presents the results obtained from the study. Section 5.1 highlights the comparison of Sentinel 2 and Pan-sharpened S2 in detecting cocoa-driven deforestation in the Tonton Forest Reserve and the accuracy assessment. Sections 5.2 and 5.3 provide information on the post-classification change detection and the evaluation of the RF model in a different landscape.

5.1 Comparison of Satellite Products for LULC Mapping

5.1.1 Sentinel 2 for LULC Mapping in the Tonton Forest Reserve

The LULC map from Sentinel 2 is presented in Figure 12, and an area of coverage of the various classes is presented in Figure 13 below. For this 2022-2023 composite, closed forest was the most dominant class in the TFR landscape, occupying 14820.81 ha (46.2%). Cocoa is the second most dominant class in the study area, occupying 42.8% (13738.10 ha). Other and open forest also covers an area of 3098.66 ha (9.7%) and 406.55 ha (1.3%), respectively.

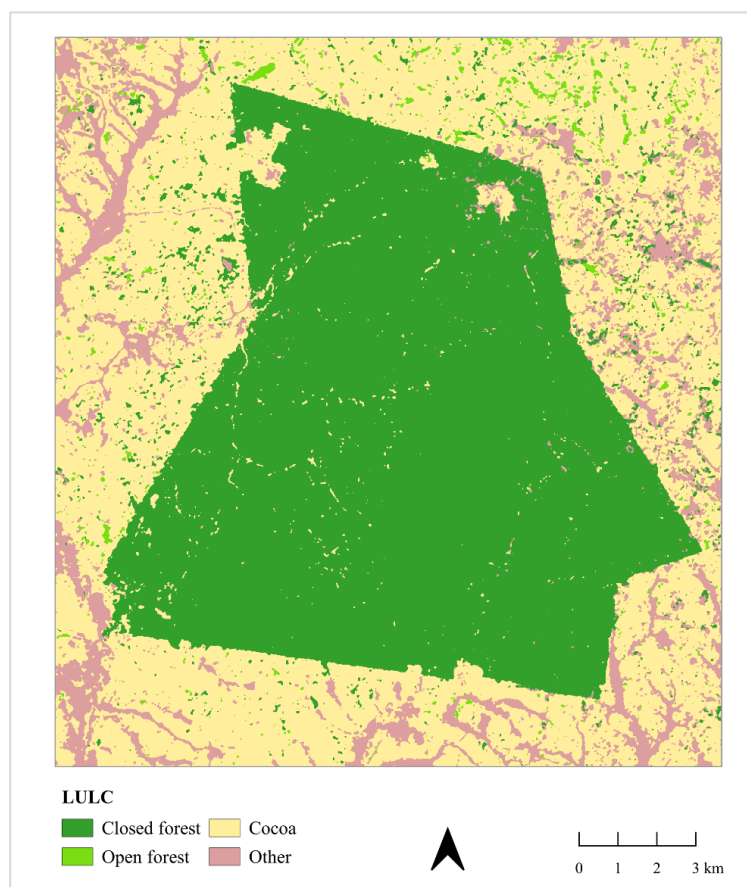


Figure 12. LULC map of Tonton Forest Reserve in 2023 using Sentinel 2

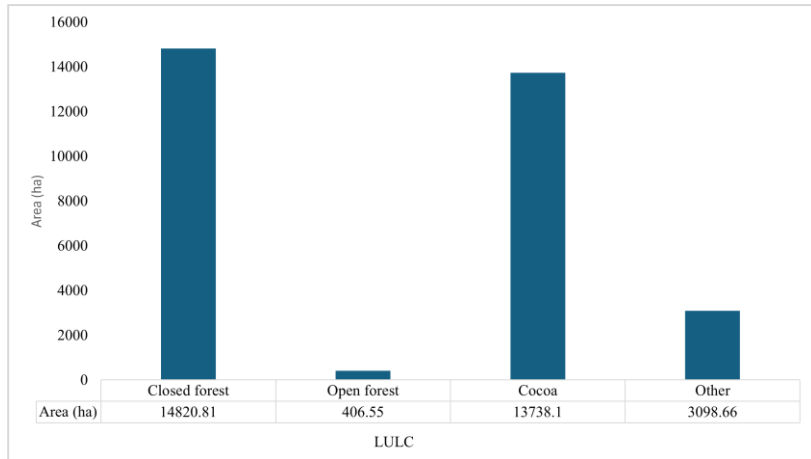


Figure 13. Area coverage of LULC classes in the Tonton Forest Reserve in 2023

5.1.2 Planet NICFI Imagery for LULC mapping in the Tonton Forest Reserve

The LULC map from Planet is presented in Figure 14, and the area coverage of the various classes is presented in Figure 15. For this year, closed forest was the most dominant class in the TFR landscape, occupying 15482.3 ha (48.2%). Cocoa is the second most dominant class in the study area, constituting 37.7% of the total (12108.70 ha). Other and open forests also cover an area of 4082.99 ha (12.7%) and 417.0 ha (1.3%1), respectively.

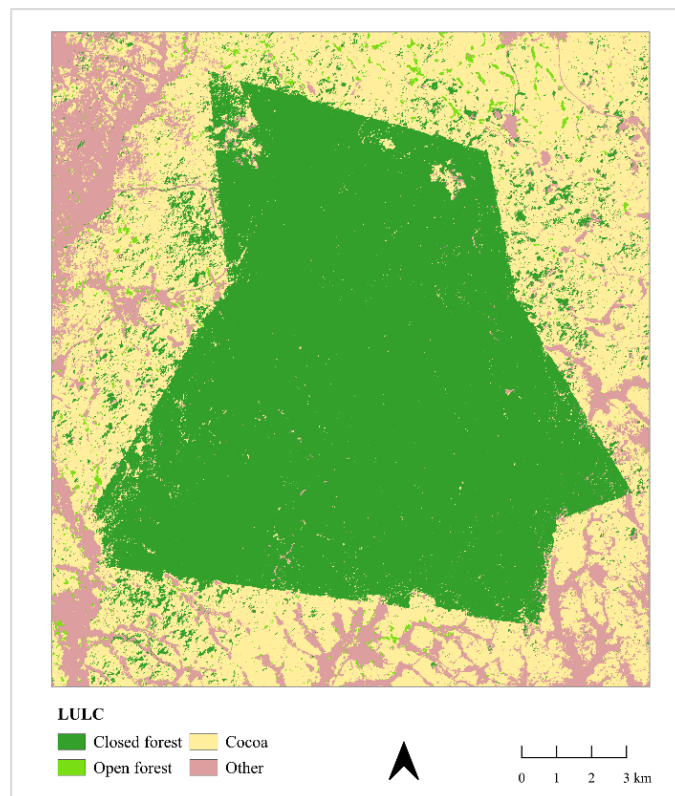


Figure 14. LULC map of Tonton Forest Reserve in 2023 using Planet NICFI

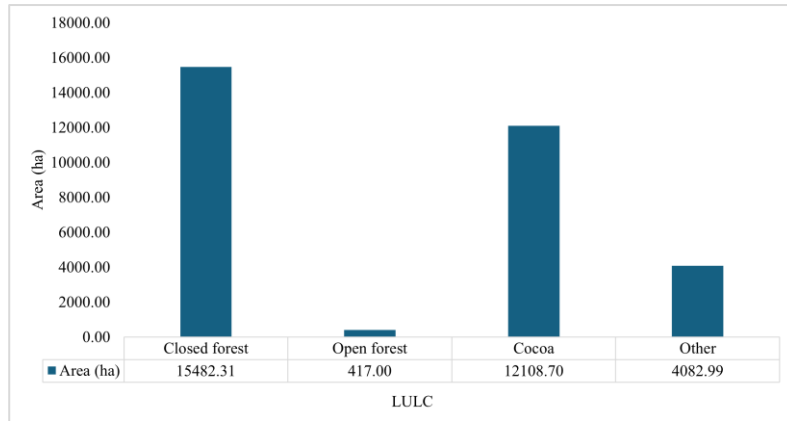


Figure 15. Area coverage of LULC classes in the Tonton Forest Reserve in 2023

5.1.3 Pan-sharpened Sentinel 2 Image for LULC mapping in the Tonton Forest Reserve

The LULC map and area coverage of the Pan-sharpened Sentinel 2 image are presented in Figures 16 and 17, respectively. Closed forest was the dominant class in the landscape, occupying 45.03% of the total. Cocoa was the second most dominant landscape, with an area coverage of 10745.47 ha (33.51%). Open forest has an area coverage of 1039.46 ha (3.24%), and other has an area coverage of 5841.63 ha (18.22%).

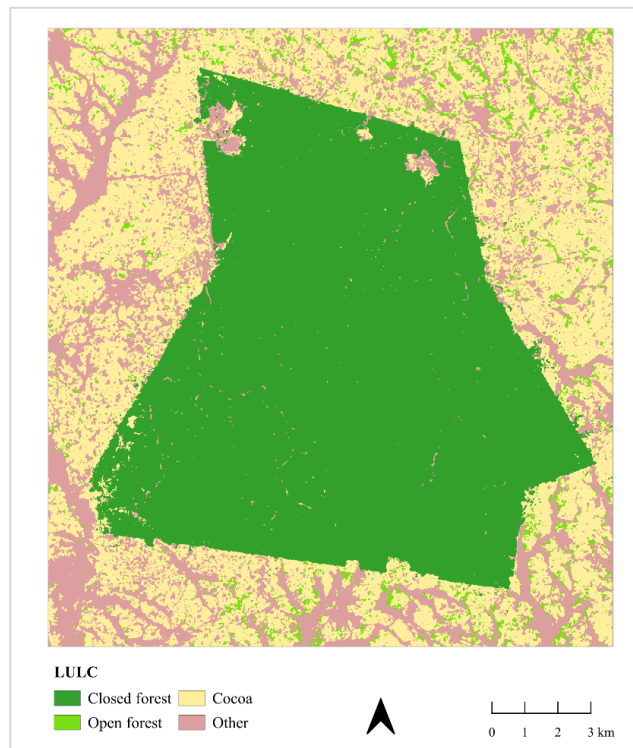


Figure 16. LULC map of Tonton Forest Reserve in 2023 using the Pan-sharpened Sentinel 2 image

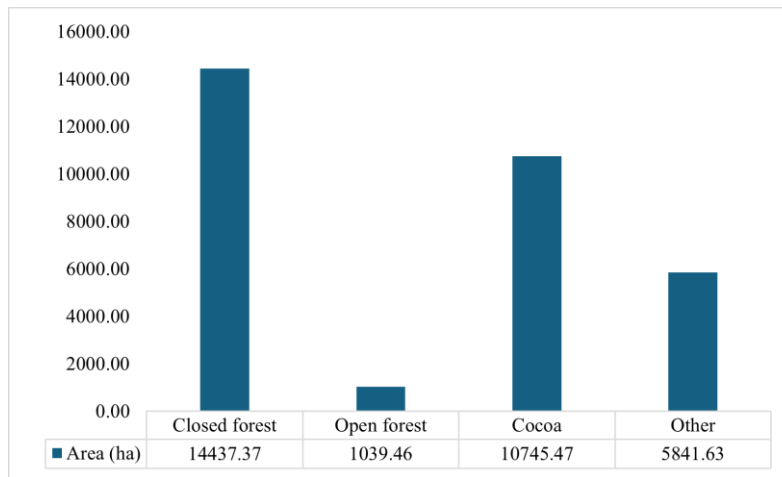


Figure 17. Area coverage of LULC classes in the Tonton Forest Reserve in 2023

5.1.4 Accuracy Assessment

The table below presents the accuracy assessment results of the Sentinel 2, Planet NICFI, and Pan-sharpened Sentinel 2 LULC maps. The overall accuracy, producer's accuracy, user's accuracy and kappa coefficient were used to verify the quality of the classified maps. The overall accuracy of the LULC map based on S2 was 86.5%, 87.5% for the Planet NICFI LULC map, and 96.5% for the LULC map based on the Pan-sharpened Sentinel 2 dataset. From these results, the best satellite product in classifying the cocoa forest landscape is the Pan-sharpened Sentinel 2 dataset.

Table 2. Classification accuracy assessment for the different satellite products in the Tonton Forest Reserve

LULC Class	Sentinel 2		Planet NICFI		Pan-sharpened Sentinel 2	
	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)
Closed forest	96.0	85.7	100.0	86.2	100.0	98.0
Open forest	82.0	97.6	84.0	100.0	98.0	100.0
Cocoa	82.0	74.5	78.0	81.3	88.0	97.7
Other	86.4	91.5	88.0	84.6	100.0	90.1
Overall accuracy	86.5		87.5		96.5	
Kappa	82.0		83.3		95.3	

The confusion matrix for the classified LULC map based on Sentinel 2 indicating the level of misclassifications is shown in Figure 18 below. Closed forests were classified properly. However, there were misclassifications in open forests, cocoa, and others. In some cases, open forest was misclassified as cocoa or other, and cocoa was misclassified as another, closed forest or open forest. Others were misclassified as cocoa and closed forests in some instances.

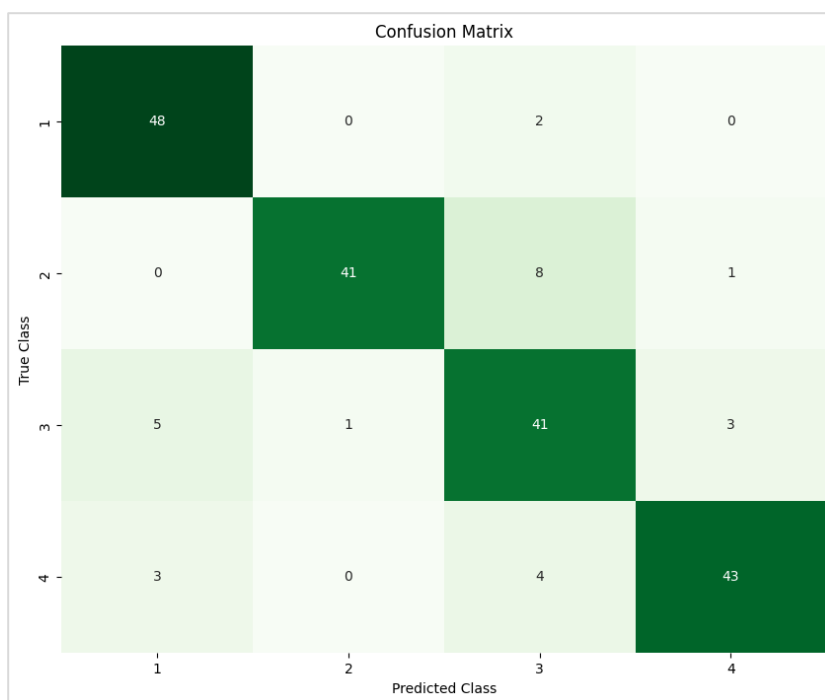


Figure 18. Confusion matrix of the TFR classified map of 2023 based on Sentinel 2

The confusion matrix for the classified LULC map based on Planet NICFI indicating the level of misclassifications is shown in Figure 19 below. Closed forests were classified well in the landscape. Open forests were misclassified as cocoa and other classes; cocoa was misclassified as closed forest and other, other was misclassified as closed forest and cocoa.

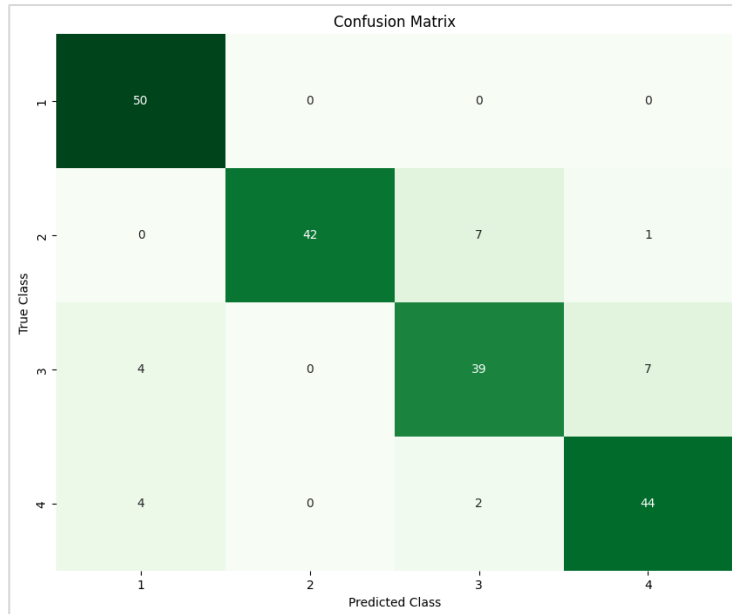


Figure 19. Confusion matrix of the TFR classified map of 2023 based on Planet NICFI. The confusion matrix for the classified LULC map based on the Pan-sharpened Sentinel 2 image indicating the level of misclassifications is shown in Figure 20 below. Closed forests and others were classified properly in the landscape. Open forests were misclassified as cocoa, cocoa was misclassified as closed forest.

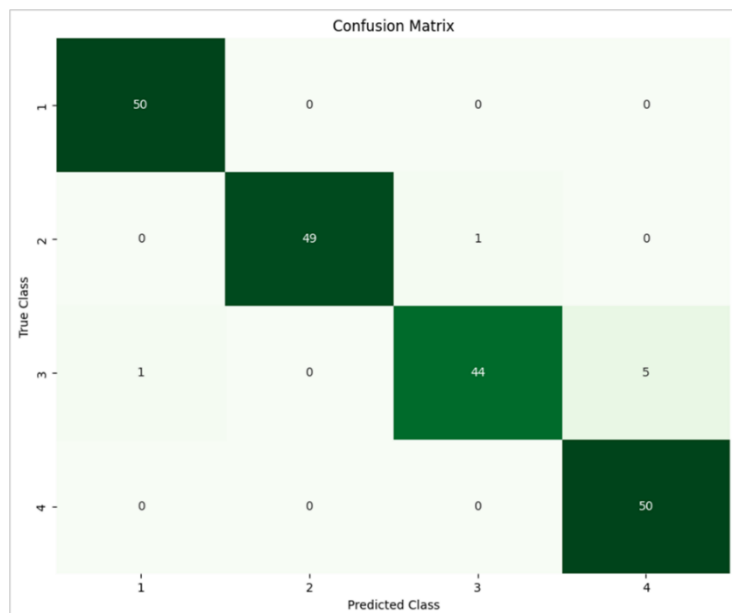


Figure 20. Confusion matrix of the TFR classified map of 2023 based on Pan-sharpened Sentinel 2

Comparing the area coverage from the three products, there are differences within the classes (Figure 21). Closed forest is over estimated in the Planet NICFI image which is as a result of the presence of haze leading to misclassifications. Open forest has a higher area coverage in

the Pan-sharpened image due to the enhancement of the spatial detail. The total area of cocoa is relatively higher in the Sentinel 2 image compared to this others and this is due to the inability of segregating the croplands or barelands within the cocoa farms. The Pan-sharpened image does this segregation better in this case. Other has a lower area coverage in mainly because the croplands, barelands and all other classes are appear well in the Pan-sharpened Sentinel 2 image as a result of the enhanced spatial resolution.

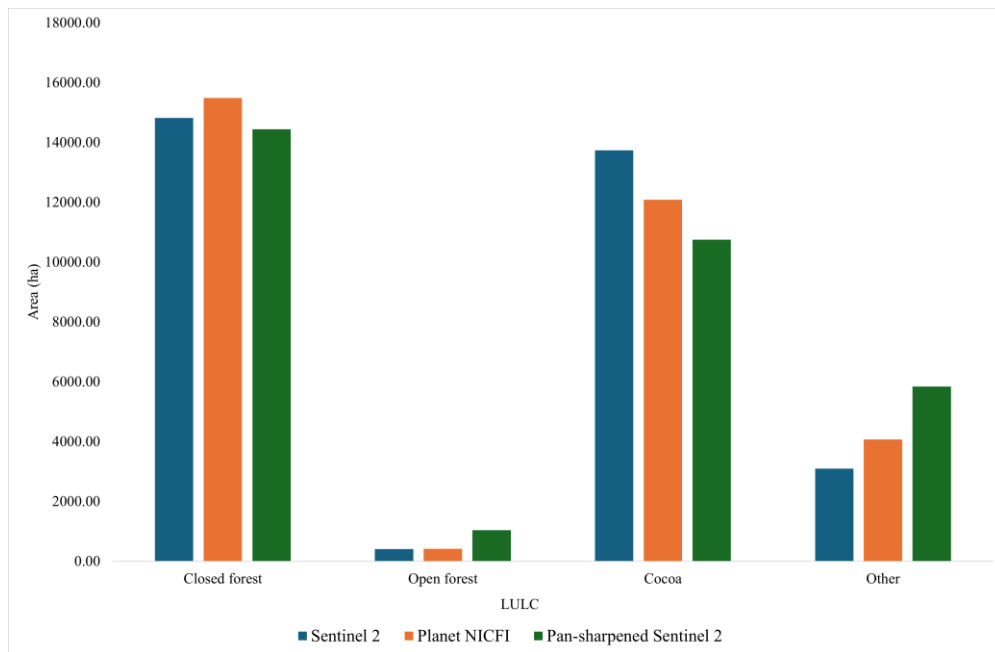


Figure 21 . Comparison of the area coverage of the three datasets

5.2 Post-Classification Change Detection

The most effective satellite product and model was used to predict the previous year to understand the land use patterns of 2022. The Pan-sharpened Sentinel 2 LULC map and area coverage for the Tonton Forest Reserve are shown in Figures 22 and 23 below. In the landscape, closed forest was the dominant class, occupying 45.03% of the land. Cocoa was the second most dominant class in the landscape, occupying 29.05% of the land area. Open forest and other had an area coverage of 1606.10 ha (5.01%) and 6704.24 ha (20.91%, respectively).

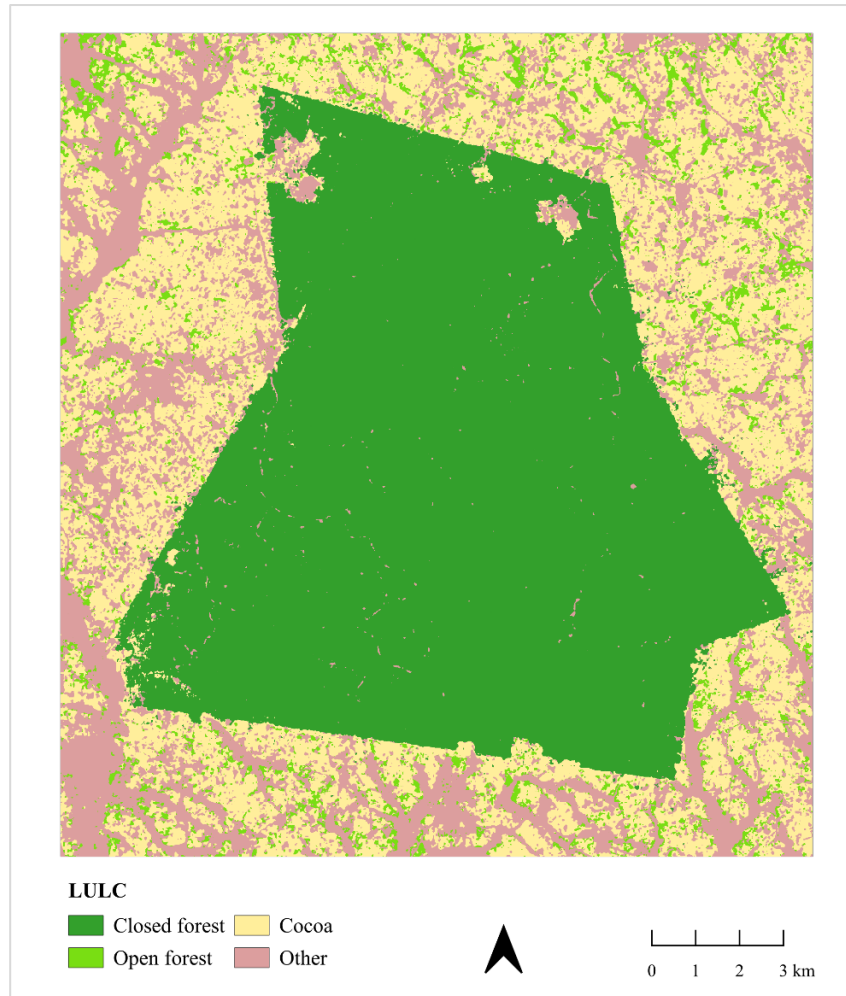


Figure 22. LULC map of Tonton Forest Reserve in 2022 using the Pan-sharpened Sentinel 2

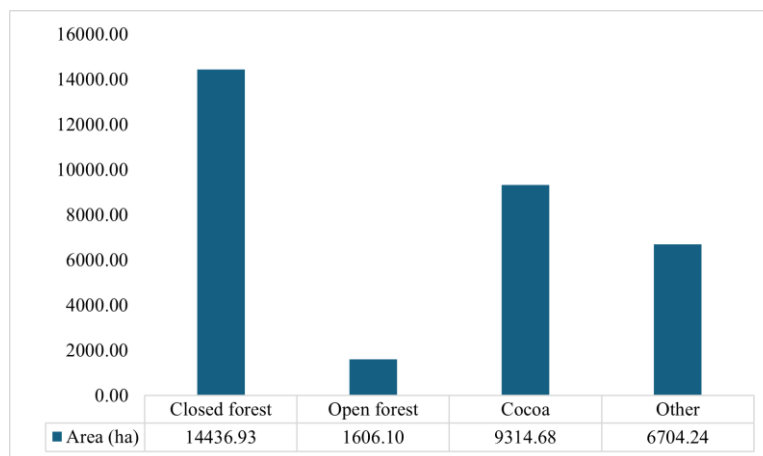


Figure 23. Area coverage of Tonton Forest Reserve in 2022 using Pan-sharpened Sentinel 2. The overall accuracy, kappa co-efficient, producer, and user accuracies of the classified are presented in Table 3 below. The overall accuracy of this LULC map is 95.0%. The confusion matrix is shown in Figure 24 below with misclassifications, particularly in open forests and cocoa.

Table 3. Classification accuracy assessment for the Pan-sharpened Sentinel 2 in the Tonton Forest Reserve (2022)

LULC Class	Producer's accuracy (%)	User's accuracy (%)
Closed forest	100	100.0
Open forest	96.0	94.1
Cocoa	84.0	100.0
Other	100.0	87.7
Overall accuracy	95.0	
Kappa	93.3	

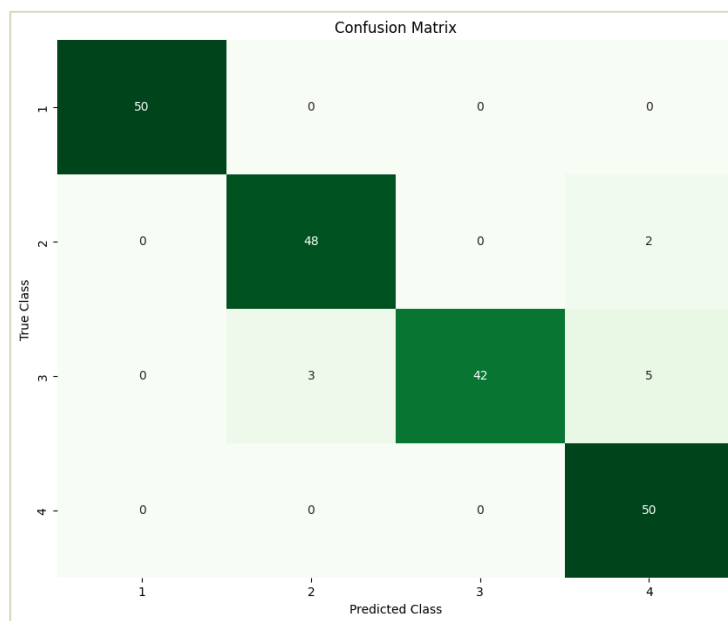


Figure 24. Confusion matrix of the TFR classified map of 2022 based on Pan-sharpened Sentinel 2

The cross-tabulation matrix in Table 4 and the transition map in Figure 25 below highlight all the changes that occurred in the landscape between 2022 and 2023. Over the period, 29396.93 ha remained unchanged, and 2664.85 ha changed from one land use to another.

Table 4. 2022-2023 cross-tabulation matrix for the Tonton Forest Reserve

LULC	Closed forest	Open forest	Cocoa	Other
Closed forest	14436.93	0.00	0.00	0.00
Open forest	0.01	1039.46	431.77	134.82
Cocoa	23.00	0.00	8764.31	550.12
Other	0.20	0.00	1547.70	5156.23

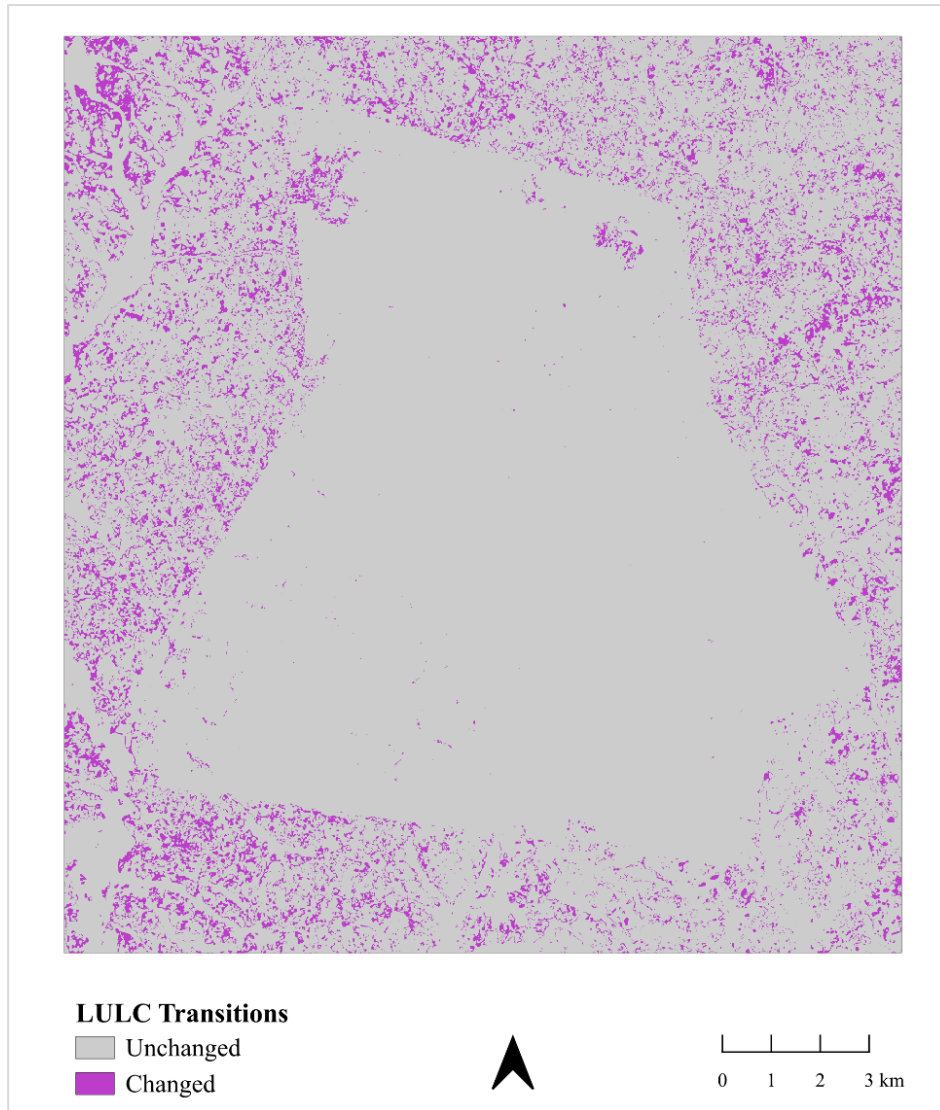


Figure 25. LULC transitions in the Tonton Forest Reserve between 2022 and 2023. Specifically for cocoa-driven deforestation, transitions from closed and open forest to cocoa over the period are highlighted in Figure 26 below. Closed forests were not converted to cocoa. However, 431.77 ha of open forests were converted to cocoa within one year. The producer accuracy obtained for the transitions to cocoa is 100%, indicating that these transitions reflect the true state of the classified map in 2023 with no errors.

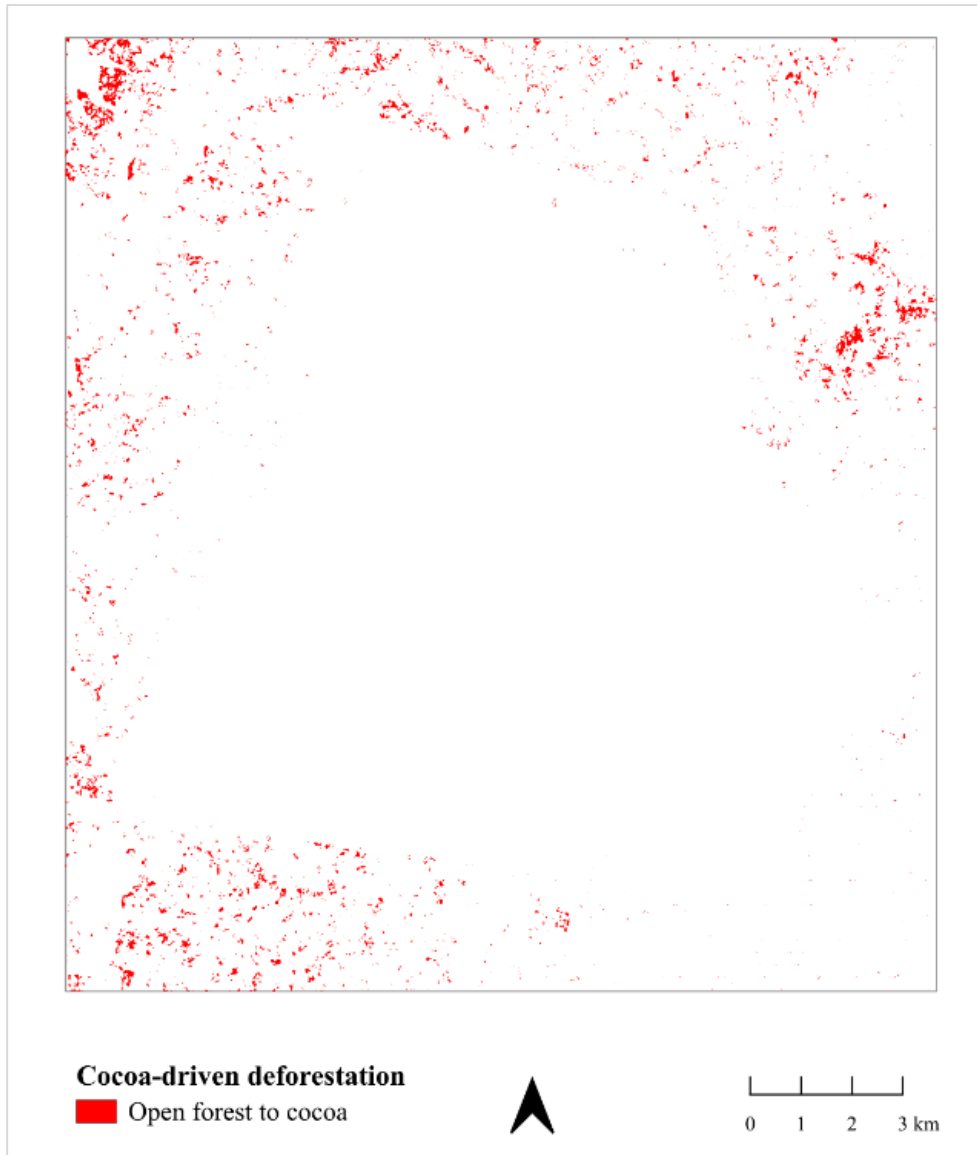


Figure 26. Cocoa-driven deforestation in the Tonton Forest Reserve between 2022 and 2023

5.3 Model Evaluation in a Different Landscape for LULC Mapping

Figures 27 and 28 below present the map and area coverage of the best model evaluated in the Bia Protected Area. The model performed well, considering no additional training data was created for this area. Cocoa was the dominant class in the landscape, occupying 54.76% of the land area. The second most dominant class was closed forest, with an area coverage of 31003.15 ha (34.26%). Open forests and others occupy 5.94% and 5.04% of land, respectively.

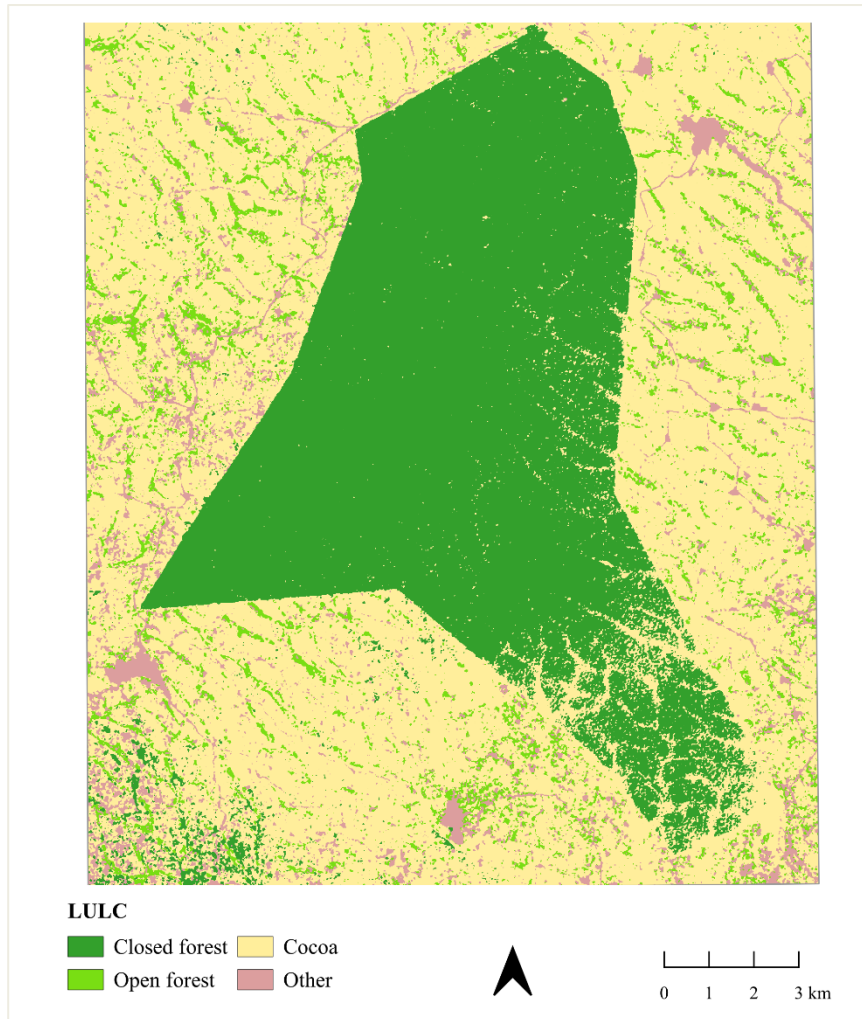


Figure 27. LULC map of the Bia Protected Area in 2023

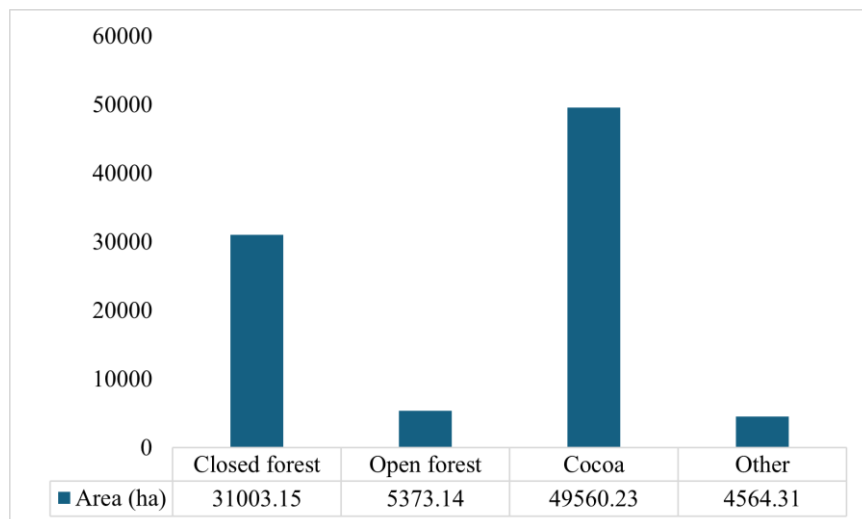


Figure 28. Area coverage of the Bia Protected Area in 2023

The overall accuracy of the LULC map is 88.5%, with a kappa of 84.6% (Table 5). There were some misclassifications in all the LULC classes. Closed forests were misclassified as cocoa, open forests were misclassified as cocoa, and cocoa was misclassified as closed forest, open forest, and other (Figure 29). Other was misclassified as closed forest and cocoa.

Table 5. Classification accuracy assessment for LULC map in the Bia Protected Area

LULC Class	Producer's accuracy (%)	User's accuracy (%)
Closed forest	91.8	91.8
Open forest	88.0	97.7
Cocoa	90.1	75.4
Other	84.0	93.3
Overall accuracy	88.5	
Kappa	84.6	

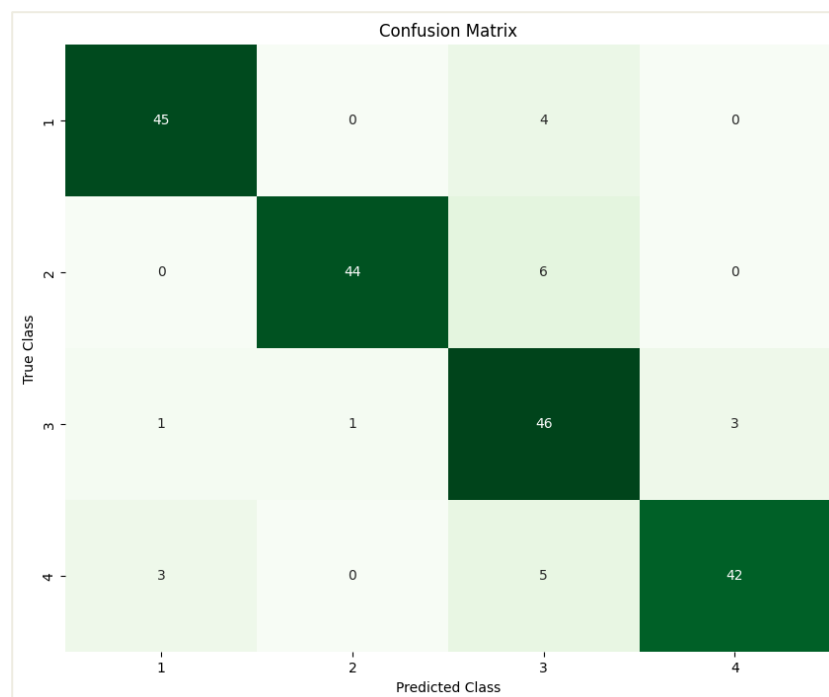


Figure 29. Confusion matrix of the Bia Protected Area LULC map

6. Discussion

6.1 Comparison of different satellite products for LULC mapping in the Tonton Forest Reserve

From the results, the Pan-sharpened Sentinel 2 datasets gave the best accuracy and outperformed the Sentinel 2 and Planet NICFI. The overall accuracies obtained 86.5% for S2, 87.5% for Planet NICFI and 96.5% for the Pan-sharpened Sentinel 2. The performance of this Pan-sharpened dataset can be attributed to the enhanced spatial resolution of the image, which allows for a better detection of details in the study area. In the case of Sentinel 2, the limiting factor was the comparatively higher resolution, which does not properly highlight details such as croplands or barelands that are found within the cocoa-growing areas. According to Kalisheck et al. (2022), although Sentinel 2 effectively classifies these cocoa-forest mosaic landscapes, it overestimates the cocoa areas due to the inability to properly segregate other land uses found between the farms. The Pan-sharpened dataset, therefore, addresses this concern by providing an improved spatial resolution while maintaining the spectral bands.

Although Planet NICFI provides a higher temporal resolution than Sentinel 2, the limiting factor in classifying the landscape can be attributed to haze and other atmospheric interferences. These atmospheric interferences persisted despite the images being analysis-ready and having undergone atmospheric corrections. Planet NICFI may perform better in other landscapes with less atmospheric interference. Its application in high cloud cover areas such as Ghana Planet NICFI will require improving image quality. This study indicates that in LULC mapping, spatial resolution alone is not enough; image quality plays a major role in providing results that are a representation of the landscape. The combination of high-resolution and high-quality images, as in the Pan-sharpened Sentinel 2 images, is essential for accurately mapping Ghana's cocoa forest mosaic landscape. Additionally, the use of multiple composites and improvement in cloud mask algorithms could enhance the accuracy of LULC maps produced for areas like Ghana using Planet NICFI.

6.2 Detecting cocoa-driven deforestation in the Tonton Forest Reserve

Results from the post-classification change detection highlight how cocoa drives deforestation in the Tonton Forest Reserve. The model prediction for the LULC mapping of the previous year produced high accuracy, which implies that the classified map represents the landscape. Over the one year, the analysis revealed that 431.77 ha of cocoa plantations have expanded into open forest rather than closed forest areas. This is because, unlike closed forests, which are

regulated, ensuring little or no deforestation, open forests are more accessible for land use conversions such as cocoa. A major factor influencing the conversion of these land use conversions is the land and tree tenure system in these areas.

In most cases, closed forests are owned by the government, which reduces the conversion rates to other LULC types, whereas open forest areas are privately owned, giving landowners the right to convert from one LULC to another freely. As a result of ownership rights of these lands, conversion rates in open forest areas are relatively difficult to manage as farmers are the sole owners who decide what to use their lands for. Ashiagbor et al. (2022) corroborate these findings in their study in the Juabiso-Bia landscape in Ghana, where cocoa-driven deforestation is prevalent in off-reserve forests (open forests) and admitted farms which have eventually been converted to cocoa rather than closed forests. The 1999 Ghana Land Use Policy states, “*Land categories outside Ghana’s permanent forest and wildlife estates are available for agriculture, timber, mining and other extractive industries, and human settlement within the context of a national land-use plan.*” To address issues of cocoa-driven deforestation, existing land use policies need to be revised and policies such as the EUDR to regulate the use of land for sustainable cocoa production should be implemented.

Land use conversions from open forests to cocoa are driven by the global demand for chocolate made from cocoa. Ghana is the second-largest producer of cocoa globally due to favorable climatic factors such as consistent rainfall patterns and fertile soils, as well as support from the Ghana Cocoa Board (Cocobod). The cocoa industry contributes significantly to the country’s foreign exchange earnings due to high export levels. The Government of Ghana, through Cocobod, introduced policies to increase cocoa production, which motivated farmers to extend cocoa farms to achieve the national desired production and export capacity. Smallholder farmers obtain increased incomes, improving their livelihoods and compelling them to convert their other land uses to cocoa to make more money. In an attempt to meet the global demand due to the rising population, farmers tend to convert forest reserves to cocoa as there is no new land. Farmers will utilize on-reserves for cocoa production once land availability gets scarce in the off-reserve areas to increase their outputs. They understand on-reserve boundaries and consider deforestation in such areas an illegal activity that influences their decision to convert to cocoa. Although other studies indicate that cocoa drives deforestation in closed forests, this unfolds over a longer timeframe, making cocoa-driven deforestation less common within a year. Cocoa encroached on-reserve forests by about 9% compared to 91% in off-reserve areas

between 1986 and 2017 (Ashiagbor et al., 2022). Generally, croplands and other land uses are converted easily to cocoa rather than closed forests with several restrictions. The comparison approach used for this post-classification change detection was validated to check the accuracy of the changes that have occurred and how they reflect the landscape. An overall accuracy of 100% was obtained for the conversions from open forest to cocoa, which is a true representation of this conversion in the landscape.

6.3 Model Evaluation in a Different Landscape for LULC Mapping

From the results, the model evaluation in the Bia Protected Area was effective and gave an overall accuracy of 88.5%. This implies that the model properly learned patterns applicable in a different landscape due to the similarities and generalizations of the LULC classes. The LULC classes chosen and the representative training data created captured the landscape's variability and diversity, making the model transferable. However, there were some limitations in the model's performance, which is attributed to the presence of haze, which introduced noise in the satellite image and affected the classification results. There is a clear indication that with high-quality images, model transferability is possible in the cocoa-forest mosaic landscape and should be explored in other landscapes to test the robustness of the model.

While studies focus on the performance of machine learning classifiers for mapping the cocoa-forest mosaic landscape and change detection, a gap exists regarding the transferability of these models across different years in the same landscape. Furthermore, attention has not been focused on investigating the transferability of the model across different landscapes. This research highlights the potential of the transferability of models over time and across the cocoa forest mosaic landscape. Adopting such approaches in mapping the cocoa-forest mosaic landscape reduces redundancy, provides consistency in analysis, and ensures the same methodologies are used, scalability to different geographic regions with minimal modifications regardless of how big they are, and adaptability. Landscape-specific mapping is necessary in certain contexts. However, findings from this study emphasize the potential of the transferability of models across landscapes, provided that the models are properly trained with less specific LULC classes to a particular landscape. This means that it is not always necessary to conduct landscape-specific mapping since the transferable models yield satisfactory results, particularly for cocoa mapping. Landscape-specific mapping will be important if the LULC classes are only specific to a particular area; this approach can be used in the context of more general classes such as closed forest, open forest, cocoa, and others. The decision to use

landscape-specific mapping or transferable models depends on the project's goal and the expected outcomes.

7. Conclusion and Recommendations

7.1 Conclusion

This study provides insights into remote sensing and machine learning techniques for land use land cover mapping, focusing on cocoa-driven deforestation. Utilising Pan-sharpened Sentinel 2 provides the highest accuracy in mapping the cocoa-forest mosaic landscape compared to Sentinel 2 and Planet NICFI. This high accuracy is attributed to the enhanced spatial detail as a result of pan-sharpening the Sentinel 2 image using the high resolution Planet NICFI. In this case, spectral bands of Sentinel 2 are maintained which are essential in mapping such heterogeneous landscapes compared to Planet only, which has fewer spectral bands.

Cocoa-driven deforestation in the Tonton Forest Reserve is more evident in open forests rather than closed forests over one year. This is because the open forests/off-reserve areas have fewer regulations, which facilitate easy land use conversions. However, in the case of on-reserve/closed forest areas, strict regulations slow down the rate at which these areas are converted to cocoa farms. To minimize the rate at which open forests are converted, ensuring compliance to the EUDR will play a major role such that farmers will be involved in sustainable cocoa production.

The transferability of the model in a different landscape underscores its robustness for LULC mapping. The study concludes that, although the model was trained in the Tonton Forest Reserve area, it is applicable in the Bia Protected Area. This implies that monitoring efforts in different landscapes in the cocoa forest area can yield good results based on this methodology. The study suggests that improving the image quality through more complex atmospheric corrections could increase the accuracy of the results of the classified map, thereby enhancing the transferability of the model.

7.2 Recommendations

Based on the study findings, there is a need to improve atmospheric corrections in the satellite images. Utilising more than a two-year composite could fix this issue; however, this restricts frequent monitoring of the cocoa-forest mosaic landscape and will not be applicable in cases such as the EUDR, which requires close monitoring of the landscape. This study focused solely on utilizing free and open-source satellite imager for analysis, however, commercial products like Planet Imagery, which might have undergone a higher level of pre-processing can be explored for such purposes to improve image quality. Further studies need to assess the

transferability of the random forest model across other landscapes and different periods to evaluate the effectiveness of the model. These findings are relevant, particularly for the EUDR, since cocoa farms that took over forests have been identified. Considering that farmers will provide the boundaries of their farms, this analysis can highlight the farms that go against the EUDR. Stakeholders can implement these methodologies to ensure sustainable cocoa production.

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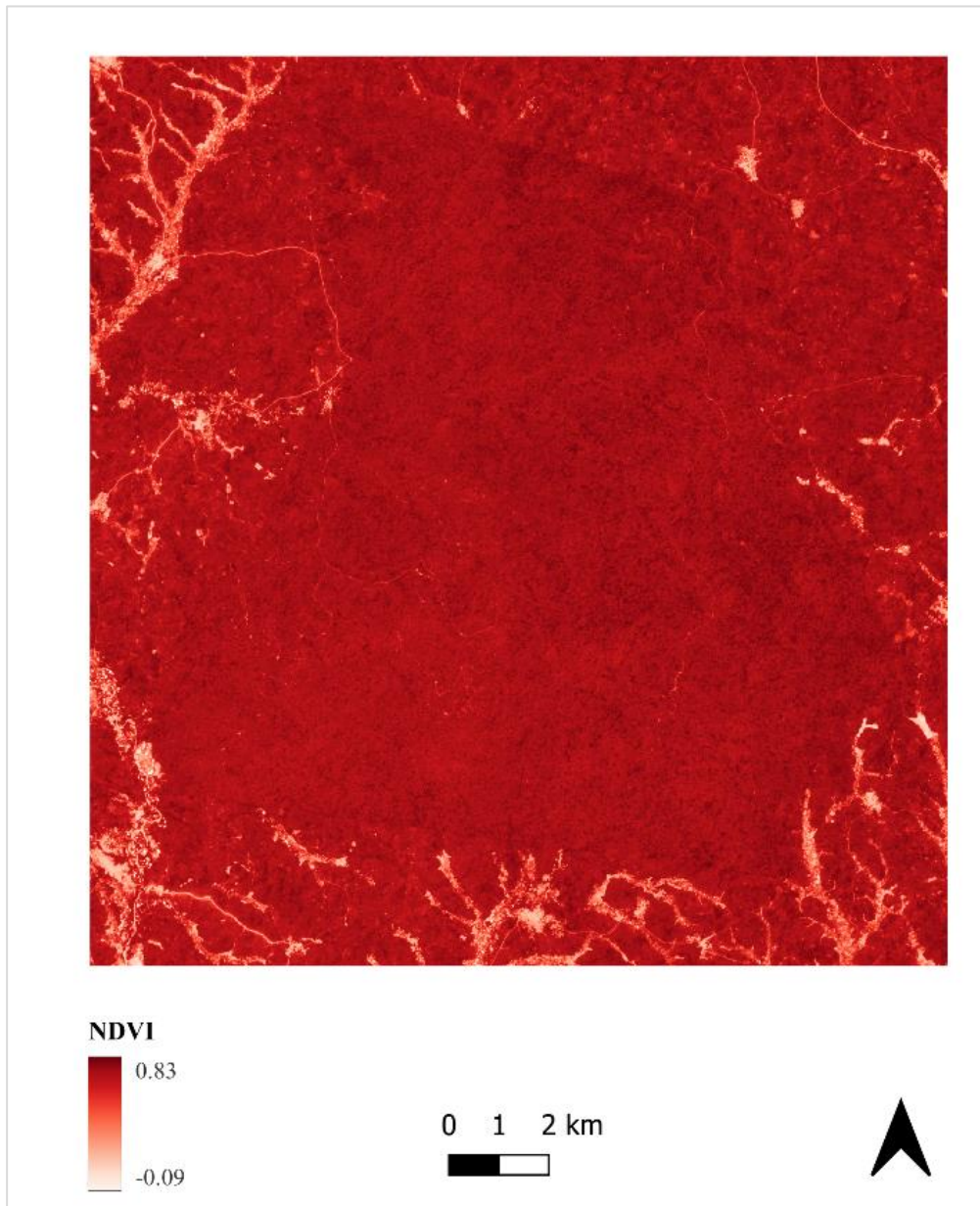
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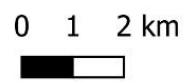
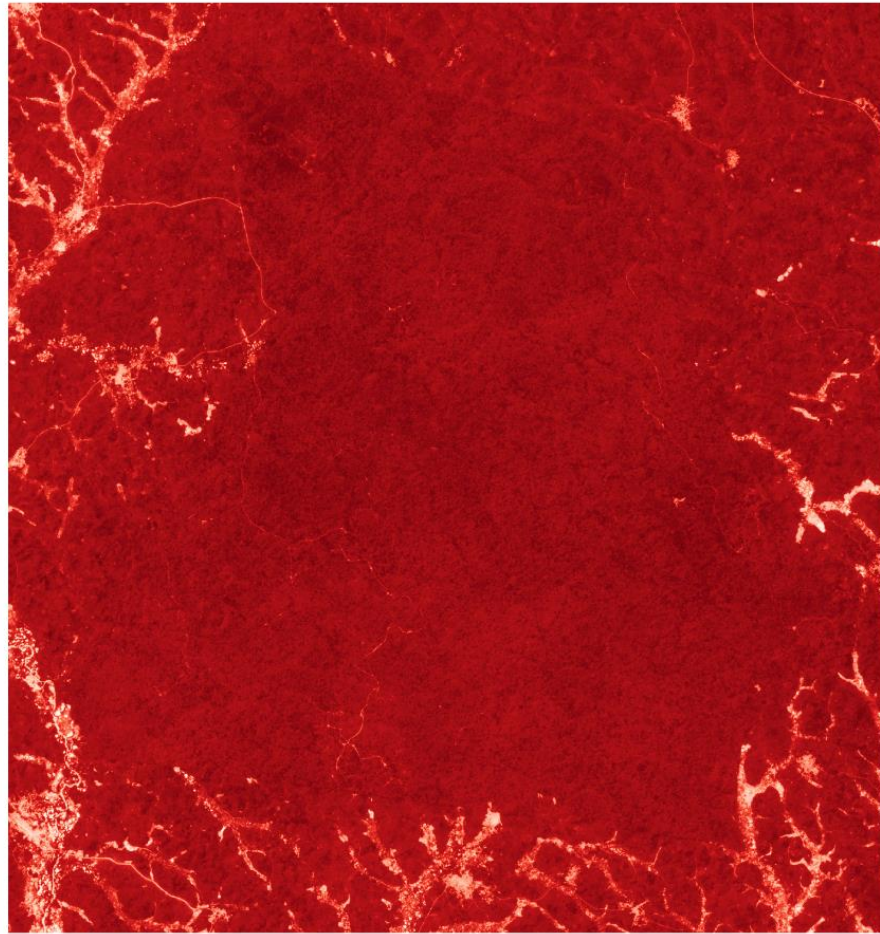
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9. Appendices

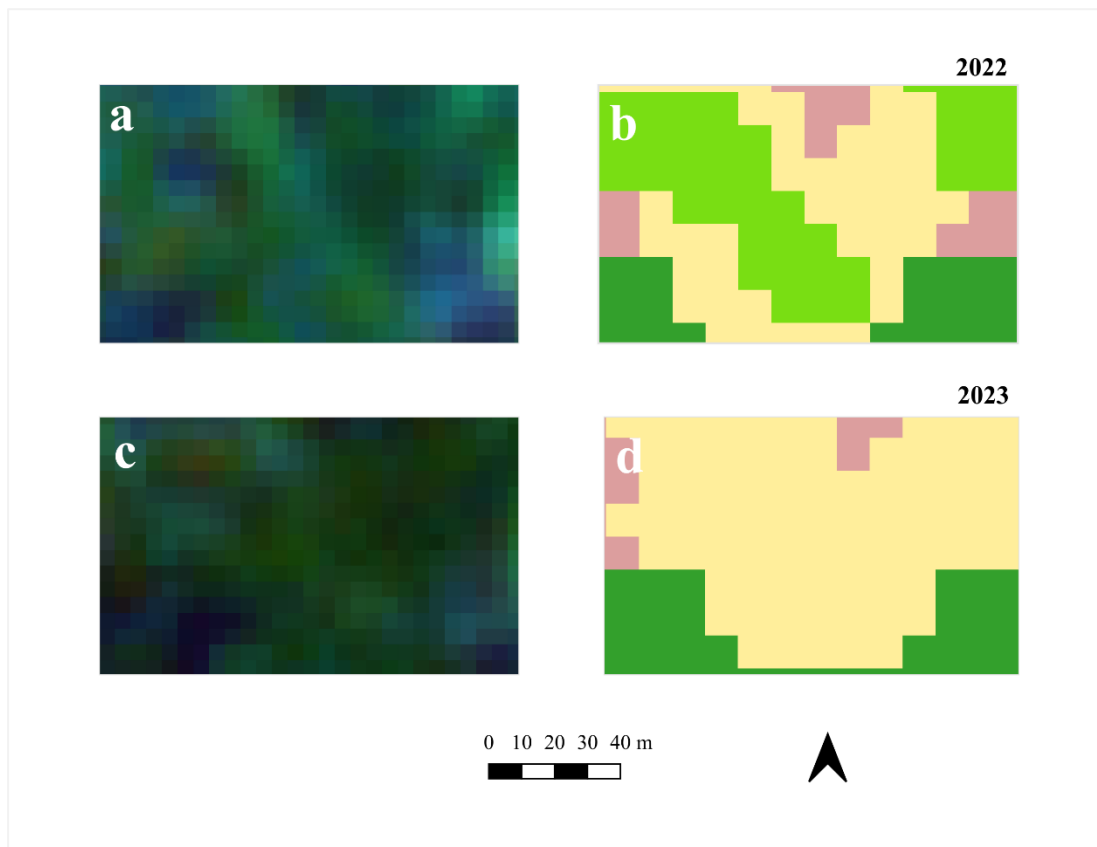
Sentinel 2 NDVI for the Tonton Forest Reserve in 2023



Planet NICFI NDVI for the Tonton Forest Reserve in 2023



Open forest to cocoa between 2022 and 2023



Leveraging Remote Sensing and Machine Learning to Detect Cocoa-Driven Deforestation in Landscape-Specific Contexts

Asare-Ansah Akua Oparebea

Deforestation, the alarming loss of forests, has become a global issue, with millions of hectares of forest lost each year, which has implications for ecosystems, biodiversity, and climate change. Ghana contributes to the global deforestation rates mainly due to cocoa expansion, mining activities, urbanization, logging and others like them. Cocoa expansion is on the rise due to the economic benefits farmers derive from it, as a result it is driving the loss of forests which thrive well in the same landscape. The European Union Deforestation Regulation aims to reduce the rate of cocoa-driven deforestation by ensuring that farmers are able to prove that their cocoa pods are not from a deforested area.

This study aims to evaluate the performance of remote sensing approaches and machine learning techniques in detecting cocoa-driven deforestation in landscape-specific contexts in Ghana. It compares Sentinel 2, Planet NICFI and a Pan-Sharpended Sentinel 2 image to understand which best maps the landscape. It also looks into a change detection analysis to identify patterns of cocoa-driven deforestation. Based on the best model for LULC mapping of the landscape, it is evaluated in a different area to evaluate its performance.

The overall accuracy of the Pan-sharpened Sentinel 2 image was 96.5%. This was selected as the best in mapping the cocoa-forest mosaic landscape. There were 431.77 ha of open forests that have been converted to cocoa between 2022 and 2023. The overall accuracy of the model when tested in a different landscape was 88.5%. This approach is efficient in detecting cocoa-driven deforestation in Ghana.

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