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Author(s)	ANAK SUAB, Stanley
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by

STANLEY ANAK SUAB

B.A. Social Sciences (Hons.) Geography, Universiti Malaysia Sabah
M.Sc., Global Environmental Management (GEM), Hokkaido University

APPROVED BY SUPERVISORY COMMITTEE

Chairperson: Assoc. Prof. Dr. Ram AVTAR

Committee members:

1. Prof. Teiji Watanabe
2. Prof. Shiro Tsuyuzaki
3. Dr. Alexius Korom (UiTM, Malaysia)

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Abstract

Tropical forests, including those in Borneo, play a crucial role in global hydrological, biochemical, and energy cycles, and they are home to high biodiversity. Monitoring and managing these forests are of global significance. Borneo, the world's third largest island shared by five Kalimantan provinces of Indonesia, the States of Sabah and Sarawak of Malaysia and Negara Brunei Darussalam is famous for its rich tropical flora and fauna. The tropical forests in Borneo are essential for maintaining biodiversity, mitigating global climate change and supporting local livelihoods. However, Borneo has experienced deforestation due to past industrial-scale and illegal logging that resulted in degraded forests. Since then, the degraded and remaining forest has been converted to oil palm, industrial forest, rubber plantations and other types of agriculture. The ideal tropical climate facilitates the high productivity and fast growth of forests and plantations. Industrial Forest plantations have progressed over three decades in Borneo. Indonesia and Malaysia are the primary producers, which account for approximately 50% and 30% of global palm oil production. A recent study showed deforestation has been slowing down since 2012, which is attributed by a combination of factors like low crude oil palm prices, improved fire prevention measures, wetter conditions and government policies. Oil palm is a perennial crop with over 25 years of productive life cycle, has a low land footprint compared to other global vegetable oil productions, and is potentially sustainable if well managed. Meanwhile, Industrial Tree Plantations (ITP) can produce a consistent supply of timber compared to logging of natural forests.

However, sustainable management practices of both tropical forests and plantations are needed to balance them and ensure sustainable and progressive socio-economic growth in the region of Borneo. A sustainably well-managed tropical forest and plantations will also help address the implementation of the United Nations Sustainable Development Goals (SDGs) and Reduction of Emissions from Deforestation and Forest Degradation Plus (REDD+). Sustainable forests and plantations in Borneo face numerous challenges due to factors such as LULC changes, deforestation, unsustainable use and management practices. To address these challenges, the application of advanced geospatial and remote sensing technologies holds immense potential. Geospatial and remote sensing techniques are important in mapping, monitoring, assessment, estimation, planning and decision support for sustainable tropical forest and plantation management. Up-to-date geospatial information is needed to accurately monitor, and address issues related to the sustainable management of forests and plantations in Borneo, especially at local scale. Applying multi-sensor remote sensing techniques can obtain comprehensive specific, relevant and reliable information for appropriate, effective management decisions. For this purpose, this research is specifically designed to explore the potential of advanced multi-sensor remote sensing techniques for sustainable tropical forest and plantation management.

The initial study was conducted to analyse the dynamic changes in multi-temporal LULC of the forest and plantations mainly focus on identifying primary sources or drivers of the land cover conversion. The years 2010, 2017, 2019, and 2023 LULC maps were produced using multi-sensor technique and machine learning achieved overall accuracies of 81% (2010), 88% (2017), 77% (2019), and 87% (2023), respectively. Detailed 14 LULC classes were: forest, mangrove, acacia, oil palm, secondary forest, eucalyptus, infrastructures, soil clearcut, rubber,

aquaculture, nipah, beach sand including cloud and shadows covered areas were mapped at resolutions of 10 meters. LULC change analyses were conducted for the year 2010-2017, 2017-2019, 2019-2023 and 2010-2023. The results indicate that between 2010 and 2017, the majority of LULC classes increased, except *Acacia*, which decreased by -5,258.30 ha or -3.22% per year, and secondary forest, which decreased by -1,963.28 ha or -2.61% per year. During this period, 2,666.38 ha (1.13%) of the forest was converted to oil palm, followed by 779.21 ha (0.33%) of secondary forest. Additionally, 373.50 ha (0.16%) of soil clearcut area was converted, along with 52.64 ha (0.02%) of forest. Between 2017 and 2019, most LULC classes decreased, with forest cover increasing by 184.57 ha at a rate of 0.24 ha/year or 0.00%. Between 2019 and 2023, the majority of LULC classes decreased, with forest cover decreasing by -1,301.56 ha, while mangrove increased by 1,321.58 ha at a rate of 0.01% per year, and *Acacia* decreased by -2,653.02 ha at a rate of -0.03% per year. Oil palm increased by 1,111.99 ha. Between 2010 and 2017, 2,666.38 ha (1.13%) of forest was converted to oil palm, followed by 779.21 ha (0.33%) of secondary forest. Rubber plantations showed that between 2010 and 2017, 373.50 ha (0.16%) of soil clearcut area was converted, followed by 52.64 ha (0.02%) of forest. Conversions to aquaculture showed that between 2010 and 2017, most areas were converted from mangrove (261.31 ha or 0.11%) and *Acacia* (251.67 ha or 0.11%). From 2019-2023, 2,428.56 ha (1.03%) of *Acacia* was replaced by *Eucalyptus*. The study demonstrated the LULC changes throughout the observation year and helped to understand the dynamics of the multi-temporal changes.

The second study was on the assessment of forests outside plantations. Random field sampling of a size 15x15m plot was designed for four sites: Bawing in the northwest, Mangkapon in the south east, Maringan in the north east and Telaga in the southwest side. A total of 73 plots were established and a total of 2,333 individual trees were recorded. All sites were dominated by many *Acacia mangium* except for Mangkapon, which was predominantly secondary forest. In the field, Maringan was noted to have the highest number of mangrove trees with dense spacing. The analysis includes stand density, basal area, volume, Above Ground Biomass (AGB) estimation, carbon stock estimation, and carbon dioxide (CO₂) to estimate the equivalent amount of carbon dioxide. Results show *Acacia* and secondary forest mostly have young trees with smaller DBH 7-25cm, height 7-12m, high stand density per ha and average AGB/ha between 56-79 t/ha. Oil palm is also young aged around 3 years old and have a height of 5m. Mangrove stands are very dense, with 2,266 trees/ha high in AGB 309t/ha, and carbon stock is estimated at 145 tC/ha. The observed average density of *Acacia mangium* stands (679/ha) implies a probable stand age between 7-11 years. The average CO₂ of mangroves in the study area is estimated at 533.39 t/ha. Oil palms in the study area is at 3 years old with a stand density of 112/ha with a basal area of 58m²/ha, a volume only 163m³/ha, AGB of 18.5 t/ha, carbon 8.68 tC/ha and CO₂ of 31.84 t/ha. On the other hand, for Secondary forest, the stand density is 780/ha, basal of 193 m²/ha., volume of 1,753 m³/ha, AGB 56.92 t/ha, carbon 26.75 tC/ha, and CO₂ of 98.09 t/ha. This study presented the assessment of the status of forests outside plantations. Which significantly contributes to mitigating climate change by sequestering atmospheric carbon dioxide. These forests can be utilised for carbon storage and sink and must be sustainably managed.

The third study was on canopy height estimations of tropical forests and plantations, providing helpful information on the conditions and growth essential to sustainable management. The

study explored the potential of estimation models and TDX InSAR acquisitions for estimating and mapping tropical forest and plantation canopy heights in Northern Sabah, Malaysian Borneo. InSAR-based coherence data was used and the method of (the SINC) model and two machine learning (ML) models of Random Forest (RF), Symbolic Regression (SR), and corresponding LULC also multi-sensor references dataset for the estimations. 70% of the ICESat-2 ATL08 data was used to train the ML models and the remaining 30% was used for the validation. The RF and SR models' out-of-bag (OOB) RMSE was 5.4 m and 5.96 m, respectively. Validation against the reference dataset resulted in RMSE of 6.06 m for the 2011 SR best model, 10.36 m for the 2017 SR, and 7.58 m for the 2019 RF best model. The overall accuracies of LULC maps are 86%, 91%, and 83%, respectively, for years 2010, 2017, and 2019. The accuracies by LULC class were 3.92 m for the 2011 Mangrove RF best model, 6.11 m for the 2017 Mangrove SR, and 4.35 m for the 2019 Rubber RF. We also validated the results by LULC using field inventory data for 2011 and 2019 which showed RMSEs between 4.06m to 7.74m with SR as the best model. In terms of canopy height classes and spatial distributions by LULC, we observed non-uniform variations for all 2011 model results, with the SINC model overestimated. The 2017 and 2019 height patterns showed a slight increase in all forest and plantation LULC canopy heights from 10-15 m to 15-20 m height classes. The results highlight the potential of InSAR-based tropical forest and plantation canopy height estimations useful for sustainable management.

The fourth study was on environmental sustainability assessment (SA) using multi-sensor remote sensing and the Multi Criteria Decision Analysis (MCDA) model. SA is useful for forests and plantations in Borneo due to the importance of environmental protection through identification and mitigation. Five sustainability indicator layers, namely slope and soil protection, riparian buffer reserve, landscape connectivity and quality, high conservation value (HCV), and water turbidity, were developed from the LULC layers combining standards from the Environment Protection Department (EPD), Roundtable on Sustainable Palm Oil (RSPO) and Forest Management Plan (FMP). The result shows that, overall, 61% of the study area is in the high sustainability category, 31% in the medium category, and 8% in the low category. While breakdown by the five designated land use boundaries shows ITP: 49% high, 46% medium and 5% low. Forest reserve boundary: 29% high, 45% medium, and 26% low. Village boundary: 72% high, 13% Medium and 14% low. Oil palm plantations: 5% high, 81% medium and 14% low. Rubber plantations: 9% high, 77% medium and 14% low. Both oil palm and rubber plantations are mostly in the medium class due to the monocropping land use type, which is also shown as low in the landscape connectivity and quality of individual sustainability indicator layers. The study presented the concept of using multi-sensor remote sensing for LULC mapping with geospatial MCDA for environmental sustainability assessment.

Overall, the study's results, methodology and findings presented in this research using multi-sensor remote sensing technique would be useful for sustainable management of tropical forests and plantations in Borneo and other tropical regions.

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Stan.

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Stanley Anak Suab

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Abbreviations & Symbols

Abbreviations	Definitions
AGB	Above Ground Biomass
ALOS (AVNIR-2)	Advanced Long Observing Satellite (Advanced Visible and Near Infrared Radiometer type 2)
CHM	Canopy Height Model
CoSSC	Co-registered Single look Slant range Complex
DLR	German Aerospace Center/Deutsches Zentrum für Luft- und Raumfahrt e.V.
EVI	Enhanced Vegetation Index
FSC	Forest Stewardship Council
FVC	Fractional Vegetation Cover
GAO/CAO	Global Airborne Observatory/Carnegie Airborne Observatory
GEE	Google Earth Engine
ICESat-2 ATLAS	Ice, Cloud, and land Elevation Satellite 2
IfSAR/InSAR	Interferometric Synthetic Aperture Radar
ITP	Industrial Tree Plantations
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
LPDAAC	NASA Land Processes Distributed Active Archive Center
LULC	Land Use Land Cover
MCDA	Multi-criteria Decision Analysis
ML	Machine Learning
NASA GEDI	National Aeronautics and Space Administration Global Ecosystem Dynamics Investigation
NDVI	Normalized difference vegetation index
NDWI	Normalized difference water index
OOB	Out of Bag
RF	Random Forest
RSPO	Roundtable on Sustainable Palm Oil
RVoG	Random Volume over Ground
SAR	Synthetic Aperture Radar
SR	Symbolic Regression
SRTM	Shuttle Radar Topography Mission
TanDEM-X/TDX	TerraSAR-X add-on for Digital Elevation Measurement

1. Introduction

1.1. Background

1.1.1. Forest and plantation from global perspective.

The tropical forests are located around the equatorial regions such as the Amazons in south America, the Congo basin in central Africa, Indo-Malayan in Asia, and the Australasian regions ([Hartshorn, 2001](#)). Tropical forests including those in Borneo are ecologically unique and play a crucial role in global hydrological and climate regulation, biochemical processes, carbon cycling, and energy flows. They are home to more than 50% of the planet's biodiversity and store around a quarter of the world's terrestrial carbon reserve ([Ahlheim et al., 2015](#); [Funk et al., 2019](#); [Reed et al., 2020](#); [Velasategui-Montoya et al., 2022](#)). Over time, these tropical forests have undergone significant changes, with deforestation being a major threat. The conversion of tropical forests into other land uses, such as subsistence farming, cattle ranches, farms, industrial agriculture crops, and oil palm plantations has been a major trend ([Carlson & Garrett, 2018](#)). The driving factors behind these land use changes include demographic expansion, with consequent booming demands for agricultural land, nations economic growth and development, and the shift towards market-oriented economies ([Drigo, 2005](#)). These changes in land use have led to substantial impacts on biodiversity, global carbon cycle, and climate change. Monitoring and managing these forests are of global significance ([Loh et al., 2022](#)). In this research, the focus is narrowed down to Borneo Island with focus case studies on the Northern of Borneo.

1.1.2. Forest and plantations in Borneo.

Borneo, the World's third largest Island (748,168 sqkm), is best known for its most biodiverse and carbon-rich tropical forests ([Vaughan, 2020](#)). Borneo is shared by the states of Sabah and Sarawak, Malaysia (26.7%), Negara Brunei Darussalam (0.6%), and West Central, South-North, and East, Kalimantan provinces of Indonesia (72.6%) ([Paramitha, 2016](#)). The Island is located in Southeast Asia and is significant in the context of global biodiversity, climate regulation and its role as a carbon-sink/storage ([Labrière et al., 2015](#)). The tropical forests in Borneo are important for maintaining biodiversity, mitigating climate change, and supporting local livelihoods. However, large-scale industrial and illegal logging in the past had slowly depleted Borneo's forest ([Carlson et al., 2013](#); [Gaveau et al., 2014](#)), and eventually, the conversion of natural forests to Oil palm, Industrial forest plantations and other forms of agriculture is the major drivers of deforestation ([Gaveau et al., 2016](#); [Mori, 2023](#)). Increasing

global demand for food, energy, and other industrial raw materials correspondingly increases the demand for Oil palm by 7% per year (Purnomo *et al.*, 2020). In 2017 Indonesia contributed approximately 50% and Malaysia 30% of global production of Palm oil (Shigetomi *et al.*, 2020; Union, Conservation, & Nature, 2018). Additionally, the ideal tropical climate facilitates the high productivity and fast growth of forests and plantations (Varmola & Carle, 2002). In 2019 the total area of planted Oil palm in Indonesia and Malaysia was 16.3 million hectares and 5.74 million hectares, respectively (Ariesca *et al.*, 2023; Balu *et al.*, 2018).

In the Borneo states of Sabah and Sarawak, Oil palm plantations accounts for 26.6% and 26.8% of the total oil palm planted in Malaysia in 2017. Meanwhile, Industrial Forest plantations have progressed over three decades in the Borneo states of Sabah and Sarawak which mainly include *Acacia mangium* species. In 2018, the total forest plantation area was documented as 300,521 ha in Sabah and 403,017 ha in Sarawak (Lee, 2018). The first commercial *Acacia mangium* plantation in Sabah was in 1976 where it was introduced for reforestation of grassland and poor soils and degraded lands by shifting cultivation (Lee, 2018; Udarbe & Hepburn, 1986), especially in the study area. In contrast, Sarawak only started large-scale forest plantations in the late 1990s following the amendments of forest Ordinance 1996 and the adoption of planted forest rules 1997 (Lee, 2018).

Early *Acacia* plantations were initially free from pests and diseases; however, before 2010, termites and root-rot disease were identified as affecting second-rotation *Acacia mangium* in Indonesia, Vietnam, and Malaysia (Lee, 2018). Ceratocystis wilt emerged as a new threat to *Acacia mangium* plantations in southeast Asia first reported in Riau Province in 2010 (Tarigan *et al.*, 2011). The same diseases then also reported in Vietnam and Malaysia were first reported in eastern Sabah in 2011 and Sarawak first observed in late 2011 (Lee, 2018; Maid *et al.*, 2018). By 2014, the *Acacia* plantations in Sabah have been severely impacted by diseases (Maid & Ratnam, 2014). The widespread disease affecting forest plantations involving *Acacia mangium* has subsequently led to significant reductions in production. For instance, the total export volume for Sarawak decreased from 1.1 million m³ in 2017 to 699,154 m³ in 2018 and further declined to 413,806 m³ in 2020 (STIDC, 2022). Since 2018, many forest plantations in southeast Asia, such as in Indonesia and Sabah, have switched to *Eucalyptus pellita* (Lee, 2018). On the other hand, Oil palm plantations also face many challenges, including increased incidence of new and existing pests/diseases and the risk of climate change, such as rainfall

patterns and downstream issues related to supply chains and market sentiment (Murphy *et al.*, 2021).

Forest area in Borneo declined by 14% (6.04M ha) and converted into mainly industrial forests and Oil palm plantations between 2001 and 2017. However, plantation expansion-related forest conversion in Borneo has slowed since 2012 (Gaveau *et al.*, 2019). This is attributed to a combination of factors including low crude palm oil price, improved fire prevention measures, wetter conditions, and government policies (Gaveau *et al.*, 2019). In 2011, the Indonesian government instituted a nationwide moratorium on issuing new permits for the use of primary forests, which was extended in 2018, indicating commitment to forest conservation (UNEP, 2019). In Sabah and Sarawak, Malaysian Borneo, the governments of both states have established laws and regulations aimed at protecting and managing forests sustainably as well as sustainable plantations (Keeton-Olsen, 2021). Sabah is one of the first states in the world to adopt the Roundtable for Sustainable Palm Oil (RSPO) jurisdiction approach for Oil Palm plantations (Ng *et al.*, 2022).

Moreover, non-governmental organisations are also working on promoting certification such as Forest Stewardship Council (FSC) for wood and timber products which allows responsible harvesting in addition to protecting local community rights and wildlife habitat. Also, such organizations help to promote responsible oil palm plantation development in Borneo on degraded lands through RSPO and urge international companies to buy only sustainably produced palm oil (Walker, 2013). Despite the positive trend, ongoing monitoring and effective management strategies are needed to ensure the sustainable future of Borneo's tropical forest and plantation landscape (UNEP, 2019).

1.1.3. Importance and challenges of sustainable tropical forest and plantations management in Borneo

The rising global demand for forest products underscores the significance of plantations due to a higher wood-production rate than natural forests. Hence, poorly managed logging of forests degrades the respective ecosystems and leaves them susceptible to further damage (Pipa & Doug, 2014). On the other hand, oil palm is a perennial crop with over 25 years productive life cycle with a low land footprint as compared to other vegetable oil productions globally potentially be sustainable if well managed (Murphy *et al.*, 2021). However, sustainable management practice of both tropical forests and plantations is needed to ensure sustainable

and progressive socio-economic growth in the region of Borneo. A sustainably well managed tropical forest and plantations help to implement the United Nations Sustainable Development Goals (SDGs) 1, 2, 3, 4, 8, 10, 13 & 15 which in turn benefits the locals and the environment.

In addition, sustainable forest management is an important element of REDD+ because of its multiple roles in commercial timber supply, job generation, biodiversity conservation, and reductions in carbon emissions from forest degradation (Bayrak & Marafa, 2016; Sasaki *et al.*, 2016). Sustainable tropical forest and plantation management in Borneo faces several challenges among those highlighted by (Alamgir *et al.*, 2020; Laurance, 2016) are; better governance, improved land use planning and empowerment of local communities to manage their forest resources. Given the importance and challenges, there is a pressing need for sustainable management of Borneo's tropical forests and plantation landscapes this to help conserve biodiversity, maintain ecological processes, and support the livelihood of local communities also contributes to climate change mitigation by reducing carbon emissions from deforestation and forest degradations.

1.1.4. The role and importance of Geospatial and Remote Sensing techniques in sustainable tropical forest and plantations management in Borneo

The tropical forests and plantations in Borneo face numerous challenges due to factors such as land use and land cover (LULC) changes, deforestation, and unsustainable use and management practices. To address these challenges, the application of advanced geospatial technologies holds immense potential. Geospatial techniques play an important role in several key ways such as mapping, monitoring, assessment, estimation, planning and decision support for sustainable tropical forest and plantation management. Previous study Pfeifer *et al.*, (2016) highlighted remote sensing imagery can be used to map Borneo's degradation of forests based on biophysical attributes. The study found significant relationships between field-measured structure and satellite-derived spectral and texture information which can explain 62% variation in biophysical structures across forest and oil palm plantations in the Stability of Altered Forest Ecosystem (SAFE) project site in east of Sabah. The utilization of geospatial techniques can help in the LULC changes monitoring particularly deforestation and expansion as shown in a previous study Curran *et al.*, (2004). They studied lowland forest in Kalimantan where they found that cumulative loss in the buffer zones led to isolated protected forests. Additionally, remote sensing-derived information can be used to verify ecological conditions and guide sustainable practices (Aguma & Hussin, 2009).

Multi-sensor remote sensing techniques shall enable comprehensive and precise monitoring, offering insights crucial for informed decision-making and sustainable resource management. Remote sensing and geospatial techniques can provide a cost-effective way of large-scale environmental monitoring and assessment in tropical forests and plantations. [Loh et al., \(2022\)](#), combine existing SRTM and multi-temporal airborne LiDAR data to estimate AGB changes between 2012 and 2017 of degraded and intact forest in Ulu Padas in Sabah. Accurate AGB estimations in forests are vital carbon stocks indicators for monitoring and managing carbon emissions and sequestrations. Multi-sensor data fusion of optical and SAR-derived indices can help to discriminate between native tropical forests, oil palm and rubber, plantations at higher accuracy (>80%) as demonstrated in a study done in Kalimantan utilising Landsat-8 Operational Land Imager (OLI) and Sentinel-1 ([Sari et al., 2021](#)).

Another study utilised L-band ALOS-2 PALSAR-2, C-band Sentinel-1, and Landsat-8 OLI optical to map the extent of Oil palm and rubber plantations at regional scale in west Kalimantan and Myanmar with very high overall accuracies of 96% and 98% respectively ([Torbick et al., 2016](#)). Multi-sensor remote sensing techniques can be used to monitor forest degradation, selective logging and forest fires which in return are useful guiding protect the logged forests from further degradation ([Gao et al., 2020](#); [Jackson & Adam, 2020](#)). Multi-sensor remote sensing techniques can provide relevant, timely and accurate information to monitor status of oil palm plantation monitoring of status and the progress of oil palm development ([Chong et al., 2017](#); [Mohd Najib et al., 2020](#); [Pohl, 2014](#)).

1.2. Problem and significance of the research

The unavailability of up-to-date geospatial information causes difficulty in accurately monitoring and assessing the state and health for sustainable management of forests and plantations in Borneo especially at local scale such as in the study area. Previous studies by [Asner et al., \(2021\)](#); [Hadi et al., \(2018\)](#); [Langer et al., \(2007\)](#) revealed that medium spatial resolution satellite data (25-30m) was effectively used to map and monitor larger areas. A study by [Tian et al., \(2020\)](#) on vegetation phenology found that satellite imagery with coarser spatial resolution has more mixed pixels while suggesting the use of finer than 30m reduces uncertainties. Integrating data from multiple sensors or sources can be utilised to obtain comprehensive, specific, relevant, and reliable information for appropriate and effective management decisions. Studying at a local scale can help to understand the impacts of regional and global issues such as climate change, economic factors, pests, and diseases related to forests and plantations locally thus, help develop strategies to mitigate.

Furthermore, if local sustainable forest and plantation management is not properly addressed may result in the loss of local unique biodiversity, exacerbate global carbon emission and negative impacts on local socio-economic livelihood. This research will help address issues and challenges unique to the Borneo region which includes factors such as diverse forest types and land uses. Also contribute to the development methods and strategies that allow for good resource management practices in minimizing negative environmental impacts from plantation land uses. The outputs of this research will provide policymakers and stakeholders with science-based information to make informed decisions regarding forest and plantation management in Borneo. The research develops methodologies that leverage multi-sensor remote sensing techniques to address the challenges and promote sustainable forest and plantation management practices in the Borneo region.

1.3. Research questions

The research questions are as the followings:

- How can multi-sensor remote sensing technique be used to map and monitor spatio-temporal changes also identification of tropical forest conversion into plantations LULC?
- What is the status and potential of forests outside plantations and managed forests in the study area?
- How can multi-sensor remote sensing techniques (InSAR, LiDAR, Optical & other data) be effectively employed to map and monitor the canopy height (structure) of tropical forests and plantations in the study area?
- How does integration of data from different sources and multi-sensor remote sensing data be used to assess the environmental sustainability of tropical forest and plantation landscape?
- What are the challenges and opportunities in applying this technique to a temporally dynamic tropical forest and plantation landscape in the study area?

1.4. Research aims and objectives

This research endeavours to delve into the systematic monitoring of Borneo's tropical forests and plantations through the integration of multi-sensor remote sensing and geospatial techniques. The primary aim of this research is to explore the potential of advanced multi-sensor remote sensing techniques for sustainable tropical forest and plantations management. The specific objectives are:

1. Multi-temporal LULC changes monitoring: Mapping and assessing the LULC changes of forest conversion to plantation.
2. Status of forest outside managed forest and plantations: A ground survey assessment of Aboveground Biomass (AGB) and Carbon estimation on the status & conditions of forest outside plantations.
3. Structural study of the forest and plantation: To map and estimate forest and plantations canopy height estimations using TanDEM-X InSAR and multi-sensor technique.
4. Sustainability assessment: To assess the environmental sustainability of the study area using a multi-sensor remote sensing technique and Multi Criteria Decision Analysis (MCDA) model.

1.5. Thesis outline

This Thesis consists of seven chapters: Chapter 1 is on general introduction to the background of this research and the framework. Chapter 2 overviews the study area and overall methodology. Chapter 3 monitors LULC changes using multi-sensor techniques investigating the conversion of forests into plantations. Chapter 4 study on Above Ground Biomass (AGB) and carbon estimation in the mangroves, *Acacia mangium*, oil palm and secondary forest outside the plantations based on ground survey. Chapter 5 explores the potential of TDX InSAR and Multi-sensor for structural studies of the forest and plantations. Chapter 6 study on the environmental sustainability assessment using the multi-sensor technique and geospatial Multi Criteria Decision Analysis (MCDA) model. Chapter 7 concludes the findings of this research also, the challenges and future opportunities in sustainable tropical forest and plantations management research. The outline structure of this Thesis is as described in Figure 1.1.

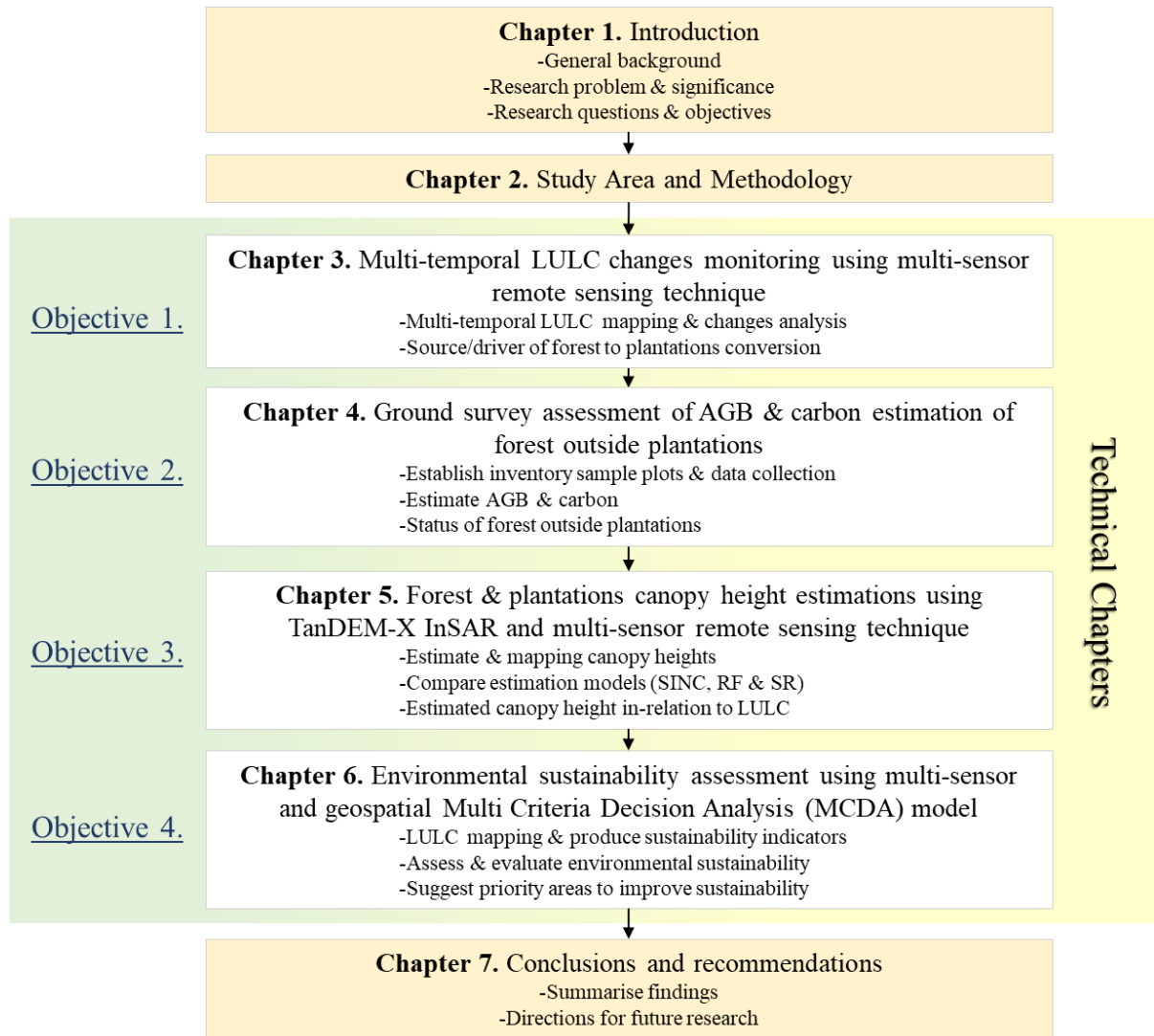


Figure 1.1. A synoptic view of Thesis structure including main chapters and its objectives.

2. Study area and methodology

This chapter provides an overview of the study area and research methodology employed regarding the technical chapters (3, 4, 5 & 6) of this thesis.

2.1. Study area

The study site (Fig. 2.1) is located in the northern part of Sabah, Malaysia encompassing the Bengkoka Peninsula, Banggi Island, and Malawali Island (Fig. 2.1b). Area of interest spans from approximately between latitude $6^{\circ} 44' 2.23''$ N to $7^{\circ} 19' 19.53''$ N and longitude $116^{\circ} 58' 37.59''$ E to $117^{\circ} 22' 34.98''$ E. The terrain varies from coastal plains to undulating and hilly areas with some steep slopes. Elevation ranges from sea level up to approximately 221 meters at the center of the study area. The primary geological formation is the Bogaya formation, primarily composed of sandstone and mudstone (Felix, 1991). The climate is tropical with average mean surface temperatures consistently around 26.9°C to 28.5°C , and high mean annual precipitation of 3,085 mm per year (World Bank Group & Asian Development Bank, 2021).

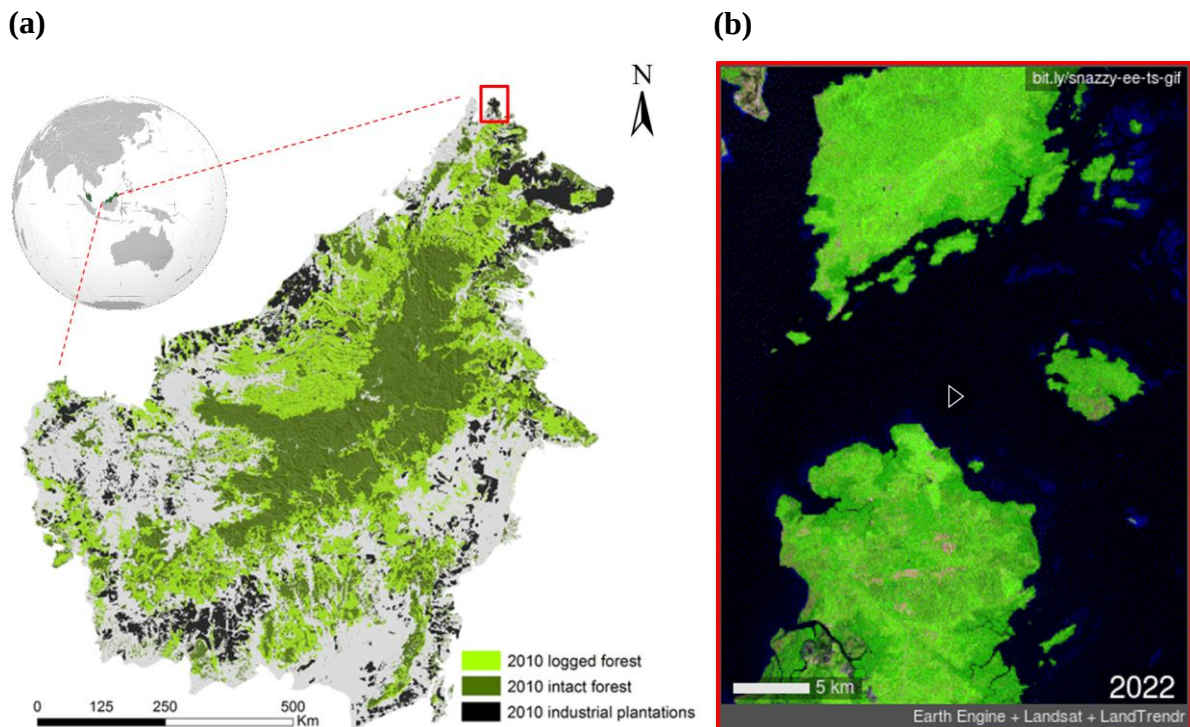


Figure 2.1. (a) Location of Borneo relative to Southeast Asia with study area in red box. Borneo timelapse map adapted from (Gaveau *et al.*, 2014). (b) Study Area of Interest (AOI) from LandTrendr powered by Earth Engine.

The Land Use and Land Cover (LULC) include mangrove forests, nipah mangroves, mixed forests with small-holder rubber plantations and crop patches, orchards, secondary growth forests, Industrial Tree Plantations (ITP), predominantly fast-growing *Acacia mangium*, wild *Acacia*, Oil palm plantations, rubber plantations and villages. The ITPs were established in the early 1980s as part of a reforestation, afforestation and resettlement initiative led by the Sabah Government in collaboration with the Sabah Forestry Department and supported by the World Bank (JICA, 1984). *Acacia mangium* is the preferred species in ITP due to fast growing, flexibility to grow on poor and degraded soil (Hon & Shibata, 1970). *Acacia* timber are harvestable after 7 years high survival rate 50-60% yield volume between 150 and 170m³ ha⁻¹ (Lee, 2018). In 2002, approximately 72% (106,581 hectares) fast-growing tree species planted in Sabah were *Acacia mangium* (Abe et al., 2005).

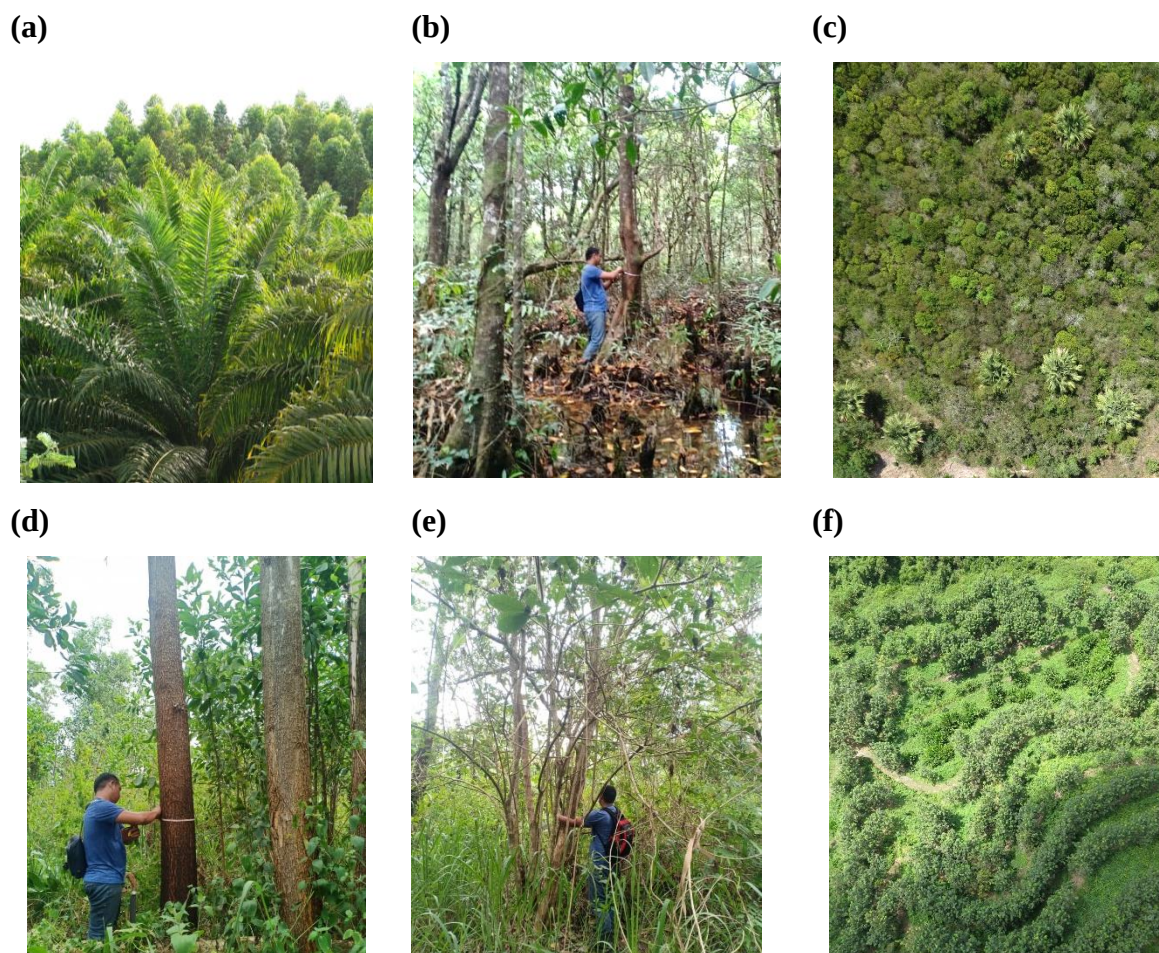


Figure 2.2. LULC in the study area: (a) Oil Palm plantations with ITP in the background, (b) Mangrove forest, (c) Aerial view of mixed forests, (d) Mature *Acacia mangium*, (e) Secondary forest, (f) Aerial view of Rubber plantations.

2.2. Methodology

As introduced in the outline, this Thesis comprises four technical investigations which are presented in chapter 3 to chapter 6. These technical chapters are based on the prior research questions and guided by the specific objectives designed for this thesis.

(Chapter 3) LULC maps were prepared, and multi-temporal LULC changes analysis was done. The investigation was focused on the changes and rate also on what are the sources/drivers of the LULC changes especially forest conversion into plantations.

(Chapter 4) The investigation on forests outside plantations or managed forests where usually underestimated in terms of the potentials and values of Aboveground Biomass (AGB) and Carbon. In this investigation, forest inventory data were collected by establishing random field inventory sample plots. Based on the inventory data, analyses were done to calculate the volume, stand density, AGB, Carbon stock and CO₂ equivalent. The results are used for assessing the forests conditions and identify its potentials.

(Chapter 5) Structural study on the estimation and mapping of forest and plantation canopy height using InSAR combined with multi-sensor remote sensing technique utilizing the TanDEM-X satellite imageries covering the years 2011, 2017 and 2019. Three methods of SINC model and two Machine Learning models (Random Forest & Symbolic Regression) were used and compared in terms of their accuracies based on the reference dataset. Also, LULC maps were produced for the respective years for stratifications of canopy height estimation in forest and plantations LULC classes.

(Chapter 6) Environmental sustainability assessment, LULC map of year 2023 was produced, and five sustainability indicator layers were generated according to standards based on references and standard sustainability as guide. Analysis was done using geospatial MCDA model where sustainability was categorised into low, medium or high. Results highlight the priority areas in the study area of its sustainability status.

The preceding technical chapter three on the LULC mapping and changes analysis, is a crucial prerequisite for the subsequent technical chapters presented in this study. The spatio-temporal LULC maps for the years 2010, 2017 and 2019, in conjunction with the inventory data presented in chapter four combined with TanDEM-X (TDX) data are employed in chapter five for the canopy height estimation. Additionally, the 2023 LULC map is used in chapter six for the environmental sustainability assessment.

3. Multi-temporal land use and land cover change monitoring of tropical forest and plantations landscapes in Borneo using multi-sensor remote sensing technique

3.1. Introduction

The monitoring of Land Use and Land Cover (LULC) represents crucial technical chapters in this thesis, complementing the succeeding chapters of canopy height estimations and environmental sustainability assessment. This chapter investigates the LULC changes within the study area. The transformation of the Earth's land surface due to human activities is globally referred to as LULC change (Hassan *et al.*, 2016). LULC changes reflect the anthropogenic forcing behaviours on Earth's surface also is the main contributor to global climate change as well as one of the influential environmental issues for worldwide considerations (Gogoi *et al.*, 2019; Hao *et al.*, 2021). Monitoring LULC changes in tropical forest and plantation landscapes, especially in Borneo is essential because it represents critical ecological and economic resources at both regional also to global. Previous studies Pongratz *et al.*, (2021); Sari *et al.*, (2023); Taiwo *et al.*, (2023) demonstrated that changes in the tropical and plantations LULC affect global climate change. Tropical forest coverage and distributions in Borneo are important to regional scale and global environmental ecosystem services, vegetation, and biodiversity (Boul *et al.*, 2022). Economic prosperity has impacted land use activities such as the conversion of forests into agricultural land or urbanization causing fast change decrease in forest cover (Seyam *et al.*, 2023; Velastegui-Montoya *et al.*, 2022).

Monitoring LULC is important for guiding the sustainable management of forests and plantations. In recent years there has been growing recognition in the importance of addressing deforestation and degradation in the plantation's supply chain (in the study area: timber, oil palm & rubber). LULC data play an important role in evaluating landscape state, change, pressures and potential management responses (Abate & Singh, 2011). Government, non-profit organisations and plantations companies are increasingly proactive in addressing the issue of deforestation and forest degradation which in the case of Borneo usually related to plantation expansions in the past (Langer *et al.*, 2007). The technique of geospatial LULC change detection has been extensively employed to identify and describe significant alterations in LULC characteristics using multi-sensor and multi-temporal remotely sensed data.

LULC changes analysis is done to understand the impacts of human activities on the environment, particularly Sabah, where rapid LULC in Borneo has been observed. LULC

changes such as deforestation and conversion of land for plantations and agriculture can significantly affect the local and global climate, biodiversity and ecosystem services. A previous study (Payus *et al.*, 2020) in the Kota Kinabalu district in Sabah showed a dramatic decrease in forest area replaced by agriculture and land clearing between 2014 and 2019 revealed that LULC transformation affects the water resources where the demand mostly for agriculture at 43% and only 0.22% for domestic and industrial use. In Sabah, changes in forest land use and management have been significant over the past decades with commercial timber harvesting and large-scale conversion of natural forests into industrial plantations and agricultural land use prevalent (Reynolds *et al.*, 2011). However, efforts have also been made to protect and restore forests which highlighting the importance of monitoring LULC changes for sustainable management.

Multi-sensor remote sensing technique plays a pivotal role in LULC analysis by providing accurate and comprehensive data on LULC changes (Vivekananda *et al.*, 2021). Combining satellite data from different sensors can enhance the understanding of LULC changes and their impacts. The integration of SAR in the LULC classification process alongside optical data where surface reflectance and vegetation indices of optical and values of backscatter coefficient in different polarizations are combined yields better results in distinguishing specific LULC classes (Prudente *et al.*, 2022). A previous study by Zhou *et al.*, (2018) found that a combination of texture and coherence features from multi-sensor data could achieve overall classification accuracy of up to 91%. The use of multi-sensor data conclusively eliminates the disadvantage of only relying on a single sensor.

Simultaneously literature search was done to acquire information related to LULC about the study area especially the type of LULC and the area sizes as summarised in Table 3.1. This information is important as a reference to the LULC mapping. The LULC information on the study area were on mangrove, *Acacia mangium*, *Eucalyptus pellita*, rubber plantation and aquaculture. There was no information found for Oil palm plantations. The overall aim of this study is to map the LULC changes in the study area by using a multi-sensor remote sensing technique. Meanwhile the specific objectives designed for this study are as follows;

1. To map the temporal LULC of the study area through utilisation of multi-sensor data.
2. To investigate the multi-temporal LULC changes dynamic particularly focusing on forest and plantations LULC.

3. To investigate the sources or drivers of the land conversion of the forest and plantations LULC.

Table 3.1. Recorded land uses areas in the study area.

Forest/Plantations/Land Use type	Place	Area Approx. (ha)	Status	Reference
Mangrove Forest <i>*Including Nipah</i>	Bengkoka Peninsula	13,636 ha	FR Class V	(Tangah <i>et al.</i> , 2015)
Mangrove Forest	Banggi Island	11,504 ha	FR Class V	
Mangrove Forest	Malawali Island	791 ha	FR Class V	
<i>Acacia mangium</i>	Bengkoka Peninsula	3,185 ha	Nov. 2019 Planting record	(GFS, 2019)
Eucalyptus Pelitta	Bengkoka Peninsula	5,311 ha	Nov. 2019 Planting record	
Rubber Plantations	Banggi Island	4,500 ha <i>*Not total area planted</i>	FELCRA Berhad land consolidation and rehabilitation project	(Sulehan & Awang, 2010)
Aquaculture Shrimp including mangrove forest clearing	Bengkoka Peninsula (Kampung Sungai Elo)	900 ha Mangrove cleared	*2022 unofficial report	(Wen, 2022)

3.2. Materials & method

3.2.1. Study area

The study area location is similar to the previous chapters which covers Bengkoka Peninsula, Malawali Island and part of Banggi Island. LULC of the study area mainly composed of mixed native forest, secondary forest, mangroves, plantations such as rubber, oil palm and ITP. Details about the study area also discussed in earlier chapter. Figure 3.1. shows the location of the study area and Area of Interest (AOI) with Sentinel-2 fused with PlanetScope imageries in true colour composites in the background. The satellite imageries were acquired in April 2023.

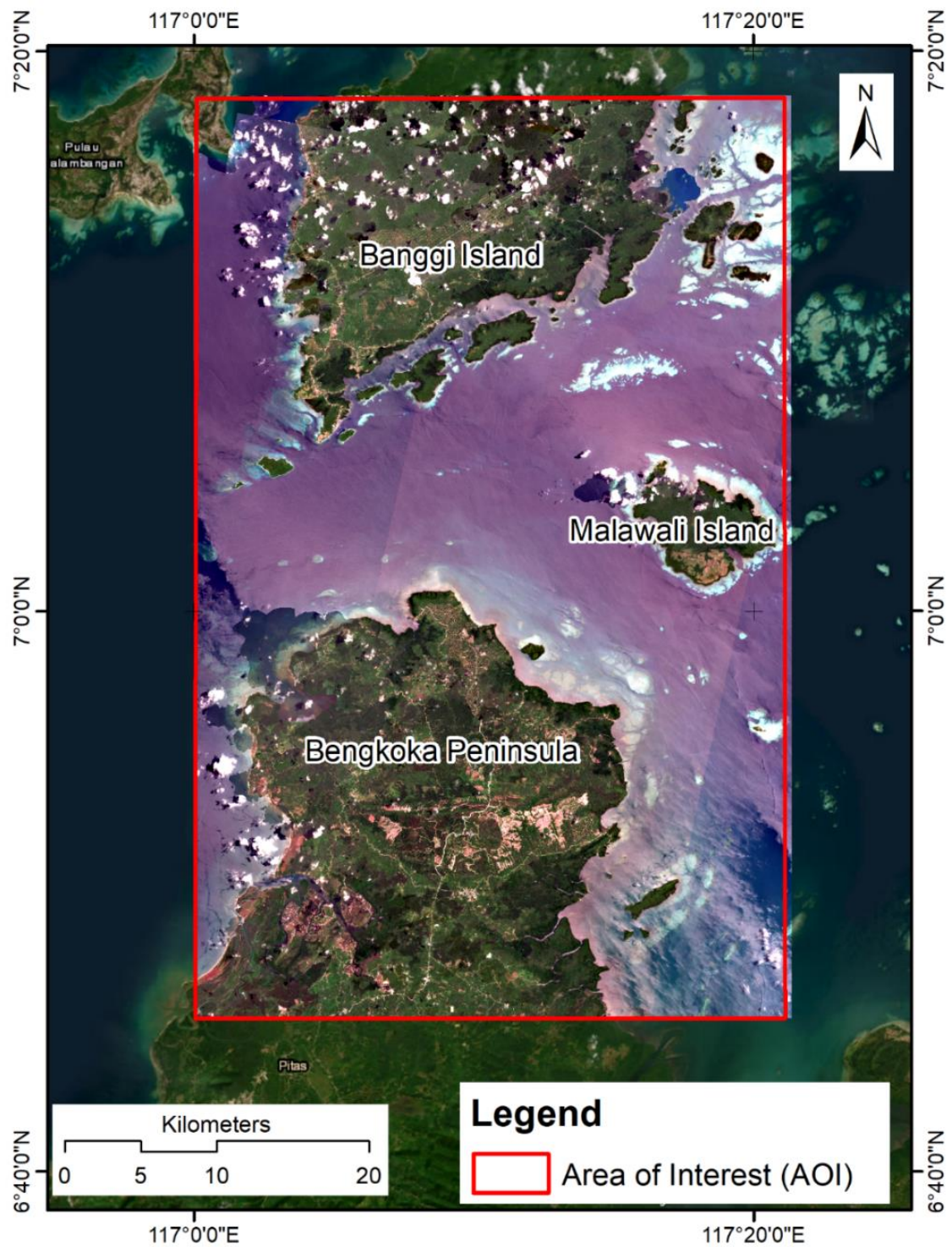


Figure 3.1. Location of the study area of Bengkoka Peninsula, Malawali Island and part of Banggi Island.

3.2.2. Dataset & LULC mapping

A collection of multi-sensor satellite imageries such as used in the next case studies in this thesis were used in this study. The fused satellite imageries cover the year 2010, 2017, 2019 & 2023. All the pre-processing such as sub-setting, radiometric and geometric corrections, data fusion, vegetation indices and LULC sampling are all done in the GEE environment. This initial part of the satellite imagery interpretation is important as distortion correction and cloud shadow removal are necessary (Chuvieco, 2020). The generated LULC maps were post-classification edited, prepared, and analysed using GIS software. The ground truth sampling collected used in chapters 3, 4 and 6 case studies together with point samples collected from high-resolution Google Earth and PlanetScope was used in the accuracy assessment. For the analysis of the changes, the LULC maps were compared by year pairs. Changes extent, rate, directions of changes and unchanged areas were the results of the analyses. The methodology of this study is illustrated in Figure 3.2. while the LULC classes are summarised in Table 3.2.

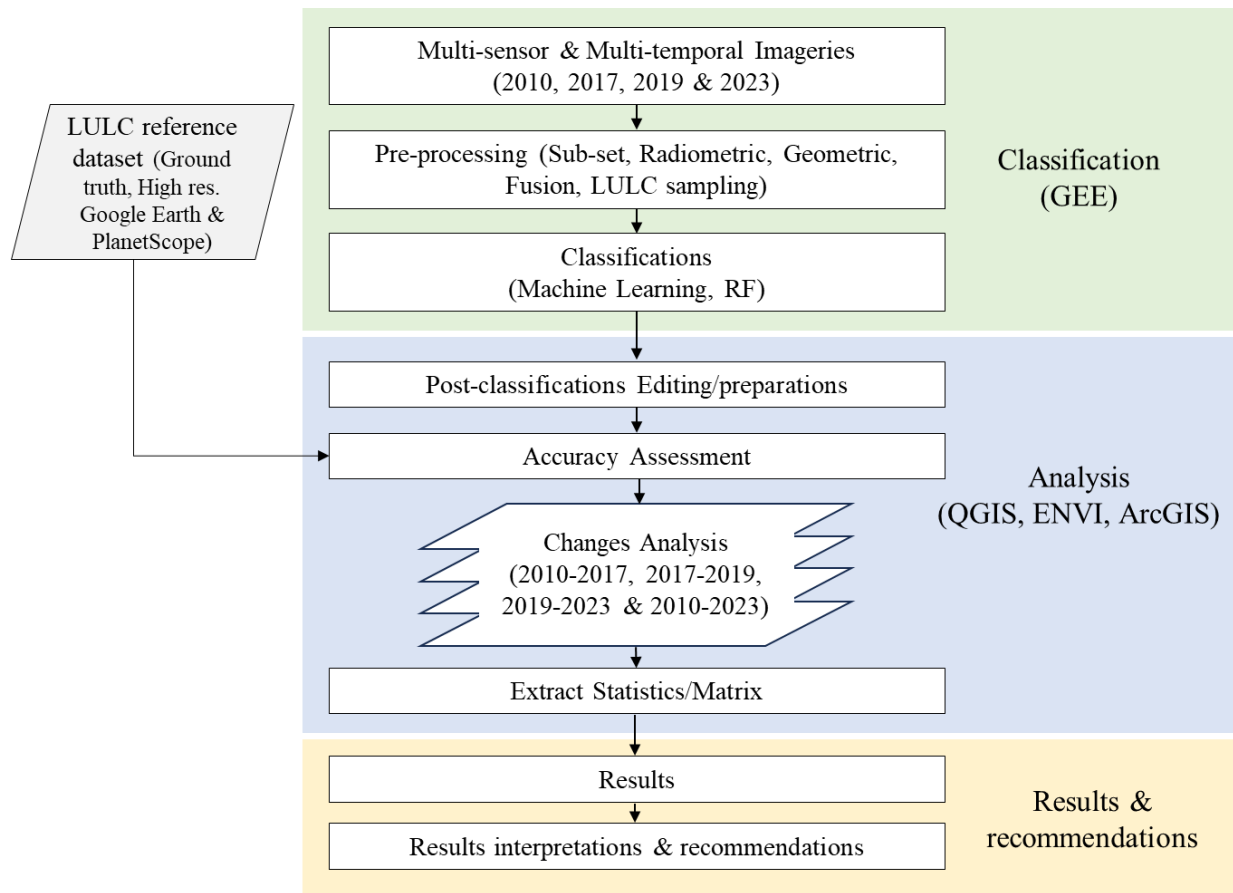


Figure 3.2. Methodology of this study.

Table 3.2. LULC classes summary.

LUC Classes	Definitions/Descriptions
1. Forest	Patches of natural forest of mixed tropical tree species. May include scattered matured small-holder rubber plantations, fruit orchards, and other small-holder farms.
2. Mangrove Forest	Includes all types of Mangrove species and all three mangrove zones in Sabah; seaward/riverine margins, main mangrove and back mangrove.
3. <i>Acacia mangium</i>	Acacia plantations also including wild Acacia forests.
4. Oil palm Plantations	Consist of Industrial & Small-holders plantation areas. Very distinguishable area boundaries, uniform crown shape, planting rows, and canopy textures of Oil palms.
5. Secondary forest	Secondary forest regrowth and regeneration. May includes replanted forest areas and small to medium woody shrubs, bushes and shifting cultivation by villagers.
6. Eucalyptus Pellita (EP)	E. Pellita replacing <i>Acacia M.</i> inside the ITP planted since 2019.
7. Infrastructures	Include all types of buildup such as; roads (paved, dirt roads, logging roads & gravel), public buildings such as Halls, Clinics, Shop-lots, Schools, village private houses etc.
8. Soil/Clearcut	Exposed soil areas result of clearing for plantations or agriculture purposes, timber harvesting/logging, also includes small areas that naturally not covered by vegetation.
9. Waterbody	Sea, rivers and lakes.
10. Rubber	Rubber (<i>Hevea Brasiliensis</i>) Plantations.
11. Aquaculture	Includes commercial and small-scale fish & shrimp/prawns ponds
12. Nipah	<i>Nypa Fruticans</i> or local name Nipah Palm also known as Mangrove palm.
13. Beach & Sand	Beaches, coastal areas, and areas covered in sand.
14. Cloud & Shadow	Remaining cloud & shadow after intensive cloud and shadow masking using secondary satellite imageries.

3.2.3. LULC changes extent & rate analysis

The LULC changes, extent and change rate analysis method used in this study were adapted from [Abebe et al., \(2022\)](#). The LULC changes were calculated by pair-wise comparison of the initial and current year maps, also the percentages of changes were calculated where changes divide by the initial year times a hundred. The changes rate was calculated where changes divide number of years between the initial and current. While the changes rate in percentages was calculated where change rate per year divides the initial year time hundred. The formulas are summarised in Table 3.3.

Table 3.3. Formulas for the changes extent and changes rate analysis.

Changes	Formulas
1. LULC Changes	<i>Initial Year – Current Year</i>
2. Changes %	<i>(Changes / Initial Year) x 100</i>
3. Changes rate /Year	<i>Changes / Number of years between initial & current</i>
4. Changes rate %	<i>(Changes rate/year / Initial year) x 100</i>

3.3. Results

3.3.1. LULC classification maps

Four LULC maps were produced covering the years 2010, 2017, 2019 & latest 2023 (Fig. 3.3). Statistics of the LULC maps were also generated in hectarage shown in table 3.4 and percentages in figure 3.4. There are slight differences in the total area of 2.79ha due to the subset with the AOI and conversion of raster to vector for the GIS analysis. Currently, majority of the LULC in the study area is forest cover, followed by mangroves, acacia, oil palm plantations, secondary forest, and eucalyptus plantations. As per information provided by the plantation manager, the replanting of logged *Acacia mangium* with Eucalyptus was commenced in year 2019 prompted by years of susceptibility to diseases especially Ceratocystis wilt ([Maid & Ratnam, 2014](#); [Syazwan et al., 2021](#)).

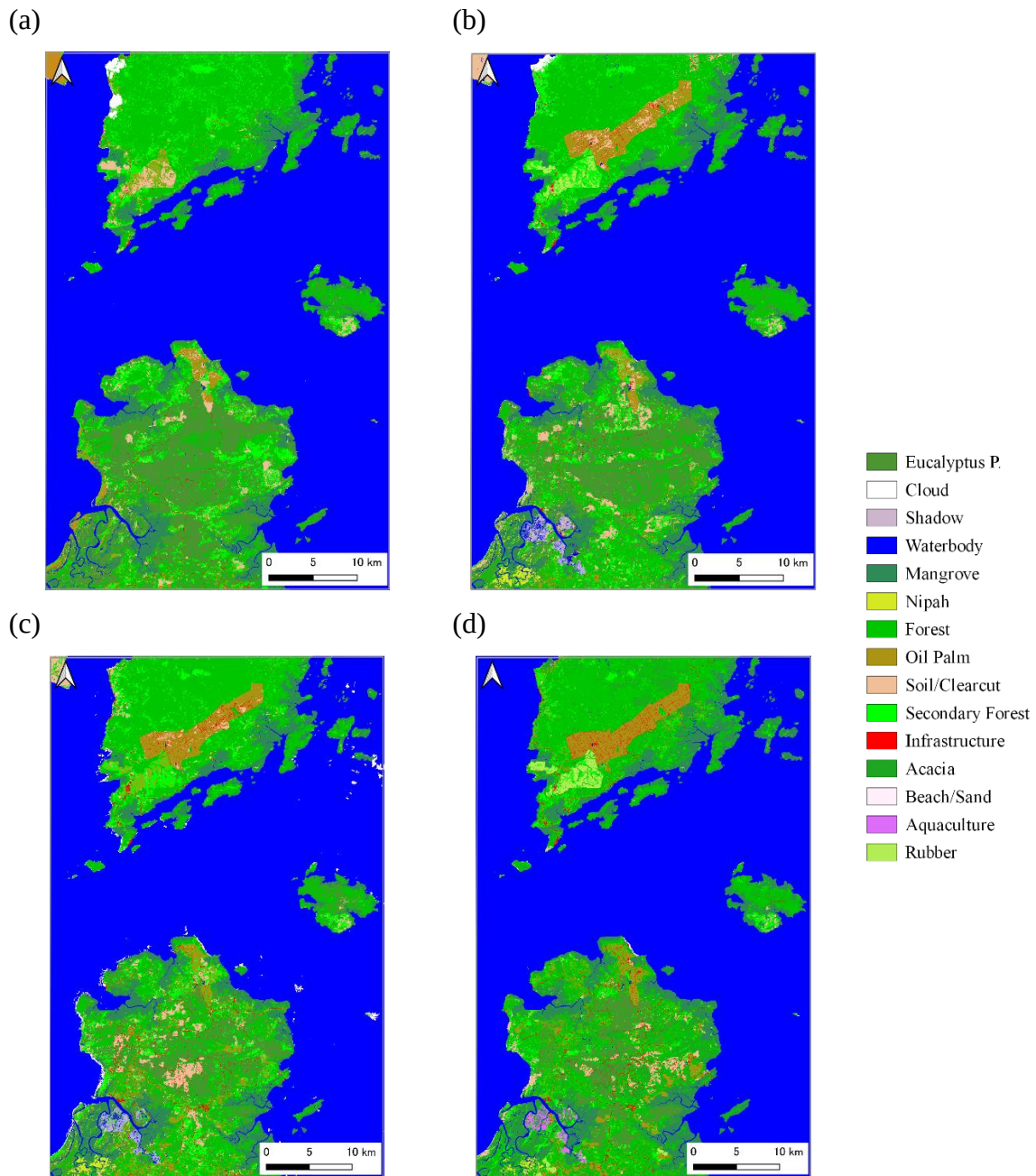


Figure 3.3. LULC maps of the study area of year (a) 2010, (b) 2017, (c) 2019 & (d) 2023.

The LULC classification for 2010 shown majority of the study area covered by Forest 38,974.15 ha (16.58%), followed by Acacia 23,319.66 ha (9.93%), Mangrove 15,796.86 ha (6.72%), Secondary forest 10,760.60 ha (4.58%), Soil/clearcut 4,025.97 ha (1.71), oil palm 1,846.01 ha (0.79%), Rubber 654.04 ha (0.28%), Infrastructures 524.13 (0.22%), Nipah 200.39 ha (0.09%) and Beach/sand 39.30 ha (0.02%) respectively. Meanwhile 2017, the majority also Forest 38,955.28 ha (16.58%), Acacia, 18,061.36 ha (7.69%), Mangrove 17,829.88 ha (7.59%), Secondary forest 8,797.32 ha (3.74%), Oil palm 4,51.80 ha (1.92%), Soil/clearcut 4,375.57 ha

(1.86%), Infrastructures 1,053.32 ha (0.45%), Nipah 931.85 ha (0.40%), Rubber 808.99 ha (0.34%), Aquaculture 673.73 ha (0.29%) was mapped for the first time and Beach/sand 168.70 ha (0.07%). In 2019 majority also covered by Forest 39,139.85 ha (16.66%), Mangrove 17,091.05 ha (7.27%), Acacia 14,657.98 ha (6.24%), Secondary forest 10,467.53 ha (4.46%), Oil palm 6,772.24 ha (2.88%), Soil/clearcut 4,062.25 ha (1.73%), Infrastructures 2,035.85 ha (0.87%), Beach/sand 1,163.68 ha (0.50%), Nipah 791.67 ha (0.34%), Rubber 698.85 ha (0.30%) and followed by Aquaculture 645.81 ha (0.27%). Lastly in 2023, majority Forest cover 37,838.29 ha (16.11%), Mangrove 18,412.63 ha (7.84%), Acacia 12,004.96 ha (5.11%), Oil palm 7,884.23 ha (3.36%), Secondary forest 6,869.20 ha (2.92%), first time mapped Eucalyptus 6,310.50 ha (2.69%), Infrastructures 2,246.99 ha (0.96%), Soil/clearcut 2,207.39 ha (0.94%), Rubber 1,411.07 ha (0.60%), Aquaculture 578.49 ha (0.25%) and Beach/sand 122.98 ha (0.05%).

Table 3.4. Summary statistics of study area LULC in hectarage year 2010, 2017, 2019 & 2023.

Classes	2010	2017	2019	2023
1. Forest	38,947.15	38,955.28	39,139.85	37,838.29
2. Mangrove	15,796.86	17,829.88	17,091.05	18,412.63
3. Acacia m.	23,319.66	18,061.36	14,657.98	12,004.96
4. Oil palm	1,846.01	4,501.80	6,772.24	7,884.23
5. Secondary Forest	10,760.60	8,797.32	10,467.53	6,869.20
6. Eucalyptus	-	-	-	6,310.50
7. Infrastructures	524.13	1,053.32	2,035.85	2,246.99
8. Soil Clearcut	4,025.97	4,375.57	4,062.25	2,207.39
9. Waterbody	138,262.81	138,517.97	137,381.26	138,676.54
10. Rubber	654.04	808.99	698.85	1,411.07
11. Aquaculture	-	673.73	645.81	578.49
12. Nipah	200.39	931.85	791.67	342.69
13. Beach/Sand	39.30	168.70	1,163.68	122.98
14. Cloud & Shadow	570.25	270.67	36.36	40.82
Total	234,947.17	234,946.44	234,944.38	234,946.78

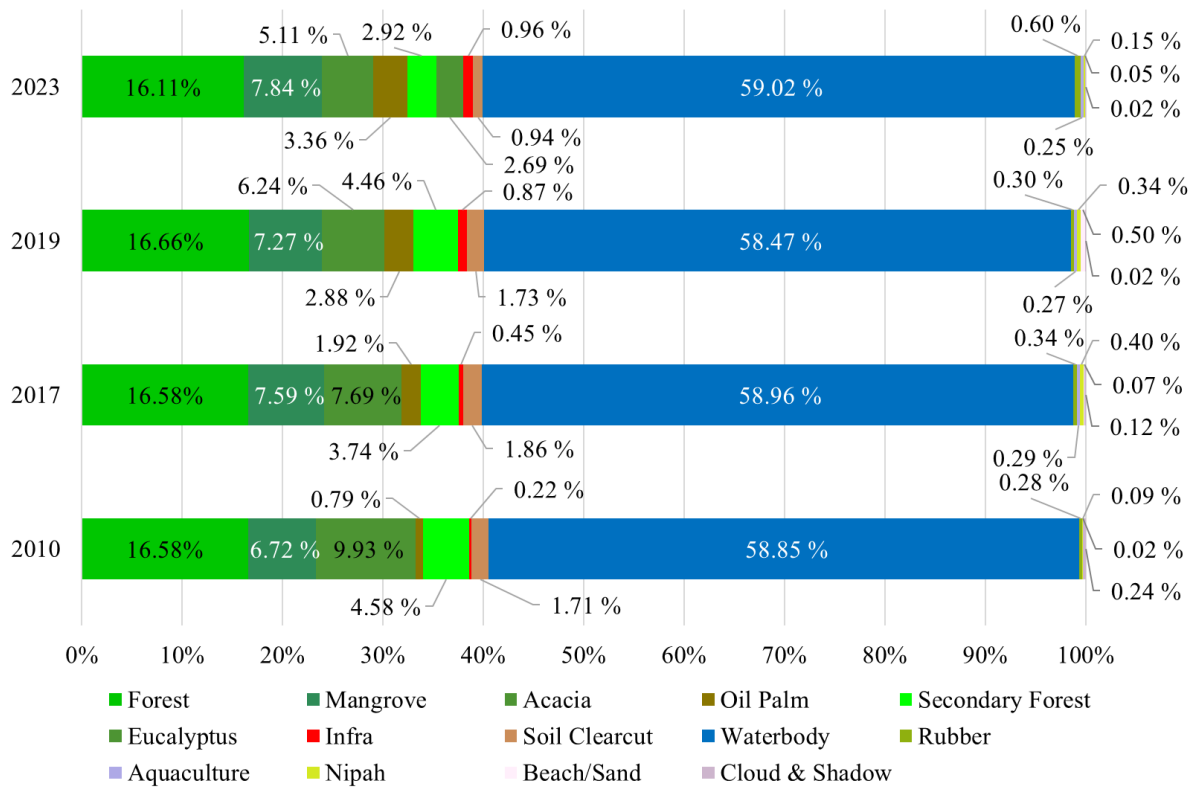


Figure 3.4. LULC composition of the study area in percentages year 2010, 2017, 2019 & 2023.

Based on the bar chart in Figure 3.4. shows that the main LULC classes of forest and mangrove area coverage are stable throughout the observed years. The secondary forest and soil/clearcut were steadily decreased and there was a steady increase in the Oil palm plantations and infrastructures area cover. Meanwhile, the waterbody area was significantly unchanged only a small 0.5% difference across the monitoring period with the year 2023 highest. The increase and decrease observed with waterbody and beach/sand were likely to be caused by variations in local climatic conditions or tidal during the satellite imageries acquisitions. The detailed analysis on the spatio-temporal of the extent and rate of changes are discussed in the next sub chapters.

3.3.2. Maps accuracy assessment

As reported in the previous chapters the LULC maps accuracy was: 81% (2010), 88% (2017), 77% (2019) and 87% (2023). These LULC maps were initially produced for the earlier analyses of canopy height estimations and sustainability assessment. The LULC maps were used in this chapter to analyse the spatio-temporal LULC of the study area to monitor and examine the changes.

3.3.3. Spatio-temporal LULC changes

The spatiotemporal extent and rate of changes were computed for each year pairs: 2010-2017, 2017-2019, 2019-2023 and 2010-2023. Also, the change directions analysis was computed for forest and plantation classes: Oil palm, Rubber, Aquaculture, and Eucalyptus. It is to investigate the sources of LULC conversion of these classes. The increased LULC areas are in blue meanwhile the decreased noted in red numbers.

3.3.3.1. 2010 – 2017 LULC changes

Between 2010-2017, the majority of the LULC classes increased except for Acacia decreased by -5,258.30 ha or -3.22%/year and Secondary forest by -1,963.28 ha or -2.61%/year. Forest cover increased by 8.13 ha or only 1.16 ha/year, Mangrove increased by 2,033.02 ha or 1.84%/year, oil palm recorded a drastic increase by 2,655.78 ha or 20.55%/year, Infrastructure 529.19 ha, Soil/clearcut 349.60 ha or 14.42%/year, Rubber increased 154.95 ha or 3.38%/year, Nipah 731.46 ha or 52.12%/year, Beach/sand increased 129.40 ha or 47.04%/year and Aquaculture was not mapped in the year 2010. Detailed LULC changes extent and rate between 2010 and 2017 are summarised in table 3.5.

Table 3.5. Extent and rate of LULC changes between 2010 and 2017 in the study area.

LULC	2010 ha	2017 ha	Changes ha %		Avg. chg. rate ha/yr. %	
Forest	38,947.15	38,955.28	8.13	0.02	1.16	0.00
Mangrove	15,796.86	17,829.88	2,033.02	12.87	290.43	1.84
Acacia m.	23,319.66	18,061.36	-5,258.30	-22.55	-751.19	-3.22
Oil palm	1,846.01	4,501.80	2,655.78	143.87	379.40	20.55
Secondary Forest	10,760.60	8,797.32	-1,963.28	-18.25	-280.47	-2.61
Eucalyptus	-	-	-	-	-	-
Infrastructures	524.13	1,053.32	529.19	100.97	75.60	14.42
Soil Clearcut	4,025.97	4,375.57	349.60	8.68	49.94	1.24
Waterbody	138,262.81	138,517.97	255.15	0.18	36.45	0.03
Rubber	654.04	808.99	154.95	23.69	22.14	3.38
Aquaculture	-	673.73	-	-	-	-
Nipah	200.39	931.85	731.46	365.03	104.49	52.15
Beach/Sand	39.30	168.70	129.40	329.28	18.49	47.04
Cloud & Shadow	570.25	270.67	-299.58	-52.53	-42.80	-7.50
Total	234,947.17	234,946.44	-	-	-	-

3.3.3.2. 2017 – 2019 LULC changes

Between 2017-2019, the majority of the LULC classes area decreased. Forest cover increased by 184.57 ha but only at the rate of 0.24 ha/year or 0.00%. Mangrove decreased -738.83 ha or -0.01%/year, Acacia decreased -3,403.38 ha or at rate -0.05%/year, Oil palm increased 2,270.45 ha or rate 0.56%/year, Secondary forest also increased 1,370.21 ha at 0.11%/year, Infrastructures increased by 982.53 ha or 4.43%/year, Soil Clearcut decreased -1,136.71 ha, Rubber also decreased -110.24 ha at -0.84%/year, Aquaculture decreased -27.92 ha or -0.31%/year, Nipah decreased -140.18 ha and Beach/sand area increased 994.98 ha. The details of the changes for 2017-2019 are summarised in Table 3.6.

Table 3.6. Extent and rate of LULC changes between 2017 and 2019 in the study area.

LULC	2017 ha	2019 ha	Changes ha %		Avg. chg. rate ha/yr. %	
Forest	8,955.28	39,139.85	184.57	0.47	0.24	0.00
Mangrove	17,829.88	17,091.05	-738.83	-4.14	-2.07	-0.01
Acacia m.	18,061.36	14,657.98	-3,403.38	-18.84	-9.42	-0.05
Oil palm	4,501.80	6,772.24	2,270.45	50.43	25.22	0.56
Secondary Forest	8,797.32	10,467.53	1,670.21	18.99	9.49	0.11
Eucalyptus	-	-	-	-	-	-
Infrastructures	1,053.32	2,035.85	982.53	93.28	46.64	4.43
Soil Clearcut	4,375.57	4,062.25	-313.32	-7.16	-3.58	-0.08
Waterbody	138,517.97	137,381.26	-1,136.71	-0.82	-0.41	-0.00
Rubber	808.99	698.85	-110.14	-13.61	-6.81	-0.84
Aquaculture	673.73	645.81	-27.92	-4.14	-2.07	-0.31
Nipah	931.85	791.67	-140.18	-15.04	-7.52	-0.81
Beach/Sand	168.70	1,163.68	994.98	589.79	294.89	174.80
Cloud & Shadow	270.67	36.36	-234.31	-86.57	-43.28	-15.99
Total	234,946.44	234,944.38	-	-	-	-

3.3.3.3. 2019 – 2023 LULC changes

The year 2019-2023 change also shows a majority of classes decreased. Forest cover decreased by -1,301.56 ha, however, Mangrove increased by 1,321.58 ha or at a rate of 0.01%/year, Acacia decreased by -2,653.02 ha or at rate of -0.03%/year, Oil palm increased 1,111.99 ha at rate of 0.06%/year, Secondary forest mostly decreased by -3,598.33 ha at a rate of -0.08%/year, Infrastructures increased 211.14 ha, Soil Clearcut decreased by -1,854.86 ha at a rate of -0.28%/year, Rubber increased 712.22 ha at a rate 3.65%/year, Aquaculture decreased by -67.32 ha, Nipah also decreased -448.98 ha and Beach/Sand decreased by -1,040.70 ha. The details of the changes are summarised in Table 3.7.

Table 3.7. Extent and rate of LULC changes between 2019 and 2023 in the study area.

LULC	2019	2023	Changes		Avg. chg. rate	
	ha	ha	ha	%	ha/yr.	%
Forest	39,139.85	37,838.29	-1,301.56	-3.33	-0.83	-0.00
Mangrove	17,091.05	18,412.63	1,321.58	7.73	1.93	0.01
Acacia m.	14,657.98	12,004.96	-2,653.02	-18.10	-4.52	-0.03
Oil palm	6,772.24	7,884.23	1,111.99	16.42	4.10	0.06
Secondary Forest	10,467.53	6,869.20	-3,598.33	-34.38	-8.59	-0.08
Eucalyptus	-	6,310.50	-	-	-	-
Infrastructures	2,035.85	2,246.99	211.14	10.37	2.59	0.13
Soil Clearcut	4,062.25	2,207.39	-1,854.86	-45.66	-11.42	-0.28
Waterbody	137,381.26	138,676.54	1,295.28	0.94	0.24	0.00
Rubber	698.85	1,411.07	712.22	101.91	25.48	3.65
Aquaculture	645.81	578.49	-67.32	-10.42	-2.61	-0.40
Nipah	791.67	342.69	-448.98	-56.71	-14.18	-1.79
Beach/Sand	1,163.68	122.98	-1,040.70	-89.43	-22.36	-1.92
Cloud & Shadow	36.36	40.82	4.46	12.27	3.07	8.44
Total	234,944.38	234,946.78	-	-	-	-

3.3.3.4. 2010 – 2023 LULC changes

Meanwhile, the changes during the 13-years period of monitoring mostly increased. However, forest cover generally decreased by -1,108.86 ha but at a slow rate of -0.41 ha/year. Mangrove the other hand, increased by 2,615.77 ha at rate of 0.01%/year, Acacia cover greatly decreased by -11,314.70 ha at the rate of -0.03%/year, Oil Palm increased by 6,038.22 ha at a rate of 2.53%/year, Secondary forest decreased by -3,891.40 ha at a rate of -0.05%/year, Infrastructures increased 1,722.86 ha at rate of 8.96%/year, Soil Clearcut areas decreased by -1,818.58 ha at a rate of -0.16%/year, Rubber increased 757.03 ha at rate of 2.53%/year, Nipah increased 142.30 ha and Beach/Sand increased 83.68 ha. Details of the overall changes are summarised in table 3.8.

Table 3.8. Extent and rate of LULC changes between 2010 and 2023 in the study area.

LULC	2010	2023	Changes		Avg. chg. rate	
	ha	ha	ha	%	ha/yr.	%
Forest	38,947.15	37,838.29	-1,108.86	-2.85	-0.41	-0.00
Mangrove	15,796.86	18,412.63	2,615.77	16.56	2.37	0.01
Acacia m.	23,319.66	12,004.96	-11,314.70	-48.52	-6.93	-0.03
Oil palm	1,846.01	7,884.23	6,038.22	327.10	46.73	2.53
Secondary Forest	10,760.60	6,869.20	-3,891.40	-36.16	-5.17	-0.05
Eucalyptus	-	6,310.50	-	-	-	-
Infrastructures	524.13	2,246.99	1,722.86	328.71	46.96	8.96
Soil Clearcut	4,025.97	2,207.39	-1,818.58	-45.17	-6.45	-0.16
Waterbody	138,262.81	138,676.54	413.73	0.30	0.04	0.00
Rubber	654.04	1,411.07	757.03	115.75	16.54	2.53
Aquaculture	-	578.49	-	-	-	-
Nipah	200.39	342.69	142.30	71.02	10.15	5.06
Beach/Sand	39.30	122.98	83.68	212.94	30.42	77.41
Cloud & Shadow	570.25	40.82	-529.43	-92.84	-13.26	-2.33
Total	234,947.17	234,946.78	-	-	-	-

3.3.4. LULC directions of changes (Conversions)

The most important aspect of LULC change detection as addressed by [Abate & Singh, \(2011\)](#) is to determine what happened, and which LULC class is changing to the other classes. Such information will serve as vital information in management decisions. Therefore, an analysis to determine the direction of changes was done.

3.3.4.1. LULC changes to oil palm plantations

The analysis was further conducted to investigate and quantify the source of conversions for the LULC classes of Oil palm plantations. Between 2010-2017, the forest underwent a conversion of 2,666.38 ha (1.13%) to Oil palm, with the secondary forest at 779.21 ha (0.33%), soil clearcut at 226.75 ha (0.10%), acacia at 183.31 ha (0.08%), and a small portion of mangrove at 4.58 ha (0.00%). From 2017-2019, the main conversion was still from forest to Oil palm, amounting to 1,202.79 ha (0.51%), followed by secondary forest at 590.96 ha (0.25%), soil clearcut at 601.96 ha (0.26%), acacia at 736.48 ha (0.31%), and a small portion

of mangrove at 4.65 ha (0.00%). For 2019-2023, the forest accounted for 1,416.64 ha (0.60%) conversion to Oil palm, followed by secondary forest at 917.31 ha (0.39%), soil clearcut at 539.85 ha (0.23%), acacia at 364.28 ha (0.16%), and mangrove at 4.65 ha (0.00%). During 2010-2023, the major conversion to Oil palm was from forest cover at 4,085.39 ha (1.74%), followed by secondary forest at 1,484.98 ha (0.63%), acacia at 958.93 ha (0.41%), soil clearcut at 493.67 ha (0.21%), and a small conversion from mangrove area at 48.18 ha (0.02%). The changes in percentage directions or origins of conversion into Oil palm area as illustrated in Figure 3.5.

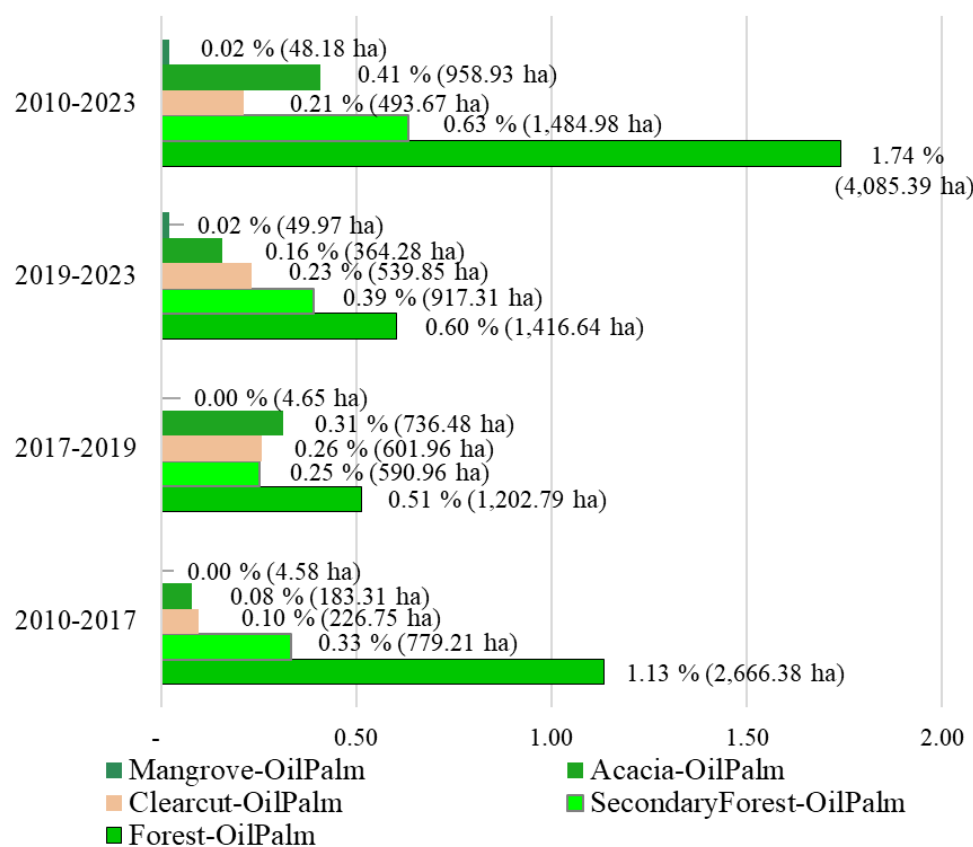


Figure 3.5. Summary percentages of LULC conversion to oil palm Plantations.

3.3.4.2. LULC changes to Rubber plantations

The analysis of LULC conversion into rubber plantations revealed that between 2010-2017, 373.50 ha (0.16%) of soil clearcut area was converted, followed by 52.64 ha (0.02%) from forest, 36.73 ha (0.02%) from oil palm, 31.55 ha (0.01%) from secondary forest, and 6.17 ha from acacia. Between 2017-2019, the main conversion was from secondary forest to rubber plantations, with 168.60 ha (0.07%) converted, followed by 20.79 ha (0.01%) from forest, 1.32 ha from acacia, and 0.67 ha from oil palm. From 2019-2023, secondary forest remained the

primary source of LULC conversion to rubber plantations, with 532.23 ha (0.23%) converted, followed by 243.01 ha (0.10%) from forest, and 16 ha each from soil clearcut, oil palm, and acacia. In the overall comparison between 2010-2023, the majority of LULC conversion to rubber plantations was from soil clearcut area at 607.19 ha (0.26%), followed by 111.83 ha (0.05%) from forest, 105.49 ha (0.04%) from secondary forest, 56.85 ha (0.02%) from oil palm, and 28.10 ha (0.01%) from acacia. The details of LULC conversion to Rubber Plantations are summarised in Figure 3.6.

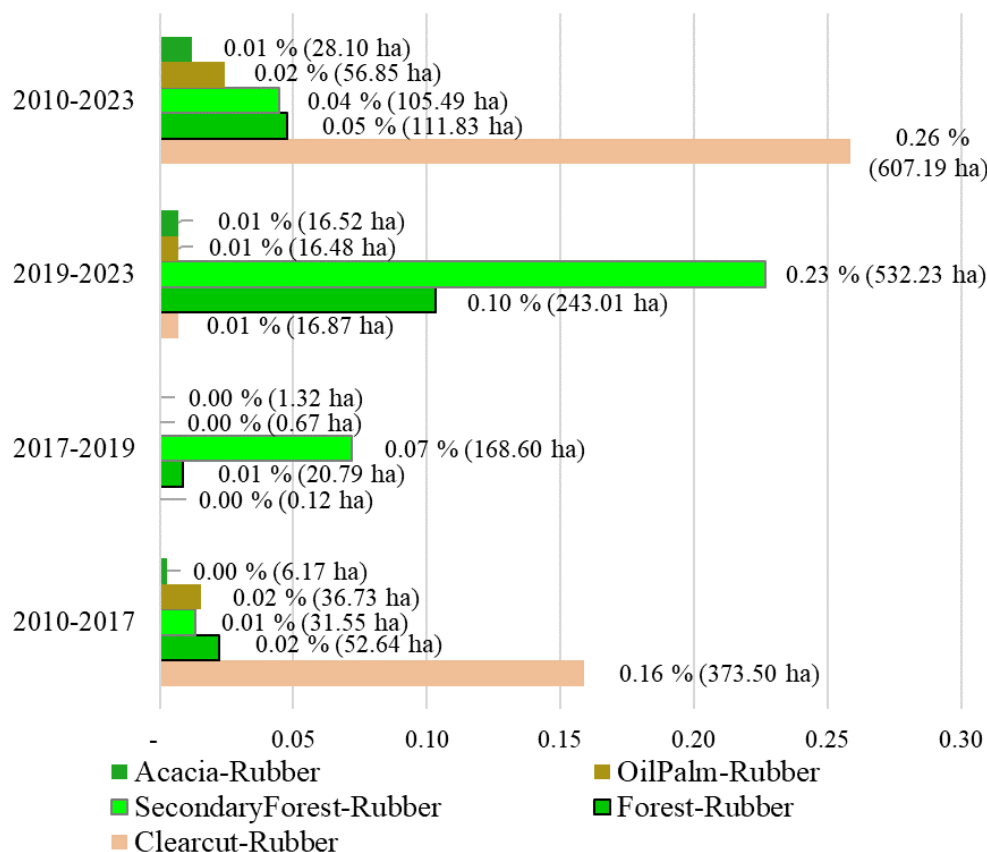


Figure 3.6. Summary percentages of LULC conversion to Rubber Plantations between all year pairs.

3.3.4.3. LULC changes to Aquaculture

The analysis of LULC conversions to aquaculture (Fig. 3.7) indicates that between 2010-2017, the majority of the converted areas were from mangroves, amounting to 261.31 ha (0.11%), and acacia, amounting to 251.67 ha (0.11%). Additionally, there was a conversion of 42.22 ha (0.02%) from forest cover, 42.83 ha (0.02%) from soil clearcut, 4.78 ha from Nipah, and 1.77 ha from waterbody. Between 2017 and 2019, the primary conversion was from soil clearcut,

with 115.59 ha (0.05%) converted, followed by 80.97 ha (0.03%) from waterbody, which were areas of previously cleared mangroves that were seasonally submerged in water. Secondary forest, acacia, mangrove, forest, and Nipah also underwent conversion to aquaculture during this period. From 2019-2023, the majority of LULC conversion to aquaculture was from a waterbody, with 144.5 ha (0.06%) converted, also originating from previously cleared mangrove areas that were seasonally submerged in water. This was followed by conversions from forest area at 63.10 ha (0.03%), secondary forest at 32.92 ha (0.01%), acacia at 17.82 ha (0.01%), soil clearcut at 15.48 ha (0.01%), and Nipah at 3.32 ha. In the overall comparison between 2010-2023, the majority of the conversion to aquaculture was from mangroves at 272.31 ha (0.12%), followed by acacia at 199.20 ha (0.08%), then forest at 40.91 ha (0.02%), secondary forest at 32.92 ha (0.01%), soil clearcut at 27.86 ha (0.01%), Nipah at 4.56 ha, and waterbody at only 0.60 ha.

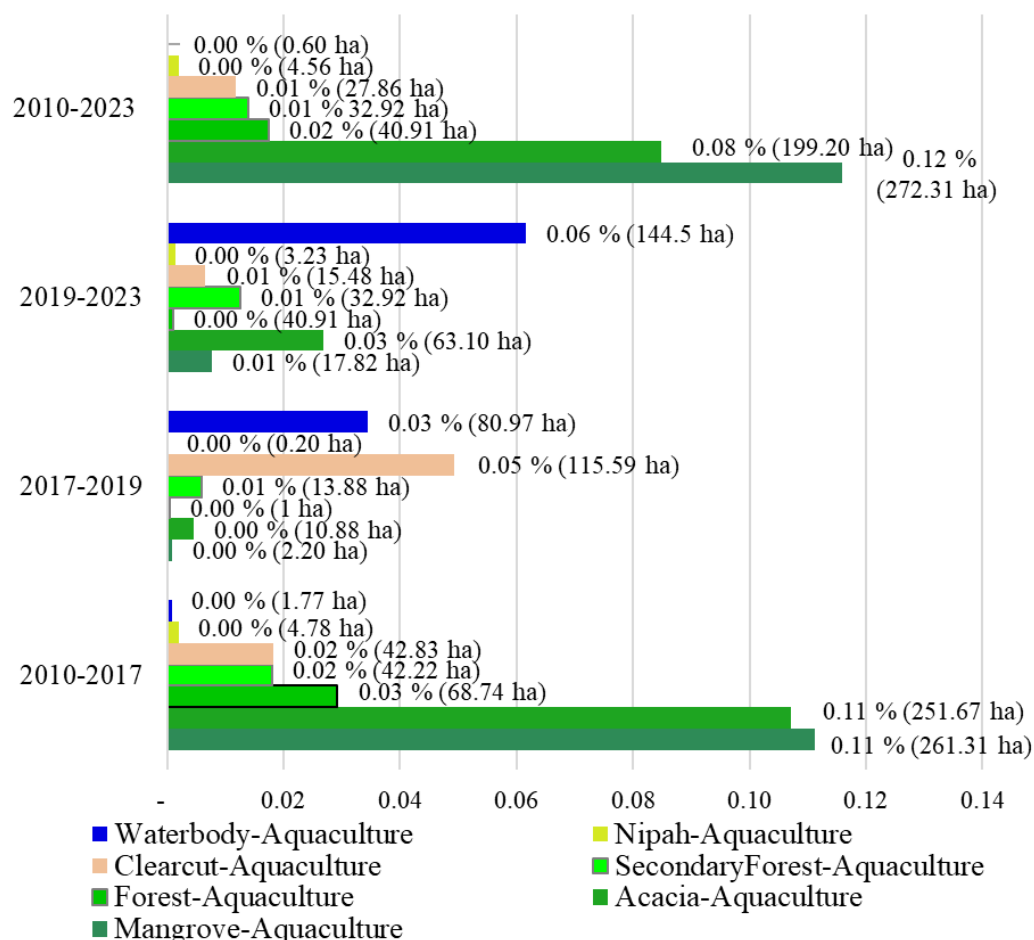


Figure 3.7. Summary percentages of LULC conversion to Aquaculture.

3.3.4.4. LULC changes to Acacia

All of the LULC changes to Acacia were from Forest cover. Between 2010-2017 3,840.47 ha (1.63%) of Forest cover changed to Acacia, followed by Secondary forest at 2,003.05 ha (0.85%), Mangrove 771.52 ha (0.33%), Soil Clearcut 688.05 ha (0.28%) and Oil palm 167.27 ha (0.07%). In 2017-2019, 3,256.35 ha (1.39%) of Forest cover changed to Acacia, Secondary forest 924.96 ha (0.39%), followed by Soil Clearcut 795.54 ha (0.34%), Mangrove 344.21 ha (0.15%) and lastly Oil palm 93.02 ha (0.04%). Between 2019-2023 4,558.29 Forest cover changes into Acacia, followed by Mangrove 1,433.98 ha (0.61%), Secondary forest by 811.23 ha (0.35%), Soil Clearcut 295.63 ha (0.13%) and Oil palm 285.18 ha (0.12%). Meanwhile, for LULC 2010-2023, Forest was the main change to Acacia with 4,270.99 ha (1.82%), followed by Secondary forest at 1,257.43 ha (0.54%), then Mangrove at 1,050.51 ha (0.45%), Soil Clearcut 361.89 ha (0.15%) and lastly Oil palm 110.45 ha (0.05%). Forest and Secondary forest are two main classes preferred for conversion into Acacia meanwhile can be observed some portions of other LULC classes also changed into Acacia which due to Acacia can grow much faster and take over other species. The details of LULC changes to Acacia are illustrated in Figure 3.8.

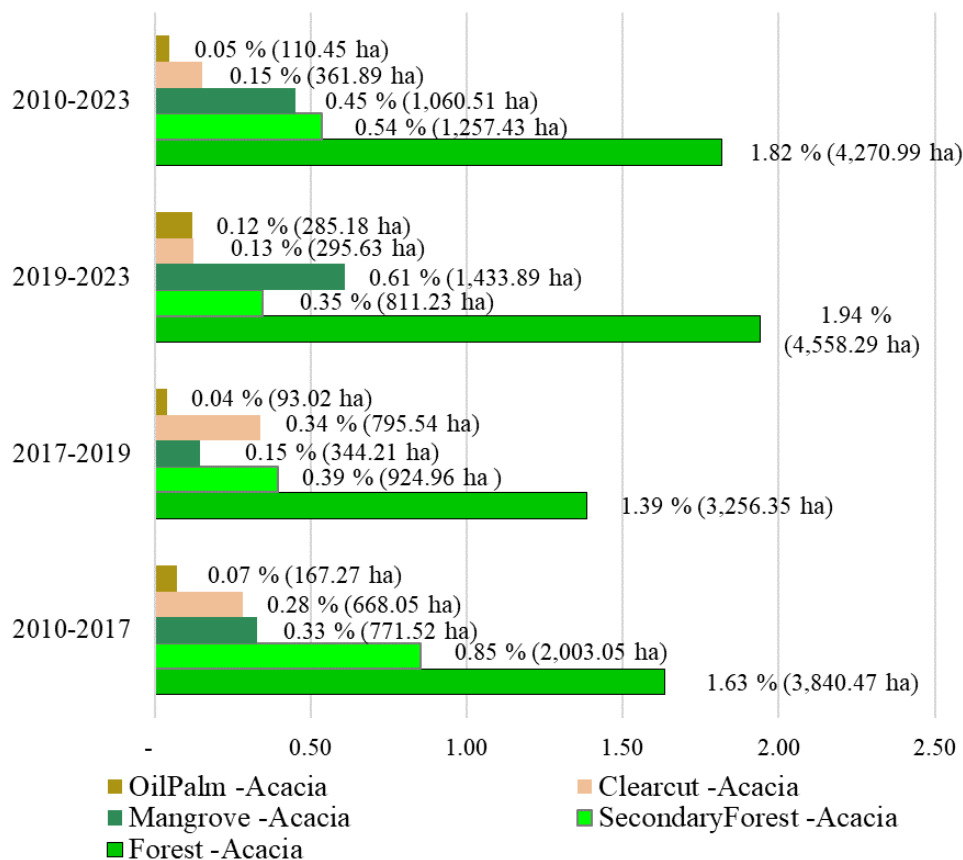


Figure 3.8. Summary percentages of LULC conversion to Acacia mangium plantations.

3.3.4.5. LULC changes to Eucalyptus

The replanting of harvested Acacia with Eucalyptus has only in the ITP area since 2019. During the period of 2019-2023, 2,428.56 ha (1.03%) of Acacia was replaced by Eucalyptus, 1,398.39 ha (0.60%) of Secondary forest, followed by Soil Clearcut area at 1,254.04 ha (0.53%) these were Acacia areas which recently clear harvested and lastly Secondary forest 752.57 ha (0.32%). While comparison of the year 2010-2023 shows the majority of the area replaced by Eucalyptus was Acacia with 5,196.81 ha (2.21% of the AOI), only 805.58 ha (0.34%) of Forest converted into Eucalyptus, Secondary forest 158.19 ha (0.07%), and finally Soil Clearcut 85.32 ha (0.04%). Details of the LULC changes into Eucalyptus as illustrated in figure 3.9.

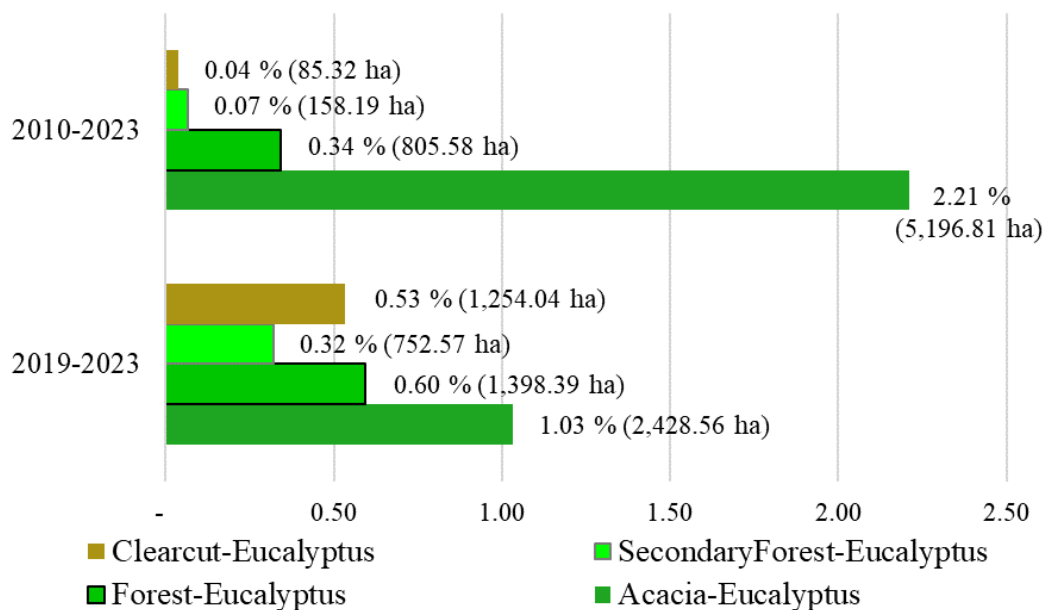


Figure 3.9. Summary percentages of LULC conversion to *Eucalyptus Pelitta* Plantations.

3.3.5.Unchanged LULC

Besides changes, unchanged areas were also mapped and quantified. This was done by year pair comparison of each LULC class. Between 2010-2017 the major LULC classes which unchanged are: Forest covered 26,410.71 ha (11%) of 38,947.15 ha (16.11%) in 2010 were unchanged, followed by Mangrove forest 13,124.51 ha (6%) out of 15,796.86 ha (6%) and Acacia 10,434.28 ha (4%) unchanged out of 23,319.66 ha (9%) in 2010. While comparison of year 2017-2019 shows 30,033.60 ha (13%) out of 38,955.28 ha (16%) in 2017 of the Forest cover was unchanged, followed by Mangrove 15,611.46 ha (7%) out of 17,829.88 ha (7%) unchanged, then Acacia only 8,848.01 ha (4%) out of 18,061.36 ha (7%) in 2017 were

unchanged. Between 2019-2023 shows Forest cover unchanged at 25,905.81 ha (11%) out of 39,139.85 ha (16%) in 2019, followed by Mangrove 13,460.92 ha (6%) out of 17,091.05 ha (7%) in 2019 and Acacia only 4,028.97 ha (2%) out of 14,657.98 ha (6%) in 2019 were unchanged. The unchanged LULC details are summarised in the Table 3.9.

Table 3.9. Summary of unchanged LULC classes.

LULC	2010-2017		2017-2019		2019-2023		2010-2023	
	ha	%	ha	%	ha	%	ha	%
Forest	26,410.71	11	30,033.60	13	25,905.81	11	23,272.50	10
Mangrove	13,124.51	6	15,611.46	7	13,460.92	6	12,195.04	5
Acacia m.	10,434.28	4	8,845.01	4	4,028.97	2	4,676.19	2
Oil palm	615.88	0	3,481.59	1	4,329.96	2	712.67	0
Secondary Forest	2,452.37	1	3,623.71	2	2,550.45	1	1,792.57	1
Eucalyptus	-	-	-	-	-	-	-	-
Infrastructures	171.06	0	498.94	0	828.09	0	258.24	0
Soil Clearcut	792.50	0	714.52	0	305.31	0	478.56	0
Waterbody	137,807.32	59	136,934.09	58	137,026.00	58	137,953.36	59
Rubber	299.57	0	507.04	0	581.73	0	486.31	0
Aquaculture	-	-	413.29	0	270.86	0	-	-
Nipah	41.38	0	452.21	0	233.55	0	6.86	0
Beach/Sand	7.16	0	70.81	0	72.19	0	6.40	0
Cloud & Shadow	142.07	0	0.08	0	0.06	0	0.26	0
Total	192,298.81	82	201,186.35	86	189,593.90	81	181,838.97	77
Changed Area Total	42,647.65	18	33,758.01	14	45,352.34	19	53,108.19	23
Grand Total	234,946.45	100	234,944.36	100	234,946.24	100	234,947.16	100

3.4. Discussion

3.4.1. Spatio-temporal changes

The three major LULC classes of the study area are forest, mangrove, and acacia. Both Forest and mangrove cover are relatively consistent over time while acacia shows a significant area decreased over time due to clearcut timber harvesting and replacement with eucalyptus. As per mangrove land cover, results show mangrove area in 2023 covers 18,412 ha less than literature which is 25,931 ha, however exact area extent was not mentioned. Based on the record, 3,485

ha Acacia was planted in 2019. Secondary forest shows a fluctuational decrease from 4.58% in 2010 to 3.74% in 2017 then rose back to 4.46% in 2019 and a sharp drop to 2.92% in 2023. Soil/clearcut shows a gentle drop from 1.71% to 1.86%, 1.73%, and 0.94% for the four-observation period years respectively. The decrease is due to conversion to oil palm plantations where in 2010 only covered 0.79%, in 2019 increased to 1.92%, 2019 2.88% and finally 2023 3.36%. Infrastructures also show a steady increase from 0.22% in 2010 to 0.45% in 2017, then in 2019 0.87% and finally increased to 0.96% in 2023. The rubber plantation class shows a slight increase from 0.28% in 2010 to 0.34% in 2017 small decrease to 0.30% in 2019 and increase to 0.60% in 2023. Literature mentioned total rubber is 4,500 ha, however until 2023, only 1,411 ha area was planted. According to literature, the planned aquaculture area will cover approximately 900 ha however, results show only 578 ha area remaining in 2023. The aquaculture area changes steadily decreased between 2017 to 2023 confirming the abandonment of the project site while overgrown by mangroves. Meanwhile, other classes did not show significant changes over time.

3.4.2. Driving factors of LULC changes

The majority of the conversion into Oil palm plantations was from forest land cover whereas in 2010-2023 LULC changes show 4,085 ha area converted followed by secondary forest 1,848 ha. However, overall forest land cover experienced only a slight decreased where total area cover remained around 16% of the study area during the monitoring period. The peak changes of the forest into Oil palm in the study area were between 2010-2017. Previous study by [Wan et al., \(2020\)](#) recorded that between 1990 to 2018, a total of 103,474 ha of forest were converted into Oil palm plantations. Rubber plantation was observed to have been converted from previously cleared land in the early stage (2010-2017), only during 2019-2023 observation shown conversion was from the secondary forest at 532 ha. While aquaculture's main source of LULC conversion was mangrove where between 2010-2023, a total of 272 ha and 199 ha of forest land cover were converted. *Acacia mangium* is mostly conversion from forest and secondary forest, however slowly being replaced with Eucalyptus.

3.5. Conclusions

In conclusion, this study presented the LULC changes analysis of the study area specifically investigating the changes and the conversion into plantations. It is important to note that the result figures represent the cumulative conversion up to the time of this study, the future figure may be higher if LULC conversion trends continue which also depends on the global supply and demand of palm oil, rubber also other commodities. Such a scenario may pose a significant

threat to the remaining forest and regenerating secondary forest also the biodiversity they support. Therefore, future studies may continue to monitor the LULC changes in the study area.

4. Ground survey assessment of Above Ground Biomass (AGB) and Carbon estimation of forests outside plantations in Bengkoka Peninsula, Sabah Malaysian Borneo

4.1. Introduction

The accumulation of Above Ground Biomass (AGB) and carbon stock in the forest over some time reflects a complex process that is caused by a multitude of factors. This includes plant growth and mortality, natural disturbances and human-driven land use changes ([Asner *et al.*, 2018](#)). Forest covers 30% or approximately 4 billion hectares of global land area, it provides essential ecosystem services, timber, food fuel, non-timber products, water conservation and clean air ([UN ECOSOC, 2017](#)). Forests outside of forest reserves or Industrial Tree Plantations (ITP) or managed forests are often overlooked and undervalued in their resource potential ([Liu *et al.*, 2023](#); [Thomas *et al.*, 2021](#)). However, these forest areas are comparably important same as managed forests in terms of Biomass and Carbon storage in terms of their capability and capacity.

Forest trees outside managed forests and plantations play a crucial role in the global carbon cycle and contribute significantly to mitigating climate change by sequestering carbon dioxide from the atmosphere. It is also contributes to the Global Forest Goals target to increase forest area by 3% worldwide by 2030 under the United Nations Strategic Plan for Forests 2017-2030 (UNSPF) ([FAO, 2020](#)). The importance of sustainable management of forest trees outside forests is crucial in integrated implementation of the 2030 agenda for sustainable development UNSDG particularly SDG 15 “Sustainably manage forests, combat desertification, halt and reverse land degradation, halt biodiversity loss” ([UN ECOSOC, 2017](#)). Reducing Emissions from Deforestation and Forest Degradation (REDD+) program recognises that forest degradation and deforestation are related to the loss of carbon stocks in remaining forest land. This loss contributes to increased greenhouse gas emissions and exacerbates climate change ([Goetz *et al.*, 2015](#)). Carbon stock is defined as the absolute quantity of carbon held within a pool at a specific time ([UN-REDD, 2023](#)). It is a critical measure in understanding the role of forests in the global carbon cycle and in assessing the potential impacts of forest management practices on carbon sequestration and storage.

Forestry measurements, including those of AGB and carbon stock, are important for understanding the structure and composition of the forest ecosystem. They also play a crucial

role in assessing environmental sustainability in management. These measurements provide valuable data that can inform forest management decisions and contribute to the development of strategies for sustainable forest management also for REDD+ Monitoring Reporting and Verifications (MRV) systems practices (Avtar *et al.*, 2020). Given the lack of studies on the forest outside the plantations particularly in the study area, therefore this study aimed to assess the status of mangroves, *Acacia mangium*, Oil palm and secondary forest in the study area. Meanwhile, specific objectives of this study are:

1. To establish sample plots and collect inventory data of forests outside the plantations in the study area.
2. To estimate the stand density, basal area, volume, AGB, carbon stock and to estimate carbon dioxide (CO₂) equivalent of the forest stock.
3. Suggest the best scenario sustainable management practice based on the assessment of the forests outside plantations.

This study will provide baseline information and reference regarding the status, growth (DBH, height, basal, AGB & carbon) and conditions of the forests outside plantations in the study area and generally Borneo. Estimates of AGB, carbon and carbon dioxide intake can be indicators of the forest recovery or degradation which is important to the natural ecosystem in a plantation landscape such as in Borneo. The study is important for understanding the contribution of these land uses to carbon sequestration and storage, as well as for assessing their environmental sustainability. This research can contribute to SDGs by assessing the carbon sequestration potential of forests and plantations in Borneo and identifying strategies to reduce greenhouse gas emissions from LULC changes (Biswas *et al.*, 2020; Estoque, 2020).

4.2. Materials and methods

4.2.1. Study sites

This study was conducted in the mixed LULC landscape of Bengkoka Peninsula, located in the north of Sabah. The LULC types in the study area mainly include *Acacia mangium*, mangrove forest, oil palm, and secondary forest. The inventory sampling sites were selected based on the accessibility factor, with road access for easy logistics. The location of the sample plots forest inventory sites was shown in the map Figure 4.1b.

4.2.2. Inventory sampling

Random sampling plots of size 15x15m were established in the four sites namely Bawing in the northwest, Mangkapon in the southeast, Maringan in the northeast and Telaga in southwest of Bengkoka peninsula (Fig. 4.1). Trees with DBH >7cm were measured during forest inventory data collection. Information on DBH, height, species and status dead or alive were also recorded.

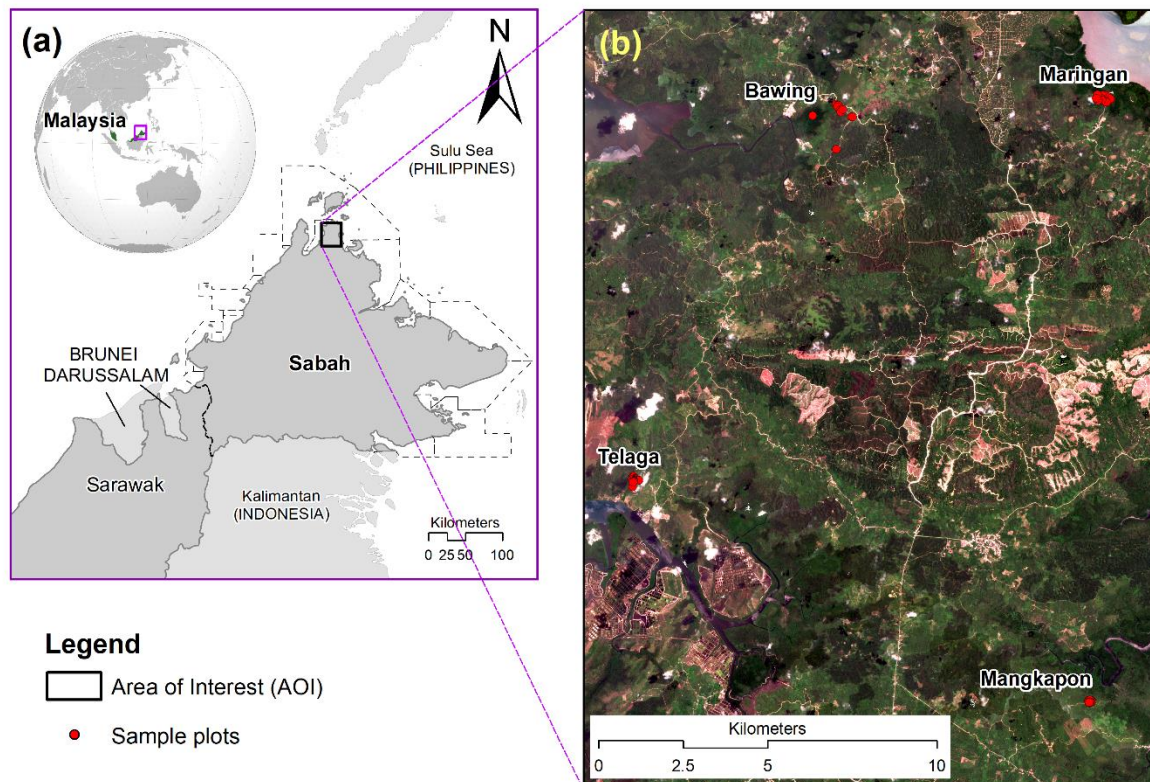


Figure 4.1. (a) Map overview of the study area location in Northern Sabah, Malaysian Borneo and (b) Locations of inventory sampling sites. Background, 2023 Sentinel-2 fused with PlanetScope satellite imagery in true colour composite.

4.2.3. Analysis

The inventory data was filtered, rearranged, and analysed based on the measurement formulas as summarised in Table 4.1. The analyses include stand density, basal area, volume, Above Ground Biomass (AGB) estimation, carbon stock estimation and carbon dioxide (CO₂) equivalent to estimate the amount of carbon dioxide equivalent if the trees are removed.

Stands density measurement is important aspect of forestry as it is the measure number of trees within the plot area, normally presented in stand per hectares. This is important for understanding the structure and composition of the forest. It can be used for determining what kind of silvicultural prescriptions and estimating timber volumes (Khan *et al.*, 2020). Basal area is the method involve measuring the diameter at DBH of each tree in the sampling plot. Basal area is used to represent the size of individual trees and the density of forest stands. Basal area is the tree cross-sectional area of the tree stem measured at breast height level (Nazeri *et al.*, 2021). The volume simply refers to the amount of wood in a forest stand which is typically measured in cubic meters. Volume measurements are important for estimating timber volume and assessing the productivity of forest ecosystems (Spetich & Shifley, 2017). Above Ground Biomass (AGB) estimations on the amount of living plant material above the ground in a forest stand. Usually measured in metric tons per hectare. The AGB estimation is important for assessing the carbon sequestration potential of forest ecosystems and for monitoring changes in forest structure over time (Baul *et al.*, 2021).

On the other hand, carbon stock estimation is the measure of carbon stored in a forest which is typically measured in metric tons per hectare. Carbon stock estimation is important in assessing contribution of forest to carbon sequestration and storage also monitoring changes in carbon stocks (Ikhsan *et al.*, 2021; Khan *et al.*, 2020). Carbon dioxide (CO₂) equivalent refers to the amount of CO₂ that would have the same global warming potential as a given amount of another greenhouse gas. The forest carbon dioxide sequestration was determined by multiplying the weight of the carbon dioxide with carbon weight. Carbon weight value is equivalent to 12 atomic mass units while carbon dioxide is 44 which includes two oxygen atoms of 16 units each. This means one ton of carbon is equivalent to 3.67 tons of carbon dioxide and multiplied by the calculated amount of carbon stock to get the value of carbon dioxide sequestration equivalent.

Table 4.1. Summary of measurement parameters.

Measurements	Formula	References
1. Stands Density	Total number of trees / Plot area	(Ikhsan <i>et al.</i> , 2021)
2. Basal Area (m ²)	$3.142 \times (\text{DBH}/2)^2$	(Bettinger <i>et al.</i> , 2017)
3. Volume	$V = 0.25 \times 3.14 \times \text{DBH}^2 \times H \times 0.6$	(Ikhsan <i>et al.</i> , 2021)

4. Above Ground Biomass (AGB) Kg.	1. Mangrove = $10.800 \times H \text{ (m)} + 34.994$	1. (Wong <i>et al.</i> , 2020)
	2. Acacia Mangium = $0.1173 \times DBH^{2.454}$	2. (Adam & Jusoh, 2018)
	3. Secondary Forest = $0.0829 \times DBH^{2.43}$	3. (Kenzo <i>et al.</i> , 2009)
	4. Oil palm = $37.47 \times H + 3.6334z$	4. (Nunes <i>et al.</i> , 2017)
5. Carbon Stock	47% of AGB	(Shrestha, 2011)
6. CO ₂ equivalent	(44/12) x carbon stock (ton/ha)	(Ikhsan <i>et al.</i> , 2021)

4.3. Results

4.3.1. Vegetation composition

There are four groups of vegetation species or types recorded in the sites: *Acacia mangium*, Mangrove forest, Oil palm and Secondary forest. A total of 73 inventory sample plots were established with total of 2,333 individual trees recorded. All sites were dominated by a large number of *Acacia mangium* except for Mangkapon only recorded Secondary forest. In the field, Maringan was noted to have the highest number of mangrove trees with dense spacing. It was observed that *Acacia mangium* recorded mortality with a higher rate of 45% in Maringan plots compared to Telaga (25%) and Bawing (5%). The recorded dead trees are still standing but without leaves. Field observations found that the trees are infected by *Ceratocystis wilt* disease which is a common infection and widespread in certain population of wild *Acacia* similar in the ITP as reported by Maid & Ratnam, (2014). However, large of the wild *Acacia mangium* population outside ITP exhibits some level of resistance as noted in a recent study by Wingfield *et al.*, (2023). Details of the vegetation composition from inventory sampling are summarised in Table 4.2.

Table 4.2. Inventory data summary of the sites.

Location & Species/Type	No. of trees	No. dead trees	Min-Max DBH (cm)	Mean DBH (cm)	Min-Max Height (m)	Mean Height (m)
1. Bawing (no of plots = 14)						
<i>Acacia mangium</i>	261	13 (5%)	7.10-46.50	15.64	7.70-31.40	15.84
Mangrove	234	-	7.20-35.50	15.77	6.60-19.90	12.90
Secondary Forest	31	1	7.00-41.20	12.28	8.40-25.80	12.46
Total	526	14 (2%)	-	-	-	-
2. Maringan (no of plots = 24)						
<i>Acacia mangium</i>	95	43 (45%)	7.40-23.80	15.14	4.00-22.80	12.38
Mangrove	837	1	7.00-26.80	14.54	5.00-15.70	11.28
Oil palm	8	0	-	-	1.20-6.00	4.40

Secondary Forest	165	2	7.00-40.00	12.87	4.80-19.60	9.90
Total	1,105	46 (4%)	-	-	-	-
3. Telaga (no of plots = 17)						
<i>Acacia mangium</i>	118	30 (25%)	7.00-42.00	13.18	1.00-31.00	8.92
Oil palm	25		8.60-8.60	8.60	4.00-14.00	4.77
Secondary Forest	65	-	7.00-29.50	14.26	4.00-21.70	10.24
Total	208	30 (14%)	-	-	-	-
4. Mangkapon (no of plots = 18)						
Secondary Forest	494	-	7.00-53.00	15.11	4.00-38.20	12.38
Total	494	-	-	-	-	-

The DBH distributions as summarised in Figure 4.2 show that Bawing site recorded the greatest number of small diameter (7-15cm) *Acacia mangium* trees and Mangkapon which is predominantly Secondary forest recorded the most number of small trees of the same diameter group. The sampling plots selected for Mengkapon are located at the roadside near an old log yard. A similar scenario also can be observed in corresponding height distributions (5-15m) for the two sites and vegetation group as illustrated in figure 4.2. Additionally, mangroves in Maringan recorded the greatest number of diameters between 10-15cm with a height group of 5-15m which accounted for more than 300 trees.

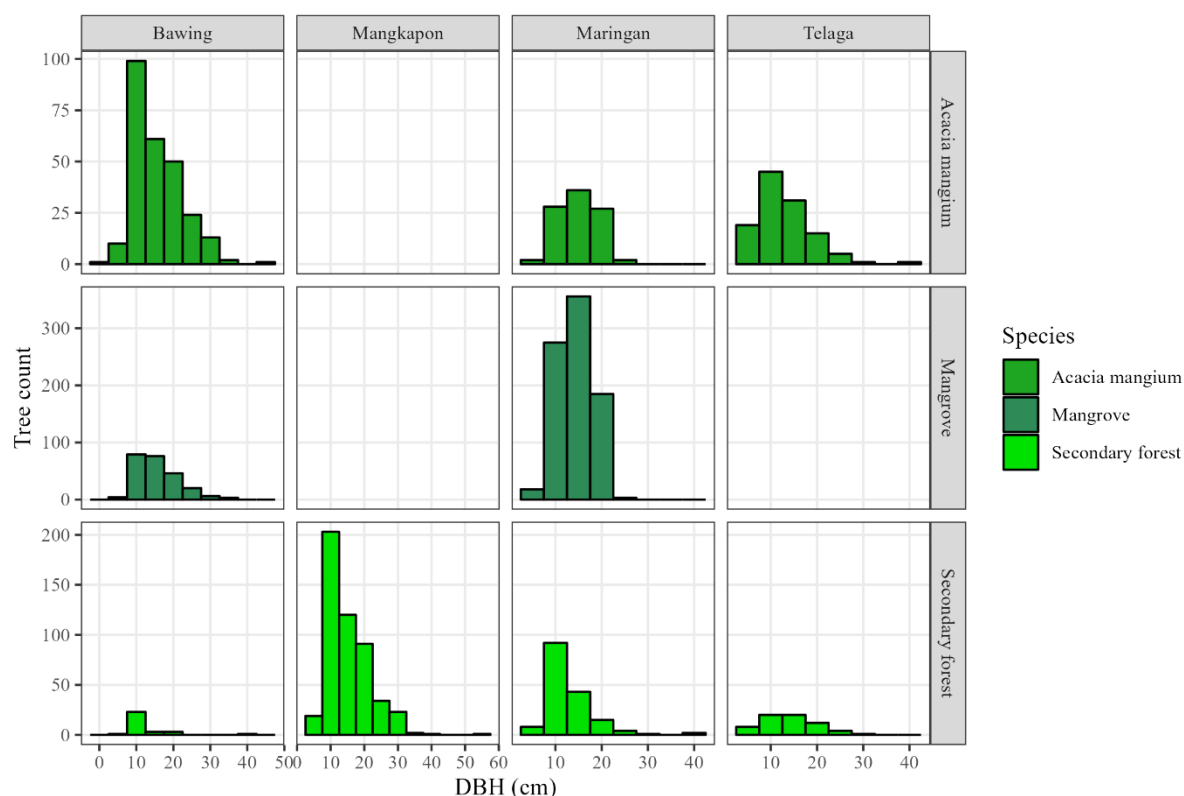


Figure 4.2. Diameter at Breast Height (DBH) distributions for all sites: Bawing, Maringan, Telaga and Mangkapon with breakdown by species group.

Site Bawing recorded small numbers of the Secondary forest group (31 trees) with diameter between 7-15cm and height between 5-15m. Significant number of mangroves (234) also recorded in Bawing with diameter between 7-20cm and height between 5-15m group. Meanwhile site Telaga is predominantly *Acacia mangium* with 118 trees recorded and diameter between 7-15cm and height around group of 5-18m tall. The Telaga sampling site is located near the previous log-yard and Chip mill of *Acacia mangium* logs sites.

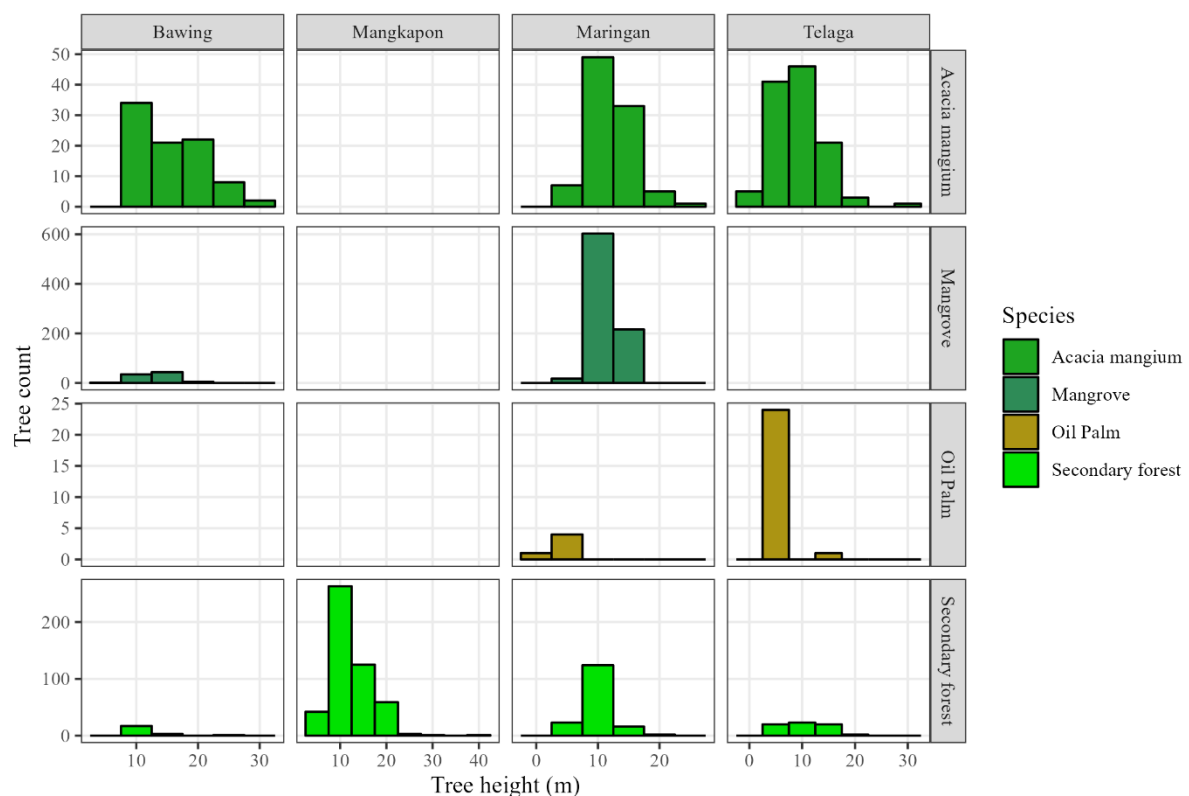


Figure 4.3. Height distributions for all sites: Bawing, Maringan, Telaga and Mangkapon with breakdown by species group.

Overall summary of DBH by species shows the distributions of diameter at lower sizes between 7-25cm groups as illustrated in figure 4.4. with mean height around 12-15m except for the Oil palm (table 4.2) where only some were recorded. According to field observations and information gathered from villagers, the oil palm area is approximately 3 years old. *Acacia mangium* in Bawing recorded the tallest max height at 46.50m followed by Secondary forest tallest at 41.20m. It was observed in Bawing that the mean height of *Acacia mangium*, (15.84m), Mangrove (12.90m) and Secondary forest (12.46m) are the highest compare to other sites. This

suggests that growth stages varying regeneration phases among wild *Acacia mangium* even though are widespread all over Bengkoka peninsula. In relation to Secondary forest height, the tall max height shows that some native species are thriving even due to past shifting and rapid LULC changes in the study area. This was shown by overall DBH (Fig. 4.4) and height (Fig. 4.5), shows Secondary forest between DBH 10-20cm and height between 7-15m that Secondary forest are in growing. stages

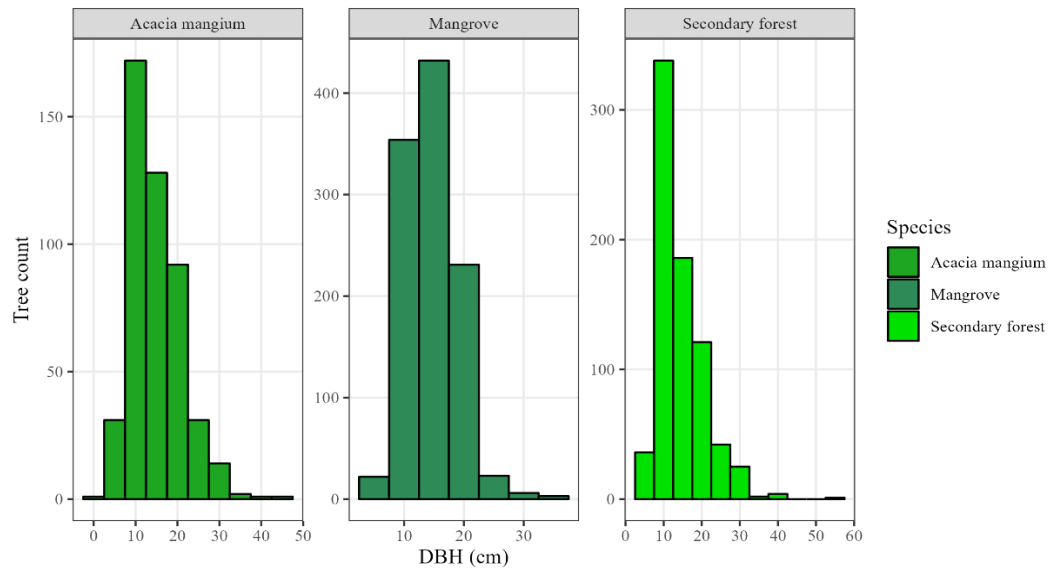


Figure 4.4. Diameter at Breast Height (DBH) distributions by species group.

The figure 6.4 above illustrates the overall tree DBH classes by species groups of *Acacia mangium*, Mangrove and Secondary forest. Meanwhile figure 4.5 below illustrates the summary of heights classes of *Acacia mangium*, Mangrove, Oil palm and Secondary forest.

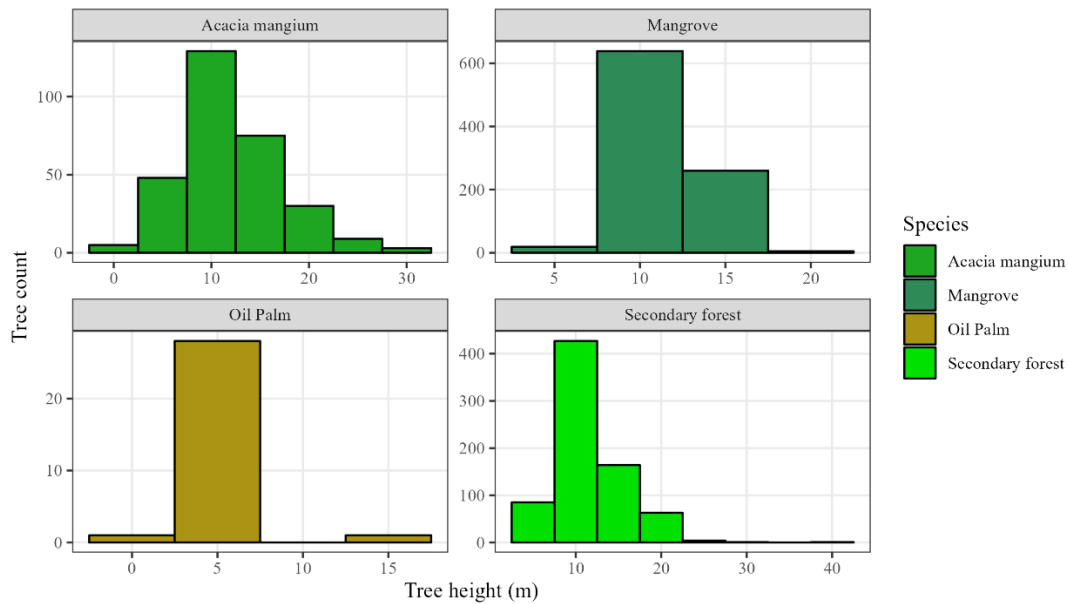


Figure 4.5. Height distributions by species group.

4.3.2. Average Stands, Density, Volume, AGB, Carbon and CO₂ equivalent.

In this study, the average density of *Acacia mangium* is 679 trees per hectares. Normally stem density decreased as the stand age increased (Nazeri *et al.*, 2021). A recent study by (Nirsatmanto *et al.*, 2023) of hybrid Acacia in plantations in Indonesia reported stand density range from 1,600 to 2,500 stems/ha of young Acacia. The basal area recorded was 204m²/ha and volume are 1,948m³/ha. While the AGB recorded was 79.80 t/ha where by in the case of *Acacia mangium* stem biomass is accounted for 80-85% of the total biomass while branches 12-16% and leaves 3-8% (Jusoh *et al.*, 2017). The average carbon recorded in the study area is 37.50 tC/ha with CO₂eq of 137.62 t/ha. The stand density recorded more in mangrove with 2,266 stems/ha with basal area of 187m²/ha and volume of 1,400 m³/ha. The AGB for mangrove was 145.34 tC/ha. Previous study (Wong *et al.*, 2020) done on mangrove in Kota Marudu in Sabah recorded average of 196.88 tC/ha. Additionally, the recorded average CO₂eq of mangrove in the study area is 532.90 t/ha. Oil palm in the study area are approximately 3 years old with stand density of 112/ha with basal area of 58m²/ha, volume only 163m³/ha, AGB of 8.5 t/ha, carbon 8.68 tC/ha and CO₂eq of 31.84 t/ha. For reference, the average planting density of industrial scale Oil palm plantations is at 142 ± Oil palm trees per hectares (Greenshields *et al.*, 2023). On the other hand, for Secondary forest the stand density is 780/ha, basal of 193 m²/ha., volume of 1,753 m³/ha, AGB 56.92 t/ha, carbon 26.75 tC/ha and CO₂eq of 98.09 t/ha. The results of average stands density, basal area, volume, AGB and CO₂eq are summarised in the table 4.3 below.

Table 4.3. Summary of average stands density, basal area, volume, AGB and CO₂ equivalent.

Species	Avg. Stand Density/ha	Avg. Basal Area m ² /ha	Avg. Volume m ³ /ha	Avg. AGB t/ha	Avg. Carbon Stock tC/ha	Avg. CO ₂ eq t/ha
<i>Acacia mangium</i>	679	204.81	1,948.80	79.80	37.50	137.62
Mangrove	2,266	187.07	1,400.37	309.23	145.34	533.39
Oil palm	112	58.10	163.73	18.47	8.68	31.85
Secondary forest	780	193.49	1,753.66	56.92	26.75	98.17

4.3.3. Total AGB, Carbon & CO₂

The total AGB, carbon and CO₂eq also analysed by the vegetation categories also by the sites as illustrated in the figure 4.6. The measure of AGB is primary while carbon usually 47% of AGB and CO₂eq about less than double of AGB. Among all the four sites, can be observed that mangrove stores the most amount of AGB and carbon followed by secondary forest in Mangkapon and *Acacia mangium* in Bawing. In contrast, Telaga site recorded low AGB for *Acacia mangium*, Oil palm and Secondary forest. Bawing site recorded highest total AGB of 35 tons of *Acacia mangium* while Maringan and Telaga both sites recorded 10 tons. Mangkapon site dominated by Secondary forest which recorded highest AGB of 40 tons while other sites recorded low AGB for the same species category. Oil palm in Telaga recorded higher AGB of 4.5 tons compared to in Maringan only at 0.8 tons.

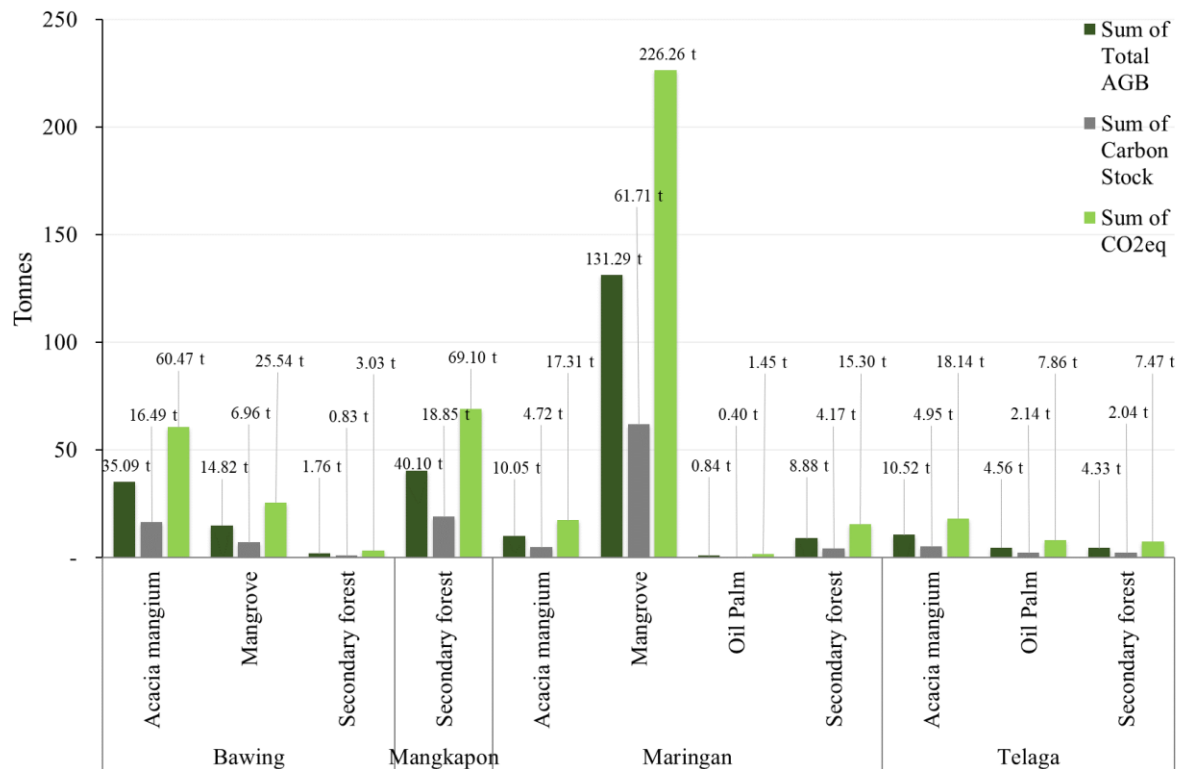


Figure 4.6. Total AGB, Carbon & CO₂ for all sites by vegetation species/group.

4.3.4. AGB, Carbon & CO₂ per-hectares.

In terms of AGB, carbon and CO₂eq by hectare, result shows that still mangrove in Maringan site is highest at 583 t/ha also followed by Secondary forest in Mangkapon at 178 t/ha and *Acacia mangium* in Bawing site at 155 t/ha. Oil palm in Telaga site recorded high AGB/ha of 20 t/ha compare to in Maringan site only 3.7 t/ha. The AGB, carbon and CO₂eq by hectare values are illustrated in figure 4.7.

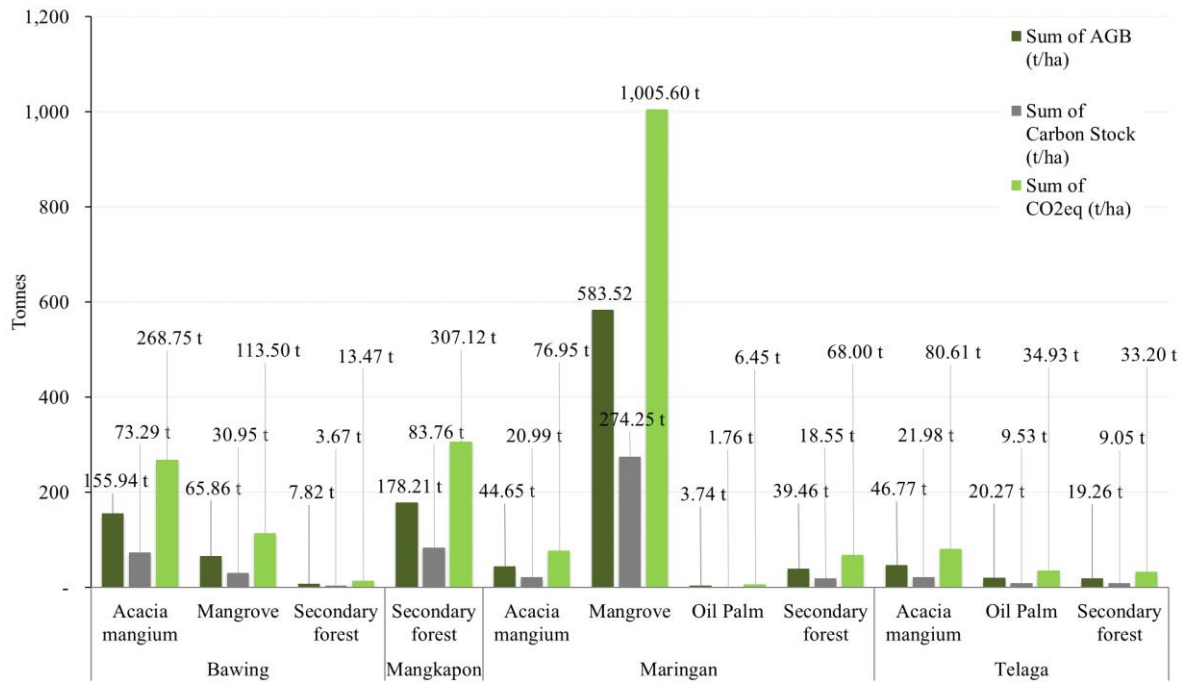


Figure 4.7. AGB, Carbon & CO₂ for all sites by vegetation species/group per-hectares.

4.4. Discussion

The main limitation to this study was, unable to identify specific species of Mangrove and vegetation in the Secondary forest due to shortage of time and resources. This short coming is recommended to be addressed in the future study also suggest for more sampling sites with more data be collected for future study. The observed average density of *Acacia mangium* stands (679/ha) implies a probable stand age of 7-11 years, this in line with the findings of [Traoré et al., \(2018\)](#) reported stand counts of 715-553 for 7-11 years old respectively for *Acacia mangium*. Similarly, [Tan et al., \(2020\)](#) reported 890/ha and 1,016/ha 6 years old planted and naturally regenerated *Acacia mangium* in Bengkoka Forest Reserve. Meanwhile, for mature Oil palm plantations the carbon stocks are between 20 and 50 tC/ha the growth rate is high in early years and decreases towards the end of economic lifespan ([Kho & Jepsen, 2015](#)). For the tropical forest the carbon ranging from 4 to 384 tC/ha & Oil palm 2 to 60 tC/ha. The thriving Secondary forest in the study area potentially be manage under as High Conservation Value (HCV). Recent study by [William et al., \(2023\)](#) in forest concession in Kota Marudu which is not far from the study area shows that Secondary forest within ITP contributes to a diverse mammal assemblage. Secondary forests hold the potential for restoration and to be managed sustainably. However, even though the total stem density is similar, the structure of the forest

differs notably in areas that have been selectively logged. This difference is characterized by a lack of large trees and an excess of saplings. Such alterations in the forest structure could potentially affect the functioning of the ecosystem. Specifically, the above-ground biomass and carbon reserves in areas that have undergone selective logging were found to be only 60% of those in primary forests, even after a recovery period of 22 years (Hector *et al.*, 2011).

4.5. Conclusion

The study presented assessment of AGB, carbon and CO₂ for the *Acacia mangium*, mangrove, secondary forest and Oil palm in the study area based on ground forest sample inventory data. The results shows that all land cover species recorded slightly lower stands, density, volume, AGB, Carbon and CO₂ as compared to previous and related studies. Furthermore, the land cover outside managed forest and plantations in the study area shown potential of accumulating more AGB thus absorbing more CO₂ in the future. Mangrove and Secondary forest of the study area should be sustainably managed considering the role in biodiversity and ecosystem services. This study findings will contribute to meeting several United Nations Sustainable Development Goals (UNSDGs), including Goal 13 “*Take urgent action to combat climate change and its impacts*” and Goal 15 “*Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss*”. Also, UNSDG goal 13 climate action “*take urgent action to combat climate change and its impacts*”. In conclusion, the forests outside the plantations in the study area is potentially be managed and be conserved based on the findings presented in this study.

5. Mapping of temporally dynamic tropical forest and plantations canopy height in Borneo utilizing TanDEM-X InSAR and multi-sensor remote sensing data

5.1. Introduction

Canopy height estimation using SAR remote sensing provide essential information on the biophysical parameters such as vertical extent, canopy structure, growth also expansion of forests and plantations. Canopy height data can also be utilized to estimate plantations production and to simulate the aboveground biomass (AGB) associated with forest ecosystems (Pourshamsi *et al.*, 2021). The ability to distinguish between successional phases, identify forest logging activity, and assess plant growth, mortality, and deforestation may all be conducted using canopy height information (Avtar *et al.*, 2012; Bispo *et al.*, 2019; Kugler *et al.*, 2015). As the forest canopy grows both horizontally and vertically, the biomass in forests and plantations increases. The growth and productivity of the forest as a carbon sink is an indication of important ecological processes may be seen as a temporal increase in the canopy height (Zhang *et al.*, 2016). In contrast, the absence/loss of any forest canopy indicates that the forest had been disturbed by factors such as logging operations, wind damage, or forest fire. A decrease in the height of the forest canopy implies a decrease in the overall complexity of the aboveground structure. This leads to a decline in the diversity of trees that make up the fundamental framework of tropical forests. Additionally, the simplification of the habitat occurs due to the presence of monocrop plantations, which results in a significant loss or decrease in the variety of plant and animal species (Turner *et al.*, 2011). Undiscovered disturbance occurrences in tropical forests can result in permanent destruction or degradation, while unmapped plantations cause information gaps that may result in not being well managed and lead to low productivity. For tropical forests and plantations to be managed sustainably, such derived canopy height is essential. Using a multi-sensor remote sensing technique, it is possible to reliably evaluate the state of tropical forests and plantations, changes in their dynamics and how they have evolved over time (Trier *et al.*, 2018).

Canopy height measurements using a traditional field inventory and a terrestrial laser scanner (TLS) produce highly accurate data. However, the method is time-consuming and only covers small areas (Disney, 2019; Zang & Wang, 2023). In tropical forest, it is often difficult or even impossible to accurately measure the tree height from the ground due to the complex

and dense multi canopy tree structure (Larjavaara & Muller-landau, 2013). High-quality data can also be produced via mapping using airborne light detection and ranging (LiDAR) or airborne laser scanner (ALS) and with optical photogrammetry from aircraft and unmanned aerial vehicle (UAV) systems. While aircraft can cover vast areas, their use is often prohibitively expensive, whereas UAVs are more affordable but only cover limited areas. These constraints restrict the quantity of data that can be gathered over extended time periods and at higher costs. Data provided through Interferometric Synthetic Aperture Radar InSAR and multi-sensor remote sensing techniques are important for studying the structural properties due to the ability of SARs to penetrate cloud, covers in day/night operations; this feature is especially important in tropical regions with persistent cloud cover such as Borneo (Hoekman *et al.*, 2010). The TerraSAR-X add-on for Digital Elevation Measurement (TanDEM-X, hereafter refer as TDX) satellite, a short wavelength (3 cm) X-band SAR, is part of a satellite pair that offers multi-temporal observations with global coverage. TDX data have comparatively high spatial resolution and do not suffer from temporal decorrelation. The X-band has low canopy penetration capability, which is suitable for canopy height modelling, however, this band may be affected by canopy density, seasonal variation in canopy leaf cover, and rain conditions (Bispo *et al.*, 2019). Hoekman *et al.*, (2010), Larjavaara & Muller-landau, (2013) and Cloude *et al.*, (2013) demonstrated that single-pass TDX coherence data (correlation between pairs) show good sensitivity to forest height and structure. InSAR coherence data values range between 0 to 1, with lower values indicating the presence of tall vegetation like forests, while higher coherence values suggest a lower height in vegetation coverage (Potapov *et al.*, 2021).

Because of these characteristics, recent studies (Chen *et al.*, 2021; Gomez *et al.*, 2021; Schlund & Boehm, 2021; Schlund *et al.*, 2023; Zhang *et al.*, 2022) have shown that TDX and other SAR data provide a valuable resource for sustainable tropical forest and plantation management and can contribute to various sustainable development goals (SDGs) and Reducing Emissions from Deforestation and forest Degradation+ (REDD+) initiatives. Workflows for deriving height metrics from SAR data generally rely on establishing an empirical relationship between InSAR coherence data and measured reference heights such as those from LiDAR or field measurements (Raveendrakumar *et al.*, 2022). In addition, there is a geometric relationship between the SAR signal and forest height that can be estimated using InSAR techniques (Raveendrakumar *et al.*, 2022).

The accuracy of canopy height estimated from InSAR coherence can vary depending on various factors, including the Land Use Land Cover (LULC) class (De Luca *et al.*, 2022). Many recent studies have integrated InSAR coherence data and optical biophysical variables to classify forest cover and discriminate it from the surrounding land cover (Norovsuren *et al.*, 2023). In this study, we considered the forests and plantations LULC types in relation to the canopy height estimations and mapping. In the study area, the LULC comprises a distinctive combination of mangrove forest, mixed forest, nipah palm mangrove, secondary forest, *Acacia mangium*, rubber and oil palm plantation. Uniqueness of this study is its focus on a wide range of tropical forest types and plantation land uses landscape, presenting a new case study for the region of interest. This contrast with previous studies which typically addressed only limited number of specific types of forest or land uses. Table 5.1. summarised the previous studies related to the canopy height of various LULC in the study area.

Table 5.1. Reported known canopy height and characteristics of LULC classes related to the study area.

LULC Classes	Recorded Canopy Height Range (m)	References
Mangrove forest	2–11.30 m (Sabah)	(Mojiol <i>et al.</i> , 2019)
Nipah mangrove	8.6–11.6 m (Klias Pen. & Sepangar Bay, Sabah)	(Mohd-Lokman <i>et al.</i> , 2012)
Rubber plantations	25–30 m (<i>Hevea Brasiliensis</i>)	(Ong <i>et al.</i> , 2021)
Secondary forest	10–20 m (<i>Macaranga</i> at Tenompok FR, Crocker Range, Sabah)	(Nagano <i>et al.</i> , 2019)
Oil palm	15 m (25 years old, Malay Peninsula)	(Tan <i>et al.</i> , 2014)
Shrubs	3 m (Uni. Malaysia Sabah main Campus)	(Majuakim <i>et al.</i> , 2018)
<i>Acacia mangium</i> in plantations	21.8–33.7 m (FRC, Sepilok, Sabah) 30.2–32.4 m (A. Hybrid & A. Super bulk, Bintulu, Sarawak)	(Abe <i>et al.</i> , 2005) (Jusoh <i>et al.</i> , 2017)

The study aims to assess the potential of canopy height estimation models based on TDX and evaluate the effectiveness of multi-sensor remote sensing for canopy height estimation and mapping in complex dynamic LULC landscape. Meanwhile the study objectives are:

1. Firstly, to estimate and mapping canopy heights of the forests and plantations of the study area using TDX InSAR supported by multi-sensor remote sensing dataset.

2. Secondly to compare the different models of canopy height estimations namely the SAR Interferometric Normalized Coherence (SINC) forest inversion model also two Machine Learning Model of Random Forest (RF) and Symbolic Regression (SR).
3. Thirdly assess the height estimations in relation to forest and plantations LULC also distributions of canopy height patterns and height variations.

The resulting high-resolution canopy height maps will be cross-checked and validated with other data products such as the latest space-borne LiDAR Global Ecosystem Dynamics Investigation (GEDI) data (National Aeronautics and Space Administration (NASA), USA and Global Aerial Observatory: Top of Canopy Height (GAO TCH) ([Asner *et al.*, 2021](#)) and forest inventory data. , this study will provide valuable information for sustainable management of dynamic tropical forests and plantations in the study area also will serve as reference for similar studies in Borneo and other tropical regions. The study also important to address the knowledge gap on canopy height information of the study area, improving precision and temporal resolution of canopy height mapping in dynamic tropical forest and plantations landscape particularly Borneo region. The study also will serve as reference for similar studies in Borneo and other tropical regions.

5.2. Materials and methods

5.2.1. Study area

The study area located in the northern part of Sabah in Borneo. Details about the study area is summarised in chapter 2.1. Area of Interest (AOI) for this chapter as described in the map.

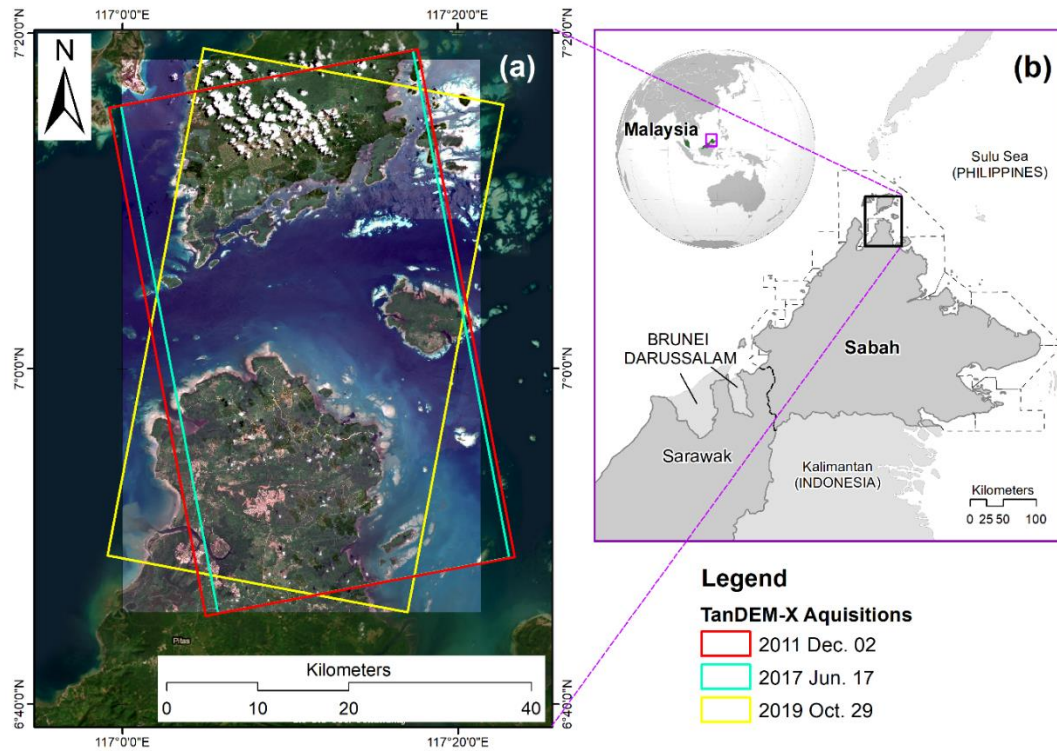


Figure 5.1. (a) Map showing extent of the TanDEM-X acquisitions with the Sentinel-2 2019 in true colour combination as background over the study area and (b) map overview of the study area location in Northern Sabah, Malaysian Borneo.

5.2.2. Dataset: Main InSAR, Land Use Land Cover (LULC) and supporting/references Dataset.

Three categories of dataset were considered in this study: the TanDEM-X Interferometric Radar dataset as the primary data source, multispectral optical satellite dataset for the LULC mapping, and supporting data such field inventory data and current forest height products such as references. Secondary datasets included optical imagery from ALOS AVNIR-2¹ from 2010 to pair with the 2011 TanDEM-X data. Notably, we chose this dataset as the only alternative multispectral dataset available for the study area, as Landsat 7 ETM+ had SLC sensor error that caused missing data strips. For 2017, we used Sentinel-2 optical imagery to produce a LULC map and later post edited using the PlanetScope imageries to edit the remaining cloud and shadow covered areas. The 2019 LULC map was also produced using Sentinel- 2 dataset. Supporting and reference data included terrain elevation data from SRTM v3, forest field inventory data, Global Aerial Observatory (GAO) Tree Canopy Height (TCH) data from 2016,

¹ Advanced Land Observing Satellite (ALOS) Advanced Visible and Near Infrared Radiometer-2 (AVNIR2)

and Ice Cloud and Land Elevation Satellite-2 (ICESat-2) LiDAR, CHM sample points from Interferometric Synthetic Aperture Radar (IfSAR) and GEDI LiDAR-derived Forest canopy height datasets. The datasets used in this study are summarized in Table 5.2.

Table 5.2. Summary of the datasets used in this study.

Sensors	2008	2010	2011	2012	2016	2017	2018	2019	2023
Main Dataset									
TanDEM-X									
LULC Secondary Dataset									
ALOS AVNIR 2									
PlanetScope									
Sentinel-2									
Supporting & Reference Dataset									
SRTM v3									
ICESat-2									
Field Inventory									
IfSAR CHM									
TCH (GAO)									
GEDI LiDAR									

Three TanDEM-X (TerraSAR add-on for Digital Elevation Measurement X-band) single-polarized (horizontal polarization transmit and receive: HH) interferometric radar datasets, acquired on December 2nd, 2011, June 17th, 2017, and October 29th, 2019, were used in this study (TanDEM-X acquisitions shown in Fig. 5.1). The TanDEM-X is a bistatic SAR mission launched in 2010 by the German Aerospace Center (DLR) its observations are not affected by temporal decorrelation and atmospheric disturbance (e.g. from movements induced by wind) (Zink, 2015) thus allowing for forest height estimation from pure volume decorrelation by interferometric coherence analysis (Astor *et al.*, 2012; Olesk *et al.*, 2015). The TanDEM X-band of 3 cm wavelength can penetrate through the forest to ground level or can contain no ground contribution as being reflected from the tree crowns depending on canopies structures. Scattering from the top layers of the canopy makes it possible to generate height estimates using the scattering phase center location. However, with single polarized images, the inversion models must be corrected, and a DEM included for terrain elevation (Zhiyong *et al.*, 2022). The main data acquisition details are summarized in Table 5.3 which were extracted from the original metadata file, consist of; date, orbit, incidence angle, perpendicular baseline, height of ambiguity (HoA) and K values.

Table 5.3. TanDEM-X acquisition parameters.

Acquisition Date	Orbit	Incidence Angle (°)	Perp. Baseline (m)	Height of Ambiguity (m)	K Values
02 Dec. 2011	Ascending	38.71	163.58	75.98	0.103785
17 Jun. 2017	Ascending	38.40	338.92	36.40	0.2149505
29 Oct. 2019	Descending	41.32	303.21	44.32	0.185293

5.2.3. Estimation and mapping of canopy height using TanDEM-X (TDX) InSAR data

TDX co-registered pairs were downloaded from the DLR website in single look Co-registered Single look Slant range Complex (CoSSC) SAR format, and all were acquired in ‘bistatic/strip map’ mode. The simultaneous data acquisition by TDX satellites are free from temporal decorrelation issues (Duque *et al.*, 2012; Fritz *et al.*, 2012; Schlund & Boehm, 2021). According to (Bispo *et al.*, 2019), the interferometric coherence is observable that links SAR data with physical structure of a forest. We used three methods to estimate the canopy height using TDX coherence data: (i). SINC model as reported by Wen *et al.*, (2020), (ii) Random Forest (RF) and (iii) Symbolic Regression (SR) as reported by Ghosh *et al.*, (2020).

5.2.3.1. SINC Model

The SINC model or inverse sine function of the InSAR coherence is a physical model for forest height inversion (Chen *et al.*, 2016; Gomez *et al.*, 2021). SINC model is a simplified form of the random volume over ground (of the RVoG) model (Wen *et al.*, 2020). Canopy height can be estimated from single polarization (HH) TDX interferometry coherence data (Choi *et al.*, 2020; Cloude *et al.*, 2013) using the SINC model compared to the RVoG model which requires full polarimetric SAR data for the inversion (Gomez *et al.*, 2021). Figure 2 shows the flow chart of the model used. TDX coherence is the normalized complex correlation coefficient measure between master and slave acquisition (Martone *et al.*, 2012; Olesk *et al.*, 2016). It is a measure of similarity between two SAR images (Soja *et al.*, 2015).

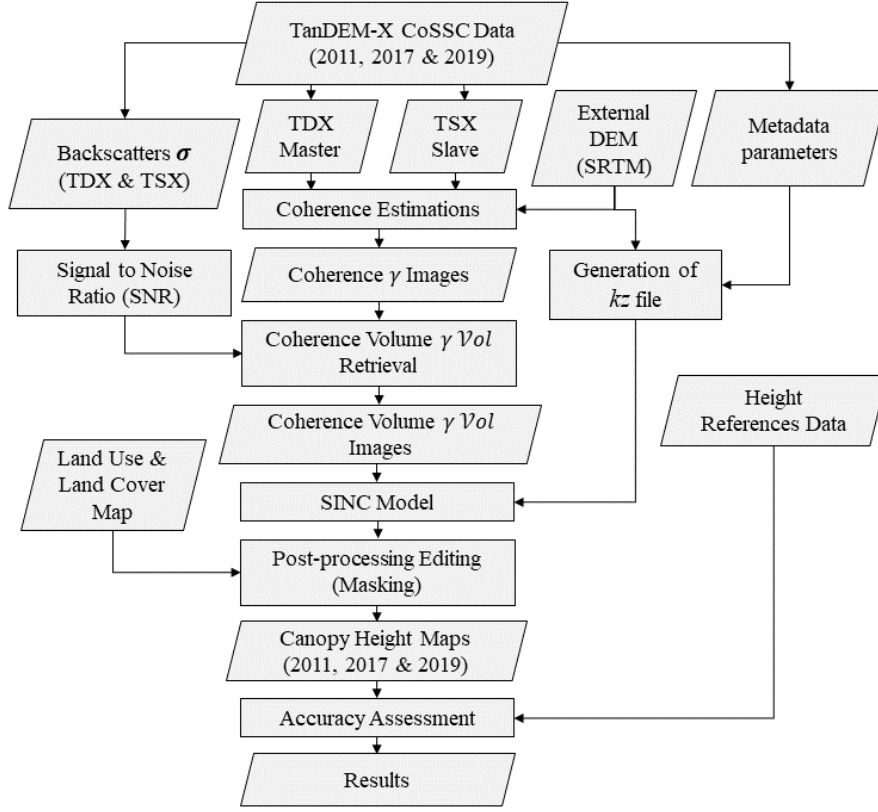


Figure 5.2. Workflow of canopy height estimation from TDX data using the SINC Model. SINC: inverse sine function of the InSAR coherence.

First, we extracted the height of ambiguity (HoA) of the TDX pairs and satellite incidence angle from original metadata. We also calculated the local incidence angle image using the SRTM slope map and then converted from degrees to radian. The coherence was computed from TDX pairs (Master TDX and Slave TSX) in SNAP software. Flat-earth phase subtraction was conducted using SRTM DEM which, automatically downloaded by the software. The coherence calculations are given by:

$$\gamma = \frac{\langle S_1 S_2^* \rangle}{\sqrt{\langle |S_1|^2 \rangle \cdot \langle |S_2|^2 \rangle}} \quad (1)$$

where γ is the complex interferometric coherence, S_1 is the master image, and S_2 is the slave image [Gomez et al., \(2021\)](#). Second, the Signal to noise ratio (SNR) from the backscatter σ was determined as follows:

$$\gamma_{SNR} = \frac{1}{1 + (SNR)^{-1}} = \frac{1}{\sqrt{(1 + SNR_1^{-1})(1 + SNR_2^{-1})}} \quad (2)$$

The noise level value of the SLC of master SNR_1 and slave images SNR_2 were obtained from TDX metadata [Wen et al., \(2020\)](#). γ_{SNR} was used to correct the coherence for volume retrieval as follows:

$$\gamma_v = \frac{\gamma}{\gamma_{SNR}} \quad (3)$$

We generated the *local* wavenumber k_z file accounting for the local angle of incidence on slope terrain [Chen et al., \(2016\)](#):

$$k_z = \frac{4\pi B_n}{\lambda} \frac{1}{R \sin \theta_i} = \frac{K}{\sin \theta} \Rightarrow K = \frac{2\pi \sin \theta_0}{\sin \theta}. \quad (4)$$

The constant K can be derived from the nominal angle of incidence θ_0 at the scene center and corresponding to the HoA of TDX data. Finally, we calculated the SINC function model as described by [Chen et al., \(2016\)](#) and [Wen et al., \(2020\)](#).

$$h_v \approx \frac{2\pi}{k_z} \left(1 - \frac{2}{\pi} \sin^{-1}(|\gamma_v|^{0.8}) \right) \quad (5)$$

where h_v represents the forest height and γ_v is the forest volume decorrelation ([Wen et al., 2020](#)). Post-processing editing of masking LULC areas other than forest and plantations was carried out to produce the final canopy height maps. Then the estimated canopy height maps were assessed using the height reference dataset corresponding to the respective years of 2011 field inventory, 2017 GAO TCH map, and the 2019 NASA GEDI data canopy height. The workflow processes of the SINC model are illustrated as in figure 5.2.

5.2.3.2. Machine Learning algorithm (ML) Models

We considered two supervised learning approaches to estimate forest height models, namely SR and RF regression. For both models, the reference canopy height data used for training were LiDAR derived canopy height estimates from ICESat-2 ATL08 data product. The same set of input (predictor) variables was considered: TDX coherence, the DEM and slope data from SRTM, and two vegetation indices; leaf area index (LAI) and fraction of vegetation cover (FVC) (refer Table 5.6). The attributes of these variables are discussed below.

To predict height maps for both 2017 and 2019, we simultaneously considered ICESat-2 data captured for both years. The 2018 ATL08 data were overlaid with the predictor variables from 2017, and 2019 ATL08 data with predictor variables from 2019. To train the models, data

from 2017 and 2019 were combined, resulting in 4,552 observations; 70% of the data were used to train the height models, while the remaining 30% were used for validation of trained models.

a. Random Forest regressor (RF)

The RF model was applied using the randomForest (Liaw & Wiener, 2002) R package, with default parameter options, namely, “500 trees in the forest”. The model applied one variable per split. The trained model was saved in R data format file (.rds. Electronic file), for later use in height predictions. To evaluate the model's accuracy, the out of bag (OOB) error was calculated during model training, and the model was further evaluated by calculating RMSE for predictions in the test data set (30% of the total 4,552 observations).

b. Symbolic Regression (SR)

The SR is a supervised learning approach that aims to generate a simple mathematical formula that approximates the relationship between input variables and a response variable. SR algorithms often rely on iteratively combining and modifying different functions to form a model, by evaluating the generated model against observed data, and then retaining the good model components for the next iteration. ‘Good model components’ refer to those with low complexity that contribute to a better model fit for the observed data. This relies on methods from genetic programming (Koza, 1994). An advantage of SR is that an interpretable model is produced in the form of a mathematical formula that describes the relationship between predictor and response variables.

In this study, we followed the methodology proposed by (Ghosh *et al.*, 2020) for SR-based forest height modelling. The SR python module PySR (Cranmer *et al.*, 2020) was used to implement the SR workflow. In PySR it is necessary to specify operators (mathematical functions or operations) that the algorithm may consider when trying to find a suitable formula to fit the data set. The allowed binary operators included multiplication, division, addition, and subtraction. The allowed binary operators considered were natural exponential (e^x), square, cube, negative, and natural logarithm ($\ln$). Then the algorithm was applied to run for 200 iterations, in which the best equations in one iteration were retained in the following iteration, and further mutated. The quality of newly generated equations was evaluated by a least-squares loss function. Other hyperparameter options were used as default parameters.

Following algorithm completion, the formula with the lowest loss value was held as the final equation for height. Then the accuracy of this equation was validated by comparing the

predicted forest height against observed values in the validation data set (1,366 ICESat-2 height estimates) using the root mean square error (RMSE) metric.

The final RF and SR models obtained during training were used to predict forest canopy height for the entire study area. This was achieved with the R package terra's functions 'lapp()', and 'predict()' for spatial raster objects. As input, we used raster images of predictor variables that were generated before. This resulted in height maps in the EPSG:4326 projection, with spatial resolution of approximately 9.2 x 9.2 m per pixel. Height maps were produced for 2011, 2017, and 2019. Since the models were trained on combined observations from 2017 and 2019, accuracy was not distinguishing the year. Figure 3 illustrates the workflow implementation of the machine learning models of SR and RF.

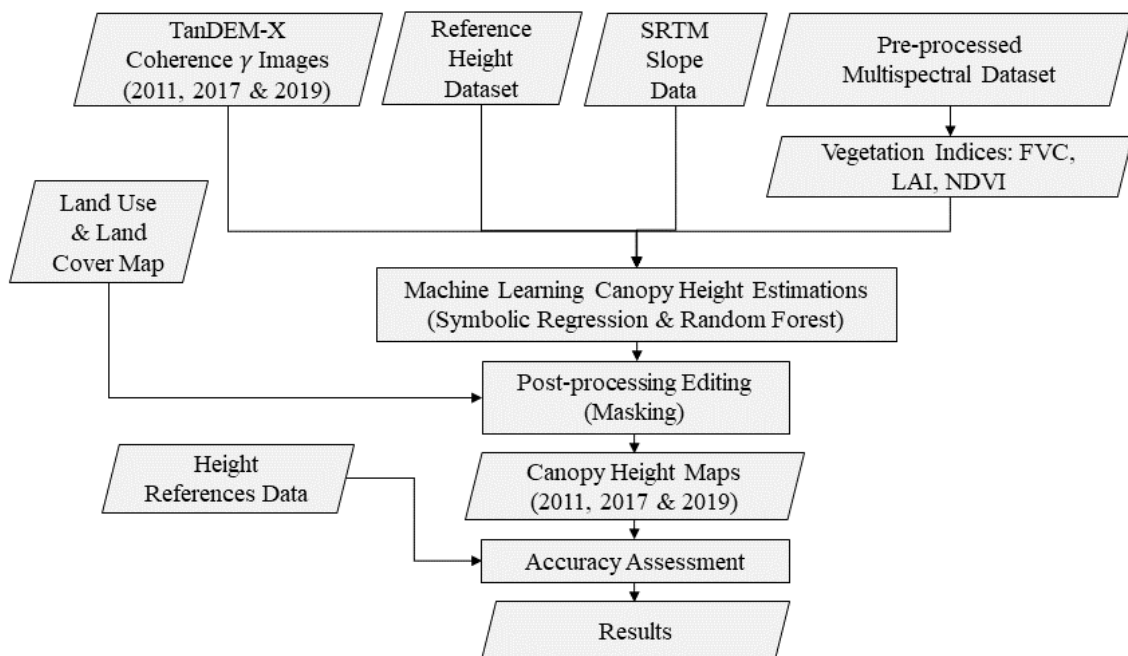


Figure 5.3. Workflow of canopy height estimation from TDX data using Machine Learning method. FVC: fraction of vegetation cover; LAI: leaf area index; NDVI: normalized difference vegetation index.

5.2.4. LULC Mapping and secondary dataset processing

The LULC data were mapped to facilitate the stratification of the estimated height according to LULC classes and precision of canopy height estimation for validation purposes. Optical multispectral satellite imagery was selected corresponding to the TDX data acquisition years. However, in the case of year 2011, we could not find suitable imagery due to the severe cloud

and shadow cover and SLC error in Landsat 7 satellite. Therefore, AVNIR-2 10 m images matching with Sentinel-2 imagery were used to generate LULC maps. Notably, there were no suitable AVNIR-2 acquisitions available over the study area for the year 2011 due to long repeat cycle of 46 days (Rosenqvist *et al.*, 2004) and due to an end of service in early that year (Operational from May 2006 to May 2011) and other available ANVIR-2 imagery being heavily covered by clouds and shadows. Therefore, we used two scenes of the ALOS AVNIR-2 2010 imageries as summarised in table 3.4.

All multispectral imagery were pre-processed, intensive cloud and shadow masking, and classification were conducted in the Google Earth Engine (GEE) environment. Meanwhile post-classification editing was carried out using ENVI and QGIS software. Detailed workflow of the LULC mapping is summarized in Figure A1. We applied the lowest 20% cloud cover filter for the imagery search. Meanwhile for the 2017 LULC mapping, we used pan-sharpened Sentinel-2 multispectral satellite imagery (MSI) combining three single-date scenes from July 5th, with less than 20% cloud cover, as the primary layer and one scene from August. High resolution Planet Labs mosaic images from August were used in post-classification editing. Sentinel-2 MSI has been available since 2015, still operational and having 5-day revisit frequency. To map the 2019 LULC, we also used Sentinel-2 MSI of surface reflectance harmonized (SRH) (Claverie *et al.*, 2018) imagery of three scenes from different dates (from October and November) as the primary layer, in combination with three scenes from April and three scenes from May with less than 20% cloud cover. All satellite imagery data were selected considering the closest date corresponding to the 2017 and 2019 TDX data. Details and specifications of the multispectral imagery used in the LULC mapping are summarized in table 5.4.

Table 5.4. Summary of Multispectral Satellite Imageries used to map the LULC.

Year	Data Set	Satellite/Sensor	Acquisition Dates	Bands & Vegetation Indices Used	Repeat Cycle
2010	Primary imageries	ALOS AVNIR-2 (10m.resolution)	12 Jul. 2010 (2 Scenes)	Blue, Green, Red, NiR & NDVI, NDWI	46 days
	Secondary imageries for cloud & shadow covered area	ALOS AVNIR-2 (10m.resolution)	27 Aug. 2010 (2 Scenes)		
2017	Primary imageries	Sentinel-2 MSI (10m. Pan-Sharp)	05 Jul. 2017 (3 Scenes)	Blue, Green, Red, Red Edge	5 days

	Secondary imageries for cloud & shadow covered area	Sentinel-2 MSI (10m. Pan-Sharp)	29 Aug. 2017 (1 Scenes)	1, NiR, SWIR 1, NDVI & NDWI	Rapid, multiple cube satellites
		*Planet Labs (3m.)	27 Aug. 2017 (Mosaic only covers Bengkoka Peninsula)	Blue, Green, Red & NiR	
2019	Primary imageries	Sentinel-2 MSI SR Harmonized (10m. Pan-Sharp)	03 Oct. 2019 12 Nov. 2019 17 Nov. 2019	Blue, Green, Red, Red Edge	5 days
	Secondary imageries for cloud & shadow covered area	Sentinel-2 MSI SR Harmonized (10m. Pan-Sharp)	21 Apr. 2019 (3 Scenes) 16 May. 2019 (3 Scenes)	1, NiR, SWIR 1, NDVI & NDWI	

*Used only in the post-classification editing.

There were twelve LULC classes identified in the study area and used in the multispectral satellite imagery classifications. We employed a ML method using a RF classifier in GEE for the image classifications, since RF classifiers are robust to noises and outliers (Gislason *et al.*, 2006; Shetty, 2019). LULC classes were as follows: Infrastructures, Waterbody, Acacia forest, Mangrove forest, Nipah, forest, Oil palm, Clearcut, Secondary forest, Aquaculture, Beach and sand as well as areas covered with Cloud and Shadow.

Several vegetation indices used in the LULC classifications (NDVI & MNDWI), and in the Machine Learning canopy height estimations (FVC & LAI) were also generated (Table 5.5). These vegetation indices are important spectral features in LULC mappings; additionally, these indices establish a link between the ICESat-2 and the TDX coherence data in the later canopy height estimations using the two ML models (Jiang *et al.*, 2021).

Table 5.5. Vegetation indices used in this study.

Vegetation Index	Formula	References
Normalized difference vegetation index (NDVI)	$(\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED})$	(Rouse, <i>et al.</i> , 1974)
Normalized difference water index (NDWI)	$(\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$	(McFeeters, 1996)
Fractional Vegetation Cover (FVC)	$(\text{NDVI} - \text{NDVI}_{\min}) / (\text{NDVI}_{\max} - \text{NDVI}_{\min})$	(Dinget <i>et al.</i> , 2016)
Leaf Area Index (LAI)	$(2.5 * ((\text{NIR} - \text{RED}) / (\text{NIR} + 6 * \text{RED} - 7.5 * \text{BLUE} + 1)))$	(Xue & Su, 2017)

$$(3.618 \cdot \text{EVI} - 0.118)$$

*EVI: Enhanced Vegetation Index

5.2.5. Supporting and references dataset processing

5.2.5.1. SRTM DEM

NASA SRTM V3 data (1 arc second: 30 m resolution) were applied as a terrain reference to calculate the local angle of incidence and kz parameter required for the height estimation using the SINC model in GEE. Meanwhile, the same SRTM DEM V3 was used to generate TDX coherence downloaded automatically during the coherence estimation in SNAP software. SRTM was applied to generate the terrain slope map used in the SINC model estimation. Also, the terrain slope map and SRTM V3 were used in the ML canopy height estimations in the models.

5.2.5.2. ICESat-2 ATLAS dataset

Vegetation canopy height data derived from NASA's ICESat-2 mission were downloaded which available from Open Altimetry ([Khalsa et al., 2022](#)) website for the study area; the data were captured over multiple months in 2018 and 2019 (Fig. A2, A3 & Table A2). ICESat-2/ATLAS is a space-borne photon-counting LiDAR launched in 2018 ([Liu et al., 2021](#); [Markus et al., 2017](#)). The mission was primarily designed for ice surface observations; however, the data can also be used to measure terrain and vegetation canopy metric. The mission supplies a level-3A data product for land and vegetation elevation called ATL08 ([Neuenschwander & Magruder, 2019](#); [Neuenschwander & Pitts, 2019](#)). The ATL08 product reports terrain and canopy height metrics for 100 m. sections along the satellite track, with a ground sampling resolution of approximately 17m. The vegetation canopy height metric we considered was 'h_canopy', which evaluates height at the 98th percentile of canopy height estimates in the 100 m track segment. This variable is a suitable indicator of canopy height for the segment, as it is less susceptible to high values caused by data noise ([Guerra-Hernández et al., 2022](#)). The ATL08 dataset reports height uncertainty in the variable "h_canopy_u". We filtered out track segments that had height uncertainty above 7 m (~4% of observations). The ATL08 observations for track segments are georeferenced with point geometries, however, the data represent information for a spatial footprint of approximately 100 x 17 m along the track. We made 100 x 17 m buffers around the points, which were used to sample predictor variables by aggregating (averaging) the raster values in the buffers.

5.2.5.3. Forest inventory dataset

Inventory data previously supplied by forest management company were collected throughout the year 2011 and 2012 use to validate the 2011 canopy height estimation results of *Acacia Mangium* LULC. This dataset only covers the *Acacia Mangium* plantation areas from 367 permanent sample plots and a total of 1,940 records of individual trees. The plots are sampling units designed in circles of 11.28m radius covering 400m² area. The recorded maximum height at 28.70 m (2011) and 27.14 m (2012) (Fig. A4, Table A4 & A5). The raw field inventory data tabular data were processed by grouping individual trees record according to plot number then mean height of each plot were calculated. The inventory plot's locations were mapped in GIS using coordinates from the tabular records. We also collected forest inventory data in early year 2023 using 15 x 15meters random sampling pots of Mangrove, wild *Acacia Mangium* and Secondary forest areas. A total of 62 plots were recorded with 20 plots for Mangrove, 18 for *Acacia Mangium* and 54 of Secondary forest.

5.2.5.4. Global Airborne Observatory (GAO) Top of Canopy Height (TCH) data

The GAO formerly known as Carnegie Airborne Observatory (CAO), is an advanced remote sensing mapping aircraft developed by asnerlab.org. of Arizona State University. The Global Airborne Observatory (GAO) Top of Canopy Height (TCH) data used in this study is a 30 m resolution interpolation map based on LiDAR collected all over Sabah in 2016 (Asner *et al.*, 2018). The canopy mean height recorded in GAO data is at 7.7 m while maximum height is at 27.19 m. The TCH data used in this study was downloaded from the online repository <https://zenodo.org/record/4549461> in raster format (Asner *et al.*, 2021) (Fig. A5 & Table A6).

5.2.5.5. NASA Global Ecosystem Dynamics Investigation (GEDI) L2A geolocated elevation and height metrics product

The GEDI is a waveform space-borne LiDAR mounted on the International Space Station designed for global ecosystem and forest observation which started operation in April 2019 (Dubayah *et al.*, 2020). GEDI data products are available via NASA Land Processes Distributed Active Archive Center (LPDAAC) lpdaac.usgs.gov and through GEE. GEDI samples the footprints of 25 m resolution every 60 m along eight data tracks that are 600 m apart each laser spot (Dubayah *et al.*, 2020). For this study we used the GEDI level 2A of rh98 top canopy height mean height collected on month of June, July, August, and September 2019. These data were accessed in GEE and were downloaded in raster format, each monthly data collection was processed into vector format in QGIS then combined into one layer (Fig. A6 & Table A7).

5.2.6. Validation of the estimated canopy heights and LULC classifications

We validated the 2011 results using inventory data, 2017 results using the GAO TCH and 2019 results using GEDI. The ML RF and SR models were trained using 70% of the 2018 and 2019 ICESat-2 data and the remaining 30% used for model validation. The accuracies were assessed using the coefficient of determination (R^2) of a linear model fit between the predicted and reference height values, and RMSE between predicted and reference height (in meters). Meanwhile, the LULC maps were validated using randomly generated ground samples collected from high resolution google earth imagery and planet labs imagery. Overall accuracy and kappa coefficient k of the LULC maps are also calculated.

5.3. Results

The outcome of this study focusses on the mapping of temporal dynamic tropical forest and plantations canopy height in Borneo utilizing TDX InSAR and supported by multi-sensor remote sensing data. In this study three forest height models were generated, using alternative height modelling approaches. These were (1) the SINC model, that established an empirical relationship between canopy height and SAR coherence, (2) a Random Forest regression model that considered SAR coherence, terrain and land cover variables as predictors and satellite Lidar based height estimates for training data, and (3) a height model derived using symbolic regression. The SR derived model can be expressed in the form of a simple equation describing the relationship between canopy height and predictor variables. The three models were used to generate canopy height maps for three separate years (2011 Fig. 5.4, 2017 Fig. 5.5, & 2019 Fig. 5.6). The produced maps were then compared against existing reference datasets for validation using randomly generated sampling points ($n=999$ for 2011, $n=1,000$ for 2017 & 2019). We summarized the statistics of the canopy height maps (2011 Table 5.7, 2017 Table 5.8, & 2019 Table 5.9) at 2% lower bound, median, and upper 98% upper percentile to remove outliers. The canopy height maps were also evaluated by comparing height estimates in particular land use types with reported heights common for the type of canopy or land use.

5.4. Model results

5.4.1. SINC Model

The first estimation model SINC model's height estimates ranges between 13.96 m to 26.07 m for 2011, 10.50 m to 27.03 m, and 14.16 m to 26.24 m for 2019. While median recorded at 17.93 m, 16.70 m, and 17.16 m for the three years respectively. The SINC model canopy height maps are shown in Fig. 5.4a, Fig. 5.6a, and Fig. 5.8a.

5.4.2. Random Forest

The second estimation model of RF model accuracy can be evaluated with respect to the canopy height data used for model training (ATL08 canopy height estimates), in addition to the comparison with the external reference height datasets. With respect to the training data, this model obtained an RMSE = 5.4 m for out of bag (OOB) errors, and RMSE = 5.5 m for the validation data set (30% of original ATL08 data). The % Variance explained for the model was 48.23% in the training and 47.95% in the test set respectively. ‘% Var explained’ by the model can be interpreted similarly to an R^2 value. The relative importance of the predictor variables was reported (Table 3.6). SAR coherence is the most important variable in the RF model, followed by the terrain elevation (DEM) and the fraction of vegetation cover (FVC).

Table 5.6. Variable importance, described by % increase in MSE when model variable is permuted (%IncMSE) and increase in node purity when variable is permuted (IncNodePurity). Higher values indicate higher importance.

Variables	%IncMSE	IncNodePurity
Coherence	109.30	57786.61
DEM	57.34	35570.71
FVC	49.09	26269.91
LAI	26.25	22536.51
Slope	25.12	23992.24

5.4.3. Symbolic Regression

The third model of Symbolic regression was used to find an equation describing the relationship between canopy height and predictor variables: coherence, terrain (DEM and slope) and vegetation cover (FVC and LAI). As mentioned previously, SR model simplified the final equation only include the related useful variables, in this case LAI and slope are removed. The canopy height equation that obtained lowest RMSE for the validation set of ATL08 height data is given below in equation 6, with coefficients rounded to 3 significant figures. This model obtained (RMSE = 5.96 m, $R^2 = 0.404$).

$$H_{canopy} = 0.0633DEM - 25.8coherence^3 + e^{2FVC} + 19.8 \quad (6)$$

In this equation, height increases as coherence decreases, increases with fraction of vegetation cover, and increases slightly with elevation. The benefit of this modelling approach is that an easily interpretable model is generated.

5.4.4. Estimated Interferometric TDX canopy heights maps and accuracies

The estimations from three temporal years and three models resulted in a total of nine canopy height maps which are comprehensively discussed in each of the results sub-sections corresponding to the years 2011, 2017 and 2019.

5.4.4.1. Year: 2011

The 2011 results were assessed using 344 random IfSAR reference data sampling points. The height estimates for 2011 differ between models (Table 5.4, Fig. 5.5, & Fig. 5.6) with SINC model 2nd percentile is higher (13.96 m) compared to the RF (8.3 m) and SR (1.32 m). Median height of 2011 models ranging from 11.55 m (RF model), 17.93 m (SINC model), to 20.72 m (SR model). The RF and SR models underestimated 98th percentile at (23.18m & 23.82 m) compared to SINC model (26.07 m). Also, shown in the canopy height class maps (Fig. 3.4) also in Fig. 3.12a, SINC model overestimated compared to RF and SR. When evaluated against the IfSAR CHM, the height models obtained RMSE values between 12.35 m (SINC), 7.05 m (RF) and 6.06 m (SR). The model estimation for 2011 also does not reflect the height variation observed in the reference data, as indicated by low R^2 values for all models ($R^2 = 0.13$ for SINC, $R^2 = 0.0908$ RF, & $R^2 = 0.1216$ SR). We observed that the RF result is affected by cloud and shadows from satellite imagery used to produce the vegetation indices used in the RF model where the areas are labelled as no height. The SR model was the best estimation model overall in capturing the height variations, RMSE and R^2 value.

Table 5.7. Summary of the Estimated Canopy Height for the year 2011 by percentiles.

Models	2 nd Perc. (m)	Median (m)	98 th Perc. (m)
SINC	13.96	17.93	26.07
RF	8.3	11.55	23.18
SR	1.32	20.72	23.82

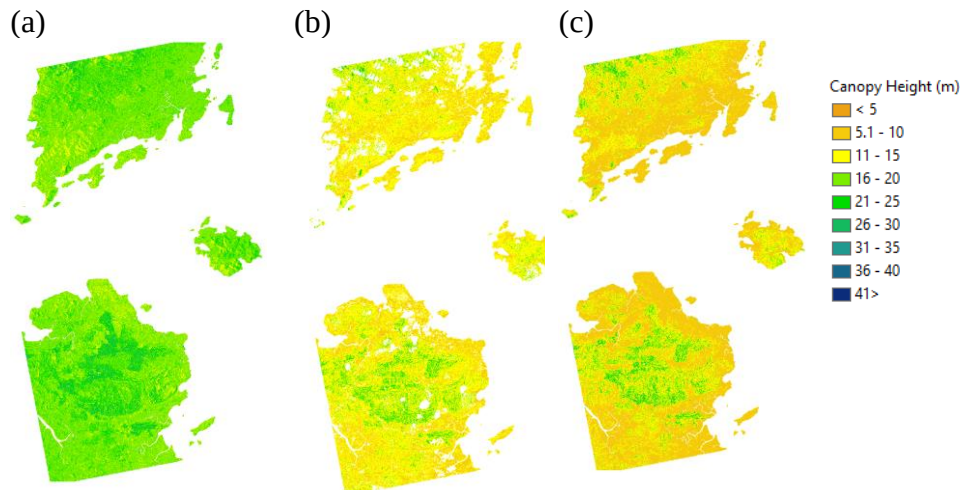


Figure 5.4. Estimated Canopy Height of 2011(a) SINC model, (b) RF, and (c) SR.

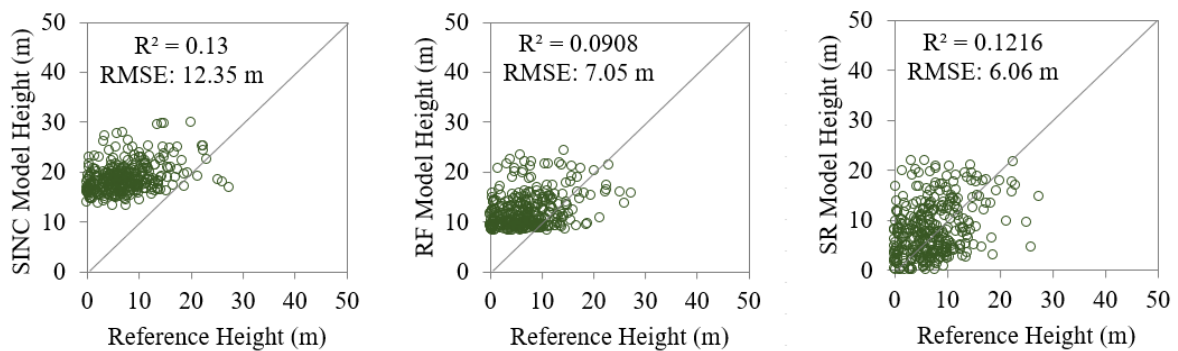


Figure 5.5. Correlation plots for the 2011 Estimated Canopy Heights against IfSAR.

5.4.4.2. Year: 2017

In the 2017 canopy height maps of all models show a cleared area for Oil palm plantations in the Banggi Island located north (Fig. 4.6). All models showed almost uniform height variations shown in the canopy height classes maps. The SINC model 2nd percentile higher (10.50 m) compared to RF (8.75 m) and SR (6.32 m). The median height is estimated between 16.70 m (SINC), 17.29 m (RF), and 21.96 m (SR). Max height of RF and SR model estimates were generally higher than the GAO TCH reference height (Max = 27.19 m, refer Supplementary Figure A5 & Table A6) leading to high RMSE (10.49 m and 10.36 m for RF and SR respectively, Fig. 3.7) even after resampled to GAO resolution (30 m). In terms of capturing variation in height across the study area, the estimates from all models correspond closer to the reference GAO Tree Canopy Height (TCH) product from 2016. The agreement was best for the RF model ($R^2 = 0.37$, $n = 1,000$), but also similar for the SR model ($R^2 = 0.36$). However, as with 2011, the SINC model does not capture the full height range observed in the reference

height data (Fig. 5.12b shorter whiskers). Overall best model estimation for 2017 is also SR in capturing the height variations, both RMSE and R^2 values.

Table 5.8. Summary of the Estimated Canopy Height for the year 2017 by percentiles.

Models	2 nd Perc. (m)	Median (m)	98 th Perc. (m)
SINC	10.50	16.70	27.03
RF	8.75	17.29	29.65
SR	6.32	21.94	28.36

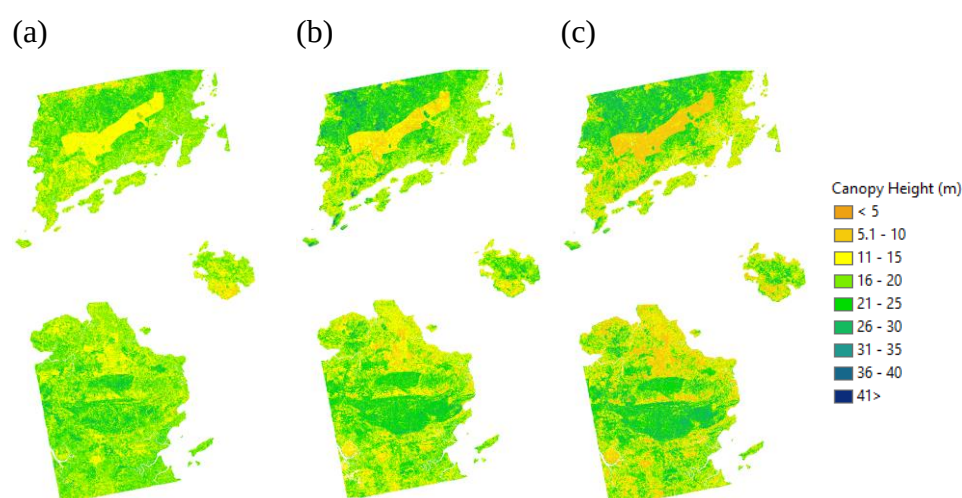


Figure 5.6. Estimated Canopy Height of 2017 (a) SINC model, (b) RF, and (c) SR.

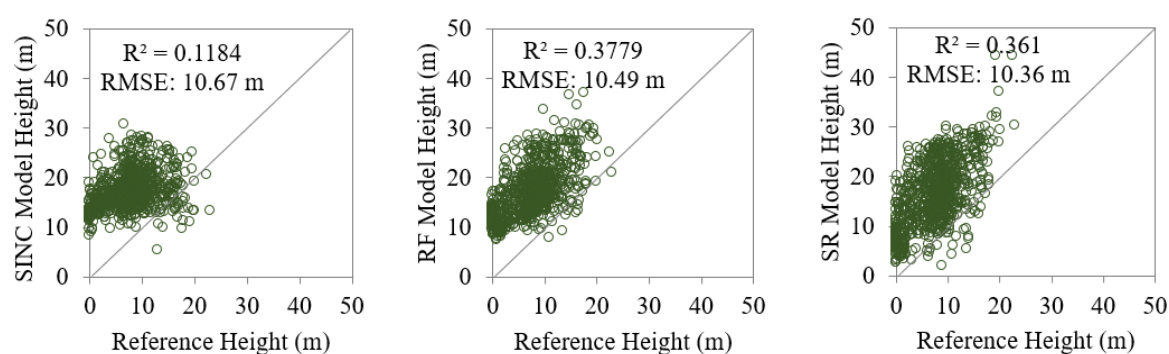


Figure 5.7. Correlation plots for the 2017 Estimated Canopy Heights against 2016 GAO TCH data.

5.4.4.3. Year: 2019

Notably, variations in canopy heights are apparent across the three models (see Table 5.11, Fig. 5.8, & Fig. 5.9). The SINC model's 2nd percentile surpasses both RF (9 m) and SR (9.58 m). The estimated median height is relatively consistent, with values of 17.76 m (SINC), 18.33 m

(RF), and 21.20 m (SR). However, the GEDI reference height demonstrates a lower mean height of 15.10 m but a higher maximum of 44.28 m (see Figure A6 & Table A7). In contrast, the 2019 SINC canopy height model underestimates the 98th percentile at 26.24 m (Table 5.11), while RF and SR show similar values at 29.68 m and 29.58 m, respectively. The overall best model for 2019 is RF with the highest agreement ($R^2 = 0.32$, $n = 1,000$), followed by the SR model.

Table 5.9. Summary of the Estimated Canopy Height for the year 2019 by percentiles.

Models	2 nd Perc. (m)	Median (m)	98 th Perc. (m)
SINC	14.16	17.76	26.24
RF	9	18.33	29.68
SR	9.58	21.20	29.58

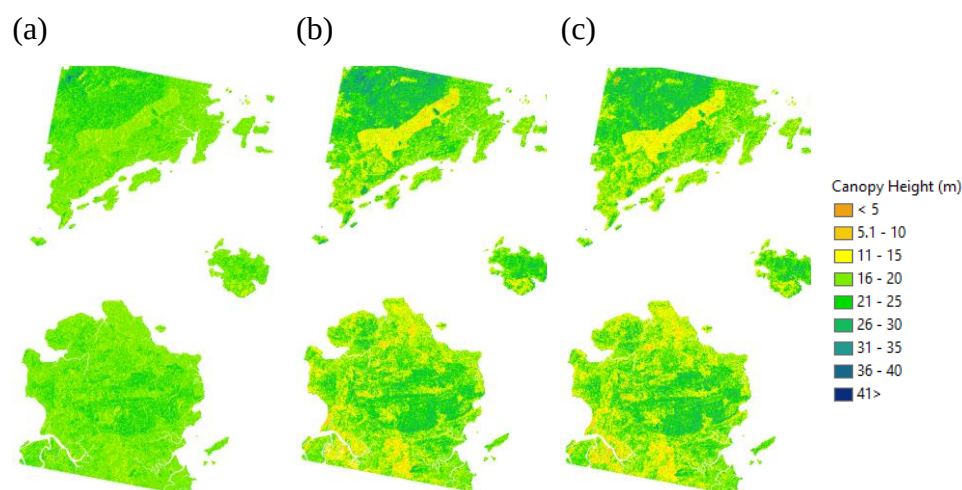


Figure 5.8. Estimated Canopy Height of 2019 (a) SINC model, (b) RF, and (c) SR.

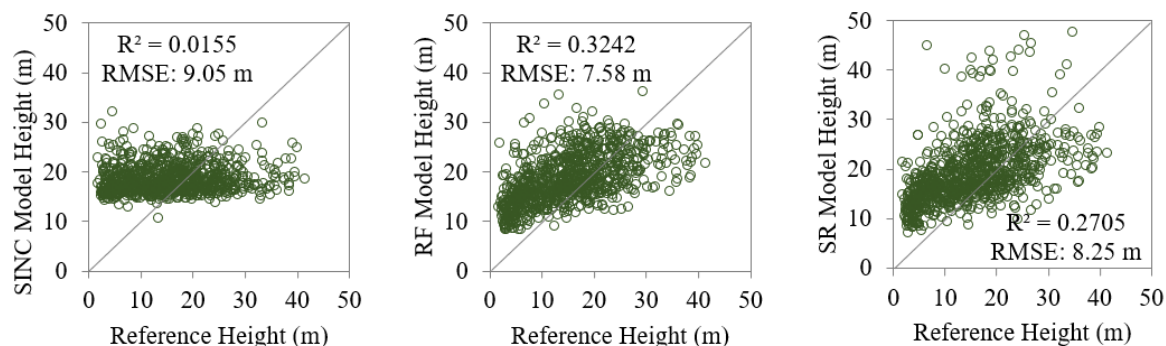


Figure 5.9. Correlation plots for the 2019 Estimated Canopy Heights against 2019 NASA GEDI.

5.4.5. LULC maps accuracy assessment

Figure 5.10 shows LULC maps produced for 2010, 2017 and 2019 respectively. In all three years the main LULC are Forest (> 40%) followed by Acacia, Mangrove and Secondary forest. Oil palm covered a comparatively small area, but increased between 2011 to 2019, to approximately (3%) of the study area. A total of 812 random samples were used for 2010 and 2017 LULC map accuracy assessment while 813 sample for the 2019 map. Overall Accuracy and Kappa Coefficient K for the three maps are 86% (k 81%), 91% (k 88%) and 83% (k 77%) respectively. The clearcut area in the 2019 LULC map of the Bengkoka peninsula appears as 11-15m height classes in the canopy height maps. This discrepancy is attributed to the timing of data acquisition. The TDX data was acquired on 29th October, while the S-2 imagery was acquired on 17th November 2019 after the timber harvesting took place.

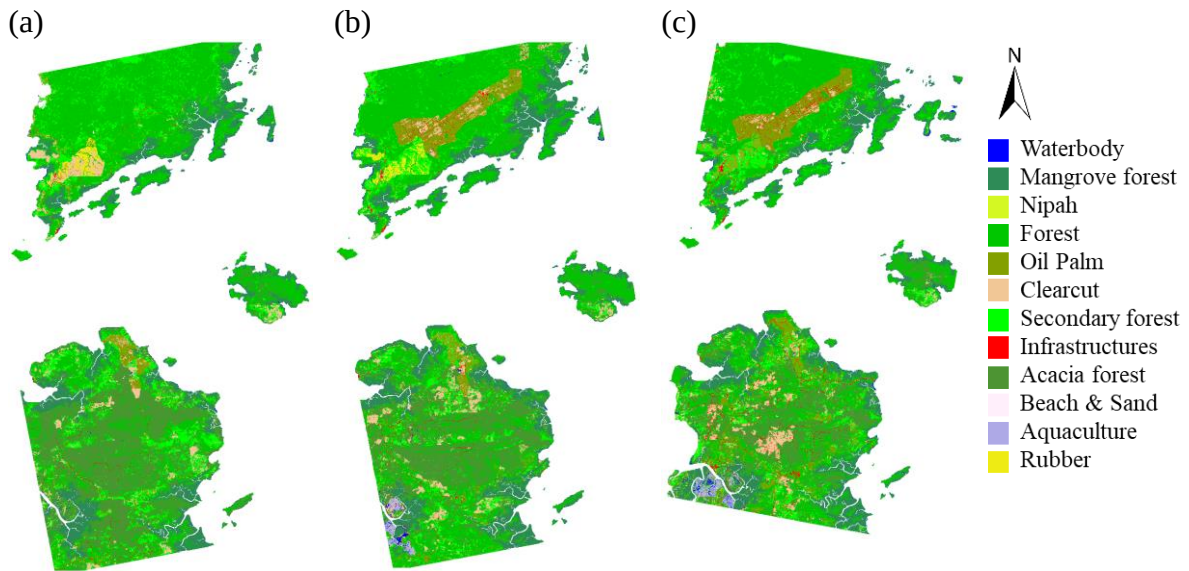


Figure 5.10. LULC maps of year (a) 2010, (b) 2017 and (c) 2019.

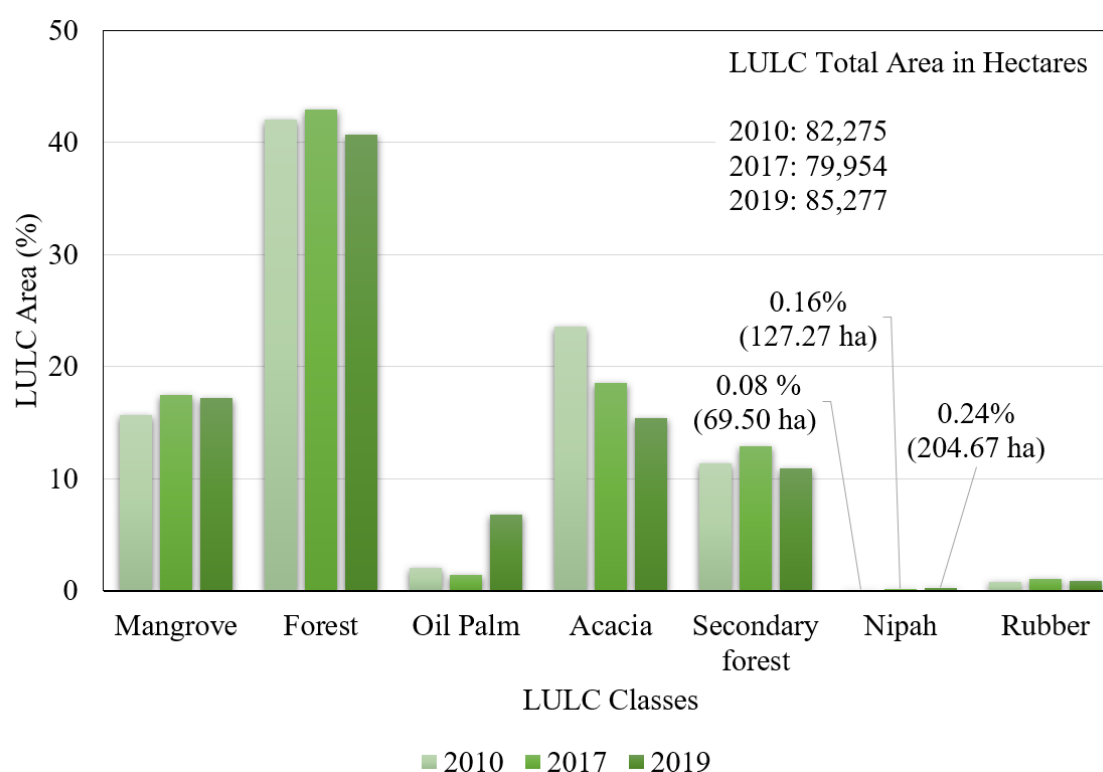


Figure 5.11. Percentages of the forest and plantations LULC maps.

Table 5.10. Accuracy of the LULC Maps.

LULC Map Year	Accuracy		
	Number of Sample	Overall Accuracy	Kappa Coefficient <i>k</i>
2010	812	86%	81%
2017	812	91%	88%
2019	813	83%	77%

5.4.6. Estimated canopy height accuracies respective to forest and plantations LULC

The RMSE and coefficient of determination (R^2) were calculated to measure the accuracy of produced canopy height maps stratified by forest and plantations LULC classes (Table 5.13). The 2011 SINC by LULC results showed RMSE values close to the overall SINC RMSE (12.35 m) except for the inventory RMSE (4.06 m) (Table 5.11). The 2011 SR by LULC shown lower RMSE (< 7 m) and R^2 compared to RF model which also similar with the overall RF accuracy (7.05 m). The 2017 LULC RMSE is higher as compared to the overall RMSE (above best SR model 10.36 m). The SR model by LULC shows better RMSE except in Rubber land

use. The 2019 by LULC show moderate RMSE (<10 m) for all models higher than the overall (RMSE range 8.25 to 9.05 m). There were no RMSE and R² recorded for Nipah LULC due to very sparse and significantly small area patches in the TDX scene (Fig. 5.11).

Table 5.11. Validation of estimated canopy height by forests and plantations LULC; RMSE and coefficient of determination (R²) against reference dataset IfSAR (2011), GAO TCH (2017) & NASA GEDI (2019). RMSE colour coded from low value (blue), medium (white), to high value (red). R² colour coded from low value (orange), to medium (yellow) to high value (green).

LULC	SINC		RF		SR	
	RMSE (m)	R ²	RMSE (m)	R ²	RMSE (m)	R ²
2011						
Mangrove	10.48	0.03	3.92	0.00	5.25	0.01
Forest	12.43	0.01	6.89	0.03	5.70	0.03
Oil palm	13.32	0.50	6.83	0.22	3.23	0.25
Acacia m.	12.21	0.13	7.69	0.08	6.72	0.15
Secondary Forest	13.94	0.08	8.79	0.14	5.79	0.11
2017						
Mangrove	8.54	0.02	6.95	0.22	6.11	0.07
Forest	10.10	0.02	10.59	0.41	10.99	0.43
Oil palm	12.20	0.49	10.14	0.20	7.28	0.48
Acacia m.	12.72	0.12	13.49	0.24	13.72	0.17
Secondary Forest	10.88	0.14	10.43	0.27	9.47	0.30
Rubber	13.45	0.04	14.86	0.12	15.64	0.08
2019						
Mangrove	5.83	0.04	5.44	0.10	5.81	0.05
Forest	7.36	0.18	7.78	0.19	9.18	0.14
Oil palm	9.15	0.27	7.26	0.52	7.67	0.45
Acacia m.	9.51	0.40	8.84	0.28	8.91	0.29
Secondary Forest	8.62	0.21	7.90	0.31	8.31	0.30
Rubber	5.14	0.61	4.35	0.00	4.86	0.13

The result by LULC classes also validated against the field inventory data of year 2011 & 2012 for the 2011 canopy height model results and only the 2019 results with recently collected data for Mangrove, wild *Acacia Mangium* and Secondary forest. For the 2023 inventory data we carefully filtered the sample plots and excluded areas in which the LULC has changed. Here we assume that there are not drastic canopy height changes between 2019 and 2023 for the selected plots. We did not compare the 2023 inventory with the year 2017 and 2011 canopy height estimations results considering the too wide years gap. Results shown that

for the 2019 Mangrove SR is the best model with 4.99 m RMSE close to the GEDI 5.81 m (Table 5.12). Meanwhile for the Acacia, RF RMSE is the lowest at 4.46 m with better R^2 (0.24) value however not much difference with the SR model at 4.62 m RMSE. The secondary forest also showed RF as best model with RMSE 6.87 m not much difference with the SR at 6.96 m RMSE as summarized in table 5.12.

Table 5.12. Validation of estimated canopy height by forests and plantations LULC using inventory data; RMSE and coefficient of determination (R^2) against field measured inventory dataset. RMSE colour coded from low value (blue), medium (white), to high value (red). R^2 colour coded from low value (orange), to medium (yellow) to high value (green).

LULC	SINC RMSE (m)	R^2	RF RMSE (m)	R^2	SR RMSE (m)	R^2
2011						
Acacia m. (Plantations)	4.06	0.07	7.74	0.06	8.69	0.09
2019						
Mangrove	5.81	0.05	5.03	0.04	4.99	0.12
Acacia (Wild)	5.71	0.38	4.46	0.24	4.62	0.17
Secondary Forest	7.27	0.05	6.87	0.04	6.96	0.07

5.4.7. Estimated canopy height by forest and plantations LULC

We summarized the canopy height results by LULC (Fig. 5.12) showing patterns and height variations for the three years. In 2011 results the canopy heights generally vary across the models with SINC model overestimate for Mangrove, Oil palm, and secondary forest classes (all above 15 m) and lower canopy heights were not captured (Fig. 5.4a). The 2017 and 2019 canopy height models shown almost even levels. The 2019 SINC model underestimate heights by ± 5 m with variations not captured as seen in Fig. 5.12c range and in Fig. 5.8a the cleared Oil palm plantation is not so visible as compared to the RF and SR results. While the SINC model does not adequately capture the vertical variations across the various forests and plantations LULC heights shown by shorter whiskers compare to RF and SR models. We also summarized the average height of model results by LULC in Table 5.4 to compare the variations and agreement between models in the mean heights. As mentioned earlier, the 2011 SINC model shown generally higher mean height of all LULC classes then the RF and SR models. Meanwhile the 2017 and 2019 all model results shown comparably similar estimation ranges across all LULC classes.

Table 5.13. Average height of estimated canopy height by forests and plantations LULC by models.

LULC	SINC	RF	SR
2011			
Mangrove	9.81	5.39	3.42
Forest	10.39	7.47	6.97
Oil palm	9.33	6.23	3.84
Acacia	11.55	8.77	8.33
Secondary forest	9.83	7.19	5.42
Rubber	9.05	7.09	3.21
Nipah	9.82	5.69	4.31
2017			
Mangrove	9.95	9.25	8.84
Forest	10.72	12.22	12.92
Oil palm	8.10	7.76	6.90
Acacia	11.78	12.24	12.63
Secondary forest	9.05	9.07	9.22
Rubber	9.53	10.28	10.94
Nipah	10.71	10.04	10.32
2019			
Mangrove	9.63	9.64	9.91
Forest	11.00	12.86	13.81
Oil palm	9.23	8.87	9.06
Acacia	11.23	12.28	12.55
Secondary forest	10.17	10.47	10.91
Rubber	9.92	11.23	11.19
Nipah	10.83	10.06	10.89

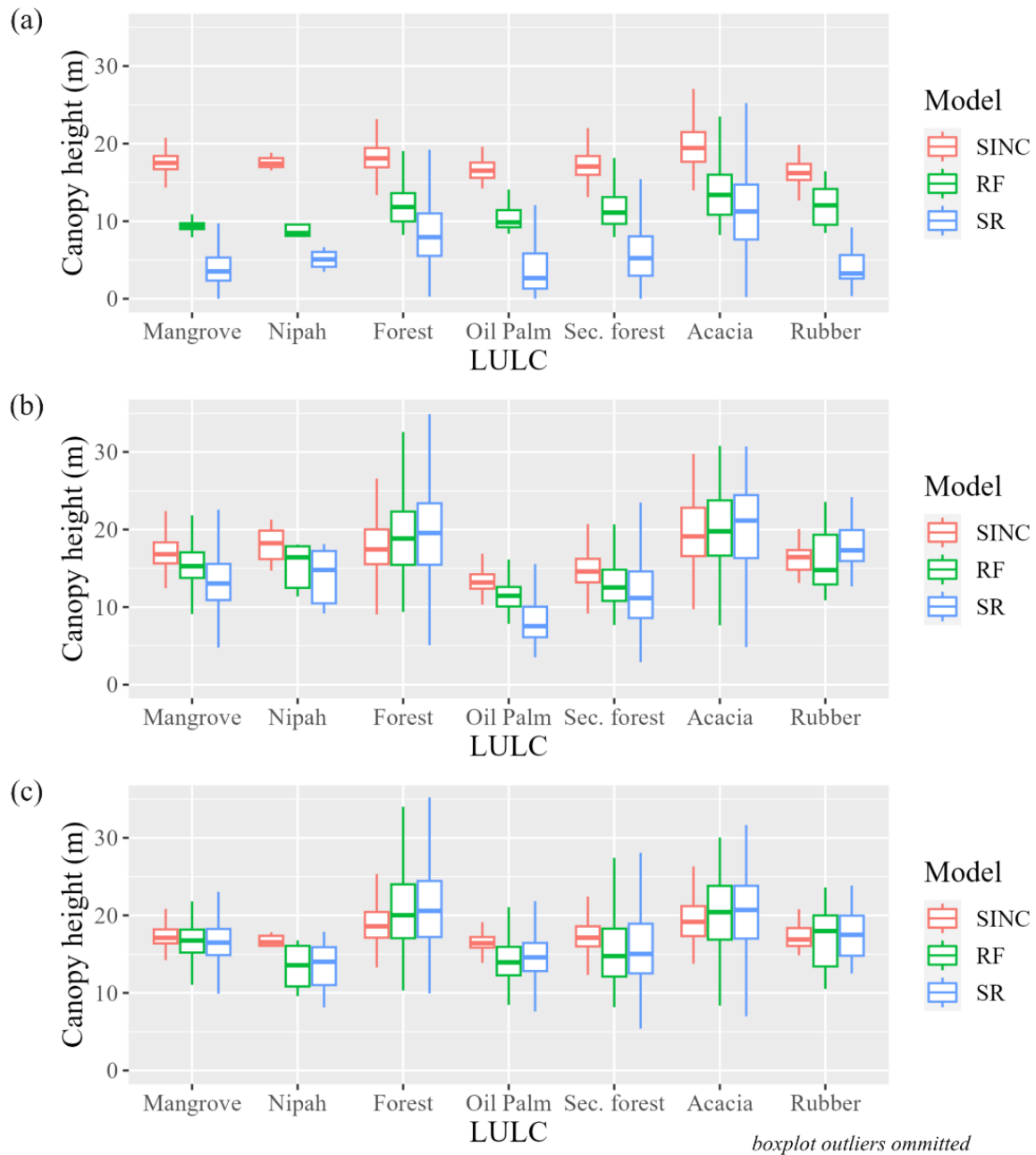


Figure 5.12. Estimated canopy height models by Forest and Plantation LULC classes of year (a) 2011, (b) 2017 and (c) 2019. Box plots indicate first quartile, median and third quartile of the height variability. Whiskers indicate the height range.

In terms of spatial distributions, we classified the canopy height models by 5 m intervals (maps Fig. 5.4, 5.6, & 5.8), for 2011 the SINC model (Fig. 5.13) estimated between 43% to 85% of the 15-20 m canopy height class for all forest and plantation LULC. The RF model estimated between 18% for (Acacia) to 81% (Mangrove) of the 5–10 m canopy height class.

The SR model estimated below 5 m (refer Fig. 5.13a.) for mangrove, oil palm, and Secondary forest between 50% to 65.5% of the LULC area.

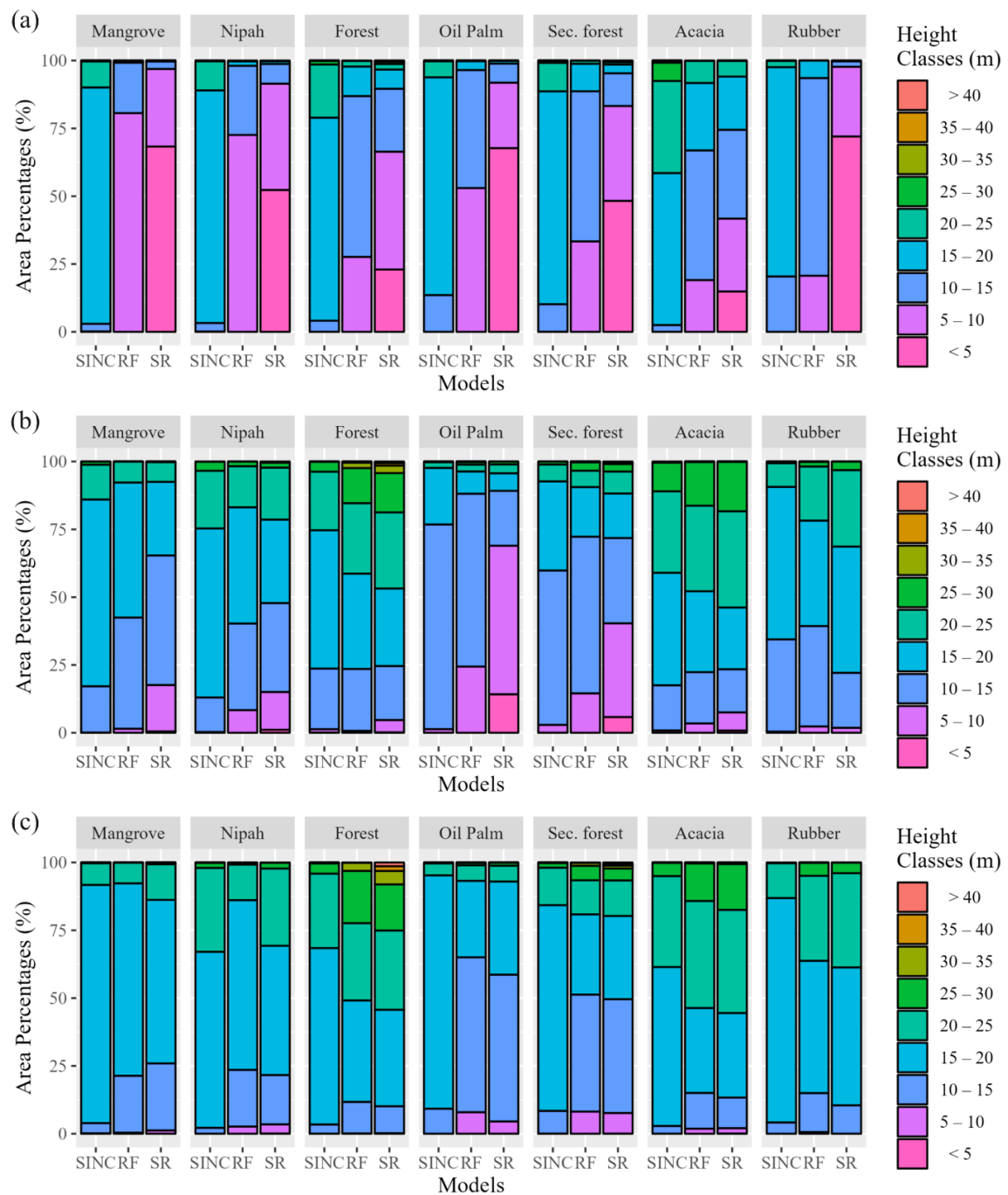


Figure 5.13. Percentages of canopy height classes spatial distributions by Forest and Plantation LULC of year (a) 2011, (b) 2017 and (c) 2019.

Meanwhile spatial canopy height distributions of 2017 for all result models showed less 5–10 m height class for all LULC classes compared to 2011. The 2017 results recorded more

of the 10–15 m and 15–20 m canopy height classes for all LULC between 20% to 62% and 12% to 65% respectively (Fig. 5.13b). The 2019 results recorded more of the 15-20m for all LULC classes between 26% to 81% with SINC model the highest for mangrove. In the 2019 results more of the 15-20 m canopy height classes recorded for all LULC classes between 25% to 87% for all LULC. Forest LULC for 2019 recorded a slight increase of the 30 -35 m height class and additional of small percentages of the 35-40 m canopy height class in the RF and SR models compared to the 2017 (Fig. 5.13c).

5.5. Discussion

In this study canopy height were estimated for the northern Sabah, Malaysian Borneo. Maps of canopy height were produced for the three years: 2011, 2017 and 2019, using three different model approaches, resulting in 9 canopy height maps in total, with spatial resolution of 10 m per pixel. The produced height metrics were evaluated against existing forest inventory data and other canopy height products such as the Global Aerial Observatory (GAO) tree canopy height map from 2016 and 2019 GEDI spaceborne LiDAR. The estimated canopy metrics were also aggregated and analyzed according to LULC types in the study area. The primary objective of this work was to generate high-resolution canopy height information in Northern Sabah, that can support studies on land use and sustainability of forests and plantations management in the study area.

5.5.1. Canopy height estimates

In this paper, we presented our findings on canopy height estimation based on TDX InSAR coherence. Our ML models show that besides coherence, the important variables for canopy height estimation according to importance are DEM, FVC, and LAI whereas slope is the least important. [Ghosh \(2020\)](#) identified LAI, FVC, and DEM as important variables. We employed two models, Random Forest (RF) and Simple Regression (SR), for canopy height estimation, and the out-of-bag Root Mean Square Error (RMSE) of the RF model was found to be 5.4 m (Section 5.1.2.), whereas the SR model had an RMSE of 5.96 m (Section 5.1.3.). Additionally, we performed a validation, which resulted in an RMSE of 5.5 m (Section 5.1.2.) for the RF model. Our estimates consistently showed higher canopy height than the GAO product, which is likely due to the GAO's lower resolution of 30 m. In addition, GAO TCH product was produced from interpolation of sparsely located Airborne LiDAR points over the study area, refer ([Asner et al., 2018](#)). However, despite downscaling our results for accuracy assessment, we still observed a higher RMSE of 10.49 m than the GAO product. Our SINC model results

for 2017 and 2019 shown comparably good accuracy as to the ML models however underestimations of canopy heights are observed.

We found that our canopy height estimations for different forest types generally aligned with the literature, with some minor differences that were attributable to RMSE. For instance, for Nipah and mangrove, our results showed maximum heights between 18-21 m, with RMSE ranging between 3.92 (RF) - 10.48 m (SINC). In comparison, the literature suggested heights of around 11 m (Mohd-Lokman *et al.*, 2012). For secondary forest, our results ranged from 15-26 m, with RMSE between 7.94-11.61 m, whereas the literature suggested heights between 10-30 m (Nagano *et al.*, 2019; Ong *et al.*, 2021). For Oil palm, our results ranged from 12-24 m, whereas literature suggested a height of 15 m (Tan *et al.*, 2014). For *Acacia mangium*, our results ranged from 26-32 m, with the literature suggesting heights of around 30-34 m (Abe *et al.*, 2005; Jusoh *et al.*, 2017). We noted that RMSE could be a factor contributing to the differences observed.

Our analysis revealed that the limitation of single polarization, single baseline, and short wavelength interferometry for forest height estimation is underestimation due to extinction coefficient, as noted by Chen *et al.*, (2018) & Praks *et al.*, (2012). We compared the accuracy of our canopy height estimations to other studies and found that the RMSEs of our three models were similar to those reported by Schlund *et al.*, (2016), who studied tropical low land in Sumatra, with RMSEs between 6.42 – 10.25 m. Additionally, Stovall *et al.*, (2021) reported an RMSE of 6.9 m for mangrove forest in Gabon and rainforest. Raveendrakumar *et al.*, (2022) reported their RMSE between 3.4-13.8 m of 8 TDX dataset in western Ghats, India. We noted that the estimations using TDX coherence are based purely on the SAR volume contribution, which could be higher in the lower canopy than in the taller canopy, as suggested by Schlund *et al.*, (2023). This could explain why the estimation results of all models at 98th percentile is slightly lower than the reference data (ICESat-2, GAO, GEDI), except for inventory (only cover acacia), which recorded higher maximum height up to 44.28 m for GEDI. Lastly, we found that slope was the least important variable in our ML canopy height estimation models, which is consistent with previous studies. We believe this is due to the gentle slope of our study area, which is not located in a mountainous region. Therefore, we did not consider slope influence on the canopy height accuracy in our analysis.

5.5.2. Limitations and recommendations

Despite the promising results of this study, we acknowledge several limitations that may have influenced our results. Firstly, the lack of field inventory data for 2017 and 2019 limited our ability to precisely validate the accuracy of the canopy height maps. In addition, high-resolution airborne LiDAR data was not available for the study area, which may have affected the precision of our validation results. Secondly, the accuracy assessment of the canopy height model was based on the 2011 inventory which only covers forest and acacia LULC and 2023 cover mangroves, *Acacia mangium* outside plantations and secondary forest. This may have introduced errors and biases in the 2011 model results, particularly in areas with different LULC types. Also, we were unable to collect field inventory data other LULC such as Nipah, Oil palm, rubber due to logistic and no permissions from the landowners. Thirdly, the historical temporal coverage of ICESat/GLASS data has limited coverage for the study area, and GEDI data was not available before 2019. This may have limited our ability to assess changes in canopy height over time, which is an essential aspect of forest and plantation mapping. Lastly, our canopy height estimations and maps are based on the TDX InSAR data, which is subject to biases and limitations of the TDX SAR specifications.

To address these limitations, we recommend that future studies incorporate complete field inventory data and integrate high precision ground or airborne LiDAR measurements, especially for validation and accuracy assessment of the model results. This will improve the accuracy and precision of the canopy height maps and provide more reliable estimates of forest and plantation cover. Moreover, future studies should also consider temporal canopy height changes analysis to assess changes in forest and plantation cover over time. This will allow for more accurate monitoring of forest and plantations health, timber harvesting, forest regeneration, or forest encroachment for the forest and plantations to be well sustainably managed.

From our study, we have learnt that the challenge of working with multi-sensor data, particularly the alignment of data from different acquisition dates. In addition, high RMSE and low R² as observed in the validation tables may relate to the way different sensor measure canopy height as mentioned by (A. Neuenschwander & Pitts, 2019), but the reasoning extends to other sensors considered in this study. The increasing frequency of data acquisition by multi-sensor and various satellites in the future is expected to reduce the likelihood of wider acquisition date gaps, especially in the context of SAR, optical and space LiDAR data applications.

5.6. Conclusions

This study aimed to estimate and map forest and plantations LULC types using TDX InSAR data. Despite the acknowledged limitations in our approach, we believe that our results provide a useful basis for identifying potential areas for large-scale forest and plantation mapping. Based on the results the SR best is model for 2011 & 2017 canopy height estimations, while RF is best model for 2019 results followed by SR model. Our study demonstrated the potential of TDX data for canopy height estimations and mapping in combination with multi-sensor remote sensing data. Furthermore, we recommend testing of dual or full polarization InSAR and the integration of high precision LiDAR measurements and complete field inventory data to improve the accuracy and precision of future studies. The use of multiple sensors such as TDX, GEDI, and ICESat-2 is also recommended, as it can provide wider coverage for forests and plantation canopy height estimations and mapping. Lastly, it is important to note that the unavailability of complete field data and terrestrial or airborne LiDAR are limitations to this study. Nonetheless, our results highlight the potential of InSAR data for forest and plantations canopy height mapping, and future studies can build upon our findings to develop more accurate and precise mapping techniques for the study area or in Borneo or other similar tropical landscapes.

6. Environmental sustainability assessment of tropical forest and plantations landscape in Borneo using multi-sensor remote sensing technique and Geospatial Multi Criteria Decision Analysis (MCDA)

6.1. Introduction

Sustainably well managed tropical forest and plantations ensure the balance between socioeconomic benefits and maintaining landscape ecosystems. This is particularly important for Borneo, a region with extensive and biodiverse tropical forest but also widespread ITP and plantations such as Oil palm and Rubber that play an important socio-economic role for the region (Bryan *et al.*, 2013). The forest and plantation landscape in Borneo has become highly fragmented and is currently the focus of numerous biodiversity conservation initiatives (Anderson *et al.*, 2022). Risk to biodiversity, and forest fragmentation is particularly pronounced in the Borneo lowlands and Sabah (Anderson *et al.*, 2022; Ocampo-Peñuela *et al.*, 2020), with oil palm plantations accounted for 26.6% of Sabah's land cover in 2022 (MPOB, 2022). The conversion of tropical rainforests into Oil palm plantations is the primary environmental impact of the industry (Paterson & Lima 2018). On the other hand, the Industrial Tree Plantations (ITP), Oil palm and agriculture sectors contribute significant income to the local economy of Sabah. It was reported in 2022 that Oil palm the largest agricultural sub-sector contributed 9.6% out of the total MYR12.5 billion (Approximately USD2.6 billion) agricultural sector to the state's GDP and is thus considered vital to regional economic and socioeconomic development (Bernama, 2023). This highlights the need for the management of forests and commercial plantations in a way that both protects natural assets and ecosystems and ensures economic development and stable livelihoods for local communities.

In light of the issue of sustainable management of tropical forests and plantations in Borneo, the applications of multi-sensor remote sensing techniques and geospatial techniques provide a cost-effective way of large-scale environmental monitoring and assessment (Ocampo-Peñuela *et al.*, 2020). The commitment to responsible and sustainable management of forest and plantations stretches into the distant future, where the assessment must be done on time. This is to aid in identifying high-risk areas, preventing environmental degradation and providing the necessary insights for replanting or restoration efforts. Sustainability assessment is important not only for addressing REDD+ and UNSDG initiatives but also for

certification purposes and to address transparency issues related to traceability, measurement and mitigation to minimise or alleviate the adverse impacts of plantations (Biswas *et al.*, 2020).

Sustainability assessment (SA) is important for oil palm, ITP, and other agricultural activities in Borneo due to several reasons. Firstly environmental protection and sustainability assessment help to identify and mitigate the negative impacts of LULC changes such as habitat loss, deforestation and greenhouse gas emissions (Mohd Hanafiah *et al.*, 2022; Murphy *et al.*, 2021). Secondly, sustainability assessment is important for biodiversity conservation. It helps to identify and preserve High Conservation Value (HCV) such as riparian zones and to promote sustainable land management practices that support biodiversity conservation (Osei *et al.*, 2022). The third reason is that sustainability helps to ensure that LULC changes are socially and economically sustainable by promoting good practices supporting smallholders and sustainable livelihoods. In addition, sustainability assessment is a requirement for certification schemes such as RSPO, FSC and MTCC. Sustainability indicators are used to assess the sustainability of LULC and to monitor progress towards the United Nation Sustainability Goals (UNSDG).

SA studies can contribute to meeting several UNSDGs such as goal 15 life on land, which is to *“protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification and halt and reverse land degradation and halt biodiversity loss”*. This study can contribute to this goal through the results, which help to identify to strategies towards improving conservation and sustainable land management (United Nations, 2023). SA also to meet UNSDG goal 9 *“build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation”*. This study can contribute to this goal by promoting the use of multi-sensor remote sensing techniques and geospatial MCDA for sustainable forest and plantation management in Borneo (D’Adamo & Gastaldi, 2022).

Multi-sensor remote sensing technique involves the use of multiple sources of remotely sensed imageries to improve the accuracy and reliability of LULC mapping. The technique offers several advantages over using single source data for mapping tropical forest and plantation landscapes. Firstly, it enables the integration of data with diverse spatial, spectral and temporal resolutions thus allowing for a more comprehensive and detailed characterization of the land surface (Srivastava & Gupta, 2003). Additionally, the use of multi-sensor data can

enhance the capacity to monitor LULC changes overtime providing a complete providing a complete understanding of the landscape dynamics (Roy & Inamdar, 2019). Furthermore, combination of data from different sensors can improve the accuracy of LULC mapping particularly in tropical forest and plantations with complex and heterogeneous land cover (Nguyen *et al.*, 2020). The technique also supports the identification and characterization of specific land cover types, differentiations of forest types or agricultural crops by leveraging the unique capabilities of individual sensors (Nguyen & Henebry, 2019). Overall, multi-sensor remote sensing technique offers a powerful and flexible tool for LULC mapping in tropical forest and plantation landscapes enabling more accurate, detailed, and timely information for the environmental monitoring, assessment and land management applications (Zhu *et al.*, 2022).

Multi-criteria decision analysis (MCDA) is a decision-making approach that aids in formally structuring complex decisions and evaluating multiple often conflicting or criteria (Greene *et al.*, 2011). In the context of geospatial studies, MCDA is used to assess environmental sustainability by integrating various criteria and spatial data to support decision-making related to LULC and in this study in tropical forest and plantation landscapes. This approach allows decision-makers to consider and balance multiple factors, such as topography, LULC type, ecological and social significance values when evaluating different land use options (Mohamadzadeh *et al.*, 2020). MCDA in geospatial studies involves the integration of geospatial data and value judgements to solve spatial problems. By combining spatial data with qualitative and quantitative criteria, MCDA can provide a comprehensive framework for assessing the environmental sustainability of land use options in tropical forest and plantations (Anaconda *et al.*, 2023; Cammerino *et al.*, 2023). This approach enables the consideration of diverse factors such as biodiversity, slope and soil protection, water quality and landscape connectivity in the decision-making process, ultimately supporting the identification of land use strategies that are more environmentally sustainable.

The use of MCDA in geospatial studies is supported by various literature which demonstrate its application in different environmental contexts. For example, Chen, (2014) used MCDA for land use suitability assessment where the results provided valuable inputs for policy and decision makers on urban extensions. Another study by Yalcin, (2020) presented GIS-MCDA based model for determining glacier vulnerability. These examples illustrate the versatility of MCDA in addressing diverse environmental challenges, including those related to LULC in tropical forest and plantation landscapes. By integrating spatial data and multiple

criteria, MCDA supports more informed decision-making and can help identify land use options that are more environmentally sustainable.

In this study, we utilized high-resolution Sentinel-1 (S1) C-band Synthetic Aperture Radar (SAR), Sentinel-2 (S2) Multi-spectral, and PlanetScope satellite imageries for the LULC mapping. The use of S1, S2 and PlanetScope for LULC mapping offers several advantages over traditional sensors like Landsat. S-1 SAR is particularly useful in areas with frequent cloud cover such as tropical regions like Borneo, as it can penetrate clouds and shadow covers also day or night operations (Dingle *et al.*, 2020; Ngo *et al.*, 2020; Ohki & Shimada, 2018). Additionally, SAR is sensitive to the structure, geometry and dielectric properties of forest and plantations thus providing useful information complementing optical data (Musthafa *et al.*, 2020; Priyanka *et al.*, 2023). S-2 and PlanetScope on the other hand, provide high-resolution optical imagery that is useful for differentiating between different types of LULC, such as different trees species in a forest and different crop type in the plantations (Dagne *et al.*, 2023). The combination of these two sensors allows for a more comprehensive understanding of LULC in tropical regions, as the strengths of one sensor can compensate for the weakness of the other. This led to more accurate and detailed LULC maps which are crucial for effective sustainable land use management.

In the context of this study, the application of MCDA to assess the environmental sustainability of the tropical forest and plantation landscape in Borneo was proposed. MCDA is a basic scientific decision-making method that combines multiple criteria to evaluate and rank different best alternatives or scenarios in order of preference (Yuan *et al.*, 2022). MCDA is one ‘decision-aid’ or evaluation framework that is frequently used for forest management (Acosta & Corral, 2017) and other natural resource management applications (Gamini *et al.*, 2006).

This study aims to assess the environmental sustainability of tropical forest and plantations in Borneo using multi-sensor remote sensing techniques and geospatial MCDA model. Meanwhile the specific objectives of this study area are as the following:

- i. To map the current LULC extent of the study area and produce sustainability indicators based on existing literatures and standard guidelines.

- ii. Assess and evaluate the environmental sustainability of the study area landscape using MCDA.
- iii. To highlight the benefits of using multi-sensor and effectiveness using multi-sensor and MCDA for environmental sustainability assessment in improving sustainable management of tropical forest and plantations in the study area.

The findings of the study will provide spatially explicit insights into the environmental sustainability of tropical forests and plantations in the study region. This information is an important input for decision-making and planning for biodiversity conservation efforts and sustainable management of natural resources in the study area and Borneo region in general. Additionally, the results will provide a model for assessing the environmental sustainability of other forest-plantation landscapes using multi-sensor remote sensing and geospatial MCDA techniques, which may also be extended for use in other tropical regions or case studies.

6.2. Materials and methods

6.2.1. Study area

The study area is located in the northern part of Sabah state in Borneo. The study area covers Bengkoka Peninsula, Malawali Island, and part of Banggi Island. As described in detail in chapter 2, the area is composed of a unique mixture of tropical forests and plantations landscapes. The forests consist of mixed patches of lowland natural tropical forest, secondary forest, mangrove, and nipah. While the major plantations in the study area are Oil palm, rubber plantations, and ITP.

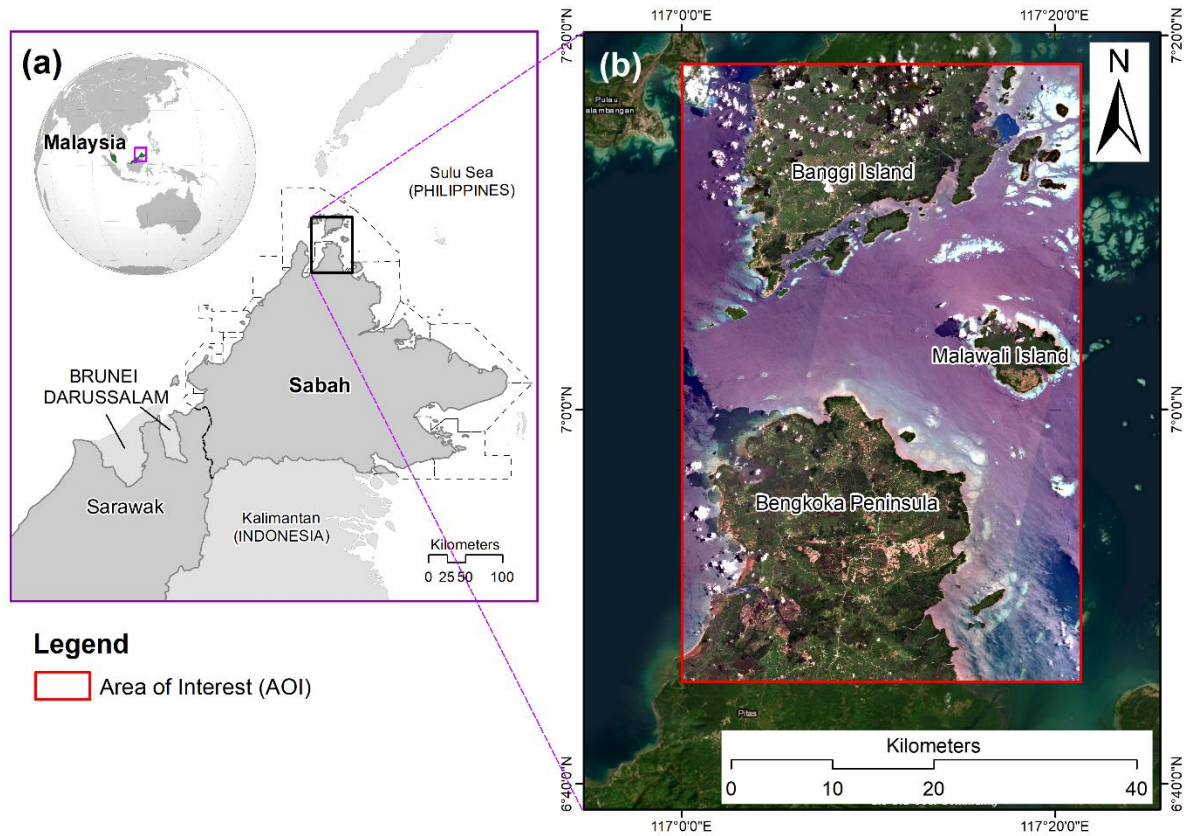


Figure 6.1. (a) Map overview of the study area location in Northern Sabah, Malaysian Borneo and (b) map showing the Area of Interest (AOI) with Sentinel-2 and PlanetScope fused satellite imagery (April 2023).

6.2.2. Dataset & processing

Two categories of datasets used for the LULC mapping and to produce the sustainability indicators were multi-sensor combination of S-1, S-2, PlanetScope and ancillary dataset of SRTM also forest operation base map. The data used are summarized in table 6.1. All Satellite data were acquired in April 2023 while ancillary dataset of SRTM updated Version 3 was released in 2015, while the forest operations base map was updated in 2021.

The S-1 SAR Ground Range Detected (GRD) Vertical transmit and return (VV), Vertical transmit and Horizontal return (VH) and ratio of VV/VH was acquired on 30th April 2023. S-2 GRD product is focused SAR data that has been detected, multi-looked and projected to the ground range using Earth ellipsoid model (sentinels.copernicus.eu). The S-1 SAR GRD data is widely used for LULC mapping. Three scenes of S-2 Surface Reflectance (SR) Harmonized imageries were acquired on 30th April 2023 and sets of PlanetScope (16th Apr. 2023, 3 scenes

and 18th Apr. 2023, 4 scenes) were used for the LULC mapping. The very high-resolution PlanetScope imagerys were resampled from 3m resolution to 10m according to S-2 for the data fusion. The S-2 and PlanetScope bands consists of Blue (B), Green (G), Red (R) and Near-Infrared (NiR)

Table 6.1. Summary of the dataset used in this study. Consist of LULC mapping and Ancillary dataset.

LULC Mapping			
Sensors	Collection date	Number of scenes	Bands & Indices
Sentinel-1	30 Apr. 2023	1	VV, VH & VV/VH
Sentinel-2	30 Apr. 2023	3	B, G, R, NiR, NDVI & NDWI
PlanetScope	16 Apr. 2023	3	B, G, R, NiR, NDVI &
	18 Apr. 2023	4	NDWI
Ancillary Dataset			
Data Type/Sources	Year	Derived/documented features	
SRTM v3	Updated 2015	Slope map	
Forest operations base map	Updated 2021	Cultural sites, HCVF, water catchment areas, Riparian reserves, wetlands, tree plantation boundary & Forest Reserves boundaries.	

6.3. LULC mapping

In the context of land use and land cover (LULC) mapping, the fusion of Sentinel-2 (S2) with PlanetScope imagerys necessitates an initial radiometric correction. It is essential that the number of bands is consistent, and the optional spatial resolution and radiometric resolution are aligned. This process ensures that the data from both sources are harmonized and can be effectively integrated for LULC mapping. The radiometric correction and alignment of these parameters are fundamental to the accurate and reliable fusion of S2 and PlanetScope imagerys for LULC mapping, enabling the generation of high-quality and consistent output data. Note that the value range of Sentinel-2 is 0– 3,000 and PlanetScope value is higher, need to reduce planet range 0 -1 by dividing by highest value 99.98% percentile. Cloud and shadow covered areas were masked in S-2 composite and fused with the PlanetScope composite imagery. A number of vegetation indices layers were generated namely NDVI, NDWI and NDTI (table 6.2.) LULC classification was done using Statistical Machine Intelligence and Learning Engine (SMILE) Random Forest (RF) machine-learning Google Earth Engine (GEE) classifier for the

LULC classifications (Google, n.d.). All variable bands (B, G, R, NIR, NDVI, NDWI, VV, VH & VV/VH) were used in the classification. Previous study (Qu *et al.*, 2021) found that the use of auxiliary datasets can improve accuracy of LULC classification.

Table 6.2. Indices used in this study.

Vegetation Index	Purpose	Formula	References
1. Normalized difference vegetation index (NDVI)	Discrimination of Non-vegetation/Vegetation cover and health.	$(\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED})$	(Rouse <i>et al.</i> , 1974)
2. Normalized difference water index (NDWI)	Identification of waterbody areas	$(\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$	(Chen <i>et al.</i> , 2022; McFeeters, 1996)
3. Normalized Water Turbidity Index (NDTI)	Identification of waterbody quality.	$(\text{RED} - \text{GREEN}) / (\text{RED} + \text{GREEN})$	(Bid & Siddique, 2019; Chen <i>et al.</i> , 2022; Shivangi <i>et al.</i> , 2011)

6.4. Spatial Multi-criteria Decision Analysis (MCDA) sustainability analysis

To gauge the environmental sustainability of the study area, criteria and indicators that encompass important aspects of soil and slope erosion, riparian reserves, landscape connectivity and quality, HCV and water quality were established. In this study, sustainability is categorised into scores of Low, Medium and High corresponding to the LULC layers (table 6.3).

Table 6.3. LULC sustainability categories weightage (Scores).

Sustainability Categories (Scores)	LULC Layers	Descriptions
1. Low	Infrastructure, Soil/Clearcut & Aquaculture	Activities involved removing/clearing natural vegetations and cutting slopes.
2. Medium	Secondary forest, Rubber, Acacia, Eucalyptus Pellita, Oil palm	Non-natural vegetation including regeneration of secondary forest replacing original vegetations.
3. High	Waterbody, Nipah, Forest, Mangrove & Beach Sand	Natural permanent vegetations.
No scores/Excluded	Cloud & Shadow	-

The methodology of this study is based on the spatial structure of the MCDA which consist of procedures that involve sharing of geographic data and preferences according to specified rules (Malczewski, 1999). The main advantage of the integration of GIS and MCDA is to have unique capabilities that complement each other (Gigovic *et al.*, 2018). In this GIS-based Multi-Criteria Decision Analysis (MCDA) model, the data storage, manipulation, management, analysis, and visualization capabilities of GIS are integrated with MCDA, which encompasses procedures, techniques, and algorithms for structuring decision problems, evaluating decision alternatives, and assessing environmental sustainability. This approach combines spatial data, decision maker preferences, and decision rules to solve spatial problems and make informed decisions. The integration of GIS with MCDA enables the transformation and combination of geographical data and value judgments, providing a comprehensive framework for addressing complex spatial decision-making challenges. The MCDA procedure employed in this study is illustrated in detailed in figure 6.3.

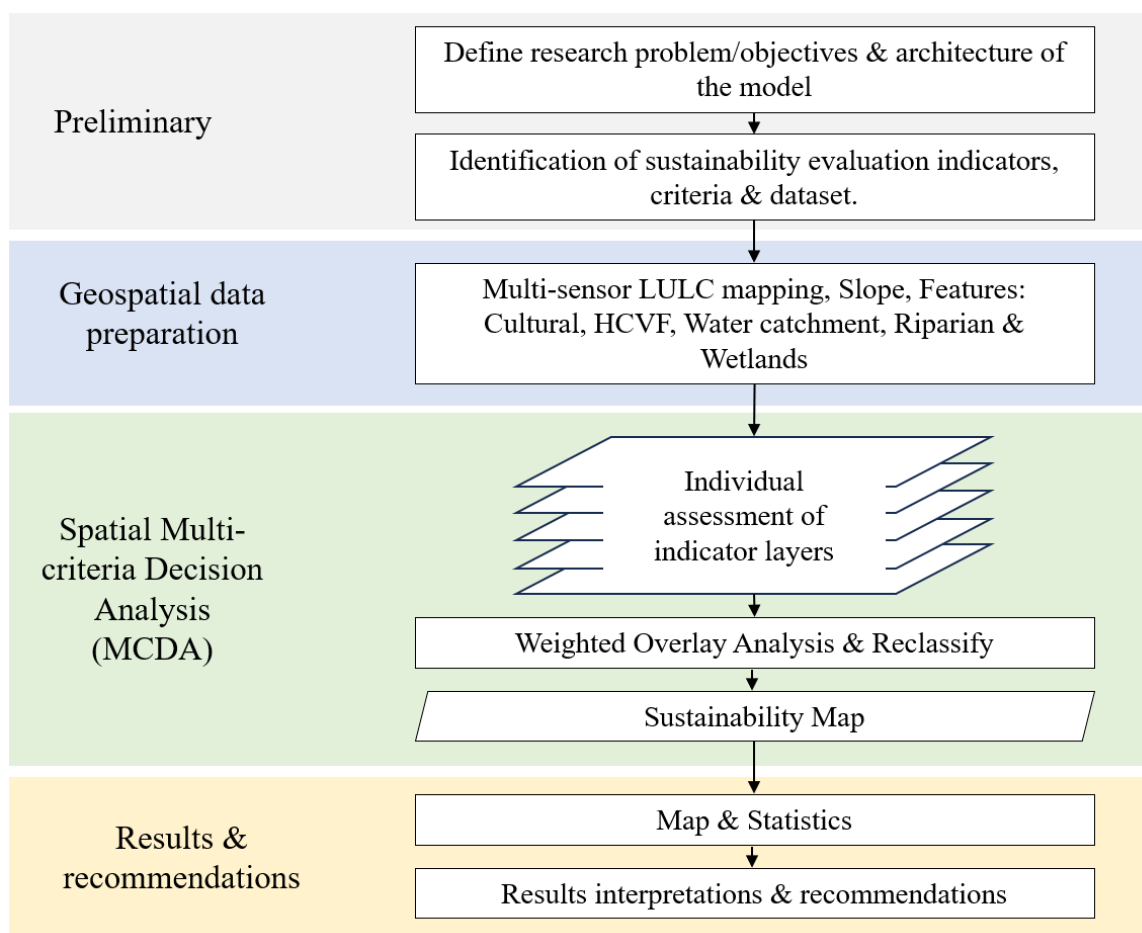


Figure 6.2. Sustainability analysis workflow of this study using Spatial Multi-criteria Decision Analysis (MCDA) (adapted from (Gigovic *et al.*, 2018).

The workflow of sustainability analysis in this study as illustrated in figure 6.2, starts with defining the research problem that defines the objective and the architecture of the MCDA model. Eventually, continue with the identification of sustainability evaluation indicators and criteria in this case sustainability categories scores as described in table 6.3 & 6.4. Then second phase is the geospatial data preparation where all the indicator layers are mapped and generated. In the third phase is the analysis where all indicator layers are analysed using weighted overlay analysis to produce the final sustainability map. In the last phase the map and statistics of results are produced and finally interpretations and recommendation are drawn. The detailed indicator layers generation workflow and analysis of the MCDA model were illustrated in figure 6.3.

In this study, five sustainability indicators were used to assess the environmental sustainability of the study site. These indicators were selected based on their relevance to the study objectives and ability to provide insights on sustainability. Previous studies [Hristov & Chirico \(2019\)](#) & [Wong et al., \(2023\)](#) have identified range of indicators related to biodiversity, water quality, erosions and slopes protection and riparian reserves.

6.4.1. Slopes and erosion protection

In Sabah land use (clearing and cutting) involving slope gradient of 20° degrees or more are prescribed under EPD EIA order 2005 and requires EIA report ([EPD Sabah, 2012a](#)). Activities like Reduced Impact Logging (RIL) only permitted up to slope gradient of 25° degrees ([EPD Sabah, 2012b](#)) and should clearly marked on map. Previous study shown that the widely use legume cover crop *Mucuna bracteata* (MB) in Oil palm plantations effectively reduced surface runoff and soil erosions ([Wawan et al., 2019](#)). In this study, any soil clearing and slope cutting area of more than 25 degrees are considered as having low sustainability.

6.4.2. River buffer

The river buffer zone vegetation plays important role in regulating water quality, protecting aquatic ecosystem and wildlife habitats ([Bedell et al., 2017](#)). Previous studies shown riparian reserves sustain biodiversity within cultivated land ([Mitchell et al., 2018](#); [Seaman et al., 2019](#)). In Sabah riparian reserves are useful for preservation of native vegetation along bordering waterbodies and riverbanks useful for mitigation strategy reducing negative impacts from land use changes in plantations. Therefore retaining, restoration, maintenance and management of riparian within Oil palm plantation and ITP is useful strategy to improve biodiversity conservation ([Pianzin et al., 2021](#)). Riparian reserve is one of the certifications requirements for sustainable Oil palm under the Roundtable on Sustainable Palm Oil Scheme (RSPO) also

ITP certifications under the Forest Stewardship Council (FSC) or Malaysia Timber Certification Scheme MTCC. In Sabah, the EPD legislation presently requires riparian buffers with a minimum of 20-30m wide to be retained on all streams with width of 3 m and 10 m (EPD Sabah, 2012b, 2012c).

6.4.3. Landscape connectivity and quality

The landscape connectivity depicts the links between forest patches across the landscape and habitat of flora and fauna. Landscape connectivity and the quality of the landscape are important ensuring habitat connectivity thus maintain viable populations of flora and fauna, and Borneo is host to several iconic species like Bornean orangutans (*Pongo pygmaeus*), pygmy elephants (*Elephas maximus borneensis*), bearded pigs (*Sus barbatus*) and sun bears (*Helarctos malayanus*) (Alamgir *et al.*, 2020). Connectivity between remaining forested areas with Oil palm plantations needs to be retained for the movement of terrestrial species and in this study the standard used for class sustainability rating is based on the RSPO Manual of Best Management Practices (BMPs) (table 6.4.) Conservation and forest cover criterion focus on maintaining the integrity of forest ecosystem and protecting biodiversity. Involves measures prevention of deforestation, habitat fragmentation and loss of endangered species.

6.4.4. High Conservation Values (HCV)

HCV can be defined as areas that are identified as valuable in terms of biological, ecological, social or cultural significance or critical importance within a specific landscape or site. There are six categories of HCVs as defined in HCV network Common guidance for identification of HCVs (Brown *et al.*, 2013).

- i. Species diversity, site where there is concentrations of biological diversity including endemic species, rare, threatened or endangered species that are significant at local, national, regional and global.
- ii. Landscape-level ecosystems and mosaics, large landscape-level ecosystems and mosaics that are significant at national, regional, and global scale. Which contain viable populations of the great majority of the naturally occurring species in natural patterns of distribution and abundance.
- iii. Ecosystems and habitats, where rare, threatened, or endangered ecosystems, habitats and refugia.
- iv. Basic ecosystem service in critical situations including protection of water catchments and control of erosion of vulnerable soils and slopes.

- v. Community needs, referring to sites and resources fundamental for satisfying the necessities of local communities or indigenous peoples for livelihoods, health, nutrition, water etc..) identified through engagement with communities or indigenous peoples.
- vi. Cultural values: sites, resources, habitats and landscapes of national or global archaeological or historical significance and/or of critical cultural, ecological, economic or religious/sacred importance for the traditional cultures of local communities or indigenous peoples identified through engagement of these peoples.

The HCV concept was first developed by FSC® for forestry however it was adopted by RSPO for Oil palm also other certification schemes and organisations that aim to maintain, enhance significant and critical environmental and social values as part of responsible management (Brown *et al.*, 2013; Gray, 2017). In this study, the HCV layers are extracted from the Forest Operation Basemap, which was officially demarcated on the ground by the forest management company with the local communities. The HCVs includes wetlands, cultural sites and HCV forests.

6.4.5. Water turbidity

Sustainable water management, maintaining water quality and availability within forest ecosystem and plantations are important for socio-economic and the environment. Sabah Environment Protection Department (EPD) requires the forest and plantation companies to submit EIA report prepared by EPD appointed consultant which includes water quality monitoring every 4 months (AFI, 2018). Sediment loads and improper waste handling from plantations or forest operations may degrade water quality. The infiltration of chemicals into waterways can seriously affect aquatic life and freshwater supply. Main element compounded in fertilizers like nitrogen (N), Pottasium (K), Phosphorus (P) and magnesium (Mg) may end up in watercourses through washed surface soil, leaching of soluble compounds into groundwater, and runoff that carries both soluble and insoluble compounds (EPD Sabah, 2012c).

Table 6.4. Classification of NDTI values adopted from (Shivangi *et al.*, 2011).

Classification	This study
Low = Mean – Standard deviation	Low = -0.2823
Medium = Mean + Standard deviation	Medium = -0.0751
High = More than moderate	High = >-0.0751
	Standard Deviation: 0.1036, Mean: -0.1787

In this study water turbidity was monitored using remotely sensed data measured by Normalised Difference Turbidity Index (NDTI). The NDTI is a remote sensing technique widely used for identify water turbidity cause by sediment, it is the ratio of red and green bands of solar spectrum (Bid & Siddique, 2019; Chen *et al.*, 2022; Subramaniam & Saxena, 2011). The classification of NDTI value was calculated by the value of mean and standard deviation. The class values for low, medium and high was calculated by the following formulas in table 4.4.

Table 6.5. Sustainability indicators, criteria for the related LULC, sustainability criteria, clas and sustainability ratings.

Indicators	Criteria	Related LULC/Features	Class Sustainability rating			References
			Low (1)	Medium (2)	High (3)	
1. Slopes and erosion protection.	Clear cut surface. Steep slope >25° should not open	Soil/Clearcut, Infrastructure & Plantation layers	> 25°	10° – 25°	≤ 10°	(AFI Sdn. Bhd., 2018; EPD Sabah, 2012a)
2. Riparian reserves.	Vegetation cover within buffer zones (m)	Water catchment areas, Rivers & Streams buffer,	30m-40m	20m-30m	≤ 20m	(AFI Sdn. Bhd., 2018; Gray, 2017)
3. Landscape connectivity and quality.	Proximity of natural vegetation (m)	Mangrove, Forest, Nipah & Secondary Forest	> 50m	50m-25m	≤ 25m	(Gray, 2017)
4. High Conservation Values (HCV).	Natural vegetation should be intact no clearings or other land use (m)	Wetlands, Cultural sites & HCV Forest	< 20m	20m-30m	30m-40m	(AFI Sdn. Bhd., 2018) & Forest ops. base map
5. Water turbidity.	Classes of NDTI index value range.	All water bodies	Mean - SD	Mean + SD	> Medium	(Shivangi <i>et al.</i> , 2011)

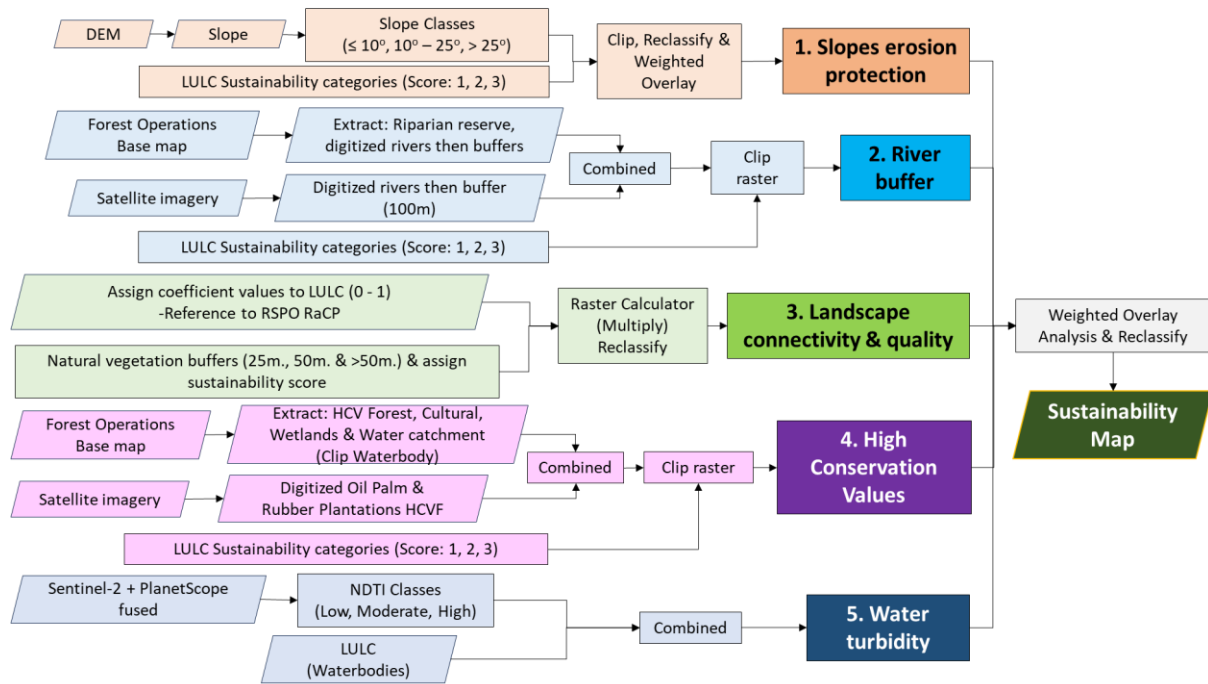


Figure 6.3. Detailed workflow of the indicators weighted overlay analysis of the MCDA model for producing the sustainability index maps.

6.5. Results

6.5.1. LULC map & accuracy assessment

The 2023 LULC were mapped (Fig 6.4) into the 14 classifications, and accuracy assessment was done using 2,382 sample points comprised of ground and also sample points from high resolution google Earth imagery. Overall accuracy achieved was 87.24% with kappa coefficient (k) of 85.89% (Table 6.6). Majority of the overall LULC (Fig. 6.5a & Table 6.7) of 39% are forest, followed by 19% mangrove, 12% acacia, 8% oil palm, 7% secondary forest, 6% eucalyptus, 2% infrastructures, 2% waterbody, 2% rubber, 1% aquaculture and 0% nipah (Fig 6.5a.). Meanwhile, breakdown according to the boundaries of gazetted areas (Fig. 6.5b & Table 6.7) shows that ITP is 40% consist of forest, 24% eucalyptus, 13% acacia, 8% oil palm, 6% secondary forest, 5% mangrove and rubber only 0.02% or 6 hectares. Forest reserves boundary areas consist of 27% forest, 21% of the remaining wild acacia, 20% already planted with eucalyptus, 16% clearcut results of the acacia harvesting for replanting with Eucalyptus, 7% both infrastructures of road networks and secondary forest, while 2% oil palm. The village boundary is 58% forest, 19% secondary forest, 14% infrastructure, 4% Acacia and 3% oil palm. Meanwhile, the oil palm boundary majority at 81% oil palm, 10% infrastructures, 4% forest and secondary forest. Lastly, rubber boundary at 68% consist, of rubber, 22% secondary forest and 7% forest which are in the riparian buffer areas, both 1% mangrove and soil or clearcut.

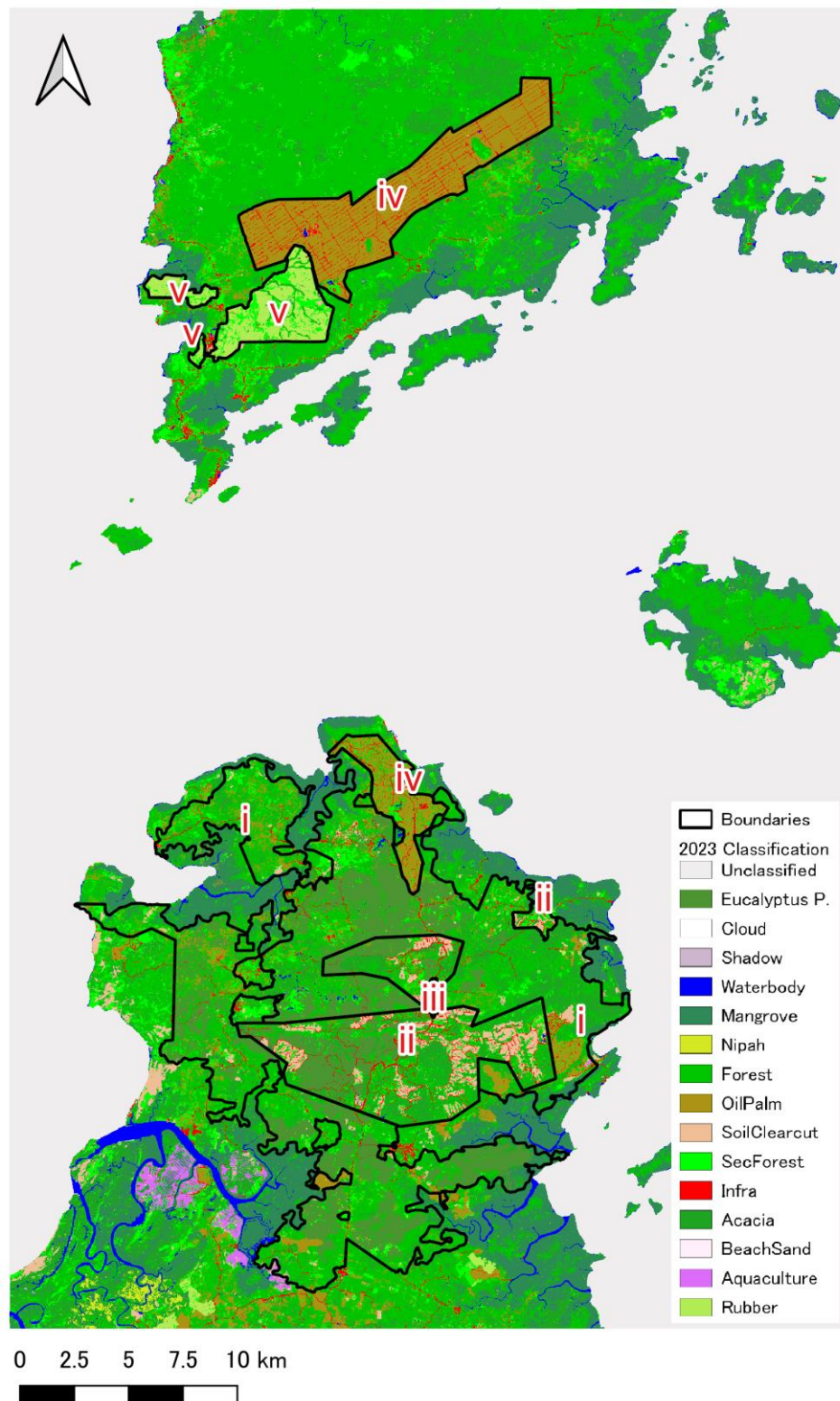


Figure 6.4. Year 2023 LULC map of the study area with five boundaries of gazetted areas: (i). Industrial Tree Plantations (ITP), (ii). forest reserves, (iii). village reserves, (iv). oil palm plantations and (v). rubber plantations.

Table 6.6. Accuracy assessment summary of the LULC.

LULC Accuracy			
Year	Number of Sample	Overall Accuracy	Kappa Coefficient <i>k</i>
2023	2,382	87.24%	85.89%

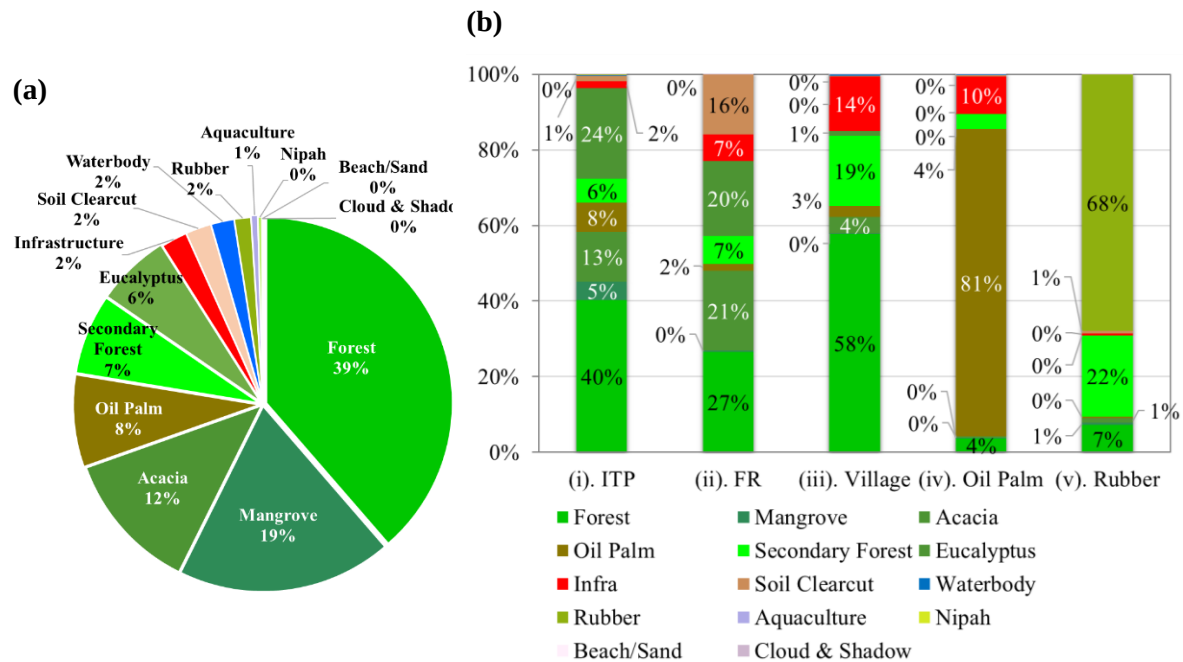


Figure 6.5. 2023 LULC percentages by: (a) overall study area and (b) five boundaries.

Table 6.7. 2023 LULC classes statistics and assigned sustainability coefficient values for MCDA model.

Land Use and Land Cover (LULC)	Hectares (ha)	Percentages (%)	Assigned sustainability coefficient values (0 – 1)
Forest	37,953.98	39	1
Mangrove	18,331.81	19	1
Acacia m.	12,031.82	12	0.5
Oil Palm	7,887.85	8	0.5
Secondary Forest	6,862.00	7	0.7
Eucalyptus	6,309.90	6	0.5
Infrastructure	2,232.54	2	0
Soil Clearcut	2,195.56	2	0
Waterbody	1,980.68	2	-
Rubber	1,411.45	1	0.5
Aquaculture	578.36	1	0
Nipah	341.98	0	1
Beach/Sand	37.95	0	0
Cloud & Shadow	40.32	0	-
Total	96,639.05	100	-

We also assigned the LULC classes (Table 4.7) with sustainability coefficient values according to the RSPO Recommendation and Compensation Procedure (RaCP) vegetation coefficient category values standards (RSPO, 2015).

Table 6.8. 2023 LULC classes statistics by five boundaries of gazetted areas.

LULC	(i). ITP		(ii). FR		(iii). Village		(iv). Oil Palm		(v). Rubber	
	ha	%	ha	%	ha	%	ha	%	ha	%
Forest	8,216.52	40	1,723.66	27	52.17	58	197.14	4	27.76	7
Mangrove	,004.83	5	9.98	0	0.06	0	2.61	0	9.47	1
<i>Acacia m.</i>	2,676.97	13	1,357.37	21	3.92	4	20.13	0	25.34	1
Oil Palm	1,565.32	8	119.82	2	2.63	3	4,254.55	81	4.48	0
Secondary Forest	1,288.03	6	482.80	7	16.80	19	211.99	4	381.84	22
Eucalyptus	4,909.27	24	1,282.04	20	1.08	1	0.03	0	-	0
Infrastructure	381.90	2	449.36	7	13.03	14	514.05	10	7.41	0
Soil Clearcut	273.83	1	1,024.59	16	0.10	0	22.20	0	12.52	1
Waterbody	53.82	0	6.33	0	0.33	0	12.18	0	0.05	0
Rubber	5.97	0	-	-	-	-	0.55	0	1,203.13	68
Aquaculture	11.64	0	-	-	-	-	-	-	-	0
Nipah	15.42	0	1.19	0	-	-	0.33	0	0.26	0
Beach/Sand	1.37	0	0.58	0	0.09	0	0.04	0	-	0
Cloud & Shadow	2.69	0	0.39	0	0.05	0	0.72	0	0.49	0
Total	20,407.57	100	6,468.13	100	90.26	100	5,236.52	100	1,772.74	100

6.5.2. Environmental sustainability indicator map layers

The five individual sustainability indicator maps (Fig 6.6) were produces based on the previously mentioned workflow (Fig. 6.3). Also, we compiled five boundaries of gazetted areas as in map below (Fig 6.6f).

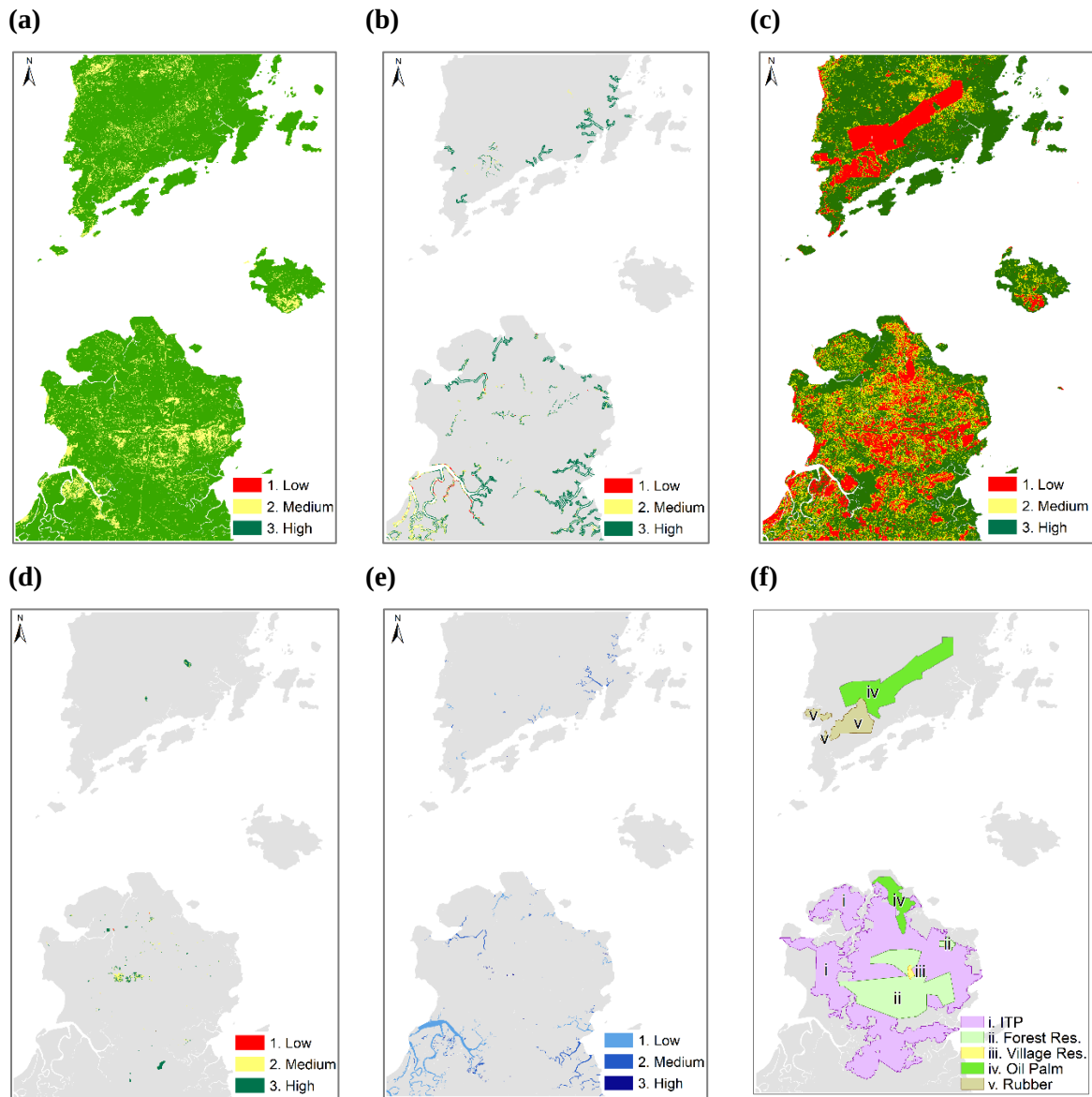


Figure 6.6. Environmental sustainability indicator map layers; (a) slope and soil erosion protection, (b) riparian reserves, (c) landscape connectivity and quality, (d) High Conservation Values (HCV), (e) water quality & (f) five boundaries of gazetted areas of i. Industrial Tree Plantations (ITP), ii. forest reserves, iii. village reserves, iv. oil palm plantations and v. rubber plantations. In map layers (b), (d) & (e) non-related features are in grey.

Statistics of the individual sustainability indicators were extracted (Fig. 6.7). For slope and soil erosion protection map majority at 89% are in high sustainability class and 11% medium and no low sustainable class was recorded. Riparian reserve areas also are majority highly sustainable at 79%, medium at 19% and only 3% categorised as low. Landscape connectivity and quality map recorded 63% at high sustainability class, 17% medium and 20% in low sustainability class. This is due to monocrop type of land use such as oil palm, rubber

and ITP plantations that cover large areas and has no or less near natural vegetation cover connectivity. Meanwhile HCV are mostly in high sustainability class at 59%, medium at 39% and very less of low sustainability at only 2%. The water quality majority at 61% are in low sustainability class. Evidently the rivers that are in this low sustainability class are located near to the modified land uses such as aquaculture, timber harvesting or clearings, oil palm and infrastructures where the water bodies quality are attributed to surface run-off. While 32% medium, 2% of the water quality is high and the rest 5% un-classified are small rivers which are difficult to determine the NDTI value due to limitation of S-1 fused PlanetScope produced final 10m resolution imagery.

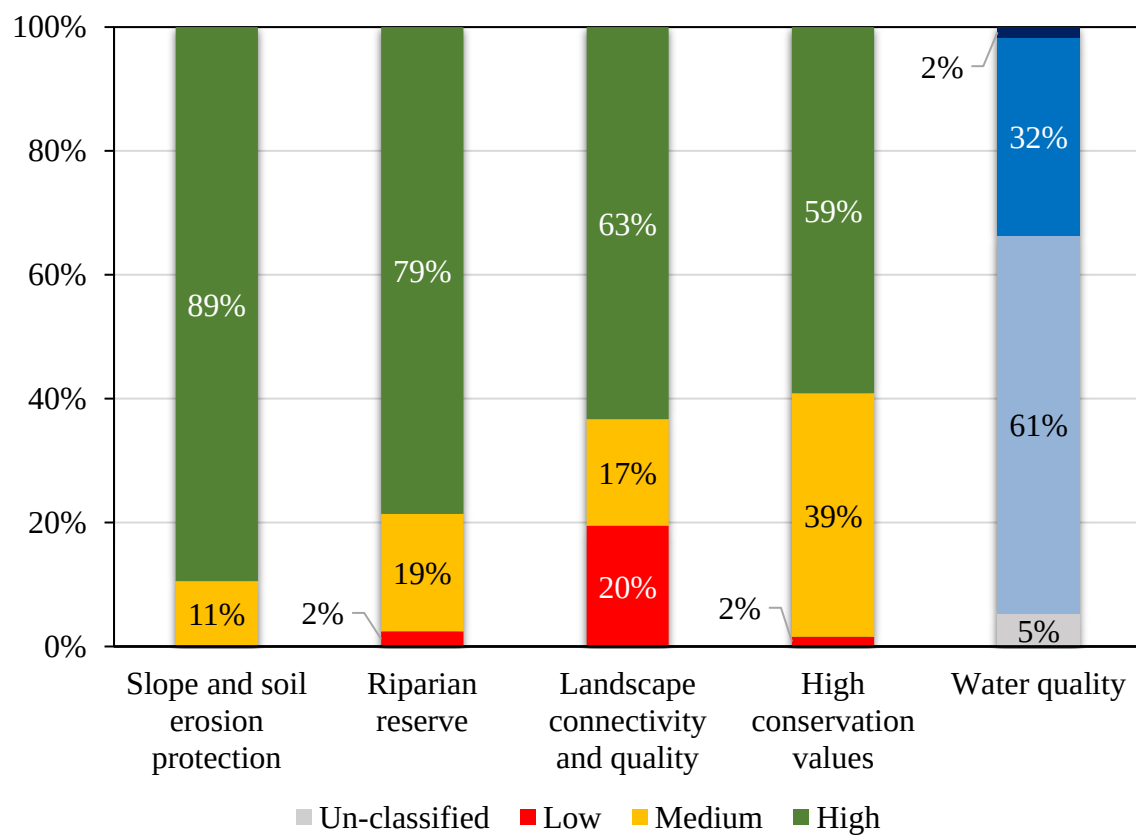


Figure 6.7. Percentages of sustainability indicators by sustainability categories (scores): un-classified, low, medium and high.

6.5.3. Geospatial Multi-Criteria Decision Analysis (MCDA)

Majority of the overall sustainability score at 61% (58,995.06 hectares) are highly sustainable, 31% (30,182.49 hectares) are medium and only 8% (7,398.73 hectares) are low (Fig 6.8 & Fig 6.9a). Can be observed from the sustainability score map (Fig. 6.8) that in the southwest part river networks are in the low sustainability class contributed by clearings of mangrove forest

for aquaculture land uses. Other river networks that connected to the ITP or plantations are also in the low sustainability class. The oil palm and rubber plantations are predominantly medium class in terms of sustainability because lack of monoculture crops and break the linkage of forest cover. Similar in the Forest Reserve area where currently timber harvesting is ongoing which causes clearcut of planted forest. The ITP areas are mostly medium sustainability score due to monoculture nature of the forest plantation. It is obvious that undisturbed mangrove forest falls in the highly sustainable class.

Meanwhile within the gazetted boundaries (Fig 6.9b), 49% of the ITP are highly sustainable, 46% medium and only 5% low which attributed by the land clearing of timber harvesting in some of the areas. The FR having 45% in medium class, 29% high and 26% low also due to clearing. The village boundary area is 72% high, 14% low and 13% medium class. Meanwhile 81% of oil palm are medium, 14% low sustainable and only 5% are sustainable. Lastly rubber boundary areas with 77% medium, 14% low and only 9% high. Both oil palm and rubber plantations are majority in medium class due to monocropping land use type which also shown as low in the landscape connectivity and quality individual sustainability indicator layer (Fig 6.6c).

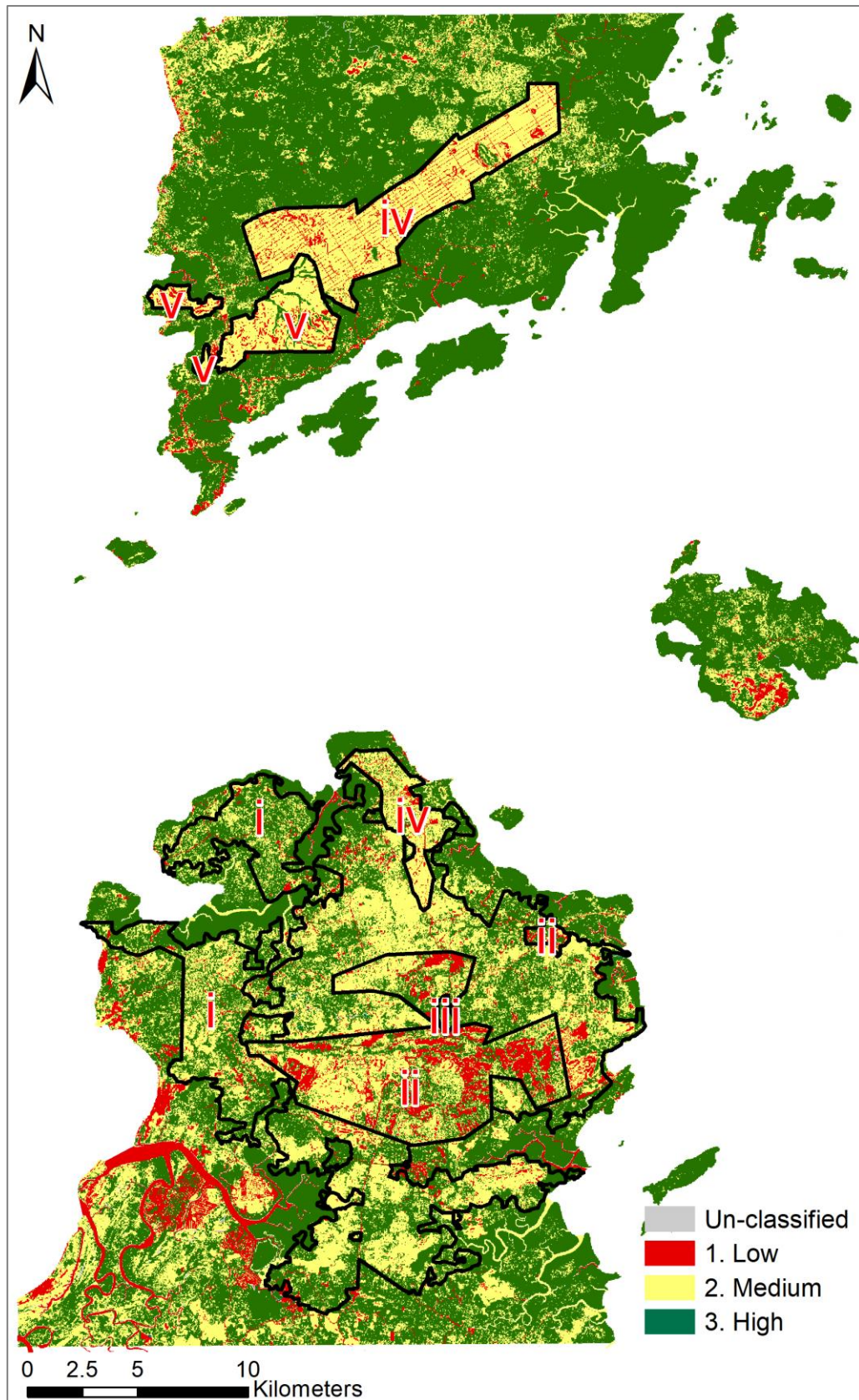


Figure 6.8. Sustainability score map of the study area with five boundaries of designated areas: i. Industrial Tree Plantations (ITP), ii. forest reserves, iii. village reserves, iv. oil palm plantations and v. rubber plantations.

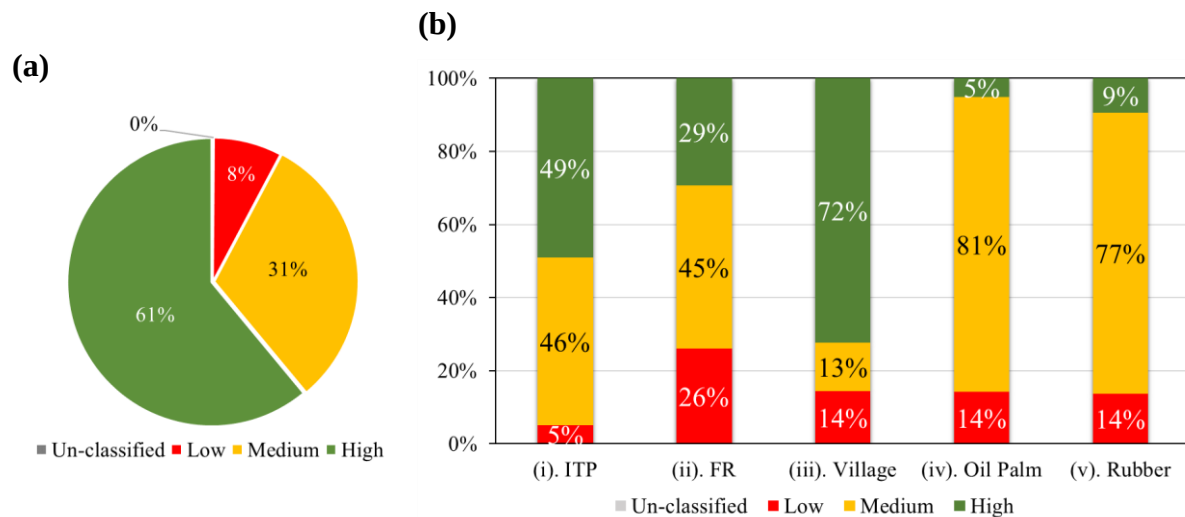


Figure 6.9. Percentages of the sustainability classes by: (a) overall study area and (b) five boundary areas.

Detailed statistics of the MCDA model by five boundaries of gazetted areas are summarised (Table 6.9). The ITP is the biggest area consist of a total of 20,407.57 hectares, followed by forest reserve 6,468.13 hectares, oil palm at 5,236.52 hectares, then rubber plantation at 1,772.74 hectares and lastly the village reserve is 90.26 hectares.

Table 6.9. Summary of the sustainability classes according to the five boundaries of gazetted areas of; (i). Industrial Tree Plantations (ITP), (ii). forest reserves, (iii). village reserves, (iv). oil palm plantations and (v). rubber plantations.

Classes	(i). ITP		(ii). FR		(iii). Village		(iv). Oil Palm		(v). Rubber	
	ha	%	ha	%	ha	%	ha	%	ha	%
Un-classified	13.47	0	5.49	0	-	0	0.81	0	0.05	0
Low	1,023.05	5	1,674.83	26	13.00	14	742.26	14	244.01	14
Medium	9,356.44	46	,891.43	45	12.01	13	4,226.32	81	1,362.88	77
High	10,014.61	49	,896.38	29	65.25	72	267.13	5	165.80	9
Total	20,407.57	100	6,468.13	100	90.26	100	5,236.52	100	1,772.74	100

6.6. Discussions

6.6.1. Benefits of multi-sensor LULC mapping

The synergistic use of S1-S2 and fusion with PlanetScope satellite imageries reduced effects of cloud and shadows in the classifications. Thus, good LULC classification map result was

produced with high overall accuracy of 87%. The incorporation of S-1 SAR imagery allows mapping of LULC based on physical characteristics such as roughness, moisture and structures combined with S-2 and PlanetScope high-resolution optical which are useful for detailed visual and spectral based detailed discrimination of LULC classes which led to richer information thus increasing classification accuracies (Van Tricht *et al.*, 2018). Other benefits of employing multi-sensor remote sensing technique are, SAR overcomes the limitations of optical remote sensing which can be affected by cloud cover and shadows especially tropical regions like Borneo. These limitations are mitigated by SAR because active sensor could penetrate cloud cover. A study by (Sharifi *et al.*, 2022) of mangrove forest mapping in west Asia shows that the use of only S-1 with S-2 is sufficient to overcome cloud cover issue and for better mapping and monitoring of mangrove forests. The multi-sensor used of SAR and optical also enhances detection of specific LULC features especially in complex tropical forest and plantations landscapes such as in the study area (Solórzano *et al.*, 2021). The use of multi-sensor be effectively combined with Machine Learning applications algorithm to improve the accuracy of LULC mapping (Jarayee *et al.*, 2022).

6.6.2. Effectiveness of using multi-sensor MCDA model for assessing environmental sustainability

The use of high-resolution multi-scale remote sensing data for mapping of forest and plantations LULC is highly effective considering the wide area coverage with high level of details in the classification. This enabled the indicator layers of based on the assessment criteria possibly be produced. The five indicators were 1. Slope erosion protection, 2. Riparian reserves, 3. Landscape connectivity and quality and 4. High Conservation Values (HCVs) and 5. Water turbidity. Subsequently, the indicator layers were analysed using MCDA model for the sustainability assessment. As discussed in the results sections, 61% of the water quality indicator layer was identified in the low sustainable category followed by 20% of the landscape connectivity and quality indicator layer. Meanwhile in the final sustainability map result shows overall, 61% of the total study area are identified as still highly sustainable and breakdown by boundary layer shown the village reserve 72% are highly sustainable. Oil palm and rubber plantations LULC are identified as 81% and 77% respectively in medium sustainability category. This attributed by the fact that the two LULC are monocrop type of land cover which possibly less capacity in ecosystem functions. Additionally, oil palm and rubber plantation sites were prepared in the way where terraces were constructed, and crops were planted in systematic

way. The ITP and FR however comparably higher sustainable at 49% and 29% respectively. This is due to the rubber and ITP land cover type mimics the natural forests although single tree species and there was usually no terrain modification required for the tree planting. The use of MCDA model made it possible to effectively identify and map areas according to sustainability categories.

6.7. Conclusions

This study presented a concept use of multi-sensor remote sensing technique combined with geospatial multi-criteria decision analysis (MCDA) for the environmental sustainability assessment of tropical forest and plantation landscape in Borneo. The combination of high-resolution SAR and optical data demonstrated that detailed LULC map and indicator layers can be produced which are crucial for the analysis. The results will help contribute to achieving SDGs that are also applicable for certification purposes of the plantations. The systematic workflow developed in this could also be applied to other future case studies with more indicator layers and improved details.

7. Conclusion, limitations and opportunities in sustainable tropical forest and plantations management.

This thesis emphasizes the significance of employing multi-sensor remote sensing techniques for the sustainable management of forests and plantations in Borneo, focusing on a case study in northern Sabah. The findings presented across the four technical chapters illustrate the efficacy of multi-sensor remote sensing technique in detailed mapping of land use land cover (LULC) classes, estimating canopy height, evaluating environmental sustainability, and monitoring LULC changes, especially investigation on LULC conversion into plantations. Furthermore, one of the technical chapters delves into the assessment and potential of forests beyond plantations. The methodologies and outcomes offer valuable insights for local stakeholders and managers to make informed decisions and advocate for sustainable practices.

7.1. Results with regards to research objectives

The use of multi-sensor remote sensing technique demonstrated in this research help to enhance the accuracy and efficiency of monitoring and managing tropical forest and plantations in Borneo.

7.2. First objective: Monitoring Land Use and Land Cover (LULC) changes of tropical forest and plantations landscapes in Borneo using multi-sensor remote sensing technique

As detailed in Chapter 3, this study demonstrated the utilization of a multi-sensor remote sensing approach to accurately map detailed LULC classes of forest and plantations within the study area. This chapter aimed to investigate the dynamic multi-temporal changes in LULC in the study area, focusing on identifying the sources or drivers of LULC conversion. The LULC changes were analyzed for the pairs of years 2010-2017, 2017-2019, and 2019-2023, with assessments of the extent and rate of changes derived. The overall accuracies of 2010, 2017, 2019, and 2023 LULC maps were at 86%, 91%, 83%, and 87% respectively. These LULC maps were also used in the analysis in the fifth and sixth technical chapters. Integrating SAR data in the LULC classification process alongside optical data yielded enhanced results in distinguishing specific LULC classes ([Prudente et al., 2022](#)). Multi-sensor remote sensing technique is pivotal in LULC analysis by providing accurate and comprehensive data on LULC changes ([Vivekananda et al., 2021](#)). The study revealed dynamic changes in LULC categories, including increases, decreases and areas remaining unchanged between each pair of years. Forest and mangrove areas exhibited stability over the observed years, while secondary forest,

Acacia plantations, and soil/clearcut areas decreased. Conversely, there was a consistent rise in Oil Palm plantations and infrastructure coverage. The study identified oil palm cultivation as a significant driver of forest conversion between 2010-2017, attributed rubber plantations to previous land clearing, observed mangrove conversion into aquaculture zones, and noted the replacement of Acacia with Eucalyptus plantations. Overall, this research provided valuable insight into the effective use of multi-sensor remote sensing techniques for detailed mapping of LULC classes and understanding spatio-temporal dynamics of LULC changes within the study area.

7.3. Second objective: Ground survey assessment of Above Ground Biomass (AGB) and Carbon estimation forest outside plantations in Bengkoka Peninsula, Sabah Borneo

This study, detailed in Chapter 4, aimed to evaluate the Aboveground Biomass (AGB) and estimate carbon and carbon dioxide levels in the forest beyond plantations in the study area. Forest outside managed forests and plantations are pivotal in the global carbon cycle, playing a significant role in mitigating climate change by sequestering carbon dioxide from the atmosphere. Despite their importance, these forests are often overlooked and undervalued regarding their carbon sequestration potential. The four main vegetation groups identified in the sites are: *Acacia mangium*, Mangrove forest, Oil palm and Secondary forest. A total of 73 plots were established, documenting 2,333 individual trees. *Acacia mangium* predominated across all sites except for Mangkapon, which exclusively featured Secondary forest. The analysis encompassed parameters like stand density, basal area, volume, Above Ground Biomass (AGB) estimation, carbon stock estimation and carbon dioxide (CO₂) equivalent emissions if deforested. *Acacia mangium* and secondary forests primarily consisted of young trees with smaller diameters (7-25cm), a height of 7-12m, high stand density per hectare, and average AGB/ha ranging from 56-79 t/ha. Oil palms were relatively young at around three years old, with a height of 5m. The mangrove forest exhibited high density with 2,266 trees/ha but stood out for its substantial AGB of 309t/ha and carbon stock 145tC/ha compared to a simlaly mangrove in Kota Marudu as reported by [Wong et al., \(2020\)](#) at 196 tC/ha. In conclusion, the forests outside the plantations in the study area possess significant potential management and conservation to enhance sustainability efforts, aid in climate change mitigation, and preserve essential ecosystem services.

7.4. Third objective: Mapping of temporally dynamic tropical forest and plantations canopy height in Borneo using TanDEM-X InSAR utilizing multi-sensor remote sensing data

This study, as detailed in chapter 5, showcased the integrated utilization of TanDEM-X InSAR and multi-sensor remote sensing data for canopy height estimations of forest and plantations LULC in the study area. The research employed InSAR coherence data alongside the SINC model method and two machine learning (ML) algorithms: Random Forest (RF) model, and Symbolic Regression (SR) model and corresponding LULC also multi-sensor references dataset for the estimations. Validation against reference dataset yielded Root Mean Square Error (RMSE) values of 6.06 m for the best SR model in 2011, 10.36 m for 2017 SR and 7.58 m for best RF model in 2019. The accuracies by LULC classes were 3.92 m for the best Mangrove RF model in 2011, 6.11 m for 2017 Mangrove SR, and 4.35 m for 2019 Rubber RF model. This study's novelty lies in its comprehensive coverage of various tropical forest and plantation LULC within the study area, unlike previous studies typically addressed only one or few specific types of forest or land uses. In conclusion, the research underscored the synergistic integration of multi-sensor remote sensing data for accurate estimations and mapping of canopy heights in tropical forests and plantations.

7.5. Fourth objective: Environmental sustainability assessment of tropical forest and plantations landscape in Borneo using multi-sensor remote sensing technique and Geospatial Multi Criteria Decision Analysis (MCDA)

This study, as detailed in chapter 6, aimed to evaluate the environmental sustainability of the research area through the application of a multi-sensor remote sensing technique and a Multi-Criteria Decision Analysis (MCDA) model. The findings revealed that 61% (58,995.06 ha) of the total area exhibited highly sustainability, 31% (30,182.49 ha) demonstrated medium sustainability, and only 8% (7,398.73 ha) fell into the low sustainability category. The research showcased the effectiveness of synergistic use of Sentinel-1, Sentinel-2 and fusion with PlanetScope satellite imagery to mitigate cloud and shadow effects classifications, resulting in high overall LULC classification accuracy of >87%. By incorporating S-1 Synthetic Aperture Radar (SAR) imagery for mapping based on physical characteristics such as roughness, moisture and structure, along with optical S-2 and high-resolution PlanetScope for detailed spectral discrimination of LULC classes, the study achieved enhanced classification accuracies (Van Tricht *et al.*, 2018). Furthermore, the study identified that 61% of the water quality

indicator layer and 20% of the landscape connectivity and quality indicator layer were categorised as low sustainable. This was primarily influenced by the proximity of affected rivers to land uses such as aquaculture, timber harvesting, land clearings, oil palm plantations and infrastructure developments, impacting the water quality due to surface run-off. In conclusion, the innovative utilization of multi-sensor data enabled the production of detailed LULC map and indicator layers crucial for environmental sustainability assessment in geospatial MDCA model. The outcomes can help in achieving SDGs and useful for evaluation of certification purpose for the plantations. The workflow developed in this study also can be applied to future case study with additional indicators, more detailed and improved sustainability indicators.

7.6. Significance of the study and recommendations for sustainable tropical forest and plantations in Northern Borneo

The significance of the research derived from the findings detailed in the technical chapters as follows:

1. The utilization of multi-sensor remote sensing data (optical, SAR, LiDAR) offers a comprehensive and detailed insight into the status and dynamics of tropical forest and plantations in the case study of Northern Borneo.
2. The integration of multi-sensor remote sensing data facilitates precise LULC mapping and creation of indicator layers essential for sustainability assessment using MCDA in GIS.
3. Implementation of sustainable management practices guided by insights derived from multi-sensor remote sensing will lead to effective conservation and utilisation of forest resources in Borneo.
4. Multi-sensor remote sensing techniques contribute significantly to addressing specific challenges in Borneo, such as diverse forest types, varying land, uses and the need for biodiversity preservation while supporting economic interests.
5. The adoption of multi-sensor remote sensing techniques ultimately leads to improved policymaking and decision support for sustainable forest and plantation management in Borneo region.

The recommendations derived from the detailed findings in the technical chapters for sustainable tropical forest and plantations in the study area are as follows:

1. Recognising the significance of comprehending LULC dynamics, it is recommended to implement continuous LULC monitoring utilising open-access high-resolution multi-sensor data, including upcoming satellite missions, in conjunction with applications of Unmanned Aerial Vehicle (UAV) or Drone data and field-based measurements.
2. The study findings on the Above Ground Biomass (AGB) and carbon stock estimation, coupled with environmental sustainability assessment, strongly recommend the conservation of Nipah and Mangrove forests in the study area. Additionally, the rehabilitation of abandoned aquaculture sites back into Mangrove forest ecosystems is proposed to reconnect the fragmented Mangrove habitats, enhancing the overall ecological integrity and resilience of the landscape.
3. Acknowledging the importance of preserving sensitive zones such as remaining forest patches, river buffer zones, and High Conservation Value areas (HCVs), it is strongly advised for both plantation companies and small holders to refrain from expanding into these areas to prevent ecosystem damage and disturbances caused by land use activities.
4. It is suggested that plantations prioritise certification and environmental compliance by incorporating research-based insights, such as those from this study, to identify specific key areas for sustainability enhancements in the study area and across other regions in Borneo.
5. Local stake holders, including plantation companies, government and private agencies, and local communities, should be informed about the current environmental conditions based on research findings to enhance their understanding of the prevailing circumstances. This awareness can facilitate improvements in their management practices towards sustainability.

7.7. Limitations of the study and recommendation for future research opportunities

Despite potential of the multi-sensor remote sensing technique, the study acknowledges limitations as the following:

1. Firstly, limitations posed by incomplete or unavailable dataset. The lack of available airborne LiDAR, complete historical field data, and other reference data which are crucial to be used in the canopy height estimations, LULC changes and above ground biomass (AGB) and carbon estimations.
2. Secondly, the study focused on a short time frame of 2010-2023 for LULC changes. Future research could investigate a longer, decadal time frame to better understand the dynamics of LULC changes.

3. Thirdly, due to limited resources constraints, the study was only able to sample 4 sites, which limited the ability to identify specific species in the secondary and mangrove forest categories.

Therefore, for future studies could improve the based on the following recommendations:

1. With the growing number of future multi-sensor remote sensing data acquisition, continuous field data collection including future data acquisition using ground or airborne LiDAR, will improve the accuracy and precision in the forest and plantations mapping also canopy height measurement.
2. Future research could explore the spatial effects of *Ceratotystis wilt.* and other diseases on *Acacia mangium* populations, both wild and planted.
3. Future studies should consider monitoring the status and health of *Eucalyptus pellita*, an important tree species in the Industrial Tree Plantation (ITP) in Borneo.
4. Future research could investigate and compare the resilient levels between wild and planted tree species, which could provide valuable insights for forest management and conservation efforts.
5. The recommendations and methodologies developed in this study could be applied to other parts of Borneo and other tropical regions, to improve our understanding of multi-sensor remote sensing techniques and the applications in forest and plantations monitoring and sustainable management.
6. The future studies will include below ground forest biomass and carbon also further investigation to estimate the forest age in the study area.

Building upon the insights gained from this study, the scientific community can address the identified limitations and incorporate the recommended future research directions. This will enable a more comprehensive understanding of the potential and challenges associated with the application of multi-sensor remote sensing techniques in tropical forest environments. By addressing these gaps and exploring the proposed research avenues, the scientific community can further advance the knowledge and capabilities in this field, ultimately contributing to more effective monitoring and management of tropical forest ecosystems.

7.8. Concluding remarks

In conclusion, findings of this study demonstrate the potential of multi-sensor remote sensing techniques in enhancing the classification and mapping of LULC in the tropical forest and plantations landscape in Borneo. This capability is crucial for the sustainable management also

conservation of important ecosystems in Borneo. The technical studies presented in this thesis provide valuable insights from the results, and the methodologies developed can be further improved by future research. These methodologies are essential for a wide application, including estimating aboveground biomass changes, discriminating between native forests and plantations, mapping the extent of plantations, monitoring forest degradation, and monitoring plantations. The information derived from this research will contribute to guiding the development and implementation of sustainable management practices to conserve biodiversity, maintain environmental stability and quality, support local livelihoods, and help in mitigate climate change. To further enhance the potential of multi-sensor remote sensing techniques, future studies should explore the application of these methodologies in other parts of Borneo and tropical regions. This will contribute to a more comprehensive understanding of the utility and limitations of these techniques, ultimately leading to more effective and sustainable management of tropical forests and plantations.

References

- Abate Shiferaw, & K.L. Singh. (2011). Evaluating The Land Use And Land Cover Dynamics In Borena Woreda South Wollo Highlands, Ethiopia. *Ethiopian Journal of Business and Economics*, 2(1), 69–104. <https://www.ajol.info/index.php/ejbe/article/view/111836/101604>
- Abe H., Itoh S., Shibata M., Ogata K., Kitin P. B. P., & Fujii T. (2005). *Tree species of timber imported to Japan from Southeast Asia*. https://www.jircas.go.jp/en/publication/research_results/2005_14
- Acosta, M., & Corral, S. (2017). Multicriteria Decision Analysis and Participatory Decision Support Systems in Forest Management. *Forests*, 8(4), 116. <https://doi.org/10.3390/f8040116>
- Adam, N. S., & Jusoh, I. (2018). Allometric Model for Predicting Aboveground Biomass and Carbon Stock of Acacia Plantations in Sarawak, Malaysia. *BioResources*, 13(4), 7381–7394. <https://doi.org/10.15376/biores.13.4.7381-7394>
- AFI Sdn. Bhd. (2018). *AFI Public Forest Management Plan 2016-2025 (Revision 02 Feb. 2022)*. <http://afisb.com.my/wp-content/uploads/2018/07/99020002-AFI-Forest-Management-Plan-Public-Version-1.pdf>
- Aguma, R., & Hussin, Y. A. (2009). *The use of Remote Sensing and GIS to Support Sustainable Management of Tropical Forest in East Kalimantan, Indonesia*. Geospatialworld.Net. <https://www.geospatialworld.net/article/the-use-of-remote-sensing-and-gis-to-support-sustainable-management-of-tropical-forest-in-east-kalimantan-indonesia/>
- Ahlheim, M., Börger, T., & Frör, O. (2015). Replacing rubber plantations by rain forest in Southwest China—who would gain and how much? *Environmental Monitoring and Assessment*, 187(2), 3. <https://doi.org/10.1007/s10661-014-4088-8>
- Alamgir, M., Campbell, M. J., Sloan, S., Engert, J., Word, J., & Laurance, W. F. (2020). Emerging challenges for sustainable development and forest conservation in Sarawak, Borneo. *PLOS ONE*, 15(3), e0229614. <https://doi.org/10.1371/journal.pone.0229614>
- Anaconda Mopan, Y. E., Solis Pino, A. F., Rubiano-Ovalle, O., Paz, H., & Ramirez Mejia, I. (2023). Spatial Analysis of the Suitability of Hass Avocado Cultivation in the Cauca

- Department, Colombia, Using Multi-Criteria Decision Analysis and Geographic Information Systems. *ISPRS International Journal of Geo-Information*, 12(4), 136. <https://doi.org/10.3390/ijgi12040136>
- Anderson, J. A., McClean, C. J., Sim, S., Pettoirelli, N., Jelling, A., Tangah, J., & Hill, J. K. (2022). Weak edge effects on trees in Bornean rainforest remnants bordering oil palm. *Biotropica*, 54(4), 921–932. <https://doi.org/10.1111/btp.13115>
- Ariesca, R., Sau, A. A. W. T., Adinugroho, W. C., Setiawan, A. A. R., Ahamed, T., & Noguchi, R. (2023). Land Swap Option for Sustainable Production of Oil Palm Plantations in Kalimantan, Indonesia. *Sustainability (Switzerland)*, 15(3). <https://doi.org/10.3390/su15032394>
- Asner, G. P., Brodrick, P. G., & Heckler, J. (2021). *Global Airborne Observatory: Forest Canopy Height and Carbon Stocks for Sabah, Borneo Malaysia (Version 1.0)*. <https://doi.org/10.5281/zenodo.4549461>
- Asner, G. P., Brodrick, P. G., Philipson, C., Vaughn, N. R., Martin, R. E., Knapp, D. E., Heckler, J., Evans, L. J., Jucker, T., Goossens, B., Stark, D. J., Reynolds, G., Ong, R., Renneboog, N., Kugan, F., & Coomes, D. A. (2018). Mapped aboveground carbon stocks to advance forest conservation and recovery in Malaysian Borneo. *Biological Conservation*, 217(November 2017), 289–310. <https://doi.org/10.1016/j.biocon.2017.10.020>
- Astor Toraño Caicoya, Florian Kugler, Matteo Pardini, I. H. & K. P. (2012). Forest vertical structure characterization for Biomass estimation with Remote Sensing systems (Synthetic aperture radar): Spatial scale implications. *ForestSAT 2012*. https://elib.dlr.de/75846/1/ForestSAT2012_abstract_torano.pdf
- Avtar, R., Sawada, H., Takeuchi, W., & Singh, G. (2012). Characterization of forests and deforestation in Cambodia using ALOS/PALSAR observation. *Geocarto International*, 27(2), 119–137. <https://doi.org/10.1080/10106049.2011.626081>
- Avtar, R., Tsusaka, K., & Herath, S. (2020). Assessment of forest carbon stocks for REDD+ implementation in the muyong forest system of Ifugao, Philippines. *Environmental Monitoring and Assessment*, 192(9), 571. <https://doi.org/10.1007/s10661-020-08531-8>
- Balu Nambiappan, Azman Ismail, Nordadilah Hashim, Ismail, N., Shahari, D. N., Idris, N. A. N., Omar, N., Salleh, K. M., Hassan, N. A. M., & Kushairi., A. (2018). Malaysia: 100

- Years of Resilient Palm Oil Economic Performance. *Journal of Oil Palm Research*, 30(1), 13–25. <https://doi.org/10.21894/jopr.2018.0014>
- Baul, T. K., Chakraborty, A., Nandi, R., Mohiuddin, M., Kilpeläinen, A., & Sultana, T. (2021). Effects of tree species diversity and stand structure on carbon stocks of homestead forests in Maheshkhali Island, Southern Bangladesh. *Carbon Balance and Management*, 16(1), 11. <https://doi.org/10.1186/s13021-021-00175-6>
- Bayrak, M., & Marafa, L. (2016). Ten Years of REDD+: A Critical Review of the Impact of REDD+ on Forest-Dependent Communities. *Sustainability*, 8(7), 620. <https://doi.org/10.3390/su8070620>
- Bedell, E., Leslie, M., Fankhauser, K., Burnett, J., Wing, M. G., & Thomas, E. A. (2017). Unmanned aerial vehicle-based structure from motion biomass inventory estimates. *Journal of Applied Remote Sensing*, 11(2), 026026. <https://doi.org/10.1117/1.jrs.11.026026>
- Bernama. (2023). Sabah GDP grew by 3.7% in 2022, says assistant minister. *Bernama.Com*. <https://www.bernama.com/en/business/news.php?id=2214952>
- Bettinger, P., Boston, K., Siry, J. P., & Grebner, D. L. (2017). Advanced Planning Techniques. In *Forest Management and Planning* (pp. 177–199). Elsevier. <https://doi.org/10.1016/B978-0-12-809476-1.00008-4>
- Bid, S., & Siddique, G. (2019). Identification of seasonal variation of water turbidity using NDTI method in Panchet Hill Dam, India. *Modeling Earth Systems and Environment*, 5(4), 1179–1200. <https://doi.org/10.1007/s40808-019-00609-8>
- Bispo, Polyanna, D., Conceição, Pardini, M., Papathanassiou, K. P., Kugler, F., Balzter, H., Rains, D., Roberto, J., Rizaev, I. G., Tansey, K., Nara, M., & Spinelli, L. (2019). Remote Sensing of Environment Mapping forest successional stages in the Brazilian Amazon using forest heights derived from TanDEM-X SAR interferometry. *Remote Sensing of Environment*, 232(July), 111194. <https://doi.org/10.1016/j.rse.2019.05.013>
- Biswas, S., Huang, Q., Anand, A., Mon, M. S., Arnold, F. E., & Leimgruber, P. (2020). A multi sensor approach to forest type mapping for advancing monitoring of sustainable development goals (SDG) in Myanmar. *Remote Sensing*, 12(19), 1–21. <https://doi.org/10.3390/rs12193220>

- Boul Lefevre, N., Keller, N., Plagnat-Cantoreggi, P., Godoong, E., Dray, A., & Philipson, C. D. (2022). The value of logged tropical forests: A study of ecosystem services in Sabah, Borneo. *Environmental Science & Policy*, 128, 56–67. <https://doi.org/10.1016/j.envsci.2021.11.003>
- Brown, E., Dudley, N., Lindhe, A., Muhtaman, D. R., Stewart, C., & Synnott, T. (2013). *Common Guidance for the High Conservation Values A good practice guide for identifying HCVs across different ecosystems and production systems*. October.
- Bryan, J. E., Shearman, P. L., Asner, G. P., Knapp, D. E., Aoro, G., & Lokes, B. (2013). Extreme Differences in Forest Degradation in Borneo: Comparing Practices in Sarawak, Sabah, and Brunei. *PLoS ONE*, 8(7). <https://doi.org/10.1371/journal.pone.0069679>
- Cammerino, A. R. B., Ingaramo, M., Piacquadio, L., & Monteleone, M. (2023). Assessing and Mapping Forest Functions through a GIS-Based, Multi-Criteria Approach as a Participative Planning Tool: An Application Analysis. *Forests*, 14(5), 934. <https://doi.org/10.3390/f14050934>
- Carlson, K. M., Curran, L. M., Asner, G. P., Pittman, A. M., Trigg, S. N., & Marion Adeney, J. (2013). Carbon emissions from forest conversion by Kalimantan oil palm plantations. *Nature Climate Change*, 3(3), 283–287. <https://doi.org/10.1038/nclimate1702>
- Carlson, K. M., & Garrett, R. D. (2018). Environmental Impacts of Tropical Soybean and Palm Oil Crops. In *Oxford Research Encyclopedia of Environmental Science*. Oxford University Press. <https://doi.org/10.1093/acrefore/9780199389414.013.234>
- Chen, H., Cloude, S. R., Goodenough, D. G., & Fellow, L. (2016). Forest Canopy Height Estimation Using Tandem-X Coherence Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9(7), 3177–3188. <https://doi.org/10.1109/JSTARS.2016.2582722>
- Chen, H., Cloude, S. R., Goodenough, D. G., Hill, D. A., & Nسدoly, A. (2018). Radar forest height estimation in mountainous terrain using tandem-x coherence data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 11(10), 3443–3452. <https://doi.org/10.1109/JSTARS.2018.2866059>
- Chen, H., Cloude, S. R., & White, J. C. (2021). *Using GEDI Waveforms for Improved TanDEM-X Forest Height Mapping : A Combined SINC + Legendre Approach*. 1–12.

- Chen, J. (2014). GIS-based multi-criteria analysis for land use suitability assessment in City of Regina. *Environmental Systems Research*, 3(1), 13. <https://doi.org/10.1186/2193-2697-3-13>
- Chen, X., Chen, W., Bai, Y., & Wen, X. (2022). Changes in turbidity and human activities along Haihe River Basin during lockdown of COVID-19 using satellite data. *Environmental Science and Pollution Research*, 29(3), 3702–3717. <https://doi.org/10.1007/s11356-021-15928-6>
- Choi, C., Guliaev, R., Cazcarra-Bes, V., Pardini, M., & Papathanassiou, K. P. (2020). Forest Height Estimation from Tandem-X InSAR Coherence Magnitude Towards Large Scale Applications. *IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium*, 3413–3415. <https://doi.org/10.1109/IGARSS39084.2020.9323839>
- Chong, K. L., Kanniah, K. D., Pohl, C., & Tan, K. P. (2017). A review of remote sensing applications for oil palm studies. *Geo-Spatial Information Science*, 20(2), 184–200. <https://doi.org/10.1080/10095020.2017.1337317>
- Chuvieco, E. (2020). *Fundamentals of Satellite Remote Sensing*. CRC Press. <https://doi.org/10.1201/9780429506482>
- Claverie, M., Ju, J., Masek, J. G., Dungan, J. L., Vermote, E. F., Roger, J., Skakun, S. V., & Justice, C. (2018). Remote Sensing of Environment The Harmonized Landsat and Sentinel-2 surface reflectance data set. *Remote Sensing of Environment*, 219(August), 145–161. <https://doi.org/10.1016/j.rse.2018.09.002>
- Cloude, S. R., Chen, H., & Goodenough, D. G. (2013). Forest height estimation and validation using Tandem-X polinsar. *International Geoscience and Remote Sensing Symposium (IGARSS)*, 1, 1889–1892. <https://doi.org/10.1109/IGARSS.2013.6723172>
- Cranmer, M., Cranmer, K., Spergel, D., & Battaglia, P. (2020). *Discovering Symbolic Models from Deep Learning with Inductive Biases*. *NeurIPS*, 1–14.
- Curran, L. M., Trigg, S. N., McDonald, A. K., Astiani, D., Hardiono, Y. M., Siregar, P., Caniago, I., & Kasischke, E. (2004). Lowland Forest Loss in Protected Areas of Indonesian Borneo. *Science*, 303(5660), 1000–1003. <https://doi.org/10.1126/science.1091714>

- D'Adamo, I., & Gastaldi, M. (2022). Sustainable Development Goals: A Regional Overview Based on Multi-Criteria Decision Analysis. *Sustainability*, 14(15), 9779. <https://doi.org/10.3390/su14159779>
- Dagne, S. S., Hirpha, H. H., Tekoye, A. T., Dessie, Y. B., & Endeshaw, A. A. (2023). Fusion of sentinel-1 SAR and sentinel-2 MSI data for accurate Urban land use-land cover classification in Gondar City, Ethiopia. *Environmental Systems Research*, 12(1), 40. <https://doi.org/10.1186/s40068-023-00324-5>
- De Luca, G., M. N. Silva, J., Di Fazio, S., & Modica, G. (2022). Integrated use of Sentinel-1 and Sentinel-2 data and open-source machine learning algorithms for land cover mapping in a Mediterranean region. *European Journal of Remote Sensing*, 55(1), 52–70. <https://doi.org/10.1080/22797254.2021.2018667>
- Dingle Robertson, L., M. Davidson, A., McNairn, H., Hosseini, M., Mitchell, S., de Abelleira, D., Verón, S., le Maire, G., Plannells, M., Valero, S., Ahmadian, N., Coffin, A., Bosch, D., H. Cosh, M., Basso, B., & Saliendra, N. (2020). C-band synthetic aperture radar (SAR) imagery for the classification of diverse cropping systems. *International Journal of Remote Sensing*, 41(24), 9628–9649. <https://doi.org/10.1080/01431161.2020.1805136>
- Disney, M. (2019). Terrestrial LiDAR: a three-dimensional revolution in how we look at trees. *New Phytologist*, 222(4), 1736–1741. <https://doi.org/10.1111/nph.15517>
- Drigo, R. (2005). Trends and patterns of tropical land use change. In *Forests, Water and People in the Humid Tropics* (pp. 9–39). Cambridge University Press. <https://doi.org/10.1017/CBO9780511535666.006>
- Dubayah, R., Bryan, J., Goetz, S., Fatoyinbo, L., Hansen, M., Healey, S., Hofton, M., Hurtt, G., Kellner, J., Luthcke, S., Armston, J., Tang, H., Duncanson, L., Hancock, S., Jantz, P., Marselis, S., Patterson, P. L., Qi, W., & Silva, C. (2020). Science of Remote Sensing The Global Ecosystem Dynamics Investigation : High-resolution laser ranging of the Earth ' s forests and topography. *Science of Remote Sensing*, 1(January), 100002. <https://doi.org/10.1016/j.srs.2020.100002>
- Duque, S., Balss, U., Rossi, C., Fritz, T., & Balzer, W. (2012). *TanDEM-X Payload Ground Segment CoSSC Generation and Interferometric Considerations*. <https://tandemx-science.dlr.de/pdfs/TD-PGS-TN->

- EPD Sabah. (2012a). *Environmental Impact Assessment (EIA): Guidelines for Construction on Hill Slopes*. Environment Protection Department (EPF) Sabah. https://epd.sabah.gov.my/v3/wp-content/uploads/2022/11/EIA_Guidelines_HillSlope.pdf
- EPD Sabah. (2012b). *Environmental Impact Assessment (EIA): Guidelines for Forest Harvesting (Logging) and Forest Plantation Establishment*. https://epd.sabah.gov.my/v3/wp-content/uploads/2022/11/EIA_Guidelines_Forestry.pdf
- EPD Sabah. (2012c). *Environmental Impact Assessment (EIA): Guidelines for Oil Palm Plantation*.
- Estoque, R. (2020). A Review of the Sustainability Concept and the State of SDG Monitoring Using Remote Sensing. *Remote Sensing*, 12(11), 1770. <https://doi.org/10.3390/rs12111770>
- FAO. (2020). *Global Forest Resources Assessment 2020*. Food and Agriculture Organization of the United Nations. <https://doi.org/10.4060/ca9825en>
- Fritz, T., Brautigam, B., Krieger, G., & Zink, M. (2012). *TanDEM-X Ground Segment: TanDEM-X Experimental Product Description*. https://tandemx-science.dlr.de/pdfs/TD-GS-PS-3028_TanDEM-X-Experimental-Product-Description_1.2.pdf
- Funk, J. M., Aguilar-Amuchastegui, N., Baldwin-Cantello, W., Busch, J., Chuvasov, E., Evans, T., Griffin, B., Harris, N., Ferreira, M. N., Petersen, K., Phillips, O., Soares, M. G., & van der Hoff, R. J. A. (2019). Securing the climate benefits of stable forests. *Climate Policy*, 19(7), 845–860. <https://doi.org/10.1080/14693062.2019.1598838>
- Gamini Herath, Tony Prato, & (eds). (2006). Using multi-criteria decision analysis in Natural Resource Management. In *Environmental Sciences* (Vol. 4, Issue 2). <https://doi.org/10.1080/15693430701317637>
- Gao, Y., Skutsch, M., Paneque-Gálvez, J., & Ghilardi, A. (2020). Remote sensing of forest degradation: a review. *Environmental Research Letters*, 15(10), 103001. <https://doi.org/10.1088/1748-9326/abaad7>
- Gaveau, D. L. A., Locatelli, B., Salim, M. A., Yaen, H., Pacheco, P., & Sheil, D. (2019). Rise

- and fall of forest loss and industrial plantations in Borneo (2000–2017). *Conservation Letters*, 12(3), 1–8. <https://doi.org/10.1111/conl.12622>
- Gaveau, D. L. A., Salim, M. A., Hergoualc’h, K., Locatelli, B., Sloan, S., Wooster, M., Marlier, M. E., Molidena, E., Yaen, H., DeFries, R., Verchot, L., Murdiyarso, D., Nasi, R., Holmgren, P., & Sheil, D. (2014). Major atmospheric emissions from peat fires in Southeast Asia during non-drought years: evidence from the 2013 Sumatran fires. *Scientific Reports*, 4(1), 6112. <https://doi.org/10.1038/srep06112>
- Gaveau, D. L. A., Sheil, D., Husnayaen, Salim, M. A., Arjasakusuma, S., Ancrenaz, M., Pacheco, P., & Meijaard, E. (2016). Rapid conversions and avoided deforestation: examining four decades of industrial plantation expansion in Borneo. *Scientific Reports*, 6(1), 32017. <https://doi.org/10.1038/srep32017>
- GFS. (2019). *Sabah TLAS Audit Report: Sabah Legality Standard Principles 1 – 4 FDS-TLAS-006*. <https://www.gfsinc.biz/wp-content/uploads/2016/12/GFSSBH-003-055-TLAS-P1-4-Summary-SAFODA-AFI-Nov-2019.pdf>
- Ghosh, S. M., Behera, M. D., & Paramanik, S. (2020). Canopy height estimation using sentinel series images through machine learning models in a Mangrove Forest. *Remote Sensing*, 12(9). <https://doi.org/10.3390/RS12091519>
- Gigović, L., Jakovljević, G., Sekulović, D., & Regodić, M. (2018). GIS Multi-Criteria Analysis for Identifying and Mapping Forest Fire Hazard: Nevesinje, Bosnia and Herzegovina. *Tehnicki Vjesnik - Technical Gazette*, 25(3). <https://doi.org/10.17559/TV-20151230211722>
- Gislason, P. O., Benediktsson, J. A., & Sveinsson, J. R. (2006). *Random Forests for land cover classification*. 27, 294–300. <https://doi.org/10.1016/j.patrec.2005.08.011>
- Goetz, S. J., Hansen, M., Houghton, R. A., Walker, W., Laporte, N., & Busch, J. (2015). Measurement and monitoring needs, capabilities and potential for addressing reduced emissions from deforestation and forest degradation under REDD+. *Environmental Research Letters*, 10(12). <https://doi.org/10.1088/1748-9326/10/12/123001>
- Gogoi, P. P., Vinoj, V., Swain, D., Roberts, G., Dash, J., & Tripathy, S. (2019). Land use and land cover change effect on surface temperature over Eastern India. *Scientific Reports*, 9(1), 8859. <https://doi.org/10.1038/s41598-019-45213-z>

- Gomez, C., Lopez-Sanchez, J. M., Romero-Puig, N., Zhu, J., Fu, H., He, W., Xie, Y., & Xie, Q. (2021). Canopy Height Estimation in Mediterranean Forests of Spain with TanDEM-X Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 2956–2970. <https://doi.org/10.1109/JSTARS.2021.3060691>
- Google. (n.d.). *Google Earth Engine*. Retrieved July 10, 2023, from <https://developers.google.com/earth-engine/apidocs/ee-classifier-smilerandomforest>
- Gray, C. L. (2017). RSPO Manual on Best Management Practices (BMPs) for the Management and Rehabilitation of Riparian Reserves RSPO Manual on Best Management Practices (BMPs) for the Management and Rehabilitation of Riparian Reserves Holly Barclay , Claudia L . Gray , Sa. *Kuala ...*, November. <https://doi.org/10.13140/RG.2.2.17011.22561>
- Greene, R., Devillers, R., Luther, J. E., & Eddy, B. G. (2011). GIS-Based Multiple-Criteria Decision Analysis. *Geography Compass*, 5(6), 412–432. <https://doi.org/10.1111/j.1749-8198.2011.00431.x>
- Greenshields, B., von der Lühe, B., Schwarz, F., Hughes, H. J., Tjoa, A., Kotowska, M., Brambach, F., & Sauer, D. (2023). Estimating oil-palm Si storage, Si return to soils, and Si losses through harvest in smallholder oil-palm plantations of Sumatra, Indonesia. *Biogeosciences*, 20(7), 1259–1276. <https://doi.org/10.5194/bg-20-1259-2023>
- Guerra-Hernández, J., Narine, L. L., Pascual, A., Gonzalez-Ferreiro, E., Botequim, B., Malambo, L., Neuenschwander, A., Popescu, S. C., & Godinho, S. (2022). Aboveground biomass mapping by integrating ICESat-2, Sentinel-1, Sentinel-2, ALOS2/PALSAR2, and topographic information in Mediterranean forests. *GIScience and Remote Sensing*, 59(1), 1509–1533. <https://doi.org/10.1080/15481603.2022.2115599>
- Hadi, Krasovskii, A., Maus, V., Yowargana, P., Pietsch, S., & Rautiainen, M. (2018). Monitoring Deforestation in Rainforests Using Satellite Data: A Pilot Study from Kalimantan, Indonesia. *Forests*, 9(7), 389. <https://doi.org/10.3390/f9070389>
- Hao, S., Zhu, F., & Cui, Y. (2021). Land use and land cover change detection and spatial distribution on the Tibetan Plateau. *Scientific Reports*, 11(1), 7531. <https://doi.org/10.1038/s41598-021-87215-w>
- Hartshorn, G. S. (2001). Tropical Forest Ecosystems. In *Encyclopedia of Biodiversity* (pp. 701–

- 710). Elsevier. <https://doi.org/10.1016/B0-12-226865-2/00275-3>
- Hassan, Z., Shabbir, R., Ahmad, S. S., Malik, A. H., Aziz, N., Butt, A., & Erum, S. (2016). Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan. *SpringerPlus*, 5(1), 812. <https://doi.org/10.1186/s40064-016-2414-z>
- Hector, A., Philipson, C., Saner, P., Chamagne, J., Dzulkipli, D., O'Brien, M., Snaddon, J. L., Ulok, P., Weilenmann, M., Reynolds, G., & Godfray, H. C. J. (2011). The Sabah Biodiversity Experiment: a long-term test of the role of tree diversity in restoring tropical forest structure and functioning. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 366(1582), 3303–3315. <https://doi.org/10.1098/rstb.2011.0094>
- Hoekman, D., Quinones, M., & Vissers, M. (2010). K&C Science Report – Phase 1 Tropical Forest and Wetlands Mapping, Case Study Borneo. *The ALOS Kyoto & Carbon Initiative Science Team Reports Phase 1 (2006-2008)*, 33–44. http://www.eorc.jaxa.jp/ALOS/en/kyoto/phase_1/KC-Phase1-report_Hoekman.pdf
- Hon, J., & Shibata, S. (1970). A Review on Land Use in the Malaysian State of Sarawak, Borneo and Recommendations for Wildlife Conservation Inside Production Forest Environment. *Borneo Journal of Resource Science and Technology*, 3(2), 22–35. <https://doi.org/10.33736/bjrst.244.2013>
- Hristov, I., & Chirico, A. (2019). The Role of Sustainability Key Performance Indicators (KPIs) in Implementing Sustainable Strategies. *Sustainability*, 11(20), 5742. <https://doi.org/10.3390/su11205742>
- Ikhsan, H. Z., Sakya, A. T., Nufus, M., & Pertiwi, Y. A. B. (2021). Estimation of aboveground biomass and carbon stock in a pine-mahogany mixture stands at specific purpose forest area of Gunung Bromo, Karanganyar. *IOP Conference Series: Earth and Environmental Science*, 637(1), 012021. <https://doi.org/10.1088/1755-1315/637/1/012021>
- J. Malczewski. (1999). *GIS and Multicriteria Decision Analysis*. John Wiley & Sons.
- Jackson, C., & Adam, E. (2020). Remote sensing of selective logging in tropical forests: current state and future directions. *IForest - Biogeosciences and Forestry*, 13(1), 286–300. <https://doi.org/10.3832/ifor3301-013>

- Jarayee, A. N., Shafri, H. Z. M., Ang, Y., Lee, Y. P., Bakar, S. A., Abidin, H., Lim, H. S., & Abdullah, R. (2022). Oil Palm Plantation Land Cover and Age Mapping Using Sentinel-2 Satellite Imagery and Machine Learning Algorithms. *IOP Conference Series: Earth and Environmental Science*, 1051(1), 012024. <https://doi.org/10.1088/1755-1315/1051/1/012024>
- Jiang, F., Zhao, F., Ma, K., Li, D., & Sun, H. (2021). Mapping the forest canopy height in northern China by synergizing ICESat-2 with sentinel-2 using a stacking algorithm. *Remote Sensing*, 13(8). <https://doi.org/10.3390/rs13081535>
- Jusoh, I., Suteh, J. K., & Adam, N. S. (2017). Growth and yield of *Acacia mangium* based on permanent sampling plots in a plantation. *Transactions on Science and Technology*, 4(4), 513–518. <http://transectscience.org/>
- Keeton-Olsen, D. (2021). *In Malaysian Borneo's rainforests, powerful state governments set their own rules*. News.Mongabay.Com. <https://news.mongabay.com/2021/02/in-malaysian-borneos-rainforests-powerful-state-government-set-their-own-rules/>
- Kenzo, T., Ichie, T., Hattori, D., Itioka, T., Handa, C., Ohkubo, T., Kendawang, J. J., Nakamura, M., Sakaguchi, M., Takahashi, N., Okamoto, M., Tanaka-Oda, A., Sakurai, K., & Ninomiya, I. (2009). Development of allometric relationships for accurate estimation of above- and below-ground biomass in tropical secondary forests in Sarawak, Malaysia. *Journal of Tropical Ecology*, 25(4), 371–386. <https://doi.org/10.1017/S02664674090006129>
- Khalsa, S. J. S., Borsa, A., Nandigam, V., Phan, M., Lin, K., Crosby, C., Fricker, H., Baru, C., & Lopez, L. (2022). OpenAltimetry - rapid analysis and visualization of Spaceborne altimeter data. *Earth Science Informatics*, 15(3), 1471–1480. <https://doi.org/10.1007/s12145-020-00520-2>
- Khan, M. N. I., Islam, M. R., Rahman, A., Azad, M. S., Mollick, A. S., Kamruzzaman, M., Sadath, M. N., Feroz, S. M., Rakkibu, M. G., & Knohl, A. (2020). Allometric relationships of stand level carbon stocks to basal area, tree height and wood density of nine tree species in Bangladesh. *Global Ecology and Conservation*, 22, e01025. <https://doi.org/10.1016/j.gecco.2020.e01025>
- Kho, L. K., & Jepsen, M. R. (2015). Carbon stock of oil palm plantations and tropical forests

- in Malaysia: A review. *Singapore Journal of Tropical Geography*, 36(2), 249–266.
<https://doi.org/10.1111/sjtg.12100>
- Koza, J. R. (1994). Genetic programming as a means for programming computers by natural selection. *Statistics and Computing*, 4(2), 87–112. <https://doi.org/10.1007/BF00175355>
- Kugler, F., Seung-Kuk Lee, Hajnsek, I., & Papathanassiou, K. P. (2015). Forest Height Estimation by Means of Pol-InSAR Data Inversion: The Role of the Vertical Wavenumber. *IEEE Transactions on Geoscience and Remote Sensing*, 53(10), 5294–5311.
<https://doi.org/10.1109/TGRS.2015.2420996>
- Labrière, N., Laumonier, Y., Locatelli, B., Vieilledent, G., & Comptour, M. (2015). Ecosystem Services and Biodiversity in a Rapidly Transforming Landscape in Northern Borneo. *PLOS ONE*, 10(10), e0140423. <https://doi.org/10.1371/journal.pone.0140423>
- Langer, A., Miettinen, J., & Seigert, F. (2007). Land cover change 2002–2005 in Borneo and the role of fire derived from MODIS imagery. *Global Change Biology*, 13(11), 2329–2340. <https://doi.org/10.1111/j.1365-2486.2007.01442.x>
- Larjavaara, M., & Muller-landau, H. C. (2013). Measuring tree height: A quantitative comparison of two common field methods in a moist tropical forest Measuring tree height : a quantitative comparison of two common field methods in a moist tropical forest. *Mehtods in Ecology and Evolution*, 2013. <https://doi.org/10.1111/2041-210X.12071>
- Laurance, W. (2016). Lessons from Research for Sustainable Development and Conservation in Borneo. *Forests*, 7(12), 314. <https://doi.org/10.3390/f7120314>
- Lee, S. (2018). Observations on The Successes and Failures of Acacia Plantations in Sabah and Sarawak and The Way Forward. *Journal Of Tropical Forest Science*, 30(5), 468–475.
<https://doi.org/10.26525/jtfs2018.30.5.468475>
- Lee, S. S. (2018). Observations on the successes and failures of acacia plantations in Sabah and Sarawak and the way forward. *Journal of Tropical Forest Science*, 30(5), 468–475.
<https://doi.org/10.26525/jtfs2018.30.5.468475>
- Liaw, A., & Wiener, M. (2002). Classification and Regression by randomForest. *R News*, 2 (3)(December), 18–22.
- Liu, A., Cheng, X., & Chen, Z. (2021). Remote Sensing of Environment Performance

- evaluation of GEDI and ICESat-2 laser altimeter data for terrain and canopy height retrievals. *Remote Sensing of Environment*, 264, 112571. <https://doi.org/10.1016/j.rse.2021.112571>
- Liu, S., Brandt, M., Nord-Larsen, T., Chave, J., Reiner, F., Lang, N., Tong, X., Ciais, P., Igel, C., Pascual, A., Guerra-Hernandez, J., Li, S., Mugabowindekwe, M., Saatchi, S., Yue, Y., Chen, Z., & Fensholt, R. (2023). The overlooked contribution of trees outside forests to tree cover and woody biomass across Europe. *Science Advances*, 9(37), eadh4097. <https://doi.org/10.1126/sciadv.adh4097>
- Loh, H. Y., James, D., Ioki, K., Wong, W. V. C., Tsuyuki, S., & Phua, M.-H. (2022). Estimating aboveground biomass changes in a human-modified tropical montane forest of Borneo using multi-temporal airborne LiDAR data. *Remote Sensing Applications: Society and Environment*, 28, 100821. <https://doi.org/10.1016/j.rsase.2022.100821>
- Maid, M., Latif, A. A., Gan, E., Salfinas, N., Kitingan, C., Maycock, C. R., & Ratnam, W. (2018). First report of stem Canker disease on acacia mangium induced by lasiodiplodia theobromae and lasiodiplodia pseudotheobromae species in Sabah, Malaysia. *Malaysian Applied Biology*, 47(3), 147–151.
- Maid, M., & Ratnam, W. (2014). Incidences and severity of vascular wilt in acacia mangium plantations in sabah, malaysia. *AIP Conference Proceedings*, 1614(October), 784–789. <https://doi.org/10.1063/1.4895302>
- Majuakim, L., Lee, A., Ling, M., & Gisil, J. (2018). An Inventory of Flora in Urban Forests of Universiti Malaysia Sabah, Malaysia. *Journal of Tropical Biology and Conservation*, 15, 173–188.
- Markus, T., Neumann, T., Martino, A., Abdalati, W., Brunt, K., Csatho, B., Farrell, S., Fricker, H., Gardner, A., Harding, D., Jasinski, M., Kwok, R., Magruder, L., Lubin, D., Luthcke, S., Morison, J., Nelson, R., Neuenschwander, A., Palm, S., ... Zwally, J. (2017). Remote Sensing of Environment The Ice , Cloud , and land Elevation Satellite-2 (ICESat-2): Science requirements , concept , and implementation. *Remote Sensing of Environment*, 190, 260–273. <https://doi.org/10.1016/j.rse.2016.12.029>
- Martone, M., Bräutigam, B., Rizzoli, P., Gonzalez, C., Bachmann, M., & Krieger, G. (2012). Coherence evaluation of TanDEM-X interferometric data. *ISPRS Journal of*

- Photogrammetry and Remote Sensing*, 73(December 2010), 21–29.
<https://doi.org/10.1016/j.isprsjprs.2012.06.006>
- McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *Int. J. Remote Sens.*, 17, 1425–1432.
- Mitchell, S. L., Edwards, D. P., Bernard, H., Coomes, D., Jucker, T., Davies, Z. G., & Struebig, M. J. (2018). Riparian reserves help protect forest bird communities in oil palm dominated landscapes. *Journal of Applied Ecology*, 55(6), 2744–2755. <https://doi.org/10.1111/1365-2664.13233>
- Mohamadzadeh, P., Pourmoradian, S., Feizizadeh, B., Sharifi, A., & Vogdrup-Schmidt, M. (2020). A GIS-Based Approach for Spatially-Explicit Sustainable Development Assessments in East Azerbaijan Province, Iran. *Sustainability*, 12(24), 10413. <https://doi.org/10.3390/su122410413>
- Mohd-Lokman, H., Choo, C. Y., & Norman, K. (2012). Mangrove diversity and biomass in Klias and Sepangar Bay, Sabah, Malaysia. *Journal of Tropical Biology and Conservation*, 8, 1–11.
- Mohd Hanafiah, K., Abd Mutalib, A. H., Miard, P., Goh, C. S., Mohd Sah, S. A., & Ruppert, N. (2022). Impact of Malaysian palm oil on sustainable development goals: co-benefits and trade-offs across mitigation strategies. *Sustainability Science*, 17(4), 1639–1661. <https://doi.org/10.1007/s11625-021-01052-4>
- Mohd Najib, N. E., Kanniah, K. D., Cracknell, A. P., & Yu, L. (2020). Synergy of Active and Passive Remote Sensing Data for Effective Mapping of Oil Palm Plantation in Malaysia. *Forests*, 11(8), 858. <https://doi.org/10.3390/f11080858>
- Mojiol, A. R., Maisyahirah, W., Mohd, M., Ali, M., & Hussein, S. (2019). *Tree Species Diversity of Mangrove at Tunku Abdul Rahman Park , Sabah Malaysia*. 3(9), 181–187. <https://doi.org/10.31080/ASAG.2019.03.0631>
- Mori, T. (2023). Effects of tropical forest conversion into oil palm plantations on nitrous oxide emissions: A meta-analysis. *Journal of Forestry Research*, 34(3), 865–869. <https://doi.org/10.1007/s11676-022-01493-2>
- MPOB. (2022). *Overview of the Malaysian Oil Palm industry 2022*.

<https://bepi.mpob.gov.my/images/overview/Overview2022.pdf>

- Murphy, D. J., Goggin, K., & Paterson, R. R. M. (2021). Oil palm in the 2020s and beyond: challenges and solutions. *CABI Agriculture and Bioscience*, 2(1), 39. <https://doi.org/10.1186/s43170-021-00058-3>
- Musthafa, M., Khati, U., & Singh, G. (2020). Sensitivity of PolSAR decomposition to forest disturbance and regrowth dynamics in a managed forest. *Advances in Space Research*, 66(8), 1863–1875. <https://doi.org/10.1016/j.asr.2020.07.007>
- Nagano, H., Okada, K., Nakashima, Y., Samejima, H., & Willcox, D. (2019). *Habitat use of Bornean Ferret Badger Melogale everetti in Sabah , Malaysian Borneo*. 2, 25–33.
- Nazeri, A., Jusoh, I., & Wasli, M. E. (2021). Growth of Acacia mangium at different stand ages and soil physicochemical properties in Sarawak, Malaysia. *Pertanika Journal of Tropical Agricultural Science*, 44(4), 773–793. <https://doi.org/10.47836/PJTAS.44.4.05>
- Neuenschwander, A. L., & Magruder, L. A. (2019). Canopy and Terrain Height Retrievals with ICESat-2: A First Look. *Remote Sensing*, 11(14), 1721. <https://doi.org/10.3390/rs11141721>
- Neuenschwander, A., & Pitts, K. (2019). Remote Sensing of Environment The ATL08 land and vegetation product for the ICESat-2 Mission. *Remote Sensing of Environment*, 221(April 2018), 247–259. <https://doi.org/10.1016/j.rse.2018.11.005>
- Ng, J. S. C., Chervier, C., Ancrenaz, M., Naito, D., & Karsenty, A. (2022). Recent forest and land-use policy changes in Sabah, Malaysian Borneo: Are they truly transformational? *Land Use Policy*, 121, 106308. <https://doi.org/10.1016/j.landusepol.2022.106308>
- Ngo, K. D., Lechner, A. M., & Vu, T. T. (2020). Land cover mapping of the Mekong Delta to support natural resource management with multi-temporal Sentinel-1A synthetic aperture radar imagery. *Remote Sensing Applications: Society and Environment*, 17, 100272. <https://doi.org/10.1016/j.rsase.2019.100272>
- Nguyen, H. T. T., Doan, T. M., Tomppo, E., & McRoberts, R. E. (2020). Land Use/Land Cover Mapping Using Multitemporal Sentinel-2 Imagery and Four Classification Methods—A Case Study from Dak Nong, Vietnam. *Remote Sensing*, 12(9), 1367. <https://doi.org/10.3390/rs12091367>

- Nguyen, L. H., & Henebry, G. M. (2019). Characterizing Land Use/Land Cover Using Multi-Sensor Time Series from the Perspective of Land Surface Phenology. *Remote Sensing*, 11(14), 1677. <https://doi.org/10.3390/rs11141677>
- Nirsatmanto, A., Sunarti, S., Putri, A. I., Herawan, T., Kartikawati, N. K., Haryjanto, L., Lestari, F., & Rimbawanto, A. (2023). Eucalyptus pellita and Acacia hybrid species: potential bioenergy plantation in managing the risk of invasive in Indonesia. *IOP Conference Series: Earth and Environmental Science*, 1182(1), 012019. <https://doi.org/10.1088/1755-1315/1182/1/012019>
- Norovsuren, B., Tseveen, B., & Renchin, T. (2023). Development of the spectral forest index in the Khangai region , Mongolia using Sentinel-2 imagery. *Forest Science and Technology*, 19(1), 1–11. <https://doi.org/10.1080/21580103.2022.2153928>
- Nunes, M., Ewers, R., Turner, E., & Coomes, D. (2017). Mapping Aboveground Carbon in Oil Palm Plantations Using LiDAR: A Comparison of Tree-Centric versus Area-Based Approaches. *Remote Sensing*, 9(8), 816. <https://doi.org/10.3390/rs9080816>
- Ocampo-Peñuela, N., Garcia-Ulloa, J., Kornecki, I., Philipson, C. D., & Ghazoul, J. (2020). Impacts of Four Decades of Forest Loss on Vertebrate Functional Habitat on Borneo. *Frontiers in Forests and Global Change*, 3(May), 1–13. <https://doi.org/10.3389/ffgc.2020.00053>
- Ohki, M., & Shimada, M. (2018). Large-Area Land Use and Land Cover Classification With Quad, Compact, and Dual Polarization SAR Data by PALSAR-2. *IEEE Transactions on Geoscience and Remote Sensing*, 56(9), 5550–5557. <https://doi.org/10.1109/TGRS.2018.2819694>
- Olesk, A., Praks, J., Antropov, O., Zalite, K., & Arumäe, T. (2016). Interferometric SAR Coherence Models for Characterization of Hemiboreal Forests Using. *Remote Sensing*, 8. <https://doi.org/10.3390/rs8090700>
- Olesk, A., Voormansik, K., Vain, A., Noorma, M., & Praks, J. (2015). Seasonal Differences in Forest Height Estimation from Interferometric TanDEM-X Coherence Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(12), 5565–5572. <https://doi.org/10.1109/JSTARS.2015.2501648>
- Ong, Chin Wei & Shamsul, B. A. R. (2021). Rubber Tree Cultivation and Improvement in

- Malaysia : Anatomical and Morphological Studies on *Hevea brasiliensis* and *Hevea camargoana*. *Journal of Agriculture and Crops*, 7, 27–32. <https://doi.org/https://doi.org/10.32861/jac.71.27.32>
- Osei Darkwah, D., & Ong-Abdullah, M. (2022). Sustainability of the Oil Palm Industry. In *Elaeis guineensis*. IntechOpen. <https://doi.org/10.5772/intechopen.100156>
- Paramitha Yanindraputri. (2016). Balancing Sustainable Growth and Forest Conservation through Spatial Planning for a Green Economy in the Heart of Borneo. *ASEAN-Canada Working Paper Series ,Singapore*, 3. <https://www.jstor.org/stable/pdf/resrep17192.pdf>
- Payus, C., Ann Huey, L., & Farrah Adn, F. A. (2020). Satellite Imagery System in Water Resources Management: Impacts from the Land Use and Land Cover Change. *Asian Journal of Scientific Research*, 13(3), 197–204. <https://doi.org/10.3923/ajsr.2020.197.204>
- Pfeifer, M., Kor, L., Nilus, R., Turner, E., Cusack, J., Lysenko, I., Khoo, M., Chey, V. K., Chung, A. C., & Ewers, R. M. (2016). Mapping the structure of Borneo’s tropical forests across a degradation gradient. *Remote Sensing of Environment*, 176, 84–97. <https://doi.org/10.1016/j.rse.2016.01.014>
- Pianzin, A., Wong, A., & Bernard, H. (2021). Riparian reserves serve as a critical refuge for Asian Otters (*Aonyx cinereus* and *Lutrogale perspicillata*) In Oil palm dominated landscapes of Sabah, Malaysian Borneo. *IUCN/SSC Otter Specialist Group Bulletin*, 38(3), 133–154.
- Pipa Elias, & Doug Boucher. (2014). Planting for the future: How Demand for Wood Products Could be Friendly to Tropical Forests. In *Union of Concerned Scientists* (Issue October). <https://www.ucsusa.org/sites/default/files/attach/2014/10/planting-for-the-future.pdf>
- Pohl, C. (2014). Mapping palm oil expansion using SAR to study the impact on the CO₂ cycle. *IOP Conference Series: Earth and Environmental Science*, 20, 012012. <https://doi.org/10.1088/1755-1315/20/1/012012>
- Pongratz, J., Schwingshackl, C., Bultan, S., Obermeier, W., Havermann, F., & Guo, S. (2021). Land Use Effects on Climate: Current State, Recent Progress, and Emerging Topics. *Current Climate Change Reports*, 7(4), 99–120. <https://doi.org/10.1007/s40641-021-00178-y>

- Potapov, P., Li, X., Hernandez-serna, A., Tyukavina, A., Hansen, M. C., Kommareddy, A., Pickens, A., Turubanova, S., Tang, H., Edibaldo, C., Armston, J., Dubayah, R., Blair, J. B., & Hofton, M. (2021). Mapping global forest canopy height through integration of GEDI and Landsat data. *Remote Sensing of Environment*, 253(August 2020), 112165. <https://doi.org/10.1016/j.rse.2020.112165>
- Pourshamsi, M., Xia, J., Yokoya, N., Garcia, M., Laval, M., Pottier, E., & Balzter, H. (2021). Tropical forest canopy height estimation from combined polarimetric SAR and LiDAR using machine-learning. *ISPRS Journal of Photogrammetry and Remote Sensing*, 172(May 2020), 79–94. <https://doi.org/10.1016/j.isprsjprs.2020.11.008>
- Praks, J., Hallikainen, M., Antropov, O., & Molina, D. (2012). Boreal forest tree height estimation from interferometric TanDEM-X images. *2012 IEEE International Geoscience and Remote Sensing Symposium, January*, 1262–1265. <https://doi.org/10.1109/IGARSS.2012.6351309>
- Priyanka, Rajat, Avtar, R., Malik, R., Musthafa, M., Rathore, V. S., Kumar, P., & Singh, G. (2023). Forest plantation species classification using Full-Pol-Time-Averaged SAR scattering powers. *Remote Sensing Applications: Society and Environment*, 29, 100924. <https://doi.org/10.1016/j.rsase.2023.100924>
- Prudente, V. H. R., Skakun, S., Oldoni, L. V., A. M. Xaud, H., Xaud, M. R., Adami, M., & Sanches, I. D. (2022). Multisensor approach to land use and land cover mapping in Brazilian Amazon. *ISPRS Journal of Photogrammetry and Remote Sensing*, 189, 95–109. <https://doi.org/10.1016/j.isprsjprs.2022.04.025>
- Purnomo, H., Okarda, B., Dermawan, A., Ilham, Q. P., Pacheco, P., Nurfatriani, F., & Suhendang, E. (2020). Reconciling oil palm economic development and environmental conservation in Indonesia: A value chain dynamic approach. *Forest Policy and Economics*, 111(January 2019), 102089. <https://doi.org/10.1016/j.forpol.2020.102089>
- Qu, L., Chen, Z., Li, M., Zhi, J., & Wang, H. (2021). Accuracy Improvements to Pixel-Based and Object-Based LULC Classification with Auxiliary Datasets from Google Earth Engine. *Remote Sensing*, 13(3), 453. <https://doi.org/10.3390/rs13030453>
- Raveendrakumar, S., Khati, U., Musthafa, M., Singh, G., & Tebaldini, S. (2022). Use of TanDEM-X PolInSAR for canopy height retrieval over tropical forests in the Western

- Ghats, India. *Frontiers in Forests and Global Change*, 5. <https://doi.org/10.3389/ffgc.2022.836205>
- Reed, S. C., Reibold, R., Cavaleri, M. A., Alonso-Rodríguez, A. M., Berberich, M. E., & Wood, T. E. (2020). *Soil biogeochemical responses of a tropical forest to warming and hurricane disturbance* (pp. 225–252). <https://doi.org/10.1016/bs.aecr.2020.01.007>
- Reynolds, G., Payne, J., Sinun, W., Mosigil, G., & Walsh, R. P. D. (2011). Changes in forest land use and management in Sabah, Malaysian Borneo, 1990–2010, with a focus on the Danum Valley region. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 366(1582), 3168–3176. <https://doi.org/10.1098/rstb.2011.0154>
- Rosenqvist, A., Shimada, M., & Watanabe, M. (2004). *ALOS PALSAR : Technical outline and mission concepts*. 1(7), 1–7.
- Rouse, J. W., Haas, H. & Deering, W. (1974). Monitoring Vegetation Systems in the Great Plains with ERTS. *Third Earth Resources Technology Satellite-1 Symposium*, 309–317.
- Roy, A., & Inamdar, A. B. (2019). Multi-temporal Land Use Land Cover (LULC) change analysis of a dry semi-arid river basin in western India following a robust multi-sensor satellite image calibration strategy. *Heliyon*, 5(4), e01478. <https://doi.org/10.1016/j.heliyon.2019.e01478>
- RSPO. (2015). *Remediation and Compensation Procedure (RaCP) Related to Land Clearance Without Prior High Conservation Value (HCV) Assessment*. <https://rspo.org/wp-content/uploads/rspo-remediation-and-compensation-procedures-english.pdf>
- Sari, I. L., Weston, C. J., Newnham, G. J., & Volkova, L. (2021). Developing Multi-Source Indices to Discriminate between Native Tropical Forests, Oil Palm and Rubber Plantations in Indonesia. *Remote Sensing*, 14(1), 3. <https://doi.org/10.3390/rs14010003>
- Sari, I. L., Weston, C. J., Newnham, G. J., & Volkova, L. (2023). Land cover modelling for tropical forest vulnerability prediction in Kalimantan, Indonesia. *Remote Sensing Applications: Society and Environment*, 32, 101003. <https://doi.org/10.1016/j.rsase.2023.101003>
- Sasaki, N., Asner, G. P., Pan, Y., Knorr, W., Durst, P. B., Ma, H. O., Abe, I., Lowe, A. J., Koh, L. P., & Putz, F. E. (2016). Sustainable Management of Tropical Forests Can Reduce

- Carbon Emissions and Stabilize Timber Production. *Frontiers in Environmental Science*, 4. <https://doi.org/10.3389/fenvs.2016.00050>
- Schlund, M., & Boehm, H. V. (2021). Assessment of linear relationships between TanDEM-X coherence and canopy height as well as aboveground biomass in tropical forests. *International Journal of Remote Sensing*, 42(9), 3405–3425. <https://doi.org/10.1080/01431161.2020.1871101>
- Schlund, M., von Poncet, F., Kuntz, S., Boehm, H. D. V., Hoekman, D. H., & Schmullius, C. (2016). TanDEM-X elevation model data for canopy height and aboveground biomass retrieval in a tropical peat swamp forest. *International Journal of Remote Sensing*, 37(21), 5021–5044. <https://doi.org/10.1080/01431161.2016.1226001>
- Schlund, M., Wenzel, A., Camarretta, N., Stiegler, C., & Erasmi, S. (2023). Vegetation canopy height estimation in dynamic tropical landscapes with TanDEM-X supported by GEDI data. *Methods in Ecology and Evolution*, 14(7), 1639–1656. <https://doi.org/10.1111/2041-210X.13933>
- Seaman, D. J. I., Bernard, H., Ancrenaz, M., Coomes, D., Swinfield, T., Milodowski, D. T., Humle, T., & Struebig, M. J. (2019). Densities of Bornean orang-utans (*Pongo pygmaeus morio*) in heavily degraded forest and oil palm plantations in Sabah, Borneo. *American Journal of Primatology*, 81(8). <https://doi.org/10.1002/ajp.23030>
- Seyam, M. M. H., Haque, M. R., & Rahman, M. M. (2023). Identifying the land use land cover (LULC) changes using remote sensing and GIS approach: A case study at Bhaluka in Mymensingh, Bangladesh. *Case Studies in Chemical and Environmental Engineering*, 7, 100293. <https://doi.org/10.1016/j.cscee.2022.100293>
- Sharifi, A., Felegari, S., & Tariq, A. (2022). Mangrove forests mapping using Sentinel-1 and Sentinel-2 satellite images. *Arabian Journal of Geosciences*, 15(20), 1593. <https://doi.org/10.1007/s12517-022-10867-z>
- Shetty, S. (2019). *Analysis of Machine Learning Classifiers for LULC Classification on Google Earth Engine*. *Analysis of Machine Learning Classifiers for LULC Classification on Google Earth Engine*.
- Shigetomi, Y., Ishimura, Y., & Yamamoto, Y. (2020). Trends in global dependency on the Indonesian palm oil and resultant environmental impacts. *Scientific Reports*, 10(1), 20624.

<https://doi.org/10.1038/s41598-020-77458-4>

- Shivangi Somvanshi, P. Kunwar, Singh, N. B., & Kachhwaha, T. S. (2011). *Water Turbidity Assessment in Part of Gomti River Using High Resolution Google Earth's Quickbird satellite data*. April. <https://geospatialworldforum.org/2011/proceeding/pdf/Shivangifullpaper.pdf>
- Shrestha, S. K. (2011). *Carbon Stock Estimation Using Very High Resolution satellite Imagery and Individual Crown Segmentation*. MSc Thesis. http://www.itc.nl/library/papers_2011/msc/nrm/shrestha.pdf
- Soja, M. J., Persson, H. J., & Ulander, L. M. H. (2015). Detection of forest change and robust estimation of forest height from two-level model inversion of multi-temporal, single-pass InSAR data. *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, 3886–3889. <https://doi.org/10.1109/IGARSS.2015.7326673>
- Solórzano, J. V., Mas, J. F., Gao, Y., & Gallardo-Cruz, J. A. (2021). Land Use Land Cover Classification with U-Net: Advantages of Combining Sentinel-1 and Sentinel-2 Imagery. *Remote Sensing*, 13(18), 3600. <https://doi.org/10.3390/rs13183600>
- Spetich, M. A., & Shifley, S. R. (2017). Guidelines for sampling aboveground biomass and carbon in mature central hardwood forests. *Proceedings of the 20th Central Hardwood Forest Conference*, 7. https://www.fs.usda.gov/nrs/pubs/gtr/gtr-nrs-p-167papers/26-spetich-et-al_2016-CHFC.pdf
- Srivastava S. K. & Gupta R. D. (2003). Monitoring of Changes in Land Use/Land Cover using Multi-sensor Satellite Data. *Map India Conference*, 1–7.
- STIDC. (2022). *Statistics of Timber and Timber Product Sarawak 2022*. https://www.sarawaktimber.gov.my/modules/web/pages.php?mod=download&sub=download_show&id=197
- Stovall, A. E. L., Fatoyinbo, T., Thomas, N. M., Armston, J., Simard, M., Trettin, C., Vancelas, R., Zogo, O., Akendengue, I., Debina, M., Mekui, A., Kemoe, M., Ondo, E., Su, J., Lagomasino, D., Lee, S., Calvin, J., Obame, N., Derrick, G., & Zame, C. (2021). *Science of Remote Sensing Comprehensive comparison of airborne and spaceborne SAR and LiDAR estimates of forest structure in the tallest mangrove forest on earth*. 4(August). <https://doi.org/10.1016/j.srs.2021.100034>

- Subramaniam, S.; Saxena, M. (2011). Automated Algorithm for Extraction of Wetlands from IRS RESOURCESAT LISS III Data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science, Volume XXXVIII, Part 8/W20,2011, XXXVIII*(November).
- Sulehan, J., & Awang, H. A. (2010). Communities at the Edge: Pulau Banggi in Transition. *Hakusan Review of Anthropology*, 13. https://toyo.repo.nii.ac.jp/?action=repository_action_common_download&item_id=2417&item_no=1&attribute_id=18&file_no=1
- Taiwo, B. E., Kafy, A.- Al, Samuel, A. A., Rahaman, Z. A., Ayowole, O. E., Shahrier, M., Dutti, B. M., Rahman, M. T., Peter, O. T., & Abosede, O. O. (2023). Monitoring and predicting the influences of land use/land cover change on cropland characteristics and drought severity using remote sensing techniques. *Environmental and Sustainability Indicators*, 18, 100248. <https://doi.org/10.1016/j.indic.2023.100248>
- Tan, C. H., Awang Besar, N., Jalloh, M. B., Mahali, M., & Masri, N. (2020). Above and Below Ground Carbon Stock of Acacia Mangium stand in Sabah, Malaysia. *Borneo Science | The Journal of Science and Technology*, 41(1), 9–18. <http://borneoscience.ums.edu.my/?author=2&paged=3>
- Tan, K. P., Kanniah, K. D., & Cracknell, A. P. (2014). On the upstream inputs into the MODIS primary productivity products using biometric data from oil palm plantations. *International Journal of Remote Sensing*, 35(6), 2215–2246. <https://doi.org/10.1080/01431161.2014.889865>
- Tangah, J., Bajau, F. E., Jilimin, W., Baba, S., Chan, H. T., & Kezuka, M. (2015). *Rehabilitation of Mangroves in Sabah the SFD-ISME Collaboration (2011-2014)*. Sabah Forestry Department, International Society for Mangrove Ecosystems and Tokio Marine and Nichido fire Insurance Co. Ltd.
- Tarigan, M., Roux, J., Van Wyk, M., Tjahjono, B., & Wingfield, M. J. (2011). A new wilt and die-back disease of Acacia mangium associated with Ceratocystis manginecans and C. acaciivora sp. nov. in Indonesia. *South African Journal of Botany*, 77(2), 292–304. <https://doi.org/10.1016/j.sajb.2010.08.006>
- Thomas, N., Baltezar, P., Lagomasino, D., Stovall, A., Iqbal, Z., & Fatoyinbo, L. (2021). Trees

- outside forests are an underestimated resource in a country with low forest cover. *Scientific Reports*, 11(1), 7919. <https://doi.org/10.1038/s41598-021-86944-2>
- Tian, J., Zhu, X., Wu, J., Shen, M., & Chen, J. (2020). Coarse-Resolution Satellite Images Overestimate Urbanization Effects on Vegetation Spring Phenology. *Remote Sensing*, 12(1), 117. <https://doi.org/10.3390/rs12010117>
- Torbick, N., Ledoux, L., Salas, W., & Zhao, M. (2016). Regional Mapping of Plantation Extent Using Multisensor Imagery. *Remote Sensing*, 8(3), 236. <https://doi.org/10.3390/rs8030236>
- Traoré, S., Djomo, A. N., N'guessan, A. K., Coulibaly, B., Ahoba, A., Gnahoua, G. M., N'guessan, É. K., Adou Yao, C. Y., N'Dja, J. K., & Guédé, N. Z. (2018). Stand Structure, Allometric Equations, Biomass and Carbon Sequestration Capacity of *Acacia mangium* Wild. (Mimosaceae) in Cote d'Ivoire. *Open Journal of Forestry*, 08(01), 42–60. <https://doi.org/10.4236/ojf.2018.81004>
- Trier, Ø. D., Salberg, A.-B., Haarpaintner, J., Aarsten, D., Terje Gobakken, & Næsset, E. (2018). Multi sensor forest vegetation height mapping methods for Tanzania. *European Journal of Remote Sensing*, 51(1), 587–606. <https://doi.org/10.1080/22797254.2018.1461533>
- Turner, E. C., Snaddon, J. L., Ewers, R. M., Fayle, T. M., & Foster, W. A. (2011). The Impact of Oil Palm Expansion on Environmental Change: Putting Conservation Research in Context. In *Environmental Impact of Biofuels* (Issue September). InTech. <https://doi.org/10.5772/20263>
- Udarbe M.P., & Hepburn, A. (1986). Development of *Acacia mangium* as a plantation species in Sabah. *Proceedings of an International Workshop Held at the Forestry Training Centre*.
- UN-REDD. (2023). *Carbon Stock*. UN FAO. <https://www.un-redd.org/glossary/carbon-stock>
- UN ECOSOC. (2017). *United Nations strategic plan for forests 2017-2030 and Quadrennial Programme of Work of the United Nations Forum on Forests for the Period 2017-2020*. https://www.un.org/esa/forests/wp-content/uploads/2016/12/UNSPF_AdvUnedited.pdf
- UNEP. (2019). *Deforestation in Borneo is slowing, but regulation remains key*. <https://www.unep.org/news-and-stories/story/deforestation-borneo-slowing-regulation->

remains-key

- Union, I., Conservation, F. O. R., & Nature, O. F. (2018). Oil palm and biodiversity: a situation analysis by the IUCN Oil Palm Task Force. In E. Meijaard, J. Garcia-Ulloa, D. Sheil, K. M. Carlson, S. A. Wich, D. Juffe-Bignoli, & T. M. Brooks (Eds.), *Oil palm and biodiversity: a situation analysis by the IUCN Oil Palm Task Force*. IUCN, International Union for Conservation of Nature. <https://doi.org/10.2305/IUCN.CH.2018.11.en>
- United Nations (UN). (2023). *The 17 Goals*. <https://sdgs.un.org/goals>
- Van Tricht, K., Gobin, A., Gilliams, S., & Piccard, I. (2018). Synergistic Use of Radar Sentinel-1 and Optical Sentinel-2 Imagery for Crop Mapping: A Case Study for Belgium. *Remote Sensing*, 10(10), 1642. <https://doi.org/10.3390/rs10101642>
- Varmola, M. I., & Carle, J. B. (2002). The importance of hardwood plantations in the tropics and sub-tropics. *International Forestry Review*, 4(2), 110–121. <https://doi.org/10.1505/IFOR.4.2.110.17439>
- Vaughan, D. (2020). *The Largest Islands in the World*. Encyclopedia Britannica. <https://www.britannica.com/list/the-largest-islands-in-the-world>
- Velastegui-Montoya, A., Montalván-Burbano, N., Peña-Villacreses, G., de Lima, A., & Herrera-Franco, G. (2022). Land Use and Land Cover in Tropical Forest: Global Research. *Forests*, 13(10), 1709. <https://doi.org/10.3390/f13101709>
- Vivekananda, G., Swathi, R., & Sujith, A. (2021). Multi-temporal image analysis for LULC classification and change detection. *European Journal of Remote Sensing*, 54(sup2), 189–199. <https://doi.org/10.1080/22797254.2020.1771215>
- Walker, L. (2013). *In Borneo's Forests, Impacts and Opportunities*. Wwww.Worldwildlife.Org. <https://www.worldwildlife.org/stories/in-borneo-s-forests-impacts-and-opportunities>
- Wan Mohd Jaafar, W. S., Said, N. F. S., Abdul Maulud, K. N., Uning, R., Latif, M. T., Muhmad Kamarulzaman, A. M., Mohan, M., Pradhan, B., Saad, S. N. M., Broadbent, E. N., Cardil, A., Silva, C. A., & Takriff, M. S. (2020). Carbon Emissions from Oil Palm Induced Forest and Peatland Conversion in Sabah and Sarawak, Malaysia. *Forests*, 11(12), 1285. <https://doi.org/10.3390/f11121285>
- Wawan, Dini, I. R., & Hapsoh. (2019). The effect of legume cover crop *Mucuna bracteata* on

- soil physical properties, runoff and erosion in three slopes of immature oil palm plantation. *IOP Conference Series: Earth and Environmental Science*, 250(1). <https://doi.org/10.1088/1755-1315/250/1/012021>
- Wen, C. Y. (2022). *Pitas Villagers Restoring Mangroves Destroyed by Failed Shrimp Farm*. Macaranga.Org. <https://www.macaranga.org/pitas-villagers-restoring-mangroves-destroyed-by-failed-shrimp-farm/>
- Wen, Z., Zhao, L., Zhang, W., Chen, E., & Xu, K. (2020). The Effects of Coherence Calculation on Forest Height Estimation Using SINC Model. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIII-B1-2, 637–642. <https://doi.org/10.5194/isprs-archives-XLIII-B1-2020-637-2020>
- William, W. O., van Manen, F. T., Sharp, S. P., & Ratnayake, S. (2023). Secondary forest within a timber plantation concession in Borneo contributes to a diverse mammal assemblage. *Global Ecology and Conservation*, 43, e02474. <https://doi.org/10.1016/j.gecco.2023.e02474>
- Wingfield, M. J., Wingfield, B. D., Warburton, P., Japarudin, Y., Lapammu, M., Abdul Rauf, M. R., Boden, D., & Barnes, I. (2023). Ceratocystis Wilt of Acacia Mangium in Sabah: Understanding the Disease and Reducing Its Impact. *Journal of Tropical Forest Science*, 35, 51–66. <https://doi.org/10.26525/jtfs2023.35S.SI.51>
- Wong, Y. Bin, Gibbins, C., Azhar, B., Phan, S. S., Scholefield, P., Azmi, R., & Lechner, A. M. (2023). Smallholder oil palm plantation sustainability assessment using multi-criteria analysis and unmanned aerial vehicles. *Environmental Monitoring and Assessment*, 195(5). <https://doi.org/10.1007/s10661-023-11113-z>
- Wong, C. J., James, D., Besar, N. A., Kamlun, K. U., Tangah, J., Tsuyuki, S., & Phua, M. H. (2020). Estimating Mangrove above-ground biomass loss due to deforestation in Malaysian Northern Borneo between 2000 and 2015 using SRTM and landsat images. *Forests*, 11(9). <https://doi.org/10.3390/F11091018>
- Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of Sensors*, 2017. <https://doi.org/10.1155/2017/1353691>
- Yalcin, M. (2020). A GIS-Based Multi-Criteria Decision Analysis Model for Determining

- Glacier Vulnerability. *ISPRS International Journal of Geo-Information*, 9(3), 180. <https://doi.org/10.3390/ijgi9030180>
- Yanling Ding, Hongyan Zhang, Zhenwang Li, Xiaoping Xin, X. Z. & K. Z. (2016). Comparison of fractional vegetation cover estimations using dimidiate pixel models and look-up table inversions of the PROSAIL model from Landsat 8 OLI data. *Journal of Applied Remote Sensing*, 10(April). <https://doi.org/10.1117/1.JRS.10.036022>
- Yuan, Z., Wen, B., He, C., Zhou, J., Zhou, Z., & Xu, F. (2022). Application of Multi-Criteria Decision-Making Analysis to Rural Spatial Sustainability Evaluation: A Systematic Review. *International Journal of Environmental Research and Public Health*, 19(11), 6572. <https://doi.org/10.3390/ijerph19116572>
- Zang, J., & Wang, X. (2023). Field-measured canopy height may not be as accurate and heritable as believed – Evidence from advanced 3D sensing. *Plant Methods*, 1–24. <https://doi.org/10.1186/s13007-023-01012-2>
- Zhang, J., Nielsen, S. E., Mao, L., Chen, S., & Svenning, J. (2016). Regional and historical factors supplement current climate in shaping global forest canopy height. *Journal of Ecology*, 104(2), 469–478. <https://doi.org/10.1111/1365-2745.12510>
- Zhang Tao, Zhu Jianjun, F. H. & W. C. (2022). Single Baseline TanDEM-X InSAR Coherence Inversion of Forest Height. *Journal of Surveying and Mapping*, 51(9), 1931–1941. <https://doi.org/10.11947/j.AGCS.2022.20210298>
- Zhiyong, S., Tingting, W., Chao, X., & Tao, Z. (2022). Terrain effect analysis and compensation method for polarimetric synthetic aperture radar interferometry height parameter inversion. *IET Radar, Sonar & Navigation*, 16, 1924–1935. <https://doi.org/10.1049/rsn2.12306>
- Zhou, T., Li, Z., & Pan, J. (2018). Multi-Feature Classification of Multi-Sensor Satellite Imagery Based on Dual-Polarimetric Sentinel-1A, Landsat-8 OLI, and Hyperion Images for Urban Land-Cover Classification. *Sensors*, 18(2), 373. <https://doi.org/10.3390/s18020373>
- Zhu, Z., Qiu, S., & Ye, S. (2022). Remote sensing of land change: A multifaceted perspective. *Remote Sensing of Environment*, 282, 113266. <https://doi.org/10.1016/j.rse.2022.113266>

Zink, M. (2015). TanDEM-X Mission Status. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XL-7/W3(May 2015), 1345–1352. <https://doi.org/10.5194/isprsarchives-XL-7-W3-1345-2015>

A. Appendices

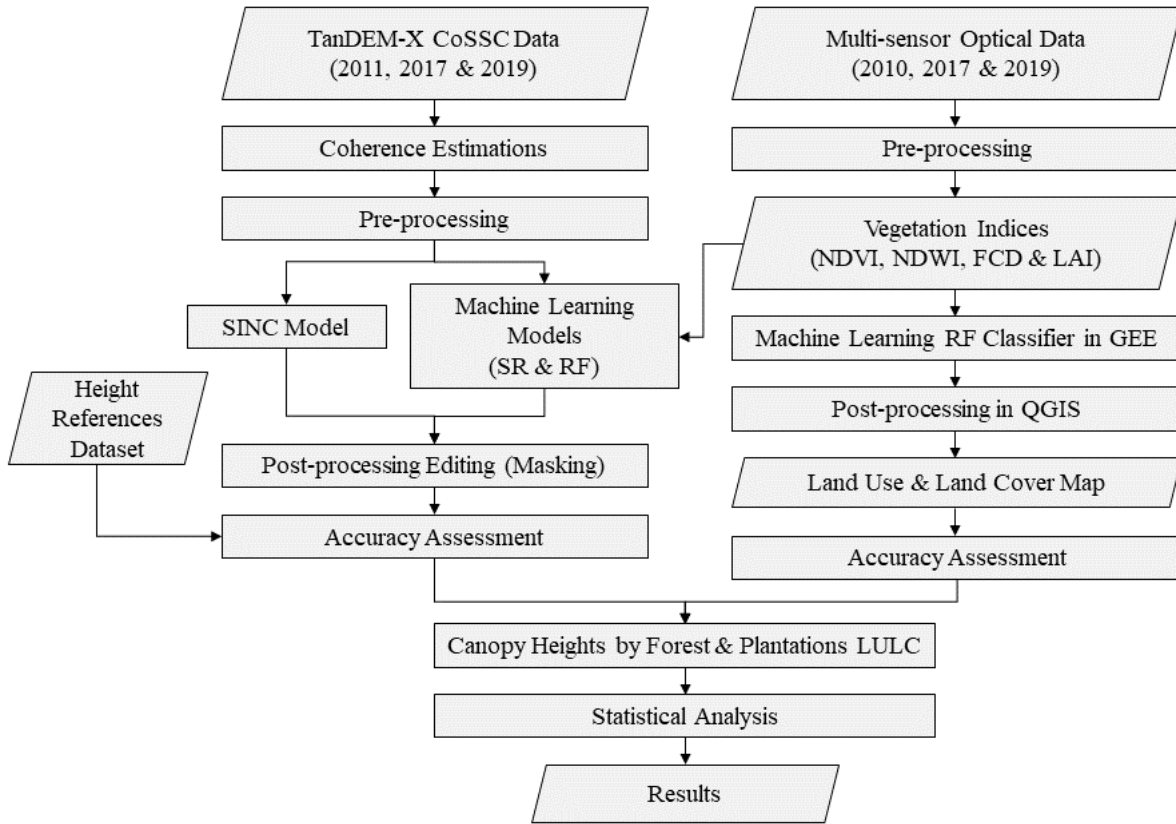


Figure A1. Workflow of Canopy Height Estimations.

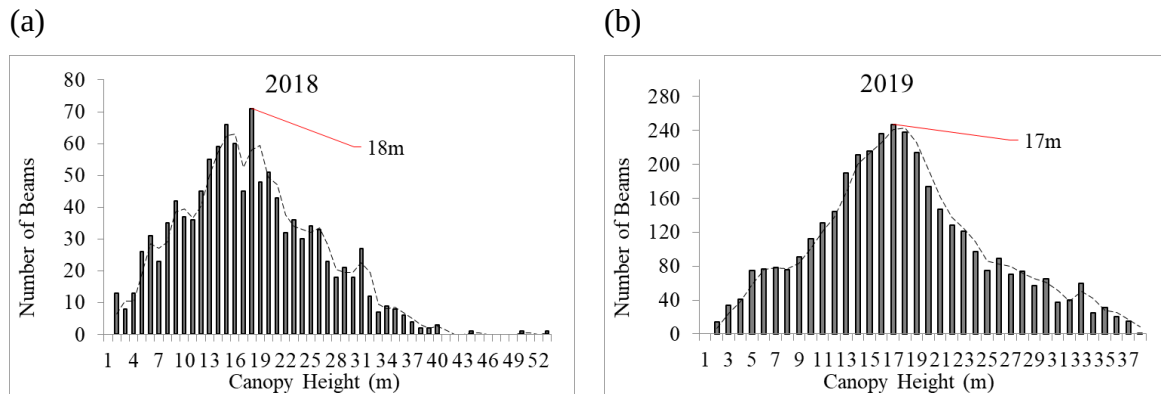


Figure A2. ICESat-2 Data 2018 within the 2017 TanDEM-X acquisition boundary (a) and 2019 ICESat-2 within the 2019 TanDEM-X acquisition (b) with SRTM at the background over the study area.

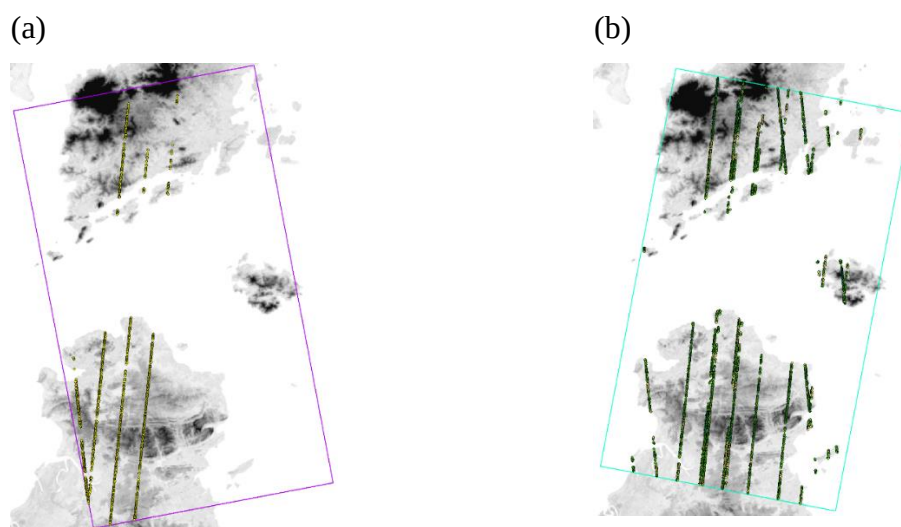


Figure A3. ICESat-2 Data 2018 within the 2017 TanDEM-X acquisition boundary (a) and 2019 ICESat-2 within the 2019 TanDEM-X acquisition (b) with SRTM at the background over the study area.

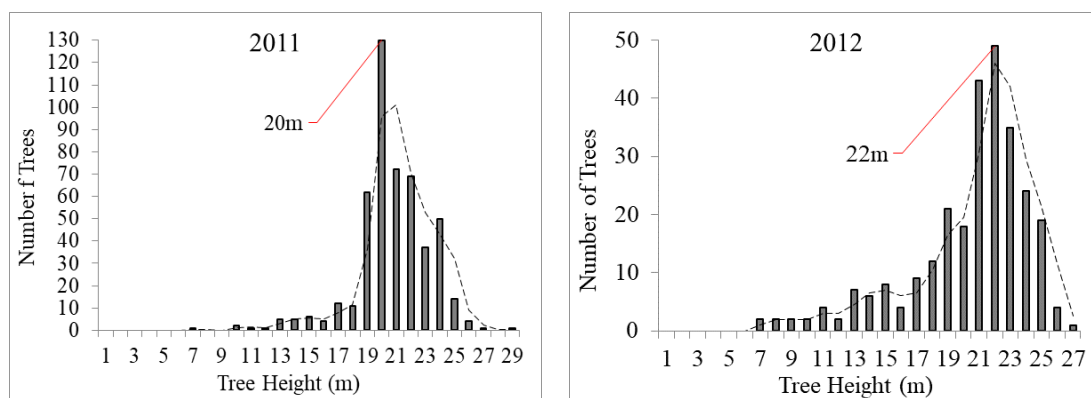


Figure A4. Histogram of the Forest Inventory Data.

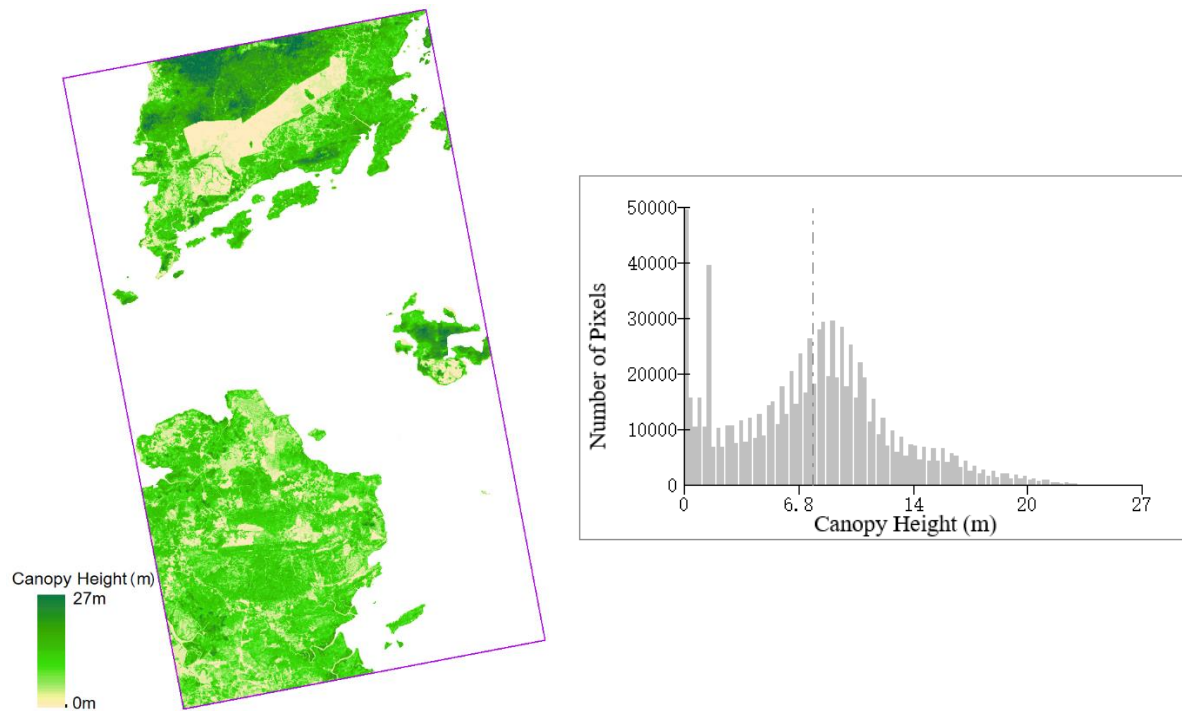


Figure A5. Global Airborne Observatory (GAO) Tree Canopy Height (TCH) Data (2016) and histogram within the 2017 TanDEM-X Data Acquisition Boundary over the Study Area. Also TCH histogram of the GAO Data.

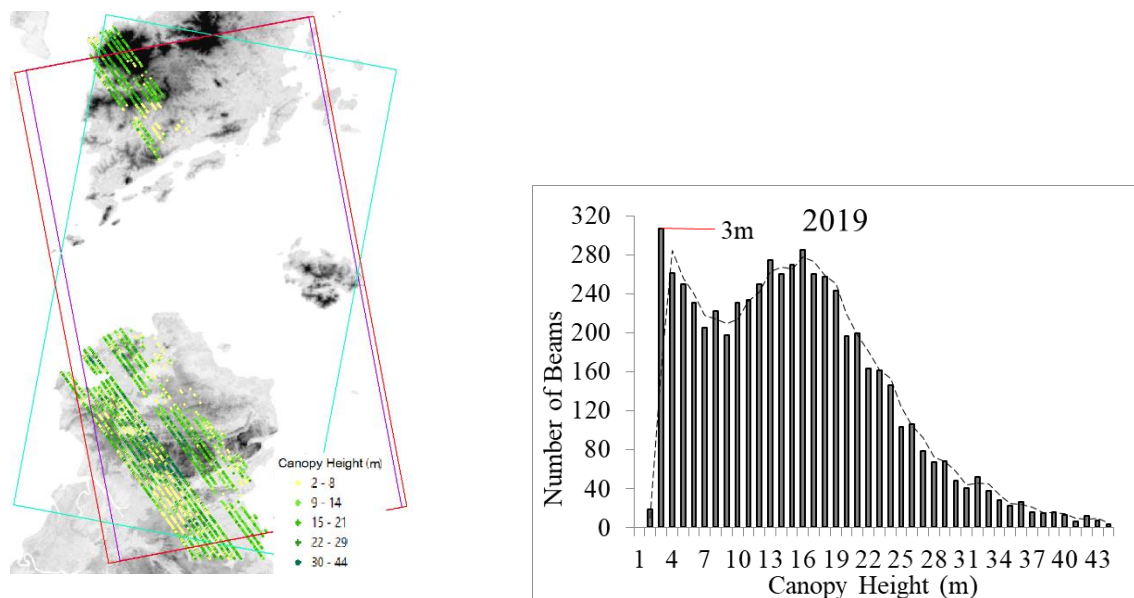


Figure A6. Global Ecosystem Dynamics Investigation (GEDI) Canopy Height Data (2019) with histogram and SRTM in the background. Also, with TanDEM-X Acquisitions 2011 (Red), 2017 (Purple) and 2019 (Light Blue).

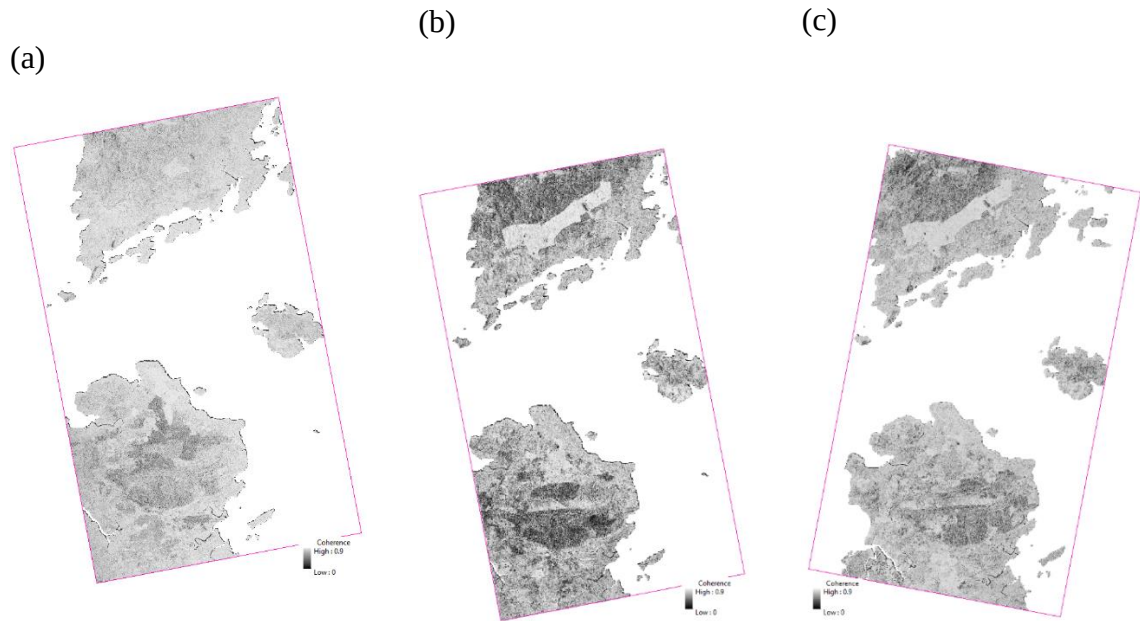


Figure A7. TanDEM-X Generated Coherence of years 2011 (a), 2017 (b) and 2019 (c).



Figure A8. Example of clear-cut timber harvesting of planted *Acacia mangium*, with 5 years old *Eucalyptus pellita* in the background. Photo taken on 15 August 2023 in Bengkoka FR facing east view.

Table A.1. TanDEM-X acquisition parameters.

Acquisition Date	Orbit	Incidence Angle (°)	Perp. Baseline (m)	Height of Ambiguity (m)
02 Dec. 2011	Ascending	38.71	163.58	75.98
17 Jun. 2017	Ascending	38.40	338.92	36.40
29 Oct. 2019	Descending	41.32	303.21	44.32

Table A.2. Summary of the ICESAT-2 ATLAS Data Collection used.

Collection Date	Ref. Ground Track	Orbit Lines	Number of Selected Scan Beams
20 Nov. 2018	Middle	Descending	903
29 Nov. 2018	West	Ascending	234
19 Feb. 2019	Middle	Descending	1,011
21 May. 2019	Middle	Descending	1,453
29 May. 2019	West	Ascending	166
20 Aug. 2019	West	Descending	11
19 Nov. 2019	East	Descending	535
Total			4,313

Table A.3. Summary of ICESAT-2 ATLAS Data of Canopy Height.

Collection Year	Number of Selected Beams	CH Min (m)	CH Mean (m)	CH Max (m)
2018	1,137	1.47	17.60	53.38
2019	3,915	1.56	17.67	37.57

Table A.4. Summary of Mean Diameter at Breast Height (CBH), Commercial Bole Height (CBH), Tree Height (TH), Tree Height at Maximum and Minimum.

Collection Year	No. of Plots	No. of Trees	DBH Mean (cm.)	CBH Mean (m.)	TH Mean (m.)	TH Min (m)	TH Max (m)
2011	93	488	34.07	18.35	20.50	6.5	28.70
2012	274	1,452	25.37	15.74	20.15	6.61	27.14

Table A.5. Summary of 2023 field inventory dataset

	Mangrove	Acacia Mangium	Secondary Forest
Max height (m)	14.44	17.39	16.80
Mean height (m)	11.26	12.89	12.41
Min height (m)	9.88	8.75	10.02

Table A.6. Summary of the Global Airborne Observatory (GAO) Tree Canopy Height (TCH) Data.

Acquisition Year	Pixels Resolution	CH Min (m)	CH Mean (m)	CH Max (m)
2016	30m	0	7.70	27.19

Table A.7. Summary of GEDI L2A Dataset

Collection Year	Number of Selected Beams	CH Min (m)	CH Mean (m)	CH Max (m)
2019	5,885	1.91	15.10	44.28

Table A.8. Variable importance, described by % increase in MSE when model variable is permuted (%IncMSE) and increase in node purity when variable is permuted (IncNodePurity). Higher values indicate higher importance.

Variables	%IncMSE	IncNodePurity
Coherence	109.30	57786.61
DEM	57.34	35570.71
FVC	49.09	26269.91
LAI	26.25	22536.51
Slope	25.12	23992.24

Table A.9. Summary of the Estimated Canopy Height for the year 2011 by percentiles.

Models	2nd Perc. (m)	Median (m)	98th Perc. (m)
SINC	13.96	17.93	26.07
RF	8.3	11.55	23.18
SR	1.32	20.72	23.82

Table A.10. Summary of the Estimated Canopy Height for the year 2017 by percentiles.

Models	2nd Perc. (m)	Median (m)	98th Perc. (m)
SINC	10.50	16.70	27.03
RF	8.75	17.29	29.65
SR	6.32	21.94	28.36

Table A.11. Summary of the Estimated Canopy Height for the year 2019 by percentiles.

Models	2nd Perc. (m)	Median (m)	98th Perc. (m)
SINC	14.16	17.76	26.24
RF	9	18.33	29.68
SR	9.58	21.20	29.58