Advancing Malaysia's Forest Monitoring Through Remote Sensing: Integrating Landsat and Google Earth Engine for Carbon Stock Assessment

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Abstract: *Malaysia remains firmly committed to maintaining at least 50% forest cover, underscoring its role in global climate mitigation through advanced spatial data integration. To enhance the accuracy and transparency of forest monitoring, Malaysia adopts a stepwise reporting approach aligned with Biennial Update Reports (BUR-3 in 2018 and BUR-4 in 2022) and the Biennial Transparency Report (BTR-1 in 2024). This study leverages Google Earth Engine (GEE)-derived activity data and Landsat imagery collected at approximately five-year intervals from 2005 to 2024, facilitating a transition from gazetted area-based statistics to satellite-driven verification. This methodological refinement significantly improves the precision of Forest Reference Level (FRL) and Forest Reference Emission Level (FREL) assessments, strengthening national reporting frameworks. The analysis reveals that Malaysia's forested areas span 18,492,684 hectares, covering approximately 56% of the nation's landmass. A comprehensive forest carbon inventory estimates total forest carbon stock has exhibited a slight decline from 3.27 billion MgC in 2005 to 3.17 billion MgC in 2024, while the total carbon dioxide (CO_2) sink at 11.6 billion $MgCO_2$ for 2024. These findings highlight Malaysia's substantial contribution to climate change mitigation, as its forests continue to sequester approximately 65% of the nation's total emissions, annually. By harnessing cutting-edge remote sensing technologies, Malaysia reinforces the integrity of its forest monitoring system, enabling data-driven policy decisions and reaffirming its commitment to sustainable forest management and long-term climate resilience.*

Keywords: *forest monitoring, remote sensing, carbon stock assessment, GEE*

Introduction

Forests play a critical role in global climate regulation, acting as significant carbon sinks. Developing countries, including Malaysia, are actively engaged in REDD+ (Reducing Emissions from Deforestation and Forest Degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks) initiatives to mitigate climate change. A fundamental requirement for REDD+ is the establishment of accurate Forest Reference Level (FRL) and Forest Reference Emission Level (FREL), which serve as benchmarks for assessing a country's performance in reducing emissions and enhancing carbon removals from the forest sector.

Malaysia has a long-standing commitment to maintaining at least 50% forest cover and aims to achieve carbon neutrality by 2050. Accurate and transparent Measurement, Reporting, and Verification (MRV) frameworks are crucial for tracking progress towards these national goals and Nationally Determined Contributions (NDCs) under the Paris Agreement. This paper details Malaysia's advanced methodological approach to FRL/FREL development, emphasizing the integration of remote sensing technologies, particularly Landsat imagery and Google Earth Engine (GEE), with comprehensive ground inventory data to provide a more precise and dynamic assessment of forest resources.

Despite Malaysia's progressive adoption of remote sensing technologies, several persistent challenges hinder the full operationalization of its forest monitoring systems. Fassnacht et al. (2024) highlight that while remote sensing is increasingly used in forestry, its uptake into operational programs remains uneven due to technical limitations and validation gaps. In Malaysia, the reliance on Landsat imagery at five-year intervals may overlook short-term forest degradation events, reducing the responsiveness of MRV systems (REDD Plus, 2025). Furthermore, Ismail et al. (2024) note that thematic forestry applications – such as forest inventory and conservation – often lack harmonized methodologies across regions, complicating national-level reporting. The National Forest Monitoring System (NFMS), though robust, faces integration issues between ground-based inventories and satellite-derived data, especially in ecologically diverse zones like in Sarawak and Sabah, which are not covered by NFMS. Additionally, map validation remains a critical bottleneck; without standardized protocols, the accuracy of forest cover classifications and carbon stock estimates may be compromised (Fassnacht et al., 2024). These challenges underscore the need for enhanced temporal resolution, cross-sectoral data harmonization, and rigorous validation frameworks to ensure Malaysia's forest monitoring system remains scientifically credible and policy-relevant.

Literature Review

Malaysia's forest monitoring has undergone a significant transformation with the integration of remote sensing technologies, particularly Landsat imagery and Google Earth Engine (GEE). These platforms have enabled large-scale, high-resolution assessments of forest cover and carbon stocks, addressing long-standing challenges in tropical forest monitoring such as cloud cover and data accessibility. Hamdan (2022) demonstrated the utility of free-access satellite data in quantifying land use change and forest sector emissions, processing over 580

Landsat images to produce seamless mosaics across Malaysia. This approach allowed for the identification of forest types and deforestation hotspots, contributing to more accurate LULUCF (Land Use, Land Use Change, and Forestry) sector reporting.

Recent studies in Malaysia have increasingly adopted GEE for Land Use and Land Cover (LULC) classification, leveraging its cloud-based processing and access to multi-temporal satellite archives. Zeng et al. (2021) compared seven combinations of Landsat 8, Sentinel-2, and spectral indices for mapping the Johor River Basin, finding that hybrid datasets (e.g., Landsat + Sentinel-2 + NDVI/EVI) significantly improved classification accuracy, reaching up to 86%. However, the study also noted that cloud cover and seasonal variability posed challenges for consistent image acquisition in tropical regions.

In contrast, Muhammad et al. (2023) focused on Peninsular Malaysia using Random Forest classifiers on Landsat imagery alone, achieving high accuracy but with limited class separability in mixed agroforestry zones. These variations underscore a key limitation: while GEE enables scalable analysis, classification accuracy is highly sensitive to input combinations, training sample quality, and landscape heterogeneity. Moreover, studies often lack standardized validation protocols, making cross-comparison difficult. The absence of belowground or soil carbon layers further restricts ecological completeness. As highlighted by Tesfaye et al. (2024), integrating auxiliary variables like elevation and topographic indices can enhance spectral separability, but such approaches remain underutilized in Malaysian contexts.

Complementing this, Muhammad et al. (2023) applied machine learning algorithms, i.e. Random Forest and Support Vector Machines on GEE to classify forest cover in Peninsular Malaysia. Their study revealed that Random Forest outperformed other classifiers in terms of accuracy, with Kappa coefficients exceeding 0.87 for both 2010 and 2020, reinforcing the reliability of GEE for automated land cover mapping. These advancements support Malaysia's transition from gazetted statistics to satellite-driven verification, enhancing the precision of FREL and carbon stock inventories. Together, these studies underscore the strategic value of remote sensing in strengthening Malaysia's climate reporting and forest governance frameworks.

Methodology

To enhance the accuracy and transparency of Malaysia's FRL/FREL assessments, this study adopts a satellite-driven methodology using GEE. The approach integrates multi-temporal Landsat imagery collected at approximately five-year intervals from 2005 to 2024, enabling consistent monitoring of forest cover dynamics across the country. Activity data are derived through supervised classification and change detection algorithms within GEE, replacing traditional gazetted area-based statistics with spatially explicit, verifiable outputs. This stepwise methodology aligns with Malaysia's BUR-3, BUR-4 and the BTR-1, ensuring coherence with national greenhouse gas inventories and REDD+ reporting requirements. By leveraging GEE's cloud-based processing and access to historical satellite archives, the study facilitates large-scale carbon stock estimation and forest area mapping, while minimizing data gaps due to cloud cover and seasonal variability. The refined outputs support the calculation of annual biomass loss and carbon sequestration rates, strengthening Malaysia's capacity to report forest-related emissions and removals with scientific rigor and policy relevance.

a. Data Collection and Sources

The FRL/FREL development in this study employed a stepwise approach, prioritizing consistent and reliable data. Landsat satellite imagery from 2005, 2010, 2015, 2020, and 2024 served as the primary source for activity data, facilitating the quantification of historical land cover changes. These images were processed using GEE, a cloud-based geospatial analysis platform, for efficient large-scale analysis. The emission factor used was based on the average carbon loss due to deforestation and forest degradation, crucial for estimating annual greenhouse gas emissions linked to land-use changes.

b. Field Inventory Data

Field inventory data, collected from 2011 to 2023, covered all forest types in Malaysia (dry inland, peat swamp, and mangrove forests) (Hamdan et al., 2025). A stratified random sampling design ensured representation of various forest conditions (virgin, totally protected, logged, secondary, and degraded areas). Sampling plots were designed in clusters, with specific nest radii for measuring different tree sizes (Table 1). Allometric equations, such as those by Chave et al. (2014) for inland forests, Kauffman et al. (2016) for peat swamp, and Kauffman & Donato (2012) for mangroves, were used to estimate Aboveground Biomass (AGB), which was then converted to Aboveground Carbon (AGC) using a constant carbon fraction of 0.47.

Table 1: Summary of Living Tree Measurement in Different Forest Types.

Forest Type	Nest Radius (m)	Tree Category	Tree Size, DBH (cm)
Dry Inland Forest	2	Sapling	< 5 cm (≥1.3 m in height)
	4	Small	5 - 14.9 cm
	12	Medium	15 - 29.9 cm
	20	Large	≥30 cm
Peat Swamp Forest	2	Sapling	< 5 cm (≥1.3 m in height)
	4	Small - Medium	5 - 9.9 cm
	10	Large	≥10 cm
Mangrove Forest	2	Sapling	< 5 cm (≥1.3 m in height)
	7	Small - Large	≥5 cm

c. Forest Cover Classification and Analysis

The Random Forest (RF) classification process in GEE began with the preprocessing of Landsat imagery, including radiometric and geometric corrections and cloud masking using QA bands. Spectral indices such as normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) were calculated to enhance vegetation signal detection. Training samples representing "forest" and "non-forest" classes were derived from ground-truth data and high-resolution imagery, then compiled into a labeled 'FeatureCollection'. The RF classifier was instantiated using 'ee.Classifier.smile RandomForest()' and trained on selected spectral bands and vegetation indices. Once trained, the model was applied to classify the full image stack, producing a binary land cover map. Accuracy assessment was conducted using a confusion matrix and Kappa coefficient, with validation points withheld from training to ensure statistical robustness (Table 2).

To improve classification accuracy, additional vegetation indices and topographic variables were integrated. Normalized difference moisture index (NDMI) was used to capture vegetation moisture, while modified soil-adjusted vegetation index (MSAVI) minimized soil background interference – especially useful in sparsely vegetated zones. Generalized NDVI (GNDVI) enhanced sensitivity to chlorophyll content, and modified normalized difference water index (MNDWI) helped mask water bodies near riparian forests. Normalized difference built-up index (NDBI) was included to distinguish built-up areas from vegetated zones.

Elevation, slope, and aspect data derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) were added to account for terrain-driven vegetation patterns. Studies such as Al-Doski et al. (2022) demonstrated that combining NDVI and DEM variables improved classification accuracy by up to 8.77%, particularly in complex tropical landscapes like Sarawak.

Post-classification analysis was conducted in ArcGIS Pro to refine outputs and support spatial reporting. The classified raster was exported from GEE and imported into ArcGIS, where it underwent reclassification and vector conversion for area calculations. Zonal statistics were used to quantify forest cover within administrative boundaries, and overlay analysis identified deforestation hotspots. These outputs were visualized through thematic maps and dashboards, supporting FRL/FREL reporting and stakeholder engagement with spatially explicit, policy-relevant insights.

Table 2: Variables Employed in the Classification.

Parameter	Peninsular Malaysia	Sabah	Sarawak
Total sample points	23,407	3,511	3,476
Training sample points	16,385	2,458	2,433
Accuracy assessment points	7,022	1,053	1,043

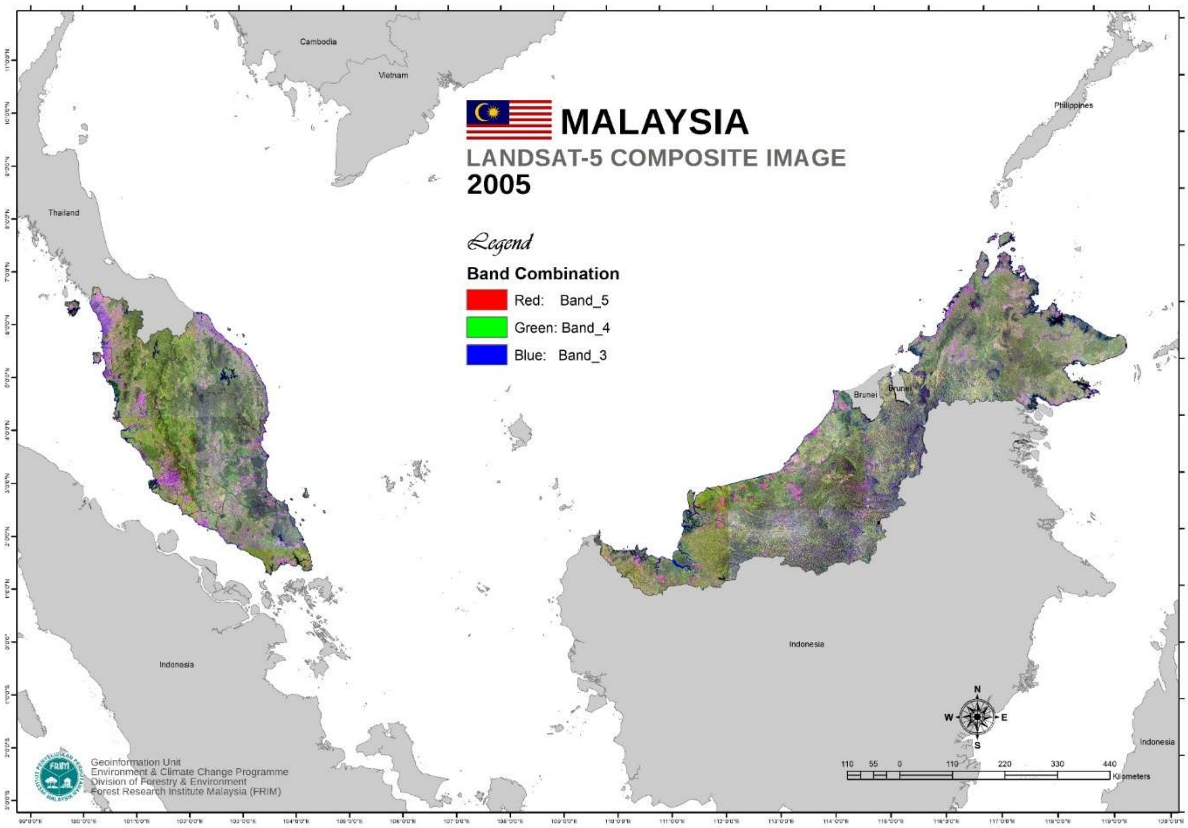

Figure 1: Landsat-5 Image Composite over Malaysia in Year 2005.

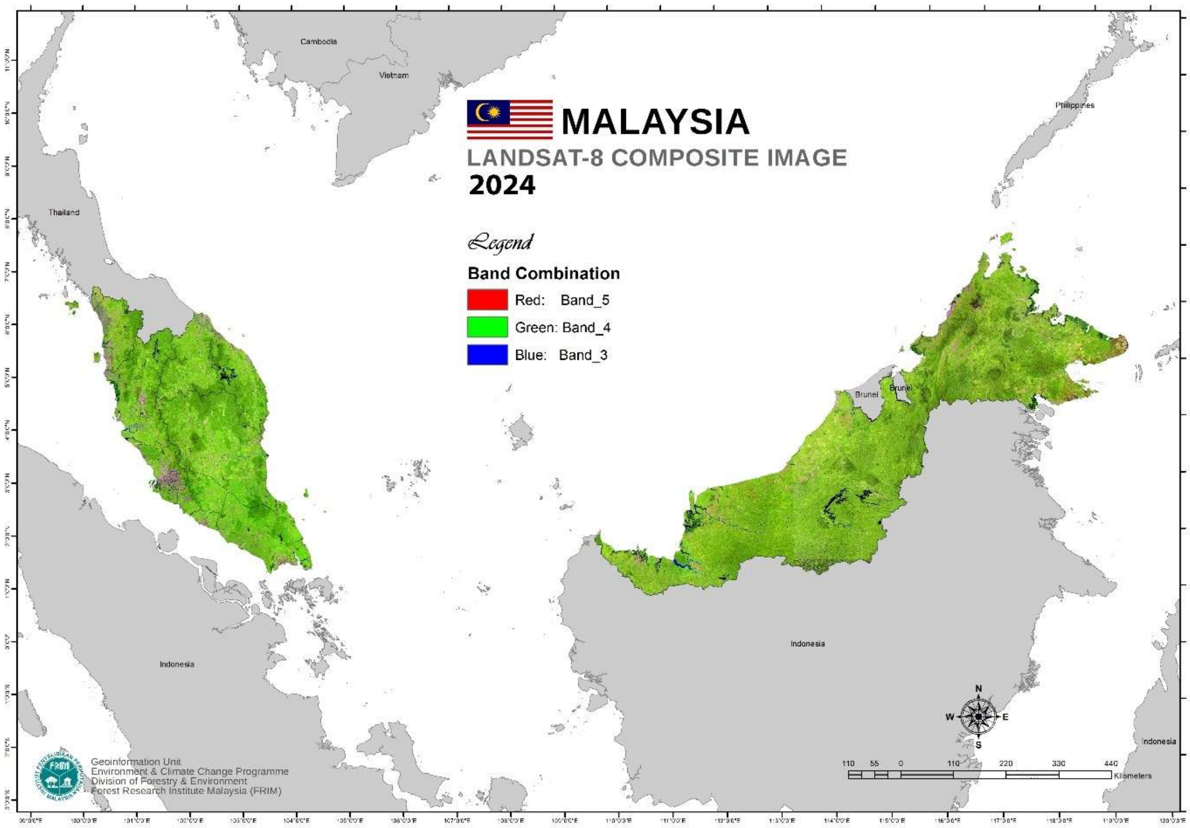

Figure 2: Landsat-8 Image Composite over Malaysia in Year 2024.

Results and Analysis

a. Forest Cover and Changes Analysis

The study revealed that, with 18.49 million ha (55.89%) in 2024, Malaysia maintained over 50% of its forest cover against the total landmass of 33,087,346 ha (JUPEM, 2025). Our satellite-based analysis, as detailed in Table 3, consistently yielded higher estimates of total forest cover compared to official figures, attributed to the enhanced detection capabilities of the methodology.

Table 3: Data of Forest Cover Generated from This Study (ha).

Year	Peninsular Malaysia	Sabah	Sarawak	Total
2005	5,888,960.73	5,069,574.63	8,113,331.40	19,071,866.76
2010	5,930,344.62	5,060,196.63	8,046,485.00	19,037,026.25
2015	5,809,422.31	4,957,017.02	7,882,413.67	18,648,853.00
2020	5,747,463.66	4,982,646.80	7,779,864.32	18,509,974.78
2024	5,742,223.85	4,974,763.73	7,775,696.44	18,492,684.02

Table 4 compares forest cover estimates from gazetted areas and official statistics versus satellite-derived data. Table 5.8 in the hands highlight the composition of forest cover against the landmass of Malaysia. These tables compare forest cover estimates from two different sources: this study's analysis and Ministry of Natural Resources & Environmental Sustainability (NRES) reporting over multiple years. The study's estimates are consistently higher than those reported by NRES, with notable differences in absolute figures. The 4% additional forest cover detected may reflect recent regrowth and conservation areas that are not yet fully integrated into official national statistics.

Between 2005 and 2024, Malaysia experienced a net forest loss of 579,182.74 ha (3.0%), with an annual deforestation rate of 0.03%. Between 2010 and 2015, Malaysia experienced the highest rate of deforestation, averaging 77,634 ha/yr. This accelerated forest loss was predominantly attributed to agricultural expansion, particularly for oil palm and rubber cultivation, commercial logging activities, and large-scale infrastructure projects, including the development of hydroelectric facilities such as Bakun, Puah, and Tembat.

Subsequent periods exhibited a marked decline in deforestation rates, with the annual average decreasing to 27,775 ha/yr between 2015 and 2020, and further to 4,322 ha/yr from 2020 to 2024 (Table 5). This downward trend suggests a potential shift in land-use dynamics, regulatory enforcement, or conservation interventions during the latter periods.

Table 4: Comparison of extents of forest cover in Malaysia between data generated from this study and the official data reported by NRES.

Year	**Forest cover generated by this study (ha)**	**Forest cover from NRES Reporting (ha)**	**Difference (ha)**	**Difference (%)**
2005	19,071,866	17,814,712	1,257,155	6.59
2010	19,037,026	17,926,964	1,110,062	5.83
2015	18,648,853	18,389,686	259,167	1.39
2020	18,509,974	18,045,319	464,655	2.51
2024	18,492,684	n.a	n.a	n.a
Average (%)				4.08

Table 5: Total and Annual Rate of Deforestation in Malaysia.

Time Series	**Total deforestation (ha)**	**Rate of deforestation (ha/yr)**	**Rate of deforestation (%/yr)**
2005 - 2010	34,841	6,968.10	0.04
2010 - 2015	388,173	77,634.65	0.41
2015 - 2020	138,878	27,775.64	0.15
2020 - 2024	17,291	4,322.69	0.02
Total	579,183	6,142.16	0.03

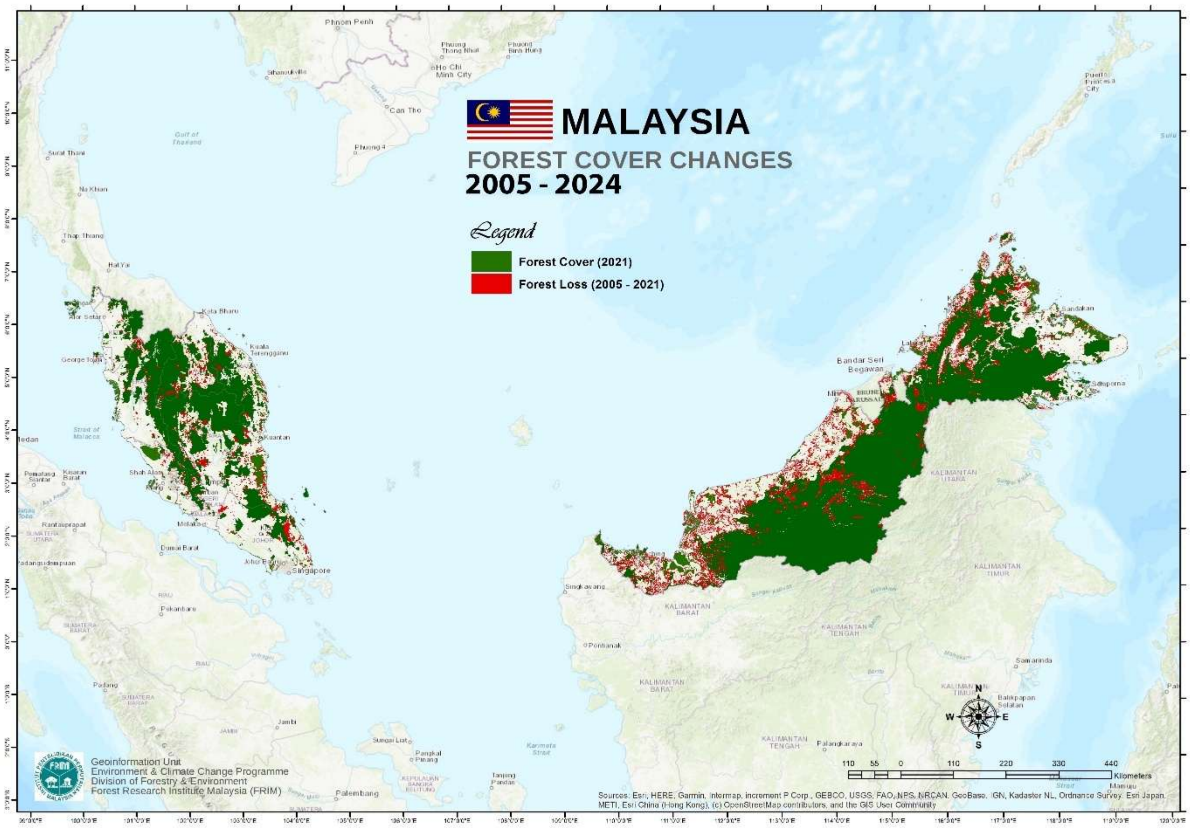

Figure 3: Changes of Forest Cover in Malaysia between Years 2005 and 2024.

b. Classification Accuracy

To ensure data reliability and precision, the classification products underwent rigorous accuracy assessments, summarized in Table 6. The results indicated an impressive average of 94% overall accuracy coupled with a Kappa statistic of 0.88, confirming the classification's robustness and suitability for official reporting. With such high reliability, Malaysia is well-positioned to adopt this sophisticated mapping strategy for enhanced environmental monitoring and compliance with international standards.

This is the true power of GEE, a tool that enables data-driven decisions for conservation and sustainable development. Malaysia stands at a pivotal moment to revolutionize its reporting methods, embracing cutting-edge technologies while ensuring accuracy and compliance with international standards. With this transformation, the country is well-positioned to enter carbon forestry-based projects anytime, securing its place in global environmental initiatives.

Table 6: Accuracy of classification results.

Overall Accuracy: Measures the proportion of correctly classified instances out of the total instances. While useful, Accuracy can be misleading for imbalanced datasets.			
Year	**Peninsular Malaysia**	**Sabah**	**Sarawak**
2005	0.93	0.92	0.94
2010	0.94	0.92	0.94
2015	0.96	0.94	0.96
2020	0.95	0.94	0.96
2024	0.94	0.95	0.94
Kappa (Cohen's Kappa): Adjusts accuracy by considering the likelihood of agreement occurring by chance. It ranges from -1 to 1, where 1 indicates perfect agreement and 0 means agreement is due to chance.			
Year	**Peninsular Malaysia**	**Sabah**	**Sarawak**
2005	0.86	0.83	0.80
2010	0.88	0.84	0.82
2015	0.91	0.87	0.89
2020	0.90	0.87	0.88
2024	0.89	0.88	0.86

c. Estimated Carbon Dioxide Emissions

The estimated average AGC across different forest types showed significant distinctions. The total average AGC across different forest types in Malaysia, based on the Tier-2 sampling approach, exhibited significant distinctions (Table 7). The total carbon stock estimated for all forested areas in Malaysia in 2024 was at approximately 3.17 billion Mg C (Table 8).

Table 7: Summary of AGC in Major Forests in Malaysia.

No.	Major Forests	AGC (Mg C/ha)
1	Inland Forest	171.45 ± 67.00
2	Peat Swamp Forest	109.51 ± 60.78
3	Mangrove Forest	91.50 ± 76.18

Table 8: Summary of Carbon Stock, CO_2 Sequestered in the Forests in Malaysia.

Year	**Forest Cover (ha)**	**Total Carbon Stock (Mg C)**	**Total CO_2 sequestered (Mg CO_2)**
2005	19,071,867	3,269,871,556	11,990,618,996
2010	19,037,026	3,263,898,151	11,968,714,518
2015	18,648,853	3,197,345,847	11,724,667,220
2020	18,509,975	3,173,535,176	11,637,353,491
2024	18,492,684	3,170,570,675	11,626,482,666

It is also notable that the largest deforestation occurred between year 2010 and 2015, with a total of forest loss of 388,173 ha (refer to Table 5). This period saw a surge in activities that contributed to forest clearing, driven by economic and industrial demands. One of the main causes was the expansion of palm oil plantations. Malaysia is one of the largest producers of palm oil, and during these years, global demand for the commodity skyrocketed. To meet production needs, vast areas of forest were converted into palm oil plantations, leading to large-scale deforestation.

Another contributing factor was commercial logging and conversion of natural forests into plantation forest. The timber industry played a crucial role in Malaysia's economy, and high-value hardwood trees were extensively harvested for export. Additionally, urbanization and infrastructure development led to forest losses. Malaysia saw rapid economic growth, resulting in more construction of roads, housing developments, and industrial zones. This transformation required large land areas, often leading to deforestation.

Agricultural expansion beyond palm oil also played a role. Rubber plantations, along with other commercial farming ventures, increased during this period. As with palm oil, forests were cleared to make room for crops that would provide economic benefits.

Using this data, the impact of deforestation on carbon stock loss and emissions was estimated. The total emissions were recorded at 364,136,329.79 Mg CO_2, with an annual average of 19,165,070 Mg CO_2, as outlined in Table 9. Additionally, the yearly emission trends were assessed for each time interval. Based on these estimates, the FRL/FREL was established, as illustrated in Figure 5. Assuming a mean carbon sequestration rate of 3.5 MgC/ha/yr (Bernal et al. 2018), the estimated annual carbon dioxide removal by Malaysian forests amounts to 237,344,353 $MgCO_2$ per annum.

Table 9: Summary of CO_2 Emission Resulted from Deforestations in Malaysia.

Time Series	Total Carbon Loss (Mg C)	Total Emission (Mg CO_2)	Annual Emission (Mg CO_2/yr)
2005 - 2010	5,973,405	21,904,477.75	4,380,895.55
2010 - 2015	66,552,304	244,047,297.71	48,809,459.54
2015 - 2020	23,810,671	87,313,729.89	17,462,745.98
2020 - 2024	2,964,501	10,870,824.44	2,717,706.11
Total	99,300,880.77	364,136,329.79	19,165,069.99

The established FRL/FREL for Malaysia, based on a linear trend analysis from 2005 to 2024, indicates a significant mitigation achievement. While the Business-as-Usual (BAU) scenario projected emissions of approximately 20,000,000 Mg CO_2 per year in 2024, actual data revealed a net carbon removal of 2,717,706 $MgCO_2$ per year, signifying that Malaysia's forests acted as a carbon sink. This represents a net carbon savings of 22,717,706 $MgCO_2$, primarily due to stricter environmental policies and enhanced conservation initiatives implemented since 2015.

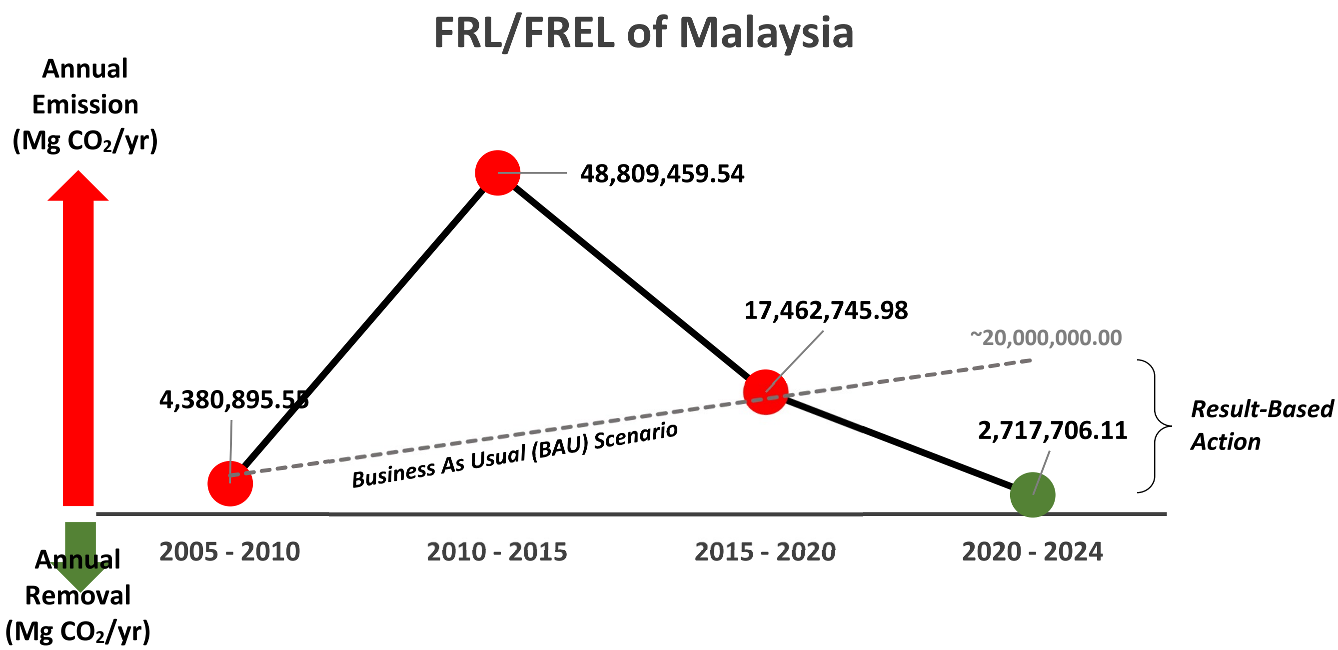

Figure 5: The established FRL/FREL for Malaysia.

This outcome represents a result-based mitigation achievement. The slowdown in deforestation rates since 2015 can be attributed to the implementation of stricter environmental policies and enhanced conservation initiatives. Despite this progress, the legacy effects of past deforestation remain substantial, reinforcing the urgent need for sustainable landuse strategies and continued forest protection efforts in Malaysia. Although the estimates incorporate a few assumptions and generalizations, the presented data demonstrated an overall scenario of CO_2 emissions from deforestation activities in Malaysia.

Even though deforestation contributed significantly to CO_2 emissions in the LULUCF sector, the remaining forests continue to play a role in CO_2 sequestration as they regenerate. The rate of CO_2 sequestration, on the other hand, is quite sluggish and is highly dependent on the overall management strategies used in the forests. This is also common in Permanent Forest Reserves (PRFs), where some lands are reserved for production and managed under sustainable forest management (SFM) practices.

Discussion

The integration of Landsat imagery and Google Earth Engine (GEE) with ground inventory data significantly enhances Malaysia's forest monitoring capabilities. The higher forest cover estimates and carbon removal capacities identified in this study, compared to official reports, underscore the value of advanced remote sensing techniques in capturing subtle changes in forest dynamics. This refined approach provides a more transparent and accurate basis for FRL/FREL reporting, aligning with international standards and strengthening Malaysia's position in global climate action.

The observed net increase in forest cover and the significant carbon sink function of Malaysia's forests between 2019 and 2024 are encouraging. These trends demonstrate the positive impact of national conservation policies, sustainable logging practices, and reforestation programs. However, the legacy effects of historical deforestation, particularly between 2010 and 2015 due to agricultural expansion and infrastructure development, highlight the continuous need for stringent land-use planning and enforcement.

The discrepancy between the carbon removal estimates in this study and the BTR-1 report emphasizes the importance of harmonized methodologies and data integration processes. Future reporting should adopt integrated geospatial-based approaches, leveraging high-resolution imagery and cloud computing models, to minimize underestimations and ensure a comprehensive representation of forest contributions to climate mitigation.

Conclusion

Malaysia has made significant progress in advancing its forest monitoring through the integration of Landsat and Google Earth Engine for carbon stock assessment. The methodology presented in this paper provides a robust and transparent framework for FRL/FREL reporting, demonstrating a higher forest cover and carbon removal capacity than previously reported. This success reinforces Malaysia's commitment to maintaining over 50% forest cover and achieving net-zero emissions by 2050. The robust methodology, combining satellite imagery and GEE with extensive ground inventory, offers a higher level of transparency, consistency, and accuracy, making Malaysia a leader in carbon forestry-based projects.

The classification accuracy averaged 94% with a Kappa statistic of 0.88, affirming the reliability of the remote sensing approach. While a net forest loss of 579,183 ha (3%) occurred between 2005 and 2024, primarily driven by agricultural expansion and infrastructure. The estimated total carbon stock for 2024 was approximately 3.17 billion MgC, with a higher annual carbon removal capacity of 237,344 $GgCO_2$ compared to the BTR-1 reported 212,284 $GgCO_2$. This suggests a potential underestimation in previous reports. The established FRL/FREL indicates a significant mitigation achievement, with Malaysia's forests acting as a net carbon sink, saving 22,717,706 $MgCO_2$ in 2024 compared to a Business-as-Usual (BAU) scenario.

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