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Free-Access Satellite Data for Land Use Change and Forest Sector in Malaysia

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Abstract - Malaysia's recent economic growth is associated with a variety of environmental hazards, all of which contribute to the depletion of forest resources and thus to climate change. The need for more space for multiple land developments has led to the destruction of existing forests. This paper demonstrates how remote sensing data was utilised to map and quantify tropical forest changes on a regional scale in Malaysia. We created a continuous mosaic of Malaysian Landsat satellite data using image processing at 5-year intervals for 15 years. The challenge was to create cloudless images in a tropical country that are always covered with clouds. These datasets were used to identify forest coverage and changes in Malaysia. It is one of the key elements of land use, land use change and forest sector (LULUCF) for climate change assessment. From 2005 to 2020, a total of 580 Landsat images were processed to create a seamless wall-to-wall image across Malaysia. Forests were identified based on image classification and classified into three main types: dry inland forests, peat swamps, and mangroves. Post-classification change detection methods identified areas converted from forest to other land use. From 2005 to 2020, the total deforestation area was 1,087,030 ha, and the annual deforestation rate was about 72,469 ha (or 0.37% per year). As a result, total CO_2 emissions have reached 689.26 million Mg CO_2, at an annual rate of 45.95 million Mg CO_2 yr^{-1}. The study demonstrated that, despite some issues with the cloud cover, using various satellite images from optical sensors is the most appropriate for monitoring deforestation in the Malaysian region.

Keywords - Free-access data, Forest ecosystem, Deforestation, Carbon emission

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1. Introduction

Tropical forests are important for mitigating climate change, but human activity continues to replace many forests for other land uses. Forest carbon must be quantified and monitored at a high spatial and temporal resolution to promote more sustainable forest usage. Tropical forests are one of the most important ecosystems for tackling climate change challenges since they are known to store enormous amounts of carbon (Brendan et al., 2020). Due to a lack of data, accessibility, and various technical challenges, retrieving tropical forest carbon over wide areas has been difficult for decades. For the last three decades, remote sensing has been employed to estimate forest carbon and has proven effective (Lu, 2006; Nurul Ain & Zulkiflee, 2017). Even though there are concerns and disagreements about estimating accuracy, the study is ongoing. While optical or synthetic aperture radar (SAR) systems have the potential for biomass retrieval, some difficulties remain unresolved. SAR methods are always limited by signal saturation at significant biomass levels, whereas the cloud impedes optical remote sensing (Hamdan et al., 2017).

Optical sensors, on the other hand, provide better methods for assessing biomass. Multispectral images can be used to create a variety of spectral signatures and vegetation indices, making the interpretation of biophysical features of forests much easier. These are the most notable differences between optical and SAR systems, which has led to the preference for optical satellite data in vegetation research.

As demand from the global energy industry grows, countries will work together to reduce anthropogenic greenhouse gas (GHG) emissions, keep global warming below pre-industrial levels below 2°C, and have a global climate. It is important to prevent the catastrophic effects of fluctuations. Curbing the effects of global climate change can be an important social goal today and in the coming decades. Tropical countries contribute to carbon emissions primarily through deforestation and deforestation. Carbon emissions account for about 10% of the world’s total carbon emissions yearly (Pearson et al., 2017). In this regard, Malaysia makes a clear plan on how to fulfil its promises at the United Nations (UN) Climate Change Conference 2021 (COP-26) and seriously considers global trends in its commitment to climate change. Malaysia also promises to end deforestation by 2030 and presents an updated NDC or climate target to reduce the economy’s carbon intensity (as a percentage of GDP) by 45% by 2030. Malaysia also set a goal to reach carbon neutrality by 2050.

National and international measures aimed at mitigating the effects of global warming include lowering emissions from deforestation and forest degradation, forest conservation (REDD+), and carbon offset. To reach this goal, each country’s carbon emissions from deforestation and forest degradation must be quantified and tracked over time. A precise, cost-effective, and high-resolution method of monitoring changes in above-ground carbon stocks is required at such broad geographic scales. The subject of this research is the usefulness of space-borne remote sensing, particularly free-access Landsat satellite images, in measuring changes in forest cover and biomass in Malaysia.

2. Materials and Method

2.1 Landsat Data Acquisition

This study used Landsat data to predict greenhouse gas emissions and removals for 2005 to 2020, with a 5-year gap. These data were chosen because they are available as independent data, have a stable time series, and are compatible with other data sources. Furthermore, no publication has activity data derived from Landsat satellite images over Malaysia. Cloud cover always interferes with optical images of the Malaysian region. Therefore, a large dataset was required to create a continuous mosaic of cloudless images. The Landsat images used in this study covering the whole of Malaysia are summarised in Tables 1 and 2 and Figure 1 (Hamdan et al. 2021).

Table 1. Landsat images that were used in this study as activity data

Satellite	Sensor	Date of acquisition	Time series (year)
Landsat-5	Thematic Mapper (TM)	January 2004 - December 2006	2005
		January 2009 - December 2011	2010
Landsat-8	Operational Land Imager (OLI)	January 2014 - December 2016	2015
		January 2018 – March 2020	2020

Table 2. An overview of the Landsat scene dataset needed to create seamless mosaics across Malaysia

Landsat Datasets			
Region	**West Malaysia**	**East Malaysia**	
State	Peninsular Malaysia	Sarawak	Sabah
Scene ID (Path/Row)	128/055 - 057 127/056 - 058 126/056 - 059 125/058 - 059	121/058 - 059 120/058 - 059 119/057 - 059 118/058 - 059	118/055 - 057 117/055 - 057 116/056 - 057
Number of scenes	12	9	8
Scenes required to produce seamless data	60	45	40
Scenes acquired to produce time series data	240	180	160
Total number of scenes	580		

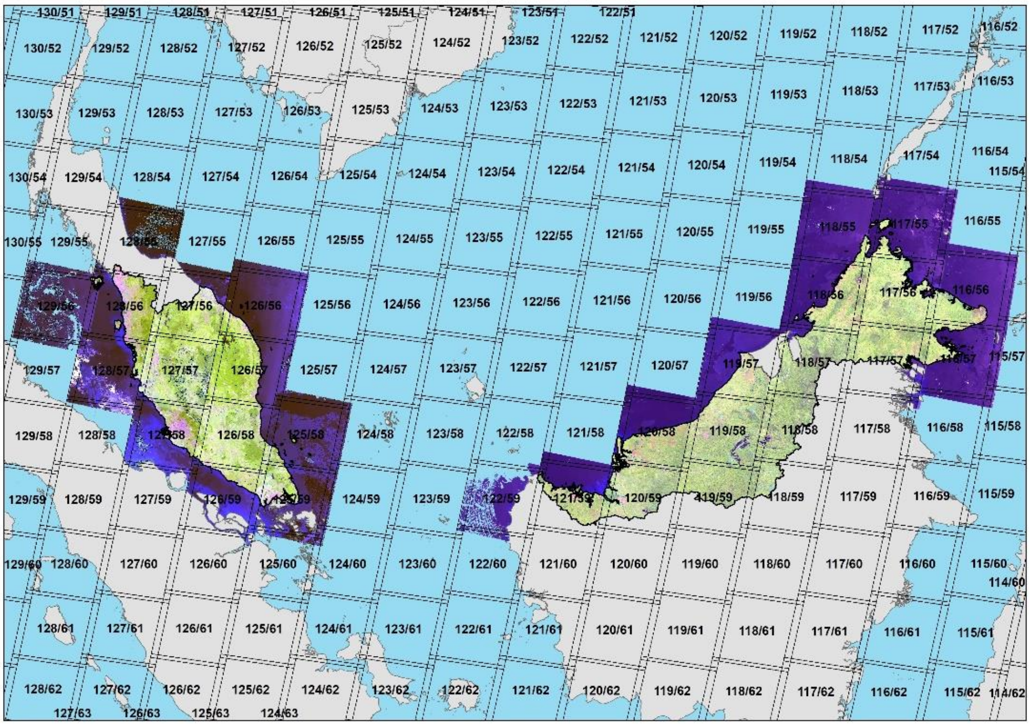

Figure 1. Landsat scene coverage throughout Malaysia

2.2 Production of Seamless Satellite Images

Referring to Table 1, only 29 scenes of Landsat images are required to cover the entire region of Malaysia. However, Malaysia is constantly shrouded in clouds that are impossible to remove entirely due to its location in the tropics. Many images taken at different times over the same area are required to make a cloudless image. For further processing, the study set limits on the five best images of the same scene taken within three years of the target year. These images show less than 30% cloudiness and must be taken within the specified period (Table 2). Landsat satellites with a 16-day repeat-cycle produce about 22 scenes yearly in the same landscape, but finding the best five images in three years is challenging. The main reason is the Malaysian atmosphere, especially the hills and the widespread cloud cover during the monsoon season (October-February). In most scenes, cloudiness is 10-90%, so it is very unlikely to obtain images with less than 30% cloudiness.

However, this issue was solved by some high-quality scenes. Clouds in these images were detected and masked using the F_Mask algorithm (Qiu et al., 2019). Figures 2 and 3 show a cloud masking that created a cloudless mosaic of scene 126/058 taken from various data (Hamdan et al., 2021). This process repeats with other scenes and intervals (2005, 2010, 2015, and 2020). A total of 580 scenes were processed to generate seamless mosaic images over time. The final product is shown in Figure 4 (Hamdan et al., 2021). The outcome was satisfactory, but about 1% of hollow pixels still appear in the image, especially at high altitudes and mountain peaks. This is due to clouds always present regardless of the weather or season.

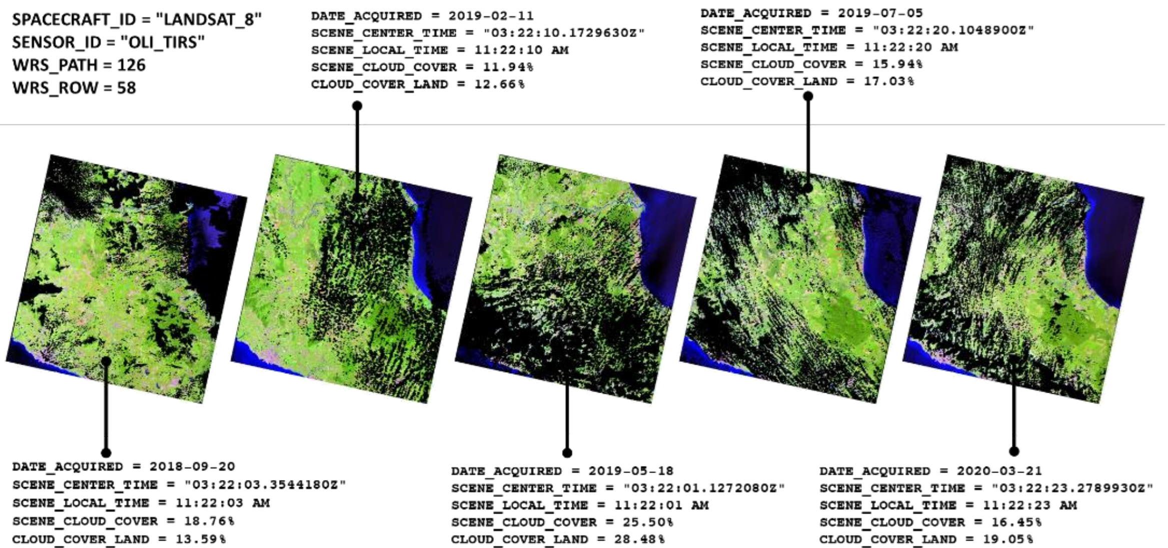

Figure 2. The cloud masking process of Landsat scene 126/058

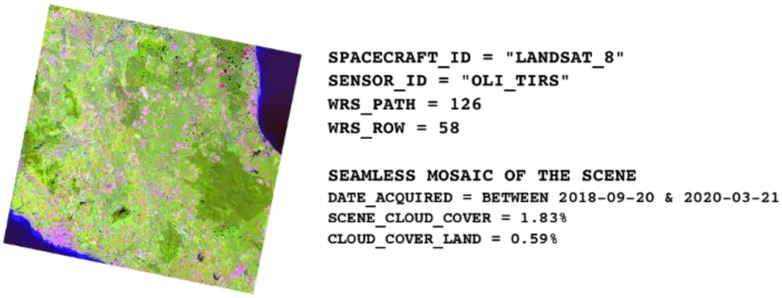

Figure 3. Cloudless image of Landsat scene 126/058

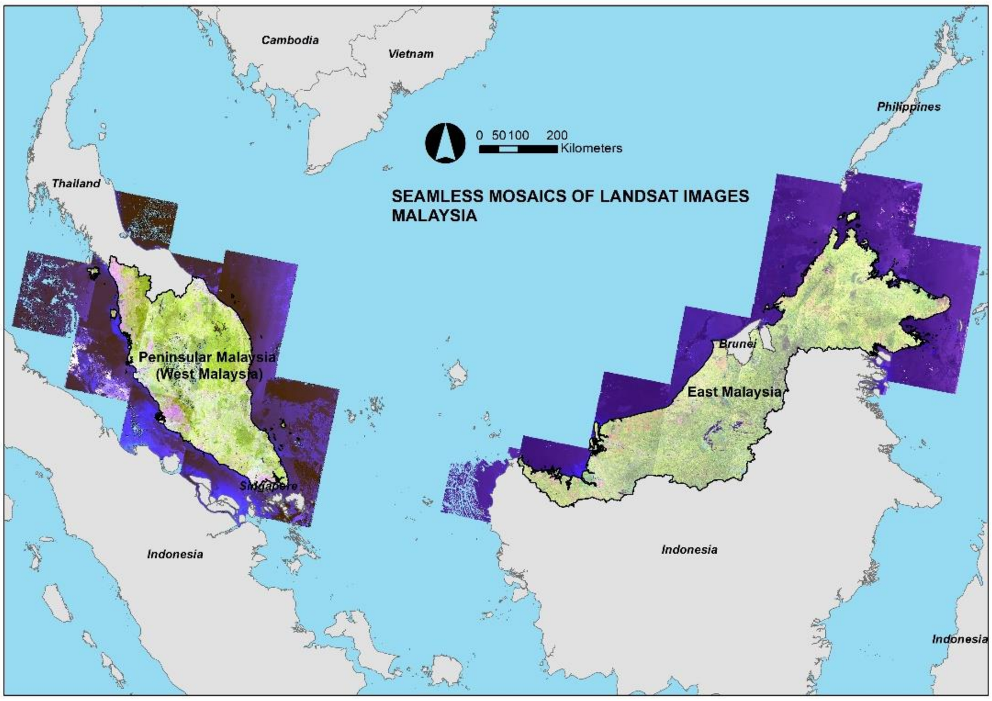

Figure 4. Cloudless image of Landsat images over Malaysia

2.3 Classification of Forests

The threshold to define the forest area in national statistics (minimum mapping unit - MMU) is 0.5 ha, minimum canopy cover is 30% or minimum height at maturity is 5 m. This includes all areas with woody vegetation along. It also includes systems with vegetation structures that are currently below the threshold but may reach thresholds expected to be exceeded on the forest area category thresholds defined by the Intergovernmental Panel on Climate Change (IPCC). They are categorised nationally by managed, unmanaged, and ecosystem types (IPCC, 2019). This study divides forests into three major ecosystem types: inland forests, peat swamp forests, and mangrove forests. These areas are further subdivided into Permanent Conservation Forests (PRF) or Permanent Forest Estates (PFE) or Permanent Forest Reserves (PFR) as managed categories, with the rest of the area outside the managed area being state land forests (NRE, 2018).

2.4 CO_2 Emissions Estimation

Carbon dioxide (CO_2) is a significant greenhouse gas that plays a vital role in regulating the Earth's climate. According to the IPCC, there are two basic approaches for estimating carbon emissions or removals: the Gain-Loss Method (GLM) and the Stock-Difference Method (SDM). The calculation method for this study is determined by Tier-2 level SDM using CO_2 based on Hamdan et al. (2018). Then multiply the result by 44/12 or 3.67 carbon (C) units. Since emissions from forestry activities are considered, the CO_2 in this study is solely due to carbon accumulation in the forest and is not comparable to emissions from other gases. Therefore, the reported emissions are carbon dioxide (CO_2), not carbon dioxide equivalent (CO_2e).

The IPCC Guidelines provide a standard methodology that includes Tier-1 emission factors (IPCC, 2019). The Tier-1 level is designed to be the easiest to use, and the 2006 IPCC guidelines provide equations and default parameter values (such as emissions and inventory change factors). Emission factors are derived from readily available statistics and are often derived from globally available sources for estimating activity data (e.g., deforestation rates, global forest coverage maps, etc.). However, this data is usually spatially coarse.

Tier-2 levels, on the other hand, use the same or similar activity data as Tier-1 levels but apply emission and inventory change factors based on country- or region-specific data. Emission factors by country are better suited to the local climatic region and land use system. Tier-2 often applies to higher temporal and spatial resolutions and more fragmented activity data, and activity statistics are further subdivided.

At the Tier-3 level, the following higher-order approaches are used. Models and resource measurement systems that adapt to national circumstances are driven by high-resolution activity data repeated over time and decomposed at the sub-country level. Higher-order approaches provide more accurate estimates than lower-order approaches. The carbon stock (Mg C) estimated by the stand change method is the result of multiplying the forest area (ha) by the carbon stock per unit area (Mg C ha^{-1}). The carbon stock of the entire project area at a given time are determined by calculating the product of each forest type and the carbon stock per unit area occupied by that type and summing the results of all forest types.

$$C_t = \sum_{i=1}^{n}(A_i \times C_i) \qquad \text{(Eq. 1)}$$

Where:

C_t = total carbon stock at a certain time t (Mg C)

A_i = area occupied by forest type i (ha)

C_i = carbon stock per unit area of type i (Mg C ha^{-1})

The emission is calculated as the difference of carbon stocks for a given forest area at two points in time, which is expressed as

$$\Delta C = (C_{t1} - C_{t2}) / (t_2 - t_1) \qquad \text{(Eq. 2)}$$

Where:

ΔC = annual carbon stock change in biomass (Mg C yr^{-1})

C_{t1} = carbon stock at time 1 (Mg C)

C_{t2} = carbon stock at time 2 (Mg C)

3. Results and Discussions

3.1 The Classified Forests

Before interpreting and classifying forests with satellite images, it is important to understand Malaysia's forest sector's situation and management practices. Various secondary data are advantageous and can speed up the classification process. To ensure the classification is done correctly, spatial information such as PRF boundaries, management regimes, forest types, and locations of various ecosystems are necessary. This image classification delineated forests from other land features. This procedure was carried out with the help of the traditional supervised classification approach. On the images, several training sets were chosen. Forest training sets were created using unchanged forest areas derived from secondary spatial data, while the other land cover classes were established using manual image interpretation. The same training set was used for the forest class for all series.

The most challenging aspect of image classification was dealing with large amounts of data and producing classification results with minimum uncertainty. Manual modification of classification findings was expected, and it had to be done several times, which was a tiresome and time-consuming operation. However, this product is satisfactory, and an example of the 2020 classification results is shown in Figure 5. Pixel format classification results have been converted to vector format (.shp) for further analysis and post-classification recognition processes. The regions classified from the images of each forest type were determined from the vector data. Statistics of forest areas obtained from vector data are summarised in Table 3 in 2020.

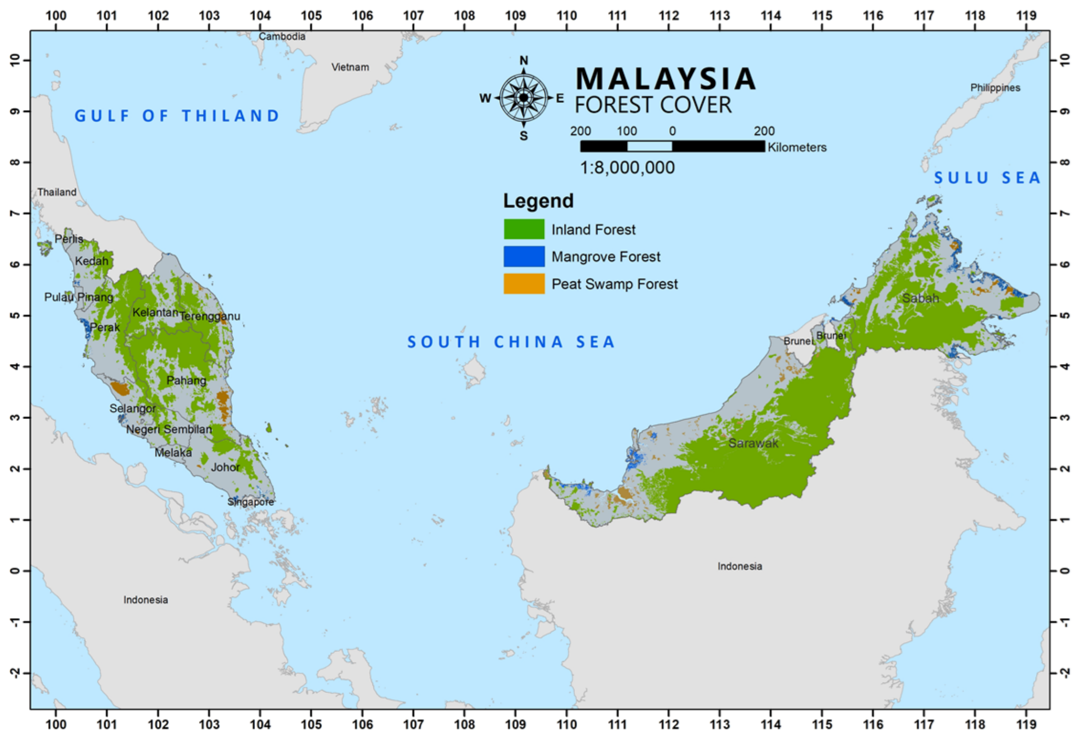

Figure 5. The produced forest covers from the image classification

Table 3. The forest covers in Malaysia as of the year 2020

Region	**Forest Cover (ha)**			**Total Forest Cover (ha)**	**Land Area* (ha)**	**Percentage (%)**
	Inland Forest (a)	Peat Swamp Forest (b)	Mangrove Forest (c)	(d) = (a)+(b)+(c)	(e)	(f)=(d)/(e)* 100
Peninsular Malaysia	5,338,082	243,504	110,953	5,692,539	13,100,367	43.5
Sarawak	7,328,029	320,207	139,890	7,788,126	12,444,951	62.6
Sabah	4,273,536	97,276	378,195	4,749,007	7,390,224	64.3
Total	16,939,647	660,987	629,038	18,229,673	32,935,542	55.3

**Sources*: *Department of Survey and Mapping Malaysia, Lands and Surveys Department, Sabah and Department of Land and Survey, Sarawak.*

3.2 Changes in Forest Cover

Deforestation is defined as a permanent human-induced conversion from forest to non-forest. All stands are cleared, and the land is cleared and used for other purposes. Temporary changes in land use, such as timber harvesting within a forest reserve (up to 25 years of rotation), are not considered deforestation (MESTECC, 2018). In the broadest sense, deforestation is the conversion of forests to alternative permanent non-forest areas, usually for agriculture, grazing, urban development, or clearing areas from natural vegetation cover. Depleting forest plants results in a loss of population and plant biodiversity (Omran & Schwarz, 2020). Multiple variables and pressures contribute to deforestation, including agricultural conversion, infrastructural development, timber extraction, agricultural product prices, and a complex combination of additional instructional and location-specific factors (UNFCCC, 2020), which can be particularly important in some areas.

A rough estimate is that Malaysia's total forest loss from 2000 to 2012 was 14.4% of the 2000 forest area (Butler, 2013). The expansion of oil palm was the main reason for this number. The oil palm plantations in Malaysia have increased from 5.59 million to 11.56 million. From 2000 to 2018, it increased by 5.98 million ha, with a growth rate of 106.96%. The area of oil palm plantations in western Malaysia increased by 2.53 million ha, with a growth rate of 82.77%. In East Malaysia, the area increased by 3.45 million ha, and the growth rate was 136.14% (Li et al., 2020). Oil palm growth accelerated from 2000 to 2010 and slowed after 2010. Deforestation was also caused by other activities such as the expansion of rubber plantations, hydropower plant construction, mining, illegal logging, and natural disasters such as wildfires, shifting cultivation, tsunamis, and erosion.

In contrast, according to this study, deforestation from 2005 to 2020 was only a loss of 1,087,030 ha (5.6%) of forest area in year 2005, with an annual deforestation rate of 0.37%. Therefore, this study proved that the rates reported by (Butler, 2013) were incorrect. Forest area decreased from 19,316,702 ha in 2005 to 18,229,672 ha in 2020 (Table 4). This is mainly due to the conversion of forests to farmlands and settlements development, which reduced only about 3.4% of Malaysia's total forest area.

Table 4. Forest cover in Malaysia (ha)

Year	Forest cover (ha)				Percentage cover (%)
	Inland forest	Peat swamp forest	Mangrove forest	Total	
2005	17,949,753	700,401	666,547	19,316,702	58.7
2010	17,329,165	676,186	643,502	18,648,853	56.6
2015	17,088,338	666,789	634,559	18,389,686	55.8
2020	16,939,647	660,987	629,038	18,229,672	55.3

**Considering the landmass of Malaysia as 32,935,542 ha.*

3.3 Forest Carbon Stock

Above-ground biomass (AGB) includes all living above-ground plants such as stems, branches, twigs, and leaves. This study used the well-known allometric equation to determine the AGB of inland forests (Chave et al., 2014). This equation is produced based on trees sampled in the lowlands and hilly forests of the western Malaysian peninsula. Wood density was obtained from the Global Wood Density Database (Chave et al., 2005). A biomass expansion factor of 0.47 was used to convert biomass to carbon storage. According to a previous study, Table 5 shows the average carbon reserves from all carbon pools of Malaysian primaeval forest types (Hamdan et al., 2018). A comprehensive overview of carbon stocks in Malaysia's various forest types and conditions was also produced by (Kho & Jepsen, 2015; Syafinie & Ainuddin, 2015). However, in this study, only the above-ground component of carbon pools was used to calculate CO_2 emissions.

The most important parameters that play a role in causing variations in carbon stock estimations are: (i) the selection of the study site, (ii) the use of different allometric equations in the estimations, (iii) the application of different sampling design/ protocols, (iv) levels of disturbances in the forest, and (v) harvesting/logging practises in production forest. Although logging activities with selective harvesting conducted within forest reserves are not considered deforestation, they reduce the carbon stock by about 29 to 64 Mg C ha^{-1}, depending on the logging methods employed (Azian et al., 2019).

Table 5. Carbon stock in all carbon pools in major types of forests in Malaysia (Mg C ha^{-1})

Forest type	Carbon stock (Mg C ha^{-1})					
	Above-ground	Below-ground	Dead-wood	Litter	Soil	Total
Inland forest	174.49	35.22	4.92	1.29	48.40	264.32
Peat swamp forest	168.63	35.95	21.40	2.19	188.10	416.27
Mangrove forest	135.45	48.57	22.12	3.88	54.87	264.89

3.4 CO_2 Emission

Assuming that CO_2 emissions are due to deforestation, the total emissions from 2005 to 2020 are approximately 689.26 million Mg CO_2, and the annual emissions are 45.95 million Mg CO_2. This corresponds to a carbon loss of approximately 12.53 million Mg C. Table 6 summarises trends in CO_2 emissions generated between 2005 and 2020. According to the trend, deforestation surged between 2005 and 2010 and reduced between 2010 and 2020. This was primarily due to increased government understanding of REDD+ initiatives, improved management procedures for various conservation activities, and the government's mitigation actions. Although the estimates incorporate a few assumptions and generalisations, the presented data might present an overall scenario of CO_2 emissions from deforestation activities in Malaysia.

Table 6. CO_2 emissions resulted from deforestation in Malaysia (2005-2020)

Time Series	CO_2 emission (million Mg CO_2)			Total
	Inland forest	Peat swamp forest	Mangrove forest	
2005-2010	397.05	14.97	11.45	423.47
2010-2015	154.08	5.81	4.44	164.33
2015-2020	95.13	3.59	2.74	101.46

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 PRFs, where some land is reserved for production and managed by sustainable forest management (SFM) practices. The average rate of sequestration for the major types of forests in Malaysia is summarised in Table 7.

According to an analysis of CO_2 emissions and removals from the LULUCF sector in Malaysia, the activity data used to assess emissions and removals within the remaining forest area categories is particularly important. In this scenario, we used data from the Forest Department to estimate emissions from upstream forestry projects. Between 2005 and 2010, Peninsular contributed a net reduction of approximately 140,000 Mg CO_2 from this category. After that, net emissions from 2015 to 2020 were 23.53 million Mg CO_2, while net emissions from 2010 to 2015 were 14.31 million Mg CO_2. Meanwhile, Sabah contributed to the net removal of forest land to the rest of the forest land. Mg CO_2 in 5 years from 2005 to 2010. Then, the emissions were further removed at -0.49 million Mg CO_2 generated between 2010 and 2015, and it became even larger between 2015 and 2020, with a net removal amount of 72.62 million Mg CO_2. Sarawak contributed a net reduction of about -11.83 million Mg CO_2. The five-year Mg CO_2 from 2005 to 2010 continued for several years from 2010 to 2015, with a net removal of 90.44 million Mg CO_2. However, emissions have declined from 2015 to 2020, with net emissions of 48.87 million Mg CO_2. Table 8 summarises the net issuance and withdrawal changes between 2005 and 2020.

Table 7. Rate of carbon sequestration in major forest types in Malaysia (MESTECC, 2018)

Forest type	**Growth rate AGB (Mg ha^{-1} yr^{-1})**	**Carbon sequestration* (Mg C ha^{-1} yr^{-1})**
Inland	9.3	4.37
Peat swamp	9.2	4.23
Mangrove	11	5.17

**Carbon conversion factor: 0.47.*

Table 8. Summary of CO_2 emission for forest land remaining forest land

Year	**Net (million Mg CO_2)**			
	Peninsular Malaysia	Sabah	Sarawak	Total
2005-2010	-0.14	-16.22	-11.83	-28.19
2010-2015	14.31	-0.49	-90.44	-76.62
2015-2020	23.53	-72.62	48.87	-0.22

Note: The -ve sign is net removal, and the +ve sign is net emission.

4. Conclusion

This study showed that remote sensing and other support data help quantify forest carbon and emissions in Malaysia's forest sector. The data had technical challenges but were successfully resolved using appropriate image processing protocols. Landsat satellite images collected at 5-year intervals between 2005 and 2020 were processed to create seamless and continuous images throughout Malaysia. The image classification shows forests divided into three major types: dry inland forests, peat swamp forests, and mangroves. Post-classification change detection methods identified areas converted from forest to other land use. Forest area increased from approximately 19.3 million ha (2005) to 18.2 million ha in 2020.

Studies show that deforestation between 2005 and 2020 resulted in the loss of 1,087,030 ha (5.6%) of forests. The forested areas in 2005 was reduced at a rate of deforestation of 0.37% per year. As a result, total CO_2 emissions was 101.46 million Mg CO_2. The study also estimated total CO_2 emissions and removals in the remaining forest areas. Forests were also found to have caused emissions due to the timber production. However, overall estimates show that this category can still isolate carbon and remove 105.03 million Mg of CO_2 for 15 years (2005-2020).

The study found that using a series of satellite images captured by optical sensors was the most effective way to monitor deforestation in Malaysia. Cloud covers cause severe problems with optical visibility datasets, but recent advances in remote sensing, computer technology, and image analysis processing technology provide ways of solution.

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