Remote Sensing Image Analysis for Identification of Peat Thickness Using Spectral Transformation Approach: Case Study of Bengkalis Island, Riau, Indonesia

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Abstract

Peatland plays an important role in the global climate. Balancing economic, social and conservation needs on peatland utilization become an obligation in developing sustainable peatland regulation. To identify the appropriate land function in the peatland environment, the depth of peat is the main property to manage those balance needs. On the other hand, vast areas of peatland changing hinder rapid peat depth mapping method to have high accuracy. Multi-temporal remote sensing data were used to identify peatland-related land-use changes. The vegetation and wetness indices spectral transformations had been analyzed. The method used for the accuracy test in this study was correlation and regression analysis for modeling and the Standard Error of Estimate (SEE). The results of this study showed that the vegetation indices (NDVI, SAVI, and MSARVI) and NDSI were not able to obtain peat thickness models due to the unstable vegetation and land cover changes. However, the NDWI was fairly satisfied with the statistical assessment and was able to model the peat thickness with 41.96% accuracy. The determination of a sample design, the number and distribution of samples in preserved land covers, and the unexplained variables and external factors in this study need to be considered in further research. The vegetation indices and wetness indices potentially can be the alternative variables to construct the peat depth map.

1. Introduction

Indonesia is home to 13.3 million ha of tropical peatlands (Anda et al., 2021) becoming one of the largest among other countries in the world (Dargie et al., 2017). Peatlands in the country were formed by the prolonged accumulation of decomposed organic materials for thousands of years, that subsequently molded a biconvex shape in general (Rieley & Page, 2016). Therefore, the thickness of accumulated peat soils reflects the amount of stored carbon, reaching 10-fold the carbon storage above the ground (Draper et al., 2014; Rudiyanto, Minasny, Setiawan, et al., 2016). This indicates that Indonesia has a massive contribution to soil carbon storage worldwide, yet on the other hand is also potential as the highest carbon emitter caused by the vast peatland degradation in these (Page et al., 2011). Carbon emission of drained peatland in Indonesia has occurred, releasing approximately 632 Tg/yr CO_2 (Jauhiainen et al., 2008). The original pristine peatlands were converted to other land uses, widely for agriculture and plantations to support food and economic needs (Umarhadi et al., 2022). However, the use for plantations is not completely appropriate for peatlands, taking an example of the failure of the Mega Rice Project in 1996 that established one million ha of rice fields over peatlands, ended up being abandoned and caused severe environmental issues (e.g., land fires) (Hergoualc'h et al., 2018).

The government of Indonesia has attempted to conserve the peatlands area, starting by issuing several forms of provisions and agreements regarding the development and management of peatlands, and the recent one is the establishment of the Peat Restoration Agency in 2016 (Harrison et al., 2020). However, it still does not dampen the exploitation activities on a large scale, worsened by the land burning as the first common treatment for irresponsible peatland clearing. Development and management of peatlands as productive land cannot be applied to all types or classifications of peat soils.

Indonesian Government (2016) declared only shallow peat soils with under three meters of depth can be used as productive land. Whereas thicker peat soils should be strictly designated for conservation because they are very fragile and vulnerable. On the other hand, the existing peatland conversion ignores those considerations, where peatland below 3 meters has been also exploited (Wahyunto et al., 2016).

Along with the times, mapping of peatlands has advanced with the presence of remote sensing technology, taking the advantage of its cost-effectiveness, quickness, and precision to facilitate field activities (Rudiyanto, Minasny, & Setiawan, 2016). Several studies estimated peat thickness with the approach of elevation as both variables are linearly correlated considering the dome shape (Jaenicke et al., 2008; Rudiyanto et al., 2018; Vernimmen et al., 2020). Besides elevation, peat depth information could be described also by several factors, such as the characteristic of land cover characteristic. For instance, with every increase of peat thickness, the vegetation that can grow on it will be lower or stunted (Page et al., 1999). In addition, the peat condition is always wet and humid both in the dry and rainy seasons (Noor, 2001). Hence, remote sensing data particularly optical sensors could be employed for rapid mapping peat depth. Sentinel-2B imagery provides 13 spectral bands and is beneficial to be used for creating vegetation index and water index which both are related to peat depth information.

Consequently, the identification of peat thickness using remote sensing followed by field observation is crucial to be explored. Hence, a balanced condition can be formed between productive land and conservative land. This research aims to measure the ability of remote sensing which is converted into vegetation and water index with field observation to estimate peat depth. Subsequently, the development and management of peat for productive land is better targeted and minimizes environmental damage.

2. Study Area

The research location is in Bengkalis Island, Bengkalis Regency, Riau Province. Centered at approximately 102° 17' 43.364″ E and 1° 28' 2.524″ S (Figure 1). The Bengkalis Regency has an area of 7,793.93 km^2 (Kabupaten Bengkalis, 2019). Elevation within the study area ranges from 0–27 m.a.s.l. with flat topography and most of the areas are covered by peat soils. However, the peatlands on the island are currently under degradation causing the loss of carbon from the organic soils (Umarhadi et al., 2021).

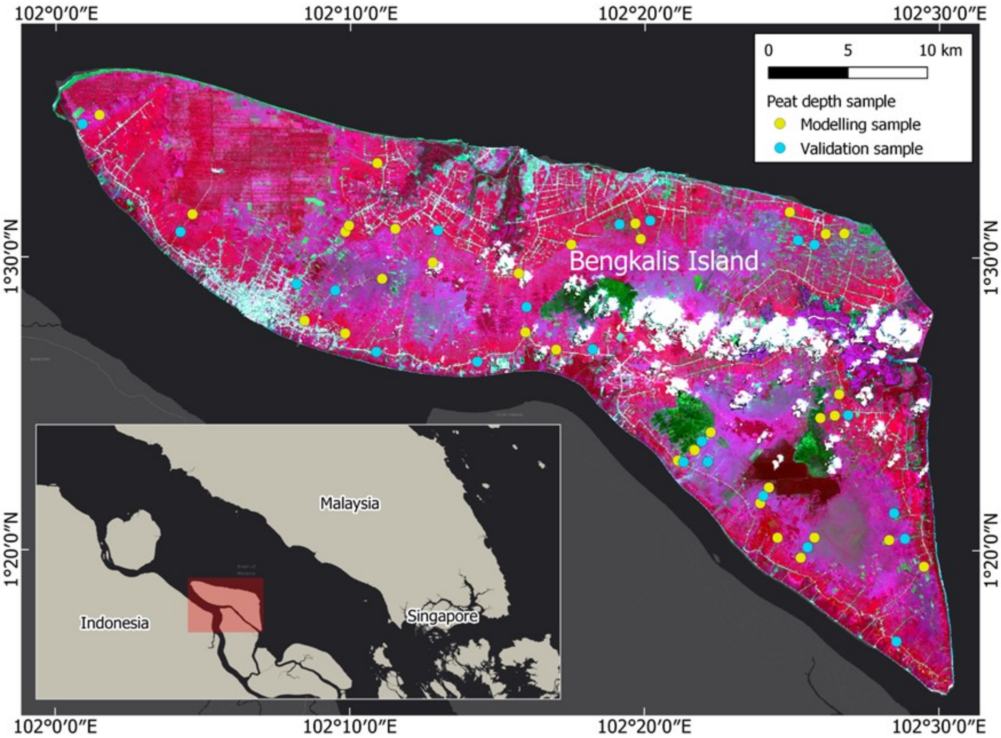

Figure 1: Overview of the study area in Bengkalis Island with a background of Sentinel-2B on 8,4,3 false-color composite acquired on 6 May 2019

Bengkalis Island is a tidal topogenic peat island with two types of rocks, which are young superficial deposits and older superficial deposits. Information based on the geological map of Bengkalis, young surficial deposits here are in the form of clay, silt, clean gravel, vegetation rafts, peat swamps, and coral reefs. Meanwhile, older superficial deposits are in the form of clays, silts, clayey gravel, vegetation rafts, and granite sands. These deposits dominate the island of Bengkalis in almost all parts of the island. Most of the island consists of organosol soils, which are types of soil that contain a lot of organic matter and gleisol soil.

3. Data and Method

The main data used to identify peat thickness is Sentinel-2B data on Bengkalis Island with an acquisition time of 6 May 2019 which is close to the field survey in April - May 2019 so the temporal bias and corresponding pixel values are minimal. The flowchart of this study is presented in Figure 2. The preprocessing method for Sentinel-2B was converting Top of Atmosphere (TOA) into at surface reflectance with the Dark Object Subtraction method in ENVI software. Landsat 5 TM was acquired in July 1998 for land cover change analysis. Hence, the spatial resolution of Sentinel-2B was resampled into 30 meters based on Landsat 5 TM spatial resolution.

3.1 Field Survey

The field survey was conducted from April until May 2019. The purposive sampling method was used to determine the peat information from the field based on the accessibility. Ideally, peat depth is modeled based on the elevation data which indicates the peat dome information (Rudiyanto et al., 2018). The freely accessible elevation data (e.g., SRTM DEM and DEMNAS) represent the surface elevation instead of terrain, hence the contribution of objects over peat surface may lead to biased results. Meanwhile, LiDAR data that is commonly used is not freely available. Therefore, it was not reliable for this study, since the study area is dominated by vegetated land cover. In addition, systematic sampling can be used to show the depth in the entire area. However, in this research, mapping peat depth with systematic grid sampling was not feasible because of accessibility.

Peat thickness data was obtained from peat depth measurements using peat drills. Furthermore, the drilling method was perpendicular to the soil surface. Peat depth information was obtained by measuring the distance of the peat layer before mineral soil layers were distinguished. Vegetation canopy density data was also taken using the hemispherical photograph. A total of 55 spatially distributed peat depth and vegetation canopy density sample data were obtained, 33 of which were used to create a peat depth model toward sentinel-2B data whereas the remaining 22 samples are for assessing the accuracy of the model (Figure 1).

3.2 Image Transformation

Sentinel-2B Level 1C images have been radiometrically and geometrically corrected hence the spatial displacement between image pixels and the corresponding location in the field is relatively not significant. Atmospheric correction was applied to achieve the surface reflectance by using the DOS1 (Dark Object Subtraction 1) method and processed in ENVI software. The concept of DOS is to remove the atmospheric contribution in the pixel value by observing the dark object pixel value. The darkest object in the image is assumed to have a value of 0, however, due to the existence of the atmosphere, there is an offset value in the darkest object. The surface reflectance is achieved by subtracting the offset value from the darkest object. The lowest value in the image is supposed to be 0 and it indicates there is no atmospheric effect (Chavez, 1988 and Yan and Li, 2018). Image masking was performed to eliminate other objects that could affect the process and analysis. The objects such as clouds and shadows that caused the absence of surface information need to be removed. The image masking process was performed manually through visual interpretation and set the boundary of unwanted objects. Removed pixels will have no data value and be visualized as no information. This study used spectral transformation methods to identify peat thickness. The methods were three types of vegetation indices and two types of wetness indices. Those types of indices as an approach method were selected to compare and identify the most suitable spatial transformation approach for peat thickness mapping. Details of the spectral transformations used can be seen as follows (Table 1).

Based on Table 1, each vegetation and wetness index have different sensitivity against different field condition. NDVI (Normalized Difference Vegetation Index) represents the basic vegetation index which has a range of -1 to 1. SAVI (Soil Adjusted Vegetation Index) minimizes the soil effect toward the brightness of the vegetation canopy.

Table 1: Equations of vegetation and wetness indices used in this study

Index	Algorithm	References
NDVI	(ρNIR- ρRed)/(ρNIR+ ρRed)	(Rouse et al., 1974)
SAVI	(ρNIR-ρRed)/(ρNIR+ρRed+L)*(1+L)	(Rondeaux et al., 1996)
MSARVI	2ρNIR+1- √(〖[(2ρNIR+1)〗 ^2- γ(ρNIR-ρRB)]) / 2	(Huete et al., 1992)
NDWI	(ρGreen- ρNIR)/(ρGreen+ ρNIR)	(Rokni et al., 2014)
NDSI	(ρSWIR- ρNIR)/(ρSWIR+ ρNIR)	(Domiri, 2006)

Description:
ρRB: ρRed- γ(ρBlue- ρRed)
ρRed: Red reflectance value
ρBlue: Blue reflectance value
ρGreen: Green reflectance value
ρNIR: Near infrared reflectance value
ρSWIR : Middle Infrared reflectance value
L: Enlightenment soil background correction
γ: 1.0

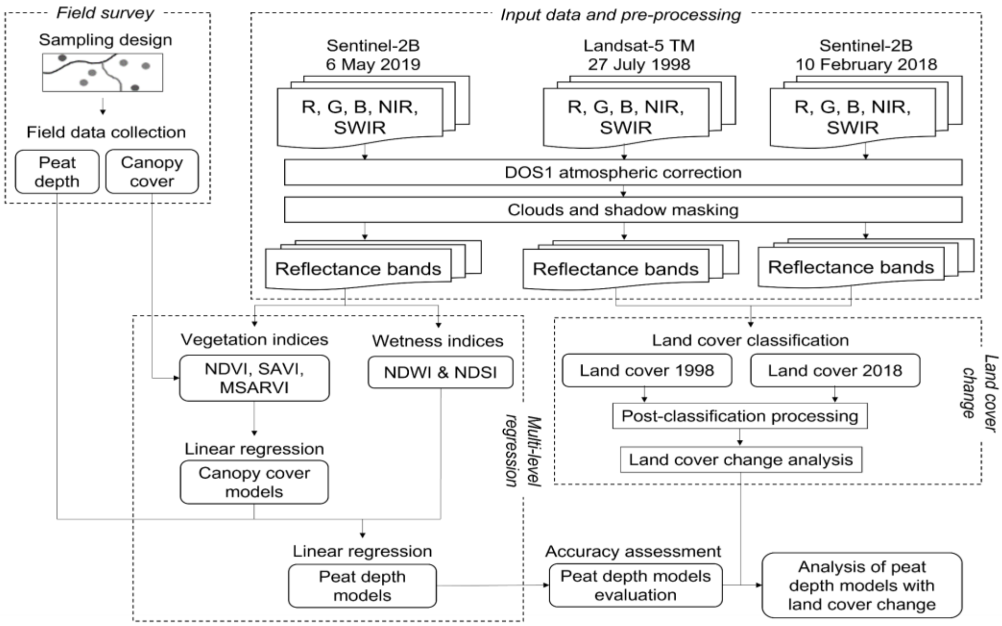

Figure 2: Methodology of this study

Furthermore, MSARVI (Modified Soil and Atmospheric Resistant Vegetation Index) is a modification toward weakness of other vegetation indices which could detect greenness level of vegetation and reduce the effect of soil and atmosphere. On wetness index, NDWI (Normalized Difference Wetness Index) could detect the condition of surface wetness, and NDSI (Normalized Dryness Surface Index) for detecting dryness surface.

3.3 Peat Depth Modeling and Statistical Analysis

Mapping peat depth and its extent is crucial for carbon stock estimation and peatland management. Peat depth could be assessed by its vegetation canopy. When the canopy density is high, the depth of peat is low. This statement is justified by the fact that peat soil interferes with the vegetation fertility above the soil. This study utilized three vegetation indices which are NDVI, SAVI, and MSARVI to analyze canopy density. On the other hand, the peat ecosystem is highly correlated by the wet condition because of the large water reservoir. Therefore, we also used two wetness indices to be compared, namely NDWI and NDSI, respectively.

Regression analysis on this research used multilevel regression to produce peat thickness information. To obtain vegetation canopy estimation, we used correlation and regression measurement toward NDVI, SAVI, and MSARVI indices. Furthermore, to measure data normality, we tested using the Kolmogorov-Smirnov method. Then, a data normality test is performed to see whether the data is normally distributed or not. Correlation and regression analysis methods to see the relationship between variables and make a model of peat thickness. Then to find out the accuracy value used the Standard Error of Estimate (SEE) method.

4. Results and Discussion

4.1 Transformation of Vegetation and Wetness Indices

This study used the vegetation index and the wetness index as spectral transformation approaches. Both transformations were used because they can sharpen certain information while suppressing or eliminating other information (Danoedoro, 2012). Proper pre-processing image is important to achieve reliable vegetation and wetness indices. The atmosphere effect was removed by applying the DOS method, and unnecessary objects such as clouds have been masked to obtain reliable results. The results of the spectral transformation using vegetation index ranges from -1 to 1 (Table 2). Derived vegetation indices and wetness indices values were evaluated through visual evaluation compared to false-color composite for vegetation of the study area to make sure of its reliability (Huang et al., 2021; Loranty et al., 2018). NDVI values represent quite well the vegetation canopy density based on false-color composite in Figure 1. The high value of NDVI indicates dense vegetation that is visualized as darker color in the false-color composite image. It can be seen that the SAVI and MSARVI values have a narrow range of values in comparison with NDVI but still show a high canopy density. The higher minimum value indicates that MSARVI is very effective in suppressing objects other than vegetation, but in distinguishing the density of vegetation on Bengkalis Island, MSARVI becomes less effective. NDWI and NDSI wetness index values also have a range of -1 to 1. Based on the research of (Bala et al., 2018), negative values on NDWI indicate the object of built-up area, land, and open land. While vegetation objects are shown with very low negative values. While positive values indicate objects of water bodies. In contrast to NDWI, a negative value on NDSI indicates a water body object. While a positive value on NDSI shows open land objects and built-up land. While the vegetation object is negative but it is closer to the value of 0. The NDWI showed that Bengkalis Island has a very high wetness level, and these results are supported by the fact that most of the island is dominated by peat and vegetation. On the other hand, the NDSI range showed that Bengkalis Island has a very low to moderate level of land drought, it also means that Bengkalis Island has a very high degree of wetness.

4.2 Identification of Peat Thickness through Vegetation Index

Multi-level regression analysis was used in this research to identify peat thickness through vegetation indices. Correlation and regression analysis were performed to obtain the estimation of vegetation canopy cover model based on NDVI, SAVI, MSARVI in comparison with the canopy cover data from the field survey. Data normality was measured using the Kolmogorov-Smirnov method before data correlation analysis. The results showed that the canopy cover data in the field were normally distributed with a data set value of 0.088. The data is relatively normal because it is below the critical value of the Kolmogorov-Smirnov for an alpha value of 0.05 (0.23) (Massey, 1951). The probability plot graph also shows that the data distribution is almost parallel to the 1:1 linear line, which means the field canopy cover data is normally distributed and tends to have a lot of variances (Figure 3).

The results of correlation analysis showed that the relationship between data was quite strong (r = 0.401 - 0.600) and unidirectional. In Table 3, the best index to describe canopy density in the field is the SAVI index (r = 0.433). However, NDVI and MSARVI still have a strong relationship. The results of regression analysis showed that the ability of NDVI, SAVI, and MSARVI in explaining the canopy cover in the field through imagery was only 17.09%; 18.79%; 18.29%, respectively. Then the F-significance value >0.05 (α) and the t-value <2.09302 also stated that the predictor variable did not significantly affect Y-variable (Williams, 1984). Regression equations (Table 4) were used to generate a canopy cover density model as shown in Figure 4.

Table 2: The statistics of indices value from Sentinel-2B

Index	Minimum Value	Maximum Value	Mean	Std. Deviation
NDVI	-0.54	0.87	0.69	0.14
SAVI	-0.17	0.71	0.16	0.22
MSARVI	0	0.58	0.11	0.15
NDWI	-0.76	0.93	-0.11	0.15
NDSI	-0.94	0.52	-0.62	0.17

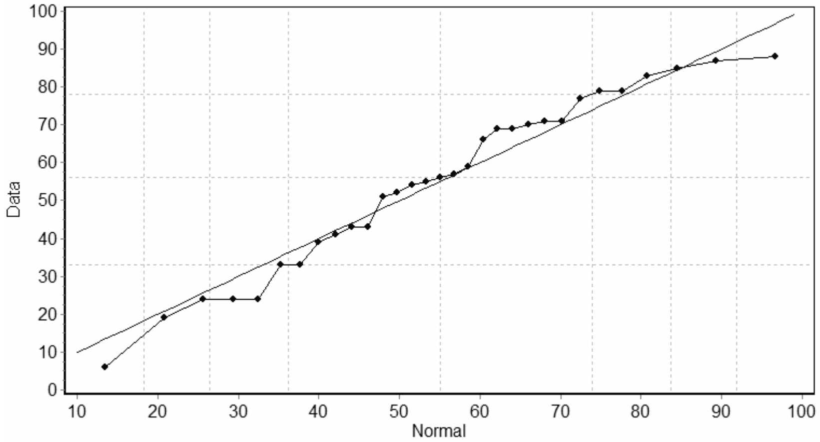

Figure 3: The probability plot graph of canopy cover

Table 3: Matrix of correlation values (r) between canopy cover and vegetation indices

	Canopy Cover	*NDVI*	*SAVI*	*MSARVI*
Canopy Cover	1			
NDVI	0.41	1		
SAVI	0.43	0.98	1	
MSARVI	0.43	0.92	0.98	1

Table 4: Regression analysis results of canopy cover

	R Square (R^2)	*F-Significance*	*t-value*	*t-significance*	*Regression Equation*
NDVI	0.17	0.08	1.87	0.08	y =119.52x - 32.017
SAVI	0.19	0.06	1.98	0.06	y =136.38x - 9.2967
MSARVI	0.18	0.07	1.95	0.07	y =221.93x - 17.934

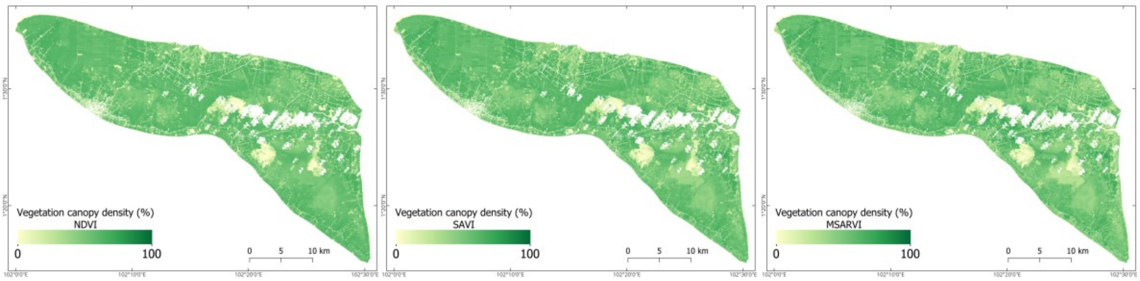

Figure 4: Vegetation canopy density models based on three vegetation indices (i.e., NDVI, SAVI, and MSARVI)

Table 5: Matrix of correlation values (r) between the field data of peat thickness and the peat thickness models based on vegetation indices

	Peat Thickness	*NDVI Model*	*SAVI Model*	*MSARVI Model*
Peat Thickness	1			
NDVI Model	-0.11	1		
SAVI Model	-0.16	0.96	1	
MSARVI Model	-0.18	0.84	0.96	1

Table 6: Regression analysis results of peat thickness based on vegetation indices

	R Square (R^2)	*F-Significance*	*t-value*	*t-significance*	*Regression Equation*
NDVI Model	0.01	0.55	-0.60	0.55	y = -3.6194x + 650.38
SAVI Model	0.02	0.38	-0.88	0.38	y = -5.1048x + 724.27
MSARVI Model	0.03	0.32	-1.00	0.32	y = -5.7767x + 757.29

The NDVI, SAVI, and the MSARVI model are then tested for accuracy using the Standard Error of Estimate (SEE) method. The results for those indices are 69.14%, 69.68%, and 70.32% accuracy, respectively. The estimated map of vegetation canopy density with the highest accuracy value is based on MSARVI transformation with an accuracy value of 70.32%. Based on Figure 4, the low to very low-density canopy class is in the middle of the island with high peat thickness (identification based on field data). Then, the medium class with a canopy density of 40 - 60% is also still scattered in the middle of the island, and the canopy density is high to very high in small parts around the island. In addition, the pattern of tree canopy density in Bengkalis Island slightly represents the condition of the peat thickness and shares a similar idea to the previous theory and the general situation in the field. The regression results between vegetation canopy density models from NDVI, SAVI, and MSARVI and peat depth were not significant with 0.55, 0.38, and 0.32, respectively (Table 5 and Table 6).

Therefore, due to the insignificant regression results among those variables, a peat depth map was not able to be obtained. Significant spatial autocorrelation was noticed in the sampling design which may affect the results (Griffith & Chun, 2016; Ramezan et al., 2019). It also indicates the observed peat thickness in the study area was not enough. As mentioned, limited access to reach the study area was the obstacle to collecting samples. Different land cover on peat and its historical change may affect the inconsistent results. The results described that these vegetation canopy density models from vegetation indices are not good enough to elucidate the condition of peat thickness.

4.3 Identification of Peat Thickness through Wetness Index

Analysis through the wetness index was not applied a two-step process of accuracy testing due to the limitations of the wet soil testers in the field. The results of the wetness index regression with the peat thickness data in the field also have poor performance although it is slightly higher than the regression index of vegetation. The regression results of NDWI and NDSI show an F-significance value of 0.1 and 0.33, respectively (Table 7 and Table 8), indicating that only NDWI has a significant result. Therefore, only NDWI was conducted to obtain the peat depth model. The peat depth model is shown in Figure 5 by only considering the peatlands area, thus non-Peat areas were masked out. The ability to explain the condition of peat thickness in the field through the NDWI wetness index is 19.22%. NDWI values in Bengkalis Island were mostly influenced by vegetation coverage, especially at the location of the samples were taken. However, in some parts, the open land was observed in wet conditions because of thick peatland, even though the value is much lower than the others. This might be caused by the small amount of vegetation that grows on it. While identification of wetness using NDSI was slightly irrelevant because the relationship and translation of the information are not well described. Therefore, NDSI is not suitable enough to identify peat thickness because of the possibility of data misinterpretation. The accuracy of the peat thickness map is 41.96% for the NDWI model. The relationship between the two variables will be very clear and strong if the land cover on peat is still in the natural form. Poor performance results were also caused by the indirect effect of surface topography and peat thickness on the vegetation changes. However, the significant effect may come from other characteristics of peatlands such as hydrological dynamics, chemical properties, and organic matter. Where the three characteristics occur as a form of balance between peat accumulation and peat degradation of natural forest (Page et al., 1999).

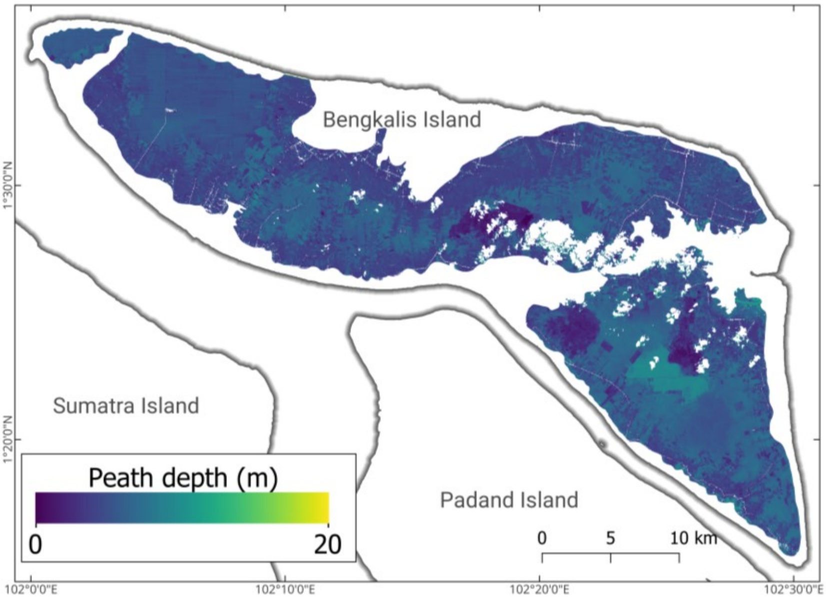

Figure 5: Peat thickness model based on NDWI with only considering the peatlands area

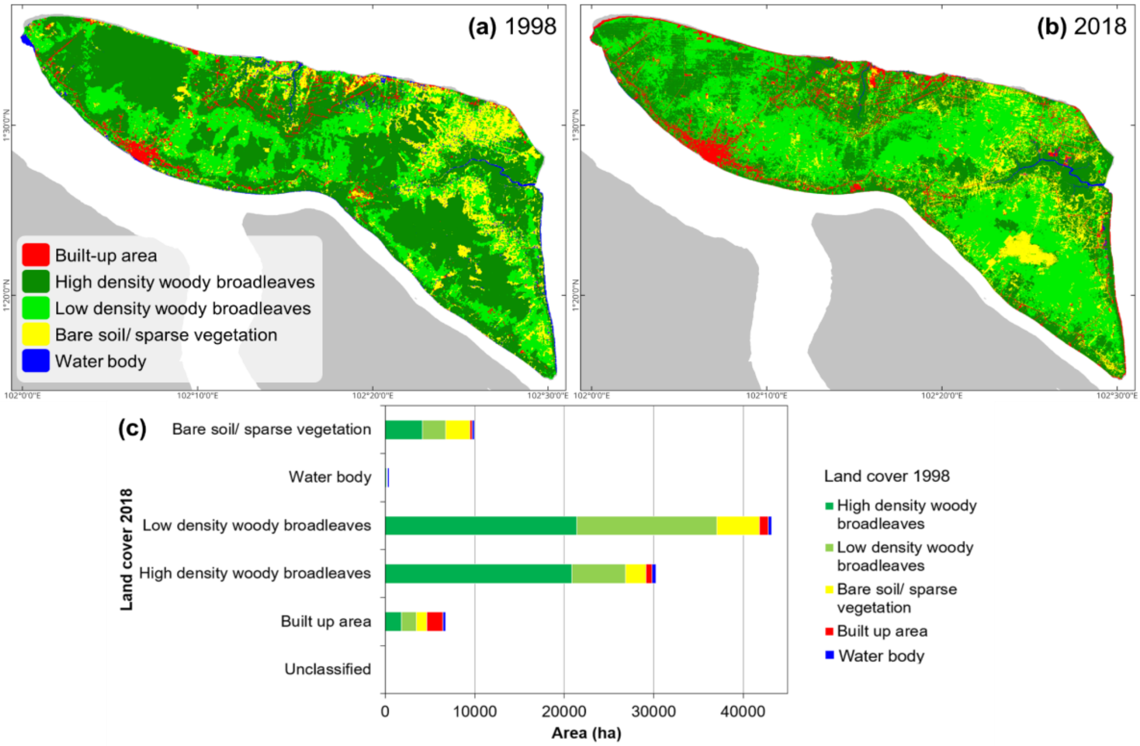

Figure 6: Land cover of Bengkalis Island in (a) 1998 and (b) 2018, and (c) area of land cover in 2018 with the change from 1998

Table 7: Matrix of correlation values (r) between the field data of peat thickness and the peat thickness models based on NDWI and NDSI

	Peat Thickness	***NDWI***	***NDSI***
Peat Thickness	1		
NDWI	0.44	1	
NDSI	-0.17	-0.27	1

Table 8: Regression analysis results of peat thickness models based on NDWI and NDSI

	R Square (R^2)	*F-Significance*	*t-value*	*t-significance*	*Regression Equation*
NDWI	0.19	0.01	2.71	0.01	y = 1458.5x + 732.98
NDSI	0.03	0.33	-0.99	0.33	y = -568.2x + 127.29

4.4 Land Cover Change

Human activities have been interfering with the sustainability of peatlands in Bengkalis Island. Based on the land cover change analysis (Figure 6), a massive area of forests (high-density woody broadleaves) has been converted to low-density woody vegetation associated with plantations, leaving only 33.38% (30,256 ha) of the total area as a forested area in 2018 (Figure 6). Most of the area has been converted into mixed gardens, oil palm, or rubber plantations, which was discovered during a field survey of the changed locations. However, due to the limited availability of high-resolution satellite imagery, the detailed land cover classes were not employed in this study. Built-up area increased significantly as well to reach 6,772 ha in the recent observation date, however, they are mainly located in the coastal area, i.e., in the transition between peatlands and non-peatlands (mineral soils). The relationship between canopy cover and peat thickness is very low for all indices due to the condition of degraded peatlands in Bengkalis Island. Canopy cover might be well correlated with peat thickness where peatlands are still in pristine condition without any disturbance.

Peatlands in our study area have been degraded massively, reportedly since the 1970s, consisting of land drainage and conversion to plantations (Umarhadi et al., 2022). This led to the remaining forests not being in the ideal condition of peat swamp forests. Future studies should investigate the similar methods applied in the peatlands that are still naturally preserved.

5. Conclusion

This study determines the peat thickness map based on the wetness index and the vegetation canopy density derived from the vegetation index. Multispectral images of Sentinel-2B provide necessary bands for image transformations. Three vegetation indices (i.e., NDVI, SAVI, and MSARVI) and two wetness indices (i.e., NDWI and NDSI) were used to obtain a spatial model of peat thickness. In general, the employed vegetation indices represented the vegetation greenness quite well to obtain vegetation canopy density models. However, the regression results of the vegetation canopy density models with peat thickness data collected from the field are not significant. Therefore, these models were not able to obtain a peat thickness model. It indicates the unstable condition of preserved land cover on peat such as degraded vegetation canopy density affected the results. On other hand, the sampling design was not satisfactory enough to represent the wide range of peat thickness variance due to limited access in the study area. Similar to NDSI, this wetness index does not have a significant regression result on peat thickness. The NDWI wetness index has quite a significance based on the regression results so that a spatial model of peat thickness is obtained. However, the accuracy of the spatial model of peat thickness from NDWI has an accuracy rate of only 41%. The results need to be improved to achieve an accurate peat thickness map. The determination of a sample design that considers spatial autocorrelation, the number and distribution of samples in preserved land covers, and unexplained variables and external factors in this study need to be considered in further research. The vegetation indices and wetness indices potentially can be the alternative variables to construct the peat depth map.

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