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Effects of Peatland Fires on Above-ground Carbon Stocks in Kepulauan Meranti Regency, Riau Province

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Abstract

Peat fires substantially alter ecosystem dynamics and carbon storage, making it essential to understand how fire-related components affect post-fire carbon stocks. This study aims to estimate the above-ground carbon stock on burned peatlands in Kepulauan Meranti Regency, Riau Province, and examine how fire recurrence, last fire occurrence, and burn severity influence the carbon stock using a modified regression model and remote sensing data. The normalized burn ratio index difference between post- and pre-fire was used to calculate burn severity. The continuous predictor variable was transformed using a natural logarithm to generate the best-fit model. The 2014 burned peatland stored the highest carbon, whereas the 2020 burned peatland was the lowest. The 2020 fire period was the most severe compared to the 2014 and 2018–2019 fires, although it had a smaller burned area. This study highlights that fire-related components significantly affect post-fire peatland above-ground carbon stocks, particularly last fire occurrence and burn severity. Meanwhile, fire recurrence had the weakest impact and correlation with above-ground carbon stock compared to other predictors, likely due to the brief intervals between fire events in 2018 and 2019, which may have restricted ecosystem recovery and limited carbon storage capacity.

Keywords: *biomass, burn severity, natural logarithm, regression model, remote sensing*

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Introduction

Forest and land fires have been identified as one of the significant environmental alteration issues in the tropics that impact the global climate as they directly release greenhouse gas (GHG) emissions (Kukavskaya et al., 2013; Manaswini & Reddy, 2015; Osaki et al., 2016). Recently, there has been increased interest and recognition in peat globally due to the importance of peatlands as carbon sinks and stores (equivalent to about 15% of the carbon stored globally) and their role in global environmental change processes (Osaki et al., 2016; Warren et al., 2017). Unfortunately, land use change and management that cause damage to tropical peatlands have led to significant carbon releases instead of carbon sinks (Wit et al., 2015; Leng et al., 2019).

Peatlands are vital components of wetland ecosystems because of their crucial role in the carbon cycle, significantly influencing global climate change (Shen et al., 2015; Guo et al., 2017). Studies of wetland biomass have focused mainly on above-ground biomass (AGB) (Wan et al., 2018). The estimation of AGB has become an essential way to estimate above-ground forest carbon stock, understand the carbon cycle of the ecosystem, and reflect the status of the ecosystem (Guo et al., 2017; Dumitraşcu et al., 2020). The AGB is often estimated using allometric equations that relate more easily measurable parameters, such as diameter-at-breast-height (dbh) and tree height (Wilkes et al., 2018). More than 80% of the carbon in peat forests stored in vegetation is found in standing trees (Hergoualc'h et al., 2018). Therefore, the calculation of this pool is essential to consider.

Peatlands in Indonesia are widely distributed along the coastal areas of Kalimantan, Sumatra, and West Papua. Sumatra has the largest peatland area in Indonesia, and the largest in Sumatra exists in Riau (Osaki et al., 2016). However, Riau is among Indonesia's most prone to forest and land fires (Darmawan et al. 2016). The area of land and forest fires in the Kepulauan Meranti is among the highest in Riau in recent years (Astika et al., 2022). Peat fires were the most significant contributors to national GHG emissions in 2015, accounting for approximately 33.8% of total emissions (MoEF, 2019). At least 70.5% of all fires from 2001–2018 occurred in Sumatra's peat swamp forests (Vetrita & Cochrane, 2020).

Fire regime, including fire frequency, is critical for identifying changes in ecosystem fire patterns (Vetrita & Cochrane, 2020). Second fires are more likely to occur because of above-ground fuel loads, such as tree trunks that remain unburned from the first fire (Hoscilo et al., 2011; Page & Hooijer, 2016). Therefore, it is essential to

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understand peatland fire information, such as location, burned area, and last occurrence, to protect the surrounding environment (Guo et al., 2017). Other vital components include burn severity, one of the indicators used to assess fire effects within burned areas (Roy et al., 2006).

Tropical peatland fires with vegetation changes have a meaningful impact on the carbon cycle, affecting both ecosystem functionality and climate change (Shen et al., 2015; Harenda et al., 2017). When peatlands burn, vegetation loss disrupts their role as carbon sinks and balancers, leading to significant carbon release (Guo et al., 2017). Previously, Numata et al. (2011) focused on reconstructing fire history by examining fire frequency, severity, and time since the last fire in a forested landscape. Still, Numata et al. (2011) did not fully explore the effects of these factors on carbon stock. By addressing this gap, this study aims to estimate above-ground carbon stock on burned peatlands in Kepulauan Meranti Regency, Riau Province, using the allometric model. Additionally, it investigates how fire-related components, such as fire recurrence, last fire occurrence, and burn severity, affect above-ground carbon stock using a modified linear regression model, leveraging remote sensing data. For the record, this study will use the term "burn severity" instead of "fire severity" (Keeley, 2009).

Methods

Study area Kepulauan Meranti Regency in Riau Province is unique because almost the entire land is peatland. Sampling for this study was carried out in three villages with varying fire occurrences: Tenan (2014), Lukun (2018–2019), and Bungur (2020) (Figure 1). Lukun Village represents an area with recurrent fires, while Tenan and Bungur experienced single fire events. In this study, fire recurrence is defined as the number of times fire has affected specific areas within the 2014–2021 period. This approach aligns with Vetrita and Cochrane (2020), who suggest quantifying fire events over a given area in a defined period. Here, it is adapted to measure fire recurrence. Konecny et al. (2016) determined the recurrent fires by overlaying each burned area for each year of fire occurrence.

Data collection Data collected included satellite imagery to identify burned peatland areas and estimate fire severity and dbh measurements for carbon stock estimation.

Satellite data Peatland fire detection was conducted using Moderate Resolution Imaging Spectroradiometer (MODIS) C61 Terra/Aqua satellite data for hotspots (https://firms.modaps.eosdis.nasa.gov) with a confidence level of >80%, covering historical hotspots for 2014, 2018, 2019, and 2020. The hotspot pattern informed pre-fire, peak, and post-fire periods. Burn severity was assessed using Landsat 8 C2 L1TP satellite images (30 m resolution) from the US Geological Survey (USGS) (https://earthexplorer.usgs.gov), which were processed with radiometric correction to convert digital numbers (DN) to top of atmosphere (ToA) reflectance. Two images were used per fire event: one before and one after peak fire.

Field data Traditionally, methods of vegetation biomass assessment are based on field surveying, which is very accurate (Li et al., 2021). The study sites–Tenan Village (2014), Lukun Village (2018–2019), and Bungur Village (2020)–were determined based on the last fire occurrences to examine the temporal effects on carbon stock. Twenty-four sample plots, accessible and representative of burn conditions, were surveyed in September 2021. The number

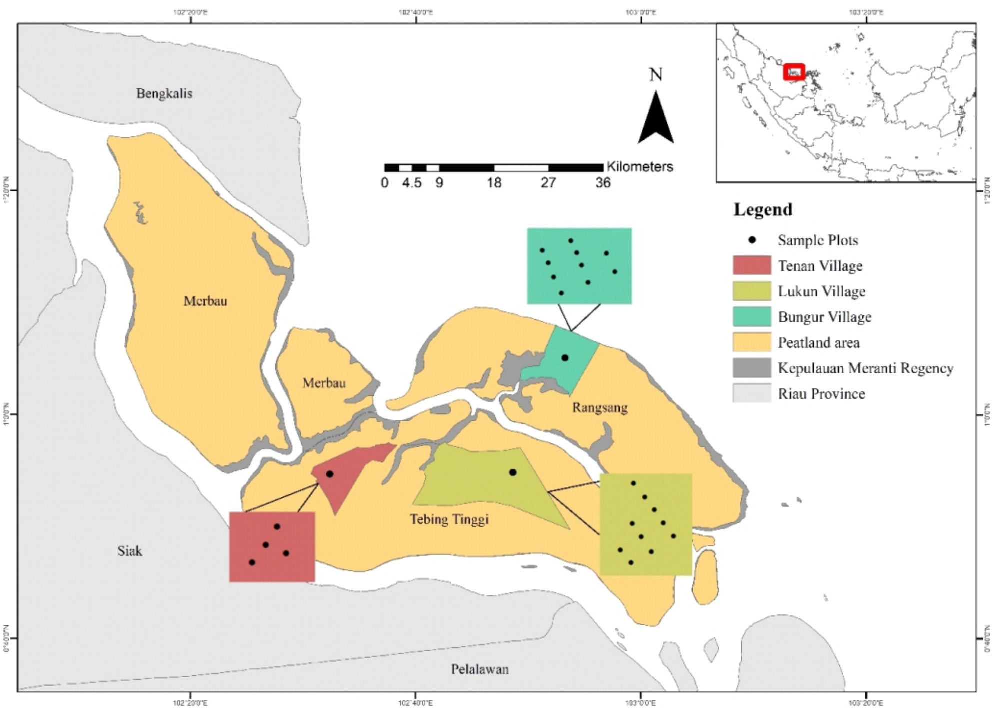

Figure 1 Study area in Kepulauan Meranti Regency, Riau Province.

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of plots in Tenan Village was the lowest, as the last fire occurred in 2014, resulting in denser vegetation, making it more challenging and time-consuming to establish plots. Once sites were selected, the first plot was randomly chosen. Subsequent plots were established along a continuous transect in the same direction as the first plot. This method was adapted from Volkova et al. (2020), who used a grid layout with set spacing; however, a continuous transect approach was used here, without a fixed distance between plots, to accommodate site-specific conditions.

Square plots of 20 m × 20 m for trees, 10 m ×10 m for poles, and 5 m × 5 m for saplings were utilized to measure dbh (Figure 2) (Irawan & Purwanto, 2020). Although the destructive method accurately determines the biomass, it is time- and resource-consuming, strenuous, destructive, and expensive (Vashum & Jayakumar, 2012). Hence, samples in this study were taken non-destructively with dbh measurements. However, there is an ambiguity in choosing a particular allometric model type for predicting biomass (Pandey et al., 2022), as the accuracy of biomass estimation using dbh measurements can vary. This study categorized vegetation based on dbh, with trees (≥20 cm), poles (10–20 cm), and saplings (2.5–10 cm).

To ensure biomass estimation accuracy, the measured dbh from each tree was input into the allometric model for mixed species in tropical peat swamp forest ecosystems developed by Manuri et al. (2014). This model, validated using destructive sampling of 148 trees from Sumatran and Kalimantan peatlands, has an R^2 value of 96.9%, indicating a high level of accuracy in biomass estimation. Pandey et al. (2022) suggest that allometric models for biomass prediction based on specific ecological regions could increase the model's accuracy.

Identification of burned areas False-color composite images using short-wave infrared 1 (SWIR 1), near-infrared (NIR), and red bands were created to distinguish between burned and unburned areas. A band combination is applied to pre- and post-fire images to determine the location of the training samples. Pre-fire images were captured in January 2014, February 2018, February 2019, and January 2020, while post-fire images were taken in April 2014, March 2018,

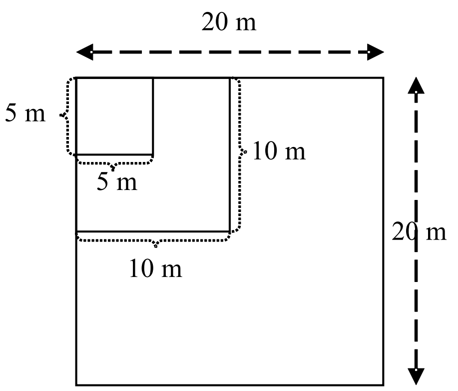

Figure 2 Sample plot design for above-ground carbon stock assessment of burned peatlands in Kepulauan Meranti Regency.

May 2019, and March 2020. Composites of bands 1–7 of Landsat 8 OLI provide optimization in producing high-quality training samples that have implications for classification results (Jiang et al., 2018). Sample points were placed by examining color changes between pre- and post-fire images, with hotspot data overlaid to indicate areas experiencing color changes.

Calculation of burn severity The burned area can be estimated using the normalized burn ratio (NBR) index (Verma et al., 2015), which is effective for detecting burned vegetation areas (Harris et al., 2011; Indratmoko & Rizqihandari, 2017). NBR was calculated from Landsat 8's NIR and SWIR 2 bands for each pre- and post-fire image, as shown in Equation *[1]*.

$$NBR = \frac{NIR - SWIR\ 2}{NIR + SWIR\ 2} \qquad [1]$$

Burn severity was then estimated using the difference normalized burn ratio (dNBR), calculated as shown in Equation *[2]*.

$$dNBR = NBR\ pre - NBR\ post \qquad [2]$$

A high dNBR indicates severe damage, while a low dNBR implies a high vegetation growth.

Classification of burn severity level Burn severity was classified using thresholds based on the mean (μ) and standard deviation (σ) values of dNBR data, following the NASI's (2015) method. Severity levels were defined as follows: low (μ2σ ≤ dNBR < μσ), moderate (μσ ≤ dNBR < μ), and high (dNBR ≥ μ). Unclassified cells were labeled as unburned, using ArcMap's "Con" function to apply these classifications across the dNBR raster.

Biomass and carbon stock estimation The biomass was estimated using the allometric models for mixed species in tropical peat swamp forest ecosystems (Manuri et al., 2014; Equation *[3]*), which are reliable and non-destructive in estimating above-ground carbon stocks (Nyamugama & Kakembo, 2015). The AGB was converted into carbon fractions using the IPCC's global factor of 0.47 (IPCC, 2006; Equation *[4]*).

$$AGB = 0.136dbh^{2.513} \qquad [3]$$

$$C = 0.47AGB \qquad [4]$$

note: *AGB* is the estimated biomass from vegetation (kg), *dbh* is the diameter measured in the field (cm), and *C* is the estimated carbon stock from vegetation. All measured carbon sources were totaled per sub-plot and extrapolated based on the sub-plot area (Manuri et al., 2011; Equation *[5]*).

$$\Sigma C_n = ((\Sigma C_{\text{sub-plot } a})\ \frac{10}{A\ \text{sub-plot } a}) + ((\Sigma C_{\text{sub-plot } b})\ \frac{10}{A\ \text{sub-plot } b})$$
$$((\Sigma C_{\text{sub-plot } c})\ \frac{10}{A\ \text{sub-plot } c}) \qquad [5]$$

note: ΣC_n is the total carbon stock in each plot (Mg ha^{-1}), $\Sigma C_{\text{sub-plot } a}$ is the total carbon stocks in sub-plot 20 m × 20 m (kg), $\Sigma C_{\text{sub-plot } b}$ is the total carbon stocks in sub-plot 10 m ×10 m (kg), $\Sigma C_{\text{sub-plot } c}$ is the total carbon stocks in sub-plot 5 m × 5

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m (kg), *A* sub-plot *a* is the area of 20 m × 20 m, *A* sub-plot *b* is the area of 10 m ×10 m, *A* sub-plot *c* is the area of 5 m × 5 m, 10 is the conversion factor value. After calculating the total carbon stocks for each plot, the mean carbon stock for all plots in each stratum (last fire occurrence: 2014, 2018–2019, and 2020) was computed (Manuri et al., 2011; Equation *[6]*).

$$\bar{C}_{stratum\text{-}i} = \frac{\Sigma C}{n} \qquad [6]$$

note: $\bar{C}_{stratum\text{-}i}$ is the mean carbon stocks in each stratum (Mg ha^{-1}), ΣC is the total carbon stocks of the entire plot in a stratum (Mg ha^{-1}), and n is the number of sample plots in the stratum.

Statistical analysis Pearson correlation and multiple linear regression were used to analyze the impact of fire-related components on above-ground carbon stock, computed using R's "stats" package. We applied a natural logarithm (*ln*) transformation to the continuous variable, as log-linear regression minimizes bias in biomass estimation (Chidumayo, 2013). The model is shown in Equation *[7]*.

$$Y = \beta_0 + \beta_1 ln(x_1) + \beta_2 x_2 + \beta_3 x_3 \qquad [7]$$

note: Y is carbon stock, x_1 is the burn severity, x_2 is the fire recurrence, x_3 is the last fire occurrence, β_0 is the intercept, and $\beta_1, \beta_2, \beta_3$ each is the coefficient of x_1, x_2, x_3. Then, classical assumption tests were performed, including linearity, multicollinearity, normality, and homoscedasticity. The model must not violate all of those classical assumptions. All the tests were performed with R's "performance" package.

Results and Discussion

Temporal hotspot distribution Forest fire predictions can be made based on the time of hotspot occurrences (Usman et al., 2015). The temporal distribution of hotspots in Kepulauan Meranti (Figure 3) shows a consistent yearly pattern, with peak fire activity occurring between February and March, as corroborated by Yulianti et al. (2012) and Riyadi et al. (2022). Additionally, a second peak of fires was observed in 2019 around August–September. In several other areas, particularly southern Sumatra, hotspots often increase from August to October (Yulianti et al., 2012; Thoha et al., 2014; Setyawati & Suwarsono, 2017).

The occurrence of two peak fires within a single year can be detected earlier by analyzing historical patterns. Thus, forest fire control activities, such as fire prevention through patrols, especially during the dry season, can be implemented (Budiningsih et al., 2022), because there is a gap between the first and second peak fires.

The 2014 period shows the highest number of hotspots, while the number in other periods is much lower. Riyadi et al. (2022) also showed that the number of hotspots in 2014 recorded the highest for forest fires in Kepulauan Meranti during 2001–2021. Increased hotspots in 2014 were triggered by the El Niño phenomenon (Kirana et al., 2016).

Burned area and burn severity estimation Burned areas differ from hotspots because burned areas are actual fires, while hotspots are potential fires (Suwarsono et al., 2013). Belenguer-Plomer et al. (2019) stated that burned areas were considered anomalies since fires are inconsistent spatial and

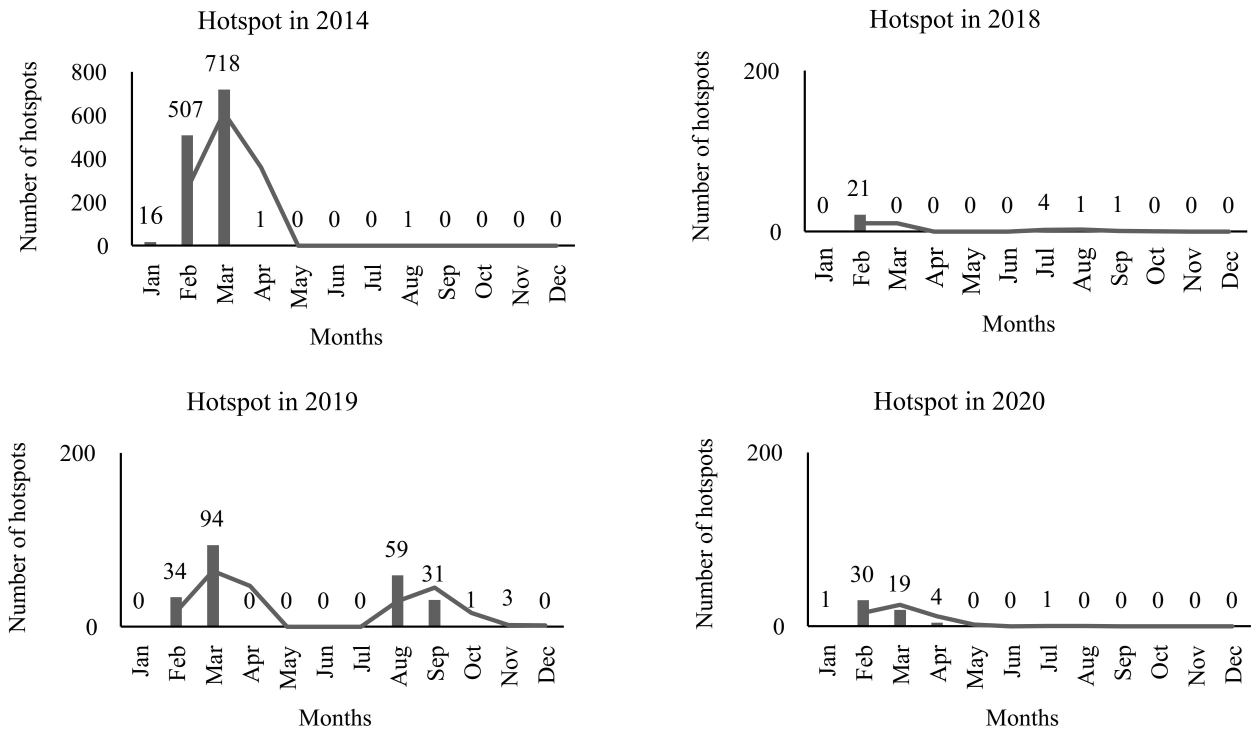

Figure 3 Temporal hotspot distribution in Kepulauan Meranti Regency.

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temporal events. Moreover, several factors affect the burned area mapping from remote sensing data, including the scene characteristics (cloud cover is one of the most relevant in this case). We used the NBR index to digitally detect changes between pre- and post-fire images in the peatlands (Figure 4). Healthy vegetation has a very high reflectance in the NIR spectrum and low reflectance in the SWIR spectrum (Komba et al., 2021). Meanwhile, for the damaged or lost vegetation, the opposite applies. Burned areas caused a decrease in NBR values (de Carvalho Jr. et al., 2015).

Burn severity estimation was based on the difference between pre- and post-fire NBR values. The bitemporal index dNBR is preferred for fire severity studies because it describes the degree of ecosystem change and improves the detection of changes in vegetation cover (Fraser et al., 2017; Castillo et al., 2020). Sirin and Medvedeva (2022) also revealed that the difference in pre- and post-fire index values can provide better accuracy than using index values only for the post-fire period. Training data samples were extracted to obtain the mean and standard deviation from pixels of pre-fire NBR, post-fire NBR, and dNBR (Table 1).

The post-fire NBR value decreased from the pre-fire NBR value, indicating the dNBR, a critical metric for assessing fire severity (Athanasakis et al., 2017). A higher dNBR value indicates a higher likelihood of a pixel being a burned area, while a lower dNBR value suggests it is likely unburned (Afira & Wijayanto, 2022). As presented in Table 1, the dNBR values for 2014 and 2018–2019 were significantly lower than those for 2020, indicating that the 2020 fire resulted in the most severe burning of peatland. Furthermore, we categorized the burn severity levels into low, moderate, and high (Figure 5).

Severe fire activity on peatlands results in the burning of deep peat layers and can last for several months (Flannigan et al., 2009). Based on Manaswini and Reddy (2015), the difference in severity depends on environmental factors. Previously, a study by Conard et al. (2002) stated that burn severity is potentially influenced by changing land use practices, fire management policies, or climate patterns. Therefore, it is crucial to understand peat fires to establish more effective control methods (Leng et al., 2019).

Carbon stock estimation Estimating the accumulated biomass in the forest ecosystem is essential for assessing the productivity of the forest (Vashum & Jayakumar, 2012), mainly after the fire events. The post-fire AGB representing this study's carbon stock showed contrasting values (Table 2). The post-fire AGB values indicate a clear trend: peatlands burned in 2014 stored 35.21 Mg C ha^{-1} after seven years, while those burned in 2018–2019 stored only 12.30 Mg C ha^{-1} after two years. The peatlands burned in 2020 exhibited the lowest carbon stock, with just 1.31 Mg C ha^{-1} after one year. These findings are consistent with other studies, which show that carbon stocks generally increase with time since the last fire. For instance, Dharmawan et al. (2013) reported carbon stocks of 26.13 Mg C ha^{-1} eight years

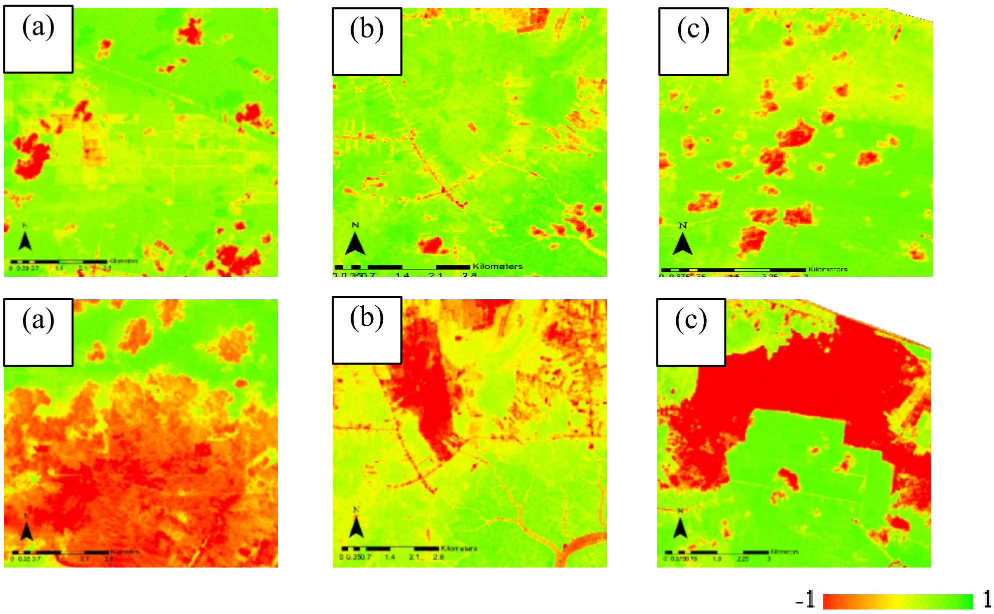

Figure 4 Changes between pre-fire (top) and post-fire (bottom) using the NBR index for (a) 2014, (b) 2018–2019, and (c) 2020 in Kepulauan Meranti Regency.

Table 1 Statistical summary of NBR indices used for burn severity estimation in Kepulauan Meranti Regency

Fire period	NBR pre		NBR post		dNBR	
	Mean	SD	Mean	SD	Mean	SD
2014	0.76	0.02	0.39	0.04	0.38	0.04
2018–2019	0.57	0.12	0.25	0.11	0.32	0.16
2020	0.70	0.02	0.01	0.09	0.69	0.09

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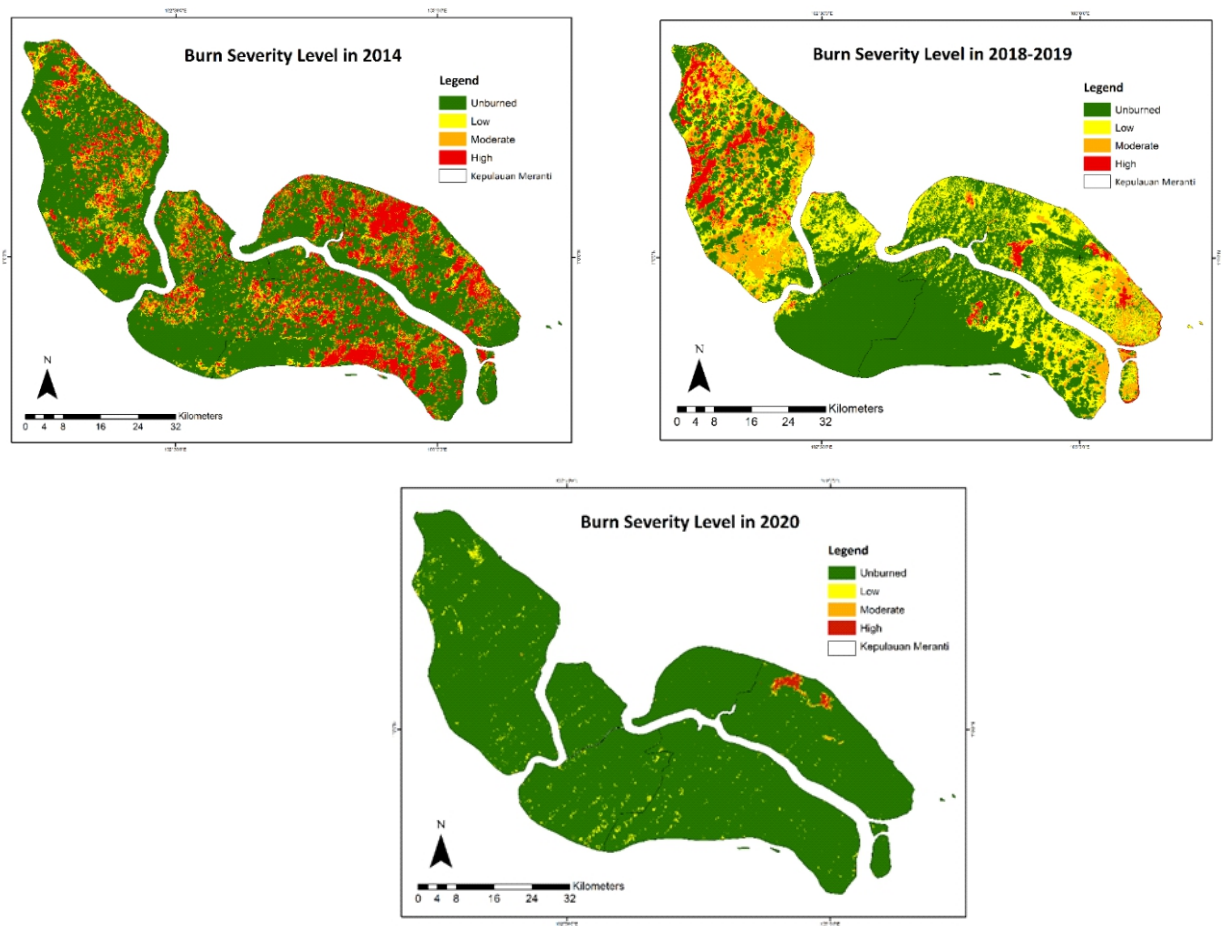

Figure 5 Burn severity levels for each fire event period in Kepulauan Meranti Regency.

Table 2 The value of above-ground biomass (AGB) and carbon stock after the fire in Kepulauan Meranti Regency

Fire period	Treatment	AGB (Mg ha^{-1})	Carbon stock (Mg ha^{-1})
2014	1 fire; 7 years after the last fire	74.917	35.211
2018–2019	2 fires; 2 years after the last fire	26.165	12.298
2020	1 fire; 1 year after the last fire	2.787	1.310

post-burning, while Krisnawati et al. (2021) found 12.70 Mg C ha^{-1} four years after burning and 103.40 Mg C ha^{-1} after 16 years without fire.

In this study, peatlands burned seven and two years prior had comparable above-ground carbon stocks, indicating stability over time. In contrast, the carbon stock in peatlands burned just one year prior was significantly lower, highlighting a stark difference. This finding suggests that even a short time difference can significantly affect carbon storage, with the one-year post-fire carbon stock being notably reduced compared to the two-year post-fire peatlands. The low carbon stock observed one year post-fire underscores how fire-related components influence carbon dynamics. Local factors, such as species composition, climate, disturbance levels, and other environmental conditions, likely influence these variations in carbon stock. Our analysis specifically focused on these fire-related components. Overall, peatlands burned in 2014 stored nearly three times more above-ground carbon than those burned in 2018–2019, while those burned in 2018–2019 stored almost ten times more above-ground carbon than those burned in 2020. Previous studies support that peat forests with longer intervals since the last fire store significantly more carbon. A study by Toriyama et al. (2014) revealed that the AGB of undisturbed peat swamp forests was around forty times greater than that of recently burned peatlands. Krisnawati et al. (2021) also found that primary peat forests could store up to 115.60 Mg C ha^{-1}, far exceeding the carbon stocks observed in this study (Table 2).

Moreover, non-woody vegetation dominates in the early stages of forest regeneration after three years without burning, as shown by Hoscilo et al. (2011). According to Sato et al. (2016), forest biomass has not fully recovered after eight to ten years of fire. It indicates the slow recovery of forest biomass, which explains why carbon stocks in recently burned peatlands remain low. The significant carbon loss

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from burned peatlands in 2020 (one year post-fire) highlights slow biomass recovery, resulting in much lower carbon stock than in other areas.

Effect of fires on above-ground carbon stock Initially, we transformed the response variable (carbon stock) using a natural logarithm (*ln*). However, the model violates the assumption of homoscedasticity. Hence, we back-transformed the response variable. We use variance increase factors (VIFs) to check the collinearity between variables. If the VIF ≥10, there are multiple relationships between variables (Uyanik & Guler, 2013), which can weaken the model (Nimon & Oswald, 2013). Our model shows the low VIF value for each variable, i.e., burn severity (1.48), fire recurrence (1.37), and last fire occurrence (1.26). The residuals appear normally distributed (p-value > 0.05), and the error variance appears homoscedastic (p-value > 0.05). Statistically, the model met all the requirements of classical assumptions (Figure 6).

A multiple regression analysis was performed to examine whether the predictor variables statistically affect the response variable (Table 3). The coefficient of the parameter indicates that carbon stock increases by 1% as the last fire occurrence increases by 3.48%, fire recurrence decreases by 5.77%, and the logarithmic natural form of burn severity decreases by 26.38%. Our model suggests that carbon stock has increased by 3.48% yearly since the last fire. Additionally, for every unit decrease in fire recurrence,

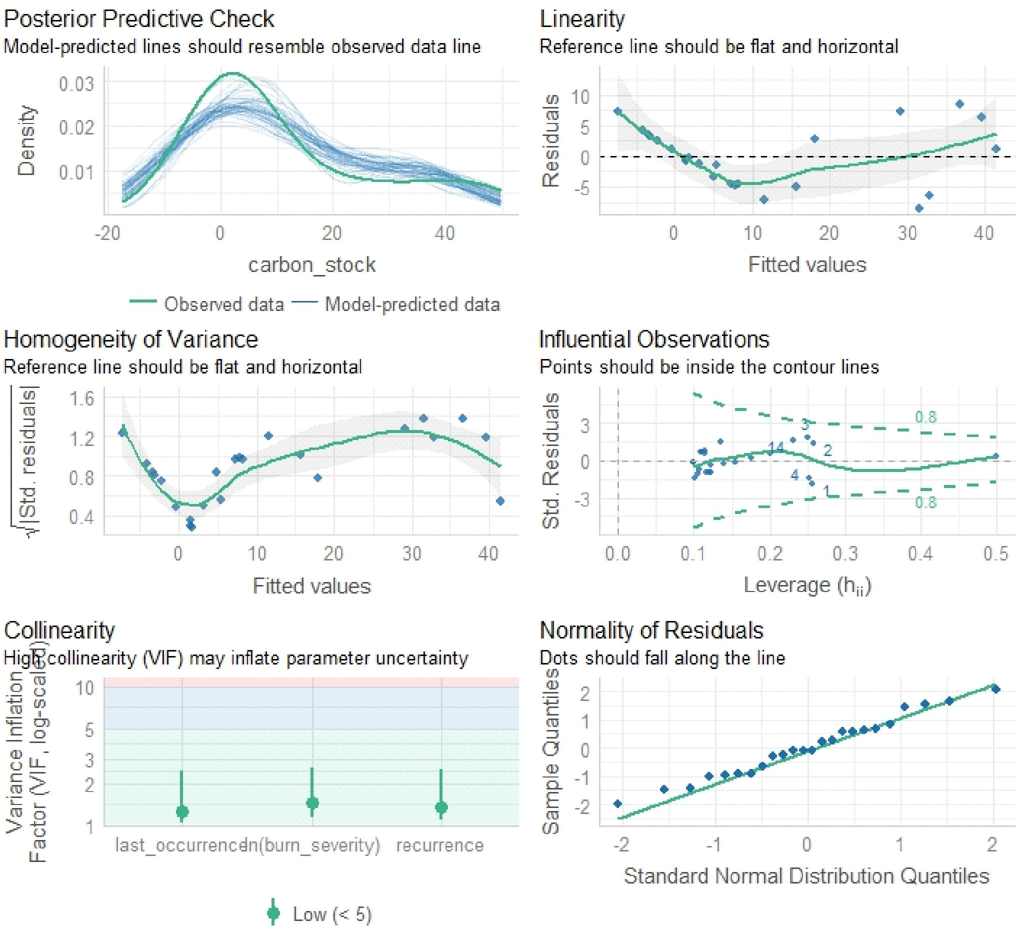

Figure 6 Results of classical assumption tests for the carbon stock model in burned peatlands.

Table 3 Multiple regression of carbon stock as a response to the last fire occurrence, fire recurrence, and a natural logarithm form of burn severity as predictors

Parameter		Coefficient	Std. error	p
-	B_0	-10.0595	3.6907	0.0130*
Ln burn severity[1]	B_1	-26.3806	2.9808	2.37e-08***
Fire recurrence	B_2	-5.7669	2.5256	0.0335*
Last fire occurrence	B_3	3.4786	0.5701	5.80e-06***

Note: [1]natural logarithm form of burn severity; [*]significance level in the range [0.01, 0.05); [***]significance level in the range [0, 0.001) carbon stock increases by 5.77%, and for every unit decrease in the natural logarithm of burn severity, carbon stock increases by a substantial 26.38%. These findings indicate that the time elapsed since the last fire and reductions in burn severity and fire recurrence have a significant positive impact on carbon stock (p-value < 0.001). This model has R^2 = 90.88% and *adjusted* R^2 = 89.51%. It indicates that the predictor variable in the model can predict 90.88% of the variance in carbon stock. If burn severity was not transformed using the natural logarithm, the model has a lower R^2 (80.93%) and *adjusted* R^2 (78.06%). This study found that simultaneously, burn severity, fire recurrence, and last fire occurrence significantly affect the carbon stock (p-value < 0.001). When examined individually, each predictor also significantly affects carbon stock, but with varying significance levels. Burn severity (p-value < 0.001) and last fire occurrence (p-value < 0.001) are more significant predictors than fire recurrence (p-value < 0.05).

Nonetheless, Lin et al. (2013) stated no practical rules for adjusting significance levels. The differences in carbon stocks across various fire periods reveal the significant influence of fire-related components. The last fire occurrence and burn severity emerged as the most critical factors affecting the above-ground carbon stock. Each fire period displayed distinct burn severity levels (Table 4), determined using thresholds based on the mean (μ) and standard deviation (σ) of NBRpost and dNBR values. Remarkably, even though the burned area in 2020 (one year post-fire) was smaller, the burn severity was the highest, leading to an almost tenfold decrease in above-ground carbon stock compared to the peatlands that repeatedly burned in 2018–2019 (two years post-fire). This sharp decline shows that while the time since the last fire is crucial for the carbon stock recovery process, burn severity can drastically alter the recovery process, even quickly. High burn severity can slow down biomass recovery, resulting in significantly lower carbon stocks than in areas with lower burn severity.

Carbon stock reduction in a once heavily burned forest is close to the twice burned forest (Martins et al., 2012). These recurring fires may not contribute to the damage or loss of biomass from subsequent fires (Balch et al., 2011). There may be a substantial delay in the transition of standing dead trees to surface fuel stocks (Balch et al., 2008). Cochrane and Laurance (2002) mentioned that the remaining trees would continue to die for two or more years after the initial fire. Thus, subsequent fires are considered less significant than the initial, possibly due to the extremely short intervals between two recurring fires that resulted in insufficient fuel (biomass).

Although fire recurrence is less important in this study, Numata et al. (2011) found that the effects of burn severity become more significant in forests that have burned repeatedly. Martins et al. (2012) indicated that burn severity reduced the dynamics of biomass recovery. Moreover, Turetsky et al. (2015) revealed that burn severity that leads to deeper burning in peatlands causes carbon loss. Regarding the last fire occurrence, recently and repeatedly burned peat forest is either dominated by young vegetation regrowth or bare ground, with a low density of dead trees remaining from previous fires (Konecny et al., 2016; Siahaan et al., 2020). An increase in pioneer individuals and species through natural rejuvenation occurred two years after the fires (Agus et al., 2019). More time is required before the vegetation can rebuild a sufficient amount of biomass and fuel load to sustain a new fire (Hoscilo et al., 2011).

We also conducted a correlation analysis to determine the relationship between each predictor variable and the response variable (carbon stock). The correlation coefficients (r) of each predictor variable for carbon stock are, respectively, burn severity (r = -0.77), fire recurrence (r = 0.04), and last fire occurrence (r = 0.72). Dormann et al. (2013) mention that a correlated variable with $|r|$ >0.7 is most commonly applied in various fields of science and is considered strong. There is a correlation between forest fires and biomass loss, which has implications for carbon stock (Sannigrahi et al., 2020).

The burn severity in this study strongly correlates with burned peatland above-ground carbon stock. We visualize the relationship between burn severity as the continuous predictor variable and carbon stock as the response variable in a graph (Figure 7). It showed that the direction of the line is negative, indicating that higher burn severity is associated with lower carbon stock and vice versa. Notably, the most severely burned peatlands in 2020 (one year post-fire) had an above-ground carbon stock nearly ten times lower than that

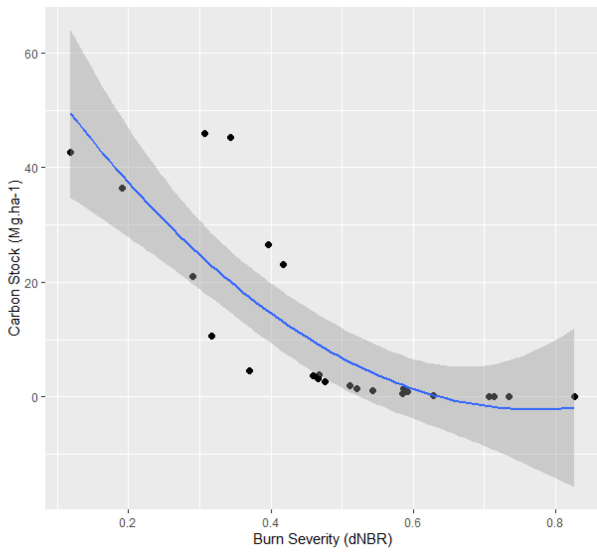

Figure 7 Relationship between burn severity and carbon stock in burned peatlands.

Table 4 Burn severity levels determined by thresholds from each fire period in Kepulauan Meranti Regency

Fire period	Burn severity level		
	Low	Moderate	High
2014	0.29 ≤ dNBR < 0.33	0.33 ≤ dNBR < 0.38	dNBR ≥ 0.38
2018–2019	0.01 ≤ dNBR < 0.16	0.16 ≤ dNBR < 0.32	dNBR ≥ 0.32
2020	0.51 ≤ dNBR < 0.60	0.60 ≤ dNBR < 0.69	dNBR ≥ 0.69

of peatlands burned recurrently in 2018–2019 (two years post-fire), despite the only one-year difference between these fire periods. In addition, the last fire occurrence also strongly correlates with carbon stock, and the direction is positive. Peatlands that have been unburned for longer periods show a marked increase in carbon stock. Specifically, peatlands that have not burned for seven years (last burned in 2014) have approximately three times higher carbon stock than those that experienced fire only two years prior (which last burned in the recurrent fires of 2018–2019). It indicates a substantial carbon accumulation over time in areas with longer fire-free intervals. Meanwhile, fire recurrence in this study has a weak positive correlation with carbon stock (close to 0), indicating that it has a minimal impact on the findings of this research.

Conclusion

The 2014 burned peatlands stored the highest carbon, while the burned peatlands in 2020 had the lowest carbon stock. This study revealed that all predictor variables (burn severity, fire recurrence, and last fire occurrence) significantly affect the carbon stock. Burn severity, in particular, was found to have a substantial impact, with higher severity leading to significantly lower carbon stocks, even though it has a smaller burned area. It also had the strongest correlation among the predictors. The last fire occurrence significantly affected peatland carbon stock and strongly correlated with carbon stock, but burn severity can influence the recovery process. Among other predictors, fire recurrence had the least significant effect and the weakest correlation with above-ground carbon stock. This limited impact may be attributed to the short intervals between the fire events in 2018 and 2019, which likely reduced the time for notable ecosystem recovery and carbon accumulation.

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