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Full Length Research Article

Spatial Model of Carbon Stocks in Special Purpose Forest Area (KHDTK) Mungku Baru, Central Kalimantan Province, Indonesia

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ABSTRACT

This study aims to estimate vegetation biomass and spatial distribution of carbon stocks in Special Purpose Forest Area (KHDTK) Mungku Baru, Palangka Raya City, Central Kalimantan Province, Indonesia. KHDTK Mungku Baru is a former logging area from the 1970s, which has undergone secondary succession and is dominated by pole and sapling levels. The approach used in this study involves remote sensing technology and field inventory data, which allows carbon stock calculations to be carried out quickly and accurately over a very large area. A linear regression algorithm was used to obtain a spatial model of carbon stocks using NDVI obtained from Landsat as a predictor. The developed model shows positive correlation results with an R^2 value of 0.70; an Adjusted R^2 value of 0.69 with a p-level < 0.05, and RMSE of 42 tons/ha. This carbon stock mapping results serve as a basis for formulating various management plans for KHDTK Mungku Baru regarding ecological, social, and economic aspects.

1. Introduction

Global warming, caused by increased greenhouse gas emissions due to human activity, significantly impacts ecosystems and the environment. Deforestation and conversion of forest functions will affect global warming. Deforestation has caused carbon emissions that accelerate greenhouse gas concentration in the atmosphere. Land use changes from forests to agricultural land produce CO_2 emissions (Barati et al. 2023; Jin et al. 2019), affecting ecosystems' ability to store carbon (Pan et al. 2023). Vegetation is one of the important components of natural carbon dioxide absorbers on land (Peng et al. 2023; Zhang et al. 2013), and can potentially affect land surface temperature. The loss of vegetation has a major impact on increasing land surface temperatures (Alkama et al. 2022; Ba et al. 2024; Li et al. 2023; Wolff et al. 2018). The negative impact of climate change on forestry is the potential for increased forest fires, pest outbreaks and hydro-geomorphic changes (Altman et al. 2024; Vacek et al. 2023).

The Indonesian Government's efforts to address the issue of climate change, for example, focusing on risk reduction and disaster mitigation (Sarjito 2023) through Law Number 7 of 2021 by imposing a tax on carbon emissions (Olpah et al. 2023), aims to reduce carbon emissions and promote sustainable economic development (Diaz et al. 2023). One of the Indonesian Government's efforts to achieve the FOLU Net Sink 2030 initiative in the forestry sector is to increase carbon absorption through sustainable forest management (Simorangkir et al. 2024) and optimize unproductive land. Changing the management of Special Purpose Forest Area can be an alternative to reducing the negative impact of non-management of forests.

Special purpose forest area (KHDTK) located in Mungku Baru Village, Rakumpit District, Palangka Raya City, Central Kalimantan, is known as KHDTK Mungku Baru, has been demarcated forest boundary delineation where in 2022. The next stage is a forest inventory to determine the potential of forest resources. Remote sensing technology allows forest inventory to be carried out efficiently, accurately and economically because land cover data can be monitored via satellite imagery. Remote sensing technology is used to measure the productivity of terrestrial ecosystems and biodiversity (Sannigrahi et al. 2020) and calculate carbon stocks and spatial distribution of biomass in forests (Shen et al. 2020; Zimbres et al. 2021).

The study aimed to ascertain the spatial distribution of carbon stock in the KHDTK Mungku Baru area. The results of this study allow area managers to identify areas with significant potential for carbon emission reduction and regions that have been degraded, which will become the basis for developing the KHDTK Mungku Baru Long-Term Management Plan.

2. Materials and Methods

2.1. Study Area

This research was conducted in KHDTK Mungku Baru, which covers 4,970.3 ha and functions as a forest production area (**Fig. 1**). It is one of the 26 KHDTKs in Indonesia managed by university. The area was a former logging area in the 1970s that underwent secondary succession. The pioneer tree type dominates the area.

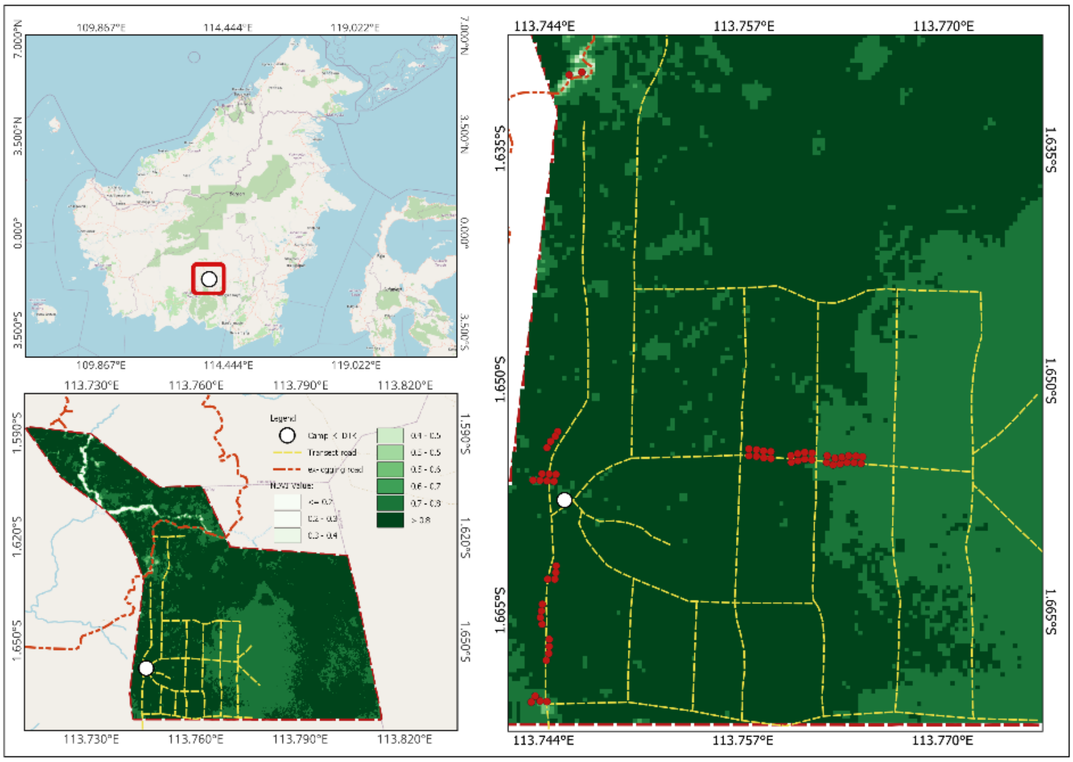

Fig. 1. Study area, NDVI Value and sampling plots.

2.2. Vegetation Inventory

Vegetation inventory was carried out on 57 plots following transect roads. The plots measured 30 m × 30 m for tree and woody necromass levels, 10 m × 10 m for pole levels, 5 m × 5 m for sapling levels and 2 m × 2 m for seedling and understory levels.

The plots are square with dimensions of 30 m × 30 m according to the resolution of 1 pixel of Landsat-9 satellite imagery. The observation plots were determined using stratified purposive sampling, considering the NDVI class in the KHDTK Mungku Baru. NDVI value 0.6–0.7 covers an area of 39.02 ha or 0.8% of the KHDTK area; class 0.7–0.8 covers an area of 2,695.55 ha (54.3%); class 0.8–0.9 covers an area 2,162.29 ha (43.5%); this is the basis for determining the sampling plot.

Quantitative parameters include tree type, diameter at breast height (1.3 m from the base of the tree), and height free of branches. The diameter at breast height is measured with the help of a phiband, the height of the free branches is measured using a clinometer, identification of tree species with the help of local communities and the Biodiversity, Forest Structure and Conservation Importance of the Mungku Baru Education Forest report.

2.3. Carbon Stock Estimation

Vegetation carbon stock data estimation is based on biomass and organic matter content in aboveground biomass, belowground biomass, litter, and dead wood. Calculating aboveground biomass, belowground biomass, litter, dead trees, and dead wood refers to (BSN 2019). Weight tree type refers to the Global Wood Density Database (Zanne et al. 2009) and Wood Densities of Tropical Tree Species (Reyes et al. 1992).

Calculation of carbon vegetation biomass of saplings, poles and trees using the formula:

$$C_{veg} = \frac{1}{4}\pi \; x \; dbh^2 \; x \; t \; x \; f \; x \; BJ \; x \; BEF \; x \; \%C \; organic \qquad (1)$$

where carbon vegetation biomass (*Cveg*) is calculated using the diameter at breast height (*dbh*), tree height without branches (*t*), tree shape factor (*f*), wood density (*BJ*), biomass expansion factor (*BEF*), and a constant organic carbon percentage of 0.47% (*%C organic*).

The seedling and understorey levels were measured destructively by cutting all parts of the vegetation above the ground surface from small plots measuring 0.5 x 0.5 m, calculating the total wet weight, and oven at 70–105° C until constant. Calculation of seedling and understorey carbon using the formula:

$$C_{tb} = \left(\frac{Bks \; x \; Bbt}{Bbs}\right) x \; \%C \; organic \qquad (2)$$

where the seedling and understorey carbon (C_{bt}), units are kg; (*Bks*) is the dry weight of the sample; (*Bbt*) is the total wet weight, and (*Bbs*) is the wet weight of the sample.

Calculation of vegetation root carbon using the formula:

$$C_{bbp} = NAP \; x \; Bap \; x \; \%C \; organic \qquad (3)$$

where to calculate the total belowground biomass carbon stock (*Cbbp*) is given by multiplying the aboveground biomass (*Bap*) by the shoot root ratio value (*NAP*) and incorporating the organic carbon percentage of 0.47%. *Bap* is a term for aboveground biomass, which consists of biomass of vegetation at the sapling, pole, and tree level, as well as biomass from seedlings and understory plants.

Litter necromass, taken from a 0.5 x 0.5 m plot that is the same as the observation plot for seedlings and understorey, calculate the total wet weight, take a sample of ± 300 gr, oven at a temperature of 70–105° C until constant. The equation for calculating litter carbon refers to equation 2.

Woody necromass is divided into dead trees and dead wood. Calculation of dead trees with the formula:

$$C_{dead\ tree} = \frac{1}{4}\pi\ x\ dbh^2\ x\ t\ x\ f\ x\ BJ\ x\ \%C\ organic \quad (4)$$

$$C_{dead\ wood} = \frac{1}{4}\pi\left(\frac{D_1+D_2}{2x100}\right)^2\ x\ p\ x\ BJ\ x\ \%C\ organic \quad (5)$$

where D1 is the diameter of the base of the dead wood and D2 is the diameter of the tip of the dead wood.

The calculation of total carbon stocks is a modification of (BSN 2019), with units of kg/plots, to make it easier to find the relationship between NDVI values and total carbon stocks in each plot. Assuming the plot size is the same as the resolution of 1 pixel of Landsat 9 imagery:

$$C_n = \frac{C_x}{1000}\frac{10000}{l_{plot}} \quad (6)$$

where *Cn* is the carbon content/plot in each carbon pool, units ton/ha; *Cx* is the carbon content in each carbon pool in each plot, units kg; *lplot* is the plot area in each carbon pool, units m^2.

2.4. Satellite Data Processing

Landsat-9 imagery can be accessed through the United States Geological Survey (USGS) selected in the KHDTK Mungku Baru region. The chosen data is from September 2023, with a cloud cover of less than 5%. It is processed into vegetation index data using the Normalized Difference Vegetation Index (NDVI), utilizing the infrared and near-infrared channels on the previously corrected image.

Radiometric correction is a process of correcting errors caused by optical system malfunctions, atmospheric interference of electromagnetic radiation energy, and errors resulting from the impact of solar elevation angles (Hussein 2022). Atmospheric correction aims to reduce the reflectance of objects after the normalization of lighting conditions and the removal of atmospheric effects.

This index can also be used to measure the health level of trees, the stress level of trees, canopy density, and tree carbon reserves (Govaerts and Verhulst 2010), as well as assess regional and global environmental, ecological conditions (Hossain and Li 2021; Lin et al. 2022). Based on (Omar and Kawamukai 2021), the NDVI value is calculated using the Equation:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (7)$$

where *NIR* is Near Infra Red Channel and *RED* is Red Channel.

2.5. Spatial Carbon Stock Model

Carbon stock estimation is done by creating a regression equation between NDVI and carbon stock estimation in the field. The carbon potential estimation from the developed model is then compared with the carbon potential information from each test plot. Because it uses 1 variable, statistical parameters such as R2, adjusted R2, p-level and RMSE are used to assess the strength of the relationship. The regression results are then used as a formula in the raster calculator feature of the QGIS program to predict carbon stock based on NDVI.

3. Results and Discussion

3.1. Diversity of Species, Biomass, and Carbon Stock

The survey results obtained 1,469 vegetation from the level of saplings, poles and trees, with 44 families and 111 species identified. Measurement of species diversity of a community using the Shannon Wiener index (H'), species evenness using the Evenness Index (E), and the Margalef index to measure species richness. Measurement of the Shannon-wiener Index for the sapling, pole and tree levels shows that species diversity in KHDTK Mungku Baru is quite high (**Table 1**).

Table 1. Species diversity in KHDTK Mungku Baru

Level	Species diversity		
	Shannon-wiener	Evenness	Margalef
Sapling	3.61	0.85	11.32
Poles	3.63	0.86	10.86
Tree	3.44	0.83	9.99

Meanwhile, species evenness indicates that the distribution among species is fairly balanced within the community. The species richness value suggests that the plant community in KHDTK Mungku Baru has high species richness, indicating that the habitat is in good condition. The total number of individuals found at the sapling level of all species was 485 individuals, the pole level was 436 individuals, and the tree level was 548 individuals. The types of plants with the highest number of individuals at the level of saplings, poles and trees are presented in **Table 2**.

Table 2. Plants with the highest number of individuals

Level	Species	Quantity	H'
Sapling	*Eugenia* sp.	72	0.28
	Calophyllum sp.	34	0.19
	Calophyllum pulcherrimum	31	0.18
	Palaquium sp.	29	0.17
Pole	*Eugenia* sp.	61	0.27
	Calophyllum pulcherrimum	36	0.21
	Calophyllum sp.	35	0.20
	Tristaniopsis obovata	23	0.15
Tree	*Combretocarpus rotundatus*	56	0.23
	Eugenia sp.	47	0.21
	Calophyllum sp.	37	0.18
	Shorea uliginosa	37	0.18

The diversity of trees and complex stratification causes more solar radiation that can be converted into chemical energy, affecting plants' metabolism. The result of the metabolism is the growth and addition of biomass. The existence of vegetation will affect the high levels of carbon storage on land. Biomass will continue to increase as photosynthesis occurs, as vegetation captures carbon from the air and turns it into organic matter. Plant species' static spatial structure and diversity will affect carbon storage in ecosystems through biomass and soil carbon (Yang et al. 2024). The average tree level contributes 40.76% of aboveground biomass carbon stocks, 37.93% of pole levels, 15.94% of saplings and 5.37% of understory plants (**Fig. 2**).

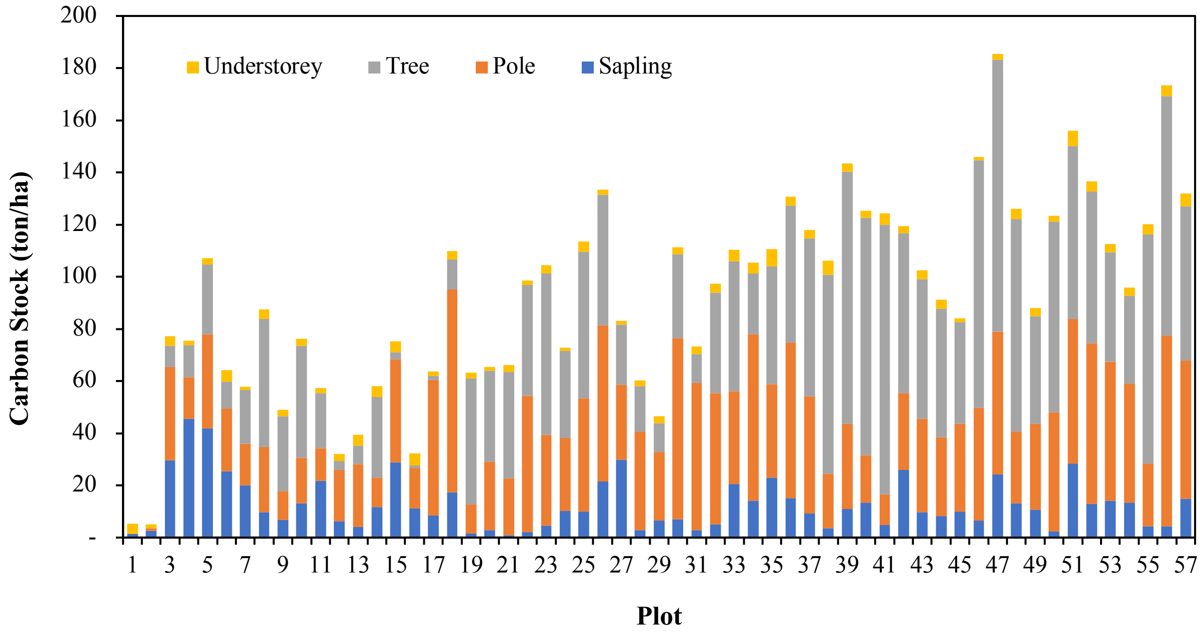

Fig. 2. Aboveground biomass carbon stocks (tons/ha).

The larger the diameter and height of the tree will positively impact the amount of aboveground carbon stocks. Tree-level plants, especially those with wide crowns, will influence the growth of pole levels, saplings, seedlings, and other understory plants. Solar radiation will easily reach the bottom of the forest if the vegetation that makes up it is trees with a narrow canopy, thereby helping in photosynthesis and preserving the understorey (Dormann et al. 2020). The existence of understory plants, in addition to storing carbon, also protects the soil from erosion and creates a soil microclimate (Wardhani et al. 2020). The more complex the vegetation structure, the greater the impact on the forest's carbon stock.

Aboveground biomass contributes for the largest carbon compared to belowground biomass, litter and woody necromasses, which amounts to 79.97%, 13.91%, 3.20%, and 2.93% of the total carbon stock. The presence of litter, dead trees and dead wood also affects the carbon stock in the landscape. Even though the amount is small, dead material shows that carbon is still stored and not degraded directly in nature.

3.2. NDVI Correlation with Carbon Stock

NDVI values indicate vegetation density and health through satellite image analysis and have a positive correlation value with vegetation in forests, as well as detecting stress due to drought, tree death and other environmental impacts (Buras et al. 2021). Estimating carbon stock by utilizing NDVI and establishing regression equations between NDVI measurements and field-based carbon stock calculations. Field-based linear regression analysis of carbon stock and selected vegetation indices is shown in **Table 3**. The results of the NDVI and carbon stock regression are shown in **Table 4**.

Table 3. Linear regression between NDVI and carbon stock

Regression Statistics	
Multiple R	0.84
R Square	0.70
Adjusted R Square	0.69
Standard Error	19.81
RMSE	42

Table 4. Linear regression result between NDVI and carbon stock

	Coeff.	**SE**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**	**Lower 95.0%**	**Upper 95.0%**
Intercept	-509.54	70.35	-7.24	2.63	-652.68	-366.41	-652.68	-366.41
NDVI	787.16	89.33	8.81	3.48	605.42	968.90	605.42	968.90

Notes: Coeff = Coefficients, SE = standard error.

The resulting regression equation is y = 787.16x – 509.54. The model showed a strong fit to the data, as evidenced by the R^2 value of 0.70 and the Adjusted R^2 value of 0.69, which account for the proportion of variability explained by the independent variables when adjusting for the number of predictors. In addition, the model was statistically significant with a p-value of less than 0.05, indicating that the observed relationships are unlikely to occur due to random chance. The Root Mean Square Error (RMSE) of 42 tonnes/ha reflects the average deviation between predicted and observed values, which measures the model's predictive accuracy. Visually, the relationship is shown in **Fig. 3**.

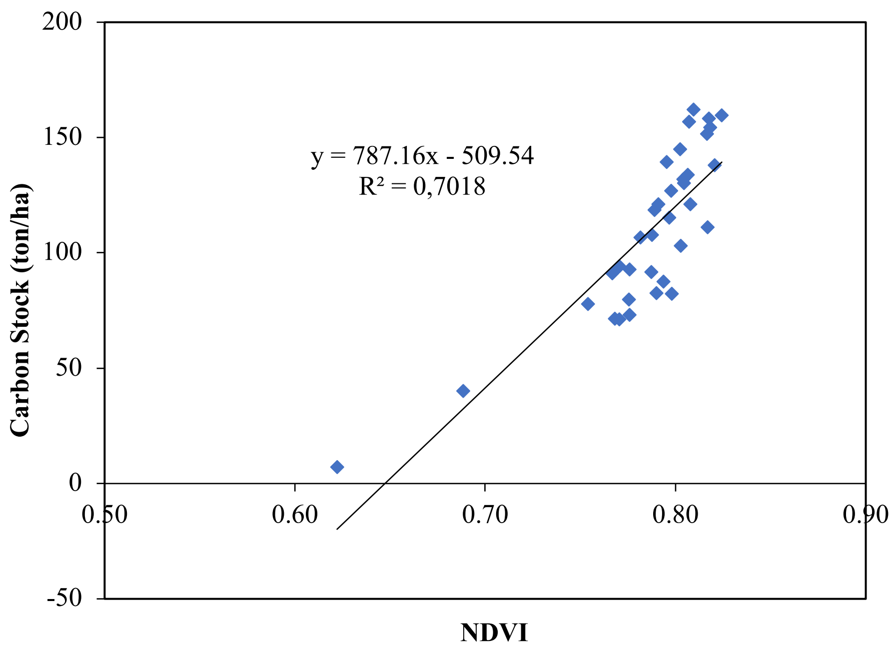

Fig. 3. Linear regression of the relationship between NDVI and carbon stock.

The coefficient of determination value is 0.7018. This means the NDVI value can explain 70.18% of the total carbon, while other variables influence the rest. This indicates a strong relationship between NDVI values, total carbon biomass, and necromass. The determination coefficient values are strong if greater than 0.67, moderate if 0.33–0.67, and weak if 0.19–0.33

(Chin and Marcoulides 1998). However, the equation has a drawback in this model, namely, if the NDVI value is below 0.65, the calculation results will produce a negative value, which may be ecologically or physically irrelevant or uninterpretable. However, data collection was carried out in areas with NDVI values above 0.7, so this model is still suitable for describing conditions in the area.

3.3. Spatial Carbon Stock Distribution in KHDTK Mungku Baru

The resulting regression equation used to predict the distribution of carbon stocks in the KHDTK Mungku Baru is spatially presented in **Fig. 4**.

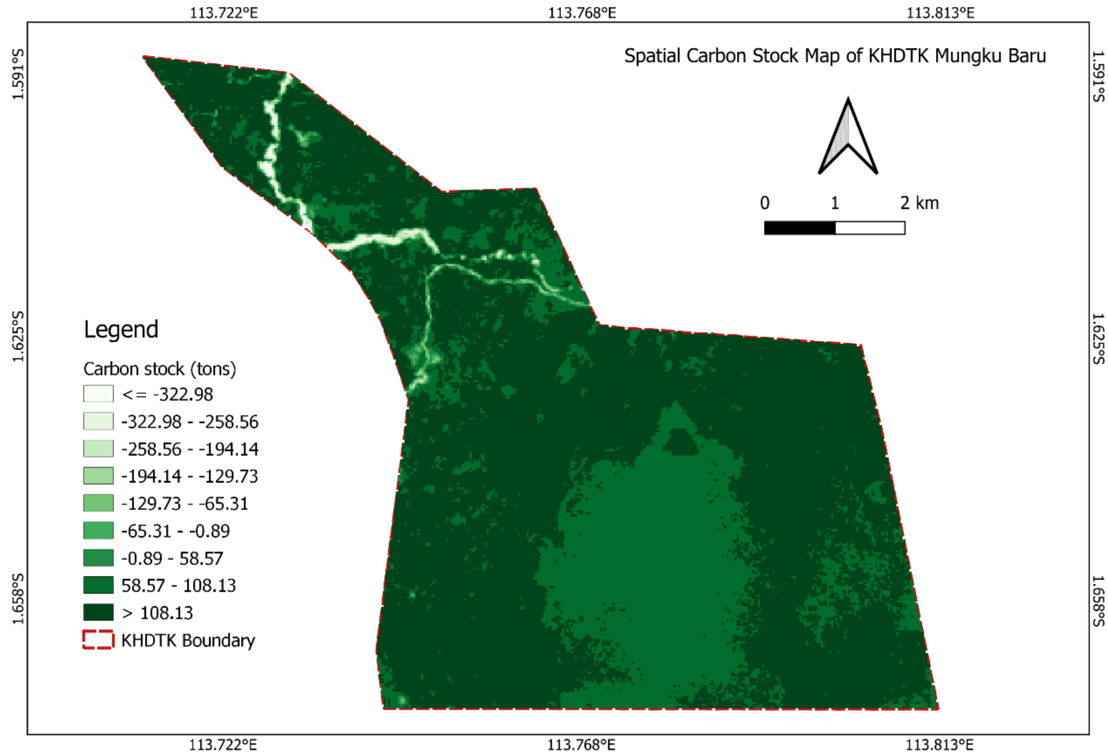

Fig 4. Distribution of carbon reserves in KHDTK Mungku Baru (tons/ha).

3.4. Discussion

The diversity of vegetation species found affects the amount of carbon stock. Carbon stock measurement in this study is based on the diameter at breast high, branch-free height and wood density. Larger diameter and higher wood density will increase carbon stocks. Larger diameters and higher wood density will increase carbon stocks. Tree height substantially impacts greater carbon storage in aboveground biomass than poles, saplings and lower plants. This illustrates that larger tree diameters are associated with increased carbon storage capacity in vegetation. Trees with large diameters have a crucial function in adding to the carbon stocks in the forest (Enkossa et al. 2023; Hot Marnaek et al. 2024; Joshi et al. 2024; Mensah et al. 2020; Ng et al. 2021). Furthermore, the carbon store is influenced by wood density (Borges et al. 2021; Khan et al. 2020; Thakur et al. 2024). As the forest ages, the amount of plant material on the surface will increase, and there will be variations in how different tree species, such as softwood and hardwood (Aryal et al. 2024).

Necromass is a substantial source of organic matter in tropical rainforests, renowned for their better soil quality. Slow decomposition processes and erosion caused by rainfall affect the presence of materials on the soil surface. The level of biodiversity in planted tree species has a significant impact on the rate of decomposition (Getaneh et al. 2022). Greater tree species diversity results in increased decomposition rates. The decomposition rate will be accelerated by increased litter production and soil surface temperatures (Chimdessa 2023).

The Mungku Baru KHDTK is dominated by pole and sapling levels, characterized by the highest species diversity index at the pole and sapling levels compared to the tree level. This indicates that the natural regeneration process is going well, leading to the potential for increased carbon storage in the KHDTK over time without significant disturbance. The natural regeneration process of an area is influenced by one of the availability of dispersal agents, for example *Combretocarpus rotundatus,* which is spread by wind (Blackham et al. 2014). *Eugenia* sp, *C. rotundatus*, and *Shorea uliginosa* are pioneer plants growing quickly in open conditions (Rochmayanto et al. 2021; Suwito et al. 2021).

Pioneer plants, including tree and shrub species, play a role in stabilizing degraded soil conditions (Castilla et al. 2016), facilitating the transition from deforestation to secondary forest ecosystems (Nursanti et al. 2022). The presence of pioneer plants will accelerate the secondary succession process by building land cover, changing the surrounding microclimate and providing microhabitats for other plants. The impact will increase biodiversity, increase carbon conservation, and ecosystem sustainability. (Smith et al. 2022).

KHDTK Mungku Baru has a dominant NDVI value of 0.7 – 0.9, indicating dense and healthy vegetation conditions. High NDVI values indicate a higher level of photosynthesis, so much carbon is bound to plants and indicates a large biomass potential. Large biomass will increase the value of carbon reserves, helping to reduce the concentration of CO_2 in the atmosphere. NDVI can be used to determine land coverage (Gandhi et al. 2015) and estimate biomass (Wang et al. 2016; Wani et al. 2021), and can predict carbon reserves in managed forest ecosystems (Chinembiri et al. 2023).

Carbon stock measurements will be more precise if carried out directly in the field because this method can accurately capture data. However, implementing carbon stock inventory often faces several obstacles, such as the large area to be measured, high operational costs, and the need for significant human resources. To overcome these challenges, using satellite imagery can be an effective solution, allowing for large-scale data collection that is more efficient and resource-saving. A combined approach between field inventory and vegetation indices (NDVI, SAVI, and ARVI) was used to spatially model aboveground biomass and carbon stocks of different land uses (Bordoloi et al. 2022). NDVI is one of the most important indicators used to detect vegetation cover in various periods using remote sensing. In addition, NDVI is used to assess the ecological conditions of the environment regionally and globally (Hossain and Li 2021; Lin et al. 2022).

The resulting regression equation is $y = 787.16x – 509.54$ with an R^2 value of 0.70, while the Adjusted R^2 value is 0.69 with a p-level of <0,05 and an RMSE of 42 tons/ha. There is a strong correlation between carbon reserves and NDVI levels, meaning that higher NDVI values indicate larger carbon reserves. A geographic model map depicting the distribution of carbon stocks can assist managers in formulating their forthcoming management strategy for environmental, social, and economic sustainability. The manager of KHDTK Mungku Baru must establish a system for managing blocks and plots to facilitate the planning and organization of various management activities. These activities include rehabilitating areas with low NDVI values by utilizing natural resources to minimize operational expenses and enhance species diversity, utilizing Non-Timber Forest Products (NTFPs) and environmental services to boost community income in forested areas, and carrying out forest protection and conservation initiatives.

4. Conclusions

This study successfully developed a spatial model of carbon stocks in the KHDTK Mungku Baru area, providing a detailed understanding of the spatial distribution of carbon stocks within the region. The findings highlight areas with significant potential for carbon emission reduction and degraded areas requiring rehabilitation. These insights are a critical foundation for informed decision-making and formulating the KHDTK Mungku Baru Long-Term Management Plan, enabling sustainable forest management practices and supporting conservation and climate change mitigation efforts.

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