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Estimating carbon storage using remote sensing in the Selo Resort forest area of Mount Merbabu National Park, Central Java, Indonesia

MUHAMMAD NUR SULTON[1], NUR ROHMAYANI ANGGELIKA PUTRI[1], RACHEL SANISCARA NUGRAHENI[1], RATIH NUR AFIFAH[1], RIZKY NUR FADILAH[1], MUHAMMAD INDRAWAN[1], LIA KUSUMANINGRUM[1], SUTARNO[2], SUNARTO[1], SUGIYARTO[2], PRAKASH PRADHAN[3], AHMAD DWI SETYAWAN[1,4,♥]

[1]Department of Environmental Sciences, Faculty of Mathematics and Natural Sciences, Universitas Sebelas Maret. Jl. Ir. Sutami 36A, Surakarta 57126, Central Java, Indonesia. Tel./fax.: +62-271-663375, ♥email: volatileoils@gmail.com

[2]Department of Biology, Faculty of Mathematics and Natural Sciences, Universitas Sebelas Maret. Jl. Ir. Sutami 36A, Surakarta 57126, Central Java, Indonesia

[3]West Bengal Biodiversity Board, Department of Environment, Government of West Bengal. Salt Lake, Sector-III, FD415A, Poura Bhawan, 4th Floor, Kolkata, West Bengal, India

[4]Biodiversity Research Group, Universitas Sebelas Maret. Jl. Ir. Sutami 36A, Surakarta 57126, Central Java, Indonesia

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Abstract. *Sulton MN, Putri NRA, Nugraheni RS, Afifah RN, Fadilah RN, Indrawan M, Kusumaningrum L, Sutarno, Sunarto, Sugiyarto, Pradhan P, Setyawan AD. 2023. Estimating carbon storage using remote sensing in the Selo Resort forest area of Mount Merbabu National Park, Central Java, Indonesia. Biodiversitas 24: 6264-6270.* This study is of paramount importance for long-term climate change mitigation efforts, as it aims to estimate carbon storage and assess land cover density in Selo Resort forest area of Mount Merbabu National Park (MMbNP), Central Java, Indonesia, utilizing remote sensing techniques. Sentinel 2A satellite imagery, acquired on May 28, 2023, serves as the foundational dataset for this research. Employing ArcGIS 10.5, the satellite imagery was processed to derive the Normalized Difference Vegetation Index (NDVI), a critical parameter in this analysis. The NDVI values were subsequently employed to categorize land cover density, leading to the classification of land into five distinct classes: non-vegetation, shrubs, low density, medium density, and high density. This classification process enabled the determination of land cover density. The calculated values for each density class, namely low, medium, and high-density land cover, revealed substantial carbon storage potentials: 12,357.99 tons C, 92,871.04 tons C, and 73,542.06 tons C, respectively. Moreover, the computed areas for low, medium, and high-density cover were 202.59 ha, 364.93 ha, and 348.26 ha, respectively. This study underscores the need for ongoing monitoring to detect changes in land cover and to implement afforestation initiatives in areas with low-density vegetation. Such efforts are crucial for the preservation of land cover and the associated carbon storage benefits, thereby contributing to broader climate change mitigation strategies.

Keywords: Carbon absorption, NDVI, *Pinus merkusii*, Sentinel-2A, vegetation density

INTRODUCTION

Forests play an important role in both absorbing carbon dioxide (CO_2) from the atmosphere and providing habitat for diverse ecosystems (Mantymaa et al. 2023). Forests in Indonesia, often referred to as world's ‘lungs’, are primary sources of oxygen, vital for sustaining life (Shafitri et al. 2018). Global, forest ecosystems are estimated to absorb more than 300 billion tons of CO_2 emissions annually, while deforestation releases around 3 billion tons of CO_2 into the atmosphere (Raihan et al. 2023). Forests serve as significant carbon reservoirs, effectively capturing excess carbon dioxide from the air and converting it into oxygen through the process of photosynthesis (Wahyuni and Suranto 2021). Moreover, tropical forests in Indonesia are renowned for their rich biodiversity and substantial carbon stores (Suryandari et al. 2019). Recognizing the foundational role of carbon stocks and their distribution patterns in supporting human survival and development, these factors serve as critical indicators of terrestrial ecosystem services. The biogeochemical processes that underlie energy flows and material cycles depend fundamentally on the carbon sequestration capacity of vegetation and soil (Sannigrahi et al. 2020).

The forest area of Mount Merbabu National Park is one of the extensively used forest regions in Indonesia (Marhaento 2016). This National Park falls within the administrative boundaries of three districts, i.e.: Boyolali District, Magelang District, and Semarang District, all located in Central Java Province, Indonesia (Fitriani et al. 2020). Mount Merbabu National Park has an area of around 5,725 hectares with rich biodiversity (Riadi et al. 2018). Within this national park, various hiking trails are available for climbers to explore, including the Wekas Route, the Suwanting Route, the Selo Route, the Central Route, and the Thekelan Route. The Selo Line in the Mount Merbabu National Park area was selected as the observation site due to its remarkable plant biodiversity compared to other areas, making it a region with high potential for carbon sequestration (Kusumaningrum and Izdihar 2022).

Carbon sequestration in terrestrial ecosystems plays a crucial role in climate regulation by absorbing Greenhouse Gases (GHG) and contributing to the global carbon balance

(Solomon et al. 2007). The process of Reducing Emissions from Deforestation and Forest Degradation (REDD+), which involves calculating emissions, relies on land cover change data derived from remote sensing. This data helps assess local emission and absorption factors, as well as forest damage due to activities like illegal logging and fires (Noor'an et al. 2015). The use of remote sensing methods for regular monitoring and land conditions across large areas is an economically viable approach (Chen et al. 2019). Notably, different land use and land cover types exhibit significant differences in their carbon sequestration capacity. These differences directly influence vegetation and soil distribution, ultimately impacting the carbon storage of terrestrial ecosystems (Zheng and Zheng 2023).

Forests, given their extensive spatial nature, are particularly suited for carbon storage calculations using remote sensing technology. This approach proves most effective in estimating biomass at the regional level, especially when field data is difficult to obtain (Anaya et al. 2009). Significant changes in carbon storage are observed in cropland, woodland, and abandoned land, primarily due to their high carbon density values. Conversion to other land use types with lower carbon density values leads to substantial carbon storage losses. In contrast, changes in grassland, water bodies, and built-up land result in relatively minor shifts in carbon storage (Xu et al. 2023). It is important to note that data and measurements of carbon storage in natural forests on the island of Java are limited (Noor'an et al. 2015). Therefore, this study aims to use remote sensing techniques to estimate carbon stocks and delineate areas based on vegetation density within Mount Merbabu National Park, Central Java Province, Indonesia.

MATERIALS AND METHODS

Study area

This study focused on estimating carbon storage in the Mount Merbabu National Park, specifically, in the Selo Resort area situated within the Selo Sub-district of Boyolali District, Central Java Province, Indonesia (Figure 1). The Mount Merbabu National Park encompasses an elevation range of 600-2,968 meters above sea level (m asl.), with the highest peak reaching 3,142 m asl. (Rahmayanti 2022). Geographically, Mount Merbabu National Park is located at coordinates 110°32' E-110° 48' E and 7°38' S-7°48' S. Topographically, the park predominantly consists of hills and mountains, with varying slopes, classified into three categories: class I (0-25%), class II (25-40%), and class III (>40%). This region experiences an annual rainfall of 2,000-3,000 mm, and maintains an average temperature of 17-30°C. The park has three distinct ecosystems: low mountain ecosystems (1,000-1,500 m asl.), upper mountains (1,500-2,400 m asl.), and sub-alpine mountains (> 2,400 m asl.) (Setiawan et al. 2018).

The study area of Selo Resort covers seven villages, namely Jrakah, Selo, Tarubatang, Samiran, Senden, Lencoh, and Jeruk. Most of the Selo Resort area is included in the rehabilitation zone with land cover mostly consisting of shrubs, grass, and part of it is a plantation forest ecosystem with a dominance of *Pinus merkusii* Jungh. & de Vriese, especially in the west of the Mount Merbabu National Park area (KLHK 2014). In addition, the area of Selo Resort with slope, such as Tarubatang, Tuk Pakis, Tuk Babon campsites, etc. are also included in the natural tourism and hiking trail utilization zones. Meanwhile, the hiking trail zone of the Selo Resort area also includes villages of Jeruk, Jrakah, Senden, and Tarubatang.

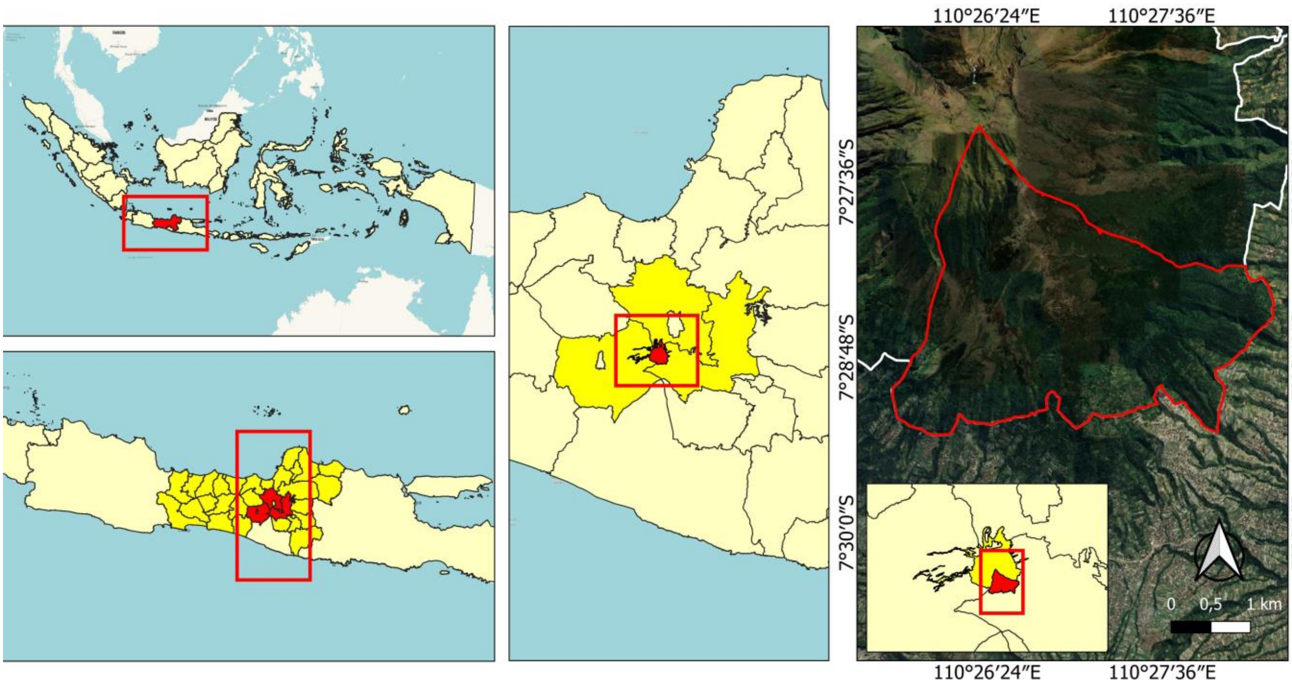

Figure 1. Map of study location in Mount Merbabu National Park's Selo Resort, Boyolali District, Central Java Province, Indonesia

Research materials

This study employs remote sensing data to analyze carbon stocks at the study area of Mount Merbabu National Park (MMbNP) Selo Resort. The satellite imagery utilized in this study was sourced from the high-resolution Sentinel 2A, obtained from https://scihub.copernicus.eu/dhus/#/home. The Sentinel imagery used for this study corresponds to level 2-A data acquired on 28 May 2023, with a cloud cover percentage of 2.95%. Sentinel-2 represents the inaugural satellite launched under the European Space Agency (ESA) Copernicus program (Szantoi and Strobl 2019). Sentinel data finds application in diverse fields, including environmental monitoring, spatial planning, water, forestry, vegetation, carbon assessment, natural resource management, and global agricultural assessments (Gunawansa et al. 2022). Sentinel-2 satellite imagery comprises 13 bands (Table 1). For this study, Sentinel-2A imagery with a spatial resolution of 10 m was employed, meaning that each pixel corresponds to an area of 100 m^2 or 0.01 ha. While, ground checks were conducted on May-June 2023.

Various software tools were utilized in this research, including QGIS for surface reflectance correction or enhancement of pixel values to align with terrestrial features (Whyte et al. 2018), ArcGis 10.5 for NDVI model creation and NDVI result classification, MS Excel for data processing and calculations, and MS Word for article composition. Regarding the classification of potential carbon storage within each density class, the classification build upon prior research conducted at Mount Merbabu National Park (MMbNP) Selo Resort by Kusumaningrum and Izdihar (2022); The land cover classes at Mount Merbabu National Park (MMbNP) Selo Resort exhibit potential carbon storage values of 61 tons/ha for low density, 254.49 tons/ha for medium density, and 211.17 tons/ha for high density (Table 2). The carbon storage potential of trees is ultimately influenced by species diversity, age (stem diameter) and density. Thus, areas with higher tree densities may have lower carbon storage potential than those with lower tree densities.

Image processing procedure

The analysis of remote-sensed Sentinel 2-A satellite imagery was conducted through ArcGIS 10.5. This analysis employed the Normalized Difference Vegetation Index (NDVI) algorithm, which is a pixel-based technique that enables the calculation of vegetation density. According to Klompmaker et al. (2018), the NDVI value was calculated as the measured ratio of reflection between the red band (R) and the near-infrared (NIR) band within the electromagnetic wave spectrum. These two bands were selected as parameters for vegetation index measurements due to their susceptibility to chlorophyll absorption and/or green vegetation. In a general sense, the NDVI formula can be expressed through the following equation:

$$NDVI = (NIR-R)/ (NIR + R)$$

Where:
NDVI : Normalized Difference Vegetation Index
NIR : Near Infrared Band
R : Red Band

In this study, the band 8 of Sentinel 2-A served as the near-infrared band (NIR) and band 4 as the red band (R). Therefore, the formula utilized for used was "NDVI = (band 8-band 4)/(band 8 + band 4)". This NDVI algorithm generates index values ranging from minimum of (-1) to maximum values (1). Each index value represents a pixel's vegetation density, spanning from non-vegetated areas to those with the densest vegetation cover (Ashok et al. 2021).

Data analysis

NDVI plays a crucial role in identifying soil density soil boundaries by distinguishing characteristics such as shape, color, texture, and area boundaries (Andini et al. 2018). In this study, analysis of the Sentinel 2-A satellite image revealed a range of NDVI values (Figure 2) ranging from 0.21-0.59; 0.59-0.70; 0.70-0.77; 0.77-0.82; and 0.82-0.91. The results of land cover monitoring are based on the principle that the green color reflect radiation from the infrared spectrum (Yuniasih 2017). Consequently, when the NDVI value approaches 1.0, it signifies lush land cover or high land cover density, as marked by dark green regions. Subsequently, pixel calculations were employed to determine the area covered by each density class, achieved by multiplying the number of pixels by their respective size. It's worth noting that Sentinel 2 satellite imagery has a spatial resolution of 10 m, which implies that each pixel corresponds to an area of 100 m^2 or 0.01 ha (Karlsen et al. 2021). The calculation of carbon stock areas commences from regions with NDVI values between 0.70-0.77 or areas with low land cover up to NDVI values 0.82-0.91, signifying areas with high land cover.

Table 1. Band number, spectral region, central wavelength (µm), spatial resolution (m) of Sentinel-2 (Sòria-Perpinyà et al. 2022)

Band number	Spectral region	Central wavelength (µm)	Spatial resolution (m)
1	Coastal aerosol	442.7	60
2	Blue	492.4	10
3	Green	559.8	10
4	Red	664.6	10
5	Red-edge1	704.1	20
6	Red-edge2	740.5	20
7	Red-edge3	782.8	20
8	NIR	832.8	10
8a	NIR narrow	864.7	20
9	Water vapor	945.1	60
10	SWIR/Cirrus	1373.5	60
11	SWIR1	1613.7	20
12	SWIR2	2202.4	20

Table 2. Classification of land cover density is based on the normalized vegetation difference index with the total potential carbon storage in each density class

Normalized Difference Vegetation Index (NDVI)	Density class	Total carbon storage (ton ha^{-1})*
0.7<NDVI<0.77	Low density	61
0.77<NDVI<0.82	Medium density	254.49
0.82<NDVI<0.91	High density	211.17

Note: * The total carbon storage for each land cover class referred to Kusumaningrum and Izdihar (2022)

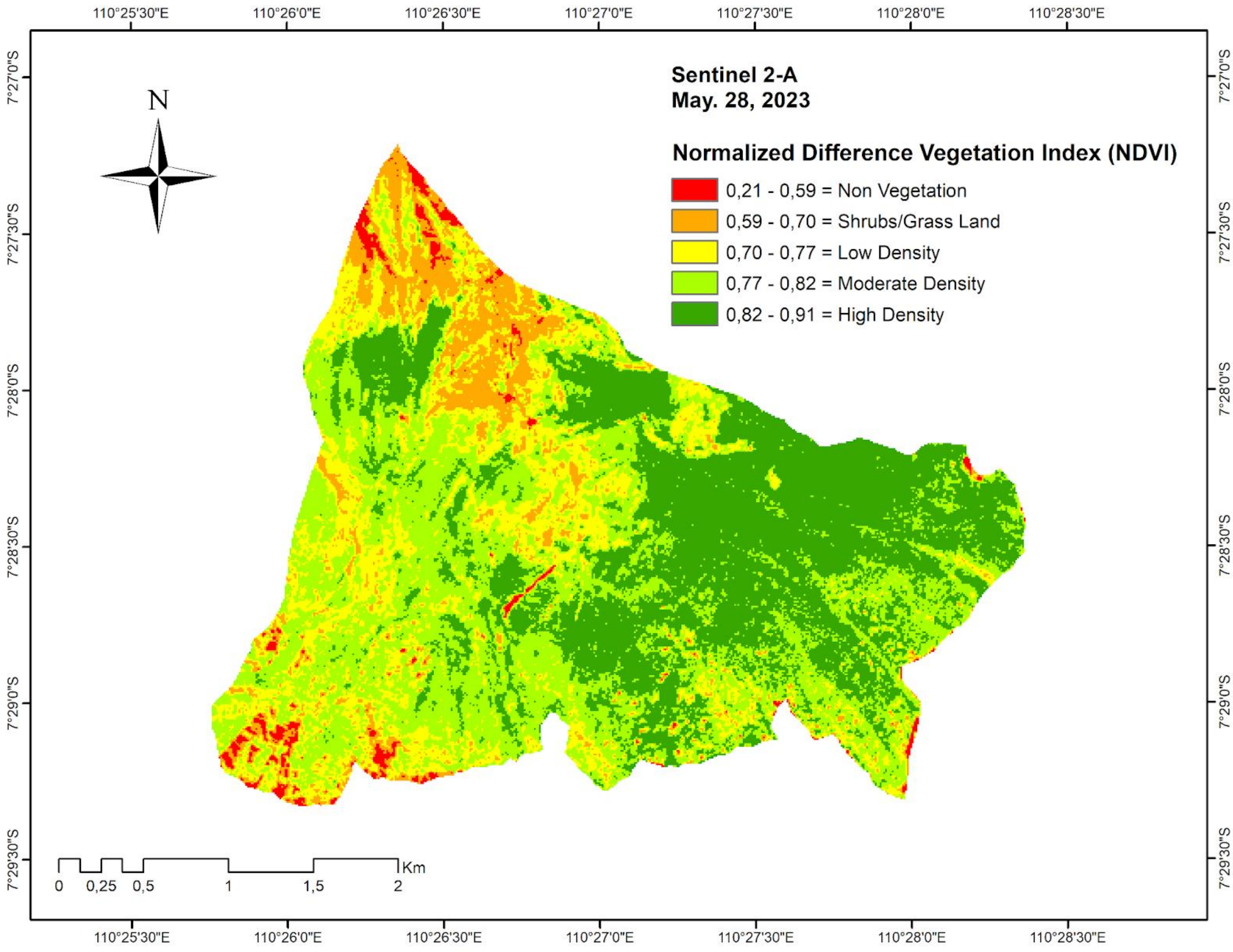

Figure 2. Spatial distribution of NDVI within the study area for each land cover class

RESULTS AND DISCUSSION

NDVI threshold and land cover class

The NDVI values obtained at Mount Merbabu Selo Resort National Park ranged from 0.2 to 0.9, primarily within hilly and highland areas. Most of the study locations exhibited medium to high tree-density characteristics, which were estimated from the number of pixel percentages. Specifically, NDVI values falling within the range of 0.2-0.5 corresponded to non-forest vegetation, while values from 0.5-0.7 indicated shrub and grassland vegetation. In the NDVI scale, water registers below 0; non-vegetation falls between 0 to 0.3; non-forest vegetation ranges between 0.3 to 0.4, and the forest vegetation is represented by values exceeding 0.4 (Arifin et al. 2019). Following Sadono et al. (2023), NDVI classifications that signify the potential for carbon storage within each density class (>0.7) are categorized as Table 3.

Figure 3 illustrates the pixel distribution of NDVI values, highlighting a substantial concentration in carbon storage values exceeding 0.7, with a peak at 0.72-0.82. The distribution gradually tapers off as NDVI values surpass 0.9. Notably, the NDVI range of 0.2-0.5, corresponding to non-forest vegetation area within the study area, occupies a relatively small area, estimated at only 0.2 ha. Mount Merbabu's topography exhibits distinct characteristics. The western slopes are densely vegetated with primary dryland forests, while the northern region is dominated by paddy fields and vegetable gardens (Siregar and Asbi 2020). An NDVI range of 0.59-0.7, observed along the slopes of Mount Merbabu indicates the prevalence of high shrubs and grasslands. In this context, higher the NDVI values correlate with denser vegetation and greater carbon stored within Mount Merbabu Selo Resort National Park.

Table 3. Classification of forest cover density based on NDVI values

Normalized Difference Vegetation Index (NDVI)	Density Class
$0.21 < NDVI \leq 0.59$	Non vegetation
$0.59 < NDVI \leq 0.7$	Shrubs/grassland
$0.7 < NDVI \leq 0.77$	Low density
$0.77 < NDVI \leq 0.82$	Medium density
$0.82 < NDVI \leq 0.91$	High density

Area calculation based on the number of pixels

The estimation of area was determined through the classification of NDVI range into five distinct classes. Subsequently, the pixel count within each class was multiplied by the image resolution, which stands at 10m × 10m. To delineate the vegetated area category, the criteria provided by Sadono et al. (2023), served as a reference, with a threshold beginning at NDVI range exceeding 0.7, signifying varying level of vegetation density. Table 2 presents the NDVI ranges based on the study of Kusumaningrum and Izdihar (2022), which are employed as a reference for estimating carbon storage based on vegetation density class. The total estimated area within the study region, as determined through remote sensing analysis, encompasses 1,024.92 ha, consisting of approximately 102,492 pixels. It's noteworthy that the area with the largest pixel count also corresponds to the most substantial estimated area. The area within the medium density category characterized by an NDVI range of 0.77-0.82, encompassing 36,493 pixels, equivalent to 364.93 ha. This medium vegetation density region predominantly occupies the western part of the study location, identifiable by the light green indicator on the land cover map (Figure 2). The medium density category accounts for 35.61% of the total area. Furthermore, the second largest estimated area falls within the high-density category, constituting 33.98% of the total area. This region, distinguished by a dark green indicator color on the land cover map, prevails in the eastern part of the study site, with an NDVI range of 0.82-0.91. Awaliyan and Sulistioadi (2018) emphasized that an NDVI value exceeding 0.72 already qualifies as vegetation. The prevalence of the medium-density category can be attributed to the dominance of pine trees (*P. merkusii*) in the forest ecosystem in Mount Merbabu National Park, particularly in its western part (KLHK 2014).

Meanwhile, the non-vegetated areas, classified within the non-vegetation and shrubs/grasslands categories, encompass 10,914 pixels. Each estimated area for non-vegetation spans 18.67 ha, accounting for 1.82% of the total study area. The shrubland/grassland category covers 90.47 ha, constituting 8.83% of the total study area, as shown in Table 4. Notably, land cover within the shrubs/grasslands category seems to proliferate in regions with altitudes proximate to the summit. This phenomenon may be attributed to abiotic factors exerting influence over density and diversity of vegetation. According to Sitanggang et al. (2017), the type and density of vegetation are influenced by temperature factors and the altitude of the location. Furthermore, it's worth noting that Selo Resort falls within the zone designated for hiking trails and natural tourism activities. Consequently, images classified as non-vegetation may be associated with this utilization zone. In the slope areas, Selo Resort remains adjacent to plantations, accounting for areas categorized as non-vegetation.

Total carbon storage estimation

Based on the calculations presented in Table 5, the estimated total carbon in Mount Merbabu National Park, Selo Resort, spanning an area of 915.78 ha, amounted to 178,771.09 tons of carbon. The low-density class contributes a modest 6.91% to this total, equivalent to an estimated carbon content of 12,357.99 tons C. In contrast, the medium-density class, emerges as the most substantial contributor, accounting for 51.95% of the total carbon storage, with a combined carbon storage of 92,871.04 tons C. High-density areas contributed 41.14% of the total carbon storage, amounting to 73,542.06 tons C. Meanwhile, the low-density areas exhibited the lowest carbon content. This is primarily due to their limited forested area compared to medium and high density regions, resulting in lower carbon storage values. Medium-density areas, on the other hand, demonstrated the highest carbon content compared to high-density areas, mainly because medium-density forests cover a larger expanse and thus store a greater volume of carbon.

The difference in forest area between medium and high-density forests significantly impacts their respective carbon storage quantities (Larekeng et al. 2021). As observed by Bhatti et al. (2023), variations in carbon storage can be attributed to factors such as the stand number, composition, and area. A study by Nguyen and Nguyen (2016) conducted in Bach Ma National Park, Vietnam, similarly found that the highest estimated carbon storage occurred within the high category at 144.16 tonnes/ha. Meanwhile, medium-density forests and restoration forests registered biomass values of 43.17 tons/ha and 20.31 tons/ha, respectively. A study in Ba Be National Park, Vietnam by Dong et al. (2020) also revealed that the largest estimated carbon storage, at 273.17 tons/ha fell within the high-density category. This was followed by the medium-density category, which amounted to 136.23 tons/ha, while the low-density category contained only 42.06 tons/ha.

Management implication

The captured satellite imagery and the derived NDVI values, which indicate the area and vegetation density, serve as the foundation for estimating the potential for carbon storage within Mount Merbabu National Park. These results are pivotal for monitoring and evaluating land cover density in the region. The area and density of the land are critical parameters for calculating the potential for carbon absorption, which, in turn, helps mitigate high concentrations of carbon dioxide in the atmosphere. Based on these calculations, the majority of the land cover density falls into the medium-density category, followed by high-density, with low density covering the smallest area. The remote sensing method has also been used by PT ABT to determine the area of biomass in KPHP unit X Tebo Timur, Jambi, Indonesia to calculate carbon absorption and storage as a measure to mitigate the release of high carbon emissions into the atmosphere (Firmansyah et al. 2022). Firmansyah et al. (2022) used various remote sensing analyses to obtain estimates of carbon stocks at PT ABT. The results show the correlation of the remote sensing model in the medium class for MSRVI (Modified Simple Ratio Vegetation Index) analysis.

Table 4. Area estimation and proportion of land cover based on the value of NDVI and the number of pixels

NDVI range	Density level/land cover	Number of pixels (10m×10m)	Estimated area (ha)	Proportion (%)
Non-area				
0.21-0.59	Non-vegetation	1,867	18.67	1.82%
0.59-0.70	Shrubs/grassland	9,047	90.47	8.83%
Area				
0.70-0.77	Low density	20,259	202.59	19.77%
0.77-0.82	Medium density	36,493	364.93	35.61%
0.82-0.91	High density	34,826	348.26	33.98%

Table 5. Total carbon storage and area classified by density class

Density class	Estimated area (ha)	Total carbon storage (ton ha^{-1})*	Total carbon storage (ton C)	Proportion (%)
Low density	202.59	61	12,357.99	6.91%
Medium density	364.93	254,49	92,871.04	51.95%
High density	348.26	211,17	73,542.06	41.14%
	915.78		178,771.09	

Note: *Kusumaningrum and Izdihar (2022)

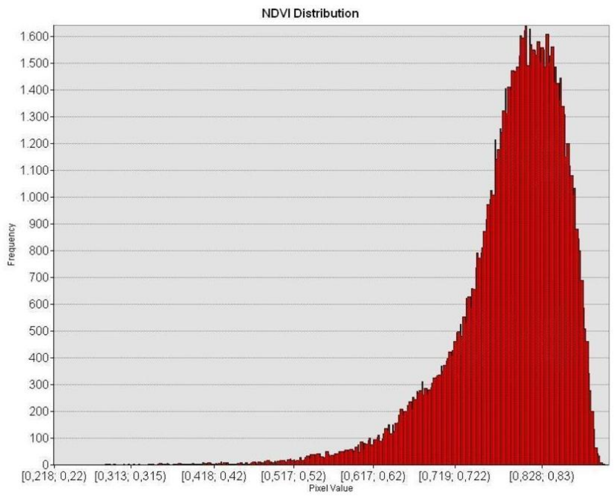

Figure 3. NDVI distribution over pixel values

Although current land cover values remain high, future projections suggest potential reductions in land cover, which would impact carbon dioxide absorption in the atmosphere. Lower land cover in an area results in decreased potential for carbon dioxide absorption (Suyana et al. 2022). Several factors contribute to reduced land cover density, including natural disasters such as forest fires, extreme weather events, and climate change. Additionally, changes in land use patterns contribute to reduced land cover density. Based on the monitoring data, it is feasible to continue conducting comprehensive land cover monitoring in the Mount Merbabu area using remote sensing techniques. Moreover, it is imperative to augment the land cover by closely monitoring tree planting and reforestation efforts in areas with low-vegetation density. This approach holds potential to significantly enhance carbon absorption capabilities. For instance, monitoring the rehabilitation activities on critical lands has shown promising results in increasing vegetation density, as evidenced by the growing density of the Serayu Hulu watershed in Central Java Province (Kartika et al. 2019). In this study, the NDVI method was employed to track rehabilitation trends. As vegetation thrives, land cover density naturally increases, leading to higher NDVI values.

The estimated total carbon storage in Merbabu National Park (MMbNP), classified by NDVI into non-vegetation, shrubs, low-density, medium-density, and high-density land, is as follows: 12,357.99 tons C for low-density, 92,871.04 tons C for medium-density, and 73,542.06 tons C for high-density. Concurrently, the computed areas for low, medium, and high cover density were 202.59 ha, 364.93 ha, and 348.26 ha, respectively. Notably, the carbon storage potential based on vegetation density of vegetation in the Merbabu National Park is highest in zones classified as medium and high-density due to their substantial tree population and larger land area compared to other land cover types.

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