

Spatial mapping of mangrove carbon stocks in mixed aquaculture-industrial landscapes of Kendal regency via Sentinel-2

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ABSTRACT

Based on the Master Plan for the Acceleration and Expansion of Indonesia's Economic Development Kendal Regency is positioned as the industrial gateway to the Semarang Metropolitan Region. through the development of the Kendal Industrial Park. The development of the area was carried out by removing approximately 42–210 hectares of mangrove (2015–2024), so that one of its functions as a carbon absorber and storage medium is reduced. Calculations of the potential carbon stock of existing mangroves are needed as a baseline for identifying the impact of industrial area expansion. The objective of this study is to produce a baseline of carbon sequestration potential from mangrove. Research data using Sentinel-2 MSI Level-2A and field survey data measuring AGC parameters. The research method utilized multispectral random forest classification, spectral transformation, and AGC carbon stock calculations. The results showed that the mangrove at the study site covered an area of 492.37 hectares, of which approximately 393.75 hectares were in an industrial zone with a very high mapping accuracy of 0.91. The AGC measurement results in the field had an average of 31.83 tons/hectare for the predictor group and 31.83 tons/hectare for the validator group. The correlation results of 11 vegetation indices with AGC show that the GNDVI ($r=0.543$), SAVI ($r=0.512$) and EVI ($r=0.504$) indices have a very high to high correlation, while the MDI ($r=0.143$) and WFI ($r=0.222$) indices had the lowest correlations. The results of carbon stock calculations based on vegetation indices show an average value of 688,990.21 tons, with the highest calculation results produced by the MDI index with a value of 1,234,201.39 tons and the GNDVI index producing the lowest estimated value of approximately 434,494.73 tons. The AGC potential mapping model results with the highest accuracy were obtained from the SAVI ($r=0.76$), EVI ($r=0.75$), and ARVI ($r=0.75$). Conclusion: The use of appropriate vegetation indices, such as GNDVI, SAVI, EVI, and ARVI, can provide accurate information regarding the potential carbon stock in mangrove. Recommendation: future studies should involve all minor species compositions at the study site. The results of this study support the achievement of SDGs Point 11 (Sustainable cities and communities) and Point 13 (Climate action).

Keyword: spatial mapping, mangrove carbon stocks, Sentinel-2.

INTRODUCTION

The development of industrial areas will have a positive impact on development and economic growth, but on the other hand, it can also lead to a decline in environmental quality (Haryanto et al.,

2021) (Jie et al., 2023). In Indonesia, the industrial sector is one of the main pillars supporting national economic development, backed by abundant natural resources such as oil, natural gas, minerals, and rubber. Based on data from the Ministry of Industry, as of 2023 there are more than 140

industrial estates developing across the archipelago, contributing around 20% to the national gross domestic product (Sultan, 2024). Industrial estates in Indonesia are distributed across 24 provinces with a total area of approximately 70,000 hectares, of which around 61.76% are located on the island of Java. Investment in Java's industrial estates has increased significantly since 2010, driven by integration into the global supply chain through the ASEAN Economic Community (AEC) in 2015. The development of industrial areas has driven the growth of Java's gross domestic product per capita to 1.5 times the national average (Nugraheni and Lestari, 2006). Approximately 60% of the industrial areas developed on Java Island were built on agricultural land, forests, and wetlands that previously served as ecosystem buffers (Supriatna and Lenz, 2025). Spatial planning policies that prioritize industrial investment are a major factor in accelerating land conversion without adequate environmental impact assessments. Based on data from the Ministry of Environment and Forestry, there has been a significant decline in the environmental quality index from 68.2 in 2019 to 65.4 in 2022, which was caused by a 40% weighting of air and water degradation due to industry (Sidiq et al., 2024; Pujiati et al., 2025).

Approximately 70–75% of industrial estate development on Java Island is concentrated in coastal areas, particularly on the north coast (Rizal and Apriliani, 2020). This phenomenon is caused by various factors, such as flat topography dominated by alluvial plains, which facilitates infrastructure development, and the availability of vast land areas, which facilitates the development of area-based industries. In addition, the coastal region of Java has direct connectivity to international seaports, which are essential for export-oriented industries, thereby reducing logistics costs by 30–40%. The region is also accessible by the North Coast Highway, which is Indonesia's main land transportation artery stretching 1,000 km and serving as the backbone of industrial logistics via land routes. One of the new areas on Java Island undergoing regional-based industrial development is the Kendal Regency coastline. Based on the 2011–2025 Master Plan for the Acceleration and Expansion of Indonesian Economic Development, Kendal Regency is positioned as an industrial gateway in the Semarang Metropolitan Region (SMR) with the development of the Kendal Industrial Park (KIP), which began operations in 2013. The establishment of KIP is in accordance

with the 2011–2031 spatial planning of Kendal Regency, which designates the eastern coastal area as the center for KIP development. KIP was developed in Brangong District and Kaliwungu District in 2016 in an area of 2,200 hectares (Cholis et al., 2023; Baihaqi et al., 2019).

The development of KIP resulted in changes in land use, where during 2005–2017 there was an increase in built-up land of 289.52 hectares by converting 65.92 hectares of vegetation area (Sadewo and Buchori, 2018), one of them is the mangrove ecosystem (Sidiq et al., 2024). The expansion of KIP into the coastal areas of Brangsong and Kaliwungu has resulted in a reduction in mangrove area of approximately 42–210 hectares (2015–2024). The 2023 mangrove ecosystem identification results show an area of approximately 120.99 hectares, of which only about 20.40 hectares are in good condition. Mangroves are endemic ecosystems in coastal areas that play an important role in absorbing and storing carbon from the atmosphere, where mangrove carbon stocks are calculated based on the biomass of trees growing in that location (Ray et al., 2011). Mangrove carbon stock measurements are obtained from several parameters, including: stem diameter, tree height, and mangrove species. The measurement results are then used to calculate carbon sequestration using a standard conversion factor of approximately 47% of the dry biomass of mangroves. The carbon stock in mangrove biomass can reach hundreds of tons per hectare, with one hectare of mangroves capable of sequestering and storing around 300–400 tons of carbon, depending on the location, age, and condition of the ecosystem (Harishma et al., 2020). Based on this description, there is an urgent need for research on the importance of calculating the potential carbon stock of existing mangroves as basic data for identifying the impact of industrial area expansion. In addition, the data obtained can be used as a baseline for projecting the decline in carbon stock due to land conversion and designing mangrove conservation strategies. This study aims to compile a baseline of carbon sequestration potential from mangrove ecosystems and identify the accuracy levels of various types of vegetation indices in calculating above ground carbon (AGC) on the coast of Kendal Regency.

The calculation of mangrove carbon stock potential can use the spectral transformation method of remote sensing imagery through canopy density-based vegetation indices. This method has several advantages that make it very effective and

efficient, namely fast calculation estimates covering a very large area, utilizing imagery data with various temporal resolutions and levels of detail (Huang et al., 2021). This enables dynamic, real-time monitoring of carbon stocks, which is crucial for detecting changes in land use in coastal areas. The calculation of potential carbon stocks in this study uses 11 vegetation indices, each of which has varying sensitivity in recording spectral responses. Therefore, the use of 11 indices is expected to provide more comprehensive information on variations in biomass and carbon stocks in the field. This approach is a novelty in research, where previous studies only used 2–3 vegetation indices, whereas this study uses 11 vegetation indices that can make an important contribution with variations in methods for calculating carbon stocks with varying degrees of accuracy. This study uses primary data from Sentinel-2 MSI Level-2A imagery obtained from the Google Earth Engine (GEE) platform, Sentinel 2A provides 10–20 meter multispectral data capable of recording mangrove vegetation structures with good accuracy. In addition, these images have high temporal resolution (5 days), enabling dynamic and periodic monitoring of carbon stock changes. Next, for data processing, we utilized a classification model using the random forest (RF) algorithm on the GEE platform, which was chosen for its high accuracy and robustness against noise, with a configuration of 100 decision trees and five variables per split (Fariz and Faniza, 2023; Amalia et al., 2024).

METHODOLOGY

Research sites

The mangrove ecosystem on the coast of Kendal Regency is geographically located on the

north coast of Central Java, covering four subdistricts, namely Patebon, Kendal City, Brangsong, and Kaliwungu. Based on Kendal Regency's Spatial Planning, the area has been designated as a developing industrial area. The spatial distribution of mangroves is found in pond embankments and tidal areas of varying widths. This area is strategic because it is located between industrial development and natural coastal ecosystems, making it an important area to study in the context of blue carbon conservation amid industrial development pressures. The following image shows the location of coastal research in Kendal Regency (Figure 1).

Satellite image data collection

The data used in this study are Sentinel-2 MSI Level-2A images from the GEE platform. These images are surface reflectance products that have been atmospherically corrected and orthorectified using the UTM/WGS84 projection system. Level-2A products were chosen because they have been processed using a digital elevation model (DEM) to project the images into accurate cartographic coordinates. The specifications of the Sentinel-2A images used include:

- Spatial resolution 10 meter – Band Blue (~490 nm), Green (~560 nm), Red (~665 nm), NIR (~842 nm).
- Spatial resolution 20 meter – Band Vegetation Red Edge (~705 nm, ~740 nm, ~783 nm, ~865 nm), dan SWIR (~1610 nm dan ~2190 nm).
- Spatial resolution 60 meter – Band Coastal Aerosol (~443 nm), Water Vapour (~940 nm), dan Cirrus (~1375 nm).

The image acquisition period was selected between April and May 2025, considering that

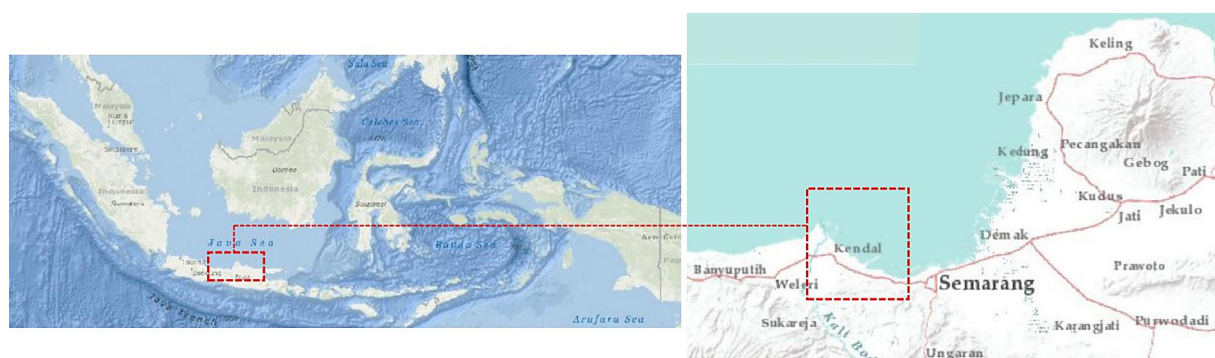


Figure 1. Research sites

this period marks the beginning of the dry season, thereby minimizing cloud cover. This timing also takes into account tidal conditions and optimal mangrove vegetation activity for spectral analysis. The images used are limited by a cloud cover criterion of less than 20% to ensure good data quality. Cloud masking is performed using the quality assessment (QA60) band and the median reducer function available on the GEE platform.

Field data collection

Data collection was adjusted to the satellite image acquisition period to ensure temporal consistency between field data and remote sensing data. A total of 80 sample points were taken using stratified random sampling adjusted for accessibility at each location. The sampling points were divided proportionally based on the spatial characteristics of mangroves in each region. Furthermore, sample point measurements were carried out with the following conditions:

Each sampling location uses a square plot measuring 10×10 meters in accordance with the spatial resolution of Sentinel-2A imagery. Transect lines are drawn perpendicular to the coastline or river towards the mainland, adjusted to the shape of pixels in remote sensing imagery.

Mangrove species identification was carried out using an ecological approach, taking into account mangrove characteristics and growth zones. Breast height diameter was measured on each plot for trees with a diameter ≥ 10 cm because this size contributes significantly to the estimation of above-ground biomass. Stem diameter was measured at adult breast height or approximately 1.3 meters above ground level, with measurement rules adjusted for the irregular conditions of mangrove stems.

A total of 80 samples were collected in the field. These were then divided into 60 samples as predictors and 20 samples as validators. This was based on the study (Sugara et al., 2022) and (Hidayah et al., 2022) which used 60 samples, which is more than other studies (Suardana and Nandika, 2023).

Sentinel-2 image processing

The classification of mangrove and non-mangrove cover was carried out on the GEE platform using Sentinel-2 MSI Level-2A composite images with cloud cover $\leq 20\%$. The cloud masking

process utilized the QA60 band and median reducer function to produce cloud-free annual composites in Kendal Regency and its surroundings. The classification model uses the RF algorithm, which was chosen for its high accuracy and robustness against noise, with a configuration of 100 decision trees and five variables per split (Fariz and Faniza, 2023)(Amalia et al., 2024). The 'Connected Pixel Count' spatial filter in GEE is applied to eliminate pixel noise, retaining only areas with ≥ 10 connected pixels.

In the classification, this study used 300 points (100 mangroves, 200 non-mangroves) as training samples. The training samples were collected using stratified random sampling to represent mangrove, water/pond, built-up land, non-mangrove vegetation, and open land classes. Input features include all bands from Sentinel-2A, both 10 m and 20 m resolution. (Farzanmanesh et al., 2024), as well as vegetation indices such as NDVI, water indices such as NDWI, and built-up land indices such as NDBI. NDVI and NDWI are used to facilitate the separation of aquaculture ponds and mangroves (Gupta et al., 2018), while NDBI was involved because it is sensitive to developed land, including industries located in some parts of the study area (Fariz and Faniza, 2023). Next, a validation sample of 250 points was also taken to test the accuracy of the classification results, which were later calculated using the kappa method.

Vegetation index processing

This study compares eleven vegetation indices to develop a model for estimating mangrove carbon stocks above ground. The vegetation indices used are shown in the following Table 1.

A comparison of 11 Sentinel-2A image-based vegetation indices was conducted to identify and model carbon stocks in mangrove ecosystems. Generic indices such as NDVI and GNDVI are effective for mapping the extent of mangroves because they reflect general vegetation through differences in NIR and red or green band reflectance. The SAVI index helps reduce bias due to background soil variation at the edges of open mangrove forests by adjusting NDVI values using a soil constant (L) (Zhen et al., 2021). Meanwhile, the ARVI and EVI indices improve the accuracy of biomass estimates in coastal areas that are often foggy or smoky through blue band correction and additional coefficients to reduce the effects of aerosols (Tran et al., 2022). Specialized mangrove

Table 1. Vegetation index algorithm

Vegetation index	Algorithm	References
NDVI (normalized difference vegetation index)	$(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$	Rouse, 1973
(Fariz nad Faniza, 2023)IRECI (inverted red edge chlorophyll index)	$(\text{NIR} - \text{Red}) / (\text{Red Edge 1} / \text{Red Edge 2})$	Frampton et al, 2013
SAVI (soil-adjusted vegetation index)	$((\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red} + 0.5)) \times (1 + 0.5)$	Huete, 1988
CMRI (combined mangrove recognition index)	$\text{NDVI} - \text{NDWI}$	Gupta et al, 2018
GNDVI (green normalized difference vegetation index)	$(\text{NIR} - \text{Green}) / (\text{NIR} + \text{Green})$	Gitelson and Merzlyak, 1996
RENDVI (red-edge normalized difference vegetation)	$(\text{Red Edge 2} - \text{Red}) / (\text{Red Edge 2} + \text{Red})$	Fernández-Manso et al, 2016
NDRE (normalized difference red-edge)	$(\text{NIR} - \text{Red Edge}) / (\text{NIR} + \text{Red Edge})$	Barnes et al, 2000)
WFI (wetland forest index)	$(\text{NIR} - \text{Red}) / \text{SWIR2}$	Jia et al, 2019
ARVI (atmospherically resistant vegetation index)	$(\text{NIR} - (\text{Red} - (\text{Red} - \text{Blue}))) / (\text{NIR} + (\text{Red} - (\text{Red} - \text{Blue})))$	Kaufman and Tanre, 1992
EVI (enhanced vegetation index)	$2.5 \times ((\text{NIR} - \text{Red}) / (\text{NIR} + 6 \times \text{Red} - 7.5 \times \text{Blue} + 1))$	Hueta, 2002
MDI (mangrove discrimination index)	$(\text{NIR} - \text{SWIR2}) / \text{SWIR2}$	Wang et al, 2018

indices such as CMRI utilize differences in greenness and water content in mangrove leaves to improve the discrimination of mangroves from non-mangrove vegetation (Mishra and Sethi, 2023), while MDI highlights the spectral characteristics typical of mangroves under saline water pressure with a combination of red edge and NIR bands (Vasquez et al., 2023).

Furthermore, red-edge-based indices (IRECI, RENDVI, NDRE) proved to be more sensitive to chlorophyll content and mangrove leaf structure (Suardana et al., 2023; (Farzanmanesh et al., 2024; Munawaroh et al., 2025), thereby improving carbon stock estimates in the upper canopy layer. The WFI index is specifically designed for the identification of swamp forests, including mangroves, by highlighting conditions of high humidity (Jia et al., 2019), and EVI can overcome NDVI saturation in dense canopy cover, which is common in mature mangroves (Tran et al., 2022). By comparing these various indices, the most accurate index for mapping mangrove carbon stocks under various environmental conditions can be identified (Nguyen, 2021).

Above ground carbon estimates

Above ground carbon (AGC) estimates were obtained from field data that had been collected. Before obtaining AGC values, the biomass above the mangrove soil surface was calculated for each species found.. The mangrove species identified in this study were *Avicennia marina* and *Rhizophora*

mucronata, because although there are 11 types of mangroves in the study area, these two species are very dominant throughout the area (Irsadi et al., 2025). AGC calculations use allometric equations specifically designed for Asian mangroves, making them highly relevant for use in Indonesia. The allometric equations used in this study (Table 2) are calculated from AGB based on the standard published in Indonesian National Standard (SNI) 7724:2011, whereby 0.47 or 47% of biomass is carbon. AGC is calculated using the equation:

$$AGC = AGB \times 0.47. \quad (1)$$

Above ground carbon model development

The development of the above-ground carbon estimation model in this study used 80 sample points from field measurements, which were divided into 60 predictor data (75%) and 20 validator data (25%) following common practices in statistical modeling. The modeling approach uses simple linear regression analysis for one independent variable, with AGC as the dependent variable and 11 Sentinel-2A vegetation indices as independent variables. The model development stages began with a correlation analysis between each vegetation index and field AGC using 60 predictor data, followed by the construction of linear regression equations for each vegetation index. Once the linear regression equations have been constructed, the next step is to apply the regression equations to Sentinel-2A images to

Table 2. Alomertrik equation for above ground carbon estimation

Species	Algorithm	Wood density	References
<i>Rhizophora mucronata</i>	$B = 0.128 \times D^{2.60}$	0.8483	Fromard et al., (1998)
<i>Avicenia marina</i>	$B = 0.1848 \times D^{2.2}$	0.6700	Hakim et al, 2016; Farahisah and Yulianda, 2021

Note: D is the DBH of the tree in cm; ρ is the wood density in g cm^{-3} .

produce 11 vegetation index-based AGC models. Finally, the models are validated using correlation (R) and root mean square error (RMSE).

Next, model validation was performed using 20 validator data that had been set aside to test the accuracy of each AGC model prediction. The best model was selected based on the combination of the highest R value (≥ 0.6 as a sufficiently high accuracy threshold) and the lowest RMSE to minimize prediction errors. The formula used is as follows.

$$RMSE = \sqrt{(\sum(Y_{predict} - Y_{observe})^2 / n)} \quad (2)$$

$$MAE = \sum|Y_{predict} - Y_{observe}| / n \quad (3)$$

where: n is the number of validation samples.

The model with the highest R^2 and lowest RMSE will be selected as the best model for estimating mangrove carbon stocks in coastal areas in Kendal Regency. The following Figure 2 shows the research flowchart.

RESULT AND DISCUSSION

Mangrove mapping in research study based multispectral classification

Mangrove mapping using multispectral classification poses its own challenges, as these objects are highly susceptible to mix-pixel in medium-to-low resolution images. The study site is a mangrove ecosystem associated with industrial areas, fish ponds, settlements, and agricultural land (Fariha et al., 2021; Sidiq et al., 2025; Fariz et al., 2025), potential misclassification of mapped mangroves due to mix-pixel, especially for mangrove objects around fish ponds (Rahmandhana and Kamal, 2022). In general, the difference between mangrove and non-mangrove objects in Sentinel-2A RGB false color composite images (NIR, SWIR, red) is clearly visible, with mangroves appearing darker due to their relatively high NIR, SWIR, and red values. The NIR

and red bands are sensitive to vegetation greenness, while the SWIR band is highly responsive to soil moisture affected by tides. Thus, with this approach, mangrove mapping can be carried out more accurately despite the challenges of land cover heterogeneity in industrial coastal areas.

This study used Sentinel-2A composite images to map mangroves on the coast of Kendal Regency, specifically in Patebon District, Kendal City District, Brangsong District, and Kaliwungu District, with the results detecting 492.37 hectares of mangroves. Random Forest classification produced very high accuracy, with an overall accuracy of 0.91 and a kappa of 0.81. This high level of accuracy was possible due to the limited number of classes used, uniform sampling points, and consideration of tides and cloud cover. The classification results were highly consistent with field data, but the mapping results still contained classification errors, where wet agricultural land and shrubs around the ponds were still included in the mangrove class. This required manual intervention, namely visual interpretation to separate the classification results (Fariz et al, 2024). The following image shows the spatial distribution of mangroves at the research site (Figure 3).

Carbon stock calculation based above ground carbon

Carbon stock is the amount of carbon stored in various types of ecosystems, such as vegetation biomass, with one calculation method using AGC focusing on estimating the carbon stored in mangrove biomass above ground, such as trunks, leaves, branches, and fruit. Field measurements of mangrove carbon stock at the research site showed that the range of carbon values above ground level varied considerably, reflecting the heterogeneity of mangrove vegetation in the transitional area between fishponds and industrial areas on the Kendal coast. In the predictor data group, AGC values ranged from 4.66 to 79.95 tons/hectare, with an average of 31.83 tons/hectare, while in the validator data, the range of values

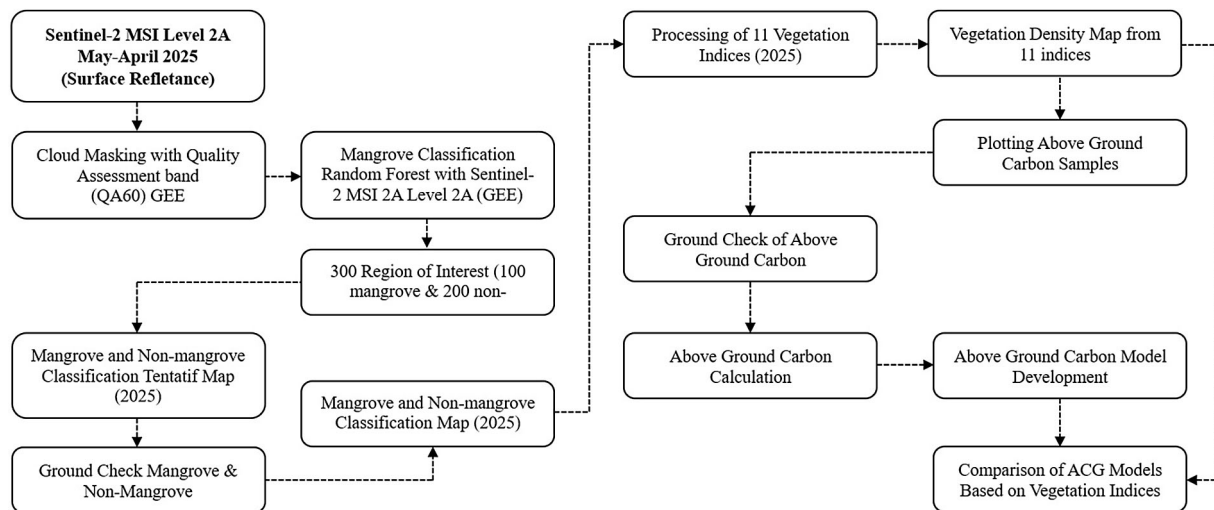


Figure 2. Research flowchart



Figure 3. Spatial distribution map of mangroves in research sites

was between 2.32 and 60.90 tons/hectare, with an average of 28.9 tons/hectare. This difference indicates structural and physiological variations between mangrove plots due to environmental factors such as salinity, water depth, and anthropogenic pressure. These values were then used as a basis for testing the relationship between actual carbon stocks in the field and various vegetation

indices resulting from the transformation of Sentinel-2A images, with the aim of assessing the extent to which spectral parameters can represent variations in biomass and carbon stocks in mangrove ecosystems spatially.

After obtaining the AGC measurement results, a correlation test was conducted with vegetation indices, where 11 vegetation indices were used in

this study, each with its own characteristics, and tested in the field to obtain correlation values (R), where a stronger correlation is indicated by an R value closer to 1. The results of linear regression analysis between field AGC values and 11 vegetation indices from Sentinel-2A imagery show that GNDVI has the highest correlation ($r = 0.543$), followed by NDVI ($r=0.534$), ARVI ($r=0.523$), SAVI ($r=0.512$), and EVI ($r=0.504$). Based on these correlation values, these five indices provide an overview that the differences in the NIR, Red, and Green bands directly capture variations in mangrove biomass well. Based on the results of the linear regression analysis, GNDVI showed the highest correlation value with AGC ($r=0.543$), indicating that this index is more sensitive in responding to variations in mangrove biomass than other indices. Furthermore, there are SAVI and EVI indices that have relatively high correlation values, where both indices are sensitive to vegetation by reducing the effects of the atmosphere and soil. The following Table 3 presents the correlation between the results of vegetation index processing and AGC values at the research location.

Conversely, the spectral transformations MDI ($r=0.143$) and WFI ($r=0.222$) showed the lowest correlation, indicating low sensitivity to variations in mangrove carbon stocks in the Kendal coastal area. Based on the correlation values obtained, these two vegetation indices are less effective for mapping variations in mangrove biomass, which are more influenced by vegetation structure and density, but are more sensitive in reflecting moisture conditions or water content around vegetation, such as ponds and marine waters. In addition, mangroves with varying moisture levels

also affect MDI and WFI values differently, making these two indices less capable of accurately distinguishing variations in carbon stocks. The following Figure 4 shows the correlation between actual carbon stocks and the results of processing the Sentinel 2A image vegetation index.

Calculation and correlation of carbon stock values based on spectral transformation of vegetation indices with above ground carbon

Carbon stock calculations were performed using the spectral transformation method of 11 vegetation indices based on canopy density and through potential calculations using the AGC approach based on field parameter calculations. The results of the calculations using both methods were then tested for accuracy using the RMSE method and for precision using correlation. Based on the results of total carbon stock calculations from various vegetation indices, there appears to be significant variation in values. The MDI index produced the highest carbon stock estimate, reaching approximately 1,234,201.39 tons, which indicates its sensitivity to variations in mangrove biomass structure. Conversely, the GNDVI index provided the lowest estimate, approximately 434,494.73 tons, a value that reflects its limitations in capturing canopy dynamics in mangrove ecosystems. In general, the average total carbon stock of the eleven vegetation indices reached 688,990.21 tons with a median value of around 621,829.56 tons, where the variation in values indicates that most indices produce relatively consistent estimates in the middle range. Based on the total carbon stock table, the three vegetation indices that showed the best performance in the correlation and RMSE tests, namely SAVI, EVI, and ARVI, also showed high and consistent carbon stock estimation results. SAVI recorded a total carbon stock of approximately 621,828.62 tons, followed by EVI with 664,222.65 tons, and ARVI with 448,379.04 tons. These values confirm that, in addition to excelling in model accuracy (high correlation and low RMSE), the three indices are also capable of representing the potential carbon stock of mangroves in significant amounts. The differences in results between the indices further reinforce the reasons why SAVI, EVI, and ARVI are considered the optimal indices for mapping AGC potential in mangrove areas. The following Table 4 shows the results of

Table 3. Correlation results of vegetation index processing with AGC values

Vegetation index	Linear regression equation	Correlation (R)
NDVI	$108.18x - 48.174$	0.53
IRECI	$36.847x + 10.951$	0.43
SAVI	$88.334x - 5.8136$	0.51
CMRI	$96.184x + 3.2415$	0.36
GNDVI	$114.15x - 35.615$	0.54
RENDVI	$80.039x - 26.279$	0.34
NDRE	$100.11x - 11.121$	0.48
WFI	$1.9012x + 19.872$	0.22
ARVI	$113.08x - 49.879$	0.52
EVI	$69.66x - 1.9731$	0.50
MDI	$1.1806x + 24.393$	0.14

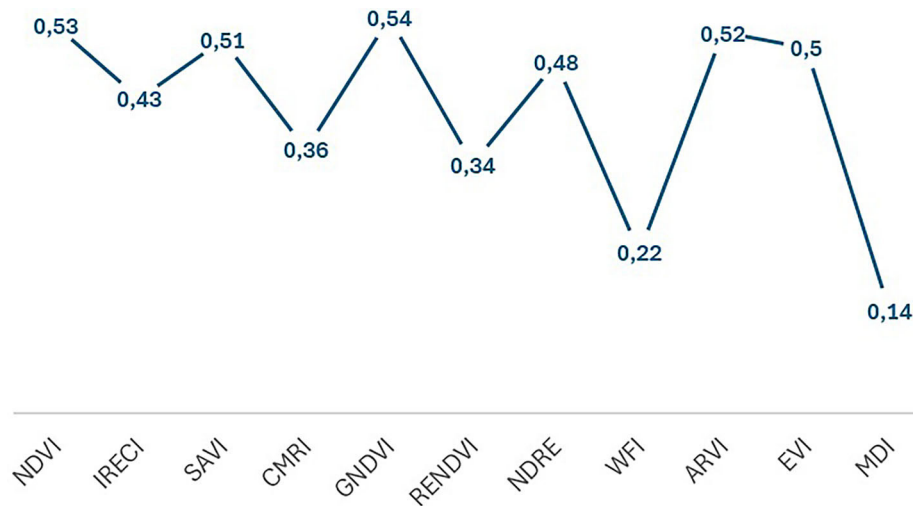


Figure 4. Graph of correlation vegetation index processing with AGC values

carbon stock calculations from 11 vegetation indices at the study site.

Next, the carbon stock calculations from both methods were correlated, whereby the spatial model with the highest correlation value and best RMSE was used as the optimal model for mangrove AGC estimation (Figure 5). The results of AGC model validation using 20 data points showed significant differences from the eleven Sentinel-2A vegetation indices. The highest Pearson correlation coefficient was achieved by SAVI ($r=0.756$), which outperformed EVI ($r=0.753$) and ARVI ($r=0.745$). NDVI ($r=0.722$) and GNDVI ($r=0.713$) also maintained good performance, while CMRI ($r=0.248$) and MDI ($r=0.467$) showed the lowest correlations. In terms of accuracy (RMSE), ARVI had the smallest prediction error of 11.86 tons/hectares, followed by SAVI (12.17 tons/hectares), EVI (12.35 tons/hectares),

NDVI (12.36 tons/hectares), and GNDVI (12.38 tons/hectares). Conversely, CMRI (17.91 tons/hectares) and MDI (17.64 tons/hectares) showed the highest RMSE (Figure 7). The following Table 5 presents the correlation results and RMSE values of the AGC carbon stock estimation model with 11 vegetation indices. Meanwhile, Figure 6 shows the spatial distribution of AGC resulting from the processing of the SAVI vegetation index.

The high accuracy of the SAVI, EVI, and ARVI vegetation index processing results indicate that soil and atmospheric corrections are very important in estimating mangrove carbon stocks associated with ponds, industrial land, and substrate variations. EVI is able to overcome the problem of NDVI saturation in areas with high biomass through the use of the blue band for atmospheric correction and canopy background adjustment factors, thereby providing higher sensitivity to

Table 4. Carbon stock calculation results using vegetation index

Vegetation indexes	Min value	Max value	Total carbon stock (ton)
RENDVI	0	42.56	486309.86
NDVI	0	47.55	488141.54
NDRE	0	54.93	787041.36
MDI	24	52.78	1234201.39
IRECI	7.6	63.15	756119.17
GNDVI	0	53.50	434493.73
EVI	0	55.36	664222.65
CMRI	0	66.15	515498.85
WFI	3.34	59.54	1142650.23
ARVI	0	47.89	448379.04
SAVI	0	52.60	621828.62

Table 5. Correlation results and RMSE of AGC carbon stock estimation model based on vegetation index

Vegetation index	Correlation (R)	RMSE
NDVI	0.72	12.36
IRECI	0.66	14.02
SAVI	0.76	12.17
CMRI	0.25	17.91
GNDVI	0.71	12.38
RENDVI	0.45	16.05
NDRE	0.69	14.11
WFI	0.56	16.80
ARVI	0.75	11.86
EVI	0.75	12.35
MDI	0.47	17.64

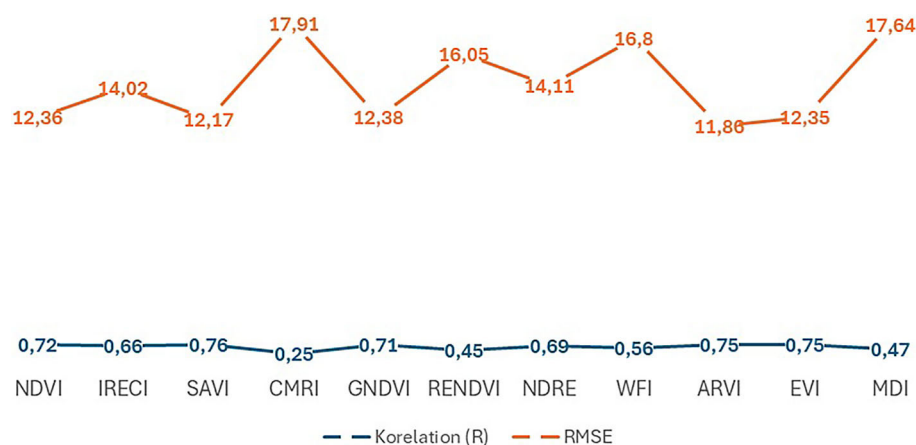
canopy structure variations (Sun et al., 2020). ARVI shows atmospheric resistance four times better than NDVI through a self-correction process using the blue band to correct for the aerosol effect on the red band, which is critical in coastal areas with dynamic atmospheric conditions (Wicaksono et al., 2016; Yumnaristya et al., 2023).

DISCUSSION

Based on its spatial distribution, it shows that mangroves in the industrial zoning area based on spatial planning cover an area of 393.75 hectares. Mangroves in the eastern part tend to be fewer because the area is used for the development of the Kendal Industrial Park, while the western part does not yet have an industrial area. Mangroves in the study area have a spatial distribution pattern that is influenced by environmental and anthropogenic

factors, with most of them scattered along the Boddri River estuary and pond areas that have brackish water and sedimentation conditions that support mangrove growth. In addition, mangroves grow in a linear pattern along the pond area, following the boundaries of the pond embankments, where they function as a natural buffer zone to reduce erosion and as a natural filter that filters water flow from the ponds to the sea (van Bijsterveldt et al., 2020; Sidik et al., 2021). Furthermore, there are also mangroves concentrated along the coastline bordering the open sea, where this area is a tidal zone with stable sedimentation conditions. This group of mangroves functions as a natural barrier that protects the land from waves to prevent abrasion and is an important area for carbon storage (Asari et al., 2021; Amos and Akib, 2023). Based on its distribution pattern, this reflects the adaptation of the mangrove ecosystem to environmental conditions and human activities on the Kendal coast, where this pattern also reflects that mangroves in the region face pressure from land conversion for productive enterprises, including industrial estate development.

The results of processing related to the correlation between vegetation indices and AGC values show that GNDVI has the highest correlation value with AGC values ($r=0.543$), where the GNDVI algorithm uses Green and NIR bands that enable it to more effectively reflect the condition of mangrove ecosystems with specific spectral characteristics, such as chlorophyll content and leaf structure (Zhen et al., 2021). Furthermore, there are SAVI and EVI indices that have relatively high correlation values, where both indices are sensitive to vegetation by reducing the effects of the atmosphere and soil (Tran et al., 2022).

**Figure 5.** Correlation graph and RMSE of AGC carbon stock estimation model based on vegetation index

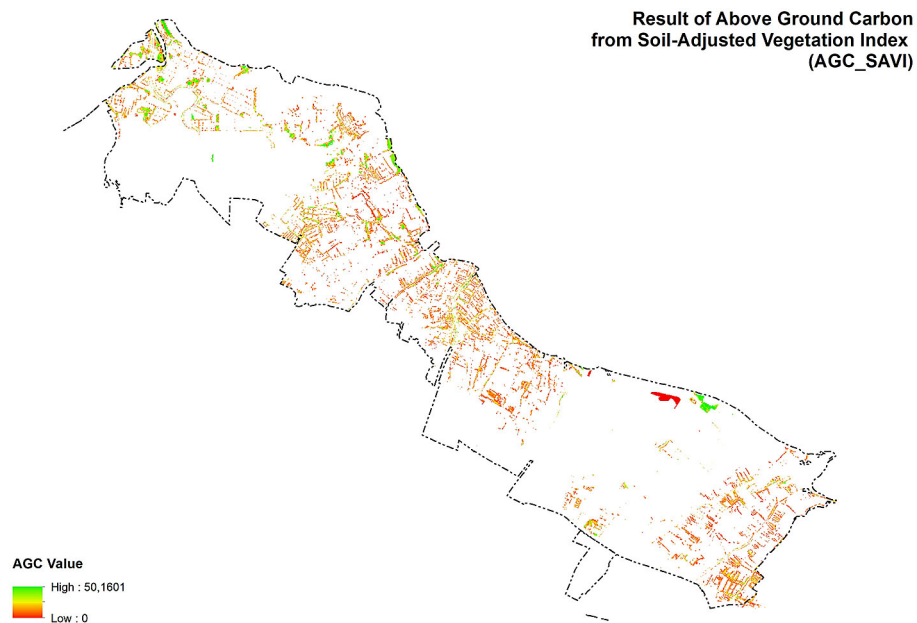


Figure 6. Spatial distribution of AGC results from processing SAVI ($R=0.76$)

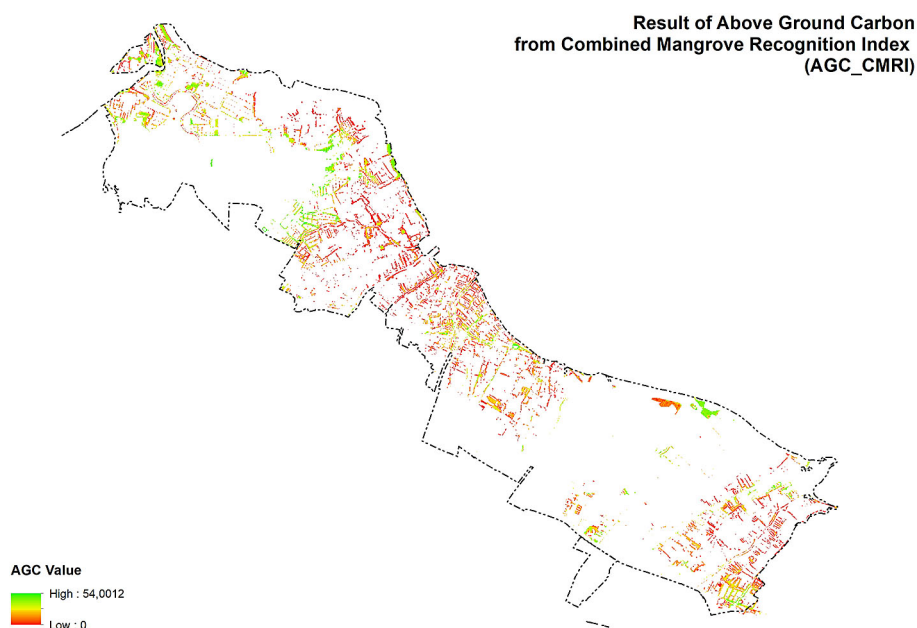


Figure 7. Spatial distribution of AGC results from processing CMRI ($R=0.25$)

Thus, even though they do not have the highest correlation values, both indices can provide accurate information in calculating mangrove biomass potential. Conversely, the spectral transformations MDI ($r=0.143$) and WFI ($r=0.222$) show the lowest correlation, indicating low sensitivity to variations in mangrove carbon stocks in the Kendal coastal area. MDI and WFI are less capable of accurately distinguishing variations in carbon stocks. Environmental factors such as muddy soil conditions, tidal areas, and other non-mangrove

vegetation mixtures also have the potential to influence the spectral response captured by these two indices, thereby reducing their correlation with AGC values in the study area (Vasquez et al., 2023). These results show the importance of selecting indices with appropriate spectral capabilities, such as generic indices NDVI and GNDVI, which are capable of capturing biomass, while soil-adjusted and atmospherically corrected indices such as SAVI and ARVI provide consistent moderate correlations. However, the

simultaneous use of several indices can also provide a more comprehensive picture.

Furthermore, the development of an AGC model based on vegetation indices showed a high level of accuracy in the processing of SAVI ($r=0.76$), EVI ($r=0.75$), and ARVI ($r=0.75$) indices. These values indicate that soil and atmospheric corrections are very important in estimating mangrove carbon stocks associated with ponds, industrial land, and substrate variations in the Kendal coastal area. SAVI utilizes the soil adjustment factor (L) to reduce the effect of soil brightness on the spectral canopy of mixed soil-mangrove vegetation pixels (Ligono and Okolie, 2022; Rhyma et al., 2020). This correction reduces substrate reflectance bias in sparsely canopy mangroves in the intertidal zone, thereby improving the accuracy of vegetation cover estimates (Aji et al., 2023). EVI is able to overcome the problem of NDVI saturation in areas with high biomass by using the blue band for atmospheric correction and canopy background adjustment factors, thereby providing higher sensitivity to canopy structure variations (Sun et al., 2020). ARVI shows atmospheric resistance four times better than NDVI through a self-correction process using the blue band to correct for the aerosol effect on the red band, which is critical in coastal areas with dynamic atmospheric conditions (Wicaksono et al., 2016; Yumnaristya et al., 2023). These three indices physically overcome complex spectral challenges resulting from electromagnetic interactions with the atmosphere, ground cover, and vegetation cover, whereas the mangrove-specific index fails to address the complexity of pixels mixed with ponds and artificial infrastructure. Thus, SAVI, EVI, and ARVI provide more accurate and precise AGC estimates. In addition, the results of the total carbon stock calculation also show that the three best indices (SAVI, EVI, ARVI) produce relatively consistent carbon stock estimates in the medium-high range, thus supporting the validity of the correlation and RMSE test results. However, there are indications that some indices, including SAVI and EVI, have the potential to slightly underestimate areas with dense canopy, while ARVI in some industrial-pond locations is assumed to be overestimated due to highly sensitive atmospheric corrections. This finding is important to note because it shows that even though the three indices are optimal, there is still a spatial bias that needs

to be further examined so that the AGC estimation results are more representative of variations in field conditions.

This study has several limitations that need to be addressed in future works, where the AGC model developed was only calibrated on the two most dominant species, *Avicennia marina* and *Rhizophora mucronata*, while minor species such as *Bruguiera*, although very few, could potentially contribute to the total carbon stock estimate. Therefore, future research should involve the entire composition of mangrove species and map the spatial distribution of the community to improve the accuracy and transferability of the model (Pham et al., 2021; Macreadie, 2019). In addition, integrating Sentinel-1 radar data with Sentinel-2 can reduce mix-pixel and saturation errors that commonly occur in heterogeneous land cover in industrial areas and fish ponds in the Kendal Coast region (Pinkeaw et al., 2024). Considering that coastal industrialization can affect the sustainability of mangrove ecosystems (Sejati et al., 2020), Therefore, the development of an ensemble model that combines SAVI, EVI, and ARVI should also be attempted (Suardana et al., 2023). Future work will support more robust, transferable, and relevant estimates of blue carbon stocks for conservation policy in coastal industrial areas.

CONCLUSIONS

Based on the research results, it can be concluded that the mangrove ecosystem at the research site covers an area of 492.37 hectares, of which approximately 393.75 hectares are located in an industrial zone. The accuracy of the random forest classification for the mapping is very high at around 0.91 and kappa 0.81. The AGC measurements in the field had an average of 31.83 tons/hectare for the predictor group, while the AGC values for the validator group had an average of 28.9 tons/hectare. The correlation results between vegetation indices and AGC show that the GNDVI ($r=0.543$), SAVI ($r=0.512$), and EVI ($r=0.504$) indices have a very high to high correlation, while the MDI ($r=0.143$) and WFI ($r=0.222$) indices have the lowest correlation in representing AGC values from index values. However, using several indices simultaneously to calculate AGC potential can provide more comprehensive information. The results of carbon stock calculations based on vegetation indices show an average value of 688,990.21 tons,

with the highest calculation results produced by the MDI index with a value of 1,234,201.39 tons and the GNDVI index producing the lowest estimated value of around 434,494.73 tons. The AGC potential mapping model results with the highest accuracy were obtained from the SAVI ($r=0.76$), EVI ($r=0.75$) and ARVI ($r=0.75$) indices, indicating that soil and atmospheric correlations are very important in estimating mangrove carbon stocks associated with ponds, industrial land and coastal substrate variations. The results of this study support the achievement of SDGs Point 11 (Sustainable cities and communities) and Point 13 (Climate action). A limitation of this study is that the ACG model developed was only calibrated for two dominant species in the study area, namely *Avicennia marina* and *Rhizophora mucronata*. Therefore, future studies should involve the entire mangrove composition at the study site.

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