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Forest Biomass Estimation through the Integration of UAV Imagery and Vegetation Indices: Toward Accurate and Efficient Monitoring

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ABSTRACT

Forest biomass estimation method using drone imagery and vegetation index, focusing on the effectiveness and efficiency of the approach. Using high-resolution drone imagery, this study analyzes vegetation structure and density, and supports the development of a more accurate biomass estimation model compared to traditional methods. Drone imagery has the advantage of collecting data quickly and in real time, especially in areas that are difficult to access manually. Vegetation indices, such as NDVI, are used to assess vegetation health and density, which are closely related to biomass estimation. The combination of drone imagery and vegetation indices can produce more detailed data, support 3D vegetation modeling, and help estimate biomass volume over time. This study is expected to produce data and biomass estimation models that support sustainable forest management as well as technical recommendations for the use of drones for vegetation monitoring. The findings of this study show that the proposed method produces an estimation accuracy of 85.2% based on field validation data calculated using simple linear regression. The findings of this study are expected to make a significant contribution to the development of drone-based technology for efficient and environmentally friendly natural resource management.

1. INTRODUCTION

Forests are one of the most important ecosystems on Earth because they function as carbon dioxide sinks, habitats for various species, regulators of the hydrological cycle, and protectors of soil fertility. Forests also offer economic and ecological benefits, such as fuel, building materials, and sources of biomass energy. A forest is a field of trees that is a natural living association with its environment that is determined by the government. Such areas exist in many places around the world and function as carbon dioxide sinks, animal habitats, regulators of hydrological currents, and soil conservation. This is one of the most important parts of the Earth's biosphere [1].

Forest biomass refers to the total amount of living organic matter within a forest ecosystem, encompassing trees, shrubs, and other vegetation components. The utilization of forest biomass has been increasingly recognized as an environmentally friendly approach to supporting energy sustainability and reducing greenhouse gas emissions. Biomass, derived directly or indirectly from plant materials, can be used for various purposes, including fuel, construction materials, animal feed, and other commercial products. As a renewable energy source, biomass is considered sustainable because its carbon emissions are largely offset by the carbon absorbed during plant growth, thereby minimizing its contribution to net atmospheric CO_2 levels.

Accurate estimation of forest biomass is therefore a critical aspect of sustainable natural resource management, particularly in the context of climate change mitigation and carbon stock assessment. Conventional biomass estimation methods rely primarily on direct field measurements, such as tree diameter and height sampling, which are often time-consuming, labor-intensive, costly, and difficult to implement in remote or inaccessible forest areas. These constraints limit the efficiency and spatial coverage of traditional approaches and highlight the need for alternative methods that can provide reliable biomass estimates with greater efficiency.

Recent advances in remote sensing technologies have introduced drone-based imagery as a promising alternative for forest biomass estimation. Unmanned aerial vehicles (UAVs) are capable of acquiring high-resolution data in near real time and can be deployed flexibly over areas that are difficult to access through ground surveys. When equipped with multispectral sensors, UAVs enable detailed analysis of vegetation structure and canopy characteristics. Vegetation indices, particularly the Normalized Difference Vegetation Index (NDVI), are widely used to assess vegetation health and density, which are closely related to biomass distribution. Vegetation index values can represent vegetation cover percentage, photosynthetic activity, fraction of absorbed photosynthetically active radiation (fAPAR), and carbon dioxide absorption potential [2]. As spectral transformations applied to multi-band imagery, vegetation indices are effective for highlighting vegetation density parameters such as biomass, chlorophyll concentration, and leaf area index (LAI) [3].

Most previous studies on biomass estimation have predominantly relied on satellite imagery, which typically provides moderate spatial resolution and may be insufficient to capture fine-scale variability in heterogeneous forest environments. Furthermore, while the use of multiple vegetation indices has been shown to improve estimation accuracy, the integration of high-resolution UAV imagery with three-dimensional (3D) vegetation modeling remains relatively limited. Additional research is therefore needed to examine the extent to which UAV-derived vegetation indices and 3D vegetation structures can enhance biomass estimation accuracy compared to conventional field-based methods, which are constrained in their ability to represent spatial variability.

This study aims to evaluate the potential of combining drone imagery and vegetation indices to produce more accurate and efficient forest biomass estimates. The primary objective is to develop a biomass estimation model that supports sustainable forest management by improving data quality and reducing operational costs relative to traditional approaches. The results of this research are expected to contribute to the development of drone-based remote sensing technologies for environmentally sustainable and efficient forest resource monitoring.

2. RELATED WORK

The development of unmanned aerial vehicle (UAV) technology has provided a promising alternative for high-resolution vegetation monitoring. UAVs offer flexible data acquisition and superior spatial detail compared to satellite platforms. Shofiyanti [11], [12] demonstrated the potential of unmanned aircraft for detailed mapping and monitoring of crops and agricultural land, highlighting their applicability for vegetation observation. Subsequent studies extended the use of UAV imagery to environmental applications, including sustainable agricultural planning based on drone-derived spatial information [10].

In addition to spectral information, UAV imagery enables the extraction of spatial and textural features that can support vegetation and land cover analysis. Deo Hernando et al. [7] showed that color and texture features derived from drone imagery can improve land use classification performance, suggesting their potential relevance for vegetation characterization. Furthermore, comparisons between UAV-based multispectral imagery and satellite data have indicated that UAV-derived vegetation indices, such as NDVI, can provide more detailed and localized information, particularly in coastal and mangrove ecosystems [13]. Vegetation indices remain a central component in biomass-related studies due to their ability to represent vegetation density and health. Early theoretical foundations of digital image processing and vegetation index transformation for remote sensing applications were established by Danoedoro [16] and further applied in vegetation density analysis [15]. These indices have also been used to estimate carbon absorption capacity in forested and mangrove areas, demonstrating their relevance for carbon stock assessment [18].

Despite these advancements, several challenges remain in forest biomass estimation. While advanced computational techniques, including optimization and intelligent algorithms, have been explored in various environmental applications [14], many biomass estimation studies still rely either on satellite imagery or on complex models that require substantial data and computational resources. Relatively fewer studies focus on the combined use of high-resolution UAV imagery and vegetation indices within simplified estimation frameworks that balance accuracy, efficiency, and practical applicability. This study addresses this gap by evaluating the use of UAV-derived vegetation indices for forest biomass estimation, with an emphasis on operational feasibility and support for sustainable forest management.

3. METHODOLOGY

This study employs a drone-based remote sensing approach combined with vegetation index analysis to estimate forest biomass. High-resolution multispectral drone imagery was acquired over the study area to capture detailed spatial information on vegetation structure and canopy conditions. The collected imagery was first subjected to geometric and radiometric corrections to ensure spatial accuracy and to minimize radiometric distortions caused by sensor characteristics and illumination conditions. Following the preprocessing stage, vegetation indices were calculated from the corrected imagery. The Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) were used to represent vegetation health, density, and photosynthetic activity, which are closely related to biomass distribution. These indices were derived from multispectral bands and analyzed to characterize spatial variability in vegetation cover across the study area.

Forest biomass estimation was conducted by integrating vegetation index values with a three-dimensional (3D) vegetation model generated from drone imagery. The 3D representation provides additional structural information that supports biomass volume estimation beyond two-dimensional spectral analysis. A simple linear regression model was then developed to relate vegetation index values to biomass measurements obtained from field surveys.

Model validation was performed by comparing the estimated biomass values with field-measured data collected at selected sample plots. This validation step was used to assess the reliability of the proposed approach. Furthermore, the performance of the drone-based biomass estimation method was qualitatively compared with conventional field-based approaches in terms of efficiency, data coverage, and practical applicability. The overall methodology is designed to support sustainable forest management by providing a cost-effective and accurate alternative for forest biomass monitoring.

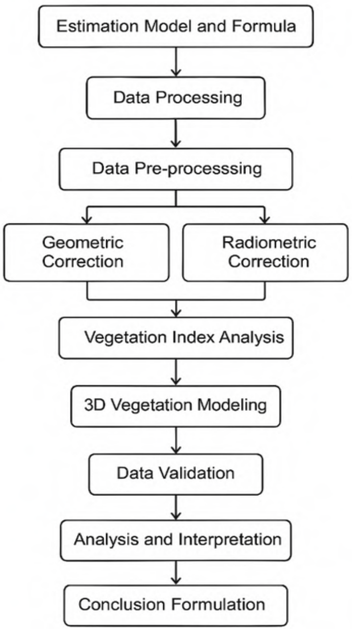

FIGURE 1. DATA PROCESSING AND ANALYSIS WORKFLOW

3.1 Estimation Model and Formula

In this research, forest biomass estimation was performed using a simple linear regression model that relates vegetation index values to field-measured biomass data. The Normalized Difference Vegetation Index (NDVI) was selected as the independent variable due to its strong relationship with vegetation density and canopy condition. The regression model is expressed as follows:

$$\textbf{Biomass} = \mathrm{a}\, x\, NDVI + \mathrm{b} \tag{1}$$

Where the coefficients a and b are determined based on fitting to field validation data. Field biomass data were collected from ten sampling points distributed across the study area. At each sampling location, biomass measurements were obtained through direct tree diameter observations using a relascope, supported by standard field measurement procedures. These field measurements served as reference data for calibrating and validating the regression model. The performance of the estimation model was evaluated using the coefficient of determination (R^2). The resulting R^2 value of 0.852 indicates a strong linear relationship between NDVI values derived from drone imagery and the corresponding field-measured biomass, suggesting that the proposed model is capable of providing reliable biomass estimates at the study site.

3.2 Data Collection

The data used in this study consist of high-resolution drone imagery and vegetation index values derived from multispectral data. The primary dataset comprises multispectral UAV images acquired over the study area, which provide detailed spatial information on vegetation cover and canopy characteristics. From these images, vegetation indices, including the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), were calculated to represent vegetation health and density. In addition to spectral information, ancillary data were collected to support the analysis. These data include geographic coordinates of the study area and descriptive environmental information related to site conditions. Such metadata were used to ensure accurate spatial referencing and to support the interpretation of vegetation patterns observed in the drone imagery.

Field data were also collected as reference information for model calibration and validation. These data were obtained from selected sampling points and include measurements related to vegetation structure, which were used to link vegetation index values with actual biomass conditions. All data collection activities were planned and conducted to ensure consistency between remote sensing data acquisition and field observations.

3.3 Data Processing

The steps taken include several main stages. The first stage is data pre-processing, which is processing raw data into a format that is ready to be analyzed by performing geometric and radiometric corrections on drone images.

a. The purpose of geometric correction is to remove spatial distortions in an image so that each pixel has an accurate geographic position. Steps:
   - Identify Distortion: Distortion can occur due to camera perspective, drone movement, or terrain effects.
   - Processing: Use GPS and Inertial Measurement Unit (IMU) data from the drone to calculate the camera position and orientation when shooting. Apply algorithms such as Affine Transformation or Rubbersheet Transformation to correct distortion.
   - Geo-referencing: Matching imagery to geographic coordinates using Ground Control Points (GCPs) taken in the field. Software such as ArcGIS, QGIS, or Agisoft Metashape are often used.
   - Tools that can be used: GIS software: ArcGIS, QGIS. Photogrammetry: Pix4D, Agisoft Metashape.

b. Radiometric correction aims to improve the visual quality of an image by correcting pixel intensity values due to variations in lighting, atmosphere, or sensor sensitivity.
   - Atmospheric Correction: Remove atmospheric influences (haze, thin clouds) that can affect the spectrum. Apply algorithms such as Dark Object Subtraction (DOS) or other methods such as FLAASH (Fast Line-of-sight Atmospheric Analysis of Hypercubes).
   - Sensor Correction: Calibrate the drone sensor to reduce the effects of noise or non-linearity. Apply normalization methods to equalize pixel values between multiple images.
   - Histogram Adjustment: Use Histogram Equalization to increase image contrast. Apply color or contrast correction to get uniform data.

- Tools That Can Be Used: Image Processing Software: ENVI, ERDAS Imagine, MATLAB. Python Libraries: OpenCV, scikit-image, or rasterio.

Next step, vegetation index analysis is carried out by calculating index values such as NDVI and EVI using analysis software such as QGIS, ArcGIS, or Python. The final stage is 3D vegetation modeling, which utilizes image data to create three-dimensional vegetation structures to support biomass volume estimation.

3.4 Data Validation

Model validation was conducted by comparing forest biomass estimates derived from drone imagery and vegetation indices with corresponding field measurement data. Field observations, which served as reference data, were used to evaluate the consistency between estimated biomass values and actual biomass conditions at selected sampling locations. The validation process aims to assess the reliability of the proposed estimation model by examining the degree of agreement between remotely sensed estimates and ground-based measurements. This step is essential to ensure that the developed model provides credible biomass estimates and can be applied confidently in subsequent analyses and forest monitoring activities.

3.5 Analysis and Interpretation

The biomass estimation results were analyzed based on vegetation cover and density parameters derived from vegetation indices. Spatial variations in biomass distribution were interpreted in relation to NDVI and EVI values to examine patterns of vegetation condition across the study area. This analysis provides insight into how variations in vegetation density influence biomass estimates obtained from drone imagery. Furthermore, the efficiency and accuracy of the drone-based biomass estimation approach were evaluated through comparison with conventional field-based methods. The comparison focused on aspects such as data acquisition time, spatial coverage, and the level of detail obtained from each approach. Through this comparative analysis, the strengths and limitations of drone imagery and vegetation index-based methods were identified, particularly in terms of their applicability for practical and sustainable forest monitoring.

4. RESULT AND DISCUSSION

4.1 3D Vegetation Model Analysis

Figure 2 illustrates the three-dimensional (3D) vegetation model generated from high-resolution drone imagery. The model provides a spatial representation of vegetation structure, allowing variations in canopy height and density to be visually identified across the study area. Compared to conventional two-dimensional imagery, the 3D model offers additional structural information that supports a more comprehensive interpretation of vegetation conditions related to biomass distribution. The spatial pattern observed in the 3D vegetation model indicates heterogeneous vegetation structure, with denser canopy formations occurring in localized areas and more open or sparse vegetation distributed elsewhere. These structural variations suggest differences in biomass accumulation, which are further examined through vegetation index analysis. The presence of vertical vegetation information from the 3D model complements spectral-based indicators and enhances the interpretation of biomass estimates, particularly in areas with complex vegetation arrangements.

FIGURE 1. 3D VEGETATION MODEL

TABLE 1. NDVI TABLE BASED ON CLASSIFICATION INTERVALS

NDVI Class	NDVI Range	Vegetation Description
Very Low	< 0.00	Water bodies or non-vegetated surfaces (e.g., buildings, bare soil)
Low	0.00 – 0.20	Open land or areas with very sparse vegetation cover.
Moderate	0.21 – 0.40	Shrubland or sparsely distributed vegetation.
High	0.41 – 0.60	Moderately dense vegetation such as agricultural land or gardens
Very High	0.61 – 1.00	Dense vegetation such as forested areas or green wetlands

Table 1 presents the classification of NDVI values used to characterize vegetation conditions in the study area. NDVI values were grouped into five classes, ranging from non-vegetated surfaces to areas with dense vegetation cover. This classification serves as a basis for interpreting vegetation density and its potential contribution to forest biomass. NDVI values below 0.0 represent non-vegetated surfaces such as water bodies, built-up areas, or exposed soil, indicating negligible biomass potential. Low NDVI values in the range of 0.00–0.20 correspond to open land or areas with very sparse vegetation cover. These zones contribute minimally to overall biomass due to limited vegetation density.

Moderate NDVI values (0.21–0.40) are associated with shrub-dominated areas or sparsely distributed vegetation, reflecting transitional vegetation conditions. Higher NDVI values between 0.41 and 0.60 indicate moderately dense vegetation, such as agricultural land, gardens, or mixed vegetation cover, which generally exhibit higher biomass accumulation. The highest NDVI class (0.61–1.00) represents areas with dense vegetation cover, typically forested or wetland environments, where biomass potential is expected to be highest. This classification provides a structured framework for interpreting the spatial distribution of vegetation observed in the NDVI map and supports subsequent biomass estimation analysis. By linking NDVI classes with vegetation characteristics, the table facilitates the identification of priority areas for biomass assessment, forest conservation, and land management planning.

TABLE 2. ESTIMATION OF NDVI PIXEL DISTRIBUTION TABLE BASED ON MAP COLOR

NDVI Range	Estimated Pixel	Percentage (%)	Color Interpretation
< 0.00	~5%	±5%	Dark red areas, very limited vegetation
0.00–0.20	~40%	±40%	Dominated by pale yellow color
0.21–0.40	~30%	±30%	Slight greenish appearance
0.41–0.60	~20%	±20%	Bright green areas, sporadically distributed
0.61–1.00	~5%	±5%	Dark green areas, very limited in extent

Table 2 summarizes the estimated spatial distribution of NDVI values based on visual interpretation of the NDVI map. Areas with NDVI values below 0.0 are represented by dark red tones and correspond to non-vegetated surfaces such as water bodies, built-up land, or exposed soil, indicating negligible biomass potential. These areas occupy only a small proportion of the study area. Low NDVI values ranging from 0.00 to 0.20 dominate the map, accounting for approximately 40% of the total area. This class is characterized by pale yellow colors and represents open land or areas with very sparse vegetation cover. Moderate NDVI values (0.21–0.40), shown by slightly greenish tones, occupy about 30% of the area and are typically associated with shrubland or sparsely distributed vegetation.

Higher NDVI values between 0.41 and 0.60 account for around 20% of the study area and are represented by brighter green colors. These areas indicate moderately dense vegetation, such as agricultural land or mixed vegetation cover, which generally exhibit higher biomass potential. Only a small fraction of the area (approximately 5%) shows very high NDVI values above 0.60, represented by dark green colors, corresponding to dense vegetation such as forested areas. The uneven distribution of NDVI values suggests that vegetation cover within the study area is spatially heterogeneous rather than uniformly distributed. This spatial pattern highlights the importance of high-resolution drone imagery for capturing detailed variations in vegetation density, which are critical for accurate forest biomass estimation and spatially explicit land management analysis.

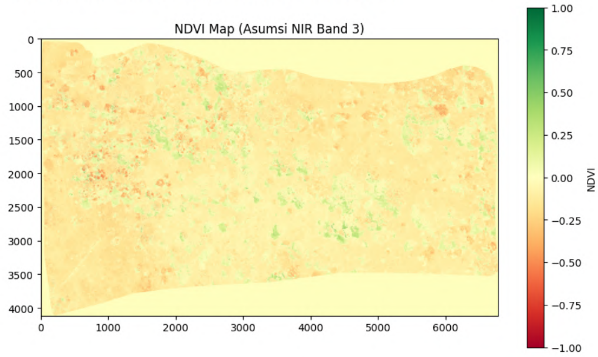

FIGURE 3. NDVI (NORMALIZED DIFFERENCE VEGETATION INDEX) VISUALIZATION RESULTS IN COLOR MAP FORM

Figure 3 presents the spatial distribution of vegetation based on the Normalized Difference Vegetation Index (NDVI), calculated under the assumption that the near-infrared (NIR) band corresponds to Band 3. The NDVI map is visualized using a color gradient ranging from red, representing low NDVI values, to dark green, indicating high NDVI values. This color variation reflects differences in vegetation density and health across the study area. Areas depicted in green tones correspond to high NDVI values (generally above 0.40), indicating dense and healthy vegetation such as forested areas, productive plantations, or natural vegetation with active photosynthetic processes. These areas exhibit high vegetation cover and, consequently, a high potential for biomass accumulation. In contrast, regions shown in yellow to orange colors, with NDVI values between approximately 0.10 and 0.40, represent moderate vegetation cover, including shrubs, grasslands, or agricultural land with lower photosynthetic activity, resulting in moderate to low biomass potential. Areas colored red to dark red, characterized by NDVI values below 0.10 or negative, indicate non-vegetated or sparsely vegetated surfaces such as bare soil, built-up areas, roads, or water bodies, where biomass potential is minimal or absent.

The NDVI map reveals an uneven spatial distribution of vegetation within the study area. Higher concentrations of dense vegetation are observed mainly in the central to lower parts of the explain the map, while the upper sections are dominated by lower NDVI values, indicating sparser or less healthy vegetation cover. This fragmented and patchy vegetation pattern suggests spatial heterogeneity rather than a uniform vegetation landscape, which directly influences the overall biomass estimation results. In addition, the presence of invalid NDVI values, indicated by computational warnings during processing, reflects pixels where the sum of NIR and red reflectance values approaches zero. Such conditions commonly occur in non-vegetated areas, including water surfaces or shadowed regions. These pixels produce undefined NDVI values and were therefore excluded or treated separately in subsequent analyses to avoid bias in biomass estimation.

Based on the NDVI spatial patterns shown in Figure 3, areas with high NDVI values can be identified as priority locations for biomass estimation due to their higher vegetation productivity and potential carbon storage. Conversely, areas with low NDVI values may be considered targets for land rehabilitation or vegetation enhancement programs. When combined with field measurement data and empirical regression models linking NDVI values to biomass quantities (e.g., tons per hectare), the NDVI map provides not only a visual representation of vegetation health but also a robust basis for quantitative biomass estimation and sustainable forest management planning.

The results of this research have important implications for sustainable forest management. The use of drone imagery combined with vegetation indices enables more efficient forest monitoring in terms of time, cost, and spatial coverage. Compared to conventional field-based approaches, UAV-based data acquisition allows periodic updates of vegetation information without the need for intensive and repetitive manual measurements.

From a practical perspective, the proposed approach can support various forest management activities. High-resolution drone imagery facilitates the monitoring of land cover changes over time, allowing early detection of vegetation loss or recovery. Vegetation index analysis can also be used to identify priority areas for conservation based on vegetation density and biomass potential. In addition, areas experiencing land degradation or reduced vegetation cover can be identified more effectively, supporting targeted rehabilitation efforts. Furthermore, biomass estimation derived from drone imagery and vegetation indices can serve as preliminary input for carbon stock assessment, including applications related to carbon accounting and the REDD+ scheme. By providing timely and spatially detailed biomass information, this approach contributes to more informed decision-making in forest management and environmentally sustainable land-use planning.

5. CONCLUSIONS

This research demonstrates that forest biomass estimation can be performed reliably using drone imagery combined with vegetation index analysis. Through appropriate image preprocessing and vegetation index extraction, a strong relationship between UAV-derived NDVI values and field-measured biomass was observed, confirming the effectiveness of remote sensing techniques for biomass estimation in the study area. The results also indicate that drone-based approaches offer clear advantages over conventional field-based methods in terms of operational efficiency and spatial coverage. High-resolution UAV imagery enables detailed vegetation mapping and supports more precise biomass estimation, particularly in areas where access for ground surveys is limited. Nevertheless, several factors may influence estimation accuracy, including image resolution, atmospheric conditions during data acquisition, and variability in land cover types. Overall, the integration of drone technology and vegetation index analysis provides a practical framework for periodic forest monitoring with reduced time and cost requirements. The biomass estimation model developed in this study can serve as a baseline for future improvements, including the incorporation of additional field data and advanced analytical techniques. Such developments may further enhance the accuracy and applicability of UAV-based biomass monitoring systems, contributing to more effective and sustainable forest resource management.

Future research may consider the use of more advanced multispectral or hyperspectral data to further improve the accuracy of forest biomass estimation. Richer spectral information is expected to enhance vegetation classification and increase the reliability of vegetation index calculations. In addition, model performance can be strengthened by incorporating more diverse and representative field data for validation. Direct biomass measurements obtained using standardized field instruments may provide more robust reference data for model calibration.

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