Prisma Sains: Jurnal Pengkajian Ilmu dan Pembelajaran Matematika dan IPA IKIP Mataram
https://e-journal.undikma.ac.id/index.php/prismasains/index
e-mail: prismasains.pkpsm@gmail.com

July 2026. Vol. 14, No. 3
p-ISSN: 2338-4530
e-ISSN: 2540-7899
_pp. 1642-1655_

Mapping Mangrove Blue Carbon via Unmanned Aerial Vehicles: A Systematic Review of Methodological Trends

Ludwick Satria Romadoni, *Eko Susetyarini, Muhammad Rifky Ardiansyah
Department of Biology Education, Universitas Muhammadiyah Malang, Malang, Indonesia
*Corresponding Author e-mail: susetyorini@umm.ac.id

Received: June 2026; Revised: June 2026; Published: July 2026

Abstract

Accurate quantification of mangrove blue carbon stocks requires precise, non-destructive, and cost-effective methodologies. However, conventional satellite imagery often suffers from moderate resolution and cloud cover, while traditional vegetation indices face optical saturation in dense coastal canopies. To address these core issues, this study conducted a Systematic Literature Review (SLR) using the PRISMA protocol to evaluate the use of Unmanned Aerial Vehicles (UAVs) in coastal carbon estimation. A targeted search of the Scopus database (2017–2026) yielded 37 peer-reviewed articles for thematic and qualitative synthesis. The synthesis reveals a significant paradigm shift toward UAV-based RGB sensors. Scientific findings indicate that advanced visual indices, specifically the Mangrove Vegetation Index (MVI) and Excess Green (ExG), are frequently reported as highly effective for reducing substrate reflectance bias and mitigating optical saturation. Furthermore, 59.5% of the reviewed studies integrated these spatial features with Machine Learning algorithms, primarily Random Forest and Support Vector Machine, to model non-linear biomass relationships and substantially reduce the Root Mean Square Error (RMSE). In conclusion, while UAV-RGB mapping demonstrates high potential, current linear interpolation methods struggle with dense interlocking canopies, causing over-fitted delineations. Future research must transition to discrete spatial algorithms with elevated threshold calibrations to accurately isolate individual tree crowns.

Keywords: Biomass; Blue carbon; Machine learning; Mangrove; Unmanned aerial vehicles

How to Cite: Romadoni, L. S., Susetyarini, E., & Ardiansyah, M. R. (2026). Mapping Mangrove Blue Carbon via Unmanned Aerial Vehicles: A Systematic Review of Methodological Trends. *Prisma Sains: Jurnal Pengkajian Ilmu Dan Pembelajaran Matematika Dan IPA IKIP Mataram*, *14*(3), 1642–1655. https://doi.org/10.33394/j-ps.v14i3.21031

https://doi.org/10.33394/j-ps.v14i3.21031

INTRODUCTION

Mangrove ecosystems are among the most efficient carbon sinks on Earth, playing a central role in mitigating global climate change through the storage of blue carbon. While total blue carbon encompasses both belowground soil organic carbon and aboveground biomass (AGB), estimating AGB serves as a critical and measurable proxy for assessing the overall carbon storage capacity of these ecosystems. Historically, biomass inventory has relied heavily on plot-based field surveys that are destructive, labor-intensive, and difficult to apply spatially across rugged coastal landscapes (Pradisty et al., 2025; Wang et al., 2020). To overcome these limitations, satellite-based remote sensing has long been used, but it is often constrained by moderate spatial resolution and high cloud cover in tropical regions, making mapping at the individual stand level challenging (Zhu et al., 2020).

With the advancement of spatial technology, a paradigm shift has occurred towards the use of Unmanned Aerial Vehicles (UAVs). However, a sensor gap remains in current monitoring efforts. While LiDAR and multispectral sensors provide highly detailed structural data, their deployment is often constrained by prohibitive operational costs (Gu et al., 2026; Liang et al., 2022). Consequently, commercial RGB (Red, Green, Blue) cameras have emerged as a more accessible and cost-effective alternative for repetitive monitoring, though their use introduces specific technical challenges (Azzahra et al., 2025; Pradisty et al., 2025).

The utilization of very high-resolution optical imagery introduces a subsequent analytical gap. Conventional vegetation indices often experience spectral saturation when applied to coastal forest ecosystems with high Leaf Area Index (LAI) density. Furthermore, they are vulnerable to mixed-pixel blending caused by reflectance bias from mud substrates and tidal inundation. To address this background noise, recent studies have adopted RGB-derived indices such as the Mangrove Vegetation Index (MVI) and Excess Green (ExG). When integrated with Machine Learning algorithms (e.g., Random Forest and Support Vector Machine), these specific indices have shown the potential to improve prediction accuracy by modeling non-linear spatial relationships and reducing the Root Mean Square Error (RMSE) (Qiu et al., 2019; Zhuang et al., 2026).

Despite improvements in sensor deployment and analytical modeling, a critical segmentation gap persists in the 3D metric post-processing stage, representing the most urgent unresolved issue in recent literature: the precise delineation of Individual Tree Crowns (ITC). Mangrove ecosystems are characterized by wild, interlocking, and highly dense canopy architectures. As demonstrated by recent studies (Navarro et al., 2019; Wang et al., 2020), accurately isolating individual crowns in these dense environments remains difficult. Standard spatial delineation modeling relying on linear interpolation techniques frequently reveals systemic weaknesses, where extraction threshold values cause area generalization and result in overlapping or over-fitted individual crown estimations (Romadoni et al., 2025). Precisely isolating these canopies before extracting indices like MVI is essential, yet a standardized computational approach remains elusive.

Therefore, the novelty of this Systematic Literature Review (SLR) lies in its comprehensive synthesis of these three methodological frontiers, with a specific focus on identifying solutions to the ITC segmentation gap in UAV-RGB mapping. This study aims to: (1) evaluate trends in utilizing UAV-RGB imagery and advanced indices (MVI and ExG) for AGB and blue carbon proxy estimation; (2) critically assess the performance of integrating these indices with machine learning algorithms; and (3) analyze current computational limitations in canopy segmentation to formulate future research directions for precision coastal ecosystem monitoring.

METHOD

This research employed a Systematic Literature Review (SLR) design, adhering strictly to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The review protocol was not registered in a prospective database (e.g., PROSPERO), as this study focuses on methodological trends in remote sensing rather than clinical outcomes. This method was chosen to ensure transparency, reproducibility, and objectivity in synthesizing literature regarding the quantification of aboveground biomass (AGB) and blue carbon stocks in mangrove ecosystems using UAV-based remote sensing.

The literature search was conducted on May 3, 2026, focusing exclusively on the Scopus database. Scopus was selected because it is one of the largest, most comprehensive, and rigorously curated databases for peer-reviewed literature in environmental sciences, engineering, and remote sensing. The search utilized a specific Boolean query applied to Titles, Abstracts, and Keywords: (TITLE-ABS-KEY ("mangrove*") AND TITLE-ABS-KEY ("blue carbon" OR "biomass" OR "aboveground biomass" OR "AGB") AND TITLE-ABS-KEY ("UAV" OR "Unmanned Aerial Vehicle" OR "drone*" OR "RGB") AND TITLE-ABS-KEY ("vegetation index" OR "mapping" OR "estimation")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (OA, "all")) AND (LIMIT-TO (EXACTKEYWORD, "Mangrove") OR LIMIT-TO (EXACTKEYWORD, "Aboveground Biomass") OR LIMIT-TO (EXACTKEYWORD, "Unmanned Aerial Vehicles (uav)") OR

LIMIT-TO (EXACTKEYWORD, "Machine Learning") OR LIMIT-TO (EXACTKEYWORD, "Lidar") OR LIMIT-TO (EXACTKEYWORD, "Remote Sensing")).

While restricting the search to Scopus and utilizing exact-keyword filters introduces a potential selection bias possibly excluding relevant studies indexed only in Web of Science or IEEE Xplore, or those using alternative terminologies this approach was strictly chosen to establish a highly standardized, quality-controlled baseline of the most prominent methodological trends.

To ensure the relevance and quality of the synthesized literature, strict inclusion and exclusion criteria were established prior to the screening process (Table 1).

Table 1. Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Timeframe	Published between 2017 and 2026	Published prior to 2017.
Document Type	Original research articles	Review articles, conference papers, proceedings, book chapters, editorials.
Language	English	Non-English publications.
Subject/Scope	Mangrove ecosystems, UAV-based remote sensing, AGB/carbon estimation	Non-mangrove vegetation, satellite-only studies, hardware/antenna focus.
Accessibility	Open Access (OA)	Paywalled (Non-OA) articles.

The screening process involved four phases (Figure 1). Initially, 76 records were identified. Title and abstract screening was conducted independently by two reviewers (L.S.R and M.R.A). Any disagreements regarding study eligibility were resolved through discussion and consensus with a third reviewer (R.E.S). Following the removal of non-original articles (n=17) and non-English articles (n=6), an accessibility filter was applied. Exactly 11 paywalled (non-open access) articles were excluded, leaving 42 fully Open Access articles (encompassing Gold, Green, Hybrid, and Bronze OA categories). While excluding paywalled studies may slightly narrow the scope, this decision was scientifically justified to ensure full-text reproducibility, allowing detailed extraction of proprietary algorithms, flight parameters, and field validation protocols that are often obscured in abstracts. Finally, 5 studies were excluded for falling outside the ecological scope (e.g., focusing on inland plantations or coastal fauna monitoring), resulting in 37 included studies.

To distinguish strong scientific evidence from weak evidence, a quality appraisal was conducted on the 37 included studies. Each article was critically evaluated based on the presence of rigorous field validation, adequate sample size (number of validation plots), transparency of sensor radiometric calibration, and the explicit reporting of accuracy metrics (e.g., R^2, RMSE, MAE). A quantitative meta-analysis was not possible due to extreme methodological heterogeneity across the studies, which included varying flight altitudes, distinct biomass allometric equations, and highly diverse mangrove species structures. Consequently, a systematic thematic and qualitative synthesis was performed.

Based on the subject areas of the 37 analyzed literatures (Figure 2), publications were dominated by Environmental Sciences (25.5%), followed by Agricultural and Biological Sciences (18.9%), and Earth and Planetary Sciences (17.9%). The distribution of this data indicates that studies on coastal carbon stock mapping based on UAVs are highly multidisciplinary and require a strong approach from the spatial and computational sciences.

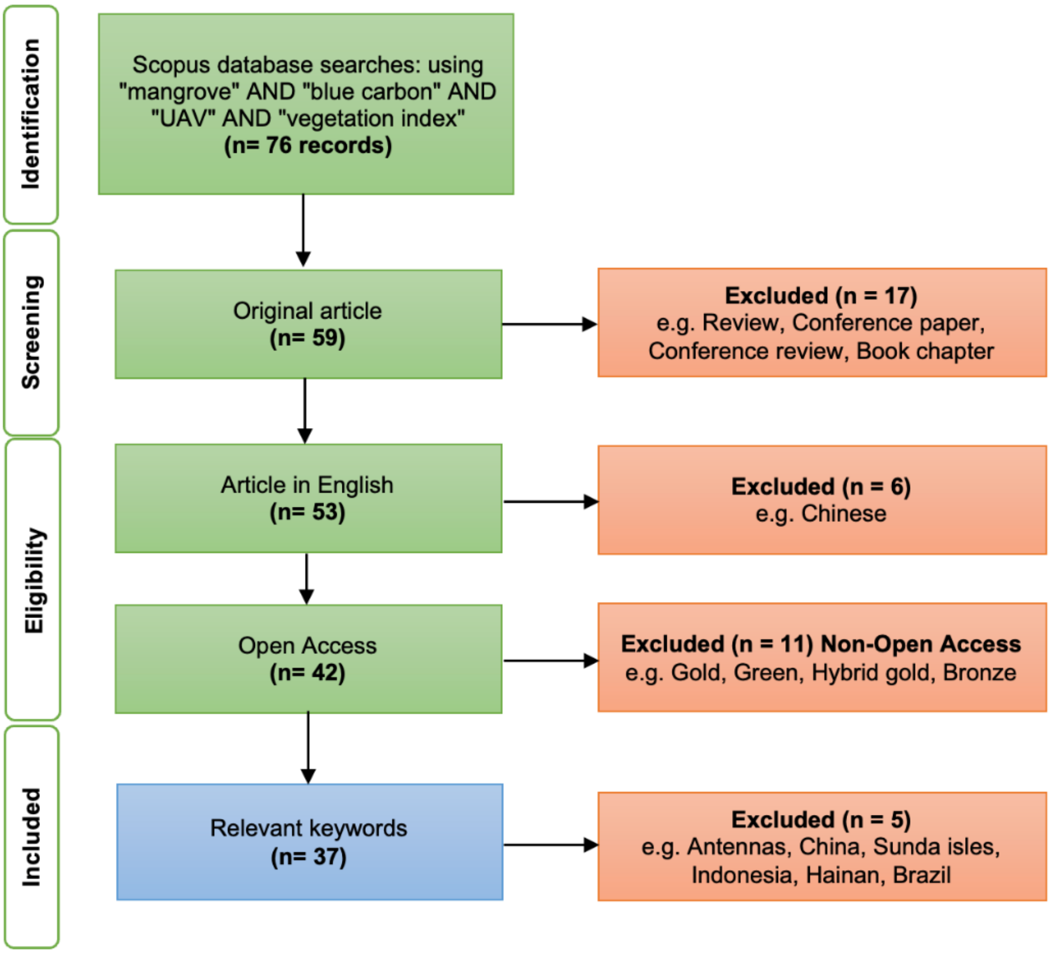

Figure 1. PRISMA Diagram

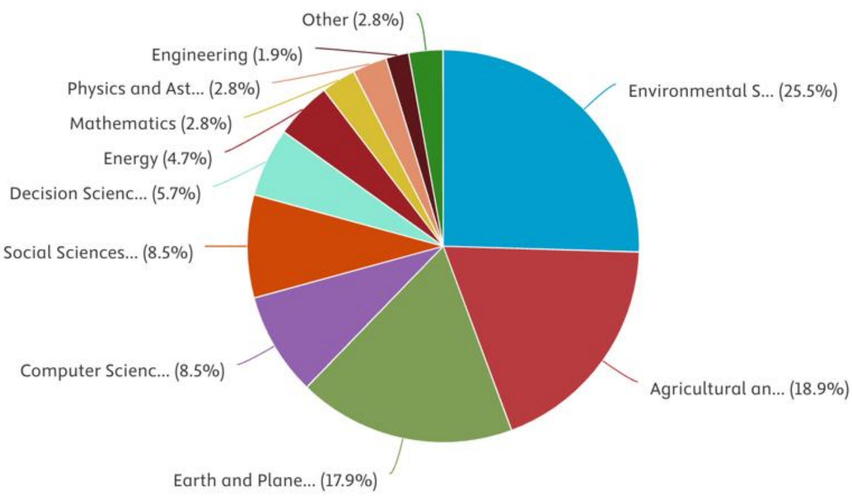

Figure 2. Subject Area

RESULTS AND DISCUSSION

Table 2 summarizes the research methodologies and key findings of the 37 selected studies regarding the use of UAV technology for blue carbon mapping in mangrove ecosystems. This table illustrates a wide variety of research approaches, sensor instrument variations, spatial indices used, and extraction algorithms. Overall, a purely statistical quantitative synthesis was not conducted due to the highly heterogeneous nature of the mangrove canopy cover and vegetation species across the literature.

Table 2. Quantitative Synthesis of UAV-Based Mangrove Biomass Methodologies

Author	Study Location & Species	Sensor Type & Altitude	Analytical Algorithm	Validation Plots & Accuracy Metrics	Key Limitations
(Wu et al., 2026)	Hainan Island, China / Mangrove	UAV-LiDAR	Hierarchical Machine Learning	Cross-validated; R^2 = 0.686	Lack of interpretability and robustness in conventional models
(Pungpa et al., 2025)	Nakhon Si Thammarat, Thailand / *R. mucronata, R. apiculata, A. marina*	UAV-Optical (RGB)	Multiple Regression Analysis	Ground-truthed; R^2 = 0.73, RMSE = 22.0 t/ha	Optical saturation at high LAI; relies on multiple VIs
(Schürholz et al., 2023)	Utría NP, Colombia / *P. rhizophorae, R. mangle*	UAV-Optical (RGB)	Deep Learning (CNNs)	33% Instance precision, 97% semantic precision	Overlapping border regions require complex merging algorithms
(Saliu et al., 2021)	Malaysia / Mangrove	UAV-Optical (RGB)	Statistical Comparison	Error range = 7.1% – 15%	Accuracy heavily affected by tree form and isolated vs. canopy status
(Zhuang et al., 2026)	China / Mangrove	UAV-LiDAR	Deep Learning (RAP-CNN)	Training & validation sets; R^2 = 0.76, RMSE = 8.39 Mg/ha	Complex inaccessible habitats limit high-quality traditional sampling
(Qiu et al., 2019)	China / Six mangrove species	UAV-LiDAR	Random Forest (RF)	Field sample plots; R^2 = 0.67, RMSE = 38.95 Mg/ha	Limitation in spatial detail using grid-based RF models
(Conroy et al., 2025)	Great Barrier Reef, Australia / *R. stylosa*	RPA-LiDAR & Multispectral	Regression Analyses	Field plot data; R^2 > 0.8	Suboptimal growth in older zones and high cyclone exposure
(Fu et al., 2025)	China / *A. marina, A. corniculatum*	UAV-LiDAR	RF, PLSR, MDN	Cross-validated; R^2 = 0.897 (A. marina)	Accurately estimating height in complex coastal environments is challenging
(Duan et al., 2025)	Kenya / Juvenile mangrove	UAV-LiDAR & High-overlap RGB	Ensemble Regression	Field plots; MAE = 1.79 kg, R^2 = 0.71	Plot-level metrics lack detailed spatial information for individual trees
(Mai et al., 2025)	Guangxi, China / Mangrove	UAV-LiDAR	RF with Recursive Feature Elimination	Field plots; R^2 = 0.75, RMSE = 14.18 Mg/ha	Structural complexity and spectral saturation in dense canopies
(Huang et al., 2025)	Hainan, China / Mangrove	UAV-LiDAR	Support Vector Machine (SVM)	Field measurements; R^2 = 0.885,	High feature redundancy requiring Mutual

Author	Study Location & Species	Sensor Type & Altitude	Analytical Algorithm	Validation Plots & Accuracy Metrics	Key Limitations
				RMSE = 0.47 kg/m²	Information feature selection
(L. Chen et al., 2026)	Hainan, China / Mangrove	UAV-LiDAR	Geo-balanced Optimization (RF)	Field validations; $R^2 = 0.74$, RMSE = 1.12 m	Spectral saturation causing systematic bias (under/overestimation)
(Y. Zhu et al., 2020)	Qi'ao Island, China / Mangrove plantation	UAV-Optical (DSM)	Random Forest (RF)	127 samples; RMSE = 25.69 t/ha	Saturation effect in dense optical and SAR imagery
(Lassalle et al., 2023)	Baixada Santista, Brazil / Mangrove	Drone Hyperspectral & Laser Scanning	Spatial Modeling	Biomass loss estimation: 9.8–91.2 t/ha	Long-term sublethal pollution effects stunt biomass recovery
(Liu et al., 2026)	Hainan, China / Mangrove	UAV-Optical	GBDT & Random Forest (RF)	Strong field agreement; $R^2 = 0.89$ (Height)	Complex and variable growth environments pose monitoring challenges
(Pradisty et al., 2025)	Bali, Indonesia / Natural & restored mangroves	UAV-Optical (RGB)	Spatial Modeling (Lorey's height)	Cross-validated with CSM; Mean AGB = 240 Mg/ha	Ecosystem complexity and varying forest structures
(Iryanthony et al., 2025)	Central Java, Indonesia / *R. mucronata, R. stylosa*	UAV-Optical (RGB) [120m AGL]	Allometric Equations	CE90 = 0.02 m; RMSE = 8.95 mg/ha	High reliance on accurate Global Navigation Satellite System (GNSS)
(Navarro et al., 2019)	Senegal / Young mangrove plantations	UAV-Optical (RGB)	Support Vector Regression (SVR)	95 sample plots; RMSE = 0.21 m (height)	Remote locations make traditional field measurements difficult
(Gu et al., 2026)	Coastal Wetlands, China / Mangrove & Benthic fauna	UAV-Optical (RGB)	Deep Learning (YOLOv5/v8, CNN)	Extracted community metrics matching manual surveys	Traditional surveys are labor-intensive, time-consuming, and invasive
(Li et al., 2024)	South China / 6 dominant species	UAV-LiDAR	Curve Fitting / Spatial Modeling	Cross-validated; Improved accuracy via curve fit	Low penetration and difficulty distinguishing vegetation types
(Wirasatriya et al., 2022)	Karimunjawa, Indonesia / Mangrove	UAV-Optical (RGB)	Allometric Equations	High accuracy DSM & DTM	Overlapping canopies affect exact individual tree delineation

Author	Study Location & Species	Sensor Type & Altitude	Analytical Algorithm	Validation Plots & Accuracy Metrics	Key Limitations
(Karimi et al., 2025)	Southern Iran / *A. marina*	UAV-Optical (RGB)	SfM Photogrammetry & Allometry	Validated with field data; Estimates $p > 0.05$	Drone-based heights differed significantly from field measurements
(Fu et al., 2023)	Beibu Gulf, China / *A. corniculatum, C. malaccensi*	UAV-Multispectral	ASEL & MPViT (Ensemble Learning)	Classification accuracy = 95.5% - 97.3%	Data redundancy and subjectivity in parameter tuning
(Ma et al., 2026)	Chonburi, Thailand / Mangrove	UAV-SfM & SAR	AGBT/F~U~S Upscaling Method	Reduction in error: ΔRMSE ≈ 66 Mg/ha	Model stability struggles under limited training data conditions
(Azzahra et al., 2025)	Saleh Bay, Indonesia / Mangrove	UAV-Optical (Drone-derived)	Regression Analysis	Strong correlation; $R^2 = 0.863$	Optical indices saturation at extremely high density covers
(Wang et al., 2020)	Hainan, China / Diverse species	UAV-LiDAR	G-LiDAR-S2 Upscaling Model	Field plots; $R^2 = 0.62$, RMSE = 50.36 Mg/ha	High species diversity hinders extensive plot-based sampling
(Ye & Weng, 2025)	China / Mangrove	UAV-Optical	Hybrid Neural Network (Vision Transformer)	88,645 samples; Overall Accuracy = 95.91%	Poor transferability under highly dynamic tidal conditions
(Liang et al., 2022)	Tropical Area / Rubber (Comparative Study)	UAV-Optical (RGB)	Support Vector Regression (SVR)	Cross-validated; $R^2 = 0.752$, RMSE = 28.72 t/ha	Extracting texture features without optimal parameters causes errors
(Xiang et al., 2024)	Shenzhen, China / H. littoralis (Semi-mangrove)	UAV-Hyperspectral	XGBoost & Random Forest (RF)	Cross-validated; $R^2 = 0.749$, RMSE = 1.72 kg/m²	Previous studies overlooked remote monitoring of rare species
(Jiang et al., 2021)	Global / Mangrove	UAV-Hyperspectral	Random Forest (RF) & SVM	Feature extracted; Overall Accuracy = 95.89%	Natural and anthropogenic activities cause continuous area loss
(Wang et al., 2019)	Hainan, China / Mangrove	UAV-LiDAR	LiDAR-S2 Model	Field plots; $R^2 = 0.67$, RMSE = 1.90 m	Extreme challenges during sampling in intertidal mudflats
(Y. Zhu et al., 2024)	Global / Mangrove	UAV-LiDAR	GA-ANN Wrapper	Reduced RMSEr by 5.80%	Scale-related challenges and expanded set of variables in integration

Author	Study Location & Species	Sensor Type & Altitude	Analytical Algorithm	Validation Plots & Accuracy Metrics	Key Limitations
(Tian et al., 2022)	Guangxi, China / *S. apetala* (Invasive)	UAV-LiDAR	Catboost Regressor (CBR)	Plot investigation; $R^2 = 0.76$, RMSE = 11.17 Mg/ha	Standard Light Gradient Boosting performed poorly ($R^2 = 0.35$)
(Pradisty et al., 2025)	Tropical Region / Restored mangrove	UAV-LiDAR	Random Forest (RF)	Spatial cross-validation; $R^2 = 0.55$, RMSE = 56.4 Mg/ha	Unreliable model transferability to non-restoration areas
(Warfield & Leon, 2019)	Global / Juvenile & mature mangrove	UAV-SfM (RGB)	Surface Differencing Method	12% - 42% volume difference vs. TLS	SfM-MVS poorly captured complex inner forest structure
(R. Chen et al., 2023)	Fujian, China / *K. obovata*	UAV-LiDAR	Random Forest (RF)	Derived CHM; $R^2 = 0.71$, RMSE = 0.91 m	Highly complicated nature of horizontal and vertical mangrove systems
(Z. Zhu et al., 2022)	Southeastern China / Subtropical mangrove	UAV-SfM (Optical)	Empirical EVI-height-AGB Eq	Space-for-time hypothesis	Significant spectral saturation effects in stands older than 15 years

Note: R^2 = Coefficient of Determination; RMSE = Root Mean Square Error; MAE = Mean Absolute Error; LAI = Leaf Area Index; AGB = Aboveground Biomass; SfM = Structure from Motion; CHM = Canopy Height Model.

As a comparison of analytical trends, Table 3 constructs a thematic synthesis of the most crucial findings extracted from the 37 main literatures. In-depth analysis shows that current academic discourse is massively centered on two spatial modeling axes: the evaluation of RGB optical sensor performance along with its advanced derivative indices, and a fundamental transition in canopy architecture extraction methods.

Table 3. Summary of Analytical Synthesis and Thematic Findings

Thematic Extraction Focus	Summary of Specific Key Findings	Article References
Performance of RGB Camera-Based Indices	The application of conventional vegetation indices is increasingly being phased out to mitigate optical saturation effects. Advanced indices derived purely from visual channels particularly the Mangrove Vegetation Index (MVI) and Excess Green (ExG) have consistently proven superior in separating mangrove canopies from muddy substrate backgrounds and tidal water reflectance, yielding high cost-effectiveness.	(Azzahra et al., 2025; Gu et al., 2026; Jiang et al., 2021; Liang et al., 2022)
Accuracy of Machine Learning Integration	Analytical modeling has undergone a massive transformation (accounting for 59.5% of the literature), shifting from conventional regression to the application of advanced Machine Learning, specifically Random Forest (RF) and Support Vector Machine (SVM). These algorithms	(L. Chen et al., 2026; Fu et al., 2025; Huang et al., 2025; Liang et al., 2022; Mai et al., 2025; Pradisty et al., 2025; Qiu et al., 2019; Xiang

Thematic Extraction Focus	Summary of Specific Key Findings	Article References
	overcome the limitations of linear correlation by deciphering complex multi-variable interactions (spectral indices and Canopy Height Models/CHM), thereby significantly reducing error rates.	et al., 2024; Zhuang et al., 2026)
Challenges in 3D Spatial Segmentation Precision	Under extensive and extremely dense canopy conditions, standard delineation techniques frequently yield merged or overlapping outputs. Conventional spatial interpolation is still unable to perfectly isolate individual tree structures. Therefore, calibrating advanced segmentation techniques to accurately map individual tree architectures remains the most prominent research challenge.	(Li et al., 2024; Navarro et al., 2019; Schürholz et al., 2023; Wang et al., 2019, 2020; Wu et al., 2026)

The systematic review exposes a fundamental shift in platform preference from conventional satellites to the extensive utilization of Unmanned Aerial Vehicles (UAVs). The integration of UAVs with optical camera sensors particularly commercial RGB sensors offers a highly efficient operational cost ratio compared to LiDAR. These low-altitude optical platforms mitigate the temporal and spatial constraints of satellite imagery, providing the sub-meter resolution necessary for coastal ecology studies.

However, this resolution shift introduces a specific analytical challenge: optical wave saturation. Studies (Azzahra et al., 2025; Gu et al., 2026) report that traditional vegetation indices often yield biased estimations when applied to high-resolution UAV imagery, particularly due to the high Leaf Area Index (LAI) values inherent in dense *Rhizophora* stands. Consequently, current methodological trends demonstrate a strong transition toward indices designed specifically for the visual channel, such as the Mangrove Vegetation Index (MVI) and Excess Green (ExG). These advanced indices have been reported as highly effective instruments for noise reduction; they actively isolate foliage pigments from substrate reflectance biases caused by tidal inundation and mud deposits a systemic limitation in prior satellite-based methodologies.

The integration of advanced spectral indices is significantly optimized when paired with Machine Learning (ML) algorithms. Based on the extracted data, 22 out of the 37 reviewed studies (59.5%) utilized ML for spatial modeling, shifting away from conventional linear regression. Algorithms such as Random Forest (RF) and Support Vector Machine (SVM) dominate the literature due to their robustness against spatial data multicollinearity.

These ML models effectively decipher complex, non-linear interactions by combining 3D structural parameters (e.g., Canopy Height Models/CHM) with 2D spectral indices (MVI and ExG). Multiple studies highlighted in Table 2 reported that this integration substantially lowered the Root Mean Square Error (RMSE) and improved the Coefficient of Determination (R^2) during field validation, demonstrating superior predictive performance for AGB estimation compared to traditional empirical models.

Despite the establishment of robust remote sensing models, this review identifies Individual Tree Crown (ITC) delineation as a persistent methodological gap in the post-processing stage. Mangrove architectures in wild estuarine environments are characterized by dense, interlocking canopies. A critical evaluation of prior research reveals that standard spatial delineation modeling, particularly those relying on linear interpolation techniques (e.g., local maxima filtering or basic watershed segmentation), frequently results in systemic weaknesses.

When segmentation threshold parameters are inadequately calibrated, the interpolation generalizes the spatial area, causing adjacent crown volumes to merge (over-fitting).

Accurately isolating these canopies through advanced, discrete-based segmentation algorithms with elevated threshold calibrations remains the most prominent computational hurdle before metric extraction can be executed flawlessly.

While UAV-based modeling presents significant advancements, several inherent limitations must be acknowledged. First, UAV operations are heavily constrained by physical and environmental factors, including limited battery life, strict aviation flight regulations, wind interference, and the critical need to synchronize flights with low-tide windows to minimize water reflectance. Furthermore, reliance on RGB imagery requires rigorous radiometric calibration to account for varying illumination and shadow effects within the dense canopy.

Finally, it is crucial to clarify the distinction between AGB and total blue carbon accounting. While the reviewed literature frequently utilizes the term "blue carbon," UAV-based photogrammetry and LiDAR are strictly limited to measuring aboveground structural metrics. AGB serves merely as a measurable proxy; comprehensive blue carbon inventories must ultimately integrate belowground root biomass and soil organic carbon (SOC), which currently remain beyond the reach of aerial remote sensing alone. Future research must prioritize standardized field validation protocols, multi-site testing across diverse mangrove species, and the development of hybrid models that integrate UAV-RGB data with satellite and localized SOC sampling to achieve holistic blue carbon accounting.

CONCLUSION

The Conclusion part describes the answers to the hypotheses and/or research objectives or scientific findings obtained. The conclusion does not contain a repetition of the results and discussion, but rather summarizes the findings as expected in the objectives or hypotheses. In addition, implications, significance of research results, and recommendations for further studies are also presented in this section.

This systematic review establishes that there is a significant methodological paradigm shift toward the use of Unmanned Aerial Vehicles (UAVs) as highly effective survey instruments for coastal monitoring. To overcome the optical saturation effects frequently encountered in satellite imagery, advanced optical indices such as the Mangrove Vegetation Index (MVI) and Excess Green (ExG) have emerged as robust alternatives for isolating active canopy pigments from environmental reflectance biases. The quality of spatial feature mapping is further enhanced by the prevalent adoption of Machine Learning modelling specifically Random Forest (RF) and Support Vector Machine (SVM) which accounts for nearly 60% of recent analytical approaches. This integration effectively models non-linear spatial interactions and reduces the Root Mean Square Error (RMSE) in Aboveground Biomass (AGB) estimation.

However, despite these advancements, Individual Tree Crown (ITC) delineation under dense interlocking canopy conditions remains a persistent technical challenge. Furthermore, it must be acknowledged that the extreme methodological heterogeneity across the reviewed studies encompassing diverse flight parameters, varied allometric equations, and different mangrove species prevents firm generalization of a single "best" algorithm. Therefore, while UAV-RGB and Machine Learning integration is highly promising, continuous calibration is required to adapt to specific coastal environments.

RECOMMENDATION

While UAV-based modeling demonstrates high potential, future research must expand beyond algorithmic improvements. Although transitioning from linear interpolation to discrete-based spatial modeling with elevated threshold calibrations is necessary for precise canopy delineation, researchers must also address broader operational limitations. Future studies are highly recommended to: (1) establish standardized field validation protocols to ensure comparability across studies; (2) conduct multi-site testing across different mangrove species and varying canopy structures; (3) integrate multisource data by combining cost-effective UAV-RGB imagery with LiDAR structural metrics and satellite data for regional upscaling;

and (4) develop strict radiometric and tidal correction procedures prior to index extraction. Ultimately, future scientific discourse must maintain a clear distinction between AGB estimation and total blue carbon accounting, ensuring that aerial monitoring is coupled with belowground soil organic carbon (SOC) assessments for holistic climate mitigation reporting.

ACKNOWLEDGMENTS

The authors would like to thank the Department of Biology Education, Universitas Muhammadiyah Malang, for providing the necessary institutional facilities and database access to conduct this systematic literature review.

FUNDING INFORMATION

This research received no external funding.

AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ludwick Satria Romadoni	✓	✓	✓		✓			✓	✓	✓	✓		✓	
Eko susetyarini	✓	✓		✓		✓	✓	✓		✓	✓	✓		✓
M. Rifky Ardyansyah		✓	✓			✓		✓		✓				

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Not applicable. This study is a systematic literature review and does not involve human participants.

ETHICAL APPROVAL

Not applicable. This study does not involve human or animal subjects.

DATA AVAILABILITY

The data that support the findings of this study are available within the article.

REFERENCES

Azzahra, R. Y., Yulius, Agus, S. B., Aditama, F. A., Arifin, T., Putra, A., Rahmania, R., Heriati, A., Prihantono, J., Purbani, D., Salim, H. L., Ramdhan, M., Wahyono, A., Sadad, Ningsih, A., & Asyiri, A. (2025). Advancing mangrove carbon stock monitoring with drone and Pleiades imagery on Gilibakau Island-Saleh Bay, Indonesia. *Journal of Marine and Island Cultures, 14*(1), 88–101. https://doi.org/10.21463/jmic.2025.14.1.06

Chen, L., Wan, B., Chen, Z., Cheng, C., Wu, M., Qiu, P., & Wang, D. (2026). AEZGO: A novel approach for mapping mangrove canopy height using UAV Lidar data and Sentinel-2 images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 19*, 9226–9240. https://doi.org/10.1109/JSTARS.2026.3668886

Chen, R., Zhang, R., Zhao, C., Wang, Z., & Jia, M. (2023). High-resolution mapping of mangrove species height in Fujian Zhangjiangkou National Mangrove Nature Reserve combined GF-2, GF-3, and UAV-LiDAR. *Remote Sensing, 15*(24). https://doi.org/10.3390/rs15245645

Conroy, B. M., Hamylton, S. M., Kelleway, J. J., Asbridge, E. F., Woodroffe, C. D., & Rogers, K. (2025). Mangrove above-ground biomass and production are related to forest age at Low Isles, Great Barrier Reef. *Ecology and Evolution, 15*(9). https://doi.org/10.1002/ece3.72048

Duan, M., Sanchez-Azofeifa, A., Abdulmajeed, M., Turner, D., Buckingham, K., Odari, A., Mtwana, J., Kipkoech, S., & Kasraee, N. (2025). Aboveground carbon estimation in a mangrove ecosystem using UAV-based remote sensing and machine learning. *Ecological Indicators, 178*. https://doi.org/10.1016/j.ecolind.2025.113950

Fu, B., He, X., Liang, Y., Deng, T., Li, H., He, H., Jia, M., Fan, D., & Wang, F. (2023). Examination of the performance of ASEL and MPViT algorithms for classifying mangrove species of multiple natural reserves of Beibu Gulf, south China. *Ecological Indicators, 154*. https://doi.org/10.1016/j.ecolind.2023.110870

Fu, B., Wei, Y., Jiang, L., Yao, H., Li, X., Yang, Y., Jia, M., & Sun, W. (2025). Estimation of mangrove heights and aboveground biomass using UAV-LiDAR, Sentinel-1 and ZY-3 stereo images. *Ecological Informatics, 88*. https://doi.org/10.1016/j.ecoinf.2025.103160

Gu, X., Chen, G., Capinha, C., Wang, W., Lu, X., & Wang, M. (2026). Automating coastal bioindicator acquisition with deep learning: Crab community monitoring for enhanced wetland management. *Ecological Indicators, 182*. https://doi.org/10.1016/j.ecolind.2025.114577

Huang, S., Zhang, Z., Sun, Y., Song, W., & Meng, J. (2025). Enhancing mangrove aboveground biomass estimation with UAV-LiDAR: A novel mutual information-based feature selection approach. *Sustainability, 17*(7). https://doi.org/10.3390/su17073004

Iryanthony, S. B., Wirasatriya, A., Pribadi, R., Purnomo, P. W., Muchtar, E., Basyuni, M., & Wijayanto, D. (2025). High-resolution unmanned aerial vehicles (UAV) imagery for estimating above and below-ground biomass in mangroves of Rembang, Central Java, Indonesia. *Biodiversitas, 26*(5), 2065–2078. https://doi.org/10.13057/biodiv/d260505

Jiang, Y., Zhang, L., Yan, M., Qi, J., Fu, T., Fan, S., & Chen, B. (2021). High-resolution mangrove forests classification with machine learning using WorldView and UAV hyperspectral data. *Remote Sensing, 13*(8). https://doi.org/10.3390/rs13081529

Karimi, A., Abtahi, B., & Kabiri, K. (2025). Mapping and estimating blue carbon in mangrove forests using drone and field-based tree height data: A cost-effective tool for conservation and management. *Forests, 16*(7). https://doi.org/10.3390/f16071196

Lassalle, G., Scafutto, R. D. M., Lourenço, R. A., Mazzafera, P., & de Souza Filho, C. R. (2023). Remote sensing reveals unprecedented sublethal impacts of a 40-year-old oil spill on mangroves. *Environmental Pollution, 331*. https://doi.org/10.1016/j.envpol.2023.121859

Li, S., Zhu, Z., Deng, W., Zhu, Q., Xu, Z., Peng, B., Guo, F., Zhang, Y., & Yang, Z. (2024). Estimation of aboveground biomass of different vegetation types in mangrove forests based on UAV remote sensing. *Sustainable Horizons, 11*. https://doi.org/10.1016/j.horiz.2024.100100

Liang, Y., Kou, W., Lai, H., Wang, J., Wang, Q., Xu, W., Wang, H., & Lu, N. (2022). Improved estimation of aboveground biomass in rubber plantations by fusing spectral and textural information from UAV-based RGB imagery. *Ecological Indicators, 142*. https://doi.org/10.1016/j.ecolind.2022.109286

Liu, Z., Yin, Z., Zhao, W., Feng, Z., Pei, H., Grimaldi, P., & Qiu, Z. (2026). Spatiotemporal patterns of aboveground carbon storage in Hainan mangroves based on machine learning and multi-source remote sensing data. *Forests, 17*(1). https://doi.org/10.3390/f17010131

Ma, J., Guo, Z., Feng, H., Zhang, Z., Xu, W., Ning, H., & Shen, J. (2026). Combining UAV-SfM, SAR, MSI and field surveys for estimation of above ground biomass in mangrove forest of Chonburi, Thailand. *Scientific Reports, 16*(1). https://doi.org/10.1038/s41598-025-34281-z

Mai, X., Li, Q., Xu, W., Deng, S., Wang, W., Wu, W., Zhang, W., & Wang, Y. (2025). Estimation of mangrove aboveground carbon using integrated UAV-LiDAR and satellite data. *Sustainability, 17*(18). https://doi.org/10.3390/su17188211

Navarro, J. A., Algeet, N., Fernández-Landa, A., Esteban, J., Rodríguez-Noriega, P., & Guillén-Climent, M. L. (2019). Integration of UAV, Sentinel-1, and Sentinel-2 data for mangrove plantation aboveground biomass monitoring in Senegal. *Remote Sensing, 11*(1). https://doi.org/10.3390/rs11010077

Pradisty, N. A., Schlund, M., Horstman, E. M., & Willemen, L. (2025). Estimating canopy height and aboveground biomass in tropical mangrove restoration areas through multisource remote sensing. *Ecological Informatics, 92*. https://doi.org/10.1016/j.ecoinf.2025.103522

Pungpa, S., Jaroensutasinee, K., Jaroensutasinee, M., Srisang, W., Chumkiew, S., & Sparrow, E. B. (2025). Integrating satellite and UAV imagery for mangrove aboveground biomass and carbon stock modeling. *Journal of Human, Earth, and Future, 6*(2), 474–487. https://doi.org/10.28991/HEF-2025-06-02-014

Qiu, P., Wang, D., Zou, X., Yang, X., Xie, G., Xu, S., & Zhong, Z. (2019). Finer resolution estimation and mapping of mangrove biomass using UAV LiDAR and WorldView-2 data. *Forests, 10*(10). https://doi.org/10.3390/f10100871

Romadoni, L. S., Husamah, H., & Ganiyu, B. (2025). Accuracy comparison of remote sensing methods (UAV, LiDAR, Radar) and field allometry in mangrove blue carbon quantification: A systematic literature review. *Green and Tropical Laboratory for Sustainability, 2*(2), 58–61. https://doi.org/10.22219/gtlabs.v2i2.43380

Saliu, I. S., Satyanarayana, B., Bin Fisol, M. A., Wolswijk, G., Decannière, C., Lucas, R., Otero, V., & Dahdouh-Guebas, F. (2021). An accuracy analysis of mangrove tree height mensuration using forestry techniques, hypsometers and UAVs. *Estuarine, Coastal and Shelf Science, 248*. https://doi.org/10.1016/j.ecss.2020.106971

Schürholz, D., Castellanos-Galindo, G. A., Casella, E., Mejía-Rentería, J. C., & Chennu, A. (2023). Seeing the forest for the trees: Mapping cover and counting trees from aerial images of a mangrove forest using artificial intelligence. *Remote Sensing, 15*(13). https://doi.org/10.3390/rs15133334

Tian, Y., Zhang, Q., Huang, H., Huang, Y., Tao, J., Zhou, G., Zhang, Y., Yang, Y., & Lin, J. (2022). Aboveground biomass of typical invasive mangroves and its distribution patterns using UAV-LiDAR data in a subtropical estuary: Maoling River estuary, Guangxi, China. *Ecological Indicators, 136*. https://doi.org/10.1016/j.ecolind.2022.108694

Wang, D., Wan, B., Liu, J., Su, Y., Guo, Q., Qiu, P., & Wu, X. (2020). Estimating aboveground biomass of the mangrove forests on northeast Hainan Island in China using an upscaling method from field plots, UAV-LiDAR data and Sentinel-2 imagery. *International Journal of Applied Earth Observation and Geoinformation, 85*. https://doi.org/10.1016/j.jag.2019.101986

Wang, D., Wan, B., Qiu, P., Zuo, Z., Wang, R., & Wu, X. (2019). Mapping height and aboveground biomass of mangrove forests on Hainan Island using UAV-LiDAR sampling. *Remote Sensing, 11*(18). https://doi.org/10.3390/rs11182156

Warfield, A. D., & Leon, J. X. (2019). Estimating mangrove forest volume using terrestrial laser scanning and UAV-derived structure-from-motion. *Drones, 3*(2), 1–17. https://doi.org/10.3390/drones3020032

Wirasatriya, A., Pribadi, R., Iryanthony, S. B., Maslukah, L., Sugianto, D. N., Helmi, M., Ananta, R. R., Adi, N. S., Kepel, T. L., Ati, R. N. A., Kusumaningtyas, M. A., Suwa, R., Ray, R., Nakamura, T., & Nadaoka, K. (2022). Mangrove above-ground biomass and carbon stock in the Karimunjawa-Kemujan Islands estimated from unmanned aerial vehicle-imagery. *Sustainability, 14*(2). https://doi.org/10.3390/su14020706

Wu, M., Wang, D., Wan, B., Qiu, P., Gao, C., & Chen, Z. (2026). Improving interpretability of mangrove aboveground biomass modeling via ecological knowledge: Machine learning based hierarchical models. *International Journal of Digital Earth, 19*(1). https://doi.org/10.1080/17538947.2026.2620197

Xiang, H., Shen, Z., Tan, L., Gao, C., Wu, G., & Wang, J. (2024). Community identification and carbon storage monitoring of *Heritiera littoralis* with UAV hyperspectral imaging. *Ecological Indicators, 167*. https://doi.org/10.1016/j.ecolind.2024.112653

Ye, L., & Weng, Q. (2025). A hybrid neural network for mangrove mapping considering tide states using Sentinel-2 imagery. *Remote Sensing of Environment, 329*. https://doi.org/10.1016/j.rse.2025.114917

Zhu, Y., Liu, K., Myint, S. W., Du, Z., Li, Y., Cao, J., Liu, L., & Wu, Z. (2020). Integration of GF2 optical, GF3 SAR, and UAV data for estimating aboveground biomass of China's largest artificially planted mangroves. *Remote Sensing, 12*(12). https://doi.org/10.3390/RS12122039

Zhu, Y., Myint, S. W., Liu, K., Liu, L., & Cao, J. (2024). Integration of UAV LiDAR and WorldView-2 images for modeling mangrove aboveground biomass with GA-ANN wrapper. *Ecological Processes, 13*(1). https://doi.org/10.1186/s13717-024-00566-w

Zhu, Z., Huang, M., Zhou, Z., Chen, G., & Zhu, X. (2022). Stronger conservation promotes mangrove biomass accumulation: Insights from spatially explicit assessments using UAV and Landsat data. *Remote Sensing in Ecology and Conservation, 8*(5), 656–669. https://doi.org/10.1002/rse2.268

Zhuang, J., Huang, P., Liu, G., Wu, S., Qiu, P., & Chen, H. (2026). RAP-CNN: A deep learning framework for mangrove aboveground biomass estimation using multisource remote sensing data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 19*, 8838–8849. https://doi.org/10.1109/JSTARS.2026.3668218