Preliminary Biomass Estimation and UAV Image Exploration of In-situ *Phyllanthus rufuschaneyi* in Sabah Ultramafic Soils

Alexius Korom [1 2*], Nur Ain Munirah Amaruddin[3], Evy Michelle Emison[3] , Rimi Repin[4], John Sugau[5] and Imam Purwadi[6]

[1]Faculty of Plantation and Agrotechnology, Universiti Teknologi MARA Sabah Branch, Kota Kinabalu, Malaysia

[2]TANiLAB, Universiti Teknologi MARA Sabah Branch, Kota Kinabalu, Malaysia

[3]Centre of Postgraduate Studies, Universiti Teknologi MARA Sabah Branch, Kota Kinabalu, Malaysia

[4]Sabah Parks, Kota Kinabalu, Malaysia

[5]Forest Research Centre, Sabah Forest Department, Sandakan, Malaysia

[6]Botanickel Sabah, Malaysia

*alexi502@uitm.edu.my

Abstract: *Phyllanthus rufuschaneyi is a recently identified nickel hyperaccumulator with promising potential for agromining in ultramafic regions of Sabah, Malaysia. This study reports preliminary findings from a field campaign aimed at: a) understanding the relationship between biomass and selected biophysical parameters, and b) exploring the potential detection of the spatial distribution of individual biomass using UAV images. The study site is located at the degraded ultramafic soil area in Garas Hill of Ranau district. A total of 36 destructive treelet samples and one plot of 10x10 meters field measurements, consisting of 90 readings, were conducted to quantify fresh biomass and record plant characteristics. Samples were selected based on height, ranging from 103 to 620 cm at approximately 1-meter intervals. The dataset consists of measurements such as plant height, canopy size, and various biomass weights of components: leaves, rachises, trunk and roots. Initial analysis shows the power function demonstrated the highest predictive capacity, with an R^2 value of 0.913-0.927 for height, followed by trunk diameter (R^2 of 0.823-0.892), canopy size (R^2 of 0.552-0.655) and root length (R^2 of 0.417-0.614), suggesting potential for predictive modeling. Concurrently, aerial data were captured at a flying altitude of 130 meters using a DJI Phantom 4 Pro UAV to assess the plot-level spatial patterns. Based on early manual observations, ideal dimensions for the detection of individuals or clumping trees are exhibiting a height of at least 300 cm, a crown diameter of 100 cm or greater, and an estimated biomass equal to or exceeding 3000 grams. Although complete biomass modeling is still underway, these early results demonstrate the feasibility of integrating ground measurements with aerial data for biomass estimation of Phyllanthus rufuschaneyi, laying the foundation for non-destructive monitoring and sustainable metal cropping systems.*

Keywords: Biomass estimation, hyperaccumulator plant, Phyllanthus rufuschaneyi, ultramafic soils, UAV remote sensing

Introduction

Accurate biomass estimation is essential for ecological research, sustainable land management, and emerging agromining practices. Biomass quantification informs plant productivity, carbon sequestration, and nutrient cycling (Brown, 1997; Chave et al., 2005).

In the case of hyperaccumulator species, biomass estimation provides insight into metal uptake and accumulation dynamics that are critical for bio-ore recovery (van der Ent et al., 2013). Traditional destructive sampling remains the benchmark for precise biomass measurement; however, it is time-consuming, costly, and unsuitable for rare or threatened species (Henry et al., 2011). As a practical alternative, allometric equations—linking measurable plant traits such as height, trunk diameter, or canopy size to biomass—offer a non-destructive approach for estimating aboveground biomass (Basuki et al., 2009).

Phyllanthus rufuschaneyi—recently reclassified as *Emblica rufuschaneyi* (Bouman et al., 2022)—is a nickel (Ni) hyperaccumulator endemic to Sabah, Malaysia. This small treelet, less than 10 meters in height, can accumulate up to 2–3% Ni in its aboveground biomass, making it one of the most promising candidates for agromining (van der Ent et al., 2015a). With global demand for critical metals such as Ni and cobalt (Co) rising due to green technologies, agromining has emerged as a sustainable alternative to conventional mining, particularly in ultramafic soils where metal-rich ores are abundant but conventional extraction is economically and environmentally challenging (Nkrumah et al., 2016; Rabbani et al., 2024; van der Ent et al., 2015b). The cultivation of *Phyllanthus rufuschaneyi* as a perennial "metal crop" offers dual benefits: recovery of bio-ore and rehabilitation of degraded ultramafic landscapes. Despite this potential, little progress has been made in developing robust allometric equations to estimate biomass and bio-ore yield for this newly identified species.

Advances in remote sensing provide new opportunities for addressing this knowledge gap. Unmanned Aerial Vehicles (UAVs), equipped with high-resolution cameras and multispectral sensors, have been widely used in forestry and agricultural studies to extract plant characteristics such as canopy size, height, and vegetation indices (Chong et al., 2017; Gonzalez et al., 2010; Mareya et al., 2018). The Structure-from-Motion (SfM) technique enables three-dimensional reconstruction of plant canopies, making UAV-derived imagery a cost-effective tool for biomass estimation (Dandois and Ellis, 2013). While UAV applications in biomass modeling are well established in forestry and plantation crops, their use for hyperaccumulator plants is still limited (Eltaher et al., 2019; Ma et al., 2024; Purwadi et al., 2023).

This study addresses these gaps by exploring the relationship between field-measured biomass and biophysical traits of *Phyllanthus rufuschaneyi* while assessing UAV imagery for spatial mapping. Specifically, it aims to evaluate the feasibility of integrating destructive sampling with UAV-based observations to derive preliminary biomass estimation models.

Furthermore, the study investigates the potential of UAV data for detecting individual plants and clumped growth formations in situ. These findings contribute to the development of non-destructive biomass monitoring tools, which are critical for scaling up sustainable agromining and ecological restoration in ultramafic landscapes of Sabah.

Literature Review

a. Biomass Estimation and Allometric Equation

Accurate biomass estimation is central to ecological monitoring, carbon accounting, and sustainable resource management. Traditionally, biomass is measured using destructive sampling, which involves harvesting plant tissues and weighing their components. While highly accurate, this method is impractical for large-scale monitoring and unsuitable for endangered or endemic species (Daba and Soromessa, 2019). To address this, allometric equations have been developed to predict biomass from easily measurable plant parameters such as diameter, height, and canopy size (Basuki et al., 2022; Goodman et al., 2014). These equations reduce the need for destructive sampling and allow for efficient estimation across broad landscapes. However, species-specific equations are often required since plant architecture and growth dynamics vary significantly between taxa and ecosystems (Aabeyir et al., 2020).

For hyperaccumulator plants, such as *Phyllanthus rufuschaneyi*, there remains a lack of established allometric models. As highlighted in previous studies, most biomass models focus on timber or agroforestry species, leaving knowledge gaps in specialized plants of economic and ecological significance, especially in agromining contexts (Han and Park, 2020; Korom et al., 2016). Establishing robust biomass–canopy diameter relationships for *Phyllanthus rufuschaneyi* is thus vital for its effective management and utilization in metal cropping systems.

b. UAV Remote Sensing for Plant Biophysical Analysis

Advancements in UAV remote sensing have transformed biomass estimation by enabling high-resolution and spatially explicit monitoring. UAV-mounted RGB and multispectral cameras allow the extraction of plant biophysical parameters such as canopy height, crown diameter, and vegetation indices (Avtar et al., 2020; Hu et al., 2018). SfM photogrammetry techniques have been widely applied for reconstructing 3D canopy structures, offering accurate measurements comparable to ground surveys (Mlambo et al., 2017; Sedrati et al., 2022).

Although UAV applications in forestry and agriculture are well-established, their integration into agromining remains underexplored. For ultramafic ecosystems, where hyperaccumulator plants like *Phyllanthus rufuschaneyi* thrive, UAV-based monitoring provides an opportunity to quantify biomass and growth patterns non-destructively. This integration would support both ecological conservation and metal recovery industries by reducing field effort, improving scalability, and offering precise temporal monitoring. To date, no published research has reported UAV-based biomass modeling specifically for *Phyllanthus rufuschaneyi*, highlighting a significant research gap.

Materials and Methods

a. Study Site

The study was conducted at Bukit Garas, Ranau, Sabah, Malaysia, an ultramafic site characterized by soils enriched with heavy metals, particularly nickel, chromium, and cobalt. The site lies within the coordinates 116°47′59.0″ E, 6°05′20.0″ N and forms part of the Kinabalu National Geopark, which was recently recognized as a UNESCO Global Geopark (Fig. 1a). This location is of particular interest due to its serpentine parent material, which has long been associated with high concentrations of heavy metals and unique soil chemistry that restricts plant diversity while favouring metal-tolerant and hyperaccumulator species (Tashakor et al., 2011).

The area represents a degraded forest ecosystem that was severely impacted by the 1997 El Niño-induced fire, but has since naturally regenerated, providing an in-situ environment where wild populations of *Phyllanthus rufuschaneyi* thrive. This endemic nickel hyperaccumulator species is listed under the IUCN Red List but holds promise as a future metal crop for sustainable agromining initiatives in Sabah (Tsen et al., 2021). The unique ecological conditions of ultramafic soils in Bukit Garas make it an ideal natural laboratory to study biomass dynamics and remote sensing applications for hyperaccumulator plants.

b. Field Data Collection

A targeted sampling strategy was adopted to capture the variability of *Phyllanthus rufuschaneyi* individuals across different growth stages within the predefined site area of interest (AOI) (Fig. 1b). Tree selection was primarily based on plant height, which served as a practical indicator to represent individuals from diverse age groups, canopy sizes, and growth stages, ensuring comprehensive coverage of population variability (Hu et al., 2018; Poorter et al., 2015). Samples were destructively collected within a 10 m × 10 m field plot and selected based on plant height at approximately 1 m intervals to provide plot-scale biomass reference data.

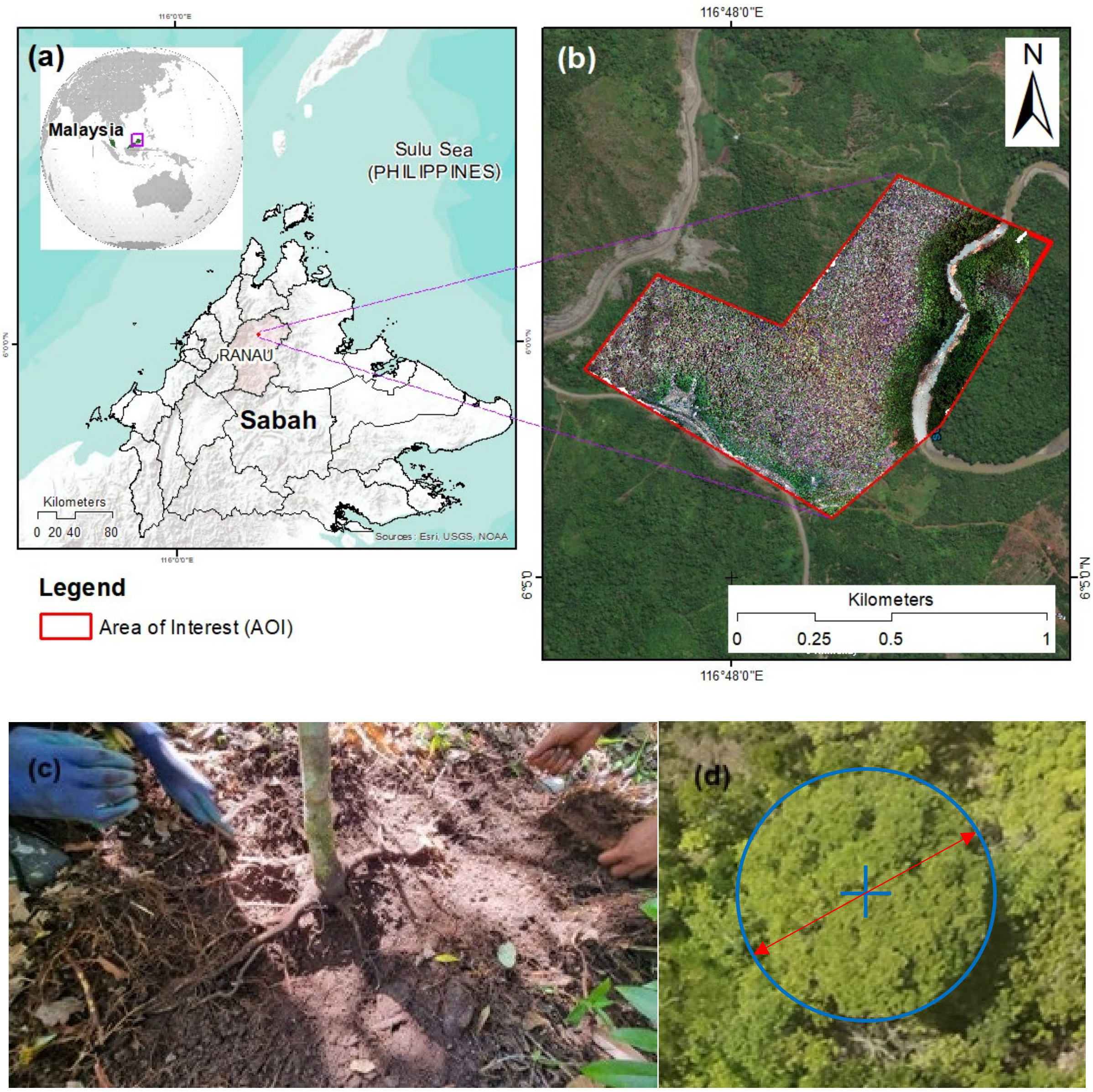


Figure 1. (a) Map showing the location of Ranau District in Sabah, Malaysia, (b) Study site AOI at Bukit Garas, Ranau, with UAV image in the background, (c) Careful uprooting of the selected sampling plant during field data collection, (d) Illustration of canopy diameter of the plant

Given the species' endemic status, sampling was carried out with minimal disturbance and strict adherence to restrictions. Each selected treelet was carefully uprooted to preserve the root system (Fig. 1c), enabling precise measurement of root length and biomass (Rossi et al., 2022). Plant components—including trunk, roots, leaves, and rachises—were separated, measured, and weighed (Picard et al., 2012). Complementing the destructive sampling, one

10 × 10 m plot was established, where individual plant measurements were done. Heights were recorded from the plant base to the shoot apical meristem using measuring tapes, while canopy diameter and perimeter were measured from a top-view projection (Interagency Technical Reference, 1996). Trunk diameter was recorded at basal and upper sections using callipers to account for variability in stem taper. The biomass at the individual level was estimated using a species-specific allometric equation registered under Malaysian copyright (MyIPO, 2025), formulated based on a power model as below:

$$\text{Individual biomass} = 0.043 \times \text{Canopy Diameter}^{2.297} \qquad \text{Eqn. 1}$$

The integration of both destructive measurements and field plot readings provided robust ground-truth data for developing biomass estimation models and validating UAV-derived observations.

c. UAV Data Acquisition

UAV surveys were conducted using a DJI Phantom 4 Pro platform equipped with an integrated 20-megapixel RGB camera featuring a 1-inch CMOS sensor and real-time kinematic referencing was deployed during data acquisition to improve spatial accuracy. This platform was selected for its proven reliability in ecological monitoring and its capacity to capture high-resolution imagery suitable for object-based image analysis and vegetation mapping (Hu et al., 2018; Husson et al., 2016).

The UAV flights were performed over the Bukit Garas undulating topography under stable weather conditions to minimize the influence of cloud cover, wind, and shadowing on image quality. A safe flight altitude of 130 m above ground level was maintained from the base point elevation, which produced a ground sampling distance (GSD) of approximately 3.6 cm per pixel, enabling the detection of small crown structures typical of *Phyllanthus rufuschaneyi* treelets (Mauya et al., 2015). The flight mission ensures complete coverage and minimizes gaps by imposing 80% forward and 75% side overlap of the imagery.

A pre-programmed flight path was executed using DJI GS Pro software, which allowed for consistent flight lines and uniform image capture across the survey area. All imagery was stored in TIF format and later converted into orthomosaics and digital surface models (DSMs) using Agisoft software. This UAV-based dataset provided the spatially explicit imagery necessary for correlating crown attributes with field-based biomass measurements and for exploring automated detection approaches for *Phyllanthus rufuschaneyi* individuals.

d. Data Analysis

The data analysis involved integrating field-derived biomass measurements with UAV-based imagery to explore relationships between biophysical parameters and aboveground biomass of *Phyllanthus rufuschaneyi*. Field data collected through destructive sampling and plot-based measurements were first compiled to establish a reference dataset of plant height, canopy dimensions, basal diameter, and biomass components (leaves, rachises, trunk, and roots). Statistical preprocessing was conducted to ensure consistency, remove outliers, and normalize measurements where appropriate (Poorter et al., 2015).

For biomass modeling, regression analyses were employed to assess the relationships between biomass and plant variables. Several functional forms, including linear, exponential, and power models, were tested to determine the best-fitting model. Goodness-of-fit was evaluated using the coefficient of determination (R^2) and the statistical significance of the regression coefficients, with F-statistics used to test overall model validity (Chave et al., 2014; Ketterings et al., 2001).

UAV-derived imagery was carefully examined to match the plant spatial distribution patterns with the field data within the study plot. The vegetation features were compared manually to gain insight into the implementation of segmentation techniques in object-based image analysis (OBIA). These canopy parameters were cross-referenced with field measurements to evaluate the feasibility of non-destructive biomass estimation. Visual assessment was performed to identify spectral and spatial features that correlated strongly with biomass accumulation (Biswal et al., 2024; Lu et al., 2012).

The integration of field data with UAV imagery provided a preliminary framework for developing species-specific allometric equations and spatial biomass models. Although full predictive modeling is ongoing, this step laid the groundwork for testing UAV-assisted monitoring systems in sustainable agromining practices.

Results

a. Statistical Analysis

A total of 36 individual *Phyllanthus rufuschaneyi* treelet samples were destructively harvested to quantify the biomass components, including leaves, rachises, trunk, and roots. The summary of fieldwork data collection is presented in Table 1. The minimum and maximum heights recorded during the fieldwork were 103 cm and 620 cm, covering a broad spectrum of growth stages representative of natural ultramafic stands. The mean plant height was 335.8 cm (±25.75 SE), with a standard deviation of 154.49 cm, reflecting substantial structural variability among individuals. Canopy dimensions also varied widely, with crown diameters ranging from below 100 cm in younger individuals to above 300 cm in mature treelets, suggesting a diverse architecture influenced by microhabitat conditions.

Table 1. Statistical descriptive for fresh components weight of *Phyllanthus rufuschaneyi* hyperaccumulator plant for n=36 destructive samples

				Component biomass				
	Height (cm)	**Basal trunk diameter (cm)**	**Canopy diameter (cm)**	**Leaves (gm)**	**Rachises (gm)**	**Trunk (gm)**	**Roots (gm)**	**Biomass (gm)**
Mean	335.8	2.3	85.7	166	88	1094	315	1883
SE	25.75	0.19	6.27	27.7	20.3	203.8	51.0	348.7
Med	345	2.25	78.0	96.5	43	636	231	1017
Mode	345	1.3	47.7	20	10	40	20	90
SD	154.49	1.15	37.62	166.15	121.99	1223.05	306.10	2092.47
Skew	0.179	0.723	0.590	1.447	3.510	1.659	1.067	1.672
Min	103	0.8	24.4	10	5	40	20	90
Max	620	5.0	164.9	626	680	5188	1014	9139

Note: SE standard error, Med median, SD standard deviation, Skew skewness, Min minimum, and Max maximum

The statistical results above indicate that biomass distribution across plant components was heterogeneous, with trunks generally contributing the largest proportion of total dry mass, followed by leaves and rachises, while roots accounted for smaller but significant fractions. Such allocation patterns are consistent with other hyperaccumulator species reported in ultramafic ecosystems, where investment in shoot biomass supports enhanced uptake and translocation of metals (Bouman et al., 2018; Peer et al., 2005).

At the plot level, 90 individual plant measurements were recorded, which were summarized in Table 2. Plot-based data provided insight into stand-level variation, capturing density patterns, crown overlap, and clumping behaviour commonly observed in situ. This dataset highlighted the challenge of distinguishing individual crowns in dense clusters, a factor with implications for UAV-based biomass detection.

Table 2: Statistical summary of individual plant measurements in the 10 m X 10 m plot

	Height (cm)	**Basal trunk diameter (cm)**	**Canopy diameter (cm)**	**Biomass (gm)**
Mean	256.022	1.541	86.206	1812.462
SE	16.98	0.14	5.23	257.48
Min	36.0	0.3	27.0	83.4
Max	705.0	6.8	243.0	12977.9
Skew	0.702	1.947	1.096	2.410

Note: SE standard error, Min minimum, Max maximum, and Skew skewness

The dataset established an empirical baseline for developing allometric models. The variation observed in height, basal trunk diameter, crown dimensions, and biomass components highlights the need to incorporate multiple predictors for accurate biomass estimation. Furthermore, the inclusion of plot-level data enables a more realistic assessment of biomass distribution in natural stands, thereby supporting the integration of UAV-based imagery with field-based models.

b. Biomass Allometric Relationships and Model Fit

The analysis of field measurements revealed strong correlations between biomass and selected biophysical parameters of *Phyllanthus rufuschaneyi*. Regression models were developed to examine the predictive capacity of height, trunk diameter, canopy size, and root length against the observed biomass. Among the tested models (linear, exponential, and power functions), the power function consistently provided the best fit, in line with established patterns in tree biomass modeling (Chave et al., 2014; Picard et al., 2012). A summary of the best model regression is presented in Table 3.

Table 3. Model summary and parameter estimate for regression estimation analysis between the dependent variable Biomass and various independent plant biophysical variables

Plant biophysical	**Equation**	**Model Summary**		**Parameter Estimates**	
		R^2	**F**	***a***	***b***
Height (cm)	Exponential	0.913	358.587	59.912	0.008
	Power*	0.927	433.040	0.001	2.407
Trunk diameter (cm)	Linear	0.842	181.865	-2831.905	3202.672
	Exponential	0.823	158.000	49.161	2.002
	Power*	0.892	279.746	363.709	3.081
Canopy area (cm^2)	Exponential	0.569	44.888	288.680	.000
	Power*	0.655	64.656	0.056	1.148
Canopy diameter (cm)	Linear	0.552	41.932	-1659.464	41.328
	Power*	0.655	64.656	0.043	2.297
	Exponential*	0.655	64.549	81.638	0.028
Root length (cm)	Linear	0.417	24.316	-1298.392	71.571
	Power*	0.614	54.163	0.198	2.286

Notes: R^2 is the coefficient of determination of the equation function, F stands for F-statistic is a measure of the ratio of the variance explained by the model to the variance that cannot be explained by the model (residual variance), df1 is the number of groups minus one, df2 is the total number of observations minus the number of groups, and *a* and *b* is the parameter estimates which relate to the equation functions. All the models have df1 = 1 and df2 = 34, with significance at $p < 0.01$. The symbol * represents the best model for each variable.

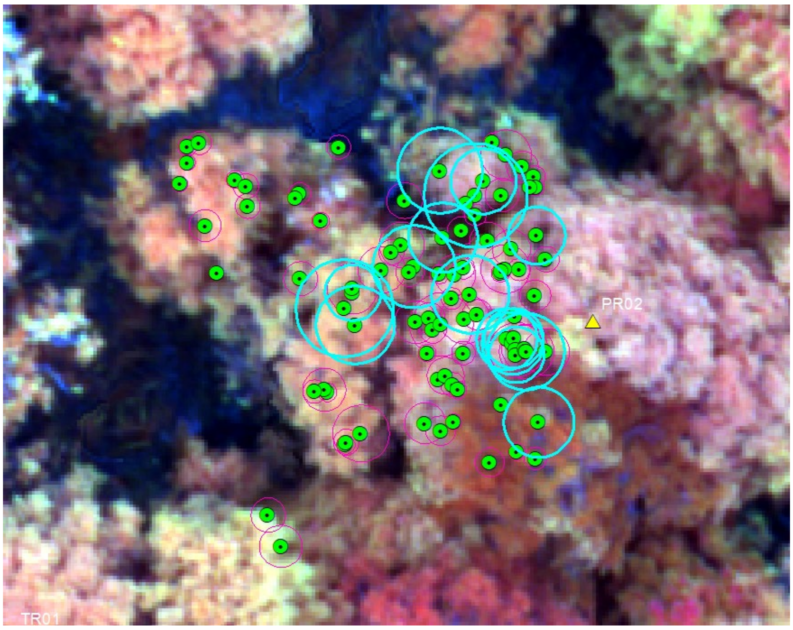
The results indicated that plant height was the strongest predictor of aboveground biomass, with coefficients of determination (R^2 = 0.913–0.927) across models. Trunk diameter also demonstrated high predictive capacity (R^2 = 0.823–0.892), confirming its role as a reliable variable in allometric relationships. In contrast, canopy size showed moderate correlations (R^2 = 0.552–0.655), while root length exhibited weaker associations (R^2 = 0.417–0.614). These findings suggest that the morphological traits, particularly height and trunk diameter, can serve as effective proxies for estimating biomass in this hyperaccumulator species.

Model validation through F-statistics confirmed that the power-based regressions were statistically significant ($p < 0.01$), indicating robustness in the derived equations. However, variability observed in canopy and root parameters highlights the influence of ecological factors such as clumping growth forms, crown overlap, and heterogeneous soil conditions typical of ultramafic environments (van der Ent et al., 2015a). These findings highlight the importance of refining species-specific equations to reduce uncertainty in biomass estimation, particularly in agromining applications where accurate predictions of bio-ore yield are critical.

c. UAV Image Exploration

UAV-based image acquisition provided high-resolution orthomosaics that enabled preliminary spatial exploration of *Phyllanthus rufuschaneyi* distribution within the study plot. A clear distinction between canopy structures and vegetation cover is easily observed in the image of 3.6 cm per pixel resolution. The orthorectified images were processed to identify spatial patterns of crown distribution, canopy overlap, and potential clumping of individuals, which are the key features influencing biomass estimation.

Manual visual interpretation revealed that individuals or clumped stands of *Phyllanthus rufuschaneyi* were most readily detectable when their dimensions exceeded certain thresholds, namely height ≥ 300 cm, crown diameter ≥ 100 cm, and biomass ≥ 3000 gm (Fig. 2). These thresholds correspond to the results from field-based measurements and serve as practical benchmarks for OBIA approaches. The spatial distribution of the *Phyllanthus rufuschaneyi* plants is likely detectable based on the spectral white colour. Canopies smaller than these thresholds exhibited poor separability from surrounding vegetation, highlighting the challenge of detecting younger or smaller individuals from aerial images.



Biophysical	Threshold
Height	≥ 300 cm
Crown diameter	≥ 100 cm
Biomass	≥ 3000 gm

Display mode of image:
Red Edge, Green, Blue

Figure 2. The pink-coloured round shape represents the average canopy diameter of individual tree crowns. Query selection was performed based on the mentioned threshold, which displayed a corresponding distribution of the selected species *Phyllanthus rufuschaneyi* (blue-coloured round shape).

Furthermore, UAV-derived imagery facilitated the visualization of spatial heterogeneity in canopy density within the ultramafic site. Areas with higher crown overlap suggested potential over- or underestimation of biomass if traditional allometric equations are applied without adjustments for crown clumping effects. This underscores the necessity of refining species-specific allometric models by integrating remote sensing indicators with field-based measurements, as suggested by prior studies in biomass estimation and precision forestry (Dandois and Ellis, 2013; Korom et al., 2016; Lu et al., 2016).

Discussion

This study highlights the importance of biomass estimation in advancing agromining practices, particularly for *Phyllanthus rufuschaneyi*, a nickel hyperaccumulator native to Sabah's ultramafic soils. The strong predictive relationships observed, especially with power functions, demonstrate that plant height and trunk diameter serve as reliable proxies for biomass, consistent with global findings in biomass allometry (Chave et al., 2014). The feasibility of UAV-derived imagery further strengthens the monitoring framework by offering spatially explicit data on canopy structure and distribution, thus reducing reliance on destructive sampling. Detection thresholds identified in this study (≥300 cm height, ≥100 cm crown diameter, ≥3000 gm biomass) provide operational benchmarks for UAV monitoring, ensuring reliable detection of individuals or clumped trees that are most relevant to biomass yield in agromining (Gini et al., 2014). These insights establish a foundation for precision monitoring of bio-ore crops while supporting sustainable harvesting strategies.

Despite these encouraging results, several challenges remain. Crown overlap among clumped individuals complicates object-based image analysis, potentially inflating or underestimating biomass when canopy boundaries are indistinct. Image resolution limitations further affect the accuracy of segmentation, particularly for smaller individuals that fall below the established detection thresholds. These constraints underscore the need for refined methods, such as advanced segmentation algorithms that integrate artificial intelligence techniques and incorporate 3D canopy metrics from UAV photogrammetry, to enhance prediction accuracy (Puliti et al., 2015). Compared with prior work in forestry and agriculture, this study provides an early example of the adaptation of remote sensing tools to the emerging agromining sector (van der Ent et al., 2015b). While global applications of UAVs in biomass monitoring focus primarily on carbon storage, the adaptation here emphasizes nickel yield, positioning this work at the frontier of sustainable bio-ore production.

Conclusions

This study presents preliminary findings on biomass estimation and UAV image exploration of *Phyllanthus rufuschaneyi* in Sabah's ultramafic soils, demonstrating that power functions based on plant height and trunk diameter provide the strongest predictive capacity, while UAV-derived imagery enables spatial assessment of canopy distribution with reliable detection thresholds (≥300 cm height, ≥100 cm crown diameter, ≥3000 g biomass). These results confirm the feasibility of integrating ground-based allometric equations with aerial data for non-destructive biomass monitoring, supporting the advancement of agromining and sustainable land-use practices in degraded ultramafic environments. Looking ahead, further refinement of allometric models through larger and more diverse datasets, combined with advanced UAV-based object-based image analysis and machine learning integration, will enhance crown delineation, reduce errors from canopy overlap and image resolution limits, and strengthen predictive modeling for bio-ore yield estimation, positioning *Phyllanthus rufuschaneyi* as a cornerstone species for sustainable agromining in Malaysia and beyond.

Acknowledgement

This research was financially supported under the FRGS 2021 project, file number FRGS/1/2021/WAB03/UITM/02/2, which was funded by the Ministry of Higher Education, Malaysia.

References

Aabeyir, R., Adu-Bredu, S., Agyare, W. A., and Weir, M. J. C. (2020). Allometric models for estimating aboveground biomass in the tropical woodlands of Ghana, West Africa. *Forest Ecosystems*, 7(1). https://doi.org/10.1186/s40663-020-00250-3

Avtar, R., Suab, S. A., Syukur, M. S., Korom, A., Umarhadi, D. A., and Yunus, A. P. (2020). Assessing the Influence of UAV Altitude on Extracted Biophysical Parameters of Young Oil Palm. *Remote Sensing*, 12(3030), 1–21. https://doi.org/10.3390/rs12183030

Basuki, T. M., Leksono, B., Baral, H., Andini, S., Wahyuni, N. S., Artati, Y., Choi, E., Shin, S., Kim, R., Yang, A. R., Samsudin, Y. B., and Windyarini, E. (2022). Allometric Equations for the Biomass Estimation of Calophyllum inophyllum L. in Java, Indonesia. *Forests*, 13(7), 1–15. https://doi.org/10.3390/f13071057

Basuki, T. M., van Laake, P. E., Skidmore, a. K., and Hussin, Y. a. (2009). Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management*, 257(8), 1684–1694. https://doi.org/10.1016/j.foreco.2009.01.027

Biswal, S., Pathak, N., Chatterjee, C., and Mailapalli, D. R. (2024). Estimation of aboveground biomass from spectral and textural characteristics of paddy crop using UAV-multispectral images and machine learning techniques. *Geocarto International*, 39(1). https://doi.org/10.1080/10106049.2024.2364725

Bouman, R., van Welzen, P., Sumail, S., Echevarria, G., Erskine, P. D., and van der Ent, A. (2018). Phyllanthus rufuschaneyi: a new nickel hyperaccumulator from Sabah (Borneo Island) with potential for tropical agromining. *Botanical Studies*, 59(1). https://doi.org/10.1186/s40529-018-0225-y

Bouman, R. W., Kebler, P. J. A., Telford, I. R. H., Bruhl, J. J., Strijk, J. S., Saunders, R. M. K., Esser, H. J., Falcón-Hidalgo, B., and van Welzen, P. C. (2022). A revised phylogenetic classification of tribe Phyllantheae (Phyllanthaceae). In *Phytotaxa* (Vol. 540, Issue 1). https://doi.org/10.11646/phytotaxa.540.1.1

Brown, S. (1997). Estimating Biomass and Biomass Change of Tropical Forests: A Primer. FAO Forestry Paper 134, January 1997, 1–44.

Chave, J., Andalo, C., Brown, S., Cairns, M. a, Chambers, J. Q., Eamus, D., Fölster, H., Fromard, F., Higuchi, N., Kira, T., Lescure, J.-P., Nelson, B. W., Ogawa, H., Puig, H., Riéra, B., and Yamakura, T. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*, 145(1), 87–99. https://doi.org/10.1007/s00442-005-0100-x

Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M. S., Delitti, W. B. C., Duque, A., Eid, T., Fearnside, P. M., Goodman, R. C., Henry, M., Martínez-Yrízar, A., Mugasha, W. A., Muller-Landau, H. C., Mencuccini, M., Nelson, B. W., Ngomanda, A., Nogueira, E. M., Ortiz-Malavassi, E., … Vieilledent, G. (2014). Improved allometric models to estimate the aboveground biomass of tropical trees. *Global Change Biology*, 20(10), 3177–3190. https://doi.org/10.1111/gcb.12629

Chong, K. L., Kanniah, K. D., Pohl, C., and Tan, K. P. (2017). A review of remote sensing applications for oil palm studies. *Geo-Spatial Information Science*, 20(2), 184–200. https://doi.org/10.1080/10095020.2017.1337317

Daba, D. E., and Soromessa, T. (2019). Allometric equations for aboveground biomass estimation of Diospyros abyssinica (Hiern) F. White tree species. *Ecosystem Health and Sustainability*, 5(1), 86–97. https://doi.org/10.1080/20964129.2019.1591169

Dandois, J. P., and Ellis, E. C. (2013). High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. *Remote Sensing of Environment*, 136, 259–276. https://doi.org/10.1016/j.rse.2013.04.005

Eltaher, G. T., Ahmed, D. A., El-Beheiry, M., and Sharaf El-Din, A. (2019). Biomass estimation and heavy metal accumulation by Pluchea dioscoridis (L.) DC. in the Middle Nile Delta, (Egypt): Perspectives for phytoremediation. *South African Journal of Botany*, 127, 153–166. https://doi.org/10.1016/j.sajb.2019.08.053

Gini, R., Passoni, D., Pinto, L., and Sona, G. (2014). Use of unmanned aerial systems for multispectral survey and tree classification: A test in a park area of northern Italy. European *Journal of Remote Sensing*, 47(1), 251–269. https://doi.org/10.5721/EuJRS20144716

Gonzalez, P., Asner, G. P., Battles, J. J., Lefsky, M. a., Waring, K. M., and Palace, M. (2010). Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California. *Remote Sensing of Environment*, 114(7), 1561–1575. https://doi.org/10.1016/j.rse.2010.02.011

Goodman, R. C., Phillips, O. L., and Baker, T. R. (2014). The importance of crown dimensions to improve tropical tree biomass estimates. *Ecological Applications*, 24(4), 680–698. https://doi.org/10.1890/13-0070.1

Han, S. H., and Park, B. B. (2020). Comparison of allometric equation and destructive measurement of carbon storage of naturally regenerated understory in a Pinus rigida plantation in South Korea. *Forests*, 11(4). https://doi.org/10.3390/F11040425

Henry, M., Picard, N., Trotta, C., Manlay, R. J., Valentini, R., Bernoux, M., and Saint-André, L. (2011). Estimating tree biomass of sub-Saharan African forests: A review of available allometric equations. *Silva Fennica*, 45(3), 477–569. https://doi.org/10.14214/sf.38

Hu, P., Chapman, S. C., Wang, X., Potgieter, A., Duan, T., Jordan, D., Guo, Y., and Zheng, B. (2018). Estimation of plant height using a high throughput phenotyping platform based on unmanned aerial vehicle and self-calibration: Example for sorghum breeding. *European Journal of Agronomy*, 95(November 2017), 24–32. https://doi.org/10.1016/j.eja.2018.02.004

Husson, E., Ecke, F., and Reese, H. (2016). Comparison of manual mapping and automated object-based image analysis of non-submerged aquatic vegetation from very-high-resolution UAS images. *Remote Sensing*, 8(9), 1–18. https://doi.org/10.3390/rs8090724

Interagency Technical Reference. (1996). Sampling Vegetation Attributes. In Trend Studies (1999th ed.). Bureau of Land Management's National Applied Resource Sciences Center.

Ketterings, Q. M., Coe, R., Van Noordwijk, M., Ambagau', Y., and Palm, C. A. (2001). Reducing uncertainty in the use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forests. *Forest Ecology and Management*, 146, 199–209. https://doi.org/10.1016/S0378-1127(00)00460-6

Korom, A., Phua, M.-H., and Matsuura, T. (2016). Relationship between crown canopy size and aboveground biomass of oil palms: an evaluation of allometric models. *Sains Malaysiana*, 45(4), 523–533.

Lu, D., Chen, Q., Wang, G., Liu, L., Li, G., and Moran, E. (2016). A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems. *International Journal of Digital Earth*, 9(1), 63–105. https://doi.org/10.1080/17538947.2014.990526

Lu, D., Chen, Q., Wang, G., Moran, E., Batistella, M., Zhang, M., Vaglio Laurin, G., and Saah, D. (2012). Aboveground Forest Biomass Estimation with Landsat and LiDAR Data and Uncertainty Analysis of the Estimates. *International Journal of Forestry Research*, 2012(1), 1–16. https://doi.org/10.1155/2012/436537

Ma, T., Zhang, C., Ji, L., Zuo, Z., Beckline, M., Hu, Y., Li, X., and Xiao, X. (2024). Development of forest aboveground biomass estimation, its problems and future solutions: A review. *Ecological Indicators*, 159(February), 111653. https://doi.org/10.1016/j.ecolind.2024.111653

Mareya, H. T., Tagwireyi, P., Ndaimani, H., Gara, T. W., and Gwenzi, D. (2018). Estimating Tree Crown Area and Aboveground Biomass in Miombo Woodlands from High-Resolution RGB-Only Imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 11(3), 868–875. https://doi.org/10.1109/JSTARS.2018.2799386

Mauya, E. W. . E. W., Hansen, E. H. . E. H., Gobakken, T. . T., Bollandsås, O. M. O. M. ., Malimbwi, R. E. R. E. ., and Næsset, E. E. . (2015). Effects of field plot size on prediction accuracy of aboveground biomass in airborne laser scanning-assisted inventories in tropical rain forests of Tanzania. *Carbon Balance and Management*, 10(1), 10. https://doi.org/10.1186/s13021-015-0021-x

Mlambo, R., Woodhouse, I. H., Gerard, F., and Anderson, K. (2017). Structure from motion (SfM) photogrammetry with drone data: A low cost method for monitoring greenhouse gas emissions from forests in developing countries. *Forests*, 8(3). https://doi.org/10.3390/f8030068

MyIPO (2025). Allometric equation for canopy diameter-based biomass estimation of Phyllanthus rufuschaneyi (Copyright Registration No. CRLY2025S01396). *Intellectual Property Corporation of Malaysia* (MyIPO)

Nkrumah, P. N., Baker, A. J. M., Chaney, R. L., Erskine, P. D., Echevarria, G., Morel, J. L., and van der Ent, A. (2016). Current status and challenges in developing nickel phytomining: an agronomic perspective. *Plant and Soil*, 406(1–2), 55–69. https://doi.org/10.1007/s11104-016-2859-4

Peer, W. A., Baxter, I. R., Richards, E. L., Freeman, J. L., and Murphy, A. S. (2005). Phytoremediation and Hyperaccumulator Plants. In Topics in current genetics (Issue August 2005). https://doi.org/10.1007/4735

Picard, N., Saint-Andre, L., and Henry, M. (2012). Manual for building tree volume and biomass allometric equations: From field measurement to prediction. *Food and Agricultural Organization of the United Nations*, Rome, and Centre de Cooperation Internationale en Recherche Agronomique pour le Developpement, Montpellier.

Poorter, H., Jagodzinski, A. M., Ruiz-Peinado, R., Kuyah, S., Luo, Y., Oleksyn, J., Usoltsev, V. A., Buckley, T. N., Reich, P. B., and Sack, L. (2015). How does biomass distribution change with size and differ among species? An analysis for 1200 plant species from five continents. *New Phytologist*, 208(3), 736–749. https://doi.org/10.1111/nph.13571

Puliti, S., Ørka, H. O., Gobakken, T., and Næsset, E. (2015). Inventory of small forest areas using an unmanned aerial system. *Remote Sensing*, 7(8), 9632–9654. https://doi.org/10.3390/rs70809632

Purwadi, I., Erskine, P. D., and van der Ent, A. (2023). Reflectance spectroscopy as a promising tool for 'sensing' metals in hyperaccumulator plants. *Planta*, 258(2), 1–13. https://doi.org/10.1007/s00425-023-04167-3

Rabbani, M., Taqi Rabbani, M., Muthoni, F., Sun, Y., and Vahidi, E. (2024). Advancing phytomining: Harnessing plant potential for sustainable rare earth element extraction. *Bioresource Technology*, 401, 130751. https://doi.org/https://doi.org/10.1016/j.biortech.2024.130751

Rossi, R., Costafreda-Aumedes, S., Summerer, S., Moriondo, M., Leolini, L., Cellini, F., Bindi, M., and Petrozza, A. (2022). A comparison of high-throughput imaging methods for quantifying plant growth traits and estimating above-ground biomass accumulation. *European Journal of Agronomy*, 141(May), 126634. https://doi.org/10.1016/j.eja.2022.126634

Sedrati, M., Morales, J. A., El M'rini, A., Anthony, E. J., Bulot, G., Le Gall, R., and Tadibaght, A. (2022). Using UAV and Structure-From-Motion Photogrammetry for the Detection of Boulder Movement by Storms on a Rocky Shore Platform in Laghdira, Northwest Morocco. *Remote Sensing*, 14(16). https://doi.org/10.3390/rs14164102

Tashakor, M., Yaacob, W. Z. W., and Mohamad, H. (2011). Speciation and Availability of Cr, Ni and Co IN Serpentine Soils of Ranau, Sabah. *American Journal of Geoscience*, 2(1), 4–9. https://doi.org/10.3844/ajgsp.2011.4.9

Tsen, S., Maycock, C. R., Khoo, E., Maryani, A., Nilus, R., Sugau, J., and Pereira, J. T. (2021). Phyllanthus rufuschaneyi. https://dx.doi.org/10.2305/IUCN.UK.2021-%0A1.RLTS.T162024997A162033754.en

van der Ent, A., Baker, A. J. M., Reeves, R. D., Pollard, A. J., and Schat, H. (2013). Hyperaccumulators of metal and metalloid trace elements: Facts and fiction. *Plant and Soil*, 362(1–2), 319–334. https://doi.org/10.1007/s11104-012-1287-3

van der Ent, A., Erskine, P., and Sumail, S. (2015a). Ecology of nickel hyperaccumulator plants from ultramafic soils in Sabah (Malaysia). *Chemoecology*, 25(5), 243–259. https://doi.org/10.1007/s00049-015-0192-7 van der Ent, A., Baker, A. J. M., Reeves, R. D., Chaney, R. L., Anderson, C. W. N., Meech, J. A., Erskine, P. D., Simonnot, M. O., Vaughan, J., Morel, J. L., Echevarria, G., Fogliani, B., Rongliang, Q., and Mulligan, D. R. (2015b). Agromining: Farming for metals in the future? *Environmental Science and Technology*, 49(8), 4773–4780. https://doi.org/10.1021/es506031u