MODELING ABOVEGROUND BIOMASS USING NON-REDUNDANT VEGETATION INDICES FROM PLANETSCOPE IMAGERY VIA MULTIPLE LINEAR REGRESSION IN PLANTED FORESTS

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INTRODUCTION

Aboveground biomass (AGB) is a crucial parameter in forest monitoring, carbon stock assessment, and ecological studies. Remote sensing, particularly the use of vegetation indices (VIs), has become a practical approach for estimating AGB. However, redundancy among VIs often reduces accuracy, as many indices share similar spectral characteristics. This study explores an approach to improve biomass estimation accuracy by applying Pearson Correlation Matrix (PCM) analysis to identify non-redundant indices, followed by regression-based modeling using high-resolution PlanetScope imagery in Wanagama Forest, Yogyakarta, Indonesia.

PROBLEM STATEMENT

- Single VIs often show redundancy and saturation → poor AGB estimates.
- PlanetScope offers multiple VIs, but many are highly correlated → multicollinearity issue.
- Reliable AGB model requires:
- Selecting low-redundancy indices.
- Combining them effectively to improve prediction accuracy.

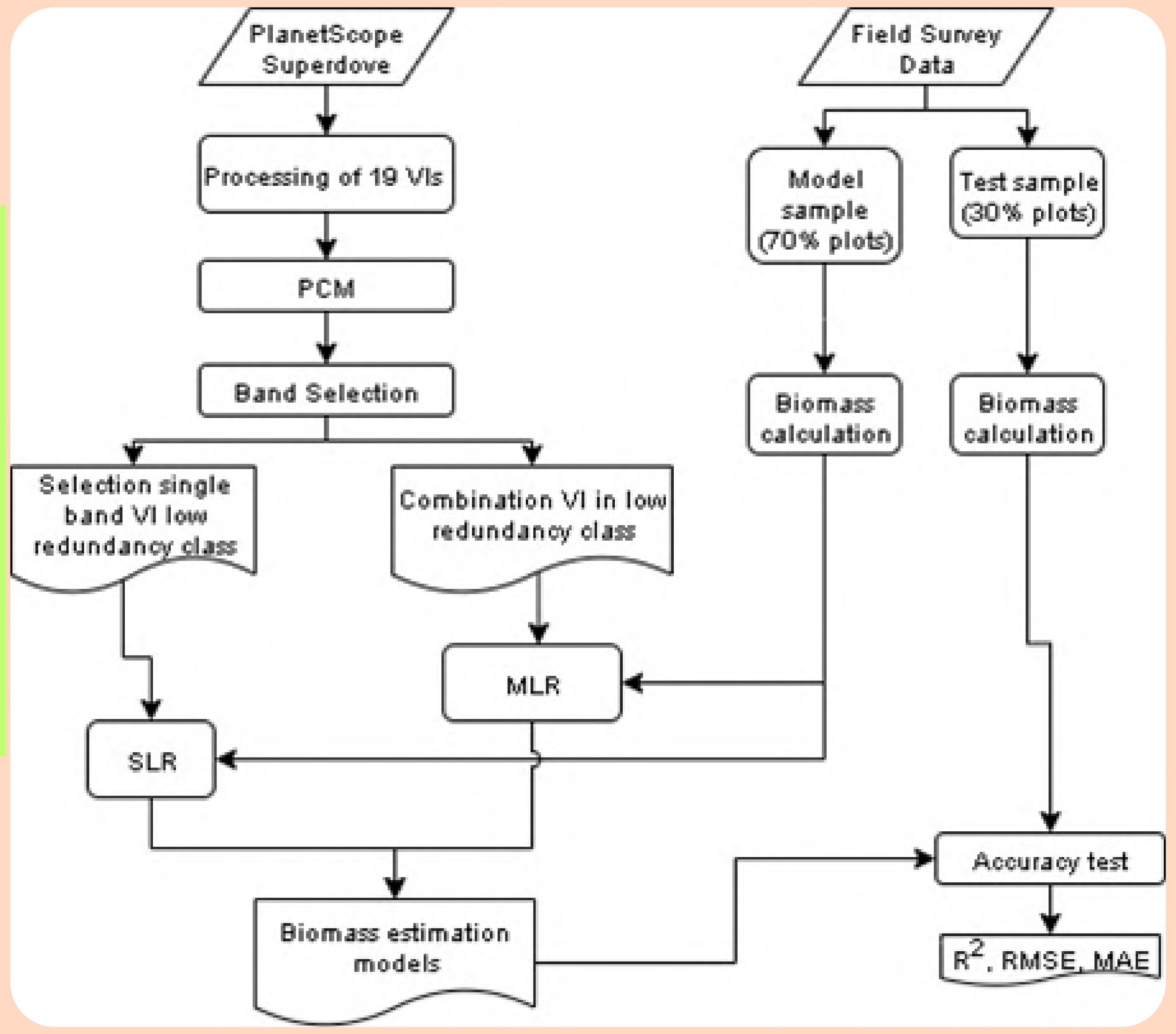
OBJECTIVE

This study aims to enhance the estimation of AGB in Wanagama Forest, Yogyakarta, by:

- Selecting non-redundant vegetation indices using Pearson Correlation Matrix (PCM).
- Developing regression models - Simple Linear Regression (SLR) for single indices and Multiple Linear Regression (MLR) for combinations.
- Evaluating model accuracy using R^2, RMSE, and MAE.
- Producing a spatial distribution map of AGB based on the best-performing model.

METHODOLOGY

FLOWCHART OF METHODOLOGY



RESULT AND DISCUSSION

The Pearson correlation analysis of 19 vegetation indices (Table 2) identified GNDVI, CIVE, MGRVI, RGR, and BGR as the most effective predictors of aboveground biomass (AGB). While simple linear regression using single indices (Figure 2) provided only moderate accuracy, combining indices in multiple linear regression models significantly improved performance. The best model (Com1-) achieved R = 0.826 and R^2 = 0.683 (Table 4), confirming the advantage of using non-redundant index combinations. A comparison of calibration and validation (Figure 3) showed consistent results, indicating the robustness of the model. The spatial distribution map of AGB in Wanagama Forest (Figure 4) further illustrates variability across the landscape, with higher biomass values concentrated in dense planted forest stands.

18 VEGETATION INDICES

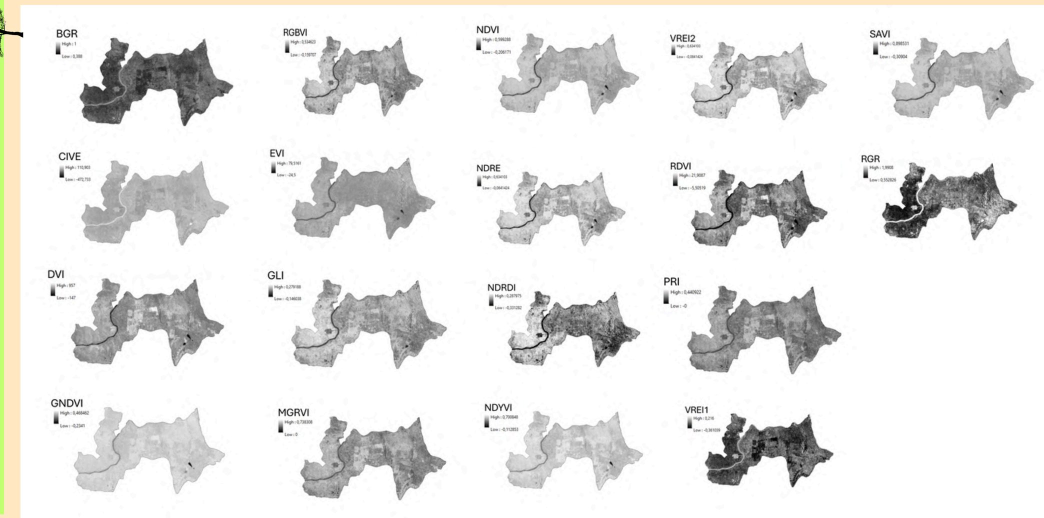


TABLE & FIGURE

- Low redundancy (-)
- Low redundancy (+)
- Moderate redundancy
- High redundancy
- Very strong correlation or strong inverse

TABLE 2

	NDVI	EVI	SAVI	GNDVI	NDRE	NDYVI	CIVE	MGRVI	RGBVI	GLI	NGRDI	RGR	BGR	PRI	VREI1	VREI2	DVI	RDVI
NDVI	1.00	0.86	0.88	0.93	0.92	0.96	-0.70	-0.77	0.77	0.77	0.77	-0.78	-0.67	0.65	0.92	0.92	0.78	0.91
EVI	0.86	1.00	1.00	0.84	0.82	0.84	-0.65	-0.63	0.62	0.63	0.63	-0.63	-0.54	0.53	0.79	0.82	0.99	0.99
SAVI	0.88	1.00	1.00	0.87	0.84	0.88	-0.65	-0.62	0.63	0.63	0.62	-0.62	-0.56	0.56	0.80	0.84	0.98	1.00
GNDVI	0.93	0.84	0.87	1.00	0.92	0.96	-0.42	-0.49	0.51	0.51	0.49	-0.50	-0.47	0.46	0.76	0.92	0.78	0.89
NDRE	0.92	0.82	0.84	0.92	1.00	0.90	-0.50	-0.62	0.62	0.62	0.62	-0.62	-0.53	0.53	0.73	1.00	0.75	0.86
NDYVI	0.96	0.84	0.88	0.96	0.90	1.00	-0.63	-0.64	0.70	0.69	0.64	-0.65	-0.70	0.69	0.85	0.90	0.78	0.90
CIVE	-0.70	-0.65	-0.65	-0.42	-0.50	-0.63	1.00	0.90	-0.94	-0.93	-0.90	0.91	0.87	-0.85	-0.81	-0.50	-0.61	-0.67
MGRVI	-0.77	-0.63	-0.62	-0.49	-0.62	-0.64	0.90	1.00	-0.95	-0.98	-1.00	1.00	0.79	-0.78	-0.89	-0.62	-0.55	-0.66
RGBVI	0.77	0.62	0.63	0.51	0.62	0.70	-0.94	-0.95	1.00	1.00	0.95	-0.95	-0.94	0.93	0.87	0.62	0.55	0.66
GLI	0.77	0.63	0.63	0.51	0.62	0.69	-0.93	-0.98	1.00	1.00	0.98	-0.97	-0.90	0.90	0.88	0.62	0.56	0.66
NGRDI	0.77	0.63	0.62	0.49	0.62	0.64	-0.90	-1.00	0.95	0.98	1.00	-1.00	-0.79	0.78	0.89	0.62	0.55	0.66
RGR	-0.78	-0.63	-0.62	-0.50	-0.62	-0.65	0.91	1.00	-0.95	-0.97	-1.00	1.00	0.79	-0.78	-0.89	-0.62	-0.54	-0.66
BGR	-0.67	-0.54	-0.56	-0.47	-0.53	-0.70	0.87	0.79	-0.94	-0.90	-0.79	0.79	1.00	-1.00	-0.75	-0.53	-0.50	-0.59
PRI	0.65	0.53	0.56	0.46	0.53	0.69	-0.85	-0.78	0.93	0.90	0.78	-0.78	-1.00	1.00	0.74	0.53	0.49	0.58
VREI1	0.92	0.79	0.80	0.76	0.73	0.85	-0.81	-0.89	0.87	0.88	0.89	-0.89	-0.75	0.74	1.00	0.73	0.70	0.83
VREI2	0.92	0.82	0.84	0.92	1.00	0.90	-0.50	-0.62	0.62	0.62	0.62	-0.62	-0.53	0.53	0.73	1.00	0.75	0.86
DVI	0.78	0.99	0.98	0.78	0.75	0.78	-0.61	-0.55	0.55	0.56	0.55	-0.54	-0.50	0.49	0.70	0.75	1.00	0.97
RDVI	0.91	0.99	1.00	0.89	0.86	0.90	-0.67	-0.66	0.66	0.66	0.66	-0.66	-0.59	0.58	0.83	0.86	0.97	1.00

TABLE COMBINATION

Single	Mixed Combinations (No	Separated
GNDVI CIVE MGRVI NGRDI RGR BGR PRI DVI	**Comb 1:** GNDVI – CIVE – MGRVI – NGRDI – RGR – BGR – PRI	**Comb 1(+):** GNDVI – NGRDI – PRI
	Comb 2: BGR – GNDVI – DVI	**Comb 2(+):** PRI – GNDVI – DVI
	Comb 3: PRI – GNDVI – DVI	**Comb 1(–):** GNDVI – CIVE – MGRVI – RGR – BGR
	Comb 4: DVI – BGR – PRI	**Comb 2(–):** BGR – GNDVI – DVI

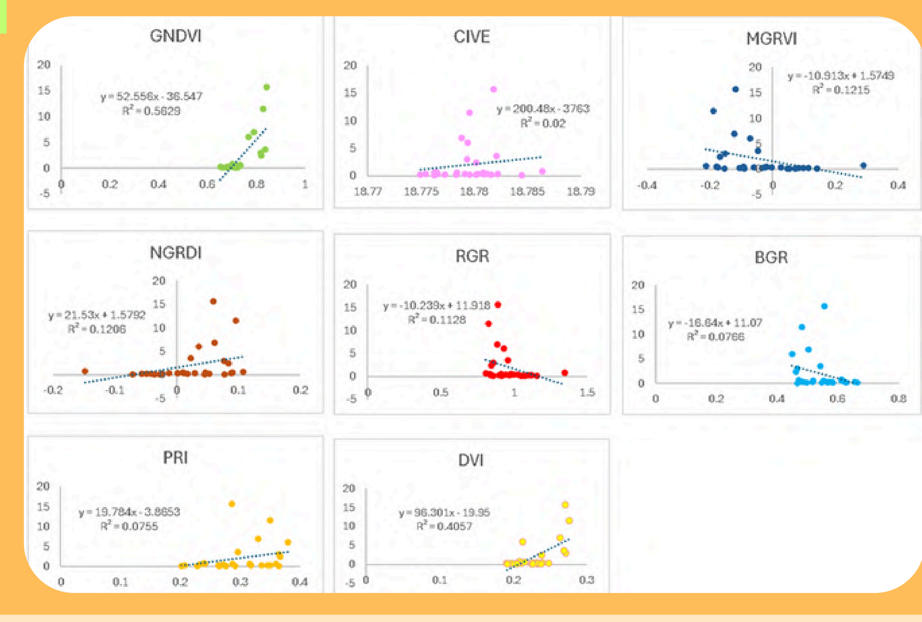


FIGURE 2

TABLE 4

Regres	Com1	Com2	Com3	Com4	Com1	Com2	Com1-	Com2-
Multi	82	69	56	74	64	56	82	69
R	68	48	31	54	4	31	67	48

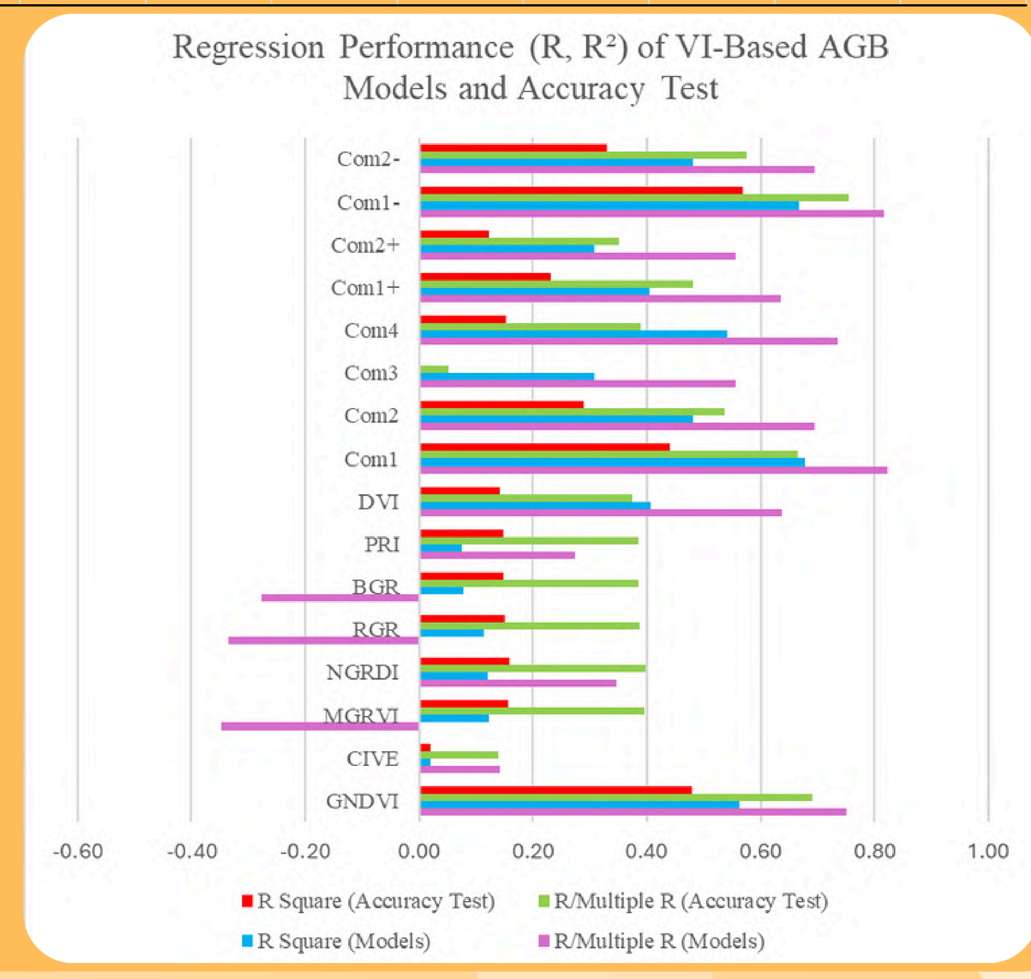
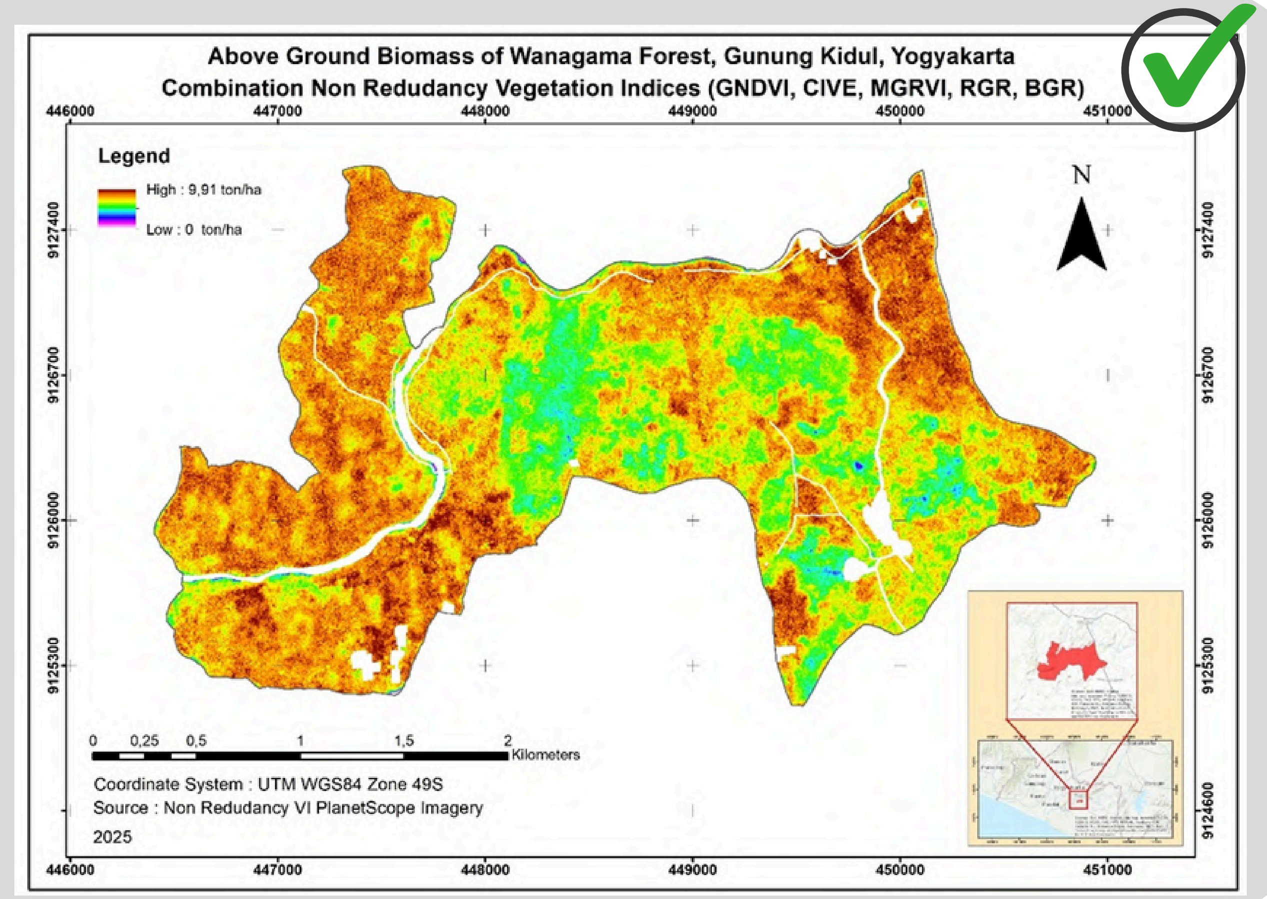
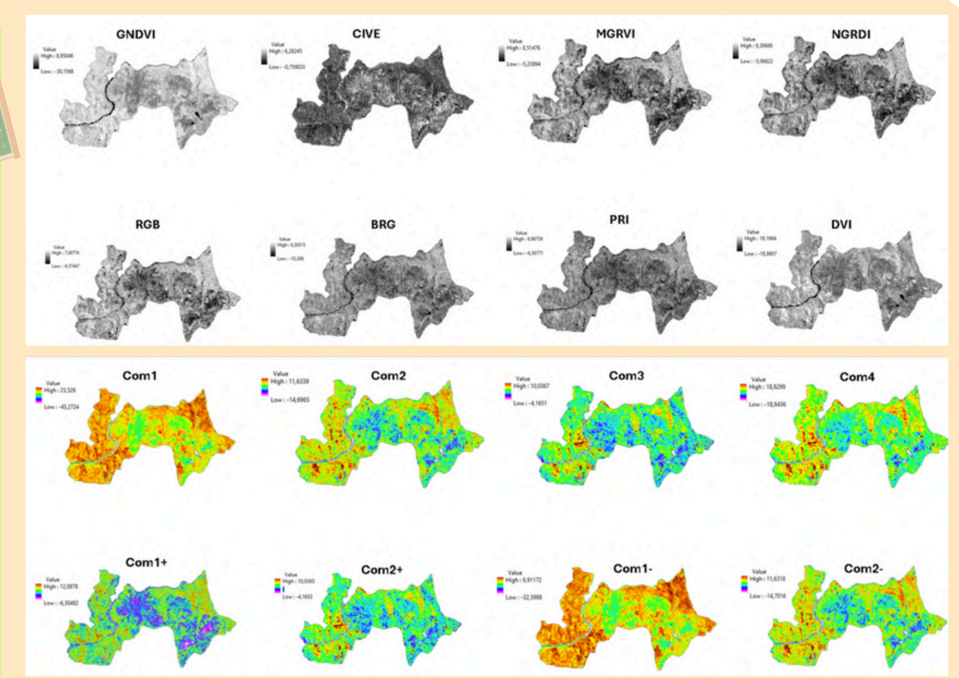


FIGURE 3: COMPARISON OF REGRESSION PERFORMANCE (R, R²) BETWEEN MODEL CALIBRATION AND ACCURACY TEST FOR VI-BASED AGB ESTIMATION



ABOVEGROUND BIOMASS (AGB) MAP



CONCLUSION

This study demonstrates that combining non-redundant vegetation indices from PlanetScope imagery significantly improves the accuracy of aboveground biomass (AGB) estimation compared to using single indices. The best-performing model (Com1-), which integrates both NIR- and visible-based indices, achieved high consistency between calibration and validation and produced realistic spatial patterns of biomass in Wanagama Forest. These findings highlight the importance of selecting indices with complementary spectral properties to minimize redundancy and enhance model robustness for forest biomass monitoring.

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