



Integrating seasonal greenness dynamics for improved forest type discrimination in Lualaba Province (DRC): implications for sustainable forest management

Médard Mpanda Mukenza^{a,b,*}, John Kikuni Tchowa^{b,c}, Hugo de Lame^c,
Timothée Besisa Nguba^{c,d}, Jan Bogaert^c, Yannick Useni Sikuzani^a,
Jean-François Bastin^c

^a Ecology, Ecological Restoration and Landscape Unit, Faculty of Agronomics Sciences, University of Lubumbashi, Lubumbashi P.O. Box 1825, Democratic Republic of the Congo

^b Department of Plant Science, Faculty of Agronomic Sciences, Université de Kolwezi, Kolwezi, Democratic Republic of the Congo

^c Teaching and Research Center (TERRA), Gembloux Agro-Bio Tech—Université de Liège, 5030 Gembloux, Belgium

^d Regional Postgraduate School for Integrated Management of Forests and Tropical Territories (ERAIFT), Kinshasa, P.O. Box 15,373, Democratic Republic of the Congo

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ABSTRACT

Forests in Lualaba Province, Democratic Republic of the Congo (DRC), are increasingly threatened by logging activities, agricultural expansion, and recurrent bushfires. Yet, little is known about the spatial extent and the structural and functional diversity of the main forest types—dry dense forests, gallery forests, and miombo woodlands. Understanding these differences is crucial, as each forest type faces distinct ecological pressures and provides unique ecosystem services, including climate regulation, biodiversity conservation, and livelihood support. This study evaluates the potential of Sentinel-2 time-series imagery to discriminate forest types by explicitly incorporating seasonal variability in canopy greenness in a seasonally dry tropical context. Monthly NDVI composites for 2024 were used to derive annual and seasonal averages, as well as intra-annual coefficients of variation, capturing vegetation-specific responses to seasonal dynamics. A spatially stratified validation framework implemented in Google Earth Engine was used to assess model robustness. The best-performing classification achieved an overall accuracy of 80.66% and a macro-averaged F1-score of 81% across all eight land-cover classes (Model M2). Results indicate that the dry season (June–September) provides the strongest spectral separation among forest types, underscoring the importance of temporal information for characterising vegetation heterogeneity. By integrating seasonal canopy greenness dynamics into forest-type mapping, this study demonstrates a reproducible, scalable approach for mapping seasonally dry tropical forests. The resulting maps provide an operational framework for forest-type discrimination in seasonally dry tropical landscapes and support sustainable forest management, conservation planning, and climate-resilient land-use strategies in southern DRC and comparable tropical regions.

* Corresponding author.

E-mail address: Mpanda.Mukenza@unilu.ac.cd (M.M. Mukenza).

Introduction

Despite advances in remote sensing, tropical forest mapping still often relies on coarse forest/non-forest classifications that obscure ecological complexity and functional heterogeneity. Global and regional land-cover products generally overlook the diversity of forest formations and their seasonal dynamics, limiting ecological interpretation and locally adapted management [1,2]. Recent studies nonetheless demonstrate that medium-resolution satellite imagery, when combined with temporal and ecological information, can improve forest-type discrimination, highlighting the need to move beyond static structural maps toward functionally informed representations [3,4].

This challenge is particularly acute in Central Africa, where climatic gradients and human pressures create highly heterogeneous forest landscapes [5,6]. Lualaba Province in southeastern DRC exemplifies this complexity: a transitional zone where humid gallery forests, dry dense forests, and miombo woodlands coexist over short distances [7–10]. Despite this ecological diversity, available maps rely on coarse forest categories, failing to represent the spatial and functional variation essential for ecosystem services and local livelihoods. Although mapping efforts in the Katanga region are increasing, no high-resolution product currently exists that reliably distinguishes miombo woodland, dry dense forest, and gallery forest based on seasonal functional contrasts. Existing products either aggregate all forest formations into a single class or lack the spatial resolution and temporal information required to capture these ecologically distinct units [7–11]. This gap limits both ecological interpretation and the operational use of forest maps in a region characterised by strong seasonal and functional heterogeneity.

Located on the Katangese plateau between the humid Congo Basin and the drier southern African savannas, Lualaba Province experiences a sub-humid tropical climate with a marked dry season [12]. This setting supports a mosaic of forest formations, including miombo woodlands, dry dense forests, and gallery forests, each with distinct structural and functional traits. Miombo woodlands exhibit strong seasonal canopy dynamics associated with leaf phenology and high anthropogenic pressure; dry, dense forests maintain a more stable canopy but are often spectrally confused with miombo; and gallery forests remain evergreen along riparian corridors but often face underrepresentation in inventories [10–16].

Lualaba thus represents an ideal case study for seasonally informed forest mapping, bridging advances in remote sensing with the ecological realities of Central African forests.

Conventional approaches, often based on single-date satellite imagery and static spectral indices, fail to capture the temporal dynamics and functional variability that distinguish forest formations [9,10,17,18]. This limitation is particularly pronounced in tropical sub-humid ecosystems, where forest types exhibit overlapping spectral signatures during certain periods of the year. As a result, static classifications can misrepresent the true spatial extent and ecological status of forests, undermining both ecological understanding and management decisions.

Seasonal spectral approaches leveraging intra-annual reflectance variability reveal differences in canopy dynamics that remain undetectable in single-date imagery [19,20]. The Sentinel-2 constellation, combining high spatial resolution, frequent revisits, and rich spectral information, provides an effective basis for capturing these phenological signals in seasonally dry tropical forests [21–25]. While these datasets have known limitations—such as index saturation in dense canopies, spectral confusion between ecologically distinct but spectrally similar formations, and sensitivity to atmospheric conditions—these challenges can be addressed through context-aware interpretation, temporal smoothing, and spatially stratified validation [26], thereby enhancing both the accuracy and reproducibility of forest-type discrimination.

In parallel, advances in cloud-based geospatial platforms, particularly Google Earth Engine (GEE), facilitate the large-scale processing of high-frequency satellite data and the implementation of spatial cross-validation frameworks [27]. Such approaches allow models to be trained and tested on distinct subsets of the landscape, reducing spatial autocorrelation biases and providing a robust assessment of classification performance [3,4]. By combining seasonal spectral metrics with robust machine learning frameworks, it becomes possible to reliably differentiate miombo woodlands, dry dense forests, and gallery forests, while simultaneously generating maps that are both ecologically informative and operationally relevant.

Overall, integrating seasonal greenness dynamics into forest mapping represents both a regional and methodological advancement, providing a practical framework for improved forest management in seasonally dry tropical environments. Unlike static land-cover approaches, this strategy captures seasonal functional contrasts in vegetation and helps bridge spectral-temporal analysis with the ecological interpretation of miombo forest formations. In this study, seasonal canopy dynamics are analysed at a functional scale, focusing on dry–wet transitions and periods of sustained canopy activity. We present the first application of Sentinel-2 seasonal spectral information to forest-type discrimination in the Congolese miombo, using targeted temporal windows selected to maximize ecological contrast among formations. The overarching objective is to evaluate the potential of Sentinel-2 time-series imagery, combined with seasonally aggregated phenological indicators, to discriminate the main forest formations in Lualaba. We hypothesise that ecophysiological differences among miombo woodland, dry dense forest, and gallery forest are reflected in distinct seasonal trajectories of canopy vigour and stability that persist after monthly temporal aggregation.

Materials and methods

Study area: lualaba province (DR Congo)

Lualaba Province, in southeastern DRC (Fig. 1), covers approximately 120,000 km² and exhibits pronounced ecological heterogeneity shaped by climatic, topographic, and edaphic gradients [10,12]. Located on the Katangese plateau, a transitional zone between humid Congo Basin forests and drier savannas, the region receives 1200–1600 mm of annual precipitation and has a mean temperature

of around 25 °C [10,12]. This combination of climatic variability, heterogeneous soils (Ferralsols, Acrisols, Arenosols [28,29]), and mosaic vegetation supports three dominant forest types: miombo woodlands, dry dense forests, and hydromorphic gallery forests [12]. These forest formations differ in leaf phenology and ecophysiological strategies, characteristics that influence seasonal variations in spectral responses observed in Sentinel-2 imagery and therefore underpin our analysis of seasonal greenness dynamics for forest-type discrimination.

Sentinel-2 imagery acquisition and reference sampling design

Seasonal spectral contrasts and vegetation greenness dynamics were analysed using Sentinel-2 imagery processed within GEE [27]. Three phenologically contrasting periods were defined for 2024: April–May (rainy-to-dry season transition), June–September (peak dry season), and October–November (onset of the rainy season). The main rainy season (December–March) was excluded due to persistent cloud cover and spectral homogenization among forest types [30], whereas the early rainy transition (October–November) was retained to capture canopy reactivation. Sentinel-2 scenes pre-processed with Sen2Cor [31] were filtered for cloud cover below 10% and subsequently masked using the QA60 band and the Scene Classification Layer (SCL). Pixels identified as clouds, cirrus, shadows, saturated, or defective were excluded. The filtered images were then aggregated into monthly median composites to reduce spectral noise, residual atmospheric artefacts, and scene-specific variability while preserving dominant seasonal phenological contrasts at the regional scale [32]. To verify that atmospheric masking did not introduce bias into NDVI trajectories, additional quality diagnostics were conducted, including (i) assessment of the percentage of removed pixels, (ii) evaluation of valid observation counts by month and by land-cover class, and (iii) comparison of NDVI distributions before and after masking. All 1250 initial Sentinel-2 images were retained after masking, indicating that filtering was applied at the pixel level without altering the temporal continuity of observations. In total, 1250 Sentinel-2 images (Appendix A) were used, unevenly distributed between April and November, with higher acquisition density during the dry season and a marked decrease during the rainy season. Atmospheric bands B1, B9, and B10 (60 m spatial resolution) were excluded as they are not suitable for vegetation monitoring [33,34] (Table 1).

A reference dataset consisting of 1200 geo-referenced plots (0.5 ha each) was established through augmented visual interpretation using Collect Earth [35]. In this protocol, each plot is represented by a central geographic point used as the training sample, rather than a polygon used for direct satellite-pixel extraction. Land-cover labels were assigned through expert visual interpretation based on multi-source information, including very high-resolution imagery (Google Earth and Bing Maps), and detailed knowledge of the study area. A plot was considered homogeneous when the area surrounding the central point visually corresponded to a single land-cover class, with no observable land-use transitions, linear features, or ecotones in the immediate vicinity of the point. To minimise mixed-pixel effects at the Sentinel-2 spatial resolution (10 m), training points were intentionally positioned at the core of homogeneous land-cover patches and away from boundaries such as roads, rivers, agricultural edges or vegetation transitions. To ensure this homogeneity, $\geq 90\%$ of the $\approx 70\text{ m} \times 70\text{ m}$ window surrounding each point had to visually correspond to a single land-cover class. Although a 0.5-ha plot theoretically corresponds to approximately 50 Sentinel-2 pixels, only the visually validated central point was

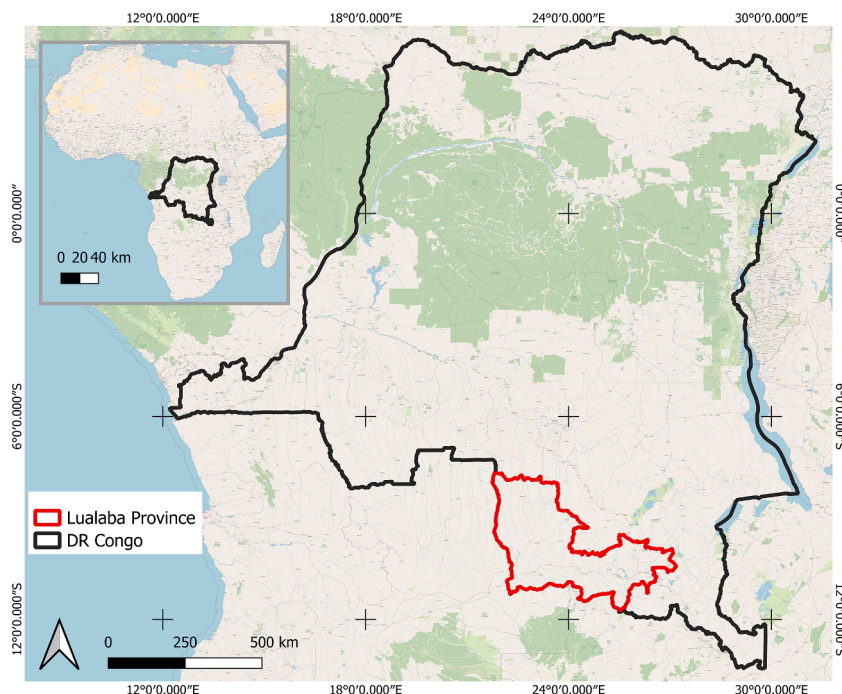


Fig. 1. Geographical location map of Lualaba Province, situated in the southeastern part of the Democratic Republic of the Congo (DR Congo).

Table 1

Overview of sentinel-2 MSI spectral bands analysed, including central wavelengths, spatial resolutions, and their roles in vegetation monitoring, water analysis, and atmospheric correction.

Band	Name	Central Wavelength (nm)	Resolution (m)	Main Application
B2	Blue	490	10	Water vs. bare soil differentiation
B3	Green	560	10	Preliminary vegetation assessment
B4	Red	665	10	Vegetation health (chlorophyll absorption)
B5	Red Edge 1	705	20	Fine detection of plant chlorophyll
B6	Red Edge 2	740	20	Analysis of canopy structure
B7	Red Edge 3	783	20	Monitoring vegetation growth
B8	Near Infrared (NIR)	842	10	Biomass and vegetation vigour
B8A	Narrow NIR	865	20	Enhanced vegetation accuracy
B11	SWIR 1	1610	20	Canopy water content, water stress
B12	SWIR 2	2190	20	Forest/soil/cloud differentiation

used for spectral feature extraction and supervised model training. Field verification was conducted on 30% of the plots ($n = 360$) during a ground survey in June 2024, including GPS localisation and photographic documentation of vegetation structure and land use. Owing to the strong prior familiarity with the study area and the interpretation protocol applied, no plot labels required modification following field validation, confirming the consistency and reliability of the reference dataset. This approach follows the standard Collect Earth sampling protocol, in which the interpreted point represents the sampling unit used for supervised learning rather than a zonal extraction of satellite pixels [35]. All validated plot centres were exported as a FeatureCollection in GEE ([Appendix B](#)) and used to (i) extract spectral metrics and (ii) train and validate supervised classification models (Section 2.5).

NDVI extraction and spectral signatures from sentinel-2 images

NDVI was computed for each georeferenced plot using bands B8 (NIR) and B4 (red) in GEE, allowing characterisation of photosynthetic activity and intra-annual trajectories for all land-cover classes. NDVI robustness for vegetation monitoring is well documented, ranging from long-term global time series to the detection of tropical forest degradation [36–38]. Reflectance values of Sentinel-2 bands relevant for classification ([Table 1](#)) were averaged by band and class using `ee.Reducer.mean()`, producing mean spectral signatures for each vegetation type ([Fig. 2](#)). These spectro-temporal profiles—NDVI and reflectance—enabled the characterisation of seasonal greenness dynamics and served as the empirical foundation for model training and validation [39,40].

Analysis of seasonal spectral dynamics and identification of discriminant variables

Seasonal dynamics analysis aimed to identify periods and spectral bands most relevant for discriminating forest types [41]. Monthly time series of spectral indices were constructed for each forest type. Univariate analyses assessed the discriminative power of each spectral index for each month, using plot-level observations as the independent sampling units. Sample sizes corresponded to the number of reference plots available per forest type and month. Normality was tested using the Shapiro–Wilk test, and homogeneity of variance was assessed prior to parametric analyses. When the ANOVA assumptions were met, a one-way ANOVA was conducted, followed by Tukey's HSD for pairwise post hoc comparisons. For non-normal data or when assumptions were violated, the Kruskal–Wallis test was used, followed by Dunn's test with Bonferroni correction for pairwise comparisons. Test statistics (F for ANOVA, H for the Kruskal–Wallis test, and Z for post hoc tests) were reported along with p-values and effect sizes to ensure transparent statistical reporting. The coefficient of variation (CV) of NDVI quantified seasonal amplitude and highlighted seasonal contrasts in canopy greenness among miombo, gallery, and dry dense forests. Effect sizes were reported as η^2 (eta-squared) where ANOVA assumptions



Fig. 2. Aerial view of the main forest types in Lualaba [11], illustrated by examples with geographical coordinates: (a) gallery forest, with its linear arrangement along rivers and dense riparian vegetation – Kapanga (–8.093, 22.155); (b) dry dense forest, marked by a closed, homogeneous, and continuous canopy – Lubudi (–10.03, 25.32); (c) miombo woodland, with a more open canopy and gaps between tree crowns – Mutshatsha (–11.322, 25.509).

were met, and ϵ^2 (epsilon-squared) as the non-parametric effect size for Kruskal–Wallis tests. For pairwise post-hoc comparisons, Cohen's d was used following Tukey HSD, and rank-biserial correlation (r) was used following Dunn's test. Bootstrap 95% confidence intervals (1000 iterations, with replacement) were computed for pairwise median NDVI differences between forest types during the peak dry season (June–September) using the 447 forest reference plots. For each iteration, both samples were independently resampled with replacement, and the difference between the sample medians was recorded. The 2.5th and 97.5th percentiles of the resulting distribution served as the lower and upper bounds of the 95% CI. An IC that strictly excludes zero indicates that the observed median difference is unlikely to have arisen by chance, complementing the Kruskal–Wallis and Dunn's test results. Results are reported in Section 3.1.1 and illustrated in Appendix E (Figs. E1–E2). This analysis guided the selection of the most discriminant temporal windows and spectral bands for subsequent classification [41,42].

Supervised classification with random forest and spatial stratification

The reference dataset (Section 2.2) was stratified by land-cover class and spatially balanced to ensure representative sampling across the study area. To explicitly address spatial autocorrelation, the study area was partitioned into five contiguous 5×5 km blocks using the BlockCV package [26] in R (Fig. 3). One block was reserved as the spatially independent validation set ($n = 212$) while the remaining four blocks constituted the training set ($n = 988$). This design enforces geographic separation between training and validation samples, thereby reducing spatial autocorrelation bias during model evaluation. This constitutes a single spatially stratified train–test split; no rotation of validation blocks was performed.

Supervised classifications were conducted to assess the ability of Sentinel-2 multispectral and seasonal metrics to discriminate the main forest formations of Lualaba Province. The Random Forest (RF) algorithm was selected for its robustness to noise, resistance to overfitting, and ability to model non-linear relationships [43,44], while providing variable-importance metrics that support ecological interpretation. The RF model was implemented with 500 trees, a value widely reported to ensure stable predictions and robust variable importance estimates while maintaining reasonable computational cost [43,45]. Trees were fully grown (minimum node size = 1), following the original Random Forest formulation [43]. A reduced bootstrap sampling rate of 25% was applied to increase tree diversity and reduce inter-tree correlation, an approach shown to support model generalisation in heterogeneous or noisy datasets [46, 47].

Following spatial stratification, the reference dataset was partitioned into spatially independent training ($n = 988$) and validation ($n = 212$) subsets. These datasets were exported as CSV files and imported into GEE, where classification and accuracy assessment were performed using the stratified samples. Sentinel-2 imagery was classified using multiple RF models designed to explicitly account for seasonal spectral variability. Rather than relying on a single annual composite, three complementary classification strategies were implemented: (i) a baseline model using all Sentinel-2 spectral bands aggregated as median composites over the entire study period (April–November); (ii) bands restricted to the most discriminant seasonal window, identified through class-specific NDVI dynamics; (iii) a reduced subset of spectral bands during the discriminant phenological period, selected based on variable importance metrics. For each strategy, spectral bands and NDVI layers from the selected composites were concatenated to form the predictor set, allowing the classifier to jointly exploit spectral information and seasonal variability.

After classification, all non-forest land-cover types (Wooded savannah, Grassland / Wetland, Agriculture, water bodies, and Built-

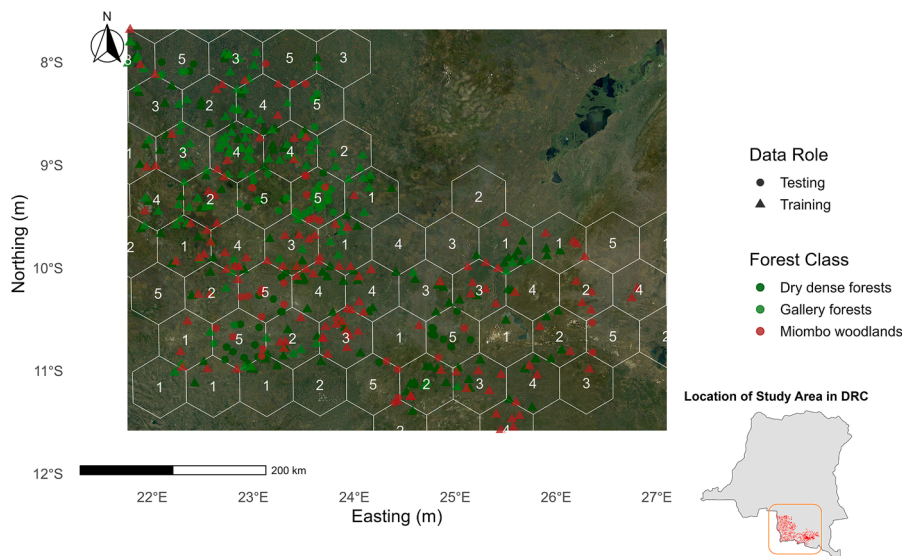


Fig. 3. Spatial distribution of training and validation points generated through spatial stratification using 5 spatial blocks. Only the forest classes considered in this study are displayed, with points assigned to training and validation datasets. This representation avoids visual clutter and highlights the spatial independence between samples used for model calibration and evaluation.

up / Bare soil) were aggregated into a single non-forest class for thematic interpretation and map presentation, in order to align with the primary objective of the study — the discrimination among forest types rather than the detailed characterisation of non-forest land covers. However, all accuracy assessments were performed on the original eight-class classification outputs without any aggregation. Confusion matrices were exported from GEE as absolute sample counts, with reference data represented in rows and predicted classes in columns [10,48], and all metrics were computed from spatially independent validation samples generated through spatial stratification. The accuracy metrics reported in Appendix C, therefore, reflect the full eight-class scheme and are directly traceable to these raw count matrices.

Model performance was assessed using confusion matrices exported from Google Earth Engine, with absolute sample counts as the basis; reference classes were represented in rows and predicted classes in columns. Accuracy metrics were computed from spatially independent validation samples generated through spatial stratification, following standard remote sensing practice [10,48].

Overall Accuracy (OA) was computed as:

$$OA = (\sum n_{ii})/N$$

where n_{ii} represents the number of correctly classified samples for class i (diagonal elements of the confusion matrix) and N is the total number of validation samples.

Producer's Accuracy (PA) and User's Accuracy (UA) were calculated as:

$$PA_i = n_{ii} / (\sum_j n_{ij})$$

$$UA_i = n_{ii} / (\sum_j n_{ji})$$

where n_{ij} denotes the number of samples of reference class i predicted as class j , and n_{ji} denotes the number of samples predicted as class i that belong to reference class j .

The F1-score was computed as the harmonic mean of PA and UA:

$$F1_i = (2 \times PA_i \times UA_i) / (PA_i + UA_i)$$

Confusion matrices are reported as absolute sample counts in Appendix C (Table C1). All accuracy metrics reported therein were computed directly and consistently from these count matrices using the formulas above. To assess the statistical significance of the difference in overall accuracy between models M1 and M2, a paired bootstrap resampling procedure was used. For each of 1000 iterations, a bootstrap resample of the validation set ($n = 212$, with replacement) was drawn, and the difference in OA between M1 and M2 was computed. The proportion of bootstrap samples in which M2 OA did not exceed M1 OA served as the one-tailed p-value. A significance threshold of $\alpha = 0.01$ was applied. Spatial agreement analyses between classification strategies were performed to identify areas of classification uncertainty and to assess the robustness of the seasonal greenness dynamics-based approach.

Comparative datasets and external validation

To further assess the reliability and added value of the forest map produced in this study, we compared our results with two external datasets. First, we used the work of Useni et al. [10], which considered a single undifferentiated forest class (mainly miombo

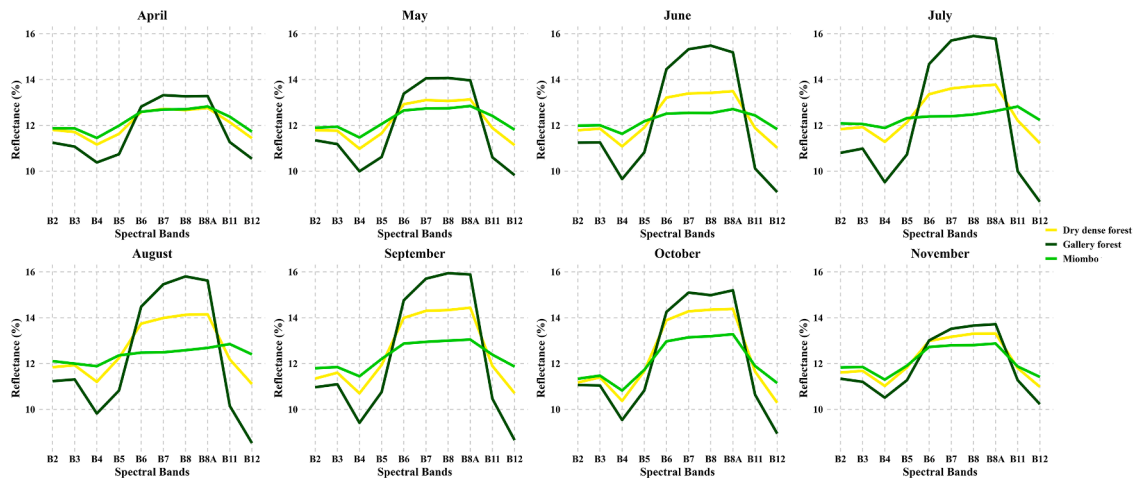


Fig. 4. Seasonal variations in spectral signatures of different forest types in Lualaba for 2024, derived from Sentinel-2 imagery. The period from June to September, using near-infrared bands (B6–B8A) and shortwave infrared bands (B11–B12), provides the highest discriminative potential for distinguishing among forest types. The rainy season (December–March) was excluded due to persistent cloud cover and spectral homogenization caused by widespread photosynthetic activity.

woodlands). Second, we mobilised the Copernicus Land Cover 2019 (PROBAV_LC100, 100 m) [49]. While LC100 has a coarser resolution and a classification scheme different from our three forest classes, we aggregated similar forest types to provide a meaningful thematic comparison. These comparative datasets were used to highlight the added value of our Sentinel-2-based, phenology-informed mapping in capturing forest diversity and improving spatial detail, rather than for strict pixel-level validation.

Results

Spectral separability and vegetation type discrimination

Seasonal spectral response of Lualaba forest types (2024)

Fig. 4 illustrates the seasonal spectral response of the three main forest types in Lualaba—dry dense forest, gallery forest, and miombo woodland—derived from Sentinel-2 imagery for 2024. Spectral statistics were computed from balanced samples of 150 plots per forest type (total $n = 450$ forest plots per monthly analysis). Mean spectral profiles computed over eight months exhibit the expected vegetation signal, with low reflectance in the visible bands (B2–B4), a pronounced peak in the near-infrared (B6–B8A) and decreasing reflectance in the shortwave infrared (B11–B12).

Seasonal contrasts were strongest during the peak dry season (June–September), as confirmed by Kruskal–Wallis tests ($H = 112.6$, $df = 2$, $n = 450$, $p < 0.001$), followed by Dunn’s post-hoc comparisons with Bonferroni correction ($Z = 3.9$ – 6.8 , $p < 0.001$), with non-parametric effect sizes ranging from moderate to large ($\epsilon^2 = 0.75$; rank-biserial $r = -0.66$ to -1.00). Bootstrap 95% confidence intervals on pairwise median NDVI differences (1000 iterations, with replacement) confirmed consistent and substantial separation among all three forest type pairs during the peak dry season (GF vs DDF: $\Delta = +0.190$, 95% CI $[+0.166, +0.209]$; GF vs MW: $\Delta = +0.297$, 95% CI $[+0.286, +0.310]$; DDF vs MW: $\Delta = +0.107$, 95% CI $[+0.088, +0.135]$; all 95% CIs strictly exclude zero; see Appendix E, Figs. E1–E2). Near-infrared bands (B6–B8A) consistently enhanced the contrast between gallery forests and other formations, while shortwave infrared bands (B11–B12) further differentiated forest types through their sensitivity to canopy moisture. In contrast, weaker spectral separability was observed during the transitional months (April–May and October–November), particularly between dry dense forest and miombo woodland (Kruskal–Wallis: $H = 4.7$, $df = 2$, $n = 450$, $p = 0.096$). These periods were characterised by increased spectral overlap across multiple bands, reflecting both convergence in canopy conditions and higher uncertainty in ecotonal areas. This pattern was spatially consistent with zones of elevated classification uncertainty identified in subsequent analyses (Figs. 8 and 9).

It should be noted that the seasonal patterns presented here are derived from monthly median composites and exclude the peak rainy season (December–March). Consequently, the results emphasise seasonal contrasts rather than short-term or intra-monthly phenological transitions. The spectral signal primarily reflects differences in seasonal stability and variability of canopy vigour across forest types, forming the basis for their discrimination within the classification framework.

Overall, these results indicate that dry-season spectral contrasts, particularly in the near-infrared and shortwave infrared domains, provide the most robust information for distinguishing miombo woodlands, dry dense forests, and gallery forests in this landscape. The

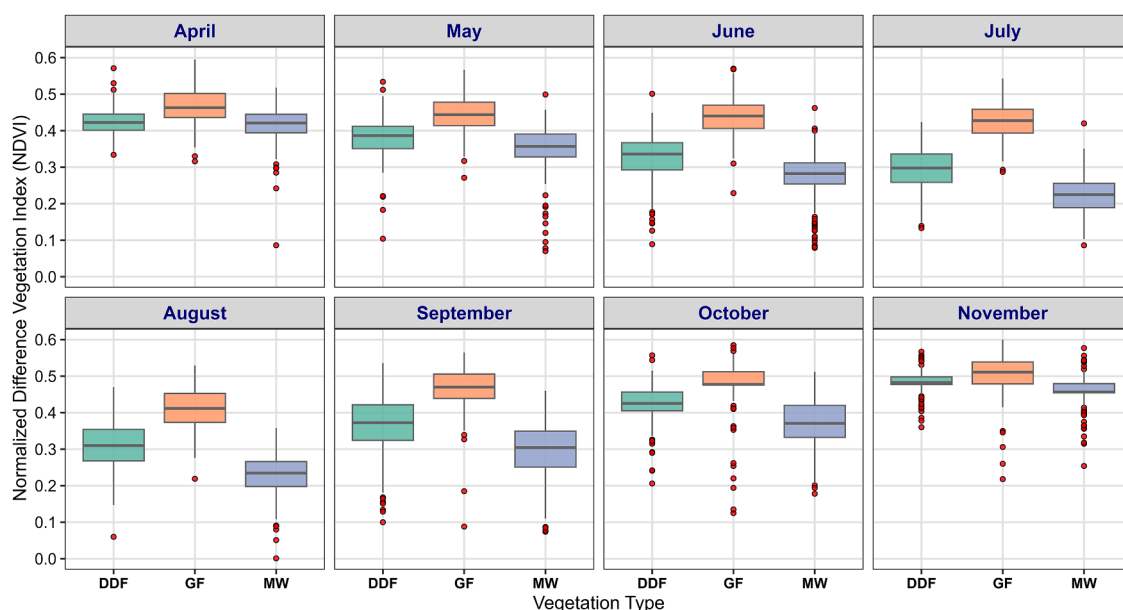


Fig. 5. Monthly variation of NDVI by vegetation type in Lualaba for 2024, derived from Sentinel-2 imagery. The higher and more stable values observed in gallery forests indicate a more constant photosynthetic activity throughout the year. DDF: dry dense forest, GF: gallery forest, and MW: miombo woodland.

implications and limitations of this seasonal focus are further examined in the Discussion.

Seasonal greenness and spectral characterisation of Lualaba forest formations

Analysis of NDVI-derived seasonal dynamics reveals distinct patterns among the main forest formations of Lualaba (Figs. 5–7). Gallery forests exhibit the lowest intra-annual variability (coefficient of variation, CV), with consistently high NDVI values throughout the analysed period (April–November). This pattern reflects dense canopy cover and relatively stable photosynthetic activity; however, the exclusion of the rainy season (December–March) prevents full characterisation of the annual canopy cycle. Miombo woodlands show the highest NDVI variability, with marked declines during the dry season (May–August) and recovery at the onset of rains. Dry, dense forests occupy an intermediate position, showing moderate declines in NDVI during the dry season. NDVI spatial patterns highlight heterogeneity in transition zones, particularly along riparian corridors and mosaic landscapes, where intermediate values increase classification uncertainty. In miombo woodlands, NDVI declines sharply during the dry season (May–August) and recovers rapidly at the onset of rains, reflecting the predominantly deciduous character of miombo species. This strong intra-annual contrast in canopy greenness is spatially evident in the NDVI maps (Fig. 6).

In August, at the peak of the dry season, NDVI patterns reveal marked spatial heterogeneity, with higher greenness along riparian zones and scattered patches of miombo with reduced canopy cover. By November, at the onset of the rainy season, NDVI values become more uniform across the landscape, indicating widespread leaf flushing and reduced differentiation among forest types. These spatial patterns highlight areas of potential classification uncertainty in transitional mosaics, particularly for miombo and dry dense forest. All NDVI differences were tested statistically using balanced samples of $n = 150$ plots per forest type (total $n = 450$) and assessed using Kruskal–Wallis tests, followed by Dunn’s post-hoc comparisons with Bonferroni correction, confirming significant differences between forest types during peak discriminant periods ($H = 97.6$, $df = 2$, $p < 0.001$). Effect sizes were quantified using non-parametric effect size estimates: ε^2 (epsilon-squared) = 0.75 for the global Kruskal–Wallis test, and rank-biserial correlation ($r = -0.66$ to -1.00) for pairwise post-hoc comparisons, with bootstrap 95% CIs on median NDVI differences all strictly excluding zero (GF vs DDF: [+0.166, +0.209]; GF vs MW: [+0.286, +0.310]; DDF vs MW: [+0.088, +0.135]; see Appendix E), providing quantitative support for these contrasts.

Figs. 5–7 summarise monthly NDVI variation, spatial heterogeneity, and intra-annual variability, emphasising patterns relevant to forest-type discrimination while acknowledging the methodological limitations introduced by temporal smoothing and seasonal exclusion.

Influence of spectral–temporal variable selection on forest classification accuracy

The classification results obtained from the three models, based on different selections of Sentinel-2 spectral–temporal variables (Figs. 8 and 9), indicate that both temporal and spectral choices substantially influence forest-type discrimination. Classification accuracy was evaluated using a spatially independent validation dataset derived from spatial stratification (Section 2.5), ensuring that training and validation samples were not spatially autocorrelated. Full confusion matrices and all derived metrics are presented in Appendix C (Table C1).

For Model M1, which integrates all spectral bands over the full temporal series, the overall accuracy reached 69.81%. The confusion matrix reveals strong class-dependent performance differences. Gallery forest was almost perfectly classified ($PA = 97.14\%$; $F1 = 95.77\%$), whereas dry dense forest and miombo woodland showed substantial confusion: only 75.00% of dry dense forest samples were correctly classified, with 15.62% misassigned to miombo woodland, and only 40.00% of miombo woodland samples were

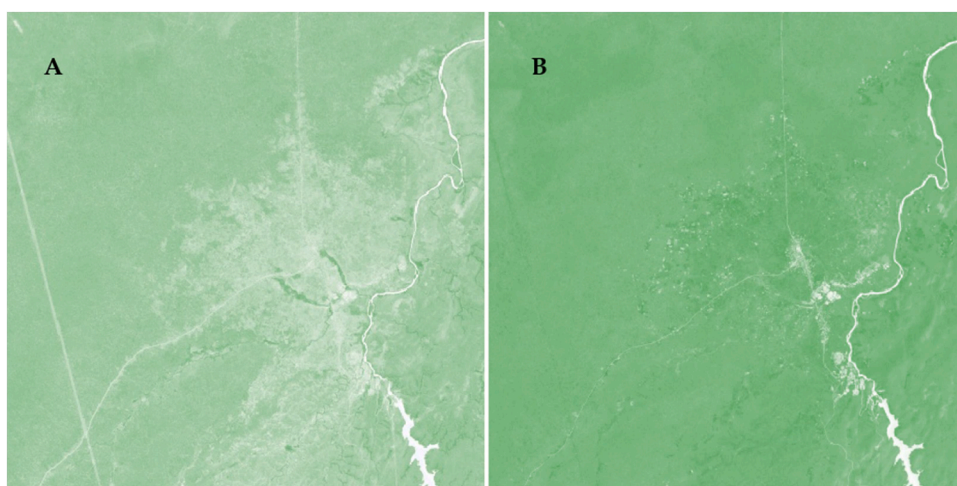


Fig. 6. NDVI maps of the Busanga region (–10.121433, 25.398744; Lualaba) for August (A) and November (B) 2024, derived from Sentinel-2 imagery. In August, corresponding to the peak of the dry season, NDVI patterns exhibit marked spatial contrasts across the landscape. In November, at the onset of the rainy season, NDVI values appear more uniform, indicating widespread photosynthetic activity and reduced differentiation among land cover types.

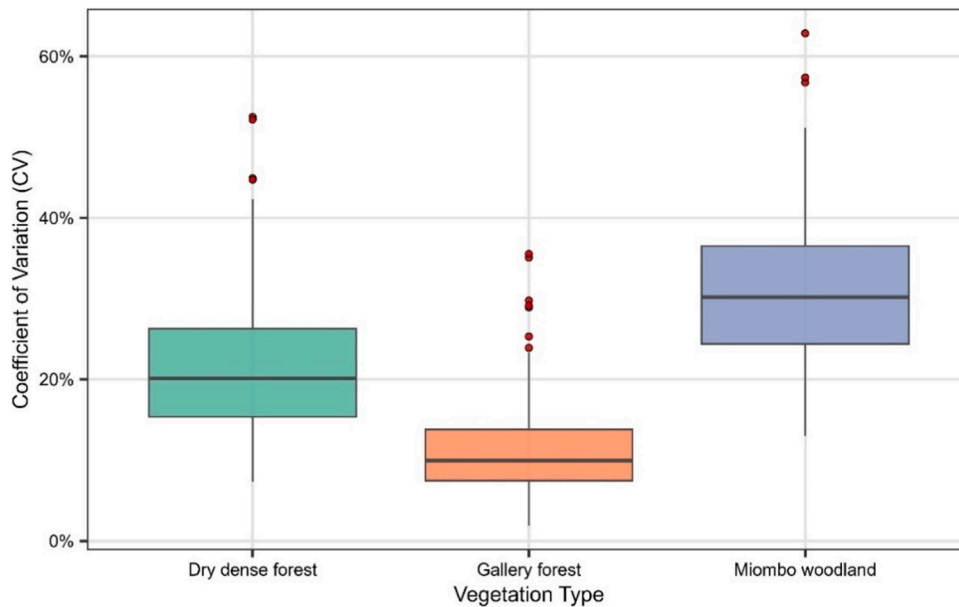


Fig. 7. Coefficient of variation (CV) of NDVI by vegetation type in Lualaba for 2024, derived from Sentinel-2 imagery. This metric expresses the relative annual variability of photosynthetic activity, which is higher in miombo woodlands and lower in gallery forests, thereby highlighting clear ecophysiological contrasts among forest types.

correctly identified, with 33.33% confused with non-forest classes. These misclassifications explain the low F1-score of miombo woodland (46.15%) and indicate limited class separability when using the full annual spectral signal. Performance was also moderate for wooded savannah (PA = 40.91%) and grassland/wetland (PA = 57.69%), reflecting spectral overlap among non-forest classes during the full growing season.

Model M2, which restricts the analysis to the most discriminant temporal window while retaining all spectral bands, achieved the highest overall accuracy (80.66%). The confusion matrix shows a clear improvement across nearly all classes. Miombo woodland producer's accuracy rose to 80.00%, with confusion with non-forest classes reduced to 10.00%. The gallery forest remained consistently well identified (PA = 97.14%; F1 = 97.14%), and water bodies were perfectly classified (PA = UA = 100%). Built-up/bare soil also improved markedly (PA = 96.88%). These gains are reflected in higher class-specific F1-scores; bootstrap resampling (1000 paired iterations) confirmed that the OA improvement of M2 over M1 (+10.85 percentage points; OA M1 = 69.81%, OA M2 = 80.66%) was statistically significant ($p < 0.001$; 95% bootstrap CI: [+6.60, +15.57] pp; see Appendix E, Figures E3). The main remaining confusion involves dry dense forest misassigned to miombo woodland (21.88%), and wooded savannah, which remained the most difficult class to separate (PA = 45.45%), reflecting its intermediate spectral position between forest and open non-forest classes.

Model M3, combining the discriminant temporal window with a reduced spectral subset, yielded a slightly lower overall accuracy (77.83%). Performance for miombo woodland (PA = 80.00%) and gallery forest (PA = 94.29%) remained high, and water bodies continued to be perfectly classified (PA = 100%). However, dry dense forest accuracy was unchanged relative to M2 (PA = 71.88%), and wooded savannah declined further (PA = 36.36%), suggesting that the removed spectral bands contributed information relevant to separating spectrally ambiguous non-forest classes. These results indicate that spectral band reduction did not provide additional benefits beyond temporal optimisation and introduced modest performance losses in heterogeneous non-forest classes.

Across all models, spatial disagreement and uncertainty maps (Figs. 8 and 9) show that classification errors are concentrated in transitional mosaic areas, particularly in the southeastern part of the study area, consistent with the recurrent misclassification pathways between dry dense forest, miombo woodland, and wooded savannah identified in the confusion matrices. Overall, improvements in classification performance are primarily driven by temporal window selection rather than spectral dimensionality reduction, and the adopted approach is sufficient to meet the study's objective of distinguishing major forest formations at regional scale.

Comparison with existing studies

Comparison with previous mapping efforts highlights the added value of integrating Sentinel-2 phenology (Fig. 10). Useni et al. [10], using Landsat 30 m annual composites, estimated 30,327 km² of forest in Lualaba but aggregated all forest types as “miombo woodland,” underestimating total cover and omitting dry, dense and gallery forests. The Copernicus Land Cover dataset [49] reported 71,977 km², yet its coarse 100 m resolution and generalised classes tend to overestimate forest extent and ignore local heterogeneity, especially in transitional mosaics.

Our Sentinel-2-based approach (10 m resolution, phenology-informed temporal windows) produced an intermediate, more balanced estimate of 64,349 km², distinguishing miombo woodland, dry dense forest, and gallery forest. Spatial differences with Useni and Copernicus are concentrated in ecotones and riparian zones, demonstrating the phenology-based method's ability to capture fine-

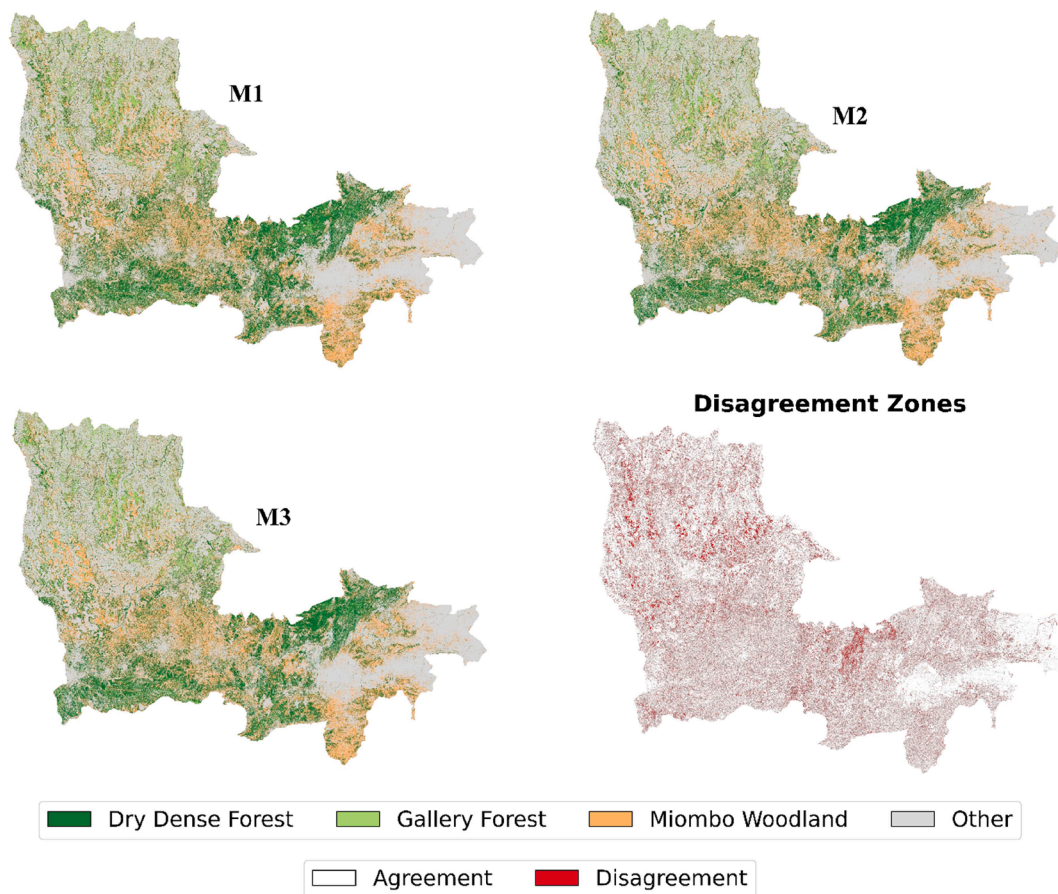


Fig. 8. Comparison of forest classification models (M1, M2, M3) in Lualaba for 2024 using Sentinel-2 data, and analysis of their spatial consistency. The figure highlights areas of agreement and disagreement among the models.

scale ecological variation. By combining higher spatial and thematic resolution with temporal dynamics, this approach improves forest-type mapping, supports ecological interpretation, and informs site-specific conservation planning.

Discussion

Contribution of phenological dynamics to forest discrimination

Seasonal Sentinel-2 time series effectively capture seasonal canopy contrasts among Lualaba's main forest types, particularly during the dry season (June–September), when water limitation amplifies functional differences [50–52]. Miombo woodlands show pronounced NDVI declines under dry-season stress, dry dense forests exhibit moderate decreases, and gallery forests maintain relatively stable NDVI due to sustained water availability [53,54]. These patterns should therefore be interpreted as seasonal functional contrasts detectable at monthly temporal resolution rather than direct observations of fine-scale phenological transitions.

The strong discriminative power of near-infrared (B6–B8A) and shortwave-infrared (B11–B12) bands reflects their sensitivity to key biophysical traits. NIR bands are closely related to leaf area index and internal leaf structure, making them responsive to seasonal changes in canopy density [55]. Consequently, deciduous miombo woodlands exhibit marked NIR reductions during the dry season, whereas gallery forests maintain high and stable NIR reflectance due to persistent foliage, with dry dense forests showing intermediate behaviour. In contrast, SWIR bands are particularly sensitive to vegetation water content and canopy moisture [56], capturing differences in water-use strategies among forest types: permanent access to water in gallery forests, pronounced dry-season water stress in miombo woodlands, and buffered moisture conditions in dry dense forests.

It is important to note that the reported patterns reflect seasonal contrasts detectable within the available eight-month dataset, rather than full annual or fine-scale phenological timing. Observed spectral convergence during transitional months and reduced separability between miombo and dry dense forests partly result from methodological constraints, including median compositing and the exclusion of December–March [30], and are therefore interpreted as data-limited outcomes rather than novel ecological signals.

Despite these limitations, the phenology-informed approach provides measurable improvements within the study area compared with previous mapping products [1,2,7–11,49]. By integrating seasonal NDVI metrics, our study discriminates forest types at 10 m

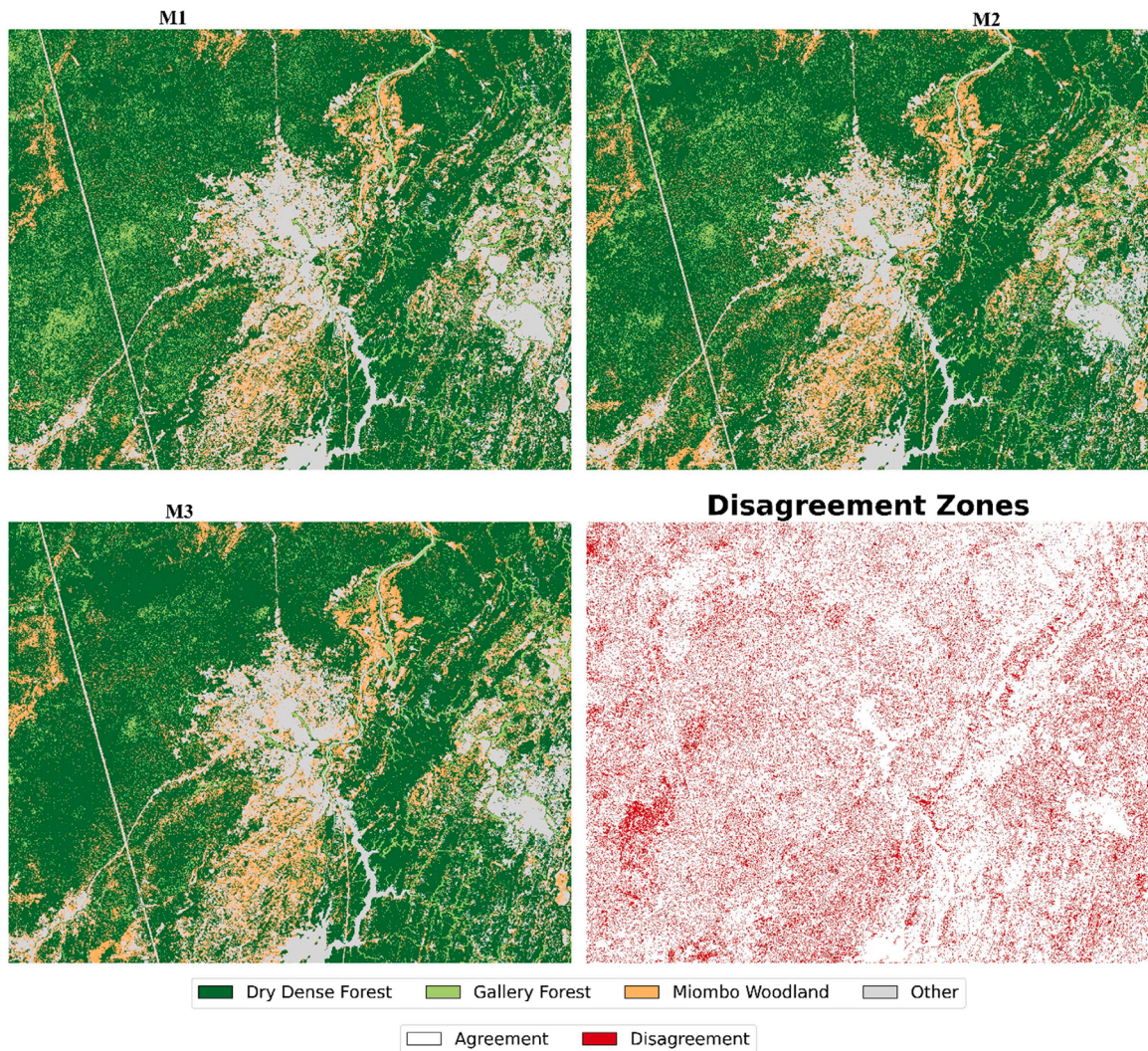


Fig. 9. Comparison of forest classification models (M1, M2, M3) in Lualaba for 2024 using Sentinel-2 data, highlighting spatial consistency and areas of disagreement, with a detailed zoom on the Busanga zone.

resolution, capturing heterogeneity overlooked by coarser global datasets [10,49]. Misclassification is primarily concentrated in ecotones and transitional mosaics, highlighting areas of inherent uncertainty relevant for future conservation and management planning [57–60].

Finally, the complementary information from mean NDVI and intra-annual variability (coefficient of variation) confirms that phenological metrics enhance forest-type discrimination: gallery forests by stable greenness, miombo by high seasonal amplitude, and dry dense forests by intermediate dynamics. These results demonstrate the added value of phenology-based classification, while explicitly situating interpretation within the constraints of the dataset.

Ecological implications of spectro-phenological contrasts

NDVI-derived phenological dynamics and spectral signatures reveal contrasts among Lualaba's main forest types that largely reflect seasonal functional differences detectable within the available dataset, rather than fine-scale ecological processes. Gallery forests maintain consistently high NDVI and low variability due to their persistent canopy cover and access to water along riparian zones [61,62]. While these patterns align with known ecological traits, the truncated eight-month dataset limits the direct observation of mechanisms such as groundwater buffering; thus, we interpret these results primarily as seasonally stable spectral signatures.

Miombo woodlands show higher intra-annual NDVI variability, reflecting partial leaf shedding and canopy reduction during the dry season [63]. This variability, accentuated in fragmented or disturbed areas, explains higher misclassification rates where spectral trajectories overlap with dry dense forests. Dry dense forests exhibit intermediate NDVI dynamics, with moderate seasonal declines that converge spectrally with miombo during transitional months [64,65].

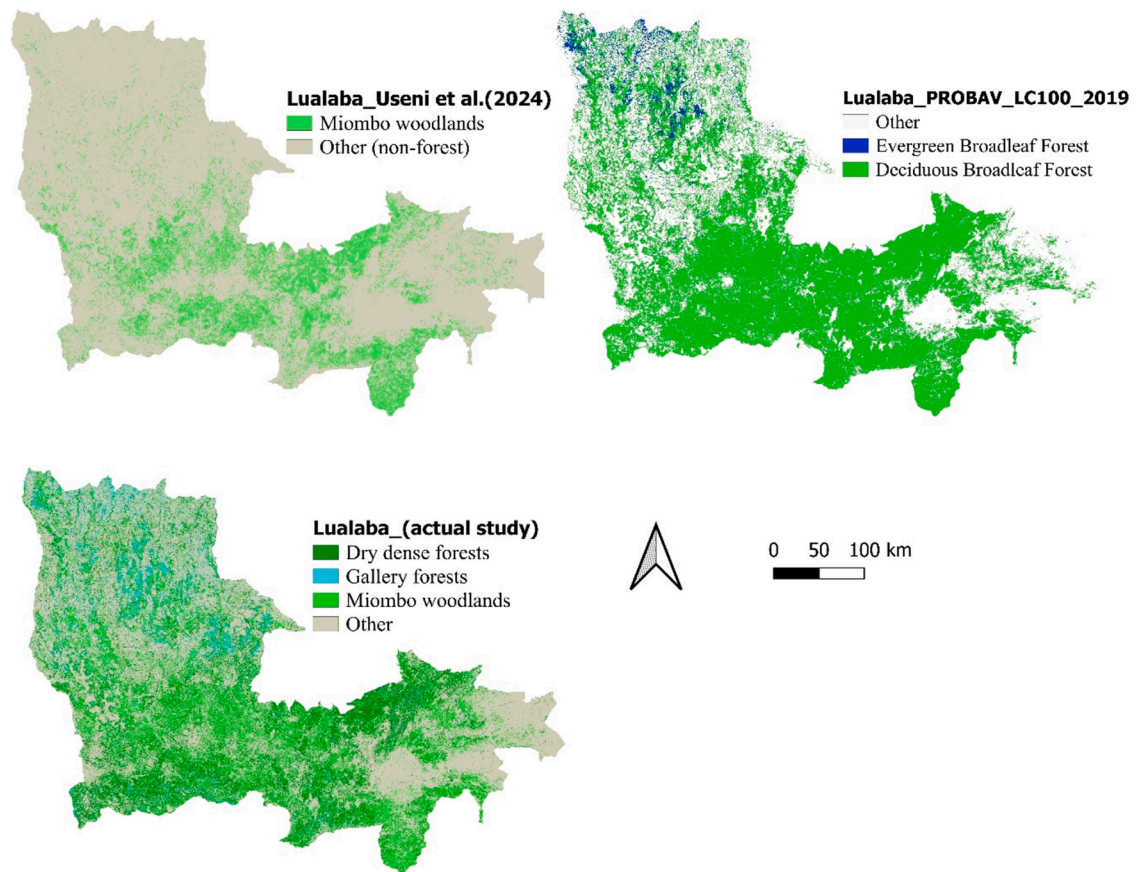


Fig. 10. Comparative visualisation of forest cover estimates from the three datasets—Copernicus Land Cover [49], Useni et al. [10], and the present study—illustrating how higher spatial resolution and the incorporation of phenological information markedly improve forest-type discrimination and mapping reliability. The figure synthesises spatial concordance and thematic discrepancies across datasets, highlighting the enhanced capacity of the phenology-based Sentinel-2 approach to capture fine-scale ecological variability within the Lualaba landscape.

Methodological contribution of Sentinel-2 time series and the random forest model

The use of Sentinel-2 time series allows the capture of seasonal vegetation dynamics that are inaccessible to single-date approaches. By combining multispectral bands—particularly red-edge and shortwave infrared (SWIR)—with monthly NDVI profiles, our models exploit inter-seasonal variability to enhance forest-type separability in heterogeneous tropical landscapes [66,67]. While multiple indices can be derived from Sentinel-2, NDVI alone provided sufficient discriminatory power for Lualaba forests, reflecting functional contrasts among gallery forests, dry dense forests, and miombo woodlands without unnecessary computational complexity [68,69].

The comparison of Models M1–M3 demonstrates that temporal targeting drives classification performance. Aggregating all spectral data over the full period (M1) yielded moderate OA (69.81%) and high confusion between the miombo and non-forest classes. Restricting analysis to the most phenologically discriminative period (M2, June–September) improved OA to 80.66% and consistently increased class-specific F1-scores, indicating that capturing dry-season phenology is more critical than using longer time series. Dimensional reduction (M3) slightly reduced OA (77.83%), suggesting that subtle spectral information may be lost in heterogeneous mosaics. All models, however, produced coherent spatial patterns, with disagreement concentrated in ecotones and transitional areas, consistent with known structural overlap [57,70,71].

The Random Forest algorithm effectively handled the high-dimensional Sentinel-2 dataset, ranking temporal features as the most important while confirming the relevance of red-edge and SWIR bands (B6–B8A, B11–B12). Spatial stratification using BlockCV was applied to ensure spatial independence between training and validation samples, thereby reducing spatial autocorrelation during model evaluation.

Overall, these results highlight a transparent, reproducible, and transferable methodological framework for forest-type mapping in complex tropical landscapes. They also underline the primary importance of temporal optimisation over spectral accumulation or aggressive feature reduction, while acknowledging that classification uncertainty persists in ecotonal zones and structurally heterogeneous forests.

Implications for forest management and policy in Lualaba

Integrating phenological dynamics into high-resolution forest mapping substantially improves the discrimination of major forest formations in Lualaba. Our analyses demonstrate that miombo woodlands, dry dense forests, and gallery forests exhibit distinct seasonal behaviours, as captured by NDVI dynamics and spectral-temporal patterns. These differences directly inform forest cover estimates and highlight ecologically critical habitats that are often underrepresented or misclassified in existing regional and global datasets [1,2,7–11,49].

From a management perspective, phenology-informed maps provide a more reliable basis for targeted interventions. Accurate delineation of miombo woodlands, sensitive to fire and seasonal water stress, can inform fire management and restoration planning. Clear identification of gallery forests supports the protection of riparian corridors and associated ecosystem services. Differentiating dry dense forests enables more precise monitoring of selective logging and early detection of degradation. By highlighting areas of classification uncertainty, particularly in ecotones, these maps also help managers prioritise monitoring efforts where misclassification is most likely.

At the policy level, these maps can be integrated into spatial decision-support tools to guide land-use planning, conservation prioritisation, and resource allocation, as shown in similar contexts in Zambia [72] and Ghana [73]. Coupling phenology-based mapping with ecosystem service assessments [74] allows policymakers to align conservation objectives with local livelihoods and development needs. In the DRC, initiatives such as the Improved Forest and Landscape Management Project [75] illustrate how spatially explicit, robust forest information can strengthen governance and improve landscape-scale forest management.

Limitations of the approach and perspectives for improvement

The spectro-phenological contrasts captured in this study provide valuable information for forest mapping and management, highlighting forest types that are robustly discriminated and areas requiring caution due to methodological and ecological constraints. The use of monthly median composites reduces spectral noise, residual cloud contamination, and scene-specific variability [32], but also smooths intra-monthly fluctuations, thereby preventing the detection of short-term phenological events such as leaf flush or senescence onset. Consequently, the study captures seasonal functional contrasts rather than fine-scale phenological timing, and observed patterns should be interpreted as relative seasonal stability rather than continuous year-round trajectories.

The peak rainy season (December–March) was excluded due to persistent cloud cover and spectral homogenization, limiting characterisation of the complete annual cycle, particularly for evergreen gallery forests. However, the early rainy transition (October–November) was retained to capture canopy reactivation and the dominant seasonal contrasts relevant to classification.

The spatial resolution of Sentinel-2 (10–20 m) constrains the detection of fine-scale heterogeneity, especially in transitional or ecotonal areas. High-resolution datasets, including drone- and LiDAR-derived products and PlanetScope imagery (5 m), combined with deep learning, have shown improved performance in mapping fragmented or heterogeneous landscapes [76,77].

From a modelling perspective, the Random Forest classifier is robust for multidimensional spectral–temporal data, but

interpretability remains limited. Explainable AI (XAI) methods such as SHAP, LIME, and Crown-CAM offer promising approaches for understanding variable contributions [78]. Qualitative comparison with external datasets ([10,49]) revealed discrepancies mainly in riparian corridors and heterogeneous mosaics, highlighting the added value of phenology-informed Sentinel-2 mapping.

Future work should integrate Synthetic Aperture Radar (SAR) data, e.g., Sentinel-1, to overcome optical limitations during the rainy season. Combining Sentinel-1 and Sentinel-2 time series would allow a more complete assessment of annual vegetation dynamics, improve characterisation of evergreen gallery forests, and strengthen phenology-informed forest-type discrimination across the full seasonal cycle [79].

Conclusion

This study demonstrates that Sentinel-2 time-series analysis provides a robust and reproducible framework for discriminating tropical forest formations in Lualaba Province by integrating their spectro-seasonal canopy dynamics. Focusing on seasonally targeted periods and leveraging near- and shortwave infrared bands, the approach achieved high classification accuracy, with the dry season identified as the most discriminative period. This confirms that combining temporal and spectral information overcomes the limitations of single-date classifications, which often mask functional heterogeneity. The study also contributes to the ecological interpretation of seasonal functional differences, revealing how phenological variability reflects differences in structure, function, and resilience among miombo woodlands, dry dense forests, and gallery forests. Despite limitations such as cloud cover during the rainy season and underrepresentation of transitional or degraded vegetation, the methodology is operationally relevant, reproducible, and transferable. Future work could integrate complementary datasets (e.g., radar and LiDAR) and employ explainable AI frameworks to improve accuracy and interpretability. Overall, the results offer actionable insights for land-use planning, conservation prioritisation, and sustainable forest management, bridging remote sensing, ecology, and governance to support Central Africa's Forest landscapes under increasing anthropogenic pressure.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix A

List of Sentinel-2 image identifiers used in the analysis A CSV file containing the identifiers of the 1250 Sentinel-2 images used in this study can be accessed at the following link: [Google Drive – Sentinel-2 Image Identifiers](#).

Appendix B

Georeferenced plots The complete set of georeferenced plots is available at the following link: [Google Drive – Georeferenced Plots](#).

Appendix C

Confusion matrices and accuracy metrics for Models M1, M2 and M3.

Table C1

Confusion matrices (absolute sample counts) for the three Random Forest classification models, computed from the spatially independent validation subset ($n = 212$) derived from the spatial training–testing partition of the reference dataset. Rows represent reference (ground-truth) classes; columns represent predicted classes. Diagonal cells (highlighted in green) indicate correct classifications. All accuracy metrics are derived directly from these count matrices using the formulas stated in Section 2.5 and reproduced below. DDF = Dry dense forest; GF = Gallery forest; MW = Miombo woodland; WS = Wooded savannah; GL = Grassland/Wetland; Ag = Agriculture; Wa = Water; Bu = Built-up/Bare soil; PA = Producer's Accuracy; UA = User's Accuracy; OA = Overall Accuracy; F1 = F1-score.

Reference	Model 1	Classified (predicted)								Row total	PA (%)	F1 (%)
	Reference \ Predicted	DDF	GF	MW	WS	GL	Ag	Wa	Bu	Total	PA %	F1 %
	Dry dense forest	24	1	5	2	0	0	0	0	32	75.00	72.73
	Gallery forest	1	34	0	0	0	0	0	0	35	97.14	95.77
	Miombo woodland	8	0	12	4	6	0	0	0	30	40.00	46.15
	Wooded savannah	1	0	2	9	6	4	0	0	22	40.91	36.73
	Grassland / Wetland	0	1	3	6	15	1	0	0	26	57.69	55.56
	Agriculture	0	0	0	6	0	22	0	1	29	75.86	72.13
	Water	0	0	0	0	1	1	4	0	6	66.67	80.00
	Built-up / Bare soil	0	0	0	0	0	4	0	28	32	87.50	91.80
Col. total	34	36	22	27	28	32	4	29	212			
UA (%)	70.59	94.44	54.55	33.33	53.57	68.75	100.00	96.55				
OA (%)	69.81											

Reference	Model 2	Classified (predicted)								Row total	PA (%)	F1 (%)
	Reference \ Predicted	DDF	GF	MW	WS	GL	Ag	Wa	Bu	Total	PA %	F1 %
	Dry dense forest	23	1	7	1	0	0	0	0	32	71.88	77.97
	Gallery forest	1	34	0	0	0	0	0	0	35	97.14	97.14
	Miombo woodland	3	0	24	3	0	0	0	0	30	80.00	73.85
	Wooded savannah	0	0	3	10	5	4	0	0	22	45.45	43.48
	Grassland / Wetland	0	0	1	4	21	0	0	0	26	80.77	80.77
	Agriculture	0	0	0	6	0	22	0	1	29	75.86	78.57
	Water	0	0	0	0	0	0	6	0	6	100.00	100.00
	Built-up / Bare soil	0	0	0	0	0	1	0	31	32	96.88	96.88
Col. total	27	35	35	24	26	27	6	32	212			
UA (%)	85.19	97.14	68.57	41.67	80.77	81.48	100.00	96.88				
OA (%)	80.66											

Reference	Model 3	Classified (predicted)								Row total	PA (%)	F1 (%)
	Reference \ Predicted	DDF	GF	MW	WS	GL	Ag	Wa	Bu	Total	PA %	F1 %
	Dry dense forest	23	1	7	1	0	0	0	0	32	71.88	75.41
	Gallery forest	2	33	0	0	0	0	0	0	35	94.29	94.29
	Miombo woodland	3	0	24	2	1	0	0	0	30	80.00	75.00
	Wooded savannah	1	0	2	8	6	5	0	0	22	36.36	41.03
	Grassland / Wetland	0	1	1	2	21	1	0	0	26	80.77	77.78
	Agriculture	0	0	0	4	0	22	0	3	29	75.86	72.13
	Water	0	0	0	0	0	0	6	0	6	100.00	100.00
	Built-up / Bare soil	0	0	0	0	0	4	0	28	32	87.50	88.89
Col. total	29	35	34	17	28	32	6	31	212			
UA (%)	79.31	94.29	70.59	47.06	75.00	68.75	100.00	90.32				
OA (%)	77.83											

Appendix D. Validation of atmospheric masking and NDVI robustness

Appendix D presents diagnostic analyses conducted to evaluate the effects of QA60 and Scene Classification Layer (SCL) masking on Sentinel-2 imagery and to verify that residual clouds or shadows do not bias NDVI trajectories. The figures successively assess (i) the proportion of pixels removed by masking, (ii) the temporal and thematic distribution of valid observations, and (iii) the statistical behaviour of NDVI values before and after masking. Together, these diagnostics demonstrate that atmospheric filtering improves spectral quality while preserving temporal consistency and ecological interpretability of NDVI signals.

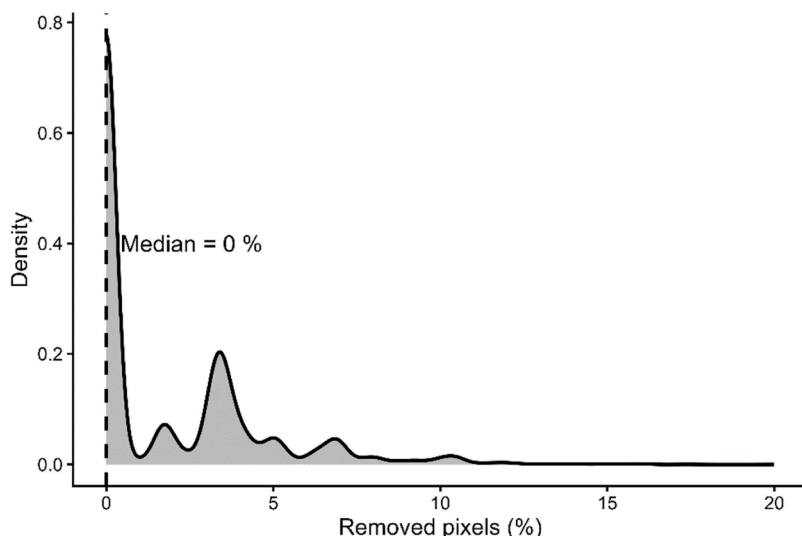


Fig. D1. Distribution of the percentage of pixels removed after application of the combined QA60 and Scene Classification Layer (SCL) masking on Sentinel-2 imagery. The density curve represents the distribution of removal rates across all processed observations, while the dashed vertical line indicates the median value (0%). The strong concentration of values near zero demonstrates that atmospheric masking removes only a small proportion of pixels for most scenes, confirming that QA60–SCL filtering improves spectral reliability without substantially reducing data availability.

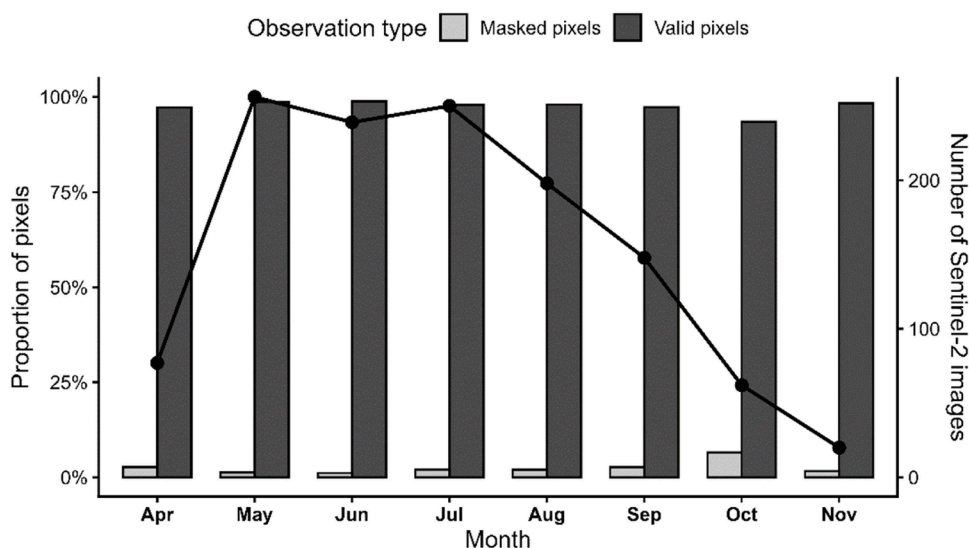


Fig. D2. Monthly Sentinel-2 data quality diagnostics for 2024. Bars represent the proportion (%) of valid and masked pixels after QA60–SCL masking, while the black line indicates the total number of Sentinel-2 images available per month. The consistently high proportion of valid pixels (>93%) demonstrates that masking does not introduce significant temporal bias despite seasonal variations in image availability.

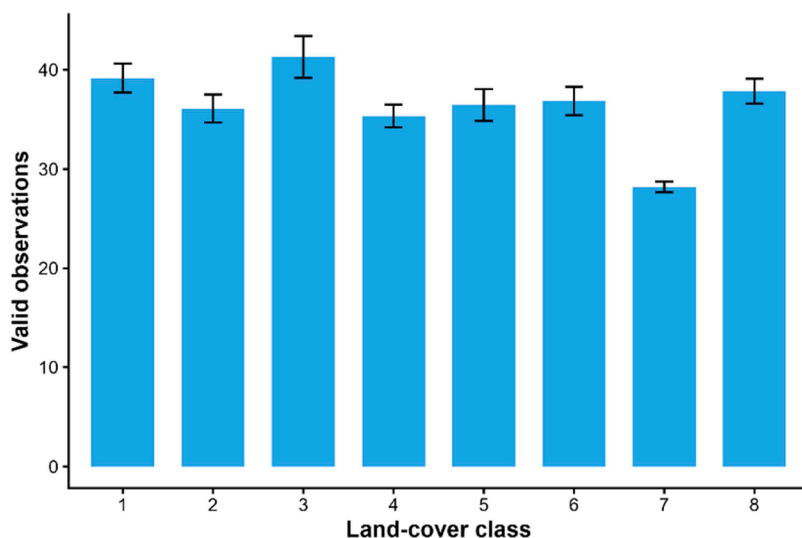


Fig. D3. Number of valid Sentinel-2 observations per land-cover class after QA60-SCL masking (bars = mean $\pm$ standard error). Valid observations correspond to pixels retained after cloud and shadow removal. Similar observation counts across classes indicate homogeneous temporal sampling, excluding bias related to unequal data availability. Classes: (1) Dry dense forest, (2) Gallery forest, (3) Miombo woodland, (4) Wooded savannah, (5) Grassland/Wetland, (6) Agriculture, (7) Water, (8) Built-up/Bare soil.

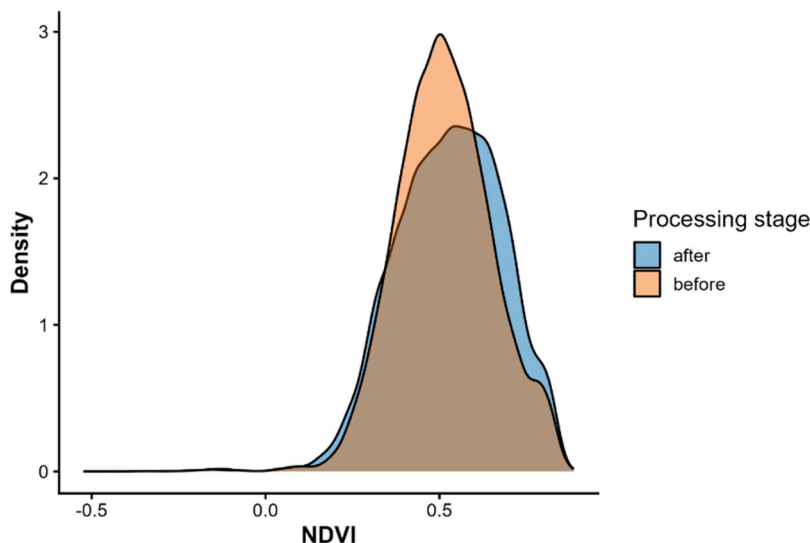


Fig. D4. NDVI distributions before and after cloud and shadow masking using Sentinel-2 QA60 and SCL masks. Curves represent kernel density estimations, where the *Density* axis reflects the relative concentration of NDVI values independent of sample size. Higher density values indicate stronger clustering of observations around specific NDVI ranges rather than an increase in pixel number. The reduction of low-NDVI tails after masking demonstrates removal of shadow-related spectral noise and confirms that residual shadows do not bias NDVI trajectories.

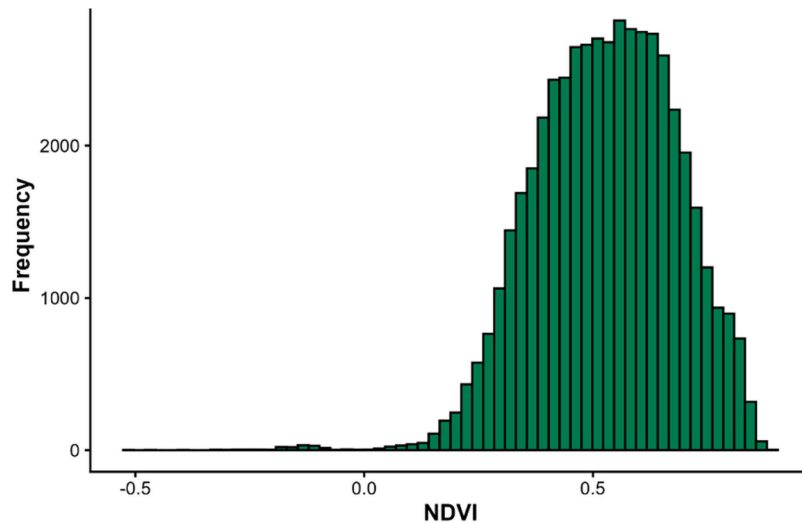


Fig. D5. Frequency distribution of NDVI values derived from the final dataset after QA60–SCL masking and monthly median compositing ($n \approx 50,000$ randomly sampled pixels). The unimodal distribution dominated by positive NDVI values indicates a stable vegetation signal and the absence of significant residual atmospheric contamination.

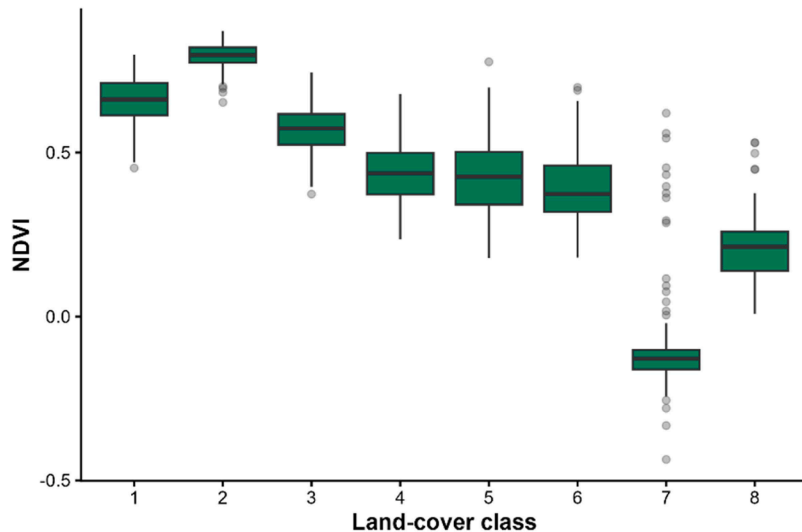


Fig. D6. NDVI distribution by land-cover class derived from independent sampling points. Classes: (1) Dry dense forest, (2) Gallery forest, (3) Miombo woodland, (4) Wooded savannah, (5) Grassland/Wetland, (6) Agriculture, (7) Water, (8) Built-up/Bare soil. The progressive NDVI gradient from forested to non-vegetated surfaces confirms ecological consistency of the spectral signal after atmospheric masking.

Appendix E

Bootstrap 95% Confidence Intervals on Pairwise Median NDVI Differences and Overall Accuracy Comparison.

This appendix provides the graphical and tabular results supporting the bootstrap 95% confidence interval analyses reported in Sections 2.4 and 3.1.1–3.1.3 of the main manuscript. Three figures are presented: [Figs. D1–D6](#) and [E1](#) illustrates the seasonal NDVI distributions by forest type with bootstrap CIs on medians; [Fig. E2](#) shows the pairwise differences in median NDVI during the peak dry season; and [Fig. E3](#) presents the bootstrap distribution of the Overall Accuracy difference between Models M1 and M2. All bootstrap analyses used 1,000 iterations with replacement (seed = 42).

Figure E1. Seasonal NDVI distributions by forest type with 95% bootstrap confidence intervals on medians
Lualaba Province, 2024 — error bars = 95% bootstrap CI (1,000 iterations, with replacement)

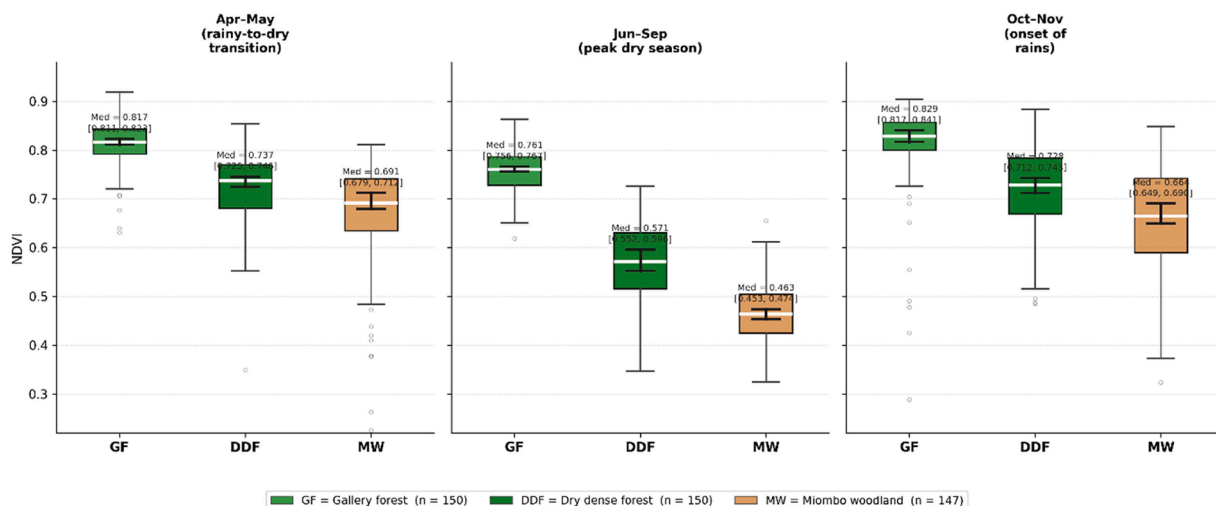


Fig. E1. Seasonal NDVI distributions by forest type for three phenological periods (April–May: rainy-to-dry transition; June–September: peak dry season; October–November: onset of rains), derived from Sentinel-2 imagery (Lualaba Province, 2024). Boxes show the interquartile range; the white horizontal line indicates the median; whiskers extend to $1.5 \times$ the interquartile range; open circles represent outliers. Black error bars above each box indicate the 95% bootstrap confidence interval on the median (1000 iterations, with replacement). Values annotated above the error bars report the observed median (top) and the 95% CI bounds [lower, upper]. The peak dry season (June–September) shows the clearest separation among forest types, particularly between the Gallery forest (GF) and the Miombo woodland (MW). DDF = Dry dense forest ($n = 150$); GF = Gallery forest ($n = 150$); MW = Miombo woodland ($n = 147$).

Figure E2. Pairwise differences in median NDVI during the peak dry season (Jun–Sep 2024) with 95% bootstrap confidence intervals (1,000 iterations, with replacement) — all CIs strictly exclude zero

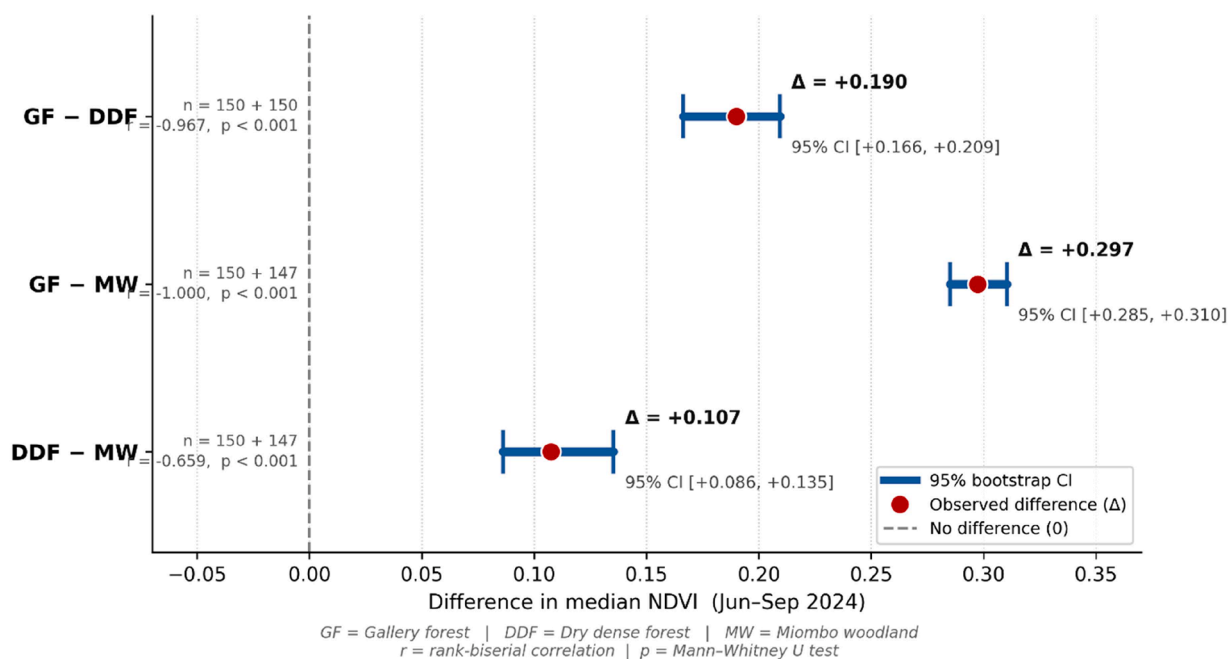


Fig. E2. Forest-plot of pairwise differences in median NDVI during the peak dry season (June–September 2024) between the three main forest types of Lualaba Province. The red dot indicates the observed difference in sample medians (Δ); horizontal blue bars represent the 95% bootstrap confidence interval (1000 iterations, with replacement). The grey dashed vertical line marks zero (no difference). Values to the right of each bar report the observed Δ and the 95% CI bounds [lower, upper]. All three 95% CIs strictly exclude zero, confirming a statistically robust and ecologically meaningful separation among all pairwise forest-type comparisons during the peak dry season. Rank-biserial correlation (r) values and p -values from Dunn's test with Bonferroni correction are indicated to the left of each row. GF = Gallery forest; DDF = Dry dense forest; MW =

Miombo woodland. GF vs DDF: $\Delta = +0.190$, 95% CI [+0.166, +0.209], $r = -0.967$; GF vs MW: $\Delta = +0.297$, 95% CI [+0.286, +0.310], $r = -1.000$; DDF vs MW: $\Delta = +0.107$, 95% CI [+0.088, +0.135], $r = -0.659$.

Figure E3. Bootstrap distribution of the Overall Accuracy (OA) difference (M2 – M1)
M1 = full season, all bands | M2 = dry season (Jun-Sep), all bands | $n_{boot} = 1,000$

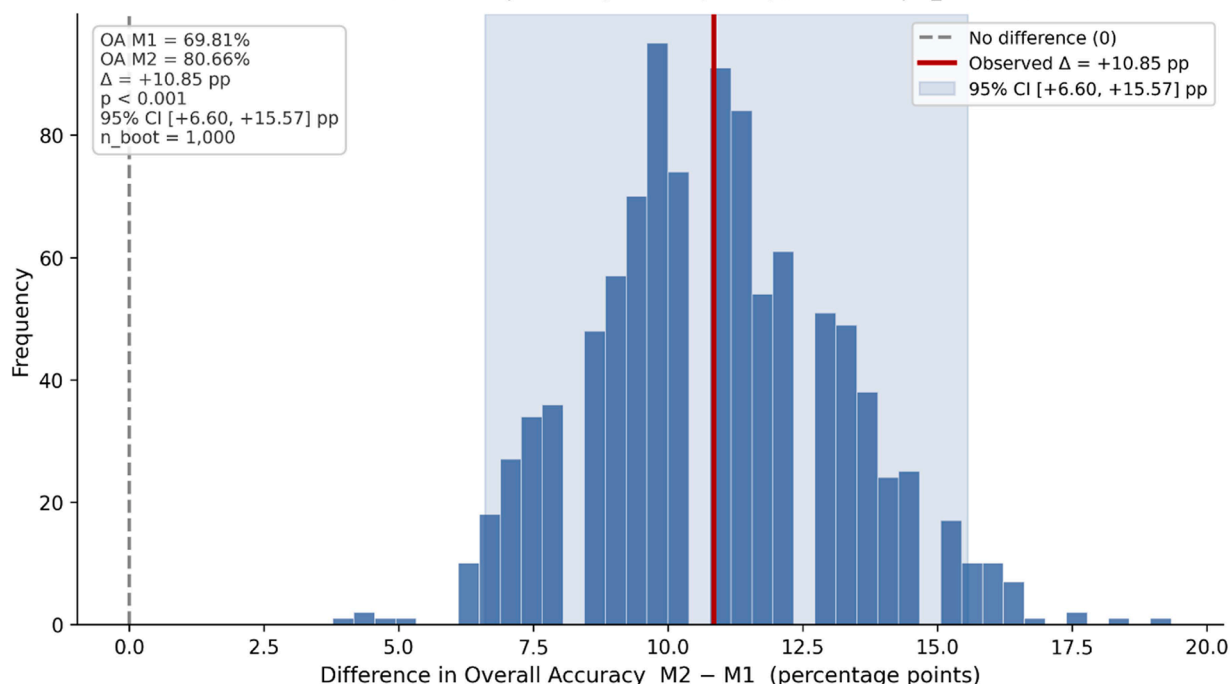


Fig. E3. Bootstrap distribution of the Overall Accuracy (OA) difference between Model M2 (dry season, June–September, all spectral bands) and Model M1 (full season, April–November, all spectral bands), derived from 1000 paired bootstrap resamples of the spatially independent validation set ($n = 212$). For each iteration, the same bootstrap indices were applied to both models, and the difference $OA_2 - OA_1$ was recorded. The red vertical line marks the observed difference ($\Delta = +10.85$ percentage points; OA M1 = 69.81%, OA M2 = 80.66%). The grey dashed vertical line marks zero (no improvement). The blue shaded band represents the 95% bootstrap confidence interval ([+6.60, +15.57] pp). None of the 1000 bootstrap iterations produced a difference ≤ 0 , yielding a one-tailed $p < 0.001$. M1 = baseline model (full temporal window); M2 = best-performing model (peak dry season window).

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