A Decision-Support Tool for Managing Tree-Cover in Smallholder Cocoa Agroforestry Systems

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Abstract

In cocoa agroforestry systems (AFS), tree-cover is a fundamental driver of ecosystem functioning and crop productivity. However, for smallholders, implementing specific cover targets remains challenging because tree-cover is difficult to measure without specialized equipment and technical skills. Consequently, sustainability standards and technical guidelines typically rely on simplified structural metrics, such as tree density or basal area, as proxies for cover. This study addresses the technical disconnect between these simplified metrics and actual canopy outcomes. Using data from 150 plots in Côte d'Ivoire, we developed a Beta regression model within a Bayesian framework to estimate tree-cover from standard inventory data. Our results show that tree density or basal area alone are unreliable predictors of cover, whereas a model integrating both variables achieves high accuracy ($\boldsymbol{R^2 = 0.89}$). Our results also demonstrate that existing guidelines can lead to highly variable canopy conditions that deviate markedly from intended cover targets. We propose a state-space representation as a decision-support tool to help smallholders estimate tree-cover and to provide a scientific basis for updating existing policies and standards. This framework allows smallholders to visualize management trajectories, driven by recruitment, tree growth, and mortality, to steer their systems toward ecologically meaningful cover targets.

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Introduction

Across tropical regions, cocoa is largely produced by smallholders within tree-based farming landscapes. In these agroforestry systems (AFS), the management of shade is a longstanding challenge because it shapes not only cocoa growth and yields, but also the long-term functioning and resilience of the production system. Cocoa was historically cultivated under diverse forest canopies, yet successive waves of deforestation and intensification have simplified canopy structure and increased exposure to climatic and biotic stresses. In parallel, breeding programs and management recommendations have increasingly promoted varieties and practices optimized for full-sun conditions. Although such systems can deliver high yields in the short term, they often decline markedly after a few decades as soils are depleted, microclimatic stress intensifies, and vulnerability to pests and diseases increases [1, 2]. Full-sun cocoa is also environmentally costly, contributing to climate change and biodiversity loss [3]. Together, these limitations underscore the need to (re)introduce shade trees and to support smallholders in actively managing shade within cocoa farms, an orientation that is now echoed in restoration and sustainability agendas.

In line with these objectives, agroforestry has gained strong political support. At the African level, the African Forest Landscape Restoration Initiative (AFR100) embodies the collective ambition of African countries to restore 100 million hectares of degraded land by 2030 through assisted natural regeneration, tree planting, and agroforestry. In Côte d'Ivoire, the world's largest cocoa producer, this ambition is reflected in the national Strategy for the Preservation, Rehabilitation, and Expansion of Forests (SPREF), which targets 20% forest cover by 2045 through sustainable forest management, forest restoration, and the promotion of AFS. In the cocoa sector itself, the ARS 1000 sustainability standard developed by the African Organization for Standardization (ARSO) promotes agroforestry by encouraging the retention and (re)introduction of shade trees.

These policy and standard-setting efforts ultimately need to be translated into technical targets that can be monitored and managed on farms. Tree-cover (the fraction of ground area overlain by the vertical projection of tree crowns) is a particularly relevant focus because it plays a central role in the functioning of AFS. It directly determines how much light and rainfall reach the cocoa understory and, by doing so, controls cocoa productivity, but also shapes local microclimate (temperature, humidity and vapour pressure deficit; [4]), and key processes such as soil moisture conservation [5], litter inputs [6, 7], and habitat provision [8].

In line with its central functional role, several studies have proposed indicative tree-cover levels to guide cocoa AFS management. A frequently recommended target is around 30% tree-cover, consistent with evidence that production peaks near this level [9]. More broadly, a multi-objective assessment recommend keeping tree-cover in an intermediate range (up to 30%) as a pragmatic compromise between production yield, pest control, climate adaptation and mitigation, and biodiversity conservation [10]. Where CSSVD management is a priority, a higher target of 50% tree-cover has been suggested, as it was associated with reduced CSSVD severity [11].

Although these indicative targets provide useful guidance, they face two practical obstacles. First, tree-cover is hard to measure: accurate estimates often require crown mapping [12], hemispherical photography [13], densiometer protocols [14], or drone/remote-sensing approaches [15], methods that are time-consuming and demand equipment and technical skills that most smallholders do not have. Second, even when a cover value is known, it is difficult for smallholders to translate a target into actionable decisions, such as how many trees to retain, recruit, or remove, and what sizes.

To overcome these practical obstacles, most technical guidelines and sustainability standards rely instead on stand-structure proxies that are straightforward to inventory, notably tree density (trees$\cdot$ha^{-1}) and, more rarely, total basal area (m$^2\cdot$ha^{-1}). For example, Côte d'Ivoire's national implementation of the ARS 1000 standard recommends maintaining 25–40 trees$\cdot$ha^{-1} [16], while the national REDD+ strategy suggests 50 trees$\cdot$ha^{-1} as a threshold for classifying a system as cocoa agroforestry [17]. In Ghana, COCOBOD guidelines propose 15–18 shade trees$\cdot$ha^{-1} [18]. Basal-area prescriptions are rarer, but they exist in private standards and technical references: the Fair for Life label, for instance, provides a premium when shade-tree basal area exceeds 5 m$^2\cdot$ha^{-1} [19], while 8 m$^2\cdot$ha^{-1} has been proposed as a minimum threshold for classifying a system as cocoa agroforestry [20]. Other recommendations focus on relative BA target for cocoa, defined as the share of total stand BA carried by cocoa trees (cocoa BA / (cocoa BA + trees BA)); a cocoa relative basal area at or below 40% has been suggested as a benchmark for long-term sustainability [21, 22].

Yet, these proxy-based prescriptions have a critical limitation: the extent to which they actually translate into the targeted tree-cover remains largely unquantified. In closed-canopy forests, stand structure is constrained by competition for space and light, which imposes upper bounds on tree density for a given mean tree size. This constraint is commonly formalized by the self-thinning line [23], which represents the upper limit of tree packing and describes how maximum stand density declines as individual tree size increases due to density-dependent mortality. Although forest stands do not continuously lie on this boundary, it acts as an attractor: as stands develop and canopy closure is approached, competitive interactions progressively restrict the range of feasible combinations of tree number and tree size. As a result, once canopy closure is reached, tree density and basal area become tightly coupled, and either metric provides a reasonable proxy for space occupancy. In contrast, cocoa AFS function as open-canopy ecosystems that typically operate well below this competitive packing limit. Because canopy closure is neither reached nor maintained, density-dependent constraints are relaxed, allowing a wide range of structural configurations for a given level of tree-cover. A given tree density may therefore correspond to very different basal areas depending on tree size distributions, and conversely, the same basal area can arise from either few large trees or many small ones. Under these conditions, neither density nor basal area alone provides a reliable indication of canopy cover, potentially creating a disconnect between proxy-based prescriptions and the canopy outcomes they are intended to achieve.

The present study addresses this gap by developing an operational tool linking tree-cover to basal area and density in cocoa AFS. Using detailed crown measurements from 150 plots distributed across Côte d'Ivoire's cocoa belt, we (i) tested the capacity of these two metrics, alone and in combination, to predict plot-level tree-cover, and (ii) selected the best-performing model to build a practical tool for estimating tree-cover from standard inventory data and for visualizing how stand dynamics and management operations (recruitment, growth, mortality) may affect tree-cover.

By connecting easily measurable stand attributes to tree-cover, this approach bridges field-level management practices with broader restoration and sustainability targets, and provides a concrete pathway for integrating tree-cover into the management and regulatory frameworks that govern cocoa AFS.

Material and methods

Study area

We established 150 plots across the cocoa production area of Côte d'Ivoire, grouped into 15 sites of 10 plots each (Fig. 1). Each plot corresponds to a management unit operated by a farmer or manager, with sizes ranging from 0.30 to 5.16 ha, covering a total of 240.28 ha. The sampling design spanned a broad gradient of structural complexity, from simplified AFS with low tree density and a single stratum, to complex AFS with high tree density and multiple strata. The study area spans a climate gradient, with mean annual precipitation decreasing from 2500 mm in the south to 1100 mm in the north, and a mean annual temperature of 26.5 °C. Vegetation ranges from evergreen forests in the south to semi-deciduous forests in the north.

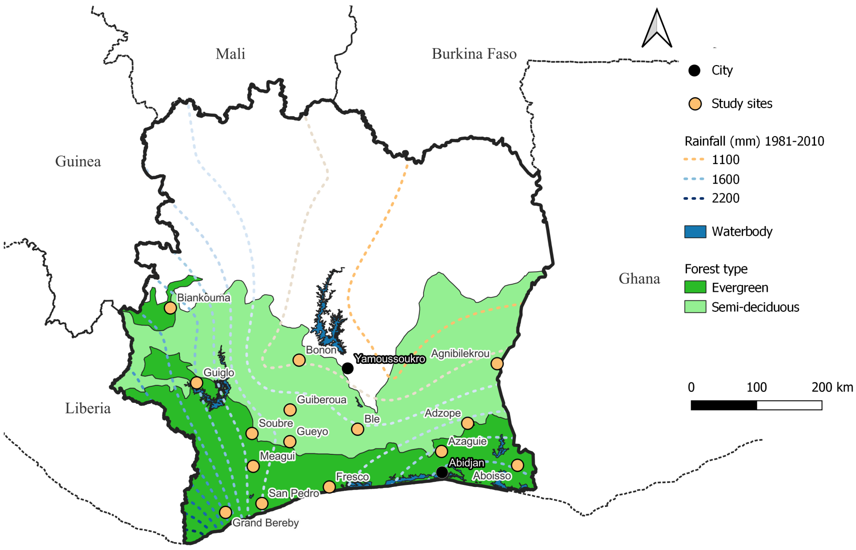


Fig. 1: Location of the 15 study sites (from [24]).

Data collection and computation of stand metrics

In each plot, we measured the diameter at breast height (dbh), spatial coordinates, and crown radii of all trees (including palm trees) with dbh ≥ 10 cm, excluding cocoa trees. Accordingly, throughout the manuscript, tree density, basal area, and tree-cover refer to the associated (non-cocoa) tree component of cocoa AFS. Crown radii were recorded in eight cardinal and intercardinal directions (N, NE, E, SE, S, SW, W, NW), allowing us to characterize the size and shape of individual crowns. In total, we inventoried 11,730 trees across all plots.

From these measurements, we computed individual tree-cover as the ground-projected area of each crown (Figure 2). We then computed plot-level tree-cover by combining all individual crown projections into a single polygon and dividing its area by the plot area. In this computation, crown overlaps were accounted for, so that overlapping areas contributed only once to the total. Plot-level cover was therefore expressed as the fraction of the plot surface occupied by non-cocoa tree crowns. For each plot, we also derived tree density (number of trees per hectare) and total basal area (sum of individual basal areas per hectare). Table 1 presents a summary of plot-level data and Figure 3 shows their distributions and pairwise relationships.

	min	median	max
Surface	0.30	1.35	5.16
Cover	0.01	0.21	0.55
N	4.73	49.61	154.74
BA	0.16	4.66	26.23

Table 1: Summary of plot-level data. Surface: plot area (ha); Cover: proportion of plot area covered by tree crowns; N: tree density (trees$\cdot$ha^{-1}); BA: total basal area (m$^2\cdot$ha^{-1}).

Modelling

We modelled plot-level tree-cover (C, bounded between 0 and 1) as a function of total basal area (BA, m$^2\cdot$ha^{-1}) and tree density (N, trees$\cdot$ha^{-1}).

To identify the best predictors and their relationship with cover, we fitted a set of candidate models comprising all possible combinations of BA and N (i.e., models with only BA, only N, or both). For each predictor, we also considered three alternative transformations: identity (untransformed), square-root, and logarithm. The square-root and logarithmic transformations were tested to capture potential saturating effects of BA and N on cover. In total, this yielded 15 candidate models.

Because the response variable (C) is bounded between 0 and 1, all models were specified as beta regressions. The general structure was:

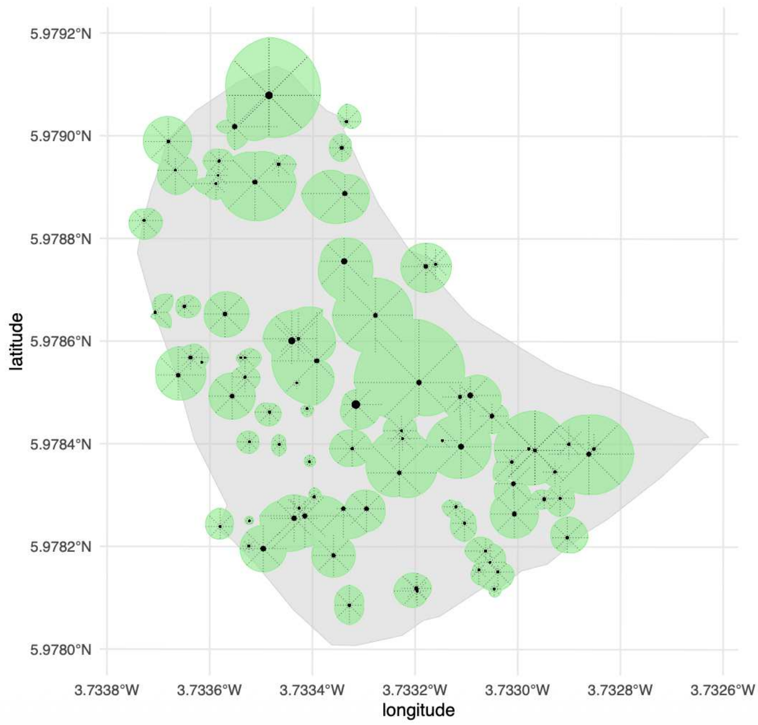


Fig. 2: Tree-cover in plot 9 at the Adzope site. The grey polygon represents the cocoa field, black dots mark the positions of tree trunks, with their sizes proportional to tree diameters, and dotted lines show the eight crown radii measured for each tree. The green polygons represent the projected tree crowns on the ground. Plot-level tree-cover is calculated as the ratio of green area to grey area.

$$C_i \sim Beta(\mu_i \cdot \phi, (1 - \mu_i) \cdot \phi) \tag{1}$$

$$logit(\mu_i) = \theta_0 + \sum_{k=1}^{p} \theta_k f_k(Z_{ik}), \tag{2}$$

where C_i is the observed tree-cover for plot i, μ_i the expected cover, and ϕ the precision parameter of the *Beta* distribution. The linear predictor includes an intercept term θ_0 and regression coefficients θ_k associated with predictors Z_{ik}. The index k denotes the predictor number in a given model, while p is the total number of predictors included (either one or two, depending on the model). The predictors Z_{ik} correspond to basal area and/or tree density for plot i, and the functions $f_k(\cdot)$ represent their possible transformations (identity, square-root, or logarithm).

We fitted the model in a Bayesian framework using *Stan* [25] via the *rstan* package [26] in the *R* environment [27]. Posterior inference relied on Hamiltonian Monte Carlo (HMC) algorithm with the no-U-turn sampler (NUTS). We ran four independent chains, each with 2000 iterations including 1000 warm-up iterations. We assessed

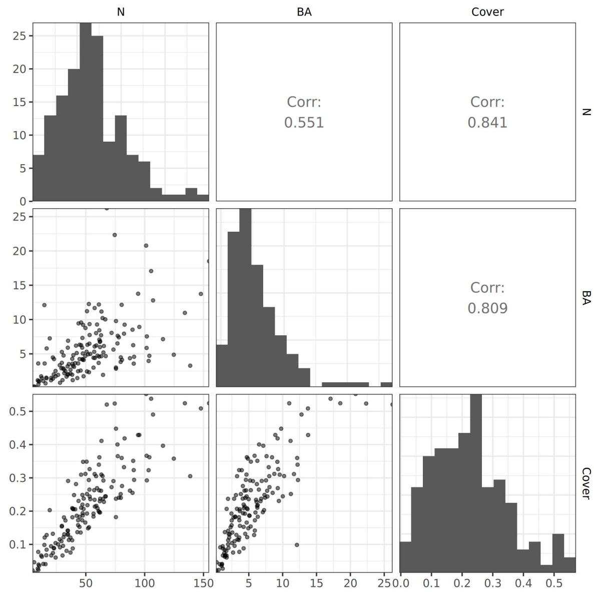


Fig. 3: Distributions and pairwise relationships of plot-level data. Cover: proportion of plot area covered by tree crowns; N: tree density (trees$\cdot$ha^{-1}); BA: total basal area (m$^2\cdot$ha^{-1}). Diagonal panels show variable distributions, lower panels show bivariate scatterplots, and upper panels report Pearson correlation coefficients.

convergence using visual inspection of trace plots, the potential scale reduction factor ($\hat{R}$; threshold ≤ 1.1), and effective sample sizes (bulk and tail ESS). Model adequacy was further evaluated using posterior predictive checks.

Model comparison

We compared model performance using three different metrics:

1. The coefficient of determination (R^2), which quantifies the proportion of variance in observed values explained by the model and therefore reflects overall goodness of fit.
2. The root mean square error (RMSE), which expresses the average size of the prediction errors, reported in the same units as the response variable.
3. The mean square deviation (MSD; [28]), which measures total prediction error and can be decomposed into three distinct and additive components:
   - Squared bias (SB), capturing systematic differences between predicted and observed values. A high SB indicates that the model consistently over- or underestimates observations.
   - Nonunity slope (NU), reflecting differences in how predictions follow the variability of observed values. A high NU indicates that prediction accuracy varies with

the magnitude of observations, meaning the model fits some parts of the range better than others.

- Lack of correlation (LC), representing random error not explained by the model. A high LC shows that predictions fail to capture part of the observed variability.

Together, these metrics provide complementary perspectives on model performance: R^2 indicates explanatory power, RMSE quantifies the magnitude of prediction errors, and MSD breaks down prediction error into its underlying components.

Cover prediction

We used the best-performing model to predict tree-cover across a range of realistic combinations of tree density (N) and basal area (BA). We synthesized these cover predictions into a state-space graph in the (N, BA) plane (with an associated lookup table), providing an operational tool to estimate plot-level tree-cover from standard inventory data.

We also examined how stand dynamics, i.e. recruitment (via natural regeneration or planting), growth and mortality (natural or due to logging), translate into cover trajectories within this state-space to support management decisions. In this representation, a stand can be represented by a point with coordinates (N, BA), and demographic processes or management operations impacting stand structure (N and/or BA) can move this point across the state-space. We therefore graphically represented the shifts induced by: (i) the recruitment of 5 or 10 trees with a diameter of 10 cm, (ii) a 2 or 5 cm increase in quadratic mean diameter due to growth, and (iii) the removal of 3 or 5 trees with diameters equal to the quadratic mean diameter.

Results

Model comparison

Model performance improves markedly when both tree density and basal area are included: R^2 exceeds 0.81, RMSE falls below 0.06, and more than 86% of the error is random (Figure 4). In contrast, single-variable models show weaker performance, with R^2 values below 0.73 down to 0.59, RMSE values exceeding 0.06 up to 0.08, and a less random error structure, with more than 25% of the total error attributable to variation in prediction accuracy across observations. These results highlight the relevance of jointly considering tree density and basal area to better grasp cover variation.

Finally, models perform best when logarithmic or square-root transformations are applied, confirming that the effects of density and basal area on cover tend to saturate.

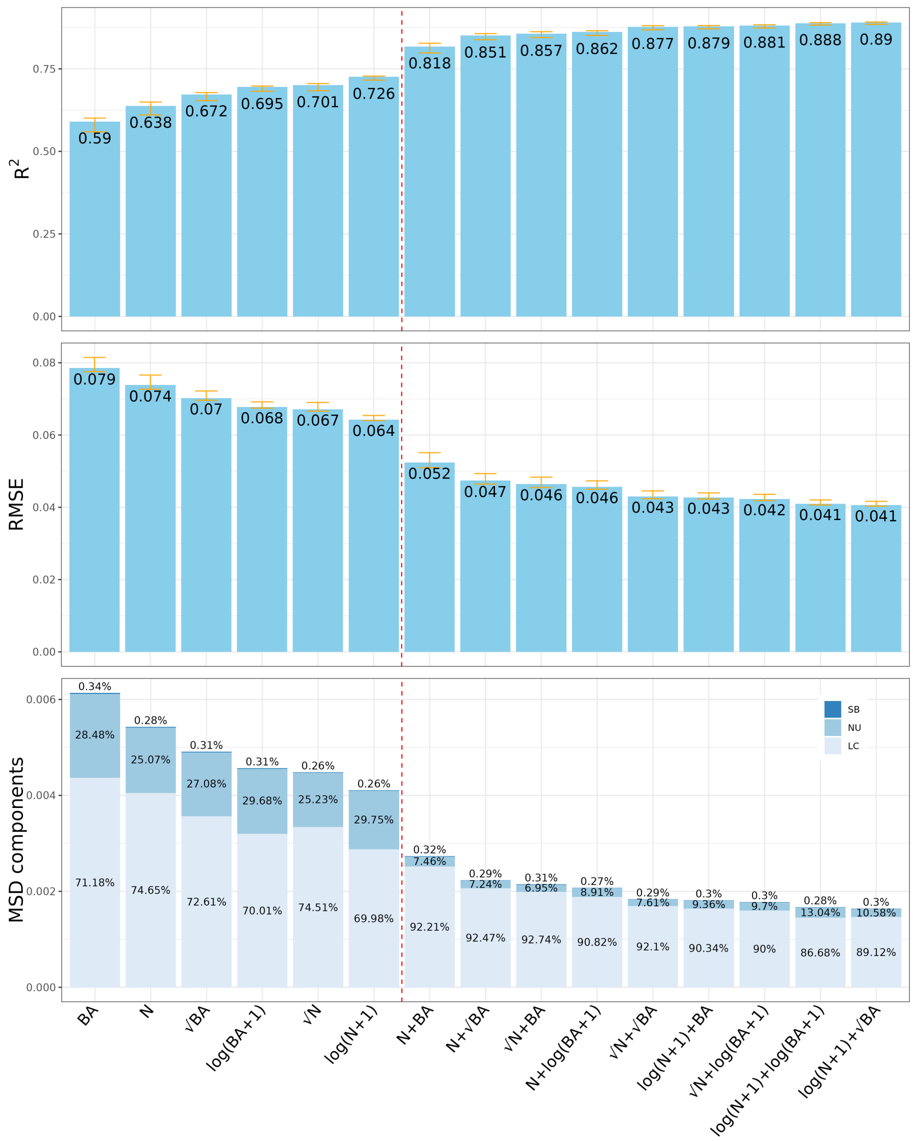


Fig. 4: Goodness of fit, prediction errors and their underlying components for the 15 candidate models. The top panel shows the coefficient of determination (R^2), and the middle panel shows the root mean square error (RMSE). In both panels, orange bars represent 95% credible intervals (2.5th and 97.5th percentiles), and black numbers indicate posterior medians. The bottom panel shows the mean square deviation (MSD) and its three components: squared bias (SB), nonunity slope (NU), and lack of correlation (LC). The percentage labels indicate the relative contribution of each component to total MSD. The vertical red dashed line, visible in all three panels, separates models using a single predictor (BA or N) on the left from those combining both predictors on the right.

Cover prediction

The best-performing model combines a logarithmic effect of tree density with a square-root effect of basal area (log(N+1) + $\sqrt{\text{BA}}$). Its coefficient of determination (R^2) is 0.89, indicating that the model explains 89% of the variation in tree-cover. Its root mean square error (RMSE) is 0.04, meaning that, on average, cover predictions deviate by 0.04 from observed values. Finally, the decomposition of its mean square deviation (MSD) shows that prediction error is predominantly random (LC = 89.12%) with the remaining error (NU = 10.58%) reflecting minor variation in prediction accuracy across observations and a negligible systematic bias (SB = 0.3).

Figure 5 presents the predicted relationship between plot-level tree-cover, tree density, and total basal area, as derived from the best-performing model (log(N+1) + $\sqrt{\text{BA}}$), represented as a state-space graph in the (N, BA) plane. It shows a clear increase in tree-cover with both variables, illustrating their complementariyy: for a given density, cover rises with basal area, and for a given basal area, it increases with density. For operational use, Table S1 of the Supplementary Information provides a lookup table of predicted cover values for combinations of tree density and basal area classes.

Figure 6 illustrates how the three main demographic processes driving stand dynamics (recruitment, growth, and mortality) can affect stand structure (N and/or BA) and translate into cover trajectories within the state space. Recruitment mainly increases stand density and, to a lesser extent, basal area, shifting the stand position to the right and slightly upward in the state space. Tree growth increases basal area, moving stands upward. Conversely, mortality reduces both basal area and density, moving stands downward and to the left. These natural or management-driven processes ultimately act in combination to shape the overall stand trajectory within the state space.

Discussion

The primary finding of this study is that tree-cover in cocoa AFS can be predicted accurately when tree density (N) and basal area (BA) are considered jointly. While these metrics are commonly used independently as proxies for canopy conditions, our results show that each captures only part of the structural signal underlying cover. This reflects the fact that tree-cover emerges from two complementary dimensions of stand structure: the number of crowns occupying horizontal space and the size of those crowns, which is closely linked to stem diameter and basal area. In cocoa AFS, these two dimensions vary largely independently because stand structure is shaped not only by tree growth, but also by farmer-driven recruitment and selective removal operating on uneven-aged, species-diverse communities. Shade trees originate from a mix of natural regeneration and planting, are retained or logged individually, and span a wide range of sizes and functional types [24, 29]. As a result, density is weakly constrained by competition, while basal area reflects the cumulative growth of a small or large number of trees depending on management history. Similar canopy cover can therefore arise from contrasting structural configurations, ranging from many small trees to few large ones. By integrating both density and basal area, our model captures this

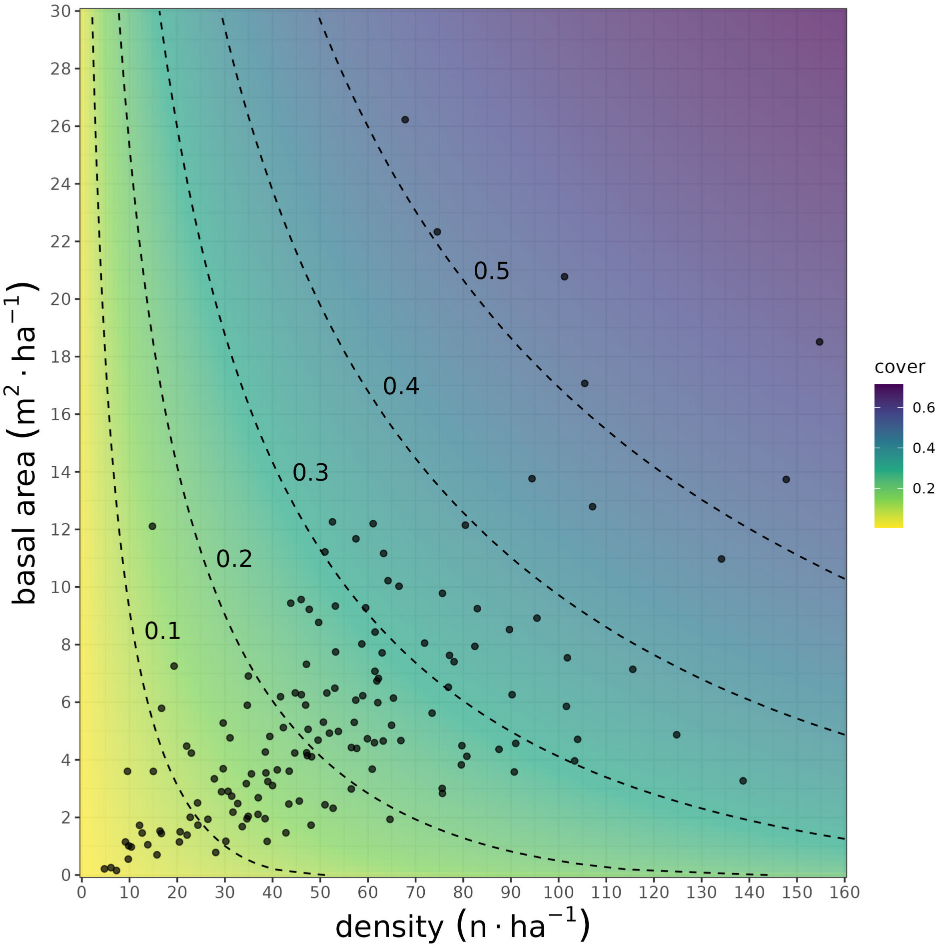
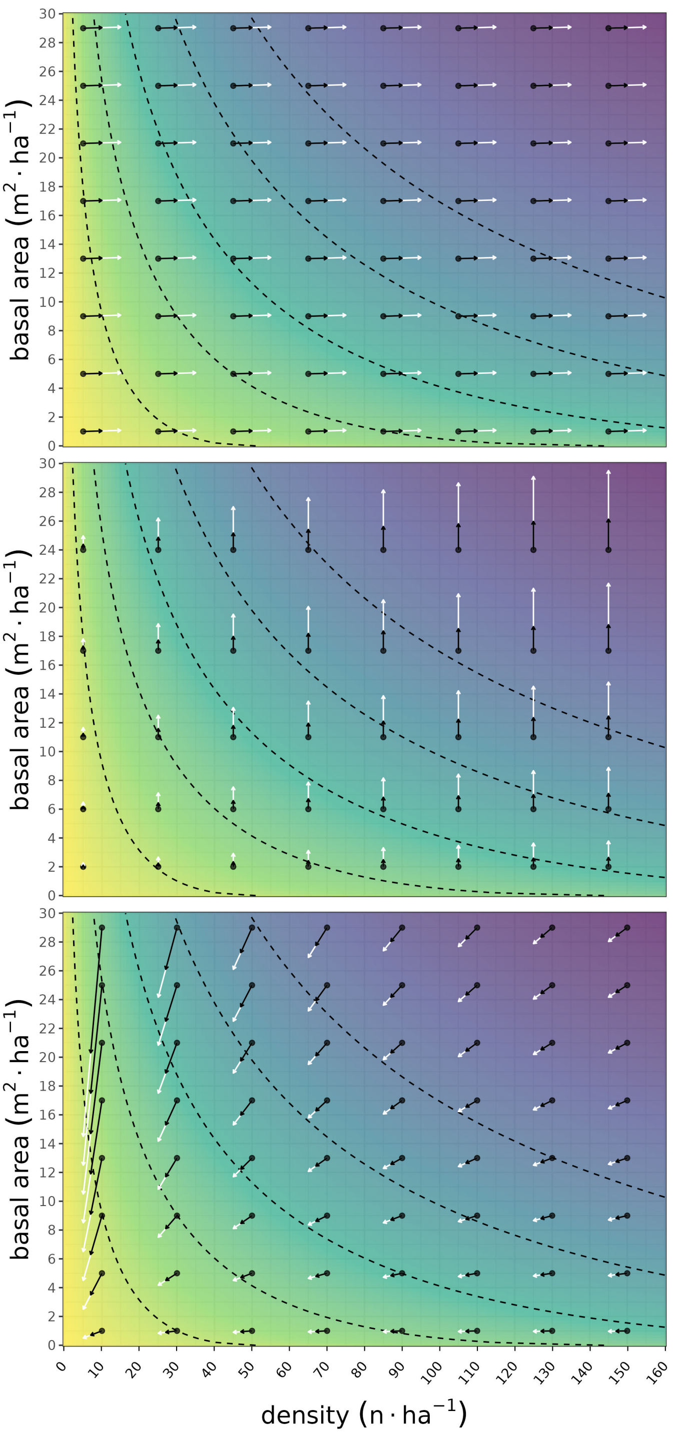


Fig. 5: Predicted plot-level tree-cover as a function of tree density and total basal area. Cover is represented by color shading, with darker tones indicating higher predicted cover values. Black dashed contour lines show specific cover levels (from 0.1 to 0.5, in 0.1 increments). Black dots represent the 150 field plots used for model calibration.

management-driven decoupling between tree number and tree size, providing a mechanistic explanation for the limited performance of single-variable prescriptions and highlighting why proxy-based guidelines based on either metric alone cannot ensure consistent canopy outcomes.

Applying our model to existing standards illustrates why current density-based targets are insufficient to achieve predictable canopy outcomes. For example, the Côte d'Ivoire ARS 1000 standard recommends 25–40 trees·ha^{-1}. Our results indicate that these density prescriptions can translate into vastly different tree-cover levels depending on tree size: at 25 trees·ha^{-1}, predicted cover may remain below 10% if the trees


basal area $(m^2 \cdot ha^{-1})$
basal area $(m^2 \cdot ha^{-1})$
basal area $(m^2 \cdot ha^{-1})$
density $(n \cdot ha^{-1})$
0
2
4
6
8
10
12
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28
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0
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130
140
150
160

Fig. 6: Effect of tree growth, recruitment, and mortality on plot-level tree-cover. Arrows illustrate how these three key processes driving stand dynamics affect plot-level tree-cover and move stands within the state space (presented in Figure 5). The top panel shows the effect of recruitment, which primarily increases tree density and slightly increases basal area, moving stands to the right and slightly upward; black and white arrows represent the addition of 5 and 10 trees (dbh = 10 cm), respectively. The middle panel shows the effect of growth, which increases basal area and moves stands upward; black and white arrows indicate an increase in quadratic mean diameter of 2 cm and 5 cm, respectively. The bottom panel shows the effect of logging or mortality, which reduce both basal area and density, moving stands downward and to the left; black and white arrows represent the removal of 3 and 5 trees (dbh = quadratic mean diameter), respectively.

are small, but can exceed 30% if they are large (Table S1). A similar ambiguity arises with basal area prescriptions. For instance, a threshold of $5\text{m}^2{\cdot}\text{ha}^{-1}$ of basal area may correspond to negligible cover (3%) when concentrated in a few trees, but to much higher cover ($\geq$ 30%) when it is distributed among many trees. From a management perspective, this ambiguity is critical because smallholders typically rely on a single readily available indicator, most often tree density. Such one-dimensional thresholds provide little guidance on actual cover status: identical tree counts may correspond to either insufficient or excessive shade. By jointly considering density and basal area, our framework enables a simple structural diagnosis of the stand, allowing managers to infer current tree-cover from standard inventory data and to assess whether their system is under- or over-shaded relative to target levels. This highlights an urgent need to update standards and technical guidelines, moving toward explicit tree-cover objectives.

Beyond static estimation, the state-space representation proposed here (Fig. 5 and 6) serves as a dynamic decision-support tool comparable to the stocking charts or density-management diagrams used in forestry (e.g., Reineke's Stand Density Index or Gingrich diagrams; [30]). In forestry, such diagrams are essential for guiding thinning and harvest operations to maintain stands within a zone of optimal growth. Similarly, our results show how standard demographic processes (recruitment, growth, and mortality) drive trajectories through the *cover space*.

For smallholders, this approach offers a significant advantage over single-variable guidelines: it visualizes the continuum of canopy closure and supports the planning of silvicultural interventions to reach specific targets. For instance, natural mortality or tree logging shifts the stand state downward and to the left (reducing both density and BA), while recruitment pushes the system primarily to the right (increasing density). Retaining trees allows the stand to move upward along the BA axis as individuals increase in size without a change in density. This visualization empowers managers to determine the precise combination of recruitment (through planting or natural regeneration), retention, or thinning required to maintain a target cover level. Such a framework provides the flexibility for farmers to reach cover targets through diverse structural pathways tailored to their specific situation and needs.

By formalizing canopy cover as an emergent property of the joint density–size structure, our work directly transfers established silvicultural principles into the management of cocoa AFS. Similarly, representing management as trajectories driven by recruitment, growth, and mortality, we provide a shared language for researchers, foresters, and agroforestry practitioners. More broadly, this approach responds to a growing need in agroforestry science to move beyond static, single-metric prescriptions toward integrative frameworks that explicitly connect stand structure to ecosystem functioning. This need is becoming increasingly pressing as agroforestry is simultaneously mobilized to address production, climate adaptation and mitigation, biodiversity conservation, and forest landscape restoration objectives. By positioning tree-cover, a primary driver of AFS functioning, at the centre of the management framework, our results open a pathway toward sustainability standards grounded in a robust scientific basis. This shift toward ecosystem-functioning indicators could help make standards more ecologically meaningful, moving away from structural thresholds that are arbitrary (i.e., lacking a clear functional or evidence-based link to ecosystem services) and that currently dominate agroforestry policy.

Future work could extend this framework in three complementary directions. First, although the model already explains most of the observed variability in tree-cover ($R^2 = 0.89$), external validation across countries and agroecological zones would help assess transferability and, where needed, derive regional calibration factors. Importantly, our dataset already integrates mixed-origin systems combining remnant forest trees, spontaneous regeneration, and planted trees, suggesting that the density–basal area–cover relationship is robust across diverse structural configurations. We therefore expect major departures mainly in simplified systems dominated by a single tree origin, where crown allometry and growth trajectories may differ more systematically (e.g., purely planted or purely spontaneous stands). Second, remaining variability likely reflects secondary effects of species composition and crown architecture; incorporating simple descriptors such as functional types or crown allometry proxies could further refine predictions. Finally, linking predicted cover states to agronomic and socio-economic outcomes (yield, pest and disease pressure, income, carbon storage) would move the framework from canopy estimation toward multi-objective decision support aligned with smallholder priorities and sustainability targets.

Conclusion

Our results show that tree-cover in cocoa AFS can be reliably estimated from standard inventory data when tree density and basal area are considered jointly, whereas either metric alone captures only part of the variability in cover. Grounded in forest science, our approach helps translate tree-cover prescriptions into practical management levers that smallholders can apply to steer their farms toward targeted canopy conditions. In doing so, it offers a straightforward pathway to operationalize sustainability standards and policies, and to support the management of resilient, productive cocoa AFS.

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Declarations

All authors have no conflicts of interest.

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Supplementary Information

Basal Area ($m^2 \cdot ha^{-1}$)	Tree Density ($trees \cdot ha^{-1}$) (0,5]	(5,10]	(10,15]	(15,20]	(20,30]	(30,40]	(40,50]	(50,60]	(60,80]	(80,100]	(100,120]
(0,2]	2	4	6	7	9	11	13	15	18	21	23
(2,4]	3	5	7	9	12	15	17	19	23	26	29
(4,6]	3	6	9	11	14	17	20	23	26	30	34
(6,8]	4	8	10	13	16	20	23	26	30	34	37
(8,10]	5	9	12	15	18	22	26	29	33	37	41
(10,12]	5	10	13	16	20	24	28	31	36	40	44
(12,14]	6	11	15	18	22	27	31	34	38	43	47
(14,16]	6	12	16	19	24	29	33	36	41	46	49
(16,18]	7	13	17	21	26	31	35	39	43	48	52
(18,20]	8	14	19	23	28	33	37	41	46	51	54
(20,22]	8	15	20	24	30	35	40	43	48	53	57
(22,24]	9	16	22	26	31	37	42	46	50	55	59
(24,26]	10	17	23	28	33	39	44	48	52	57	61
(26,28]	11	19	25	29	35	41	46	50	54	59	63
(28,30]	11	20	26	31	37	43	48	51	56	61	64

Table S1: Predicted tree-cover values (%) as a function of stand density ($trees \cdot ha^{-1}$) and basal area ($m^2 \cdot ha^{-1}$) classes. This table serves as a discrete representation of the state-space graph (Figure 5), providing a tool to estimate plot-level tree-cover based on standard forest inventory metrics. To improve readability, cover values below 20% are indicated in orange, while values from 20% up to and including 30% are indicated in green.