Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Tree-scale production gap analysis of the clove tree (Syzygium aromaticum): structural determinants and climatic drivers in Madagascar

Manon Desmurs

manon.desmurs@cirad.fr

https://orcid.org/0009-0000-2568-2966

Mickaël Rajoeliharivelo

Éric Malézieux

https://orcid.org/0000-0002-5706-9610

Frédéric Normand

https://orcid.org/0000-0002-4322-8262

Pascal Danthu

https://orcid.org/0000-0002-9607-8253

Isabelle Michel

https://orcid.org/0000-0002-8040-6363

Vololoniriana Razafimaharo

https://orcid.org/0009-0007-5155-3157

Julien Sarron

https://orcid.org/0000-0002-9584-4227

Research Article

Keywords: Stochastic frontier analysis, production gap, irregular flowering, smallholder farming, tropical perennial crops, crown surface area, flowering intensity, rainfall deficit, Madagascar

Posted Date: June 16th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9446121/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Abstract

Improving productivity while maintaining ecological complexity remains a central challenge for sustainable intensification in tropical agroforestry systems. Production gap analysis has emerged as a key method for diagnosing the difference between actual and attainable production, yet applications to individual tree scales in heterogeneous perennial systems remain scarce. The clove tree (*Syzygium aromaticum*), whose buds constitute Madagascar's second-largest export crop, exhibits strong inter-annual and intra-field production variability driven by endogenous flowering cycles and climatic fluctuations. A total of 126 trees were monitored over two contrasting seasons (2024 and 2025), integrating exhaustive harvest measurements, dendrometric variables, drone-derived competition indices, and flowering intensity assessments. Attainable production and production gaps were estimated using stochastic frontier analysis, allowing simultaneous estimation of structural determinants and management drivers of inefficiency. Here we show that production gap analysis at the tree scale can be applied to irregular-flowering perennial crops embedded in structurally complex agroforestry systems. Mean observed production of 3.1 kg tree^{-1} against a mean attainable production of 17.4 kg tree^{-1} yields an average production gap of 81.8%, substantially larger than those reported for intensively managed perennial crops. Doubling estimated crown lateral surface area increased attainable production by approximately 76%, while trunk diameter exerted an additional positive effect. Production gaps widened from 72% in 2024 to 92% in 2025, coinciding with a rainfall deficit and increased dry spell intensity during the January-April period, when floral bud initiation is thought to occur, although the causal role of these climatic factors requires validation across additional seasons. These findings identify concrete leverage points for improving clove productivity, including crown expansion through adapted pruning and spacing and more frequent weed control in fields where labor and capital allow. More broadly, this work provides a transferable method for diagnosing productivity constraints in irregular-flowering tropical perennial crops in heterogeneous agroforestry landscapes.

1. Introduction

Tropical perennial crops play a central role in rural livelihoods and food security, particularly in smallholder agroforestry systems where they provide both income and ecological services (Malézieux 2012; Mbow et al. 2014). Yet their productivity remains highly variable and frequently below attainable levels. Achieving sustainable intensification in these systems requires a robust understanding of both the magnitude of production gaps, defined as the difference between actual and attainable production, and the structural, environmental, and management factors that prevent crops from reaching their production potential (van Ittersum et al. 2013; Sarron et al. 2023). While yield gap methods have been widely applied to annual crops and more recently to perennial crops at the orchard scale (Van Ittersum et al. 2013; Woittiez et al. 2017; Zhang et al. 2019), Sarron et al. (2023) extended this concept to the individual tree scale in mango, introducing the production gap method to account for tree endogenous factors such as crown architecture and trunk diameter. Their application is, however, limited to monospecific orchards, and no equivalent method has been applied to species cultivated within

structurally complex agroforestry systems, where long lifespans, spatial heterogeneity, and irregular flowering cycles further complicate the context and the application of the method.

The clove tree (*Syzygium aromaticum* (L.) Merr. & L.M.Perry) is a high-value perennial crop whose dried flower buds are among the most traded spices globally. Clove bud, the immature floral bud harvested before anthesis and sun-dried to produce the commercial spice, is Madagascar's second-largest export product, with the country being the world's dominant supplier to international markets (Danthu et al. 2020). Clove buds are borne on small inflorescences whose peduncles and pedicels, collectively referred to as clove stems (Fig. 1a), are harvested together with the buds and subsequently separated by hand before drying (Danthu et al. 2014). Clove is cultivated along Madagascar's east coast, primarily within the Analanjirofo region, where it has progressively replaced shifting rice cultivation over recent decades (Mariel et al. 2023). This transition has generated a diversity of clove-based systems ranging from simplified stands to structurally complex agroforestry configurations (Fig. 1b; Desmurs et al. 2026). For smallholder farmers, clove represents a primary source of cash income and a cornerstone of household food security (Danthu et al. 2024).

Despite its economic importance, clove productivity remains low and extremely variable both among and within fields. This variability arises from irregular flowering cycles (Razakaratrimo et al. 2018), whose molecular regulation remains poorly understood, with the Terminal Flower 1 gene only recently characterized in this species (Darwati et al. 2025), strong spatial heterogeneity linked to soil conditions and competitive interactions (Martin and Dabek 1988), and limited adoption of adapted management practices (Danthu et al. 2014). Pronounced inter-annual production fluctuations further complicate harvest planning and market regulation (Danthu et al. 2020).

Yet quantitative assessments of clove production at the individual tree scale remain scarce, and most existing estimates rely on farmer surveys or regional statistics that mask within-field heterogeneity (Roth et al. 2019). Individual tree production ranges from approximately 1 to 25 kg of dried buds per year depending on tree age, size, and year (Maistre 1955; Roth et al. 2019), but these estimates are rarely linked to measurable structural or environmental drivers. Unlike for annual crops, there are few process-based models for fruit trees and there is no model for clove, making empirical frontier-based approaches an alternate method for estimating attainable production under local conditions (Sarron et al. 2023). Until now, the magnitude of production gaps for clove and their structural, environmental, and management determinants remain poorly understood.

Sarron et al. (2023) adapted the production gap concept to the individual tree scale in mango using stochastic frontier analysis. In this method, three categories of factors are distinguished. Production-defining factors, including crown architecture, trunk diameter, and competitive environment, determine attainable production (P_{att}), defined as the maximum production achievable under prevailing local biophysical conditions given a tree's structural characteristics. Actual production (P_a) is production observed at harvest. Production-limiting factors, such as soil fertility or water availability, and production-reducing factors, such as pest damage or tree management, prevent trees from reaching P_{att}, thereby

generating the production gap ($P_g = P_{att} – P_a$). As with mango, clove exhibits high structural and production heterogeneity within fields, marked by inter-annual fluctuations driven by irregular flowering cycles. To date, only Martin and Riley (1989) have attempted to quantify clove production at the individual tree scale, by relating tree yield to canopy area and a visual score for bud differentiation, but without a framework to distinguish attainable from actual production or to disentangle the factors generating the production gap.

Here we applied tree-scale production gap analysis to clove trees for the first time. Specifically, we (i) quantified actual production and estimated attainable production using stochastic frontier analysis, integrating structural traits and competitive environment as production-defining factors; and (ii) identified the production-limiting and production-reducing factors and their relative contributions to observed production gaps across two contrasting seasons, including inter-annual climatic variability, field management practices, and topographic covariates.

2. Materials and Methods

Study site

The study was conducted in Antsirakoraka village (17°27'S, 49°16'E), Vavatenina District, Analanjirofo Region, on Madagascar's east coast, the region accounting for the majority of Madagascar's clove exports (Danthu et al. 2020). The climate is hot and humid tropical, with rainfall occurring throughout the year (mean annual rainfall: 2,025 mm yr^{-1}, range: 1,733-2,447 mm yr^{-1}; 2015–2024). Rainfall is strongly seasonal, peaking in January-March (300–350 mm $month^{-1}$) and declining in June-November (80–125 mm $month^{-1}$). Mean annual temperature is 22.1°C with limited inter-annual variability. All climatic variables were estimated from ERA5-Land daily atmospheric reanalysis data (0.1° resolution; Muñoz-Sabater et al., 2021). These data were also used to characterize climatic conditions during the January-April period, when floral bud initiation is thought to occur based on the phenological calendar of Razakaratrimo et al. (2018), for the two monitored seasons (2024 and 2025) and a reference high-production year (2017, selected based on Madagascar's peak clove export volume over the 2016–2025 period and farmer recollections; ITC 2025). Climatic variables extracted for this period included cumulative rainfall, maximum 5-day cumulative rainfall (RX5day), longest dry spell duration (longest sequence of consecutive days with rainfall below 1 mm), number of days exceeding 20 mm, number of days with maximum temperature exceeding 30°C, and mean temperature.

The landscape comprises a narrow north-south valley with irrigated rice lowlands bordered by hillslopes dominated by clove cultivation. These hillslopes exhibit steep topographic gradients. Soils are predominantly ferralsols or acrisols of variable depth depending on topographic position and erosion intensity (Mariel et al. 2022).

Tree sampling, flowering intensity and structure variables

Experimental design and tree selection

An initial survey conducted in early 2024 characterized 218 mature, flowering clove trees across 11 fields managed by 8 farmers, capturing the full range of tree sizes and flowering intensities present in the study area. A total of 126 trees were selected from this pool by stratified random sampling, based on crown volume and flowering intensity terciles, ensuring balanced representation across size and flowering intensity classes, yielding 252 tree-year observations. The study was carried out over two consecutive seasons, 2024 and 2025. Crown volume categories were: Small (less than 15 m^3, n = 42), Medium (15-37.4 m^3, n = 42), and Large (more than 37.4 m^3, n = 42). All 126 trees underwent annual shoot pruning for essential oil production from leaves in 2023, 2024, and 2025, as confirmed by farmer interviews. This practice systematically targets orthotropic vegetative shoots while generally preserving productive plagiotropic flowering shoots located at the lateral edge of the tree canopy.

Tree crown dimensions

Tree structural variables were measured once in September 2024, after the 2024 pruning season. For each tree, we measured total height and crown base height using a Vertex 5 dendrometer (Haglöf, Sweden) and a tape measure, respectively, two perpendicular crown diameters, and trunk circumference at breast height (CBH, at 1.30 m). CBH was converted to trunk diameter at breast height (DBH = CBH/π) to facilitate comparison with relationships reported in the literature (Arimalala et al. 2019), and served as a proxy for tree age as individual ages were unknown. Crown depth was calculated as the difference between total height and crown base height, and mean crown radius as the average of the two perpendicular radii. Although annual pruning primarily targets orthotropic vegetative shoots and modifies crown geometry to some extent, crown dimensions were considered stable across both study years as this practice removes a small fraction of total crown volume and is unlikely to alter overall crown shape at the inter-annual scale.

Crown shape was approximated as a cone ($V = 1/3\ \pi r^2 h$), consistent with the tapered architecture commonly observed in pruned clove trees where orthotropic shoot removal promotes a conical canopy profile. Lateral crown surface area was then calculated as $S = \pi r\sqrt{(r^2 + h^2)}$. Since clove inflorescences develop exclusively at terminal shoots distributed across the lateral crown surface (Maistre 1955), S represents the biologically relevant productive area and was selected as the primary structural predictor in all models.

Flowering intensity

Flowering intensity (FI, %) was assessed annually in September 2024 and 2025, at floral bud development stage D' (Razakaratrimo et al. 2018), when buds are growing but petals are not yet visible, approximately 2–3 months prior to harvest. For each tree, ten peripheral shoots were randomly sampled across the entire crown surface, covering all aspects and crown heights. On each shoot, the number of terminal axes (N) and the number of flowering terminal axes bearing clove buds (n) were counted. Tree-level flowering intensity was calculated as the mean of the ten shoot-level ratios: FI (%) = mean (n/N) × 100. Mean FI was 47.5% (range: 7.5–95.4%) in 2024 and 18.0% (range: 0.0–90.4%) in 2025, reflecting

strong inter-annual variability and strong variability in flowering intensity among trees across the two monitored seasons.

Complete clove production per tree was recorded during November-December 2024 and October 2025-January 2026 to quantify biological bud production at the tree scale. For each tree, all mature clove buds were harvested at stage E' of Razakaratrimo et al. (2018), corresponding to the optimal harvest stage associated with the highest essential oil content and eugenol concentration (Razafimamonjison et al. 2013), with their stems from the entire crown. Fresh weight with stems was measured immediately using a portable balance (± 1 g precision). The harvest was then manually de-stemmed and fresh weight without stems was recorded. This variable, fresh biological production prior to drying or further processing, was used as actual production (P_a, kg tree^{-1}) in all analyses.

Load index (LI) was calculated as the ratio of actual production to lateral crown surface (P_a/S; kg m^{-2}) to enable size-independent productivity comparisons across trees and years.

Production gap method: definitions and variable measurements

Following the method of Sarron et al. (2023), attainable production (P_{att}) was defined as the maximum production achievable per tree under prevailing pedoclimatic conditions and optimized management, and actual production (P_a) as the production per tree observed at harvest. Production-limiting factors, such as suboptimal water or nutrient availability, and production-reducing factors, such as pest damage or inadequate management practices, prevent trees from reaching P_{att}, thereby generating the production gap ($P_g = P_{att} - P_a$). Descriptive statistics of all variables are provided in Table 1.

Production-defining factors

Three variables were used to describe production-defining factors: lateral crown surface area (S, m²), diameter at breast height (DBH, cm), and a local competition index. S was used as a descriptor of tree crown dimensions and of tree production potential, and DBH as a proxy of tree age. Since no clove tree cultivars have been identified in Madagascar (Razakaratrimo et al. 2018), cultivar was not included as a production-defining factor. Local competitive pressure was quantified using the Schütz competition index (Schütz 1989), computed within a fixed 7 m radius around each tree. This radius was chosen to encompass the competitive zone of a neighbor tree planted at the typical Malagasy interplanting distance of 8–10 m (Danthu et al. 2014), beyond which competitive effects were considered negligible. A fixed radius, rather than a crown-proportional radius, was used to ensure comparability across trees of contrasting sizes. The index was calculated as:

$$IC_{Sch\ddot{u}tz,i} = \sum_{\substack{j=1 \\ j \neq i}}^{n} 0.65 \frac{H_j - H_i}{r_i + r_j} + [0.5 - \frac{E_{ij}}{r_i + r_j}]$$

1

where H_i and H_j are heights of the studied tree *i* and neighbor *j* (m); r_i and r_j are crown radii (m); and E_{ij} is the edge-to-edge distance between crowns (m). A neighbor *j* was considered a competitor if $E_{ij} \leq 0.5\ (r_i + r_j)\ + 0.65(\mathrm{H_j} - H_i)$, meaning that only trees whose crowns overlap or are sufficiently taller than the studied tree are considered competitors. Trees shorter than the studied tree contribute negatively to the index, reflecting their subordinate competitive status. Higher overall values indicate stronger competitive pressure on tree *i*.

Crown radii and heights required for the Schütz index were extracted from a canopy height model (CHM) derived from drone imagery. Each of the 11 fields was surveyed using a DJI Phantom 4 RTK equipped with an RGB sensor at 60 m flight height. Orthomosaic images were processed in Pix4Dmapper Pro (v4.8.4; Pix4D SA, Lausanne, Switzerland) to generate a digital surface model and digital terrain model at 2.42 cm pixel⁻¹ resolution. The canopy height model was computed as the difference between the digital surface model and the digital terrain model (Sarron et al. 2018). Individual tree crowns were delineated using a hybrid approach combining a variable window filter and marker-controlled watershed segmentation (ForestTools package; Plowright 2023), with manual validation in QGIS. Crown maximum height and radius were extracted from the resulting crown polygons.

Production-limiting and production-reducing factors

Four variables were used as factors preventing trees from reaching their attainable production: field altitude, field slope, weeding frequency, and harvest year. Altitude and slope were considered production-limiting factors, used here as proxies for soil fertility and water availability, which vary along the topographic gradient of the study area. Weeding frequency was considered a production-reducing factor, as it reflects the intensity of weed control during the growing cycle. Harvest year was included as a control variable to capture unmeasured inter-annual variation in climate and tree irregular bearing. The final set of variables retained in the model was determined by backward likelihood ratio tests, removing variables whose exclusion did not significantly reduce model fit.

As field altitude and slope can affect soil fertility and moisture status (Mariel et al. 2022), we used them as proxies for tree nutrient and water status. Since farmers neither irrigate nor fertilize their clove trees, altitude and slope represent the primary source of variation in soil resource availability across fields. Both variables were extracted from the digital terrain model and averaged over each of the 11 field extents, yielding one value of mean altitude (m) and one value of mean slope (%) per field.

Weeding frequency was recorded as the number of manual weeding events per field in year n-1, collected through farmer interviews and lagged by one year to align with the timing of floral bud initiation in January (Martin and Dabek 1988; Razakaratrimo et al. 2018). Although only two values were observed within the study area (1 or 2 interventions per year), weeding frequency was treated as a numerical variable consistent with its nature as a count variable that could take higher values in other contexts. The estimated coefficient therefore represents the change in inefficiency associated with one additional weeding intervention per year. Harvest year was included as a categorical variable to account for inter-annual variation in rainfall and other unmeasured climatic factors during the January-April period.

All numerical predictors used as production-limiting and production-reducing factors were scaled by their standard deviation prior to estimation to facilitate numerical convergence of the maximum likelihood estimator.

Stochastic frontier model specification and estimation

Attainable production and the effects of production-defining, limiting, and reducing factors were assessed using stochastic frontier analysis (Battese and Coelli 1995; Sarron et al. 2023). This method decomposes the deviation of actual production from attainable production into two components: a symmetric noise term (v_{it}, Eq. 2) capturing measurement error and other random variation, and a one-sided inefficiency term (u_{it}, Equations 2 and 3) capturing the combined effect of production-limiting and production-reducing factors on the gap between actual and attainable production. The frontier production function (Eq. 2) relates actual production to production-defining factors, while the inefficiency component (Eq. 3) models u_{it} as a function of production-limiting and production-reducing factors.

Functional form of the frontier production function was selected by likelihood ratio tests between Cobb-Douglas and translog specifications. Although the translog specification yielded a significantly better fit (likelihood ratio test: $\chi^2(6) = 83.6$, $p < 0.001$), it rendered all inefficiency determinants non-significant, likely due to over-parameterization relative to available degrees of freedom (252 observations across 126 trees and 2 years). The Cobb-Douglas specification was therefore retained on the basis of parsimony and interpretability. Following Battese and Coelli (1995), a stochastic frontier model was specified in which the inefficiency term u_{it} is modeled as a linear function of observable covariates, allowing simultaneous estimation of the frontier production function and the determinants of the gap between actual and attainable production, consistent with the objective of identifying production-limiting and production-reducing factors.

Prior to specifying the frontier production function, climatic variables were evaluated as potential production-defining factors. Mean annual temperature showed negligible inter-annual variation (22.9°C in 2024 vs. 22.9°C in 2025) and was therefore not retained. Mean temperature during the January-April period was similarly stable between years (25.3°C in 2024 vs. 25.9°C in 2025). Rainfall was not included as a production-defining factor because ERA5-Land data provide a single value per year for the entire study area, making it collinear with the harvest year variable already included in the inefficiency component. No other climatic variable showed sufficient spatial or temporal variation to be included as a production-defining factor in the frontier.

The frontier production function was specified as:

$$\ln\left(P_{a,it}\right) = \beta_0 + \beta_1 \ln\left(\mathrm{S_i}\right) + \beta_2 \ln\left(DBH_i\right) + \beta_3 \ln\left(IC_{Schütz,i}\right) + v_{it} - u_{it}$$

2

with:

$$u_{it} = \delta_0 + \delta_1 Year_t + \delta_2 Slope_p + \delta_3 Altitude_p + \delta_4 Weeding_{p(t-1)} + \epsilon_{it}$$

3

where $P_{a,it}$ is the actual clove production (kg tree⁻¹) of tree i in year t; β_0 is the intercept and β_1, β_2, β_3 are the frontier coefficients associated with each production-defining factor; $v_{it} \sim N(0, \sigma_v^2)$ captures symmetric statistical noise; $u_{it} \sim N^+(0, \sigma_u^2)$ is a non-negative term representing inefficiency, i.e. the extent to which actual production falls below attainable production for a given combination of production-defining factors; δ_0 is the intercept and δ_1, δ_2, δ_3, δ_4 are the inefficiency parameters to be estimated, with positive values indicating an increase in the gap between actual and attainable production; and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is the residual of the inefficiency regression.

From the estimated model, tree level efficiency (E), was defined as $\mathrm{E_{it}} = \exp(-u_{it})$, ranging from 0 to 1, where $\mathrm{E_{it}} = 1$ indicates that actual production equals attainable production. The relative production gap was then defined as $P_{g,rel,it} = 100 \times (1 - E_{it})$ (%). Attainable production was derived as:

$$\mathrm{P_{att,it}} = \frac{P_{a,it}}{E_{it}}$$

4

Trees with zero production (n = 43, all recorded in 2025) were retained in the dataset using a small offset: $\ln(P_a + 10^{-6}$ kg), negligible relative to mean positive production in 2024 (4.622 kg tree⁻¹). Among these zero-production trees, 27 showed no detectable flowering in September 2025 and therefore represent true biological zeros. The remaining 16 had recorded positive flowering intensity at the September assessment (range: 1.0–27.4%) but yielded no harvestable buds at harvest, indicating bud loss between the flowering assessment and harvest. These trees were retained in the analysis as they represent genuine biological outcomes rather than missing data. A sensitivity analysis excluding zero-production observations yielded substantially different frontier coefficients for crown surface area (0.82 vs. 1.35) and DBH (0.44 vs. −0.19, with a sign reversal), and increased the mean relative production gap by 12 percentage points, confirming that zero-production trees cannot be treated as missing data: their exclusion would introduce systematic bias in parameter estimation, particularly for the structural determinants of attainable production.

Statistical analyses

Production values are reported in kg tree⁻¹ throughout. Inter-annual differences in production variables (P_a, P_{att}, load index, and efficiency) were assessed using paired Wilcoxon signed-rank tests, given the repeated-measures structure (same 126 trees in 2024 and 2025) and non-normal distributions (Shapiro-Wilk test). Individual tree responses between 2024 and 2025 were classified into four categories based on relative production change: total collapse ($P_a = 0$ in 2025), severe decline (more than 60% reduction), moderate decline (20–60% reduction), and stable or increasing production (less than 20% decline).

Differences in structural and management variables across these four categories were assessed using Kruskal-Wallis tests with Dunn post-hoc tests and Bonferroni correction for multiple comparisons. Spearman rank correlation coefficients were used to assess monotonic associations between relative production change and continuous tree-level variables (crown surface area, DBH, Schütz index, flowering intensity, and load index). A significance threshold of $\alpha = 0.05$ was applied to all tests.

To decompose the relative contributions of tree-level and field-level factors to inter-annual production change, a linear mixed model was fitted with relative production change ($(P_{a,2025} - P_{a,2024}) / P_{a,2025} \times 100$, %) as the response variable, field as a random effect, and crown surface area, DBH, Schütz competition index, load index 2024, altitude, slope, and weeding frequency as fixed effects. Marginal R^2 (R^2_m, variance explained by fixed effects alone) and conditional R^2 (R^2_c, variance explained by both fixed and random effects) were computed following Nakagawa and Schielzeth (2013) using the *performance* package (Lüdecke et al. 2021).

All analyses were performed in R 4.3.2 (R Core Team 2023) using the packages *frontier* (Coelli and Henningsen 2020), *ForestTools* (Plowright 2023), *performance* (Lüdecke et al. 2021), *terra* (Hijmans 2024), and *sf* (Pebesma 2018).

3. Results and discussion

Stochastic production frontier and drivers of attainable production

Model performance and production gap

The stochastic frontier model converged successfully (log-likelihood = − 556.3, AIC = 1134.7, BIC = 1173.5). The gamma parameter reached its upper boundary ($\gamma = 1.00$, $\sigma^2 = 164.9$), indicating that the model attributed virtually all variance in production to the inefficiency term rather than to statistical noise. This boundary solution likely reflects two non-mutually exclusive factors: the large morphological variability among sampled trees, which generates genuine between-tree differences in production efficiency, and the limited capacity of a two-year panel to reliably separate the inefficiency component from the noise term when both are estimated simultaneously. Results should therefore be interpreted as reflecting the combined effect of true production inefficiency and residual unmeasured variation, rather than as a precise statistical decomposition of the two components.

Mean actual production was 3.1 kg tree^{-1}, while mean attainable production reached 17.4 kg tree^{-1}, yielding a mean production gap of 14.3 kg tree^{-1} and a mean relative gap of 81.8% (Table 1, Fig. 2a). Production gaps were highly variable among trees and between years, with efficiency ranging from near 0 to approximately 0.80. Frontier coefficients and inefficiency determinants are presented in Table 2. Compared to mango, where the mean relative production gap reached 37.5% under extensive management conditions (Sarron et al. 2023), the gap observed here is substantially larger, reflecting both the irregular flowering behavior of clove and the minimal agronomic inputs characteristic of smallholder agroforestry systems.

Table 1

Descriptive statistics (mean, SD, min, max) of variables used in the stochastic frontier analysis (n = 252 tree-years, 126 trees × 2 years). Frontier variables enter the production frontier (Eq. 2); inefficiency variables enter the inefficiency component (Eq. 3). Year is categorical (2024 reference, 2025 contrast).

Variable	Role	Mean	SD	Min	Max
Actual production, P_a (kg tree^{-1})	Response	3.06	4.55	0.00	35.05
Lateral crown surface area, S (m²)	Frontier	43.00	25.70	7.60	120.00
DBH (cm)	Frontier	18.90	11.00	4.80	61.40
Schütz competition index	Frontier	1.90	1.50	0.00	7.40
Altitude (m)	Inefficiency	124.00	24.60	97.00	211.00
Slope (°)	Inefficiency	22.00	4.90	12.80	31.40
Weeding frequency (events yr^{-1})	Inefficiency	1.40	0.50	1.00	2.00
Year (2024/2025)	Inefficiency	—	—	—	—

Table 2

Stochastic frontier analysis results (n = 252 tree-years). Frontier variables were log-transformed (ln); inefficiency variables were scaled by their standard deviation. SE: standard error; z: Wald statistic. Significance codes: *** p < 0.001, · p ≤ 0.05, ns p > 0.05.

Component	Variable	Estimate	SE	z	p-value
Frontier	Intercept	5.376	0.043	124.18	< 0.001 ***
(production-defining factors)	Lateral cone surface area	0.818	0.024	34.30	< 0.001 ***
	DBH	0.438	0.018	25.05	< 0.001 ***
	Competition index	−0.033	0.005	−6.91	< 0.001 ***
Inefficiency	Intercept	−56.6	15.1	−3.75	< 0.001 ***
(production-limiting and reducing factors)	Altitude	−26.0	16.1	−1.62	0.106 ns
	Slope	−9.5	10.6	−0.90	0.367 ns
	Weeding frequency	−16.3	8.3	−1.96	0.050 ·
	Year	93.9	7.6	12.31	< 0.001 ***
Determinants of attainable production					

Three production-defining factors were significant (Table 2). Lateral crown surface area (S) exerted the strongest effect (frontier coefficient = 0.82, $p < 0.001$): a 10% increase in S corresponded to an 8.2% increase in P_{att}, and doubling S increased P_{att} by approximately 76%. This near-proportional relationship reflects clove's biological constraint: inflorescences develop exclusively at terminal shoots distributed across the lateral crown surface (Maistre 1955), making P_{att} inherently limited by the number of peripheral flowering sites rather than total canopy volume. In perennial crops where production depends on the number of terminal flowering shoots, crown surface area is recognized as the primary structural determinant of reproductive output (Normand and Lauri 2018). The substantial scatter in actual production around this relationship (Fig. 2b), particularly among trees with large crown dimensions that nonetheless showed low actual production, demonstrates that crown surface area sets the production potential of a tree but does not determine actual production, and that production-limiting and production-reducing factors modulate the extent to which this structural potential is achieved.

DBH showed a substantial positive effect (frontier coefficient = 0.438, $p < 0.001$): a 10% increase in DBH corresponded to a 4.4% increase in P_{att}, and trees with DBH = 30 cm had an estimated 62% higher P_{att} than trees with DBH = 10 cm (Fig. 2c). DBH was used here as a proxy for tree age (Arimalala et al. 2019), integrating age-related processes that accumulate over the tree's lifetime, including carbohydrate reserve accumulation and physiological maturity, and that enhance reproductive capacity beyond what crown dimensions alone reflect (Goldschmidt and Sadka 2021). Although DBH and crown surface area were strongly correlated in our sample (Spearman rho = 0.87, $p < 0.001$), their independent positive effects in the frontier model suggest that each captures a distinct dimension of tree structural capacity: crown surface area reflects the current availability of peripheral flowering sites, while DBH integrates the cumulative physiological development of the tree over its lifetime. Together they define the structural production ceiling of individual trees, consistent with findings on mango where crown dimensions and trunk circumference are primary determinants of attainable production at the tree scale (Sarron et al. 2023).

Local competition (Schütz index, 7 m radius) had a significant but modest negative effect on P_{att} (frontier coefficient = -0.03, $p < 0.001$): doubling competitive pressure reduced P_{att} by only 3.4%, corresponding to approximately 1.2 kg $tree^{-1}$ for a tree of medium dimensions across the observed interquartile range (Fig. 2d). The absence of a significant bivariate relationship between the Schütz index and actual production ($R^2 < 0.01$, $p = 0.84$, Fig. 2d) is consistent with this modest effect size, and reflects the fact that the negative effect of competition on P_{att} only becomes detectable when crown surface area and DBH are simultaneously controlled for in the frontier model. Overall, clove trees appeared little affected by competition from neighboring trees despite planting densities that are sometimes high in Malagasy agroforestry systems. Two non-mutually exclusive hypotheses may explain this pattern. First, annual shoot pruning maintains a conical crown architecture that limits lateral crown expansion, reducing crown overlap between neighboring trees even at relatively high planting densities. As a result, clove inflorescences, which develop exclusively at terminal shoots on the outer crown surface, remain largely exposed to incident light despite the presence of neighboring trees, so that P_{att} is limited by

peripheral flowering site availability rather than by light competition with neighbors. Second, allelopathic properties of clove extracts and eugenol have been demonstrated to inhibit seed germination of understory plant species under laboratory conditions (Mazzafera 2003; Jose and Surendran 2020). In the field context of steep hillslopes with limited management access, this mechanism could partially limit the establishment of fast-growing understory vegetation, reducing competition for soil water and nutrients, a competitive pressure that the Schütz index does not capture, as it considers only neighboring trees rather than understory vegetation. Whether naturally occurring eugenol concentrations are sufficient to produce such effects at the field scale remains untested. It is also worth noting that neighboring trees may provide partial wind protection during the critical floral bud initiation period, potentially offsetting their negative competitive effects on light and water availability. Farmers reported that trees better protected from wind during the *manandoka* period (January-April; Razakaratrimo et al. 2018) tended to produce higher and more consistent yields, suggesting that the net effect of neighboring trees on clove production may be context-dependent. The fixed 7 m radius used to compute the Schütz index, while chosen to reflect typical Malagasy interplanting distances (Danthu et al. 2014), may not fully capture the actual competitive zone of clove trees given their shallow root system (Maistre 1955), and future studies should evaluate the sensitivity of competition estimates to neighborhood radius in these agroforestry configurations.

Among production-defining factors not included in the frontier model, climatic variables including temperature, solar radiation, and atmospheric CO_2 concentration are known to influence reproductive physiology and carbon assimilation in perennial crops (van Ittersum et al. 2013). As described in Section 2.5, temperature showed negligible inter-annual variation and rainfall was collinear with the harvest year variable, precluding their inclusion as production-defining factors. Finer-scale variation in solar radiation and vapor pressure deficit, which could not be assessed at the field level with ERA5-Land reanalysis data alone, may contribute to residual unexplained variation in P_{att} among fields. Future studies incorporating in situ microclimatic measurements would help disentangle these effects from structural and competitive determinants.

Drivers of production inefficiency

Inter-annual variation dominated the inefficiency structure: the 2025 coefficient (93.9, $p < 0.001$) indicated a dramatic increase in relative production gaps relative to 2024, consistent with the irregular flowering cycles characteristic of clove and explored further in Section 3.2.

Altitude and slope were retained in the inefficiency model as between-field control covariates rather than as individually interpretable inefficiency determinants. Their joint contribution to model fit was marginal (likelihood ratio test: $\chi^2(2) = 4.87$, $p = 0.088$) and individual coefficients were non-significantly different from 0 ($p = 0.106$ and $p = 0.367$, respectively). Nevertheless, their exclusion substantially altered the estimates of other inefficiency parameters, particularly the year effect (93.9 vs. 68.3) and weeding frequency (-16.3 vs. -25.6), indicating that they absorb between-field variance that would otherwise

confound these estimates. The two variables were, moreover, moderately correlated at the field scale (Spearman rho = 0.63, p = 0.044), which prevents partitioning of their individual contributions.

The negative signs of both coefficients suggest a tendency for higher-altitude and steeper-slope fields to show smaller production gaps. Rather than a direct topographic effect on soil resources, this pattern likely reflects confounding with plantation age and farmer experience: higher-altitude fields in the study valley coincided with older, more established plantations managed by more experienced farmers. The limited between-field variation (n = 11 fields; altitude range 97–211 m) and the absence of direct soil measurements further preclude robust independent interpretation of these topographic effects.

Weeding frequency had a borderline significant negative effect on inefficiency (coefficient = -16.3, p = 0.050), indicating that fields receiving more frequent manual weeding tended to exhibit smaller relative production gaps. Within the observed range of 1 to 2 interventions per year, the beneficial effects of reduced weed competition for soil nitrogen availability (Martin and Dabek 1988) likely explain this pattern. Farmers confirmed that well-weeded plots tend to produce more consistently, and noted that weeding residues are left at the base of trees as mulch rather than exported, which may further enhance soil moisture retention and nutrient cycling, consistent with experimental evidence that leaf litter accumulation under clove trees improves water and nutrient availability (Martin 1990). This effect may also partly reflect covariation with overall farmer management attentiveness and resource endowment: in smallholder systems, farmers with greater access to labor and capital tend to invest more broadly across all management practices simultaneously, making it difficult to isolate the specific contribution of weeding alone (Tittonell and Giller 2013).

Several production-limiting and production-reducing factors could not be included in the inefficiency model. Soil fertility and water availability are primary drivers of suboptimal tree nutrition in tropical agroforestry systems, but neither could be directly measured here: no soil sampling was conducted, farmers do not irrigate or fertilize their clove trees in the study area, and field topography served only as a coarse proxy for pedoclimatic conditions. Direct measurement of soil physical and chemical properties across fields would be required to disentangle the contributions of nutrient and water availability to production inefficiency. Farmers additionally identified the collection of *karetsiky* (fallen clove leaves harvested for essential oil distillation) as a progressive driver of soil fertility decline, noting that repeated raking removes the superficial organic layer and exposes surface roots, a practice that acts in direct opposition to the beneficial mulching effect of weeding residues described above, and which is consistent with experimental observations that mechanical disturbance of surface soil around clove trees causes root exposure and progressive soil loss (Martin 1990). Since *karetsiky* collection intensity was not recorded in this study, its contribution to between-field variability in soil fertility and production inefficiency could not be assessed, and represents an additional unmeasured factor warranting inclusion in future monitoring. Future studies should also quantify *andretra* (*Chrysotypus mabilianum*) infestation intensity continuously, as this wood-boring caterpillar can harbor between 1 and 40 larvae per tree annually (Dubois and Ranaivosoa 1966), damaging internal wood tissue and potentially reducing the aerial biomass available for flowering, with its contribution to between-tree variability in production gaps

remaining unresolved. The contribution of these unmeasured field-scale factors to between-field variability in production gaps is further explored in Section 3.2, where a mixed model approach is used to quantify the relative importance of field-level versus tree-level drivers of inter-annual production change.

Inter-annual variability and climatic drivers

Production collapse and heterogeneity of individual tree responses

Between 2024 and 2025, mean actual production declined by 67%, from 4.6 ± 5.5 to 1.5 ± 2.5 kg tree^{-1} (Wilcoxon signed-rank, $p < 0.001$). In 2024, no tree showed complete reproductive failure, though production was already highly variable (interquartile range: 1.3 to 5.6 kg tree^{-1}, median: 2.5 kg tree^{-1}). In 2025, 34% of trees exhibited complete reproductive failure, and median production fell to 0.5 kg tree^{-1} (interquartile range: 0.0 to 1.7 kg tree^{-1}). Load index declined from 104.4 ± 90.9 to 31.8 ± 44.5 g m^{-2} ($p < 0.001$), indicating that the production decline was not an artifact of crown size differences among trees. The relative production gap widened from 72.1 ± 24.0% in 2024 to 91.5 ± 11.9% in 2025, while mean efficiency declined from 0.28 ± 0.24 to 0.09 ± 0.12 ($p < 0.001$). Because production-defining factors were measured once and held constant across years, attainable production was identical by model construction in both seasons (17.4 ± 12.3 kg tree^{-1}). The 2025 collapse therefore entirely reflects increased inefficiency rather than any change in attainable production capacity, an interpretation consistent with the absence of major physical disturbance to the sampled trees between seasons.

This average decline masked extreme heterogeneity in individual tree responses (Fig. 3). Among the 126 monitored trees, 43 (34.1%) experienced total production collapse, 46 (36.5%) severe decline, 15 (11.9%) moderate decline, and 22 (17.5%) stable or increasing production (Fig. 3a). The median relative production change across all 126 trees was − 84% (Fig. 3b). Among trees with stable or increasing production, 9 (7.1%) achieved gains exceeding + 20% relative to 2024. These trees likely represent individuals in an ascending phase of the endogenous flowering cycle, having accumulated larger carbohydrate reserves during a relatively low-production 2024 season (Razakaratrimo et al. 2018; Goldschmidt and Sadka 2021).

Crown surface area, DBH, and Schütz index did not explain differences in relative production change between years (Kruskal-Wallis: all $p > 0.05$; Spearman: all $p > 0.05$). The 2024 flowering intensity was the only variable that differed significantly across production change categories (Kruskal-Wallis: $\chi^2(3) = 10.84$, $p = 0.013$): trees with stable or increasing production in 2025 had significantly lower 2024 flowering intensity than severely declining trees (means: 30.7% vs. 56.6%; Bonferroni-corrected $p = 0.007$). However, no significant linear relationship between 2024 flowering intensity and relative production change was detected (Spearman $p = 0.206$; Fig. 3c). This pattern is consistent with a threshold depletion effect rather than a continuous one (Goldschmidt and Sadka 2021): heavy flowering in 2024 increased vulnerability to severe decline without determining the magnitude of the reduction in actual production.

The linear mixed model with field as random effect and altitude, slope, and weeding frequency as fixed effects explained 27.7% of variance in relative production change ($R^2c = 0.277$), with fixed effects alone accounting for 8.2% ($R^2m = 0.082$). The addition of individual tree-level variables did not significantly improve model fit (likelihood ratio test: $p = 0.190$), confirming that structural tree characteristics did not explain between-tree differences in production change.

The strong field-level effect was confirmed by a Kruskal-Wallis test ($\chi^2(10) = 35.43$, $p < 0.001$), with mean relative production gaps ranging from 45.5% to 93.0% across the 11 monitored fields, and median relative production change between 2024 and 2025 ranging from – 3.7% to -100% depending on the field. The predominance of the field-level random effect points to unmeasured factors operating at the field scale, including those identified in Section 3.1, such as soil fertility - which could be impacted by *karetsiky* collection intensity - plantation age, and farmer experience, but also field-scale synchrony of flowering driven by shared microclimate and management history among trees of similar age within a field. Farmers similarly reported the existence of consistently good and poor producing fields in the village, confirming that some fields maintained production while others experienced near-total collapse.

The large variability in individual production changes likely reflects the superimposition of the climatic stress signal onto individual variation in two interacting factors. First, trees with lower flowering intensity in 2024 had likely accumulated larger carbohydrate reserves, enabling sustained or increased reproductive output in 2025 (Goldschmidt and Sadka 2021). Second, trees reaching sensitive floral bud initiation stages at different times during the January-April period may have been differentially exposed to climatic stress, as individual variation in the timing of floral bud initiation has been observed in clove (Razakaratrimo et al. 2018)

Climatic determinants of inter-annual production variability

The 2025 production collapse coincided with markedly different climatic conditions during this critical period. ERA5-Land data for the two monitored seasons were compared with the 2017 reference high-production year. Cumulative January-April rainfall differed markedly across the three years: 1,771 mm in 2024, 1,119 mm in 2017, and 1,074 mm in 2025. Despite similar cumulative totals in 2017 and 2025, rainfall distribution differed substantially (Fig. 4): RX5day reached 368 mm in 2017 and 348 mm in 2024, compared to only 216 mm in 2025, indicating weaker and more fragmented rainfall events in 2025. The longest dry spell reached 8 consecutive days in 2025 compared to only 3 days in 2017. Among the climatic variables examined, dry spell intensity and rainfall distribution most clearly differentiated 2025 from both 2024 and the 2017 reference year, suggesting that rainfall distribution rather than cumulative totals alone may be the more relevant driver of reproductive success during this period. Early work by De Haut De Sigy (1967) identified a regional-scale correlation between cumulative September-November rainfall and national clove export volumes in Madagascar, though the mechanistic interpretation of this relationship remains unclear given that this period overlaps with the clove harvesting season. Our study focuses on a distinct and mechanistically grounded window, the January-April period, during which floral

induction is thought to occur, and characterizes dry spell intensity rather than cumulative totals as a candidate driver of inter-annual production variability, at the field scale rather than the regional scale.

Visual inspection of daily rainfall patterns (Fig. 4) suggests contrasting seasonal distributions between the reference year 2017 and the low-production year 2025: in 2017, rainfall was relatively sparse before early March and more abundant thereafter, whereas in 2025 the pattern was reversed, with heavier rainfall concentrated in January-February followed by a prolonged water deficit from March onwards, coinciding with the period of active floral bud initiation. In 2024, rainfall was more evenly distributed throughout the period. Whether the timing of the transition from wet to dry conditions within the January-April window rather than its overall intensity is a primary driver of reproductive success remains to be tested across additional years.

Farmers confirmed during the restitution session that a good balance between dry and wet conditions during the *manandoka* period is critical for reproductive success, and that a prolonged water deficit rather than absolute drought, as rainfall occurred daily throughout the period, as experienced in 2025 is associated with production failure. Farmers also noted that wind during this period causes leaf and young inflorescence loss, and that abundant accumulation of *karetsiky* in March-April is locally perceived as an early indicator of a poor production season, as excessive leaf fall may reflect both wind-induced mechanical stress and water deficit during floral bud initiation. ERA5-Land wind data did not reveal marked inter-annual differences in mean wind speed during January-April (1.86 m/s in 2017, 2.17 m/s in 2024, 1.75 m/s in 2025), but these daily average values do not capture short-duration gusts that may be responsible for the bud detachment reported by farmers.

Mean temperature showed negligible variation across the three years during January-April (25.0°C in 2017, 25.3°C in 2024, 25.9°C in 2025), confirming that mean temperature cannot account for the observed inter-annual differences in production. However, the number of days with maximum temperature exceeding 30°C was notably higher in 2025 (24 days) than in 2024 (9 days) or 2017 (12 days). Critically, these high-temperature episodes in 2025 systematically coincided with periods of near-zero rainfall: a first episode occurred in late January (25–31 January, T_{max} up to 33.8°C, daily rainfall below 2 mm), and a second, more intense episode occurred in late February to early March (26 February – 4 March, T_{max} up to 34.2°C, daily rainfall below 1 mm), coinciding with the period of active floral bud initiation. This co-occurrence of thermal and water stress may have intensified evaporative demand and further compromised floral induction during this critical window.

Whether the 2025 collapse reflects climatic stress, endogenous low-flowering phases, or their interaction cannot be resolved from two years of observation. Farmers themselves reported a shift in production dynamics since the 1980s: production cycles previously marked by clear five-year peaks have become less predictable since 2020, which they attribute to changing climate. ERA5-Land data provide only 0.1° spatial resolution, plot-level soil water status was unmeasured, and the number of contrasted seasons available remains limited. Multi-year validation with in situ hydrometeorological data is required to

establish causality and determine the relative importance of rainfall timing, distribution, and intensity in clove reproductive dynamics.

4. Conclusion

This study demonstrates for the first time that tree-scale production gap analysis is applicable to irregular-flowering perennial crops embedded in structurally complex agroforestry systems, extending the method developed for intensively managed mango orchards (Sarron et al. 2023) to a smallholder context with minimal agronomic inputs. Mean actual production of 3.1 kg tree^{-1} (fresh weight with stems) is broadly consistent with historical estimates for Madagascar, where individual tree production ranges from approximately 1 to 25 kg of dried buds per year depending on tree age, size, and year (Maistre 1955; Roth et al. 2019), and where production in good years was reported at approximately 3 kg of dried buds for trees of around 15 years (Maistre 1955). The wide range observed in our sample, from 0 to 35 kg tree^{-1} fresh weight with stems, is consistent with this documented heterogeneity, though direct comparison remains limited by differences in measurement units (fresh weight with stems versus dried buds) and inter-annual variability. Mean attainable production of 17.4 kg tree^{-1} yielded an average production gap of 81.8%, substantially larger than the 37.5% gap reported for mango under extensive smallholder management (Sarron et al. 2023). This large gap is consistent with two non-mutually exclusive factors: the irregular flowering behavior characteristic of clove, and the minimal agronomic inputs characteristic of smallholder agroforestry systems in the study area. Disentangling their relative contributions would require multi-year monitoring under contrasting management conditions.

Crown surface area and trunk diameter defined the structural production ceiling, confirming that crown expansion through adapted pruning and spacing represents the primary lever for increasing attainable production at the tree scale. Weeding frequency emerged as a significant management driver of production inefficiency, suggesting that more frequent weed control could reduce production gaps in fields where labor and capital allow. January-April rainfall distribution and dry spell intensity coincided with the inter-annual production collapse observed between 2024 and 2025, identifying this climatic window as a candidate early indicator of clove production seasons, although causal interpretation requires validation across additional seasons.

Several limitations constrain the interpretation of these results. The two-year observation period prevents robust separation of endogenous flowering cycles from climatic effects, and the absence of soil measurements limits the characterization of production-limiting factors at the field scale. Yet our results consistently show that both types of factors influence clove production: structural and management factors operating at the tree and field scale, respectively, drive the magnitude of production gaps, while climatic variability during the January-April period drives their inter-annual dynamics. Future work should therefore prioritize multi-year monitoring to disentangle the contributions of irregular flowering cycles and climatic variability, in situ hydrometeorological measurements to resolve the role of rainfall distribution at fine spatial and temporal scales, and direct soil characterization to quantify nutrient and water availability as drivers of production inefficiency. Coupling the production gap method

with UAV-derived crown variables would further enable field-scale estimates of attainable production without exhaustive ground campaigns, extending its operational applicability to clove production management in Madagascar and beyond.

Declarations

Declarations

Conflicts of interest

The authors have no relevant financial or non-financial interests to disclose.

Ethics approval

The CIRAD ethics committee does not deliver ethical approval for research involving humans. The work was carried out in collaboration with the University of Antananarivo within the framework of the 'Forêts et Biodiversité à Madagascar' platform (CIRAD-FOFIFA-University of Antananarivo). Before conducting the study, a meeting was organized with the village leader and farmers of Antsirakoraka to fully inform them of the purpose, methodology, and expected benefits of the research. Written consent was provided by the village leader.

Consent to participate

All farmers participated voluntarily and were free from coercion, with the right to withdraw at any time. Participation was formalized through written purchase agreements for clove bud harvest, which constituted explicit consent for tree access, exhaustive harvest monitoring, and use of production data for research purposes. The involvement of a locally-born field assistant ensured that local rules, customs, and the rights and well-being of participants were respected throughout the study.

Consent for publication

Not applicable.

AI use statement

Claude Sonnet 4.6 (Anthropic) was used to assist with English writing and reformulation during manuscript preparation. All content was reviewed, validated, and approved by the authors. The authors take full responsibility for the integrity of the work.

Funding

This study was funded by the French National Research Agency (ANR) under Grant Agreement No. ANR-22-CE32-0002 (BiodivClo project). Institutional support was provided by Cirad, FOFIFA, and the 'Forêts et Biodiversité à Madagascar' collaboration platform.

Authors' contributions

Conceptualization: M.D., J.S., É.M. and P.D.; Methodology: M.D., J.S., É.M. and F.N.; Software: M.D. and M.R.; Investigation: M.D., M.R. and V.R.; Formal analysis: M.D. and M.R.; Visualization: M.D.; Writing – original draft: M.D.; Writing – review and editing: M.D., É.M., P.D., I.M., F.N., V.R. and J.S.; Supervision: J.S., É.M., I.M. and P.D.; Project administration: J.S.; Funding acquisition: J.S.

Acknowledgements

We express our gratitude to the farmers and local authorities of Antsirakoraka for their hospitality and support during data collection. Fieldwork was conducted within the BiodivClo project ("Biodiversity for the resilience of clove-based agroecosystems in Madagascar"), coordinated by CIRAD (UPR HortSys) in collaboration with FOFIFA (Madagascar), within the framework of the research partnership platform ‘Forêts et Biodiversité à Madagascar’. We warmly thank Corélie Chancelle Hantanirina (FOFIFA CRR-Est, Toamasina) and Tahianjanahary Razafimahaleo for their invaluable support during fieldwork. We are grateful to David Marsh for careful English proofreading.

Data availability

The datasets generated and analyzed during the current study are not publicly available but are available from the corresponding author on reasonable request.

Code availability

R scripts developed for stochastic frontier analysis, drone-derived canopy variable extraction, and statistical analyses are available from the corresponding author on reasonable request.

References

1. Arimalala N, Penot E, Michels T et al (2019) Clove based cropping systems on the east coast of Madagascar: how history leaves its mark on the landscape. Agroforest Syst 93:1577–1592. https://doi.org/10.1007/s10457-018-0268-9
2. Battese GE, Coelli TJ (1995) A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir Econ 20:325–332. https://doi.org/10.1007/BF01205442
3. Coelli T, Henningsen A (2020) frontier: Stochastic Frontier Analysis

4. Danthu P, Penot E, Ranoarisoa KM et al (2014) Le giroflier de Madagascar: une introduction réussie, un avenir à construire. Bois trop 320:83–96. https://doi.org/10.19182/bft2014.320.a20547
5. Danthu P, Sarron J, Penot E et al (2024) The agroforests of the east coast of Madagascar. Trop Issues 136–142. https://doi.org/10.55515/HDZZ3352
6. Danthu P, Simanjuntak R, Fawbush F et al (2020) The clove tree and its products (clove bud, clove oil, eugenol): Prosperous today but what of tomorrow's restrictions? Fruits 75:224–242. https://doi.org/10.17660/th2020/75.5.5
7. Darwati I, Santoso TJ, Rachmat A et al (2025) Isolation and expression of terminal flower1 (TFL1) gene in clove (Syzygium aromaticum L). BMC Res Notes 19:4. https://doi.org/10.1186/s13104-025-07581-w
8. De Sigy H G (1967) Contribution à l'étude de la production de clous de girofle à Madagascar en rapport avec la pluviométrie, vol 11. Institut de Recherches Agronomiques à Madagascar
9. Desmurs M, Sarron J, Rahantarivelo E et al (2026) Diversification–specialisation dynamics in Madagascar's clove landscapes: the role of rice land availability. Agroforest Syst 100:111. https://doi.org/10.1007/s10457-026-01491-x
10. Dubois J, Ranaivosoa H (1966) Chrysotypus mabilianum Viette chenille mineuse du giroflier (Andretra). Biologie et lutte mécanique. L'Agronomie Tropicale Série 3 Agronomie Générale Etudes Scientifiques 21:822–836
11. Goldschmidt EE, Sadka A (2021) Yield alternation: horticulture, physiology, molecular biology, and evolution. Hortic reviews 48:363–418
12. Hijmans RJ (2024) terra: Spatial Data Analysis
13. ITC (2025) Trade Map. https://www.trademap.org. Accessed 26 Mar 2026
14. Jose AM, Surendran D (2020) Comparative allelopathic effect of Syzygium aromaticum and Myristica fragrans on seed germination of Amaranthus cruentus. J Adv Sci Res 11:347–349
15. Lüdecke D, Ben-Shachar MS, Patil I et al (2021) performance: An R Package for Assessment, Comparison and Testing of Statistical Models. J Open Source Softw 6:3139. https://doi.org/10.21105/joss.03139
16. Maistre J (1955) Le giroflier à Madagascar et Zanzibar. L'Agronomie tropicale 10:413–448
17. Malézieux E (2012) Designing cropping systems from nature. Agron Sustain Dev 32:15–29. https://doi.org/10.1007/s13593-011-0027-z
18. Mariel J, Freycon V, Randriamalala J et al (2022) Local Knowledge of the Interactions between Agrobiodiversity and Soil: A Fertile Substrate for Adapting to Changes in the Soil in Madagascar? J Ethnobiol 42:180–197. https://doi.org/10.2993/0278-0771-42.2.180
19. Mariel J, Penot E, Labeyrie V et al (2023) From shifting rice cultivation (tavy) to agroforestry systems: a century of changing land use on the East Coast of Madagascar. Agroforest Syst 97:415–431. https://doi.org/10.1007/s10457-022-00761-8

20. Martin PJ (1990) Comparison of the growth and yielding of clove trees under different ring weeding and fertilizer regimens. Crop Prot 9:415–421. https://doi.org/10.1016/0261-2194(90)90130-Y
21. Martin PJ, Dabek AJ (1988) The role of agronomic factors in the juvenile decline condition of clove trees in Zanzibar. Trop Pest Manag 34:271–277. https://doi.org/10.1080/09670878809371256
22. Martin PJ, Riley J (1989) Indirect method for estimating clove tree yields. Trop Agric 66:361–364
23. Mazzafera P (2003) Efeito alelopático do extrato alcoólico do cravo-da-índia e eugenol. Braz J Bot 26:231–238
24. Mbow C, Smith P, Skole D et al (2014) Achieving mitigation and adaptation to climate change through sustainable agroforestry practices in Africa. Curr Opin Environ Sustain 6:8–14. https://doi.org/10.1016/j.cosust.2013.09.002
25. Muñoz-Sabater J, Dutra E, Agustí-Panareda A et al (2021) ERA5-Land: a state-of-the-art global reanalysis dataset for land applications. Earth Syst Sci Data 13:4349–4383. https://doi.org/10.5194/essd-13-4349-2021
26. Nakagawa S, Schielzeth H (2013) A general and simple method for obtaining R^2 from generalized linear mixed-effects models. Methods Ecol Evol 4:133–142. https://doi.org/10.1111/j.2041-210x.2012.00261.x
27. Normand F, Lauri P-É (2018) Advances in understanding mango tree growth and canopy development. In: Galán Saúco V, Lu P (eds) Achieving sustainable cultivation of mangoes. Burleigh Dodds Science Publishing, Cambridge, pp 87–119 (ISBN 978-1-78676-132-3)
28. Pebesma E (2018) Simple Features for R: Standardized Support for Spatial Vector Data. R J 10:439–446. https://doi.org/10.32614/RJ-2018-009
29. Plowright A (2023) ForestTools: Tools for Analyzing. Remote Sensing Forest Data
30. R Core Team (2023) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria
31. Razafimamonjison G, Jahiel M, Ramanoelina P et al (2013) Effects of phenological stages on yield and composition of essential oil of Syzygium aromaticum buds from Madagascar. Int J Basic Appl Sci 2:312–318. https://doi.org/10.14419/ijbas.v2i4.1100
32. Razakaratrimo JT, Jahiel M, Jeannoda V, Normand F (2018) Phenology and flowering of the clove tree, an irregular bearing spice crop. Acta Hortic 1228:369–376. https://doi.org/10.17660/ActaHortic.2018.1228.55
33. Roth SIB, Leiterer R, Volpi M et al (2019) Automated detection of individual clove trees for yield quantification in northeastern Madagascar based on multi-spectral satellite data. Remote Sens Environ 221:144–156. https://doi.org/10.1016/j.rse.2018.11.009
34. Sarron J, Faye E, Nordey T et al (2023) Assessing production gaps at the tree scale: definition and application to mango (Mangifera indica L.) in West Africa. Agron Sustain Dev 43:62. https://doi.org/10.1007/s13593-023-00920-w

35. Sarron J, Malézieux É, Sané CAB, Faye É (2018) Mango Yield Mapping at the Orchard Scale Based on Tree Structure and Land Cover Assessed by UAV. Remote Sensing 10:1900. https://doi.org/10.3390/rs10121900
36. Schütz J-P (1989) Zum Problem der Konkurrenz in Mischbeständen. Schweizerische Z fur Forstwesen 140:1069–1083
37. Tittonell P, Giller KE (2013) When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. Field Crops Res 143:76–90. https://doi.org/10.1016/j.fcr.2012.10.007
38. Van Ittersum MK, Cassman KG, Grassini P et al (2013) Yield gap analysis with local to global relevance—A review. Field Crops Res 143:4–17. https://doi.org/10.1016/j.fcr.2012.09.009
39. Woittiez LS, Van Wijk MT, Slingerland M et al (2017) Yield gaps in oil palm: A quantitative review of contributing factors. Eur J Agron 83:57–77. https://doi.org/10.1016/j.eja.2016.11.002
40. Zhang D, Wang C, Li X et al (2019) Correlation of production constraints with the yield gap of apple cropping systems in Luochuan County, China. J Integr Agric 18:1714–1725. https://doi.org/10.1016/S2095-3119(18)62098-2

Figures

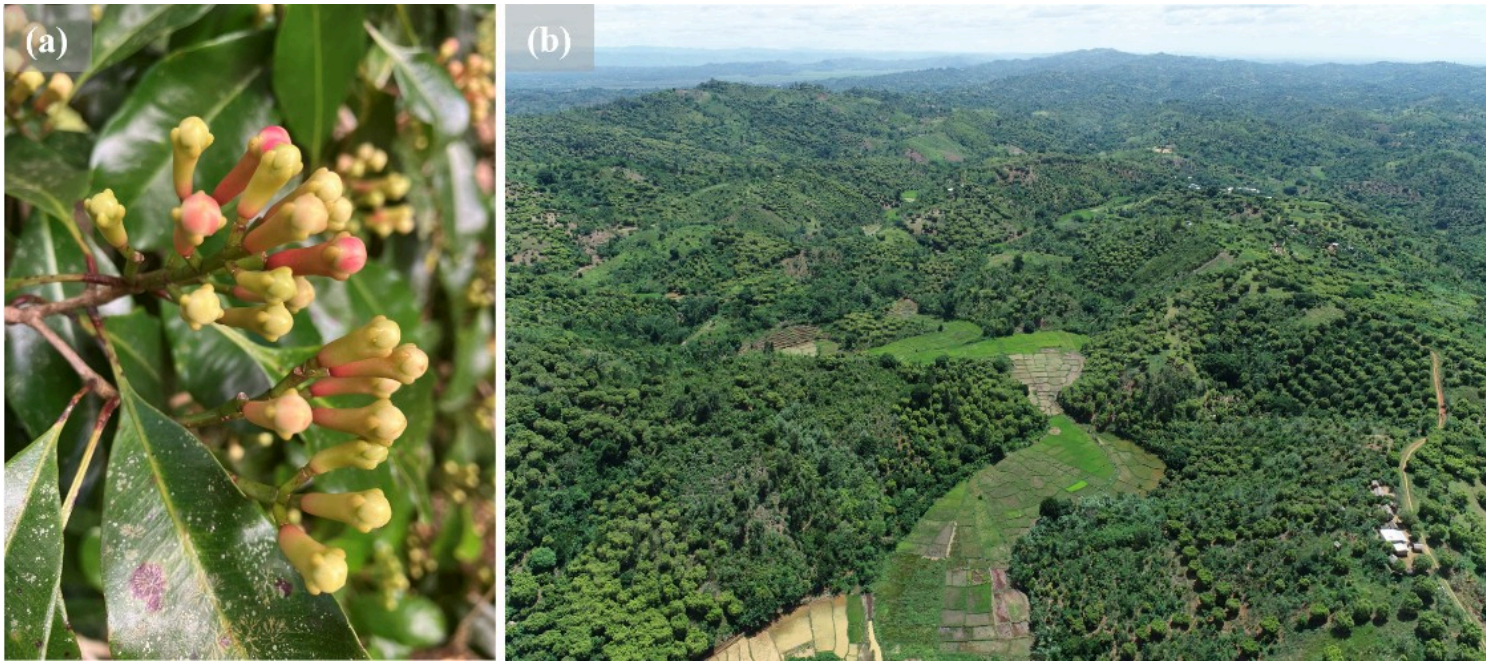


Figure 1

(a) Clove buds (*S. aromaticum*) at optimal harvest stage (Photocredit: M. Desmurs) (b) Landscape-scale view of clove-based agroforestry systems embedded in a mosaic of cultivated fields and forest patches on Madagascar's east coast. (Photocredit: J. Sarron)

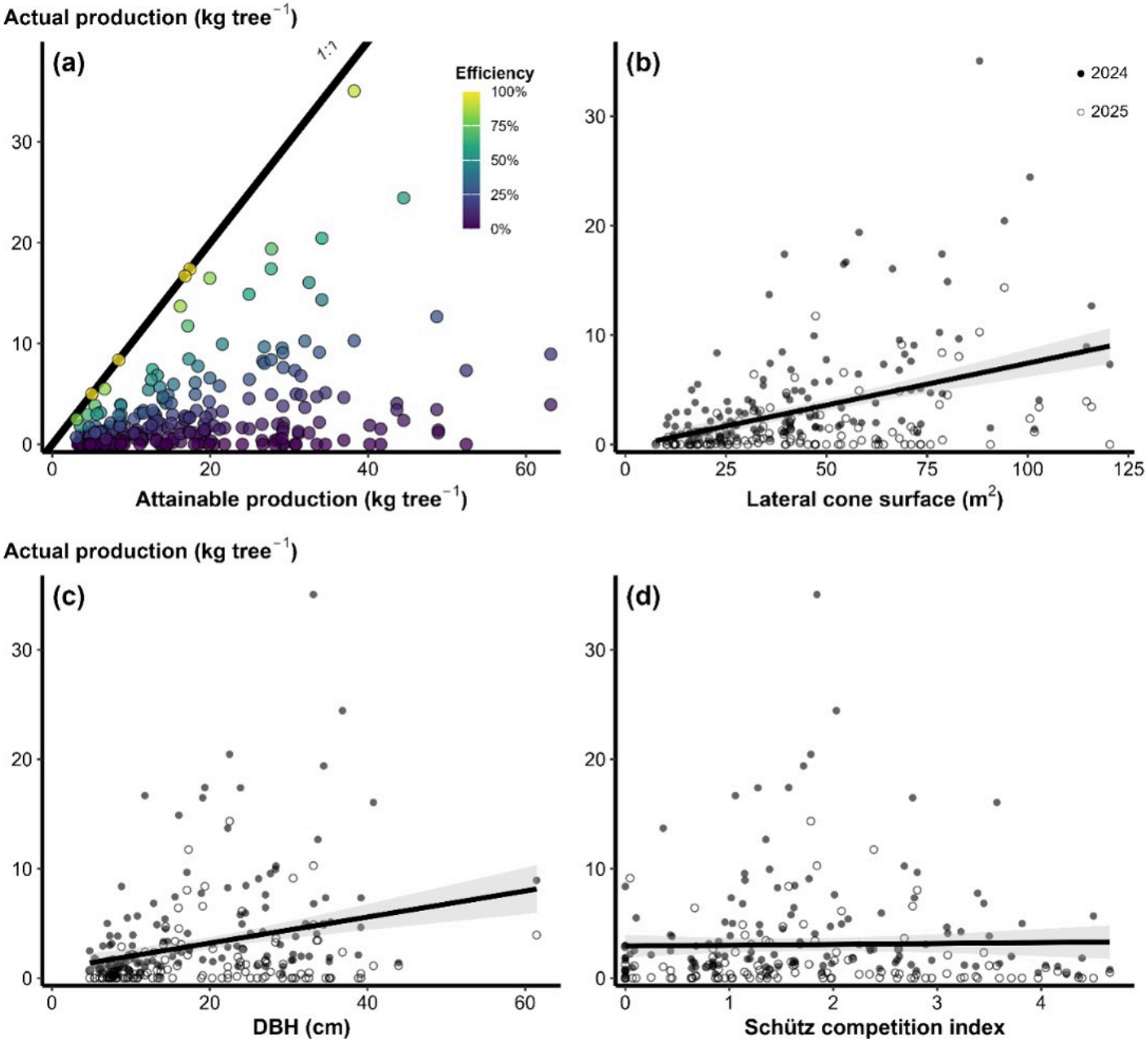


Figure 2

Structural determinants of actual clove production (n = 252 tree-years; one data point per tree per year). (a) Actual vs. attainable production; solid line = 1:1; point color indicates tree-level efficiency E (continuous scale, 0-100%). (b-d) Actual production vs. lateral cone surface area S (b), DBH (c), and Schütz competition index (d); solid lines = linear regression with 95% CI. Regression statistics: (b) R^2 = 0.19, $p < 0.001$; (c) R^2 = 0.08, $p < 0.001$; (d) $R^2 < 0.01$, $p = 0.84$. Filled circles = 2024, open circles = 2025.

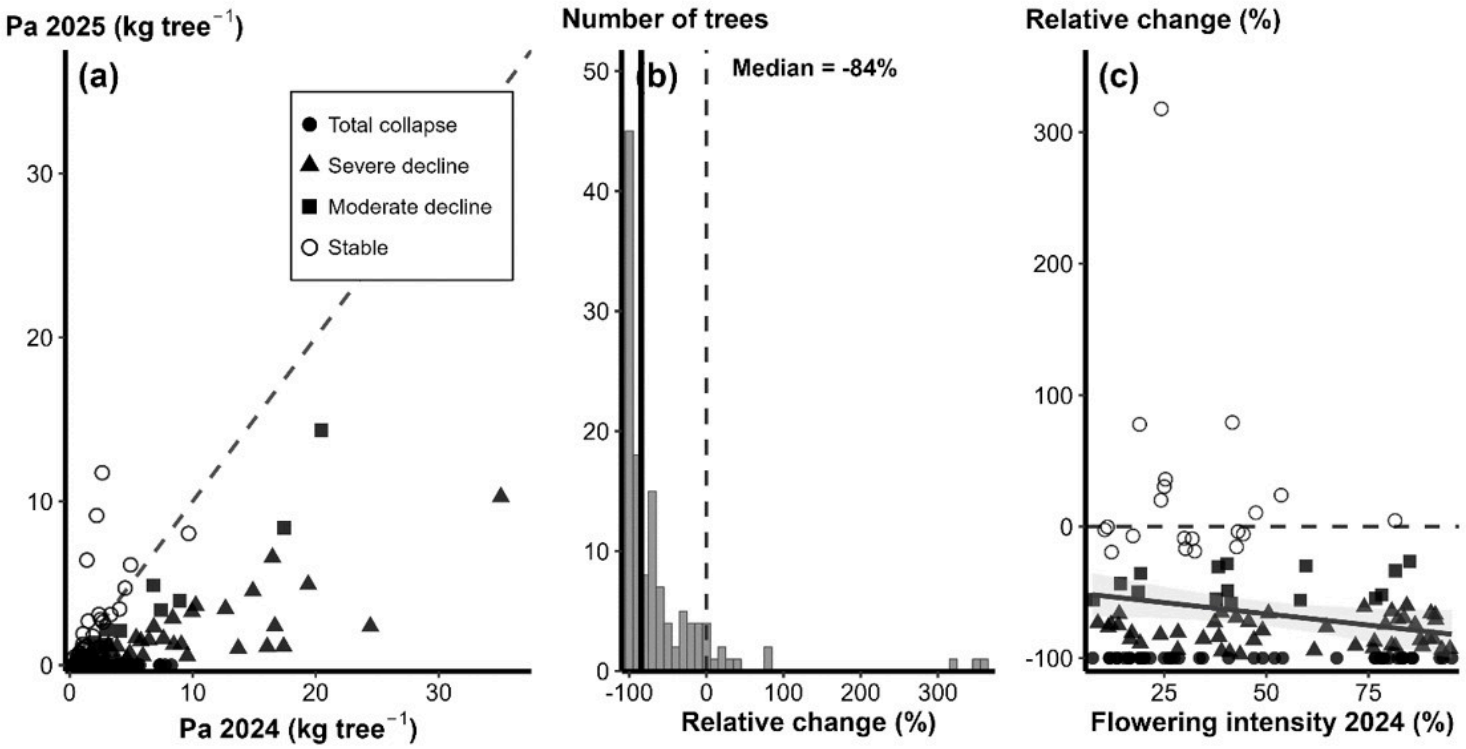


Figure 3

Inter-annual changes in actual production between 2024 and 2025 (n = 126 trees). (a) Pa in 2025 vs. 2024; dashed line = 1:1; filled circle = total collapse (Pa = 0), filled triangle = severe decline (>60% reduction), filled square = moderate decline (20-60%), open circle = stable or increasing (<20% decline). (b) Frequency distribution of relative production change; dashed vertical line = zero change; solid vertical line = median (-84%). (c) Relative production change vs. 2024 flowering intensity; dashed horizontal line = zero change; solid line = linear regression with 95% CI (Spearman rho = -0.11, p = 0.206); symbols as in (a).

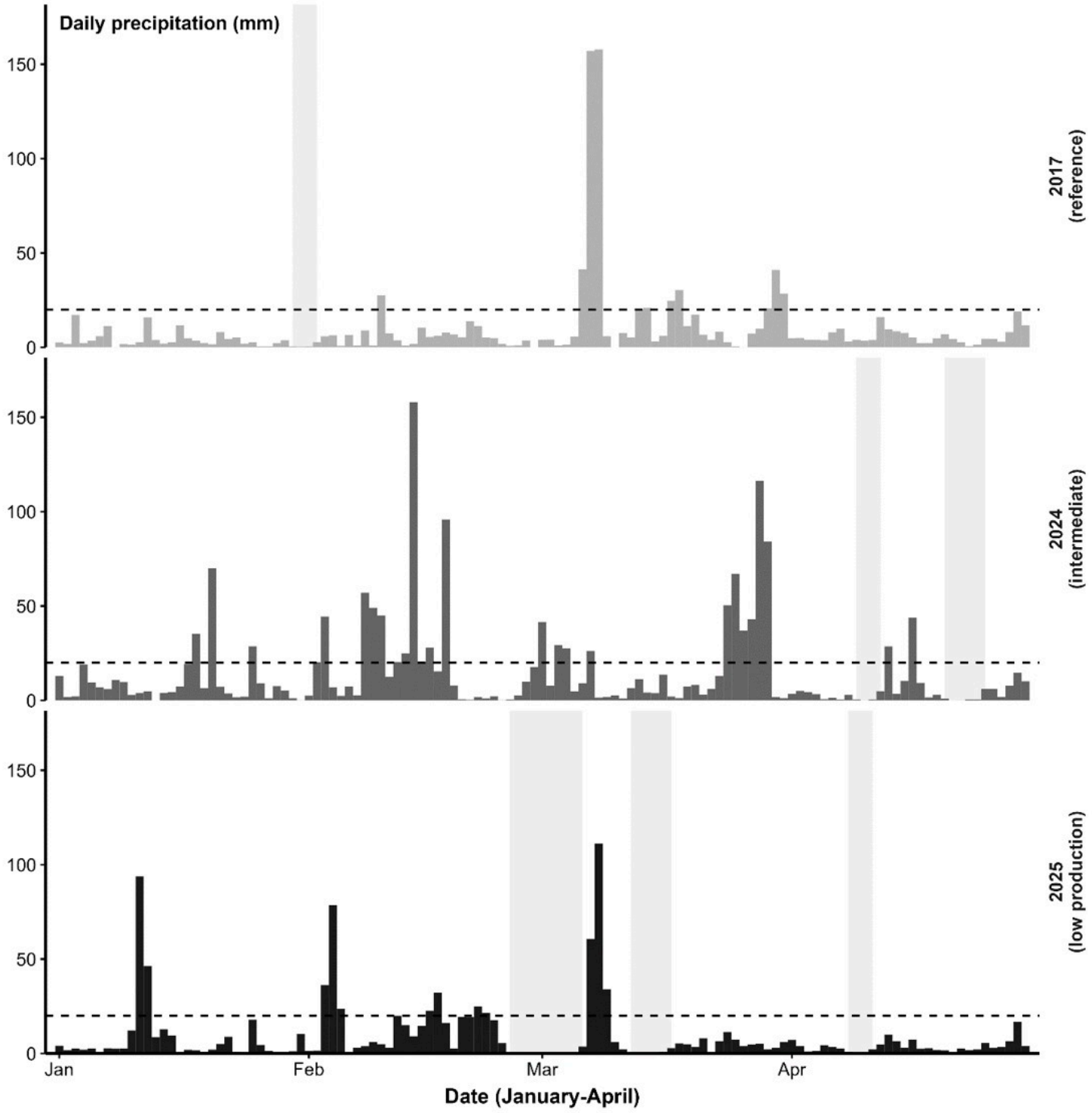


Figure 4

Daily precipitation (mm) during the January-April period, when floral bud initiation is thought to occur, for a reference high-production year (2017), an intermediate-production year (2024), and the low-production year (2025), derived from ERA5-Land atmospheric reanalysis data (Muñoz-Sabater et al. 2021). Dashed horizontal line indicates the 20 mm threshold. Grey shading indicates dry spells of three or more consecutive days with precipitation below 1 mm.