Heterogeneous multidimensional efficiency effects of agro-ecological pest management transition and intensification in smallholder systems: Evidence from mango fruit fly control in Kenya

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Abstract

Agro-ecological transition is an important step towards sustainable and resilient food systems in the face of systemic threats from climate-change-induced disturbances. In smallholder systems, the transition towards agro-ecological pest management (APM) offers the prospect of reconciling agronomic performance with environmental and social imperatives by replacing indiscriminate chemical applications with locally-derived biorational options. However, the efficiency implications of APM transitions remain insufficiently documented, particularly in smallholder systems and in relation to invasive alien pests that are prone to resurgence and reinfestation under suboptimal management. This paper evaluates whether the adoption and intensification of APM improve both technical and eco-efficiency in smallholder settings, with a focus on the Oriental fruit fly (*Bactrocera dorsalis* L.) in mango (*Mangifera indica* L.) orchards. We apply a latent class stochastic metafrontier model to a sample of 418 orchard managers from Makueni County, Kenya, selected through a multistage sampling procedure. This approach enables us to classify orchard managers into non-adopters, non-intensive adopters, and intensive adopters, and to compute meta-technical and meta-eco-efficiency scores, from which we derive an environmentally adjusted efficiency measure. We find no significant sample selection bias and treatment effects are estimated using a doubly robust Inverse-probability-weighted regression adjustment estimator. Intensive adoption had a positive average treatment effect (ATE) and average treatment effect on the treated (ATT) of 8.1% and 5.6%, respectively, whereas non-intensive adoption showed no significant effect (ATE = –1.1%, ATT = –1.5%). Efficiency effects were heterogeneous and inefficiency varied with orchard manager's APM adoption intensity, education level, orchard prospects, group membership, and participation in knowledge co-creation activities. Policymakers and development practitioners should support farmers by institutionalising continuous learning and establishing multi-pronged participatory training platforms that use existing social networks.

Keywords: agroecology, agro-ecological pest management, fruit fly, technical efficiency, eco-efficiency, environmentally adjusted efficiency, mango, latent class stochastic metafrontier

JEL Classification: C38 , D24 , Q12 , Q16 , Q57

1 Introduction

Agriculture faces the dual challenge of simultaneously decoupling productivity from environmental footprints while improving the food security for a growing global population [1]. Historically, attempts to improve productivity have relied on conventional intensification approaches, increasingly relying on external inputs to bolster food production and stabilise yields. The Green Revolution epitomised this paradigm, where the intensive use of synthetic pesticides, fertilisers, and improved cultivars drastically increased global food production by more than 50% [2, 3]. Although this intensification mitigated the need for additional land conversions, reducing the pressure on marginal lands, forests, and riparian areas to meet increasing food demand, the cumulative and pervasive reliance on synthetic damage-control inputs such as pesticides has led to a series of ecological, economic, and health-related concerns [4–7]. This has prompted calls for sustainable transitions that leverage ecological processes to maintain or increase yields.

Recently, a growing stream of literature has examined the extent to which sustainable intensification can match conventional yields in practice [8–11]. This debate is particularly relevant for smallholder systems, where resource constraints, as well as biotic and abiotic pressures, pose increasing threats to agricultural sustainability. Unlike organic systems that have been shown to achieve lower yields between 19–25% so that an increase of 23–33% in land size is required to meet the current output levels under conventional systems [12], agro-ecological systems have been found to improve yields as well as land and labour productivity in smallholder systems by countering local constraints [8, 13].

Mango (*Mangifera indica* L.) is Kenya's second most important fruit crop after banana [14]. However, tephritid fruit fly, particularly *Bactrocera dorsalis* (Diptera: Tephritidae), poses a major constraint to mango productivity and marketing, causing fruit and quality loss if improperly managed. This polyphagous pest inflicts extensive damage, with yield losses reported to range from 30% to as high as 90% [15, 16]. Female flies oviposit within the fruit, and subsequent larval feeding not only renders the fruit unmarketable, but also predisposes it to secondary bacterial infections, compounding yield losses [15]. Conventional fruit fly control typically relies on chemical insecticides, which often act quickly to reduce infestations but are often associated with high external costs, including pesticide residues, human health risks, loss of beneficial insects, and pest resistance [17]. In contrast, agro-ecological pest management (APM) offers a holistic alternative through a suite of locally available eco-friendly practices [18–26], including orchard sanitation, the release of natural enemies such as ovivorous ants and parasitoid wasps, the application of biopesticides, food baits, male annihilation technique [27], and other cultural and indigenous controls [28–31]. Transitioning to effective APM requires farmers to synchronise and intensify pest-control efforts not through blanket chemical applications but by adopting ecologically grounded, indigenous, locally available, knowledge-intensive biorational practices.

It has been argued that the conscious adoption of agro-ecological practices can potentially close yield gaps, maintain ecological integrity, reduce reliance on synthetic pesticides, and improve resource-use efficiency at the farm level [1, 17, 32, 33]. Farm-level analyses in Kenya found that APM-adopting mango smallholders obtained higher yields [29, 34] and higher net income [29, 34–37] while using significantly less inorganic pesticides [29, 38]. It has also been found that APM uptake increases inclusivity in decision making by enhancing women empowerment [39]. These findings support the optimistic view that APM can improve both productivity, social and environmental performance of farming systems, ultimately enhancing eco-efficiency.

Eco-efficiency (EE) refers to the ratio of economic value added to the associated deleterious environmental impacts [40, 41]. The EE index requires optimising the ratio of agricultural outputs to environmental impacts and has been promoted as a strategy to quantify the benefits of sustainable pest management, such as APM [42–44]. By lowering the environmental footprint of food production without sacrificing yield, APM can increase the output gained per unit of environmental cost, a key requirement for sustainability.

Extant studies on the EE of mango production vary considerably in scope, context and methodology. Basset-Mens et al. [45] used a cradle-to-farm-gate life cycle analysis to compare locally grown and imported mango, apple, peach, and clementine in French markets. Their results showed that mango generally performed well in various environmental impact categories such as eco-toxicity and eutrophication. However, the authors acknowledged that fruit fly was not as problematic in these contexts as it is in Africa. Additionally, due to the broader scope of the study, there were uncertainties in obtaining representative data for the individual crops, which could have increased uncertainty in the results. Similarly, in southern Iran, Rasoolizadeh et al. [46] evaluated the EE of five tropical fruits (guava, mango, banana, jujube, and sapodilla) using life cycle analysis approach. Mango emerged with the highest EE score, outperforming the other fruits. Although the life cycle analysis procedure is a useful approach in aggregation of environmental impacts, it is a subjective weighting method that relies on expert judgement in the assignment of pressure weights. This can potentially bias estimates as the resulting EE index could be a function of the expert's values and beliefs [47]. To overcome the pitfalls of life cycle analysis, Heidenreich et al. [48] employed an input-oriented order-m approach with Data Envelopment Analysis to measure EE among mango, macadamia, coffee and cocoa farms in Kenya and Ghana. Their findings indicated substantial variability, with mango farms ranking as least efficient and requiring a 25% cut in environmental pressures to reach optimal performance. Although the study accounted for regional heterogeneities in the production environment, the authors presupposed uniform production technologies and ecological conditions at the orchard level. The assumption of uniform production technologies is often restrictive and is rarely observed in smallholder systems.

Existing studies on the efficiency effects of pest management strategies have predominantly focused on economic performance, particularly technical efficiency (TE), while largely overlooking the environmental implications of such practices. For instance, Yi et al. [49] investigated productivity and TE disparities among shallot farmers in Indonesia, distinguishing growers by their compliance to alternative pest management protocols. Similarly, Rahman and Norton [50] examined the impacts of integrated pest management adoption on the TE of eggplant growers in Bangladesh. More recently, Rodrigues et al. [51] evaluated the TE of biological pest control adoption in Brazil, accounting for heterogeneity between intensive and non-intensive user subgroups.

In this paper, we contribute to this discourse by evaluating whether the transition to and intensive adoption of APM can enhance multidimensional farm-level efficiency. Following Andrieu et al. [52], we implement a multi-criteria approach to explicitly accommodate both economic and ecological performance of APM by analysing EE alongside the traditional TE. We then derive an environmentally adjusted efficiency score that reflects the dual objectives of optimising input conversion and minimising environmental externalities, providing a better picture from a sustainability perspective. To the best of our knowledge, this is the first attempt at examining the multidimensional efficiency effects of agro-ecological transitions in smallholder systems, particularly in relation to invasive alien pests that are prone to resurgence and reinfestation under suboptimal management.

The remainder of the paper is structured as follows. Section 2 describes the materials and methods including the study area, sampling procedure, data collection, and analytical framework. In Section 3, we present the empirical results and discuss the findings. We then conclude in Section 4 by outlining avenues for future research and prospects for scaling up agro-ecological transitions in smallholder systems, with reference to broader policy implications.

2 Materials and methods

2.1 Study area, sampling technique and data collection

We utilised a subset of observational data from a household survey conducted in Makueni county, Kenya. Makueni County spans an area of 8,214 square kilometres, located between latitudes $1°35'$ and $2°59'$S and longitudes $37°10'$ to $38°30'$E (Figure 1), with a population of approximately 1,098,584 [53]. The county majorly has a low-lying terrain, with diverse agro-ecological zones (see Figure 1). The hillier sections receive about 800–1200 mm of rainfall annually, whereas its lower plains receive as low annual rainfall as 250–400 mm. The county's average annual rainfall is estimated at 500–750 mm making it ideal for growing most crops. Mean air temperatures range from 20.2°C to 35.8°C, with the hills remaining noticeably cooler [54]. This warm climate favours production of fruit crops such as mango and citrus.

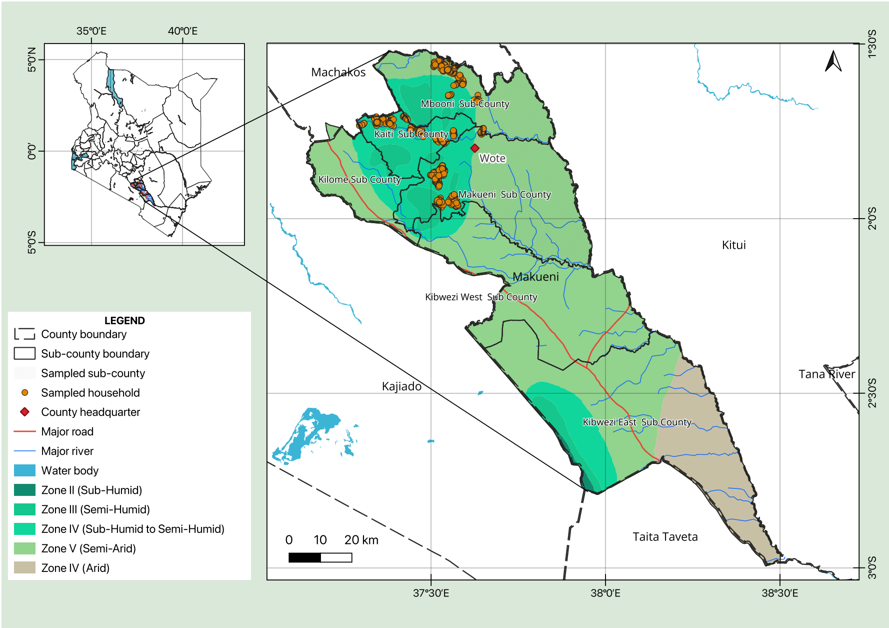


Fig. 1: Map of Makueni county showing its agro-ecological zones and location of sampled households.

To determine the required sample size, the Yamane [55] formula was applied, using a known population of 28,696 mango farmers in the county [56]. A multistage sampling strategy was implemented. First, Makueni County was purposively selected because it is Kenya's main mango producing region, facilitated, in part, by its proximity to important export hubs, such as Nairobi and Mombasa, as well as favourable climatic conditions for mango production. In the second stage, the Makueni, Mbooni, and Kaiti sub-counties were chosen due to their prominence in mango production. In the third stage, six wards and 12 sub-wards were randomly selected within these sub-counties. Finally, since almost all households in the selected areas grow mango, systematic random sampling was employed within these areas to select every third household.

Mango orchard managers were identified as key respondents due to their direct control and awareness of most orchard-level activities. The interviews were conducted between August and September 2023 by trained enumerators, with informed consent obtained at the beginning of each interview. Of 434 orchard managers interviewed, nine responses were excluded after controlling for non-exposure bias, and seven were discarded due to incomplete responses. This resulted in 418 valid responses for subsequent analyses.

2.2 Analytical framework

2.2.1 System boundary and life cycle inventory

We adopted a farm gate approach as the system boundary, so that production extends only to the point where materials leave the orchard, assuming no value addition occurs within the orchard. This delimitation ensures that all input quantities and ecological pressures are under direct control of the orchard manager. To allow global comparison, the functional unit chosen was one hectare (ha) of mango orchard and all inputs, outputs, and environmental pressures were normalised per ha. Typically, smallholder mango production involves farm activities such as tillage, fertilisation, control of pests, diseases, and weeds, and harvesting.

The selection of an eco-efficiency indicator depends on the availability of data, the interest of the policymaker, and the intended use of the resulting scores [11, 41], and remains largely an empirical matter [57]. We considered six environmental pressures from mango production following the relevant literature (Table 1). Water resource pressures were excluded because smallholder mango systems in SSA are predominantly rainfed.

We employed the value-added approach for the desirable output, net value added (NVA), which permits a natural interpretation of the EE scores. Since a typical mango farming household consumes part of its production, the NVA from mango was calculated incorporating the value of the fruit consumed. Following Kuosmanen and Kortelainen [47], labour costs were not deducted from the NVA because they represent wages and rents circulating within society, rather than costs of production. In contrast to regions where collusive practices among orchard owners and financiers intensify labour exploitation, thereby diminishing the overall societal benefits from farming, such as those documented by Sacramento and Cañete [72] in the context of Philippine mango fruit farming, the relatively competitive labour market in Makueni discourages such collusion behaviours, ultimately ensuring better protection for orchard labourers. Machinery depreciation and maintenance were not considered because smallholders in developing countries such as Kenya typically use negligible amounts of machinery in mango production.

All orchards were assumed to have a uniform selling price to ensure that variations in economic performance arise from technical management rather than price differences. Based on insights gathered from key informants, the market price of mango typically ranges between KES 15–30 per kilogram of fresh fruit, with fluctuations largely influenced by seasonality. Given that all yield data reported in this study pertain to the main (on-) season, when market prices are generally lower due to peak production, we adopted a conservative pricing approach by using the lower bound of the price range (KES 15/kg, corresponding to $\approx$ USD 0.117/kg based on the exchange rate at the time of the survey).

Table 1: Summary of indicators and equations used to measure environmental impacts in mango production

Indicator	Description	Computation	References and notes
Carbon footprint (CF)	Estimates total greenhouse gas (GHG) emissions from orchard i, accounting for external inputs, direct field emissions, and carbon sequestration potential.	$\mathrm{CF}_i = (\mathrm{GHG\ from\ inputs}_i + \mathrm{GHG\ from\ field}_i) - \mathrm{GHG\ sequestered}_i$, $\mathrm{GHG}_{i\psi} = \sum_{\psi=1}^{\Psi} (\mathrm{AD}_{i\psi} \cdot \mathrm{EF}_{\psi})$	Manure production (enteric fermentation) emissions excluded; 4 kg/CE/ha for field cultivation [58]. A ten-year-old mango orchard sequestration potential: 11.04tCO_2eq/ha (approx. 1.1tCO_2eq/ha/yr) [59]. Emission factors obtained from IPCC [60], Walling and Vaneeckhaute [61], Nayak et al. [62], Cech et al. [63].
Toxicity (TOX)	Quantifies toxicity from hazardous pesticides based on active ingredient quantities.	Based on total quantity (in kg AI/ha/yr) of hazardous active ingredients applied.	Hazardous classification per PAN International List 2024 [64]; cross-checked against Kenya Pest Control Products Board data.
Nutrient balance (N, P)	Measures nutrient (ζ_i) input-output gap to assess deficits or surpluses in nitrogen (N) and phosphorus (P) (in kg/ha/yr)	ζ_i balance $= \mathbf{a}' \cdot X_{\zeta i} - \mathbf{b}' \cdot Y_{\zeta i}$ ζ_i deficit $= \begin{cases} \mid \zeta_i \text{ balance} \mid, \text{if } \zeta_i \text{ balance} < 0 \\ 0, \text{otherwise} \end{cases}$ $\zeta_i \text{ surplus} = \begin{cases} \zeta_i \text{ balance}, \text{if } \zeta_i \text{ balance} > 0 \\ 0, \text{otherwise} \end{cases}$	Nutrient flows estimated from input labels and fruit composition data. Only deficit variables retained due to limited surplus observations[1]. Approach based on materials balance principle [65, 66].
Energy balance (EN)	Assesses energy inputs vs outputs (in MJ/ha/yr).	Input = energy from labour, manure, fertilisers, pesticides; Output = energy from harvested mango fruits.	Energy content: 0.25–0.795 MJ per 100g dried mango [67]. Fresh fruit composition: 83.4% water [68]. Emission/energy factors from Heimpel et al. [69].
Specialisation (SP)	Proxy for biodiversity loss due to monoculture tendency.	$\mathrm{SP}_i = \frac{\mathrm{Mango\ area}_i}{\mathrm{Total\ orchard\ area}_i}$	Higher values indicate increased monoculture and potential biodiversity loss. Based on Heidenreich et al. [48].

Notes: Abbreviations:—AD, activity data; AI, active ingredient; CE, carbon equivalent; CO_2eq, carbon dioxide equivalent; EF, emission factor; hg, hectogram; MJ, megajoules.

[1] Only two orchards exhibited nitrogen surplus and twelve phosphorus surplus; hence, surplus variables were omitted from the main analysis models. Ideally, nutrient balance would include soil stocks and be estimated dynamically [70, 71], but such data were not available.

2.3 Empirical framework

2.3.1 Latent class stochastic metafrontier

To assess the efficiency with which orchard managers convert resources into desirable outputs while limiting undesirable by-products, we employ a production-frontier approach rooted in classical efficiency theory [73]. In this framework, it is assumed that each orchard manager uses the inputs optimally to achieve the maximum possible output with minimum deleterious environmental impacts such as pollution or resource depletion. We adopt an output-oriented perspective to evaluate how much orchard managers can increase their desirable outputs without consuming additional inputs or increasing deleterious by-products. From a sustainability perspective, an orchard can be considered output inefficient while still having room to reduce environmental impacts. Pareto–Koopmans efficiency is achieved when no further improvements in yield or net value added are possible without increasing input or environmental degradation, thus balancing productivity, resource conservation, and broader societal goals [74, 75]. The production frontier represents the highest possible production level under similar technological and environmental conditions, and any deviation from this frontier is attributed to inefficiency [76].

Smallholders rarely use homogeneous technologies due to resource and socio-economic constraints, requiring a mechanism for accounting for potential technological heterogeneity in their production. However, the qualitative classification of individuals into technology-specific groups based on observed and unobserved characteristics is often a complex process that risks introducing bias, particularly when threshold identification levels are non-trivial. To address this challenge, we employ a latent class stochastic frontier (LCSF) procedure formalised in Greene [77] to estimate the posterior probability, $\mathbf{\Pi}(i, j)$, of an orchard manager i's membership in class j, conditioned on observed (separating) variables $\mathbf{s}_i$. The class assignment is usually based on the largest $\mathbf{\Pi}(i, j)$ obtained for class j using Bayes rule and parametrised using a multinomial logit function as:

$$\mathbf{\Pi}(i, j) = \frac{\exp(\mathbf{s}_i; \Omega_j)}{\sum_{c=1}^{C} \exp(\mathbf{s}_i; \Omega_j)} \tag{1}$$

The probability of membership in class j, is computed as:

$$Pr(i, j) = \frac{2}{\sqrt{\sigma_{v|j}^2 + \sigma_{u|j}^2}} \phi \left(\frac{\xi_{i|j}}{\sqrt{\sigma_{v|j}^2 + \sigma_{u|j}^2}} \right) \Phi \left(- \left(\frac{\sigma_{u|j}}{\sigma_{v|j}} \right) \frac{\xi_{i|j}}{\sqrt{\sigma_{v|j}^2 + \sigma_{u|j}^2}} \right), \tag{2}$$

and the associated loglikelihood function is the weighted sum of the j-class likelihood functions:

$$\log L = \sum_{i=1}^{N} \log \left(\sum_{j=1}^{2} \mathbf{\Pi}(i, j) \cdot Pr(i \mid j) \right) \tag{3}$$

The determination of the optimal number of classes is guided by the model's information criterion. The Bayesian Information Criterion is often preferred and the model with the lowest absolute value is selected.

We first classified farmers as adopters or non-adopters of APM, according to the criteria described in Owili et al. [30]. However, without an objective APM intensity threshold to define cut-off levels, the number of distinct adopter subgroups and the heterogeneity within the adopter class remained indeterminate. Consequently, we applied the LCSF model exclusively to the subsample of APM adopters. The approach identified two classes of APM adopters, which we classified as non-intensive and intensive adopters. We continue this discussion in Section 3.3.1. Thus, together with the non-adopter category, our sample consisted of three classes of orchard managers.

The ideal approach to controlling for selection bias in observational studies is to use a randomised experiment so that all individuals have equal chances of assignment to each treatment class. However, this approach was not feasible in this study due to cost implications. To test for the presence of selectivity bias in the presence of heterogeneous technologies, we employ the bias-corrected LCSF procedure proposed by Dakpo et al. [78]. The approach uses a more efficient quadrature method within the LCSF framework as an alternative to the maximum simulated likelihood approach derived by Greene [79], and mitigates confounding bias from unobservables. In our case, the coefficient of the selectivity variable RHO (ρ) was not significantly different from zero at 5%, in the pooled and class-specific frontiers, indicating that our sample does not suffer from selection bias. This implies that the standard LCSF suffices to estimate regime-specific frontiers and efficiencies.

Following Aigner et al. [80] and Meeusen and van Den Broeck [81], we estimate two output-oriented stochastic frontiers for each of the three classes of farmers: (i) a production frontier that captures technical efficiency and (ii) a damage or pressure-generating technology (PGT) function that assesses eco-efficiency, as:

$$\begin{aligned}
\ln Y_{i|j} &= \ln f^j\big(\mathbf{X}_{ik|j}, \boldsymbol{\beta}\big) + v_{i|j} \ - \ u_{i|j}, \qquad \mathrm{TE}_{i|j} = \exp\big(-u_{i|j}\big),\\
\ln \mathrm{NVA}_{i|j} &= \ln D^j\big(\mathbf{P}_{ik|j}, \boldsymbol{\tau}\big) + \nu_{i|j} \ - \ \mu_{i|j}, \qquad \mathrm{EE}_{i|j} = \exp\big(-\mu_{i|j}\big)\\
\mathrm{PGT} &= \{(\mathrm{NVA}, \mathbf{P}) \in \\
&\qquad \mathbb{R}_+^{N+1} \mid \text{NVA can be produced with } \mathbf{P} \text{ pressures}\},
\end{aligned} \tag{4}$$

where $\ln Y_{i|j}$ is the logarithm of mango yield per hectare for the i^{th} orchard managed by a farmer in the j^{th} class, $\mathbf{X}_{ik|j}$ is a $1 \times K$ vector of normalised positive inputs, and $\boldsymbol{\beta}$ is the coefficient vector of interest. Similarly, $\ln \mathrm{NVA}_{i|j}$ denotes the logarithm of net value added, $\mathbf{P}_{ik|j}$ a vector of normalised environmental pressures, and $\boldsymbol{\tau}$ the parameter vector. For each orchard $i = 1, \dots, N$ and class $j = 0, 1, 2$, $v_{i|j} \sim N(0, \sigma_v^2)$ and $\nu_{i|j} \sim N(0, \sigma_\nu^2)$ are iid white-noise errors, independent of the inefficiency terms. $u_{i|j} \geq 0 \sim N^+\big(0, \sigma_u^2\big)$ and $\mu_{i|j} \geq 0 \sim N^+(0, \sigma_\mu^2)$ are half-normal inefficiency terms. $\mathrm{TE}_{i|j} \in [0, 1]$ and $\mathrm{EE}_{i|j} \in [0, 1]$ denote technical and eco-efficiency, respectively.

The zero-observation problem is a common productivity analysis pitfall, particularly in smallholder systems, where farmers may fail to apply some inputs, resulting in a large proportion of genuine zeros in the dataset. To accommodate this, we apply an inverse hyperbolic sine (IHS) transformation, which, unlike the logarithm, is defined for zero and negative values and naturally approximates $\ln(x)$ for a sufficiently large x [82]. Since the IHS transformation can be adversely affected by the chosen unit of measurement [83], following Aihounton and Henningsen [82], we perform several tests to determine the appropriateness of the chosen units of measurement and the corresponding scaling factors. The results are displayed in Table A2 of Appendix A.

We perform likelihood ratio (LR) tests for the deterministic kernels $\ln f^j(\bullet)$ and $\ln D^j(\bullet)$ of Equation (4). In both cases, the test strongly rejects the Cobb-Douglass specification in favour of the log-linear Translog functional form (see Table A1 of the Appendix A). Although often associated with multicollinearity, the Translog specification is flexible and has the ability to capture non-linearities in the regressors, allows for potential substitutions among inputs, and places no constraints on returns to scale [84]. All terms of Translog are normalised by their geometric means to allow the first-order coefficients of the stochastic frontier to be interpreted as partial elasticities with respect to the mango yields at the sample mean [85]. To satisfy the regularity conditions, we impose monotonicity on all inputs using a three-step procedure developed by Henningsen and Henning [86].

To account for technological heterogeneity across the three adoption classes and enable meaningful benchmarking, we embed the LCSF within a metafrontier framework. A persistent misconception is that the standard LCSF automatically provides a common benchmark for all technology regimes, making efficiency scores directly comparable. Many recent studies fall prey to this error by reporting cross-technology efficiency comparisons from LCSF results. Since the estimation of LCSF implies technology heterogeneity, it follows, therefore, that a metafrontier estimation is required. While LCSF is robust at uncovering unobserved "technology regimes", it does *not* produce an enveloping frontier for benchmarking. Only by nesting class-specific frontiers under a shared metafrontier can one validly compare efficiency scores across regimes [87].

To justify the metafrontier estimation, we conduct generalised likelihood-ratio (GLR) tests. The GLR test statistic follows a Chi-square distribution under the null hypothesis and, in our case, is obtained as:

$$-2\left(\log \mathrm{L}\big(\ln f^0(\bullet)\big) + \sum_{i=1}^{N} \log\left[\sum_{j=1}^{2} \mathbf{\Pi}(i,j)\cdot Pr(i,j)\right] - \log \mathrm{L}\big(\ln f^M(\bullet)\big)\right) \tag{5}$$

where $\log \mathrm{L}\big(\ln f^0(\bullet)\big)$ is the loglikelihood of the non-adopters frontier model and $\log \mathrm{L}\big(\ln f^M(\bullet)\big)$ is the loglikelihood of the metafrontier. The GLR tests strongly rejected the null hypotheses, confirming that the technologies used among the three adoption groups are heterogeneous and differ systematically (Table A1 of the Appendix A). In other words, farmers in the three adoption groups have different production possibility frontiers, making them directly incomparable. Empirically, this suggests that estimating a metafrontier provides a better fit compared to the three separate class-specific frontiers. By definition, a metafrontier is an overarching technology that encompasses multiple class-specific frontiers, forming a common benchmark technology available to the whole industry and is similar for all farmers [87, 88].

In a two-stage procedure, we first estimate the class-specific frontiers as in Equation (4). In the second stage, the predicted fitted values $\ln \hat{f}^j(\bullet)$ and $\ln \hat{D}^j(\bullet)$ from the three groups are pooled to construct metafrontiers, following Huang et al. [89]:

$$
\begin{aligned}
\ln \hat{f}^j(\mathbf{X}_{i|j}, \boldsymbol{\beta}) &= \ln f^M(\mathbf{X}_{i|j}, \boldsymbol{\beta}) - u_{i|j}^M + v_{i|j}^M, \quad \mathrm{MTE}_{i|j} = e^{-u_{i|j}^M} \times e^{-u_{i|j}}, \\
\ln \hat{D}^j(\mathbf{P}_{i|j}, \boldsymbol{\tau}) &= \ln D^M(\mathbf{P}_{i|j}, \boldsymbol{\tau}) - \mu_{i|j}^M + \nu_{i|j}^M, \quad \mathrm{MEE}_{i|j} = e^{-\mu_{i|j}^M} \times e^{-\mu_{i|j}},
\end{aligned}
\tag{6}
$$

where Equation (6) has the usual properties of the frontiers given in Equation (4); however, $u_{i|j}^M$ and $\mu_{i|j}^M$ denote the non-negative technology gap ratio (TGR) and the PGT gap ratio (PTGR) component for production and eco-efficiency frontiers, respectively, and are distributed as $u_i^M \geq 0 \sim N^+(0, \sigma_u^2)$ and $\mu_{i|j}^M \geq 0 \sim N^+(0, \sigma_u^2)$. In this case, $v_{i|j}^M \sim N(0, \sigma_\nu^2)$ and $\nu_{i|j}^M \sim N(0, \sigma_\nu^2)$ may not be iid and are therefore assumed to be asymptotically normally distributed. MTE and MEE refer to the meta-technical efficiency and meta-eco-efficiency scores, respectively. The MTE and MEE scores are directly comparable between the various technology classes relative to the metafrontier.

In mango production, TGR represents the ratio of predicted mango yield of a class-specific production frontier to the potential mango yield given by the metafrontier, and thus shows the position of the class-specific production frontier relative to the frontier achievable by the industry as a whole. Thus, the metafrontier allows for the segregation of production inefficiencies into those caused by poor agronomic practices and those caused by technology gaps within the industry. In this study, technology gaps quantify the extent to which various pest management technologies deviate from global best practice and therefore can inform policy interventions aimed at the promotion of best-performing pest management strategies. These gaps arise from the choice of a particular pest management technology from the various technologies available to the industry as a whole, depending on their accessibility to the individual farmers and the rates of technology adoption.

2.3.2 Environmental adjustment procedure

We compute environmentally adjusted composite measures for both efficiency and the technology gap as:

$$
\begin{aligned}
\mathrm{MTE}_{i|j}^{\mathrm{adj}} &= \prod_{q \in \{u_{i|j}^M,\, u_{i|j},\, \mu_{i|j}^M,\, \mu_{i|j}\}} e^{-q} \;=\; \exp\big[-\big(u_{i|j}^M + u_{i|j} + \mu_{i|j}^M + \mu_{i|j}\big)\big], \\
\mathrm{TGR}_{i|j}^{\mathrm{adj}} &= \prod_{r \in \{\mu_{i|j}^M,\, u_{i|j}^M\}} e^{-r} \;=\; \exp\big[-\big(\mu_{i|j}^M + u_{i|j}^M\big)\big].
\end{aligned}
\tag{7}
$$

The multiplicative operator endows both composites with several desirable properties. First, strict monotonicity holds in every argument so that an improvement in either $\mathrm{MTE}_{i|j}$ or $\mathrm{MEE}_{i|j}$ raises $\mathrm{MTE}_{i|j}^{\mathrm{adj}}$, and an improvement in either $\mathrm{TGR}_{i|j}$ or $\mathrm{PTGR}_{i|j}$

raises $\mathrm{TGR}_{i|j}^{\mathrm{adj}}$, *ceteris paribus*. Second, the products are bilinear, symmetric and homogeneous of degree two, ensuring that no single component is given precedence over its counterpart. Third, the aggregation rule is non-compensatory and effectively penalises poor performance so that a deficiency in one component cannot be masked by superiority in the other. As any component approaches zero, the corresponding composite measure is driven sharply downwards, constraining overall performance by the weakest link. Consequently, the formulation is consistent with the notion that sustainable performance enforces holistic progress both in technical efficiency and eco-efficiency, while aiming at closing the technology gaps as well. Finally, since each component index satisfies: $\mathrm{MTE}_{i|j}, \mathrm{MEE}_{i|j}, \mathrm{TGR}_{i|j}, \mathrm{PTGR}_{i|j} \in [0,1]$; hence, the adjusted scores $\mathrm{MTE}_{i|j}^{\mathrm{adj}}$ and $\mathrm{TGR}_{i|j}^{\mathrm{adj}}$ are properly bounded within the unit interval, rendering interpretation straightforward.

For policy purposes, we model drivers of environmentally adjusted inefficiency, $\mathrm{MTIE}_{i|j}^{\mathrm{adj}}$, using a fractional probit as:

$$\begin{aligned} \mathrm{MTIE}_{i|j}^{\mathrm{adj}} &= G(\boldsymbol{\delta}; Z_{i|j}) = \delta_0 + \delta_1 Z_{1i|j} + \cdots + \delta_n Z_{ni|j} \\ \mathrm{MTIE}_{i|j}^{\mathrm{adj}} &= 1 - \mathrm{MTE}_{i|j}^{\mathrm{adj}} \end{aligned} \tag{8}$$

where $G(\cdot)$ is the Bernoulli specification of the quasi-maximum likelihood estimator of the standard normal cumulative density function with a probit link, $(\delta_{0|j}, \cdots, \delta_{n|j})$ are the parameters of interest, and $(Z_{1i|j} + \cdots + Z_{ni|j})$ are exogenous variables that are hypothesised to influence orchard-level adjusted inefficiency. Since it is widely recognised that multi-step estimation procedures are generally associated with biased standard errors [90, 91], we apply a bootstrap procedure following Simar and Wilson [92] and Simar and Wilson [93] with 1000 replications to correct the standard errors.

2.3.3 Inverse-probability-weighted regression adjustment for multi-valued treatment effect estimation

To determine the effect of APM transition and intensification regimes, we subject the $\mathrm{MTE}_{i|j}^{\mathrm{adj}}$ scores to an inverse-probability-weighted regression adjustment (IPWRA) procedure. In this framework, for each adoption level $A \in \{0, 1, 2\}$ where 0, 1 and 2 denote non-adopters, non-intensive adopters and intensive adopters, respectively, the average potential outcome (POMean) is estimated as:

$$\hat{\Theta}(a) = \mathbb{E}\left[\hat{\theta}(a, Z_i) + \frac{1\left[A_i = a\right]\left(\mathrm{MTE}_{i|j}^{\mathrm{adj}} - \hat{\theta}(a, Z_i)\right)}{\hat{Pr}_a(Z_i)}\right]. \tag{9}$$

Here, $\hat{\theta}(a, Z_i)$ denotes the predicted outcome under treatment level a and is modelled using a fractional probit specification such that $\hat{\theta}(a, Z_i) = \Phi\left(Z_i \hat{\delta}_a\right)$, with $\Phi(\cdot)$ representing the standard normal cumulative distribution function. The probability of receiving treatment level a is estimated using a multinomial logit model. The inclusion of both an outcome regression and inverse probability weighting guarantees a consistent estimation of treatment effects provided that either of the models is correctly specified and hence doubly robust. The treatment effects are then determined by comparing the estimated POMeans at different treatment levels, to obtain the average treatment effect (ATE) and the average treatment effect on the treated (ATT).

$$
\begin{aligned}
\mathrm{ATE}_{1,0} &= \mathbb{E}[\mathrm{MTE}^{\mathrm{adj}}_{i|1} - \mathrm{MTE}^{\mathrm{adj}}_{i|0}] \qquad & \mathrm{ATT}_{1,0} &= \mathbb{E}[\mathrm{MTE}^{\mathrm{adj}}_{i|1} - \mathrm{MTE}^{\mathrm{adj}}_{i|0} \mid A_i = 1] \\
\mathrm{ATE}_{2,0} &= \mathbb{E}[\mathrm{MTE}^{\mathrm{adj}}_{i|2} - \mathrm{MTE}^{\mathrm{adj}}_{i|0}] \qquad & \mathrm{ATT}_{2,0} &= \mathbb{E}[\mathrm{MTE}^{\mathrm{adj}}_{i|2} - \mathrm{MTE}^{\mathrm{adj}}_{i|0} \mid A_i = 2] \qquad (10) \\
\mathrm{ATE}_{2,1} &= \mathbb{E}[\mathrm{MTE}^{\mathrm{adj}}_{i|2} - \mathrm{MTE}^{\mathrm{adj}}_{i|1}] \qquad & \mathrm{ATT}_{2,1} &= \mathbb{E}[\mathrm{MTE}^{\mathrm{adj}}_{i|2} - \mathrm{MTE}^{\mathrm{adj}}_{i|1} \mid A_i = 2]
\end{aligned}
$$

As a robustness check for selectivity bias from observables, we compare the IPWRA estimates with those obtained from a propensity score matching (PSM) and regression adjustment (RA). Whereas RA depends on a correct specification of the outcome model $\hat{\theta}(a, Z_i)$, the PSM relies on propensity scores $\hat{Pr}_a(Z_i)$ to match an orchard manager in a treatment class with an orchard manager from the control group based on similar characteristics. In this case, a propensity score is a conditional probability of an orchard manager being assigned to a treatment class based on a vector of their observed covariates. We impose both covariate balance and common support to ensure that for every combination of covariates, there is a non-zero probability of being treated and untreated. To determine the potential influence of unobserved confounding in both models, we perform a sensitivity analysis to assess the stability and validity of our treatment effect estimates using Oster's δ [94]. Oster's δ indicates how strong the influence of unobservables would need to be, relative to the influence of observed covariates, to reduce the estimated treatment effect to zero.

It has been shown that the benefits of adopting APM do not apply uniformly in all contexts [see 95]. To uncover heterogeneities in treatment effects, we use the doubly robust conditional average treatment effect (DRCATE) visualisation procedure proposed by Lee et al. [96]. This procedure models the conditional average treatment effect (CATE) function using an augmented inverse probability weighting estimator of a covariate of interest by combining a propensity score model with a local linear regression for the POMeans and ATEs.

3 Results and discussion

3.1 Adoption of agro-ecological fruit fly management options

Figure 2 illustrates the distribution of adopters across three broad categories of APM practices, including habitat management, orchard sanitation, and reactive options. Adoption rates were moderate, with habitat management being the most adopted category, followed by orchard sanitation and reactive options. The most common practices were regular scouting and monitoring, the management of alternate hosts, and male annihilation, which were adopted by at least half of the respondents.

Within habitat management category, adoption was highest for regular scouting and monitoring (53.5%), management of alternate hosts (50.2%), and inter-tree raking (43.3%), suggesting a preference for ecologically grounded practices that are relatively

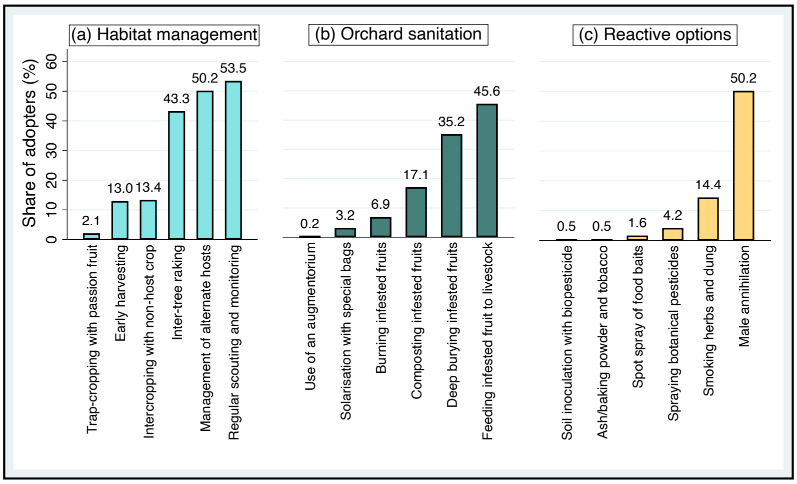


Fig. 2: APM adoption rates by category of practice. **Source:** Survey Data (2023).

straightforward to implement. In contrast, adoption of more specialised practices such as intercropping with non-host crops and trap-cropping with passion fruit remained limited. For orchard sanitation, feeding infested fruit to livestock (45.6%) and deep burying of infested fruits (35.2%) were the most widely adopted, whereas technical measures like solarisation and the use of an augmentorium were negligible. The pattern was even more pronounced in reactive control strategies in which male annihilation (50.2%) was the only widely adopted method, while all other approaches, including the use of biopesticides and botanical sprays, showed limited uptake. These findings indicate the uneven diffusion of APM options, with adoption strongly skewed toward practices that are familiar, locally adaptable, and possibly less resource-intensive.

3.2 Characteristics of adopters and non-adopters of APM

Table 2 shows the characteristics of the surveyed orchard managers, disaggregated by their APM adoption classes. The average orchard size was 0.56 ha, confirming that most of the producers in the sample are smallholders. On average, non-intensive adopters used slightly more land than intensive adopters. As expected, labour consumption was higher among intensive adopters than among non-intensive adopters. Intensive adopters implemented more labour-intensive practices and also applied slightly more inputs such as fertilisers and manure, which could have consumed additional labour due to input application.

The intensive class exhibited greater specialisation, as indicated in their average tree density of 164 trees/ha, compared to 108 and 136 trees/ha among non-adopters and non-intensive adopters, respectively, on average.

On average, adopters applied 0.95 L/ha more insecticides (both organic and inorganic combined) than conventional farmers. This was expected, as organic pesticides are typically applied in larger quantities than their inorganic counterparts used by

Table 2: Characteristics of pooled, non-adopters, non-intensive, and intensive adopters of APM

		Pooled	Non-adopters	Non-intensive	Intensive
Variable	**Parameter**	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Dependent variables					
Mango yield (kg/ha/yr)		7519.57 (8387.30)	6212.13 (5661.27)	6709.11 (7358.06)	10248.68 (11536.16)
Net value added ('00 KES/ha/yr)		1099.42 (1258.48)	908.15 (851.09)	974.69 (1102.30)	1505.10 (1732.42)
Inputs (Technical efficiency)					
Land (ha)	β_{LA}	0.56 (0.51)	0.55 (0.47)	0.61 (0.64)	0.52 (0.40)
Labour (mandays/ha/yr)	β_{LB}	15.83 (23.46)	14.24 (20.55)	13.75 (14.50)	20.31 (32.74)
Fertilisers (kg/ha/yr)†	β_{FE}	3.326 (8.226)	3.750 (9.280)	2.090 (3.285)	4.004 (9.954)
Insecticides (kg/ha/yr)†‡	β_{IN}	2.293 (4.751)	1.734 (2.237)	2.922 (7.139)	2.443 (4.226)
Fungicides (kg/ha/yr)†	β_{FU}	2.023 (2.789)	1.873 (2.293)	2.055 (2.685)	2.207 (3.474)
Manure (kg/ha/yr)†	β_{MA}	2879.989 (682.297)	2664.754 (655.092)	1972.930 (330.520)	4135.138 (933.808)
Inputs (Eco-efficiency)					
CF (kg CO_2eq/ha/yr)	τ_{GHG}	13553.91 (42084.30)	12270.58 (40395.36)	7641.39 (21018.92)	21562.91 (57302.25)
N deficits (kg/ha/yr)†	τ_{ND}	437.630 (827.031)	401.820 (792.651)	315.146 (421.365)	616.844 (1119.670)
P deficits (kg/ha/yr)†	τ_{PD}	66.362 (131.142)	64.274 (143.168)	46.883 (62.631)	89.663 (160.002)
Toxicity (kg AI/ha/yr)†	τ_{TOX}	3.041 (6.030)	2.710 (5.768)	3.186 (4.749)	3.366 (7.454)
Energy deficits (MJ/ha/yr)	τ_{EN}	1438.64 (3226.29)	1329.75 (3090.08)	1008.73 (1570.57)	2043.44 (4418.51)
Specialisation (proportion)	τ_{SP}	0.33 (0.28)	0.27 (0.24)	0.34 (0.31)	0.41 (0.30)
Observations		418	173	125	120

Notes: *, ** and *** denote significance at the 10, 5 and 1% levels, respectively. Values in parentheses are standard deviations. Abbreviations:—AI, active ingredient; CF, carbon footprint; CO_2eq, carbon dioxide equivalent; MJ, megajoules. † Variables marked with this symbol were transformed using the inverse hyperbolic sine (IHS) to preserve observations with genuine zero values and subsequently re-scaled for analysis. In order to mitigate any potential distortionary effects of the IHS transformation, inputs used in the technical efficiency estimation were rescaled to centigrams (cg), while those in the eco-efficiency estimation were rescaled to hectograms (hg) (refer to Table A2 for details). ‡This variable is a composite of both organic and inorganic insecticides. The average exchange rate for the reference period (December 2022 to March 2023) was KES 128/USD. **Source:** Survey Data (2023).

non-adopters. Among adopters, non-intensive users applied 1.13 L/ha of organic insecticides on average, compared to 0.94 L/ha by intensive adopters, which explains the higher overall insecticide use among adopters. As expexted *a priori*, intensive adopters applied 0.23 L/ha less inorganic insecticide than non-adopters. This finding is consistent with the results of Midingoyi et al. [29] and Mwungu et al. [38], who found that adopters of integrated pest management used significantly less synthetic pesticides than non-adopters. These results suggest that integrating multiple pest control strategies can effectively reduce reliance on the often-costly chemical pesticides. In contrast, non-intensive adopters used slightly more inorganic insecticides than non-adopters, with an average difference of 0.06 L/ha.

In line with expectations, the amount of carbon footprints and energy deficits were highest among the intensive class, due to their higher output levels and input consumption, respectively. It is well established that the level of output is positively correlated with the level of emissions [97]. Intensive adopters recorded the highest rates of nutrient depletion, which could be due to their high nutrient efficiency. Rapid uptake of nutrients by high-yielding trees can lead to net nutrient mining if replenishment does not fully match crop demand. Non-intensive adopters had the lowest nutrient depletion rates.

On average, adopters achieved significantly higher mango yields (2,231kg/ha more than non-adopters) which translated into substantially higher net value added, amounting to an additional KES 32,633 per ha (approx. USD 255.7 per ha). On the other hand, intensive and non-intensive adopters recorded 4036kg/ha (approx. KES 60,548 per ha or USD 473.8 per ha) and 496.98kg/ha (approx. KES 7,455 per ha or USD 58.2 per ha), respectively, more than non-adopters. This is in line with previous studies that have reported increased net income from the adoption of sustainable fruit fly management practices [29, 34–37].

3.3 Empirical results

3.3.1 Class-specific stochastic frontier elasticities

Table 3 shows the parameter estimates of the class-specific stochastic frontier for the technical efficiency model. The coefficient of the gamma (γ) variable approximates unity for all models, indicating that the proportion of total error variance due to inefficiency is relatively high. This suggests that most of the deviation from the frontier is due to inefficiency and justifies the use of the more complex stochastic frontier procedure over simple alternatives such as ordinary least squares. Monotonicity holds adequately for all inputs in all models (see Table A3 in Appendix A).

The LCSF identified two distinct groups among APM-adopting orchard managers. Attempts to estimate models with additional classes failed to converge, indicating that the two-class model was optimal and at saturation [78]. The average posterior probabilities of class membership for intensive and non-intensive orchard managers based on the LCSF is 84% and 89%, respectively. The coefficient of the separating variable "number of APM practices adopted" is negative, implying that the likelihood of being assigned to Class 1 decreases with higher uptake of APM practices. This suggests that Class 1 and Class 2 can be broadly categorised as non-intensive and intensive

Table 3: Estimates of class-specific stochastic frontier models (Translog) for technical efficiency

	Single class SF	**Two class LCSF**	
	Non-adopters	**Class 1 (Non-intensive)**	**Class 2 (Intensive)**
Parameter	Coef. (SE)	Coef. (SE)	Coef. (SE)
β_0	0.048 (0.055)	-0.100 (0.107)	0.357*** (0.061)
β_{LA}	-0.556*** (0.121)	-0.643*** (0.134)	-0.245* (0.144)
β_{FE}	0.157** (0.068)	0.693*** (0.135)	0.052 (0.072)
β_{FU}	0.191*** (0.041)	-0.013 (0.129)	-0.300*** (0.101)
β_{IN}	0.275** (0.126)	0.263** (0.118)	0.240** (0.104)
β_{LB}	0.047 (0.074)	-0.609*** (0.138)	0.537*** (0.119)
β_{MA}	-0.044 (0.051)	-0.816*** (0.160)	-0.139** (0.070)
β_{LA^2}	-0.434 (0.321)	0.331 (0.238)	0.807*** (0.273)
β_{FE^2}	-0.115* (0.065)	-0.504*** (0.125)	-0.261*** (0.046)
β_{FU^2}	-0.208** (0.083)	-0.321*** (0.098)	-0.096 (0.069)
β_{IN^2}	-0.059 (0.128)	-0.147** (0.067)	-0.143*** (0.052)
β_{LB^2}	0.520*** (0.154)	-0.623*** (0.231)	-0.811*** (0.262)
β_{MA^2}	0.214** (0.087)	0.700** (0.288)	-0.036 (0.065)
$\beta_{\mathrm{LA} \times \mathrm{FE}}$	0.402*** (0.052)	-0.051 (0.102)	0.405*** (0.086)
$\beta_{\mathrm{LA} \times \mathrm{FU}}$	-0.088 (0.084)	-0.094 (0.126)	-0.127 (0.102)
$\beta_{\mathrm{LA} \times \mathrm{IN}}$	-0.033 (0.173)	0.504*** (0.143)	-0.239* (0.123)
$\beta_{\mathrm{LA} \times \mathrm{LB}}$	0.104 (0.153)	0.012 (0.167)	0.239* (0.138)
$\beta_{\mathrm{LA} \times \mathrm{MA}}$	-0.150 (0.128)	0.187 (0.221)	0.563*** (0.124)
$\beta_{\mathrm{FE} \times \mathrm{FU}}$	0.056 (0.043)	0.084 (0.062)	0.231*** (0.053)
$\beta_{\mathrm{FE} \times \mathrm{IN}}$	-0.043 (0.032)	-0.172** (0.077)	0.055 (0.038)
$\beta_{\mathrm{FE} \times \mathrm{LB}}$	0.210*** (0.065)	-0.071 (0.153)	-0.217** (0.106)
$\beta_{\mathrm{FE} \times \mathrm{MA}}$	-0.013 (0.043)	-0.037 (0.116)	-0.024 (0.040)
$\beta_{\mathrm{FU} \times \mathrm{IN}}$	0.020 (0.082)	0.172*** (0.060)	-0.044 (0.031)
$\beta_{\mathrm{FU} \times \mathrm{LB}}$	-0.132 (0.104)	-0.020 (0.138)	0.362*** (0.098)
$\beta_{\mathrm{FU} \times \mathrm{MA}}$	0.056 (0.038)	0.106 (0.107)	0.243*** (0.063)
$\beta_{\mathrm{IN} \times \mathrm{LB}}$	0.163 (0.127)	0.234** (0.103)	-0.051 (0.089)
$\beta_{\mathrm{IN} \times \mathrm{MA}}$	-0.175*** (0.062)	0.137* (0.074)	-0.103** (0.044)
$\beta_{\mathrm{LB} \times \mathrm{MA}}$	-0.255* (0.135)	0.974*** (0.182)	-0.140 (0.114)
σ_u	0.340	—	
σ_v	0.000	—	
σ	0.583	—	
γ	1.000	—	
$\log L$	-11.627	-22.391	
Separating variables			
Constant		1.300** (0.534)	
APM practices adopted		-4.540** (1.993)	
APM intensity/tree/ha		-0.075 (0.149)	
Posterior probability	1.000	0.891	0.836
APM intensity	0.000	0.223	0.267
Observations	173	125	120

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Abbreviations:—FE, fertilisers; FU, fungicides; IN, insecticides; LA, land; LB, labour; LCSF, latent class stochastic frontier; MA, manure; and SF, stochastic frontier. Values in parentheses are standard errors. **Source:** Survey Data (2023) adopters, respectively. To validate this classification, we analysed the extent of adoption of APM within each predicted class. The average intensity of APM adoption among all adopters was 24.5%, equivalent to about four of the eighteen practices considered. The non-intensive class (Class 1) adopted slightly below this average at 22%, about four practices, whereas the intensive class (Class 2) adopted above the average at 27%, translating to approximately five practices.

Class-specific frontier estimates for technical efficiency show substantial heterogeneity in production technologies, which reveals the limitations of uniform, one-size-fits-all assumptions of the production environment when promoting sustainable agriculture, particularly in smallholder systems. In fact, of the 28 elasticities, only 3 (insecticide, land-fungicide- and fertiliser-manure interactions) were consistent in all three classes. The expected diminishing marginal returns mostly hold for the non-adopter class, with orchard size (land) as the only input exhibiting an inverse elasticity with respect to mango yield at the sample mean. Whereas initial increments in land, labour and manure decrease the yields at the sample average for the non-intensive class, all else equal, fungicides and manure appear to reduce yields among the intensive class.

The main results of the class-specific frontier parameters for the eco-efficiency model are presented in Table 4. The results show a high degree of variation in the magnitude and direction of the environmental impact categories in the three models. The squared and interaction terms show strong non-linear relationships and interdependencies among environmental indicators, suggesting that trade-offs and complementarities between inputs critically affect eco-efficiency. As expected, the elasticity of net value added with various environmental impact categories as well as their interactions are mostly negative across the three classes at the sample mean. This suggests that these deleterious impact categories reduce the net value added and should therefore be minimised to improve the sustainability of the orchards. Nutrient deficits exhibit the largest elasticities. In particular, the non-intensive class is associated with large coefficients for phosphorus and nitrogen deficits, suggesting complex nutrient management challenges compared to the other classes.

3.3.2 Latent class stochastic metafrontier elasticities

Our primary focus was to assess how APM transitions and intensification create technological heterogeneity and how the transition influences orchard-level efficiency outcomes in smallholder contexts. To this end, we focus the ensuing discussion on the metafrontier results. Table 5 presents the parameter estimates of the latent class stochastic metafrontier model for both technical and eco-efficiency. The estimated input elasticities suggest diminishing marginal returns across most inputs, consistent with the quasi-concavity condition of the assumed production technology.

The results indicate that, at the sample mean, land exhibits a negative elasticity, indicating a 0.43% decline in mango yield for every percentage increase in the orchard area. However, beyond a certain point, output eventually increase with further land expansion. An extensive review by Menzel and Lagadec [98] found an inverse relationship between yields per tree and tree density, alongside a positive association between total yields and tree density. Similarly, Zhang et al. [99] reported a positive relationship

Table 4: Estimates of class-specific stochastic frontier models (Translog) for eco-efficiency

	Single class SF	**Two class LCSF**	
	Non-adopters	**Class 1 (Non-intensive)**	**Class 2 (Intensive)**
Parameter	Coef. (SE)	Coef. (SE)	Coef. (SE)
τ_0	−2.564*** (0.803)	2.474*** (0.867)	0.207 (0.833)
τ_{CF}	2.516*** (0.786)	−1.347 (1.168)	1.548 (1.411)
τ_{ND}	8.087*** (2.376)	6.476 (7.118)	−1.415 (3.666)
τ_{PD}	−3.643*** (1.145)	−10.877* (6.297)	0.109 (3.005)
τ_{TOX}	1.365*** (0.388)	−0.498 (0.490)	0.914** (0.406)
τ_{EN}	−2.233*** (0.526)	1.339** (0.544)	−0.284 (0.667)
τ_{SP}	−0.065** (0.032)	−0.226*** (0.050)	0.149** (0.061)
τ_{CF^2}	−1.413** (0.697)	−1.107 (1.231)	−2.335** (1.101)
τ_{ND^2}	−6.805** (2.964)	−70.461** (28.799)	5.210*** (1.943)
τ_{PD^2}	−0.981** (0.471)	−47.625*** (17.376)	−0.589 (0.879)
τ_{TOX^2}	−0.126* (0.071)	−0.204** (0.080)	−0.108* (0.065)
τ_{EN^2}	−1.397*** (0.280)	−0.926*** (0.191)	−0.304 (0.282)
τ_{SP^2}	−0.003 (0.002)	0.001 (0.003)	0.005** (0.002)
$\tau_{\mathrm{CF\times ND}}$	−3.508*** (1.346)	3.603 (3.748)	−0.592 (2.884)
$\tau_{\mathrm{CF\times PD}}$	1.927** (0.908)	−0.700 (2.770)	1.250 (2.113)
$\tau_{\mathrm{CF\times TOX}}$	−0.573* (0.316)	−0.125 (0.232)	−0.173 (0.252)
$\tau_{\mathrm{CF\times EN}}$	0.786** (0.324)	−0.388 (0.359)	−0.153 (0.489)
$\tau_{\mathrm{CF\times SP}}$	−0.041 (0.029)	0.002 (0.056)	−0.073** (0.037)
$\tau_{\mathrm{ND\times PD}}$	2.954*** (0.887)	61.216*** (22.883)	−0.962 (1.146)
$\tau_{\mathrm{ND\times TOX}}$	−1.475*** (0.563)	8.042*** (2.694)	−0.378 (2.059)
$\tau_{\mathrm{ND\times EN}}$	2.799*** (0.519)	−5.560* (2.844)	−0.240 (1.429)
$\tau_{\mathrm{ND\times SP}}$	0.156*** (0.044)	0.603*** (0.146)	−0.161 (0.232)
$\tau_{\mathrm{PD\times TOX}}$	0.063 (0.200)	−7.560*** (2.231)	−0.585 (1.640)
$\tau_{\mathrm{PD\times EN}}$	−0.705*** (0.180)	4.869** (2.308)	0.602 (1.135)
$\tau_{\mathrm{PD\times SP}}$	−0.062*** (0.019)	−0.346*** (0.107)	0.073 (0.188)
$\tau_{\mathrm{TOX\times EN}}$	0.663*** (0.217)	0.310*** (0.107)	0.333*** (0.124)
$\tau_{\mathrm{TOX\times SP}}$	−0.004 (0.011)	−0.008 (0.016)	0.008 (0.010)
$\tau_{\mathrm{EN\times SP}}$	0.008 (0.016)	−0.026 (0.025)	0.020 (0.021)
σ_μ	0.007	0.003	0.004
σ_ν	0.000	0.000	0.000
σ	0.082	0.058	0.061
γ	0.984	0.999	0.994
$\log L$	296.005	261.517	242.819
Observations	173	125	120

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Abbreviations:—CF, carbon footprint; LCSF, latent class stochastic frontier; ND, nitrogen deficit; PD, phosphorus deficit; TOX, pesticide toxicity; EN, energy balance; SF, stochastic frontier; SP, specialisation. Values in parentheses are standard errors. **Source:** Survey Data (2023)

between yield and tree density at levels comparable to those observed in Makueni and noted diminishing marginal returns at higher densities. These findings suggest that although individual tree productivity decreases with increasing density, overall land productivity improves, implying that intensive land use through higher tree density can

Table 5: Estimates of latent class stochastic metafrontier models (Translog) for technical efficiency and eco-efficiency

Technical efficiency		**Eco-efficiency**	
Parameter	Coef. (SE)	Parameter	Coef. (SE)
β_0	0.271*** (0.030)	τ_0	1.284*** (0.150)
β_{LA}	-0.431*** (0.063)	τ_{CF}	0.171 (0.281)
β_{FE}	0.063* (0.036)	τ_{ND}	-1.397*** (0.352)
β_{FU}	0.144*** (0.043)	τ_{PD}	-1.109*** (0.231)
β_{IN}	0.173*** (0.044)	τ_{TOX}	0.515*** (0.090)
β_{LB}	0.200*** (0.056)	τ_{EN}	0.125 (0.133)
β_{MA}	-0.129*** (0.050)	τ_{SP}	-0.017 (0.012)
β_{LA^2}	0.338*** (0.125)	τ_{CF^2}	-1.348*** (0.303)
β_{FE^2}	-0.074** (0.030)	τ_{ND^2}	3.005*** (0.277)
β_{FU^2}	-0.188*** (0.041)	τ_{PD^2}	-0.395*** (0.115)
β_{IN^2}	-0.026 (0.027)	τ_{TOX^2}	-0.103*** (0.024)
β_{LB^2}	0.506*** (0.079)	τ_{EN^2}	-0.684*** (0.087)
β_{MA^2}	0.201*** (0.051)	τ_{SP^2}	-0.002*** (0.001)
$\beta_{\mathrm{LA}\times\mathrm{FE}}$	0.173*** (0.038)	$\tau_{\mathrm{CF}\times\mathrm{ND}}$	0.289 (0.357)
$\beta_{\mathrm{LA}\times\mathrm{FU}}$	-0.112** (0.052)	$\tau_{\mathrm{CF}\times\mathrm{PD}}$	0.862*** (0.213)
$\beta_{\mathrm{LA}\times\mathrm{IN}}$	0.118** (0.057)	$\tau_{\mathrm{CF}\times\mathrm{TOX}}$	-0.144** (0.072)
$\beta_{\mathrm{LA}\times\mathrm{LB}}$	0.177** (0.073)	$\tau_{\mathrm{CF}\times\mathrm{EN}}$	-0.085 (0.126)
$\beta_{\mathrm{LA}\times\mathrm{MA}}$	0.040 (0.052)	$\tau_{\mathrm{CF}\times\mathrm{SP}}$	-0.048*** (0.011)
$\beta_{\mathrm{FE}\times\mathrm{FU}}$	0.077*** (0.019)	$\tau_{\mathrm{ND}\times\mathrm{PD}}$	0.432*** (0.152)
$\beta_{\mathrm{FE}\times\mathrm{IN}}$	-0.018 (0.021)	$\tau_{\mathrm{ND}\times\mathrm{TOX}}$	-0.497*** (0.140)
$\beta_{\mathrm{FE}\times\mathrm{LB}}$	0.142*** (0.039)	$\tau_{\mathrm{ND}\times\mathrm{EN}}$	0.252 (0.164)
$\beta_{\mathrm{FE}\times\mathrm{MA}}$	-0.035 (0.025)	$\tau_{\mathrm{ND}\times\mathrm{SP}}$	0.070*** (0.016)
$\beta_{\mathrm{FU}\times\mathrm{IN}}$	0.006 (0.025)	$\tau_{\mathrm{PD}\times\mathrm{TOX}}$	-0.073 (0.057)
$\beta_{\mathrm{FU}\times\mathrm{LB}}$	-0.071 (0.049)	$\tau_{\mathrm{PD}\times\mathrm{EN}}$	-0.001 (0.092)
$\beta_{\mathrm{FU}\times\mathrm{MA}}$	0.031 (0.027)	$\tau_{\mathrm{PD}\times\mathrm{SP}}$	-0.018** (0.008)
$\beta_{\mathrm{IN}\times\mathrm{LB}}$	0.008 (0.066)	$\tau_{\mathrm{TOX}\times\mathrm{EN}}$	0.256*** (0.038)
$\beta_{\mathrm{IN}\times\mathrm{MA}}$	-0.017 (0.019)	$\tau_{\mathrm{TOX}\times\mathrm{SP}}$	-0.006* (0.003)
$\beta_{\mathrm{LB}\times\mathrm{MA}}$	-0.292*** (0.057)	$\tau_{\mathrm{EN}\times\mathrm{SP}}$	0.014** (0.006)
σ_u	1.135		0.070
σ_v	0.005		0.000
σ	1.068		0.266
γ	0.996		0.995
$\log L$	33.365		946.908
Observations	418		418

Notes: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Elasticities are evaluated at the sample geometric mean. Abbreviations:—CF, carbon footprints; EN, energy deficits; FE, fertilisers; FU, fungicides; IN, insecticides; LA, land; LB, labour; MA, manure; ND, nitrogen deficits; PD, phosphorus deficits; SP, specialisation; and TOX, toxicity. Values in parentheses are standard errors. **Source**: Survey Data (2023).

enhance total yields. The observed non-linear pattern may also reflect initial inefficiencies and resource constraints faced by smallholders as orchard size increases, followed by improved management once farms expand, when commercialisation becomes more feasible and economies of scale can be exploited.

Labour exhibits an elasticity of 0.20 at the sample mean, implying that a one-percent increase in man-days devoted to orchard tasks increases mango yield by

0.20%. The marginal product of labour rises rather than falls within the observed range, indicating convexity of the production function for labour use. In practical terms, once a basic labour threshold is met, each extra man-day allows more thorough canopy management, quicker detection and correction of pest or nutrient problems, and more precise timing of cultural operations, all of which reinforce one another. These complementarities mean that the marginal product of labour rises as additional hands are brought in, so that yield gains are incremental.

Yield response to manure application is U-shaped with an inverse elasticity of yields with respect to manure at low application rates and increments in yields with manure application at higher manure application rates beyond some threshold. Small application rates often involve fresh or partially matured manure, which can introduce high concentrations of ammonium and soluble salts into the feeder-root zone, causing localised root scorch and transient micronutrient imbalances that redirect assimilates toward vegetative flushes at the expense of floral initiation and fruit set. Over time, with increased volumes and when manure is fully decomposed or has mineralised *in situ*, its release of nutrients often aligns with the orchard's nutrient demand throughout flowering and fruit expansion with improved soil structure and microbial activity, increasing yields.

Fertiliser use shows a positive elasticity of 0.06, suggesting that a 1% increase in fertiliser use improves the mango yield by 0.06% at the sample mean. Diminishing marginal returns are observed at higher fertiliser application rates beyond some threshold. Our findings show that fertiliser application is more effective in larger orchards, possibly due to a better nutrient distribution. These findings align with Zhang et al. [99]'s evidence that fertilisation management is a key limiting factor in mango productivity. In the same light, nutrient deficits show an inverse relationship to NVA. In line with expectations, a percentage increase in nitrogen and phosphorus deficits per hectare reduces NVA by 1.41% and 1.16%, respectively. Nitrogen and phosphorus are crucial to maintaining soil fertility and crop productivity, so deficits directly translate into lower economic output in the form of fewer harvested fruits. Although the detrimental impact of nitrogen deficits decreases at higher levels, possibly as orchards adapt or change management strategies, the results show that phosphorus deficits intensify this effect. Nitrogen deficits appear less harmful in highly specialised orchards with higher tree densities.

Our study shows that each percentage point increase in the application of fungicide improves mango yield by 0.14% at the sample mean, although the benefits diminish at higher application levels. These findings are corroborated by El-Nasr et al. [100] who obtained similar results using a randomised complete block design with ten replications in an Egyptian mango orchard growing the Keitt variety. The study found that the foliar application of sulphur significantly reduced the incidence and severity of powdery mildew, particularly after the second and third sprayings, thus increasing mango productivity and the physical and chemical characteristics of fruits.

In line with expectations, insecticide use is positively related to yields. A 1% increase in insecticide use improves the output by 0.17% at the sample mean. This finding is in line with several studies that have arrived as similar conclusions [29, 34]. The results also indicate that increased effectiveness of insecticides is realised in larger orchards than on smaller orchards. Larger orchards are often correlated with higher levels of expertise. Additionally, larger orchards permit adoption of several systematic pest management strategies. When pesticides are part of a broad pest management strategy, the overall effectiveness of pesticides is improved.

Pesticide-related toxicity is positively related to NVA. Within certain limits, the use of toxic substances such as insecticides, fungicides and herbicides can increase yields and thereby increase NVA, despite potential environmental and health costs. However, excessive use of hazardous chemicals eventually becomes counterproductive, as it kills beneficial organisms vital for ecosystem functioning [101] and poisons farm workers when used improperly [17, 102], reducing productivity.

As expected, diminishing gains in NVA are observed from higher CO_2 emissions, toxicity, and energy deficits once CO_2 emissions exceed a certain threshold, beyond which emissions begin to undermine productivity and reduce the net contribution to economic value added. This inverted U-shaped relationship is analogous to the environmental Kuznets curve hypothesis, which suggests a positive correlation between economic growth and deleterious environmental impacts, followed by a diminishing, and eventually inverse relationship at higher levels of economic growth beyond some threshold. Several studies have reached a similar conclusion. A review by Alae-Carew et al. [103] found that fruit yields increased with higher concentrations of CO_2. Kumar et al. [104] also found strong positive correlations between carbon footprint and yields in maize-wheat systems in India. In contrast, a macro-level study in Ethiopia by Mulusew and Hong [105] reported a negative association between carbon emissions and agricultural productivity.

Orchard-level energy consumption directly depends on the quantity of intermediate inputs used. Consequently, it is inversely related to the net value added at higher levels of economic output. Our findings corroborate this intuition and show an inverse relationship with NVA at higher levels of energy use, suggesting that higher energy inputs reduce the economic value added.

3.3.3 Distribution of efficiencies and technology gap ratios

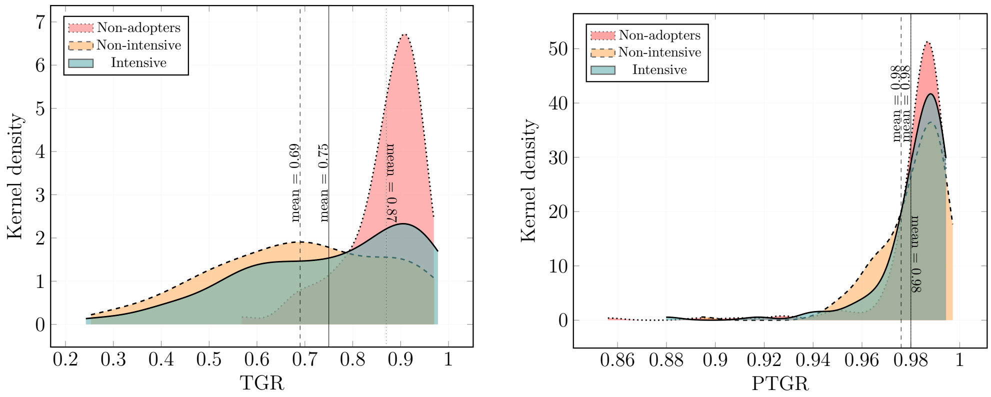
Table 6 shows the distribution of efficiencies and technology gap ratios across the three classes, along with the environmentally adjusted scores. Figure 4 presents the distribution of adjusted TGR. For ease of comparison, we also present the distribution of TGR (Figure 3a) and PTGR (Figure 3b) for various adoption classes. The average TGR was 78% across all farmers. For non-adopters, this value was highest at 87% while for adopters, the score was 69%. However, both groups had almost identical PTGR (98%). The PTGRs remained relatively similar across all groups on average. These results for PTGRs align with those of Weltin and Hüttel [9] who found that the eco-efficiency technology gap was almost at the frontier (99%) of system technology.

The average TGR^{adj} for the pooled sample was 77%, suggesting that the overall technology used by all the orchard managers surveyed is relatively advanced although not at the frontier (Figure 4). The adopters require more improvements (29.3%) to attain the same level of output as the best available technology in the industry compared to non-adopters (14.8%). On the other hand, non-intensive and intensive classes had TGR^{adj} averaging 68% and 74%, representing a moderate and relatively

Table 6: Distribution of efficiencies and technology gap ratios

Category	*Technical efficiency metrics*				*Eco-efficiency metrics*				*Environmentally adjusted metrics*			
	Metric	Mean	SD	Min–Max	Metric	Mean	SD	Min–Max	Metric	Mean	SD	Min–Max
	TE	0.702	0.143	0.243–0.933	EE	0.947	0.044	0.701–0.995			—	
Pooled	TGR	0.781	0.166	0.243–0.978	PTGR	**0.982**	0.016	0.856–0.997	TGR^{adj}	0.767	0.165	0.238–0.970
	MTE	0.623	0.190	0.110–0.968	MEE	0.934	0.045	0.677–0.993	MTE^{adj}	0.586	0.187	0.075–0.956
	TE	0.833	0.081	0.321–0.965	EE	0.967	0.024	0.842–0.993			—	
Adopters	TGR	0.720	0.184	0.243–0.978	PTGR	0.981	0.015	0.878–0.997	TGR^{adj}	0.707	0.182	0.238–0.970
	MTE	0.645	0.188	0.205–0.968	MEE	0.937	0.038	0.765–0.993	MTE^{adj}	0.607	0.184	0.172–0.956
	TE	0.689	0.223	0.114–1.000	EE	0.946	0.050	0.682–0.995			—	
Non-adopters	TGR	**0.868**	0.079	0.568–0.969	PTGR	**0.982**	0.016	0.856–0.994	TGR^{adj}	**0.852**	0.078	0.558–0.958
	MTE	0.593	0.188	0.110–0.934	MEE	0.929	0.052	0.677–0.983	MTE^{adj}	0.556	0.189	0.075–0.912
	TE	0.868	0.122	0.421–0.984	EE	0.955	0.033	0.866–0.998			—	
Non-intensive	TGR	0.690	0.181	0.253–0.971	PTGR	0.980	0.014	0.894–0.997	TGR^{adj}	0.677	0.181	0.251–0.964
	MTE	0.594	0.165	0.241–0.933	MEE	0.936	0.037	0.843–0.989	MTE^{adj}	0.556	0.162	0.226–0.900
	TE	**0.935**	0.138	0.241–1.000	EE	0.956	0.039	0.773–0.999			—	
Intensive	TGR	0.752	0.181	0.243–0.978	PTGR	**0.982**	0.016	0.879–0.994	TGR_{adj}	0.739	0.178	0.238–0.970
	MTE	**0.699**	0.195	0.205–0.968	MEE	**0.938**	0.040	0.765–0.993	MTE^{adj}	**0.660**	0.192	0.172–0.956

Notes: Abbreviations:—TE, technical efficiency; TGR: technology gap ratio; MTE: meta-technical efficiency; EE: eco-efficiency; MEE: meta-eco-efficiency; PTGR: pressure-generating TGR; SD: standard deviation. Bold values highlight the highest figures across all categories. TE and EE are derived from class-specific frontiers and are, therefore, not directly comparable; all other metrics derive from the metafrontiers and are therefore comparable across farmer categories. **Source**: Survey Data (2023).



(a) **(b)**

Fig. 3: Distributions of **(a)** TGR and **(b)** PTGR across adoption categories. **Source**: Survey Data (2023)

close distance from the frontier technology, respectively. This indicates that conventional farmers' predominant use of synthetic pesticides in fruit fly management puts them closer to the most efficient technology in the industry. This high TGR^{adj} for pesticide-reliant orchards is consistent with the well-documented yield gap favouring conventional practices over low external input systems [12]. In the current case, this can be attributed to the potent short-term efficacy of synthetic pesticides in suppressing fruit fly, consequently reducing yield losses.

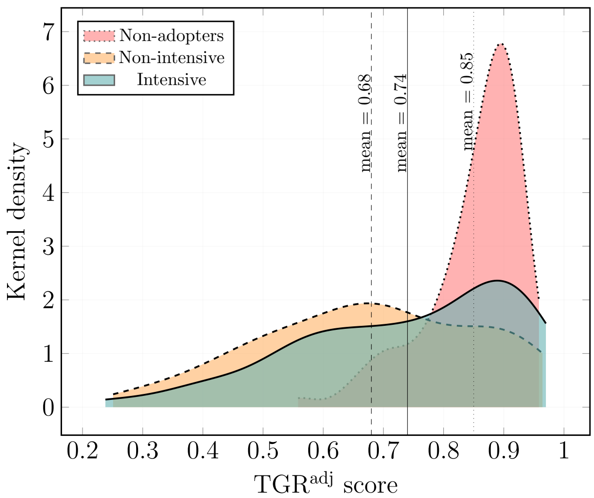
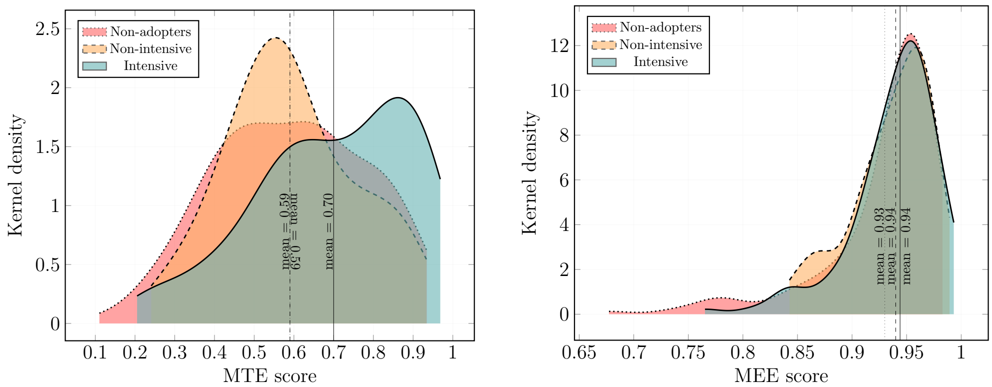


Fig. 4: Distribution of adjusted TGR for various adoption classes. **Source**: Survey Data (2023)

Turning to efficiency scores, our findings show an average MTE gap of 11% between intensive (MTE = 70%) and the non-intensive (MTE = 59%) and conventional (MTE = 59%) classes (Figure 5a). This finding agrees with the results of Rodrigues et al. [51] who found that intensive adopters of biological pest control methods were more technically efficient (86.3%) than non-intensive adopters (82.3%) in Brazilian agricultural systems. On the other hand, our results show only slight differences in MEE among the three classes of farmers. All classes had average MEE between 93–94%, with intensive and non-intensive adopters only marginally ahead of the conventional class (Figure 5b). Weltin and Hüttel [9] found that farmers practicing sustainable intensification were associated with higher eco-efficiency (75%) than non-intensive group (63%) in Italian farms.



(a) **(b)**

Fig. 5: Distributions of **(a)** MTE and **(b)** MEE across adoption categories. **Source**: Survey Data (2023)

The MTE^{adj} incorporates ecological footprints, thus providing a more precise measure of productive efficiency from a sustainability perspective. On average, orchards operate at 59% of their potential production once environmental constraints are taken into account, leaving a shortfall of 41% relative to the frontier (Figure 5 and 6). This indicates a significant efficiency gap, suggesting a considerable room for improvement in achieving optimal performance at current input levels. A subgroup analysis indicates that the distribution of efficiency scores is more dispersed among adopters than among non-adopters. Adopters attain a higher average efficiency score (61%) compared to non-adopters (56%), suggesting that although APM users are closer to the frontier, both groups exhibit substantial efficiency gaps with the frontier potential.

The stark difference in MTE between intensive and non-intensive and non-adopter classes persists even after accounting for ecological footprints. While the intensive class achieves an average MTE^{adj} of 66%, non-intensive and non-adopter classes are 10 percentage points below the intensive class efficiency. Thus, there are no efficiency gains in non-intensive adoption relative to conventional farmers. These findings suggest that, under intensive management, mango yield could potentially be increased by

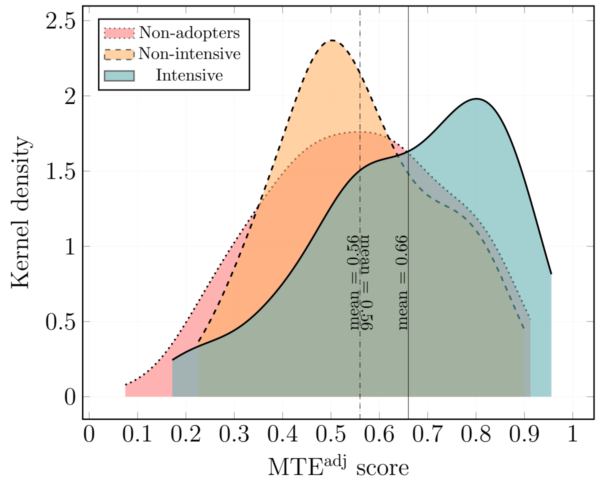


Fig. 6: Distribution of adjusted MTE for various adoption classes. **Source**: Survey Data (2023)

approximately 34% without consuming additional inputs, as opposed to a 44% increase for the non-intensive class. Limited adoption may fail to substantially reduce pest pressure while still incurring additional labour and learning costs, yielding little net benefit. Ultimately, effective fruit fly suppression requires a coordinated, integrated set of practices rather than isolated measures, which are easily undermined by re-infestation.

3.4 Treatment effects, sensitivity analysis and robustness checks

Table 7 presents the treatment effect estimates from IPWRA (fractional probit), PSM (linear regression), and RA (fractional probit). Despite differences in estimators, the methods produce substantively similar point estimates, confirming our earlier finding of negligible selectivity bias on observables. We further assess sensitivity to omitted variables using Oster's δ. In IPWRA and RA models, δ falls between 0.97 and 1.72, and 0.97 and 1.53, respectively, while in PSM models it ranges from 0.95 to 1.60, indicating a relatively strong degree of robustness, since unobserved confounders would need to be almost at least as influential as included covariates to reduce the estimated effects to zero. This confirms the insignificant ρ initially observed in the frontier models. The common-support diagnostics for PSM are displayed in Figure 7. Together, these findings provide compelling evidence that the estimated treatment effects are robust and unbiased. However, given the attractive doubly robust property of IPWRA, we focus the subsequent discussion on the results from Columns 1–6 of Table 7.

The results indicate that the adoption of APM is associated with a positive ATE of 0.32, although significant only at the 10% level, with a POMean of 0.575. This indicates that in a counterfactual scenario in which no one in the sample adopted APM, the average MTE^{adj} score would be approximately 57.5%. In contrast, had

Table 7: Estimated treatment effects

		IPWRA			PSM		RA	
	Treatment	Coef. (SE)	POMean	Oster's δ	Coef. (SE)	Oster's δ	Coef. (SE)	Oster's δ
ATE	Non-intensive	-0.011 (0.020)	0.564***	1.108	-0.014 (0.025)	1.013	-0.014 (0.021)	0.991
	Intensive	0.081*** (0.026)	0.576***	1.660	0.070** (0.031)	1.621	0.077*** (0.025)	1.530
	Intensive†	0.091*** (0.022)	0.558***	0.973	0.078*** (0.027)	0.954	0.092*** (0.023)	0.971
	Adopter	0.032* (0.017)	0.575***	1.724	0.049* (0.025)	1.447	0.034* (0.020)	1.502
ATT	Non-intensive	-0.015 (0.024)	0.574***		-0.011 (0.038)		-0.012 (0.024)	
	Intensive	0.056** (0.025)	0.607***		0.061** (0.029)		0.068** (0.029)	
	Intensive†	0.105*** (0.024)	0.557***		0.114*** (0.026)		0.104*** (0.024)	
	Adopter	0.020 (0.021)	0.588***		0.027 (0.032)		0.028 (0.021)	

Notes: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. POMean represents potential outcome mean for untreated group. Oster's δ values indicate robustness to selection on unobservables—values near or above 1 imply that unobserved confounders would need to be at least as influential as included covariates to nullify the estimated effects. †These estimates are relative to the non-intensive group; the rest are relative to non-adopters. Values in parentheses are heteroskedasticity robust standard errors. **Source**: Survey Data (2023).

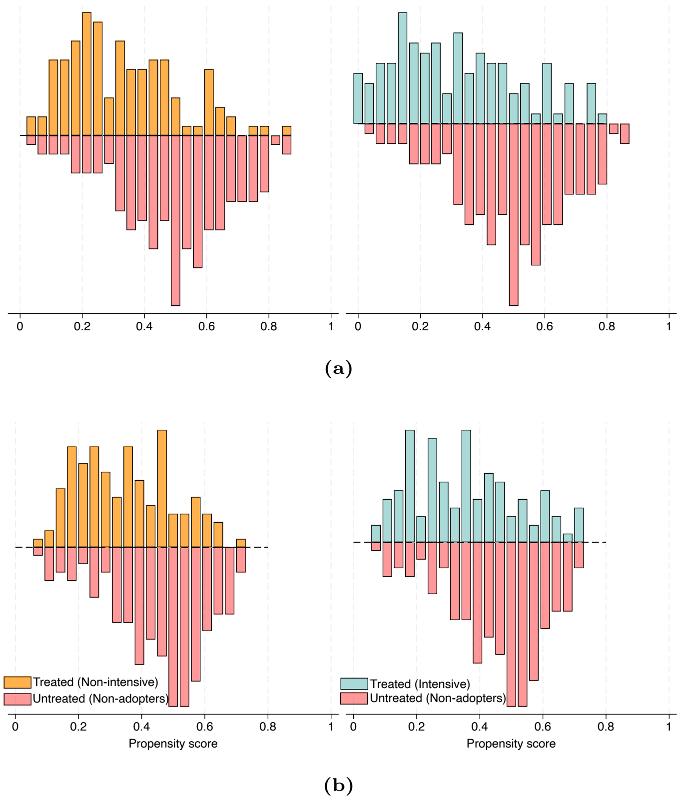


Fig. 7: Common support (CS) mirror bars: **(a)** before imposing CS and **(b)** after imposing CS.

all orchard managers adopted the APM, the MTE^{adj} scores would have increased by 3.2 percentage points on average. However, according to the ATT, orchard managers who actually adopted APM improved their scores by 2 percentage points on average. Non-intensive adoption produces a small, negative effect (ATE = –0.011) that is not statistically significant, and its associated POMean of 0.564. This suggests that in a counterfactual world where no orchard manager in the sample adopted APM, the average efficiency score would be about 56.4%. Based on the ATT estimate, the non-intensive class realised an insignificant decline of 1.5 percentage points in the efficiency score on average.

In contrast, intensive use of APM is associated with a positive significant ATE of 0.81, with a POMean of 0.576. This implies that if all farmers transitioned from non-adoption to intensive APM use, their efficiency score would increase by roughly 8.1 percentage points on average, up from the baseline of 57.6% if no one adopts the APM. According to ATT, intensive APM adopters were, on average, associated with significant increments of 5.6 percentage points in the MTE^{adj} score. The magnitude of the ATE increases by a percentage when intensive and non-intensive classes are compared, with a POMean of 0.558. Interestingly, the ATT based on this comparison is higher than the ATE by 1.6 percentage points, indicating a potential selection bias. However, the consistency of IPWRA, PSM and RA results, together with Oster's δ, provides strong confidence that this finding is not an artefact of selectivity or omitted variable bias, therefore, a possible heterogeneity in treatment effects. We discuss this shortly in Subsection 3.5. In essence, based on Oster's δ coefficients, the selection on observables would have to be at least 95.4% as influential as the observed covariates to explain away these results.

Similar findings have been reported in extant literature. In Kenya, a comprehensive IPM package for mango fruit flies disseminated by the ICIPE was found be associated with a 54.5% reduction in produce rejection and up to 22.4% increase in farmers' net income in pilot areas [36]. In a larger trial, mango farmers using various components and combinations of the IPM package saw fruit loss drop by 30%, pesticide expenditure nearly halved, and net income rise by 48% compared to non-adopters on average [34]. In conformity to our findings, the study found that while intensive adopters increased net income by 115%, those who used only one component reported 7% decline in net income. Midingoyi et al. [29] found that while the introduction of 1-2 IPM practices raised yields by between 6–27% and farm income by roughly 9–33% relative to non-adoption, intensive users (those who implemented three or more practices) recorded yield advantages of 95% and income improvements of 137% compared to non-adopters. Pecenka et al. [106] found that using only some IPM options did not significantly reduce crop damage, whereas a full suite of IPM practices nearly eliminated (up to 95%) chemical sprays through conservation of wild pollinators and natural enemies while maintaining yields, improving profitability while enhancing ecosystem services. These findings demonstrate that with sufficient intensification and proper management, agro-ecological approaches can match or even outperform the productivity of pesticide-reliant systems, lending weight to the idea that sustainable intensification is achievable.

3.5 Heterogeneity in treatment effects

The CATE estimates reveal considerable heterogeneity in MTE^{adj} attributable to the intensity of APM adoption (Figure 8). Orchard managers who perceive the pest as severe experience the highest treatment effects (Figure 8a). These farmers are likely to be more conscious and intentional in their approach to suppressing the pest since they already recognise its potential effects on yields. Participation in co-creation activities lifts the CATE well above the sample-wide ATE, with 95% confidence bands that remain entirely above zero (Figure 8i). This reflects the central role of knowledge sharing in labour-intensive agro-ecological systems. Farmer-to-farmer learning reduces search and experimentation costs, enabling faster mastery of synergistic interactions of APM options that lead to efficiency gains. The CATE curve slopes upwards beyond upper primary schooling, attaining a marked upward shift at roughly 10 years of education, indicating that better educated orchard managers experience the highest positive effects from APM use (Figure 8d). The diminishing marginal return beyond secondary schooling, however, suggests that basic agronomic literacy rather than advanced credentials is sufficient for sizeable gains. Educated farmers are more likely to process technical information better, adjust input mixes and time operations precisely, thereby capturing the synergistic effects of APM.

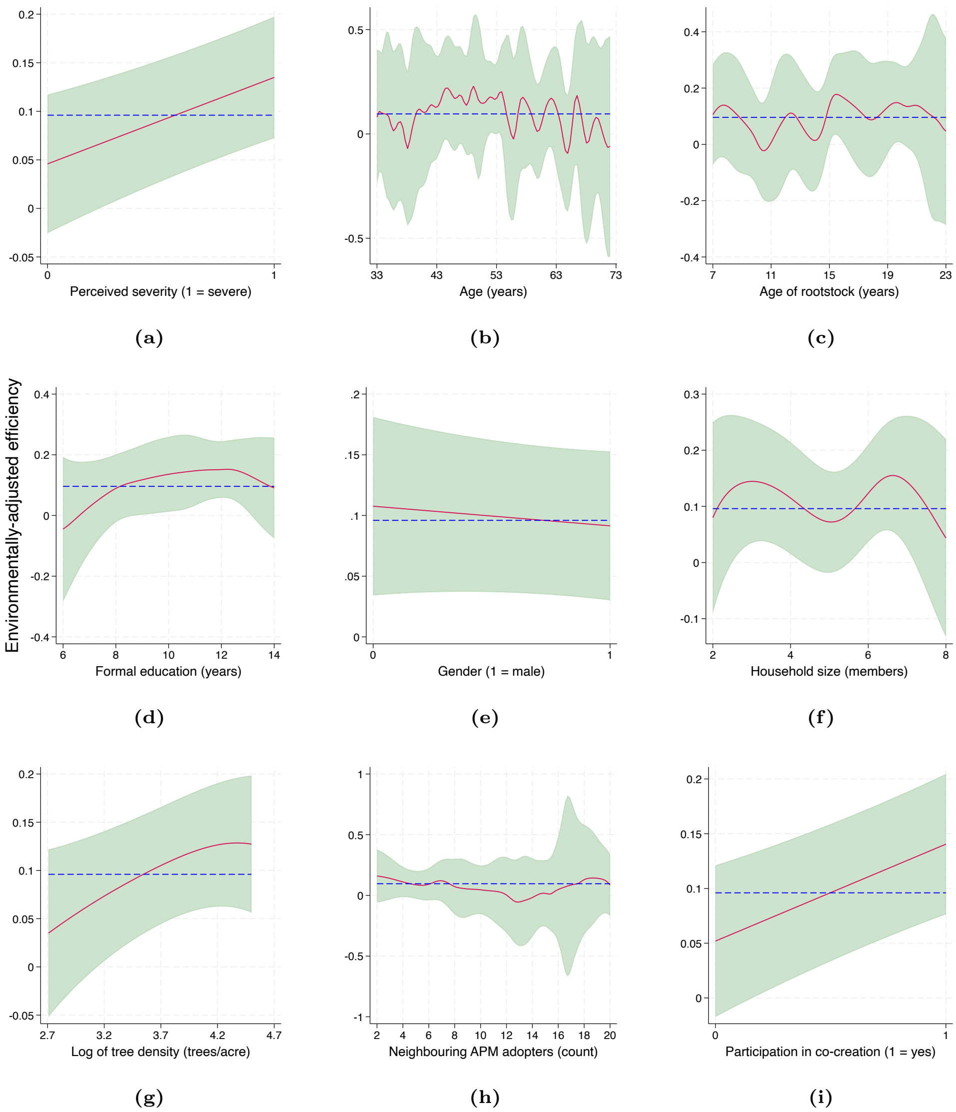


Fig. 8: Doubly robust conditional average treatment effect (DRCATE) estimates illustrating heterogeneous effects on environmentally adjusted efficiency. The dotted blue line depicts the ATE, the solid line the CATE, and the olive-teal shaded band the 95% confidence interval. **Source**: Survey Data (2023)

Other social-context variables such as gender, age, household size, and number of neighbouring adopters all produce CATE ribbons that overlap zero almost everywhere (Figures 8e , 8b, 8f, and 8h). Among the adopters, gender and age of the manager do not yield significant differences, illustrating that, conditional on access to information and resources, women and older farmers can benefit equally from APM. This suggests that the APM's effectiveness is relatively gender-neutral and resilient to variations in orchard-manager's age, household labour endowment or peer adoption density. Balogun et al. [107] reported similar results in a study of Nigerian pineapple farms. This finding aligns with the principle of fairness in agroecology. Tailored information transfer mechanisms can close any residual gaps.

In contrast, biophysical moderators exert a selective influence on $\mathrm{MTE}^{\mathrm{adj}}$. Orchard density displays a concave pattern, with moderate densities between 20–66 trees/acre yielding more positive CATEs, whereas poorly and overly dense orchards do not (Figure 8g). Managing canopy competition and pest microclimates could be easier at intermediate densities, allowing the APM intervention to reach full agronomic potential. Rootstock age exhibits wide confidence intervals that straddle zero throughout (Figure 8c), implying negligible and highly uncertain moderation.

3.6 Drivers of environmentally adjusted inefficiency

Table 8 presents the average marginal effects from a bootstrap fractional probit regression for the determinants of adjusted inefficiency. The Wald test statistic was significant at the 1% level, confirming the joint significance of the predictors. A negative coefficient shows that a variable reduces inefficiency and vice versa.

We found a non-linear relationship between APM adoption intensity and inefficiency. In the initial stages, greater adoption of APM practices reduces inefficiency, but beyond some threshold, increased intensification begins to undermine efficiency. This finding suggests a possible optimal level of APM adoption after which adding more practices yields less benefit and may even strain the farmer's management capacity. The APM is a complex strategy with high labour demand for proper coordination of practices. Beyond some optimal mix, the farmer could experience management fatigue or confusion, leading to suboptimal management. This non-linear effect suggests that sustainable intensification needs to be optimised, not maximised. For instance, certain combinations of integrated pest management components have been found to provide the highest impact, whereas other combinations are less beneficial [34, 95]. This suggests that what matters is selecting the right mix of agro-ecological options rather than simply implementing as many as possible. Policymakers and extension agents should thus emphasise an optimal integration approach by encouraging farmers to adopt a sufficient breadth of APM measures to reliably control fruit flies, but also guide them on which combinations are most synergistic to avoid overburdening them. The evidence of a non-linear effect also has a behavioural dimension. If farmers try to adopt APM practices "too much too fast," with limited knowledge of their synergistic interactions, they might become overwhelmed and experience diminishing returns in the short-run, which could discourage them or their peers from persevering with APM, leading to dis-adoption. Thus, managing the intensity of adoption to match farmers' capacity and context is important for sustained adoption and efficiency improvements.

Table 8: Estimates of bootstrap fractional probit for the determinants of environmentally adjusted inefficiency

Variable	**Coef. (SE)**	**AME (SE)**
Formal education (years)	-0.016** (0.007)	-0.006** (0.003)
Household size (count)	-0.012 (0.009)	-0.005 (0.003)
Gender (1 = male)	-0.048 (0.054)	-0.018 (0.021)
Intensity (semi-continuous)	-1.400*** (0.505)	-0.538*** (0.193)
Intensity squared	4.554*** (1.475)	1.748*** (0.564)
Orchard prospects (1 = positive)	-0.200** (0.095)	-0.077** (0.036)
Age of rootstock (years)	-0.008** (0.003)	-0.003** (0.001)
ln(Tree density (trees/acre))	-0.049 (0.036)	-0.019 (0.014)
Number of orchards (count)	0.013 (0.046)	0.005 (0.018)
Group membership (1 = yes)	-0.125** (0.051)	-0.048** (0.019)
Credit access (1 = yes)	0.153* (0.088)	0.059* (0.034)
Off-farm income (KES/year)†	-0.007 (0.006)	-0.003 (0.002)
Mango export quantity (kg)	-0.001*** (0.000)	-0.001*** (0.000)
Co-creation (1 = yes)	-0.117** (0.048)	-0.045** (0.018)
Extension access (1 = yes)	-0.005 (0.051)	-0.002 (0.020)
Distance to input market (meters)	0.007 (0.018)	0.003 (0.007)
Constant	0.650*** (0.227)	
Log pseudo-likelihood	-279.512	
Wald $\chi^2(16)$	57.94***	
Pseudo R^2	0.14	
Replications	1000	
Observations	418	

Notes: *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. † This variable was transformed using an inverse hyperbolic sine to reduce skewness and heteroscedasticity while accommodating zero observations. AME denotes the average marginal effect. Values in parentheses are bootstrapped standard errors. **Source:** Survey Data (2023).

Having a positive attitude towards orchard prospects reduced inefficiency by 7.7%. A positive outlook corresponds to a longer-term investment mindset. Optimistic farmers are willing to experiment and invest time and resources now for future payoffs. In contrast, farmers who are uncertain about their orchard's future might be less motivated to implement new practices, or may cut back on management effort, reducing efficiency. This result aligns with the role of expectations in input decisions and technology adoption. Growers who believe mango farming has a viable future are more inclined to adopt sustainable practices so that expected returns drive current adoption behaviour. Policies aimed at boosting farmer morale and outlook, such as financial incentives, recognition programs, and support services, can enhance efficiency. Extension programs should incorporate elements that foster positive attitudes, such as success stories and motivational training.

Membership in a group decreased inefficiency by 4.8%, suggesting that collective action and group dynamics can enhance efficiency. Similar findings were reported by Rodrigues et al. [51] in Brazilian agricultural regions, where efficiency increased with association membership. Groups often provide platforms for sharing knowledge, resources, and support, which can lead to improved management practices and reduced inefficiency. Social capital facilitate the exchange of information and best practices among members, leading to better-informed decisions and more efficient practices [108]. Membership in a group can also provide better access to resources such as credit, improved inputs, and technology, which can enhance efficiency. Groups can also facilitate collective bargaining for negotiating better prices for inputs and outputs, reducing their costs. In pest management, farmer groups can also be used as avenues for coordinating interventions (e.g., synchronising fruit fly sanitation across villages), to achieve scale effects that an individual cannot [109].

Participation in knowledge co-creation and co-production activities reduced inefficiency by 4.5%. Collaborative learning enable the sharing of best practices, experiences, and innovative solutions among farmers, researchers, and other stakeholders. Co-creation activities can lead to the development of tailored solutions that are sustainable and well-suited to local conditions and challenges [53, 110]. Working together also fosters trust and strengthens social networks, which can facilitate the adoption and intensive use of sustainable practices and innovations [111]. Farmers who have worked alongside researchers or extension agents to test and refine APM strategies are likely to gain deeper insights into pest ecology and control methods, allowing them to fine-tune their practices. Extension programs should prioritise participatory approaches, engaging farmers and other stakeholders in the development and dissemination of agricultural innovations. Farmer field schools, participatory research and multi-stakeholder platforms focused on collaborative skills and participatory methods can further enhance the effectiveness of knowledge co-creation and co-production activities. Such participatory extension ethos have been shown to build lasting skills and confidence among farmers, thus improving outcomes even past the expiration of the formal projects [109].

Each additional year of formal education associated with a 0.6% reduction in inefficiency. Education has a direct link to better problem-solving skills, increased awareness in eco-friendly production, better absorption and implementation of complex agro-ecological knowledge, optimal management of farm operations, and increased adaptation to new technologies. Additionally, more educated farmers might be better at seeking out and utilising information from research, extension services, and peer networks to improve their orchard management capabilities. Education has long been recognised as a driver of farm level efficiency, effectively by improving managerial ability [108]. For example, various studies have found that fruit farmers with more schooling achieve significantly higher output from the same input bundle than their less-educated peers [112–114], even though some studies such as Mensah and Brümmer [115] have reported negative impact. Understanding the biology of pests and the proper implementation of IPM tactics can be knowledge-intensive; thus, education lowers the barriers to effective adoption of APM. Enhancing the reach and quality of extension services can provide orchard managers with the necessary knowledge and support to improve their practices. Creation of digital tools and platforms to access information and connect with other orchard managers and experts can lower barriers to access pest management knowledge and innovations.

Orchards with older rootstocks were associated with lower inefficiency. This aligns with the findings of Reddy et al. [116] and Smith et al. [117], who reported a positive correlation between cumulative fruit yield during the initial 16 years and that of the subsequent years, although the yields in successive years were not directly correlated. Heidenreich et al. [48] also found a positive relationship between efficiency and age of trees. Older mature trees (within a reasonable age) often have well-established root systems, greater resilience to environmental stress, and more consistent production levels as they reach full production potentials. Established trees require less intensive management, which might lead to less consumption of inputs. Furthermore, farmers with older trees are often more experienced in orchard management, making them more knowledgeable about various farming aspects, and hence more efficient. The observation may also be due to life-cycle effects. Young orchards are still in establishment phase and therefore produce lower yields with the same level of pest management. As trees mature, yield rises faster than pest control costs, raising efficiency. Although older rootstocks can be more efficient, they may start to decrease productivity at some point. Therefore, it is important to balance the age profile of trees within an orchard for optimal performance. We did not find a significant effect of planting density or number of orchard plots on the efficiency, suggesting that within the observed range, variations in how intensively trees are planted did not systematically affect how well inputs were converted to harvested fruit. Both sparse and dense orchards have trade-offs. Although dense orchards get higher yield per area, they face more pest pressure and competition that even out in efficiency terms.

The quantity of mango fruit exported was negatively associated with inefficiency. Farmers who export larger fruit quantities are more likely to adopt sustainable practices to meet the strict export standards. Additionally, these farmers are likely to be more commercialised, prioritising minimal consumption of inputs as a profit maximisation strategy.

It should be noted that access to extension services did not show a significant impact on efficiency in our analysis. Although this might seem counter-intuitive, as extension is usually expected to improve farmers' knowledge and performance, the current extension services in the study region are not yet effective in promoting APM or improving management relative to what farmers learn from other sources. In fact, extension messages from private providers (such as input companies) and agricultural officers have in the past focused on conventional practices and general advice, rather than the specialised support needed for mastering the new agro-ecological techniques. In contrast, the strong effects of group-based learning and co-creation suggest that innovative, participatory forms of knowledge transfer have been more impactful than traditional top-down extension in this context. Unless extension agents are well-trained in the new technology and engage intensively with farmers, the uptake of such complex practices can remain lackadaisical. More interactive and farmer-centered extension approaches, such as group trainings, demonstrations, and on-farm trials, are needed to translate access to advice into actual productivity and efficiency gains at the orchard level.

Limitations of the study

Although this study provides insights on the efficiency effects of agro-ecological transitions in smallholder settings, it was not without limitations. First, our data do not account for the temporal dimensions of economic and ecological sustainability. We focused on intermediate inputs, externalities, and outputs but not on longer-term eco-efficiency impacts. Therefore, these findings should be interpreted with caution. Future analyses with longitudinal data spanning multiple seasons and with larger sample sizes could uncover more insights as various pest population dynamics, such as resurgence, resistance, or secondary pest outbreaks, could be captured. Second, the overall level of intensification of the APM measures in our sample was generally low. On average, all adopters implemented only four practices out of the 18 practices considered. This reflects the fact that most farmers are still lower in the agro-ecological transition pathway. As more farmers transition and effectively intensify APM, we expect the aggregate ecological benefits of such transitions to be more pronounced at both the farm level and the landscape scale.

4 Conclusions and policy implications

Agro-ecological pest management offers a holistic and synergistic alternative that can yield win-win outcomes in economic, environmental and social terms. Our findings corroborate this eco-efficiency premise and suggest that by shifting to, and subsequently intensifying APM, farmers can narrow and ultimately surpass the productivity and efficiency gap vis-á-vis conventional farmers. Although the theoretical yield frontier of chemical pest control remains higher, intensive APM adopters operated closer to their frontier, whereas many conventional growers underperformed relative to the latent potential of their technology. Thus, efficiency in management can be as important as the choice of a technology itself.

Promoting APM is not only an environmental imperative, but also an avenue for rural economic development. Efficient production means lower unit costs and better profitability, which is vital to livelihoods and food security. As more farmers adopt APM intensively, the aggregate supply of mango could increase or stabilise in the face of pest pressure, contributing to food security and improving farm income. A shift to APM facilitates compliance with strict export requirements, such as the European Union's Maximum Residue Level regulations, and avoids costly fruit rejection and frequent bans, thus securing access to lucrative markets. Policymakers should link orchard managers to agro-ecological certification programs targeting high value markets or alternatively create conditions that aid in the provision of agro-ecological price premiums. This could create an additional economic incentive for orchard managers to accelerate their transition to agro-ecological farming.

It should be emphasised that the efficiency gains for intensive adopters in our study stemmed primarily from achieving higher fruit yields and concomitantly fewer yield losses rather than from systematic reductions in input usage or mitigation of negative outputs, compared to other classes. Chemical savings did not differentiate efficiency scores, in part because most smallholders already apply minimal insecticides for cost reasons. This can be observed in the environmental benefits of intensive APM adoption that are only marginally ahead of the non-adopters group. Realising productivity gains currently requires considerable knowledge and management skill, and farmers face a private trade-off between short-term yield maximisation and long-term sustainability. There is need for conserted efforts among all stakeholders in the mango value chain that aim to support farmers during the transition phase so that the task of maintaining environmental intergrity is not left to farmers alone. Policy interventions should therefore be carefully designed to create enabling conditions for farmers to overcome the initial hurdles of adoption and intensification.

Given the diminishing returns observed at high levels of APM intensification, extension agents and policymakers should also emphasise quality and optimisation of practices over sheer quantity. It is important to communicate to farmers that adopting a core set of well-chosen APM strategies and executing them properly will likely yield the best results.

The lack of efficiency gains among non-intensive adopters suggests a potential risk for farmers who attempt APM in a limited way since they may not immediately see its benefits and could dis-adopt these practices. This outcome would stall the broader goal of reducing reliance on chemical pesticides. Policies should aim to lower the entry costs and risks of full APM adoption. One direct approach could be through financial support. Subsidies or cost-sharing programs for APM inputs can encourage more widespread and intensive adoption. By offsetting these costs initially, farmers can implement a comprehensive set of practices and are more likely to see positive results, which could facilitate sustained use. Ensuring the local availability of APM inputs and technologies is vital. Even if farmers are motivated, they cannot adopt practices that are inaccessible. This requires strengthening supply chains by encouraging local enterprises or cooperatives to produce and sell these inputs at reduced costs. Policymakers could provide incentives such as tax breaks or grants for agribusinesses that focus on sustainable crop protection products, thus integrating APM supplies into mainstream agricultural markets. When farmers can easily access and afford the needed inputs at the right time, the friction of adopting APM is greatly reduced.

The need for area-wide collective action is critical in the management of mobile pests such as fruit fly. Without neighbouring orchards practising orchard sanitation and baiting, mobile pests can quickly reinfest treated plots, discouraging sustained adoption of APM. Widespread partial or piecemeal uptake may therefore trap farmers in a vicious cycle of disappointment and dis-adoption, leading to reversion to chemical control.

Knowledge and training programs should be improved and re-oriented towards participatory learning. This calls for a multi-pronged approach to capacity building. Traditional extension services should be updated to include specific training on APM techniques since many extension officers in the past predominantly advised on chemical control. Ministries of agriculture could design sessions for "training of trainers" to equip extension staff with the latest agro-ecological knowledge, possibly in partnership with research organisations and universities. Moreover, farmer field schools and other participatory training models should be increased in mango-growing regions. This experiential learning can convincingly demonstrate the efficacy of APM, addressing the skepticism that many farmers may naturally have. We recommend scaling up participatory learning platforms where farmers not only receive information but also actively experiment, observe, and share experiences. Such platforms should create local champions to mentor other farmers. This peer mentorship can sustain knowledge dissemination beyond the life of formal programs.

In strengthening training, social networks and farmer groups should be leveraged. Governments and development agencies can foster the formation of mango farmer associations or integrate pest management topics into existing cooperative meetings. These groups can serve as conduits for collective training sessions, bulk purchasing of inputs, and even coordination of pest control efforts. For example, a community group could organise a weekly "orchard sanitation day" where all members ensure that no fallen fruit remains in their farms, thereby collectively reducing the area-wide pest reservoir. Policies could facilitate this by employing village-based facilitators to mobilise such actions. Strengthening farmer organisations also improves their bargaining power in the value chain, indirectly aiding efficiency by potentially securing better fruit prices and reduced input costs through group purchasing.

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Declarations

Ethics declaration. All relevant ethical approvals were obtained prior to the surveys.

Consent to participate. The consent to participate in the survey was obtained from the respondents prior to the interviews.

Consent to publish. The consent to be published was obtained from the respondents prior to the interviews.

Competing interests. The authors declare that this research was conducted without any financial, commercial, or other ties perceivable as potential conflicts of interest.

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Appendix A

Table A1: Likelihood ratio tests for functional form and technology heterogeneity

Model	Test	Null hypothesis (H_0)	Statistic	*p*-value
TE	LR	Cobb-Douglas	113.290***	0.000
EE	LR	Cobb-Douglas	710.300***	0.000
TE	GLR	No systematic error variance	134.766***	0.000
EE	GLR	No systematic error variance	293.135***	0.000

Notes: *** denotes statistical significance at the 1% level. Abbreviations: LR, Likelihood ratio; GLR, Generalised likelihood ratio. **Source**: Survey Data (2023).

Table A2: IHS unit of measurement tests and scaling factors **Source**: Survey Data (2023).

Scale factor	Unit	R^2	P^2	LogL	LogL-Adj	Kolmogorov-Smirnov	Shapiro-Wilk	Shapiro-Fancia	Anderson	Jarque-Bera	Pearson	Kurtosis	Skewness	Breusch-Pagan	RESET
IHS unit of measurement tests and scaling factors TE (Translog)															
10^{-9}	10^{9}	**0.96**	0.89	59.30	**-8789.54**	0.42	0.35	0.34	48.02	21455182.81	1104.44	54.10	3.12	149.26	2041.87
10^{-8}	10^{8}	0.94	**0.90**	20.20	-7845.43	0.40	0.46	0.45	44.10	831422.46	1088.67	22.67	0.71	164.70	1476.85
10^{-7}	10^{7}	0.92	0.89	-0.72	-6883.15	0.38	0.49	0.48	42.83	779096.82	1130.68	28.55	2.51	153.87	1056.10
10^{-6}	10^{6}	0.67	0.64	-214.85	-6114.10	0.15	0.91	0.91	5.69	94.51	449.52	6.74	-0.41	69.22	11.20
10^{-5}	10^{5}	0.54	0.52	-281.63	-5200.15	0.19	0.91	0.91	8.64	187.36	379.89	4.67	-1.13	35.25	9.18
10^{-4}	10^{4}	0.34	0.31	-392.02	-4424.55	0.14	0.93	0.93	8.03	37.39	429.80	3.22	-0.78	31.95	28.32
10^{-3}	10^{3}	0.21	0.17	-458.06	-4119.24	0.10	0.96	0.96	4.54	53.49	129.99	3.65	-0.67	17.88	2.31
10^{-2}	10^{2}	0.31	0.29	**-499.18**	-4129.92	**0.05**	**0.99**	**0.99**	0.96	10.24	58.56	3.40	-0.30	5.92	1.83
10^{-1}	10^{1}	0.25	0.22	-402.43	-4032.56	0.07	0.98	0.98	2.04	16.96	44.62	3.31	-0.51	8.09	1.08
1	1	0.19	0.14	-312.05	-3942.17	0.06	**0.99**	**0.99**	0.50	1.96	22.01	2.83	-0.21	8.05	1.53
10^{1}	10^{-1}	0.20	0.08	-167.72	-3797.84	0.06	**0.99**	0.98	0.34	6.67	14.67	4.04	-0.28	8.75	0.28
10^{2}	10^{-2}	0.20	0.04	-110.79	-3740.90	0.06	**0.99**	**0.99**	0.40	1.57	6.34	3.38	-0.13	7.03	**0.07**
10^{3}	10^{-3}	0.16	-0.07	-57.05	-3687.17	0.11	0.96	0.97	0.53	2.21	12.02	3.14	0.43	**5.08**	0.48
10^{4}	10^{-4}	0.26	-5.45	-21.60	-3651.72	0.12	0.98	0.98	0.22	**0.03**	**2.22**	2.79	-0.09	10.49	1.04
10^{5}	10^{-5}	0.65	-0.09	-16.41	-3646.52	0.10	0.97	0.98	0.18	0.48	**2.22**	2.07	0.10	6.08	1.54
10^{6}	10^{-6}	0.62	-0.23	-15.65	-3645.77	0.15	0.95	0.96	0.37	0.84	6.47	**1.80**	**-0.05**	8.94	0.32
10^{7}	10^{-7}	0.46	-0.59	-15.55	-3645.66	0.30	0.84	0.81	1.03	53.58	15.50	5.68	-1.56	5.57	0.11
10^{8}	10^{-8}	0.80	-0.16	-7.70	-3637.82	0.14	0.93	0.94	0.43	0.63	4.86	2.11	0.35	9.57	0.21
10^{9}	10^{-9}	0.47	-4.66	-11.88	-3642.00	0.17	0.94	0.96	**0.30**	0.65	4.00	**1.80**	0.26	7.87	0.23
IHS unit of measurement tests and scaling factors EE (Translog)															
10^{-9}	10^{9}	0.39	0.37	-489.12	**-9337.96**	0.10	0.96	0.96	4.34	61.52	102.54	3.69	-0.74	27.29	6.18
10^{-8}	10^{8}	0.39	0.37	-489.17	-8354.80	0.10	0.96	0.96	4.39	62.50	103.08	3.69	-0.74	27.26	6.15
10^{-7}	10^{7}	0.39	0.37	**-495.39**	-7377.88	0.10	**0.97**	**0.97**	4.09	46.59	118.05	3.48	-0.68	31.32	5.44
10^{-6}	10^{6}	0.40	0.38	-471.13	-6375.65	0.08	0.96	0.96	4.68	99.07	103.29	4.07	-0.82	25.65	3.72
10^{-5}	10^{5}	0.43	0.42	-470.71	-5546.57	0.10	0.95	0.95	6.00	63.64	143.91	3.43	-0.79	28.31	6.04
10^{-4}	10^{4}	0.53	0.51	-427.38	-5230.58	0.10	0.96	0.96	5.18	44.90	83.63	3.32	-0.68	56.05	6.76
10^{-3}	10^{3}	0.51	0.49	-429.66	-5216.41	0.12	0.92	0.91	8.89	988.49	125.95	7.65	-1.15	37.18	9.63
10^{-2}	10^{2}	0.52	0.43	-269.97	-5056.42	**0.07**	0.94	0.93	2.84	361.48	62.46	8.12	**0.06**	69.11	30.76
10^{-1}	10^{1}	0.46	0.35	-261.70	-5048.15	**0.07**	**0.97**	0.96	1.18	79.12	29.53	5.68	0.16	79.00	51.13
1	1	0.54	0.42	-66.76	-4853.22	0.13	0.95	0.95	1.16	11.96	11.64	3.90	0.29	18.88	3.40
10^{1}	10^{-1}	**0.90**	**-45.75**	-2.52	-4788.98	0.16	0.92	0.93	**0.34**	**0.27**	**2.00**	**2.06**	0.31	**7.24**	**0.20**
10^{2}	10^{-2}	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10^{3}	10^{-3}	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10^{4}	10^{-4}	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10^{5}	10^{-5}	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10^{6}	10^{-6}	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10^{7}	10^{-7}	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10^{8}	10^{-8}	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10^{9}	10^{-9}	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table A3: Percentage of orchard managers satisfying monotonicity conditions for various models

	Technical efficiency					**Eco-efficiency**			
Variable	Single class (pooled)	Single class (non-adopters)	Class 1 (non-intensive)	Class 2 (intensive)	Variable	Single class (pooled)	Single class (non-adopters)	Class 1 (non-intensive)	Class 2 (intensive)
Land	88.04	92.49	86.40	81.67	Carbon footprint	87.56	93.06	89.60	96.67
Labour	71.77	89.60	89.60	89.17	Nitrogen deficits	92.82	92.49	100.00	99.17
Fertilisers	98.33	98.27	83.20	83.33	Phosphorus deficits	83.25	86.71	89.60	85.00
Insecticides	76.08	83.82	91.20	92.50	Toxicity	92.34	87.28	92.80	95.00
Fungicides	82.78	98.27	96.80	81.67	Energy balance	82.06	90.75	88.00	99.17
Manure	85.89	96.53	89.60	83.33	Specialisation	91.63	97.69	94.40	97.50
Observations	418	173	125	120		418	173	125	120