Research Square

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

Evaluating the economic impact of agroforestry on cocoa production: Evidence from Côte d'Ivoire

N'Golo Konaté

konate7ngolo@gmail.com

Jean Lorougnon Guédé University https://orcid.org/0009-0008-8485-8528

Auguste K. Kouakou

Jean Lorougnon Guédé University https://orcid.org/0000-0002-4486-2046

Yaya Ouattara

Jean Lorougnon Guédé University

Kouakou Kouassi Apollinaire

Jean Lorougnon Guédé University

Patrick Jagoret

CIRAD, UMR ABSys, Montpellier, France ; ESA/INP-HB, Yamoussoukro, Côte d'Ivoire
https://orcid.org/0000-0002-4490-2538

Yao S. S. Barima

Jean Lorougnon Guédé University https://orcid.org/0000-0001-9840-6989

Research Article

Keywords: Agroforestry, Cocoa, Income, Yield, Côte d'Ivoire, full-sun systems

Posted Date: March 31st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9220341/v1

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

Additional Declarations: The authors declare no competing interests.

Title: Evaluating the economic impact of agroforestry on cocoa production: Evidence from Côte d'Ivoire

N'Golo Konaté[1*]

Auguste K. Kouakou[2]

Yaya Ouattara[3]

Kouakou Kouassi Apollinaire[4]

Patrick Jagoret[5]

Yao S. S. Barima[6]

1 Jean Lorougnon Guédé University. UFR Economic Sciences and Management/UFR Environment, konate7ngolo@gmail.com; ORCID: 0009-0008-8485-8528

2 Jean Lorougnon Guédé University. UFR Economic Sciences and Management, augustekk@gmail.com; ORCID: 0000-0002-4486-2046

3 Jean Lorougnon Guédé University. UFR Economic Sciences and Management, ouattarayaya@yahoo.fr

4 Jean Lorougnon Guédé University. UFR Environment, apokouassi.kak@gmail.com

5 CIRAD, UMR ABSys, Montpellier, France ; ESA/INP-HB, Yamoussoukro, Côte d'Ivoire, patrick.jagoret@cirad.fr; ORCID : 0000-0002-4490-2538

6 Jean Lorougnon Guédé University. UFR Environment, byssabas@gmail.com; ORCID : 0000-0001-9840-6989

* Correspondence: konate7ngolo@gmail.com

Conflict of interests: The authors declare no conflicts of interest.

Funding: This study on evaluating the economic impact of agroforestry on cocoa production: Evidence from Côte d'Ivoire was conducted within the framework of the Cocoa4Future (C4F) project, which is funded by the European DeSIRA initiative under grant agreement No. FOOD/2019/412-132 and by the French Development Agency. The C4F project pools a broad range of skills and expertise to meet West African cocoa production development challenges. It brings together many partners jointly striving to place people and the environment at the core of tomorrow's cocoa production.

Abstract

Côte d'Ivoire, the leading cocoa producer in the world, faces increasing challenges concerning the sustainability of its cocoa farming. Agroforestry is frequently proposed as a viable option to harmonize agricultural productivity with environmental sustainability. Nevertheless, limited empirical research has quantified its true economic impacts inside the Ivorian environment.

This study aims to assess the influence of agroforestry on cocoa yields and agricultural income in Côte d'Ivoire. Primary data were collected from 228 cocoa producers across three major production zones (Bonon, Soubré, and Biankouma). To address observable and unobservable selection bias, Propensity Score Matching (PSM) and Endogenous Switching Regression (ESR) models were applied. These complementary approaches allow for robust causal inference regarding the effects of agroforestry compared to full-sun systems. The findings indicate that agroforestry substantially enhances agricultural income and productivity. The PSM estimates show an average yield increase of 116.68 kg/ha (approximately 22%) and an income gain of 128,341 FCFA/ha (around 25%) relative to full-sun systems. The ESR model confirms positive causal effects, revealing yield gains of 90.87 kg/ha (up to 36%) and income increases of 66,396 FCFA/ha (approximately 23%). Overall, agroforestry enhances the economic performance of cocoa farming systems. This study offers robust empirical evidence supporting agroforestry as a mechanism for the sustainable enhancement of cocoa producers' performance in Côte d'Ivoire.

Keywords: Agroforestry; Cocoa; Income; Yield; Côte d'Ivoire; full-sun systems

1. Introduction

Côte d'Ivoire is the world's leading cocoa producer, with an estimated contribution of over 40% of the global supply (ICCO 2023). This sector is an essential pillar of the national economy. Indeed, it represents about 15% of the GDP and nearly 40% of export revenues (ICCO 2023). However, despite this strategic importance, Ivorian cocoa farming faces numerous major challenges. Among these challenges are accelerated deforestation, soil depletion, the effects of climate change, and, above all, the persistent low incomes of small producers (Läderach et al. 2013; Ruf et al. 2019; Olwig et al. 2024; Barima et al. 2020).

In this context, agroforestry, which involves combining trees with agricultural crops on the same plot, appears as a promising solution (Jagoret et al. 2014). It is perceived as a sustainable production model, capable of restoring soil fertility, enhancing biodiversity, and ensuring better economic resilience for farmers (Schwendenmann et al. 2010; Vaast and Somarriba 2014; Schroth et al. 2016). Increasingly promoted by development programs and NGOs (Miller et al. 2020; Castle et al. 2021), agroforestry benefits from growing financial support, with several million dollars mobilised in recent years to design and implement agroforestry projects in Côte d'Ivoire (Bockel et al. 2021). Yet, its adoption rate remains limited and varied depending on local contexts and producer profiles (Konaté 2021; Kouassi et al. 2021).

Moreover, few rigorous empirical studies have been conducted to measure the actual impact of agroforestry on the economic performance of cocoa farmers in Côte d'Ivoire. The available meta-analyses highlight the near absence of robust empirical evidence in the Ivorian context (Miller et al. 2020; Niether et al. 2020; Koutouleas et al. 2022). The majority of the work done is limited to a descriptive approach, without resorting to counterfactual evaluation methods (Hegde and Bull 2011; Haggar et al. 2017). This makes it difficult to develop evidence-based public policies (Miller et al. 2020). It is in this perspective that the present research is situated, whose main objective is to evaluate the effects of agroforestry on cocoa yield and agricultural income of Ivorian cocoa farmers. This work aims to contribute to the reflection on sustainable agricultural models.

In order to ground this reflection in a rigorous scientific framework, it is wise to examine existing works on the links between agroforestry, agricultural yield, and the income of cocoa producers. In terms of productivity, numerous empirical studies have sought to measure the effects of agroforestry on the productivity of agricultural systems. Overall, the results indicate that agroforestry systems can maintain, or even improve, agricultural yields. For example, Armengot et al. (2016) compared agroforestry systems and monocultures of cocoa in Peru. Their study reveals that, although yields are slightly lower in shaded systems, the return on labour is higher due to product diversification and reduced costs associated with integrated disease management. A global meta-analysis by Baier et al. (2023) on maize reports an overall negative effect on yields. Conversely, Bado et al. (2021), in the Sahel, observed an improvement in the productivity of millet and cowpea when they are cultivated with Ziziphus mauritiana, due to a more favourable microclimate and better efficiency in the use of water and nutrients. More rigorously, Festus et al. (2020) used a double difference method to evaluate the effects of an agroforestry program in Malawi. They observe a significant increase in yields in agroforestry systems. This study is one of the rare examples of a well-structured ex post impact assessment in a low-income country. Finally, a systematic review by Castle et al. (2021) confirms that agroforestry interventions can have positive effects on productivity, particularly by reducing losses due to climatic stresses. However, the authors specify that less than 20% of the studies reviewed are based on rigorous evaluation approaches.

One of the major objectives of agroforestry is to strengthen the economic resilience of agricultural households through income diversification. In China, Dai et al. (2017) employed a propensity score matching method to

evaluate the impact of tree intercropping on income. They show that this practice significantly improves the income of small producers, particularly through the commercialisation of woody and non-woody products. In Sudan, Fahmi et al. (2018) used the same method to evaluate the performance of traditional agroforestry parks. The results indicate better yield stability during periods of drought and increased income compared to monocultures. In Cameroon, René et al. (2023) show that certification and tree diversity improve net incomes of cocoa producers in agroforestry systems, although they do not establish a rigorous causal relationship. Similarly, using ex ante economic simulations, Ramírez et al. (2001) indicate that cocoa-banana-timber systems provide more stable long-term economic returns than monoculture systems.

2. Methodology

2.1. Study area

Three agroecological zones of Côte d'Ivoire served as the field for this study, and the selected cocoa farms belong to the agroforestry plot network of the Cocoa4Future project observatory. These sites were selected based on an East-West gradient, which corresponds to the evolution of the main cocoa production areas in Côte d'Ivoire. These sites are distributed in the localities of Bonon in the Center-West, Soubré in the South-West, and Biankouman in the West (**Fig. 1**). The Bonon site represents the epicentre of the second cocoa production zone, which experienced high production in the 1990s. As for the Soubré site, it is representative of the current premier cocoa production zone. Finally, the Biankouma site located in the west of the country is considered the future major cocoa production area (Barima et al. 2020; Konan et al. 2023). It has recorded strong growth in cocoa production since 2010.

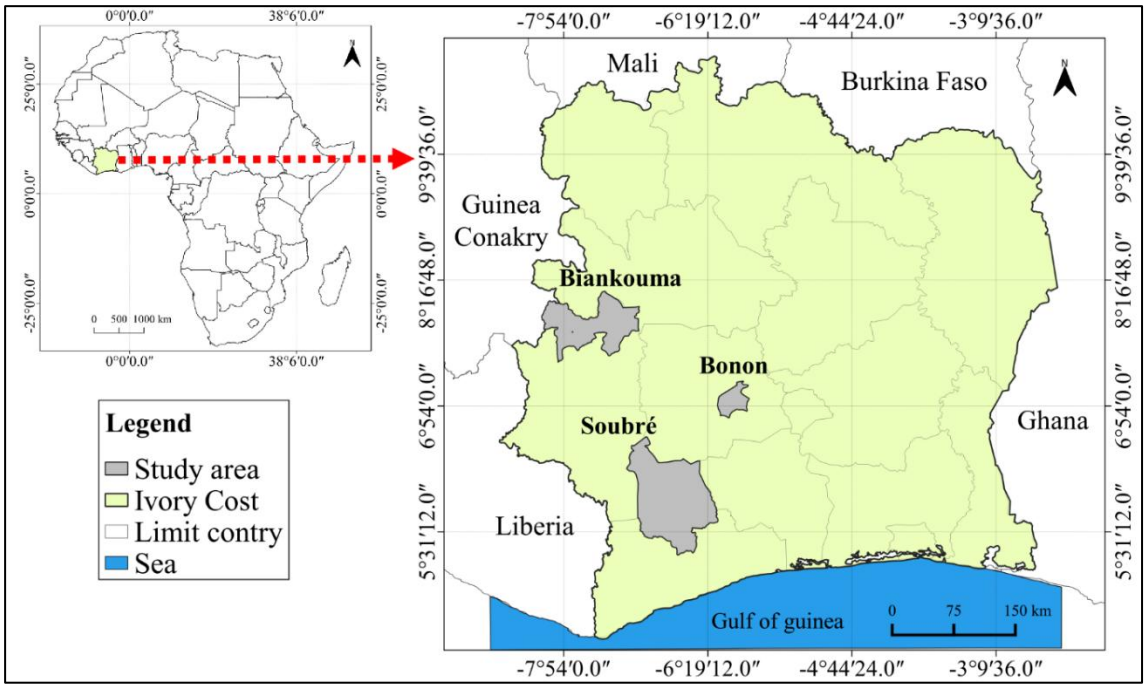


Fig. 1 : Map of the study sites

2.2. Sampling and data collection

The data used in this work are primary data collected within the framework of the Cocoa4Future project observatory. They were collected from a sample of 228 cocoa farmers randomly selected. These data are of two

types, both socioeconomic and floristic. The socioeconomic data comes from a questionnaire administered to cocoa farmers.

For floristic data, floristic inventories were conducted in all the cocoa plots belonging to the selected producers. The first step was to delineate the plantations using a GPS, in order to accurately determine the area of each plot. In a second step, itinerant surveys were conducted in these plantations. This method consisted of systematically traversing the cocoa plantations in all directions to note and georeference all the plant species encountered. The individuals surveyed were those with a diameter at breast height (DBH) greater than or equal to 2.5 cm, in accordance with the methodological recommendations of (Vroh et al., 2010). Finally, this was complemented by surface surveys. At this level, plots of 625 m² (25 m x 25 m) were installed within the cocoa plantations. This installation was guided by the area of the plantations as well as the age of the cocoa trees. Inside each plot, the number of cocoa trees was systematically counted to estimate the density of cocoa trees per farm.

2.3. The variables of the models

The identification of the explanatory variables retained to estimate propensity scores is based on a set of recent empirical studies (Hegde and Bull 2011; Kuntashula and Mungatana 2013; Haggar et al. 2017; Miller et al. 2020; Castle et al. 2021; Baier et al. 2023). Unlike some approaches, we include in our analyses the density of cocoa trees as well as that of associated crops. The associated crops considered include rubber, coffee, and cashew. We hypothesise that their consideration is essential for understanding agroforestry dynamics. Indeed, in a logic of intensification, some producers may be led to substitute these commercial species for forest species. This in turn leads to forms of monoculture. Although associated crops can also provide favourable shade for cocoa trees (Ruf et al., 2019), they are equally elements for which agroforestry systems are sought (Koutouleas et al. 2022). Thus, the selected variables are presented in **Table 1**.

Table 1 : List of variables retained for models' estimations

Variable	Description
Age of Producer	Age of the principal farmer (in years)
Education Level	Highest educational attainment of the farmer
Experience	Number of years of experience in cocoa cultivation
Area (Farm Size)	Size of the cocoa plot (in hectares)
Assets	Number of agricultural assets if the household
Working time (Labour Time)	Total time devoted to agricultural activities (in man-days)
Phyto. Products (litres)	Total quantity of plant-protection products used (in litres)
Labour Cost (thousand CFA)	Expenditure on hired labour (in thousands of CFA francs)
Phyto. Cost (thousand CFA)	Expenditure on plant-protection products (in thousands of CFA francs)
Density of Associated Crops	Number of perennial associated crops per hectare (cashew, rubber, coffee)
Cocoa Tree Density	Number of mature cocoa trees per hectare
Distance Field–Village	Distance between the cocoa plot and the farmer's home village (in km)
Land Acquisition Mode	Means of land access (inheritance, purchase, etc.)
Membership of a Cooperative	1 = member of a cooperative; 0 = non-member
Training in Cocoa Cultivation	1 = received training in cocoa cultivation; 0 = no training
Yield	Annual cocoa production per hectare (kg/ha)
Agricultural Income	Total agricultural income per hectare (CFA francs/ha)

2.4. Data analysis

To define the treatment and comparison groups, we rely on the typology proposed by Ruf (2011), which distinguishes agroforestry systems from full-sun systems based on the density of associated trees. According to

this typology, a plot containing fewer than 10 trees per hectare is considered a full-sun system, while a plot containing strictly more than 10 trees per hectare is considered agroforestry. This density criterion was therefore used to establish the comparison groups. Thus, farms with fewer than 10 associated trees per hectare are classified in the comparison group (full sun farming). On the other hand, farms with more than 10 associated trees per hectare are considered the treatment group. The underlying assumption is that, with equal socioeconomic characteristics, the difference in performance (yield and income) between the two groups is attributable to agroforestry practices. The farms in full sun thus constitute the necessary counterfactual to estimate the average impact of agroforestry.

2.5. Choice of impact assessment method

The approach falls within the field of quasi-experimental methods due to the impossibility of randomly assigning operators to different groups. Thus, the propensity score matching (PSM) method is often applied to generate perfect counterfactuals, introduced by Rosenbaum and Rubin (1983). Indeed, this method involves matching each agroforestry practitioner with a full-sun practitioner sharing similar observable characteristics.

The main advantage of PSM is to bypass the "curse of dimensionality" associated with exact matching on multiple variables. Indeed, instead of matching individuals on all their covariates, they are matched on a single synthetic variable, namely the propensity score. It is defined as the conditional probability of adopting agroforestry given the observed characteristics (Heckman et al. 1998). This score ranges between 0 and 1 and condenses all relevant information into a single indicator.

However, this method is not without limitations. Two main problems are often raised. The first is the problem of common support, which arises when no credible match can be found for some individuals in the treated group. In this case, it is advisable to exclude these observations to keep only comparable pairs, at the risk, however, of losing a significant portion of the data (Becker and Ichino 2002). The second problem lies in the difficulty of finding individuals with exactly identical scores, even within the support region. To address this, several matching techniques have been proposed, including nearest neighbour matching, radius matching, kernel matching, or stratification (Becker and Ichino 2002). In our study, we opt for nearest neighbour matching. In addition to its simplicity to implement, it allows for the creation of comparable groups while retaining a maximum number of observations, which is essential to ensure the statistical robustness of our results.

In this case, we either have: $Z_i \epsilon \{0, 1\}$ a binary variable indicating whether farmer *i* practices agroforestry (Z_i=1) or not (Z_i=0). We then define two potential outcomes as follows:

Y_{i1} : the outcome if the farmer adopts agroforestry

Y_{i0} : the outcome if the farmer does not adopt it

Thus, the effect of the treatment for an individual is given by:

$$\Delta_i = Y_{i1} - Y_{i0}$$

The propensity score being defined as the probability of adopting agroforestry, conditional on the covariates X_i, we have:

$$p(X_i) = P(Z_i = 1 | X_i)$$

According to Rosenbaum and Rubin (1983), under the assumption of conditional independence:

177 $$(Y_{i1}, Y_{i0}) \perp Z_i | X_i$$

178 and under the common support assumption, we can estimate the average treatment effect on the treated (ATT) by:

179 $$ATT = E[Y_{i1} - Y_{iO} | Z_i = 1] \approx \frac{1}{N_T}\left(\sum_{i \epsilon T} Y_i - \sum_{j \epsilon C(i)} W_{ij} Y_j\right)$$

180 Where *T* is the set of treated individuals, C(*i*) is the set of control units paired with the unit and W_{ij} are the weights
181 associated with each pairing.

182 Although the PSM method allows for the correction of selection bias on observed variables, it does not account
183 for biases related to unobservable factors that influence both the decision to adopt agroforestry and agricultural
184 outcomes (yield, income). This type of bias is common in contexts where producers self-select their production
185 system based on unmeasured preferences or capabilities (motivation, risk aversion, technical know-how, etc.). To
186 overcome this limitation, we complement the analysis with an endogenous switching regression (ESR), a method
187 derived from Heckman's selection model (Omodara et al. 2022; Bai et al. 2024). This method allows for the
188 separate estimation of two outcome functions. The first is for producers who have adopted agroforestry, and the
189 second is for those who have not. The estimation of these two functions is complemented by a simultaneous
190 modelling of the adoption decision. This model has recently been used in agricultural studies (Wossen et al. 2017;
191 Temesgen et al. 2024). However, there is an almost complete lack of applications in agroforestry.

192 The first step of the model is to model the decision to adopt agroforestry through a selection equation. We assume
193 that each producer *i* makes a dichotomous choice based on a latent utility function A_i^*, such that:

194 $A_i^* = Z_{i\gamma} + \mu_i$

195 where A_i^* is the unobserved latent utility related to the adoption of agroforestry; Z_i is vector of explanatory
196 variables influencing the adoption decision; μ_i error term assumed to be normally distributed.

197 The observable behaviour is as follows:

198 $$A_i = \begin{cases} 1 \;\; if \; A_i^* > 0, adoption \; of \; agroforestry \\ 0 \quad\;\; if \; no \; adoption \; of \; agroforestry \end{cases}$$

199 Subsequently, two separate outcome equations are estimated for the two groups of producers (adopters and non-
200 adopters):

201 $$Y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i} \;\; si \; A_i = 1$$

202 $$Y_{0i} = X_{0i}\beta_0 + \varepsilon_{0i} \;\; si \; A_i = 0$$

203 Where Y_{1i} is the yield or income of producers who have adopted agroforestry; Y_{0i} the yield or income of producers
204 in full sun; X_i the set of explanatory variables common to both equations; ε_{1i} and ε_{Oi} the error terms.

205 To correct the selection bias, we introduce the Heckman correction term (λ_i) derived from the selection equation
206 into each equation, allowing us to estimate the following versions:

207 $$Y_{1i} = X_{1i}\beta_1 + \rho_1\sigma_1\lambda_{1i} + \mu_{1i}$$

208 $$Y_{0i} = X_{0i}\beta_0 + \rho_0\sigma_0\lambda_{0i} + \mu_{0i}$$

209 where :

λ_{1i} and λ_{0i} : the selection correction terms (inverse Mills ratio) calculated from the probit model; ρ and σ respectively represent the correlations and standard deviations of the errors in each regime.

3. Results

3.1. Theories of change

The Theory of Change framework (Fig. 2) conceptualizes the pathways through which agroforestry influences cocoa farmers' performance. It is structured around four sequential stages: exploration, adoption, intermediate outcomes, and final impacts. The exploration stage focuses on identifying tree species compatible with cocoa production and assessing the economic performance of agroforestry systems, thereby informing technical and strategic decision-making.

The adoption stage addresses the enabling conditions required for farmers' engagement with agroforestry practices, including awareness-raising, capacity building, and improved access to quality planting material. These conditions support the appropriation of agroforestry practices tailored to local priorities and market requirements, with effective adoption reflecting a substantive change in farmers' behavior.

Adoption leads to intermediate outcomes such as improved land management, enhanced soil fertility, increased agricultural yields, and reduced production costs. Strengthened vegetation cover further contributes to higher agroforestry income, diversified revenue sources, improved access to food products, and reduced food expenditures. Collectively, these outcomes translate into long-term improvements in farmers' economic and social well-being.

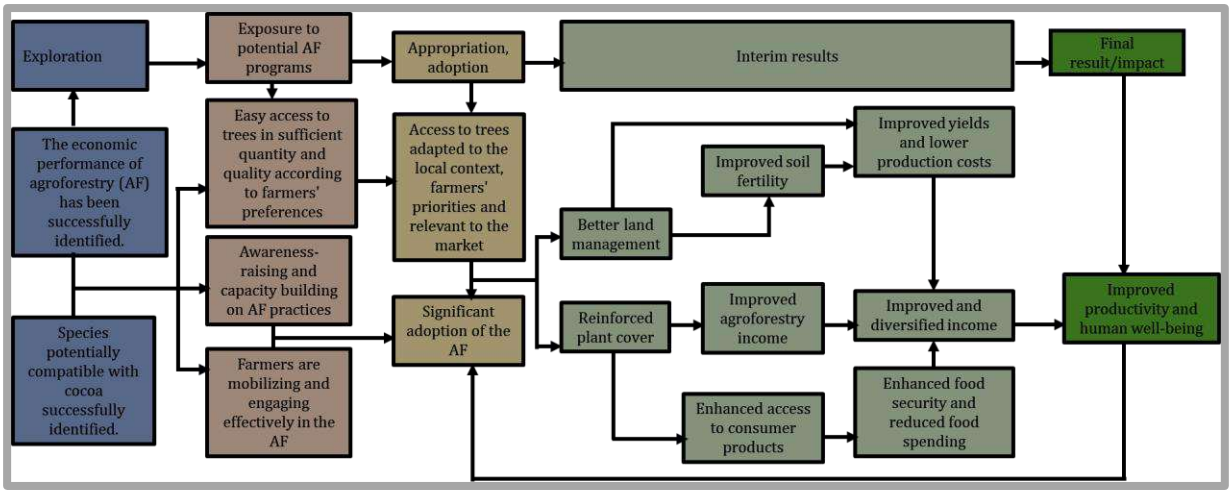


Fig. 2 : theory of change

3.2. Description of the variables of the models

The analysis highlights differences between the two groups. Three variables stand out due to statistically significant differences between treated producers and untreated producers. Indeed, producers who have adopted agroforestry have an average of 2.24 active members in their household, compared to 1.71 for non-adopters. The fields of the treated producers are significantly closer to urban centres, with an average distance of 2.58 km, compared to 3.57 km for the untreated. Regarding the average density of cocoa trees, it is significantly lower among treated producers (161.49 trees/ha) than among non-treated producers (199.70 trees/ha), at the 1%

threshold. No statistically significant difference is observed between the two groups for the other quantitative variables (**Table 2**).

Table 2 : Description of quantitative variables of the models

Variables	sample (N=228)	treated (n=107)	N. treated (n=121)	Diff. and t test
yield	639.81	622.44	655.17	32.73
Agricultural income	634353.9	629048.1	639045.7	9997.66
Area	3.11	3.19	3.06	-0.13
Age of producer	44.59	45.24	44.02	-1.23
Experience	19.79	18.86	20.62	1.76
Assets	1.96	2.24	1.71	-0.53***
Working time	102.47	88.75	114.60	25.84
Phyto products (in liter)	8.02	9.44	6.76	-2.67
Distance field-city	3.10	2.58	3.57	0.99***
Density of associated crops	4.90	3.99	5.72	1.73
Density of cocoa trees	181.77	161.49	199.70	38.21***
Cost of labour (in kfcfa)	181.93	186.25	178.10	-8.15
Cost of phyto products (in kfcfa)	47.86	52.54	43.71	-8.83

Legend: *** significance at 1%

Table 3 presents the description of the main qualitative variables included in the PSM and ESR models, namely education level, land acquisition mode, cooperative membership, and cocoa farming training. Chi-square tests were used to assess differences between adopters and non-adopters. The results show no significant differences in education level or cooperative membership between the two groups. In contrast, significant differences are observed for land acquisition mode ($p < 0.05$), with adopters more likely to have acquired land through purchase or donation, while inheritance remains predominant among non-adopters. A highly significant difference is also found for cocoa farming training ($p < 0.01$), which is substantially more common among adopters.

Table 3 : Description of qualitative variables of the models

Variable	Modalities	Proportion		Chi²	p-valeur
		treated	Non treated		
Education	none	50	59	0.59	0.309
	islamic	7	2		
	Primary	27	33		
	Secondary	27	23		
Lan acquisition mode	buy	32	29	11.70	0.020**
	Donation	13	3		
	legacy	57	77		
	Marriage	1	4		
	Plant-share	4	8		
Membership in a cooperative	yes	52	65	0.59	0.440
	no	55	56		
Training in cocoa culture	yes	46	16	25.41	0.000***
	no	61	105		

Legend: *** significance at 1%, ** significance at 5%

3.3. Results of the Propensity Score Matching model

3.3.1. Analysis of the determinants of agroforestry adoption

The Probit model is globally significant at the 1% level (Pseudo $R^2 = 0.1956$). The number of economically active household members has a positive and significant effect on the probability of adopting agroforestry: an additional active member increases adoption likelihood by 10.1%. In contrast, labor input, distance from the plot to nearby towns, and cocoa tree density negatively and significantly affect adoption. Specifically, each additional man-day reduces adoption probability by 0.17%, each additional kilometer by 2.87%, and higher cocoa density slightly but significantly lowers adoption probability. Land acquisition mode also significantly influences adoption. Compared to purchased land (reference category), inheritance and land obtained through marriage reduce the probability of adopting agroforestry by 17% and 45.6%, respectively (**Table 4**).

Table 4 : Probit regression results on the probability of treatment

Explanatory variables	Coef.	Standard error	z	p-value	dy/dx
Area (ha)	-0.0125	0.0435	-0.29	0.774	-0.0039
Experience (years)	-0.0203	0.0124	-1.64	0.102	-0.0064
Number of assets	0.3216	0.1019	3.16	0.002***	0.1010
Working time (hd)	-0.0055	0.0016	-3.43	0.001***	-0.0017
Distance field-city (km)	-0.0913	0.0371	-2.46	0.014**	-0.0287
Membership in a cooperative	-0.1271	0.2023	-0.63	0.530	-0.0399
Age of producer (years)	0.0070	0.0108	0.65	0.519	0.0022
Density of cocoa trees	-0.0027	0.0011	-2.46	0.014**	-0.0008
Phyto product (in liter)	0.0045	0.0061	0.73	0.465	0.0014
Density of associated crops	-0.0051	0.0072	-0.71	0.480	-0.0016
Education level (réf. : none)					
islamic	0.1977	0.5595	0.35	0.724	0.0627
Primary	-0.1070	0.2315	-0.46	0.644	-0.0338
Secondary	-0.1036	0.2484	-0.42	0.677	-0.0327
Land acquisition mode (réf. Buy)					
Donation	0.6967	0.4638	1.50	0.133	0.2019
Legacy	-0.5209	0.2354	-2.21	0.027**	-0.1703
Marriage	-1.6639	0.7540	-2.21	0.027**	-0.4564
Plant/Share	-0.5189	0.4759	-1.09	0.276	-0.1697
Constant (_cons)	1.1837	0.5572	2.12	0.034	
Obs.	228				
LR chi2(17)	61.64				
Prob > chi2	0.0000***				
Pseudo R2	0.1956				

Legend: *** significance at 1%, ** significance at 5%

3.3.3. Distribution of propensity scores

The propensity score overlap plot (Fig. 3) shows a satisfactory distribution of treatment probabilities between treated and untreated groups, with a common support region between 0.3 and 0.85. Sixteen treated observations falling outside this range were excluded from the ATT estimation to ensure group comparability. The observed overlap therefore supports the relevance of the propensity score approach for impact evaluation.

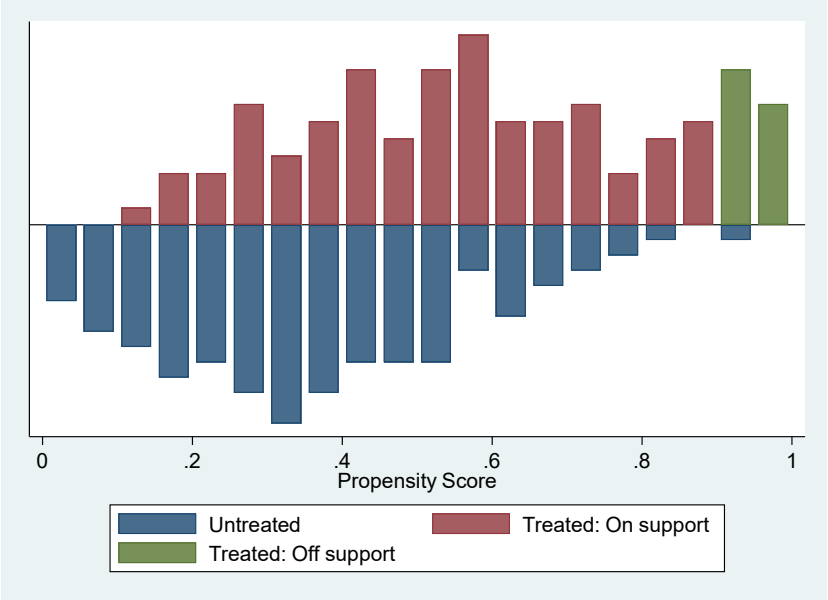


Fig. 3 : Overlap of propensity scores between groups

Although there may be good overlap, it is necessary to verify that the matching has helped reduce the initial imbalances between the treated and control groups based on the covariates. This step is a fundamental element to thus strengthen the validity of the comparisons.

3.3.4. Balancing covariates after matching

Before estimating the effect of agroforestry, **Table 5** reports the results of the covariate balance tests before and after propensity score matching. Prior to matching, several variables exhibit significant imbalances between treated and untreated groups. After matching, standardized biases are substantially reduced and generally fall below the 20% threshold, while mean comparison tests become non-significant. With the exception of education level, whose bias increases slightly but remains statistically insignificant, all covariates are adequately balanced. These results confirm that the matching procedure yields a credible comparison group for treatment effect estimation.

Table 5 : Balancing of covariates before and after matching

Variable	Unmatched	Mean		% bias	%reduct	t-test	
	Matched	Treated	Control		|bias|	t	p>|t|
Area	U	3.189	3.058	5.0	-162.3	0.38	0.708
	M	3.189	3.533	-13.0		-0.88	0.382
Experience (years)	U	18.86	20.62	-15.8	90.2	-1.19	0.234
	M	18.86	18.69	1.5		0.12	0.906
Assets	U	2.243	1.711	45.7	75.4	3.49	0.001
	M	2.243	2.374	-11.2		-0.69	0.492
Working time (hd)	U	88.76	114.6	-39.5	98.4	-2.95	0.004
	M	88.76	88.33	0.7		0.05	0.960
Education level	U	2.215	2.231	-1.3	-1291.8	-0.10	0.922
	M	2.215	2.444	-18.2		-1.37	0.172
Distance field-city	U	2.577	3.573	-40.3	76.7	-3.03	0.003
	M	2.577	2.809	-9.4		-0.79	0.432
Phyto products	U	9.437	6.764	15.3	31.8	1.18	0.241
	M	9.437	7.614	10.5		0.77	0.443
Land acquisition mode	U	2.365	2.661	-27.9	60.6	-2.10	0.037
	M	2.365	2.481	-11.0		-0.80	0.427

Membership in a cooperative	U	0.486	0.537	-10.2	-55.1	-0.77	0.442
	M	0.486	0.565	-15.8		-1.16	0.247
Age of producer	U	45.24	44.02	10.1	-63.8	0.76	0.448
	M	45.24	47.25	-16.5		-1.16	0.249
Density of cocoa trees	U	161.5	199.7	-36.3	95.3	-2.70	0.007
	M	161.5	163.3	-1.7		-0.16	0.875
Density of associated crop	U	3.986	5.716	-12.3	70.4	-0.91	0.365
	M	3.986	3.474	3.6		0.44	0.660

3.3.5. Effect of agroforestry practice on agricultural income and cocoa yield

After matching, agroforestry adopters report a higher average agricultural income than non-treated producers (647,719 FCFA versus 519,378 FCFA), corresponding to a difference of 128,341 FCFA/ha, or an increase of approximately 25%, significant at the 10% level (**Table 6**). Cocoa yield is also higher among treated producers (648.45 kg/ha versus 531.77 kg/ha), representing an average gain of 116.68 kg/ha, or an increase of about 22%, although this effect is not statistically significant. These results indicate a positive effect of agroforestry on both agricultural income and cocoa yield.

Table 6 : Effect of the treatment on agricultural income and cocoa yield

Variable	Sample	treated	Control	Difference	Difference (%)	t-stat
agricultural income	before matching	629 048.08	639045.74	–9 997.66	-	-0.17
	matched (ATT)	647 718.82	519377.59	128341.23	+24.7 %	1.71
yield	before matching	622.45	655.17	-32.73	-	-0.53
	matched (ATT)	648.45	531.77	116.68	+21.9 %	1.48

3.4. Results of the Endogenous Switching Regression model

The results reported in **Table 7** present the estimates of the ESR model for cocoa yield. In the equation for non-adopters of agroforestry, cocoa area has a negative and significant effect on yield at the 5% level, while labor input and cocoa tree density have positive and significant effects at the 1% and 5% levels, respectively. In the equation for agroforestry adopters, only labor input has a positive and significant effect on yield at the 5% level.

The selection equation indicates that training has a positive and significant effect on the probability of adopting agroforestry at the 10% level, while the number of economically active household members increases this probability at the 1% level. In contrast, labor input has a negative and significant effect at the 1% level. Agroforestry adoption is also associated with higher use of phytosanitary products. Furthermore, producers who acquired land through marriage or inheritance are less likely to adopt agroforestry, at the 5% and 10% significance levels, respectively.

The parameter rho0 (0.957), significant at the 1% level, indicates a strong negative correlation between the error terms of the yield equation for non-treated producers and the selection equation, reflecting non-random selection. In contrast, rho_1 (0.265) is not significant, indicating no evidence of selection bias among adopters. The test of independence of equations ($p = 0.0194$) confirms that the error terms are not independent and validates the ESR model specification.

Table 7 : Results of the Endogenous Switching Regression model on yield

Variables	Yield without treatment			Yield with treatment		
	Coefficient	Std. Err.	p-value	Coefficient	Std. Err.	p-value
Area	-43.598	17.980	0.015 **	-20.847	18.998	0.273
Experience	1.476	4.192	0.725	-0.818	4.248	0.847
Assets	-81.618	64.432	0.205	6.616	40.172	0.869
Working time	3.482	0.862	0.000 ***	2.898	1.481	0.050 *
Phyto products (in litres)	1.710	3.148	0.587	1.475	2.362	0.533
Cocoa tree density	0.760	0.375	0.043 **	0.174	0.791	0.826
Constant	57.751	158.207	0.715	323.224	151.587	0.033 **
		Selection equation				
Training	0.482	0.251	0.055*			
Area	-0.003	0.047	0.944			
Experience	-0.013	0.011	0.267			
Assets	0.285	0.106	0.007 ***			
Working time	-0.007	0.001	0.000 ***			
Islamic	0.028	0.416	0.947			
Primary	-0.200	0.209	0.339			
Secondary	-0.276	0.174	0.112			
Donation	0.192	0.343	0.576			
Legacy	-0.393	0.211	0.062 *			
Mariage	-1.188	0.558	0.033 **			
Plant share	-0.496	0.312	0.112			
Distance field-city	-0.061	0.037	0.103			
Phyto products	0.009	0.005	0.047**			
Cooperative	-0.106	0.181	0.558			
Age of producer	-0.004	0.008	0.596			
Density of cocoa trees	-0.0027	0.0009	0.004 ***			
Density of associated crop	-0.0017	0.005	0.740			
Constant	1.490	0.518	0.004 ***			
lns0	6.214	0.124	0.000 ***			
lns1	5.957	0.116	0.000 ***			
r0	-1.909	0.691	0.006***			
r1	0.271	0.789	0.731			
rho0	−0.957	0.058				
rho1	0.265	0.734				
sigma0	499.794	61.728				
sigma1	386.514	44.659				
chi2(2)	7.88					
Prob > chi2	0.0194					

Legend: *** significance at 1%, ** significance at 5%, * significance at 10%

The estimation of the ESR model applied to agricultural income (**Table 8**) highlights differentiated effects across producer groups. Among non-adopters of agroforestry, the cost of phytosanitary products (5%), labor input (1%), labor cost (1%), and the density of associated crops (1%) have positive and significant effects on agricultural income, while producer age (1%) and land access through donation (5%) have negative effects. Among agroforestry adopters, only labor input and labor cost show significant effects on income.

The selection equation indicates that adoption is positively influenced by training (5%), the number of economically active household members (1%), land acquisition through donation (5%), and the use of

phytosanitary inputs (1%). In contrast, distance to the plot (5%), inheritance (5%), and land access through marriage (1%) reduce the probability of adopting agroforestry. The parameter rho_0 (- 0.916), significant at the 1% level, together with the Wald test ($\chi^2 = 14.15$; $p = 0.0008$), confirms the presence of non-random selection and validates the use of the ESR model for estimating the effects on agricultural income.

Table 8 : Results of the Endogenous Switching Regression model on agricultural income

Variables	Income without treatment			Income with treatment		
	Coefficient	Std. Err.	p-value	Coefficient	Std. Err.	p-value
Area	-13195.81	11878.76	0.267	1624.179	10950.99	0.882
Cost of phyto products	3539.196	1655.116	0.032**	2472.152	1850.556	0.182
Working time	3525.433	616.3063	0.000***	3375.76	649.2741	0.000***
Cost of labour	1611.886	438.3548	0.000***	2262.877	580.199	0.000***
Plant-Share	-98299.99	97952.56	0.316	-83406.16	201562.5	0.679
Density of associated crop	3273.936	1151.878	0.004***	3758.805	4457.817	0.399
Age of producer	-6932.466	2596.276	0.008***	2595.745	2390.998	0.278
Donation	-517785.6	228359.4	0.023**	380.5685	114651.4	0.997
Constant	186206.8	141863.2	0.189	-16564.38	153332.7	0.914
		Selection equation				
Training	0.535	0.240	0.026**			
Area	0.011	0.047	0.817			
Experience	-0.016	0.011	0.153			
Assets	0.207	0.072	0.004***			
Working time	-0.007	0.001	0.000***			
Islamic	0.124	0.453	0.784			
Primary	-0.160	0.176	0.364			
Secondary	-0.203	0.186	0.274			
Donation	0.862	0.359	0.016**			
Legacy	-0.409	0.195	0.036**			
Marriage	-1.418	0.383	0.000***			
Plante-share	-0.431	0.361	0.233			
Distance field-city	-0.073	0.033	0.028**			
Phyto product	0.013	0.004	0.003***			
Member of cooperative	-0.190	0.162	0.242			
Age of producer	0.005	0.010	0.614			
Density of cocoa trees	-0.002	0.001	0.012**			
Density of associated crop	-0.001	0.006	0.917			
Constant	1.096	0.522	0.036			
lns0	12.837	0.007	0.000 ***			
lns1	12.659	0.063	0.000 ***			
r0	-1.565	0.421	0.000***			
r1	-0.152	0.268	0.570			
sigma0	375795.4	2537.696				
sigma1	314532.9	19859.25				
rho0	-0.916	0.068				
rho1	-0.151	0.262				
chi2(2)	14.15					
Prob > chi2	0.0008***					

Legend: *** significance at 1%, ** significance at 5%

After estimating the structural equations of the ESR model, treatment effects are analyzed to assess the impact of agroforestry on farm performance (**Table 9**). For cocoa yield, the ATT indicates that adopters obtain an average of 343.84 kg/ha, compared to 252.96 kg/ha in the counterfactual scenario without adoption, representing an average gain of 90.87 kg/ha, or an increase of approximately 36%, significant at the 1% level.

With respect to agricultural income, the ATT shows that adopters earn an average of 353,271 FCFA/ha, compared to 286,875 FCFA/ha without adoption, corresponding to an average gain of 66,396 FCFA/ha, or an increase of approximately 23%, significant at the 5% level. These results confirm a positive effect of agroforestry on both yield and agricultural income.

Table 9 : Treatment effects from the Endogenous Switching Regression model

Variables	Effect	Obs.	Mean	Standard dev	Difference	Difference (%)	test
Yield	ATT	107	343.84	14.60	-90.87	+35.9 %	0.0000***
	ATU	121	252.96	11.85			
Income	ATT	107	353271.4	248100	-66396.6	+23.2 %	0.0151***
	ATU	121	286874.8	155686.2			

4. Discussions

The PSM and ESR models' economic findings demonstrate that agroforestry practices greatly increase agricultural revenue and cocoa field yield. These findings contribute to the increasing amount of data demonstrating the socioeconomic advantages of agroforestry systems. The patterns demonstrate how agroforestry systems may balance sustainability and productivity. The fact that species like *Citrus sp., Cordia senegalensis, Isoberlinia doka, Morinda lucida, Morus mesozygia*, and *Raphia hookeri* can provide higher yields lends credence to this (Konaté et al. 2024). Accordingly, planting trees on cocoa farms has been successful in increasing soil fertility, making the best use of water resources, and establishing a favorable microclimate (Neupane and Thapa 2001; Roupsard et al. 2020). These benefits, which are especially evident in the outcomes of the various models, translate into increased cocoa farm productivity. Furthermore, producers can lessen the risks connected to changes in cocoa prices by diversifying their revenue streams, which is encouraged by agroforestry (René et al. 2023). Recent research on the effects of agroforestry techniques on perennial agricultural systems is in complete agreement with these findings.

First of all, our study's findings about the beneficial impact of agroforestry on income are consistent with those of Coulibaly et al. (2017) in Malawi. These authors have demonstrated how agroforestry practices increase agricultural revenue and food security. Similar findings were made by Kuntashula and Mungatana (2013), who found that households with improved fallows experienced a notable rise in well-being as indicated by household income. Nunoo and Owusu (2017) also emphasize the cocoa agroforestry systems' economic feasibility in Ghana. They show how cocoa's relationship with high-value commercial species enables income diversification and, as a result, income improvement. Surprisingly, nevertheless, Dai et al. (2017) found a causally negative relationship between agroforestry and Chinese agricultural households' income. By examining the socioeconomic characteristics, the authors discovered that the expected impact of agroforestry-based income enhancement was impeded by the land insecurity faced by farmers who are predominantly of Uyghur descent. When these peoples participated in agroforestry programs, this sentiment fueled a reluctance to devote the required time and resources. However, the costs associated with the agroforestry program they took part in were only partially compensated by the subsidies offered.

In terms of yields, our findings show that agroforestry practitioners experience a substantially greater average gain than non-practitioners. This is in line with Festus et al. (2020) findings from Malawi, which demonstrate that agroforestry systems increase crop yields. Agroforestry is completely aligned with increased farm productivity in the cocoa sector, according to other research that are not based on causality approaches (Jagoret et al. 2014). Additionally, agroforestry has supported cocoa farming in savanna regions and improved yields in previously unthinkable circumstances (Jagoret et al. 2012; Harmand et al. 2023). These findings go counter to the meta-analysis study by Niether et al. (2020). According to these scholars, cocoa agroforestry systems outperform monocultures by a factor of 25. Another meta-analysis on the impact of agroforestry on Arabica coffee yield by Koutouleas et al. (2022) supports this similar finding. But according to Niether et al. (2020), agroforestry fared better ecologically than monocultural systems since it stored 2.5 times as much carbon.

Differences in the causal effects are revealed by comparing the outcomes of the PSM and ESR models. The PSM model suggests that agroforestry adoption leads to an average increase in agricultural income of 128,341 FCFA/ha and an increase in yields of 116.68 kg/ha. These estimates are noticeably higher than those obtained from the ESR model. However, the Rosenbaum sensitivity test indicates that these results may be influenced by unobserved factors. This finding is consistent with the warnings of Kuntashula and Mungatana (2013) regarding the need for robust methods to establish causal relationships in agroforestry studies. In contrast, the ESR model, which corrects for endogeneity bias, confirms the possible presence of confounding factors. This approach therefore refines the analysis and yields more modest but statistically more robust effect estimates. For yield, the ATT is estimated at 90.87 kg/ha and is significant at the 1% level. For agricultural income, the ATT amounts to 66,396 FCFA/ha and is significant at the 5% level. These differences between the two models can be explained by the ability of the ESR model to account for unobserved factors such as motivation and access to information. This conclusion is consistent with the findings of Kuntashula and Mungatana (2013), who reported similar discrepancies between methods in their evaluation of agroforestry systems in Zambia. Similarly, Pender et al. (2008) recommend the use of rigorous methods particularly the ESR model for evaluating agroforestry policies and programs.

Designing support strategies can benefit greatly from the analysis of adoption determinants in selection equations. Land tenure, technical skills, and the quantity of available agricultural assets seem to be important factors (Place et al. 2005). The same findings, according to Pender et al. (2008) in Indonesia and (Hegde and Bull 2011) in Mozambique, indicate that the impact of agroforestry is highly dependent on land security and producers' ability to invest. The structure of agroforestry systems is also connected to the effects that have been seen. According to Roupsard et al. (2020), the species, density, and spatial layout of trees all affect how they interact with crops. According to our research, farmers frequently plant fruit trees (cola, orange, avocado, etc.) alongside cocoa to produce more marketable goods. According to (Milder et al. 2015), this arrangement thereby increases the farms' resilience. These writers emphasize how agroforestry systems can retain economic gains while improving ecological services. Nonetheless, there are still certain barriers to these systems' generalization. According to our data, indigenous producers are less likely to invest in agroforestry even if they have potentially more secure access to land. The similar findings have been reported in Kenya by earlier research (Place et al. 2005). These authors contend that fruitful investments may be hampered by indigenous people's view of land as a familial legacy.

Ecological factors must also be taken into consideration when analyzing the prospects for agroforestry systems in the future. Indeed, too much shade can lower yields, according to a study on coffee by Koutouleas et al. (2022). Therefore, it would seem that the best compromise is provided by mild and carefully controlled shading, as seen in our sample. In conclusion, the study's findings are consistent with a large body of research that acknowledges

the critical role agroforestry plays in the shift to resilient and sustainable chocolate production. To make these systems more appealing, they advocate for tightening regulations pertaining to market access, land security, and training.

5. Conclusion

The purpose of this study was to assess how agroforestry affected the financial performance of Côte d'Ivoire's cocoa growers. A sample of 228 cocoa producers was subjected to a thorough study utilizing PSM and ESR techniques. The findings unequivocally show that agroforestry greatly raises farmer yields and agricultural profits. However, some structural elements, such training, labor availability, land access methods, and market proximity, condition these impacts. These findings suggest the need for focused public policy support to eliminate obstacles to agroforestry adoption.

This study supports the applicability of this paradigm as a strategic lever for the sustainability of the Ivorian cocoa industry by helping to build an evidence basis on the economic consequences of agroforestry. Lastly, it urges more thorough assessments in different settings to gain a deeper understanding of the prerequisites for agroforestry methods to be effective.

Références

Armengot L, Barbieri P, Andres C, et al (2016) Cacao agroforestry systems have higher return on labor compared to full-sun monocultures. Agron Sustain Dev 36:70. https://doi.org/10.1007/s13593-016-0406-6

Bado BV, Whitbread A, Sanoussi Manzo ML (2021) Improving agricultural productivity using agroforestry systems: Performance of millet, cowpea, and ziziphus-based cropping systems in West Africa Sahel. Agriculture, Ecosystems & Environment 305:107175. https://doi.org/10.1016/j.agee.2020.107175

Bai EI, Ocholi A, Iheanacho AC, et al (2024) Effect of Agricultural Insurance Adoption on the Food Security of Smallholder Rice Farmers in North Central Nigeria: Application of Endogenous Switching Regression. Journal of Business and African Economy 10:27–36

Baier C, Gross A, Thevs N, Glaser B (2023) Effects of agroforestry on grain yield of maize (Zea mays L.)—A global meta-analysis. Front Sustain Food Syst 7:1167686. https://doi.org/10.3389/fsufs.2023.1167686

Barima YSS, Danmo KG, Madeleine KAT, Bogaert J (2020) Cocoa production and forest dynamics in ivory coast from 1985 to 2019. Land 9:524

Becker SO, Ichino A (2002) Estimation of Average Treatment Effects Based on Propensity Scores. The Stata Journal: Promoting communications on statistics and Stata 2:358–377. https://doi.org/10.1177/1536867X0200200403

Bockel L, Ouedraogo AS, Auguste KAA, Gopal P (2021) Analyse prospective de la filière cacao en Côte d'Ivoire 2020-2030 - Vers une politique commune de marché de cacao en Afrique de l'Ouest. FAO, Accra

Castle SE, Miller DC, Ordonez PJ, et al (2021) The impacts of agroforestry interventions on agricultural productivity, ecosystem services, and human well-being in low- and middle-income countries: A systematic review. Campbell Systematic Reviews 17:e1167. https://doi.org/10.1002/cl2.1167

Coulibaly JY, Chiputwa B, Nakelse T, Kundhlande G (2017) Adoption of agroforestry and the impact on household food security among farmers in Malawi. Agricultural systems 155:52–69

Dai X, Pu L, Rao F (2017) Assessing the Effect of a Crop-Tree Intercropping Program on Smallholders' Incomes in Rural Xinjiang, China. Sustainability 9:1542. https://doi.org/10.3390/su9091542

Fahmi MKM, Dafa-Alla D-AM, Kanninen M, Luukkanen O (2018) Impact of agroforestry parklands on crop yield and income generation: case study of rainfed farming in the semi-arid zone of Sudan. Agroforestry Systems 92:785–800. https://doi.org/10.1007/s10457-016-0048-3

Festus AO, Miller DC, McNamara PE (2020) Agroforestry as a pathway to agricultural yield impacts in climate-smart agriculture investments: Evidence from southern Malawi. Ecological Economics 167:106443. https://doi.org/10.1016/j.ecolecon.2019.106443

Haggar J, Soto G, Casanoves F, Virginio EDM (2017) Environmental-economic benefits and trade-offs on sustainably certified coffee farms. Ecological Indicators 79:330–337. https://doi.org/10.1016/j.ecolind.2017.04.023

Harmand J-M, Nijmeijer A, Sauvadet M, et al (2023) Afforestation of savannah using cocoa agroforestry: impacts on ecosystem services and effects of associated tree species on soil fertility. International Symposium on Cocoa Research (ISCR) 2022. https://doi.org/10.5281/zenodo.10213230

Heckman JJ, Ichimura H, Todd P (1998) Matching as an econometric evaluation estimator. The review of economic studies 65:261–294

Hegde R, Bull GQ (2011) Performance of an agro-forestry based Payments-for-Environmental-Services project in Mozambique: A household level analysis. Ecological Economics 71:122–130. https://doi.org/10.1016/j.ecolecon.2011.08.014

ICCO (2023) Value chain and sectoral regulatory analysis country reports côte d'ivoire country report. International Cocoa Organization (ICCO), Côte d'Ivoire

Jagoret P, Deheuvels O, Bastide P (2014) Production durable de cacao: s' inspirer de l'agroforesterie. Perspective 4-p

Jagoret P, Michel-Dounias I, Snoeck D, et al (2012) Afforestation of savannah with cocoa agroforestry systems: a small-farmer innovation in central Cameroon. Agroforest Syst 86:493–504. https://doi.org/10.1007/s10457-012-9513-9

Konan GD, Kpangui KB, Kouakou KA, Barima YSS (2023) Typologie des systèmes agroforestiers à base de cacaoyers selon le gradient de production cacaoyère en Côte d'Ivoire: Typology of cocoa-based agroforestry systems according to the cocoa production gradient in Côte d'Ivoire. Int J Bio Chem Sci 17:378–391. https://doi.org/10.4314/ijbcs.v17i2.7

Konaté N (2021) Analyse socioéconomique des exploitations familiales de cacao dans les sites de l'observatoire cocoa for future a Bonon et Soubre en Côte D'ivoire. Mémoire de Master en Economie Agricole et Agroforesterie, UFR Sciences Economiques et Gesion, Université Jean Lorougnon Guédé Daloa, Côte d'Ivoire, 99 p

Konaté N, Ouattara Y, Kouakou AK, Barima YSS (2024) Effects of Traditional Agroforestry Practices on Cocoa Yields in Côte d'Ivoire. Sustainability 16:9927. https://doi.org/10.3390/su16229927

Kouassi J-L, Kouassi A, Bene Y, et al (2021) Exploring Barriers to Agroforestry Adoption by Cocoa Farmers in South-Western Côte d'Ivoire. Sustainability 13:13075. https://doi.org/10.3390/su132313075

Koutouleas A, Sarzynski T, Bertrand B, et al (2022) Shade effects on yield across different Coffea arabica cultivars — how much is too much? A meta-analysis. Agron Sustain Dev 42:55. https://doi.org/10.1007/s13593-022-00788-2

Kuntashula E, Mungatana E (2013) Estimating the causal effect of improved fallows on farmer welfare using robust identification strategies in Chongwe, Zambia. Agroforest Syst 87:1229–1246. https://doi.org/10.1007/s10457-013-9632-y

Läderach P, Martinez-Valle A, Schroth G, Castro N (2013) Predicting the future climatic suitability for cocoa farming of the world's leading producer countries, Ghana and Côte d'Ivoire. Climatic Change 119:841–854. https://doi.org/10.1007/s10584-013-0774-8

485 Milder JC, Arbuthnot M, Blackman A, et al (2015) An agenda for assessing and improving conservation impacts
486 of sustainability standards in tropical agriculture. Conservation Biology 29:309–320.
487 https://doi.org/10.1111/cobi.12411

488 Miller DC, Ordoñez PJ, Brown SE, et al (2020) The impacts of agroforestry on agricultural productivity, ecosystem
489 services, and human well-being in low-and middle-income countries: An evidence and gap map.
490 Campbell Systematic Reviews 16:e1066. https://doi.org/10.1002/cl2.1066

491 Neupane RP, Thapa GB (2001) Impact of agroforestry intervention on soil fertility and farm income under the
492 subsistence farming system of the middle hills, Nepal. Agriculture, Ecosystems & Environment 84:157–
493 167. https://doi.org/10.1016/S0167-8809(00)00203-6

494 Niether W, Jacobi J, Blaser WJ, et al (2020) Cocoa agroforestry systems versus monocultures: a multi-dimensional
495 meta-analysis. Environ Res Lett 15:104085. https://doi.org/10.1088/1748-9326/abb053

496 Nunoo I, Owusu V (2017) Comparative analysis on financial viability of cocoa agroforestry systems in Ghana.
497 Environ Dev Sustain 19:83–98. https://doi.org/10.1007/s10668-015-9733-z

498 Olwig MF, Skovmand BA, Owusu K (eds) (2024) Agroforestry as Climate Change Adaptation: The Case of Cocoa
499 Farming in Ghana. Springer International Publishing, Cham

500 Omodara OD, Adetunji OE, Oluwasola O (2022) The nexus between agricultural loan access and farm income of
501 small-scale cassava processors in Oyo State, Nigeria: An endogenous switching regression approach.
502 Journal of Agricultural Sciences, Belgrade 67:83–104

503 Pender J, Suyanto JK, Kato E (2008) Impacts of the Hutan Kamasyarakatan social forestry program in the
504 Sumberjaya watershed, West Lampung district of Sumatra, Indonesia. Intl Food Policy Res Inst

505 Place F, Adato M, Hebinck P, Omosa M (2005) The impact of agroforestry-based soil fertility replenishment
506 practices on the poor in western Kenya. Intl Food Policy Res Inst

507 Ramírez OA, Somarriba E, Ludewigs T, Ferreira P (2001) Financial returns, stability and risk of cacao-plantain-
508 timber agroforestry systems in Central America. Agroforestry Systems 51:141–154.
509 https://doi.org/10.1023/A:1010655304724

510 René N, Luc NN, Bergaly KC, Daniel G (2023) Economic performance of certified cocoa-based agroforestry
511 systems in Cameroon. Environ Dev Sustain 25:3843–3865. https://doi.org/10.1007/s10668-022-02212-x

512 Rosenbaum PR, Rubin DB (1983) The central role of the propensity score in observational studies for causal
513 effects. Biometrika 70:41–55

514 Roupsard O, Audebert A, Ndour AP, et al (2020) How far does the tree affect the crop in agroforestry? New spatial
515 analysis methods in a Faidherbia parkland. Agriculture, Ecosystems & Environment 296:106928.
516 https://doi.org/10.1016/j.agee.2020.106928

517 Ruf F, Kone S, Bebo B (2019) Le boom de l'anacarde en Côte d'Ivoire : transition écologique et sociale des
518 systèmes à base de coton et de cacao. Cah Agric 28:21. https://doi.org/10.1051/cagri/2019019

519 Ruf FO (2011) The Myth of Complex Cocoa Agroforests: The Case of Ghana. Hum Ecol 39:373–388.
520 https://doi.org/10.1007/s10745-011-9392-0

521 Schroth G, Garcia E, Griscom BW, et al (2016) Commodity production as restoration driver in the Brazilian
522 Amazon? Pasture re-agro-forestation with cocoa (Theobroma cacao) in southern Pará. Sustain Sci
523 11:277–293. https://doi.org/10.1007/s11625-015-0330-8

524 Schwendenmann L, Veldkamp E, Moser G, et al (2010) Effects of an experimental drought on the functioning of
525 a cacao agroforestry system, Sulawesi, Indonesia. Global Change Biology 16:1515–1530.
526 https://doi.org/10.1111/j.1365-2486.2009.02034.x

527 Temesgen M, Debeb S, Erko B (2024) Impact of Coffee Technologies: A Multinomial Endogenous Switching
528 Regression Model. AJLS 12:9–15. https://doi.org/10.11648/j.ajls.20241201.12

529 Vaast P, Somarriba E (2014) Trade-offs between crop intensification and ecosystem services: the role of
530 agroforestry in cocoa cultivation. Agroforest Syst 88:947–956. https://doi.org/10.1007/s10457-014-
531 9762-x

532 Wossen T, Abdoulaye T, Alene A, et al (2017) Impacts of extension access and cooperative membership on
533 technology adoption and household welfare. Journal of Rural Studies 54:223–233.
534 https://doi.org/10.1016/j.jrurstud.2017.06.022

535