Agricultural Systems 195 (2022) 103304

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Research Paper

Sustainable intensification pathways in Sub-Saharan Africa: Assessing eco-efficiency of smallholder perennial cash crop production

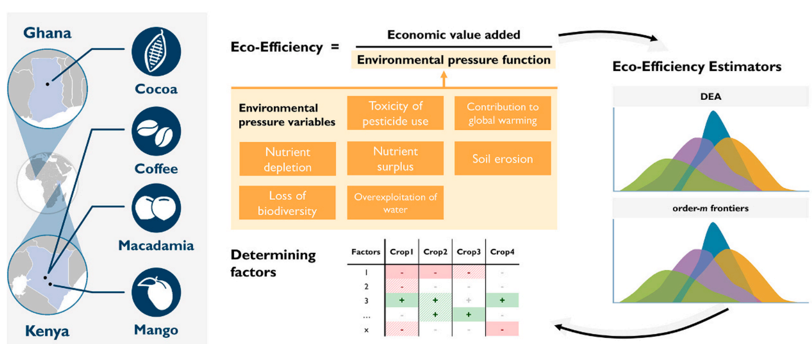
Anja Heidenreich [a,*], Christian Grovermann [a], Irene Kadzere [a], Irene S. Egyir [b], Anne Muriuki [c], Joseph Bandanaa [b,d], Joseph Clottey [b], John Ndungu [c,e], Johan Blockeel [a], Adrian Muller [a,f], Matthias Stolze [a], Christian Schader [a]

[a] Research Institute of Organic Agriculture (FiBL), Frick, Switzerland
[b] University of Ghana, Department of Agriculture Economic and Agribusiness, Legon, Accra, Ghana
[c] Kenya Agricultural & Livestock Research Organization (KALRO), Thika, Kenya
[d] University of Ghana, Institute for Environment and Sanitation Studies, Legon, Accra, Ghana
[e] University of Bonn, Center for Development Research (ZEF), Germany
[f] Swiss Federal Institute of Technology Zurich (ETHZ), Environmental Policy Lab, Zurich, Switzerland

HIGHLIGHTS

- While increased eco-efficiency matters for sustainable intensification, eco-efficiency studies of agriculture in Sub-Saharan Africa are lacking.
- We estimated eco-efficiency scores in smallholder crop production, testing the use of order-*m* frontiers and comparing it to the widely applied DEA.
- Correlations between eco-efficiency rankings of the DEA and the order-*m* approach were positive and significant, albeit not strong.
- Order-*m* efficiency scores are influenced by resource endowments, capacity development and production environment but effects are context-specific.
- Study represents the first application of input-oriented order-*m* frontiers to assess and explain eco-efficiency in the agricultural context.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Dr Guillaume Martin

Keywords:
Data envelopment analysis (DEA)
Order-*m* frontiers
Eco-efficiency
Cocoa

ABSTRACT

CONTEXT: Eco-efficiency offers a promising approach for the sustainable intensification of production systems in Sub-Saharan Africa. Data Envelopment Analysis (DEA), which is widely used for eco-efficiency analyses, is however sensitive to outliers and the analysis of the influence of external factors in the second stage requires the separability assumption to hold. Order-*m* estimators are proposed to overcome those disadvantages, but have been rarely applied in eco-efficiency analysis.

* Corresponding author.
E-mail address: anja.heidenreich@fibl.org (A. Heidenreich).

https://doi.org/10.1016/j.agsy.2021.103304
Received 12 October 2020; Received in revised form 13 October 2021; Accepted 20 October 2021
Available online 6 November 2021

Coffee
Macadamia
Mango

OBJECTIVE: This paper assesses the eco-efficiency of smallholder perennial cash crop production in Ghana and Kenya. It examines factors influencing eco-efficiency scores and in doing so, tests the application of order-*m* frontiers as a promising method for eco-efficiency analysis in the agricultural context.
METHODS: The analysis is performed for four selected perennial crop cases, namely cocoa, coffee, macadamia, and mango, applying DEA as well as the order-*m* approach to a comprehensive empirical dataset. Seven relevant environmental pressures as well as determining factors around capacity development, farm and farmer features, and crop production environment are considered.
RESULTS AND CONCLUSIONS: The distribution of eco-efficiency estimates among coffee farms showed the widest spread, which indicates the greatest potential to increase eco-efficiency. However, also the dispersion of scores within the other crop cases suggests room for improvements of eco-efficiency within the current production context. The subsequent analysis of determinants based on the order-*m* scores revealed that eco-efficiency scores were strongly influenced by variables, which measure capacity development, and resource endowments, such as labor and land, whereas the crop production environment had some influence, but results were unspecific. Generally, a positive effect is highly context-specific. The results underline the importance of designing effective training modalities and policies that allow knowledge to be put into practice, which involves the creation of marketing opportunities, the provision of targeted and regular advisory services, as well as region-wide measures to build and maintain soil fertility in a sustainable manner.
SIGNIFICANCE: To our knowledge, this study presents the first attempt to apply inputoriented order-*m* frontiers to assess eco-efficiency in the agricultural context, comparing its eco-efficiency rankings to those estimated with the widely applied DEA approach. This can inform the discussion on robust eco-efficiency assessments.

1. Introduction

The role of increasing agricultural productivity and profitability for hunger and poverty eradication in Sub-Saharan Africa (SSA) is widely recognized (Pradhan et al., 2015; Gerten et al., 2020). At the same time, unsustainable land management practices lead to a serious degradation of natural resources and ecosystems (UNEP, 2016; IPBES, 2018). Policymakers, practitioners, and scientists have rallied around the concept of sustainable intensification as a strategy for future agricultural production (FAO, 2011; Kuyper and Struik, 2014; Cassman and Grassini, 2020). While the exact implementation pathways for this concept are contested, an important underlying principle is the improvement of eco-efficiency and thus a simultaneous consideration of increases in agricultural value added per unit of land and reduction of related environmental impacts (Pretty et al., 2011; Rockström et al., 2017). Often, both aims may not be achieved at once, but already a reduction of environmental impacts without reducing yields or an increased yield without increasing environmental impacts would mean increased eco-efficiency and thus sustainability improvements.

Within the context of sustainable intensification in SSA, smallholder perennial crop production plays an important role. It enables sustainable agroforestry systems and contributes to trade revenues as can been seen across a wide range of agroecological, agronomic, and commercial contexts in countries such as Ghana and Kenya. In Ghana, for example, cocoa is the dominant export crop (ISSER, 2015) and the major source of income for approximately 800′000 farmers (World Bank, 2011). This likewise applies to coffee, which is an important cash crop in Kenya, and its production, processing, and marketing provides an income for around six million Kenyans (ICC, 2019). In addition, macadamia is another high value crop with increasing prices and growing importance for Kenya (Quiroz et al., 2019), similar to mango production, which however is primarily produced for the local markets (Kehlenbeck et al., 2012).

Despite the economic importance of these crops, productivity has nevertheless been low in most of SSA, where yield gaps continue to persist. Whereas for cocoa, 1 to 1.5 tons per hectare are attainable, the Ghanaian average remains at 0.36 tons per hectare per year (hereafter, t ha^{-1} yr^{-1}) (Danso-Abbeam, 2012). With 1.8 to 3.9 tons of coffee cherries ha^{-1} yr^{-1}, the Kenyan smallholder coffee production does also not reach the potential yield of 4.6 to 5 t ha^{-1} yr^{-1} (Kamau et al., 2016). Even though outputs stay often below the possible attainable yield, the mostly low-input agricultural production in SSA still causes substantial environmental pressures (Reynolds et al., 2015). Impacts associated with the production of these cash crops are for example biodiversity loss, pesticide contamination and soil degradation (Loland and Singh, 2004; Ntiamoah and Afrane, 2008; Reynolds et al., 2015; UNEP, 2016; Sheahan et al., 2017; IPBES, 2018; Lal and Stewart, 2019).

Agricultural production of perennial crops under current crop management practices therefore poses numerous challenges in terms of productivity and profitability as well as environmental degradation. Due to feedback loops, which are intrinsic to all agro-ecological systems, those challenges are closely related and therefore cannot be effectively addressed in isolation (Reynolds et al., 2015). In this context, a robust analytical concept is required, which enables the combined analysis of undesired environmental impacts and desired outputs, promoting sustainable intensification through the efficient use of limited resources.

Whereas technical efficiency of agricultural products is expressed as ratio of desirable output(s), such as yield or revenue, to inputs like labor, pesticides and fertilizers, eco-efficiency is measured as a ratio relating the desired output(s), mainly economic value added, to the sum of environmental pressures caused, such as greenhouse gas emissions and biodiversity loss. Improving eco-efficiency decreases the environmental impacts of production, while retaining or improving outputs (Schaltegger and Sturm, 1990). It offers a promising approach for increasing the environmental sustainability of smallholder perennial crop production. Importantly, through contrasting outputs with environmental impacts, efficiency gains are also possible without achieving potential yields, which in many smallholder contexts might cause huge challenges and may neither be the primary goal (Picazo-Tadeo et al., 2012; van Dijk et al., 2017): sustainability improvements are possible also with reducing environmental impacts for a given output or increasing outputs with given environmental impacts. Even though the concept of eco-efficiency has been applied in previous studies in the agricultural context (Wossink and Denaux, 2006; Picazo-Tadeo et al., 2011; Gómez-Limón et al., 2012; Ho et al., 2018; Grovermann et al., 2019), no systematic analysis of perennial crop production in SSA has been conducted. Furthermore, efficiency analyses often focus on specific crop production systems in individual case study regions and consequently do not allow interregional and cross-system comparisons (Danso-Abbeam, 2012; Onumah et al., 2013b; Skevas et al., 2014; Ho et al., 2018). These studies applied data envelopment analysis (DEA) combined with parametric regression to compute and explain efficiency scores. Even though it is a widely applied method, it is sensitive to outliers and the analysis of the influence of external factors on the DEA efficiency scores in the second stage is based on the separability assumption. Here, the explanatory variables are assumed to only affect the distribution of efficiency among the farms, but not the production possibilities, i.e. the position of the frontier itself (Daraio et al., 2018). Failing this assumption might lead to biased estimates and meaningless analyses of efficiency determinants. Order-*m* estimators are proposed to overcome the disadvantages of DEA (Daraio and Simar, 2007), with Kourtesi et al. (2012) being the only application in the agricultural sector, to our knowledge.

The objectives of the paper are therefore to (1) perform a robust assessment of eco-efficiency in smallholder perennial cash crop production in Ghana and Kenya as well as to (2) examine the determining factors of eco-efficiency. The analysis is performed on four selected perennial crop cases, namely cocoa, coffee, macadamia, and mango, using a comprehensive empirical dataset. Thereby, our study tests the order-*m* approach in the context of eco-efficiency estimation. Ultimately, we contribute to exploring options for improving the eco-efficiency of perennial crops and enhancing their potential within the context of smallholder perennial cash crop production in SSA.

2. Material and methods

2.1. Eco-efficiency

Following Kuosmanen and Kortelainen (2005) and Picazo-Tadeo et al. (2011), we define eco-efficiency (*EE*) as the ratio between economic value added and environmental pressures caused, and express eco-efficiency of each farm *n* ($n = 1, \ldots, N$), formally as

$$\mathrm{EE}_n = \frac{v_n}{P(p_n)} \tag{1}$$

where v_n is the economic value added and $P(.)$ is the environmental pressure function, aggregating multiple environmental pressures and thereby allowing to generate a single environmental pressure index for each farm. To do so, Kuosmanen and Kortelainen (2005) propose a weighted average of environmental pressures $p = (p_1, \ldots, p_l)$ of farm *n*:

$$P(p_n) = \sum\nolimits_{l=1}^{L} w_l p_{ln} \tag{2}$$

where w_l is the weight assigned to each environmental pressure p_l through the nonparametric benchmarking process being part of the eco-efficiency score estimation. This approach allows preventing the bias, which would result from subjectively choosing common weights a priori (Picazo-Tadeo et al., 2011). Since each decision making unit (DMU) is only compared to DMUs within the data sample, eco-efficiency scores are only expressions of relative efficiency of DMUs within that sample. It should be noted that eco-efficiency scores from different samples (i.e. different crop specific case studies) are therefore not directly comparable, but comparisons of distributions, for example, can lead to insights regarding improvement potentials within the respective production contexts.

Nonparametric frontier approaches, together with parametric stochastic frontier analysis, are commonly applied methods to determine the relative efficiency of DMUs (Charnes et al., 1978; Cooper et al., 2004). The former are well-suited for measuring eco-efficiency due to their ability to account for multiple desired or undesired inputs and outputs from different units as well as its independence of subjective aggregation weights (Kuosmanen and Kortelainen, 2005).[1] For nonparametric frontier analysis, Data Envelopment Analysis (DEA) and Free Disposal Hull (FDG) are the most common estimators (Daraio and Simar, 2007). DEA is widely applied in the context of agricultural efficiency analysis, but variants of FDH, such as order-*m* frontiers, are suggested to address certain methodological drawbacks of DEA.

2.2. Assessing eco-efficiency with data envelopment analysis

We computed crop-specific efficiency scores using the input-oriented DEA technique (Simar and Wilson, 1998). To obtain those scores, a frontier is estimated based on a sample of DMUs operating under a homogeneous production technology, using environmental and crop production data. The distance of each DMU to this 'best practice' frontier is the basis for the calculation of the efficiency scores (Picazo-Tadeo et al., 2011). The closer a DMU is located to the frontier, the higher the efficiency score ($0 \leq x \leq 1$), indicating that a reduction of environmental pressures caused or production inputs is increasingly difficult without a simultaneous decline in economic value added (Grovermann et al., 2019). Following Picazo-Tadeo et al. (2011), the eco-efficiency scores can be computed as

$$Maximize_{w_{ln'}} EE_{n'} = \frac{v_{n'}}{\sum_{l=1}^{L} w_{ln'} p_{ln'}} \tag{3}$$

subject to $\frac{v_n}{\sum_{l=1}^{L} w_{ln'} p_{ln}} \leq 1$ and $w_{ln'} \geq 0$ and the equivalent dual formulation of this problem can be expressed as

$$Minimize_{\theta_{n'}, y_n} EE_{n'} = \theta_{n'} \tag{4}$$

subject to $v_{n'} \leq \sum_{n=1}^{N} y_n v_n$ and $\theta_{n'} p_{ln'} \geq \sum_{n=1}^{N} y_n p_{ln'}$ and $y_n \geq 0$. With y_n representing the weighting of each farm *n* in the composition of the eco-efficiency frontier (Picazo-Tadeo et al., 2011). To take account of the agricultural production context, it is necessary to specify the underlying returns to scale parameter. We thus implemented the nonparametric test of constant versus variable returns to scale developed by Simar and Wilson (2020). The null hypothesis of constant returns to scale was rejected in all cases at a *p*-value of 0.003, 0.002, 0.007, and 0.000 for the cocoa, coffee, macadamia and mango case estimations, respectively. We therefore implemented variable return to scale for all four DEA models.

To analyze the determinants of eco-efficiency, commonly a truncated regression is conducted in a second stage of the analysis based on a set of explanatory variables *Z* (Simar and Wilson, 2007; Picazo-Tadeo et al., 2011). This second stage regression can provide evidence on the determinants of eco-efficiency, but only if the separability assumption holds (Daraio et al., 2018). We consequently implemented the test of separability developed by Daraio et al. (2018) and Simar and Wilson (2020) with two random splits and 1′000 bootstrap replications, leading to the result that the separability assumption does not hold in the case of our data.[2] Applying the second stage regression would therefore be

[1] We acknowledge that under this approach, the same levels of environmental pressure may be weighted differently across farms. The weights derived through the linear programming approach for the different environmental pressures can be interpreted as a reflection of the importance that a given farm attaches to each of these variables Bonfiglio et al. (2017). A high weight derived for a particular low environmental pressure may for instance be an indication that the farmer considers this environmental pressure to be particularly negative and therefore tends to limit its occurrence. To counteract this, a priori restrictions on the relative importance of different environmental pressures based on expert judgement or survey data could be incorporated (Kuosmanen and Kortelainen, 2005).

[2] In our analysis, the variables that lead to the rejection of the separability assumption are: training in organic farming, gender of household head, household size, and distance to main road.

difficult to interpret and perhaps meaningsless (Daraio et al., 2018).

2.3. Assessing eco-efficiency through order-m frontiers

The FDH estimator, as a more general version of the DEA estimator, has the same advantage as standard DEA, in that it does not require a priori specification of any functional form, but in addition it does not assume convex production sets (Daraio and Simar, 2007). However, when used as a full frontier approach, the FDH estimator is also sensitive to outliers. Cazals et al. (2002) suggested therefore the partial order-*m* frontier, where, in the input orientation, each DMU is benchmarked against a random set of *m* DMUs which produce equal or greater outputs, here economic value added *v*. Based on Daraio and Simar (2005) and Carvalho and Marques (2011) the input-oriented order-*m* eco-efficiency measure for the farm (p_n, v_n) is defined as

$$\widehat{\theta}_{m,n}(p_n, v_n) = \int_0^{\infty} \left(1 - \widehat{F}_{P_n|v_n,N}(up_n|v_n)\right)^m du \tag{5}$$

where $\widehat{F}_{P|v,N}(up_n|v_n) = \frac{\sum_{l=1}^{N} I(P(p_l) \le up_n, v_l \ge v_n)}{\sum_{l=1}^{N} I(v_l \ge v_n)}$ and $I(w)$, with $I(w) = 1$ if w is true or $I(w) = 0$ otherwise. In contrast to DEA efficiency scores, input-oriented order-*m* estimates are not limited from zero to one. Values above unity indicate that the respective farm n causes $\widehat{\theta}_{m,n}(p, v) - 1$ times less environmental pressures than the average of m peers randomly drawn from the population of farms with equal or greater economic value added. An order-*m* estimate of unity means that the farm causes the same environmental pressures as its m peers (Daraio and Simar, 2007).

$$v_n = Economic\ value\ added_n = \frac{Value\ of\ agricultural\ output_n - Labour\ cost_n - Input\ cost_n}{Crop\ area_n} \tag{7}$$

As part of the computation of the order-*m* efficiency estimates, a choice for the value of *m* is required, referring to the number of peers randomly drawn from the population of farms with equal or greater economic value added. Cazals et al. (2002) describe the process to identify *m* for which the reduction of the number of superefficient observations is stable, based on a plot displaying the percentage of super-efficient firms against increasing *m* values. Our data showed a stabilization at 94% to 99% of input-oriented super-efficient farms and an *m*-value of 65, suitable for all four crop cases (see Appendix 1).

To analyze the influence of the set of explanatory variables *Z* on the production process, order-*m* estimates are computed conditional on *Z*. Following Daraio and Simar (2005) the conditional order-*m* eco-efficiency measure is given as

$$\widehat{\theta}_m(p_n, v_n|z_n) = \int_0^{\infty} \left(1 - \widehat{F}_{P_n|v_n,Z_n,N}(up_n|v_n, z_n)\right)^m du \tag{6}$$

where $\widehat{F}_{P|v,Z,N}(up_n|v_n, z_n) = \frac{\sum_{l=1}^{N} I(P(p_l) \le up_n, V_l \ge v_n) K\left(\frac{z_n - z_l}{h}\right)}{\sum_{l=1}^{N} I(V_l \ge v_n) K\left(\frac{z_n - z_l}{h}\right)}$ and $I(w)$, with $I(w) = 1$ if w is true or $I(w) = 0$ otherwise and $K(.)$ being the kernel function and h the respective bandwidth (Carvalho and Marques, 2011). Here, we followed de Witte and Kortelainen (2013) and used a tailored mixed kernel function as well as the likelihood cross validation to obtain the optimal bandwidths.

Subsequently, a ratio of conditional order-*m* to unconditional order-*m* eco-efficiency scores $\theta_n(p, v|z)/\theta_n(p, v)$ can be constructed. In a smoothed nonparametric regression, the ratio is thereafter regressed on the explanatory variables *Z*. This process allows isolating the effect of *Z* on eco-efficiency, without being restricted by the separability assumption. To further visualize and interpret the effect of *Z* on eco-efficiency, we generated partial regression plots and applied the significance test outlined in de Witte and Kortelainen (2013) and based on Racine et al. (2006). In the input-oriented approach, a favorable effect of *Z* on eco-efficiency is shown through a decreasing regression in the partial regression plot and an increasing regression indicates an unfavorable effect of *Z* on eco-efficiency (Daraio and Simar, 2007).

2.4. Variables used in the analysis

2.4.1. Variables for computing eco-efficiency

EE (EE_n), as the ratio of desired output(s) to the sum of environmental pressures caused, accounts for the economic value added in the numerator. It encompasses information on the inputs and outputs that influence the economic value (Kuosmanen and Kortelainen, 2005), such as *value of agricultural output*, *labour cost*, and *input cost* of each farm *n* and is given in US\$ ha^{-1} yr^{-1}.

To quantify the relevant negative environmental impacts of agricultural activities in each case study, we chose a range of environmental pressure variables with relevance for the SSA context:

2.4.1.1. PPP related toxicity. While plant protection products (PPP) in SSA are encouraged to control harmful pests, they are also connected to negative health impacts (Sheahan et al., 2017), the development of resistances, and environmental pollution (Reynolds et al., 2015). Pesticide application in cocoa production in Ghana goes back 70 years (Antwi-Agyakwa et al., 2015), including government-funded mass spraying (Ntiamoah and Afrane, 2008). However, the continuing lack of knowledge among farmers about PPP types and application protocols, leads to an increase of counterfeit products as well as over- and misuse (Onwona Kwakye et al., 2019) and thus enhances environmental pressures (Claus et al., 2018). Also, chemical pesticide use among Kenyan coffee farmers contributes to the development of resistances and contaminated soils (Loland and Singh, 2004). To estimate the toxicity of applied PPP in our analysis, we quantified the amount of highly hazardous pesticides for each crop, given in kg of active ingredient ha^{-1} yr^{-1} (8) (see Appendix 2). Active ingredients were deemed highly hazardous based on the 2019 list of the Pesticide Action Network, which covers aspects of acute toxicity, long term health effects, environmental hazard criteria, and global pesticide-related conventions (PAN, 2019).

$$p_{1n} = PPP\ related\ toxicity_n = \sum_{r=1}^{R} Quantity\ active\ ingredient_{rn} \tag{8}$$

where *Quantity active ingredient*$_{rn}$ is the quantity of the highly hazardous active ingredient r ($r = 1, \ldots, R$) applied annually to the crop on farm n (in kg of r per ha^{-1} yr^{-1}).

2.4.1.2. Contribution to global warming. Even though agricultural production in SSA will be strongly affected by climate change (Niang et al., 2014), it also contributes to global warming. The highest share of greenhouse gas emissions in the lifecycle of chocolate and coffee are for example connected to their raw material production (Büsser and Jungbluth, 2009; Konstantas et al., 2018) varying between management systems and input levels (Noponen et al., 2012). We followed the carbon footprint approach to quantify greenhouse gas emissions in CO_2-e ha^{-1} yr^{-1} (BSI, 2008).

$$p_{2n} = Carbon\ footprint_n = Production\ emissions\ of\ external\ inputs_n + Direct\ field\ emissions_n \quad (9)$$

where ***Production emissions of external inputs$_n$*** are obtained through multiplying the input quantities applied annually to the crop with the respective emission factors (Nemecek and Kägi, 2007). ***Direct field emissions$_n$*** resulting from nitrogen application are calculated based on the IPPC Tier 1 equation for direct N_2O emissions from managed soils (de Klein et al., 2006) (see Appendix 3 for detailed computation).

2.4.1.3. Nutrient depletion. *Nutrient depletion* refers to arable soils with negative nutrient balances and is the most important form of chemical soil degradation in Africa (Lal and Stewart, 2019). Nitrogen (N) depletion rates are, for example, estimated at -16 kg N ha^{-1} yr^{-1} for cocoa in Ghana and at -22 kg N ha^{-1} yr^{-1} for coffee production in Kenya (Leschen et al., 2004). The consequent degradation and loss of soil fertility are serious limiting factors for agricultural productivity (Cobo et al., 2010; Kiboi et al., 2019), influencing soil microbial populations with negative consequences for food webs and ecosystem resilience (Lal and Stewart, 2019; FAO, 2020). To account for this environmental pressure, the ***Nutrient balance$_n$*** has been computed (10)

$$Nutrient\ balance_n = Nitrogen\ input_n - Nitrogen\ output_n \quad (10)$$

where ***Nitrogen input$_n$*** is the annual quantity of N added to the soil through fertilization with mineral and organic fertilizers and where ***Nitrogen output$_n$*** is the quantity of N removed from soil through harvest (see Appendix 4 for individual nitrogen uptake values per crop). In cases where nutrient removal exceeded nutrient input, the variable ***Nutrient depletion$_n$*** (in kg of N ha^{-1} yr^{-1}) has been included (*11*).

$$p_{3n} = Nutrient\ depletion_n = f(Nutrient\ balance_n) = \begin{cases} |Nutrient\ balance_n|, & Nutrient\ balance_n < 0 \\ 0, & Nutrient\ balance_n \geq 0 \end{cases} \quad (11)$$

The negative nutrient balances have been converted to their absolute value to comply with the minimization objective for all environmental pressure variables in the DEA method.

2.4.1.4. Nutrient surplus. Although synthetic nitrogen fertilizer in the context of mostly nutrient-depleted farms in SSA often improve yields, their uptake is frequently limited by the lack of other macro- and micronutrients or water. An excessive input of nutrients might therefore have negative environmental consequences and can lead to soil acidification and leaching (Reynolds et al., 2015). To complement nutrient depletion accordingly, ***Nutrient surplus$_n$*** has been included, expressed in kg of N ha^{-1} yr^{-1} (*12*).

$$p_{4n} = Nutrient\ surplus_n = f(Nutrient\ balance_k) = \begin{cases} 0, & Nutrient\ balance_n \leq 0 \\ Nutrient\ balance_n, & Nutrient\ balance_n > 0 \end{cases} \quad (12)$$

Both variables, ***Nutrient depletion$_n$*** and ***Nutrient surplus$_n$*** are mutually exclusive: whereas nutrient depletion is the absolute value of negative nitrogen balances, nutrient surplus only becomes apparent in cases of positive nitrogen balances, where then no nutrient depletion is reported. Although both variables are complementary to some extent, they were considered individually to account for their different effects on yield and thus on the economic value added.

2.4.1.5. Soil erosion. Whereas nutrient depletion leads to qualitative soil degradation, soil erosion affects the soil quantitatively, causing topsoil loss and damage to the soil biology. In SSA, this is a widespread challenge with negative impacts on production and ecosystem well-being, mainly caused by cropland mismanagement and a lack of erosion control measures (Lal and Stewart, 2019). Measures reducing soil erosion and the related loss of organic carbon, inorganic nutrients, and microbial biomass include cover crops, mulching or the reduction of water run-off through terraces (Liu et al., 2011). In the analysis, the variable ***Erosion risk$_n$*** serves as a proxy for soil erosion and indicates the percentage of steep crop area with a slope greater than 15% and without any prevention measures implemented.

$$p_{5n} = Erosion\ risk_n = \frac{Steep\ crop\ area\ without\ prevention\ measures_n}{Total\ crop\ area_n} * 100 \quad (13)$$

2.4.1.6. Loss of biodiversity. Biodiversity in SSA is threatened by various human activities including poaching, land use change and monocropping, which, among other things, result in habitat fragmentation and destruction (UNEP, 2016; IPBES, 2018). To give a general indication on the pressure exerted on the local biodiversity, we followed Gómez-Limón and Sanchez-Fernandez (2010) by including two proxies in the analysis: specialization and mean plot size.

2.4.1.6.1. Specialization. The indicator is expressed as the ratio of area occupied by the principal crop to the total farm area and gives an indication about the tendency of the farm towards monoculture.

$$p_{6n} = Specialisation_k = \frac{Area\ of\ principal\ crop_n}{Farm\ area_n} \tag{14}$$

where *Area of principal crop*$_n$ is the area occupied by the crop with the greatest area share and *Farm area*$_n$ the total farm area, both given in ha^{-1}.

2.4.1.6.2. Mean plot size. This indicator is utilized under the assumption that greater plot sizes reduce the availability of semi-natural habitat (Ricciardi et al., 2021). $\sum plot\ area_{un}$ is the sum of all plot areas per farm given in ha and u ($u = 1, \dots, U$) the number of fields per farm.

$$p_{7n} = Mean\ plot\ size_n = \frac{\sum_{u=1}^{U} plot\ area_{un}}{U_n} \tag{15}$$

2.4.1.7. Overexploitation of water resources. In the future, some regions in SSA are expected to suffer increasingly under water stress and scarcity (Niang et al., 2014). To account for this and promote an efficient usage of water, the environmental pressure variable *Irrigation*$_n$ was computed. As no other data were available, the annual amount of labor hours spent on irrigation per ha^{-1} serves as a proxy for water withdrawal:

$$p_{8n} = Water\ withdrawal_n = \frac{Labour\ hours\ for\ irrigation_n}{Crop\ area_n} \tag{16}$$

It should be noted that all output and environmental pressure variables are included in the analysis as per ha values. As the denominator is the same across these variables, the analysis remains unchanged as compared to using absolute values (Hollingsworth and Smith, 2003).

2.4.2. Covariates

We identified a range of covariates to explore their importance for the eco-efficiency estimates. These cover farmer and farm features, capacity development as well as the crop production environment. In doing so, we followed an explorative approach by including variables, which have been found relevant in similar studies. However, due to the lack of eco-efficiency assessments in the context of perennial crops in SSA, the variables are therefore largely derived from technical efficiency studies.

Assessing the association between farmer and farm features and efficiency estimates can provide evidence for more targeted policy interventions. Age, percentage of working time devoted to farming activities, farm and household size as well as access to credit, and income diversity (represented through the Simpson diversity index (Fisher et al., 1943), where 0 indicates a 100% income dependency on one crop and 1 indicates infinite diversity), were shown to be significantly relevant for technical efficiency in SSA in multiple studies and therefore included in our analysis (Ofori-Bah and Asafu-Adjaye, 2011; Danso-Abbeam, 2012; Kamau et al., 2016; Danso-Abbeam and Baiyegunhi, 2019). Even though the level of education did not show a significant effect on the technical efficiency scores in Ofori-Bah and Asafu-Adjaye (2011), Danso-Abbeam and Baiyegunhi (2019), and Onumah et al. (2013a), we included this variable nonetheless to control for its association with eco-efficiency. In addition, we considered the availability of off-farm income, gender of household head, percentage of family labor, and livestock units per ha. The latter as possible source for manure and thus nutrients, and demand for feed, influencing multiple environmental pressures.

Furthermore, the consideration of variables describing the crop production environment as well as capacity development allows exploring levers for policy measures. By considering different training topics separately, we expand the scope of the explanatory variable 'extension services' previously used in literature (Ofori-Bah and Asafu-Adjaye, 2011; Danso-Abbeam, 2012; Onumah et al., 2013b). Specifically, we assess the importance of participating in general agricultural trainings, in trainings on input use, and on environmental management as well as on organic farming. Since agricultural extension services focus often on conventional agricultural practices rather than on decreasing environmental pressures (Ho et al., 2018), we expect either no or a negative effect on eco-efficiency of the participation in general agricultural trainings as well as in trainings on input use, but a positive effect of specific trainings in environmental management as well as in organic farming on the eco-efficiency estimates. Besides, we will analyze, if the negative effect of ageing trees on technical efficiency, which was shown by Onumah et al. (2013a) and Danso-Abbeam (2012) is also visible in the case of eco-efficiency. Furthermore, the diffusion of hybrid crop varieties is often a policy objective (Kolavalli and Vigneri, 2011; Laven and Boomsma, 2012), but might result in unsustainable practices (UNDP, 2011), making this a variable of interest also for eco-efficiency assessments. Additionally, we included the distances to homesteads and main roads (each in km linear distance per field and weighted according to field size) to explore, to what extend commuting efforts are of importance in a geographical context with poor quality road networks. We tested for multicollinearity of the explanatory variables and no correlation was observed.

2.5. Data

2.5.1. Data gathering

Case studies in Ghana and Kenya were selected to cover a range of agroecological (i.e. humid and semi-arid), agronomic (i.e. predominantly arable and predominantly perennial systems), and commercial contexts. Using a structured farm household survey, primary crop

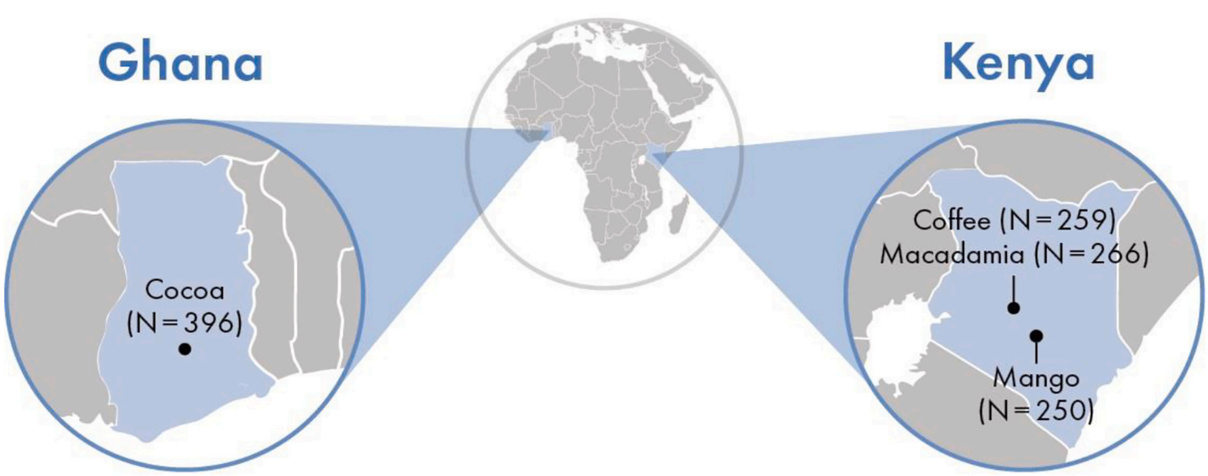


Fig. 1. Case study areas named after the analyzed crop. The number of sampled farms is displayed in brackets (N).

Table 1
Summary statistics of variables used in the efficiency computations.

	Cocoa[1]	Coffee[1]	Macadamia[1]	Mango[1]
Summary of data cleaning process				
Original	396	259	266	250
Farms identified as super-efficient	6 (2%)	16 (6%)	13 (5%)	9 (4%)
Farms identified as influential through the 'data cloud' method.	24 (6%)	20 (8%)	17 (6%)	25 (10%)
Farms identified as influential through the BACON outlier procedure	32 (8%)	8 (3%)	18 (7%)	15 (6%)
Final number of farms in the analysis	***334 (84%)***	***215 (83%)***	***218 (82%)***	***201 (80%)***
Output variable				
Economic Value Added (in thousand US$/ha^{-1} yr^{-1})	0.45 ± 0.23 (0.42)	4.56 ± 4.02 (3.21)	10.87 ± 8.49 (8.44)	1.21 ± 1.30 (0.81)
Environmental pressure variables				
PPP related toxicity (in kg/ha^{-1} yr^{-1})	0.35 ± 0.40 (0.22)	25.40 ± 17.55 (22.13)	0.00 ± 0.01 (0.00)	0.22 ± 0.55 (0.03)
Carbon footprint (in kg CO_2eq/ha^{-1} yr^{-1})	5.88 ± 5.62 (4.28)	1.48 ± 1.38 (1.13)	0.16 ± 0.35 (0.00)	7.92 ± 14.35 (2.12)
Nutrient depletion (in kg N/ha^{-1} yr^{-1})	0.12 ± 0.06 (0.12)	0.92 ± 1.44 (0.26)	2.09 ± 1.37 (1.85)	0.12 ± 0.10 (0.09)
Nutrient surplus (in kg N/ha^{-1} yr^{-1})	0.00 ± 0.00 (0.00)[a]	20.59 ± 35.80 (0.00)	0.00 ± 0.00 (0.00)[a]	0.00 ± 0.00 (0.00)[a]
Erosion risk (in % of steep crop area without prevention measurements)	60.46 ± 45.91 (100.00)	24.10 ± 41.22 (0.00)	21.17 ± 39.73 (0.00)	8.00 ± 24.04 (0.00)
Specialization (in % of crop area occupied by principal crop)	79.34 ± 14.65 (82.73)	55.70 ± 14.12 (56.16)	55.18 ± 14.41 (54.92)	50.02 ± 12.91 (49.01)
Mean plot size (in ha^{-1} yr^{-1})	1.31 ± 0.86 (1.10)	0.20 ± 0.14 (0.17)	0.22 ± 0.18 (0.17)	0.13 ± 0.09 (0.12)
Water withdrawal (in hrs/ha^{-1} yr^{-1})	0.00 ± 0.00 (0.00)[a]	0.00 ± 0.00 (0.00)[a]	0.00 ± 0.00 (0.00)[a]	0.81 ± 4.60 (0.00)

[1] n (%); Mean ± SD (Median).
[a] Excluded from efficiency computation.

production data was collected over two years (between 2015 and 2017), each spanning a minor and major cropping season. This involved 396 cocoa farms in the Ashanti region in Ghana, 250 farms with mango trees in Machakos as well as 272 farms in Kirinyaga in Kenya, with 266 of them producing macadamia and 259 of those farms growing coffee (Fig. 1).

The data contains information on harvests and sales as well as on input and labor use including expenditures. All data were specified per plot and field, with field locations and sizes recorded with GPS devices. Furthermore, the data were corrected for outlier and aggregated into yearly figures. Labor prices were fixed at 3.00 Ghanaian cedi for cocoa, and 46.43, 37.50, 37.50 Kenyan shilling for mango, coffee, and macadamia respectively. These values reflect the level of non-permanent employees above 18 years and were utilized to account for opportunity costs and ensure comparability. In addition to production and productivity data, four indicators from a sustainability assessment carried out in 2017 with the SMART-Farm Tool, RRID:SCR_018197 (Schader et al., 2016; Schader et al., 2019) were utilized as proxies for the implementation of soil erosion control measures (see Appendix 5 for a description of those indicators). To estimate the environmental pressure variable 'erosion risk', digital elevation models at 250 m spatial resolution (USGS, 2014; NASA, 2017) were used for field specific slope calculations. For the covariates 'distance to homestead' and 'distance to main road', the individual field centroids have been calculated based on the GPS field tracks. Maps indicating the main road network were used to estimate the variable 'distance to main road' (WFPGeoNode, 2018a, 2018b). Based on direct field observations and the data itself, our study assumes that farmers in each crop case operate under a similar production technology, facing similar environmental pressures. While some farm-level heterogeneity still exists, we consider that the order-*m* estimations are well suited to deal with this.

2.5.2. Data cleaning

Since DEA scores are highly sensitive to extreme values (Simar and Wilson, 2008) and we rely on observational recall data, we implemented a two-step data cleaning approach in which a method based on case deletion follows an analysis of super-efficiency. Super-efficient DMUs are known to significantly shift the DEA frontier to the outside and eliminating those has proven to work well in practical applications (Bogetoft and Otto, 2011). We classified farms with a super-efficiency of greater than three as outliers, which resulted in the removal of 6, 16, 13, and 9 farms for the cocoa, coffee, macadamia, and mango cases respectively (see Table 1). Since the identification of super-efficient DMUs does not addresses the issue of masking, the clustering of multiple outliers, we further extended the removal of super-efficient DMUs with the 'data cloud' method (Wilson, 1993; Bogetoft and Otto, 2011). This case-deletion approach was implemented and repeated four times for each crop, which resulted in eliminating 24, 20, 17, and 25 farms for the different crop cases respectively.

Table 1 indicates the final number of farms included in the analysis. To meet the 'positivity' requirement of DEA, we followed Bowlin (1998) and substituted negative values in the eco-efficiency output variable 'Economic value added' with a very small positive value (0.0001) (Sarkis, 2007). Continuous covariates were additionally examined for outlier through the use of the blocked adaptive computationally efficient outlier nominators (BACON) (Billor et al., 2000). It identifies in one run multiple outliers in a multivariate data space rather than seeking outliers variable by variable. This is an efficient outlier detection approach, which is especially useful when dealing with complex empirical data (Weber, 2010). Cases identified through this process were subsequently eliminated (see Table 1). Based on this reduced dataset, the DEA-efficiency scores were calculated (Simar and Wilson, 1998). In contrast to DEA, order-*m* estimators have the advantage of being robust against extreme values (Daraio and Simar, 2007). However, to ensure the comparability between the two methods, the reduced dataset was also used as a basis for the computation of order-*m* estimates.

The computations were done using R 4.0.3 (R Core Team, 2020), the *rDEA* (v1.2-6; Simm and Besstremyannaya (2020)), the *FEAR* (v3.1; Wilson (2020)) as well as the *frontiles* (v1.2; Daouia and Laurent (2015)), and *np* (v0.60–10; Racine and Hayfield (2020)) packages.

2.5.3. Case study characteristics

Table 1 shows the summary statistics by crop for the variables used in the calculation of the crop specific efficiency scores. Here, it is visible that the relevance of environmental pressures depends on the cropping context, with nutrient surplus being pronounced only in coffee production with an average of 20 kg N/ha^{-1} yr^{-1}, and water withdrawal solely occurring in the case of mango (Table 1). The remaining environmental pressures on the other hand are of importance in all four production environments, i.e. PPP related toxicity, contribution to global warming, nutrient depletion, soil erosion, as well as the biodiversity loss proxies specialization and mean plot size. However, cocoa shows, with a mean of 79%, the highest specialization rate, and at the same time the largest plot sizes (mean = 1.3 ha^{-1} yr^{-1}). Coffee displays the greatest application of highly hazardous pesticides with a mean of 25 kg of active ingredients ha^{-1} yr^{-1}. With a mean of 60% of steep crop

Table 2
Summary statistics of explanatory variables of efficiency scores.

	Cocoa[1]	Coffee[1]	Macadamia[1]	Mango[1]
	N = 334	N = 215	N = 218	N = 201
Covariates: Capacity development				
Training in general farm management	148 (44%)	51 (24%)	52 (24%)	19 (9.5%)
Training in input use	38 (11%)	34 (16%)	33 (15%)	6 (3.0%)
Training in environmental management	6 (1.8%)	47 (22%)	50 (23%)	9 (4.5%)
Training in organic farming	158 (47%)	65 (30%)	58 (27%)	32 (16%)
Covariates: Farm and farmer features				
Age (in years)	53.35 ± 11.93 (53.00)	56.23 ± 13.23 (55.00)	56.11 ± 13.39 (55.00)	54.76 ± 15.03 (55.00)
Working time devoted to farming activities (in %)	11.94 ± 8.85 (9.14)	9.13 ± 6.38 (7.36)	9.19 ± 6.52 (7.06)	4.70 ± 3.30 (4.14)
Level of education				
No formal	73 (22%)	33 (15%)	32 (15%)	17 (8.5%)
Primary	66 (20%)	48 (22%)	50 (23%)	105 (52%)
Secondary and further	195 (58%)	134 (62%)	136 (62%)	79 (39%)
Farm size (in ha)	2.98 ± 2.10 (2.50)	0.51 ± 0.28 (0.44)	0.51 ± 0.28 (0.45)	1.12 ± 0.75 (0.96)
Household size (Number of persons)	5.02 ± 2.60 (5.00)	2.32 ± 1.09 (2.00)	2.35 ± 1.10 (2.00)	4.36 ± 2.16 (4.00)
Family labor (% of total labor hrs)	64.13 ± 16.90 (63.82)	59.84 ± 27.45 (59.73)	60.07 ± 27.66 (58.42)	61.64 ± 27.93 (61.13)
Income diversity (index from 0 to 1)	0.64 ± 0.15 (0.68)	0.62 ± 0.12 (0.63)	0.61 ± 0.12 (0.63)	0.70 ± 0.11 (0.73)
Livestock Units (per ha)	0.05 ± 0.07 (0.02)	3.44 ± 2.95 (2.74)	3.34 ± 2.75 (2.64)	3.15 ± 2.79 (2.41)
Access to credit facilities				
Accessible	334 (100%)[a]	204 (95%)	205 (94%)	199 (99%)
Not accessible	0 (0%)	11 (5.1%)	13 (6.0%)	2 (1.0%)
Gender of household head				
Female	80 (24%)	23 (11%)	20 (9.2%)	52 (26%)
Male	254 (76%)	192 (89%)	198 (91%)	149 (74%)
Off-farm income	228 (68%)	66 (31%)	63 (29%)	80 (40%)
Covariates: Crop production environment				
Distance to homestead (in km linear distance)	2.14 ± 1.05 (1.96)	0.00 ± 0.00 (0.00)[a]	0.00 ± 0.00 (0.00)[a]	0.00 ± 0.00 (0.00)[a]
Distance to main road (in km linear distance)	0.56 ± 0.40 (0.48)	0.39 ± 0.29 (0.33)	0.37 ± 0.29 (0.31)	0.20 ± 0.22 (0.11)
Age of trees (in years)	18.29 ± 8.33 (17.00)	31.77 ± 14.36 (30.84)	22.06 ± 11.76 (19.00)	13.89 ± 7.00 (13.00)
Crop Variety (% of hybrid trees)	42.84 ± 46.77 (0.00)	34.40 ± 46.56 (0.00)	40.39 ± 45.87 (0.00)	28.43 ± 42.20 (0.00)

[1] n (%); Mean ± SD (Median).
[a] Excluded from efficiency computation.

areas without prevention measures, the highest erosion risk is found for cocoa, followed by coffee (24%) and macadamia (21%), but it shows to be of lower relevance for mango. Table 2 furthermore displays the variables related to capacity development, farmer and farm features as well as crop production environment used for the analysis of eco-efficiency determinants.

Table 3
Summary statistics of DEA and order-*m* eco-efficiency estimates.

	DEA	Unconditional order-*m*	Conditional order-*m*
Cocoa			
Mean ± SD	0.88 ± 0.07	1.23 ± 0.48	1.00 ± 0.00
Median (IQR)	0.90 (0.85, 0.94)	1.13 (1.03, 1.28)	1.00 (1.00, 1.00)
Range	0.60, 0.99	0.87, 8.21	0.96, 1.00
Coffee			
Mean ± SD	0.82 ± 0.11	1.73 ± 3.23	1.00 ± 0.00
Median (IQR)	0.84 (0.76, 0.90)	1.24 (1.08, 1.42)	1.00 (1.00, 1.00)
Range	0.51, 0.98	1.00, 36.82	1.00, 1.00
Macadamia			
Mean ± SD	0.81 ± 0.10	1.16 ± 0.23	1.00 ± 0.00
Median (IQR)	0.82 (0.75, 0.90)	1.07 (1.02, 1.20)	1.00 (1.00, 1.00)
Range	0.50, 0.98	1.00, 2.98	1.00, 1.02
Mango			
Mean ± SD	0.75 ± 0.13	1.21 ± 0.39	1.00 ± 0.02
Median (IQR)	0.77 (0.66, 0.87)	1.10 (1.01, 1.24)	1.00 (1.00, 1.00)
Range	0.41, 0.96	0.87, 4.16	0.99, 1.30

Table 4
Correlation table indicating the Pearson's correlation coefficients between farm ranks following the DEA efficiency scores and the unconditional order-*m* estimates.

	Cocoa	Coffee	Macadamia	Mango
	order-*m*	order-*m*	order-*m*	order-*m*
DEA	0.28 ***	0.20 **	0.52 ***	0.46 ***

Note: Significance codes ., *, **, ***denote significance at the 10%, 5%, 1%, and 0.1% level, respectively.

3. Results

3.1. Eco-efficiency estimates

For unconditional order-*m* estimates, exclusively values greater than 0.87 were observed, where for instance the most (least) efficient mango farm with an efficiency score of 4.16 (0.87) causes 3.16 times less (13% more) environmental pressures than the expected value of the minimum environmental pressure level of 65 other farms, drawn from the population of mango farms producing a greater or equal economic value added. With DEA scores ranging between 0.60 and 0.99 (see Table 3), cocoa farms displayed generally high eco-efficiency scores, indicating limited room for improvements within the current production context. The DEA scores of the three remaining crops ranged between 0.41 and 0.98, suggesting a greater variation among the farms. On average, following the DEA logic, cocoa farms could reduce their environmental pressures by 12% to become efficient and macadamia, coffee and mango farms by 19%, 18%, and 25%, respectively.

To facilitate the comparison of efficiency estimates, which are to be interpreted in different ways, we ranked all farms within each case study according to their DEA and unconditional order-*m* eco-efficiency estimates. A significant, but weak positive correlation between the rankings of the DEA scores and those of the order-*m* estimates was found for cocoa and coffee, while for macadamia and mango a significant positive correlation with moderate strength could be identified (see Table 4).

3.2. Determinants of eco-efficiency scores

To assess the importance of the covariates for eco-efficiency, we

Table 5
Second stage regression results indicating the association between covariates and order-*m* efficiency ratios.

	Influence	p-value	Influence	p-value	Influence	p-value	Influence	p-value
Capacity Development								
Training in general farm management (0 – No / 1 – Yes)	Favorable	**0.00**	Favorable	**0.01**	Favorable	**0.02**	Unfavorable	0.85
Training in input use (0 – No / 1 – Yes)	Favorable	**0.00**	Unfavorable	**0.00**	Unfavorable	**0.00**	Unfavorable	0.85
Training in environmental management (0 – No / 1 – Yes)	Favorable	0.25	Unfavorable	**0.03**	Unfavorable	0.08	Unfavorable	0.93
Training in organic farming (0 – No / 1 – Yes)	Unfavorable	**0.00**	Unfavorable	**0.00**	Favorable	**0.00**	Favorable	0.06
Farm & farmer features								
Age (in years)	Favorable	0.71	Unfavorable	0.16	Favorable*	**0.00**	Unfavorable	**0.05**
Working time devoted to farming (%)	Unfavorable	**0.00**	Unfavorable	**0.04**	Unfavorable	0.88	Unfavorable	0.08
Level of education (No formal/Primary/Secondary or higher)	Favorable	0.08	Unfavorable	**0.00**	Unfavorable	**0.00**	Unfavorable	**0.05**
Farm size (in ha)	Favorable	**0.02**	Unfavorable	**0.04**	Unfavorable*	0.07	Unfavorable	0.69
Household size (Number of persons)	Favorable	0.39	Unfavorable	**0.01**	Favorable*	0.27	Unfavorable	0.41
Gender of household head (0 - Female / 1 - Male)	Unfavorable	0.28	Unfavorable	**0.00**	Favorable	**0.03**	Unfavorable	**0.00**
Family labor (% of total labor hrs)	Favorable	**0.04**	Favorable	**0.01**	Favorable	**0.04**	Favorable	0.20
Access to credit facilities (0 – No / 1 – Yes) (0 – No / 1 – Yes)	n/a		Favorable	1.00	Favorable	0.15	Favorable	0.16
Income diversity (0 to 1)	Favorable	0.26	Unfavorable	0.35	Favorable	0.06	Favorable	**0.03**
Off-farm income (0 – No / 1 – Yes)	Unfavorable	**0.00**	Unfavorable	**0.00**	Unfavorable	**0.00**	Favorable	**0.05**
Livestock Units (per ha)	Favorable	0.09	Unfavorable	0.71	Favorable	**0.00**	Favorable	0.59
Crop production environment								
Distance to main road (per ha)	Favorable	0.07	Unfavorable	0.86	Favorable	0.52	Unfavorable	0.06
Distance to homestead (in km linear distance) (in km linear distance)	Unfavorable	**0.01**	n/a		n/a		n/a	
Age of trees (in years)	Unfavorable	0.82	Favorable	**0.00**	Favorable	0.34	Unfavorable	0.28
Crop Variety (% of hybrid trees)	Favorable	**0.00**	Unfavorable	**0.02**	Unfavorable	**0.00**	Unfavorable	0.49
R^2	0.51		0.94		0.77		0.50	

Note: *p*-values in bold indicate significance at least at the 5% level. The direction of the influence is based on the average effect revealed from the partial regression plots, with all other variables held constant at their medians (see Appendix 6). The asterisk marks cases, where the direction of the influence was dependent on the explanatory variable. Here, the dominant effect within the range of the mean ± SD is reported. Furthermore, the location dummies have been omitted.

computed conditional order-*m* estimates, as explained in section 1.3. Table 3 shows the comparison between the distributions of the unconditional and conditional order-*m* estimates for the four crops and the respective individual modes of *m*. The range of estimates decreased when conditioning on covariates, suggesting that the selected covariates explained much of the variation found in the unconditional order-*m* estimates (Daraio and Simar, 2007). This underlines the importance to condition the efficiency estimates on the explanatory variables. Finally, the ratio of the conditional to unconditional order-*m* estimates was then utilized as dependent variable in the nonparametric regression (Daraio and Simar, 2007). Table 5 shows the direction of the relation between the set of covariates and the order-*m* efficiency ratios for all four crop cases as obtained from the partial regression plots, with all other variables held constant at their medians (see Appendix 7) as well as the results of the significance test.

Overall, the following patterns emerged: the efficiency scores were strongly influenced by variables, which measure capacity development, and resource endowments, such as labor and land, whereas the crop production environment had some influence, but results were unspecific. Our analysis showed mixed effects of capacity development on efficiency scores. Whereas training in general farm management improved the eco-efficiency in the case of cocoa, coffee, and macadamia, an unfavorable influence of training in input use was observed for coffee and macadamia, but showed favorable effects in the case of cocoa. For training in organic farming on the other hand, a significant unfavorable effect was observed for cocoa and coffee, while the eco-efficiency improved in the cases of macadamia. Looking at farm and farmer features, a better eco-efficiency was seen in the case of cocoa and coffee, when the working time devoted to farming was reduced. In addition, the majority of eco-efficiency performances was found to be impaired by a higher level of education as well as the presence of off-farm income. Furthermore, eco-efficiency performance was positively associated with female household heads for all crops, except macadamia.

4. Discussion

Our findings suggest first of all that specific environmental pressures caused are only relevant in certain production contexts, calling for more context-specific interventions. The two biodiversity related variables appear especially negatively pronounced in the cocoa case. Here, crop management practices such as agroforestry systems might counteract biodiversity loss caused by expansion of plot sizes (Udawatta et al., 2019). Nutrient deficiency, on the other hand, was shown to be important for all crop cases, which suggests that in the current production context, no improvement in nutrient depletion seems possible without reducing outputs. This is in line with findings from other studies, such as Nunoo et al. (2014) who found low fertilizer usage in Ghanaian cocoa production systems and recommended measures to promote fertilizer use.

Our results showed a weak to moderate relationship between the DEA and unconditional order-*m* eco-efficiency scores, suggesting clear dissimilarities between the results generated by the two approaches. This should caution scientists and policy makers to refrain from relying on the DEA approach without considering its sensitivity to outliers and its need to uphold the separability assumption, which is difficult. With regard to the unconditional order-*m* eco-efficiency scores, estimates between 0.87 and 36.82 have been observed. The distribution of eco-efficiency estimates among the coffee farms showed the widest spread, which indicates the greatest potential to increase eco-efficiency. However, also the dispersion of scores within the other crop cases suggests room for improvements of eco-efficiency within the current production contexts.

We furthermore examined the determining factors of eco-efficiency and the results indicate that the selected covariates, covering farmer and farm features, capacity development as well as the crop production environment, explain much of the variation of the eco-efficiency estimates. The covariates denoting training are mostly significant in three of four crop cases. However, we found opposite effects of organic training for coffee and macadamia. These two crop cases are based on the same farm sample, but capacity development is mainly focused on organic macadamia production. This involves higher prices for certified macadamia, while coffee was not sold as certified organic and therefore the production was mostly neglected (Schader et al., 2021). Caution should be therefore exercised, when initiatives focus on single crops within diverse farming systems as negative or positive spill-over effects can occur. For cocoa, coffee, and macadamia, training in general farm management was positively associated with eco-efficiency. Earlier studies emphasize that efforts to strengthen farmer capacities, through the promotion of pest control, record keeping and farm planning foster productivity gains (Binam et al., 2008; Onumah et al., 2013b; Antwi-Agyakwa et al., 2015). Contrary to our prior expectations, our results suggest also synergies with eco-efficiency gains and training in input use in one crop case. This might be due to training curricula prioritizing a more efficient and careful use of inputs and general improvements of agricultural activities with the potential to increase economic value added and with this the numerator in the eco-efficiency equation. Despite literature pointing out decreasing environmental pressures with increasing economic prospects due to organic farming techniques (Crowder and Reganold, 2015; Seufert and Ramankutty, 2017), significant positive effects of training in organic management were only visible for macadamia in our study. The effects for cocoa and coffee were unfavorable, respecitively not significant for mango. This is likely to be related to the phenomenon that initiatives promoting organic agriculture in low-income countries often focus on omitting inputs that are prohibited in organic agriculture rather than promoting integrated soil and pest management techniques (van Elzakker and Eyhorn, 2010; Schader et al., 2021). Consequently, organic farmers often struggle to build soil fertility and control high prevalence of pests and diseases (Ran et al., 2018). In addition, compliance with organic standard is often poorly monitored and price premiums are not always realized, as was the case for cocoa and coffee (Schader et al., 2021). This negatively affects both parts of the eco-efficiency ratio. Our findings furthermore portray the long learning curve among smallholder farmers for knowledge intensive practices such as organic farming, and the fact that some of the impacts of organic farming, e.g. on soil fertility improvement and yields can take several years to be achieved (Adamtey et al., 2016; Bhullar et al., 2021).

Labor was found to be another crucial production factor. For time-critical tasks there may be seasonal peaks in labor demand and labor productivity (McCullough, 2017). Our analysis showed that the ratio of family to hired labor is positively associated with eco-efficiency for all crop cases. In labor intensive periods, such as harvest seasons, access to more family labor can be beneficial. This was also highlighted by earlier studies on coffee production (Kamau et al., 2016; Runo, 2009). However, a household size of more than four persons was negatively associated in the case of macadamia. Here, harvest and postharvest operations were mostly carried out by traders. It furthermore appears that eco-efficiency is harmed when farming is not the focus, but rather a secondary activity. Low agricultural labor productivity has been identified as an important challenge in the context of sustainable intensification in SSA (McCullough, 2017; Dahlin and Rusinamhodzi, 2019) and also our analysis showed an unfavorable relation of increased working time devoted to farming to eco-efficiency in all crop cases. This aspect suggests that farmers, who have less time at their disposal utilize their limited available time more efficiently and points at opportunities to increase labor productivity within the current production context.

In addition, genders plays a crucial role. Women are likely to be more open to and better manage innovation (FAO and AUC, 2020). Our results confirm that women can function as key change agents in communities. As regards other explanatory variables related to financial flows (credit, off-farm income) or the production context (distances, age of trees, varieties) heterogeneous effects resulted from our analysis across crops and countries.

We would further like to point out that robust and accurate explanation of eco-efficiency with empirical farm data is not a straightforward endeavor. The relationship between the eco-efficiency rankings generated by the DEA and order-*m* estimations is limited, which suggests that separability are key methodological considerations for our analysis. This was also confirmed by testing this assumption. It should be noted that order-*m* eco-efficiency estimation is still a new field of investigation and also the use of input-orientation has so far been rarely used in the order-*m* setting. In the eco-efficiency context, further studies are therefore needed to provide further guidance for the selection of *m* and the contextual application of nonparametric regressions as well as the requirements for input variables.

5. Conclusions

This paper assessed the eco-efficiency of smallholder perennial cash crop production in Ghana and Kenya and examined factors influencing the eco-efficiency scores by applying DEA and order-*m* frontiers as well as exploratively comparing these two methods. In doing so, we considered seven environmental pressures of particular relevance in the context of agricultural production in SSA, namely (1) toxicity of pesticide use, (2) contribution to global warming, (3) nutrient depletion, and (4) nutrient surplus as well as (5) soil erosion, (6) loss of biodiversity, and (7) overexploitation of water resources.

To our knowledge, this is the first study that attempts to apply input-oriented order-*m* frontiers to assess eco-efficiency in the agricultural context. It compares eco-efficiency rankings generated by this method to those generated by the widely applied DEA approach using rich empirical data and in doing so highlights the importance of testing and accounting for the separability assumption. Our subsequent regression analysis based on the order-*m* scores revealed that there is no quick fix for boosting eco-efficiency in smallholder perennial production in SSA. When examining the determining factors of eco-efficiency, it became apparent that efficiency scores are influenced by certain resource endowments, capacity development and the crop production environment. However, a positive effect is highly context-specific.

Our application uncovers various challenges: whereas the widely applied DEA approach suffers from its sensitivity to outliers and involves often second stage regressions without a prior testing of the separability assumption, and consequently the risk of a misleading interpretation of regression results, the order-m estimates and the related nonparametric regression analysis involve decisions about the selection of the m parameter. While subject to heterogeneous effects across crops, the findings have some practical implications. They underline the importance of designing effective training modalities and policies that allow knowledge to be put into practice. This involves the creation of marketing opportunities and the provision of targeted and regular advisory services. In the current production context, fertilizer application is a considerable challenge for smallholder farmers and nutrient depletion is rampant in all case studies, but most pronounced in cocoa production. Therefore, region-wide measures appear necessary to build and maintain soil fertility in a sustainable manner.

Declaration of Competing Interest

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

Acknowledgement

This work was supported by the Dutch Humanist Institute for Development Cooperation (Hivos), the Swiss Agency for Development and Cooperation (SDC) and the Mercator Foundation Switzerland through the ProEcoAfrica and OFSA projects. The authors furthermore thank Bernhard Schlatter, Adrian Haas, Lawrence Gitonga and all enumerators for contributing to the success of this study. Finally yet importantly, we thank all farmers for participating in this study and investing their time in documentation. In addition, we thank the editor (Guillaume Martin) as well as the two anonymous reviewers for their comments that helped to significantly improve the manuscript. We would also like to thank Kristoff De Witte, Yauheniya Varabyova, and Richard S. Gearhart for providing their code.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103304.

References

Adamtey, N., Musyoka, M.W., Zundel, C., Cobo, J.G., Karanja, E., Fiaboe, K.K., Muriuki, A., Mucheru-Muna, M., Vanlauwe, B., Berset, E., Messmer, M.M., Gattinger, A., Bhullar, G.S., Cadisch, G., Fliessbach, A., Mäder, P., Niggli, U., Foster, D., 2016. Productivity, profitability and partial nutrient balance in maize-based conventional and organic farming systems in Kenya. Agric. Ecosyst. Environ. 235, 61–79.

Antwi-Agyakwa, A., Osekre, E., Adu-Acheampong, R., Ninsin, K.D., 2015. Insecticide use practices in cocoa production in four regions in Ghana. West Afr J. App. Ecol. 23, 39–48.

Bhullar, G.S., Bautze, D., Adamtey, N., Armengot, L., Cicek, H., Goldmann, E., Riar, A., Rüegg, J., Schneider, M., Huber, B., 2021. What Is the Contribution of Organic Agriculture to Sustainable Development?: A Synthesis of Twelve Years (2007–2019) of the "Long-Term Farming Systems Comparisons in the Tropics (SysCom)". Research Institute of Organic Agriculture, Frick, Switzerland (40 pp.).

Billor, N., Hadi, A.S., Velleman, P.F., 2000. BACON: blocked adaptive computationally efficient outlier nominators. Comput. Stat. Data Anal. 34, 279–298.

Binam, J.N., Gockowski, J., Nkamleu, G.B., 2008. Technical efficiency and productivity potential of cocoa farmers in west African countries. Dev. Econ. 46, 242–263.

Bogetoft, P., Otto, L., 2011. Benchmarking with DEA, SFA, and R. Springer New York, New York, NY.

Bonfiglio, A., Arzeni, A., Bodini, A., 2017. Assessing eco-efficiency of arable farms in rural areas. Agric. Syst. 151, 114–125.

Bowlin, W.F., 1998. Measuring performance: an introduction to data envelopment analysis (DEA). J. Cost Anal. 15, 3–27.

BSI, 2008. PAS 2050: 2008: Specification for the Assessment of the Life Cycle Greenhouse Gas Emissions of Goods and Services.

Büsser, S., Jungbluth, N., 2009. The role of flexible packaging in the life cycle of coffee and butter. Int. J. Life Cycle Assess. 14, 80–91.

Carvalho, P., Marques, R.C., 2011. The influence of the operational environment on the efficiency of water utilities. J. Environ. Manag. 92, 2698–2707.

Cassman, K.G., Grassini, P., 2020. A global perspective on sustainable intensification research. Nat. Sustain. 3, 262–268.

Cazals, C., Florens, J.-P., Simar, L., 2002. Nonparametric frontier estimation: a robust approach. J. Econ. 106, 1–25.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444.

Claus, G., Vanhove, W., van Damme, P., Smagghe, G., 2018. Challenges in Cocoa Pollination: The Case of Côte d'Ivoire. Pollination in Plants. https://doi.org/10.5772/intechopen.75361.

Cobo, J.G., Dercon, G., Cadisch, G., 2010. Nutrient balances in African land use systems across different spatial scales: a review of approaches, challenges and progress. Agric. Ecosyst. Environ. 136, 1–15.

Cooper, W.W., Seiford, L.M., Zhu, J., 2004. Data envelopment analysis. In: Handbook on Data Envelopment Analysis. Springer, pp. 1–39.

Crowder, D.W., Reganold, J.P., 2015. Financial competitiveness of organic agriculture on a global scale. Proc. Natl. Acad. Sci. 112, 7611–7616.

Dahlin, A.S., Rusinamhodzi, L., 2019. Yield and labor relations of sustainable intensification options for smallholder farmers in sub-Saharan Africa. A meta-analysis. Agron. Sustain. Dev. 39, 32.

Danso-Abbeam, G., 2012. Technical efficiency in Ghana's cocoa industry: evidence from Bibiani-Anhwiaso-Bekwai District. J. Dev. Agric. Econ. 4.

Danso-Abbeam, G., Baiyegunhi, L., 2019. Technical efficiency and technology gap in Ghana's cocoa industry: accounting for farm heterogeneity. Appl. Econ. 1–13.

Daouia, A., Laurent, T., 2015. Package 'Frontiles': Partial Frontier Efficiency Analysis.

Daraio, C., Simar, L., 2005. Introducing environmental variables in nonparametric frontier models: a probabilistic approach. J. Prod. Anal. 24, 93–121.

Daraio, C., Simar, L., 2007. Advanced Robust and Nonparametric Methods in Efficiency Analysis: Methodology and Applications, 248. Springer, New York xxii.

Daraio, C., Simar, L., Wilson, P.W., 2018. Central limit theorems for conditional efficiency measures and tests of the 'separability' condition in non-parametric, two-stage models of production. Econ. J. 21, 170–191.

de Klein, C., Novoa, R.S.A., Ogle, S., Smith, K.A., Rochette, P., Wirth, T.C., McConkey, B. G., Mosier, A., Rypdal, K., Walsh, M., 2006. N2O Emissions From Managed Soils, and CO2 Emissions From Lime and Urea Application. IPCC guidelines for National greenhouse gas inventories, prepared by the National greenhouse gas inventories programme, 4, pp. 1–54.

de Witte, K., Kortelainen, M., 2013. What explains the performance of students in a heterogeneous environment? Conditional efficiency estimation with continuous and discrete environmental variables. Appl. Econ. 45, 2401–2412.

FAO, 2011. Save and Grow: A policymaker's Guide to the Sustainable Intensification of Smallholder Crop Production. Food and Agriculture Organization of the United Nations, Rome.

FAO, 2020. State of Knowledge of Soil Biodiversity - Status, Challenges and Potentialities. FAO (616 pp.).

FAO and AUC, 2020. Leaving No One Behind – A Regional Outlook on Gender and Agrifood Systems. Ababa, Addis (204 pp.).

Fisher, R.A., Corbet, A.S., Williams, C.B., 1943. The relation between the number of species and the number of individuals in a random sample of an animal population. J. Anim. Ecol. 12, 42.

Gerten, D., Heck, V., Jägermeyr, J., Bodirsky, B.L., Fetzer, I., Jalava, M., Kummu, M., Lucht, W., Rockström, J., Schaphoff, S., Schellnhuber, H.J., 2020. Feeding ten billion people is possible within four terrestrial planetary boundaries. Nat. Sustain. https://doi.org/10.1038/s41893-019-0465-1.

Gómez-Limón, J.A., Sanchez-Fernandez, G., 2010. Empirical evaluation of agricultural sustainability using composite indicators. Ecol. Econ. 69, 1062–1075.

Gómez-Limón, J.A., Picazo-Tadeo, A.J., Reig-Martínez, E., 2012. Eco-efficiency assessment of olive farms in Andalusia. Land Use Policy 29, 395–406.

Grovermann, C., Wossen, T., Muller, A., Nichterlein, K., Lacetera, N., 2019. Eco-efficiency and agricultural innovation systems in developing countries: evidence from macro-level analysis. PLoS One 14, e0214115.

Ho, T.Q., Hoang, V.-N., Wilson, C., Nguyen, T.-T., 2018. Eco-efficiency analysis of sustainability-certified coffee production in Vietnam. J. Clean. Prod. 183, 251–260.

Hollingsworth, B., Smith, P., 2003. Use of ratios in data envelopment analysis. Appl. Econ. Lett. 10, 733–735.

ICC, 2019. Country Coffee Profile. International Coffee Organization, ICC, Kenya. http://www.ico.org/documents/cy2018-19/icc-124-7e-profile-kenya.pdf. Accessed 14 January 2020.

IPBES, 2018. Regional and Subregional Assessments of Biodiversity and Ecosystem Services: Regional and Subregional Assessment for Africa. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, Medellin, Colombia. https://ipbes.net/assessment-reports/africa. Accessed 27 January 2020.

ISSER, 2015. The State of the Ghanaian Economy in 2014. Institute of Statistical Social and Economic Research (ISSER). https://isser.edu.gh/images/Publication_files/SGER2014_Overview.pdf. Accessed 14 January 2020.

Kamau, V., Ateka, J., Mbeche, R., Muendo, K., 2016. Assessment of the Technical Efficiency of Smallholder Coffee Farming Enterprises in Muranga, Kenya.

Kehlenbeck, K., Rohde, E., Njuguna, J.K., Jamnadass, R., 2012. Mango production in Kenya. In: Mango Cultivation in Different Countries, 1st ed., 2. Studium Press LLC, Houston, USA, pp. 186–207.

Kiboi, M.N., Ngetich, F.K., Mugendi, D.N., 2019. Nitrogen budgets and flows in African smallholder farming systems. AIMS Agricult. Food 4, 429–446.

Kolavalli, S., Vigneri, M., 2011. Cocoa in Ghana: Shaping the Success of an Economy.

Konstantas, A., Jeswani, H.K., Stamford, L., Azapagic, A., 2018. Environmental impacts of chocolate production and consumption in the UK. Food Res. Int. 106, 1012–1025.

Kourtesi, S., Fousekis, P., Polymeros, A., 2012. Conditional efficiency estimation with environmental variables: evidence from Greek cereal farms. Sci. Bull. 11, 43–52.

Kuosmanen, T., Kortelainen, M., 2005. Measuring eco-efficiency of production with data envelopment analysis. J. Ind. Ecol. 9, 59–72.

Kuyper, T.W., Struik, P.C., 2014. Epilogue: global food security, rhetoric, and the sustainable intensification debate. Curr. Opin. Environ. Sustain. 8, 71–79.

Lal, R., Stewart, B.A., 2019. Soil Degradation and Restoration in Africa. CRC Press.

Laven, A., Boomsma, M., 2012. Incentives for Sustainable Cocoa Production in Ghana.

Lesschen, J.P., Stoorvogel, J., Smaling, E., 2004. Scaling Soil Nutrient Balances. Enabling Mesolevel Applications for African Realities. FAO, Rome, Italy.

Liu, X., Zhang, S., Zhang, X., Ding, G., Cruse, R.M., 2011. Soil erosion control practices in Northeast China: a mini-review. Soil Tillage Res. 117, 44–48.

Loland, J., Singh, B.R., 2004. Copper contamination of soil and vegetation in coffee orchards after long-term use of Cu fungicides. Nutr. Cycl. Agroecosyst. 69, 203–211.

McCullough, E.B., 2017. Labor productivity and employment gaps in Sub-Saharan Africa. Food Policy 67, 133–152.

NASA, 2017. Kenya SRTM DEM 30meters. http://opendata.rcmrd.org/datasets/kenya-srtm-dem-30meters?geometry=-3.915%2C-7.711%2C79.713%2C7.624.

Nemecek, T., Kägi, T., 2007. Life Cycle Inventories of Agricultural Production Systems. Agroscope Reckenholz-Tänikon Research Station ART, Zürich and Dübendorf, 360 pp. https://db.ecoinvent.org/reports/15_Agriculture.pdf.

Niang, I., Ruppel, O.C., Abdrabo, M.A., Essel, A., Lennard, C., Padgham, J., Urquhart, P., 2014. Africa climate change 2014: impacts, adaptation, and vulnerability. In: Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change ed VR Barros et al.

Noponen, M.R., Edwards-Jones, G., Haggar, J.P., Soto, G., Attarzadeh, N., Healey, J.R., 2012. Greenhouse gas emissions in coffee grown with differing input levels under conventional and organic management. Agric. Ecosyst. Environ. 151, 6–15.

Ntiamoah, A., Afrane, G., 2008. Environmental impacts of cocoa production and processing in Ghana: life cycle assessment approach. J. Clean. Prod. 16, 1735–1740.

Nunoo, I., Frimpong, B.N., Frimpong, F.K., 2014. Fertilizer use among cocoa farmers in Ghana: the case of Sefwi Wiawso District. Int. J. Environ. 3, 22–31.

Ofori-Bah, A., Asafu-Adjaye, J., 2011. Scope economies and technical efficiency of cocoa agroforesty systems in Ghana. Ecol. Econ. 70, 1508–1518.

Onumah, J.A., Al-Hassan, R.M., Onumah, E.E., 2013a. Productivity and Technical Efficiency of Cocoa Production in Eastern Ghana, p. 14.

Onumah, J.A., Onumah, E.E., Al-Hassan, R.M., Brümmer, B., 2013b. Meta-frontier analysis of organic and conventional cocoa production in Ghana. Agric. Econ. 59, 271–280.

Onwona Kwakye, M., Mengistie, B., Ofosu-Anim, J., Nuer, A.T.K., van den Brink, P.J., 2019. Pesticide registration, distribution and use practices in Ghana. Environ. Dev. Sustain. 21, 2667–2691.

PAN, 2019. PAN International List of Highly Hazardous Pesticides. Pesticide Action Network International, 43 pp. http://pan-international.org/wp-content/uploads/PAN_HHP_List.pdf. Accessed 7 January 2020.

Picazo-Tadeo, A.J., Gómez-Limón, J.A., Reig-Martínez, E., 2011. Assessing farming eco-efficiency: a data envelopment analysis approach. J. Environ. Manag. 92, 1154–1164.

Picazo-Tadeo, A.J., Beltrán-Esteve, M., Gómez-Limón, J.A., 2012. Assessing eco-efficiency with directional distance functions. Eur. J. Oper. Res. 220, 798–809.

Pradhan, P., Fischer, G., van Velthuizen, H., Reusser, D.E., Kropp, J.P., Gonzalez-Andujar, J.L., 2015. Closing yield gaps: how sustainable can we be? PLoS One 10, e0129487.

Pretty, J., Toulmin, C., Williams, S., 2011. Sustainable intensification in African agriculture. Int. J. Agric. Sustain. 9, 5–24.

Quiroz, D., Kuepper, B., Wachira, J., Emmott, A., 2019. Value Chain Analysis of Macadamia Nuts in Kenya: Research Commissioned by CBI. Profundo, Amsterdam (98 pp.).

R Core Team, 2020. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing.

Racine, J.S., Hayfield, T., 2020. Package 'np': Nonparametric Kernel Smoothing Methods for Mixed Data Types.

Racine, J.S., Hart, J., Li, Q., 2006. Testing the significance of categorical predictor variables in nonparametric regression models. Econ. Rev. 25, 523–544.

Ran, Y., Annebäck, J., Widmark, E., Osborne, M., 2018. Boosting Technology Uptake: Some Ideas for Improving Small-Scale Mango Farming in Kenya. Stockholm Environment Institute, Stockholm (4 pp.).

Reynolds, T.W., Waddington, S.R., Anderson, C.L., Chew, A., True, Z., Cullen, A., 2015. Environmental impacts and constraints associated with the production of major food crops in Sub-Saharan Africa and South Asia. Food Secur. 7, 795–822.

Ricciardi, V., Mehrabi, Z., Wittman, H., James, D., Ramankutty, N., 2021. Higher yields and more biodiversity on smaller farms. Nat. Sustain. https://doi.org/10.1038/s41893-021-00699-2.

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., Wetterstrand, H., DeClerck, F., Shah, M., Steduto, P., de Fraiture, C., Hatibu, N., Unver, O., Bird, J., Sibanda, L., Smith, J., 2017. Sustainable intensification of agriculture for human prosperity and global sustainability. Ambio 46, 4–17.

Runo, B., 2009. Technical Efficiency Amongst Cofee Farmers in Kenya: A Case Study of Githunguri Division, Kiambu District. Thesis. University of Nairobi, Kenya. http://erepository.uonbi.ac.ke/handle/11295/5175.

Sarkis, J., 2007. Preparing your data for DEA. In: Zhu, J., Cook, W.D. (Eds.), Modeling Data Irregularities and Structural Complexities in Data Envelopment Analysis. Springer US, Boston, MA, pp. 305–320.

Schader, C., Baumgart, L., Landert, J., Muller, A., Ssebunya, B., Blockeel, J., Weisshaidinger, R., Petrasek, R., Mészáros, D., Padel, S., Gerrard, C., Smith, L., Lindenthal, T., Niggli, U., Stolze, M., 2016. Using the sustainability monitoring and assessment routine (SMART) for the systematic analysis of trade-offs and synergies between sustainability dimensions and themes at farm level. Sustainability 8, 274.

Schader, C., Curran, M., Heidenreich, A., Landert, J., Blockeel, J., Baumgart, L., Ssebunya, B., Moakes, S., Marton, S., Lazzarini, G., Niggli, U., Stolze, M., 2019. Accounting for uncertainty in multi-criteria sustainability assessments at the farm level: improving the robustness of the SMART-Farm Tool. Ecol. Indic. 106, 105503.

Schader, C., Heidenreich, A., Kadzere, I., Egyir, I., Muriuki, A., Bandanaa, J., Clottey, J., Ndungu, J., Grovermann, C., Lazzarini, G., Blockeel, J., Borgemeister, C., Muller, A., Kabi, F., Fiaboe, K., Adamtey, N., Huber, B., Niggli, U., Stolze, M., 2021. How is organic farming performing agronomically and economically in sub-Saharan Africa? Glob. Environ. Chang. 70, 102325.

Schaltegger, S., Sturm, A., 1990. Ökologische Rationalität: Ansatzpunkte zur Ausgestaltung von ökologieorientierten Managementinstrumenten. Die Unternehmung 44, 273–290.

Seufert, V., Ramankutty, N., 2017. Many shades of gray—the context-dependent performance of organic agriculture. Sci. Adv. 3, e1602638.

Sheahan, M., Barrett, C.B., Goldvale, C., 2017. Human health and pesticide use in Sub-Saharan Africa. Agric. Econ. 48, 27–41.

Simar, L., Wilson, P.W., 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Manag. Sci. 44, 49–61.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. J. Econ. 136, 31–64.

Simar, L., Wilson, P.W., 2008. Statistical Inference in Nonparametric Frontier Models: Recent Developments and Perspectives, p. 127.

Simar, L., Wilson, P.W., 2020. Hypothesis testing in nonparametric models of production using multiple sample splits. J. Prod. Anal. 53, 287–303.

Simm, J., Besstremyannaya, G., 2020. rDEA: Robust Data Envelopment Analysis (DEA) for R.

Skevas, T., Stefanou, S.E., Oude Lansink, A., 2014. Pesticide use, environmental spillovers and efficiency: a DEA risk-adjusted efficiency approach applied to Dutch arable farming. Eur. J. Oper. Res. 237, 658–664.

Udawatta, R., Rankoth, L., Jose, S., 2019. Agroforestry and biodiversity. Sustainability 11, 2879.

UNDP, 2011. Environmental Baseline Report on Cocoa in Ghana. https://www.cocoalife.org//media/cocoalife/Files/pdf/Library/Environmental%20baseline%20report%20on%20cocoa%20in%20Ghana%20UNDP.pdf. Accessed 10 January 2020.

UNEP, 2016. GEO-6 Regional Assessment for Africa. United Nations Environment Programme, Nairobi, Kenya. http://uneplive.unep.org/media/docs/assessments/GEO_6_Regional_Assessment_for_Africa_Final.pdf. Accessed 27 January 2020.

USGS, 2014. Shuttle Radar Topography Mission 1 Arc-Second Global.

van Dijk, M., Morley, T., Jongeneel, R., van Ittersum, M., Reidsma, P., Ruben, R., 2017. Disentangling agronomic and economic yield gaps: an integrated framework and application. Agric. Syst. 154, 90–99.

van Elzakker, B., Eyhorn, F., 2010. Developing sustainable value chains with smallholders. Internat. Fed. of Organic Agriculture Movements (IFOAM), Bonn (157 pp.).

Weber, S., 2010. Bacon: an effective way to detect outliers in multivariate data using Stata (and Mata). Stata J. 10, 331–338.

WFPGeoNode, 2018a. Ghana Road Network (Main Roads). https://geonode.wfp.org/layers/ogcserver.gis.wfp.org%3Ageonode%3Agha_trs_roads_osm.

WFPGeoNode, 2018b. Kenya Road Network (Main Roads). https://geonode.wfp.org/layers/ogcserver.gis.wfp.org%3Ageonode%3Aken_trs_roads_osm.

Wilson, P.W., 1993. Detecting outliers in deterministic nonparametric frontier models with multiple outputs. J. Bus. Econ. Stat. 11, 319–323.

Wilson, P.W., 2020. Package 'FEAR': Frontier Efficiency Analysis with R.

World Bank, 2011. Supply Chain Risk Assessment: Cocoa in Ghana.

Wossink, A., Denaux, Z.S., 2006. Environmental and cost efficiency of pesticide use in transgenic and conventional cotton production. Agric. Syst. 90, 312–328.