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On the palm oil-biodiversity trade-off: Environmental performance of smallholder producers

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ABSTRACT

Oil palm remains an important source of rural income in South East Asia. At the same time, Indonesia has become a hotspot for large-scale species extinction and a loss of biodiversity in favor of agricultural production. The present study sets out to assess the environmental performance of smallholder oil palm production with respect to biodiversity. Using a panel dataset that combines conventional farm data together with an account of plant diversity, we estimate a restricted hyperbolic environmental distance function. We integrate loss of biodiversity as an undesirable output into the production model which allows explaining shortfalls in environmental performance and the derivation of shadow prices of biodiversity conservation. We find a substantial environmental inefficiency, which is partly explained by both chemical and manual weeding practices, highlighting the potential for improvements in both the environmental and the economic dimension. Moreover, the value for conserving one species of the average biodiversity on a farmers plantation was 325 USD in 2018. Payments for ecosystem services schemes could be a viable policy response to conserve meaningful levels of biodiversity while simultaneously allowing smallholders to increase palm oil output. In general, addressing drivers of environmental performance in PES designs amplifies its effect without reducing output.

1. Introduction

Agriculture is strongly intertwined with the environment and therefore key to the provision and decay of ecosystem services. Biodiversity is a critical link between the two as numerous ecosystem functions rely on the diversity of organisms. For instance, the provision of food, water, medicine, fuels and fiber and air quality are vital ecosystem services that are heavily dependent on intact biodiversity (TEEB, 2010; Hooper et al., 2012). On the other hand, many forms of agricultural production and the related land use change (LUC) have been shown to critically reduce local species diversity (Grass et al., 2020; Clough et al., 2016). Both expansion and intensification of agricultural production are increasingly threatening biodiversity and species existence, which have been declining dramatically around the world (IPBES, 2019; Chaplin-Kramer et al., 2015).

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The trade-off between biodiversity and output in agriculture is particularly important not only because food is a necessity good but also because about half of the world's populations retrieve their livelihoods from activities relating to food procurement (Davis et al., 2023). Specifically, smallholder participation in food value chains have been shown to contribute to economic development. At the same time, however, smallholder production has often been associated with environmentally detrimental technologies and management practices underpinned by lax regulation. In contrast to larger production estates in high-income countries and macro level studies, relatively little work is available on the environmental performance of smallholders, conservation potential and policy implications (e.g. Rosa-Schleich et al., 2019; Meyfroidt, 2018; Savilaakso et al., 2014). Smallholders provide exceptional opportunities for conservation as their mosaic-type spatial arrangements allow for a highly diverse landscape matrix (Cisneros et al., 2022; Rudolf et al., 2020; Sayer et al., 2012). Vice versa, the negative impacts on biodiversity related to production area are considerable (Grass et al., 2020).

This paper assesses the environmental performance of smallholder oil palm producers in Indonesia. Smallholder producers in Indonesia are a particularly interesting case study as they contribute to 34% of national palm oil production (Indonesian Ministry of Agriculture, 2016). In addition, given the relatively low yields of smallholders compared with large estates, the share of the area that they manage is even larger (Euler et al., 2017; Byerlee and Viswanathan, 2018). At the same time, Indonesia has become a hotspot for large-scale species extinction and a loss of biodiversity. At the expense of several ecological crises, the palm oil boom contributes to rising exports and poverty reduction. Increases in income and consumption have been linked to palm oil production (Kubitza et al., 2018a; Qaim et al., 2020), and have been shown to contribute to the remarkably declining rates of poverty and undernourishment in the country (FAO, 2020). Nonetheless, remedying the trade-offs between economic and environmental objectives is becoming an increasingly important item on both national and intergovernmental policy agendas. More precisely, policy-makers are interested in steering production towards maximized oil palm output over minimized biodiversity loss (Wiebe et al., 2019; IPBES, 2019). However, only a few policy programs have been implemented in the region to date and even fewer have been successful (Hein, 2019). One obstacle to policy action on a meaningful scale could be the lack of valuation of biodiversity within the palm oil production system and vice versa.

Our work offers several contributions to the existing literature. First, instead of limiting the analysis exclusively to either ecological aspects of the decay of ecosystem services (e.g. Koh and Wilcove, 2008; Savilaakso et al., 2014; Fitzherbert et al., 2008; Vijay et al., 2016; Darras et al., 2019) or its socioeconomics (e.g. Chrisendo et al., 2022, 2020; Klasen et al., 2016; Lanz et al., 2018; Sibhatu, 2019; Cacho et al., 2014), we choose an interdisciplinary approach to empirically identify the underlying mechanisms of the trade-off between the two. Second, in contrast to previous work focusing on macro-relationships between biodiversity and palm oil production (e.g. Chaplin-Kramer et al., 2015; Bateman et al., 2015), we base our analysis on microeconomic data to assess the impacts of managerial skill on the trade-off. Third, we analyze the behavior of smallholder producers of palm oil. The environmental costs of palm oil production are comparably well documented for large estates, whereas little is known about the environmental performance of smallholder oil palm producers (Abman and Lundberg, 2024; Savilaakso et al., 2014; Robbins et al., 2015). Fourth, we contribute to the debate on the payments for ecosystem services (PES) policy implications and highlight the advantages and challenges related to differently-designed incentive schemes (Vorlaufer et al., 2023; Ando and Langpap, 2018; Cisneros et al., 2022; Rudolf et al., 2022; Arora et al., 2021; Ward et al., 2021; Manning et al., 2020; Salzman et al., 2018; Wunder et al., 2008).

We develop a hybrid between hyperbolic and enhanced hyperbolic distance functions (Cuesta et al., 2009) to model the production process of smallholder oil palm farmers in Sumatra, Indonesia, including biodiversity loss as an undesirable environmental output. We use a comprehensive data set on oil palm output, plant biodiversity, conventional production inputs, management practices as well as socioeconomic variables of smallholder oil palm producers to describe the trade-off between oil palm output and biodiversity loss and its underlying mechanisms. Furthermore, the duality of the approach allows us to derive shadow prices and gain insights into the opportunity cost of biodiversity conservation in this production system.

Our results indicate that smallholder oil palm production suffers from environmentally inefficient production. This implies that either substantially higher output could be achieved or – conversely – a higher local plant diversity could be maintained at the present level of input use by eliminating the environmental inefficiency of production. Similarly, overuse in input results in inefficient outcomes in terms of both desirable and undesirable outputs. Furthermore, environmental performance is linked to both manual and chemical weeding practices, as well as the migratory status of the farmer. We calculate the average abatement cost for farmers of raising average biodiversity on their plantation by one more species at 325 USD per year. Finally, simulating several PES scenarios highlights promising policy options to reduce the loss of biodiversity while simultaneously increasing smallholder output levels.

The remainder of this paper proceeds as follows. Section 2 sets the stage by providing some background on the case study and the palm oil boom. Section 3 introduces the theory and application of environmental performance measurement based on distance functions and the intuition of biodiversity measurement and presents the data. Section 4 details the results from the analysis, discusses their robustness and places them in context of the relevant literature. In Section 5, we simulate several incentive-based policy schemes. Finally Section 6 summarizes and concludes the paper.

2. Palm oil: Boom and crisis in South East Asia

In 2018, global palm oil production exceeded 70 million ton per year, making it the most important vegetable oil in terms of quantity as well as the tenth largest agricultural crop worldwide. Remarkably, back in 1980 global production levels were only at about 5 million ton and palm oil held only minor relevance in international oil and commodity markets (FAO, 2020). Being relatively more productive in terms of area and labor, it has emerged as a particularly competitive crop in some agricultural systems around the world. Although the oil palm originates in Africa, the massive expansion of palm oil mainly occurred in tropical Asia and more precisely in Indonesia and Malaysia, which together supply more than 87% of global palm oil. During the times of exponential growth in oil palm output, a variety of development indicators also sharply improved in the respective areas. For instance, the prevalence of undernourishment in Indonesia more than halved from 18.5% in 2000 to 8.3% in 2017. The poverty headcount ratio of people living off less than 1.90$ per day declined from more than 70% in the early-1980s to 6% in 2017 (World Bank, 2020). While the economic development in Indonesia is certainly tied to a multivariate set of drivers, agricultural advancement and oil palm production are a significant part of this equation. Indeed, a number of studies relate increased national palm oil income to improved rural livelihoods, rural poverty and economic development in general (e.g., Sayer et al., 2012; McCarthy et al., 2012; Kubitza et al., 2018a).

Smallholder producers are also part of the economic success of palm oil, and as of 2016 they provide 34% of palm oil output in Indonesia (Indonesian Ministry of Agriculture, 2016). Besides establishing large governmental plantations, the government proactively promoted smallholder participation in the value chain launching several programs starting in the 1980s. One prominent example is the *trasmigrasi* program which supported the relocation of some 1.7 million family farmers from the densely populated islands of Java and Bali to less-populated parts of Indonesia, including Sumatra, to cultivate – among other crops – oil palm. However, in the more recent past, smallholder participation has been declining and smallholders are increasingly marginalized within the palm oil supply chain in Indonesia. Additionally, questionable land rights policy places further pressure on smallholder producers in Indonesia (McCarthy et al., 2012; Kubitza et al., 2018b; Rist et al., 2010).

From an environmental perspective, smallholder producers are still associated with direct forest land appropriation (Kubitza et al., 2018b; Krishna et al., 2017), and notoriously low yields, which place further pressure on resource use and imply low environmental performance, at least with regards to land input (Dalheimer et al., 2022). At the same time the accelerated rates of LUC have led to several ecological crises. Against the background of massive growth of oil palm output and area expansion, the accelerated rates of LUC have led to several ecological crises. Koh and Wilcove (2008) suggest that in Malaysia and Indonesia more than 50% of the palm oil area was formerly forested land, including rain forests with exceptionally high levels of species diversity and endemism. Oil palm plantations harbor much lower levels of biodiversity than forests and dramatically alter species composition across taxonomic groups (Fitzherbert et al., 2008; Grass et al., 2020). At current rates of deforestation, Sodhi et al. (2004) predicts that 42% of biodiversity in tropical Southeast Asia could be lost by the end of the century. Similarly, tropical forests play a role in serving as the terrestrial carbon sink, storing 428 Gt of carbon. LUC has led to fundamental changes in the balance and according to the IPCC (2000), LUC in the tropics is the world's second largest green house gas (GHG) emitter, with estimates ranging from 12%–20% of global GHG emissions. Finally, other environmental problems such as wildfire hazes bearing substantial human health threats, severe soil degradation and pressured water imbalances as well as quality have been associated with the expansion of oil palm in South East Asia.

Jambi province on Sumatra Island is a point in case for both the economic palm oil boom as much as the ecological crises development. Oil palm plantations were first introduced by large governmental estates and subsequently also adopted by smallholders during 1980s and 1990s. Smallholder adoption was particularly promoted by the government by means of contract schemes (Gatto et al., 2017) and the *trasmigrasi* program in the past, although today it usually occurs independently. Between 1990 and 2018, oil palm production and plantation area increased more than tenfold from 45,000 ha to 506,000 ha and 107,000 ton to 1,142,000 ton of oil palm fruit, respectively. As of 2018, more than 200,000 households are dependent on palm oil production in Jambi province (Kubitza et al., 2018a).

On the environmental side, Jambi has been experiencing severe degradation during the recent decades. For instance, over 80% of GHG emissions in Jambi result from LUC, deforestation as well as forest and peat land degradation. At the peak of the palm oil boom, an average annual forest loss of 76,522 ha was measured between 2006 and 2009 (Hein, 2019), leading to a severe reduction of biodiversity (Rembold et al., 2017) and threatening the survival of plant and animal species (Linkie et al., 2003; IUCN, 2015).

Besides being exemplary for the oil palm boom in the face of several ecological crises, Jambi province is also a meaningful region to study the trade-off between desired and undesired outputs in the light of a long-standing tradition of incentive-based policy programs, in particular regarding biodiversity loss mitigation. Already in 2002 the Rewarding Upland Poor for Environmental Services (RUPES) by the World Agroforestry Centre (ICRAF) aimed to pinpoint key monetary benchmarks to develop incentive-based pro-poor PES in Jambi (Villamor and van Noordwijk, 2011). Since 2010, Jambi is one of Indonesia's National Council on Climate Change (DNPI) model provinces for REDD and green growth. However, environmental policy programs and particularly PES in Jambi have been short lived thus far (Hein, 2019). One crucial reason is certainly the cumbersome economic valuation of the complex dovetail of palm oil production systems – composed of smallholders and large estates – and the manifold ecosystem services in Jambi province. Policy suffers from a lack of value assessment of local ecosystem services to design fruitful incentive schemes. One particularly relevant case is the trade-off between palm oil production and biodiversity.

3. Modeling the oil palm-biodiversity trade-off

In order to quantify the trade-off between the production of fresh fruit bunches for palm oil and the associated loss of biodiversity, we need (i) an adequate measure of biodiversity, and (ii) a suitable economic model that can subsequently be parameterized with the data at hand. Regarding the latter, we propose a directional distance function in a duality framework considering one desirable output, one undesirable output as well as regular inputs of production. However, the former warrants some more attention as biodiversity is a relatively broad term. Accordingly, in order to quantify a particular environmental-economic relationship, we need to establish comprehensible concepts for both.

In this section, we focus on the derivation of the hyperbolic distance function approach to investigate the interdependence between biodiversity loss and oil palm fresh fruit bunch production. Moreover, we outline our data at hand, describe measures, and present the empirical specification.

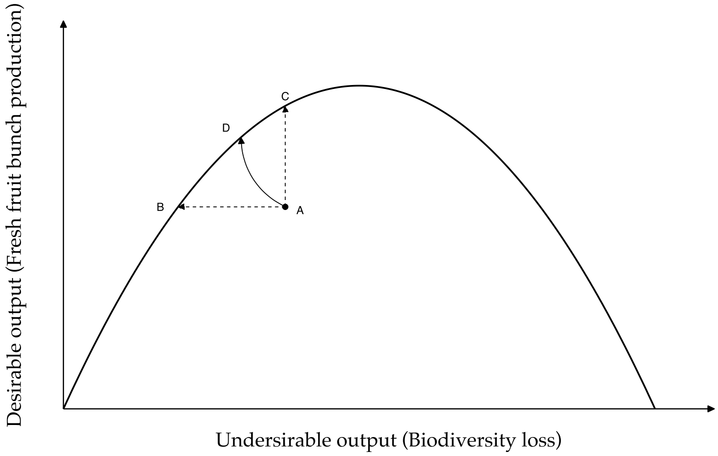

Fig. 1. Hyperbolic efficiency and directional distances.

3.1. Hyperbolic distance functions

Since the pioneering work of Aigner et al. (1977) and Meeusen and van Den Broeck (1977), a substantial body of literature uses firm or farm level data to attribute deviations between observed output and maximal obtainable output that can be produced (as defined by the production technology) to managerial performance, i.e. technical efficiency. Expanding the framework to settings in which firms produce multiple outputs and employ multiple inputs, distance functions have been proven a useful framework (Shephard, 1970). Specifically, output distance functions have become the workhorse for distinguishing between multiple outputs of production process that are desirable,[1] i.e. marketable or providing utility by some other measure. These are outputs that producers maximize. Chambers et al. (1998), Brümmer et al. (2002, 2006). However, most production processes inflict environmental externalities which are functions of desired outputs. A large body of literature models outputs that occur as unintended by-products that are utility-decreasing, i.e. undesirable, and producers neither minimize nor maximize, using environmental distance functions. (e.g. Coggins and Swinton, 1996; Chung et al., 1997; Färe et al., 2007; Hoang and Coelli, 2011; Murty et al., 2012; Kumbhakar and Tsionas, 2016; Huang et al., 2016; Dakpo et al., 2016; Tothmihaly et al., 2019; Vogel et al., 2023).

The relationship between desirable output procurement and undesirable output infliction of producers can take various forms. Considering smallholder oil palm fruit bunch production and biodiversity loss, land and land management are likely to result in the loss of biodiversity. However, biodiversity also determines the presence of pollinators, which are key to fruit formation in oil palms. Oil palms continuously set fruits throughout the year and the yield of oil palms depends on the frequency and extend of pollination. Thus, at high rates of biodiversity loss, fresh fruit bunch production will be affected negatively as the habitat for pollinators worsened. This interdependence suggest that the relationship between biodiversity loss and oil palm fresh fruit bunch production takes an inverse-u shape.

In addition to the technology that defines at what cost of biodiversity loss fresh fruit bunches are produced, farms can also suffer from inefficient management. In Fig. 1 we adapt the illustration in Skevas et al. (2018) to our inverse-u technology to describe the relationship between desirable and undesirable outputs and inefficiency at the farm level. Let us assume that a farms produce fresh fruit bunches as the desirable output but inflict biodiversity loss as an undesirable output at the same time. One specific farm, for instance, produces at point (A) and thus is inefficient as it falls short of the frontier. This specific farm could produce more fresh fruit bunches, without losing more biodiversity or, conversely, inflict less biodiversity loss while not having to give up any fresh fruit bunch production. Producer policies may aim to improve the economic performance of the farm by promoting efficiency measures to assist producers to operate closer to the frontier, which is depicted by (AC). Alternatively, producer policies may aim to improve the environmental performance of the farm by promoting efficiency measures that will assist the farmer to operate closer to the frontier, as depicted by (AB). Such policies can improve either palm oil output, biodiversity or both without trading-off each other and target management practices.

However, both potential movements as a response to the hypothetical policy changes are unlikely to occur in a straight horizontal or vertical direction (Skevas et al., 2018). Specifically, trade-offs might arise between economic and environmental performance. For instance, the participation of Finnish grain farmers to Agri-Environmental programmes (AEPs) might result in environmental improvements and simultaneous productivity losses (Bostian et al., 2020; Sidhoum et al., 2022). Similarly, more trade-offs might arise between the economic performance of the farms and other farm specific objectives, such as improved animal welfare (e.g. Hansson et al., 2018). Consequently, we assume that farms may expand desirable output and contemporaneously

[1] Another prevalent term for these outputs in the environmental economics literature is *good outputs*.

contract undesirable outputs. Therefore the joint movement will result in hyperbolic efficiency for the case of farms, which is depicted by (D) (Skevas et al., 2018).

In a parametric setting, two alternative approaches have been proposed in the literature that account for equiproportionate expansion of desirable outputs and contraction of undesirable outputs. The first is the use of a directional distance function, which requires the *a priori* assignment of a direction. The directional distance function has two major disadvantages: (i) the efficiency measure does not satisfy the key property of commensurability (Peyrache and Coelli, 2009), and (ii) it not trivial to capture the effect of determinants on efficiency (Serra et al., 2011). An alternative approach is the hyperbolic distance function (Cuesta and Zofío, 2005; Cuesta et al., 2009). This approach accounts for the equiproportionate expansion of desirable outputs and contraction of undesirable outputs, in a similar way that was presented in the figure above. Hyperbolic distance functions have been widely used to address various environmental performance problems of production processes (Skevas et al., 2018; Mamardashvili et al., 2016; Adenuga et al., 2019). One advantage of the parametric hyperbolic distance function is that it can easily capture efficiency determinants (Glass et al., 2014; Mamardashvili et al., 2016), and does not require the specification of arbitrarily-chosen directional vectors.

In essence, hyperbolic distance functions model the entire production process that includes trade-offs among inputs, between inputs and outputs and among outputs. Extending this framework to the presence of environmental outputs implies modeling negative externalities of production, which have been referred to as environmental distance functions. Assuming that a firm produces one desirable output (y) and one undesirable output (b) using inputs $\mathbf{x} = (x_1, x_2, \ldots, x_n)$, the value of the distance function is equal to the maximum possible proportional expansion in desirable output y and the proportional reduction of the undesirable outputs b that is simultaneously feasible, at a given input level. The frontier spanned by the observations for which no further expansion (reduction) is feasible constitutes an implicit function of the trade-off between economic output and the undesirable environmental output. Following Cuesta et al. (2009) we define the hyperbolic distance function as

$$D_H(\mathbf{x}, y, b) = min\left\{\theta : \left(\mathbf{x}, y \cdot \theta, \frac{b}{\theta}\right) \in P(\mathbf{x})\right\}, \tag{1}$$

where $P(\mathbf{x})$ represents the production possibility set, i.e., the feasible quantities of y and b that can be produced from the available input vector $\mathbf{x}$.

For $D_H(\mathbf{x}, y, b) = 1$, the farmer is fully efficient in the sense that no reduction of undesirable output or an increase of desirable output is possible at the given level of inputs, which also renders the distance value as a measure of environmentally-adjusted technical efficiency. In contrast to conventional measures of technical efficiency, the hyperbolic efficiency measure takes into account the negative environmental outputs of the production process and consequently may be considered a measure of environmental performance of the producing unit.

In order to allow for further adjustments in input use, the enhanced hyperbolic distance function additionally accommodates potential reductions of inputs, and therefore provides an even more flexible framework:

$$D_E(\mathbf{x}, y, b) = min\left\{\theta : \left(\frac{\mathbf{x}}{\theta}, y \cdot \theta, \frac{b}{\theta}\right) \in T\right\}, \tag{2}$$

where T represents the technology set of all combinations of y, b, and $\mathbf{x}$ that are technologically feasible.

The hyperbolic distance function has properties of (i) almost homogeneity,[2] and (ii) monotonicity, in particular non-decreasing in desirable outputs,[3] and non-increasing in undesirable outputs,[4] and non-increasing in inputs[5] (Cuesta et al., 2009). The enhanced hyperbolic distance function also allows a simultaneous contraction of inputs in addition to the asymmetric behavior of desirable and undesirable outputs, such that the almost homogeneous property is also extended to the inputs.[6] Additionally, both functions exhibit (iii) concavity: more precisely they are quasi-concave in desirable outputs for all undesirable outputs and inputs. In the enhanced hyperbolic case, this also applies for inputs, while the hyperbolic distance function is concave in inputs for all desired and undesired outputs.

However, the framework of the hyperbolic – and its more flexible version, the enhanced hyperbolic distance – function either do not allow for input contraction or they do so for all inputs. In smallholder production systems, only some of the inputs are flexible while others are not adjusted instantly such that both hyperbolic and enhanced hyperbolic distance are too restrictive. To overcome this problem, we propose a hybrid of both functions in which fixed inputs are distinguished from flexible inputs. Practically, this implies multiplying only flexible inputs by θ and not others. Thus, our restricted enhanced hyperbolic distance function becomes

$$D_R(\bar{\mathbf{x}}, \mathbf{x}, y, b) = min\left\{\theta : \left(\bar{\mathbf{x}}, \frac{\mathbf{x}}{\theta}, y \cdot \theta, \frac{b}{\theta}\right) \in T\right\}, \tag{3}$$

where $\bar{\mathbf{x}}$ now designates inputs that are fixed in the short term and $\mathbf{x}$ inputs that are variable. Based on the almost homogeneity property, we obtain an estimable form of the function by setting $\theta = \frac{1}{y}$, which is the inverse of the desirable output. y is the normalizing output of the distance function,[7] which subsequently can be expressed as

$$D_R(\bar{x}_i, x_i \cdot y_i, b_i \cdot y_i) = \frac{1}{y_i} D_R(\bar{x}_i, x_i, y_i, b_i), \tag{4}$$

[2] $D_H(\mathbf{x}, \mu y, \mu^{-1} b) = \mu D_H(\mathbf{x}, y, b)$, for $\mu > 0$.

[3] $D_H(x, \lambda y, \mathbf{x}) \leq D_H(\mathbf{x}, y, b), \lambda \in [0, 1]$.

[4] $D_H(\mathbf{x}, y, \lambda b) \leq D_H(\mathbf{x}, y, b), \lambda \geq 1$.

[5] $D_H(\lambda \mathbf{x}, y, b) \leq D_H(\mathbf{x}, y, b), \lambda \geq 1$.

[6] $D_H(\mu^{-1}\mathbf{x}, \mu y, \mu^{-1} b) = \mu D_H(\mathbf{x}, y, b)$ for $\mu > 0$.

[7] Note that (θ) can also be set equal to the undesirable output, see e.g. Huang et al. (2016).

and in logarithmized form

$$lnD_R(\bar{x}_i, x_i \cdot y_i, b_i \cdot y_i) = lnD_R(\bar{x}_i, x_i, y_i, b_i) - lny_i, \tag{5}$$

Assigning that $D_R(\bar{x}_i, x_i, y_i, b_i) = exp(-u_i)$, where u_i is the hyperbolic inefficiency (Cuesta et al., 2009), we can take Eq. (5) into the form of a stochastic production frontier by isolating y and adding the error term v_i to capture statistical noise:

$$-lny_i = lnD_R(\bar{x}_i, x_i \cdot y_i, b_i \cdot y_i) + u_i + v_i, \tag{6}$$

which can be estimated using Maximum Likelihood (ML). The procedure is equivalent to obtaining estimable forms of the regular hyperbolic and the enhanced hyperbolic distance function (Eqs. (1) and (2)).

3.2. Shadow price

The duality of the distance function allows deriving shadow prices, i.e., expressing one output, either desirable or undesirable, in units of another output. If price data for the base output are available, shadow prices are widely used to assign a price to unit changes in outputs, which are difficult to quantify endogenously. Shadow prices are a means to understand the cost at which a producer can contract a unit of undesirable output (Färe et al., 2002; Cuesta et al., 2009; Mamardashvili et al., 2016; Adenuga et al., 2019) and thereby they represent a measure of abatement costs. Another way to interpret the shadow price of biodiversity loss expresses the hypothetical cost to the producer of conserving one species. If species had that shadow price, producers would conserve as long as the marginal profit is equal to or smaller than the shadow price.

Assuming that a smallholder farmer aims to maximize profits, she faces the following problem:

$$\Pi(x, p_y, p_b) = \max_{y,b} \left\{ \frac{p_g y}{p_b b} \, : \, D_R(\bar{\mathbf{x}}, \mathbf{x}, \mathbf{y}, \mathbf{b}) \leq 1 \right\}. \tag{7}$$

where p_g and p_b are the prices for the desirable y and undesirable output b respectively. The corresponding first order conditions of the maximization problem and for the desirable and the undesirable output are:

$$\frac{p_g}{p_b b} - \lambda \frac{\partial D_R}{\partial y} y = 0 \Rightarrow \frac{p_g}{p_b b} = \lambda \frac{\partial lnD_R}{\partial lny} D_R. \tag{8}$$

$$-\frac{p_g y}{p_b b^2} - \lambda \frac{\partial D_R}{\partial b} b = 0 \Rightarrow -\frac{p_g y}{p_b b^2} = \lambda \frac{\partial lnD_R}{\partial lnb} D_R. \tag{9}$$

where λ is the Lagrange multiplier. Note that the shadow price formulation always refers to performance at the frontier, which implies no inefficiency in production ($D_R = 1$). Hence, the term (D_R) cancels out in both equations of the first order conditions. If we take the ratio of both conditions, then this results to the shadow price of b in terms of y:

$$-\frac{\frac{\partial lnD_R}{\partial lnb}}{\frac{\partial lnD_R}{\partial lny}} = \left. \frac{b}{y} \right|_{D_R=1} \tag{10}$$

which measures the amount of revenue from y that will be lost when b decreases by one unit, in absence of inefficiency.

3.3. Measuring biodiversity

Having established a suitable economic model to quantify the trade-off between conventional outputs under consideration of conventional inputs, we require an equally suitable measure of biodiversity. In the context of this study, biodiversity refers to species diversity. While there are often taxon-specific responses to LUC, plants have been shown to be reliable proxies of overall species diversity in our study region (Clough et al., 2016). Therefore, we focus on plants exclusively because they are ecologically highly relevant as well as relatively easy to record. Plants provide both habitat and energy (e.g. in the form of food) for other organisms like animals and fungi, and they can thus be considered as the foundation of terrestrial biological communities. Consequently, plant diversity is closely coupled with that of various animal groups, thus making it a proper proxy for overall diversity (e.g. Barnes et al., 2017; Potapov et al., 2019).

In addition, diversity is highly scale-dependent (Chase et al., 2018) and distinguished into (i), (α)-diversity, the diversity at a given site with presumed homogeneous environmental conditions; (ii) (γ)-diversity, the diversity of a region; and (iii) (β)-diversity, which describes the differences in species composition between sites in a region (Jost, 2007). To relate biodiversity to farmers' management practices, focusing on the (α)-diversity at the plantation level is the most adequate spatial scale, since management practices presumably vary between farmers. As recording all plant species and individuals of a plantation is eminently time-consuming, sampling plots of appropriate sizes is preferable under the assumption that they are representative of the whole plantation (Newbold et al., 2015).

Besides the matters of organism groups and scale considerations, choosing an appropriate measure is a further critical pillar of reliably quantifying biodiversity. A widely used framework of biodiversity measures are Hill-numbers (Hill, 1973) or measures of diversity of different orders q. Hill-numbers measure diversity D as a function of the number of species S and their relative abundance p_i and $q \neq 1$, which determines the sensitivity of the measure to the relative frequencies, such that

$$^{q}D = \left(\sum_{i=1}^{S} p_i^q \right)^{\frac{1}{1-q}} \tag{11}$$

One widely-used measure of α diversity is at $q = 0$ which constitutes the mere count of species, i.e. species richness (SR). Such diversity of order zero (q = 0), SR is insensitive to species frequencies and higher-order measures of diversity (q > 1), e.g. Simpson diversity with $q = 2$) are biased towards common species. Diversity of order one (q = 1) is undefined. Yet, its limit is the exponential of Shannon entropy, i.e. $ENS = \lim_{q\to 1}^{q} D = \exp\left(-\sum_{i=1}^{S} p_i \ln p_i\right)$, with $\ln p_i \times p_i = 0$ for $p_i = 0$, given the relative abundance p of a species i. This measure is also referred to as the effective number of species (ENS) and weighs rare and common species by their frequency, without disproportionately favoring either rare or common species (Jost, 2007). The ENS states the number of species in a hypothetical community with all species being equally abundant and the same Shannon entropy[8] as a given sample and thus it favors neither rare nor common species (Jost, 2007; Chao et al., 2014)

Generally, the lower the order of diversity, the more sensitive to undersampling are measures such that the real SR is difficult to assess with a reasonable amount of time and resources. Especially in diverse ecosystems like tropical forests, many species are extremely rare (Magurran and Henderson, 2003) and therefore they are likely to be missed in a given sampling plot. Consequently, the observed number of species in a plot will be a biased underestimate and highly sensitive to the number of individuals surveyed. Higher-order diversity measures, like Simpson diversity (q = 2) are more robust to undersampling because they mostly rely on common species. Their downside is the lower sensitivity to differences in diversity between samples (Fig. A.4 in Appendix A). ENS provides a good compromise between susceptibility to undersampling and sensitivity to differences between samples. Techniques of rarefaction and extrapolation that produce species accumulation curves serve to standardize measures of diversity by estimating them for a given number of individuals, which is a prerequisite for comparing the diversity of two or more communities (Chao et al., 2014).

3.4. Data

Just as much as the methods employed in this study, the data also cover two main components. Both data partitions stem from extensive socioeconomic farm household survey conducted in Jambi Province, Indonesia in 2012,2015 and 2018, as part of a larger interdisciplinary research project (Drescher et al., 2016). The dataset has been applied in other empirical works (e.g. Kubitza et al., 2018b; Euler et al., 2017; Kubitza et al., 2018a; Krishna et al., 2017; Clough et al., 2016). The panel covers all conventional input and output data required to accurately model palm oil production as well as socioeconomic variables that may help to explain managerial performance. The second partition of the data is a detailed account of plant abundance collected on a representative location on farms.

Table 1 lists the variables used in the analysis and the respective units of measurement, variable designations in the empirical part of the paper as well as key summary statistics. Production of fresh fruit bunches serves as the desirable output y while the inverse of the effective number of species (ENS) is the measure of the undesirable output b. We account for three inputs, i.e. area of production, labor and agrochemicals, which constitutes of the sum of herbicides, pesticides and fertilizers. Additionally, the age of the plantation is crucial to oil palm production since the yield of the perennial crop has a nonlinear relationship with time. Oil palms start only producing fruit bunches 3 years after plantation. Peak yields vary across regions and can start as early as seven or as late as sixteen years. Usually, at the age of 24 oil palms exhibit declining yields and after 30 years they reach production levels of zero (Corley and Tinker, 2003). In addition to the economic production variables, a range of socioeconomic variables such as age, education and household size are available for specifying the restricted hyperbolic distance function.

Variables on the migratory status of farmers have also been collected. They are particularly interesting as the government of Indonesia has been operating the *trasmigrasi* program which promoted and assisted in the reallocation of people from Java to Sumatra to cultivate oil palm. The program also offered training related to oil palm production which makes the migration variables particularly interesting to model the determinants of (in)efficiency of production. In our dataset, a dummy variable captures whether the family of the farmer itself migrated to cultivate oil palm in the past.

Regarding management practices variables on whether a farmer used chemical weeding or manual weeding are available. Weeding practices on the plot have crucial impacts on both the growth of the palms and their respective output as well as the plant biodiversity on the plot. The variable on land titles captures whether the farmer is in possession of any kind of governmental ownership certificate for his plot.[9]

With regards to biodiversity measurement, we collected plant abundance data on farms. To record the (α)-diversity of vascular plants in the understorey (including ferns, lycophytes, and seed plants), we established a square vegetation plot of 25 m^2 in each plantation. Within each plot, we assigned all plant individuals to morphospecies and counted the number of individuals per morphospecies. Each morphospecies was photographed for later species identification. Using the iNEXT-package in R (Hsieh et al., 2016), we calculated the observed per-plot species richness (SR_{obs}) and effective number of species (ENS_{obs}) (Jost, 2006). Since the number of individuals widely varied between plots with a minimum of 3, a median of 364 and a maximum of 6616, we standardized the diversity measures using the rarefaction/extrapolation procedure of Chao et al. (2014) which is implemented in Hsieh et al. (2016) with the median number of individuals ($n = 364$) as the base sample size. The plot-wise rarefaction/extrapolation curves indicated that some individual-poor plots did not adequately represent local SR while sampling coverage was sufficient for ENS. We therefore used the estimated effective number of species per 364 individuals (ENS_{est}) as our primary measure of biodiversity, although we also ran our model separately with the estimated species richness per 364 individuals (SR_{est}) for comparison and robustness checks (Appendix B.3).

[8] The Shannon entropy is a widely used diversity index that considers the relative abundances of all species.

[9] Please refer to Kubitza et al. (2018b) for a detailed overview of land ownership structure and certification in Jambi.

Table 1
Variable overview and summary statistics.

Variable	Unit	Variable	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Outputs								
Oil palm FFP[a] production	kg	y	33,744	30,896	38	15,800	42,200	204,000
Biodiversity	ENS_{est}[b]	b	5.009	2.327	1.331	3.244	6.498	15.132
Technology								
Size	ha	x_1	2.17	1.78	0	1.5	2	12
Labor	hours	x_2	2629	3068	9	1369	2893	31,008
Palm age	years	x_3	16.02	7.46	3	10	22	30
Agrochemicals	kg	x_4	7689	988	0	10	1222.5	6000
Yield	kg ha^{-1}	–	15,738	7626	152	10,658	20,000	37,860
Inefficiency								
Age	years	z_1	48.07	11.33	25	40	55	79
Education	years	z_2	7.82	4.09	0	6	12	17
HHSize	people	z_3	4.789	1.564	2	4	6	11
Transmigrant	binary	z_4	0.42	0.50	0	0	1	1
Chemical weeding	binary	z_5	0.73	0.44	0	0	1	1
Manual weeding	binary	z_6	0.31	0.46	0	0	1	1
Land title	binary	z_7	0.69	0.46	0	0	1	1

[a] Fresh fruit bunch.
[b] Effective number of species.

3.5. Empirical specification

In our distance function framework, we propose combining features of the hyperbolic as well as the enhanced hyperbolic distance function to model fresh fruit bunches of a plot in kg as the desirable output y_i and biodiversity loss on the same plot, measured as the inverse of the ENS, as the undesirable output b_i. The input variables are the size of the plot x_1, x_2 is labor, x_3 agrochemicals and x_4 the age of the plantation. While the size and age of palms are indubitably fixed inputs, we further argue that labor is also fixed as farms almost exclusively employ family labor and agrochemicals remain as the variable input.[10] We make use of the translog functional form which offers more flexibility as opposed to Cobb–Douglas or quadratic functions.[11] We employ stochastic frontier analysis (SFA) to estimate the restricted hyperbolic distance function D_R by means of ML. The final translog restricted hyperbolic distance function specification is:

$$\begin{aligned}
-lny_i = {} & \alpha_0 + \sum_{k=1}^{3}\alpha_k ln(x_{ki}) + \alpha_4 ln(x_{4i}^*) + \beta_1 ln(b_i^*) + \sum_{k=1}^{3}\beta_{1k} ln(b_i^*)ln(x_i) \\
& + \beta_{14} ln(b_i^*)ln(x_{4i}^*) + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3}\alpha_{kl} ln(x_{ki})ln(x_{li}) + \frac{1}{2}\sum_{k=1}^{3}\alpha_{k4} ln(x_k^*)ln(x_4) + \\
& + \frac{1}{2}\alpha_{44} ln(x_i)^2 + \frac{1}{2}\beta_{11} ln(b_i^*)^2 + \rho_0 t_i + u_i + v_i,
\end{aligned} \tag{12}$$

where $b_i^* = y_i * b_i$ and $x_i^* = x_i * y_i$. In order to circumvent potential convergence problems we scale all variables by dividing them by their geometric mean such that we evaluate elasticities at sample means. We also include the time trend t_i variable in the specification, which accounts for exogenous technical change. Other panel data specifications overparamterize the model given the number of observations. v_i is a normally-distributed component of the two-component error term and captures statistical noise. The other component represents the distance function value, or in other words, the inefficiency of production, also accounting for loss of plant biodiversity. We assume heteroskedasticity of u_i and consequently model it using the farmer, migratory and management practices characteristics captured in z_i. Therefore:

$$\sigma_{u,i}^2 = \exp(\tau'\mathbf{z}_i). \tag{13}$$

The parameters α, β, ρ and τ in Eqs. (11) and (12) are jointly estimated using ML. Finally, we follow Battese and Coelli (1988) and transform the individual conditional distribution of the values of the distance function, that is the one-sided error of the empirical model of Eq. (12), into a measure of efficiency that is bounded by 0 and 1. In our case at hand, the measure describes the environmental performance, considering the trade-off between fresh fruit bunch output and biodiversity,

$$EP_i = exp(-u_i). \tag{14}$$

EP is a measure of how much biodiversity is lost at no additional gain of fresh fruit bunch output, or vice versa, how much fresh fruit bunch output is forgone with no reduction of biodiversity loss, at given input levels.

[10] As robust checks, we also derive the empirical specification and estimate the corresponding enhanced hyperbolic and hyperbolic distance functions where all inputs are treated equally. We also calculate further resulting measures thereof in Appendix B.2.

[11] The translog specification is tested to be superior to the Cobb–Douglas specification using conventional tests for nested models.

Table 2
First order terms and parameter estimates of the determinants of inefficiency of the restricted hyperbolic distance function.

	$D_R(x, y, b)$	
Technology		
α_0 (Intercept)	−0.48	(0.08)***
α_1 (Size)	−0.37	(0.08)***
α_2 (Labor)	−0.06	(0.06)
α_3 (Age of Palms)	−0.26	(0.08)***
α_4 (Agrochemicals)	−0.06	(0.02)***
β_1 (Biodiversity loss)	−0.42	(0.04)***
β_{11} (Biodiversity loss)^2	0.18	(0.08)**
Inefficiency		
τ_0 (Intercept)	1.24	(2.36)
τ_1 (Age)	−0.29	(0.12)**
τ_2 (Age^2)	0.00	(0.00)**
τ_3 (Education)	−0.03	(0.43)
τ_4 (Education^2)	0.03	(0.08)
τ_5 (HH size)	0.31	(0.15)**
τ_6 (Transmigrant)	1.17	(0.48)**
τ_7 (Chemical weeding)	0.50	(0.46)
τ_8 (Manual weeding)	1.09	(0.39)***
τ_{10} (Land title)	0.98	(0.55)*

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4. Results

Our empirical model delivers several layers of results.[12] First we discuss the hyperbolic distance function. Second, we provide a brief discussion of robustness checks in support of the empirical approach. Third, we turn to the coefficients of the hyperbolic inefficiency component of the error and derive marginal effects as well their implications regarding smallholder environmental performance. Fourth, we calculate the cost of abatement by means of shadow price calculation from our dual framework.

4.1. Production technology

Table 2 exhibits the ML estimates of the first order terms and the determinants of inefficiency as well as the associated standard errors of the restricted hyperbolic distance function.[13] The coefficients capture the effect of the individual variables on the distance function value. Loss of biodiversity as well as increases in inputs augment the distance value which is reflected in the negative signs of the respective coefficients and compare well with results of other works on smallholder oil palm production concerning both biodiversity trade-off (Grass et al., 2020) and input use (Soliman et al., 2016). The effect of labor is not statistically significant, while the direction as well as magnitude are reasonable in light of the notoriously low labor intensity of oil palm production (Kubitza et al., 2018a). The first-order coefficient of the age of trees is significant and explains a large chunk of desired output. Additionally the coefficient of the time trend (ρ) suggests that environmental technology progressed by 8% between periods, i.e. over three years.

The negative and significant (β_1) positive and significant (β_{11}) evidence an inverse-U relationship between palm output and biodiversity loss. We observe both farmers with low as well as farmers with high levels of biodiversity loss at equivalent levels of output of oil palm fruits. High levels of fresh fruit bunch production is associated with low levels of biodiversity (high levels of biodiversity loss), however, only until a certain threshold where in turn, low levels of biodiversity loss are also negatively associated with fresh fruit bunch production.

Fig. 2 displays the inverted partial hyperbolic distance function which fits the observed fresh fruit bunch production measured in tonnes and biodiversity, conditional on mean input usage.[14] The producer with maximum observed biodiversity on the far right in Fig. 2 operates a relatively new (3 years) plantation that still yields low levels of fresh fruit output. Agrochemical use and weeding are low which enables a high level of biodiversity. On the other end of the spectrum and on the left side in the plot, we also observe producers with high agrochemical use and weeding practices that result in high levels of biodiversity loss, which in turn decreases pollinator populations and ultimately impedes palm productivity. In between farmers with such output structures, we also observe a wide range of farmers exhibiting either higher levels of output, lower levels of biodiversity loss or both. The maximum value of the environmental technology is at about 190 tonnes of fresh fruit bunch output and 3.15 effective species. In other words, maximized fresh fruit bunch output of producers is associated with relatively low levels of biodiversity, conditional on mean input usage in the sample.

12 The distance functions are estimated in **R** (R. Core Team, 2019) using the **npsf** package (Badunenko et al., 2019).

13 A table detailing the full list of estimated parameters is listed in Table B.8 of Annex II.

14 Note that for ease of interpretation, the function is presented in it is inverted form to reflect the data, not the theoretical environmental model, which has a negative externality on the horizontal axis.

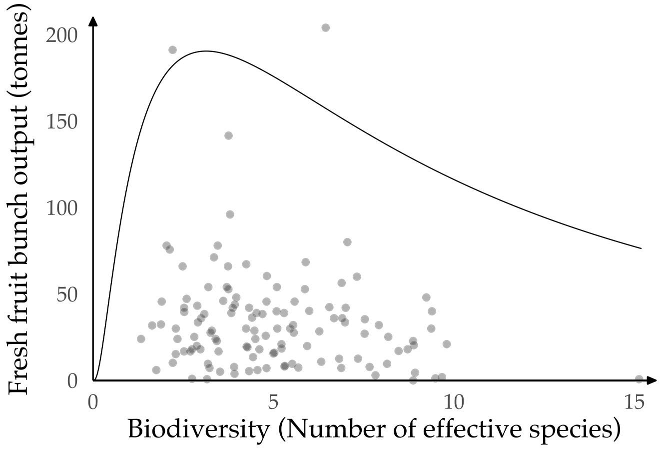

Fig. 2. Inverted partial hyperbolic distance function of fresh fruit bunch production with respect to biodiversity.

Table 3
Marginal effects of determinants of environmental performance.

	Mean	St. Dev.	Min	Max
Age	0.041	0.018	0.099	0.011
Education	0.004	0.002	0.009	0.001
Household size	−0.043	0.019	−0.105	−0.012
Transmigrant	−0.164	0.072	−0.399	−0.045
Chemical weeding	−0.070	0.031	−0.171	−0.019
Manual weeding	−0.153	0.068	−0.373	−0.042
Land title	−0.138	0.061	−0.335	−0.038

4.2. Robustness checks

A number of concerns regarding the robustness of the hyperbolic distance function and the results we derive from it arise. Specifically, our estimates hinge upon (i) the measure of biodiversity, (ii) the functional form, and (iii) potential endogeneity, which we do not account for in the baseline model.[15]

In Appendices B.2 and B.3 we estimate restricted and unrestricted hyperbolic distance functions as well as our baseline model using species richness loss as an alternative measure of biodiversity loss. Both specifications are not contradicting our main results providing some first confidence in our choice of functional from as well as the biodiversity measure.

With regards to endogeneity, the econometric estimation of distance functions in general may be prone to endogeneity (Sauer and Latacz-Lohmann, 2015). Endogeneity might arise because some regressors are functions of the error term. Nevertheless, for the hyperbolic distance function, Cuesta and Zofío (2005) argue that the almost homogeneity condition implies that while some regressors can be correlated with the error term, others can be inversely affected. Consequently, the ratios and products regressors can be regarded as exogenous. To test this empirically, we follow recent advances of Kumbhakar and Tsionas (2016) and Griffiths and Hajargasht (2016) and test for the presence of endogeneity (e.g. see Wimmer and Sauer, 2020). We present the results in Appendix B.4. The main disadvantage of these approaches in relation to our study of course is that they do not allow to include variables that affect the outputs jointly but instead neglect their interactive effects. The parameter estimates and average inefficiency measures do not differ qualitatively from the parameters in the main text, which provides support that endogeneity is not a major problem in our specification. These results confirm the assumption that smallholder producers do not optimize production with respect to biodiversity loss.

4.3. Inefficiency

Fig. 3 depicts the distribution of hyperbolic efficiency, i.e. the environmental performance scores across the sample. The mean environmental performance of production under consideration of loss of biodiversity is 0.78, implying that farm managers could expand output by 28.22% (1/0.78) and contract biodiversity loss by 22.01% (1–0.28) at the same time and at given input use, on average, respectively.

While the bottom end of Table 2 lists the parameter estimates ρ of the drivers of environmental performance Table 3 exhibits the corresponding marginal effects. We find that the age of the household head of the farm is positively associated with environmental

[15] Appendix B provides a detailed assessment and discussion of all robustness checks.

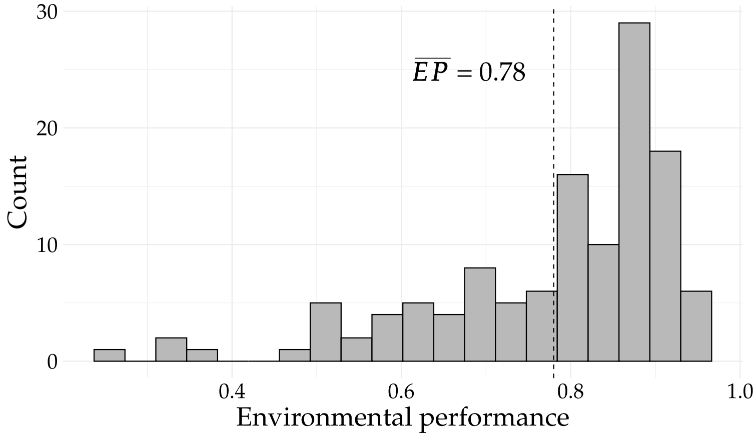

Fig. 3. Histogram of environmental performance scores of farms and mean environmental performance.

Table 4
Shadow prices in constant USD (2015).

	per farm			per ha		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.
2018	325	287	231	268	220	230
2015	369	325	262	304	250	261
2012	374	330	266	308	253	265

performance. The switched sign of the squared term additionally indicates decreasing returns in this relationship, although, the magnitude of this effect is rather small. Regarding management practices, we find large inefficiency increasing effects from chemical and manual weeding practices as well as whether the family of the farm has participated in the *trasmigrasi* program. The latter two are also statistically significant at the 5% levels in both models. Weeding – whether manual or chemical – targets the elimination of species on the plot and therefore reduces the performance of the production with respect to biodiversity. While other authors find that producers who had been associated with the *trasmigrasi* program are more productive and economically better off (Gatto et al., 2017), evidence from our model suggests that their environmental performance is worse than that of autochthonous producers. A likely explanation is found in the higher agrochemical input use of transmigrant farmers, as well as the intensified production of farmers with land titles (Kubitza et al., 2018b). Both practices disproportionally inflict stronger effects on biodiversity, albeit increasing oil palm fruit output on average.

4.4. Shadow prices

In order to derive shadow prices expressing the abatement cost of the non-marketed output, we require real market prices to solve the equation. The survey data reveals the average prices per kg of oil palm fresh fruit bunch obtained by the sampled farmers are (890), (1010) and (1023) Indonesian Rupiah (IDR) for 2012, 2015 and 2018, respectively. We deflate the Indonesian consumer price index retrieved from the Federal Reserve Bank of St. Louis (2020) and apply a constant exchange rate.[16] Making use of the duality of the distance function, we calculate shadow prices for biodiversity loss which are presented on the left-hand side of Table 4. The values indicate how much revenue would be forgone if one more species was conserved on the plot. Shadow prices reflect the dynamics on the frontier, namely in the absence of inefficiency. The shadow price of an inefficient producer would be zero since biodiversity can be increased without reducing outputs or – at least for agrochemicals – input use. The right hand side illustrates individual shadow prices divided by the respective plot size and thus it provides a measure on both a per species and per ha basis. About 33% of the farms in the sample exhibit negative shadow prices, which implies that these are scaled back to the negatively sloped portion of the function (Färe et al., 2005; O'Donnell and Coelli, 2005). We follow Färe et al. (2005) and calculate and report the summary statistics of shadow prices for the remainder of 67% of the farms.

In our sample, the value for conserving one species on a farmers plantation is 325 USD in 2018 on average. However, the variation of the shadow prices is quite substantial, confirming the results of Bateman et al. (2015) who find considerable idiosyncrasy in oil palm smallholders' capacities to conserve biodiversity. One limitation in the interpretation of shadow prices is that since we measure biodiversity on agricultural production sites our trade-off measure entails only the lower part of biodiversity. The potential relationship between oil palm production and biodiversity beyond sample values is unknown and most likely non-linear.

16 $\frac{USD}{IDR} = 0.00007$.

Table 5
Aggregated biodiversity and fresh fruit bunch production outcomes for different weeding scenarios of practice based PES measures compared with the elimination of inefficiency.

Eliminating	ΔENS	ΔENS (%)	Δy	Δy (%)
Manual weeding	10	1.7	53,013	1.3
Chemical weeding	9	1.4	42,562	1.0
All weeding	19	3.1	99,527	2.4
Inefficiency	118	19.1	1,026,078	24.7

Notes: ΔENS is the change in the number of effective species and Δy is the change in fresh fruit bunch production in kg. The columns to the right express species and production expansion in percentage terms relative to the baseline status.

To put the average shadow price in perspective, in 2018 the average farm income of smallholders in Jambi province was 2,179 USD per year. Thus, for an average farmer, the abatement cost for raising average biodiversity by one species on the whole plantation area is about 15% annual income from oil palm cultivation. In turn, the cost of eliminating biodiversity shortfalls – namely augmenting the biodiversity of all farmers to the level of the best practitioner (15.1 ENS) – would inflict costs in terms of output loss of 398,690 USD.

5. Payments for ecosystem services (PES) simulation

As shadow prices reveal the opportunity cost of producing less marketable output and instead diminish unmarketable output, shadow prices are key to designing respective conservationist policy. Although shadow prices only reflect the private marginal benefit while the social marginal benefit from conserving biodiversity remains unknown – albeit larger than the private one – they still allow us to derive supply functions for the biodiversity provision of smallholder producers.

PES are a popular policy instrument and they are frequently implemented to preserve ecosystem services (Bulte et al., 2008; Jack et al., 2008; Salzman et al., 2018; Schomers and Matzdorf, 2013; McWherter et al., 2022). In essence, PES schemes take the form of a Pigouvian subsidy in which the government subsidizes the provision of an environmental good that is otherwise not marketed. Practically, PESs are implemented in different ways depending on the specific goods as well as the desired outcomes. Among a variety of PES schemes, two prominent designs are management- and performance-based PES. The former reward producers for engaging in or refraining from specific agricultural practices that are harmful to the ecosystem service. In the latter scheme producers are compensated for providing certain levels of the ecosystem service which are set a priori (FAO, 2007; Schomers and Matzdorf, 2013). In this section we examine potential applications of both designs in the smallholder oil palm production sector of Jambi province.

In the following, we calculate the outcomes of the two alternative incentive settings to achieve higher levels biodiversity. First, we predict a management-based payment, in which participants are rewarded for engaging in or refraining from certain practices associated with environmentally detrimental outcomes. Second, we compare the management-based measure with a scenario of performance based payments that reward the participant for achieving a certain level of outcome in the environmental indicator. For the sake of simplicity, we pool the panel and confine this section to highlighting the incentive mechanisms as well as the premium and cost magnitudes of environmental policy action in Jambi.

5.1. Management-based measures

We argue that manual weeding could be a reward-worthy agricultural practice due to two particular reasons, one of which is empirical and the other theoretical. First, since weeding increases the hyperbolic distance to the production frontier and therefore lowers the environmental performance of farmers, moderating the management practice could lead to less loss of biodiversity without losing output. Second, selectively removing plant species from the plots by definition lowers biodiversity. Hence, a policy targeting manual weeding could kill two birds with one stone, namely eliminating a source of inefficiency - without a loss of productivity - as well as technologically lowering the loss of biodiversity - potentially with a loss of productivity.

Table 5 details the aggregated outcome of farmers refraining from weeding practices. Even though the marginal effects of manual weeding are substantially higher than those of chemical weeding the omission of either leads to comparable increases of both biodiversity and oil palm output at around 1.4–1.7% and 1.0–1.3% respectively. If farmers dispense of both weeding practices biodiversity could be increased by 3% and oil palm output by 2.4%, lifting the aggregate ENS by 19 species, on average, and the production level by almost 100,000 kg.

Increasing biodiversity by means of encouraging refraining from weeding practices inflicts no costs and premiums could even be zero as farmers simultaneously benefit from increased production. Nevertheless, the result that introducing a PES scheme based on rewarding refraining from weeding will yield win-win situations requires some caution in its interpretation. Although including both dummy variables in the frontier does not reveal a significant dependence of output on the respective weeding practices, both practices could be more important due to two reasons. First, the insignificant importance of weeding practices for the production technology and the importance for the environmental performance could be due to the overall low productivity. In case of non-linearity of this relationship, with further technological change farmers could reach production levels where weeding practices make a more profound difference. Second, the significance levels of the coefficients are conditional on the sample size, which is rather small. Nonetheless, the fact that the weeding practices can be associated with negative environmental performance of smallholders could feed into policy measures to mitigate biodiversity at minimal output cost.

Table 6
Policy scenarios targeting social equality, uniform biodiversity distribution and cost minimization.

	Social inclusivity	Uniform biodiversity	Cost minimizing
Inefficiency oriented			
Aggregated ENS increase	19.1%	16.7%	20%
px_1^{-1}	448$	667$	306 $
ΔY	−36,090$	−40,696$	−55,3566$
ΔENS	118	103	122
Participation	100%	98%	73%
Cost	119,489$	177,922	65,484
Weeding-inefficiency oriented			
Aggregated ENS increase	3.1%	2.3%	3.8%
px_1^{-1}	74$	337$	51$
ΔY	−48,715$	−6,124$	−104,840$
ΔENS	19	14	23
Participation	100%	99%	72%
Cost	19,697 $	89,895$	10,697$

px_1^{-1} designates the premium per land unit (ha), ΔY the change in oil palm fruit output (kg) and ΔENS the change in the effective number of species.

5.2. Performance based payments

Within performance-based PES schemes, policymakers target specific outcomes of an environmental variable, either in terms of increases or specific target levels (FAO, 2007; Bulte et al., 2008; Sattler and Matzdorf, 2013). Additionally, they set a premium – usually based per cultivation area unit – which the farmer receives if he participates in the program. The farmer's willingness to participate is equal to the shadow price. If premium payments are equal or exceed his potential loss of oil palm output, she is likely to participate, and otherwise she will not. A host of biodiversity conservation targets are conceivable. For the sake of highlighting outcomes of the mechanism of such payments, we consider two potential target levels. First we simulate policy to target a similar level of biodiversity increase that could be achieved by eliminating inefficiency in the production process. Second, we consider a policy that targets biodiversity growth levels comparable with the management based programs from the previous section. We assume that farmers are maximizing profits with regards to fresh fruit bunch output or income from the payments, while being indifferent towards biodiversity levels.

Table 6 illustrates the results of playing out different performance based PES.[17] The upper panel presents simulation of a policy that targets a similar level of biodiversity conservation compared to the magnitude of eliminating efficiency. The lower panel displays the outcomes of the policy that targets magnitudes of conservation similar to those obtained in the management-based PES of Table 5. In addition to conserving biodiversity, PES might differ in how they aim to conserve biodiversity focusing on maximizing participation in the program, uniformity of the biodiversity level in the region, or minimizing costs.

Column one presents a scenario that ensures that all farmers are willing to participate in the program, i.e. that the premium is equal to the maximum value of the farmer's willingness to pay. While such an approach might not be the most cost-efficient it favors social inclusivity alongside some level of equality of biodiversity (Ando, 2022). The second column lists the outcomes of a policy program that targets raising biodiversity to an equal standard throughout the region. In other words, the policy targets a set minimum level of species to be present at every plantation. From a biodiversity perspective this makes sense as a uniform distribution of species across space determine higher $gamma$-diversity levels. To achieve similar biodiversity increases as in the previous scenario, the policy rewards farmers with at least three and five ENS respectively and sets the premium such that all farmers are willing to participate. The third column eventually exhibits the cost minimizing results while ensuring participation rates of more than 50%.

From the three sets of results we conclude that, (i) while aiming at equal levels of biodiversity throughout the sector is ecologically highly desirable, it is by far the most expensive endeavor among the three options at hand. The policy sets in on farmers with high levels of biodiversity loss and high shadow values and targets minimum levels accordingly. On the downside, many farmers are rewarded without adjustments as their production already by-produces sufficiently little loss of biodiversity. However, individual losses in forgone production revenue are very limited. Moreover, (ii) unequal but substantial increases of biodiversity are comparably cheap to obtain.

However, although PES schemes are frequently applied to address externality problems in many different – including developing country – settings (Wunder et al., 2008; Sims and Alix-Garcia, 2017) around the world, their practicality and success are driven by transaction costs (Banerjee et al., 2017). Monitoring and measuring the provision of environmental goods is often not feasible at all and if possible associated with very high transaction costs which in turn often outpaces provision expenses, thus rendering policies as highly cost ineffective. However, remote-sensing based biodiversity monitoring opportunities are arising and could soon

[17] Appendix C of the appendix details the calculations of the PES simulation scenarios in detail.

be available at a granularity that allows cheaply determining site-specific measurements of biodiversity and other environmental indicators (Gullstrand et al., 2014).

Generally, detecting agricultural practices that are detrimental to the provision of not only desired outputs but also undesired ones is perhaps a promising start to design PES schemes. PESs often solely rely on the mere minimization of practices that are harmful to the ecosystem service and thereby neglect potential win-win scenarios which naturally should be exploited before policy targets improving environmental outcomes, which inevitably come at the cost of agricultural production. Therefore, incentive-based environmental policies are likely to be beneficial not only as they achieve the desired conservation of biodiversity but also because they might lead farmers to increase their environmental performance, i.e. producing more at a lower burden of biodiversity loss.

6. Summary and conclusion

Indonesia has become a hotspot for environmental degradation, while providing the world's largest supplies of palm oil. Smallholder farmers are substantially contributing to both palm oil production as well as the decay of ecosystem services. Concurrently, the trade-offs between oil palm production and several ecosystem services in large-scale operations are well understood, while the environmental performance of smallholders has not been addressed in the relevant literature.

In this paper we address the literature gap and derive a full environmental production function accounting for the economic desirable output, undesirable environmental degradation – measured as plant biodiversity – conventional farm inputs and socioeconomic factors as well as management practices to explain shortfalls in managerial outcomes. Additionally, the duality of the outputs enables calculating the cost of abatement in the smallholder production system, which we use to simulate several PES policy scenarios.

Our main results are fourfold. First, we find that the production of fresh fruit bunches leaves ample room to improve efficiency under consideration of environmental degradation. Oil palm output can be expanded by 28% while loss of biodiversity at given input levels could be contracted by 22%. Second, both chemical as well as manual weeding result in worsened environmental performance of oil palm production. Third, aside from potentially eliminating inefficiency, the abatement cost for increasing average biodiversity by one species on a farmers plantation amounts to 325 USD, on average, or about 15% of average annual palm oil income for smallholder oil palm producers. Fourth, PESs are promising policy options to conserve ecologically meaningful levels of biodiversity while simultaneously allowing smallholders to increase output levels. In general, identifying drivers of environmental inefficiency is key to successfully designing respective PES schemes.

Given that smallholders are important contributors to global palm oil supply, our results regarding their environmental performance suggest that improved management practices can play an important role in counteracting large-scale species extinction. Smallholders manage nearly half of Indonesia's oil palm area at comparably low yields, and effectively-designed policy aims to eliminate inefficiencies in production and reward conservation of biodiversity at average levels of opportunity costs and thereby provides promising avenues for more sustainable smallholder palm production.

CRediT authorship contribution statement

Bernhard Dalheimer: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Iordanis Parikoglou:** Writing – review & editing, Validation, Software, Methodology, Investigation, Formal analysis. **Fabian Brambach:** Writing – review & editing, Conceptualization. **Mirawati Yanita:** Writing – original draft, Conceptualization. **Holger Kreft:** Writing – review & editing, Supervision, Funding acquisition. **Bernhard Brümmer:** Writing – review & editing, Visualization, Supervision, Methodology, Conceptualization.

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Appendix A. Additional descriptives of biodiversity indicators

See Fig. A.4.

Appendix B. Robustness checks

In this section we address the problems of dependency on biodiversity measure, distance function specification, and endogeneity. First, we compare the SFA specification against the OLS specification using a Likelihood Ratio test. Second, we estimate restricted and unrestricted hyperbolic distance functions. Third, we estimate our baseline models using alternative biodiversity measures. Fourth, we estimate two-equation models to investigate the potential endogeneity between desirable and undesirable outputs as well as input and the error term.

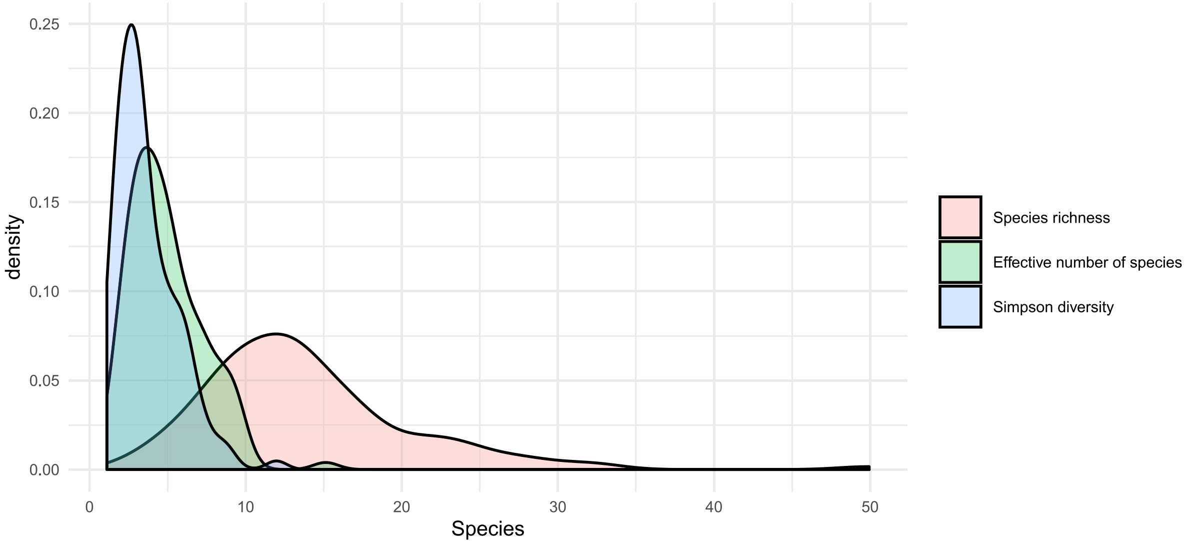

Fig. A.4. Density of sample plots with different levels of plant species diversity assessed by diversity indices of order $(q = 0)$ (SR), $(q = 1)$ (ENS), and $(q = 2)$ (Simpson diversity). SR is more sensitive to differences between samples but potentially unreliable as diversity measure when undersampling is expected.

Table B.7
Likelihood ratio test comparing OLS and error components specifications.

Model 1: OLS (no inefficiency)
Model 2: Error Components Frontier (ECF)

LogLik	Df	Chisq	Df	Pr(>Chisq)
16	−72.9			
18	−67.2	2	11.3	0.0013*

* indicates significance at the 0.001.

B.1. Likelihood ratio test comparing OLS and error components specifications

Since the model with inefficiency and without are nested, we can perform a model comparison using the likelihood ratio test to assess the error component specification (Battese and Coelli, 1992; Bruns et al., 2022). The first candidate model is translog production frontier (no inefficiency) term where the dependent is production variable and the independent are the four inputs; bad output is not part of the frontier. The second candidate model is this model, but adding a time invariant inefficiency term, that is a draw from a half-normal distribution. Both candidate models are in translog.

Under the null hypothesis (no inefficiency, only noise), the test statistic asymptotically follows a mixed χ^2 distribution (Coelli, 1995). The results from the test are reported in Table B.7 below. The estimated P-value indicates that the data clearly reject the OLS model in favor of the stochastic frontier model, i.e. there is significant technical inefficiency (see Henningsen, 2015)

B.2. Hyperbolic and enhanced hyperbolic specifications and estimation results

Furthermore, we estimate the hyperbolic and enhanced hyperbolic distance functions where *all* farm inputs are fixed and variable, respectively. Empirical specification of the hyperbolic function:

$$-lny_i = \alpha_0 + \sum_{k=1}^{4} \alpha_k ln(x_{ki}) + \beta_1 ln(b_i^*) + \sum_{k=1}^{4} \beta_{1k} ln(b_i^*) ln(x_i) + \frac{1}{2} \sum_{k=1}^{4} \sum_{l=1}^{4} \alpha_{kl} ln(x_{ki}) ln(x_{li}) + \\ + \frac{1}{2} \beta_{11} ln(b_i^*)^2 + \rho_0 t_i + u_i + v_i. \tag{B.1}$$

Empirical specification of the enhanced hyperbolic distance function:

$$-lny_i = \alpha_0 + \sum_{k=1}^{4} \alpha_k ln(x_{ki}^*) + \beta_1 ln(b_i^*) + \sum_{k=1}^{4} \beta_{1k} ln(b_i^*) ln(x_i^*) + \frac{1}{2} \sum_{k=1}^{4} \sum_{l=1}^{4} \alpha_{kl} ln(x_{ki}^*) ln(x_{li}^*) + \\ + \frac{1}{2} \beta_{11} ln(b_i^*)^2 + \rho_0 t_i + u_i + v_i. \tag{B.2}$$

Table B.8
Hyperbolic and enhanced hyperbolic distance functions.

	$D_H(x,y,b)$		$D_E(x,y,b)$	
Technology				
α_0 (Intercept)	−0.49	(0.09)***	−0.35	(0.04)***
α_1 (Size)	−0.43	(0.08)***	−0.26	(0.03)***
α_2 (Labor)	−0.06	(0.06)	−0.10	(0.03)***
α_3 (Agrochemicals)	−0.04	(0.02)	−0.00	(0.01)
α_4 (Age of palms)	−0.33	(0.09)***	−0.25	(0.03)***
β_1 (Biodiversity loss)	−0.45	(0.04)***	−0.12	(0.04)**
β_{12}	−0.07	(0.07)	0.03	(0.05)
β_{13}	−0.05	(0.05)	0.02	(0.06)
β_{14}	−0.02	(0.02)	0.01	(0.01)
β_{15}	−0.03	(0.07)	−0.02	(0.05)
α_{12}	0.04	(0.09)	−0.05	(0.05)
α_{13}	0.01	(0.02)	0.00	(0.01)
α_{14}	−0.17	(0.12)	−0.05	(0.04)
α_{23}	0.01	(0.01)	−0.01	(0.01)
α_{24}	0.18	(0.08)**	0.10	(0.03)***
α_{34}	0.03	(0.02)*	0.00	(0.01)
α_{11}	−0.15	(0.13)	0.02	(0.04)
α_{22}	−0.00	(0.03)	−0.03	(0.02)
α_{33}	−0.00	(0.01)	0.00	(0.00)
α_{44}	−0.20	(0.20)	−0.04	(0.06)
β_{11}	0.15	(0.07)**	−0.03	(0.08)
ρ_0	0.08	(0.04)**	0.07	(0.02)***
σ_v				
ω_0	−3.76	(0.40)***	−4.29	(0.15)***
Inefficiency				
τ_0	0.95	(2.42)	−1.54	(7.51)
τ_1 (Age)	−0.28	(0.13)**	−0.71	(0.41)*
τ_2 (Age^2)	0.00	(0.00)**	0.01	(0.00)*
τ_3 (Education)	−0.05	(0.44)	1.71	(2.18)
τ_4 (Education^2)	0.03	(0.08)	−0.33	(0.40)
τ_5 (HH size)	0.30	(0.16)*	0.44	(0.38)
τ_6 (Transmigrant)	1.01	(0.49)**	2.41	(1.34)*
τ_7 (Chemical weeding)	0.64	(0.50)	4.99	(3.22)
τ_8 (Manual weeding)	1.09	(0.41)***	3.66	(1.50)**
τ_{10} (Land title)	0.89	(0.59)	1.68	(1.42)
Mean TE	0.78		0.96	
Observations	123		123	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.9
Marginal effects of determinants of inefficiency (from hyperbolic and enhanced hyperbolic distance functions).

	$D_H(x,y,b)$				$D_E(x,y,b)$			
	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Age	−0.039	0.016	−0.093	−0.011	−0.018	0.029	−0.172	0.000
Education	−0.006	0.003	−0.015	−0.002	0.043	0.070	0.000	0.414
Household size	0.042	0.018	0.012	0.101	0.011	0.018	0.000	0.107
Transmigrant	0.141	0.060	0.041	0.336	0.060	0.099	0.000	0.583
Chemical weeding	0.090	0.038	0.026	0.215	0.125	0.204	0.001	1.205
Manual weeding	0.152	0.065	0.044	0.362	0.092	0.150	0.001	0.883
Land title	0.125	0.053	0.036	0.298	0.042	0.069	0.000	0.406

Table B.10
Shadow prices in '000 IDR (Derived from hyperbolic and enhanced hyperbolic distance functions.

	$D_H(x,y,b)$			$D_E(x,y,b)$		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.
2018	6381	4187	17,659	1120	11,357	107,277
2015	6381	4187	17,659	1106	11,212	105,914
2012	5551	3642	15,363	975	9880	93,330

The results of the distance functions, marginal effects and resulting shadow values are are depicted in Tables B.8–B.10, respectively.

Table B.11
Hyperbolic, restricted and enhanced hyperbolic distance functions with inverse of SR as an undesirable output.

	$D_H(x,y,b)$		$D_R(x,y,b)$		$D_E(x,y,b)$	
Technology						
α_0 (Intercept)	−0.49	(0.09)***	−0.48	(0.08)***	−0.35	(0.04)***
α_1 (Size)	−0.43	(0.08)***	−0.37	(0.08)***	−0.26	(0.03)***
α_2 (Labor)	−0.06	(0.06)	−0.06	(0.06)	−0.10	(0.03)***
α_3 (Agrochemicals)	−0.04	(0.02)	−0.06	(0.02)***	−0.00	(0.01)
α_4 (Age of palms)	−0.33	(0.09)***	−0.26	(0.08)***	−0.25	(0.03)***
β_1 (Biodiversity loss)	−0.45	(0.04)***	−0.42	(0.04)***	−0.12	(0.04)**
β_{12}	−0.07	(0.07)	−0.08	(0.06)	0.03	(0.05)
β_{13}	−0.05	(0.05)	−0.06	(0.05)	0.02	(0.06)
β_{14}	−0.02	(0.02)	−0.01	(0.01)	0.01	(0.01)
β_{15}	−0.03	(0.07)	−0.06	(0.07)	−0.02	(0.05)
α_{12}	0.04	(0.09)	0.03	(0.08)	−0.05	(0.05)
α_{13}	0.01	(0.02)	0.01	(0.02)	0.00	(0.01)
α_{14}	−0.17	(0.12)	−0.14	(0.11)	−0.05	(0.04)
α_{23}	0.01	(0.01)	0.01	(0.01)	−0.01	(0.01)
α_{24}	0.18	(0.08)**	0.16	(0.08)*	0.10	(0.03)***
α_{34}	0.03	(0.02)*	0.04	(0.01)***	0.00	(0.01)
α_{11}	−0.15	(0.13)	−0.12	(0.11)	0.02	(0.04)
α_{22}	−0.00	(0.03)	−0.00	(0.03)	−0.03	(0.02)
α_{33}	−0.00	(0.01)	−0.01	(0.00)**	0.00	(0.00)
α_{44}	−0.20	(0.20)	−0.19	(0.19)	−0.04	(0.06)
β_{11}	0.15	(0.07)**	0.18	(0.08)**	−0.03	(0.08)
ρ_0	0.08	(0.04)**	0.06	(0.04)	0.07	(0.02)***
σ_v						
ω_0	−3.76	(0.40)***	−3.94	(0.38)***	−4.29	(0.15)***
Inefficiency						
τ_0	0.95	(2.42)	1.24	(2.36)	−1.54	(7.51)
τ_1 (Age)	−0.28	(0.13)**	−0.29	(0.12)**	−0.71	(0.41)*
τ_2 (Age^2)	0.00	(0.00)**	0.00	(0.00)**	0.01	(0.00)*
τ_3 (Education)	−0.05	(0.44)	−0.03	(0.43)	1.71	(2.18)
τ_4 (Education^2)	0.03	(0.08)	0.03	(0.08)	−0.33	(0.40)
τ_5 (HH size)	0.30	(0.16)*	0.31	(0.15)**	0.44	(0.38)
τ_6 (Transmigrant)	1.01	(0.49)**	1.17	(0.48)**	2.41	(1.34)*
τ_7 (Chemical weeding)	0.64	(0.50)	0.50	(0.46)	4.99	(3.22)
τ_8 (Manual weeding)	1.09	(0.41)***	1.09	(0.39)***	3.66	(1.50)**
τ_{10} (Land title)	0.89	(0.59)	0.98	(0.55)*	1.68	(1.42)
Mean TE	0.78		0.78		0.96	
Observations	123.00		123.00		123.00	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B.3. Models with alternative biodiversity indicator: SR loss as undesired output

The main model of the paper relies on the inverse Shannon index which under the Hill number framework allows to measure biodiversity loss in terms of loss of effective number of species. While different in levels, the measure is equal to Simpson's diversity index. Another way to measure biodiversity is the simple species richness, with $q = 0$ in the Hill-numbers system. Here, we use loss of species richness, which counts the number of species, without weighing their relative abundance as an alternative measure of biodiversity. Again, we estimate restricted, unrestricted and our hybrid version of the hyperbolic distance functions and find no meaningful contradiction with the model that uses the inverse Shannon index as the biodiversity measure. That is we find similar distance elasticities and weeding activity to be relevant for inefficiency in the production process. The results are depicted in Table B.11.

B.4. Endogeneity

In this section we assess the problem of endogeneity of our approach by estimating alternative models. In general, addressing the endogeneity problem in SFA poses a formidable methodological challenge, which has been subject of a seizable strand of literature. In the case of input distance functions, many empirical papers provide ways to account for endogeneity, which usually requires the availability of input prices. For a more elaborate discussion on the endogeneity issue in an SFA setting, see Parikoglou et al. (2022).

Here we opt for two specific models to assess the problem of endogeneity. First, we implement the approach proposed in Griffiths and Hajargasht (2016) to assess whether there is a potential correlation between regressors and the error terms. Second, we consider the approach of Kumbhakar and Tsionas (2016) to assess whether modeling undesirable output in a system, accounting for endogeneity, will affect the results. Both models are estimated using Bayesian inference (Kumbhakar and Tsionas, 2016; Griffiths and Hajargasht, 2016).

Table B.12
Posterior means and credible intervals at the 95% of Eq. (B.3).

Variable	Mean	Std. dev.
Constant	−0.192	0.187
lnS	0.785	0.125
lnL	0.352	0.086
lnA	0.757	0.119
lnI	0.015	0.021
lnB	−0.207	0.138
t	−0.187	0.135
Avg. TE	0.853	
σ_v^2	0.370	
Inefficiency correlations		
constant	−2.172	0.458
lnL	−0.422	0.536
lnI	0.141	0.488
lnS	−0.158	0.558
lnB	−0.077	0.583

B.4.1. Modeling endogeneity between regressors and errors (Griffiths and Hajargasht, 2016)

Griffiths and Hajargasht (2016) considered a panel stochastic frontier model in which correlations between the effects and the regressors are based on a generalization of the correlated random effects model proposed by Mundlak (1978) and extended by Chamberlain (1984). They show that by transforming the inefficiency term into a normally distributed random term and modeling endogeneity through the mean or covariance of the normal errors, a range of stochastic frontier models with endogeneity can be handled. To model correlation between the inefficiency error u_i and some or all of the inputs, they assume that:

$$\begin{aligned} lny_t &= lnf(X_{it},t) - u_i + v_{it} \\ H(u_i) &= xi_i^{t\prime}\gamma + \varsigma_i^t \end{aligned} \tag{B.3}$$

where, $H(u_i) = ln(u_i)$, which implies that u_i has a lognormal distribution, and it is assumed to be correlated with time invariant firm specific covariates $\bar{x}_i = T^{-1}\sum_{t=1}^{T} x_i^t$. This is an extension of the model considered by Mundlak (1978) for a conventional random effects panel data model with correlated effects. After estimating the model in Eq. (B.3), we can assess whether the posterior standard deviations for the explanatory variables are quite large compared to their posterior means; if this is the case, it implies that the regressors are exogenous (Griffiths and Hajargasht, 2016). To reflect our case at hand with desirable and undesirable outputs, we estimate the model in Eq. (B.3), where desirable output is a function of inputs (area A, labor L, fertilizers F), undesirable output B and time trend t, i.e. $y_{it} = f(X_{it}, B_{it}, t)$ and we assume it is Cobb–Douglas in inputs, undesirable output and time. We choose as determinants z of potential endogeneity and u the following four variables: (i) size, (ii) labor, (iii) fertilizers and (iv) biodiversity. Table B.12 depicts the estimation results. Since the estimated standard deviations are relatively large compared to the posterior means of the estimated coefficients of size, labor, fertilizers and biodiversity in the inefficiency specification, there is no evidence of endogeneity.

B.4.2. Modeling desirable and undesirable outputs in a system (Kumbhakar and Tsionas, 2016)

In Eq. (B.3), undesirable output is part of the frontier along with other outputs. Kumbhakar and Tsionas (2016) model the production process of firms as a system of simultaneous production technologies for desirable and undesirable outputs, following the ideas of Fernandez et al. (2002, 2005). The system of equations can be presented generically as (Kumbhakar and Tsionas, 2016):

$$\begin{aligned} lny_t &= lnf(X_{it},t) - u_i + v_{1it} \\ lnB_{it} &= lnh(Y_{it},t) + v_{2it} \end{aligned} \tag{B.4}$$

where y_t is the desirable output, $f(X_{it},t)$ is a function of X inputs and the time trend t, B is the undesirable output, and $h(Y_{it},t)$ is a function of Y desirable outputs and the time trend t. This approach has two main characteristics. First, inefficiency is assumed to be only in the first equation, that is the production of the desirable output. The second is that the undesirable output is a function of desirable output in the second equation. Hence, it is assumed that farmers aim to maximize production output, and inefficiency captures the differences in their ability to achieve this; while undesirable output is a byproduct of this production process, i.e. is not directly associated with their primary production behavior. If the above system of simultaneous equations in Eq. (B.4), y_{it} is simultaneously estimated, it can control for potential endogeneity of outputs (Kumbhakar and Tsionas, 2016). Additionally then, following Kumbhakar and Tsionas (2016), we estimate the following models:

- Model M1

$$\begin{aligned} lny_t &= lnf(X_{it},t) - u_i + v_{1it} \\ lnB_{it} &= lnh(Y_{it},t) + v_{2it} \\ u_i &\sim exp(\lambda) \end{aligned} \tag{B.5}$$

Table B.13
Posterior means at the 95% credible interval of the two equation models. The upper panel lists production technologies for desirable output and the lower panel lists the undesirable output technology.

Parameters	M1	M2
Constant	0.461*	−0.443*
lnS	0.780*	0.782*
lnL	0.228*	0.238*
lnA	0.382*	0.376*
lnI	0.042	0.045
$lnS \cdot lnS$	0.051	−0.028
$lnS \cdot lnL$	0.120	0.118
$lnS \cdot lnA$	0.281	0.291
$lnS \cdot lnI$	−0.044	−0.035
$lnL \cdot lnL$	0.011	0.014
$lnL \cdot lnA$	−0.505*	−0.516*
$lnL \cdot lnI$	0.016	0.012
$lnA \cdot lnA$	−0.538*	−0.537*
$lnA \cdot lnI$	−0.025	−0.021
$lnI \cdot lnI$	0.004	0.003
t	−0.202*	−0.211*
RTS	0.65	0.65
Average TE	0.74	0.76
σ^2_{v1}	0.13	0.14
σ^2_{v2}	0.20	1.82
Undesirable output equation		
constant	0.111*	0.113*
lny	−0.097*	−0.100*
t	−0.054	−0.055

*The corresponding 95% credible interval does not contain zero.

- Model M2

$$\begin{aligned} lny_t &= lnf(X_{it}, t) - u_i + v_{1it} \\ lnB_{it} &= lnh(Y_{it}, t) + v_{2it} \\ u_i &\sim N_+(0, \sigma_u^2) \end{aligned} \tag{B.6}$$

In both models, $f(X_{it}, t)$ is translog in inputs and linear in the time trend, and $h(Y_{it}, t)$ is linear in output and time trend. The priors for M1, M2 are according to Griffin and Steel (2007), Kumbhakar and Tsionas (2016). The results are presented in Table B.13 below.

The elasticities in the frontier with respect to inputs result in decreasing returns to scale, which is consistent to the returns to scale of the main results. Furthermore, the average efficiency scores of M1 and M2 equal the average efficiency score of the hyperbolic distance function in the main text. These qualitatively similar results, along with the results in Appendix B.4.1 provide further evidence that endogeneity is not a severe problem in our model.

Appendix C. Payments for ecosystem services simulation calculations

In Section 5.2 we report the results of simulating several policy interventions. In particular, we discuss the hypothetical outcomes of PES payments. The literature on PES implementation and targeting offers plentiful approaches and often defines the externality along the social, environmental and economic dimensions of sustainability. We consider situations in which policy-makers aim at reducing total biodiversity loss to a pre-determined level and simultaneously (a) maximize participation of farmers in the program (*social inclusivity*), (b) maximize uniformity of biodiversity across farms (*uniform biodiversity*), and (c) minimize cost of the program.

We select two potential targets of biodiversity loss reduction which align in magnitude with the management-based scenarios of eliminating weeding practices and the extend of environmental performance. We assume that farmers are maximizing profits with regards to fresh fruit bunch output or income from the subsidy, while being indifferent towards biodiversity levels. Premiums are assumed to be coupled to the area, i.e. issued per ha of plantation (px_1^{-1}).

In order for farms to be willing to participate in the program the income received through the program must be higher than the forgone income from palm oil production, $p_i > p_y \frac{dy}{db}$, i.e. the premium must be higher than the shadow price of conserving biodiversity. At any payment that is larger than p_i, farms will participate in the program and at any payment that is less, farms prefer to not participate in the program

Payments are issued per unit of land input (x_1), and thus the threshold premium per ha is

$$\left(\frac{p}{x_1}\right)_i = \left(\frac{\partial D_R/\partial y}{x_1}\right)_i . \tag{C.1}$$

The total biodiversity conservation in the sample is given rearranging the first order condition of the profit maximization problem and summing over the farms that participate in the program (K), i.e.

$$\Delta ENS = \sum_{i=1}^{K} \left(\frac{\partial D_R}{\partial b} \right)_i * t_i, \tag{C.2}$$

where t_i is the targeted change of ENS per farm (number of b). Similarly, the total reduction of farm output is

$$\Delta Y = \sum_{i=1}^{K} \left(\frac{\partial D_R}{\partial y} \right)_i * t_i. \tag{C.3}$$

The share of farms that participate in the program is

$$P = \frac{K}{N}, \tag{C.4}$$

and the total cost of the program is given by the sum of the premiums times the land input (x_1)

$$C = \sum_{i=1}^{K} \left(\frac{p}{x_1} \right) x_{1i} \tag{C.5}$$

The first scenario envisages 100% participation and thus sets the premium equal the highest shadow price in the sample $\overline{\partial D_R/\partial y}$, distributed over the plantation area, $p = \frac{\overline{\partial D_R/\partial y}}{x_1}_i$, ensuring that $K = N$.

The second scenario targets a uniform biodiversity level of $\bar{t}$. In order to achieve similar total biodiversity conservation levels compared with the benchmark scenarios, each farm needs to sustain at least a minimum level. Thus here we set $t_i = \bar{t} - ENS_i$ while $t_i > 0$. In our application, the benchmark scenarios are eliminating weeding or – in the second panel – eliminating environmental inefficiency and $\bar{t}$ is 3 and 5, respectively.

The third scenario minimizes costs $C = \sum_{i=1}^{K} \left(\frac{p}{x_1} \right) x_{1i}$ conditional on $P > 0.5$.

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