Trade-off analysis of cost and nutrient efficiency of coffee farms in vietnam: A more generalised approach

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1 Introduction

Analysis of economic and environmental performance of agricultural production has received increasing attention in both the theoretical and empirical literature (Aldieri et al., 2019). Several methodological approaches have been proposed to measure environmental efficiency and to analyse trade-offs between economic and environmental performance (e.g., Fang, 2020; Shuai and Fan, 2020; Azad and Ancev, 2014; Picazo-Tadeo and Prior, 2009; Reinhard et al., 2000). Within this literature strand, Coelli et al., (2007) offer a distinct approach that utilises the material balance principle to derive cost and environmental efficiency measures. Empirical applications of Coelli et al. (2007) for the purpose of environmental and economic analysis have flourished recently (Hoang and Alauddin, 2012; Nguyen et al., 2012; Hoang and Rao, 2010). However, these empirical applications focus only on the economic and environmental trade-off of technically efficient farms, not all the farms.

Recently Aldanondo-Ochoa et al. (2017) extended Coelli's model to account for trade-off situations where farms are cost-constrained as well as environmentally constrained. Instead of focusing on improving both the cost and environmental efficiencies through increasing the technical efficiency (TE) of farms, Aldanondo-Ochoa et al. (2017) look at improving environmental efficiency by changing the combination of inputs for given levels of output and cost in their cost-constrained model. Similarly, their environmentally constrained model focuses on improving cost efficiency (CE) by changing the combination of inputs given the output level and a given environmental standard. To the best of our knowledge, however, the existing literature still places an emphasis on cost and environmental trade-offs facing technically efficient farms. It is noted that in most empirical analyses, there are more technically inefficient farms than technically efficient farms; hence improving the performance of the latter group of farms would have more immediate impacts on the overall performance of the entire sector.

To address this shortcoming in the existing literature, we propose a new way of analysing trade-off within the conventional framework of Coelli et al. (2007). Our approach delivers the following extensions. First, the trade-off between cost and environmental efficiency can be existed for both technically efficient and technically inefficient farms. Second, our approach demonstrates that each category of farms has potential for further improvement in which no trade-off is encountered. Third, farms of different categories should adopt differing strategies for enhancing economic and environmental performance. We provide an empirical illustration of the proposed approach using coffee farming data in Vietnam.

Specially, our approach demonstrates clearly that farms regardless of whether they are technically efficient or not, have different degrees of trade-offs with some technically inefficient farms having no trade-off. Allowing for these possibilities makes our approach a more generalised one in which we can categorise farms under the same production technology into four distinct production feasibility subsets. More importantly, this categorisation provides a useful approach for empirical analysis that aims at drawing policy implications. For example, empirical analysis can focus on differing options of management change in terms of input and output combinations which are available to different group of farms in order improve their performance. This approach is much more suitable than requiring all farms, especially technically inefficient farms, to follow a uniform strategy of improvement – that is, first improving technical efficiency then choosing better input combination. Additionally, our approach also demonstrates that farm managers can identify differing levels of cost/environmental trade-offs with respect to their own performance objectives. Such information could help farm managers to adjust their perceived notion of trade-offs. We demonstrate the empirical application of this new approach in the context of coffee farming in Vietnam.

Overuse of chemicals in agricultural production has been identified as a main cause of environmental problems in many parts of the world (Nguyen et al., 2012; Hoang & Coelli, 2011). In the context of coffee farming, the literature has reported on the environmental impact of intensive use of nutrients (e.g. fertilisers) in agriculture (Wu et al., 2018) and in major coffee producing countries such as Brazil, Costa Rica (Castro-Tanzi et al., 2012), Mexico (Eakin et al., 2009) and Vietnam (Amarasinghe et al., 2015). Overuse and inefficient use of chemical fertilisers has also caused many problems, i.e., environmental risks associated with poverty (Narloch and Bangalore, 2018), food safety (Seok et al., 2018), air pollution (Paungfoo-Lonhienne et al., 2019) and water pollution (Kourgialas et al., 2017). While lower consumption of nutrients reduces pollution, this requires farmers to undertake better nutrient management practices. Several studies show that farmers, especially small holders, are reluctant to reduce the consumption of fertilisers in the belief that it could reduce yields, thereby lowering profit (Jena et al., 2012; Ranjan Jena and Grote, 2017). This suggests that farmers might perceive the existence of a trade-off between environmental and economic outcomes. There is no previous empirical examination of such trade-offs in coffee production and therefore the present study aims to cover this omission.

Empirically, this study makes two important contributions. First, we quantify the cost of becoming environmentally efficient and the environmental harm which results from becoming cost-efficient for both technically efficient and inefficient farms in coffee farming. Second, our study presents the first empirical study examining both cost and nutrient efficiency of sustainability certified and non-certified farms in Vietnam.

The rest of this paper is organised as follows. Section 2 briefly describes the material balance principle's (MBP) environmental and efficiency measure. Section 3 presents a review of the existing literature on MBP-based trade-off analysis. Section 4 provides extra decompositions of trade-offs between cost and environmental performance. Section 5 presents the results of an empirical study in the context of Vietnam. Section 6 concludes the main findings, limitation and future research.

2 The original MBP approach to cost and environmental efficiency measure

Coelli et al. (2007) incorporated MBP in measuring environmental efficiency, hereafter known as nutrient-oriented environmental efficiency (NE) defined as the ratio of the minimum nutrient amount to the observed nutrient amount for any observed farm. In the input-oriented framework, the MBP model of Coelli et al. (2007) solves the following optimization problem:

$$\mathrm{NC}(\mathbf{y},\mathbf{a}) = \min_{\mathbf{x}}\{\mathbf{a}'\mathbf{x} \mid \langle \mathbf{x},\mathbf{y} \rangle \in \mathrm{T}\} \tag{1}$$

where, the feasible production set[1], T, is defined as:

$$\mathrm{T} = \{(\mathbf{y}, \mathbf{x}): \mathbf{x} \text{ can produce } \mathbf{y}\} \tag{2}$$

NC is the total amount of nutrient in vector inputs ($\mathbf{x}$) and NC = $\mathbf{a}'\mathbf{x}$ in which the vector $\mathbf{a}$ denotes non-negative nutrient contents of each input in the input vector $\mathbf{x}$. According to the MBP, nutrients consists of the inputs (fertilisers, land or water) which will be applied to the desirable outputs and the balance of the nutrients between inputs and outputs will 'run-off' to the environment.

[1] Rødseth, (2016) extended this model by accounting for pollutant control activities adopted by farmers. However, in an empirical context, the new technique is not applicable because pollutant control activities were not documented and the information on the nutrient change due to such activities was not available.

The balance of the nutrients has the potential to cause pollution, therefore, it is desirable to minimise the amount of nutrient balance. NE is defined as:

$$\mathrm{NE} = \frac{\mathrm{NC}_{\mathrm{NE}}}{\mathrm{NC}} = \frac{\mathbf{a}'\mathbf{x}_{\mathrm{NE}}}{\mathbf{a}'\mathbf{x}} \tag{3}$$

where $\mathrm{NC}_{\mathrm{NE}}$ is a solution to (1) and $\mathbf{x}_{\mathrm{NE}}$ is a vector of inputs where the nutrient amount in this vector is minimised, $\mathrm{NC}_{\mathrm{NE}} = \mathbf{a}'\mathbf{x}_{\mathrm{NE}}$. Similarly, input-oriented TE is defined as:

$$\mathrm{TE} = \theta = \frac{\mathbf{a}'\mathbf{x}_{\mathrm{TE}}}{\mathbf{a}'\mathbf{x}} = \frac{\mathrm{NC}_{\mathrm{TE}}}{\mathrm{NC}} \tag{4}$$

NE can be decomposed as follows into two components, TE and the input-oriented nutrient allocative efficiency, NAE:

$$\mathrm{NE} = \frac{\mathrm{NC}_{\mathrm{NE}}}{\mathrm{NC}} = \frac{\mathbf{a}'\mathbf{x}_{\mathrm{NE}}}{\mathbf{a}'\mathbf{x}} = \frac{\mathbf{a}'\mathbf{x}_{\mathrm{TE}}}{\mathbf{a}'\mathbf{x}} \times \frac{\mathbf{a}'\mathbf{x}_{\mathrm{NE}}}{\mathbf{a}'\mathbf{x}_{\mathrm{TE}}} = \mathrm{TE} \times \mathrm{NAE} \tag{5}$$

This way of decomposing NE into TE and NAE is identical to the decomposition of CE into TE and cost allocative efficiency (CAE):

$$\mathrm{CE} = \frac{\mathbf{w}'\mathbf{x}_{\mathrm{CE}}}{\mathbf{w}'\mathbf{x}} = \frac{\mathbf{w}'\mathbf{x}_{\mathrm{TE}}}{\mathbf{w}'\mathbf{x}} \times \frac{\mathbf{w}'\mathbf{x}_{\mathrm{CE}}}{\mathbf{w}'\mathbf{x}_{\mathrm{TE}}} = \mathrm{TE} \times \mathrm{CAE} \tag{6}$$

TE and CE can be estimated using a standard input-oriented approach, minimizing the input use given a level of output. NE is similar to CE in term of the estimation procedure where the vector of nutrient contents of the inputs, **a**, is used instead of input prices, **w**.

3 Existing approach used to analyse trade-offs between cost and nutrient efficiency

A trade-off between environmental and cost performance exists if farms aiming to increase their environmental performance incur higher levels of production costs (and vice versa). In a typical framework of MBP-based efficiency, the existing literature attempts to analyse such a trade-off by examining how farms are supposed to move to the technical efficient point (point B), the cost-efficient point (point C) and the environmental efficient points as shown in Figure 1. Farm A can become *more* technically efficient if it moves to point B, *more* cost efficient if it moves to point C and *more* environmentally efficient if it moves to point N. The information of the nutrient contents and price of inputs are used to construct iso-nutrient and iso-cost lines respectively.

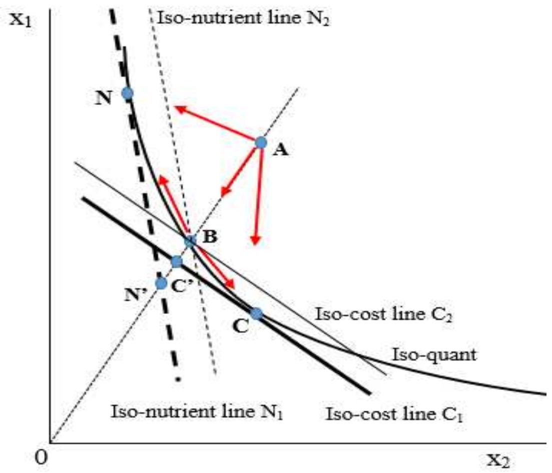


Figure 1: A typical cost and nutrient efficiency trade-off analysis

It is easy to see that for farm A, a movement towards point B captures an increase in its TE and therefore, total production cost and nutrient consumptions will decrease. Hence both cost and nutrient efficiency improves. A pathway from A to B represents a win-win outcome both for farms and the environment. However, a trade-off exists if farm B, wishing to achieve the minimum production cost (being cost efficient), decreases its environmental efficiency level. The degree of trade-off for each farm depends on their existing combinations of inputs and its targeted outcome. Particularly for technically efficient farms who stay on the iso-quant in Figure 1 within points C and N, being closer to point N (or and further away from point C) means smaller increases in the production costs if farms aim to move to the environmentally efficient point (i.e. less trade-offs). Empirically, Coelli et al. (2007) estimated a typical trade-off between points C and N for 183 Belgian pig farms from 1996 to 1997 in which movement from point C to point N could reduce 5.3% of nutrient input with a shadow cost of 27 euros per kg. Similar analysis for rice production in Korea is presented in Nguyen et al. (2012).

The original model of Coelli et al. (2007), as pointed out by Aldanondo-Ochoa (2017), does not integrate cost considerations with respect to the environmentally allocative efficiency term (i.e. NAE in equation 5) just as the cost allocative efficiency term (i.e. CAE in equation 6) does not integrate environmental considerations. Aldanondo-Ochoa (2017) presents an extension of trade-off analysis in which the cost and nutrient consumption levels of technically efficient farms are applied as operational constraints for all other farms. When minimising total production cost, total nutrient consumption is constrained to be less than or equal to the nutrient level of the technically efficient farms. Similarly, in minimising total nutrient consumption, total production cost is constrained to be less than or equal to the cost level of the technically efficient farm. In a nutshell, the levels of production cost and nutrient consumption are used as the benchmark for all inefficient farms. By doing so, possible gains in the total allocative efficiency terms (i.e. NAE and CAE) can be further decomposed into two components: one involves an economic- environmental trade-off and one does not. In the empirical examination of greenhouse horticultural production units in Spain, the authors showed that 44% of farms were using more nutrients than technically efficient farms but only 7.3% of farms had higher costs than the technically efficient farms. Extra decomposition of allocative efficiency suggested that, on average, farms can increase environmental allocative efficiency by up to 34% without incurring additional costs.

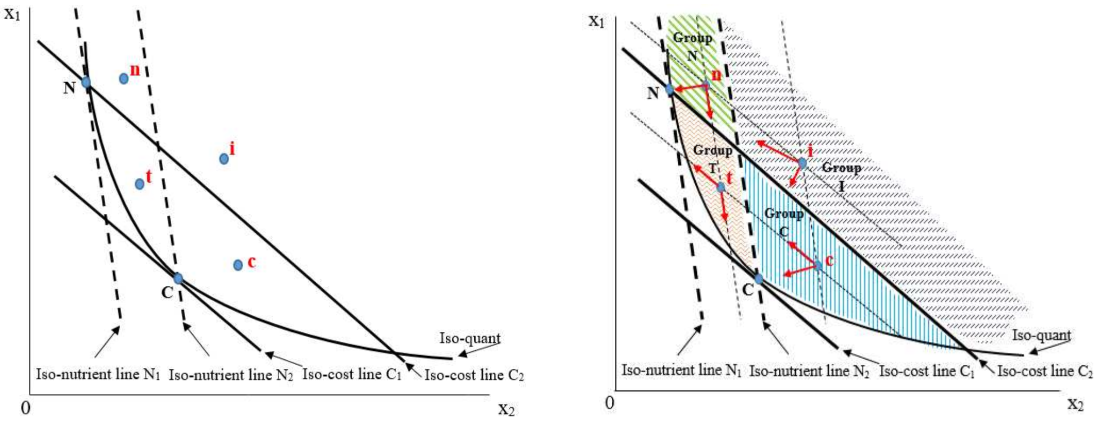
4 A generalised approach to analysing cost environmental trade-offs

What's missing in the literature is the explicit focus on the trade-off analysis for technically inefficient farms. While existing approaches can benchmark technically inefficient farms against technical efficient farms, it is also possible to benchmark additionally against either nutrient or cost-efficient farms. Implicitly, approaches to policy interventions, if any, are limited to making farms technically efficient first before analysis of trade-offs become useful. In this section, we provide a more elaborative approach to analysing trade-offs for inefficient farms.

In Figure 2a, points C and N are two unique points at which the iso-quant is tangential to iso-cost line C_1 and the iso-nutrient line. At the cost-efficient point, an iso-nutrient line N_2 can be constructed parallel to the iso-nutrient line N_1. Similarly, the iso-cost line C_2 is parallel to the iso-cost line C_1 crossing the environmentally efficient point, N. These typical iso-cost and iso-nutrient lines and the iso-quant curve in Figure 2b divide the feasible production set T into four subsets, namely

T^n, T^c, T^t, and T^i. Farms belonging to each subset are hereby classified into four respective group N, C, T and I.[2]

Figure 3 illustrates that farms belonging to each subset should have different strategies for better cost and environmental performance without necessarily moving towards to the technically



(a) (b)

Figure 2: Cost-environment trade-off

efficient frontier (i.e. iso-quant). For farm *i*, either opting for CE or NE could result in a reduction in both production cost and nutrient consumption. As indicated in Figure 3a, this farm could move within the no trade-off region (shown as the blue region) to improve both cost and environmental performance. The broader "no trade-off" region of farm *i* presents a higher level of flexibility for the farm to improve performance.[3] For farm *t*, there is always a trade-off if it insists on being cost efficient and environmentally efficient given these two efficient points, C and N, are outside the "no trade-off" region illustrated in Figure 3b. For farm *n*, moving to point N will decrease total production costs and achieve the best possible NE; meaning there is no trade-off for this group if farms aim for environmental improvement only. If farm *n* aims at being cost efficient, there exists some level of

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[2] Point *n* is a typical farm in group N in Figure 2b, representing farms using x_1^n and x_2^n inputs, $[x_1^n, x_2^n] \in T^n$, $C^n > C_2$ & $N_1 < N^n < N2$. *c* is a typical (technical inefficient) farm in group C, using x_1^c and x_2^c inputs, $[x_1^c, x_2^c] \in T^c$, $C_1 < C^c < C_2$ & $N^c > N_2$. *t* is a typical farm in group T, using x_1^t and x_2^t inputs, $[x_1^t, x_2^t] \in T^t$, $C_1 < C^t < C_2$ & $N_1 < N^t < N_2$. *i* is a typical farm, representing farms using x_1^i and x_2^i inputs, $[x_1^i, x_2^i] \in T^i$, $C^i > C_2$ & $N^i > N_2$. Note that all technically efficient farms stay on the iso-quant.

[3] Note that any movement of the farm (regardless *n, c, t* and *i*) towards the iso-quant constrained between the two arrows in the blue region could improve cost performance, environmental performance or both. The pathway through the technically efficient point discussed in the existing literature is also included in this no trade-off region. As an empirical exercise, a directional distance function approach can be used to project farms onto the frontier with a pre-determined direction of movement as long as farms are projected towards the frontier within the no trade-off region.

trade-off as long as farm *n* move out of the blue "no trade-off" region shown in Figure 3c. For farm *c*, moving to point C attains maximum CE and reduces total nutrient consumption. In practice, farm *c* could at least maintain the same level of production cost and opt for a reduction in nutrient consumption and by doing so could become more cost and environmentally efficient. Farm c again has its own region of "no-trade-off" shown as the blue region in Figure 3d. Beyond this region these farmers must employ a larger production cost to reach an environmentally efficient operation.

Our proposed approach to analysing trade-offs has several useful features. First, instead of imposing the common pathway transitioning through TE, farms - once being classified in different

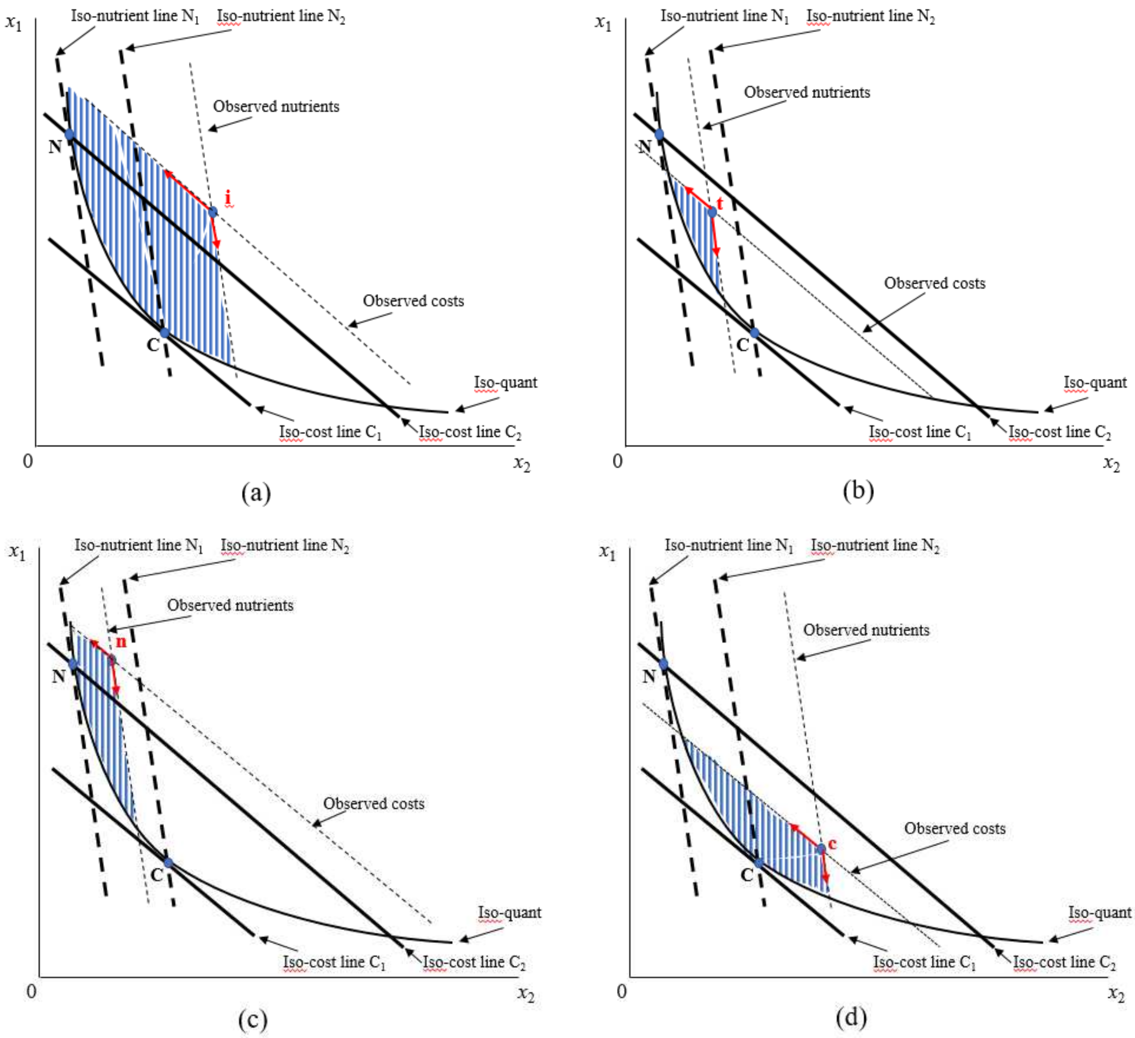

Figure 3: No trade-off regions

groups - are modelled so as to provide flexibility in choosing more acceptable strategies to improve economic and environmental performance. In particular, identifying the group membership of farms is useful for designing interventions targeting individual groups of farms rather than treating all farms indifferently. Second, a "no trade-off" region for each farm in fact represents a "win-win" set of strategies as both economic and environmental improvement can be obtained. Identification of such "no trade-off" regions for each farm can be important for stakeholders (e.g. farm managers, environmental groups, extension service providers and regulators). Third, this approach can be used to quantify the value of trade-offs. For example, farms in groups N and T need to incur higher levels of production cost to be environmentally efficient and therefore the additional cost can be used to infer the value of the shadow cost of improvement in environmental performance. In contrast, group C and T farms must use more nutrients (i.e. have a lower level of environmental standards or greater potential to cause environmental harm) to reach the cost-efficient operation. This trade-off results in a measure of harm to the environment caused by the improvement in CE. In our empirical application, we calculate both shadow cost and level of environmental harm for both technically efficient and technically inefficient farms, where applicable.

5 Empirical study

We use the dataset collected from a survey conducted in the largest coffee producing area in Vietnam. Ho et al., (2018) also provide a detailed description of coffee production in Vietnam, sampling procedures and the study site used to collect the data.

5.1 Model specifications

The differing ages of perennial trees are biologically associated with different doses of inputs, fertility, and yield (Hasnah et al., 2004; Ho et al., 2018); hence all production factors including one output (Y) and five inputs (x_1-x_5) have been were calculated per weighted tree as show in Table 1.[4]

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[4] We use a nonlinear regression model to construct weights associated with different age ranges: i.e., under eight years, from nine to fifteen years, from sixteen to twenty years and above twenty-one years. As well, Ho et al., (2018) provide details on how weights of coffee tree ages were constructed.

Table 1: Descriptive statistics of variables

	variable label	N	Mean	St. dev.	Min	Max
Y	Dried coffee output (kg/ weighted tree)	1,994	3.593	1.058	0.753	7.053
x1	Labour (man-days/ weighted tree)	1,994	0.308	0.173	0.030	1.548
x2	Land area (m^2/ weighted tree)	1,994	10.485	1.660	2.519	18.593
x3	Chemical fertilisers (kg/ weighted tree)	1,994	2.562	1.288	0.333	11.642
x4	Irrigation water (m3/ weighted tree)	1,994	1.201	0.534	0.100	5.643
x5	Other production cost (USD/ weighted tree)	1,994	0.451	0.389	0.027	3.896
w1	Labour rate (USD/day)	1,994	6.593	0.887	4.444	15.556
w2	Land and tree depreciation (USD/m^2)	1,994	0.119	0.038	0.005	0.278
w3	Price index of chemical fertilisers (USD/kg)	1,994	0.419	0.083	0.200	0.756
w4	Irrigation water price (USD/m^3)	1,994	0.000	0.000	0.000	0.000
w5	Price index of other production cost (USD)	1,994	1.000	0.000	1.000	1.000
a1	Eutrophying power of labour (kg/man-day)	1,994	0.000	0.000	0.000	0.000
a2	Eutrophying power of land area (kg/m^2)	1,994	0.009	0.000	0.009	0.009
a3	Eutrophying power of fertilisers (kg/kg of fertilisers)	1,994	0.609	0.156	0.118	1.120
a4	Eutrophying power of water (kg/m^3)	1,994	0.056	0.000	0.056	0.056
a5	Eutrophying power of other production cost kg/USD)	1,994	0.000	0.000	0.000	0.000

The output (y) was measured in kilograms of dried coffee beans. Labour (x_1) included both family and hired employment. Cultivated land area (x_2) was measured in squared meters. The weight of chemical fertilisers (x_3) was aggregated from different types of NPK fertilisers, urea, kali, potassium and other chemical fertilisers, using a price-weighted Fisher quantity index. Irrigation water amount (x_4) was calculated using the information on total irrigation time and capacity of pumps. Other production costs (x_5) were aggregated from costs, such as that for organic fertilisers[5], machinery, fuels, and transportation.

Input prices are derived from the collected data. First, for the price of labour (w_1), we used labour rate for hired labour as the price of labour including family labour. Second, land rental and crop depreciation costs were used as the price of the cultivating area (w_2). Although coffee tree density in the research region is roughly the same given that coffee trees are considered as a fixed asset, the price of land rentals and coffee tree depreciation cost vary. Such variation thus depends primarily on the potential coffee output. We found that the common rate for both land rental and crop depreciation was about 20% of the coffee output. The price of the cultivation area including land rental and crop depreciation was accordingly calculated as 20% of total income from coffee divided

[5] Organic fertilisers could be modelled as a separate input to shed more light on how combinations of inorganic and organic fertilisers impact on efficiency. However, data on nutrient content were not available in the dataset used.

by the coffee output. Third, the price index of chemical fertilisers (w_3) was estimated as the ratio of total costs of all chemical fertilisers to the Fisher quantity index of chemical fertilisers. Given farmers freely extract water for irrigation the unit price of this input (w_4) was set at zero. Last, other production costs were measured in monetary value, so we set the price of this input (w_5) to be one.

Following previous literature (Nguyen et al. 2012 and Hoang et al. 2013), we focus our analysis on nitrogen (N) and phosphorous (P) which are the primary cause of eutrophication in the water system. Labour (x_1) and other production costs (x_5) are assumed to have no nutrient content. The unit nutrient content of land area (a_2), is assumed to be equal to a constant across different land plots. We followed Nguyen et al., (2012) in assuming the nutrient content of each square meter of cultivating land to be about 0.0092 kg of eutrophying power. Chemical fertilisers and irrigation water contain both N and P. As previous studies indicated that P has more eutrophying power than N (Gold and Sims, 2005), we used a fixed set of weights (1 for N and 10 for P) to aggregate total nutrient contents of chemical and irrigation water – similar to the methodology adopted by Hoang and Nguyen (2013). Information on the percentages of N and P were readily available for fertilisers but not for irrigation water. We used the result of a previous study (Ebina et al., 1983) which estimated that one cubic meter contained about 0.0202 and 0.0036 kilograms of N and P respectively. Thus, a_4 was calculated to be 0.0202 +10 x 0.0036 =0.056 kg/ cubic metre.[6]

In the Data Envelopment Analysis (DEA) approach, it is important to specify whether the production technology exhibits variable return to scale (VRS) or constant return to scale (CRS). We estimated a Cobb-Douglas production function and tested for the null hypothesis of CRS[7]. At the 10% level of significance we failed to reject the null hypothesis, hence a CRS model was selected. The CRS-DEA models of CE and NE are specified as:

$$\min_{\mathbf{x},\lambda}\{\mathbf{w}_i'\mathbf{x}_i^c : -\mathbf{y}_i + \mathbf{Y}\lambda \geq 0, \mathbf{x}_i^c - \mathbf{X}\lambda \geq 0, \lambda \geq 0\} \tag{7}$$

$$\min_{\mathbf{x},\lambda}\{\mathbf{a}_i'\mathbf{x}_i^e : -\mathbf{y}_i + \mathbf{Y}\lambda \geq 0, \mathbf{x}_i^e - \mathbf{X}\lambda \geq 0, \lambda \geq 0\} \tag{8}$$

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[6] This treatment may not be ideal, but farmers can manage to be more efficient in using irrigation water, therefore reducing consumption of nutrients. In addition, for a given plot, it may reasonably be assumed that there are no different irrigation water sources available with different levels of nutrient content. Thus, it is argued that choosing a constant for unit nutrient content of irrigation water is a reasonable assumption.

[7] The elasticity of scale was calculated to be 0.9940 (summation of all coefficients associated with input factors). The F test statistics = 0.1646 associated P-value = 0.6850.

5.2 Efficiency results

In general, the empirical results indicate that both cost and environmental performance of coffee farmers are very low. This implies a great potential for inducing coffee farmers to enhance economic and environmental sustainability. The results are also in line with several previous studies which examined cost and environmental efficiency in agricultural production. For example, Wossink and Denaux (2006) found that the CRS environmental efficiency and the cost efficiency of pest control of conventional cotton farmers was 0.16 and 0.33 respectively. Several studies also found very low level of cost and environmental efficiency (see, for example, Aldanondo-Ochoa et al., 2017; Nguyen et al., 2012).

As shown in Table 2, the average CE scores in three crop years is estimated to be 45.8%, 45.6% and 44.8% respectively. The average is 45%, suggesting that, coffee farms could reduce total production costs by 55% without reduction in output level. Hence, holding output level and prices constant, farmers can convert these cost savings into significantly improved profit levels.

Table 2: Cost and environmental efficiency measures

	N	Mean	St. dev.	Min	Max
Crop year 2012/13					
Technical efficiency (TE)	666	0.627	0.174	0.342	1.000
Cost efficiency (CE)	666	0.458	0.148	0.071	1.000
Cost allocative efficiency (CAE)	666	0.731	0.132	0.192	1.000
Environmental efficiency (NE)	666	0.243	0.112	0.061	1.000
Nutrient allocative efficiency (NAE)	666	0.388	0.136	0.107	1.000
Crop year 2013/14					
Technical efficiency (TE)	679	0.625	0.172	0.319	1.000
Cost efficiency (CE)	679	0.456	0.147	0.130	1.000
Cost allocative efficiency (CAE)	679	0.732	0.131	0.239	1.000
Environmental efficiency (NE)	679	0.175	0.091	0.039	1.000
Nutrient allocative efficiency (NAE)	679	0.279	0.104	0.081	1.000
Crop year 2014/15					
Technical efficiency (TE)	649	0.642	0.165	0.340	1.000
Cost efficiency (CE)	649	0.448	0.148	0.144	1.000
Cost allocative efficiency (CAE)	649	0.697	0.131	0.311	1.000
Environmental efficiency (NE)	649	0.197	0.102	0.038	1.000
Nutrient allocative efficiency (NAE)	649	0.307	0.122	0.074	1.000

Two primary components of cost inefficiency are technical inefficiency and cost allocative efficiency. The mean of TE scores for the entire period ranges from 62.5% to 64.2%, indicating the potential for a proportionate reduction in the consumption of all five inputs given a constant output. The average CAE scores were 73.1%, 73.2%, and 69.7% for the crop years 2012/13, 2013/14 and

2014/15 respectively. These results suggest that adjusting the combination of inputs are as important as reducing input consumption in terms of cost savings.

The average NE scores of the three crop years were only 24.3%, 17.5%, and 19.7% respectively. This suggests that coffee farmers could successfully use input bundles that contain 75.3%, 82.5% and 80.3% less eutrophying (i.e. polluting) power of nutrients. In this way, a remarkable potential to reduce the impact of nutrient balance on the water and soil environments is demonstrated.

5.3 Analysis of cost savings and reduction in nutrient consumption

Another main goal of this paper is to estimate cost and nutrient savings if farmers are to reach three operational efficiency targets: being technically efficient, being cost efficient, and being environmentally efficient. Table 3 summarises the relative changes in total production cost and total aggregate nutrient levels for three scenarios for all farms: (1) from the current operational level to a technically efficient operation; (2) from the current operation to a cost-efficient operation; (3) from the current operation to an environmentally efficient operation.

Table 3: Cost and environmental performance

Crop year/ # of farms		Original cost per unit output (USD/kg)	Original nutrient per unit output (kg/kg)	Changes in cost and nutrient (%)				
				Current to TE	Current to CE		Current to NE	
				Nutrient/ cost change	Cost change	Nutrient change	Cost change	Nutrient change
2012/13	Mean	1.34	0.83	-37.27	-54.25	2.28	-1.81	-75.74
n1 = 666	S.D.	0.45	0.46	(55.4)	(-94.9)	(0.7)	(-1.2)	(-174.6)
2013/14	Mean	1.36	0.84	-37.47	-54.38	16.28	29.40	-82.48
n2 = 679	S.D.	0.41	0.48	(56.6)	(-96.4)	(4.7)	(17.6)	(-236.6)
2014/15	Mean	1.41	0.84	-35.80	-55.22	-39.18	21.34	-80.35
n3 = 649	S.D.	0.42	0.48	(55.2)	(-95.3)	(-22.0)	(13.1)	(-199.9)
All sample	Mean	1.37	0.84	-36.86	-54.61	-6.44	16.35	-79.54
N = 1,994	S.D.	0.43	0.47	(96.4)	(-165.5)	(-3.7)	(16.9)	(-335.6)

Asymptotic t-statistics testing of the null hypothesis of changes in cost or nutrient equal zero are in parentheses

First, the shift to a technically efficient operation, on average, could reduce cost and nutrient application by 36.8%, without reducing the coffee output. The average reduction in cost is equivalent to US $0.50 per kg of coffee output, US $2,603 per farm or about US $1,764 per hectare[8]. This is based on the average planting area of farms in the sample which is about 1.55 hectares. The reduction in nutrients is equivalent to 0.31 kilograms per kilogram of coffee output or approximately 1,560 kg of eutrophying power per farm - 1,031 kg per hectare on average[9]. There is only a small difference across the three crop years. These potential reductions are due to potential improvement in TE: hence interventions on how to reduce waste in input consumption is crucial given it can bring substantial improvements to both economic and environmental efficiency.

The movement from the current operation to the cost-efficient position could reduce the production cost by 54.6%, equivalent to, on average, US $3,856 per farm or US $2,547 per hectare. Being cost efficient also could reduce total aggregate nutrients by 6.4% on average. While cost changes are similar across the three years, changes in total consumption of nutrients associated with moving to cost efficient positions in the two latter crop years are higher than that in the first crop year (i.e. 2% increase in 2012/13 and 16% in 2013/2014). This means that, by choosing a cost-efficient bundle of inputs, farmers were likely to cause more damage to the surrounding environment. However, in the last crop year, use of the efficient bundle of inputs could also reduce aggregate nutrients by 39% (equivalent to an average of 1,658 kg of eutrophying power per farm and which could be released into to the surrounding environment).

The movement from the current production scenario to an environmentally efficient one could reduce the farm's eutrophying power by an average of 9.5% and would result in a 6.3% increase in total production cost. Such a movement would save over 3,000 kilograms of aggregate nutrients per farm, while requiring an extra cost of about US $670 per farm. In the last two sampled crop years, the results indicate that being more environmentally efficient is costly. The movement from current production to the environmentally efficient operation would effect a 75 to 80% nutrient reduction, while requiring an increase in production cost of 21.34% in 2014/15, 29.40% in 2013/14 and a decrease of 1.81% in 2012/13.

5.4 Trade-off analysis using group membership information

Table 4 presents group membership as discussed in Figure 2 and changes in the levels of costs and nutrient consumption if all farms in each group are to be cost-efficient or environmentally efficient.

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[8] In the sample, the number of weighted trees per farm is on average 1,482 tree, the average farm area is 1.514 hectares per farm and average total cost per weighted tree is $4.765 US. Hence, US $2,603 = US $4.765 per weighted tree x 1,482 trees x 36.86%, and US $1,719 = 2,603/ 1.514.

[10] The average aggregate nutrients per weighted tree is 2.857 kg.

Table 4: Changes in cost and nutrient by different groups of farms

Group	Number of obs.	Percentage (%)	Current to CE		Current to NE	
			% in C	% in N	% in C	% in N
Group C	732	36.82	-54.81	-36.47	+32.45	-83.45
Group N	118	5.94	-56.07	+39.96	-18.11	-69.56
Group T	495	24.90	-49.86	+75.42	+50.47	-73.57
Group I	643	32.34	-58.11	-44.57	-21.91	-81.94
Total	1,988	100				

Group C accounts for 36.8% of the sample. These farms only face a trade-off when moving towards the environmentally efficient point. Thus, farms in this group may choose to move to the cost-efficient point (point C in Figure 2) to increase both cost and environmental efficiency. This could help reduce production costs by 54.8% and the level of nutrients by 36.5%.

Group N consist of only 5.9% of the sample. These farms only face a trade-off between cost and nutrient consumption when moving to the cost-efficient point. However, if these farms move to the environmentally efficient point, they could also reduce their production costs. Thus, farms in this group may opt for environmental efficiency, thus decreasing their production costs. By doing so, they could save 18.1% of production costs and 69.6% of nutrient consumption. Alternatively, they may maintain the same level of nutrients and move to a lower level of production cost along their nutrient lines to improve their CE.

Group I accounts for 32.3% of the sample. This group has great potential to reduce both cost and nutrient use, meaning there is no trade-off for farms in this group. This indicates that if farms in this group wish to increase CE, they can also gain environmental efficiency. Previous literature also evidenced that farmers could find a proper strategy towards replacing chemical fertilisers by use of other low nitrogen and phosphorus content fertilisers, i.e., organic fertilisers for enhancing better both economic and environmental performance (Paungfoo-Lonhienne et al., 2019).

Farms in Group T account for 24.9% of the sample. Holding iso-cost C_1 and iso-nutrient N_1 lines constant these farms cannot achieve cost efficient operation without increasing environmental pollution and vice versa, which suggests a trade-off between being cost efficient and environmentally efficient. This type of trade-off can only be relaxed if interventions are to change the relative prices of inputs, so that iso-cost and iso-nutrient lines merge. However, each farm does not necessarily face a trade-off, for example a farm can move to the iso-quant frontier as shown in Figure 3b within the no trade-off region.

Calculating the cost of getting *all farms* to be environmentally efficient and the harm to the environment of getting *all farms* to be cost-efficient could be useful, for example in the context of policy design. To attain NE, all farms in group C and T representing 61% of the sample, must incur a higher production cost (i.e. 32.4% and 50.5% increases for groups C and T respectively). To achieve CE, group N and T farms representing 30% of the sample, must consume more nutrients (39.9% and 75.4% increases for group N and T respectively).

In addition to TE improvement, farms in different groups can follow other paths to improve cost or environmental efficiency or both. Farms in group C can attain CE and also increase environmental performance although they must incur higher costs if they want to be more environmentally efficient. This means that farms in group C could be persuaded to reach CE by improving TE and CAE. In the same way, farms in group N could be targeted to improve TE and NAE so that their focus is on being environmentally efficient. Equally, farms in group I should increase TE, then NAE and CAE. Lastly, group T farms should only increase TE while at least maintaining the same level of production cost and nutrient consumption. Both group C and group I farms could aim at improving cost efficiency as a low-cost strategy, thus achieving a higher impact on environmental performance. Additionally, farms from groups N and I could also aim at improving environmental efficiency, thus enhancing higher impact on cost performance. This is in line with several previous studies, i.e. Danso et al. (2019).

5.5 The role of the sustainability certification program

Two primary objectives of certification schemes adopted by sampled farms are promoting environmentally friendly practices and enhancing economic viability. Thus, cost and environmental efficiency can be used as important indicators of the effect of certification schemes. As often used in the empirical efficiency literature, the Wilcoxon test[10] was performed to examine the difference in the distribution of efficiency scores between the two groups of farms: certified and non-certified[11]

Table 5 shows that certified farms outperformed non-certified farms in terms of TE and nutrient allocative efficiency, which explains why certified farmers have better cost and nutrient performance. These results could imply that certification programs could present both economic benefits to farmers and environmental benefits to the wider community. Note that the self-selection issue involving whether efficient farms opt to participate in the certification program is not controlled for in this study due to lack of data; hence interpretation of the results needs caution.

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[10] It is also known as the Wilcoxon rank sum test which is commonly used in the efficiency literature to test differences between distribution of efficiency scores of a group and that of another group (see, for example, Pereira and Marques, 2017; Choi et al., 2015; Asmild and Hougaard, 2006)

[11] Note that economic benefits of having certification can be due to many other factors such as price premiums although this lies outside of the scope of the present study.

Table 5: Efficiency between certified and non-certified groups

Efficiency measures	Certified farms n = 1,067				Non-certified farms n = 927				Wilcoxon Test
	Mean	St. dev.	Min	Max	Mean	St. dev.	Min	Max	(p-value)
TE	0.649	0.178	0.319	1.000	0.611	0.160	0.341	1.000	0.0000
CE	0.470	0.151	0.177	1.000	0.435	0.141	0.071	0.937	0.0000
CAE	0.727	0.125	0.313	1.000	0.713	0.140	0.192	0.970	0.0743
NE	0.238	0.119	0.052	1.000	0.218	0.095	0.042	1.000	0.0019
NAE	0.365	0.133	0.100	1.000	0.359	0.127	0.089	1.000	0.5464

Table 6 describes variations in the mean efficiency level between certified and non-certified farms over the three crop years. While the TE level increases overtime, cost and nutrient efficiency do not exhibit a consistent trend. In the first crop year, certified farms were more cost and environmentally efficient than their non-certified counterparts due to higher TE and cost and nutrient allocative efficiency. In the second crop year certified farms performed better than non-certified farms in terms of CE but mainly due to higher TE. In the last crop year, certified farms have higher CE which is mainly driven by cost allocative efficiency (i.e. cheaper combinations of inputs).

Table 6: Efficiency between certified and non-certified farms over time

	Certified production			Non-certified production			Wilcoxon test of certified vs non-certified (p-value)		
Crop year	2012/13	2013/14	2014/15	2012/13	2013/14	2014/15	2012/13	2013/14	2014/15
# of farms	333	377	357	333	302	292			
TE	0.659	0.638	0.651	0.596	0.609	0.632	0.000	0.091	0.158
CE	0.482	0.469	0.461	0.433	0.440	0.432	0.000	0.041	0.019
CAE	0.734	0.738	0.708	0.729	0.724	0.683	0.826	0.412	0.023
NE	0.276	0.210	0.232	0.236	0.194	0.221	0.000	0.255	0.546
NAE	0.420	0.327	0.356	0.400	0.319	0.354	0.049	0.799	0.696

6 Conclusions, policy implications and future research agenda

This paper has proposed a more generalised approach to analysing trade-off between cost and environmental efficiency in the framework of the materials balance principle. This framework allows for differences in the operational objectives and improvement strategies of farmers rather than restricting them to follow the conventional pathway of first improving radial TE then improving allocative efficiency. Importantly, from an intervention perspective, the classification of farms into distinct groups and identification of no trade-off regions in this framework provide analysts with useful analytical tools. They can be used to provide valuable insights into what strategies would be more acceptable for individual farmers or farmer groups if interventions are involved in promoting sustainable production.

In our application to coffee farming in Vietnam, our paper shows that it is possible for farmers to reduce the consumption of inputs by a significant amount and consequently reduce production costs and the release of nutrient amount to the environment by 36.8%. Other words, it is possible to generate a savings of US $0.50 per kg coffee output ($2,603 per farm or about $1,764 per hectare) and reduce the aggregate nutrient application to 0.31 kilograms per kilogram of coffee output (equivalent to 1,560 kg of eutrophying power per farm or 1,031 kg per hectare). Reduction in input consumption has larger impacts on cost savings than alternating input combinations but less impacts on environmental efficiency than changing the combination of nutrient-containing inputs.

Our empirical results also show that by striving to be cost-efficient this generates a significant saving in production costs but could lead to the consumption of more nutrients for more than 30% of surveyed farms (group N and T farms). Opting for the environmentally efficient operation also involves higher production costs for more than 60% of farms (group C and T). However, over 32% of farms (group I) could move either to cost- efficient or environmentally efficient operations without incurring a trade-off. It is shown that every inefficient farm has its own no trade-off region and this region allows more flexibility for farmers to opt for better cost and environmental performance simultaneously. However, there lacks knowledge about the farmers' awareness of their trade-off situation, and this could lead to farmers using sub-optimal strategies in improving performance. This favours further research about farmers perception of their performance. From intervention perspective, policies including extension services could still focus on helping these farms to reduce the use of inputs and by doing so, both economic and environmental performance can be improved.

Another notable finding is that cost and environmental efficiency varied across farms, crop-years, sustainability certification status and regions. Generally, sustainability certified farms could perform better than their non-certified counterparts in both economic and environmental aspects. In the three sampled crop years, certified farms are found to be more cost-efficient than non-certified farms. But certified farms were more environmentally efficient than non-certified farms only in the first sampled crop year. Promoting environmentally friendly practices requires the involvement of government or better market condition for certified products.

This empirical study has several limitations. First, panel data collected through the one-off surveying method often suffers from potential errors, especially with respect the technical information on the nutrient contents of inputs. Second, the DEA technique is not able to capture well stochastic data noise. Third, the data on the actual polluting powers of various nutrient components are not available at farm (slot) levels, hence caution is needed in interpreting the magnitude of pollution. Future research could help overcome these shortcomings by utilising higher quality data. Our proposed approach could be integrated into smart farming or precise farming technologies (i.e., Boursianis et al., 2020) so that analysis on environmental and cost efficiency and the trade-offs can be analysed on a more regular and automatic manner. Finally, empirical results from this paper supports regular benchmarking practices for farms so that trade-off information can be a source of information for decision making.

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Annex 1: CAE vs NAE of farms in different groups