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Farming efficiency and environmental resource dependence: Evidence from panel data for rural Central Vietnam

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Abstract

Farming and natural resource extraction are the main livelihood strategies of the rural poor in developing countries. A better understanding of their relationship is needed to alleviate existing pressures on resources and to reduce poverty. To date, mainly monetary indicators have been used to measure environmental resource dependence. However, these are inadequate for poor people who consume rather than sell their environmental products. Therefore, we propose the Environmental Resource Dependence Index (ERDI) to better capture the multidimensionality of dependence. We analyse the relationship between farming efficiency and environmental resource dependence using a simultaneous equations model (SEM) and panel data for 2013, 2016 and 2017 from three rural provinces in Central Vietnam. Time-variant farming efficiency is estimated using a stochastic frontier model (SFM) with true random effects and Mundlak's adjustment. Our results show that monetary measures underestimate the extent of dependency. Therefore, policymakers should be careful to correctly identify those who are dependent on the environment. In addition, the results suggest that improved farming efficiency reduces the dependence on environmental resources. At the same time, higher dependence does not have a significant effect on farming efficiency.

KEYWORDS

environmental resource dependence, farming efficiency, simultaneous equations model, stochastic frontier model, Vietnam

JEL CLASSIFICATION

Q12, Q56

1 | INTRODUCTION

Rural populations in developing countries depend on farming and natural resource extraction because their access to other alternative livelihoods is often limited (Barbier, 2010; FAO, 2018). Several previous studies have explored ways to improve farming efficiency (Idris et al., 2013; Manjunatha et al., 2013) and to reduce rural dependence on natural resources (Nguyen et al., 2015; Nguyen, Do, & Grote, 2018). Farming and natural resource extraction are alternative livelihood strategies in terms of labour input, but are complementary in terms of capital input and technologies; for example, vehicles used in agriculture can also be used to transport extracted products (Nguyen, Do, Parvathi, et al., 2018). Thus, the decision to allocate inputs is made jointly. Despite this interdependence, which is important for natural resource conservation and poverty reduction, only a few studies have addressed this issue (Illukpitiya & Yanagida, 2010; Nguyen, Do, Parvathi, et al., 2018).

Farming efficiency is influenced by several factors, including agricultural technologies and farmer characteristics such as education and experience (Idris et al., 2013; Kea et al., 2016; Khai & Yabe, 2011). Technically, farming efficiency is often estimated to be time-invariant, meaning that it does not change over time. However, this assumption is not realistic (Nguyen et al., 2021). In addition, the estimation of farming efficiency may suffer from endogeneity, leading to biased results. This is caused by endogenous input factors as well as omitted variables such as agro-ecological determinants. Therefore, estimating time-variant technical efficiency while accounting for potential endogeneity has been a challenge in the literature.

Regarding natural resource extraction and dependence, previous studies often use Absolute Environmental Income (AEI) as a proxy for extraction and Relative Environmental Income (REI) as a proxy for dependence (Angelsen et al., 2014; Bierkamp et al., 2021; Córdova et al., 2013). While these studies provide useful insights, they also raise some concerns. The most obvious is that the indicators based on monetary revenues can be misleading. This is because rural people extract natural resources not only for sale but also for their own consumption, which is especially true for poor people (Angelsen et al., 2014; Nielsen et al., 2012). Moreover, environmental income is highly volatile due to seasonal and annual fluctuations (Nerfa et al., 2020). These are caused by the availability of natural resources and harvest times in agriculture. Nerfa et al. (2020) address these issues with a multidimensional index of forest dependence, called the Forest Dependence Index. However, this index only considers forests, though in fact rural households extract a number of different products that also come from other environments, such as rivers or cropland. Based on the Forest Dependence Index, here we develop an index called the Environmental Resource Dependence Index (ERDI) to overcome these limitations.

The relationship between farming efficiency and environmental resource dependence is poorly understood (Illukpitiya & Yanagida, 2010; Nguyen, Do, Parvathi, et al., 2018). A better understanding is needed to alleviate poverty and to prevent over-extraction of natural resources. This is important because the rural poor are particularly dependent on environmental resources (Angelsen et al., 2014; Bierkamp et al., 2021). Improved farming efficiency can reduce smallholder farmers' need for extraction, which reduces pressure on natural resources. However, increased efficiency may also incentivise extraction as farmers may clear forests for crop cultivation (Nguyen, Do, & Grote, 2018; Shively & Pagiola, 2004). Therefore, the objective of this paper is to empirically examine: (1) the factors that influence farming efficiency and environmental resource dependence, and (2) their interrelationship.

Our study contributes to the current literature in several ways: Firstly, existing studies on the relationship between efficiency and extraction use forest environmental income instead of dependence as a proxy for extraction (Illukpitiya & Yanagida, 2010; Nguyen, Do, Parvathi, et al., 2018). However, environmental income is not an adequate index when it comes to the rural poor. Therefore, we take a new look at the interrelationship between efficiency and dependence by using a simultaneous equations model (SEM). Secondly, the ERDI extends the Forest Dependence Index of Nerfa et al. (2020) by including non-forest ecosystems and a wider variety of environmental products. Thirdly, we estimate farming efficiency via a stochastic frontier model (SFM) with true random effects and Mundlak's adjustment. Unlike Nguyen, Do, Parvathi, et al. (2018), this allows us to obtain time-variant farming efficiency while dealing with endogeneity problems. Fourthly, to analyse the relationship between farming efficiency and environmental resource dependence, we use the comprehensive dataset from the long-term Thailand Vietnam Socio Economic Panel (TVSEP) project. Panel data allow for consistent estimates over time despite unobserved heterogeneity across households. Fifthly, we refer to the case of Vietnam in contrast to the analysis of Nguyen, Do, Parvathi, et al. (2018) on Cambodia. Although Cambodia and Vietnam are neighbouring countries, Cambodian agriculture is still more reliant on traditional and labour-intensive agriculture (Ebers et al., 2017). In addition, Vietnam is significantly affected by the degradation of natural resources such as forests and agricultural land (Van Khuc et al., 2018). The country is among the most vulnerable to climate change (Bangalore et al., 2019). Despite economic growth and success in poverty reduction, the rural population is still affected by poverty (UNDP, 2018).

The rest of the paper is structured as follows: Section 2 provides a literature review and conceptual framework for farming efficiency and environmental resource dependence. Section 3 explains the data and methodology. Section 4 presents and discusses the findings, and Section 5 provides conclusions.

2 | LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

2.1 | Farming efficiency

Farming efficiency describes the economic performance of farmers under conditions of resource scarcity (Illukpitiya & Yanagida, 2010; Nguyen, Do, Parvathi, et al., 2018). Efficient farmers make better use of the inputs and technologies available to them. Moreover, land and other inputs are limited and are also used for non-agricultural purposes. Therefore, it is important that smallholder farmers increase their farming efficiency (Kea et al., 2016). This is particularly true for the rural poor who depend on agriculture for their livelihoods and cash income—both on their own farms and through agricultural wage employment (FAO, 2018). They often face various constraints to overcome this dependency and to access other non-farm income opportunities (FAO, 2018; Nguyen, Do, Parvathi, et al., 2018).

Increasing farming efficiency has direct and indirect impacts on poverty reduction (Schneider & Gugerty, 2011). Direct positive impacts of improved efficiency result from higher production and lower unit costs of smallholder farmers. Indirect impacts consist of lower food prices, higher (real) incomes and employment generation. However, the extent of poverty reduction and the specific pathways depend on many complex and contextual factors such as rural markets or initial poverty status (Schneider & Gugerty, 2011). In addition, certain means of increasing efficiency can have harmful consequences. For instance, chemical fertilisers have been a driving force to increase agricultural production in China (Wu, 2011) and South Korea (Nguyen et al., 2012). However, the overuse of fertilisers is harmful to the environment and degrades soil, water and air quality, which can even exacerbate poverty.

Various methods for estimating farming efficiency have evolved over time. Charnes et al. (1978) developed the data envelopment analysis (DEA) as a linear programming method for estimating the efficiency of equal decision-making units with common outputs and inputs. The efficiency level is determined with respect to the most efficient unit within the sample. Since DEA is a deterministic approach, it assumes that all deviations from the production frontier are due to inefficiency, which is not realistic (Gong & Sickles, 1992).

The SFM, originally formulated by Aigner et al. (1977) and Meeusen and van den Broeck (1977), considers that these deviations are caused by inefficiency and stochastic disturbances. Therefore, they divide the error term into an inefficiency term and a noise term. In contrast to the nonparametric DEA, the SFM requires to presume a functional form of the production function. Previous studies often used a Cobb–Douglas function instead of a translog because the former is easier to estimate (Deininger & Jin, 2008; Zalkuw et al., 2014). However, the translog specification offers greater flexibility since production and substitution elasticities do not have to be constant. In addition, the structure of the collected data is crucial for further analysis. Panel data comprise repeated observations on the same units over time and thus allow researchers to control for time-invariant unobserved heterogeneity by untangling unobservable inherent factors from the actual error term (Wooldridge, 2010). Panel data allow distinguishing between time-variant and time-invariant farming efficiency. Because efficiency can change over time, Greene (2005) extends the SFM and accounts for time variance by further separating unobserved heterogeneity from the inefficiency component. In a long-term analysis, the consideration of time variance is particularly important. The correlated random effects (CRE) approach originally proposed by Mundlak (1978) controls for time-invariant unobserved heterogeneity of input variables by including time means of these variables.

2.2 | Environmental resource dependence

Environmental income contributes significantly to the livelihoods of rural populations (Angelsen et al., 2014; Córdova et al., 2013). Analysing a sample of 24 developing countries, Angelsen et al. (2014) find that around 28% of total rural income comes from uncultivated natural resources. Seventy-seven per cent of these resources are forests. The most extracted products are firewood and wild foods such as game, fruits, vegetables or fish. Environmental income is one of the main sources of income for the rural population in developing countries. It contributes to household welfare and reduces inequality in local income distribution (Bierkamp et al., 2023; Nguyen, Do, & Grote, 2018). However, environmental revenues are often overlooked by policymakers, hampering effective development and conservation programs (Wunder et al., 2014). This is due to underreporting of illegal extraction activities (Parvathi & Nguyen, 2018), ecosystem services that are hard to estimate (Liu & Huang, 2022) and difficult quantification of natural resources used for both home consumption and sale due to market imperfections (Wunder et al., 2014).

In the literature, a distinction is made between Absolute and Relative Environmental Income: AEI is the net income from extraction (Nguyen, Do, & Grote, 2018). Relative Environmental Income (REI), on the contrary, is the share of environmental income in total income (Angelsen et al., 2014; Córdova et al., 2013). It is commonly interpreted as the level of dependency on environmental resources. Several empirical studies show that those who are disadvantaged in terms of their socio-economic status are more dependent on natural resources (Angelsen et al., 2014; Nguyen et al., 2015; Nguyen, Do, & Grote, 2018). However, poverty is a complex phenomenon and cannot be reduced to a single dimension such as income. According to Sen (1993), it is also about the capability to realise certain aspects like being educated or being healthy. A lack of basic capabilities, for example, no opportunity to be educated or to stay healthy, is associated with poverty. Therefore, poverty is multidimensional and goes beyond a purely monetary or material dimension (Alkire & Foster, 2011). Also in the context of environmental resource dependence, it has to be considered that dependency is more than just the share of environmental income in total income.

There are several difficulties in using only income-based measures of environmental resource dependence: Although monetary measures are easier to estimate and compare because of a common unit, they are insufficient in situations where households tend to consume products rather than sell them (Nerfa et al., 2020; Nielsen et al., 2012). Poor people in particular use environmental products for their livelihood, while wealthier households are more likely to look for monetary income (Angelsen et al., 2014). In addition, income is a very volatile, and can vary with season and year. People are also not always able to provide clear information about household income (Nerfa et al., 2020; Nielsen et al., 2012). According to Newton et al. (2016), resource dependence is multidimensional. For example, extraction activities are exhausting and labour-intensive (Nerfa et al., 2020; Nielsen et al., 2012). Therefore, households that invest more time and effort are considered as being more dependent. In addition, environmental resources are extracted in order to deal with shocks in the absence of alternative livelihood or coping strategies (Nguyen et al., 2015; Nielsen et al., 2012). Owning few assets, and little diversification of livelihood strategies therefore tend to lead to increased dependence on natural resources in times of crisis.

In sum, REI is not suitable for capturing dependency on environmental resources. Hence, we propose an alternative index called the ERDI. This multidimensional index aims to capture different aspects of dependency in a single value. Its composition is explained in Section 3.2.2.

2.3 | Interrelationship between farming efficiency and environmental resource dependence

While there are already two detailed strands of literature on farming efficiency and environmental resource dependence, as described above, the relationship between the two has been largely ignored (Illukpitiya & Yanagida, 2010; Nguyen, Do, Parvathi, et al., 2018). It has been argued in the past that agricultural intensification leads to more deforestation and forest conversion due to higher returns to farming (Foster & Rosenzweig, 2003; Gunatileke & Chakravorty, 2003; Shively & Pagiola, 2004).

However, Gunatileke and Chakravorty (2003) and Shively and Pagiola (2004) find that improvements in agriculture can reduce pressure on forests. Agriculture and forest protection can complement each other. For example, smallholder farmers can use leaf litter collected in the forest as natural fertiliser. At the same time, they contribute to forest management by allowing more light for new, small forest plants previously covered by leaf litter (Córdova et al., 2013). Illukpitiya and Yanagida (2010) and Nguyen, Do, Parvathi, et al. (2018) focus explicitly on the relationship between farming efficiency and forest extraction. Their results suggest that improved farming efficiency reduces the extraction of forest resources as households can earn more income from farming. Thus, the opportunity cost of extraction increases, meaning less labour is allocated to the labour-intensive extraction activity. However, these two studies use forest environmental income as a proxy for extraction rather than resource dependence.

Therefore, it remains an empirical question to examine the relationship between farming efficiency and dependence on environmental resources. Furthermore, there might be an interrelationship, as similar input factors are needed for agriculture and for extraction (Nguyen, Do, Parvathi, et al., 2018). In addition, technical interdependencies in the production processes of farming and extraction should be taken into account. We address this issue using a SEM.

3 | DATA AND METHODOLOGY

3.1 | Study site and data collection

We use a 3-year panel dataset from three rural provinces in Central Vietnam. The data were collected as part of the TVSEP project. Panel data are the basis for well-designed development policies. While long-term socio-economic panel data already exist in more developed countries, they are still rare for emerging countries such as Thailand and Vietnam (Klasen & Povel, 2013). The TVSEP dataset for Vietnam covers the central provinces of Ha Tinh, Thua Thien Hue and Dak Lak (Figure 1). The sample is considered to be representative of the rural population in poor provinces of Central Vietnam because the sampling procedure includes the following steps (Hardeweg et al., 2013): First, the three provinces were selected due to their low average per capita income, high reliance on agriculture and poor infrastructure. Second, two villages from each sub-district were sampled based on the population size of the sub-district.

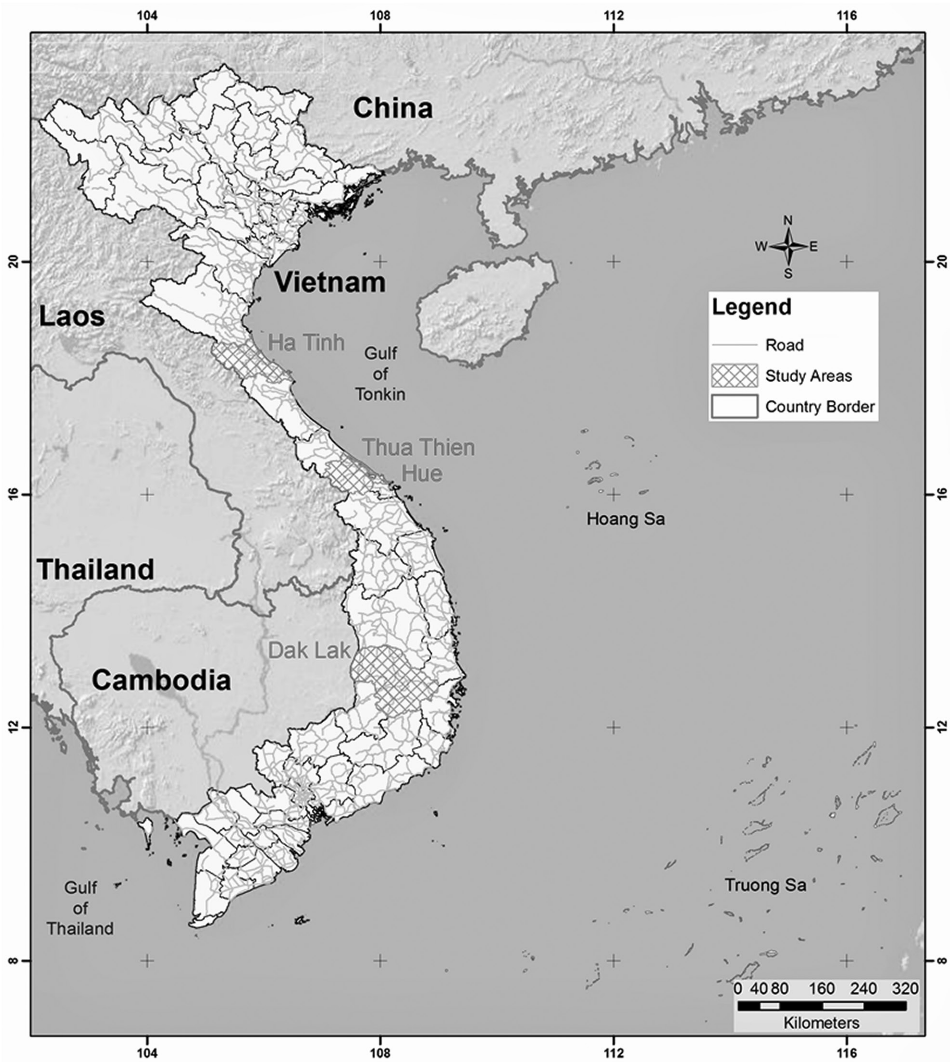

FIGURE 1 Studied provinces Ha Tinh, Thua Thien Hue and Dak Lak in Central Vietnam (Nguyen et al., 2021).

Third, 10 households per village were randomly chosen with equal selection probability. For our analysis, we limit the sample to those households that deal with the extraction of natural resources and run their own farms. Our sample for analysis consists of 1537 household observations from 212 villages in 2013, 2016 and 2017.

The survey includes a wide range of questions on socio-economic characteristics of households and their individual members such as educational qualifications, ethnicity or income and consumption patterns. The TVSEP data contain the multitude of information needed to calculate the two dependent variables: To estimate farming efficiency, a section on agriculture includes all the necessary data on output, operated cropland area, as well as labour input and expenditures. Information on extraction activities, own cultivation and purchase of various categories of environmental products is available for the ERDI. In addition, there is a section on the wealth and housing conditions of private households. The data collected refer to the last 12 months prior to the survey.

3.2 | Farming efficiency and environmental resource dependence

3.2.1 | Estimating time-variant farming efficiency

We apply the SFM of Aigner et al. (1977) and Meeusen and van den Broeck (1977):

$$y_j = x_j' \beta + v_j + u_j \tag{1}$$

where y_j is the agricultural output of farm household j. The vector x_j' stands for the input factors, and β denotes a vector for the unknown parameters. The special feature of this approach is the specification of the error term. According to Aigner et al. (1977), v_j represents the favourable and unfavourable external influencing factors that are not under the farmer's control, for example, climatic conditions. This error term is independently and equally distributed ($iidN(0, \sigma_v^2)$) around the production frontier. The second and non-negative error term u_j represents the disturbances that are under the farmer's control, such as effort and commitment of the farmer and farm workers. This inefficiency term is below the frontier production. It is assumed to follow a truncated normal distribution ($iidN^+(\mu, \sigma_u^2)$), allowing for a nonzero mode (Stevenson, 1980). By distinguishing between two error term components, it is possible to differentiate inefficient farms from farms exposed to unfavourable external conditions. The SFM is therefore well suited for analysing farming efficiency in Vietnam, where farming activities are subject to a number of risks (Bangalore et al., 2019).

To calculate the SFM for panel data, Battese and Coelli (1988) develop the time-invariant inefficiency model with random effects. It assumes that all time-invariant unobserved heterogeneity is due to inefficiency. However, the assumption of a time-invariant inefficiency is too strong. Therefore, Greene (2005) proposes the SFM with true random effects for panel data. It accounts for the time variance of inefficiency by disentangling the time-variant inefficiency from the time-invariant unobserved heterogeneity:

$$y_{jt} = \alpha + \omega_j + x_{jt}' \beta + v_{jt} + u_{jt} \tag{2}$$

where α is constant, ω_j reflects the random farm-specific and time-invariant heterogeneity ($iidN(0, \sigma_\omega^2)$), v_{jt} stands for the farm- and time-specific noise term, and u_{jt} is the time-variant inefficiency term. We estimate the model using maximum likelihood (Belotti et al., 2013). The likelihood ratio test confirms that in our analysis the translog functional form is more appropriate than the Cobb–Douglas functional form (Appendix S1). Hence, we specify the production function in a translog functional form as follows:

$$lnY_{jt} = \alpha + \omega_j + \sum_m \alpha_m lnx_{jtm} + \frac{1}{2}\sum_m \sum_n \alpha_{mn} lnx_{jtm} lnx_{jtn} + u_{jt} + \mathrm{v}_{jt} \tag{3}$$

where Y_{jt} is the monetary value of agricultural production. As input factors x_{jt}, we use the cultivated cropland area in ha, expenditures for seeds and seedlings, fertilisers, pesticides, harvesting and for other inputs, as well as the number of household members working on the farm. All monetary values are converted to 2005 PPP US$. The input variables are normalised by their respective means before estimating the model.

When calculating farming efficiency, the endogeneity of input use must be taken into account to avoid biased estimates. In our case, endogeneity can arise from unobserved omitted variables such as farm characteristics, soil quality or weather conditions. These are determinants of agricultural production and at the same time correlated with the input variables. Another reason for endogeneity can arise when agricultural production and input purchases are determined together, as farmers try to maximise output with minimal input. To address the potential endogeneity of input variables, the CRE approach of Mundlak (1978) is applied. Standard errors are clustered at the village level to adjust for common unobserved characteristics of households within a village (Abadie et al., 2017). After estimating the SFM, the corresponding farming efficiency Γ_{jt} is calculated as follows (Jondrow et al., 1982):

$$\Gamma_{jt} = E\left[exp\left(-u_{jt}\right) \mid \left(v_{jt} - u_{jt}\right)\right]. \tag{4}$$

3.2.2 | Identifying environmental resource dependence

Since the REI index is not suitable for capturing dependency on environmental resources, we develop a new index based on the Forest Dependence Index of Nerfa et al. (2020). We refer to this new index as the ERDI. It includes four different sub-indices that separately cannot measure dependence since they individually represent a single specific aspect. Only the combination of the sub-indices is an adequate measure of dependency. Figure 2 gives an overview of the composition and calculation of the ERDI. The first two sub-indices relate to environmental products and the extraction itself. The first sub-index is Extraction Importance ($\mathrm{I_i}$). It reflects the share of extracted environmental products in relation to the total amount of environmental products available to a household. We distinguish the Extraction Importance in four product groups i that reflect the diversity of natural resources: wood products (e.g., timber products and firewood), fish and seafood, fruits and vegetables, and small animals (e.g., amphibians, birds and insects). For each of these product groups, we determine the total amount in kilograms that a household had through extraction ($\mathrm{A_e}$) as well as through cultivation and purchase ($\mathrm{A_o}$) in the last 12 months. The annual amount takes into account that there are fluctuations in extraction, cultivation and purchase within the year. The extracted amount ($\mathrm{A_i}$) is divided by the total amount available ($\mathrm{A_i+A_o}$). The results are standardised across households using z-scores. This procedure is similar to calculating the REI, with the difference that no monetary values are assigned. Dependence on environmental resources increases with a higher share of extracted products.

The second sub-index is the Effort (E_j) of a household j. It can be measured in terms of labour, or time spent in extracting environmental products. For our analysis, we use the number of household members primarily engaged in extraction (M_j) relative to household size ($\mathrm{S_j}$). A larger share means that the household is more involved in extracting natural resources. Therefore, the effort and the dependence on natural resources are greater. After z-score standardisation, the Extraction Importance is aggregated across all product groups, combined with the Effort, and standardised again.

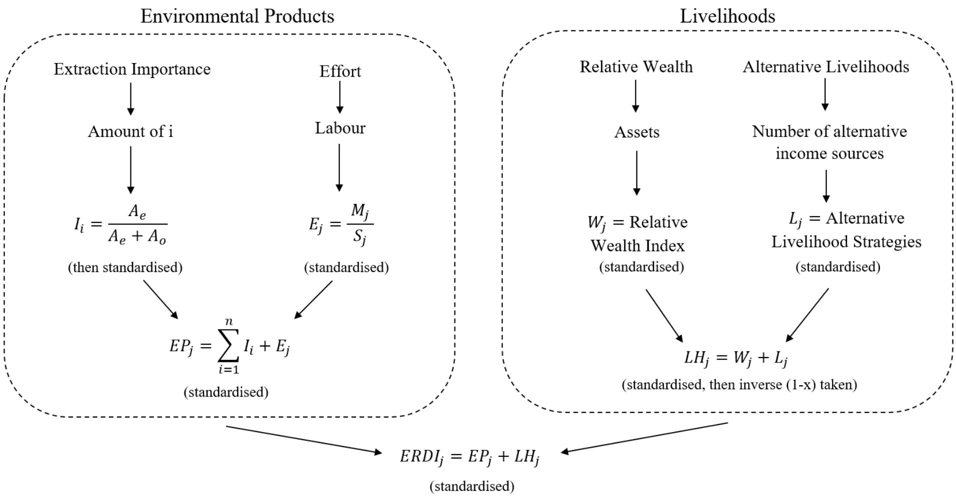

FIGURE 2 Composition and calculation of the Environmental Resource Dependence Index (ERDI) following Nerfa et al. (2020). Abbreviations: I—Extraction Importance, E—Effort, W—Relative Wealth, L—Alternative Livelihoods, A—amount, M—number of household members mainly engaged in extraction, S –household size, EP—environmental products sub-indices combined, LH—livelihoods sub-indices combined. Subscripts: i—environmental product group level, e—products from extraction, o—products from other sources (cultivation and purchase), j—household level. Note: The z-score standardisation is used throughout the calculation process.

The following two sub-indices focus on a household's livelihood. The third sub-index is Relative Wealth (W_j) based on assets. Unlike income, assets have a long-term wealth perspective as they are accumulated over time and can also be used for productive purposes (Nielsen et al., 2012). In addition, households can sell their assets to make up for lost income. Therefore, they represent an alternative to extraction activities during shocks. We use the popular Demographic and Health Survey (DHS) wealth index (Filmer & Pritchett, 2001; Rutstein & Johnson, 2004). The index is calculated using a principal component analysis, which reduces the complexity of the data and bundles the important information into orthogonal linear combinations of the variables. Our study includes 12 variables (Appendix S2): six variables related to household ownership of durable goods and six variables related to housing conditions. For the selection of variables, we follow Filmer and Pritchett (2001) as well as Rutstein and Johnson (2004) and adjust them to our sample. After calculation, the Relative Wealth sub-index is standardised.

The last sub-index relates to Alternative Livelihoods (L_j) apart from extraction. It simply counts the number of alternatives currently available to a household. We consider agriculture, off-farm wage employment, non-farm self-employment, migration, receiving transfer payments and land renting. A broader range of livelihood strategies implies risk reduction through income diversification (Ellis, 2000). Greater diversification is associated with a lower dependence on environmental resources. In contrast to the previous wealth-based sub-index, alternative livelihood strategies cover a shorter time horizon. Nevertheless, both sub-indices reflect the possible alternatives to extraction. After standardising the number of livelihood strategies, we combine the Relative Wealth and Alternative Livelihoods sub-indices. We standardise again and take the inverse since a higher value should indicate more dependence.

The final step in calculating the ERDI is to sum up the combined sub-indices and to standardise. It is important to note that the ERDI is a relative measure of environmental resource dependence, that is, it refers to the households in the sample. The reasons lie in the relativity of the wealth index and in the standardisation throughout the calculation process. A comparison between two samples is therefore only possible with pooled datasets. However, the ERDI combines different aspects of dependency into a single number and allows for a better identification of people who depend on the extraction of natural resources.

3.2.3 | Examining the interrelationship between farming efficiency and environmental resource dependence

Farming and natural resource extraction are interrelated through similar input factors and potential technical interdependencies (Nguyen, Do, Parvathi, et al., 2018). Thus, rural households who are often both farmers and extractors make decisions about the use of labour, materials and equipment at the same time. It can be assumed that both livelihood strategies influence each other. Therefore, to analyse the relationship between farming efficiency and environmental resource dependence, we use a SEM estimated with three-stage least squares as proposed by Zellner and Theil (1962). The simultaneous equations are specified as follows:

$$\Gamma_{jt} = \gamma_0 + REI_{jt} / ERDI_{jt}\gamma_1 + T_{jt}\gamma_2 + F_{jt}\gamma_3 + X_{jt}\gamma_4 + \varepsilon_{jt} \tag{5a}$$

$$REI_{jt} / ERDI_{jt} = \delta_0 + \Gamma_{jt}\delta_1 + D_{jt}\delta_2 + X_{jt}\delta_3 + \mu_{jt} \tag{5b}$$

where Γ_{jt} represents farming efficiency of household j in each time period$t$. REI_{jt} and $ERDI_{jt}$ are the indices that capture environmental resource dependence. The model is estimated twice: first with REI_{jt} as the dependent variable and second with $ERDI_{jt}$ as the dependent variable. X_{jt} stands for the independent variables (Appendix S3). To account for socio-demographic factors, we consider household mean age, mean education and ethnicity. Furthermore, household's accumulated savings and remittances are used to cover financial capital and non-farm components. The surveyed households live in three provinces, which differ in several aspects such as climate or altitude. Therefore, provincial dummies account for regional disparities that are not adequately represented by other control variables. γ and δ are the coefficients to be estimated. The error terms are represented by ε_{jt} and μ_{jt}.

In our model of Equations (5a) and (5b), endogeneity may result from the simultaneity between farming efficiency and environmental resource dependence. We therefore need instrumental variables that are included in one equation and excluded from the other equation. For farming efficiency (Equation (5a)), we use the number of agricultural machines T_{jt} such as tractors or threshing machines and the share of irrigated farmland F_{jt} as instrumental variables. Farmers are expected to be faster with agricultural machines, thereby reducing their labour input. A higher share of irrigated farmland could increase agricultural production since a constant water supply is guaranteed. Both instrumental variables satisfy the exclusion restriction as they affect farming efficiency, but not the dependence on environmental resources (Nguyen, Do, Parvathi, et al., 2018; Appendix S4). For environmental resource dependence (Equation (5b)), we use the distance D_{jt} from the household's home to the extracting ground, which is internal neither to the REI nor to the ERDI. If households are willing to travel longer distances, this indicates a higher dependence on environmental resources. Therefore, distance affects dependency, but not farming efficiency (Bierkamp et al., 2021; Nguyen, Do, & Grote, 2018; Appendix S4). In addition, the Hansen–Sargan test of overidentifying restrictions confirms that the instrumental variables are not correlated with the error terms (Appendix S5). The Breusch-Pagan Lagrange Multiplier test for independent equations validates that the error covariance matrix is not diagonal, implying that both Equations (5a) and (5b) are dependent (Breusch & Pagan, 1980; Appendix S5). In addition, some included variables such as savings and remittances might also be endogenous. For example, migration and the sending of remittances depend on many other variables that are difficult to capture, such as social networks or personal attitudes. However, calculation of correlation coefficients suggests that endogeneity of independent variables is not a serious issue (Appendix S6). Variance inflation factors indicate that there is no multicollinearity between independent variables (Appendix S7). Standard errors are bootstrapped with 1000 replications and clustered at the village level.

3.3 | Descriptive statistics

Table 1 contains some descriptive statistics of the surveyed households in the three Vietnamese provinces by year. It shows that the average household education improved slightly between 2013 and 2017. About half of the households belong to an ethnic minority. This proportion is significantly larger than in other parts of Vietnam for two reasons (Bierkamp et al., 2023). First, ethnic minorities often live in remote rural areas, particularly in the Northern Mountains and the Central Highland such as the sampled province Dak Lak. Second, they tend to rely on low-return activities such as extraction and farming. Because our sample only includes households that follow both of these livelihood strategies, the share of minorities is large. Since 2013, households receive significantly more remittances from relatives, friends and absent household members. In particular, young and well-educated people migrate to urban areas to remit money to their families back home (Bierkamp et al., 2021).

The table also includes details on the asset ownership structure and housing conditions. The items refer to the components included in the Relative Wealth Index (Appendix S2). In 2017, around 94% of the households have a phone. This number significantly increases since 2013, underscoring the important role of these devices (Hübler & Hartje, 2016). In addition, the percentage of households with a fridge significantly increases. On the contrary, television ownership significantly decreases. When it comes to vehicles, it shows that more and more households have a motorcycle. Only a few households own a car. The percentage of households with access to tap water significantly increases between 2013 and 2017, while fewer households depend on water from wells, rain or rivers. There are also improvements in toilet facilities: The share of households using a flush toilet is increasing significantly, while the share of households with a latrine or no toilet at all is falling. Fuels for cooking from firewood or charcoal tend to be less important. In 2013, around 79% of households use these fuels for cooking. In 2017, only 61% use it. Almost 100% of the households surveyed have access to electricity for lighting. The number of rooms decreases only slightly and is around three rooms per household.

4 | RESULTS AND DISCUSSION

4.1 | Estimation of farming efficiency

Table 2 summarises the agricultural output and inputs of the sampled households by year. The output, measured by the average crop value, increases significantly over the years. However, the amount of land used by households for agriculture is shrinking. This observation applies to all four crop categories considered. Due to economic growth, more land is used for other purposes than agriculture. The expenditures for harvesting and other inputs are increasing, while the expenditures for pesticides and fertilisers significantly decrease since 2013. Nevertheless, fertilisers are still the most expensive agricultural input factors.

Table 3 shows the estimates for the translog farm production function from different SFMs: the true random effects model by Greene (2005)—with and without Mundlak's adjustment—as

TABLE 1 Descriptive statistics of sampled households by year.

	2013	2016	2017	Test statistics for the change (2013–2017)
Socio-economic characteristics				
Age	31.08 (9.89)	32.76 (10.97)	34.54 (12.36)	−4.41***a
Education	7.29 (2.53)	7.56 (2.55)	7.79 (2.74)	−2.64**a
Ethnicity (1 = ethnic minority)	0.43 (0.5)	0.55 (0.5)	0.5 (0.5)	6.74***b
Savings	691.4 (3851.55)	539.2 (1598.96)	751.89 (2538.65)	−0.32a
Remittances	373.11 (1379.4)	827.62 (1827.24)	1247.6 (2343.35)	−13.37***a
Asset ownership (in % of all households in the sample)				
Phone	88.62 (31.74)	90.62 (29.19)	94.05 (23.68)	10.68***b
Television	93.17 (25.21)	91.3 (28.21)	87.33 (33.29)	9.08***b
Fridge	16.37 (37.02)	25.63 (43.71)	33.78 (47.34)	45.59***b
Bicycle	53.97 (49.88)	59.04 (49.23)	53.74 (49.91)	0.03b
Motorcycle	79.74 (40.23)	83.3 (37.34)	82.53 (38)	2.08b
Car	0.49 (6.96)	0.92 (9.52)	0.96 (9.76)	0.74b
Housing conditions (in % of all households in the sample)				
Water supply				
Rainwater, water from river, etc.	10.36 (30.5)	13.04 (33.72)	7.87 (26.95)	2.04b
Well/water bought	66.84 (47.12)	63.16 (48.29)	46.26 (49.91)	47.42***b
Tap	22.8 (41.99)	23.8 (42.6)	45.87 (49.88)	65.33***b
Toilet facility				
None	20.73 (40.57)	21.74 (41.29)	13.24 (33.93)	10.79***b
Latrine	52.68 (49.97)	48.97 (50.05)	43.38 (49.61)	9.5***b
Flush	26.6 (44.22)	29.29 (45.56)	43.38 (49.61)	34.15***b
Floor				
Dirt	6.04 (23.85)	2.06 (14.22)	1.73 (13.04)	13.31***b
Cement	62.69 (48.4)	48.74 (50.04)	43.57 (49.63)	40.33***b
Tiles, marble, etc.	31.26 (46.4)	49.2 (50.05)	54.7 (49.83)	61.72***b
Cooking fuel				
Firewood/charcoal	78.93 (40.82)	69.34 (46.16)	61.03 (48.81)	42.18***b
Gas	18.99 (39.26)	29.98 (45.87)	38.2 (48.63)	50.03***b
Electricity	2.07 (14.26)	0.69 (8.27)	0.77 (8.74)	3.26* b
Electricity	97.75 (14.83)	97.25 (16.36)	99.23 (8.74)	4.09**b
Number of rooms	2.94 (1.26)	2.82 (1.39)	2.79 (1.36)	2.23**a

Note: Standard deviations in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; a—Wilcoxon rank-sum test; b—χ^2 test.

well as the time-invariant random effects model by Battese and Coelli (1988). Since the independent variables are normalised by their respective geometric means before taking the logarithm, the coefficients can be interpreted as elasticities (Kumbhakar et al., 2014). The similar results of the different model approaches indicate the robustness of the estimates. Since the estimates for CRE do not provide significant results, time-invariant unobserved heterogeneity is not an issue in our analysis. Operated cropland area and the expenditures for fertilisers are

TABLE 2 Farm output and inputs by year.

	2013	2016	2017	Test statistics for the change (2013–2017)
Output				
Crop value (in PPP$/ha)	4057.6 (4675.48)	4631 (4110.27)	5861.12 (6840.3)	−7.05***[a]
Inputs				
Farmland (in ha) for				
…rice	0.26 (0.3)	0.13 (0.2)	0.12 (0.15)	20.37***[a]
…corn and other field crops	0.26 (0.39)	0.16 (0.25)	0.14 (0.27)	10.65***[a]
…tree crops	0.55 (0.68)	0.46 (0.57)	0.39 (0.53)	4.13***[a]
…horticulture crops	0.078 (0.15)	0.071 (0.18)	0.025 (0.048)	3.16***[a]
Expenditures (in PPP$/ha) for				
…seeds and seedlings	102.13 (205.11)	151.97 (205.38)	143.16 (204.81)	−5.46***[a]
…fertilisers	603.72 (4092.2)	401.8 (284.18)	392.57 (372.67)	−4.73***[a]
…pesticides	140.7 (1353.51)	106.26 (96.07)	102.56 (141.29)	−6.39***[a]
…harvesting	85.49 (139.98)	94.06 (116.47)	108.47 (120.17)	−4.82***[a]
…other inputs	160.24 (620.45)	182.57 (186.54)	192.50 (181)	−5.77***[a]
Number of household members engaged in own agriculture	2.15 (1.41)	2.18 (1.18)	2.1 (1.22)	0.11[a]

Note: Standard deviations in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$; a—Wilcoxon rank-sum test.

highly significant. They have the highest production elasticities, confirming the importance of land and fertilisers already reported by the World Bank (2016) and Nguyen et al. (2021). Labour has a very small and insignificant effect. Historically, Vietnamese agriculture was characterised by labour-intensive production on small plots (Nguyen et al., 2021; Van Phan & O'Brien, 2022), but our results emphasise that cropland area in particular is the limiting production factor. In the course of Vietnam's economic opening from 1986, individual land ownership rights as well as land transfer rights were strengthened (Deininger & Jin, 2008). Land was transferred to more productive and efficient farmers, implying a shift from labour-intensive to capital-intensive agriculture (Nguyen et al., 2021).

Table 4 contains the farming efficiency values per year. The efficiency estimates of Greene's (2005) model with and without Mundlak's adjustment hardly differ. The SFM values according to Battese and Coelli (1988) are somewhat higher. The efficiency levels of all model approaches increase over time, but only the estimates from Greene's (2005) model indicate significant changes. The efficiency values increase from an average value of 71.82% in 2013 to an average value of 73.76% in 2017. This means that the technical efficiency in 2017 could still be improved by around 26.24%. Empirical research shows that efficiency is positively influenced by farmer education and experience, as well as input factors such as land, seeds, labour and machinery (Ebers et al., 2017; Kea et al., 2016; Manjunatha et al., 2013; Samarpitha et al., 2016). Compared with other Southeast Asian countries, Vietnam is characterised by high farming efficiency (Ebers et al., 2017; Khai & Yabe, 2011; Nguyen et al., 2021). Based on the Vietnam Household Living Standard Survey, Khai and Yabe (2011) estimate that the overall efficiency in Vietnam is 81.6%. However, the efficiency values in our sample are clearly lower because we focus on three remote and disadvantaged rural provinces. Furthermore, our analysis is limited to the poorest households who are farmers and extractors at the same time.

TABLE 3 Estimations of farm production function from different stochastic frontier models.

	Greene (2005) + Mundlak's adjustment	Greene (2005)	Battese and Coelli (1988)
ln operated cropland area (a)	0.443*** (0.074)	0.538*** (0.045)	0.533*** (0.045)
ln seeds and seedlings expenditures (b)	0.012 (0.02)	0.016 (0.02)	0.012 (0.019)
ln fertiliser expenditures (c)	0.183*** (0.037)	0.182*** (0.035)	0.183*** (0.036)
ln pesticide expenditures (d)	0.084** (0.034)	0.087*** (0.032)	0.084*** (0.031)
ln harvesting expenditures (e)	0.023 (0.027)	0.01 (0.025)	0.013 (0.025)
ln other expenditures (f)	0.068** (0.032)	0.066** (0.03)	0.067** (0.03)
ln household labourers (g)	0.017 (0.044)	0.037 (0.044)	0.036 (0.044)
a^2	−0.012 (0.024)	−0.017 (0.025)	−0.013 (0.025)
b^2	0.002 (0.002)	0.002 (0.002)	0.001 (0.002)
c^2	0.018*** (0.004)	0.019*** (0.004)	0.018*** (0.004)
d^2	0.007** (0.004)	0.007** (0.003)	0.007** (0.003)
e^2	0.001 (0.003)	0.0005 (0.003)	0.0007 (0.003)
f^2	0.007** (0.003)	0.007** (0.003)	0.007** (0.003)
g^2	0.002 (0.006)	0.004 (0.006)	0.003 (0.006)
a × b	−0.002 (0.003)	−0.003 (0.003)	−0.002 (0.003)
a × c	−0.011** (0.005)	−0.011** (0.005)	−0.011** (0.005)
a × d	0.008 (0.005)	0.008 (0.005)	0.007 (0.005)
a × e	0.003 (0.004)	0.003 (0.004)	0.003 (0.003)
a × f	−0.001 (0.004)	−0.001 (0.004)	−0.002 (0.004)
a × g	−0.004 (0.005)	−0.006 (0.005)	−0.006 (0.004)
b × c	−0.0005 (0.0007)	−0.0004 (0.007)	−0.0003 (0.0007)
b × d	0.0004 (0.0007)	0.0004 (0.0007)	0.0002 (0.0007)
b × e	−0.00002 (0.0005)	−0.000001 (0.0005)	−0.00005 (0.0005)
b × f	0.0003 (0.0005)	0.0003 (0.0005)	0.0004 (0.0005)
b × g	−0.005 (0.0009)	−0.0006 (0.0008)	−0.0007 (0.0008)
c × d	0.0004 (0.0008)	0.0004 (0.0007)	0.0005 (0.0007)
c × e	−0.0005 (0.0008)	−0.0006 (0.0008)	−0.0003 (0.0008)
c × f	−0.0004 (0.0007)	−0.0004 (0.0008)	−0.0005 (0.0008)
c × g	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
d × e	0.0005 (0.0008)	0.0006 (0.0008)	0.0006 (0.0007)
d × f	−0.0002 (0.0007)	−0.0003 (0.0008)	−0.0003 (0.0007)
d × g	−0.000003 (0.001)	0.0002 (0.001)	0.0003 (0.001)
e × f	−0.0006 (0.0006)	−0.0005 (0.0006)	−0.0005 (0.0006)
e × g	−0.0003 (0.0004)	−0.0003 (0.0004)	−0.0002 (0.0004)
f × g	0.002** (0.0008)	0.002** (0.0008)	0.002** (0.0008)
Mean variables for time average CRE			
ln operated cropland area	0.12* (0.065)	–	–
ln seeds and seedlings expenditures	0.005 (0.006)	–	–

(Continues)

TABLE 3 (Continued)

	Greene (2005) + Mundlak's adjustment	Greene (2005)	Battese and Coelli (1988)
ln fertiliser expenditures	−0.003 (0.012)	–	–
ln pesticide expenditures	0.0002 (0.01)	–	–
ln harvesting expenditures	−0.012* (0.006)	–	–
ln other expenditures	−0.0001 (0.007)	–	–
ln household labourers	0.015 (0.011)	–	–
Constant	7.91*** (0.057)	7.91*** (0.056)	7.87*** (0.041)
No. of observations	1537	1537	1537
Log likelihood	−1628.62	−1635.57	−1633.78
Sigma_u; Sigma_v; Lambda	0.282***; 0.629***; 0.448***	0.279***; 0.635***; 0.439***	–
lnsigma2; ilgtgamma; mu	–	–	4.33***; 5.15***; −325.88***
Wald χ^2	3723.7	3009.51	3140.07
Prob > χ^2	0.0000	0.0000	0.0000

Note: Robust standard errors in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$.

TABLE 4 Farming efficiency (in %) by year estimated from different stochastic frontier models.

	2013	2016	2017	Test statistics for the change (2013–2017)
Greene (2005) + Mundlak's adjustment	70.65 (12)	71.32 (10.64)	72.86 (9.35)	−2.84***[a]
Greene (2005)	70.5 (12.03)	71.3 (10.64)	72.92 (9.19)	−3.1***[a]
Battese and Coelli (1988)	74.3 (11.41)	74.9 (10.28)	75.5 (10.2)	−1.59[a]
Average	71.82	72.51	73.76	

Note: Standard deviations in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$; a—Wilcoxon rank-sum test.

4.2 | Estimation of environmental resource dependence

A closer look at the ERDI sub-indices shows the causes of dependency on environmental resources (Figure 3). In the sample, wood products mostly come from extraction. At the same time, the Extraction Importance of fish, seafood, fruits, vegetables and small animals is low. The Effort sub-index shows that within the households examined, only a small share of household members is mainly engaged in extraction. Therefore, extraction is an additional activity rather than a main occupation. Most households have intermediate values for Relative Wealth, the third sub-index. The last sub-index on Alternative Livelihoods shows that the majority of households has two or three livelihood strategies in addition to extraction.

The distributions of ERDI and REI are very different. Figure 4 compares the histograms of both standardised indices. The distribution of REI is right skewed, while the ERDI follows a nearly normal distribution, meaning that most households have low REI values, but moderate ERDI values. These results are comparable to the results of Nerfa et al. (2020) and their case study in Malawi. The consequence is that with the usual measurement of the REI many environmentally dependent households are not identified as such. The extent of dependence is thus underestimated. In contrast to the REI, the ERDI is more comprehensive. It allows us to see where the dependence on environmental resource comes from. However, the main

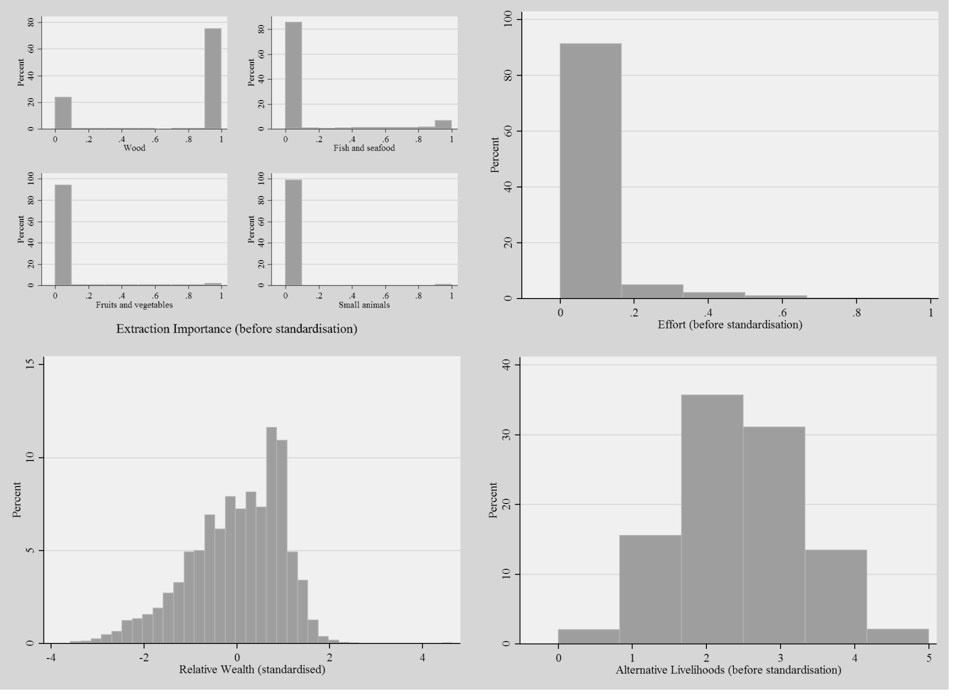

FIGURE 3 Histograms of ERDI sub-indices: Extraction Importance (top left), Effort (top right), Relative Wealth (bottom left), Alternative Livelihoods (bottom right).

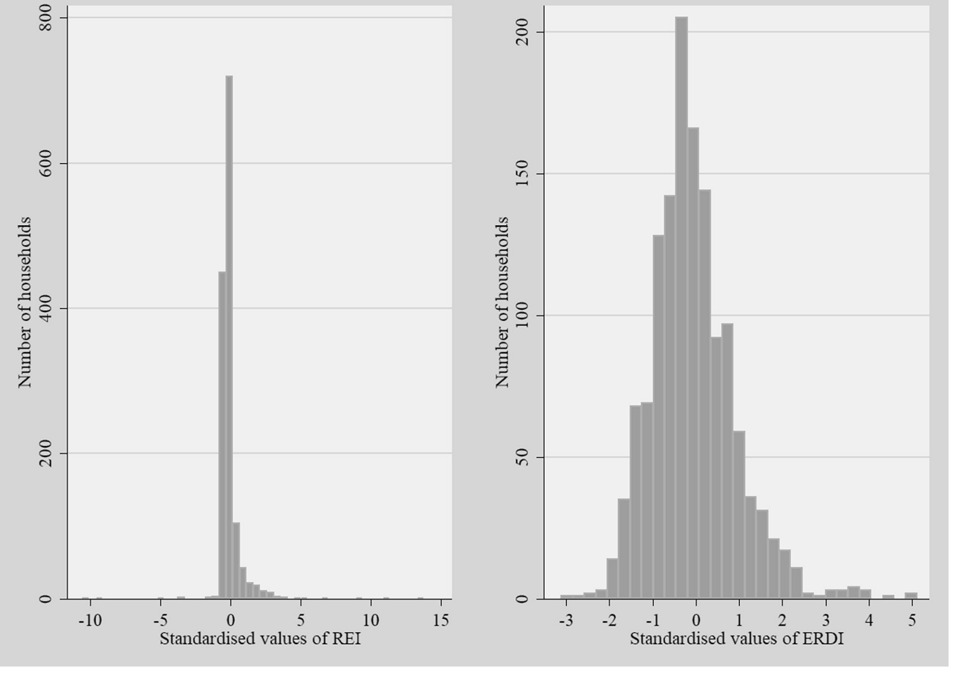

FIGURE 4 Histograms of REI (left) and ERDI (right) for sampled households.

disadvantage of the ERDI is that it is relative to the sample, that is, it cannot be compared across samples.

The existing difference between the two distributions is also confirmed by a Kolmogorov–Smirnov test, which checks whether individual households with the same ERDI have different REI values (Appendix S8). Table 5 summarises REI, ERDI and AEI values by total income quartiles. It appears that environmental resource dependence is lower for wealthier households according to both indices. However, the divergence between the poorest and the richest quartile in the ERDI is considerably larger, indicating a greater variety in dependency. The opposite pattern holds for the AEI, which is clearly larger for wealthier households. This result is consistent with previous studies (Angelsen et al., 2014; Córdova et al., 2013).

4.3 | Impact of farming efficiency on environmental resource dependence

Table 6 shows the results of the SEM with REI and ERDI as dependent variables. For farming efficiency, we rely on the model of Greene (2005) with Mundlak's adjustment. Even if it turns out that there are only minor differences to the other model approaches, it eliminates most of the possible biases. The results show that farming efficiency has a negative impact on environmental resource dependence. However, only the model using the ERDI gives significant results as it captures dependency better. Households that can increase their efficiency are less dependent on natural resources as they are better able to make a living from farming. This finding is consistent with Illukpitiya and Yanagida (2010) as well as Nguyen, Do, Parvathi, et al. (2018). Accounting for dependency places a greater focus on the poor, whose absolute levels of extraction are often lower, but who are more reliant on natural resources. Therefore, increasing farming efficiency is a useful tool to fight poverty. Our analysis also shows that greater reliance on environmental resources has no impact on efficiency. This contradicts the findings of Nguyen, Do, Parvathi, et al. (2018) from Cambodia. The reason could be that increasing dependency is pushing households to extract more. However, as we have shown before, agriculture in Vietnam is capital-intensive. Land is the limiting factor for agricultural production. At the same time, land use in Vietnam is strictly regulated, for example, converting forestland into farmland is difficult (Le, 2020). Even if households want to increase their agricultural production to escape poverty, it is not easily possible. This means that deforested land cannot be used as farmland. Therefore, increased resource dependence will not have a direct impact on efficiency in Vietnam.

The choice of other independent variables in our analysis is limited because there are many socio-economic variables that fall within the ERDI. It is not possible to identify causal relationships with these variables. Nevertheless, our analysis shows that environmental resource dependence is significantly related to the distance to the extracting ground, ethnicity, remittances and the provinces. A longer distance to the extracting ground implies a higher opportunity cost of extraction in terms of travel and labour (Nguyen, Do,

TABLE 5 REI, ERDI and AEI by total income quartiles.

	Relative Environmental Income (REI)	Environmental Resource Dependence Index (ERDI)	Absolute Environmental Income (AEI)
1st quartile	0.2 (0.5)	0.44 (0.9)	187.53 (264.54)
2nd quartile	−0.06 (0.5)	0.05 (0.85)	304.93 (502.16)
3rd quartile	−0.12 (0.52)	−0.12 (1.05)	454.52 (959.94)
4th quartile	−0.16 (0.54)	−0.42 (1.01)	842.52 (2395.97)

Note: Standard deviations in parentheses.

TABLE 6 Simultaneous equations model results with REI and ERDI as dependent variables.

	Model with REI		Model with ERDI	
	REI	**Farming efficiency**	**ERDI**	**Farming efficiency**
Farming efficiency	−0.055 (0.049)	–	−0.14** (0.068)	–
REI/ERDI	–	0.20 (5.22)	–	−0.26 (2.42)
Distance	0.004** (0.002)	-	0.012*** (0.005)	–
Agricultural machines	–	1.65* (0.9)	–	1.63** (0.81)
Irrigation share	–	−0.0002 (0.011)	–	−0.001 (0.007)
Age	−0.003 (0.004)	−0.014 (0.035)	0.001 (0.006)	−0.0018 (0.033)
Education	−0.018 (0.022)	0.3 (0.25)	0.004 (0.03)	0.3* (0.16)
Ethnicity (1 = ethnic minority)	0.11 (0.12)	−0.76 (1.37)	0.43** (0.18)	−0.74 (1.7)
Savings	0.00002 (0.00002)	0.0003** (0.0001)	0.00002 (0.00003)	0.0003** (0.0001)
Remittances	−0.00003** (0.00001)	−0.0002 (0.0002)	−0.00007*** (0.00003)	−0.0002 (0.0002)
Dak Lak (Ha Tinh as basis)	−0.42** (0.21)	−4.72*** (1.47)	−0.82** (0.33)	−4.55*** (1.25)
Thua Thien Hue (Ha Tinh as basis)	−0.084 (0.17)	−2.44*** (1.03)	−0.61** (0.24)	−2.42** (0.97)
Year 2016 (2013 as basis)	−0.047 (0.086)	0.051 (1.04)	−0.084 (0.17)	−0.093 (1.04)
Year 2017 (2013 as basis)	0.098 (0.13)	1.8** (0.86)	0.24 (0.18)	1.74** (0.81)
Constant	4.2 (3.57)	69.65*** (3.15)	10.4** (4.95)	69.86*** (1.97)
Number of observations	1537	1537	1537	1537
χ^2	50.75	88.28	85.54	90.33
$p > \chi^2$	0.0000	0.0000	0.0000	0.0000

Note: Robust standard errors bootstrapped with 1000 replications and clustered at the village level in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$.

& Grote, 2018). Therefore, a household willing to travel further is expected to invest more, and to rely more on natural resources. Ethnicity plays an important role in Vietnam, which is also reflected in our analysis. Belonging to a minority increases dependency on environmental resources due to existing inequalities. Compared with the Kinh or Chinese Hoa majority, ethnic minorities often live in remote rural areas. They face unequal access and reduced returns to education, markets and supporting services (UNDP, 2018). Therefore, minority households need to generate more income from environmental resources. Another determinant of environmental resource dependence is remittances from migrated household members. Households with a greater amount of remittances are less dependent on natural resources as they can spend the money received for both consumption and investments (Bierkamp et al., 2021).

Farming efficiency is significantly influenced by agricultural machines, education, savings and provinces. Farming households that own agricultural machines can take advantage of economies of scale. In addition, human labour is being replaced by machines, leading to lower labour costs and higher production (Ebers et al., 2017). Households with higher educated members are more efficient (Illukpitiya & Yanagida, 2010; Khai & Yabe, 2011). Well-educated farmers are better able to access and use information about farming practices and crop management. Similar positive effects can also be achieved through experience (Illukpitiya & Yanagida, 2010; Khai & Yabe, 2011), agricultural extension services (Illukpitiya & Yanagida, 2010; Kea et al., 2016), as well as the exchange with others, for example, in agricultural organisations (Idris et al., 2013). Savings have a positive impact on farming efficiency as they allow investments in agricultural assets. This is in line with Illukpitiya and Yanagida (2010) who already point out the positive relationship between total household income and farming efficiency.

5 | CONCLUSION

In order to find suitable measures for environmental protection and poverty reduction, a better understanding of the dependence on environmental resources is required. This study examines the relationship between farming efficiency and environmental resource dependence using panel data from three rural provinces in Central Vietnam. The analysis focusses on the composition of the respective determinants: Farming efficiency is calculated using a SFM with Mundlak's adjustment. The multidimensional nature of environmental resource dependence is captured by the ERDI.

Estimating the efficiency between 2013 and 2017 results in an average value of around 73%. To check the robustness of estimates, we apply different specifications of the SFM. The true random effects model gives the most reliable results because it overcomes the problematic assumption of time-invariant inefficiency and accounts for potential endogeneity.

With regard to environmental resource dependence, however, the results illustrate how important the choice of indices can be. Previous research has only measured resource dependence in monetary terms. The dependence of a household was calculated as REI, that is, environmental income in relation to total income. The proposed ERDI allows for a better representation of dependence. The importance of the extracted products, the effort of extraction, the relative wealth of the household and the alternative strategies for securing a livelihood are taken into account. A look at the ERDI shows that dependence is a more diverse topic than previously presented. Households who are not dependent according to REI are nevertheless dependent according to the ERDI.

There are also differences in the relationship between farming efficiency and environmental resource dependence. Using the ERDI shows that efficiency and dependence are negatively linked. Improved farming efficiency helps to reduce dependence. More agricultural income partially offsets income and consumption from formerly extracted products.

Simultaneously reducing poverty and strain on environmental resources is an overarching goal that poses numerous challenges. Restoring degraded ecosystems is a long-term task, but protecting the natural resource base is urgently needed and poor people must survive now. Improving farming efficiency makes a crucial contribution to reducing poverty, resource dependence and environmental exploitation. Policies must be tailored to the needs of environmentally dependent people. In this context, the proper identification of these people is important. Additionally, a biased focus on agriculture can create another poverty trap as agriculture becomes increasingly exposed to the risk of natural disasters. Therefore, policymakers should also focus on off-farm employment as an alternative to farming. In addition, promoting education that enables other livelihood strategies is essential. Protecting ecosystems requires a collective and sustainable management of natural resources.

Although the ERDI is a relative index that cannot be compared across samples due to its construction and context sensitivity, it allows for a more comprehensive understanding of environmental resource dependence. Therefore, it is necessary to analyse how the ERDI is related to other livelihood strategies. With regard to agriculture, it might be useful to further consider the heterogeneous impacts of different groups of farmers. This should be the subject of future research.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon request subject to the agreement of data confidentiality.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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