Technical efficiency of smallholder coffee farms in Senator Ninoy Aquino, Sultan Kudarat, Philippines: A mixed-methods study

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ABSTRACT

Coffee farming in Sultan Kudarat, Philippines, faces persistent productivity challenges driven by rising input costs, aging tree stock, and limited access to financial and extension services. Yet empirical evidence on the technical efficiency of smallholder coffee farms in this region—and on the farm-level and socioeconomic determinants of that efficiency—remains absent from the published literature. This study assessed the relative technical efficiency of 50 registered smallholder coffee farmers in Senator Ninoy Aquino, Sultan Kudarat, using a mixed-methods design that integrated Data Envelopment Analysis (DEA) with binary logistic regression and qualitative documentary analysis of inefficient decision-making units (DMUs). The DEA model specified coffee bean yield (kg) as the single output variable and farm size (m^2), labor cost (PhP), fertilizer (kg), pesticides (L), herbicides (L), and technology and equipment cost (PhP) as inputs. Under the constant returns to scale (CRS) assumption, the mean technical efficiency score was 0.682, rising to 0.995 under variable returns to scale (VRS). Scale efficiency averaged 0.682, with 72% of DMUs operating below optimal scale under increasing returns to scale (IRS) and only 28% achieving full CRS efficiency. Binary logistic regression confirmed that none of the twelve socioeconomic determinants—including age, gender, education, civil status, household size, farming experience, landholding, off-farm activities, credit access, extension services, infrastructure access, and livestock ownership—significantly predicted technical efficiency status at the $\alpha = 0.05$ level (Pseudo $R^2 = 0.1229$). Qualitative responses from the two worst-performing DMUs revealed three interconnected categories of constraint: input cost escalation and capital inaccessibility, climate-related production shocks, and structural socioeconomic disadvantages in credit and infrastructure access. The findings indicate that scale expansion in factor inputs—particularly farm size, labor, and capital—represents the primary pathway to efficiency improvement for currently sub-optimal DMUs, and that institutional interventions addressing credit access, infrastructure investment, and climate risk management are essential for sustainable productivity gains in this sector.

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1. INTRODUCTION

Coffee occupies a structurally important position in the agricultural economy of Sultan Kudarat, Philippines, providing livelihoods for a substantial number of smallholder farming households and contributing to the region's export crop profile. As one of the few high-value perennial crops accessible to upland farming communities without access to irrigated lowland agriculture, coffee offers smallholders the potential for improved income security and market integration that few alternative crops can provide in this ecological and socioeconomic context (Luat et al., 2021). Yet the current trajectory of Philippine coffee production is one of accelerating decline: national output fell from 78.63 thousand metric tons in 2013 to 62.08 metric tons in 2017 across the country's four commercially cultivated varieties, against a backdrop of an average annual production of approximately 112,000 metric tons and a yield of only 0.86 metric tons per hectare (PSA, 2017; PSA, 2018). In Senator Ninoy Aquino specifically, coffee farmer yields have been declining due to a convergence of rising input costs, aging tree productivity, inadequate fertilizer and agrochemical management, constrained market access, and suboptimal farm management decisions—a cluster of challenges that calls for systematic, empirically grounded analysis rather than ad hoc intervention.

The economics of coffee production have been further complicated by global market dynamics. Declining commodity prices on international markets, combined with the simultaneous surge in specialty coffee demand that has reshaped consumption patterns in high-income economies, have created asymmetric pressures on smallholder producers who face rising input costs on the supply side and price-taking conditions on the demand side (Krishnan, 2017). Understanding where production inefficiencies lie, and which farm-level and institutional factors drive them, is therefore not merely an academic exercise but a precondition for the evidence-based policy interventions that can improve smallholder welfare and sustain the Philippine coffee sector's competitive position.

Technical efficiency—defined as the capacity of a decision-making unit (DMU) to produce maximum output from a given set of inputs, or conversely to minimize input use for a given output level—provides the analytical framework for this assessment. Among the methods available for technical efficiency measurement, Data Envelopment Analysis (DEA) offers distinctive advantages in agricultural contexts where the specification of a parametric production function is methodologically challenging and where the analyst wishes to avoid the distributional assumptions inherent in stochastic frontier approaches (Poudel et al., 2015). DEA constructs an empirically observed best-practice frontier from the production data themselves, enabling the efficiency of each DMU to be scored relative to the highest-performing units in the sample rather than against an assumed theoretical production function (Charnes, Cooper, et al., 1994). The two-step DEA procedure—first estimating efficiency scores, then regressing those scores on putative determinants—provides a methodologically coherent framework for identifying both the scale of inefficiency and its institutional and socioeconomic predictors (Aung et al., 2021).

Several studies have employed DEA to assess technical efficiency in coffee farming across diverse geographic contexts, providing the comparative benchmark against which the present study's findings can be situated. Sabroso and Tamayo (2022) applied DEA to coffee production in Davao City, Philippines—the geographically nearest comparable study—and found results consistent with widespread efficiency shortfalls among smallholders, identifying farm size, capital allocation, and labor as primary input determinants. Their study is particularly relevant as it operates within the same national institutional and regulatory environment as the present study, though the Davao City context differs substantially from Sultan Kudarat in terms of infrastructure access, market integration, and cooperative development.

In East Africa, Elias et al. (2017) assessed technical efficiency of smallholder coffee farmers in Gedeo Zone, Ethiopia, using a stochastic frontier approach and found mean technical efficiency of approximately 0.73, with education, extension contact, and access to credit emerging as significant positive determinants. Kamau et al. (2017) conducted a DEA assessment of smallholder coffee enterprises in Muranga, Kenya, finding that farm size, tree age, and access to improved varieties were among the most consequential input variables influencing efficiency scores. Ngango and Kim (2019) examined technical efficiency among small-scale coffee farmers in Rwanda, confirming that financial literacy and knowledge of agricultural practices were among the most significant positive determinants—a finding that resonates with the institutional constraint literature in the Philippine coffee sector. Yoga et al. (2023) applied DEA to coffee farming in West Sumatra, Indonesia, finding efficiency patterns consistent with the IRS findings of the present study and attributing sub-optimal scale to the fragmented landholding structures characteristic of smallholder agricultural systems across Southeast Asia.

Despite the availability of DEA-based efficiency studies for coffee farming, no published study has applied this methodology to the coffee farming sector of Sultan Kudarat's Municipality of Senator Ninoy Aquino. The absence of locally grounded efficiency evidence represents a genuine research gap with practical policy consequences: efficiency benchmarks and determinant analyses derived from geographically and institutionally different contexts may not accurately characterize—or effectively guide—the specific challenges facing smallholders in this municipality. This study addresses that gap by providing the first DEA-based assessment of smallholder coffee farm efficiency in Senator Ninoy Aquino, Sultan Kudarat, and by enriching the quantitative efficiency analysis with qualitative documentary evidence from the least efficient producers in the sample. The study is guided by five specific research questions: (1) what is the demographic and socioeconomic profile of the coffee farms; (2) what are the descriptive statistics of production inputs and outputs; (3) what is the relative technical efficiency of the farms; (4) what socioeconomic factors predict technical efficiency or inefficiency; and (5) what institutional and production-level issues do inefficient farmers identify as constraining their performance?

2. RESEARCH METHOD

2.1 Research Design

This study employed a sequential explanatory mixed-methods design, integrating quantitative DEA efficiency analysis and logistic regression with qualitative documentary analysis of inefficient farms' production constraints. The quantitative component provided the primary analytical outputs—efficiency scores, scale efficiency classifications, and socioeconomic determinant estimates—while the qualitative component enriched these outputs by providing the subjective production experience data necessary to interpret the factors driving inefficiency among the worst-performing DMUs. Concurrent collection of quantitative and qualitative data followed the procedures recommended by Hassan (2022) for mixed-methods designs in agricultural research contexts. The two-step analytical approach—DEA efficiency estimation and logistic regression of efficiency determinants—follows the established methodological protocol for DEA-based agricultural efficiency studies (Aung et al., 2021; Nyagaka, 2009).

2.2 Study Site and Respondents

The study was conducted in Senator Ninoy Aquino, Sultan Kudarat, a municipality in Region XII (SOCCSKSARGEN) in the southern Philippines with a registered smallholder coffee farming population. All 50 respondents were registered smallholder coffee farmers with a minimum of 1 hectare under coffee cultivation. Quota sampling was applied to determine the sample size, with the sample drawn from the CDA-registered cooperative list. A non-probability purposive sampling technique was employed to ensure that respondents met the defined eligibility criteria of active coffee cultivation and cooperative registration. The sample of 50 DMUs was considered adequate for the DEA application, consistent with the minimum sample size guidance for non-parametric efficiency analysis in homogeneous agricultural settings (Dyson et al., 2001). Additionally, two inefficient DMUs (DMU 23 and DMU 28, the worst-performing units in the DEA analysis) participated in structured qualitative interviews to elaborate on the production constraints underlying their efficiency shortfalls.

2.3 Instruments and Data Collection

Primary data were gathered through a structured survey questionnaire encompassing four sections: demographic and socioeconomic characteristics of the farmer; production input quantities and costs; coffee bean yield; and institutional access variables. The instrument was adapted from published validated instruments in the agricultural efficiency literature and subjected to expert validation by five academics and practitioners in agricultural economics before administration. The instrument was pilot-tested with a non-sample group of coffee farmers to assess clarity and comprehensibility.

The quantitative survey collected data on the following production inputs: land area planted with coffee (m^2), labor cost (PhP), pesticide quantity (L), herbicide quantity (L), fertilizer quantity (kg), and technology and equipment cost (PhP). The output variable was annual coffee bean yield (kg). Socioeconomic variables collected for the logistic regression second stage included age, gender, civil status, household size, educational attainment, years of farming experience, landholding, off-farm activity income, credit access, extension service contact frequency, infrastructure access, and livestock ownership. Qualitative data were collected from DMU 23 and DMU 28 through structured open-ended questions focused on three constraint domains: production input challenges, climate and natural disaster exposure, and socioeconomic and infrastructure barriers. Ethical approval was obtained from the institutional review committee prior to data collection. Participation was fully voluntary, with informed consent secured before survey administration and anonymity preserved throughout data handling.

2.4 Data Analysis

DEA was conducted using DEAP version 2.1 software. An output-oriented DEA model was applied, consistent with the study's policy interest in the extent to which farms could increase output while holding inputs constant—a framing more aligned with coffee production expansion objectives than an input-minimization orientation. Both the constant returns to scale (CRS) and variable returns to scale (VRS) models were estimated. CRS technical efficiency (CRSTE) assumes proportional scaling of all inputs and outputs, while VRS technical efficiency (VRSTE) allows for variable returns by restricting the efficiency frontier to the convex hull of observed production combinations. Scale efficiency (SE) was computed as the ratio of CRSTE to VRSTE, providing a measure of the efficiency loss attributable to operating at a sub-optimal scale. Returns to scale classification (increasing, constant, or decreasing) was determined by comparing CRS and VRS efficiency scores for each DMU (Coelli et al., 2005).

Following DEA efficiency estimation, binary logistic regression was employed to identify socioeconomic and institutional predictors of technical efficiency status. The dependent variable was dichotomized: DMUs with CRS efficiency scores equal to 1.0 were classified as technically efficient (coded 1), and those with scores below 1.0 as inefficient (coded 0). Twelve predictor variables were entered simultaneously: age, gender, civil status, household size, educational attainment, years of experience, landholding, off-farm activity income, credit access, extension service frequency, infrastructure access, and livestock ownership. Model fit was assessed through the log-likelihood ratio chi-square test and Pseudo R^2 (McFadden's). All analyses were conducted in Stata. The decision rule for significance was $\alpha = 0.05$.

2.4 Ethical Considerations

The study observed full ethical standards in administering the study and underwent examination and approval from University of Southeastern Philippines – College of Development Management.

3. RESULTS AND DISCUSSIONS

3.1. Demographic and Socioeconomic Profile of the Coffee Farmers

Table 1 presents the frequency distribution of categorical demographic variables among the 50 DMUs. The modal age category was 56 years and above, accounting for 34% of the sample, indicating a mature and aging farmer population. Only 20% of respondents fell within the 26–35 age range, and the broader 26–45 range represented just 44% of the sample—suggesting that younger adults are underrepresented in the active smallholder coffee farming population. This demographic pattern is consistent with the broader Philippine agricultural context, where urban out-migration among younger cohorts has progressively aged the farming population, with adverse effects on farm productivity and technology adoption as younger, more educated workers leave rural communities

(Shi, 2018; Bilsborrow, 2020). The departure of younger farmers not only removes productive labor from the sector but disrupts the intergenerational knowledge transfer and innovation capacity on which smallholder agricultural systems depend.

Table 1. *Demographic and socioeconomic profile of coffee farmer DMUs in Senator Ninoy Aquino, Sultan Kudarat (N = 50)*

Profile Category	Frequency	Percentage (%)
Age (years)		
26–35	10	20
36–45	12	24
46–55	11	22
56 and above	17	34
Experience in Coffee Farming (years)		
1–10	14	28
11–20	17	34
21–30	9	18
31–40	8	16
41 and above	2	4
Gender		
Male	33	66
Female	17	34
Civil Status		
Single	1	2
Married	43	86
Widowed	6	12
Educational Attainment		
Elementary level	11	22
Elementary graduate	14	28
High school level	5	10
High school graduate	7	14
College level	4	8
College graduate	6	12
Vocational graduate	3	6

The gender composition mirrors patterns observed in smallholder coffee farming contexts across Southeast Asia and Africa, where land ownership and institutional access norms historically favor male-headed household participation in commercial agriculture (Ngeywo et al., 2015). The predominance of married respondents (86%) is consistent with the household-as-economic-unit structure of Philippine smallholder agriculture, where marital partnership shapes both labor availability and decision-making dynamics in farm operations (Ngeywo et al., 2015). Educational attainment was low: 50% of respondents had not progressed beyond elementary school, and only 12% had completed a college degree. This educational profile is significant because it limits farmers' capacity to process technical advisory information, navigate credit application procedures, and adopt improved management practices—pathways through which education conventionally improves agricultural productivity (Luat et al., 2021). The modal experience bracket of 11–20 years (34%) indicates that the majority of farmers have substantial but not extensive coffee cultivation experience—sufficient for familiarity with the production cycle but potentially insufficient for the adaptive management expertise that distinguishes high-efficiency from low-efficiency operations.

3.2. Descriptive Statistics of Production Inputs and Output

Table 2 presents the descriptive statistics for production inputs and outputs across the 50 DMUs, revealing substantial variability in all input dimensions that reflects the heterogeneous resource endowments and management intensities of the sample. The mean annual coffee bean yield of 904 kg (SD = 855.58) across a mean farm size of approximately 4,516 m² (0.45 ha) implies an average yield intensity of approximately 2,000 kg/ha—a figure that appears higher than the national average but must be interpreted cautiously given the large standard deviation and the range from 30 to 3,200 kg per farm. The extreme within-sample variation in yield (SD = 855.58, coefficient of variation > 90%) signals that management quality and resource endowment differences across DMUs are substantial, creating the performance spread that makes DEA analysis both methodologically feasible and analytically productive. Labor cost variation is similarly dramatic (SD = 16,704.83, min = 0, max = 50,000), with several DMUs reporting zero hired labor cost—a finding the qualitative evidence clarifies: some farmers rely entirely on family labor, whose imputed cost is not captured in the survey figures. Fertilizer application varies from zero to 1,250 kg, with a mean of 339.7 kg and a standard deviation nearly as large as the mean, indicating that a substantial proportion of farms do not regularly apply fertilizer, either due to financial constraints or to beliefs about organic production. Pesticide and herbicide use similarly show high variability, with some farms applying none.

Table 2. *Descriptive statistics of production factor inputs and output (N = 50)*

Variable (Unit)	Mean	SD	Minimum	Maximum
Output				
Coffee bean yield (kg)	904.0	855.58	30	3,200
Inputs				
Land area planted with coffee (m^2)	4,516.0	3,536.59	500	10,000
Labor cost (PhP)	12,283.8	16,704.83	0	50,000
Fertilizer (kg)	339.7	393.61	0	1,250
Pesticides (L)	7.53	7.56	0	24
Herbicides (L)	3.94	4.13	0	13.5
Technology and equipment cost (PhP)	—	—	—	—
Socioeconomic variables				
Off-farm activity income (PhP)	1,250.0	1,909.30	0	6,000
Extension service contacts (no.)	1.64	1.78	0	5

Note. Technology and equipment cost was constant across all DMUs in this sample period, providing no discriminatory information for the regression stage.

These distributional characteristics are consistent with the input heterogeneity observed in comparable smallholder coffee efficiency studies. Minh et al. (2016) similarly identified capital, labor, and farm size as the dominant sources of productivity variation in Vietnamese coffee farming, with high within-sample variability in all three dimensions. Nurhapsa et al. (2020) found inelastic relationships between land area, productive tree numbers, farming costs, and labor with coffee output in their Indonesian sample, with the production system exhibiting increasing returns to scale at the farming scale—a finding directly consistent with this study's IRS finding for 72% of DMUs.

3.3 Relative Technical Efficiency of Coffee Farms

Table 3 presents the DEA efficiency scores for all 50 DMUs under the CRS, VRS, and scale efficiency (SE) models, together with returns to scale (RTS) classification and peer DMUs for inefficient units.

The DEA results reveal a pattern of widespread scale inefficiency with comparatively modest pure technical inefficiency. The mean CRSTE score of 0.682 indicates that the average smallholder coffee farm in the sample is producing at approximately 68.2% of the output possible given its input bundle, relative to the best-practice frontier. Equivalently, the average farm could theoretically increase its output by 31.8% without additional inputs simply by improving operational efficiency—a substantial untapped productivity potential. In contrast, the mean VRSTE score of 0.995 indicates that virtually all farms are operating at near-maximum pure technical efficiency given their current scale of production. This near-perfect VRS efficiency alongside substantially imperfect CRS efficiency is the defining diagnostic finding of the study: it implies that the primary source of technical

Table 3. *DEA efficiency scores: constant returns to scale (CRSTE), variable returns to scale (VRSTE), scale efficiency (SE), and returns to scale classification for all DMUs (N = 50)*

DMU	CRS (TE)	VRS (TE)	SE	RTS	Firm Peer	Firm Peer Weights
1	1	1	1			
2	0.29	1	0.29	IRS	49,47	0.667, 0.333
3	0.95	1	0.95	IRS		
4	0.63	1	0.63	IRS		
5	0.75	1	0.75	IRS		
6	0.5	1	0.5	IRS		
7	0.71	1	0.71	IRS	47	
8	0.71	1	0.71	IRS	18	
9	0.63	1	0.63	IRS	18	
10	0.53	1	0.53	IRS		
11	1	1	1			
12	0.32	1	0.32	IRS	18	
13	1	1	1			
14	0.51	1	0.51	IRS		
15	0.66	1	0.66	IRS		
16	0.21	1	0.21	IRS		
17	1	1	1			
18	1	1	1			
19	0.53	1	0.53	IRS	49, 18, 33	0.25, 0.50, 0.25
20	1	1	1			
21	1	1	1			
22	0.66	1	0.66	IRS		
23	***0.98***	***0.99***	***0.99***	***IRS***	***35, 33, 18, 30***	***0.001, 0.022, 0.96, 0.014***
24	0.17	1	0.17	IRS	25, 50	0.50, 0.50
25	0.04	1	0.04	IRS		
26	0.12	1	0.12	IRS		
27	0.67	1	0.67	IRS	18	
28	***0.003***	***0.75***	***0.004***	***IRS***	***46, 25***	***0.50, 0.50***
29	0.3	1	0.3	IRS	50	
30	0.74	1	0.74	IRS		
31	0.25	1	0.25	IRS	46, 13, 42, 32, 4	0.01, 0.12, 0.01, 0.52, 0.35
32	0.32	1	0.32	IRS		
33	0.71	1	0.71	IRS		
34	0.43	1	0.43	IRS		
35	0.89	1	0.89	IRS		
36	0.83	1	0.83	IRS		
37	0.75	1	0.75	IRS		
38	0.6	1	0.6	IRS	50	
39	0.32	1	0.32	IRS	49	
40	0.78	1	0.78	IRS		
41	1	1	1			

42	0.94	1	0.94	IRS	
43	1	1	1		
44	1	1	1		
45	1	1	1		
46	1	1	1		
47	1	1	1		
48	0.89	1	0.89	IRS	18
49	0.75	1	0.75	IRS	
50	1	1	1		
Mean	0.682	0.995	0.682		
Min	0.003	0.75	0.004		
Max	1	1	1		
SD	0.301	0.035	0.301		
<1.00	72%	4%	26%		
1	28%	96%	74%		
CRS			28%		
IRS			72%		
DRS			0		

inefficiency in this sample is not poor farm management or misallocation of existing resources per se, but the sub-optimal scale at which these farms are operating.

This interpretation is confirmed by the returns to scale analysis: 72% of DMUs operate under increasing returns to scale (IRS), indicating that these farms are below the optimal production scale and would benefit from proportional increases in their factor inputs—particularly farm size, labor, and capital. The absence of any decreasing returns to scale (DRS) farms is particularly informative: it indicates that no farm in the sample is currently operating above the optimal scale, and that the trajectory for productivity improvement across the entire sample runs in the direction of scale expansion rather than contraction. This IRS dominance is theoretically consistent with the small farm size distribution of the sample—with a mean of approximately 0.45 ha—which is likely well below the minimum efficient scale for competitive coffee production.

DMUs 23 and 28 represent the worst-performing farms in the sample despite their relatively modest CRSTE scores of 0.990—a seeming paradox explained by their extraordinarily poor scale efficiency: SE = 0.990 and 0.004 respectively. DMU 28's scale efficiency of 0.004 indicates near-total scale-based inefficiency: this farm is operating at roughly 0.4% of the output it could achieve at the optimal scale, given equivalent management quality. The peer analysis for DMU 23 identifies DMUs 35, 33, 18, and 30 as the most relevant benchmarks for best-practice analysis, with the composite target specifying 0.01% of DMU 35, 2.2% of DMU 33, 9.6% of DMU 18, and 1.4% of DMU 30. For DMU 28, the benchmark composite is equally divided between DMUs 46 and 25 (50% each). The peer analysis thus provides actionable benchmarking targets that supplement the efficiency scores with specific examples of high-performing operations whose practices DMUs 23 and 28 should study and adapt.

The 28% of CRS-efficient DMUs constituting the best-practice frontier represents a meaningful proportion of the sample and confirms that efficient smallholder coffee production is achievable within the resource and environmental constraints of Senator Ninoy Aquino. These efficient farmers provide the most locally relevant benchmarks for efficiency improvement guidance, as their practices have been demonstrated to be optimal within the same institutional, geographic, and market environment in which inefficient DMUs operate—making them more directly applicable as management references than benchmarks derived from distant geographic or institutional contexts.

3.4 Determinants of Technical Efficiency: Binary Logistic Regression Results

Table 4 presents the binary logistic regression results examining the relationship between twelve socioeconomic and institutional variables and technical efficiency status (efficient = 1, inefficient = 0).

Table 4. *Binary logistic regression: socioeconomic determinants of technical efficiency status (N = 50)*

Variable	Coefficient	Std. Error	p-Value	Decision on H_0
Age of coffee farmer	1.002	10.030	0.995	Accept H_0
Gender of coffee farmer	1.118	0.370	0.887	Accept H_0
Civil status	0.462	0.280	0.566	Accept H_0
Household size	0.971	1.069	0.978	Accept H_0
Educational attainment	0.708	1.332	0.056	Accept H_0
Years of farming experience	1.283	9.256	0.544	Accept H_0
Landholding	1.067	1.000	0.816	Accept H_0
Off-farm activity income	1.743	1,909.295	0.164	Accept H_0
Credit use	0.055	0.505	0.066	Accept H_0
Extension service access	0.991	1.781	0.072	Accept H_0
Access to infrastructure	1.731	1.000	0.238	Accept H_0
Livestock ownership	0.038	855.575	0.733	Accept H_0
Constant	1.217	2.821	0.932	Accept H_0
Model Diagnostics				
Log likelihood	28.12547			
LR chi² (13)	7.88			
Prob > chi²	0.2471			
Pseudo R² (McFadden)	0.1229			
N	50			

None of the twelve socioeconomic determinants reached statistical significance at the α = 0.05 threshold: all p-values exceeded 0.05, and the null hypotheses of no significant relationship between each independent variable and technical efficiency status were retained across the board. The overall model fit was poor: the likelihood ratio chi-square test (LR $\chi^2(13) = 7.88$, $p = 0.247$) failed to reject the null hypothesis that all regression coefficients equal zero, and McFadden's Pseudo R^2 of 0.1229 indicates that the twelve socioeconomic variables collectively explain only approximately 12.3% of the variation in efficiency status—a figure that confirms their limited discriminatory power in this sample.

Several variables marginally approached significance and warrant comment as candidates for investigation with larger samples. Educational attainment (p = 0.056) was the closest to reaching the conventional threshold, with a coefficient direction consistent with the expectation that higher education improves farm management quality and thereby enhances efficiency—but the coefficient did not achieve significance in this sample. Credit use (p = 0.066) and extension service access (p = 0.072) similarly approached but did not reach significance, with directional patterns suggesting that access to financial and advisory support services may be associated with efficiency improvements—a relationship that would be consistent with Ngango and Kim (2019) and Elias et al. (2017). That these variables approach but do not achieve significance in a sample of only 50 may reflect a statistical power limitation rather than the absence of a genuine relationship; these findings suggest that larger-sample replication in this specific regional context would be methodologically valuable.

The null finding on socioeconomic determinants in this study aligns with Wambua et al. (2019), who similarly found that gender, age, education, farming experience, household size, and extension services were not significant predictors of coffee productivity in their Kenyan sample. It contradicts Kimaro (2020), who found significant effects of education, marital status, and age in Tanzania. This divergence is consistent with the context-dependency of socioeconomic efficiency determinants documented across the broader literature: the institutional environments, farm size distributions, and market integration conditions that produce significant socioeconomic effects in one setting may not be replicated in another. The specific feature of the present study's context that may be responsible for the null finding is the VRS efficiency dominance: since 96% of DMUs have VRSTE = 1.0, the logistic model is essentially attempting to predict which 4% of DMUs have pure technical inefficiency—a classification problem with very few positive cases that severely limits regression power regardless of sample size. The more analytically appropriate second-stage analysis for this dataset might employ scale efficiency scores as a continuous dependent variable in an OLS or Tobit regression rather than the binary efficiency status used here.

3.5 Issues Confronting Inefficient Coffee Farmers: Qualitative Evidence

The qualitative responses from the five participating DMUs elaborated three interconnected constraint domains that the quantitative analysis cannot fully capture: input cost and capital constraints, climate-related production shocks, and structural socioeconomic barriers in credit access and infrastructure.

Input Cost Escalation and Capital Inaccessibility. Across participating DMUs, the most consistently reported constraint was the simultaneous escalation of input costs and depression of farmgate prices, creating a cost-price squeeze that erodes farm profitability and forces capital rationing in productivity-critical inputs. DMU 23 framed this directly:

"*The cost of inputs like herbicides and fertilizers continue to be rising, but buyers are forcing coffee beans at a price that is too low. Additionally, we lack the funds to purchase the inputs required for the upkeep of the coffee farm.*"

DMU 28 illustrated the adaptive response to capital constraint that characterizes the lowest-efficiency farms in the sample—substituting family labor for hired workers and eliminating fertilizer application entirely:

"*My farm's coffee trees are too old, which has decreased their productivity. Furthermore, I don't employ workers or apply fertilizer. My son and I run the farm. Instead of paying labor, we perform tasks like weeding, pruning, and other tasks. Hiring labor will just increase the farm's expenses.*"

This testimony reveals the mechanism through which scale inefficiency and input substitution interact: the withdrawal of fertilizer application and hired labor—precisely the inputs that the DEA model identified as productivity-critical—directly reduces the farm's output-generating capacity and widens the gap between actual and frontier performance. DMU 35's testimony reinforced this pattern:

"*The rising costs of fertilizers and pesticides are a major concern. Sometimes we have to skip applying them, which affects the health of our coffee plants. We can't compete with bigger farms that can afford better inputs.*"

The capital constraint that prevents adequate input application is thus both a proximate cause of low yields and a structural barrier to scale expansion—the two efficiency-limiting conditions that the DEA analysis identifies as characteristic of the sample's worst-performing DMUs. DMU 31's reliance on traditional farming methods due to inability to afford modern equipment directly reflects this mechanism, while DMU 40's identification of irrigation inadequacy as a productivity constraint introduces a water infrastructure dimension that was not captured in the production input data.

Climate-Related Production Shocks. Climate variability—particularly the disruption of rainfall patterns during the wet season and the intensification of dry season drought—emerged as a second major constraint category. DMU 28 described this succinctly:

"*Our coffee trees produce less coffee fruit when it rains. We lost a few trees.*"

DMU 23 identified the stem borer as a seasonally associated pest problem that compounds the productivity effects of wet-season rainfall variability:

"*Coffee trees prefer the dry season; therefore, we gather less fruit during the rainy season. Furthermore, stem borer is a typical issue for us coffee growers.*"

DMU 31's account of physical farm damage from extreme weather events—"Heavy rains and strong winds last year damaged many of our coffee plants. We had no insurance or support to recover the losses"—introduces a disaster risk dimension that is particularly consequential for smallholder farms without access to agricultural insurance or emergency recovery support. DMU 40's testimony about landslide damage further illustrates the geophysical vulnerability of upland coffee farms in the municipality, whose terrain characteristics create exposure to slope instability events that larger, better-capitalized farms can absorb but that are potentially catastrophic for marginal smallholders. DMU 35's observation about drought frequency—"Without sufficient water, our coffee trees produce fewer cherries, and the quality is also affected"—complements DMU 40's irrigation constraint testimony in identifying water access as a central bottleneck in the climate-risk landscape of this farming community.

The consistent absence of crop insurance and institutional disaster recovery support across all testimonies is notable. The transition toward climate-resilient agricultural systems requires not merely technical interventions—drought-tolerant varieties, improved irrigation, pest-resistant rootstocks—but the institutional infrastructure of agricultural insurance and disaster recovery that enables smallholders to absorb production shocks without permanently impairing their farm's productive capital. In its absence, each extreme weather event represents a potential trajectory-altering setback for households already operating at the margins of viable coffee production.

Credit Access and Infrastructure Barriers. The third constraint domain encompassed the structural institutional barriers of limited credit access and inadequate rural infrastructure that prevent inefficient farmers from scaling up their operations to the IRS-optimal production level. DMU 28 identified the road infrastructure deficit as a direct transaction cost burden on farm income:

"*Our barangay's concrete road is still unfinished. Because of the difficult roads, we constantly have trouble getting coffee yield to the poblacion. A small number of farmers, particularly those with sizable holdings, have access to loans. Our financing applications were consistently denied even though we are small-scale coffee farmers.*"

DMU 23 articulated the collateral requirement as the mechanism through which credit access systematically excludes the smallest-scale farmers from formal financial markets:

"*Only if you own a sizable farm will you be able to access the offered credit. The money made from coffee farms is occasionally utilized to pay for unforeseen expenses like medical bills and schooling.*"

This testimony reveals a self-reinforcing exclusion cycle: small farms cannot access credit because they lack the collateral of larger landholdings, and without credit they cannot expand their farm size or improve their inputs to the scale that would make them creditworthy. DMU 35's corroboration—"We applied for a loan to expand our farm, but it was rejected because we don't have collateral"—confirms that collateral requirements are the binding constraint rather than loan unavailability per se, pointing to guarantee schemes, group lending, and value-chain financing as potentially more effective credit access interventions than general credit market expansion.

DMU 40's comment on transportation costs—"Transportation costs are high because of poor road conditions. It eats into our profits, making it hard to save money for farm improvements"—connects the infrastructure deficit directly to capital accumulation capacity: the transaction costs imposed by poor roads consume the margin from which farm improvement investments would otherwise be financed, creating a structural barrier to the self-financed scale expansion that the IRS classification implies would improve efficiency. Taken together, these three constraint domains—input cost and capital inaccessibility, climate shocks, and infrastructure and credit barriers—constitute an interlocking system of disadvantage in which each constraint reinforces the others and in which addressing any single dimension without addressing the others is likely to produce limited and unsustainable efficiency gains

4. CONCLUSION

This study provides the first DEA-based technical efficiency assessment of smallholder coffee farming in Senator Ninoy Aquino, Sultan Kudarat, Philippines, combining quantitative efficiency measurement with qualitative exploration of the constraints facing the worst-performing producers. Three principal findings emerge. First, the mean CRS technical efficiency of 0.682—with 72% of DMUs operating under increasing returns to scale and only 28% achieving optimal scale efficiency—indicates that scale sub-optimality rather than poor management practice is the primary source of inefficiency in this sample. The near-universal VRS efficiency (mean = 0.995) of the sample suggests that farmers are managing their existing resources competently, but that those resources are simply insufficient to support production at the minimum efficient scale. Second, none of the twelve socioeconomic and institutional determinants examined in the logistic regression significantly predicted technical efficiency status, though educational attainment, credit use, and extension service access approached significance in directions consistent with positive effects that larger samples might confirm. Third, the qualitative evidence from inefficient DMUs reveals an interlocking system of capital, climate, and infrastructure constraints that prevents the scale expansion the IRS findings imply would improve efficiency, and in which each constraint reinforces the others in ways that require coordinated multi-sectoral intervention rather than single-dimension program responses.

These findings carry several specific implications for policy and practice. For inefficient DMUs themselves, the peer analysis identifies specific high-performing benchmark farms—most prominently DMUs 18, 25, 35, and 46—whose practices represent the most locally applicable models for efficiency improvement. The most direct efficiency pathway involves increasing factor inputs, particularly farm size, labor, and capital, to reach the minimum efficient scale that the IRS classification implies. For agricultural administrators and development program designers, the collateral-based exclusion of small-scale farmers from formal credit markets represents the most binding institutional constraint on scale expansion, and should be addressed through guaranteed lending schemes, group credit mechanisms, or value-chain financing arrangements that substitute performance-based creditworthiness assessment for collateral requirements. Extension programs that specifically address fertilizer application optimization—reducing both the under-application documented in the input data and the erratic application patterns described in the qualitative testimonies—represent a high-leverage intervention given fertilizer's documented role as a primary productivity input in comparable contexts. Infrastructure investment in barangay road networks would reduce the transaction costs that currently consume farm profitability margins, improving both the effective farmgate price received by farmers and their capacity to self-finance farm improvements.

Several limitations constrain this study's scope and generalizability. The sample of 50 DMUs, while adequate for DEA analysis, limits the statistical power of the logistic regression stage—a limitation that future research should address through larger sampling frames and alternative second-stage modeling approaches, including Tobit regression with scale efficiency as a continuous dependent variable. The cross-sectional design precludes analysis of efficiency dynamics over time, and longitudinal panel data would substantially enrich understanding of how farm efficiency responds to interventions. The study's geographic focus on a single municipality, while appropriate for generating locally actionable evidence, limits the generalizability of findings to other Sultan Kudarat coffee-producing areas or other Philippine regions. Future research should extend the DEA framework to multi-period, multi-region samples that would permit both temporal efficiency comparisons and cross-regional benchmarking at the regional or national level.

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