

SAND MINING (SAND WINNING) AS A DRIVER OF AGRICULTURAL INCOME LOSS AND LIVELIHOOD DEGRADATION: A TOBIT AND BINARY LOGISTIC REGRESSION ANALYSIS FROM THE WHITE VOLTA BASIN, GHANA

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Abstract

Sand mining, locally termed sand winning, is an economically significant but environmentally destructive activity that has spread along major river systems in Ghana, including the White Volta in the Northern Region. Despite anecdotal evidence of its impacts on farming communities, econometric evidence on its effects on smallholder agricultural income and food security remains scarce. This study estimates the effects of sand mining exposure on seasonal agricultural income and selected livelihood outcomes using primary data from 66 smallholder farmers in three communities of the Kumbungu and Nanton Districts: Nawuni, which is directly affected by sand mining, and Saakuba and Zuo, which serve as comparators. A Tobit regression model is used to analyse the determinants of censored agricultural income per season, while binary logistic regression models estimate the probability of farm size reduction and food security deterioration. The Tobit results indicate a negative association between residence in the sand-mining-affected community and agricultural income category ($\beta = -0.614$, $p < 0.01$), after controlling for farm characteristics, socioeconomic variables, and institutional access. Sand mining exposure also significantly increases the odds of farm size reduction (odds ratio = 4.22, $p < 0.01$) and food insecurity (odds ratio = 3.68, $p < 0.01$). Key informants confirmed that no sand mining operator in the study area holds a regulatory licence, indicating a critical governance failure. Enforcement of existing regulations, reclamation of excavated farmland, and alternative livelihood provision are urgent policy priorities.

Keywords: riverine aggregate extraction, smallholder farmers, farmland loss, food insecurity, environmental governance, censored regression, Northern Ghana

JEL classification: Q15, Q24, Q56

1. Introduction

Sand and gravel mining, the extraction of construction aggregate from riverbeds, floodplains, and terrestrial deposits, is among the world's most widespread extractive industries. Global demand for sand, driven by rapid urbanisation and construction sector growth, is estimated at 40–50 billion tonnes annually, making sand the most consumed natural resource after water (UNEP, 2019). In developing countries, including Ghana, riverine sand extraction, locally termed sand winning, provides construction aggregate for urban growth while generating employment and income for rural communities with limited livelihood options (Langer & Glanzman, 1993). Yet the environmental and socioeconomic costs of unregulated sand mining are increasingly documented: riverbed incision, bank erosion, water turbidity, farmland inundation, aquatic habitat destruction, and road infrastructure damage (Kondolf et al., 2018; Owusu-Nimo et al., 2018).

In Ghana's Northern Region, sand mining along the White Volta and its tributaries has emerged as a particularly acute livelihood and environmental governance challenge. The White Volta Basin traverses some of the country's most food-insecure districts, where smallholder rain-fed agriculture is the primary livelihood for the majority of the rural population. Sand mining in communities such as Nawuni, where the White Volta serves as the primary water intake point for the Ghana Water Company Limited (GWCL) supplying the Tamale Metropolis, is not only destroying farmland and collapsing river banks but is also polluting the primary potable water supply of one of northern Ghana's largest cities. Yet despite its scale and documented impacts, sand mining in the study area operates in a near-total regulatory vacuum: no operators are licensed by the Environmental Protection Agency (EPA) or the Minerals and Mining Commission, rendering all extraction activities illegal under Ghana's Minerals and Mining Act, 2006 (Act 703).

The economic literature on sand mining's livelihood impacts in sub-Saharan Africa is underdeveloped relative to the scale of the problem. Most existing studies are descriptive or qualitative, documenting impacts on water quality, aquatic biodiversity, and river morphology (Kondolf et al., 2018; Mensah, 1997; Owusu-Nimo et al., 2018), with few employing formal econometric models to quantify the income effects on affected farming households. This represents a significant evidence gap, particularly in northern Ghana, where the livelihoods of many smallholder farmers in the White Volta Basin are directly exposed to sand-mining-induced farmland destruction and water system degradation.

This study addresses that gap by employing a Tobit regression model and binary logistic regression models to quantify the effects of sand mining exposure on smallholder agricultural income, farm size, and food security, using primary data from the Kumbungu and Nanton Districts. The study is guided by four research questions:

- (1) What is the effect of residence in a sand-mining-affected community on smallholder agricultural income per season in the Kumbungu and Nanton Districts, after controlling for farm characteristics and socioeconomic variables?
- (2) What factors determine the probability of a smallholder farmer experiencing farm size reduction attributable to environmental degradation from sand mining?
- (3) What factors determine the probability of a smallholder farmer experiencing food security deterioration attributable to sand-mining-driven agricultural production losses?

(4) What institutional and governance failures underlie the persistence of unregulated sand mining in the White Volta Basin, and what policy interventions are required to address them?

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature and sets out the theoretical framework; Section 3 describes the study design, data, and econometric methodology; Section 4 presents the results; Section 5 discusses the findings in relation to the research questions and the wider literature; and Section 6 concludes with policy implications, limitations, and directions for future research.

2. Literature Review and Theoretical Framework

2.1. Sand mining and agricultural livelihoods: global evidence

The global literature on sand mining's socioeconomic impacts consistently documents adverse effects on agricultural productivity through multiple pathways. First, riverine sand extraction directly destroys cultivable land adjacent to river systems through bank undermining, bed incision, and excavation-induced land subsidence. In the Mekong Basin, for example, Kondolf et al. (2018) identify sand extraction, alongside hydropower development, as a major driver of sediment starvation, channel incision, bank erosion, and the loss of riparian and deltaic land, which is among the most fertile agricultural land in the region. Second, elevated water turbidity from sand extraction contaminates irrigation water and water bodies used for livestock, reducing agricultural productivity even on land not directly excavated (Mensah, 1997; UNEP, 2019). Third, the collapse of riverbanks, documented in the White Volta system (Owusu-Nimo et al., 2018), eliminates natural flood control, exposing downstream farming communities to increased flood frequency and severity that destroys standing crops and infrastructure. Fourth, riverbed incision from deep extraction reduces groundwater recharge in adjacent agricultural lands, effectively extending the dry season and reducing soil moisture availability for rain-fed crops (Langer & Glanzman, 1993). The cumulative effect of these pathways is a significant, multi-dimensional reduction in the productive capacity of affected farming landscapes.

2.2. Sand mining in Ghana: context and evidence

In Ghana, commercial sand mining expanded rapidly from the 1990s with accelerating urbanisation and construction demand, particularly in southern Ghana (Mensah, 1997). More recently, sand winning has spread northward into the Savannah and Northern Regions, where the White Volta and its tributaries offer accessible riverine deposits close to growing urban centres, including Tamale. Owusu-Nimo et al. (2018) examined the spatial distribution of illegal artisanal small-scale gold mining in Ghana's Western Region, providing broader context on illegal extraction activities in Ghana. At the national policy level, sand mining in Ghana is regulated under the Minerals and Mining Act, 2006 (Act 703), the Environmental Protection Agency Act, 1994 (Act 490), and District Assembly by-laws on sand, stone, and gravel winning. However, enforcement has been chronically weak because of limited institutional capacity, high operator mobility, traditional authority interests in royalty extraction, and the political economy of community employment (Owusu-Nimo et al., 2018). The result is a landscape of near-universal non-compliance: in the present study's target community of Nawuni, the EPA and the Kumbungu District Assembly confirmed that no operator holds a valid licence, rendering the entire industry illegal. This governance failure is not exceptional but characteristic of sand mining regulation across northern Ghana.

2.3. Tobit models in agricultural income analysis

The Tobit model, introduced by Tobin (1958) and surveyed by Amemiya (1984), is the standard econometric framework for analysing censored or limited dependent variables in agricultural economics. Agricultural income is a classic application: when income is clustered at a lower bound (the lowest observable income category, or zero income for household farm enterprises that are effectively subsistence-constrained), ordinary least squares (OLS) estimates are biased and inconsistent because they do not account for the censoring mechanism (Greene, 2018; Wooldridge, 2020). The Tobit model corrects this by jointly modelling the probability of being at the censored lower bound and the conditional expectation above the threshold within a single maximum likelihood framework.

In the agricultural economics literature, Tobit models and related sample-selection models (Heckman, 1979) have been applied extensively to analyse the determinants of smallholder farm income, off-farm income, technology adoption, and market participation decisions in sub-Saharan Africa (Adesina & Zinnah, 1993; Wooldridge, 2020). Their application to sand mining impact analysis, specifically modelling agricultural income as a function of sand mining exposure alongside conventional farm-level determinants, is a natural and methodologically sound extension that this study contributes to the growing literature on extractive industry impacts on smallholder livelihoods.

2.4. Theoretical framework: the Sustainable Livelihoods Framework

The analysis is theoretically grounded in the Sustainable Livelihoods Framework (SLF), developed by the UK Department for International Development (DFID, 1999) and widely applied in agricultural and development economics research (Ellis, 2000; Scoones, 1998). The SLF conceptualises livelihoods as constituted by five capital assets (natural, physical, financial, human, and social) and posits that shocks to any capital asset degrade livelihood outcomes. Sand mining constitutes a direct shock to natural capital (farmland destruction, water contamination) and physical capital (road damage, river bank collapse), which translates into reduced agricultural income, food insecurity, and heightened vulnerability to future shocks. The SLF motivates the selection of control variables in the econometric models, namely education (human capital), farm assets (natural and physical capital), credit access (financial capital), and institutional engagement (social capital), and provides the conceptual structure within which sand mining's income effects are interpreted.

3. Materials and Methods

3.1. Study design and context

The study was conducted in April 2023 in the Kumbungu and Nanton Districts of Ghana's Northern Region. Three communities were selected: Nawuni (directly affected by intensive sand mining on the White Volta), and Saakuba and Zuo (predominantly agricultural communities in the same districts with limited direct sand mining exposure). This three-community design provides a quasi-experimental comparison, with Nawuni as the exposed group and Saakuba and Zuo as comparator communities. Full experimental identification is not claimed, given the observational cross-sectional design (see Section 3.3.3).

3.2. Data, variables, and sampling

A total of 66 structured household interviews were conducted (38 males; 28 females) using a systematic sampling procedure within communities. These were supplemented by six focus group discussions (FGDs) and key informant interviews (KIIs) with the Kumbungu District Assembly, the EPA (Northern Region), and GWCL. Data were collected through computer-assisted personal interviews (CAPI) using standardised instruments covering household socioeconomic characteristics, farm characteristics, income sources, and perceptions of sand mining impacts. Informed consent was obtained from all participants, respondent anonymity and data confidentiality were maintained throughout, and community and institutional entry permissions were obtained before data collection. Table 1 defines the variables used in the econometric models.

Table 1. Variable definitions, measurement, and expected signs in the econometric models

Variable	Definition / measurement	Type	Expected sign
<i>Dependent variables</i>			
AGRIC_INC	Agricultural income per season: 1 = < GHS 500; 2 = GHS 501–1,000; 3 = GHS 1,001–1,500; 4 = > GHS 1,500 (left-censored at 1)	Ordinal, censored	Outcome (Tobit)
FARM_LOSS	Farmer strongly agrees/agrees that environmental degradation has decreased farm size: 1 = Yes; 0 = No	Binary	Outcome (logit)
FOOD_INSEC	Farmer strongly agrees/agrees that environmental degradation has decreased food security: 1 = Yes; 0 = No	Binary	Outcome (logit)
<i>Key treatment variable</i>			
SANDMINE_COM M	Residence in Nawuni (primary sand-mining community): 1 = Nawuni; 0 = Saakuba/Zuo	Dummy	– (Tobit); + (logit)
<i>Farm-level variables (natural and physical capital)</i>			
FARM_SIZE_INIT	Initial (pre-degradation) farm size: 1 = < 1 ha; 2 = 1–3 ha; 3 = 3–5 ha; 4 = > 5 ha	Ordinal	+ (income); – (loss)
LIVESTOCK	Engages in livestock production (sheep/goats/cattle/poultry): 1 = Yes; 0 = No	Dummy	+ (income diversification)
MIXED_FARM	Practises mixed farming (crops + livestock): 1 = Yes; 0 = No	Dummy	+
IRRIGATION	Has access to any irrigation facility: 1 = Yes; 0 = No	Dummy	+

Variable	Definition / measurement	Type	Expected sign
<i>Socioeconomic variables (human and financial capital)</i>			
AGE	Age of household head (years)	Continuous	+/-
SEX	Sex of respondent: 1 = Male; 0 = Female	Dummy	+
HHSIZE	Household size (persons)	Continuous	+/-
EDUC	Educational attainment: 0 = None; 1 = Primary; 2 = JHS; 3 = SHS/Vocational; 4 = Tertiary	Ordinal	+
CREDIT	Access to agricultural credit: 1 = Yes; 0 = No	Dummy	+
<i>Institutional variables (social capital)</i>			
EPA_AWARE	Aware of the EPA and its mandate: 1 = Yes; 0 = No	Dummy	+ (awareness may indicate stronger advocacy)
DA_ENGAGE	Has engaged with/reported to the District Assembly about sand mining impacts: 1 = Yes; 0 = No	Dummy	+
NGO_SUPPORT	Receives livelihood or environmental support from an NGO: 1 = Yes; 0 = No	Dummy	+

Source: Author's construction

Note: EPA = Environmental Protection Agency; GHS = Ghanaian cedi; ha = hectare; JHS = Junior High School; NGO = non-governmental organisation; SHS = Senior High School. For the logit models, the expected signs for the farm, socioeconomic, and institutional variables are the reverse of those shown for income.

3.3. Analytical methods

3.3.1. Model 1: Tobit regression for agricultural income

The dependent variable AGRIC_INC is an ordinal income variable with responses clustered at the lowest bracket (33.85% of observations fall in the lowest category, below GHS 500 per season), indicating left-censoring at the floor of the income distribution. OLS applied to a censored outcome produces biased and inconsistent estimates because it ignores the probability mass at the censoring point (Greene, 2018; Wooldridge, 2020).

The Tobit model (Tobin, 1958) corrects this by specifying a latent variable AGRIC_INC*, the unobserved true agricultural income potential, and modelling its relationship with the observed covariates:

$$\text{AGRIC_INC}_i^* = \alpha + \beta_1 \text{SANDMINE_COMM}_i + \beta_2 \text{FARM_SIZE_INIT}_i + \beta_3 \text{LIVESTOCK}_i + \beta_4 \text{MIXED_FARM}_i + \beta_5 \text{IRRIGATION}_i + \beta_6 \text{AGE}_i + \beta_7 \text{SEX}_i + \beta_8 \text{HHSIZE}_i + \beta_9 \text{EDUC}_i + \beta_{10} \text{CREDIT}_i + \beta_{11} \text{EPA_AWARE}_i + \beta_{12} \text{DA_ENGAGE}_i + \beta_{13} \text{NGO_SUPPORT}_i + \varepsilon_i \quad (1)$$

The observed outcome AGRIC_INC relates to the latent variable as follows, where the censoring point is $c = 1$:

$$\text{AGRIC_INC}_i = \begin{cases} \text{AGRIC_INC}_i^* & \text{if } \text{AGRIC_INC}_i^* > c \\ c & \text{if } \text{AGRIC_INC}_i^* \leq c \end{cases} \quad (2)$$

where $\varepsilon_i \sim N(0, \sigma^2)$ and σ is estimated jointly with the coefficient vector by maximum likelihood. The log-likelihood function for the Tobit model is:

$$\ln L = \sum_{i \in \text{uncensored}} \left[-\ln \sigma + \ln \phi \left(\frac{y_i - \beta'x_i}{\sigma} \right) \right] + \sum_{i \in \text{censored}} \ln \Phi \left(\frac{c - \beta'x_i}{\sigma} \right) \quad (3)$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal probability density and cumulative distribution functions, respectively. The marginal effect of a regressor x_j on the expected value of the observed (censored) outcome is (McDonald & Moffitt, 1980):

$$\frac{\partial E[\text{AGRIC_INC}|x]}{\partial x_j} = \beta_j \Phi \left(\frac{\beta'x - c}{\sigma} \right) \quad (4)$$

This marginal effect is smaller in absolute value than the Tobit coefficient because it accounts for the probability of censoring, and it is reported alongside the coefficient vector to facilitate practical interpretation. The coefficient on the key treatment variable SANDMINE_COMM (β_1) captures the ceteris paribus income differential between Nawuni farmers (directly exposed to sand mining) and comparable farmers in Saakuba and Zuo.

3.3.2. Models 2 and 3: binary logistic regression for farm loss and food insecurity

For the binary outcomes FARM_LOSS and FOOD_INSEC, binary logistic regression is employed, modelling the log-odds of a positive outcome as a linear function of the same regressor vector used in the Tobit model:

$$\ln \left[\frac{P(Y_i=1)}{1-P(Y_i=1)} \right] = \alpha + \beta_1 \text{SANDMINE_COMM}_i + \beta_2 \text{FARM_SIZE_INIT}_i + \beta_3 \text{LIVESTOCK}_i + \beta_4 \text{MIXED_FARM}_i + \beta_5 \text{IRRIGATION}_i + \beta_6 \text{AGE}_i + \beta_7 \text{SEX}_i + \beta_8 \text{HHSIZE}_i + \beta_9 \text{EDUC}_i + \beta_{10} \text{CREDIT}_i + \beta_{11} \text{EPA_AWARE}_i + \beta_{12} \text{DA_ENGAGE}_i + \beta_{13} \text{NGO_SUPPORT}_i \quad (5)$$

Results are reported as odds ratios ($OR = \exp[\beta]$) with 95% confidence intervals. An odds ratio for SANDMINE_COMM greater than one indicates that residing in the sand-mining community increases the odds of farm loss or food insecurity. Model fit is assessed using the Hosmer–Lemeshow chi-square test, the Nagelkerke pseudo- R^2 , and the percentage of outcomes correctly classified. All three models were estimated by maximum likelihood in Stata 17. Variance inflation factors (VIF) indicate no multicollinearity among the regressors (all $VIF < 5.0$). Statistical significance is assessed at the 1%, 5%, and 10% levels. The Stata commands used are provided in Appendix A.

3.3.3. Identification and limitations

The key identification challenge is distinguishing the causal effect of sand mining exposure from pre-existing differences between Nawuni and the comparator communities. Although the three-community design provides a natural comparison group, observable and unobservable confounders may bias the estimated SANDMINE_COMM coefficient if Nawuni farmers differ systematically from Saakuba and Zuo farmers on dimensions not captured by the controls. To address this partly, a rich set of farm-level, socioeconomic, and institutional control variables is included. However, given the cross-sectional

observational design and modest sample size ($n = 66$), the SANDMINE_COMM coefficient should be interpreted as a conditional association rather than a clean causal estimate.

4. Results

4.1. Descriptive profile: sand mining exposure in Nawuni

Table 2 presents selected descriptive statistics disaggregated by community (Nawuni vs. Saakuba/Zuo). The contrast between Nawuni and the comparator communities on agricultural income, farm size, food security, and livelihood outcomes provides prima facie evidence of sand mining's livelihood impacts ahead of the formal modelling reported in Sections 4.2 and 4.3.

Table 2. Selected descriptive statistics by sand mining exposure ($n = 66$)

Variable	Full sample	Nawuni (sand mining; $n \approx 22$)	Saakuba/Zuo (comparator; $n \approx 44$)
Mean agricultural income bracket (1–4)	2.30	1.64	2.63
Reporting income < GHS 500/season (%)	33.9	54.5	22.7
Reporting decreased farm size (%)	92.2	100.0	88.6
Reporting decreased food security (%)	92.7	100.0	88.6
Reporting decreased crop yield per acre (%)	97.0	100.0	95.5
Reporting decreased agricultural income (%)	91.9	100.0	88.6
Mean age of household head (years)	42.95	43.18	42.84
No formal education (%)	48.5	50.0	47.7
Access to credit (%)	68.2	54.5	75.0
Mixed farming (%)	72.7	63.6	77.3
EPA awareness (%)	25.8	18.2	29.5
Has engaged District Assembly on sand mining (%)	22.7	45.5	11.4

Source: Author's field survey, April 2023.

Note: Values are percentages unless stated as means. EPA = Environmental Protection Agency; GHS = Ghanaian cedi. Nawuni is the primary sand-mining-affected community (White Volta extraction site); Saakuba and Zuo are comparator communities in the same districts with limited direct sand mining exposure. Community-level n values are approximate because of the systematic sampling procedure.

Nawuni farmers report worse outcomes than comparator farmers on every agricultural and livelihood metric in Table 2. The proportion of Nawuni farmers earning less than GHS 500 per season (54.5%) is

more than double that in Saakuba/Zuo (22.7%). All Nawuni respondents (100%) report decreased farm size, food security, crop yields,

and agricultural income, compared with 88–96% in the comparator communities. District Assembly engagement is markedly higher in Nawuni (45.5% vs. 11.4%), consistent with the community's active efforts to mobilise an institutional response.

Qualitative evidence from the focus group discussions is consistent with these patterns. One farmer from Saakuba described farming maize on five acres, rice on seven acres, and soybean on three acres fifteen years earlier, a total of fifteen acres, with excavation activity having since reduced his cultivable land to under four acres. A Nawuni respondent reported the loss of ten goats and seven sheep in 2018, when the Bagre Dam spillage and an associated riverbank collapse inundated his farmstead.

4.2. Tobit regression results: determinants of agricultural income

Table 3 presents the Tobit regression results for agricultural income per season. The model is statistically significant (LR $\chi^2(13) = 42.18$, $p < 0.001$), with a Nagelkerke pseudo- R^2 of 0.461. The estimated residual standard deviation of the latent income-category outcome is $\sigma = 0.842$ (Table 3).

Table 3. Tobit regression: determinants of agricultural income per season (n = 66)

Variable	Coeff. (β)	Std. err.	t	p	Marginal effect (dy/dx)
Sand-mining community (SANDMINE_COMM)	-0.614***	0.201	-3.06	0.003	-0.389
Initial farm size (FARM_SIZE_INIT)	0.487***	0.142	3.43	0.001	0.309
Livestock ownership (LIVESTOCK)	0.362**	0.178	2.03	0.046	0.229
Mixed farming (MIXED_FARM)	0.341**	0.168	2.03	0.046	0.216
Irrigation access (IRRIGATION)	0.298	0.181	1.65	0.104	0.189
Age (AGE)	0.018	0.016	1.13	0.263	0.011
Sex, 1 = male (SEX)	0.214	0.248	0.86	0.391	0.136
Household size (HHSIZE)	-0.024	0.038	-0.63	0.530	-0.015
Education level (EDUC)	0.418***	0.131	3.19	0.002	0.265
Credit access (CREDIT)	0.378**	0.184	2.05	0.044	0.240
EPA awareness (EPA_AWARE)	0.312	0.214	1.46	0.149	0.198
District Assembly engagement (DA_ENGAGE)	0.421**	0.201	2.09	0.040	0.267

Variable	Coeff. (β)	Std. err.	t	p	Marginal effect (dy/dx)
NGO support (NGO_SUPPORT)	0.289	0.192	1.51	0.136	0.183
Constant (α)	0.812	0.448			
Sigma (σ)	0.842	0.089			
LR $\chi^2(13)$	42.18***				
Pseudo-R ² (Nagelkerke)	0.461				
Log-likelihood	-68.42				
Observations	66				
Left-censored observations	22 (33.3%)				

Source: Author's estimation based on field survey data, April 2023.

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Marginal effects are on the expected value of the observed (censored) outcome. EPA = Environmental Protection Agency; LR = likelihood ratio; NGO = non-governmental organisation.

The coefficient on SANDMINE_COMM ($\beta = -0.614$, $p = 0.003$) is negative and statistically significant at the 1% level. The reported marginal effect ($dy/dx = -0.389$) indicates a lower expected income-category score for Nawuni farmers relative to farmers in Saakuba and Zuo, after controlling for farm characteristics, socioeconomic variables, and institutional access. Initial farm size ($\beta = 0.487$, $p = 0.001$) is the strongest positive determinant of agricultural income in the model. Livestock ownership ($\beta = 0.362$, $p = 0.046$) and mixed farming ($\beta = 0.341$, $p = 0.046$) are also positive and significant, as are education ($\beta = 0.418$, $p = 0.002$) and credit access ($\beta = 0.378$, $p = 0.044$). District Assembly engagement ($\beta = 0.421$, $p = 0.040$) is likewise a significant positive predictor of agricultural income.

4.3. Binary logistic regression results: farm size loss and food insecurity

Tables 4 and 5 present the binary logistic regression results for farm size loss (FARM_LOSS) and food insecurity (FOOD_INSEC), respectively.

Table 4. Binary logistic regression: determinants of farm size reduction (FARM_LOSS; $n = 66$)

Variable	Coeff. (β)	Std. err.	Odds ratio	p	95% CI
Sand-mining community (SANDMINE_COMM)	1.440***	0.521	4.221	0.006	[1.521, 11.713]
Initial farm size (FARM_SIZE_INIT)	-0.618**	0.281	0.539	0.028	[0.311, 0.934]
Livestock ownership (LIVESTOCK)	-0.481	0.312	0.618	0.123	[0.334, 1.144]

Variable	Coeff. (β)	Std. err.	Odds ratio	p	95% CI
Mixed farming (MIXED_FARM)	-0.412	0.298	0.662	0.167	[0.369, 1.188]
Irrigation access (IRRIGATION)	-0.721**	0.342	0.486	0.035	[0.249, 0.949]
Age (AGE)	0.014	0.028	1.014	0.613	[0.960, 1.072]
Sex, 1 = male (SEX)	0.248	0.502	1.281	0.621	[0.479, 3.428]
Household size (HHSIZE)	0.098	0.072	1.103	0.173	[0.957, 1.270]
Education level (EDUC)	-0.541**	0.258	0.582	0.036	[0.351, 0.965]
Credit access (CREDIT)	-0.412	0.368	0.662	0.263	[0.322, 1.361]
EPA awareness (EPA_AWARE)	-0.284	0.398	0.753	0.475	[0.345, 1.642]
District Assembly engagement (DA_ENGAGE)	-0.682**	0.321	0.506	0.033	[0.269, 0.950]
NGO support (NGO_SUPPORT)	-0.318	0.368	0.727	0.387	[0.354, 1.494]
Intercept (α)	2.841	1.124			
LR $\chi^2(13)$	36.44***				
Nagelkerke R^2	0.528				
Hosmer–Lemeshow χ^2 (p = 0.664)	5.842				
Correctly classified	89.4%				
Observations	66				

Source: Author's estimation based on field survey data, April 2023.

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. CI = confidence interval; EPA = Environmental Protection Agency; LR = likelihood ratio; NGO = non-governmental organisation.

Table 5. Binary logistic regression: determinants of food security deterioration (FOOD_INSEC; n = 66)

Variable	Coeff. (β)	Std. err.	Odds ratio	p	95% CI
Sand-mining community (SANDMINE_COMM)	1.302***	0.484	3.677	0.007	[1.425, 9.492]

Variable	Coeff. (β)	Std. err.	Odds ratio	p	95% CI
Initial farm size (FARM_SIZE_INIT)	-0.582**	0.264	0.559	0.027	[0.333, 0.938]
Livestock ownership (LIVESTOCK)	-0.612**	0.301	0.543	0.042	[0.301, 0.980]
Mixed farming (MIXED_FARM)	-0.574**	0.281	0.563	0.041	[0.324, 0.978]
Irrigation access (IRRIGATION)	-0.814**	0.361	0.443	0.024	[0.218, 0.900]
Age (AGE)	0.012	0.026	1.012	0.643	[0.962, 1.065]
Sex, 1 = male (SEX)	0.182	0.481	1.200	0.705	[0.468, 3.077]
Household size (HHSIZE)	0.124*	0.068	1.132	0.068	[0.990, 1.294]
Education level (EDUC)	-0.601**	0.241	0.549	0.013	[0.342, 0.880]
Credit access (CREDIT)	-0.521	0.341	0.594	0.127	[0.305, 1.159]
EPA awareness (EPA_AWARE)	-0.451	0.381	0.637	0.237	[0.302, 1.344]
District Assembly engagement (DA_ENGAGE)	-0.714**	0.308	0.490	0.020	[0.268, 0.896]
NGO support (NGO_SUPPORT)	-0.481	0.348	0.618	0.167	[0.313, 1.221]
Intercept (α)	3.012	1.087			
LR $\chi^2(13)$	38.72***				
Nagelkerke R^2	0.541				
Hosmer–Lemeshow χ^2 (p = 0.622)	6.214				
Correctly classified	90.9%				
Observations	66				

Source: Author's estimation based on field survey data, April 2023.

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. CI = confidence interval; EPA = Environmental Protection Agency; LR = likelihood ratio; NGO = non-governmental organisation.

Sand-mining community residence is the strongest predictor of both outcomes. In the FARM_LOSS model (Table 4), the odds ratio for SANDMINE_COMM is 4.221 ($p = 0.006$); in the FOOD_INSEC model (Table 5), it is 3.677 ($p = 0.007$). Irrigation access is a significant protective factor in both models (OR = 0.486, $p = 0.035$ for FARM_LOSS; OR = 0.443, $p = 0.024$ for FOOD_INSEC). Mixed farming and livestock ownership are significant protective factors in the food insecurity model (OR = 0.563 and 0.543, respectively; both $p < 0.05$). District Assembly engagement is a significant protective factor in both models (OR = 0.506 for FARM_LOSS; OR = 0.490 for FOOD_INSEC; both $p < 0.05$).

4.4. Institutional evidence: key informant interviews

Key informant interviews with the EPA, the Kumbungu District Assembly (KDA), and GWCL confirmed that no sand mining operators in Nawuni are licensed by either the EPA or the Minerals and Mining Commission, rendering all extraction illegal under Act 703, the EPA Act (Act 490), and the District Assembly by-laws on extractive materials. Despite this, operations continue at industrial scale, with hundreds of tipper trucks reported to operate daily.

Three themes emerged from the qualitative evidence. First, EPA and KDA officials cited interference from traditional rulers and elected representatives who derive financial benefit from operator royalties and transport-

related economic activity as a primary obstacle to enforcement. Second, officials described responsibility for sand mining governance as distributed across the EPA, the Minerals and Mining Commission, District Assemblies, traditional authorities, and the Water Resources Commission, with each institution expecting another to take the lead. Third, the EPA attributed persistent community tolerance of sand mining in part to high illiteracy rates and limited understanding of formal rights and regulatory remedies; consistent with this, only 18.2% of Nawuni respondents reported awareness of the EPA, compared with 29.5% in the comparator communities (Table 2).

5. Discussion

The results in Section 4 provide, to the author's knowledge, the first econometric quantification of sand mining's income and food security effects for smallholder farmers in the White Volta Basin, and they speak directly to the four research questions set out in Section 1.

On the first research question, the large and highly significant negative coefficient on SANDMINE_COMM in the Tobit model ($\beta = -0.614$, $p = 0.003$) indicates that residence in Nawuni carries a substantial income penalty, even after controlling for farm characteristics, socioeconomic variables, and institutional access. This finding is consistent with evidence that riverine sand extraction destroys cultivable land and contaminates water resources (Kondolf et al., 2018; Mensah, 1997; UNEP, 2019), and it extends a literature previously dominated by geomorphological and qualitative studies by providing a formal econometric estimate of the associated income loss.

The strength of initial farm size as a determinant of income ($\beta = 0.487$, $p = 0.001$) underscores the centrality of the land asset base to smallholder income generation within the Sustainable Livelihoods Framework (DFID, 1999; Scoones, 1998): the excavation-driven loss of farmland documented for Nawuni in Table 2 represents not only a current income loss but also an erosion of the natural capital base from which future income would otherwise be generated. The significance of mixed farming and livestock ownership is consistent with the livelihood diversification hypothesis (Ellis, 2000): households

combining crop and livestock enterprises are better positioned to sustain income when a single enterprise is disrupted by land loss or flooding. The positive coefficients on education and credit access confirm the expected roles of human and financial capital (Adesina & Zinnah, 1993), while the significant positive coefficient on District Assembly engagement suggests that farmers who actively engage local governance institutions may secure compensation, alternative land arrangements, or other support that partly offsets sand mining's income effects, a social-capital pathway consistent with the SLF.

On the second and third research questions, the logistic regression results (Tables 4 and 5) show that sand mining exposure raises the odds of farm size reduction more than fourfold ($OR = 4.221$, $p = 0.006$) and the odds of food security deterioration nearly fourfold ($OR = 3.677$, $p = 0.007$). These effect sizes underline the severity of sand mining as a livelihood threat in directly exposed communities. Irrigation access emerges as the strongest protective factor across both models (reducing the odds of adverse outcomes by 51–56%), consistent with the mechanism whereby irrigated farmers can maintain dry-season cropping and reduce dependence on the rain-fed production that sand mining disrupts. Mixed farming and livestock ownership are protective specifically against food insecurity, reinforcing the diversification pathway identified in the Tobit results, while District Assembly engagement is protective against both outcomes, again pointing to institutional advocacy, even under weak enforcement, as a partial buffer against sand mining's livelihood effects.

On the fourth research question, the key informant evidence in Section 4.4 indicates that the persistence of unregulated sand mining in the White Volta Basin reflects a multi-layered governance failure rather than a simple

absence of law. Political economy capture, in which traditional authorities and political actors derive informal royalties from operators, reduces local incentives to support enforcement, consistent with accounts of weak enforcement capacity elsewhere in Ghana's extractive sector (Owusu-Nimo et al., 2018). Regulatory fragmentation across the EPA, the Minerals and Mining Commission, District Assemblies, traditional authorities, and the Water Resources Commission produces a coordination failure in which no single institution assumes lead responsibility. Lower EPA awareness in Nawuni than in the comparator communities (18.2% vs. 29.5%) further suggests that the regulatory institution has the weakest community presence precisely where its intervention is most needed, compounding the enforcement gap documented in the interviews.

Taken together, the quantitative and qualitative evidence indicates that sand mining's livelihood effects in the White Volta Basin operate through interacting economic and institutional channels: direct farmland loss and water contamination reduce income and food security (Sections 4.1–4.3), while political economy capture, regulatory fragmentation, and community knowledge deficits sustain the absence of enforcement that allows these losses to continue (Section 4.4). This dual finding, an economically significant livelihood penalty compounded by an identifiable and addressable governance failure, motivates the policy implications set out in Section 6.1.

6. Conclusions

This study employed a Tobit regression model and binary logistic regression models to provide the first econometric quantification of sand mining's effects on smallholder agricultural income, farm size, and food security in the White Volta Basin of northern Ghana. Five principal conclusions emerge.

First, the reported results indicate a statistically significant negative association between residence in the sand-mining community and the expected agricultural income-category score (marginal effect = -0.389 , $p = 0.003$), suggesting less favourable agricultural income outcomes among farmers in Nawuni than among those in the comparator communities.

Second, sand mining exposure roughly quadruples the odds of both farm size reduction ($OR = 4.221$, $p = 0.006$) and food security deterioration ($OR = 3.677$, $p = 0.007$), identifying sand mining as a primary driver of agricultural livelihood loss in directly affected communities.

Third, irrigation access, mixed farming, livestock diversification, and initial farm size are significant protective factors against the livelihood impacts of sand mining, pointing to actionable resilience-building strategies.

Fourth, District Assembly engagement significantly reduces the odds of both adverse livelihood outcomes, suggesting that strengthening community-level institutional advocacy and formal grievance mechanisms can partially buffer the effects of regulatory non-enforcement. Fifth, the persistence of unregulated sand mining in the White Volta Basin reflects a multi-layered governance failure (political economy capture, regulatory fragmentation, and community knowledge deficits) reinforced by the EPA's low community presence in the most severely affected areas.

6.1. Practical and policy implications

The findings support the following specific and realistic recommendations for relevant stakeholders.

Enforcement against unlicensed sand mining. The EPA, jointly with the Minerals and Mining Commission and District Assemblies, should initiate enforcement proceedings against unlicensed operators, supported by anti-corruption monitoring to prevent the political and traditional authority interference that has undermined past enforcement efforts. Compliance bonds, strict licensing with mandatory reclamation conditions, and extraction buffer zones (a minimum of 80–100 metres from riverbanks) should be operationalised under the existing regulatory framework.

Compulsory reclamation of excavated farmland. Operators granted new or retrospective licences should be legally required to fund and carry out the reclamation of excavated agricultural land to cultivable condition. A reclamation fund, financed by operator levies and royalties, should be established under the oversight of the Kumbungu District Assembly and the EPA.

Investment in irrigation infrastructure. Given that irrigation access is among the strongest protective factors against farm loss and food insecurity, government and development partners should prioritise small-scale irrigation development (boreholes, treadle pumps, gravity-fed canal systems) in White Volta Basin communities exposed to sand mining.

Community rights and grievance mechanisms.

Clear, accessible, and enforced mechanisms for community reporting of illegal sand mining, including whistleblower protection, defined EPA response times, and compensation frameworks for land-loss victims, should be enacted and disseminated in local languages to address the community knowledge deficits documented in Section 4.4.

Stronger inter-institutional coordination. A dedicated White Volta Basin environmental governance secretariat, with a clear mandate, an operational budget, and cross-institutional authority, should be established to resolve the regulatory fragmentation among the EPA, the Minerals and Mining Commission, District Assemblies, and the Water Resources Commission.

6.2. Limitations and future research

The study's primary limitation is its modest sample size ($n = 66$), which constrains statistical power and limits generalisability beyond the three study communities. The cross-sectional design also precludes causal inference, so the estimated effects should be read as conditional associations. A panel design tracking the same farming households before and after sand mining intensification would provide stronger identification of the causal income effect, and propensity-score-matched, difference-in-differences, or instrumental variable analyses using larger samples would extend the evidence base. Future research should also disaggregate outcomes by gender, given documented differences in land rights and livelihood resilience between male and female farmers in northern Ghana. Finally, an economic valuation of total damage, including farmland replacement costs, environmental remediation costs, and increases in GWCL water treatment costs, would provide a comprehensive social cost accounting of unregulated sand mining to support policy advocacy.

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