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Original Research Article

Sustainable land management practices, off-farm work participation and vulnerability among farmers in Ghana: Is there a nexus?

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A B S T R A C T

Addressing issues of agricultural sustainability and vulnerability to poverty under climate change are major challenges to development in the 21st century. Accounting for the trade-off and synergies between off-farm work participation and sustainable land management on one hand, and vulnerability to poverty on the other hand, will therefore be useful to policy. In this study, we use recent farm household data from Ghana to examine the effect of off-farm work participation on intensity of adoption of sustainable land management (SLM) practices and impact of off-farm work participation on vulnerability to poverty. We employed a bivariate Tobit model to examine the determinants of SLM adoption intensity, and endogenous switching probit model to assess the impact of off-farm work participation on vulnerability to poverty. The results reveal that participation in off-farm is positively and significantly associated with adoption intensity of bunds, and organic manure. The results also show that off-farm work participation significantly reduces household vulnerability to poverty by 13%. Based on these findings, we conclude that rural development through non-farm work opportunities can lead to positive synergies between sustainable agricultural production, off-farm employment and poverty alleviation.

1. Introduction

Agriculture in Sub-Saharan Africa (SSA), especially crop production, is highly dependent on rainfall patterns. Recent evidence indicates that global climate change is likely to increase the incidence of natural hazards, as well as variability of rainfall, temperature and other climatic parameters (IPCC, 2014). Addressing both poverty and vulnerability to climate change are two of the major challenges to sustainable development in the 21st century (Tol, 2017). Poverty contributes to vulnerability, and vulnerability to climate change can also lead to outcomes that perpetuate poverty (Eriksen & O'brien, 2007). This is confirmed by the findings that more than 60% of the rural population in developing countries depend on marginal and less fertile lands (Barbier & Hochard, 2017).

As part of the measures to improve farm output of smallholder farmers, a lot of emphasis is being placed on intensification of smallholder agriculture through the use of new technologies including the use of improved and drought tolerant varieties, as well as adoption of sustainable land management (SLM) practices. However, smallholder farmers are often cash constrained, partly due to failures associated with the financial or labor markets (Abdulai & Delgado, 1999; Abidoye & Odusola, 2015). To minimize some of these cash or financial constraints, a lot of farm households engage in off-farm work during off-farm or farming season.

Even though several studies have been conducted on adoption of SLM practices in SSA (e.g. Faltermeier & Abdulai, 2009; Asfaw, Battista, & Lipper, 2016; Kassie et al., 2017), few studies have addressed adoption intensity of SLM practices and the synergies or trade-off between SLM and off-farm work. Fewer even account for the linkage between SLM adoption and vulnerability to poverty. Meanwhile, an increasing number of farm households rely on income from non-farm sources to supplement what is earned from their own production (Babatunde & Qaim, 2010; Owusu, Abdulai, & Abdul-Rahman, 2011, Woldeyohanes, Heckelei, & Surry, 2017). While there exist substantial literature on determinants and impacts of off-farm income and food security in SSA (Barrett, Reardon, & Webb, 2001; Owusu et al., 2011; Woldeyohanes et al., 2017; Zereyesus, Embaye, Tsiboe, & Amanor-Boadu, 2017), few of such studies have discussed the effect of participation in off-farm work and adoption of SLM practices on vulnerability to poverty.

The link between SLM adoption intensity and participation in off-farm work on vulnerability to poverty, are issues of interest that have not received much attention in the empirical literature. This is even more important in areas facing threats of land degradation and climate risks. A number of studies have linked

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adoption of stone and soil bunds and organic manure to improved farm productivity and household welfare (e.g. Abdulai & Huffman, 2014; Zougmore, Jalloh, & Tioro, 2014). Experimental evidence in Burkina Faso shows that during dry periods, crops on plots with stone bunds and Zai techniques can produce two to three times higher than those on control plots (Kaboré & Reij, 2004). Despite these observed benefits of SLM practices, there are instances where adoption results in exposing farm households to vulnerability to poverty (World Bank, 2009).

This study thus contributes to the literature by examining the relationship between smallholder participation in off-farm work and adoption intensity of SLM practices, and assessing the effect of participation in off-farm work and adoption of SLM practices on households' vulnerability to expected poverty. We employ survey data from Ghana and use recent developments in the impact assessment literature to address the issues set out to be achieved in the present study. As noted by Morduch (1994), households' dependence on weather dependent agriculture, poorly developed financial systems and weak social insurance, often result in stochastic poverty, an important component of vulnerability. The area selected for this study (Sudan and Guinea Savannah agro-ecological zones of Ghana) is characterized by unfavorable biophysical environment with frequent failure and uneven distribution of rainfall, poor soil quality and land degradation (Wossen, Berger, Swamikanu, & Ramilan, 2014), and high poverty incidence (44–70% from GLSS6) (GSS, 2015; Zereyesus et al., 2017).

The rest of this paper proceeds as follows. In Section 2, the literature linking non-farm sector to economic growth, agricultural technology adoption and poverty alleviation in SSA countries is reviewed and discussed. In Section 3, we present the conceptual framework and estimation strategy used in the analysis. Data and descriptive statistics are presented in Section 4, while the empirical results are presented in Section 5. Section 6 concludes with the key findings and policy implications of the study.

2. Literature review

Although food crop production is the main source of livelihood for majority of rural households in SSA, many of these households also engage in various off-farm activities, motivated by various push and pull factors (Barrett et al., 2001). A number of studies has contributed to the understanding of the role off-farm income plays in reducing poverty, enhancing investment, and promoting market participation among rural households (e.g., Owusu et al., 2011; Woldeyohanes et al., 2017). While Davis et al. (2007) put the global share of off-farm income at 58% of average total income, the study by Jolliffe (2004) found that up to 74% of rural population in 2004 were engaged in off-farm activities. While literature on some studies indicate that off-farm income provides farmers with liquid capital for purchase of yield enhancing inputs (e.g. Mathenge & Tschirley, 2015; Ma, Abdulai, & Ma, 2017), others argue that engagement in off-farm work undermines adoption of modern technologies by reducing time allocated to farm activities, which eventually leads to loss of productivity (Taylor, De Braw, & Rozelle, 2003; Woldeyohanes et al., 2017).

Although majority of the findings agree on the effect of off-farm work on enhancing household consumption and reducing poverty (e.g. Owusu et al., 2011; Mishra, Mottaleb, & Mohanty, 2015; Zereyesus et al., 2017), the literature reveals mixed findings about the effect of off-farm work on investment, agricultural output, technology adoption, input demand or market participation (Mathenge & Tschirley, 2015; Ma et al., 2017; Pfeiffer, López-Feldman, & Taylor, 2009; Woldeyohanes et al., 2017). For example, while Mathenge and Tschirley (2015) observed negative effect of off-farm work on fertilizer demand among farmers in Ethiopia, implying a labor-loss effect, the findings by Ma et al. (2017) in China, found positive effect of off-farm work participation. Although the study by Pfeiffer et al. (2009) in Mexico found positive effect of off-farm work on input demand, the impact of off-farm income on agricultural output was negative. The study by Babatunde (2015) in Nigeria however showed positive effects of off-farm income on both input demand and farm output.

Few studies in Ghana have examined the determinants and impacts off-farm work participation by rural households (Abdulai & Delgado, 1999; Owusu et al., 2011; Zereyesus et al., 2017) with different foci. For instance, the study by Abdulai and Delgado (1999) focused on the joint determinants of husbands and wives participation in off-farm employment, while that of Owusu et al. (2011) and Zereyesus et al. (2017) concentrated on impact of off-farm work participation on farm productivity, consumption and poverty. The current study focuses on the effect of off-farm work participation on adoption of sustainable land management practices and vulnerability to poverty. It also examines the extent to which adoption of sustainable land management practices is associated with vulnerability to poverty in Ghana.

3. Conceptual framework

The model presented here is inspired by economic theory of farm households involved mainly in food crop production, but can allocate part of their time to off-farm activities to earn extra cash income. The time allocation model presented here is as specified in Abdulai and Delgado (1999) and Pfeiffer et al. (2009). The model assumes that a farm household maximizes utility by allocating total time to three main activities: farm production, off-farm work and leisure; and that household produced goods (e.g. food crops) and market purchased ones, are perfect substitutes.

Based on these assumptions, the household simplified utility function can be stated as:

$$U_{max} = U\left(C, N; X^c\right), \tag{1}$$

where C refers to quantity of goods consumed by the household. N denotes leisure time; while X^c is a vector of household, farm and other environmental characteristics. The household time constraint T, can be expressed as $T = T_f + T_n + N_i$, where T_f and T_n are respectively, time allocated to farm and off-farm activities; N_i is the household's leisure time. Since a household's off-farm work time might be zero in a particular year, a non-negativity constraint is imposed on the off-farm work participation, such that is $T_n \geq 0$. Also, the household's expenditure budget constraint can be expressed as:

$$P_c C = P_q Q_c - P_z Z - w_r N + w_n T_n + E, \tag{2}$$

where P_c and C refer to the prices and quantities of goods and services consumed by the household; P_q and Q_c denote the price and quantity of farm produce; P_z and Z represent the price and quantity vectors of production inputs, as well as cost of sustainable land management practices (stone/soil bunds, organic manure). The cost of SLM is captured as part of $P_z Z$ in Eq. (2). Also, w_r and N represent the market wage and the amount of leisure respectively; while w_n and T_n represent off-farm wage and the amount of time allocated to off-farm work. E captures income from non-labor sources, such as remittances, transfers or non-farm assets of the household. The household's production technology constraint, which determines the quantity of farm produce Q can be captured as $Q(Z_i, T_f; X^c)$, where Q, Z and T_f are as already defined, and X^c refers to socioeconomic characteristics. The Lagrangian of the household's maximizing problem can therefore be stated as:

$$L = U\left(C, N; X^c\right) + \lambda_1\left\{P_{qi}Q_i\left(Z, T_f, X^c\right) - P_zZ - w_rN + w_nT_n + E - P_cC\right\} + \lambda_2\{T^* - T_f - T_n - N\}, \tag{3}$$

where λ_1 and λ_2 denote the Lagrangian multipliers associated with liquidity and time allocation constraints, respectively. The first-order conditions for maximizing utility subject to time and budget constraints, result in the following optimal choices for the allocation of labor for farm work and off-farm work as:

$$\frac{\partial L}{\partial T_f} = \lambda_1 P_q \frac{\partial Q}{\partial T_f} - \lambda_2 = 0 \; T_f \geq 0 \tag{4}$$

$$\frac{\partial L}{\partial T_n} = \lambda_1 w_n - \lambda_2 \leq 0 \;\; T_n \geq 0 \tag{5}$$

We rearrange Eqs. (4) and (5) to get return to farm and off-farm work as

$$w_n \leq \frac{\lambda_2}{\lambda_1} = P_q \frac{\partial Q}{\partial T_f} \quad , \tag{6}$$

where $\lambda_1 = \frac{\partial U}{\partial C}$ and $\lambda_2 = \frac{\partial U}{\partial N}$ refer to the marginal rate of substitution between consumption of goods and leisure, while the term $P_q \frac{\partial Q}{\partial T_f}$ refers to marginal value product of farm labor. It is worthy to note in Eq. (6) that if $w_n < \frac{\lambda_2}{\lambda_1} = P_q \frac{\partial Q}{\partial T_f}$, it implies that potential wage rate from off-farm work is less than the marginal value of an individual's leisure or on-farm work including time spent on adoption of SLM practices. This implies the allocation of time between farm and off-farm activities is sub-optimal (Abdulai & Delgado, 1999; Pfeiffer et al., 2009). On the other hand, if $w_n = \frac{\lambda_2}{\lambda_1} = P_q \frac{\partial Q}{\partial T_f}$, the off-farm wage rate is equal to the marginal value of the marginal product of farm labor and therefore a positive time allocation for off-farm work may be observed.

We can employ the above derivation of off-farm work and relate it to adoption of SLM practices, as well as the impact of off-farm work participation on vulnerability to poverty, through the Lagrangian duality theory (Nicholson & Snyder, 2008, p. 36). Thus, the farm household production problem can be specified as a profit maximizing problem with optimal solution specified as:

$$\pi = Max\left(P_{qi}Q_i - P_zZ - w_rN + w_nT_n + E\right), \text{ s. t} Q = Q\left(T_f, Z; X^c\right), \tag{7}$$

where π represents the farm's profit. Given this specification, the maximum profit as function of input and output prices, wages from off-farm work, as well as other household characteristics can be specified as:

$$\pi = \pi\left(P_{qi}, P_z, w_n; X^c\right), \tag{8}$$

A direct application of the Hotelling's lemma to Eq. (8) results in the following reduced-form specifications for farm output supply, input demand and off-farm labor supply functions:

$$\frac{\partial \pi}{\partial P_{qi}} = Q = Q_i\left(P_{qi}, \; P_z, \; w_n; \; X^c\right) \text{(output supply)} \tag{9}$$

$$\frac{\partial \pi}{\partial P_z} = -Z = Z\left(P_{qi}, \; P_z, \; w_n; \; X^c\right) \text{(input demand)} \tag{10}$$

$$\frac{\partial \pi}{\partial w_n} = T_n = T_n(P_{qi}, \; P_z, \; w_n; \; X^c) \text{(off − farm labor supply)} \tag{11}$$

As indicated earlier, $\boldsymbol{Z}$ contains variables which relate to sustainable land management practices. Specifically, the construction of stone/soil bunds by farmers in the northern savannah zone of Ghana, as a land/soil conservation measure has received attention from local government and international agencies (Abdulai & Huffman, 2014; Zougmore et al., 2014). Combined with organic manure use, bunding has been found to be sustainable land and soil management strategy on marginal lands exposed to the risk of degradation and climate change effects (e.g. Zougmore et al., 2014; Faltermeier & Abdulai, 2009).

Eq. (9)–(11) show that input and output prices, as well as off-farm wage rate tend to influence profits and demand for inputs, as well as farm output. Based on above theoretical concepts, we argue that households' participation in off-farm work may exert positive or negative impact on adoption of SLM practices ($\frac{\partial Z}{\partial w}$</>0), making the relationship an empirical issue, and relevant from development policy perspective.

3.1. Empirical model specification and estimation

SLM practices and off-farm work participation are assumed to have trade-offs and synergetic effects on household vulnerability to poverty. We start with the effect of off-farm work participation and adoption of SLM. We later present the effect of off-farm work participation and SLM on vulnerability to poverty. Formally, we assume a latent variable M^* that is unobserved, but can be represented by an observed variable, M which denotes a household's decision to adopt SLM practice or not. Thus, adoption of SLM is observed if $M^*>0$, which implies $M = 1$, otherwise $M = 0$, in which case SLM is not observed. Letting j denote household and s the specific SLM practice, the latent variable can be related to off-farm work participation, other household and farm characteristics through a structural model specified as:

$$M_{js} = \propto_j F_j + \gamma_s Y_{js} + \varnothing_s Z_{js} + \varepsilon_{js} \tag{12}$$

Where $M_{js} = 1$ if household adopts SLM practice s, 0 otherwise; s = bund construction, organic manure; F refers to off-farm work participation, Y denotes farm and environmental characteristics, while Z_{js} represents household characteristics. We employ the Tobit specification in the analysis, given the censored nature of our SLM data (farmer stated expenditures per hectare per year incurred on bunds and organic manure during the previous two production seasons).[1]

3.2. Intensity of adoption of SLM

A number of studies has employed different methods to determine adoption intensity of agricultural technologies (Nkegbe & Shankar, 2014; Pedzisa, Rugube, Winter-Nelson, Baylis, & Mazvimavi, 2016). Depending on how adoption intensity is measured, (share of land, number of components of the technology adopted, or expenditure), some studies have employed the Poisson and negative binomial (e.g. Nkegbe & Shankar, 2014) or the Tobit models (e.g. Rakshandrah & Abdulai, 2015) to assess adoption intensity. In this study, given the fact that we have data on stated expenditures on the SLM practices of interest (bunds and organic manures), we find the bivariate Tobit more appropriate for investigating adoption intensity. This approach will also enable us to examine the effect of off-farm-work participation on SLM adoption intensity, as well as assess possible complementarity or trade-off in the adoption of bunds and organic manure. Thus, the latent variable M^*_{js} is linked to the observed M_{js} as:

$$\begin{cases} M_{js} = M^*_{js} \text{ if } M^*_{js} > 0 \\ M_{js} = 0 \text{ if } M^*_{js} \leq 0 \end{cases} \tag{13}$$

This indicates that a farmer adopts SLM practice **s** if $M^*_{js}>0$. The

[1] In the case of stone bunds some farmers received support from government/NGO's. We concentrated on self-initiated and implemented bunds.

specification in Eq. (12) assumes that off-farm work participation (F) is exogenous. However, as noted earlier, off-farm work participation and credit constraint variables can be related to SLM practice adoption by simultaneity through both income and labor-loss effects thus making them potentially endogenous (Babatunde & Qaim, 2010; Taylor et al., 2003). In addressing the potential endogeneity, we employ the control function approach suggested by Wooldridge (2015). In doing so, we incorporate the observed values of off-farm work participation and credit constraint and their corresponding residuals from the first-stage regression into the bivariate tobit model, using distance to the nearest district capital as instrument, to ensure consistent estimation of these variables. We test for the exogeneity of these variables using a simple t-test (Wooldridge, 2015).

3.3. Impact of off-farm work participation on vulnerability to poverty

The effect of off-farm work participation on vulnerability to poverty can be specified as follows:

$$V_{h,t} = \delta \mathbf{F_h} + \boldsymbol{\alpha Z_h} + \varepsilon_h, \tag{14}$$

where $\mathbf{F_h}$ denotes the household's decision to participate in off-farm work or not, and $\boldsymbol{Z_h}$ household and farm characteristics which affect household vulnerability to poverty ($V_{h,t}$).

We followed the literature and determined vulnerability using expected poverty (VEP)[2] approach (Chaudhuri, Jalan, & Suryhadi, 2002; Christiaensen & Subbarao, 2005). By this approach, a household is considered vulnerable to consumption poverty in the next period if:

$$\hat{V}_{h,t} = prob\left(lnC_{h,t+i} \le lnz \middle| Z_h, F_h\right) = \Phi\left\{\frac{lnz - ln\hat{C}_h}{\sqrt{\hat{\sigma}_h}}\right\}, \tag{15}$$

where z is the poverty line, $\hat{C}_h$ is the expected consumption and $\hat{\sigma}_h$ its standard deviation which refers to the expected variations in consumption due to shocks. Φ refers to the cumulative density of the standard normal distribution. The concept of vulnerability to expected poverty defines vulnerability as the probability of household consumption falling below the poverty line z in the future, regardless of its current poverty status (Chaudhuri et al., 2002). A household with a probability of 50% or more of falling into consumption poverty in the future is considered vulnerable to poverty.

From Eq. (14), participation in off-farm work appears to be exogenous. However, off-farm work participation is potentially endogenous since the decision to participate in off-farm work is self-determined. Consequently, we specify that in a latent variable model as:

$$\begin{cases} F_h^* = \partial X_h + \omega_h \\ F_h^* = \mathbf{F_h} = \mathbf{1}\ \boldsymbol{if}\ F_h^* > 0 \\ F_h^* = 0\ if\ \partial X_h + \omega_h \le 0 \end{cases} \tag{16}$$

where X_h is a vector of variables that determine household's participation in off-farm work. If the same unobservable factors (e.g., farmers' innate ability and skill) influence the error terms ε_h in the off-farm work participation equation, and ω_h in the vulnerability equation, selection bias occurs, resulting in a correlation of the two error terms in the two specifications, such that $corr(\varepsilon_h, \omega_h) = \rho_{\varepsilon\omega}$. Consequently, any standard regression technique such as linear probability (LP) probit /logit model applied to estimate Eq. (14) produces biased results when $\rho_{\varepsilon\omega} \neq 0$. Thus, rigorous assessment of the effect of off-farm work participation on vulnerability to poverty should take into account the endogeneity of the off-farm work variable.

Some studies involving two binary outcomes have employed Heckman two-stage selection method to account for observed and unobserved heterogeneity between the participants and non-participants (e.g. Kunstashula, Chabala, & Mulenga, 2014). However, Lokshin and Sajaia (2011) indicate that, the two-stage approach generates residuals that are heteroskedastic and requires cumbersome adjustments to achieve consistent standard errors. Some studies have employed recursive bivariate probit model (RBP) to overcome this shortcoming (e.g. Ma et al., 2017). However, given our interest in estimating average treatment effects of off-farm work participation on vulnerability to poverty, this study employs an endogenous switching probit (ESP) model in our empirical analysis (Ayuya et al., 2016). The ESP model estimates the off-farm work participation Eq. (16) and the vulnerability Eqs. (17a and 17b) simultaneously, using full information maximum likelihood (FIML) approach (Lokshin & Sajaia, 2011).

The ESP approach relies on the assumption of joint normality of error terms in the off-farm work participation (Eq. (16)) and outcome (vulnerability) equations. The vulnerability status can be specified in two regimes as follows:

$$V_{hp}^* = V_{hP,t} = \alpha_P Z_{hP} + \varepsilon_{hP,t},\ V_{hP,t} = I\left(V_{hp}^* > 0\right),\ \text{if,}\mathrm{F}_h = 1 \tag{17a}$$

$$V_{hN}^* = V_{hN,t} = +\ \alpha_N Z_{hN} + \varepsilon_{hN,t},\ V_{hP,t} = I\left(V_{hN}^* > 0\right)\ \text{if}\ \mathrm{F}_h = 0 \tag{17b}$$

where V_{hp}^* and V_{hN}^* are latent variables of the observed vulnerability status, $V_{hP,t}$ and $V_{hN,t}$ for participants and non-participants in off-farm work, respectively; Z_{hN} and Z_{hP} are vectors of exogenous variables influencing household vulnerability to poverty. The parameters α_P, α_N and ∂ are to be estimated; and the error terms ε_{hP}, ε_{hN} and ω_h are assumed to be jointly and normally distributed with a mean-zero vector and correlation matrix Ω:

$$\Omega = \begin{pmatrix} 1 & \rho_N & \rho_P \\ & 1 & \rho_{PN} \\ & & 1 \end{pmatrix} \tag{18}$$

where ρ_N refers to $corr(\varepsilon_{hN}, \omega_h)$, ρ_P also indicates $corr(\varepsilon_{hN}, \omega_h)$, while ρ_{PN} is the correlation between ε_{hN} and ε_{hP} (Lokshin & Sajaia, 2011).

A significant advantage in the use of the ESP model is the possibility to derive the counterfactual cases of vulnerability for households participating in off-farm work. This enables us to estimate average treatment effect on the treated (ATT) (vulnerability status of participants in off-farm work).

The effect of off-farm work participation on vulnerability given individual household and farm characteristics Z_h can be stated as:

$$\begin{aligned} ATT = E\left(V_{hP,t} \middle| Z_h, \mathrm{F}_{\boldsymbol{h}} = 1\right) - E\left(V_{hN,t} \middle| Z_h, \mathrm{F}_h = 1\right) = pr\big(V_{hP,t} \\ = 1 \big| Z_h, \mathrm{F}_{\boldsymbol{h}} = 1\big) - E\left(V_{hN,t} = 1 \middle| Z_h, \mathrm{F}_h = 1\right) \end{aligned} \tag{19}$$

where $V_{hP,t}$ is the expected vulnerability of off-farm work participants, and $V_{hN,t}$ is the expected vulnerability outcome in the counterfactual case; while F_h indicates household's off-farm work participation status. To improve identification of the model, Lokshin and Sajaia (2011) suggest the use of exclusion restriction where X_h in Eq. (16) contain at least one variable not featured in Z_h in Eqs. (17a) and (17b). We used distance to the nearest

[2] The three stage feasible GLS approach is described in detail in Chaudhuri et al. (2002) and Christiaensen and Subbarao (2005).

Table 1
Description and summary statistics of the variables.

Variable	Variable Description	Mean	Std. Dev.
Consumption[a]	Per capita household consumption expenditure (GHS)	1295.72	2017.36
Bunds	Practices bunding (soil/stone) = 1, 0 otherwise	0.25	0.43
Organic	Applies organic manure = 1, 0 otherwise	0.37	0.48
Expend-Bunds	Expenditure on bunds (soil and stone) (GHS)	80.38	264.37
Expend-Organic	Expenditure on organic manure (GHS)	46.05	140.88
Fertilizer	Farmer applied chemical fertilizer = 1, 0 otherwise	0.29	0.45
Off-farm	Farmer is engaged in off-farm activity= 1, 0 otherwise	0.38	0.49
Vulnerability	Expected consumption poverty incidence = 1, 0 otherwise	0.67	0.47
Farm size	Total Farm size of household in ha	1.96	1.49
Education	Years of formal education of household head	5.49	5.02
Hh_size	Number of people in a household	5.95	3.08
Age	Age of farmer in years	39.64	13.83
Gender	Household head is male = 1, female = 0	0.84	0.36
Dep_ratio	Dependency ratio: the ratio of nonworking household members to working members	0.642	0.70
Livestock	Livestock ownership in tropical livestock units	1.84	4.78
Machinery	Farmers owns farm machinery = 1, 0 otherwise	0.17	0.38
Credit_constraint	Farmer is credit constrained = 1, 0 otherwise	0.39	0.49
Aid	Household received government support = 1, otherwise, 0	0.25	0.431
Group-membership	Farmer belongs to a farmer group = 1, 0 otherwise	0.31	0.46
Tenure-security	Household has full usufruct right over plot = 1, 0 otherwise		
Extension	Number of extension visits	1.13	1.49
Distance-Farm	Distance to farm (km)	2.25	3.05
Proximity-town	Distance of household to nearest district capital (km)	2.75	6.22
Sudan Savannah	Sudan Savannah = 1, 0 otherwise	0.42	0.46
Guinea Savannah	Guinea Savannah = 1, 0 otherwise	0.58	0.49
Rfcondition	Farmer prediction of rainfall condition in the next 5 years (0–1)	0.64	0.48

[b]Exchange rate is US dollar 1 = GHS 4.26 at the time of the survey.

[a] This computed using total HH expenditure (excluding expenses on SLM) and household size.

district capital (*Proximity*) as instrument to identify the ESP model and further diagnostic test revealed its validity (see Table A1).

4. Data, survey sample and descriptive statistics

The data used in this study were obtained from a survey conducted in 25 communities across five districts in Ghana. Multistage sampling procedure was employed in the survey. First, three regions (Upper East region UER, Northern region (NR) and Brong-Ahafo region (BAR)) that are among the most vulnerable in terms climate change effects, were purposively selected based on agroecology. A total of five districts were selected across three regions (UER-Sudan Savannah [Bongo and Talensi districts], NR-Guinea Savannah [Tolon and Kumbungu districts], and BAR – Transitional zone [Techiman-South district], respectively). In addition to agroecology, we considered some SLM-related programs or projects that have been implemented or are being implemented in these districts (eg. AGRA Soil Heath Project, National Soil Fertility Action Plan, or National Climate Change Policy for Ghana). Most of these projects aim at reducing land degradation, improving soil fertility and enhancing farmers' ability to cope with climate change. In the last 60 years, rainy season temperature in Northern Ghana increased around 2 °C; while the likelihood of rainfall in April decreased by 70% (Kunstmann & Yung, 2005). Overall, our sample consists of 476 farm households (147, 203 and 126 from UER, NR and BAR, respectively). We later dropped the subsample from BAR given the fact only few farmers in that region practice the SLM practices considered in this study. We took into account the land size and farmer population of the Guinea Savannah and put greater weight on the sub-sample from the NR.

We captured information on household production activities and off-farm work participation, consumption expenditures and farmers' SLM activities. In addition to stating the sustainable land management practices adopted to protect farm lands from degradation activities, as well as adverse climate effects, farmers also stated the expenditure they made in the last cropping season in respect of the specific activities. For instance the average expenses made in respect of bunds construction and organic manure use per hectare were about GHS 80 and GHS 46, respectively (see Table 1). In addition, the average per capita consumption expenditure is GHS 1295, while 38% of households engage in cash-earning off-farm work. We capture off-farm (non-farm) income to include the portion of farm household income obtained outside main farm activity (petty trading, craftwork, or salaries and pensions), and aid income[3] earned by farm households. In all more than 38% of households in the study are engaged in various forms of off-farm activities. The share of these households in different off-farm activities are reported in Fig. 1. Petty trading appear to be the most popular off-farm activity in the study area while very few respondents engaged in more than one off-farm activity. For the purpose of this study and due to the limited sample size, we captured off-farm work participation as a dummy variable in our empirical analyses, instead of the categories presented in Fig. 1.

Table 1 presents descriptive statistics for the main variables of interest for this study. As shown in the table, on average, the household head is 40 years, with about 5.5 years of formal education, and cultivating an average of 2.0 ha farm size. About 30% of farm households have implemented stone or soil bunds while 46% used organic manures as forms of SLM practices.

We constructed a proxy measure of rainfall anomaly (*Rfcondition*), based on farmers' prediction of rainfall variability. A few studies have indicated contrasting effects of precipitation variation on crop yields in SSA. For instance the study by Ward, Florax, and Flores-Lagunes (2014) indicates that precipitation variability within the season has a positive effect on aggregate cereal yield in Sub-Sahara Africa. However, Rowhani, Lobell, Linderman, and Ramankutty (2011) report that

[3] Some limited number of poor households receive income from a government assisted program dubbed Livelihood Empowerment against Poverty (LEAP). Less than ten households in our sample received such assistance.

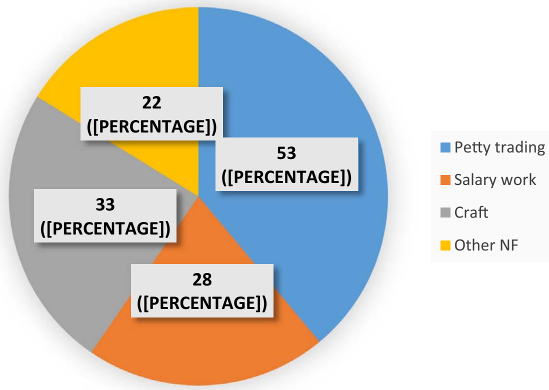

Fig. 1. Share of households in different off-farm employment activities.

precipitation variability within growing season has a negative effect on rice, maize and sorghum yields in Tanzania.

5. Results and discussions

5.1. Intensity of adoption of sustainable land management practices

Table 2 presents the results of determinants of adoption intensity of sustainable land management practices (expenditure on bunds and organic manure). Adoption intensity was estimated using a bivariate Tobit model, while controlling for endogeneity of off-farm work participation and credit constraint using a control function approach. From Table 2, the test statistics indicate positive correlation between the expenditure on bunds and that of organic manure. The likelihood ratio of joint significance of ρ_i is significant, supporting the relevance of the bivariate Tobit model in this analysis. The estimated correlation coefficient, ρ_{12} is positive and significant ($\rho_{12} = 0.54$ for full sample, 0.49 for Guinea Savannah and 0.61 for Sudan Savannah), implying that there exist some complementarity in adoption of the two SLM practices for the entire sample and for both agroecological zones.

The estimate of residual term ***(Off-resid***), derived from the first stage regression in the CF approach is not significant, indicating the absence of simultaneity bias and consistent estimation of off-farm work participation effect on adoption intensity of sustainable land management practices (Wooldridge, 2015). The residual term (***credit-resid***) is also insignificant in all models. Proximity to the district capital strongly influences the likelihood of participation in off-farm work as well as access to bank/formal credit in the first stage regressions of the CF approach (Table A1). This variable was excluded in the bivariate Tobit models.

On the effect of off-farm work participation on intensity of bunds and organic manure adoption, the results show that off-farm work participation is positive and statistically significant in the pooled sample and insignificant in Sudan savanna sub-sample. However, off-farm participation has a positive and significant effect on organic manure adoption but insignificant in the case of bunds construction, suggesting that income from off-farm participation is mostly invested in organic manure application. This results confirms that off-farm work participation can relax the cash constraints of farm households and enable them to adopt SLM practices, including soil/stone bunds and organic manure.

Turning to the effects of other covariates on adoption intensity, Table 2 reveals that education contributes positively and significantly to the adoption of bunds and organic manure in both GS and SS sub-samples. Farm size has a positive and significant effect on adoption intensity of organic manure, but negative and insignificant on bunds. This implies households with larger farm sizes are likely to increase their expenditure on organic manure, but not on bund construction. The estimate for expected rainfall condition (*RFcondition*) is positive and significant, indicating that farmers' prediction of increased variability of rainfall influences their intensity of adoption of SLM practices, a finding that is in line with that of Rowhani et al. (2011) in Tanzania. In addition, the estimate for tenure security is positive in the pooled sample and that of Guinea Savannah agro-ecological zone. This finding is consistent with economic intuition and empirical evidence elsewhere, that having longer usufruct right or longer tenure security over a parcel of farm land increases farmers' propensity to invest on it and adopt improved technologies (e.g. Abdulai et al., 2011).

The estimate for machinery is positive and significant in all equations for the pooled and disaggregated samples except bunds in the Sudan savannah. This indicates that ownership of machinery influences adoption intensity of SLM practices. Group membership, an indicator of social networks, is also found to positively and significantly influence intensity of adoption of SLM practices. Extension access plays important role in the adoption intensity of organic manure, relative to bunds construction. This means that extension efforts are channeled to the application of yield enhancing technologies compared to soil conservation practices in the study area.

5.2. Determinants of off-farm work participation and vulnerability to poverty

Table 4 reports the estimation results for the impact of off-farm work participation on households' vulnerability to poverty. The residual terms, *credit_resid* and *SLM_resid* are not significant in the off-farm work participation equation for participants and non-participants respectively, indicating the exogeneity of these variables (Wooldridge, 2015). The LR test of joint significance of correlation of the error terms rejects the null hypothesis that there is no selection bias with respect to off-farm work participation among households, justifying the use of the ESP-model. Specifically, in the case of ρ_N, unobserved factors that influence their non-participation in off-farm work also increases their probability of being vulnerable to future poverty.

We turn to the determinants of off-farm work participation (column 2) reported in Table 4. The estimate of bunds is positive and significant implying a positive association between SLM and off-farm work participation confirming income effect indicated earlier. As shown in Table 4, famers with better education are more likely to participate in off-farm work, as revealed by the positive and significant estimate of the education variable. Livestock ownership tend to positively and significantly influence farmers' decision to participate in off-farm work. This finding contrasts with that of Rakshandrah and Abdulai (2015) in Parkistan. However, this observation is possible if livestock rearing is extensive, as is largely the case in many parts of Ghana. In that case, keeping livestock is less labor intensive and farmers can still participate in off-farm work.

Credit constraint variable is positive and statistically significant, implying that farmers who are credit constrained are more likely to participate in off-farm work, a finding that is in line with previous findings (see Ma et al., 2017; Owusu et al., 2011). Finally, proximity to district capital (instrument) is negative and significant, suggesting that an increase in distance to district capital reduces the probability of participating in off-farm work.

5.3. Determinants of vulnerability to poverty

The third and fourth columns of Table 4 present the determinants

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Table 2
Results of bivariate Tobit model for Bunds and organic manure expenditures.

	Full-sample		Guinea Savannah		Sudan Savannah	
	Bunds	Organic Manure	Bunds	Organic Manure	Bunds	Organic Manure
Offfarm	2.561** (0.872)	1.080** (0.391)	0.416 (1.494)	1.296** (0.691)	1.429 (1.179)	0.276 (0.578)
Credit-constraint	-0.013 (1.817)	-2.698*** (0.846)	-0.409 (2.109)	-3.088*** (0.962)	-1.779 (3.197)	-3.068* (1.647)
Gender	-3.448 *** (0.865)	-1.428*** (0.413)	-4.668** (1.975)	-1.063 (0.964)	-0.203 (1.154)	-0.105 (0.621)
Age	0.020 (0.022)	0.001 (0.010)	-0.012 (0.029)	0.006 (0.013)	-0.016 (0.039)	-0.021 (0.021)
Education	0.039 (0.066)	0.011 (0.030)	0.198** (0.080)	0.069* (0.036)	0.519*** (0.133)	0.233*** (0.063)
Fertilizer	1.257** (0.595)	-0.036 (0.277)	1.498 ** (0.632)	0.170 (0.283)	0.401 (1.846)	-1.898 (1.075)
HH_size	0.295*** (0.081)	-0.006 (0.039)	0.336** (0.087)	-0.017 (0.041)	0.163 (0.201)	0.003 (0.111)
Farm size	-0.713*** (0.237)	0.176*** (0.098)	-0.352 (0.250)	0.244** (0.102)	-0.470 (0.532)	-0.328 (0.281)
Livestock	0.004 (0.048)	0.015 (0.020)	-0.084 (0.066)	0.047 (0.030)	0.104* (0.057)	0.029 (0.034)
RFconditon	1.140 *** (0.201)	0.671*** (0.094)	1.259*** (0.214)	0.714*** (0.096)	0.267 (1.809)	-0.230 (0.995)
Tenure security	2.173 (1.579)	1.368* (0.734)	4.111* (2.153)	2.241** (0.917)	-0.248 (2.180)	0.806 (1.187)
Distance-farm	-0.269 (0.169)	-0.062 (0.072)	0.691** (0.254)	0.091 (0.114)	-0.748*** (0.244)	-0.230 (0.111)
Group-member	0.051** (0.018)	0.037*** (0.009)	0.101*** (0.029)	0.054*** (0.014)	0.050** (0.025)	0.033** (0.012)
Extension	0.214 (0.178)	0.342*** (0.084)	0.126 (0.202)	0.249** (0.093)	0.262 (0.328)	0.617*** (0.172)
Machinery	1.937*** (0.693)	0.588*** (0.113)	2.696*** (0.806)	0.724* (0.381)	0.701 (1.254)	2.147*** (0.650)
Off_resid	-2.950 (2.178)	-1.162 (0.992)	-5.759 (3.356)	-0.895 (1.493)	-5.698 (4.800)	-1.224 (2.533)
credit_resid	-0.873 (1.759)	0.258 (0.829)	1.435 (2.065)	0.224 (0.957)	-2.046 (2.811)	0.782 (1.483)
Constant	-7.074** (2.562)	-1.834 (1.175)	-6.429 (4.167)	-4.523** (1.886)	1.948 (4.599)	4.026 (2.457)
No. obs	350/845		203/568		147/277	
σ	5.506*** (0.524)	3.298*** (0.230)	5.636*** (0.361)	2.957*** (0.127)	5.506*** (0.524)	3.297*** (0.230)
Corr. (ρ_{12})	0.615*** (0.063)		0.486*** (0.048)		0.615*** (0.063)	
Log-likehood	-2591.88		-1739.318		-775.207	
LR-test $\rho_{12} = 0$	144.64 [0.000]		73.63*** [0.000]		53.38 [0.000]	

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors. Values in square brackets are p-values.

Table 3
Differences in means of the characteristics of off-farm work participants and non-participants.

Variable	Participants	Non-participants	Diff (t-value)
	Mean	Mean	
Consumption	1372.467	1247.371	125.095 (0.66)
Consumption risk	6.877	6.555	0.322*** (4.120)
Vulnerability	0.598	0.726	-0.128** (-2.93)
Bunds	0.185	0.284	-0.100** (-2.46)
Organic	0.293	0.410	-0.117** (-2.60)
Farm size	1.990	2.001	-0.020 (-0.14)
Dependency ratio	0.585	0.680	-0.095 (-1.44)
Education	6.945	4.568	2.377*** (5.17)
Household size	5.820	5.990	0.170 (0.594)
Age	38.640	40.44	-1.800 (-1.38)
Gender	0.788	0.877	0.090** (2.60)
Livestock	4.628	2.027	2.601*** (4.27)
Machinery	0.174	0.171	0.003 (0.07)
Credit_constraint	0.342	0.435	-0.093** (-2.01)
Aid	0.196	0.277	-0.081** (-2.02)
Rfcondition	0.680	0.620	-0.056 (-1.35)
Proximity-town	3.814	6.680	2.87*** (6.24)

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are t-values

Table 4
Switch-Probit Model Off-farm participation and vulnerability to poverty.

Variable	Off-farm participation = 1 Coefficient (SE)	Participants Coefficient (SE)	Non-participants Coefficients (SE)
SLM[a]	0.298* (0.166)	0.113 (0.227)	-0.435 (0.386)
Gender	-0.682*** (0.192)	-1.861*** (0.360)	-0.199 (0.262)
Age	-0.005 (0.005)	-0.036 (0.043)	-0.054** (0.023)
Education	0.060*** (0.018)	-0.007 (-0.013)	-0.118*** (0.022)
Credit constraint	0.339** (0.138)	0.005 (0.034)	0.407** (0.158)
HH_size	0.013 (0.030)	0.114 (0.130)	0.124** (0.042)
Livestock	0.392*** (0.074)	-0.215 (0.144)	-0.403*** (0.094)
Rfcondition	0.015 (0.167)	-0.512* (0.289)	-0.239 (0.168)
Tenure-security	-0.544** (0.265)	-0.557 (0.464)	0.174 (0.300)
Machinery	0.451** (-0.177)	-0 .095 (0.396)	-0.356 (0.262)
G. Savannah	0.119 (0.183)	0.534* (0.312)	0.951*** (0.222)
Credit_resid	-0.750 (0.608)		
SLM_resid	-0.194 (0.527)		
Proximity_town	-0.121*** (0.017)		
Constant	1.430*** (0.467)	1.096 (1.274)	0.019 (0.637)
ρ_P, ρ_N		-0.339 (0.248)	-0.95*** (0.074)
No. Obser	350		
Wald test ($\rho = 0$)	22.20 *** [0.000]		
χ^2 **test of Over id**	0.212 [0.14]		
Log likelihood	-255.448 *** [0.000]		

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors
G. Savannah indicates whether the farm is in the Guinea Savannah zone or not. Sudan Savannah is the base outcome

[a] SLM is a dummy variable equal to one if the farmer adopts bunds or organic manure or both.

of vulnerability to poverty for off-farm work participants and non-participants. The finding on the effect of SLM practice adoption[4] on vulnerability is mixed, although not significant. According to the World Bank report on SLM in Niger, lower opportunity costs for labor in many rural settings, may promote land management investments that have relatively low returns to labor, and therefore increase vulnerability to poverty (World Bank, 2009). An FAO study also indicates that initial labor demands of some SLM practices result in temporary decline in yields, which can lead to increased vulnerability (Food & Agriculture Organization FAO, 2015).

Among the socioeconomic characteristics the estimate for household size is positive and significant, suggesting that larger family size is associated with increasing probability of household

[4] Bunds and organic manure were combined into a single binary variable in the ESP model since the estimation procedure used does not permit the use of indicator terms. The two terms are also found to be correlated from the bivariate Tobit model.

Table 5
Treatment effects of off-farm participation on vulnerability to poverty.

Variable	Off-farm work participation		ATT [%]	t-value
	Participant	Non-participant		
Vulnerability (overall)	0.620	0.716	- 0.096*** [- 13.40]	- 9.87
Vulnerability by SLM				
By Bunds construction	0.653	0.864	- 0.211*** [24.4]	- 12.6
By organic manure application	0.685	0.867	- 0.181*** [20.9]	- 12.86

*** represents 1% significance level.

being vulnerable, particularly for nonparticipants in off-farm work. The effect of household head education on vulnerability is negative and significant indicating that higher education of the household head decreases the likelihood of the household being vulnerable to poverty, a finding that is in line with human capital theory and education (Huffman, 2001), as well as recent studies on vulnerability in Asia (Imai, Gaiha, & Thapa, 2015). Interestingly, the estimate on coefficient of variation of rainfall, an indication of climate shock, is negative and statistically significant in the case of off-farm work participants, implying that farmers' probability of being vulnerable may decrease with rainfall variability. This situation is possible if rainfall variability also increases farmers' probability of being engaged in off-farm work, which is the case in this study. Rainfall variability has been reported by FAO (2015) to have a significant effect on consumption variance, an important component of vulnerability to poverty.

5.4. Impact of off-farm work participation on vulnerability

Even though significant differences in vulnerability between participants and non-participants can be observed in Table 3, these differences do not take into account selectivity bias due to observable and unobservable factors. Thus, we present in Table 5 the expected conditional vulnerability estimates. The results show that participants have a 62% probability of being vulnerable, while non-participants have 71.3%, representing 13.4% reduction in vulnerability due to participation in off-farm work. These estimates of vulnerability are a bit higher than that observed by Novignon, Novignon, Mussa, and Chiwaula (2012) using the Ghana Living Standards Survey (GLSS 5), probably because our study concentrated on smallholder crop farmers in the Savannah zone who have been identified to be among the poorest in Ghana (GSS, 2015). Even though current poverty is different from vulnerability, the level of poverty today contributes significantly to future poverty (Ligon & Schechter, 2003).

The impact on vulnerability was disaggregated based on SLM practice adoption. The results indicate that participants who also adopted bunds had 65.3% likelihood of being vulnerable, compared to 86.4% if they had not participated in off-farm work, resulting in a decrease of 24.4% vulnerability of falling back or remaining in poverty. In addition, off-farm work participants who also use organic manure can reduce their vulnerability likelihood by 21%.

6. Conclusions and recommendations

In this study, we examined the impact of off-farm work participation on intensity of adoption of sustainable land management practices, namely bunds and organic manure, using survey data from two agro-ecological zones in Ghana. The study also examined the impact of off-farm work participation on vulnerability to poverty. With regards to adoption intensity, we employed a bivariate Tobit model to examine the determinants of adoption intensity. In the second objective, we used an endogenous switching probit (ESP) model to assess the impact of off-farm work participation on the probability of being vulnerable to poverty.

The results show that participation in off-farm work significantly increase adoption intensity of bunds and organic manure in the pooled sample and Savannah agroecological zone sub-sample, probably due to the income effect of off-farm work participation. Farmers' perceived probability of drought occurrence, extension access, education of household head and group membership, as well as farm machinery ownership were the main drivers of adoption intensity. On the impact of off-farm work participation on vulnerability, the results show that opportunity to earn off-farm wage can significantly reduce average vulnerability to poverty. A disaggregation of the off-farm work participation impacts based on SLM practice adoption reveal significant reduction in expected vulnerability due to participation among farmers engaged in bunds construction and organic manure use. As noted by Zougmore et al. (2014), although stone bunds combined with other climate smart agricultural practices can be used by smallholder farmers to maintain food production and contribute to environmental sustainability, incentives are required to enhance farmers' adoption of these practices.

Thus, through the positive effect of off-farm work participation on intensity of adoption of sustainable land management practices, the ultimate welfare objective of reducing in vulnerability to poverty can be achieved. Therefore, policy efforts that seek to improve rural development through non-farm income opportunities can lead to positive synergies between sustainable agricultural production and off-farm employment, with the ultimate goal of reducing vulnerability to poverty.

A. Appendix

See Table A1

Table A1
First-stage regression results of determinants of off-farm work participation and credit constraints.

Variable	Off-farm work	Credit-Constraint
Gender	1.361 *** (0.325)	1.328 *** (0.287)
Age	0.003 (0.008)	−0.004 (0.006)
Education	0.078 *** (0.022)	−0.022 (0.018)
Fertilizer	0.881 *** (0.212)	0.042 (0.164)
HH_size	0.009 (0.028)	−0.058 ** (0.024)
Farm size	−0.120 * (0.072)	0.128 ** (0.062)
Livestock	−0.049 *** (0.012)	0.032 ** (0.013)
RFconditon	−0.105 (0.070)	0.178 *** (0.055)
Drainage	0.442 ** (0.192)	0.379 ** (0.153)
Group_member	−0.018 ** (0.006)	−0.011 * (0.006)
Extension	−0.032 (0.067)	0.128 ** (0.052)
Tenure-security	−0.180 (0.552)	−0.826 * (0.428)
Machinary	0.594 ** (0.278)	0.313 (0.206)
Proximity_town	0.633 *** (0.050)	0.267 *** (0.024)
Constant	−2.385 *** (0.745)	−1.468 ** (0.589)

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors.

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