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Promoting sustainable agriculture in Africa through ecosystem-based farm management practices: evidence from Ghana

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Abstract

Background: The type of farming practices employed within an agro-ecosystem have some effects on its health and sustainable agricultural production. Thus, it is important to encourage farmers to make use of ecosystem-friendly farming practices if agricultural production is to be sustainable and this requires the identification of the critical success factors. This paper therefore examined the factors to consider in promoting sustainable agriculture production in Africa through ecosystem-based farm management practices (EBFMPs) using Ghana as a case study. The study employed mixed methods—qualitative and quantitative techniques. Data were collected through key informant interviews, focus group discussions and a semi-structured questionnaire administered to 300 households. The Poisson and negative binomial models were employed to determine the factors that influence farmers' intensity of adoption of EBFMPs. Eight (8) EBFMPs were used in the paper as the dependent variable, which are organic manure application, conservation of vegetation, conservative tillage, mulching, crop rotation, intercropping with legumes, efficient drainage system and soil bunding.

Results: The paper found that the intensity of adoption of EBFMPs is significantly determined by the age of farmers, distance to farms, perception of soil fertility, knowledge of EBFMPs, number of extension visits and the type of irrigation scheme available to farmers.

Conclusions: To promote sustainable agricultural production in Ghana and elsewhere in Africa using EBFMBs, these factors must be considered.

Keywords: Africa, Agriculture, Ecosystems, Farm management practices, Ghana

Background

Agriculture production contributes to sustaining the livelihoods of many households, particularly in Africa. Despite the important roles it plays, some of the modern farming practices adopted by most farmers pose a threat to the environment [1, 2]; sustainable agricultural production [3] and the health and functional capacity of the agro-ecosystems [4]. In other words, unfriendly ecosystem farming practices create a condition that makes agricultural production costly and this traps future generations in the vicious poverty cycle [5] and the rural poor are the most disadvantaged. It is for this reason that sustaining the fertility of farmlands and maintaining ecosystems resilience has been of interest to many programmes and policies including the Comprehensive Africa Agriculture Development Programme (CAADP) and ECOWAS Agricultural Policy (ECOWAP) [6, 7]. Unfortunately, the response to these policies and programmes, especially in Sub-Saharan Africa has been low [8].

Most interventions on crop production in Ghana and elsewhere in Africa place greater emphasis on high yields with little concern on how to sustain farmlands for future benefits. For example, the focus of the Ministry of Food and Agriculture (MoFA) in Ghana has been on improving yields through dissemination of yield enhancing

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technologies [8]. These yield enhancing technologies seek to improve food availability [9], which often derail the biological functioning of the agro-ecosystems [10]. Again, a lot of studies (e.g. [11, 12]) that have been carried out in Ghana on the adoption of sustainable farm practices have paid little attention to farmers' knowledge of indigenous sustainable farm practices and how this might affect farmers' intensity of adoption.

Meanwhile, sustainable farm practices termed as ecosystem-based farm management practices (EBFMPs) can help maintain the fertility of agricultural lands and balance nutrients requirement of crops [3]. Ecosystem-based management farm practices (EBMFPs) within the context of this paper is the traditional farm-based practices (such as mulching, compost application, crop rotation, efficient drainage systems, and vegetation conservation among others) that aim at balancing agricultural output and maintaining agro-ecosystems resilience. According to [4], EBMFPs averagely conserve and boost the functional capacity of the ecosystems services through natural and biological means as well as intensive, high inputs systems.

Considering the varied functions that EBFMPs play, this paper sought to examine the factors that must be considered in promoting the adoption of EBFMPs by farmers. The paper thus provides evidence to policy formulators and implementers on some of the factors that enhance or inhibit the adoption of EBMFPs by farmers for sustainable agricultural production.

Methods

The study setting and sampling process

The study was conducted in the Upper East Region of Ghana. Ghana has varied agro-ecological zones which include the Rain Forest Zone, Coastal Savannah Zone, Semi-deciduous Forest Zone, Transitional Zone, Guinea-Savannah Zone and Sudan-Savannah Zone. The varied nature of the agro-ecological zones in Ghana makes her fairly representative of Africa, which has similar agro-ecological zones. The selection of Upper East Region was due to the fragile nature of its ecosystem that makes the need for EBFMPs to ensure sustainability in agricultural production imperative. Specifically, the study was conducted in two districts (Kassena-Nankana West District and Kassena-Nankana East District). The study districts (Fig. 1) fall within the Sudan-Savannah Vegetation Zone and has a total population of about 181,000 with about 61% from the Kassena-Nankana East District and 39% from the Kassena-Nankana West District [13]. The predominant economic activity in the area is farming with about 69% of the total population in agriculture [14].

A three-stage sampling technique was used to select study communities and households. In the first stage of the sampling, because of the critical role of irrigation in ensuring sustainable agricultural production, communities in the districts were divided into strata of community-managed and government-managed irrigation schemes of which three (3) communities each were randomly selected (Fig. 2).

In the second stage, a simple random sampling technique was used to select the required number of irrigated households from each community. According to [16], for any meaningful and more precise comparisons to be made, then a constant sample from each group, in this case community is critical. From a sample frame of 1813 households, 300 households (about 17% of the sample frame) were randomly selected for the study with each community having fifty (50) households as shown in Fig. 2. The 50 households from each community was more than 20% of the total number of households from each community, and thus representative of the communities from the view point of [16].

Theoretical and empirical review of models on sustainable farm practices

In social sciences, most studies usually deal with outcomes that are measured in counts such as number of soil conservative management practices, number of Integrated Pest Management (IPM) practices adopted, number of children as an indicator of fertility, and number of doctor visits as an indicator of health care demand among others [17]. Such studies are traditionally analysed with econometric models such as the binomial Probit or Logit models, which usually divide the dependent variable into two categories (1 = full adoption, 0 = no adoption at all) [18]. However, this might not be the true picture in most cases since technologies have different components, which could either be fully or partially adopted and binary choice models (e.g. Probit or Logit) cannot properly capture such situations. Thus, the Poisson regression or negative binomial regression models have been developed to handle such situations [18]. The count models (Poisson and negative binomial models) have the capacity to estimate the effect of a policy intervention either on the average rate or the probability of no event, a single event, or multiple events [17].

The Poisson model assumes that the response variable Y has a Poisson distribution and the logarithm of its expected value can be modeled by a linear combination of unknown parameters [19]. From [20], the model looks at the probability that the dependent variable Y (in this case the number of EBFMPs used) will be equal to a certain number y, and is represented mathematically as follows:

$$\mathrm{Prob}(Y = y) = \frac{e^{\lambda}\lambda^{y}}{y!}, \quad y = 0, 1, 2, 3 \ldots n \tag{1}$$

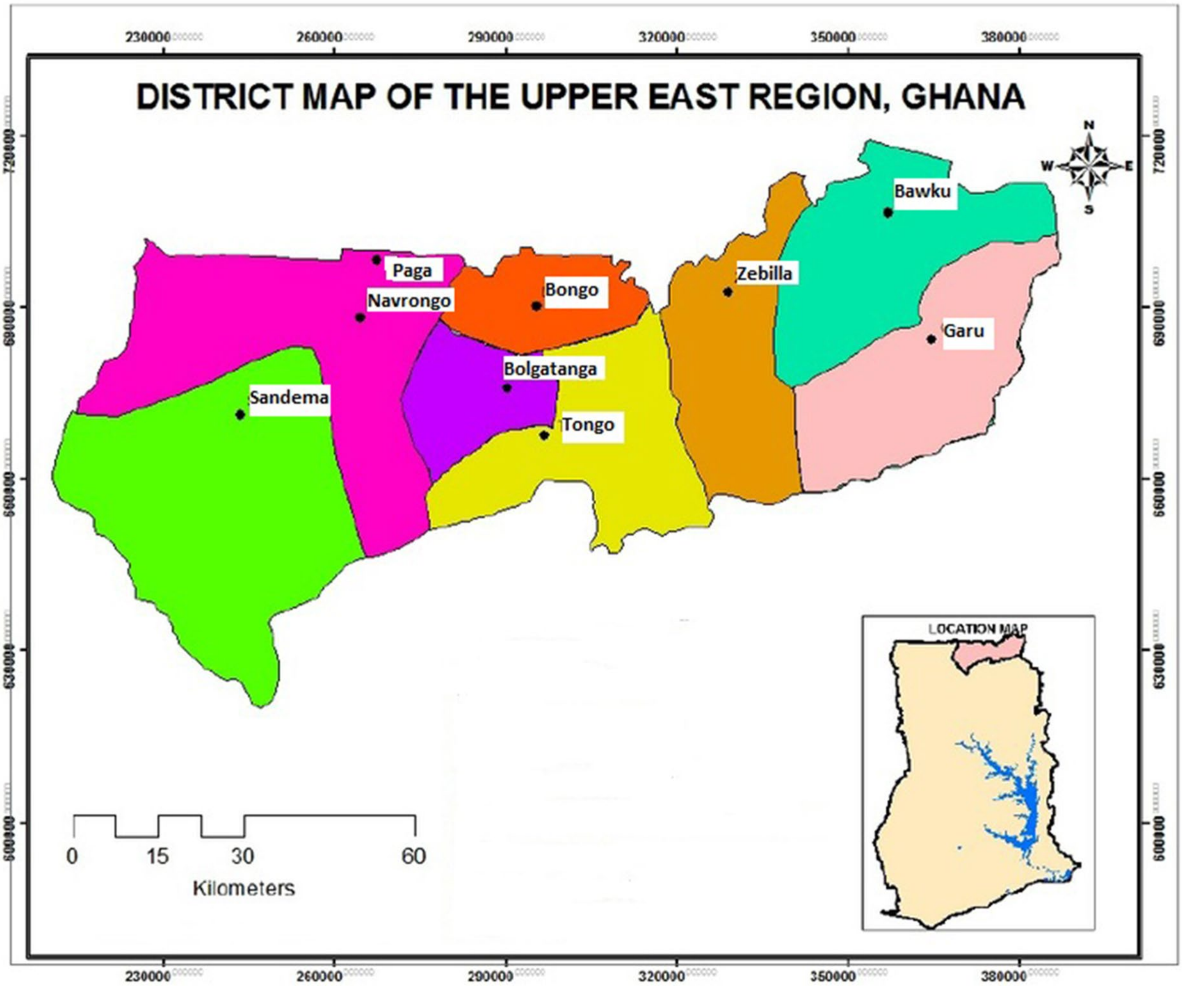

Fig. 1 A map of Kassena-Nankana Area in Upper East Region of Ghana. *Source*: [15]

where λ = is the intensity or rate parameter, $\lambda = \exp\left(X_i'\beta\right)$, $\beta =$ a vector of unknown parameters to be estimated.

The intensity parameter (λ) is assumed to be log-linearly related to the explanatory variables [8]. This is because the parameter (λ) is expressed as an exponential function of the explanatory variables. From the Poisson distribution assumption, the intensity of y is determined by the mean. This suggests that the intensity of adoption of EBFMPs is determined by the mean.

The log-likelihood function is given by the equation:

$$\ln L = \sum_{i=1,2,\ldots n} \left[-\lambda + y_i\beta' - \ln y_i!\right] \tag{2}$$

The interpretation of the coefficient is that, one unit increase in X_i will increase or decrease the average number of Y_i by the coefficient expressed as a percentage [20].

The marginal effect of a variable on the average number of events is:

$$\partial E(y_i/x_i)/\partial x_j = \beta_j \exp\left(X_i'\beta\right) \tag{3}$$

The interpretation of marginal effect is that one unit increase in X_i will increase/decrease the average number of the dependent variable by the marginal effect [20].

The key assumption is that the Poisson model has equi-dispersion property of the Poisson distribution. That is the equality of the mean and the variance specified as:

$$E\left(y/x\right) = Var(y/x) = \lambda \tag{4}$$

This property is much restrictive and often fails to hold in practice if there is 'over dispersion' in the data. This is common in developing countries like Ghana where farmers tend to recall agricultural information with a lot of discrepancies. According to [21], the Poisson model

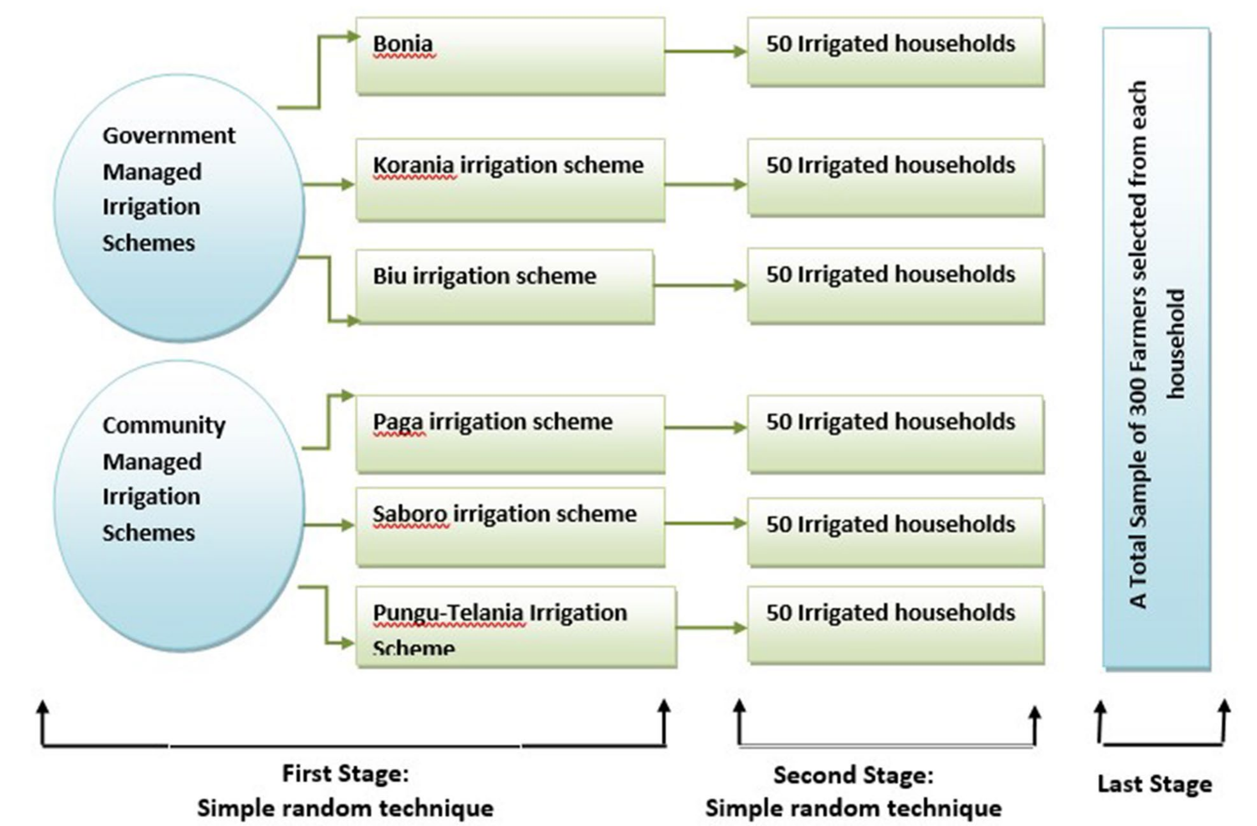

Fig. 2 Diagram showing the sampling procedure and sample size. *Source*: Authors' construction (2016)

relies heavily on an assumption that the conditional mean of outcome is equal to the conditional variance. But in practice, the conditional variance often exceeds the conditional mean. The negative binomial regression model however, deals with this problem by allowing the variance to exceed the mean [21]. Unlike the Poisson model, the negative binomial model (NBM) has a less restrictive property that the variance is not equal to the mean (μ) [22]. This is represented mathematically as follows:

$$Var(y/x) = \lambda + \alpha\lambda^2 \tag{5}$$

The negative binomial model also estimates the over-dispersion parameter α. Therefore, there is the need to test for over-dispersion. To test for the over-dispersion, the negative binomial model (NBM) which includes the over-dispersion parameter α is estimated and tested to see if α is significantly different from zero [21]. When $\alpha = 0$, it comes back to the Poisson model estimates. When $\alpha > 0$; there is over-dispersion (which frequently holds with real data). When $\alpha < 0$; there is under-dispersion (which is not very common).

These two models (Poisson and negative binomial regression models) have shown to be very simple for analysing count data and straightforward in interpretation. As a result, they are gaining greater usage by many researchers on current studies involving count data [17]. Thus, there are a number of current studies (e.g. [8, 12, 23]) on the adoption of sustainable practices that used count models.

The study by [18] was one of the first to explore the use of Poisson count regression models to analyse technology adoption. It was used to evaluate three technology transfer projects in Central America: Integrated Pest Management in Costa Rica, Agro-forestry systems in Panama, and Soil Conservation in El Salvador. However, the study by [18] has direct connection with this paper, which examined the factors to consider in promoting sustainable agriculture. Another study that employed one of the count regression models is [23]. Following [23], the adoption behaviour of farm households on farm management practices in three agro-biodiversity hotspots in India were investigated using the negative binomial count data regression model. The regression outcome revealed that farmers who received agricultural extension are more likely to use improved farm management practices. It also showed a negative relationship between cultivation of local varieties and adoption of farm management practices.

Again, in the work of [24], the Poison regression model was used to analyse the impact of farmers' experiences and perceptions of health risks of pesticides on the adoption of Integrated Pest Management (IPM) and pesticide use among small scale vegetable farmers in Nicaragua. Using the Poisson model, the authors were able to consider two levels of adoption process in that study (1) the count of IPM practices tested and (2) the count of practices actually used. The results revealed that previous experience with pesticide poisoning incidents has significant positive effect on the number of IPM practices tested by a farmer, but not on the adoption. Other factors, which showed significance, include school education, characteristics of cropping system, whether or not farmers had attended training in IPM and farmers who pay wage premiums to workers for application of pesticides.

In Ghana, the use of the Poisson and negative binomial regression models is equally gaining prominence. Classical examples include that of [8] and [12]. Nkegbe and Shankar [12] employed the Poisson model in the study to analyse the intensity of adoption of the sustainable soil and water conservation practices-composting, cover crops, agro-forestry, grass strip, soil bund and stone bund. The Gamma count was also used to further correct for over-dispersion in the data. From the empirical results of that study, access to information, social capital, per capita landholding and wealth play a crucial role in determining farmers' decision to intensively adopt sustainable soil and water conservation practices.

Again, [8] also closely tied with that of [12] except that the former had a broader scope, as it went beyond the factors that determine the adoption of the sustainable farming practices to consider the factor productivity. The study equally employed the Poisson model coupled with the stochastic frontier. From the study, credit, farm size, group membership and proximity to input sale points positively influence the adoption of conservation techniques. The covariates included gender, age, age square, education, farm size, household size, group membership, number of extension visits, credit obtained by the farmer and distance to input stores. The limitation of this study is on its inability to test for over-dispersion for the necessary corrections.

From the foregoing, the Poisson and the negative binomial regressions models are considered appropriate for this paper. It can also be deduced that all the above-mentioned studies have failed to consider farmers' knowledge of the ecosystem services as one of the factors that can influence their adoption of sustainable farm practices or EBFMPs. This paper therefore contributes to adoption studies literature on agro-ecosystems with a blend of indigenous farming practices (ecosystem-based farm management practices) knowledge and how it affects farmers' intensity of using the practices.

Empirical model specifications

To determine the factors that influence the adoption of EBFMPs, data were collected on the farm practices employed by each farmer in irrigation and rain-fed farming. These practices were then grouped into EBFMPs and non-EBFMPs. The total number of EBFMPs adopted by farmers in irrigation was then used as the dependent variable. The Poisson and negative binomial models were employed to examine the factors that influence the number of EBFMPs adopted by farmers. Below are the empirical models for the study and descriptions of the variables in Table 1:

Empirical model for community managed irrigation schemes (CIS)

$$\begin{aligned} Logy_{ci} = {} & \beta_{c0} + \beta_{c1} Age_{ci} + \beta_{c2} sex_{ci} \\ & + \beta_{c3} Educ\_d._{ci} + \beta_{c4} Ext.serv._{ci} \\ & + \beta_{c5} Fm.distance_{ci} + \beta_{c6} Soil.perceptn_{ci} \\ & + \beta_{c7} Fsize_{ci} + \beta_{c8} Knw.EBFMP_{ci} + \varepsilon_{ci} \end{aligned} \tag{6}$$

Empirical model for government managed irrigation scheme (GIS)

Table 1 Definition of variables and *apriori* expectations for adoption models

Variable	Variable definition	Units of measurement	Expected sign
Y	EBFMPs	Number of EBFMPs used	
Age	Age	Years	±
Sex	Sex	Dummy (1 = female, 0 = male)	±
Educ_d	Education	Dummy (1 = had formal education (at least JSS/JHS education), 0 = below JSS/JHS)	+
Ext.serv_d	Extension services	Dummy (1 = received at least 2 extension services last season, 0 = received 1 or no extension service)	+
Fm.distance.irr	Distance to irrigated farm	Kilometers	−
Soil.perceptn	Perception of soil fertility	Dummy (1 = fertile, 0 = not fertile)	−
Fsize.irr	Irrigable farm size	Acres	−
Knw.EBFMP	Perceived Knowledge of EBFMPs	Indexed on each EBFMP importance stated	+
Irrig_type	Category of irrigation	Dummy (1 = CIS, 0 = GIS)	+

Source: Authors' construction, 2016

$$Logy_{gi} = \beta_{g0} + \beta_{g1}Age_{gi} + \beta_{g2}sex_{gi} + \beta_{g3}Educ\_d._{gi} + \beta_{g4}Ext.serv._{gi} + \beta_{g5}Fm.distance_{gi} + \beta_{g6}Soil.perceptn_{gi} + \beta_{g7}Fsize_{gi} + \beta_{g8}Knw.EBFMP_{gi} + \varepsilon_{gi} \quad (7)$$

Empirical model for both government and community managed irrigation schemes

$$Logy_{cgi} = \beta_{cg0} + \beta_{cg1}Age_{cgi} + \beta_{cg2}sex_{cgi} + \beta_{cg3}Educ\_d._{cgi} + \beta_{cg4}Ext.visits._{cgi} + \beta_{cg5}Fm.distance.irr_{cgi} + \beta_{cg6}Soil.perceptn_{cgi} + \beta_{cg7}Fsize.irr_{cgi} + \beta_{cg8}Knw.EBFMP_{cgi} + \beta_{cg9}Irig_{cgi} + \varepsilon_{cgi} \quad (8)$$

Results and discussion

Socio-demographic characteristics of farmers

The survey found that farming is dominated by males in Ghana and likewise other parts of Africa in a broad scope (Table 2). This development emanates from the cultural and social setting of the people of Ghana and other countries in Africa, where resources (particularly productive agricultural lands) are controlled and owned by men. Until recently, farming was culturally seen as a male dominated economic activity in many parts of Africa while women were basically in-charge of sales of farm produce and other petty trading. It was revealed from the focus group discussions that agriculture is still labour intensive, which constraint women who are already preoccupied with domestic chores to engage themselves in it. Table 3 also shows that the average age of farmers is about 42 years with a standard deviation of 11 years. This suggests that averagely, the farmers in Ghana fall within the productive age cohort. Irrigation farming in several regions of Africa (e.g. Sub-Sahara Africa) has become an attractive force for most youth to engage in agriculture. The reason being that farm produce from irrigation (such as pepper, onions, tomatoes, rice among others) offer good prices relative to produce from rain-fed agriculture. Again, most of the agricultural lands owned by government-managed irrigation schemes (GIS) are operated as an open access system where the youth have an equal chance of securing lands for farming.

From Table 2, majority of the farmers had no formal education or had only basic education. The respondents' level of education shows that approximately 34% had at least Junior High School (JHS) education from the pooled data. This implies that only a few of the farmers might be able to read and understand new agricultural technologies and interventions. Like the agricultural sector in Ghana, agriculture is yet to acquire the needed level of investment in other parts of Africa, which can attract graduates from the tertiary level. As such, it is characterised by farmers with greater weakness in reading and understanding new agricultural interventions or programmes. This tend to affect farmers understanding of the nexus between new agricultural interventions and agro-ecosystems sustainability, hence they adopt practices that are not ecosystem-friendly. The survey also revealed that the mean household size of the respondents is about 6 with a standard deviation of 2 (Table 3). This means that averagely households have large potential labour force to help in farming activities. It can be observed in Table 2 that about 65% of the respondents are married while 35% otherwise (single, separated and widowed). Table 2 also shows that 71% of the respondents are household heads while 29% are not. Some household heads lost their spouses and some are staying with their children alone because of broken homes. Details of the statistics for the socio-demographic characteristics of farmers are shown in Tables 2 and 3.

Table 2 Summary statistics of categorical variables

Variables	Percentages		
	CIS	GIS	Pooled
Sex			
Females	42.00	16.00	29.00
Males	58.00	84.00	71.00
Marital status			
Married	58.00	72.67	65.33
Otherwise (single, separated and widowed)	42.00	27.33	34.67
Household head			
Yes	69.33	72.67	71.00
No	30.67	27.33	29.00
Perception of soil fertility			
Fertile	44.67	17.33	31.00
Otherwise	55.33	82.67	69.00
Education			
Had formal education (JHS education and above)	31.33	37.33	34.33
Below Junior High School (JHS) education	68.67	62.67	65.67
Extension services			
Received (at least two in the past season)	60.00	40.67	50.33
Otherwise	40.00	59.33	49.67
	$N = 150$	$N = 150$	$N = 300$

Source: Field survey, 2016

Factors influencing ecosystem-based farm management practices adoption

The paper sought to determine the factors to be considered in promoting the use of ecosystem based farm

Table 3 Summary statistics of continuous variables

Variables	CIS		GIS		Pooled	
	Mean	SD	Mean	SD	Mean	SD
Age	45.19	11.10	38.07	10.01	41.63	11.14
Household size	6.17	2.70	5.39	1.93	5.78	2.37
Farm size for irrigation (acres)	0.61	0.39	1.64	1.09	1.12	0.97
Irrigated farm distance (km)	0.95	0.59	1.53	0.94	1.24	0.84
Knowledge of EBFMPs (indexed)	16.99	3.86	15.39	3.25	16.19	3.65

Source: Field survey, 2016

management practices (EBFMPs) for sustainable agriculture in Africa. The paper focused on the adoption of EBFMPs by farmers in Ghana who are into irrigation farming because it represents the hope for the future under the current trends in climate change and variability. Besides, irrigation farming was targeted because of the critical role it plays in ensuring sustainable production in agriculture and the effect of it on the various ecosystems within a landscape. Ghana was used as a case study for Africa because of the varied nature of the country's agro-ecological zones (six types of agro-ecological zones), making her fairly representative of the continent. The paper used eight (8) EBFMPs for its analysis, which are organic manure application, conservation of vegetation, conservative tillage, mulching, crop rotation, intercropping with legumes, efficient drainage system and soil bunding (Table 4). These practices formed the basis as the dependent variable for the analysis with the Poisson and negative binomial models.

The results (Table 5) indicate that there is no over-dispersion since the test for alpha is not statistically different from zero. As such, there is sufficient evidence that the conditional mean is equal to the conditional variance and hence, the negative binomial model reduces back to the Poisson model (check "Appendix" for Poisson estimates). Even though the negative binomial regression Pseudo R^2 for the pooled data is low (about 10%), the overall significance of the model is high as indicated by the likelihood ratio Chi-square (significant at 1%). This implies that farmers' intensity of adoption of EBFMPs is determined by the set of covariates modelled in this paper. The regression results showed that farmers' age, distance to farm, perception of soil fertility, knowledge of EBFMPs, extension visits and the type of irrigation scheme the farmer cultivates significantly influence the adoption of EBFMPs.

Table 4 Distribution of EBFMPs adopted by farmers

EBFMPs adopted	Percentages		
	CIS	GIS	Pooled
Organic manure or compost application	72.00	46.67	59.33
Conservation of vegetation	76.67	52.67	64.67
Conservative tillage	81.33	36.00	58.67
Mulching	60.00	24.00	42.00
Crop rotation	28.67	38.00	33.33
Intercropping with legumes	46.00	28.67	37.33
Efficient drainage systems	47.33	22.67	35.00
Soil bunding	18.00	36.67	27.33
	$N = 150$	$N = 150$	$N = 300$

The results from the pooled data (Table 5) indicate that age of a farmer influence the adoption of EBFMPs in farming. Specifically, the results show that as farmers' age increases by 1 year, the intensity of adopting EBFMPs on farms increases and this is statistically significant at 5%. Generally, the finding suggests that old people in farming within the Ghanaian society and extensively in some parts of the African continent adopt more sustainable practices (or EBFMPs) than younger ones. Most aged farmers are still traditional with regards to agriculture production and as such, used more of the EBFMPs because they are indigenous practices learnt from forefathers. Even though, most of them cannot explain the biological functioning of the indigenous practices (which are mostly EBFMPs), they acknowledged the importance of these practices in minimising cost of production and sustaining soil fertility. This finding is however contrary to the finding of [12] which reported that the age of farmers do not influence adoption of soil and water conservation practices in northern Ghana.

The services that farmers receive from extension officers specifically, smallholder farmers under community-managed irrigation schemes (CIS) have an influence on the level at which they adopt EBFMPs. From the marginal effect regression on farmers under CIS, it suggests that those who received extension education in the previous season have greater intensity of using EBMFPs than those who had no extension education (Table 5) and this is statistically significant at 10%. Agricultural extension agents in Ghana and other parts of Africa provide information and education on agricultural production, especially new interventions. The education enlightens farmers on the

Table 5 Coefficient estimates for factors that influence EBMFPs adoption

Variables	Estimates of negative binomial model (NBM)					
	CIS		GIS		Pooled	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	1.016	0.296	0.044	0.318	0.498	0.213
Age	0.002	0.004	0.011	0.005**	0.006	0.003**
Sex	0.016	0.085	− 0.022	0.132	− 0.000	0.070
Educ_d	0.040	0.091	− 0.025	0.105	0.025	0.067
Ext_visits_d	0.160	0.094*	0.048	0.102	0.095	0.067
Fm_dist. (km)	− 0.234	0.083***	− 0.103	0.055*	− 0.146	0.046***
Fm_size (Acres)	0.040	0.106	0.005	0.046	0.005	0.042
Soil_perception	0.159	0.089*	0.239	0.123*	0.186	0.070***
Knw_EBFMPs	0.016	0.011	0.040	0.015***	0.026	0.009***
Irrig_type					0.161	0.081**
Number of observations	150		150		300	
LR chi^2(9)	42.230***		27.160***		106.860***	
Prob > chi^2	0.000		0.000		0.000	
Pseudo R^2	0.076		0.053		0.096	
Dispersion = mean						
Log likelihood	− 255.107		− 242.655		− 501.122	
Alpha	0.000		0.000		0.000	
Chibar^2(01)	0.000		0.000		0.000	
Prob ≥ chibar^2	1.000		1.000		1.000	

Source: Field survey, 2016

*, **, ***Represent 10, 5 and 1% levels of significance respectively

choice of activities at farm level and help them better understand the side effects of the practices they employ on farms. The significance and direction (positive) of the number of extension contacts are consistent with the finding of [12].

Farmers also consider the distance of their farms from places of abode in their adoption of sustainable farming practices or EBFMPs. Thus, distance to farms was found to have a negative influence on the number of EBFMPs that farmers adopt and this is statistically significant at 1, 10 and 1% for CIS, GIS and pooled models respectively. In other words, overall, when the distance to farms increases by 1 km, the intensity of adopting EBFMPs reduces in all the models. One of the major problems in terms of distance is that most farmers usually find it difficult to transport organic manure (one of the EBFMPs identified) from family compounds to farm sites. As such, only few farmers can apply organic manure on farms that are far from places of abode. It was also revealed from the focus group discussions that farms that are at the outskirts of communities or in the forests zones are usually very fertile and require little or no organic manure for greater yields. Such farms also have dense vegetation, which most farmers usually clear for farming activities.

Another factor that determines the intensity of adoption of EBFMPs is farmers' perception of soil fertility. From Table 5, perception of soil fertility is statistically significant at 10% in both CIS and GIS models. It is highly significant at 1% in the pooled model. In all the three models, it has positive effect on the intensity of adoption of EBFMPs. Farmers who perceived their farm plots to be fertile have a greater expected intensity of using EBFMPs than those who perceived their farm plots are infertile, all other things being equal. This finding is inconsistent with that of [9] who reported that farming on better soils decreases the adoption of soil improving practices. The reason given by farmers to support this finding is that those who perceived their soil fertility is low rather resort to the use of more inorganic measures to improve their soil fertility instead of the indigenous ecosystem friendly practices. Again, farmers who perceived that their soil fertility is high try to save cost by adopting organic practices to maintain the fertility of the soil. Another reason that accounts for this finding is that, farmers especially those under government-managed irrigation schemes think their soils are degraded to a non-responsive level for organic manure application. Thus, they rely on the usage of inorganic manure to improve their soils since it works faster than the organic manure.

Knowledge of farmers on the usefulness of EBFMPs affect their level of adoption of such EBFMPs (Table 5). Farmers who have more insights on the biological functions and benefits of ecosystem-based farm management practices tend to adopt more compared to those without adequate knowledge on the usefulness of EBFMPs. The result indicates that as farmers' knowledge on EBFMPs improves, the intensity of adopting EBFMPs increases and this was found to be statistically significant at 1% in both the GIS and the pooled models. Most farmers in Ghana and elsewhere in Africa, especially young and uneducated farmers focus more on yields at the expense of sustainability and this does not make them adopt EBFMPs. From the focus group discussions, most of the farmers attributed the current prevalence of strange pests and diseases in agriculture to the failure of this generation and the previous ones in maintaining some of the indigenous agricultural practices that could sustain the resilience of the agroecosystems (Table 6).

Lastly, the type of irrigation scheme or facility available to farmers influence the adoption of EBFMPs. The results in Table 5 indicate that farmers who cultivate under the community-managed irrigation schemes (CIS) have a greater intensity of adoption of EBFMPs than those under the government-managed irrigation schemes (GIS), *ceteris paribus* and the difference is statistically significant at 5%. Even though farmers in the CIS aim at maximizing yield as per their counterparts in the GIS, they are more conscious about the sustainability of their fields. This is probably because unlike the GIS where the land is publicly owned, farmers producing on CIS own the land upon which production takes place and hence have primary interest of maintaining the fertility of the farmlands even for future generations.

Conclusions and policy recommendations

The study sought to examine the factors that promote the adoption of ecosystem-based farm management practices (EBFMPs) in Africa, taking farmers in Ghana as a case study. Ghana became an ideal place because of its varied nature of agro-ecological zones. The agro-ecological zones in Ghana are into six (6) types and fairly representative of the agro-ecological zones in Africa. The Poisson and negative binomial models were employed for the analyses. The paper found that the intensity of EBFMPs adoption is significantly determined by age of farmers, distance to farms, perception of soil fertility, knowledge of EBFMPs, number of extension visits and the type of irrigation scheme available to farmers. Based on the results, it is concluded that to promote the use of EBFMPs in Ghana and other parts of Africa, it is important to focus on these factors. In other words, a focus on these factors is needed to bring about a shift from the current production system that relies heavily on intensive use of agrochemicals with negative consequences on ecosystem resilience and sustainability to a production system that is more ecosystem friendly using EBFMPs. It is therefore recommended that policy makers and implementers in Ghana and Africa generally come out with interventions that are generation specific (i.e. for the old and the young), distance neutral (i.e. not affected by distance to farmer residence), knowledge sensitive (i.e. literate and illiterate farmers) and production context specific (i.e. irrigation versus rain-fed; smallholder versus medium to large scale farmers). In all this, there is the need for policies that aim at building and sustaining robust agricultural extension systems that have at the centre ecosystem resilience and sustainability. Specifically, there is the need to review agricultural extension

Table 6 Marginal effects for factors that influence EBFMPs adoption

Variables	NBM's marginal effects					
	CIS		GIS		Pooled	
	dy/dx	SE	dy/dx	SE	dy/dx	SE
Age	0.012	0.016	0.032	0.013**	0.023	0.010**
Sex	0.070	0.357	− 0.061	0.362	− 0.001	0.238
Educ_d	0.169	0.386	− 0.069	0.290	0.088	0.232
Ext_visits_d	0.656	0.380*	0.135	0.285	0.326	0.228
Fm_dist. (km)	− 0.974	0.345***	− 0.286	0.152*	− 0.499	0.158***
Fm_size (Acres)	0.167	0.441	0.014	0.130	0.019	0.145
Soil_perception	0.669	0.378*	0.716	0.400*	0.658	0.258**
Knw_EBFMPs	0.070	0.049	0.112	0.042***	0.089	0.031***
Irrig_type					0.548	0.279**

Source: Field survey, 2016

*, **, ***Represent 10, 5 and 1% levels of significance respectively

policies to refocus them on how to expand agricultural production without compromising the biological functioning of the agro-ecosystems. Participatory approaches should be employed in the formulation and implementation of such policies to ensure community acceptability and ownership which will guarantee sustainability.

Abbreviations

CAADP: Comprehensive Africa Agriculture Development Programme; CGIAR: Consultative Group on International Agriculture Research; CIS: community managed irrigation schemes; EBFMPs: ecosystem-based farm management practices; ECOWAP: ECOWAS Agricultural Policy; GSS: Ghana Statistical Service; GIS: Government Managed Irrigation Schemes; MoFA: Ministry of Food and Agriculture; NBM: negative binomial model; IPM: Integrated Pest Management; IWMI: International Water Management Institute; WIAD: Women in Agriculture Development; WLE: Water, Land and Ecosystems; UDS: University for Development Studies.

Authors' contributions

CA designed data collection instruments, gathered data, analysed data and wrote the first draft of the manuscript. MAA, SD and FNM provided guide, corrections, inputs and supervision to the entire research study. All authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The datasets generated and analysed during the current study are available from the corresponding author on request.

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Not applicable.

Ethics approval and consent to participant

Not applicable.

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Appendix: Poisson estimates for factors that influence EBFMPs adoption by farmers

```
. poisson T_EBMFP_irr Age Sex Educ_d Ext_visits_d Fm_dist_km_irr Fm_size_irr Soil_percptn EBMFP_k
> nw Irrig_type

Iteration 0:   log likelihood = -501.12213
Iteration 1:   log likelihood = -501.12206
Iteration 2:   log likelihood = -501.12206

Poisson regression                              Number of obs   =        300
                                                LR chi2(9)      =     106.86
                                                Prob > chi2     =     0.0000
Log likelihood = -501.12206                     Pseudo R2       =     0.0963
```

T_EBMFP_irr	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Age	.0067793	.003103	2.18	0.029	.0006976	.0128611
Sex	-.0004684	.0700202	-0.01	0.995	-.1377055	.1367687
Educ_d	.0258911	.0676576	0.38	0.702	-.1067154	.1584977
Ext_visits_d	.0959868	.0670127	1.43	0.152	-.0353557	.2273294
Fm_dist_km_irr	-.14678	.0466758	-3.14	0.002	-.238263	-.055297
Fm_size_irr	.0055801	.0428365	0.13	0.896	-.078378	.0895381
Soil_percptn	.1864361	.0706725	2.64	0.008	.0479206	.3249516
EBMFP_knw	.0262394	.009294	2.82	0.005	.0080234	.0444554
Irrig_type	.1610305	.0818754	1.97	0.049	.0005578	.3215033
_cons	.4989228	.2132471	2.34	0.019	.0809661	.9168794

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