Intensity of and factors affecting land and water management practices among smallholder maize farmers in Ghana

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Abstract

Using count models, this paper assesses the intensity of land and water management practices among smallholder maize farmers in Ghana and the factors driving the number of practices adopted. Farmers' use of fertiliser, non-burning of farmland and ploughing-in of vegetative cover are the practices adopted the most. The paper cautiously notes that the farmers who combine three of the land and water management practices have the highest average productivity. Access to extension contact, credit and farmers' experiences of food shocks are important driving factors. The findings have implications for a comprehensive land and water management policy within which different strategies are articulated to increase the productivity of the farmers. Fertiliser application, no burning, zero tillage and ploughing-in of the vegetative cover are important. However, the regression results for maize yields suggest that the adoption of a high number of the technologies might not necessarily result in better yields.

Key words: intensity; land and water management practices; maize; policy measures; Ghana

1. Introduction

The economies of most African countries are highly dependent on agriculture. While agriculture may have contributed significantly to improved growth performance in some countries, it is estimated that agriculture's contribution is far less than its potential, and agriculture is growing slower than other sectors of the economy. There are productivity challenges for African agriculture, despite the significant technological advances that have taken place globally. Total factor productivity growth has averaged only 0.5% during the 2000s, well below the global average of 1.8% (Fuglie 2012). For Ghana, total factor productivity growth has averaged about 1.2% annually during the period 2001 to 2009 (Fuglie 2012).

Raising agricultural productivity provides impetus for agricultural transformation, sustainable poverty reduction and improved living standards (Timmer 1988; World Bank 2007). Ghana, like most countries in Sub-Saharan Africa, is faced with the challenge of finding a winning strategy for addressing stubbornly low agricultural productivity (Chapoto & Ragasa 2013), even though different production technologies have been extended to farmers over the years by both governmental and non-governmental organisations (Evenson & Gollin 2003; World Bank 2013). While some non-governmental organisations have partnered with government through the Ministry of Food and Agriculture (MoFA), others have initiated their own extension services to extend production technologies to farmers. Ultimately, the goals of the different stakeholders who have contributed to extending improved production technologies to farmers are similar: to help raise the productivity, output and income (and livelihood) of farmers (Evenson & Gollin 2003); to alleviate poverty and food insecurity (World Bank 2007); to increase the incomes of farm households; and to provide new employment opportunities (Minten & Barrett 2008; Noltze *et al*. 2013).

Several productivity-enhancing technologies have been developed and promoted for maize in Ghana (Chapoto & Ragasa 2013). The Ghana Grains Development Project (GGDP), which ended in 1997, for example, was a large, long-term programme focusing on the maize sector. The GGDP involved developing and disseminating several varieties of maize, evaluating various agronomic practices, producing production guides, and making a heavy investment in the extension and dissemination of improved technologies. At the same time, the Sasakawa Global 2000 programme conducted farm demonstrations to test and promote modern varieties. One of the focus technology packages that was tested and promoted was the zero-tillage package. Other technologies have also been developed and promoted. These include (i) the use of fresh certified seed every season, or at most every three cropping seasons; (ii) fertiliser use (rate, method and timing); (iii) other soil fertility-management practices (applying both organic and inorganic fertiliser; intercropping, crop rotation or crop relay with nitrogen-fixing crops; fallow systems); and (iv) timely harvesting and proper storage (MoFA/CRI/SARI 2005; Chapoto & Ragasa 2013).

This paper examines the intensity of and the factors influencing the adoption of land and water management (LWM) practices by maize farmers in Ghana. The objective is to help develop a better understanding of the drivers of intensity of adoption of LWM technologies. The analysis is expected to provide useful insights into smallholders' choice of LWM practices, and the role played by farm-specific as well as institutional factors in adoption intensity. In an operational environment in which farmers have to make ever more complex agronomic choices, it becomes increasingly important to understand the intensity of adoption (Sharma *et al*. 2011).

Following Lohr and Park (2002) and Sharma *et al.* (2011), the number of technologies adopted was interpreted as a measure of the intensity and diversity of adoption. Count data models were employed in the analysis. Many existing studies model technology adoption using a dichotomous variable (adopt or not), where determinants of this choice are assessed econometrically (Fernandez-Cornejo *et al*. 2001). However, in a number of cases it is not appropriate to model technology adoption as a simple dichotomous choice, as it is the combination of technologies employed that matters. In situations where a large number of techniques are available to farmers, technology adoption is more appropriately modelled as a multiple technology-selection problem. The literature on multiple technology adoption includes Rauniyar and Goode (1992), Chaves and Riley (2001), Fernandez-Cornejo *et al*. (2001), Lohr and Park (2002), Cooper (2003), Isgin *et al*. (2008), Sharma *et al*. (2011), Teklewold *et al*. (2013), and Kassie *et al*. (2014; 2015). Rauniyar and Goode (1992) examined the adoption of seven technologies in a sample of maize farmers in Swaziland and found that the farmers did adopt specific sets of technologies, leading them to argue that, in implementing extension activities, emphasis should be on the adoption of a package of practices and not on specific practices in isolation. Teklewold *et al*. (2013) and Kassie *et al*. (2014) note that adopting a combined set of sustainable intensification practices (SIPs) provided more net income from maize than adopting them individually, suggesting that complementarities exist among new technologies being adopted.

Lohr and Park (2002) and Isgin *et al*. (2008), in discussing the main assumptions underpinning a count of technologies as a proxy for intensity of adoption, note that (i) the adoption of any one technology does not preclude the adoption of any other, reducing the importance of the path dependence argument of Cowen and Gunby (1996); and (ii) there is no limit to the number of technologies adopted, as long as the last one adopted is profitable. Isgin *et al*. (2008), in a study of Ohio State farm operators, found that only 12% of the sample adopted more than 50% of the available technologies and reported evidence of diffused and partial adoption of the available technologies. Their count results show that several factors, including farm size, soil quality, farmer's status of indebtedness and farm location, were significantly associated with adoption intensity. Similarly, Sharma *et al*. (2011) found that 22% of farms adopted more than 50% of the 18 technologies considered in a study of UK cereal farmers. They found that total area farmed was positively related to the number of technologies adopted, whereas the number of years of experience of the farmer was negatively related.

2. Econometric methods

The methods for examining technology adoption behaviour have been explained in the literature. In principle, technology selection can be modelled using a multinomial Logit or Probit specification, where the dependent variable is a categorical variable taking a different value according to the technologies selected. Count data models can also be used to model technology selection, in which case the dependent variable is the number of technologies selected. Count data models focus on adoption intensity. The existing count data literature on technology adoption typically employs parametric specifications such as the Poisson model or the negative binomial. The number of technologies adopted is the dependent variable, and a set of farm-level characteristics are the explanatory variables (Lohr & Park 2002; Isgin *et al*. 2008; Sharma *et al*. 2011). Lohr and Park (2002) reject the Poisson model in favour of the negative binomial, Isgin *et al.* (2008) employ Poisson and negative binomial specifications, and Sharma *et al*. (2011) employ both parametric (OLS, Poisson and negative binomial specifications) and non-parametric methods. Overall, Sharma *et al.* (2011) find that there is a reasonable degree of agreement between the results generated by the various methods.

In this paper, the Poisson and negative binomial models were used to examine the intensity of technology adoption. The Poisson regression model, which is a suitable model for the estimation of count data (Greene 1997; 2000), was selected for the estimation of the farmers' decisions on the number of LWM practices to adopt. The maize farmers made a series of discrete household decisions that can be computed across an aggregation of choices to a Poisson distribution. The Poisson regression model is the development of the Poisson distribution to a non-linear regression model of the effect of independent variables, x_i, on a scalar dependent variable y. The density function for the Poisson regression is specified as:

$$f(y/x_i) = \frac{e^{-\mu_i}\mu^y}{y!}, \tag{1}$$

where the mean parameter, as the function of the regressors x_i and a parameter vector, β, is given by

$$E(y/x_i) = \mu = \exp(x'\beta) \qquad and \qquad y = 0,1,2,..... \tag{2}$$

where

$$\exp(x'\beta) = \exp(\beta_0) + \exp(\beta_1 x_1) + \exp(\beta_2 x_2)....+\exp(\beta_k x_k) \tag{3}$$

Also note that:

$$\beta_i = \frac{\partial E[y/x_i]/\partial x_i}{E[y/x_i]} = \frac{\partial \log E[y/x_i]}{\partial x_i} \tag{4}$$

This means that the coefficients of the marginal effects of the Poisson model can be interpreted as the proportionate change in the conditional mean if the j^{th} regressor changes by one unit. Finally, the Poisson model sets the variance as equal to the mean, as follows:

$$V(y/x_i) = \mu(x_i, \beta) = \exp(x'\beta) \tag{5}$$

This restriction of the equality of the mean and variance in the Poisson distribution is often not realistic, as it has been found that the conditional variance tends to exceed the mean, resulting in an over-dispersion problem (Cameron & Trivedi 1986; Grogger & Carson 1991; Winkelmann 2000). If an over-dispersion problem does exist, the conditional mean estimated with a Poisson model is still consistent, although the standard errors of β are biased downwards (Grogger & Carson 1991). A more generalised model to account for the over-dispersion problem is based on the negative binomial probability distribution, expressed as:

$$f(y/\mu,\alpha) = \frac{\Gamma(y+\alpha^{-1})}{\Gamma(y+1)\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\alpha^{-1}+\mu}\right)^{y}, \tag{6}$$

where

$$\mu = \exp(x'\beta) \qquad y = 0,1,2.... \tag{7}$$

and $\alpha \geq 0$ characterises the degree of over-dispersion (i.e. the degree to which the variance differs from the mean). That is, in the case of the negative binomial model, the variance is not equal to the mean; $V(y/x_i) = \mu + \alpha\mu^2$. Once the negative binomial model has been estimated, the presence of significant over-dispersion is given by the significance of the alpha coefficient. If the estimated alpha coefficient is significantly greater than zero, then over-dispersion is present and the estimated negative binomial model is preferable to the Poisson model. Otherwise, the negative binomial model reduces to the Poisson model. In this study, the test of equality of the mean and variance (no over-dispersion) was performed to select between the Poisson and the negative binomial model.

When modelling farmers' decisions on the number of technologies to adopt, particularly in a developing country, it may be important to consider the effect of the number of non-adopters in order to reveal the effect of excess zeros in the raw data (Long 1997; Greene 2000). To test whether the zero-inflated model fits to the data better, the Vuong (1989) test was performed.

A shortcoming of most studies in which the intensity of technology adoption has been analysed is that a higher number of technologies adopted may not necessarily mean higher productivity and therefore better welfare for adopters. As a result, we estimated a land productivity function derived from an assumed well-behaved production function to check for the relevance of the number of the technologies adopted for higher yields. The land productivity function is specified as:

$$Q_A = q(A, F, L, S, LWMP, Z_i), \tag{8}$$

where Q_A is land productivity of maize measured in metric tons per hectare, A is land size in hectares, F denotes quantity of fertiliser used measured in 50 kilogram bags, L is labour equivalent measured in man days (female days have been converted into equivalent man days using a factor of 0.70), S is seed quantity measured in kilograms, $LWMP$ is the predicted values of the Poisson regression regarding the number of LWM practices adopted, and Z_i are other socio-economic variables. It is expected, a priori, that $LWMP$ would have a positive relationship with land productivity. A neo-classical land productivity function, in the form of a Cobb–Douglas production function, was estimated. Different forms of the land productivity function, based on different terms for $LWMP$, were estimated. The adjusted R-squared and root mean standard error (MSE) values of the fitted models were considered to select the suitable regression results for discussion.

3. Data

The data were collected by administering a pretested structured questionnaire to smallholder producers selected from seven districts in five regions of Ghana in March 2010. Samples were taken from the three main geographical locations, namely Guinea Savanna zone, Transition zone (the middle belt) and Coastal Savanna zone. Considerations for the purposive selection of the districts from these zones included production levels, potential for increased production, proliferation of farmer-based organisations (FBOs), availability of agricultural and financial services, and proximity to markets. The districts selected were East Manprusi in the Northern region (Guinea Savanna zone); Ejura and Sekyere East in the Ashanti region (Transition zone); Nkoranza and Atebubu in the Brong–Ahafo region (Transition zone); Kwahu East in the Eastern region (Coastal Savanna zone); and North Tongu and Ketu South in the Volta region (Coastal Savanna zone). A total of 21 communities (four from East Manprusi, three from Ejura, two from Sekyere East, three from Nkoranza, two from Atebubu, two from Kwahu East, three from North Tongu and two from Ketu South) of smallholders were selected from a possible number of communities that could be enumerated. Within each community, a random sample of smallholder households was drawn at intervals of three to five houses, depending on the availability of a maize farmer in a selected house and the spatial distribution of houses across the study areas.

The three study zones form part of the six major agro-ecological zones of Ghana: Rain Forest, Deciduous Forest, Forest-Savannah Transition zone, Coastal Savannah, Guinea Savannah and Sudan Savannahs (the latter two comprise the Northern (Interior) Savannah) (FAO 2005; Oppong-Anane 2006). The main distinguishing climatic factor among the zones is rainfall. Rainfall distribution in the Transition and Coastal Zones is bimodal, giving a major season of 200 to 220 and 100 to 110 days and a minor growing season of 60 and 50 days respectively. In the Guinea Savanna zone, the unimodal rainfall distribution gives a growing season of 180 to 200 days (MoFA 2013). The mean annual rainfall is 1 300 mm, 800 mm and 1 100 mm for the Transition, Coastal and Guinea Savanna zones respectively (FAO 2005; MoFA 2013).

Rainfall largely determines the type of agricultural enterprise carried out in each zone (Oppong-Anane 2006). The dominant land-use systems are annual food and cash crops in the Transition zone (with maize, roots and plantain as the main food crops), annual food, cash crops and livestock in the Guinea Savanna zone (with sorghum and maize as main food crops), and annual food crops in the Coastal Savanna zone (with roots and maize as main food crops). In Ghana, about 50% of maize is produced in the Transition zone, 15% in the Guinea Savanna zone and 6% in the Coastal Savanna zone, while the remaining 29% is produced in the other three agro-ecological zones (FAO 2005).

The heterogeneous agricultural production structure indicates differences in the agricultural income structure across the regions (Breisinger *et al*. 2008). The forest zone remains the major agricultural producer, contributing about 43% of agricultural GDP, compared to about 10% contributed by the Coastal Zone, and 26.5% and 20.5% by the Southern and Northern Savannah Zones respectively. Export-oriented agricultural production plays an important role in total agricultural income for the Coast and Southern Savannah zones, while 90% of agricultural income in the Northern zone comes from staple crops and livestock (Breisinger *et al*. 2008). The poverty rate remains high, at 62.7% in the Northern Zone in 2005/2006, whereas it had dropped to 20% in the rest of Ghana (Breisinger *et al*. 2008).

The survey returned 327 administered questionnaires from the smallholder households for maize, but 292 maize farmers representing 89.3% of the maize sample were used for this study. Furthermore, the continuous variables used for the productivity regression were cleared of outliers. The list of the 13 main technologies employed for LWM practices by the respondents, and their rate of adoption, are presented in Table 1.

Table 1: Land and water management practices

Practice	Percentage of households practising (multiple responses)
Apply chemical fertilisers	66.1
No burn/land clearing (cutlass/hoe)	47.6
Plough-in vegetative cover	40.4
Zero tillage (chemical)	38.4
Ploughing across slopes	26.4
Cover cropping	19.5
Mulching	18.2
Apply manure	16.8
Ridging (including ridging across slopes)	12.0
Mounding	7.2
Earth bunding	5.4
Stone bunding	3.1
Irrigate crops	2.4

The use of practices such as fertiliser application, non-burning of land and the ploughing-in of vegetative cover is relatively high. The use of other activities, such as bunding and irrigation of crops, is much lower, possibly due to their laborious nature and initial costs.

The mean number of LWM practices adopted was 3.0, with a standard deviation of 1.87, and the modal number was 2. Only 9.58% of the maize farmers adopted more than 50% of the technologies considered (Table 2), compared to 12% and 22% estimated by Isgin *et al*. (2008) and Sharma *et al*. (2011) respectively. About 4.79% of the farmers practised none of the LWM practices. Maize farmers who adopted any three of the LWM practices were the most productive, with an estimated average land productivity of 2.43 tons/ha. Among the farmers who had adopted three of the LWM practices, those (8.57%) who had adopted the technology of no burning, zero tillage and ploughing-in of the vegetative cover were the most productive (6.03 tons/ha), followed by those (8.57%) who applied chemical fertilisers, ploughing across slopes and mulching (2.88 tons/ha). The results suggest that, besides fertiliser application, no burning and ploughing across slopes, LWM practices such as zero tillage, mulching and ploughing-in of the vegetative cover, which allow some of the natural nutrients to be returned to the soils, are important for increasing farmers' productivity. However, these estimated averages should be interpreted with caution, since the confounding factors have not been controlled for.

Table 2: Intensity of practices and land productivity

Number of land and water management practices	Frequency	Percent	Land productivity (tons/ha)
0	14	4.79	2.10
1	38	13.01	1.41
2	76	26.03	1.90
3	70	23.97	2.43
4	43	14.73	1.53
5	23	7.88	1.79
6	14	4.79	2.18
7	7	2.40	1.31
8	1	0.34	1.20
9	3	1.03	1.23
10	2	0.68	0.90
11	1	0.34	0.90
Total	292	100.00	

The tetrachoric correlation coefficients presented in Table 3 show that most (70.6%) of the significant correlation coefficients are less than 0.5 (i.e. $r < 0.5$). Rauniyar and Goode (1992) and Sharma *et al.* (2011) interpret correlation coefficients greater than 0.5 as high. Thus, in general, the estimated correlations among maize farmers' selection of LWM technologies are not high. High, positive and significant correlation coefficients among technologies suggest that technologies are selected simultaneously, whereas high, negative and significant correlation coefficients suggest that technologies turn toward mutually exclusiveness (Rauniyar & Goode 1992; Sharma *et al.* 2011). Sharma *et al.* (2011) revealed that the farmers employ a mix of integrated pest management technologies. The estimated high and positive correlation between earth bund and stone bund is because the two technologies are similar and their use together, depending on the available materials, ensures a tight bund. The estimated correlation between earth bund and either mulching, manure application or ridging is also high and positive, suggesting that the pair are selected simultaneously. Similarly, the estimated correlation between stone bund and either cover cropping, ploughing across slopes, manure application, fertiliser application or ridging is high and positive. Ridging and manure application are also highly and positively correlated, meaning they are adopted together by the farmers.

Defining significant correlation coefficients between 0.25 and 0.50 as moderate suggests that manure application is moderately and positively correlated with no burning, ploughing across slopes and ploughing-in vegetative cover, but negatively correlated with zero tillage. The estimated tetrachoric correlation coefficients suggest that manure application and zero tillage are mutually exclusive technologies for LWM. Similarly, ploughing-in vegetative cover and mulching are mutually exclusive technologies (Table 3). Zero tillage and no burning are moderately selected together. Fertiliser application, which is used by most of the maize farmers (66.1%), is either moderately or lowly correlated with the other LWM practices, except for stone bund. Thus, the exclusive promotion of the use of fertiliser, for example under the current fertiliser subsidy programme that was reinitiated in 2008, may limit the adoption of other important practices of LWM.

Table 3: Tetrachoric correlation estimates of land and water management practices

LWM practices	Earth bunding	Stone bunding	Mounding	Mulching	Cover cropping	No burning	Zero tillage	Plough-in vegetative cover	Ploughing across slopes	Apply manure	Apply fertiliser	Irrigate crop	Ridging
Earth bunding	1.000												
Stone bunding	0.894***	1.000											
Mounding	-1.000	-1.000	1.000										
Mulching	0.519***	0.344*	-0.351	1.000									
Cover cropping	0.187	0.650***	0.157	-0.065	1.000								
No burning	0.432***	0.347*	0.000	0.251**	0.182	1.000							
Zero tillage	0.069	0.069	0.124	0.375***	0.101	0.469***	1.000						
Plough-in vegetative cover	0.120	0.419**	-0.166	-0.256**	0.031	0.173*	0.086	1.000					
Ploughing across slopes	0.385**	0.567***	0.034	0.189*	0.110	0.243**	-0.098	0.260***	1.000				
Apply manure	0.544***	0.686***	-0.173	0.006	0.069	0.362***	-0.252**	0.246**	0.236**	1.000			
Apply fertiliser	0.335*	1.000**	0.152	0.221*	0.260**	0.120	0.271***	-0.096	0.149	0.099	1.000		
Irrigate crop	0.238	0.369	-1.000	-1.000	0.292	-0.051	-0.113	-0.135	-0.179	-1.000	-0.100	1.000	
Ridging	0.514***	0.845***	0.058	0.102	0.180	0.143	0.241**	0.209*	0.231*	0.561***	0.089	0.267	1.000

*** denotes 1% significance, ** denotes 5% significance and * denotes 10% significance

Table 4 presents the description, mean and standard deviation of the variables included in the regression estimations. The average size of per capita land cultivated by the maize farmers was about 0.40 ha. About 76% of the respondents were males. Most of the farmers (53.1%) had a basic level of education, but 29.4% of them had no formal education. Also, most of the maize farmers had contact with extension agents during the 2009 crop season (66.8%), saved towards farm investments (69.9%) and were members of FBOs and/or community-based organisation (CBOs) (58.5%). Few of the sampled farmers' households (14.4%) normally experienced severe food shortages. The mean of the predicted value of the number of technologies adopted from the estimated count (Poisson) model is 3.04, with minimum and maximum predicted values of 1.71 and 5.41 respectively.

Table 4: Description and summary statistics of regression variables

Variable	Description	Mean	Std. dev.
Count regression			
Number (intensity) of practices	Number of LWM practices adopted	3.034	1.8737
Gender	Sex of the respondent (male = 1; female = 0)	0.764	0.4255
Extension contact	Had extension contact in 2009 farm season (Yes = 1; No = 0)	0.668	0.4718
Save towards farm investments	Respondent saves towards farm investments (Yes = 1; No = 0)	0.699	0.4596
Experience severe food shortage	Household normally experiences severe food shortages (Yes = 1; No = 0)	0.144	0.3515
FBO membership	Respondent is member of FBO and/or CBO (Yes = 1; No = 0)	0.586	0.4934
Access to credit	Respondent has access to agricultural credit (Yes = 1; No = 0)	0.366	0.4827
Own bicycle	Respondent has own bicycle(s) (Yes = 1; No = 0)	0.668	0.4718
Own land for farming	Respondent has own land for farming (Yes = 1; No = 0)	0.589	0.4929
Land per capita	Maize farm size per household member (Ha/person)	0.400	0.5858
Education status	Respondent's educational level		
No education	No education = 1, otherwise = 0	0.294	0.4566
Basic education	Basic education = 1, otherwise = 0	0.531	0.4999
Secondary/higher	Secondary/higher education = 1, otherwise = 0	0.174	0.3803
Maize belt	Respondent's location (Transition zone = 1; otherwise = 0)	0.524	0.5003
Added variables for yield regression			
Land productivity	Output of maize per plot size (metric tons per hectare)	1.864	1.9318
Plot size	Size of maize plot cultivated (hectares)	2.326	2.2984
Fertiliser quantity	Quantity of fertiliser applied (50 kilogram bags)	7.776	11.6086
Labour quantity	Total labour equivalent (mandays)	156.979	179.3640
Seed quantity	Quantity of seed maize planted (kilograms)	59.350	85.4910
Number of practices	Predicted value of number of LWM practices adopted (from count regression)	3.044	0.5414

4. Regression results and discussion

The regression results are presented in Table 5. The results indicate a reasonable degree of uniformity regarding the sign of the parameter estimates and the statistical significance at either 5% or 10% for both the Poisson and the negative binomial specifications. The Poisson model estimation is preferred to the negative binomial model, and therefore is considered for further analysis and discussion. This is because the estimated alpha coefficient for the negative binomial model is insignificant, suggesting the absence of over-dispersion. Also, the Poisson model has marginally lower AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) estimates than the negative binomial model. The Vuong test result for the zero-inflated Poisson (ZIP) model suggests that, at the 5% level of significance, the standard Poisson model is the suitable model for describing the maize farmers' intensity of adoption of LWM practices. The estimated pseudo R-squared value is low (2.42%), but the overall significance of the Poisson model, reported by the Wald chi-squared value, is satisfactory.

Maize farmers' contact with extension, having experienced severe food shortages, having access to agricultural credit, and being located in the maize belt are positively and significantly associated with the intensity of technology adoption. On the other hand, a maize farmer being a member of a FBO/CBO and land per capita cultivated are negatively and significantly related to the intensity of technology adopted.

Table 5: Regression results of the factors influencing the intensity of adoption of land and water management practices

Variable	Poisson regression		Negative binomial regression	
	Coefficient	Robust standard error	Coefficient	Robust standard error
Gender	0.050	0.0851	0.052	0.0848
Extension contact	0.169**	0.0829	0.168**	0.0825
Save towards farm investment	0.064	0.0826	0.067	0.0822
Experience severe food shortages	0.274**	0.1186	0.274**	0.1190
FBO member	-0.138*	0.0792	-0.139*	0.0794
Credit access	0.138*	0.0820	0.138*	0.0821
Basic education[1]	-0.109	0.0763	-0.109	0.0762
Secondary/Higher education[1]	0.019	0.1049	0.021	0.1041
Land per capita	-0.099**	0.0475	-0.099**	0.0474
Own land for farming	0.095	0.0728	0.096	0.0726
Own bicycle	0.055	0.0766	0.056	0.0762
Maize belt	0.134*	0.0707	0.137*	0.0704
Constant	0.819***	0.1260	0.814***	0.1266
Ln(alpha)			-4.092	1.4804
Alpha			0.017	0.0247
Obs	292		292	
Wald chi^2 (14)	25.49		25.07	
Prob > chi^2	0.0127		0.0145	
Pseudo R^2	0.0242			
Log pseudo-likelihood	-561.996		-561.776	
AIC	1 149.992		1 151.555	
BIC	1 197.789		1 203.030	
Vuong test of ZIP vs. standard Poisson: z = 1.10 Pr > z = 0.1359				

[1] The comparative level of education is no formal education
***, ** and * are 1%, 5% and 10% critical levels respectively

The positive and significant association of the extension contact variable suggests that exposing (more) farmers to agricultural extension advice could help to increase the adoption of more LWM practices. DeGraft-Johnson *et al.* (2014) suggest that, for technologies that require some level of technical knowhow, having direct contact with extension services and projects increases the acquisition of relevant knowledge. Thus, if the high farmer–extension ratio can be reduced, the adoption of technologies will be enhanced. Ghana's growth and poverty-reduction strategy for 2006 to 2009 did seek to intensify these linkages, but a major challenge remains the low extension officer–farmer ratio, which was at 1:1 400 by the end of 2004 (NDPC 2005) and 1:1 500 in 2009 (NDPC 2010), falling short of the 1:1 200 target. Efforts therefore are needed to increase the number of extension officers and extension contact in the system, and to harness new information and communications technology (ICT) media.

Having access to agricultural credit was positively associated with the intensity of LWM practices adopted. Credit support to the agricultural sector in general continues to lag behind the support to other sectors of the economy, and this should be considered as a matter for policy action. Furthermore, while it was expected that belonging to a FBO/CBO, which normally acts as a group, would lead to a positive relationship with the adoption of technology, and in this case LWM practices, the regression result suggests otherwise. Probably, the FBOs/CBOs and their members do not have the capacity to access and adopt these practices, hence the negative relationship. Isham (2002) found out that participatory social affiliations, acting as forms of social capital, had a positive effect on the technology adoption decision in Tanzania. Similarly, Munasib and Jordan (2011) found that associational memberships had positive effects on the decision to adopt sustainable agricultural practices among Georgian farmers, and on the extent to which the farmers adopted these practices.

Interestingly, the maize farmers who normally experienced severe food shortages adopted more LWM practices (Table 5). This positive relationship means that the adoption of more LWM practices serves as an adaptation strategy in response to the regular experience of severe food shortages, perhaps as a result of irregular rainfall patterns. In a related study, Abdulai and Huffman (2014) reveal that the adoption of field ridging increased rice yields of farmers in northern Ghana. Ouédraogo *et al*. (2001) conclude that compost application is a sound technology for combating soil degradation and could contribute to increased food availability. Thus, our empirical result confirms the need for strategies to assist individuals and communities that experience food shortages on a regular basis as a result of rainfall/water shortages to increase their production through the introduction and adoption of new/improved technology. This implies that new technologies, like LWM practices, could be implemented as an integral part of relief programmes to assist farmers and rural communities in managing production risk.

Another important result is the negative and significant association due to per capita land cultivated by the maize farmers. The negative association implies that, as the relative amount of land cultivated declines due to increasing population pressure, farmers adopt more LWM practices. Thus, LWM practices that encompass a number of intensification efforts are a direct response to an increase in household populations relative to the amount of land cultivated in order to produce more. Sharma *et al*. (2011) and Isgin *et al*. (2008) have estimated that the total area farmed is positively related to the intensity of technology adopted.

The location variable is positive and significant, which means that farmers located in the maize belt adopt more LWM practices than their counterparts in other locations. This result may be interpreted to mean that the intensity of adoption of a technology for a targeted crop will be high in locations where the crop is highly cultivated, and therefore the specificity of adaptive technologies for different areas may sometimes be crucial.

As far as the relationship between land and water management practices and yield are concerned, the regression results for the land productivity functions are presented in Table 6. The estimated forms that included the terms for *LWMP* gave better adjusted R-squared and root MSE values than the estimated form that excluded *LWMP*. Similarly, they allowed socio-economic variables, namely gender, access to credit and extension contact, to count as explanatory variables, at least at the 10% level of significance, for the neo-classical land productivity function compared to the estimated form that excluded the *LWMP* term. Only the estimated form that included the natural logarithm terms of *LWMP* had a significant value for *LWMP*, hence the discussion is based on this estimated form.

As expected, conventional inputs, namely quantities of fertiliser, seed and labour employed, had positive and significant effects on land productivity. Similarly, the relationship between land productivity and size of the land cultivated was negative and significant, supporting the stylised inverse relationship between farm size and land productivity (e.g. Carletto *et al.* 2013; Gucheng *et al.* 2013; Byiringiro & Reardon 1996). The number of LWM practices used had a negative relationship with land productivity (yield) and were significant at the 10% level. The net effect of *LWMP* was negative, with an estimated mean elasticity of 0.7885 ($\partial \ln Q_A / \partial \ln LWMP$ = -2.8961 + (2 *x* 0.960 *x* ln*LWMP*)). Thus, a higher number of LWM practices adopted might not lead to higher land productivity.

Table 6: Regression results for land productivity (yield)

Variable	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)	Coefficient (standard error)
Lnplotsize	-0.607*** (0.0777)	-0.680*** (0.0797)	-0.674*** (0.0798)	-0.677*** (0.0798)
Lnfertilizer qty	0.317*** (0.0386)	0.327*** (0.0382)	0.327*** (0.0383)	0.327*** (0.0383)
Lntotal labourequivalent	0.145*** (0.0554)	0.152*** (0.0554)	0.158*** (0.0552)	0.155*** (0.0553)
Lnseedqty	0.147*** (0.0532)	0.173*** (0.0530)	0.169*** (0.0530)	0.171*** (0.0530)
Lnnumber of technologies		-2.896* (1.7552)		
Lnnumber of technologies squared		0.960 (0.7813)		
Number of technologies			-0.846 (0.5201)	1.246 (1.0220)
Number of technologies squared			0.094 (0.0783)	
Square root of number technologies				-5.268 (3.6441)
Gender	0.117 (0.0896)	0.179** (0.0903)	0.171* (0.0903)	0.175* (0.0903)
Extension contact	0.089 (0.0848)	0.162* (0.0864)	0.158* (0.0867)	0.161* (0.0865)
Maize belt	0.592*** (0.0893)	0.679*** (0.0918)	0.673*** (0.0920)	0.677*** (0.0920)
Credit access	0.070 (0. 0804)	0.162* (0.0848)	0.161* (0.0850)	0.162* (0.0849)
Constant	5.357*** (0.2987)	7.069*** (1.0081)	6.747*** (0.8672)	10.436*** (3.2372)
Number of obs.	275	275	275	275
F – Value	25.94	22.49	22.26	22.34
Prob > F	0.0000	0.0000	0.0000	0.0000
R-squared	0.4383	0.4600	0.4575	0.4588
Adj R-squared	0.4214	0.4396	0.4369	0.4383
Root MSE	0.6010	0.5914	0.5928	0.5921

5. Conclusions and policy implications

Technology adoption is crucial for the enhanced productivity of farms. This study examined the factors influencing the intensity of adoption of water and land management technologies by maize farmers in Ghana. Primary data was analysed using the Poisson and negative binomial regression models, and a Cobb–Douglas specification of the land productivity function.

The results of the descriptive statistics should be used with caution, as confounding factors have not been controlled for. The mean and modal numbers of LWM practices adopted are 3.0 and 2 respectively. Only 10% of the maize farmers adopted more than 40% of the technologies considered, and the estimated correlations among maize farmers' selection of LWM technologies are not high.

The empirical results of the fitted Poisson model reveal that access to extension services, agricultural credit, regular experience of severe food shortages, smaller amount of farmland per capita and location in the major maize belt have a positive influence on the number of LWM technologies employed. The regression results for land productivity suggest that a higher number of technologies adopted might not necessarily lead to an increased yield of maize for the farmers.

The findings have implications for the formulation of a comprehensive LWM policy within which different strategies are articulated for increasing agricultural production. The recently implemented fertiliser subsidy programme is one such strategy, but a programme that promotes the use of zero tillage and ploughing-in of the vegetative cover to help restore natural nutrients to the soils as well as to minimise erosion is also recommended. Policy measures could help to intensify these practices, which might also contribute to higher farm productivity. The provision of improved extension services and agricultural credit should be strengthened to facilitate the adoption of technology. The findings of the study also suggest that LWM practices could be used as mitigating measures to help raise the production of those who regularly experience severe food shocks. In particular, a new agricultural technology could be implemented as an integral part of relief programmes to assist farmers and the rural communities to manage production risk, although the adoption of a high number of technologies might not be relevant.

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