Journal of Development and Agricultural Economics

Volume 9 Number 6 June 2017
ISSN 2006-9774

Academic Journals

ABOUT JDAE

The Journal of Development and Agricultural Economics (JDAE) (ISSN:2006-9774) is an open access journal that provides rapid publication (monthly) of articles in all areas of the subject such as The determinants of cassava productivity and price under the farmers' collaboration with the emerging cassava processors, Economics of wetland rice production technology in the savannah region, Programming, efficiency and management of tobacco farms, review of the declining role of agriculture for economic diversity etc.

The Journal welcomes the submission of manuscripts that meet the general criteria of significance and scientific excellence. Papers will be published shortly after acceptance. All articles published in JDAE are peer- reviewed.

Contact Us

Editorial Office:	jdae@academicjournals.org
Help Desk:	helpdesk@academicjournals.org
Website:	http://www.academicjournals.org/journal/JDAE
Submit manuscript online	http://ms.academicjournals.me/

Editors

Journal of Development and Agricultural Economics

Table of Contents: Volume 9 Number 6 June, 2017

ARTICLES

Determinants of household's consumption preference for processed cocoyam in Enugu State, Nigeria 137
Adeosun K. P., Amaechina E. C. and Nnaji A. P.

Climate sensitivities and farmland values in Nepal: A spatial panel Ricardian approach 145
Samrat B. Kunwar and Alok K. Bohara

Determinants of participation in fertilizer subsidy programme among rice farmers in Ogun State, Nigeria 162
OBI-EGBEDI Ogheneruemu and BANKOLE Olaide Abdul-hameed

academicJournals

Vol. 9(6), pp. 137-144, June 2017
DOI: 10.5897/JDAE2016.0782
Article Number: 8D75CFA64357
ISSN 2006-9774

http://www.academicjournals.org/JDAE

Journal of Development and Agricultural Economics

Full Length Research Paper

Determinants of household's consumption preference for processed cocoyam in Enugu State, Nigeria

Adeosun K. P.*, Amaechina E. C. and Nnaji A. P.

Department of Agricultural Economics, University of Nigeria, Nsukka, Enugu State, Nigeria.

Received 22 September, 2016; Accepted 11 April, 2017

Cocoyam is a nutritious food crop which is consumed in different parts of Nigeria. Its importance in the food systems of many communities in Nigeria, particularly among the Igbo people is based on its nutritive value and its relative ease in cultivation. Studies on the crop focused more on production and marketing without examining consumer behaviour. Although, an understanding of the determinants of the consumption of various processed forms as well as volume consumed by households is important information for policy makers, this has scarcely been examined in Nigeria. Understanding the socio-economic dynamics that make consumers choose one form of the product and not another is crucial for ensuring the food security of the poor. This study therefore examined the factors that influenced consumption of processed cocoyam and the volume consumed. For the study, multistage sampling technique was used to select the respondents. Data collected was analyzed using multiple linear regression and multinomial logistic regression. The results show that income allocated for cocoyam consumption, hectares of cocoyam cultivated, number of times cocoyam is consumed, distance from home to market and household size are important determinants of volume of cocoyam consumed by households, while, household size, quantity of cocoyam consumed by households, farming experience, age, marital status and income spent on cocoyam are important determinants of consumption of processed cocoyam.

Key words: Consumer behaviour, household, processed cocoyam, food security.

INTRODUCTION

Cocoyam (*Colocasia* spp. *and Xanthosoma* spp.) as a crop has until recently received little attention from international and regional bodies (Agbelemoge, 2013; Onyeka 2014), mainly due to the low value given to it. However, given its potential as an affordable crop for the poor, and the increasing awareness of its health value, there is a growing focus on the crop. It negates fundamentals of increasing demand due to high population pressure as well as urban development. More people now accept the consumption of highly cherished foods within their culture. This threatens the food security of households that consume such crops. According to Onyeka (2014), cocoyam is nutritionally more important than yam and cassava in terms of higher protein, mineral and vitamins content as well as digestible starch. As a tuber crop, it belongs to the class of staple foods that

*Corresponding author. E-mail: paul.adeosun@unn.edu.ng.

provide most calorific intake by Nigerians (Amusa et al., 2011). Cocoyam remains an underutilized and poorly understood crop in spite of its potential as a food and cash crop and its higher nutritive value (Onyeka, 2014). Okeke et al. (2009) noted that the problem of malnutrition of poor nations will be difficult to solve through food aid from developed countries but rather by effective consumption of indigenous plant foods. The reason is because traditional foods are more likely to meet the household food security needs of the population, particularly the rural households than imported foods.

The crop can be processed into many forms that meet the food needs of households. Amongst the Igbo of Southeastern Nigeria, the cocoyam can be prepared in various forms (Okeke et al., 2009). Cocoyam is available almost all year round (Ndabikunze et al., 2011). Household food inadequacy problem can always be solved when the people can have easy access to food they prefer in the forms they prefer them (Amaza et al., 2009). According to Omotesho et al. (2010), food security may be described as conditions or situations which guarantee easy access to highly nutritious, affordable, socially acceptable and environmentally friendly food within a community. In this case, availability means food can be easily produced by the consumer themselves. Accessibility connotes that food can be transformed into different forms that are preferred by consumers. Affordability suggests the consumers have the purchasing power or ability to obtain food at all times (Omonona and Agoi, 2007). Therefore, if cocoyam is processed into different forms, it creates wider opportunity for its accessibility to consumers, because they have a more diverse spread of options for consuming cocoyam.

Food security can be said to be achieved if people can have access to their preferred food and in the forms they prefer it. The study therefore seeks to determine factors influencing consumption of cocoyam and preference for processed cocoyam.

Motivation for cocoyam consumption

Cocoyam (*Xanthosoma sagittifolium*) contributes significant portion of the carbohydrate content of the diet in many regions in sub-Sahara Africa and provide edible starchy storage corms or cormels (Sanful and Darko, 2010). According to Opara (2002), cocoyam is perceived to be less important than other tropical roots such as yam, cassava and sweet potato. However, they are still a major staple in some parts of the tropics and sub-tropics, particularly in the rural areas of these regions (Ojinaka et al., 2009). Cocoyam is being put to different uses like other staple foods such as yam, cassava and potatoes. Although, it is not considered as prestigious as yam, its flour has the added advantage that, it is highly digestible and so is used for ingredient in baby foods (Sanful and Darko, 2010). According to Enwelu et al. (2014), consumption of mixture of cocoyam and beans is fairly good and should be encouraged because most people in rural areas eat unbalanced diets usually made up of carbohydrates. Nutritionally, cocoyam is rich in carbohydrates with nutritional value comparable to potato and superior to cassava and yam in the possession of higher protein, mineral and vitamin contents as well as easily digestible starch (Parkinson, 1984; Splittstoesser et al., 1973). It is highly recommended for diabetic patients, the aged, children with allergies and for other persons with intestinal disorders (Plucknett, 1970). These nutritional attributes make it a good base for food preparation for infants, and it has been shown that cocoyam starch can be incorporated in the development of weaning food which is highly digestible and accessible to low-income earners (Oti and Akobundu, 2008).

Cocoyam chips are popular in the local communities in Nigeria and are used in preparing many different local cocoyam delicacies. For instance, consumers of cocoyam believe that it is both energy giving and a light food, a quality that distinguishes it from other energy giving foods like yam and cassava. The corms and cormels of cocoyam are processed by boiling, baking or frying in oil. They are also processed into different products in many parts of Nigeria. All major parts of cocoyam (corm, cormel and leaves) are edible. The young leaves are a nutritious spinach-like vegetable, which provides a lot of minerals, vitamins and thiamine (Ojinnaka et al., 2009). According to Women Group in Kwaso located in the Ashanti region of Ghana, role of cocoyam in the livelihood of rural dwellers is indispensible. When asked if they could do without cocoyam if provided with support in growing alternative crops such as plantain, cassava or yam, the women overwhelmingly exclaimed that doing without cocoyam production is a recipe for hunger which is practically impossible for them to accept. Consumption of cocoyam is seen as part of their culture and therefore cannot be replaced. Cocoyam is more preferred by the aged in the communities, and often used by mothers as weaning food in the absence of commercial baby foods. Cocoyam stores longer even after harvest, and can be left in the ground until needed, thereby providing food all year round (Onyeka, 2014).

MATERIALS AND METHODS

Study area

Enugu State of Nigeria was the study location. Enugu is among the five south eastern states including Imo, Ebonyi, Anambra and Abia. It consists of 36 States. Enugu is located between latitudes 5°61`N and longititudes 6°53`E and 7°55`E (Enugu State Agricultural Development Programme (ENADEP), 2012). The state has a total land mass of about 8,022.96 km^2. It has a population of about 4,185,509 (NPC, 2006). Most of the population lives in rural communities with farming as their major occupation. The major crops grown in the states are yam, cassava, cocoyam, rice, maize as well as variety of fruits and legumes. It boosts the local economy of the state as it is predominantly rural and major occupation is farming (Enwelu et al., 2014).

Sampling procedure

The units of analysis were households and household heads and were selected to be the target respondents in selected communities of Enugu State. For sampling procedure, a multi stage sampling technique was employed in selecting the households for the study. In the initial stage, one agricultural zone was randomly selected from the list of agricultural zones in Enugu State. The second stage involves the selection of two (2) local government areas randomly from the list of local government areas in Enugu. The third stage involved random selection of ten communities from each of the 2 local government areas, giving a total of 20 communities. Afterwards from each community, nine households were randomly selected giving 180 households.

Data for the study

Data used for the study were collected from primary sources. The data was obtained using semi-structured questionnaire and group discussion. Personal observations were used to complement the data collected. Data were collected with the use of interview questionnaire. He authors were able to collect information from 170 respondents out of the 180 households selected for the study; this represented 94% of the households sampled for study. The data collected focused on information such as the socioeconomic and institutional characteristics of the cocoyam consumers and factors that facilitate influences, consumer preference for processed cocoyam, perceived attributes of cocoyam and different forms of cocoyam are preferred by consumers.

Model specification

Ordinary linear square (OLS)

Multiple linear regression model was used in the study as stated:

$$Y = \alpha + \beta_1X_1 + \beta_2 X_{2,} \beta_3X_{3} + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + \beta_7X_7 + \beta_8X_8 + \beta_9X_9 + \beta_{10}X_{10} + \beta_{11}X_{11} + \beta_{12} X_{12} + \beta_{13}X_{13} + ų)$$

where, Y = is dependent variable (volume of cocoyam consumed per month); (X_1 – X_{13}) = explanatory variables (socioeconomic characteristics and institutional factors) ų = error term).

Multiple linear regression was employed to determine the volume of cocoyam consumed within households.

Table 1 describes econometric variables that are included in the regression model.

Multinomial logistic regression

A Logistic Regression Model (MLM) was used in the study. Estimating a Multinomial Logistic Regression involves a series of dependent outcome variables in which one is chosen as the comparison variable (Ogundele, 2014). In this case, cooked tuber which is one of the forms cocoyam is consumed was chosen as the comparison group and all other type of processed cocoyam such as *Achicha*, soup thickening, and cocoyam mixed with beans were compared with the comparison outcome. The equation for multinomial logistic model is stated:

$$\Pr(yi = j) = \frac{\exp(Xi\beta j)}{1+\sum_{j=1}^{J}\exp(Xi\beta j)} \quad (1)$$

And

$$\Pr(yi = 0) = \frac{1}{1+\sum_{j=1}^{J}\exp(Xi\beta j)} \quad (2)$$

Where ith represents a single consumer, y_i is the comparison outcome (processed cocoyam), while X_i represents a vector of independent variables. The independent variables exploded in this study included: age, gender, marital status, occupation, household size, farming experience, income spent on cocoyam consumed per month, number of times cocoyam is consumed per week within household, and quantity of cocoyam consumed per month.

RESULTS AND DISCUSSION

The result of descriptive statistics of the socioeconomic and institutional variables used in the analysis of determinants of consumer preference is presented in Table 2. Some of these variables were included in measuring household characteristics expected to influence choice of processed cocoyam. These factors include age, gender, household size, marital status, occupation (farming or trading), number of years spent in school, farm size, farming experience and distance from home to market. The average age of the respondents was 42 years. The average household size was seven out of which three are males and four are females. The average distance of home to market where the consumer purchases the cocoyam tuber was 10 km. Also, the number of times cocoyam is consumed in a week within the households shows whether the number of times cocoyam is consumed influences different forms in which cocoyam is consumed. Furthermore, farming experience was included as part of variables that influence the preference for processed cocoyam to determine if the number of years spent farming influenced the forms in which they prefer to consume cocoyam. The average number of years of schooling of the household head and farming experience are 9 and 18, respectively. The average amount of money the respondents spent on consumption of cocoyam per month is ₦1861. The gender and marital status was also captured to determine whether it influences preference for processed cocoyam. The average hectare of cocoyam cultivated by respondents is 0.9 hectares, whilst, the average farm size is 2.7 hectares. The average monthly income of the respondents is 18,691 naira.

Table 3 shows the result of the multiple regression model. Considering the regression model, it gives a coefficient of multiple determination (R^2) of 0.44. This implies that variations in the explanatory variables explained only 44% of total variation of cocoyam consumed (dependent variable). The result shows that the overall regression equation was significant at 0.05 probability level, since prob > F = 0.000. Factors such as distance from home to market, hectare of cocoyam cultivated, income spent on cocoyam per month and number of times cocoyam is consumed per week are seen to be very important determinants of cocoyam

Table 1. Description of variables included in OLS.

Category	Parameters	Coefficient	Unit of measurement
Volume of cocoyam consumed	Y		Kilogram (kg)/month
Constant	-	α	-
Age	X_1	β_1	Years
Gender	X_2	β_2	Discrete
Marital status	X_3	β_3	Discrete
Occupation	X_4	β_4	Discrete
Household size	X_5	β_5	Numbers
Monthly income	X_6	β_6	Naira
Farming experience	X_7	β_7	Years
Farm size	X_8	β_8	Hectares
Distance from home to market	X_9	β_9	Kilogram
Hectare of cocoyam cultivated	X_{10}	β_{10}	Hectares
Income spent on cocoyam consumption	X_{11}	β_{11}	Naira
Price of cocoyam	X_{12}	β_{12}	Naira
number of times cocoyam is consume per week	X_{13}	β_{13}	Numbers

Table 2. Socioeconomic and institutional characteristics of respondents.

Variable	Mean	Standard deviation	Minimum	Maximum
Age	42.96	15.51	16	90
Gender[a]	0.36	0.48	0	1
Marital status[b]	0.70	0.45	0	1
Occupation (trading)[c]	0.57	0.49	0	1
No of years spent in school	9.67	4.81	0	17
No of male household size	3.2	1.9	1	15
No of female household size	3.8	2.9	1	27
Monthly income	18691.17	15378.85	2000	70000
Farming experience	18.90	12.38	3	75
Farm size	2.70	3.22	0.25	36
Distance from home to market	10.11	16.06	0.50	75
Hectares of cocoyam cultivated	0.87	0.86	0	5
Income spent on cocoyam per month	1861.77	2019.13	0	10000
Number of time cocoyam is consumed Per week	1.33	0.71	0	4

1 if gender[a] is male; 0 otherwise (female), marital status[b] 1 if married: 0 otherwise (divorced), 1 if occupation (trading)[c]; 0 otherwise (farming). Source: Field survey, 2016.

consumed by households. They are significant and have a positive relationship with volume of cocoyam consumed by members of households. For instance, income spent on cocoyam is important because households see cocoyam as a delicacy, therefore the need for cocoyam consumption and the more money spent on cocoyam. This agrees with both the principles of preference and food security, that a consumer will allocate more income to that which has increased utility. Also if food is cheaper that means it is affordable and households can consume it more frequently. This is in accordance with the work of Omotesho et al. (2010) and Omonona and Agoi (2007) which suggest that the consumers have the purchasing power or ability to obtain food at all times. It also agrees with Oti and Akobundu (2008) that cocoyam is accessible by low income earners. The nutritive values of cocoyam may encourage households to cultivate more of it as it can serve as a substitute to other expensive foods that supply the same nutrients, this is supported by Parkinson (1984) which says, cocoyam is rich in carbohydrates with nutritional value comparable to potato, superior to cassava and yam in the possession of higher protein, mineral and vitamin contents. Not only that, cocoyam has been found to be good for infant food for weaning babies and for adult with diabetes (Plucknett, 1970). While, household size is significant and has a negative

Table 3. OLS Parameter estimates of determinants of volume of cocoyam consumed.

Variable	Coefficient/standard error	t-value
Gender	3.188(2.141)	1.49
Age	0.097(0.839)	1.16
Marital status	2.617(2.252)	1.16
Number of year spent in school	0.320(0.208)	1.56
Occupation (trading)	0.555(1.976)	0.28
Household size	-0.491(0.254)	-1.98*
Monthly income	-0.000(0.000)	-1.41
Farming experience	0.150(0.097)	1.55
Farm size	0.033(0.299)	0.11
Price of cocoyam	0.001(0.001)	0.88
Distance from home to market	0.204(0.064)	3.16**
Hectare of cocoyam cultivated	2.273(1.601)	2.06**
Income spent on cocoyam per month	0.002(0.000)	3.80***
Number of times cocoyam is consume per week	6.045(1.545)	3.91***
Constant	-9.769(7.059)	-1.38

Source: field survey, 2016; R^2 = 44%; Adjusted R^2 = 39%; F- ratio = 8.75; ***, **, *show significance levels at 1, 5 and 10%, respectively.

relationship with the volume of cocoyam consumed. This is against our *a priori* expectation that volume of cocoyam consumed will increase with an increase in the number of household members. This may suggests that different members of the household may prefer other tubers crop such as yam and cassava over cocoyam. However, most aged and children in the household consume cocoyam (Oti and Akobundu, 2008), this is because of softness and nutritive value of cocoyam. Hectare of cocoyam cultivated was significant, this shows that because of high level of importance and functions of cocoyam, households devote more of their land on cultivation of cocoyam. This agrees with interview conducted by Onyeka (2014), among women Group in Kwaso located in the Ashanti region of Ghana that received responses that the role of cocoyam in the livelihood of rural dwellers is indispensible. Also, they see cocoyam as part of their culture and therefore cannot be replaced. The characteristics of cocoyam such as energy giving, carbohydrate content, mineral content, easy to cook, light and can be prepared into different local delicacies has made it’s consumption frequent within households. This is supported by result of Sanful and Darko (2010). The distance from home to market is significant and positively related, which is against our *a-priori* expectation. This can still be attributed to the importance of cocoyam to the food security of households. That means member of households can go at any length looking for cocoyam to buy for consumption.

Processed cocoyam

Cocoyam can be transformed into different forms for consumption and these forms are preferred differently by individual household. Even within households, members have different affinities for forms of processed cocoyam. In Igbo extraction, cocoyam is consumed in different forms such as cooked tuber, achicha, while some prefer it for thickening soup, others mixed it with beans. Table 4 shows the socio economic factors responsible for different forms in which cocoyam is consumed by households.

The determinants of household’s preference for different categories of processed cocoyam were ascertained. Processed cocoyam was categorized into four namely: cooked tuber, *Achicha*, soup thickener and cocoyam mixed with beans. Table 4 presents the result of the findings. The comparison group or base category is cooked tuber. The result shows that some variables significantly influenced preference for processed cocoyam with the χ^2 value of 60.40 at 0.05 level of probability.

First, estimating the category of preference for different processed cocoyam in relation to the comparison group–preference for *Achicha*, the result shows that household size, quantity of cocoyam consumed per month positively and significantly influenced preference for *Achicha* as against cooked tubers. The positive and significant effect of household size indicates that large households are more likely to consume cocoyam in form of *Achicha* than in the form of cooked tuber. Achicha has been seen as a very local delicacy strongly attached to Igbo culture. According to Onyeka (2014), rural households see cocoyam consumption as part of their culture which may be difficult to be replaced by other food types such as yam, cassava and potatoes. This also may be because cocoyam when processed to *Achicha* tends to increase in

Table 4. Parameter estimates of determinants of preference for processed cocoyam.

Preference category	Variables	Multinomial logistic results	Marginal effects
		Coefficients/standard errors	**$\frac{dy}{dx}$/standard errors**
Achicha	Gender	0.221(0.566)	0.037(0.063)
	Age	-0.018(0.024)	0.002(0.002)
	Marital status	-0.371(0.657)	-0.063(0.064)
	Occupation	0.450(0.516)	0.045(0.061)
	Household size	0.195**(0.0917)	0.013(0.008)
	Farming experience	-0.051**(0.024)	-0.006(0.003)
	Quantity consume	0.031*(0.019)	0.001(0.002)
	Income spent on cocoyam	-0.000***(0.000)	0.000(0.000)
	Constant	2.916(1.095)	
Soup thickening	Gender	-0.096(0.833)	-0.020(0.045)
	Age	-0.073**(0.035)	-0.004(0.008)
	Marital status	0.219(0.918)	0.036(0.041)
	Occupation	0.321(0.744)	-0.005(0.042)
	Household size	0.227**(0.115)	0.003(0.005)
	Farming experience	-0.023(0.039)	0.001(0.002)
	Quantity consumed	0.044(0.027)	0.001(0.001)
	Income spent on cocoyam	-0.000***(0.000)	-0.000(0.000)
	Constant	1.819(1.422)	
Cocoyam mixed with beans	Gender	-0.925(1.450)	-4.84e-07(0.000)
	Age	0.321*(0.172)	1.57e-07(0.000)
	Marital status	17.028*(9.065)	0.000(0.000)
	Occupation	-0.556*(1.913)	-4.84e-07(0.000)
	Household size	0.572(0.431)	1.80e-07(0.000)
	Farming experience	-0.435(0.233)	-1.78e-07(0.000)
	Quantity consumed	0.135*(0.108)	4.82e-07(0.000)
	Income spent on cocoyam	-0.002(0.001)	-7.79e-07(0.000)
	Constant	-31.716(0.000)	

Source: Field survey data 2016; Comparison group- cooked tuber; LR χ^2 (24) = 60.40***; ***, **, * show significance levels at 1, 5 and 10%, respectively.

quantity and may be sufficient for large households. The positive significant effect of quantity of cocoyam suggests that households may eat more cocoyam if it is processed into Achicha, and less when it is consumed as cooked tuber.

On the other hand, farming experience and income spent on cocoyam consumed per month had a negative and significant effect on consumption of cocoyam in the form of *Achicha* as against cooked tubers. This indicates that households with high number of farming experience may prefer to consume their cocoyam in the form of cooked tuber and households with low number of farming experience prefer to eat theirs in the form of *Achicha*. This suggests that those with high farming experience cultivating cocoyam may think it is easy and take no time to process cocoyam into cooked tuber for fast consumption, while the negative and significant effect of income spent on cocoyam depicts that households spend more on cocoyam if it will be consumed as cooked tuber and less if it will be consumed as *Achicha.* This may be it takes more quantity of tuber to satisfy large household as compared to achicha which transform into large quantity.

Considering using cocoyam for soup thickening as against cooked tuber, the result in the Table 4 shows that some variables, namely: age and income spent on cocoyam had negative and significant effect on eating cocoyam as soup thickening as against cooked tuber, while, household size had positive and significant effect on eating cocoyam as soup thickening as against cooked tuber. The positive and significant effect of household size depicts that large households will prefer to use cocoyam as a soup thickening as against cooked tuber. This is a common culture in Igbo land as most soups prepared are thickened with cocoyam. On the other hand, the negative and significant effect of age of the household suggest that household with elderly household heads will prefer to eat cocoyam as cooked tuber, this support the findings of Pluckett (1970) that cocoyam is highly recommended for diabetic patients and the aged. While the negative and significant effect of income spent on cocoyam indicates that households spend more on cocoyam if it will be consumed as cooked tuber and less if it will be consumed as soup thickener. It also suggests that more quantity will be needed if cocoyam is consumed as cooked tuber as compared to when is used as soup thickener.

Finally, age and marital status have a positive and significant effect and hence control household behavior as regards the consumption of cocoyam in the form of cocoyam mixed with beans as against cooked tuber. For age of the head of the households, findings show that consumption of cocoyam mixed with beans is preferred to cooked tuber if the household head is elderly. This is because beans supply additional nutrient to cocoyam since beans contained protein nutrients. Marital status indicates that household with married people tends to eat cocoyam mixed with beans than against cooked tuber. This may be as a result of having children whose nutrient requirements need to be satisfied with the combinations because cocoyam mixed with beans supply both calories and protein as compared to eating cooked tuber alone.

Farming experience has a negative and significant effect on cocoyam mixed with beans as against cooked tuber. This suggests that households with high farming experience tend to eat less of cocoyam mixed with beans and more of cooked tuber, whilst households with low farming experience prefer cocoyam mixed with beans as against cooked tuber.

Conclusion

The importance of cocoyam as household's food components cannot be over emphasized as its seen as part of their culture and most importantly cannot be replaced by other food crops. Hence there is an urgent need for cocoyam production to be taken as one of the essential crops focused on in the process of nation's food security attainment. Therefore, households should be encouraged to cultivate more of cocoyam to enable its accessibility and affordability. This study reveals essential household's socioeconomic and institutional characteristics that influenced the volume of cocoyam consumed by households. Results from the study also reveal that households have preference for different forms of processed cocoyam. There is therefore an urgent need to invest into the development of different forms of processed cocoyam to improve their quality and make them available for consumers. This is because evidence from the study shows that households may consume cocoyam often since it is economically affordable and culturally acceptable. Also, there is a need to invest in hybrid cocoyam production to boost the quantity. Generally, cocoyam should be seen as indispensible crop as is well accepted at different forms by households. Therefore, government should include cocoyam as part of arable crops transformation programme.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

REFERENCES

Agbelemoge A (2013). Utilization of cocoyam in Rural Households in South Western Nigeria. Afr. J. Food Agric. Nutr. Dev. 13:4.

Amaza PS, Umeh JC, Hesen J, Adejobi AO (2006). Determinants and Measurement of Food Insecurity in Nigeria: Some Empirical Policy Guide. Paper Presented at the International Association of Agricultural Economists' Conference, Gold Coast, Australia, August 12-26.

Amusa TA, Enete AA, Okon UE (2011). Socioeconomic determinants of cocoyam production among small-holder farmers in Ekiti State, Nigeria. Int. J. Agric. Econ. Rural Dev. 4(2):97-109.

Enwelu IA, Asogwa NP, Nwalieji HU, Ezeano CI (2014). Assessment of constraints to cocoyam consumption in selected communities of Enugu State, Nigeria. IMPACT: Int. J. Res. Appl. Natl. Social Sci. 2(3):31-40.

Ndabikunze BK, Talwana HAL, Mongi RJ, Issa-Zacharia A, Serem AK, Palapala V, Nandi JOM (2011). Proximate and mineral composition of cocoyam (*Colocasia esculenta* L. and *Xanthosoma sagittifoliu* L.) grown along the Lake Victoria Basin in Tanzania and Uganda. Afr. J. Food Sci. 5(4):248-254.

NPC (2006). National Population of Nigeria Population figures, NPC, published bulletin, Enugu.

Ogundele O (2014). Factor influencing consumers preference for local rice in Nigeria. Afr. J. Mark. Manage. 6(4):49-55.

Ojinaka MC, Akobundu ENT, Iwe MO (2009). Cocoyam starch modification effects on functional, sensory and cookies qualities. Pak. J. Nutr. 8:558-567.

Okeke EC, Ene-obong HN, Uzuegbunam AI, Ozioko A, Umeh SI, Chukwuone N (2009). The Igbo traditional food system documented in four states in southern, Nigeria. In kuhnklien IV, Erasmus B & Spigelski D. Indigenous people's food system: the many dimensions of culture, diversity and environment for nutrition and health. FAO Center for Indigenous People's Nutrition and Environment.

Omonona BT, Agoi GA (2007). An analysis of food security situation among nigerian urban households: evidence from Lagos state, Nigeria. J. Central Eur. Agric. 8(3):397-406.

Omotesho OA, Adewumi MO, Fadimula KS (2010). Food Security and Poverty of the Rural Households in Kwara State, Nigeria. Libyan Agric. Res. Center J. Int. 1(1):56-59.

Onyeka J (2014). Status of Cocoyam (*Colocasia esculenta* and *Xanthosoma* spp) in West and Central Africa: production, Household Importance and the threat from Leaf Blight. CGIAR Report of a scoping study Commisioned by the CGIAR Research program on Roots, Tubers and Bananas (RTB). Lima (Peru).

Opara LU (2002). Edible Aroids: Postharvest Operation in: AGST/FAO: Danilo, M. (Ed.). Massey University, New Zealand.

Oti E, Akobundu ENT (2008). Potentials of cocoyam-soybean-crayfish mixtures in complementary feeding. Niger. Agric. J. 39(1):137-145.

Parkinson S (1984). The contribution of aroids in the nutrition of people in the South Pacific. In Chandra S. (ed), Edible Aroids. Clarendon Press, Oxford, UK. pp. 215-224.

Plucknett DL (1970). Status and future of the major edible aroid Colocosia, Xanthosoma, Alocasia, Cyrstosperma and Amorphophallus. In Tropical Root Crops Tomorrow: Proceedings of

the 2nd International Symposium on Tropical Root Crops, Hawaii pp. 127-135.
Sanful RE, Darko S (2010). Production of Cocoyam, Cassava and Wheat Flour Composite Rock Cake. Pak. J. Nutr. 9(8):810-814.
Splittstoesser NE, Martin FW, Rhodes AM (1973). The nutritional value of some tropical root crops. Proceed. Trop. Reg. Am. Soc. Hortic. Sci. 17:290-294.

academicJournals

Vol. 9(6), pp. 145-161, June 2017
DOI: 10.5897/JDAE2017.0822
Article Number: 4C184C364361
ISSN 2006-9774

http://www.academicjournals.org/JDAE

Journal of Development and Agricultural Economics

Full Length Research Paper

Climate sensitivities and farmland values in Nepal: A spatial panel Ricardian approach

Samrat B. Kunwar* and Alok K. Bohara

Department of Economics, New Mexico, USA.

Received 24 February, 2017; Accepted 28 April, 2017

This study presents an application of the Ricardian approach to explore the impact of climate change on farmland values in Nepal. The Ricardian approach is estimated using a panel fixed effects model, and the outcome is compared against two separate models that account for spatial correlation: a spatial autoregressive (SAR) model; and a spatial error model (SEM). The findings suggest that Nepalese farmlands are sensitive to climate change, and this result was consistent in both the non-spatial and the spatial frameworks. The inclusion of the spatial effects, however, revealed the presence of positive spatial autocorrelation and produced conservative estimates of climate change impacts. The net effect of annual increases in average temperature was negative; while the net effect of higher annual average precipitation was a positive outcome on farmland values. In particular, we found that the marginal effect of every degree increase in average annual temperature was Rs.180 /hectare ($1.80) reduction in farmland values. Likewise, for rainfall, it was found that 1 mm increase in average annual rainfall would positively affect farmland value by Rs.225/hectare ($2.25). Finally, the study findings suggested that extreme weather events could also impact the agricultural productivity and the farmland values in Nepal.

Key words: Climate change, ricardian approach, spatial panel data analysis, Nepalese agriculture, environmental valuation.

INTRODUCTION

Climate change is emerging as a significant threat facing the humanity in the 21st century. There is a consensus among researchers that variations in land and water regimes through changes in climate might pose a significant challenge to the natural and human systems (Intergovernmental Panel on Climate Change (IPCC), 2007, 2014).

Agriculture is one area that is highly sensitive to climate due to its reliance on weather patterns and climate cycles for productivity. Agriculture is also the principal use of land globally with approximately 1.2 to 1.5 billion hectares of lands under crops, while another 3.5 billion hectares are used for grazing (Howden et al., 2007).

One country that is predominantly dependent on agriculture is Nepal. Nepal is a tiny developing country located in South Asia between India and China. The Nepalese agricultural sector contributes to more than one-third to the gross domestic product (GDP), and

*Corresponding author. E-mail: sbkunwar@unm.edu.

employs more than half of the total labor force (Acharya and Bhatta, 2013). This notable dependence on agriculture makes the Nepalese farming population highly vulnerable to the impacts of climate change.

Past studies suggest that the average annual mean temperature in Nepal has increased at an annual rate of 0.06°C between 1977 and 2000 (Malla, 2009). It has subsequently led to changes in the frequency of temperature extremes with more frequent warmer days and nights; and less frequent colder days and nights (Gum et al., 2009). Precipitation, on the other hand, has not displayed any definitive trends, but evidence indicates an increasing occurrence of intense rainfall events and rising flood days over the years (Gum et al., 2009). Such instances of extreme weather events can result in desirable agricultural land being undesirable as crop yields are restricted.

These changing climatic conditions have led to shifts in cropping patterns and the agricultural sector in Nepal is consequently being severely hurt. Regmi (2007) indicated that the eastern region of Nepal faced rain deficit in 2005/06, and the crop production was reduced by 12.5% on a national basis. Likewise, while Nepal used to be rice exporter in the past, the fluctuating climate conditions has limited the rice yields, and as a result, Nepal has been a rice importer for the past few years.

Nepal's heavy dependence on rain-fed agriculture coupled with the potential distressing effect of climate change, and ultimately on the welfare of the population and the economy of the country itself, necessitates a thorough analysis on the economic impact of climate change on the agricultural sector. An exhaustive assessment of the economic impact would allow for new policy formulation on potential mitigation and adaptation strategies to combat the likely effects of climate change. In this paper, an application of the Ricardian approach is used to evaluate the economic impact of climate change on agricultural productivity in rural Nepal.

The Ricardian approach is a model of climate-land value relationship, which was developed by Mendelsohn et al. (1994) to assess the impact of climate change on farmland values in the United States. The Ricardian Method is, in fact, named after the influential classical economist David Ricardo (1772 to 1823), who argued that in a perfectly competitive market, land values would reflect land profitability.

In their paper, Mendelsohn et al. (1994) evaluated the efficacy of the traditional production function approach in estimating the impacts of climate change with a new method they developed, the '*Ricardian Method*'. The production function approach is based on crop simulation models where the climate change impacts are estimated by varying input variables, including the climate itself. Mendelsohn et al. (1994) suggested that the limitation of the production-function approach in failing to account for the numerous substitutions and adaptations that farmers make could lead to an inherent bias that results in an overestimation of the damages from climate change.

The fundamental idea of the Ricardian approach is that land values and agricultural practices are correlated with an environmental variable, climate. However, some assumptions underlie this framework. The Ricardian model assumes that farmers are rational utility maximizers, and relies on an existence of a competitive economy with perfectly functioning output and input markets. With these assumptions, the Ricardian framework asserts that if the optimal use of farmlands is agricultural production, then the observed market rent on a parcel of land should equal the annual net profits from the production of an agricultural commodity using that land (Mendelsohn et al., 1994). Thus, farmland values are the discounted value of current and future profit. Furthermore, we can observe the relationship between farm values to climate and other variables to infer the optimal use of land. Hence, depending on the positive and negative impact of climate variables, the long-run accumulation of net profit defines land value.

Although the Ricardian method has since garnered widespread attention, there have been some notable criticisms as well because of the strong assumptions it makes (Cline, 1996; Darwin, 1999; Polsky, 2004; Deschenes and Greenstone, 2007). Darwin (1999) maintained irrigation to be an essential variable and omitting it would make the model of Mendelsohn et al. (1994) inconsistent with the Ricardian principle. Cline (1996) argued that the assumption of fixed relative prices in the Ricardian approach makes it a partial-equilibrium analysis. Besides, Cline (1996) also contended that the assumption of infinitely elastic supply of irrigation at current prices is misleading. Polsky (2004) argued that because Ricardian models are strongly aligned with perfect adaptations assumption, the negative impacts are biased to be small. Deschenes and Greenstone (2007) raised doubt on the validity of cross-sectional approaches to Ricardian study and proposed the use of a fixed-effect modeling to get more stable results from the Ricardian function.

To incorporate the limitations in the ergodic assumption of spatially and temporally invariant climate sensitivities, Polsky (2004) modeled a modified regional scale Ricardian analysis by integrating spatial and temporal variations in climate. The author reasoned that ignoring spatial relationship (inter-farmer communications across county borders) to understand climate-land use relationship could not account for climatic effects in different locations or time. Following Polsky (2004) there have been few other studies that have explored the Ricardian approach by explicitly incorporating spatial correlation.

Lippert et al. (2009) accounted for spatial auto-correlation in their analysis of the Ricardian approach in German agriculture by using a spatial lag and a spatial error dependence model. Kumar (2011) studied the impact of climate change on Indian agriculture by addressing the spatial features that could influence the climate sensitivity of agriculture. The paper argued that ignoring the spatial distribution could result in enlarged estimates of climate impacts in Ricardian studies. Their estimates of climate change impacts were more conservative after incorporating spatial correction models, and this finding was consistent in both the spatial lag and the spatial error model specification. Other researchers that have explicitly treated the spatial problem in the Ricardian study are Schlenker et al. (2005) and Chatzopoulos and Lippert (2016).

A separate limitation of numerous Ricardian studies that estimate climate change – land value relationships has been with the use of cross-section data for analysis. Since climate coefficients change over time, analyzing farms' long-term changes using cross-section data may not give reliable estimates. A panel-data approach can be far superior for estimation of any hedonic models, including Ricardian analysis if panel data are available and the time varying and unvarying coefficients are correctly specified (Massetti and Mendelsohn, 2011). A panel data approach also removes year effects and can produce more reliable estimates of the climate coefficients (DeSalvo et al., 2014). Several authors (Massetti and Mendelsohn, 2011; Deschenes and Greenestone, 2011; Massetti et al., 2013), etc. have employed panel data methods to study Ricardian analysis and the trend is rising.

Finally, another issue in many Ricardian studies stems from the use of only historical averages for temperature and precipitation to assess the impact of climate change on agriculture. However, plant physiology literature argues that it is not only the average weather patterns but also the extreme weather events that could have a severe effect on crop yields and agriculture in general (Rosenzweig et al., 2001; Anyamba et al., 2014).

Through this study, we seek to address the research gaps that have been identified in Ricardian analyses, in particular, the concerns mentioned earlier. First, considering the limitations of cross-sectional data approaches in other Ricardian studies, this paper uses panel data approach to enhance estimates reliability. Second, our analysis includes additional climate variables other than seasonal averages that could potentially capture the extremities in climate. Finally, we address the importance of accounting for spatial features and our estimation strategy thereby incorporates spatial methods in the Ricardian approach. Many Ricardian studies ignore the problem of spatial correlation, but when observations are correlated across space, standard approach such as the Ordinary Least Squares (OLS) method can lead to biased and inefficient parameter estimates (LeSage and Pace, 2009). The primary contribution of this paper that separate it from previous Ricardian applications is that we include extreme climate variables, while also explicitly accounting for spatial correlation in a panel data setting to study climate change impacts on agricultural productivity in rural Nepal.

MATERIALS AND METHODS

The non-climatic data used in this paper comes from the Nepal Living Standard Survey 2003/04 (NLSS-II[1]) and 2010/2011 (NLSS-III) of the Central Bureau of Statistics (CBS), Nepal. The NLSS survey follows the Living Standards Measurement Survey (LSMS) methodology that has been developed and promoted by the World Bank.

The methodology applied in the NLSS has been used in more than 50 developing countries by the World Bank with the goal to foster increased use of household data as a basis for policymaking. The NLSS survey includes a broad range of topics related to household and community welfare, but the important socio-economic variables necessary for this paper were obtained from the rural community questionnaire of NLSS. As such, this paper focuses on the rural farming communities in Nepal. The rural community questionnaire of the NLSS was developed to interview leaders and knowledgeable persons representing the community of the enumeration areas[2] (CBS, 2004).

In this study, the primary sampling units[3] (PSUs) are used as the unit of analysis, and not the individual households. The geocoded coordinates were made available only for PSUs, but not for the households, which constrained us to use PSU level analysis to explore the spatial relationship in our study. The total sample of the NLSS-II consists of 4,008 households representing 334 PSUs, from which 100 PSUs were common in NLSS-III as well (CBS,2004). The total sample of the NLSS-III was estimated at 7200 households in 600 PSUs (CBS,2010). Among them, the NLSS-III sample is composed of all households visited by the NLSS-II in 100 of its PSU, as mentioned earlier. The final sample selected from NLSS-II and NLSS-III was 155 PSUs for this study[4]. Figure 1 plots the PSU locations used in this study.

In addition to the community welfare data from NLSS, this study used the ground station climate data for daily temperature and precipitation from 1981 to 2010, obtained from the Department of Hydrology and Meteorology, Nepal. The selection of weather stations nearest to each PSU was made in ArcGIS using multiple buffer width of 10 and 25 km radii[5]. Figure 2 shows the graph of the weather stations in Nepal, and Figure 3 presents the graph of buffer analysis undertaken to extract the weather stations nearest to each PSU. Similarly, Table 1 lists the definition of variables used in this study.

---

[1] We excluded Nepal Living Standard Survey 1996/1997 (NLSS-I) from this study due to the lack of common identifiers of NLSS-I with NLSS-II and

[2] The data obtained from NLSS in this study are the self-reported data by a knowledgeable person in a community (PSU).

[3] The PSU identifier for the rural NLSS survey are either individual wards or sub-wards, or group of contiguous wards in the same village development committee (VDC). Wards are the smallest denomination of administrative units in Nepal and are equivalent to zip codes in the United States. Likewise, VDC is the lower subdivision of a district and is similar to municipalities. Each VDC is further subdivided into several wards.

[4] The analysis of the spatial econometric model is more reliable using a balanced panel data, which restricted us to 155 PSUs to create a balanced data. Of the 155 PSUs, 100 PSUs were common in NLSS II and III, while we included another 55 PSUs to increase the sample size. In order to obtain the additional 55 PSUs, we selected only those PSUs that were adjacent to each other in NLSS II and III. So, if there was a particular PSU in NLSS-II and its neighboring PSU was used in NLSS-III, we considered the two neighbors as the same PSU. In this way, we came up with the 55 additional PSUs. It should be noted that we also ran our final analysis with only the 100 original PSUs, and the results did not substantially change from the findings presented in this paper (with 155 PSUs).

[5] In order to minimize the distance between PSU and weather stations, we extracted those weather stations that were within 10 km radius from a particular PSU of interest. However, if there were no weather stations within that radius, we extracted the stations that were within 25 km radius.

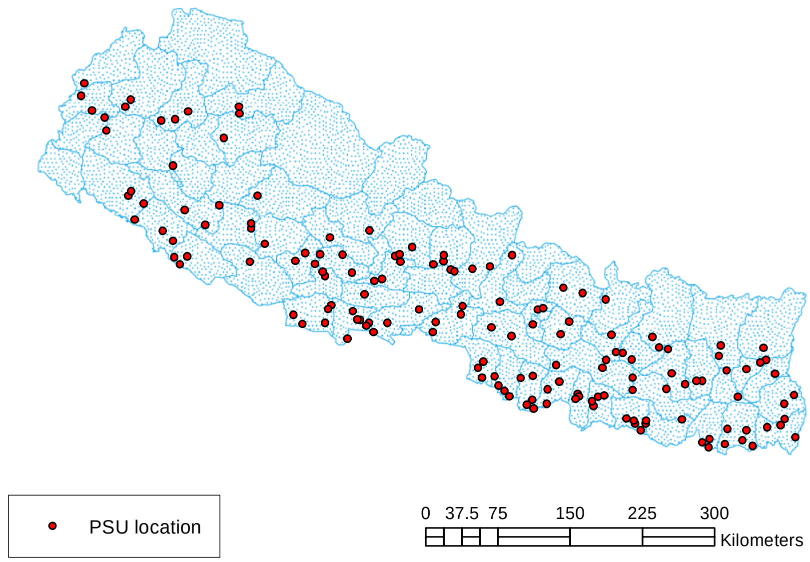

Figure 1. Plot of PSU points (Note: The map shows the location of PSUs used for the study.

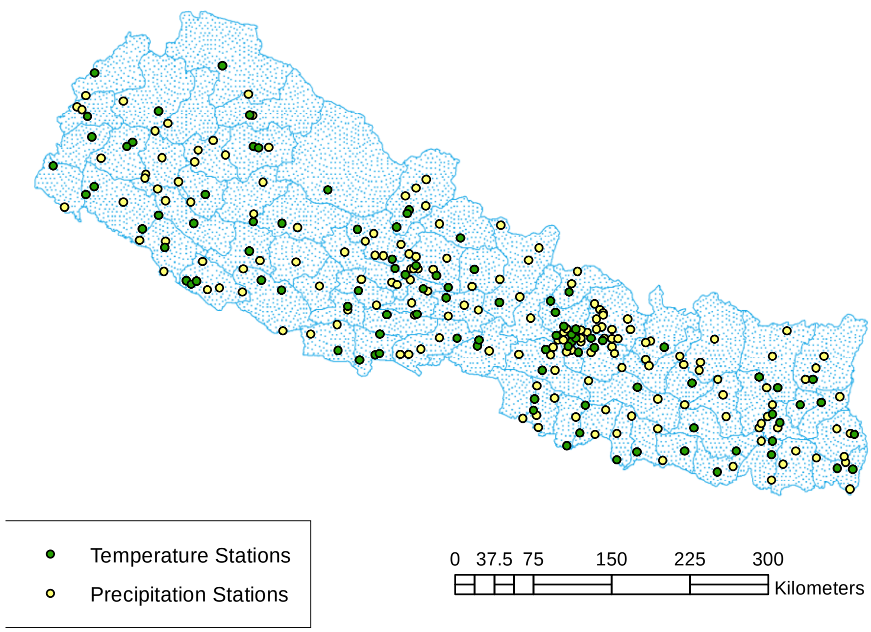

Figure 2. Plot of weather stations in Nepal (Note: The map shows the location of rainfall and temperature stations in Nepal).

Dependent variable

We used the self-reported average farmland value in each PSU as the measure of net productivity. These values have been converted to a per hectare land value in our analysis. While Ricardian papers often use net revenue or net profits as a proxy for land values, we used the actual farmland value in each PSU, since it was already available in the survey.

A criticism of using net revenue is that it is strongly influenced by the year of analysis (DeSalvo et al., 2014). Land values could be more accurate and an appropriate measure to analyze climate impacts since they reflect the expectations of net revenues across

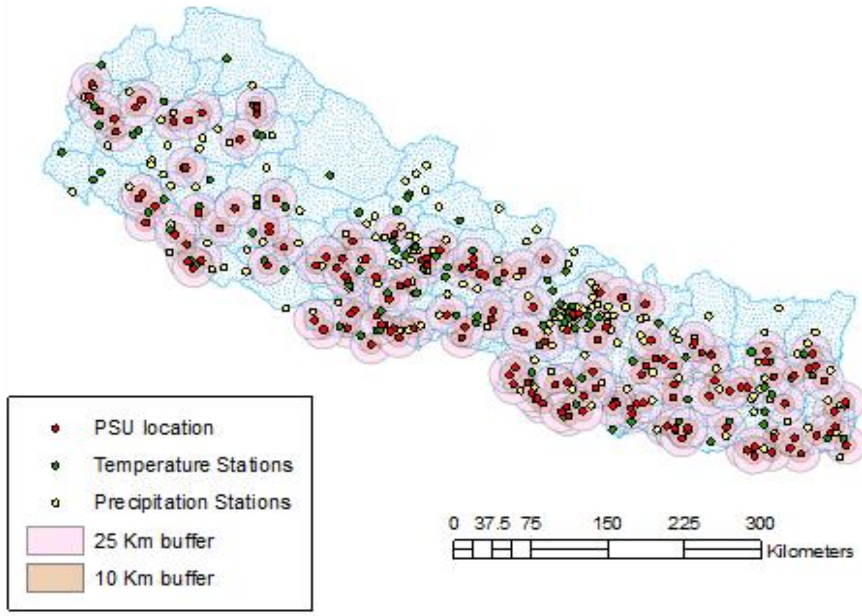

Figure 3. Buffer -10 and 25 km radius (Note: The map shows a buffer of 10 and 25 km radius from each PSU. This method was used to extract the temperature and rainfall stations to each PSU).

many years (Mendelsohn et al., 2009).

Explanatory variables

Climate variables

In order to construct the climatic variables, the daily temperature, and precipitation data for the time period 1981 to 2010 are used. Temperature and precipitation were classified into four seasons[6]: spring, summer, autumn and winter. We converted the daily average temperature and precipitation data into the four seasonal averages. In order to get the climatic data for 2002, the seasonal average from 1981 to 2002 was taken, and likewise, the seasonal average from 1989 to 2010 was used to capture the 2010 values. The 2002 and 2010 climate data, thus, capture the rolling average for the past 22 years. Using the constructed seasonal averages, the first set of climate variables used were the linear and quadratic measures of seasonal temperature and rainfall. The quadratic variables were introduced to capture the possible nonlinearities in the climate sensitivities.

Along with the seasonal averages, we constructed variables to capture climatic deviations, and also climate extremes. The motivation for the inclusion of variables to capture climate extremities comes from the plant physiology literature that argue frequency and intensity of extreme weather events could also have a significant effect on crop yields and agriculture (Rosenzweig et al., 2001; Anyamba et al., 2014). To capture the climatic variation, we constructed the deviation of the seasonal temperature and precipitation for the year 2002 and 2010, from the rolling average of the past 29 years, for each of the four seasons[7].

The other set of climatic variables were employed to capture the extremities in climate, namely, the *warm spell duration index (WSDI)* for temperature, and *simple precipitation intensity index (SDII)* for rainfall[8]. These indices are two of twenty-seven indices that have been recommended to assess extreme weather events by the World Meteorological Commission for Climatology/ World Climate Research Program (CCI/CLIVAR) expert team on climate change detection, monitoring and indices through the CLIMDEX project (*www.climdex.org)*. WSDI represents the annual count of days in each year that is part of a warm spell. More specifically, it represents the annual count of days with at least six consecutive days in which the daily maximum temperature exceeds the 90th percentile of daily maximum temperature for a 5-day running window (Bronaugh, 2015). SDII, on the other hand, represents the sum of precipitation in wet days during the day divided by the number of wet days in the year (Bronaugh, 2015).

Non-climatic variables[9]

The set of control variables used in this paper are access to irrigation facilities, access to a market center, access to a road network, access to electricity; and the presence of farmers group, all within the context of the PSUs. Access to irrigation captures

[6] Spring season = March-May; Summer season = June-August; Autumn season = September-November; Winter season = December-February.

[7] For example, the standard deviation for summer temperature in the year 2002 was constructed as follows:

$$std\_dev\_summer\_temp_{2002} = \sqrt{\text{mean (summer temp}_{2002}) - \text{mean (summer temp}_{1981-2002})}$$

[8] WSDI and SDII indices were derived using the "climdex.pcic" package available in R.

[9] While several Ricardian studies use soil type as another set of the control variable, it has been excluded in this paper due to the nature of the econometric model specification. This paper employed fixed effects model for both the non-spatial and spatial-analyses and as a result, time invariant factors like soil type have been ruled out from the analyses since these estimates are washed away.

Table 1. Variable description.

Variable	Definition
Land value	Average market value of farmlands in the PSU (self-reported) (Rs/Ha)
Spring temperature, summer temperature, autumn temperature, winter temperature	Climate-normal annual mean temperature for 29 year preceding each Census year for spring, summer, autumn and winter season (^{0}C)
Spring temperature sq., summer temperature sq., autumn temperature sq., Winter temperature sq.	Square of the climate-normal annual mean temperature for 29 year preceding each Census year for spring, summer, autumn and winter season (°C)
Spring rainfall, summer rainfall, autumn rainfall, winter rainfall	Climate-normal annual mean precipitation for 29 year preceding each census year for spring, summer, autumn and winter season (mm/year)
Spring rainfall sq., summer rainfall sq., autumn rainfall sq., Winter rainfall sq.	Square of the climate-normal annual mean precipitation for 29 year preceding each census year for spring, summer, autumn and winter season (mm/year)
Spring temp. dev, Summer temp. dev, Autumn temp. dev, Winter temp. dev	Deviation of temperature during the spring, summer, autumn and winter season of a Census year from the historical 29 year averages in each of those seasons
Spring rain. dev, summer rain. dev, autumn rain. dev, winter rain. dev	Deviation of precipitation during the spring, summer, autumn and winter season of a Census year from the historical 29 year averages in each of those seasons
WSDI	Warm spell duration index. It represents the annual count of days with at least six consecutive days in which the daily maximum temperature exceeds the 90th percentile of daily maximum temperature for a 5-day running window
SDII	Simple precipitation intensity index. It represents the sum of precipitation in wet days during the day divided by the number of wet days in the year
Population	Total population of a PSU
Road	Access to paved roads in a PSU (yes = 1, no = 0)
Irrigation facilities	Access to irrigation facilities in a PSU (yes=1, no=0)
Electricity	Access to electricity in a PSU (yes=1, no=0)
Market center	Existence of a market center in a PSU (yes=1, no=0)
Farmer's group	Existence of an active user group (farmer's group) in a PSU (yes=1, no=0)

whether the PSU has irrigation facilities available. Access to market center means if the PSU has a market center in that community. Access to road and electricity follow similar explanation as for the case of irrigation and market center. Lastly, farmers group captures the existence of user group in a community (Table 2).

Conceptual framework

In a Ricardian model, farm performance (land value or net revenue) is regressed on a set of agro-climatic and socio-economic variables to assess the impact of climate change on farm performance. Mendelsohn et al. (1994) argued that the traditional approach to measuring the impacts of climate change on agriculture, the production function approach, was a crop specific analysis and it could overestimate the impacts. To overcome this limitation, the Ricardian approach was developed, and it assumes the following specification (Mendelsohn et al., 1994):

$$V_L = \int_0^\infty P_L e^{-\rho t}\partial t = \int_0^\infty \frac{[P_i Q_i - C_i(Q_i, R, F, Z)]}{L_i}\, e^{-\rho t}\partial t \tag{1}$$

Where, farmland value (V_L) reflects the present value land (L); P_L is the net revenue per hectare; P_i and Q_i are the market price and output of the crop i respectively; $C_i(\,)$ is a function of purchased inputs (excluding land); R is a vector of input prices; F is a vector of climatic variables; Z is a vector of socioeconomic variables; t is the time, and ρ is the discount rate.

The Ricardian model assumes that a farmer will maximize his land value (or net revenue) by choosing inputs subject to climate (F) and socio-economic variables (Z). This model relies on a quadratic formulation of climatic variables and is presented as:

$$V = \beta_0 + \beta_1 F + \beta_2 F^2 + \beta_3 Z + u \tag{2}$$

Table 2. Outlines the descriptive statistics of the dependent and independent variables used in this study.

Variable	N	Mean	St. Dev.
Land value	310	35,290.740	143.103.500
Spring temperature	310	22.719	4.243
Summer temperature	310	28.586	4.190
Autumn temperature	310	19.235	3.543
Winter temperature	310	14.115	3.232
Spring temp. dev	310	1.150	0.994
Summer temp. dev	310	0.630	0.780
Autumn Temp. dev	310	0.808	0.859
Winter Temp. dev	310	0.881	0.950
Spring rainfall	310	40.626	26.231
Summer rainfall	310	252.309	100.455
Autumn rainfall	310	71.807	46.747
Winter rainfall	310	14.827	6.973
Spring rain. dev	310	2.322	2.621
Summer rain. dev	310	3.735	7.967
Autumn rain. dev	310	1.122	0.723
Winter rain. dev	310	0.441	0.446
WSDI	310	40.423	63.001
SDII	310	19.862	6.828
Population	310	1,064.410	1,095.483
Road	310	0.416	0.494
Irrigation facilities	310	0.790	0.408
Electricity	310	0.610	0.489
Market center	310	0.694	0.462
Farmer’s group	310	0.097	0.296

Sources: Climate data obtained from Department of Hydrology and Meteorology (DHM, Government of Nepal). PSU sociodemographic data obtained from the Central Bureau of Statistics (CBS), Nepal.

Where, u is an error term. The linear and a quadratic term for temperature and precipitation accounts for the nonlinear shape of the net revenue of the climate response function.

In the study analysis, we regressed the farmland value per hectare in the rural communities of Nepal as a dependent variable against climate and socio-economic variables. The independent climatic variables included the linear and quadratic temperature and precipitation for the four seasons: winter (the average for December, January, and February), spring (March, April, and May), summer (June, July, and August) and autumn (September, October, and November). In addition to the seasonal averages, the study analysis included seasonal temperature and precipitation deviation from the historical 22 years’ seasonal average.

Finally, we incorporated WSDI to measure the temperature extreme, and simple precipitation intensity index (SDII) to measure the rainfall extreme. The independent non-climatic variables include the existence of paved road in the PSU, population of the PSU, whether the PSU had irrigation facilities available, having electricity in the PSU, and the existence of market center and farmers group in the PSU.

Analytical framework

Panel fixed effects (Non-spatial model)

The analytical framework was carried out using a forward specification analysis. First, a panel fixed effects[10] model was run, and the results were compared with a spatial lag and a spatial error model. The general specification of the non-spatial fixed effects model is given by:

$$Y_{it} = \alpha_i + \gamma_t + \beta X_{it}{}' + \theta X^2{}_{it}{}' + \delta N'_{it} + \eta Z_{it}{}' + u_{it} \tag{3}$$

The subscripts *i* and *t* in equation (3) denote PSU and time, respectively. The dependent variable *Y* is the farmland value per hectare, and α represents the PSU fixed effects. It is assumed that the PSU fixed effects absorb all the unobserved PSU specific time-invariant factors such as soil and water quality that could influence the crop yields and land values. γ represents the time fixed effects, and it is presumed to control for time differences in the dependent variable which are common across PSU. The variable *X* is a vector of climate normals[11]; while N captures the vector of climate

[10] The Hausman test rejected the null hypothesis of random effects (Chi-square = 49.19; p-value = 0.011). Thus, our model specification takes the fixed effects form.

[11] Climate normal: X_{it} = {spring temperature, summer temperature, autumn temperature, winter temperature, spring precipitation, summer precipitation, autumn precipitation, winter precipitation}

deviations and extremes[12]. Finally, Z is a vector of PSU sociodemographic variables[13]; and u is an idiosyncratic error term that is assumed to be independent and identically distributed over PSUs and time, with mean zero and variance σ_u^2. The fixed effects model concentrates on differences within PSU's. Thus, it explains to what extent farmland values deviate from average PSU farmland value.

While the parameter estimates from equation (3) could provide evidence on the impact of climate change on farmland values in Nepal, the estimates could be biased if land values are spatially correlated. In fact, Tobler (1979) first law of geography states that 'near things' are more related than 'distant things'. This suggests that farmland values could be spatially auto-correlated if there is a dependency between farmland prices. In a developing country like Nepal where farmers may not have sufficient information about their land characteristics, it is likely that land values could depend on interactions across PSUs with other land owners. Patton and McErlean (2003) argue interaction among landlords in order to base their starting price may give rise to spatial relationships.

This provides a motivation to reassess our problem by incorporating the spatial framework. Additionally, spatial modeling might also reduce omitted variable bias and account for spatial heterogeneity from a data-driven perspective. Omitted variable can arise because unobservable factors (for example, location amenities, PSU prestige, water accessibility for irrigation, etc.) could influence the dependent variable (farmland values), and this can be accounted by incorporating a spatial error model (LeSage and Pace, 2009). On the other hand, a spatial autoregressive (lag) model would be crucial if we believe that herd behavior exists in farmland markets, that is, the selling price of farmlands at any particular location acts as a signal that guides the selling price of nearby lands.

Spatial models

Taking into account the potential nature of the spatial relationship in farmland markets, the study analytical framework next incorporated spatial correlation in the Ricardian model. A general specification of the related family of the spatial model takes the following form[14]:

$$y_{it} = \lambda \sum_{j=1}^{N'} w_{ij} y_{jt}' + \alpha_i + \gamma_t + \beta X_{it}' + \theta X^2{}_{it}' + \delta N_{it} + \eta Z_{it}' + u_{it}$$

$$u_{it} = \rho \sum_{j=1}^{N'} w_{ij} u_{it} + v_{it} \tag{4}$$

Equation (4) presents the specification of the panel spatial model, and it is similar to the non-spatial fixed effects model detailed in equation (3). The interpretation of parameters $(\alpha, \gamma, \beta, \theta, \delta, \eta)$ and the variables captured by *X, N* and *Z* vectors are same as in equation (3). The additional terms in the spatial model that differentiate it from the non-spatial one are the spatially lagged dependent variable, and the spatial autoregressive process in the error term. The spatial lag coefficient is captured by (λ), while (ρ) captures the spatial error coefficient. The spatial autoregressive (lag) model (SAR) posits that the dependent variable (farmland value) is influenced by the dependent variables in the adjacent units and on a set of observed local characteristics. The spatial error model (SEM), on the other hand, states that the dependent variable (farmland value) depends on a set of observable characteristics with errors that are correlated across space (Elhorst, 2014).

One of the crucial inputs that spatial models require is the weight matrix *W*, which summarizes the spatial relations between *n* spatial units. In particular, the spatial matrix assigns nonzero elements for each observation (row) whose locations (columns) belong to its neighborhood (Anselin and Bera, 1998). A row-standardized weight matrix, where the row of the spatial weight matrix sums to unity, is used in our spatial model. The *wy* term in equation (4) represents the weighted average of the surrounding observations in the dependent variable; while the *wu* term represents the weighted average of the surrounding error term. The spatial weight matrix, W, used in this paper is a 5-nearest neighbor weight matrix for the PSUs in our sample. The parameters (λ) and (ρ) measures the extent of the spatial autocorrelation. Furthermore, setting the value of ρ = 0 leads to the SAR model that exhibits relationship only in the dependent variable. Similarly, setting λ = 0 leads to the SEM, resulting in spatial dependence in only the error term. In the case of the spatial models, the parameters to be estimated are the regression coefficients $\beta, \theta, \delta \; and \; \eta$; along with the spatial lag coefficient (λ), and the spatial error coefficient, (ρ).

Marginal impacts

The standard interpretation of estimated parameters as partial derivative is no longer valid in the case of the SAR model. Intuitively, the lag model implies that the farm land values of region *i* is also influenced by the land values from neighboring regions. The marginal effects in the SAR model take the following form (LeSage and Pace, 2009):

$$\partial y_i / \partial x_{ir} = S_r(W)_{ii}$$

$$\partial y_i / \partial x_{jr} = S_r(W)_{ij} \tag{5}$$

Where, $S_r(W) = (I_n - \emptyset W)^{-1} \beta_r$. In equation (5), the subscript *i* and *j* represents location *i* and *j* respectively, while β_r is the coefficient on the r[th] explanatory variable. $S_r(W)$ is a *n X n* matrix with the diagonal elements containing the direct impacts and the off-diagonal elements representing the indirect impacts. In the SAR model, the spatial connectivity relationships mean that a change in a single explanatory variable in region *i* has a 'direct impact' on region *i* as well as an 'indirect impact' on other regions, *j≠i* (LeSage and Fischer, 2008).

The upper quantity in equation (5) captures the impact of a change in an explanatory variable (for example, temperature) at location *i* on the dependent variable at location *i,* known as the average direct impact (ADI). For example, the average direct effect shows the impact of climate change on PSU *i* on the farmland values of PSU *i*. The lower quantity, on the other hand, captures the effect of a change in the explanatory variable at location *j* on the dependent variable at location *i,* with *j≠i* and is known as the average indirect effect (AII). For example, the average indirect effect, also known as the neighboring effect, measures the impact of an increase in climate at PSU *i* on the farmland value of neighboring PSUs, averaged over all neighboring PSUs. The average direct effect can be interpreted as the own derivative, while the average indirect effect captures the cross derivative. Lastly, the

---

[12] Weather deviation and extremes: N_{it} = {spring temperature deviation, summer temperature deviation, autumn temperature deviation, winter temperature deviation, spring precipitation deviation, summer precipitation deviation, autumn precipitation deviation, winter precipitation deviation, WSDI, SDII}

[13] PSU sociodemographic variables: Z_{it} = {access to irrigation facilities, access to electricity, access to market center, population of the PSU, access to paved road, existence of farmer's group}

[14] Interested readers should refer to Elhorst, (2014) for greater detail on spatial panel data model.

average total effect (ATI) is the sum of average direct and indirect effect, and it measures the total cumulative impact. In this paper, the average total effects estimate how changes in climate affect total farmland values, taking into account both own-PSU and spillover effects.

Marginal climate impacts

Since the study climate variables contain linear and quadratic coefficients in raw form, we evaluated the marginal climate impacts (MCI) for rainfall and temperature to ease interpretation. Recalling equation (3), the MCI[15] of average annual changes in climate (temperature or precipitation) on the mean farmland value per hectare can be expressed as:

$$E\left(\frac{\partial LANDVALUE}{\partial CLIMATE}\right) = \beta + 2\theta * E(CLIMATE) \tag{6}$$

In this study, the MCI represents the change in Rs./ha of farmland value per ^{0}C or mm/year, evaluated at the mean annual climate for farmlands in Nepal.

RESULTS

The data summary (Table 2) shows that most of the variables have low standard deviation, indicating data homogeneity. The regression results[16] from the non-spatial fixed effects model (Table 3, Column 1) suggested that the spring and summer temperature; and the spring, autumn and winter rainfall impacted the farmland values. Likewise, the spring temperature deviation and the winter rainfall deviation, as well as the extreme indices in WSDI and SDII also affected the farmland values. The non-climatic variables that were found to be significant were irrigation facilities, population and the existence of market center in the PSU, all of which had a positive impact on the farmland values. The significance of these variables was almost identical in the spatial lag and the spatial error model as well (Table 3, Column 2 and 3).

While the significance of most variables were comparable in all three models, the magnitudes of the estimated climate coefficients were smaller in spatial models than the non-spatial fixed effect model. Furthermore, the spatial correlation parameter (ρ) in the spatial error model and the spatial autoregressive parameter (λ) in the spatial lag model were both significant, suggesting the presence of spatial correlation. The positive coefficient on the spatial lag parameter (λ) indicates that farmland values are positively affected by land values in the neighboring PSU's. This finding substantiates the need to incorporate spatial effects in our modeling, and ignoring these effects to explore the impact of climate change on farmland values can lead to biased estimates[17]. In order to choose the best spatial model, we relied on the lowest AIC and the BIC values (Table 3). While the estimates of the AIC and the BIC values largely favored the spatial models over the non-spatial one, the SAR model was only slightly preferred over the SEM model based on the goodness of fit estimates (Table 3).

We also found evidence that extremities in weather could affect farmland values too. This was revealed by the fact that areas with more warmer days throughout the year had higher farmland values; while areas with more intense precipitation had lower farmland values. Additionally, the climate change impact estimates displayed non-linear relationship with farmland values in certain seasons, and this result is consistent with the Ricardian hypothesis proposed by Mendelsohn et al. (1994).

Finally, we looked at the marginal effect of average annual temperature and rainfall changes in farmland values. The net effect of increasing annual temperature was negative; while the net effect of higher annual precipitation was a positive outcome on farmland values (Table 4). In particular, we found that the marginal effect of every degree increase in average annual temperature was Rs.180 /hectare ($1.80) reduction in farmland values. In contrast, every mm increase in annual average rainfall led to an increase in farmland values by Rs.225/hectare ($2.25) (US$1 = Nepali Rs.100 conversion rate of 22 April, 2015 used throughout).

DISCUSSION

The findings from both, the non-spatial and the spatial models, suggested that climate does seem to have an impact on the value of farms in Nepal. For instance, the non-spatial fixed effect model showed evidence that the average temperature during the spring and summer season; and the average rainfall during the spring, winter and the autumn season affected the farmland values.

Additionally, the presence of a nonlinear relationship between climate and land values, although present only in certain seasons, is consistent with the findings from other Ricardian studies (Mendelsohn et al., 1994; Deressa et al., 2005; Seo and Mendelsohn, 2008). The effect of temperature on farmland value was more pronounced than that of rainfall, and this suggests higher sensitivities of crop growth to temperature changes (Lobell and Burke, 2008). Regarding precipitation, the result indicated that although higher rainfall is conducive for crop development, excess rainfall could hurt the crops, and, thereby the farmland values.

[15] It is also called marginal value or Ricardian climate sensitivities (Polsky, 2004).

[16] We tested for the presence of multicollinearity, and the variance inflation factor of independent variables were less than 10, thus mitigating the concern for collinearity (Meyers, 2000). Additionally, the presence of multicollinearity would lead to unstable regression coefficients and large standard errors (Cohen et al., 2013), neither of which occurred in our analysis.

[17] We also tested for the presence of spatial correlation and lag simultaneously using the mixed spatial model, but the spatial effects were not significant in the joint model.

Table 3. Spatial and Non-spatial regression result.

Variable	Non-spatial model	Spatial models	
	(1)	(2)	(3)
	Fixed effects	Spatial error	Spatial lag
Climate Normals			
Spring temperature	$-4.705.098^{***}$ (1.499.624)	$-3.770.218^{*}$ (2.138.728)	$-3.956.385^{*}$ (2.145.844)
Spring temperature sq.	101.512^{***} (28.603)	83.418^{*} (45.813)	82.806^{*} (45.999)
Summer temperature	$5.991.240^{**}$ (2.465.669)	$4.397.611^{*}$ (2.653.571)	$5.540.327^{**}$ (2.731.009)
Summer temperature sq.	-104.679^{*} (58.102)	-74.317 (53.995)	-95.566^{*} (55.429)
Autumn temperature	$-2.353.482^{*}$ (1.328.044)	-1.305.782 (1.845.721)	-1.641.706 (1.852.688)
Autumn temperature sq.	45.178 (36.104)	19.373 (48.755)	28.268 (49.354)
Winter temperature	1.806.967 (1.656.178)	1.312.581 (1.649.897)	1.085.378 (1.653.009)
Winter temperature sq.	-68.647 (53.326)	-60.404 (55.602)	-46.325 (55.485)
Spring rainfall	34.195^{**} (16.741)	31.688^{*} (17.358)	34.674^{*} (17.907)
Spring rainfall sq.	-0.161^{**} (0.081)	-0.152 (0.110)	-0.169 (0.114)
Summer rainfall	10.342 (8.554)	16.377 (10.488)	15.076 (10.507)
Summer rainfall sq.	-0.011 (0.008)	-0.017 (0.016)	-0.017 (0.016)
Autumn rainfall	55.846^{***} (19.832)	49.805^{***} (-13.656)	51.647^{***} (13.674)
Autumn rainfall sq.	-0.393^{***} (0.130)	-0.337^{***} (0.055)	-0.354^{***} (0.054)
Winter rainfall	279.972^{***} (77.915)	275.596^{***} (64.144)	264.975^{***} (65.576)
Winter rainfall sq.	-5.282^{***} (1.417)	-5.065^{***} (1.373)	-5.185^{***} (1.421)

Table 3. Contd.

Deviation from climate normals			
Spring temp. dev	104.573** (52.130)	58.676 (62.889)	68.320 (64.283)
Summer temp. dev	98.275 (90.009)	57.341 (72.634)	84.828 (72.766)
Autumn temp. dev	-113.153 (92.014)	-150.053** (69.786)	-141.447** (71.460)
Winter temp. dev	8.259 (67.114)	36.376 (71.332)	23.136 (71.545)
Spring rain dev	-17.951 (16.312)	-12.812 (20.012)	-12.410 (20.101)
Summer rain dev	4.772 (4.563)	5.824 (6.904)	6.346 (6.887)
Autumn rain dev	-86.028 (107.969)	-81.182 (65.157)	-79.463 (64.607)
Winter rain dev	252.092* (135.636)	274.139** (118.769)	255.970** (119.601)
Climate extremes			
WSDI	3.372*** (1.286)	3.324** (1.558)	3.699** (1.535)
SDII	-27.106** (11.518)	-29.827* (16.475)	-27.633* (16.439)
Controls			
Irrigation facilities	253.018*** (78.588)	212.951* (116.922)	250.600** (119.621)
Electricity	138.826 (87.675)	131.655 (117.869)	122.340 (118.015)
Road	46.480 (100.604)	-45.574 (99.349)	-0.484 (99.096)
Population	0.140** (0.069)	0.165*** (0.044)	0.145*** (0.044)
Farmer’s group	94.422 (69.942)	160.621 (143.045)	94.629 (137.966)
Market center	222.409*** (80.611)	232.431** (91.972)	234.405** (92.028)
Rho	- -	0.357*** (0.072)	- -

Table 3. Contd.

lambda	-	-	0.351***
	-	-	(0.065)
Log Likelihood	-3.048.864	-2.777.865	-2.776.498
AIC	6.161.728	5.621.730	5.618.996
BIC	6281.299	5.745.037	5.742.303
Observations	310	310	310
Number of PSU	155	155	155
PSU FE	YES	YES	YES
Year FE	YES	YES	YES

*** p<0.01, ** p<.5, * p<0.1. Dependent variable is the farmland value per hectare (Rs./Ha). The values in the parenthesis are the standard errors. Column 1 lists the output of the non-spatial fixed effects model. Column 2 and 3 are the output of the spatial fixed effects model. Column 2 is the spatial error model (SEM), while column 3 is the spatial lag model (SAR).

In essence, the significant quadratic variables imply that climate and farmland values have a nonlinear relationship, and it is consistent with the hypothesis of Ricardian approach (Mendelsohn et al., 1994). The positive coefficient in the quadratic terms for temperature (rainfall) suggests a minimally productive level of temperature (rainfall) and either more or less temperature (rainfall) would increase land values. The negative quadratic coefficients for temperature (rainfall) indicate that there is an optimal level of climate variable from which the value function decreases in both directions (Mendelsohn et al., 1994).

The findings from Table 3 shows that the significance of the variables for both the non-spatial (Column 1) and spatial models (Column 2 and 3) was almost alike. While the sign and significance of most coefficients in the three models were comparable, the magnitudes of the climate normal variables in the non-spatial model were larger in absolute value compared to the spatial models. This finding is consistent with other papers that have examined spatial and non-spatial modeling in the context of Ricardian framework (Kumar, 2011; Baylis et al., 2011).

The linear and the quadratic temperature variable for the spring season was significant across all models, while for the summer, the variables were significant in the non-spatial (column 1) and the SAR model (column 3). Winter temperature did not have any effect on farmland values across all three models, while the linear term for the autumn temperature was significant only in the non-spatial model. Looking at column (3)[18], the turning point for spring temperature occurred at 23.88°C. This indicates that average spring temperature above 23.88°C is associated with higher crop yields, which results in higher farmland values as well.

Similarly, the turning point for summer temperature in column (3) is 28.98°C, indicating that farmland values decline when average summer temperature exceeds 29°C. This result makes sense when we consider the major agricultural outputs of Nepal. The major crops grown in Nepal are paddy, wheat, and maize (Malla, 2009); and the optimal temperature range estimated in this paper is consistent with literature that have explored these crop's life cycle. Karn (2014) found that the critical temperature threshold for rice yield in Nepal to be 29.9°C, and temperature beyond that would lead to a decline in rice yields. Bhatt et al. (2014) found that the critical maximum threshold for maize production to be 27°C in Eastern Nepal. Bannayan et al. (2004) also suggest the optimum temperature for maize growth, in general, should be between 22 to 25°C. These findings could potentially explain the results found in this paper for the decline in farmland values at temperatures below 23.88°C and beyond 28.98°C. Since the suitable temperature for both maize and rice in Nepal lies between about 22 to 30°C, it seems plausible that farmland values increase in that temperature range.

The other significant climatic variables across all three models were the winter rainfall deviation, WSDI, and SDII. In particular, higher rainfall deviation during the winter season; and areas with higher annual warmer spells, both had a positive impact on farmland values. On the other hand, areas with more intense and excessive rainfall, in general, were associated with lower farmland values. Although the winter temperature was not significant in any of the models, we believe that is due to the growth requirement of winter crops in Nepal. The main winter crops in Nepal are wheat and barley, which have been found to be highly sensitive to winter rainfall, moreso than temperature (Krishnamurthy et al., 2013). In fact, Krishnamurthy et al. (2013) state that the winter crops in Nepal are extremely sensitive to small changes in rainfall patterns while the impact of temperature on these crops is low.

The coefficients on the linear and the quadratic precipitation variables suggest that autumn and winter average rainfall affect farmland values and this result is

[18] The turning point from column (1) and (2) were similar to column (3). We used column (3) for the interpretation since that is the final model used.

Table 4. Annual marginal impact of climate change on Nepalese agriculture.

Variable	Mean land value	95% confidence interval	
Temperature (°C)	-180.692	-187.257	-174.127
	(3.349)	-	-
Precipitation (mm)	-225.850	192.060	259.641
	(17.24)	-	-

Notes: Annual marginal at the average Nepalese climate measured as a change in average land value per hectare. These values are calculated from the ATI values of the SAR model using equation (6). Standard errors are derived using the delta method.

consistent across all three models. Similarly, higher spring precipitation had a significant and positive consequence on farmland values across all three models. This result also seems plausible when we consider the harvesting period of the major crops in Nepal. The harvesting period in Nepal for rice starts from mid-October to December, while wheat is harvested in winter period. Thus, the positive coefficients in the autumn and winter rainfall imply the presence of suitable environment for these crops during harvest time, which is positively reflected on the land values. Likewise, the negative coefficients on the quadratic terms for winter and autumn precipitation imply that excessive rainfall during these seasons could potentially damage the harvest, thereby negatively affecting the land values.

The other findings were that PSU's with access to irrigation, market center, and with higher population have a positive impact on farmland values. These results also seem reasonable since PSUs with irrigation facilities would not need to rely on rain-fed agriculture for crop growth and thus, these areas have higher land values. Similarly, presence of market center provides opportunities to easily purchase different agricultural products to improve yield; and higher population implies location with better amenities that could be driving population growth, both of which would result in higher farmland values as suggested by the results in this paper. In fact, the positive impact of irrigation facilities and market center on Nepalese farmland valuation has also been confirmed by Joshi et al. (2017).

The findings from the spatial analysis revealed the need to incorporate spatial models to enhance estimation reliability. With regards to the choice between the two spatial models, we looked at the model performance parameters, the AIC, and the BIC values, which suggested SAR as a slightly better model. While the SAR model was preferred from an econometric perspective, this lag model seems probable from an intuitive viewpoint as well. It is reasonable to assume that since farmers may not know the inherent value of their land due to insufficient information about land characteristics, especially in developing countries like Nepal, land prices could thereby depend on landowner interactions across communities.

Similarly, one can also argue that farmlands surrounded by expensive lands could potentially be worth more than those surrounded by inexpensive lands. Additionally, agricultural land markets are highly localized with many buyers being farmers looking to add fields near to their existing operation (Baylis et al., 2011), which further strengthens the argument for the use of the lag model. Anselin et al. (2008) state that for an equilibrium outcome of a spatial or social interaction process where the value of a dependent variable for one agent is jointly determined with that of neighboring agents, a SAR is considered to be ideal.

We then looked at the marginal impacts of the SAR model (Appendix Table 1)[19]. The direct effect showed that for every degree increase in the spring temperature beyond the threshold value of 23.88°C, farmland values increased by Rs.85/hectare ($0.85). However, beyond 28.98°C temperature in the summer season, every degree increase in temperature reduced farmland values by Rs.98/hectare ($0.98). The average indirect impact for the spring and summer temperature were also significant, indicating that the temperature at a particular PSU also affects the land values of neighboring PSUs (as defined by the *W* matrix). The indirect effect implied that for every degree increase in spring temperature beyond 23.88°C at a particular PSU, the land values in the neighboring PSUs increased by Rs.42/hectare ($0.42).

Likewise, beyond 28.98^0 C in the summer, farmland values in the neighboring PSUs declined by Rs.49/hectare ($0.49). The significance of the indirect effect does not seem implausible since climate is not vastly dissimilar in a small spatial scale. Therefore, if spring temperature affects the land values at a particular PSU, it is likely to affect the neighboring PSUs as well. Finally, the average total impact of an increase in the spring temperature beyond 23.88°C suggested that for every degree increase, the total farmland value increased

[19]Appendix Table 2 in the appendix shows the simulated z scores for the Marginal Impacts from the spatial lag model listed in Appendix Table 1.

by Rs.127/hectare ($1.27), when taking into account the own-PSU effect and the spillover effect of a change in spring temperature. The impact of summer temperature on farmland values can be interpreted in a similar fashion. Taking into account the findings from changes in temperature, the overall net marginal effect of a degree increase in average annual temperature was a reduction in farmland values by Rs.180/hectare ($1.80) (Table 4).

Regarding rainfall, the findings suggested that the average direct impact of a mm increase in rainfall during the spring season increased farmland values by Rs.35/hectare ($0.35). Precipitation during autumn and winter season also had an impact on the farmland values. Similar to the case of spring temperature, the average indirect impact indicates that precipitation during these seasons was not only affecting farmland values at that PSU, but also the land values in the neighboring PSUs. The average direct impact of an increase in precipitation during autumn and winter season was Rs.52/hectare ($0.52) and Rs.271/hectare ($2.71) respectively. However, excessive rainfall destroys crops, and it is reflected in the lower land value captured by the negative quadratic terms. Finally, the overall net marginal impact of a mm increase in the annual mean rainfall was an increase in farmland value by Rs.225/hectare ($2.25) (Table 4).

SDII and *WSDI*, the two variables that capture the extremities in climate were also both significant. Higher *SDII* suggests the occurrence of stronger precipitation, and this has an adverse impact on farmland values. On the other hand, higher *WSDI*, which indicates greater number of warmer days, positively affects the farmland values. Heavy rainfall can cause a disruption in crop cycle balance and lead to lower yield which could negatively affect farmland values, as suggested by our findings.

The positive effect of *WSDI* also makes sense since paddy, one of the major crops in Nepal, requires an extended period of the warm growing season. Similarly, maize is another staple crop of Nepal which also requires warm days to grow properly, and thus higher *WSDI* can, in fact, lead to higher farmland values. The results for the average total impacts suggested that intense precipitation lowered farmland values by Rs.42.5/hectare ($0.425); while higher days of warm spell increased land value by Rs.5.70/hectare ($0.057). In terms of the non-climatic variables, PSUs with access to irrigation and market center had land values that were higher by Rs.386/hectare ($3.86) and Rs.361/hectare ($3.61) respectively, compared to the ones that did not have those amenities.

Conclusion

Changes in climate and the resulting changes in land use pattern are likely to have a significant impact on sectors like agriculture, forestry, water and food security (Field, 2012). While the severity of climate change impacts on agriculture could be massive, with the right mitigation and adaptation strategies, the negative consequences can be alleviated. This paper used an application of the Ricardian approach to analyze the impact of climate change on farmland values in Nepal. Taking into account the limitation of traditional Ricardian approach in failing to explicitly incorporate the spatial nature of land values, this paper employed a spatial fixed effect model to estimate climate change impacts in the context of Nepal. The results revealed significant evidence of spatial correlation and the effects of climate change were found to be more conservative in spatial models relative to the non-spatial model.

The general findings implied that Nepalese farmlands are sensitive to climate change. The average temperature during the spring and summer season; and average rainfall in the spring, autumn and winter season were found to affect crop yields and thereby, the value of farms. The net effect of annual increases in temperature was negative; while the net impact of higher annual precipitation was a positive outcome on farmland values. In particular, we found that the marginal effect of every degree increase in annual temperature was Rs.180/hectare ($1.80) reduction in farmland values. Likewise, for rainfall, it was found that 1mm increase in average annual rainfall would positively affect farmland value by Rs.225/hectare ($2.25). Additionally, the extreme weather indices suggested PSUs with a greater number of warmer days (WSDI) faced positive effect on farmland values; while PSUs with excessive precipitation (SDII) had lower farmland values.

From a modeling perspective, we found evidence of significant positive spatial correlation, and the aforementioned results are the outcome of a spatial correction model. The implication of our findings from an econometric perspective suggests the need to depart from non-spatial analysis to studies that account for spatial analysis in order to obtain more reliable estimates of climate change impacts on farmland value.

The results from this study also provide an interesting perspective from the policymaking point of view. Agricultural production is one of the major means of livelihood for most people in Nepal and as such, policies should be directed towards helping people combat the impacts of climate change. One solution could be to provide farmers support in the form of loans, access to seeds, and technical advice on crop management and water harvesting so they can better adapt to the changing climatic conditions. The poor farming population are most vulnerable to climate change, particularly because they rely heavily on rain-fed agriculture. As such, policies should be directed towards providing irrigation systems at minimal costs to these populations. Furthermore, policymakers should also provide education and awareness to farmers on the dangers of climate change as well as on the importance of employing irrigation as a way to increase their crop yields and sustain their livelihood.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

REFERENCES

Acharya SP, Bhatta GR (2013). Impact of climate change on agricultural growth in Nepal. NRB Econ. Rev. 25(2):1-16.

Anyamba A, Small JL, Britch SC, Tucker CJ, Pak EW, Reynolds CA, Crutchfield J, Linthicum KJ (2014). Recent weather extremes and impacts on agricultural production and vector-borne disease outbreak patterns. PLoS One 9(3):e92538.

Anselin L, Bera AK (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. Statistics Textbooks Monogr. 155:237-290.

Anselin L, Le Gallo J, Jayet H (2008). Spatial panel econometrics. In The econometrics of panel data Springer Berlin Heidelberg. pp. 625-660.

Bannayan M, Hoogenboom G, Crout NMJ (2004). Photothermal impact on maize performance: A simulation approach. Ecol. Model. 180(2):277-290.

Baylis K, Paulson ND, Piras G (2011). "Spatial approaches to panel data in agricultural economics: a climate change application. J. Agric. Appl. Econ. 43(3):325-338.

Bhatt D, Maskey S, Babel MS, Uhlenbrook S, Prasad KC (2014). Climate trends and impacts on crop production in the Koshi River basin of Nepal. Reg. Environ. Change 14(4):1291-1301.

Bronaugh D, Hiebert MJ (2015). Pacific Climate Impacts Consortium. climdex.pcic: PCIC Implementation of Climdex Routines [Computer software manual]. Retrived from https://CRAN.R-project.org/package=climdex.pcic (R package version 1.1-6).

Central Bureau of Statistics (CBS) (2004). Nepal Living Standards Survey: Statistical Report 2003/04, Volumes I and II. Kathmandu: National Planning Commission/ His Majesty's Government of Nepal.

Central Bureau of Statistics (CBS) (2010). Nepal Living Standards Survey: Statistical Report 2010/11, Volumes I and II. Kathmandu: National Planning Commission/ His Majesty's Government of Nepal.

Cohen J, Cohen P, West SG, Aiken LS (2013). Applied multiple regression/correlation analysis for the behavioral sciences. Routledge.

Chatzopoulos T, Lippert C (2016). Endogenous farm-type selection, endogenous irrigation, and spatial effects in Ricardian models of climate change. Euro. Rev. Agric. Econ. 43(2):217-235.

Cline WR (1996). The impact of global warming of agriculture: comment. Am. Econ. Rev. 86(5):1309-1311.

Darwin R (1999). The impact of global warming on agriculture: A Ricardian analysis: Comment. Am. Econ. Rev. 89(4):1049-1052.

Deressa T, Hassan R, Poonyth D (2005). Measuring the impact of climate change on South African agriculture: the case of sugarcane growing regions. Agrekon 44(4):524-542.

De Salvo M, Begalli D, Signorello G (2014). The Ricardian analysis twenty years after the original model: Evolution, unresolved issues and empirical problems. J. Dev. Agric. Econ. 6(3):124-131.

Deschenes O, Greenstone M (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. The American Economic Review, 97(1), 354-385.

Deschenes O, Greenstone M (2011). Using panel data models to estimate the economic impacts of climate change on agriculture. Handbook on Climate Change and Agriculture pp. 112-140.

Elhorst JP (2014). Spatial panel data models. In Spatial Econometrics. Springer Berlin Heidelberg pp. 37-93.

Field CB (2012). Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change. Cambridge University Press.

Gum W, Singh PM, Emmett B (2009). Even the Himalayas have stopped smiling': climate change, poverty and adaptation in Nepal. 'Even the Himalayas have stopped smiling': climate change, poverty and adaptation in Nepal.

Howden SM, Soussana JF, Tubiello FN, Chhetri N, Dunlop M, Meinke H (2007). Adapting agriculture to climate change. Proceed. Natl. Acad. Sci. 104(50):19691-19696.

IPCC (2007). Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, Pachauri, R.K and Reisinger, A. (eds.)]. IPCC, Geneva, Switzerland 104 p.

IPCC (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Joshi J, Ali M, Berrens RP (2017). Valuing farm access to irrigation in Nepal: A hedonic pricing model. Agric. Water Manage. 181:35-46.

Karn PK (2014). The impact of climate change on rice production in Nepal (No. 85).

Krishnamurthy PK, Hobbs C, Matthiasen A, Hollema SR, Choularton RJ, Pahari K, Kawabata M (2013). Climate risk and food security in Nepal—analysis of climate impacts on food security and livelihoods. https://cgspace.cgiar.org/handle/10568/34077

Kumar KK (2011). Climate sensitivity of Indian agriculture: do spatial effects matter?. Cambridge J. Reg. Econ. Soc. P. rsr004.

LeSage JP, Fischer MM (2008). Spatial growth regressions: model specification, estimation and interpretation. Spatial Econ. Anal. 3(3):275-304.

LeSage JP, Pace RK (2009). Introduction to Spatial Econometrics (Statistics, textbooks and monographs). CRC Press.

Lippert C, Krimly T, Aurbacher J (2009). A Ricardian analysis of the impact of climate change on agriculture in Germany. Clim. Change 97(3):593-610.

Lobell DB, Burke MB (2008). Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. Environ. Res. Lett. 3(3):034007.

Malla G (2009). Climate change and its impact on Nepalese agriculture. J. Agric. Environ. 9:62-71.

Massetti E, Mendelsohn R (2011). Estimating Ricardian models with panel data. Clim. Change Econ. 2(04):301-319.

Massetti E, Nascimento GRDC, Fortes de Oliveira A, Mendelsohn RO (2013). The Impact of Climate Change on the Brazilian Agriculture: A Ricardian Study at Microregion Level.

Mendelsohn R, Nordhaus WD, Shaw D (1994). The impact of global warming on agriculture: a Ricardian analysis. Am. Econ. Rev. pp. 753-771.

Meyers RH (2000). Classical and modern regression with applications (Duxbury Classic). Duxbury Press, Pacific Grove.

Patton M, McErlean S (2003). Spatial effects within the agricultural land market in Northern Ireland. J. Agric. Econ. 54(1):35-54.

Polsky C (2004). Putting space and time in Ricardian climate change impact studies: Agriculture in the US Great Plains, 1969–1992. Ann. Assoc. Am. Geogr. 94(3):549-564.

Rosenzweig C, Iglesias A, Yang XB, Epstein PR, Chivian E (2001). Climate change and extreme weather events; implications for food production, plant diseases, and pests. Glob. Change Hum. Health 2(2):90-104.

Schlenker W, Hanemann WM, Fisher AC (2005). Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. Am. Econ. Rev. 95(1):395-406.

Seo SN, Mendelsohn R (2008). Climate change impacts on Latin American farmland values: the role of farm type. Rev. Econ. Agron. 6(2):159-176.

Tobler WR (1979). Cellular geography. In Philosophy in geography. Springer Netherlands pp. 379-386.

APPENDIX

Appendix Table 1. Marginal impacts – spatial lag model.

Variables	Direct	Indirect	Total
Climate Normals			
Spring temperature	-4,059.016*	-2,038.298*	-6,097.314*
Spring temperature sq.	84.954*	42.661*	127.616*
Summer temperature	5,684.092*	2,854.309*	8,338,302**
Summer temperature sq.	-98.004*	-49.283*	-147.288*
Autumn temperature	-1,684.281	-845.776	-2,530.057
Autumn temperature sq.	29.038	14.520	43,559
Winter temperature	1,113.534	559.178	1,672.712
Winter temperature sq.	-47.527	-23.866	-71.393
Spring rainfall	35.573*	17.863	53.437*
Spring rainfall sq.	-0.174	-0.087	-0.261
Summer rainfall	15.467*	7.767	23.234
Summer rainfall sq.	-0.017	-0.008	-0.026
Autumn rainfall	52.987***	26.608**	79.595***
Autumn rainfall sq.	-0.364***	-0.182***	-0.547***
Winter rainfall	271.849***	136.513**	408.362***
Winter rainfall sq.	-5.320***	-2.671**	-7.991***
Deviation from Climate Normals			
Spring temperature dev	70.092	35.198	105.290
Summer temperature dev	87.028	43.702	130.731
Autumn temperature dev	-145.116*	-72.872	-217.988*
Winter temperature dev	23.736	11.919	35.656
Spring rain dev	-12.732	-6.393	-19.125
Summer rain dev	6.511	3.269	9.780
Autumn rain dev	-81.524	-40.938	-122.463
Winter rain dev	262.610**	131.873*	394.483**
Climate Extremes			
SDII	-28.350*	-14.236	-42.586*
WSDI	3.795**	1.906**	5.701**
Controls			
Irrigation facilities	257.101**	129.107*	386.209**
Electricity	125.513	63.028	188.542
Road	-0.497	-0.249	-0.747
Population	0.148***	0.074**	0.223***
Farmer's group	97.084	48.752	145.836
Market center	240.485**	120.763*	361.249**

*** $p<0.01$, ** $p<.5$, * $p<0.1$. This table shows the output of the marginal effects from the SAR model. The first column lists the average direct impact (ADI); the second lists the average indirect impact (AII); while the last column is the average total impact (ATI).

Appendix Table 2. Marginal impacts (Simulated z-value) – spatial lag model

Variables	Direct	Indirect	Total
Spring temperature	-1.906	-1.688	-1.881
Spring temperature sq.	1.872	1.657	1.845
Summer temperature	2.106	1.776	2.052
Summer temperature sq.	-1.791	-1.760	-1.754
Autumn temperature	-0.929	-0.863	-0.916
Autumn temperature sq.	0.603	0.562	0.594
Winter temperature	0.721	0.702	0.721
Winter temperature sq.	-0.902	-0.868	-0.901
Spring rainfall	1.679	1.471	1.638
Spring rainfall sq.	-1.528	-1.340	-1.486
Summer rainfall	1.696	1.498	1.662
Summer rainfall sq.	-1.292	-1.184	-1.275
Autumn rainfall	3.257	2.589	3.182
Autumn rainfall sq.	-5.702	-3.302	-5.157
Winter rainfall	4.108	2.652	3.741
Winter rainfall sq.	-3.741	-2.549	-3.463
Spring temperature dev	1.056	0.993	1.050
Summer temperature dev	1.098	1.015	1.086
Autumn temperature dev	-2.011	-1.707	-1.962
Winter temperature dev	0.318	0.305	0.316
Spring rain dev	-0.641	-0.610	-0.635
Summer rain dev	0.926	0.845	0.910
Autumn rain dev	-1.233	-1.159	-1.228
Winter rain dev	2.179	1.839	2.124
SDII	-1.595	-1.408	-1.564
WSDI	2.393	1.926	2.304
Irrigation facilities	2.075	1.755	2.022
Electricity	0.959	0.902	0.951
Road	0.032	0.026	0.030
Population	3.255	2.442	3.119
Farmer’s group	0.676	0.645	0.672
Market center	2.743	2.133	2.631

academicJournals

Vol. 9(6), pp. 162-167, June 2017
DOI: 10.5897/JDAE2017.0818
Article Number: D5814B064473
ISSN 2006-9774

http://www.academicjournals.org/JDAE

Journal of Development and Agricultural Economics

Full Length Research Paper

Determinants of participation in fertilizer subsidy programme among rice farmers in Ogun State, Nigeria

OBI-EGBEDI Ogheneruemu and BANKOLE Olaide Abdul-hameed*

Department of Agricultural Economics, University of Ibadan, Oyo State, Nigeria.

Received 14 February, 2017; Accepted 28 April, 2017

Nigerian farmers, including rice farmers, still record very low levels of fertilizer use thereby limiting productivity. Subsidies have been known to encourage fertilizer use among farmers. This paper examined the factors influencing rice farmer participation in the government's fertilizer subsidy programme. Data was collected through the aid of a well-structured questionnaire from 263 rice farmers. Descriptive and Logistic regression analyses were used to analyze the data. Statistical mean differences were found in age, household size, years of farming experience, farm size, output and total annual income between participants and non-participants. Also, participation was significantly and positively influenced by marital status, household headship, membership of farmer association/groups, motorcycle ownership, mobile phone ownership, access to credit and total farm size. The paper concludes that efforts should be geared towards encouraging membership of farmer groups, availability and timely distribution of subsidized fertilizer and the establishment of more redemption centres.

Key words: Fertilizer, growth enhancement scheme (GES), participation, rice, subsidy.

INTRODUCTION

Increased fertilizer use played a significant role in the success of the green revolution in Latin America and Asia. It helped raise agricultural productivity and farm incomes, thus laying the foundation for broader economic growth. As much as 50% of yield growth in these regions could be attributed to increased fertilizer use (Toenniessenn et al., 2008). Despite the growing evidence that fertilizers can substantially increase yields in Sub-Saharan Africa (SSA) as well as slow down soil degradation, farmers in SSA still lag far behind other developing countries in fertilizer use. The average fertilizer use in Sub-Saharan Africa (SSA) is estimated at 16 kg/ha; much lower than other parts of the world with 90 kg/ha in Middle East and North Africa, 126.6 kg/ha in North America, 127.9 kg/ha in Latin America and Caribbean, 158.5 kg/ha in South Asia and 344.3 kg/ha in East Asia and Pacific. In Nigeria, the fertilizer use was estimated at 4.5 kg/ha in 2002 and 10.9kg/ha in 2014, below the average for SSA (World Bank, 2014).

Furthermore, the results of a Food and Agricultural Organization (FAO) study spanning 1983-2000 along with some other studies (FAO and ITPS 2015, Sheldrick and Lingard, 2004; Lesschen et al., 2003; Stoorvogel and Smaling, 1990) which assessed soil nutrients (Nitrogen,

*Corresponding author. E-mail: oab.bankole@gmail.com. Tel: +2348065473997.

Phosphorus and Potassium-NPK) balances by land use systems revealed a general depletion in Africa characterized by annual negative nutrient balances. For Nigeria, the nutrient balances were -34 kg/ha in 1983 and -37 kg/ha in 2000 for N; -4 kg/ha in 1983 and -4 kg/ha in 2000 for P; and -24 kg/ha in 1983 and -31 kg/ha in 2000 for K. These figures are indicative of unrelenting nutrient mining over time (Bationo et al., 2012). The gap in fertilizer use in SSA and Nigeria relative to the rest of the world is given as one reason for the failure of the region to achieve its green revolution objectives. This failure raises the question of what types of policies and programme are needed for the region to realize the potential benefits from fertilizer usage (Kelly, 2006).

In 2006, African leaders in the context of the Comprehensive Africa Agriculture Development Programme (CAADP) through the Abuja Declaration resolved to improve the use of fertilizer as a means to achieving the region's green revolution objectives. As a follow up, the Federal Government of Nigeria (FGN) decided to disengage from direct procurement of fertilizer in favor of promoting private sector participation. This was done via the Growth Enhancement Support (GES) Programme; a fertilizer subsidy programme under the Agricultural Transformation Agenda (ATA) which set ambitious goals of increasing fertilizer use from the year 2010 level of approximately 13 to 50 kg/ha (FMARD, 2011). The GES was different from previous subsidy schemes in that it targeted beneficiaries through vouchers and the handing over of subsidized fertilizer distribution from the government to private dealers. This contrasts with previous subsidy schemes in which the government directly participated in the procurement and distribution of subsidized fertilizer through the agricultural development project (ADP) and other agencies (IFPRI, 2012).

In 2011, the Nigerian government made an effort to find a long-lasting solution to the problem of food insecurity by raising agricultural productivity and boosting food production. In order to achieve this objective, the Agricultural Transformation Agenda was launched in the same year. This was anchored on the philosophy of treating agriculture as a business rather than a development programme. The goal was to add 20 million metric tonnes (MT) of food to domestic food supply and create 3.5 million jobs by year 2015.

The GES Programme was designed as a component of the Agricultural Transformation Agenda of the Federal Government (ATA). The Federal Government of Nigeria introduced the GES which was designed to deliver government subsidized farm inputs directly to farmers via mobile phones. The GES scheme was powered by e-Wallet, an electronic distribution channel which provided an efficient and transparent system for the purchase and distribution of agricultural inputs based on a voucher system. The scheme guarantees registered farmers e-Wallet vouchers with which they could redeem fertilizers, seeds and other agricultural inputs from agro-dealers at half the cost, the other half being borne by the federal government and state government in equal proportions (FMARD, 2011). Individual farmers were registered in a national database. Each farmer was entitled to a 50% subsidy on the price of two 20 kg bags of fertilizer. This intervention became necessary as a result of the crisis that riddled the agricultural sector in the past, given its critical role for food security and economic diversification.

On inception, the aims of the GES was to migrate smallholder farmers from subsistence farming to commercialized systems over a 4 to 10 year period in order to facilitate trade and competitiveness. According to Takeshima and Liverpool-Tasi (2013), the potential in the fertilizer subsidy reform under the ATA include improved targeting through voucher and crowding-in of the commercial fertilizer sector. By June 2014, agricultural productivity and food production had increased by 17 million MT and was expected to reach 21 million MT by the end of the year and exceed the 20 million MT target set for 2015. However, challenges remain in farmer access to redemption facilities, entitlement risk (mobile phone), fertilizer quality regulation and the speed at which the private sector respond. Generally, fertilizer demand still depends on broader agricultural policies, factor endowments and farming systems.

The Federal Government under the current administration has decided to build on the achievements of the ATA by launching a new strategy known as the Agricultural Promotion Policy (APA). The plan is to solve the problems associated with the previous attempt at ensuring an efficient fertilizer distribution system. Therefore, the current policy objective is to increase productivity by ensuring timely access to high quality and price competitive inputs (FMARD, 2016). Thus, encouraging more farmer participation in the program is key to the policy success.

This study seeks to contribute to existing literature on the factors responsible for participation in the fertilizer subsidy programme. In order to achieve this, answers were provided to the following questions:

1. What differences exist in rice farmers' characteristics by their level of participation in the fertilizer subsidy programme?
2. What factors influences the participation of farmers in the fertilizer subsidy programme in the study area?

MATERIALS AND METHODS

Descriptive statistics

Descriptive statistics include the use of frequencies, percentages, means and standard deviation to analyze the socio-economic characteristics of respondents. It was also used to describe the reasons for the non-receipt of subsidized fertilizer.

Empirical estimation

The decision whether or not to participate in the fertilizer subsidy programme can be explained as a discrete binary variable, 1 for participants and 0 for non-participants. The simplest possible binary regression model is the linear probability model (LPM) in which the binary response variable is regressed on the relevant explanatory variables by using the standard Ordinary Least Square (OLS) methodology. However, it suffers from several estimation problems; one of which is that it can produce predicted probabilities outside the (0; 1) bounds (Gujarati, 2004). Other appropriate models that can be used are logit and probit. Logit and probit models usually yield similar results. Hence; the choice is not too critical, even though the logit distribution has more density mass in the bounds. Estimating participation is to define an adequate measurable indicator that will distinguish between participants and non-participants.

A binary variable indicates whether or not the farmer participates in the programme. When one is interested only in comparing outcomes for those participating (*T* = 1) with those not participating (*T* = 0), this estimate can be constructed from a probit or logit model. In this study, a participant is defined as a rice farmer that has received subsidized fertilizer in the last rice production season. The sample of participants and nonparticipants was pooled, and then participation *T* was estimated on all the observed covariates *X* in the data that are likely to determine participation. Traditional instruments used in the literature include the distance between the farm and the fertilizer selling points, or social capital proxied by how long the farmer has lived in the community (Seck, 2015). The vector of explanatory variables includes farm characteristics that may influence the probability of getting subsidized fertilizer such as farm size, access to credit, mobile phone ownership, and ownership of a means of transportation and affiliation to farmers' union.

In this analysis, participation (Z) is defined as the dependent variable which takes the value of 1, if a rice farmer participates in the fertilizer subsidy programme and 0, otherwise, that is, $Z = 1$, if a rice farmer participates in the fertilizer subsidy programme and $Z = 0$, otherwise. The logistic model postulates the probability (P_i) that participation is a function of an index $(Z_i)$where:

(Z_i) is an inverse of the standard logistic cumulative function of P_i that is, $P_i(y) = f(Z_i)$; (Z_i) is also an inverse of the standard logistic cumulative function of P_i:

$$P_i\ (y = 1) = f\ (Z_i)$$

The probability of participation is given by:

$$P_i\ (y = 1) = \left(\frac{1}{1+e}\right) - Z_i \tag{1}$$

e represents the base of natural logarithms (2.718).

The probability of no participation is given by:

$$Q_i = (y = 0) = 1 - P_i\ (y = 1)$$

Since, $1 - P_i\ (y = 1) = 1 - \frac{1}{1+e^{-Z_i}}$; $1 - P_i\ (y = 1) = \frac{1+e^{-Z_i}}{1+e^{-Z_i}} - 1\ and\ \ 1 - P_i\ (y = 1) = \frac{e^{-Z_i}}{1+e^{-Z_i}}$

But,

$$\frac{1}{P_i\ (y=1)} = 1 + e^{-Z_i} \tag{2}$$

Thus: $\frac{P_i\,(y=1)}{1-P_i(y=1)} = \frac{1}{e^{-Z_i}}$ and

$$\frac{P_i(y=1)}{1-P_i(y=1)} = e^{Z_i} \tag{3}$$

We take as comparison category, farmers who did not participate in the fertilizer subsidy programme. This means that the changes in relative risk will represent the improvement of a non-participating rice farmer given the impact of a specific variable.

The explanatory and dependent variables that were used in the econometric model (logit) are defined as follows:

$$\ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_m X_m + \varepsilon \tag{4}$$

Where, Z_i = Participation (1 = participants, 0 = non-participants); X_1 = Age in years; X_2 = Marital status (1 = single, 2 = married, 3 = divorced, 4 = widowed); X_3 = Household headship (0=female, 1=male); X_4 = Farming experience in years; X_5 = Years of education; X_6 = Ownership of a means of mobility (motorcycle) (1=Yes, 0=No); X_7 = Ownership of a mobile phone (1 = Yes, 0 = No); X_8 = Access to credit (1 = Yes, No = 0); X_9 = Membership of farmers' association/group (1 = Yes, 0 = No); X_{10} = Total farm size (in hectares);X_{11} = Ownership of land (1 = Personal, 0 = otherwise) and ε = Error term.

Data collection

This study was carried out in Ogun State in the South-Western geo-political zone of Nigeria. The state has 21 Local Government Areas (LGAs) and a projected population of 4,424,066 (NPC, 2011). The state is located in the moderately hot, humid tropical climate zone of Southwestern Nigeria and it favours the production of food crops such as maize, cassava, yam, cocoyam, soybean and rice. The major occupation of the people is farming (OGADEP, 2015). There are four Agricultural Development Project (ADP) zones in the state as categorized by the Ogun State Agricultural Development Project (OGADEP) namely Ilaro, Ijebu-Ode, Abeokuta and Ikenne zones. Thus, a peculiar nature of OGADEP is that zones are further divided into blocks and cells.

The data for the study was collected in 2015 through the use of structured questionnaires by employing a multi-stage sampling technique. Three agricultural zones were purposely selected from a total of four due to the availability of rice farmers who participated in the fertilizer subsidy programme. They are Abeokuta, Ikenne and Ilaro zones. The second stage involved the random selection of three local government areas from the selected zones, these included Ewekoro (Abeokuta Zone), Obafemi Owode (Ikenne Zone) and Yewa North (Ilaro Zone). Next, cells were randomly selected in each of the zones. Lastly, a total of 270 questionnaires were distributed to the farmers; 263 were used for analysis consisting of 113 and 150 participating and non-participating farmers respectively.

RESULTS AND DISCUSSION

Socioeconomic characteristics of participating and non-participating farmers

The description of farmer characteristics is presented in Table 1 and it reveals that both groups (participants and non-participants) have similar characteristics with only slight differences recorded. Rice farming was a male dominated activity in the study area.

Generally, there were more households headed by males than females participating in the programme. Most of the farmers were middle-aged, economically active and productive with a mean age of forty six years. The implication of this is that they are still within the

Table 1. Socio-economic characteristics of rice farmers (n=263).

Variable	Participants	Non-participants	Mean difference
Sex			
Male (%)	82.30	82.67	
Female (%)	17.70	17.33	
Age (mean)	47.92	44.80	3.12***
Household size (mean)	5.58	5.11	0.46*
Years of education (mean)	5.92	6.36	-0.44
Years of farming experience (mean)	24.98	22.33	2.66**
Rice farm size in *ha* (mean)	1.726	1.448	0.28***
Output in kg (mean)	2022.57	1526.60	495.97***
Total annual income (mean)	542,272.56	367,800.00	174472.57***

Source: Field Survey, 2015. *, **, *** implies that coefficients are statistically significant at 10, 5 and 1%, respectively.

productive class. According to Okoruwa and Ogundele (2004), being in the productive class would have a positive effect on rice production in the country. There was a significant difference in the mean ages of participants and non-participants with the average age of the participants higher than that of the non-participants.

The average household size for both groups is between five and six persons per farming household. This closely follows Okoedo-Okojie and Onemolease (2009) finding that larger household size of participants could imply that they have enough free labour for farm activities. A significant difference occurs between the mean household sizes of both groups of farmers at the 10% level.

A majority of the farmers spent an average of six years in school. There exists no significant difference in the number of years spent by farmers in school. This is consistent with the results of Azhar (1991) who reported that elementary education (4 - 6 years of schooling) does not have much effect on agricultural productivity in traditional farm settings. Other authors who lend support to this notion include Bravo-Ureta and Evenson (1994), Ajibefun and Aderinola (2003) and (Okoruwa et al., 2006).

With respect to the farm characteristics of the farmers, the average years of farming experience for participants was found to be significantly higher than that of the non-participants. There was also a significant difference in the farm size allocated to rice production between both groups of farmers with the participants having the larger sizes. This could also encourage the participating farmers to access more input for usage on their farms. Table 1 also shows that the mean output were about 2,023 and 1,527 ha for participants and non-participants while the total annual income for both groups were about ₦542,272.56 and 367800, respectively.

Factors affecting participation in the fertilizer subsidy programme

This section reports the results from the binary logistic model used to evaluate the determinants of participation of rice farmers in the fertilizer subsidy programme. The result of the regression analysis is presented in Table 2. The diagnostics reveal the model has a log likelihood of 158.59 and a chi-square statistics of 42.18; which is significant at 1%. This shows that the model is a good fit for the data. Seven of the eleven variables were statistically significant. All of the significant variables have positive signs. The variables are marital status (married), household headship (male), ownership of motorcycle, ownership of mobile phone, access to credit, membership of farmers' association/groups, and total farm size; positively associated with the probability of participation in the subsidy programme.

The coefficient of marital status (married) is significant at 5%. Thus a 1% increase in the number of married farmers may likely increase the likelihood of famers' participation by 0.53%.

With respect to household headship, the coefficient is significant and positively influences the probability of participation. Households headed by females were less likely to have received a coupon in the sample than those headed by males (consistent with the results of Chibwana et al., 2010). The marginal effect result implies that a 1% increase in the number of male headed households is likely to increase the probability of participation by about 0.43%.

The coefficient for the ownership of a means of transportation (motorcycle) was positive and statistically significant at 10%. Redemption centres are usually some kilometers away from the farmers residence, therefore, a motorcycle increases the probability of participating in the programme. This result is consistent with the study of Takeshima and Liverpool-Tasie (2013) which reported that farmers who lived closer to town are more likely to receive subsidized fertilizer. In this case, ownership of motorcycle could get a farmer to town in a timely manner. The result of the marginal effect reveals that a 1% increase in the ownership of motorcycle increases the probability of participation increases by 0.13%.

Table 2. Logit regression result of factors influencing participation in the fertilizer subsidy programme.

Variable	Coefficients (Std. Error)	t-value	Marginal effect
Age	0.0231 (0.0208)	1.11	0.0055
Marital status	2.2237** (1.0380)	2.14	0.5333
Household headship	3.3094*** (1.9778)	1.67	0.4251
Years of farm experience	-0.0023 (0.0171)	-0.13	-0.0005
Years of education	-0.0232 (0.0360)	-0.65	-0.0056
Ownership of motorcycle	0.5581* (0.2910)	1.92	0.1327
Ownership of mobile phone	1.4307*** (0.6865)	2.08	0.2745
Access to credit	0.7732** (0.3277)	2.36	0.1891
Membership of farmers' association	0.5063* (0.2920)	1.73	0.1191
Total farm size	0.1000*(0.0538)	1.86	0.0240
Ownership of land	-0.1394 (0.2974)	-0.47	0.0336
Constant	-11.3470*** (4.1236)	-2.75	

Source: Generated by Authors using Stata. *, **, *** implies that coefficients are statistically significant at 10, 5 and 1%, respectively. Number of observation = 263; LR chi^2 (13) = 42.18; Prob> chi^2 = 0.0000; Log likelihood = -158.59451; Pseudo R^2 = 0.1174.

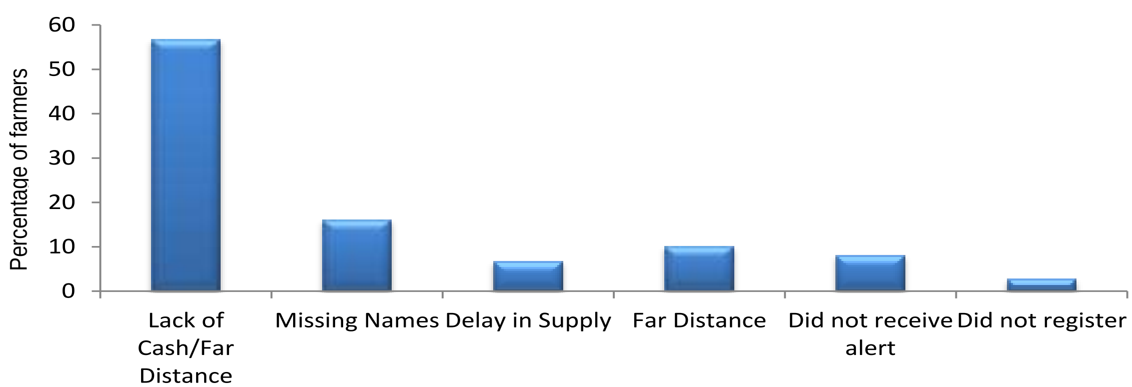

Figure 1. Reasons for non-receipt of subsidized fertilizer. Source: Field Survey, 2015.

With respect to the ownership of a mobile phone, there exists a positive and significant relationship between the variable and participation. One of the main components of the GES was that farmers must own mobile phones through which they can be alerted to retrieve their voucher. Therefore, this result is consistent with the objective of the programme as the marginal effect has shown that a 1% increase in the ownership of mobile phone was likely to increase the probability of participation increases by about 0.27%.

Access to credit also has a positive and significant relationship with participation. It is expected that a farmer might be encouraged to take advantage of the subsidy to relieve the burden of the credit facility. The result of the marginal effect shows that there is a likelihood of about 0.19% to participate in the subsidy programme with every 1% increase in access to credit facility.

Furthermore, the coefficient of the membership of a farmer association has a positive and significant effect on participation. This result is consistent with the studies of Ricker Gilbert and Jayne (2008) and Liverpool-Tasie (2012) which reported that social networks increases the probability of participation. Also, the result of the marginal effect reveals a 0.20% likelihood of a socially connected farmer to participate in the fertilizer subsidy programme.

Lastly, farm size has a positive and significant coefficient. It is expected that the bigger the farm, the more inputs that are needed to sustain production. Therefore, it provides an incentive for the farmer to take advantage of cost reduction in form of a subsidy. The result of the marginal effect shows that a 1% increase in farm size induces a 0.02% likelihood that a farmer participates in the subsidy programme.

Reasons for non-receipt of subsidized fertilizer

Figure 1 show the distribution of reasons why farmers did not participate in the fertilizer subsidy programme. About 57% of the farmers could not receive subsidized fertilizer either due to lack of cash/long distance, 16% because of missing names, 10% because of long distance and about 7% because of delay in supply. Also, 8% of the farmers did not receive an alert to redeem their vouchers while about 3% did not register.

Conclusion

This study investigated the factors/determinants responsible for rice farmer participation in the fertilizer subsidy programme using Ogun State of Nigeria as a case study. There exist statistical mean differences in age, household size, farming experience, farm size, output and total annual income between participants and non-participants. Also, the factors which significantly influence participation include marital status (married), household headship (male), ownership of a means of mobility (motorcycle), mobile phone ownership, access to credit, membership of farmers' association and total farm size. The study hereby recommends that Stakeholders (government and the private sector) should ensure the establishment of more redemption centres or make available means of mobility for farmers. Also, membership of a farmer association and other social groups should be encouraged to avoid information asymmetry. In addition, availability and timely delivery of fertilizer should be ensured to avoid farmer apathy towards the programme.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

REFERENCES

Ajibefun IA, Aderinola EA (2003). Determinants of Technical Efficiency in Traditional Agricultural Production: Application of Stochastic Frontier Modeling to Food Crop Farmers in South-Western Nigeria. AJEP. 10(2):31-56.

Azhar R (1991). Education and Technical Efficiency during the green revolution in Pakistan. Econ. Dev. Cult. Change 39:651-665.

Bationo A, Waswa B, Kihara J, Adolwa I, Vanlauwe B, Saidou K (2012). Lesson learned from long-term soil fertility management experiments in Africa. Springer Life Sci. Agric. http://www.springer.com/gp/book/9789400729377.

Bravo-Ureta BE, Evenson RE (1994). Efficiency in agricultural production: the case of peasant farmers in eastern Paraguay. Agric. Econs. 10: 27-37.

Chibwana C, Fisher M, Jumbe C, Masters W, Shively G (2010). Measuring the Impacts of Malawi's Farm Input Subsidy Programme. Paper presented at the 2010 annual meeting of the African Association of Agricultural Economists in Cape Town, South Africa. http://ssrn.com/abstract=1860867.

FAO, ITPS (2015). Food and Agricultural Organization of the United Nations and Intergovernmental Technical Panel on Soils, Rome, Italy. Status of the World's Soil Resources (SWSR) – Main Report.

FMARD (2011). Federal Ministry of Agriculture and Rural Development. Agricultural Transformation Agenda: Blueprint on Agriculture and Rural Development; A Presentation to the National Economic Management Team by the Honourable Minister of Agriculture and Rural Development, Abuja, Nigeria.

FMARD (2016). Federal Ministry of Agriculture and Rural Development. The Agricultural Promotion Policy. Building on the Successes of the ATA, Closing Key Gaps. Policy Strat. Document P 5.

Gujarati DN (2004). Qualitative Response Models in Basic Econometrics, African Edition 15:541-591.

IFPRI (2012). International Food Policy Research Institute-Africa Lead Report on Assessment of Nigeria Agriculture Transformation Agenda (ATA) and Capacity Building Needs. Africa Leadership Training and Capacity Building Programme.

Kelly VA (2006). Factors Affecting Demand for Fertilizer in Sub-Saharan Africa. Agriculture and Rural Development Discussion Paper 23. Washington, D.C.: The World Bank.

Lesschen JP, Asiamah RD, Gicheru P, Kanté S, Stoorvogel JJ, Smaling EMA (2003). Scaling Soil Nutrient balances. Rome, FAO.

Liverpool-Tasie LSO (2012). Targeted Subsidies and Private Market Participation. An Assessment of fertilizer demand in Nigeria. IFPRI Discussion Paper 01194.

NPC (2011). National Population Commission. Projected Population (2008 – 2011).

OGADEP (2015). Ogun State Agricultural Development Programme. Annual Report.

Okoedo-Okojie DU, Onemolease EA (2009). Factors affecting the adoption of yam storage technologies in the Northern Ecological zone of Edo State, Nigeria. J. Hum. Ecol. 27(2):155-160.

Okoruwa VO, Ogundele OO (2004). Technical efficiency differentials in rice production technologies in Nigeria. World J. Agric.Sci. 3(5):53-58.

Okoruwa VO, Ogundele OO, Oyewusi BO (2006). Efficiency and productivity of farmers in Nigeria: A study of rice farmers in North Central Nigeria. Poster paper prepared for presentation at the International Association of Agricultural Economists Conference, Gold Coast, Australia P 12.

Ricker-Gilbert J, Jayne TS (2008). The Impact of Fertilizer Subsidies on National Fertilizer Use: An Example from Malawi, Paper presented at the American Agricultural Economics Association Annual Meeting, Orlando, FL.

Seck A (2015). Fertilizer Subsidy and Agricultural Productivity in Senegal. Department of Economics Cheikh Anta Diop University Dakar, Senegal.

Sheldrick WF, Lingard J (2004). The use of nutrient audits to determine nutrient balances in Africa. Food Policy Vol. 29(2):61-98.

Stoorvogel JJ, Smaling EMA (1990). Assessment of Soil Nutrient Depletion in Sub-Saharan Africa: 1983-2000. Main Report, 2nd Edition. Winand Staring Centre, Wageningen. Netherlands 1:28.

Takeshima H, Liverpool-Tasie LSO (2013). Fertilizer subsidy, political influence and local food prices in sub-Saharan Africa: Evidence from Nigeria. Selected paper prepared for presentation at the Agricultural and Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013.

Toenniessenn G, Adesina A, DeVries J (2008). Building an Alliance for a Green Revolution in Africa. Annals of the New York. Acad. Sci. 1136:233-242.

World Bank (2014). Fertilizer Consumption (kilograms per hectare of arable land). Food and Agricultural Organization, electronic files and web site.

Journal of Development and Agricultural Economics

Related Journals Published by Academic Journals

- ***Journal of Plant Breeding and Crop Science***
- ***African Journal of Agricultural Research***
- ***Journal of Horticulture and Forestry***
- ***International Journal of Livestock Production***
- ***International Journal of Fisheries and Aquaculture***
- ***Journal of Cereals and Oilseeds***
- ***Journal of Soil Science and Environmental Management***
- ***Journal of Stored Products and Postharvest*** *Research*

academicJournals