Research Article

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Adoption of agricultural practices with climate smart agriculture potentials and food security among farm households in northern Nigeria

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Abstract: Despite the conceptual promise and attractiveness of Climate Smart Agriculture (CSA) in ensuring farmers’ resilience and food security, empirical evidence of its success is observed to be scanty and mixed in terms of results, thus prompting further research. In this article, we analyzed the effect of adopting six Agricultural Practices with CSA Potentials (AP-CSAPs) on food security status using recent cross-sectional data on 238 maize farmers from Northern Nigeria. Data were analyzed using descriptive statistics and Probit regression. The results showed that 92.4% of the maize farmers were male, with a mean age and household size of 44 years and nine persons, respectively. We find that 37.0% of the farm households were food insecure, and adoption of the AP-CSAPs was generally low. However, while refuse retention and agroforestry influenced food security, the remaining four practices considered did not. In addition, we find that land fragmentation, off-farm income and age influence the likelihood of being food secure. We recommend further research on the medium- to long-term effects of AP-CSAPs and suggest that policies aimed at consolidating landholdings to promote monocropping among rural farmers be discouraged.

Keywords: climate smart agriculture, food security, probit regression, adoption

1 Introduction

Food, along with oxygen and water, is a compulsory requirement for human sustenance. Food security exists when “all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life” (Perez-Escamilla and Segall-Correa 2008). While the achievement of food security for all has long been a global development target, as expressed in Sustainable Development Goal 2 “to end hunger, achieve food security and improved nutrition,” not much progress has been made in Africa compared to other regions (UNDP 2016). At least 25% of all the underfed people in the world live in Africa. Globally, only Africa has recorded a consistent decline in per capita agricultural production for the past three decades (Sasson 2012). Specifically, the percentage of food insecure people has been on the increase in Nigeria, increasing steadily from about 18% in 1986 to about 33.6% in 2004 and 41.0% in 2010 (NBS 2012).

Given that most of the poor and food insecure in SSA derive their livelihood from agriculture (Williams et al. 2015), climate change threatens to erode progress gained and undermine both present and future efforts to ensure food security. In Nigeria, about 69% of the poor engage in mostly rain-fed agriculture, thus exposing their livelihood to the vagaries of climatic fluctuations, with grave implications for food security (NBS 2012; Moyo 2016). For instance, it has been estimated that growing periods in West Africa may reduce by a quarter in the next 30 years as a result of climate change, leading to about one-third
reduction in cereal yields (Lobell et al. 2011). This makes climate change adaptation imperative for agricultural production systems in SSA, hence the promotion of “Climate Smart Agriculture” (CSA) as a sustainable alternative (FAO 2010).

CSA is an approach that is based on principles of sustainable development, which promotes the adoption of Agricultural Practices with Climate Smart Agriculture Potentials (AP-CSAPs) at the farm level (Williams et al. 2015). It aims to “sustainably increase agricultural productivity and incomes, build resilience and capacity of agricultural and food systems to adapt to climate change, and reduce or remove greenhouse gases while enhancing national food security” (Neufeldt et al. 2013). However, despite the conceptual promise and attractiveness of CSA, empirical evidence of its success under Africa’s diverse agroecologies and socioeconomic conditions are observed to still be scanty and mixed in terms of results (Neate 2013; Shittu et al. 2018). For instance, while Brüssow et al. (2015) report that implementing a climate-smart approach contributes to improved food security in Tanzania, Asfaw et al. (2016) reported no significant impact of these practices on crop outcomes in Niger. Thus, there is a need for continued empirical studies into the effects of these AP-CSAPs on crop yield, revenue and consequent livelihood outcomes.

This study contributes to filling this knowledge gap in the literature by assessing the effect of adoption of AP-CSAPs on food security using recent cross-sectional data from Northern Nigeria. Specifically, we assessed the extent of adoption of six AP-CSAPs by maize farmers across six states in the region and determined the effect of such adoption on their food security status among other covariates. Second, to better determine the effect of AP-CSAPs’ adoption on food security, we modeled the adoption of each practice as the actual proportion of farmland on which each farmer actually utilized it on his/her farm. Traditionally, a farmer is considered an adopter of a technology if he/she uses the technology on any of the plots or fraction of land in his/her farm (Nata et al. 2014; Coulibaly et al. 2017). However, farmers’ decision-making process about technology adoption is often influenced by plot-specific characteristics, and as such, a farmer may adopt a practice on some plot(s) and not on the others in his farm. Thus, in measuring the effect of the adoption of the technology, we argue that it is more beneficial to utilize the actual proportion of the farmer’s farmland on which the technology was used. Section 2 discusses our data (study area, data and sampling procedure) and the method of data analysis. Section 3 discusses the descriptive and empirical results, respectively, and the last section concludes this article.

2 Materials and methods

2.1 Study area

The study was conducted in northern Nigeria. Northern Nigeria consists of three geopolitical zones: the northwest (which consists of seven states), north-central (which consists of six states and the Federal Capital Territory) and Northeast (which consists of six states) geopolitical zones. Northern Nigeria lies between latitude 9°–14°N and longitude 3°–15°E and is bounded in the North by Niger republic, Chad and Cameroon in the East and in the West by Republic of Benin (AbdulKadir et al. 2013). It is a semi-arid region neighboring the Sahara Desert, with an annual mean precipitation of less than 600 mm. The region’s rainy season lasts for about 3–4 months, while temperature can vary between 13°C and 38°C, with an average of 29°C (Usman et al. 2013). Northern Nigeria is dominated by the Guinea, Sudan and Sahel savannahs, and the vegetation density decreases northward in response to climatic conditions. Although the region is geographically prone to drought, desertification, wind and water erosion, agriculture remains the most dominant economic activity in the region (AbdulKadir et al. 2013). Cereals (maize, rice, sorghum and millet) and cash crops (cotton and groundnut) are commonly grown in this region (Ugwu and Kanu 2012) (Figure 1).

2.2 Data and sampling procedure

This study utilized the data collected by FUNAAB-RAAF-PASANAO project, titled “Incentivizing Adoption of Climate Smart Practices in Cereals Production in Nigeria: Sociocultural and Economic Diagnosis,” which was funded by ECOWAS—Regional Agency for Agriculture and Food (RAAF). The sampling process was based on the nationwide Agricultural Development Program (ADP) structure that split each state into zones, blocks and cells for easy administration and extension outreach. As outlined by Shittu et al. (2018), cells are groups of close farming communities assigned to an Agricultural Extension Officer, while blocks are groups of five to eight cells under the supervision of a block extension supervisor. A number of blocks form a zone and each state in Nigeria has about three or four agricultural zones. A multistage sampling process was implemented in drawing respondents for this study. In stage 1, two states reputed for maize production were purposively selected from
each of the three geopolitical zones of northern Nigeria (Knoema 2019). Kaduna and Kebbi were selected from the Northwest, while Niger and Nasarawa were selected from the North-central. However, only Taraba was selected from the Northeast because of the religious unrest in the zone. In stage 2, three blocks reputed for maize production were purposively chosen from each of the five states that had been selected. (This was done in consultation with the states’ ADPs given the lack of production data per block within the states.) In stage 3, two cells were randomly selected from each block, while in the last stage, 10 maize farmers were randomly selected from each of the selected cells. After dropping households with incomplete information, this process yielded a total of 238 maize farming households that were used for the study. Data collected include farmers’ social, economic and institutional variables, adoption of AP-CSAPs as well as their livelihood characteristics.

3 Analytical framework

3.1 Descriptive statistics

Data from the household survey on key socioeconomic characteristics (sex, farm size, education, extension contact among others), adoption of AP-CSAPs and food security status were analyzed using descriptive statistics—frequencies, means and percentages.

3.2 United states department of agriculture’s food security survey module

Food security was measured using the United States Department of Agriculture’s Food Security Survey Module. It is a tool that is used to generate a score that depicts the

Figure 1: Map of Nigeria showing the study locations.
level of household food insecurity and can be classified into four categories (Obayelu 2012). Data were collected using the “18-item household food security questionnaire.” The food security status was determined from respondents’ answers to a set of questions about their typical behavior when satisfying household food needs becomes difficult (Bickel et al. 2000). Each question asks whether the behavior occurred at any time during the last 30 days (Maitra and Rao 2015) and is as a result of funds or food insufficiency and not dieting or voluntary fasting. For each household, a score is generated using the total number of questions positively responded to, ranging from 0 to 18 in households with children and 0 to 10 in households without children. Based on this score, households are then classified into four categories, namely, “high food security,” “marginal food security,” “low food security” and “very low food security” (Table 1).

### 3.3 Land fragmentation: Simpson index

Land fragmentation occurs when an individual or farming household possesses several spatially separated plots of land that are usually scattered over a wide area (Demetriou 2014). However, whether land fragmentation is a problem is still a subject of multidisciplinary debate in the literature due to the contrasting reports of various studies (Shittu 2014). Following Shittu (2014) and Sundqvist and Andersson (2006), land fragmentation was measured using the Simpson index in this study. This index is the sum of the squares of the separate plot sizes divided by the square of the total farm size. It is calculated as follows:

\[
SI = \frac{1 - \sum_{i=1}^{n} a_i^2}{A^2}
\]

where \(n\) is the number of plots an individual or household operates, \(a\) is the area of the \(i\)th plot or farm parcel (ha), \(A\) is the total area of all the plots (ha) and SI is the Simpson index, which is a value between 0 and 1.

A value of zero implies that the household farms a single, contiguous land fragment, i.e., the farm consists of only one parcel. However, a value of one means that the farm is very fragmented and operates multiple plots. This implies that the more the SI moves toward 1, the more fragmented the land holding of the household is.

### 3.4 Probit regression model: determinants of food security

The Probit regression model was used to determine the factors influencing food security among farming households in the study area. Although the USDA food security module has four classifications, the first two categories (“high food security” and “marginal food security”) were classified as food secure, while the last two (“low food security” and “very low food security”) were classified as food insecure following Maitra and Rao (2015) and Chinnakali et al. (2014).

The model is explicitly stated; thus,

\[ Y^* = X\beta + aA + \varepsilon \]  

\[ Y_i = \begin{cases} 1 \text{ if } Y_i^* > 0 \\ 0 \text{ if } Y_i^* \leq 0 \end{cases} \]

where \(Y^*\) is the underlying response variable; \(Y_i\) is 1 if household is food insecure and 0 if otherwise; \(X\) is a vector of socioeconomic and farm characteristics; and \(A\) is a vector of AP-CSAPs’ adoption, which is measured as follows: \(A_1\) represents use of green manure (proportion of farmland on which practice has been adopted), \(A_2\) represents agroforestry (proportion of farmland on which practice has been adopted), \(A_3\) represents the use of organic manure (proportion of farmland on which practice has been adopted), \(A_4\) represents crop rotation (proportion of farmland on which practice has been adopted), \(A_5\) represents refuse retention (proportion of farmland on which practice has been adopted) and \(A_6\) represents zero or minimum tillage (proportion of farmland on...
which practice has been adopted); $\beta$ and $\alpha$ are parameter estimates; and $\varepsilon$ is the error term.

### 4 Results and discussion

#### 4.1 Socioeconomic characteristics of the maize farmers

Table 2 presents the results of the socioeconomic characteristics of the respondent households. Most (92.4%) of respondents were male, and 94.1% of them were married. The average age of a maize farmer was 44 years, having a mean household size of nine persons. This suggests that the typical maize farmer was still in his economically active age and has access to family labor, which forms a significant part of farm labor (Idrisa et al. 2012; Adegboye 2016). Over half (56.3%) of the respondents had at least primary education although the average years of formal education obtained was about seven years. Most (74.0%) of them had access to extension services in the previous season, indicating a robust presence of agricultural extension services in the study area. Most (66.4%) of the respondents claimed that they had access to credit in the last cropping season, while 45.8% of them were involved in at least one off-farm activity. Furthermore, Table 2 presents that 48.7% of the respondents cultivated two or more spatially separated plots of maize. This gives credence to the fact that farmers often cultivate more than one plot of land that have inherently different characteristics (e.g., trekking distance, land type, ownership status, and size), which may influence their decision on which technology to adopt on such plots.

#### 4.2 Description of adoption of AP-CSAPs by the maize farmers

The results presented in Table 3 reveal that the adoption of the AP-CSAPs was generally low. This corresponds to the findings of McCarthy and Brubaker (2014) and Teklewold et al. (2013), who reported that CSA practices’ adoption remains generally low in sub-Saharan Africa. Green manure (17.0%) and crop rotation (29.0%) were the least adopted practices, while zero/minimum tillage was adopted on about a third (37.0%) of the respondents’ maize farms on the average. Furthermore, refuse retention was adopted on 45.0% of the maize farms on the average, while organic manure use and agroforestry were adopted on 43.0% and 42.0% of the maize farms, respectively.

| Table 2: Distribution of respondents by their socioeconomic characteristics |
|-----------------------------|----------------|----------------|
| **Variable**                | **Frequency** | **Percentage** |
| **Sex**                     |               |                |
| Male                        | 220           | 92.4           |
| Female                      | 18            | 7.6            |
| Total                       | 238           | 100            |
| **Age**                     |               |                |
| ≤20                         | 7             | 2.9            |
| 21–30                       | 35            | 14.7           |
| 31–40                       | 50            | 21.0           |
| 41–50                       | 82            | 34.5           |
| 51–60                       | 45            | 18.9           |
| >60                         | 19            | 8.0            |
| Total                       | 238           | 100            |
| **Marital status**          |               |                |
| Married                     | 224           | 94.1           |
| Single                      | 9             | 3.8            |
| Divorced                    | 5             | 2.1            |
| Total                       | 238           | 100            |
| **Educational status**      |               |                |
| None                        | 88            | 37.0           |
| Arabic                      | 16            | 6.7            |
| Primary                     | 31            | 13.0           |
| Secondary                   | 44            | 18.5           |
| Tertiary                    | 59            | 24.8           |
| Total                       | 238           | 100            |
| **Household size range**    |               |                |
| ≤4                          | 46            | 19.3           |
| 5–8                         | 95            | 39.9           |
| 9–12                        | 48            | 20.2           |
| 13–16                       | 26            | 10.9           |
| >16                         | 23            | 9.7            |
| Total                       | 238           | 100            |
| **Access to credit**        |               |                |
| No                          | 141           | 59.2           |
| Yes                         | 97            | 40.8           |
| Total                       | 238           | 100            |
| **Extension contact**       |               |                |
| No                          | 62            | 26.0           |
| Yes                         | 176           | 74.0           |
| Total                       | 238           | 100            |
| **Off-farm activities**     |               |                |
| No                          | 129           | 54.2           |
| Yes                         | 109           | 45.8           |
| Total                       | 238           | 100            |
| **Number of farm plots**    |               |                |
| 1                           | 122           | 51.3           |
| 2                           | 71            | 29.8           |
| >2                          | 45            | 18.9           |

Source: authors’ computation.
Table 4: Adoption of AP-CSAPs on the farmers’ plots

| Variable                | Mean  | Standard deviation |
|-------------------------|-------|--------------------|
| Green manure            | 0.17  | 0.34               |
| Agroforestry            | 0.42  | 0.44               |
| Organic manure          | 0.43  | 0.42               |
| Refuse retention        | 0.45  | 0.43               |
| Crop rotation           | 0.29  | 0.41               |
| Zero/minimum tillage    | 0.37  | 0.41               |

4.3 Analysis of farm households’ food security status

Table 4 presents the result of the analysis of households’ food security using the USDA food security assessment. Households were classified into four food security classes (“high food security, marginal food security, low food security and very low food security”) based on 18 food security items for households with children and 10 adult referenced items for households without children. As presented in Table 4, 50% of the households without children were highly food secure, with another 18.8% classified as marginally food secure. In comparison, 34.7% of households with children were highly food secure, while 27.9% of them were marginally food secure. This gives credence to the findings of Obayelu (2010) who reported that households with fewer members are more food secure, perhaps as a result of having less people to feed.

Pooling the households, 35.7% of the households were highly food secure, while 27.9% of them were marginally food secure. In addition, 21.0% of the households had “low food security” and “very low food security,” respectively. Combining the four USDA food security classes into two broad classes of food security (“high food security and marginal food security”) and food insecurity (“low food security and very low food security”), 63.0% of the sampled households were food secure, while 37.0% of them were food insecure.

This represents an improvement on the food security status (35.0%) reported by Davies (2009) but is less than the 70% food security situation reported by FAO (2016) in northern Nigeria using the food consumption score.

4.4 Determinants of food security among the farming households

Table 5 presents the results of the Probit regression, which was used to analyze the factors influencing the food security status of the farming households. The Wald chi-square test statistics shows that the hypothesis that all regression coefficients in the model are jointly equal to zero is rejected at 1%, indicating the fitness of the model and the relevance of the chosen independent variables. The results reveal that only two of the six AP-CSAPs evaluated significantly influenced food insecurity as presented in Table 5.

Specifically, retention of refuse negatively influenced food insecurity, suggesting that households that practice bush burning on their farms have a greater likelihood of being food insecure. This may be due to the net negative impact of bush burning on soil properties, which leads to the loss of productivity. As reported by Nigussie and Kissi (2011) and Pantami et al. (2010), although bush burning saves time and adds ash, which reduces soil acidity to the soil, its positive effect is short lived. This is because it simultaneously causes the loss of 80% nitrogen, 25% phosphorus and 21% potassium, and thus results in low yield, own food production and farm income. However, agroforestry positively influenced food insecurity at 5%, implying that households that adopted agroforestry are more likely to be food insecure. While this is against *a priori* expectation, it is likely due to the reduction in effective crop area available for cultivation necessitated by adopting agroforestry, which may lead to a decrease in the crop output and productivity initially before the tree species begin to yield benefits to the farmers (Peralta and Swindon 2016).

However, other household and farm characteristics significantly influenced food security in the study area.

Table 4: Classification of respondents’ household according to food security status

| Food security categories | Households without children | Percent | Households with children | Percent | Pooled households | Percent |
|--------------------------|----------------------------|---------|--------------------------|---------|------------------|---------|
| High food security       | 8                          | 50.0    | 77                       | 34.7    | 85               | 35.7    |
| Marginal food security   | 3                          | 18.8    | 62                       | 27.9    | 65               | 27.3    |
| Low food security        | 3                          | 18.8    | 35                       | 15.8    | 38               | 16.0    |
| Very low food security   | 2                          | 12.4    | 48                       | 21.6    | 50               | 21.0    |
| Total                    | 16                         | 100     | 222                      | 100     | 238              | 100     |
First, while the literature is replete with polarized reports on the relationship between land fragmentation and food security, the results show that land fragmentation negatively influences food insecurity and a marginal increase in the Simpson index reduces the likelihood of being food insecure by 8.7%. This could be because the cultivation of multiple plots allows farmers to exploit the variation in soil and environmental quality, cultivate diverse crops across seasons and thus minimize their production risk (Ali et al. 2015; Kadigi et al. 2017). This is consistent with the recent findings across SSA (Di Falco 2014; Knippenberg et al. 2018; Cholo et al. 2019). For instance, Cholo et al. (2019) report that farmers who produced crops on distinct plots of land have a higher likelihood of being food secure relative to farmers who produced crops in a single plot. They argue that while land fragmentation could be a form of insurance against total crop loss in the event of any shock or stress, growing different crops (which is engendered by fragmentation) that mature at different periods within a year enhances the food availability and access for farmers’ households all year round.

Consistent with other works (Reardon et al. 2007; Babatunde and Qaim 2010; Sani et al. 2014; Rahman and Mishra 2019), the result shows that off-farm income reduces the likelihood of being food insecure. Off-farm income generation is important for easing capital constraints and smoothening consumption, especially as household income is typically tied down in farm investment.

Given the seasonality of agricultural production due to rainfall (particularly in SSA where 96% of agricultural production is rain fed) and the increasing production risk due to possible climatic shocks, off-farm income is becoming increasingly important to farming households’ wellbeing (Eshetu and Mekonnen 2016; Ibrahim et al. 2019).

In addition, the results of the age of the household head negatively influences food insecurity, implying that as the farmer gets older, the less likely he is to be food

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**Table 5: Probit regression estimates of factors influencing food insecurity**

| Variables                              | Coefficient | Std error | Z-Value  | Marginal effect |
|----------------------------------------|-------------|-----------|----------|-----------------|
| Age of household head                  | -0.073**    | 0.042     | -1.73    | -0.007          |
| Age squared of household head          | 0.001       | 4.74 × 10⁻⁴ | 1.33    | 6.35 × 10⁻⁵     |
| Sex                                    | -0.458      | 0.405     | -1.13    | -0.034          |
| Years of education of household head   | 0.021       | 0.016     | 1.30     | 0.002           |
| Household size                         | 0.019       | 0.016     | 1.19     | 0.002           |
| Monthly expenditure                    | 9.73 × 10⁻⁷ | 1.03 × 10⁻⁶ | 0.95    | 9.82 × 10⁻⁸     |
| Land ownership                         | -0.171      | 0.240     | -0.71    | -0.007          |
| Access to extension contact            | 0.061       | 0.221     | 0.28     | 0.006           |
| Land dispute                           | 0.563       | 0.415     | 1.36     | 0.057           |
| Off-farm income                        | -3.56 × 10⁻⁷ | 2.03 × 10⁻⁷ | -1.75    | -3.59 × 10⁻⁸    |
| Farm size (Ha)                         | 0.006       | 0.007     | 0.88     | 0.001           |
| Farmers’ association membership        | 0.036       | 0.062     | 0.58     | 0.004           |
| Cooperative society’s membership      | -0.072      | 0.053     | -1.36    | -0.007          |
| Land fragmentation (Simpson index)     | -0.864**    | 0.391     | -2.21    | -0.087          |
| Tropical livestock unit                | -0.091      | 0.348     | -0.26    | -0.009          |
| Green manure                           | -0.172      | 0.316     | -0.55    | -0.017          |
| Agroforestry                           | 0.519**     | 0.232     | 2.23     | 0.052           |
| Organic fertilizer/compost             | 0.062       | 0.234     | 0.27     | 0.006           |
| Retain refuse                          | -0.546**    | 0.248     | -2.20    | -0.055          |
| Crop rotation                          | -0.128      | 0.226     | -0.57    | -0.013          |
| Zero/minimum tillage                   | -0.155      | 0.232     | -0.67    | -0.016          |
| Northern Guinea                        | 0.434       | 0.329     | 1.32     | 0.055           |
| Derived Savannah                       | 0.796**     | 0.320     | 2.49     | 0.123           |
| Southern Guinea                        | 1.066***    | 0.292     | 3.65     | 0.133           |
| Constant                               | 0.947       | 1.001     | 0.95     |                 |

Pseudo \(R^2 = 0.182\)

Wald \(\chi^2 (25) = 56.09\)

Prob \(> \chi^2 = 0.000\)

Log pseudolikelihood = -128.279

*, **, *** represent 10%, 5% and 1% level of significance respectively.
insecure. This could be as a result of the fact that, as a farmer gets older, his/her work experience, social network and asset base often increases, thus giving him/her leverage to produce more and thus become more food secure (Mango et al. 2014). This is especially important in a rural farm environment, where allocation of land and other productive resources are still influenced by traditional culture of respect for older people. This finding is supported in the literature by Bogale and Shimelis (2009), Arene and Anyaeji (2010) and Zhou et al. (2019) who reported similar findings in Ethiopia, Nigeria and Pakistan, respectively.

5 Conclusion

This study was carried out to determine the effect of adoption of AP-CSAPs on food security among maize farmers in northern Nigeria. We found that the proportion of farmland on which AP-CSAPs were adopted was generally low, while 37.0% of the farm households were food insecure. However, four of the six AP-CSAPs considered did not have any significant influence on food security. We attribute this to three possible reasons; first, the benefits of CSA practices may not be immediately obvious compared to the use of modern inputs (such as inorganic fertilizers), which tend to have short-term returns. However, due to the unavailability of panel data on this practices and farmers’ livelihood, we could not model the effect of AP-CSAPs’ adoption over time. Second, these practices may not always lead to increased production, but rather help farmers adapt to climate change by maintaining their production level while conserving the environment. Finally, since there is no evidence of coordinated training of farmers on these practices by extension agencies, farmers may not be applying these practices correctly to get optimum results. However, land fragmentation, off-farm income and age negatively influenced the likelihood of food insecurity. First, we recommend that further research be carried out to probe the possible effect of AP-CSAPs in the medium to long term, when the benefits it confers on farmers are expected to be evident. In addition, we recommend that off-farm activities should be encouraged among farmers to improve their likelihood of being food secure. Second, we recommend that government policies to consolidate farmland holdings to promote monocropping should be carefully considered before being introduced to rural farmers (and perhaps limited to corporate farm entities), as land fragmentation has been shown to positively influence food security and limit the possibility of total crop loss.

Conflict of interest: The authors declare no conflict of interest.

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