# Determinants of soybean adoption and performance in Northern Ghana

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**Abstract**

*Soybean has been the world's fastest growing crop over the last 15 years. Yet, as an untraditional and unfamiliar crop, soybean requires small farmers to move beyond their traditional production practices and marketing arrangements in order to produce a successful crop. We employ complexity theory to frame soybean's production and market differences as significant and non-incremental for smallholder farmers, thus making soybean a 'long-jump' agricultural technology problem. We consider three estimation strategies using a primary dataset of smallholder women soybean producers in the Upper West region of Ghana. We first employ probit and ordinary least squares (OLS) regression models to understand adoption and performance. We then employ a combined spatial-autoregressive with spatial-autoregressive disturbances (SARAR) model using generalised spatial two-stage least squares to understand cross-unit interactions in a spatial dimension. We find positive, large and significant spatial autoregressive dependence and knowledge spillover to affect the soybean yields of smallholder female farmers within spatial networks. This finding provides guidance for agricultural development practitioners regarding the importance of social interaction and information provision when promoting long-jump technologies like soybean.*

**Key words**: soybean; gender; smallholders; Ghana; technology adoption

## 1. Introduction

For most of the developing world, agriculture represents the largest employment sector and is a leading contributor to national income. Yet in many parts of Sub-Saharan Africa, agricultural productivity is extremely low, with stagnant or even declining yields (Doss 2006; Damania *et al*. 2017). As a result, there is interest in and a focus on increasing agricultural productivity through the introduction of improved agricultural technologies and management systems that have the potential to sustainably improve labour productivity, incomes, food security and general economic growth (Feder *et al*. 1985; Doss 2006; Maertens & Barrett 2013).

Agricultural technologies have predominantly taken the form of improvements to: traditional and staple crop varieties; land, soil and water management practices; and input and fertiliser utilisation through subsidy packages (Muzari *et al*. 2012 Ainembabazi & Mugisha 2014). These types of agricultural technologies, especially when introduced incrementally, can be considered as 'short-jump' technologies that do not require significant changes in the crop production portfolios and management systems of smallholder farmers.

'Long-jump' agricultural technologies, however, require greater adaptive processes by farmers. These technologies not only may involve a new crop, system of production and marketing practices, but also may even cause producers to reassess the strategies and goals of their entire farm portfolio of activities. Unlike in short jumps, long jumping involves organisational adaption without a lot of tacit knowledge relevant to the new agricultural technology (see Spulber 2012; Chun 2013).

The question of the introduction of soybean technology arises as policymakers, development agencies and donors see the potential for soybean to generate new sources of income for smallholder farmers from a new crop with growing global demand as an animal feed and resource for edible oil (Sanginga *et al*. 1999; Dogbe *et al*. 2013). Policymakers look to the transformation of rural economies in South America as a result of soybean, and thus seek to harness the technology for Africa (see Goldsmith & Montesdeoca 2018). We have yet to find any research on the soybean adoption process among smallholders. This research therefore not only fills an important empirical void, but helps policymakers differentiate between short- and long-jump technologies in general, but also soybean as a development crop compared with an improved native staple.

The specific context of this research involves women smallholder farmers newly engaged in soybean production as a result of a new development project in the Upper West region. We empirically analyse: 1) how different adoption drivers affect sustained soybean adoption versus intermittent soybean adoption; 2) how different adoption drivers affect the level of performance in soybean production as measured by yield; and 3) how the spatial interactions and spatial dependence drivers affect soybean performance in soybean production.

## 2. Literature review

Complexity theory involves the study of change within dynamic systems (Ruhl 1996). The tension between stasis and incremental or radical adaption has some appeal in the context of technological adaptation by smallholders, who face poverty in stasis, but bear acute risks that limit their ability to make radical changes. Fitness landscapes (Kauffman & Levin 1987; Levinthal 1997; Fontanari 2015) are an important concept of complexity theory, as the environment presents many ways to adapt – some incremental, thus short jumps, while others are more radical and are denoted as long jumps. The Darwinian theory of evolution depicts organisms adapting over time as environments change, thus stasis is equated with death. Complexity theory builds from Darwinian theory, with application to social groups, and in which choice, strategy, recognition of risk, consciousness of the past and the future are present. In a complex world, one may opt to adapt incrementally and minimise risk, but err due to a lack of understanding of the seriousness of the changing environment, for instance economic reality. Alternatively, change can be too dramatic and disruptive, thrusting the social organism in chaos. The search process across the fitness landscape involves appropriate levels of change, along with active learning so as to not go too slowly or too quickly, but it also requires finding balance within the changing environment.

When we apply complexity theory to agricultural technology adoption, short-jump or incremental agricultural technologies leverage the tacit knowledge, experience and core competencies of farmers to improve their agricultural productivity, instead of encouraging farmers to engage in riskier, but potentially higher pay-off, endeavours that are often associated with long-jump agricultural technologies (Goldsmith & Gow 2005). As such, short-jump agricultural technologies have a high probability of adoption by smallholder farmers, as they allow farmers to continue their traditional practices and norms and typically require fewer new assets, have a lower risk premium, and are less expensive than long-jump agricultural technologies (Muzari *et al*. 2012).

Previous literature (Adesina & Zinnah 1993; Chirwa 2005; Ainembabazi & Mugisha 2014) draws an important distinction between resource endowments and learning (information access or knowledge acquisition) as two classes of fixed costs that effect technology adoption in general. Significant ex ante knowledge investments often characterise long-jump agricultural technologies, which results in an economy to scale. For parsimony, we present a comprehensive summary of the technology adoption literature in Table 1.

To our knowledge, relatively little work has been done on the adoption process for long-jump agricultural technologies that, as discussed earlier in this paper, represent significant changes to farmer production portfolios, practices, norms and standards. In this manuscript, we build the empirical evidence for the forces that drive successful long-jump technology adoption. While we include farmer demographics, as in previous studies, we additionally analyse education level, land scale, seasonality and spatial characteristics as repressors not only of performance (yield), but also of sustained adoption.

### 2.1 Soybean as a long-jump technology

Soybean is a new agricultural technology for much of the developing world, as less than .5 of 1% of world soybean production originates from Sub-Saharan Africa excluding South Africa (Goldsmith 2014). In Africa, it is not a traditional crop, hence farmer utilisation of soybean is limited in many settings (Dogbe *et al*. 2013).

Soybean is principally a commercial crop used by processors, not households or local small retailers. Goldsmith (2017) describes the commercial nature and high management demands of soybean, which may challenge smallholders to 'jump' from traditional native staples to a new, commercial cash crop. Women farmers may be unfairly disadvantaged, as they are less able to access markets and may find male-dominated commercial markets and extension systems difficult to access or inaccessible altogether (Wendland & Sills 2008; Ragsdale *et al*. 2018). We therefore hypothesise that, as a new, non-staple commercial crop, soybean may exhibit the characteristics of a long-jump agricultural technology. To our knowledge, no research to date analyses the adoption process of commercial soybean by smallholders in a developing country setting.

### 2.2 Research setting

Soybean is a relatively new crop in Ghana. Average Ghanaian soybean yields remain well below global averages. Mbanya (2011) and Dogbe *et al*. (2013) observe very few smallholder farmers using rhizobia inoculants to promote nitrogen fixation, and other improved agricultural technologies like fertilisers, pesticides and good management practices (row planting, appropriate seed and row spacing and plant population, etc.). Awuni and Reynolds (2018) show that yields in northern Ghana using commercial soybean varieties double when using improved agricultural management strategies and inputs (i.e. a high-input/high-output production scenario).

### 2.3 Hypothesised drivers of soybean adoption

To better understand the soybean adoption process, we tested adoption by relating farmer performance in soybean production, as measured through yield, and farmer sustained, or persistent, adoption of soybean, as measured through the number of consecutive years producing soybean, to various hypothesised drivers. The specific long-jump drivers of particular interest that we studied include: farmer characteristics (education, household head and experience/extension access); economies of scale (total farm size, land allocated to soybean cultivation); market access (intention to sell grain, engagement in dry-season activities); land rights (land tenure, duration of land control); and spatial interactions among farmers (Table 2).

**Table 1: Characterisation of long-jump vs. short-jump agricultural technology adoption literature**

| Technology | Familiar, staple or traditional crop | New market exposure required | Farmer experience in the technology | New agronomic practices required | Increased scale required | New inputs required |
|---|---|---|---|---|---|---|
| Improved mangrove swamp rice adoption (Adesina & Zinnah 1993) | Yes | No | Yes | No | No | No |
| Commercial crop production by smallholders (Immink & Alarcon 1993) | No | Yes | No | Yes | Yes | Yes |
| Adoption of soybean in sub-Saharan Africa: A comparative analysis of production and utilization in Zaire and Nigeria (Shannon & Kalala 1994) | No | No | No | No | No | No |
| Dairy technology adoption (Staal *et al*. 2002) | No | Yes | No | Yes | Yes | Yes |
| Intercropping in rubber production (Herath & Takeya 2003) | Yes | No | Yes | No | No | No |
| Improved cowpea variety adoption (Alene & Manyong 2006) | Yes | No | Yes | No | No | No |
| Social learning in pineapple production (Conley & Udry 2010) | No | Yes | No | Yes | Yes | Yes |
| Bt cotton adoption (Maertens & Barrett 2013) | Yes | No | Yes | No | No | No |
| Economics of soybean production (Dogbe *et al*. 2013) | No | Yes | No | Yes | Yes | Yes |
| Technical efficiency in soybean production (Etwire *et al*. 2013) | No | Yes | No | Yes | Yes | Yes |
| Crossbred cow adoption (Edirisinghe & Holloway 2015) | Yes | Yes | No | Yes | Yes | Yes |
| Social network effects in hybrid rice adoption (Ward & Pede 2014) | Yes | No | Yes | No | No | No |
| Demand for drought-tolerant rice (Ward *et al*. 2014) | Yes | No | Yes | No | No | No |
| Transportation costs in yam, rice, cassava and maize production (Damania *et al*. 2017) | Yes | No | Yes | No | No | No |
| Oil palm adoption (Euler *et al*. 2017) | Yes | No | Yes | No | No | No |

**Table 2: Description of independent variables included in technology adoption and performance models, expected sign and rationale**

| Variables | $H_0$ sign | Rationale |
|---|---|---|
| Education | + | Farmers with more education are likely to have an increased ability to manage new agricultural technologies like soybean, and may be more capable of applying information provided through extension services and through farmer networks. I expect that farmers with more years of formal education will be more likely to be sustained adopters and experience higher performance in soybean production. |
| Household head | - | Female-headed households tend to be smaller, have lower incomes and, as a result, may be less productive than male-headed households. I therefore expect that the female farmers who are heads of household will experience lower performance in their soybean yields and will not be associated with sustained adoption of soybean. |
| Sustained adoption | + | Sustained adopters, by definition, have produced soybean for three consecutive years. Experience with new agricultural technologies changes over time. Farmers may become more proficient with the technology as they accumulate more information by using it. I expect that farmers who are sustained adopters will experience higher performance in soybean production. |
| Lead farmer | + | Lead farmers are likely to have more access to extension information and engage in more interactions and learning via extension officers and through extension information channels. I expect that lead farmers will be more likely to be sustained adopters and will experience higher performance in soybean production. |
| Farm size | + | Producers with larger farm sizes may experience economies of scale related to the production of a long-jump agricultural technology like soybean. They may be able to handle the up-front fixed and variable costs associated with soybean production more effectively. I expect that producers with larger farm sizes will be more likely to be sustained adopters and will experience higher performance in soybean production. |
| Land allocation | + | Similar to farm size, producers who allocate more hectares to soybean production may experience economies of scale that affect their adoption of, and performance in, soybean production. I expect that producers who allocate more land to soy production will be more likely to be sustained adopters and will experience higher performance in soybean production. |
| Land tenure | +/- | Farmers who borrow, lease or rent their land may not value the long-term benefits of soil correction needed for successful soybean production. Farmers who own their land, either individually or through their family, have a longer planning horizon, allowing them to see the benefits of soil correction for improved soybean cultivation. On the other hand, farmers who rent or borrow land may experience the economic benefits of soybean even in the short run. As such, the expected sign of the variable for land ownership is undetermined. |
| Duration of land control (can farm land 3+ years) | +/- | Farmers with certain, and relatively long, land tenures are likely to have longer planning horizons and shortened rates of time preference for adoption than farmers with uncertain and relatively short land tenures. On the other hand, farmers with uncertain or relatively short land tenures may experience the economic benefits of soybean even in the short run. As such, the expected sign of the variable for land ownership is undetermined. |
| Hired labour | +/- | Hired labourers may not have an attachment to the land they are servicing, and may be less likely to provide adequate services as compared to family labour. Further, hired labourers change jobs based on the service required and the time of service delivery, leading to different levels of service provided. Farmers may abandon the adoption of an agricultural technology if the technology is labour-demanding. Conversely, when a female producer decides to engage hired labour in her soybean production practice, her labour burden is reduced and, simultaneously, her independence and control may be increased. As such, the expected sign of the variable for hired labour is undetermined. |

| Variables | $H_0$ sign | Rationale |
|---|---|---|
| Intention to sell grain | + | Farmers who intend to sell their grain after harvest may be better positioned to access input and service markets, as well as buyers, aggregators and processors. I expect that farmers who intend to sell their grain will be more likely to be sustained adopters and will experience higher performance in soybean production. |
| Dry-season activities | +/- | Farmers who engage in dry-season activities have been observed to be less risk-averse than farmers without sources of dry-season income. However, these same farmers may be more diversified and thus less focused on soybean production. As such, the expected sign of the variable for engagement in dry-season activities is undetermined. |

## 2.4 Spatial interaction and technology adoption

Including measures of spatial interaction among farmers in the analysis of technology adoption provides insight into the potential roles that social networks and social learning may play in farmer decision-making and performance (Maertens & Barrett 2013; Wollni & Andersson 2014). Spatial networks are particularly important in the context of long-jump agricultural technologies like soybean because of the technical learning curve associated with a new commercial crop. In this context, neighbouring farmers help reduce the uncertainty of a new agricultural technology, thereby lowering the fixed costs of learning about the technology (Villano *et al*. 2016). We hypothesise that spatial interaction among farmers will have a positive effect on farmer performance and sustained production.

## 3. Data and descriptive statistics

The Greater Rural Opportunities for Women (GROW) project is an agricultural development initiative focused on soybean production among female smallholder farmers in the Upper West region of Ghana (Muhammed & Baker 2015). The GROW project is a six-year initiative begun in 2012 and funded by the Mennonite Economic Development Associates (MEDA), an organisation of the Canadian Department of Foreign Affairs, Trade and Development (DFATD). The GROW project strategically targets its efforts geographically within the Upper West region of northern Ghana. The GROW project began enrolling farmers in the programme in 2013. The data we use contain observations for project clients who enrolled in 2013, 2014 and 2015. Between 2013 and 2015, 59% of registered GROW project clients provided enrolment data, but did not provide post-harvest data. As this is a large share of the total sample, there is potential for attrition bias. As such, the generalisability of the results need to be taken with caution.

We use data from the 2015 growing season that provide historical information on 496 project clients going back to 2013. Of these 496 total observations, 453 had complete values across the variables used in the analysis. All farmers produced soybean in 2015.

We draw a distinction between three types of dynamic adoption: farmers who adopted and continued using a technology (sustained adopters), farmers who adopted a technology, discarded it, then returned to the technology (intermittent adopters[1]), and farmers with one year of adoption (late adopters). By evaluating these different adoption scenarios, our research addresses the inherent dynamic nature of the adoption process, and particularly the drivers behind sustained versus intermittent adoption of a long-jump agricultural technology like commercial soybean. Further, the GROW project has struggled with intermittent adoption among project participants, thus this research informs agricultural development practitioners such as GROW on factors that promote sustained adoption of new agricultural technologies.

Farmers who reported that they grew soybean consecutively in 2013, 2014 and 2015 were coded as sustained soybean adopters. Of the 453 total observations, 227 observations were sustained adopters (Table 3). Intermittent adopters reported that they grew soy in 2013, did not in 2014, and then resumed soybean cultivation in 2015. Of the 453 total observations, 38 observations were coded as intermittent adopters. A third classification designates late adopters. These farmers reported that 2015 was their first year of soybean cultivation and that they had not grown soy in 2013 or 2014. Of the 453 total observations, 188 observations were coded as late adopters. Figure 1 shows the geographic distribution of the 453 farmer sample based in the Upper West region of Ghana, classified by adopter type.

[1] We do not report on the results from the intermittent model in order to reduce the length of the manuscript.

**Table 3: Summary statistics**

| **Summary statistics** | **Full sample** | **Sustained adopter** | **Intermittent adopter** | **Late adopter** | **Statistical difference** |
|---|---|---|---|---|---|
| | **Mean** | | | | |
| Variables | (N = 453) | (N = 227) | (N = 38) | (N = 188) | |
| Education | 0.137 | 0.106 | 0.053 | 0.193 | Yes |
| Household head (= 1) | 0.084 | 0.088 | 0.105 | 0.074 | Yes |
| Lead farmer (= 1) | 0.079 | 0.062 | 0 | 0.117 | Yes |
| Farm size | 1.335 | 1.761 | 0.857 | 0.917 | No |
| Soy hectares planted (2015) | 0.545 | 0.704 | 0.426 | 0.376 | No |
| Hired labour (= 1) | 0.804 | 0.912 | 0.763 | 0.681 | No |
| Family or owned land (= 1) | 0.967 | 0.991 | 0.895 | 0.952 | No |
| Can farm land 3+ years (= 1) | 0.364 | 0.185 | 0.395 | 0.574 | Yes |
| Intent to sell grain (= 1) | 0.74 | 0.934 | 0.605 | 0.532 | No |
| Dry-season activities (= 1) | 0.565 | 0.493 | 0.632 | 0.638 | Yes |
| Yield (2015) | 748.631 | 950.034 | 486.082 | 558.517 | No |

## 4. Models

The probability of a farmer adopting an agricultural technology has typically been evaluated within the literature using probit or logit models, with flexible functional forms in the independent variables that work well for the analysis of dichotomous choices (Besley & Case 1993; Immink & Alarcon 1993; Staal *et al*. 2002; Herath & Takeya 2003; Maertens & Barrett 2013; Ainembabazi & Mugisha 2014). Yet, in reality, farmers do not decide to adopt an agricultural technology permanently at one point in time. Previous research has sought to address the idea of dynamic adoption by evaluating either the sequence or intensity of adoption by farmers when faced with an adoption package containing different components (Doss 2006; Ainembabazi & Mugisha 2014). An additional important component in understanding the dynamic adoption process relates to farmers' histories of technology use (Doss 2006). This consideration moves beyond simply asking a farmer whether or not he or she is currently using a particular technology, but rather whether he or she has ever used it in the past. Our analysis delves into this question to enable an understanding of two types of dynamic adoption: sustained (persistent) adoption, and intermittent adoption.

We draw a distinction between three types of dynamic adoption: farmers who adopted and continued using a technology (sustained adopters), farmers who adopted a technology, discarded it, then returned to the technology (intermittent adopters), and farmers with one year of adoption (late adopters). In evaluating these different adoption scenarios, the research addresses the inherent dynamic nature of the adoption process, and particularly the drivers behind sustained versus intermittent adoption of a non-incremental, long-jump technology like commercial soybean production.

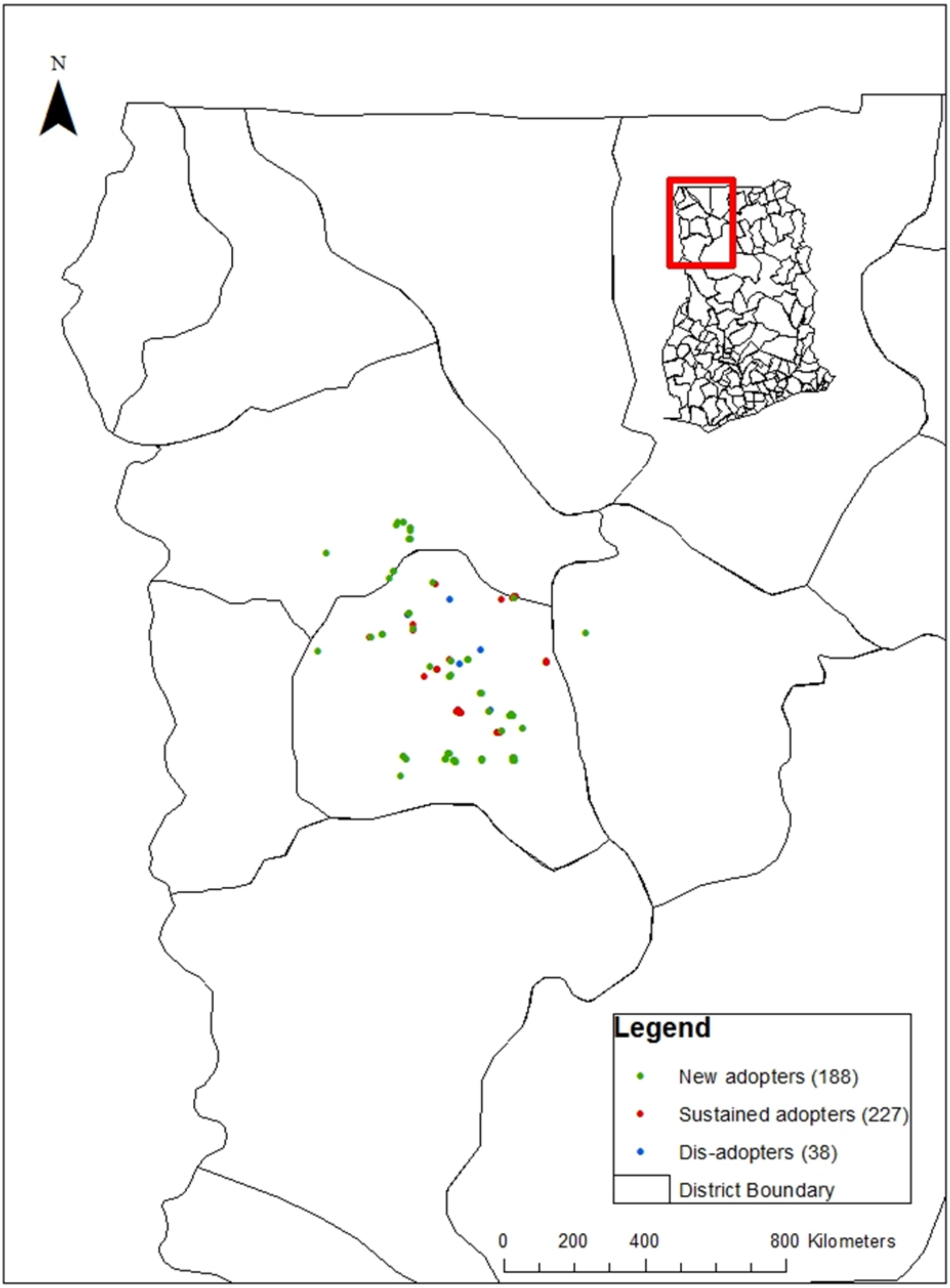


**Figure 1: Households surveyed in the Upper West region of Ghana (n = 453)**

Following Besley and Case (1993), we model the existence of sustained adoption, intermittent and late adoption using a probit regression analysis. The gain to farmer $i$ of using a new agricultural technology is parameterised as $\gamma x_i + u_i$, where $x_i$ are farm and farmer characteristics and $u_i$ is an independently and identically distributed farm-specific ex ante shock. The probability of sustained adoption or intermittent adoption can be written as:

$$Prob\{adoption\ by\ farmer\ i\} = \emptyset(yx_i/\sigma_{u)}, \quad (1)$$

where $\emptyset(\cdot)$ is the distribution function of the standard normal. In Equation (1) we measure the impact of $x_i$ on the decision of farmer $i$ to engage in either sustained, intermittent or late adoption of soybean. In this model, $x_i$ is a vector of explanatory variables related to farmer characteristics, economies of scale, market access and land rights.

**Model 1 – Sustained adoption**

Sustained adopters are given a value of 1, while late adopters are given a value of 0. As the focus of this probit regression model is on understanding what drives sustained adoption of soybean as compared to late adoption, intermittent adopters were not included in this analysis.

**Model 2 – Soybean yield performance**

We assume that farmer performance in soybean is a function of drivers related to farmer characteristics, economies of scale, market access, and land rights. We also include as an explanatory variable the effect of adopter type on soybean performance.

Farmer performance in soybean cultivation can be written as:

$$y_i = f(x_i) + \epsilon_i, \quad (2)$$

where $y_i$ denotes the yield of farmer $i$ in 2015; $x_i$ is a vector of explanatory variables for farmer $i$ (including the adopter type of farmer $i$); and $\epsilon_i$ is an error term associated with the performance of farmer $i$ in 2015.

**Model 3 – Spatial effects**

Spatial interaction among farmers may have important effects on their performance in soybean production. Following Drukker *et al*. (2013) and Ward and Pede (2014), we employ a generalised spatial two-stage least squares (GS2SLS) process that identifies the causal influences arising from spatial interactions among GROW project farmers. The GS2SLS process augments the basic linear regression model to include spatially lagged observations of the exogenous explanatory variables. As Ward and Pede (2014) note, by incorporating the spatial error component within this broader econometric specification, we control for correlations of unobservable characteristics that may condition behaviour. The framework for analysis examines both endogenous spatial effects (individual actions affect group action and vice versa), measured by the spatially lagged variable, and correlated effects (similar characteristics or conditions of spatial networks affect individuals' actions), measured by the spatial error term.

We employ a combined spatial-autoregressive (SAR) model with SAR disturbances, referred to as a SARAR model, in the analysis (Equations 3 and 4). The model of interest is given by:

$$y = Y\pi + X\beta + \lambda Wy + u \quad (3)$$

$$u = \rho Mu + \epsilon, \quad (4)$$

where:

- $y$ is an $n$ x 1 vector of observations on the dependent variable;

- $Y$ is an $n$ x $p$ matrix of observations on $p$ right-hand-side variables, and $\pi$ is the corresponding $p$ x 1 parameter vector;
- $X$ is an $n$ x $k$ matrix of observations on $k$ right-hand-side exogenous variables (where some of the variables may be spatial lags of exogenous variables), and $\beta$ is the corresponding $p$ x 1 parameter vector;
- $W$ and $M$ are $n$ x $n$ spatial-weighting matrices (with 0 diagonal elements);
- $Wy$ and $Mu$ are $n$ x 1 vectors, typically referred to as spatial lags, and $\lambda$ and $\rho$ are the corresponding scalar parameters, typically referred to as spatial-autoregressive parameters;
- $\epsilon$ is an $n$ x 1 vector of innovations

The resulting model reduces to a linear regression model with endogenous variables if $\rho = 0$ and $\lambda = 0$ (Drukker *et al.* 2013). Thus the SARAR model is an augmented form of the linear regression model that includes an additional right-hand-side variable known as a spatial lag. Following Drukker *et al.* (2013), if we let $\bar{y} = W_y$, let $\bar{y}_i$ and $y_i$ denote the $i$th element of $\bar{y}$ and $y$ respectively, and let $w_{ij}$ denote the $(i, j)$th element of W, then

$$\bar{y}_i = \sum_{j=1}^{n} w_{ij} y_j. \quad (5)$$

## 5. Results and discussion

### 5.1 Model 1 – Sustained adoption

This probit regression model presents the marginal effects showing the percent change in the probability of sustained soybean adoption. The farmer characteristics variables of *household head*, *lead farmer* and *education* were all insignificant in the probit model (Table 4). The lack of significance makes sense, as the level of household heads, lead farmers and the education level have limited variability in our sample, thus have limited power explaining yield at the margin for the entire sample.

**Table 4: Estimated probit regression results for sustained soybean adoption**

| | Variables | Estimate | Delta-method standard error |
|---|---|---|---|
| Demographic | Education | -0.017 | 0.034 |
| | Household head | 0.079 | 0.066 |
| | Lead farmer | -0.107 | 0.066 |
| Economy of scale | Farm size | .129*** | 0.019 |
| | Soy hectares planted (2015) | .303*** | 0.095 |
| Labour | Hired labour | .150*** | 0.054 |
| Market access | Dry-season activities | -.073* | 0.039 |
| | Intent to sell grain | .207*** | 0.041 |
| Land tenure | Family or owned land | 0.157 | 0.115 |
| | Can farm 3+ years | -.133*** | 0.038 |
| | *N* | 415 | |
| | *LR* $chi^2$ | 236.58 | |
| | *Prob >* $chi^2$ | 0.0000 | |
| | *Pseudo* $R^2$ | 0.4139 | |
| | *% Correctly classified* | 84.82% | |

Note: * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level

The results of the sustained adoption model indicate that each additional hectare comprising a GROW project farmer's total farm size is associated with a 12.9 percentage point *increase* in the likelihood of that producer being a sustained adopter. Similarly, each additional hectare of land allocated to soy cultivation by a GROW project farmer is associated with a 30.3 percentage point *increase* in the likelihood of that producer being a sustained adopter. These results point to the importance of economies of scale in the sustained adoption of a long-jump agricultural technology like soybean. As highlighted previously, new commercial crops like soybean require up-front fixed costs related to learning new production practices and input utilisation methods, capital investments in mechanisation for planting and threshing, and in making market linkages for input and service procurement and grain sales.

Furthermore, producers who use hired labour to produce soybean (independent of the proportion used in comparison to overall labour) are 15 percentage points *more likely* to be sustained soybean adopters. This result may point to the fact that, as women begin to adopt soybean, their independence and control over labour utilisation may increase, causing a reallocation of labour and a change in the balance between hired labour and individual/household/community labour. Also, female producers who engage hired labour for their soybean production may exhibit increased interest, dedication and commitment to soybean. This may result in higher performance in soybean production and/or sustained adoption.

Both of the market access variables related to dry-season activities and intention to sell grain are significant predictors of sustained soybean adoption. Farmers who engage in dry-season activities are seven percentage points *less likely* to be a sustained soybean adopters. An explanation for this finding may be that farmers who engage in these types of activities are less focused on soybean production than those who do not. Soybean, as a new commercial crop with a steep technical learning curve, requires farmers to exhibit a higher level of focus and specialisation to learn new agronomic practices, procure the necessary inputs and services, and make market linkages. Thus, if dry-season activities do indeed compete for farmer attention, then farmers who engage in these activities may be more diversified in their farm enterprise, and therefore potentially less focused on soybean production.

Conversely, the variable for intention to sell grain has a significant and positive effect on sustained soybean adoption. Farmers intending to sell their grain are 21 percentage points *more likely* to be engaged in sustained soybean adoption. This result may indicate that farmers who intend to sell their grain after harvest are better positioned to access input and service markets, as well as buyers, aggregators and processors. This can lead to more competitive prices for their grain, as well as for inputs and services, and may influence producers to remain engaged in soybean production and be sustained adopters. Farmers who exhibit an intention to sell their grain furthermore may recognise the role of soybean as a commercial crop rather than as a household nutrition crop, and the necessary market integration and connection that commercial soybean requires. Farmers who approach soybean cultivation as a commercial activity may also be more committed to sourcing the necessary inputs and training needed for successful production, leading to sustained adoption.

With respect to land rights, the land tenure variable is positive but not statistically significant. Farmers with individual or family ownership of their land are 16 percentage points *more likely* to engage in sustained adoption of soybean.

The duration of land control variable is negative and significant. Farmers who indicate that the duration of their land control is at least three years are 13 percentage points *less likely* to be sustained soybean adopters. This result is contrary to the hypothesis that farmers with longer durations of land control would be more likely to achieve higher yields in soybean production through longer-term investments in land improvement and soil health. Instead, the duration of land control may not be an appropriate predictor of successful performance in a new technology like soybean. Thus, more work is needed to understand how the duration of land control affects performance in long-jump technologies like soybean.

### 5.2 Model 2 – Soybean yield performance

Similar to the sustained adoption probit model, farmer characteristics of household head and education were not significant in the yield regression model (Table 5). Again, this finding may be a result of the low variability of these characteristics among the farmer sample. However, Thompson (2018) reports that education and serving as head of a household were not good predictors of success in producing soybean among farmers new to soybean in Nigeria. Thompson (2018) finds a number of misconceptions with respect to soybean production practices among the extension and development community as being the cause of this finding.

**Table 5: Estimated OLS regression results for 2015 yield**

| Variables | Estimate | Standard error |
|---|---|---|
| Education | 28.240 | 41.484 |
| Household head | -25.143 | 76.545 |
| Lead farmer | 150.887* | 80.598 |
| Sustained adopter | 101.153* | 58.910 |
| Intermittent adopter | -93.077 | 80.843 |
| Farm size | 73.015*** | 27.767 |
| Soy hectares planted (2015) | 103.528* | 62.549 |
| Hired labour | -47.353 | 64.268 |
| Dry-season activities | -132.825*** | 45.367 |
| Intent to sell grain | 327.842*** | 55.515 |
| Family or owned land | 121.584 | 120.022 |
| Can farm 3+ years | -156.815*** | 51.454 |
| *N* | 453 | |
| *R-squared* | 0.286 | |
| *F-stat (12, 440)* | 14.66 | |
| *Prob > F* | 0.0000 | |

Note: * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level

While lead farmer status was not a significant predictor of sustained soybean adoption, there is a significant effect of being a lead farmer on soybean yields. Specifically, lead farmers realised an additional 151 kilograms per hectare in their 2015 soybean yields. This result may point to the fact that being a lead farmer does not significantly change a producer's decision on whether or not to continue adopting soybean. Drivers related to market connectedness and economies of scale may instead affect commitment to soybean, as shown in the sustained adoption probit analysis. However, lead farmers received direct access to extension messaging and guidance, which seems to have a significant effect on their subsequent soybean yields. This finding is consistent with the logic that, in the context of long-jump agricultural technologies like soybean, where producers may not be able to rely on their tacit knowledge, norms and practices to engage in successful cultivation, they benefit from extension messaging and information channels.

The final farmer characteristic variable is experience in soybean production or, more specifically, adopter status. Sustained adopters, namely those who produced soybean for three consecutive years, realised an additional 101 kilograms per hectare in their 2015 soybean yields as compared to intermittent and late adopters. In contrast, intermittent adopters experienced on average 93 fewer kilograms per hectare in their 2015 yield compared to sustained adopters and late adopters, although this result is not statistically significant. These results seem to indicate that soybean performance improves over time as farmers gather more information, accumulate more resources and become more experienced in production. Furthermore, this result underlines the negative effect associated with performance due to a lack of experience of or commitment to soybean production.

The same economy of scale variables found to be significant in the probit regression model were also significant in the OLS regression, with the exception of hired labour. Specifically, farm size and land allocation for soy production both had a significant and positive effect on farmer soybean yields, increasing yields by 73 kilograms per hectare and 104 kilograms per hectare respectively. These relatively large increases in yield point to the positive benefits of economies of scale, which may enable farmers to better manage the fixed costs associated with soybean production and realise increased returns to scale. However, hired labour may not play as critical a role in soybean performance as it does in soybean adoption.

Market access measures of engagement in dry-season activities, and intention to sell grain, are both significantly associated with farmer yields. Specifically, farmers who engage in dry-season activities produce, on average, 133 kilograms per hectare *less* than farmers who are not engaged in dry-season activities. Thus, this is consistent with the findings of the probit regression mode. The hypothesis may hold then that long-jump technologies like soybean require focus and specialisation, and dry-season activities may compete for farmer attention and result in poorer performance. The implication may be broader in terms of development policy and commercial technologies like soybean. Policies advocating crop diversification among smallholders to improve resilience may be less appropriate when introducing long-jump technology adoption. Such policies stands contrary to business theory on commercial enterprises, in which specialisation, technical focus and scale economies dominate.

Farmer intention to sell grain has a very strong effect on yield. Farmers who intend to sell their grain produce, on average, 328 kilograms per hectare *more* than farmers who do not. Farmers who intend to sell their grain may maintain a deeper focus on or commitment to soybean. For example, soybean may not be simply an opportunistic crop, but more successful producers may have better understanding of both input and grain markets ahead of planting. Lower transaction costs can reduce uncertainty and allow for greater commitment to the crop in terms of seedbed preparation, input purchases, and seed care. This result highlights the importance of market connectedness and focus in determining farmer performance in soybean production.

Similar to the probit model, duration of land control is negatively associated with soybean performance. Specifically, producers who indicate that the duration of their land control is at least three years experienced lower yields, in the magnitude of 157 kilograms per hectare. The rationale behind this finding is unclear and may indicate that there is an unobservable relationship between land quality and duration of land control that drives this result. Conversely, producers who indicated that their land is owned either individually or through their family generated an additional 122 kilograms per hectare on average more than producers who lease, borrow or share their land, although this result was not statistically significant.

### 5.3 Model 3 – Spatial effects

The spatial lag parameter lambda ($\lambda$) measures the extent of spatial interaction on 2015 soybean yields (Table 6). The lambda value, at 0.644, is both positive and significant at the 1% level. In creating a minmax-normalised spatial weights matrix, the range of $\lambda$ falls between -1 and 1. Thus the value of $\lambda$ at 0.644 shows a strong effect of spatial interaction on farmer yields. This confirms the hypothesis that there is positive, large and significant spatial autoregressive dependence in soybean yields. In other words, the soybean yield of a given farmer strongly affects the soybean yield of neighbouring farmers.

This finding also highlights the potential role that social multiplier effects may play in farmer performance in soybean production. Knowledge about new agricultural technologies likely spills over within spatial networks. The positive and significant $\lambda$ value in the SARAR model indicates that farmers are expected to have higher yields if, on average, their neighbours have higher yields.

In terms of the individual independent variables included in the SARAR analysis, the results are for the most part in line with the OLS regression. However, the interpretation of the coefficients in the SARAR model differs from the OLS regression. The SARAR model assesses the impact of each independent variable on average farmer yield, while also controlling for spatial dependence in soybean yields. Thus, the magnitude of the various coefficients in the SARAR model is affected by the inclusion of the spatially lagged variable in the model.

**Table 6: Estimated SARAR model results for 2015 yield**

| Variables | Estimate | Standard error |
|---|---|---|
| Education | 16.253 | 39.883 |
| Household head | -23.462 | 75.832 |
| Lead farmer | 167.543** | 79.830 |
| Sustained adopter | 125.655** | 63.829 |
| Intermittent adopter | -89.325 | 83.184 |
| Farm size | 53.807** | 27.868 |
| Soy hectares planted (2015) | 57.380 | 61.847 |
| Hired labour | -25.272 | 62.861 |
| Dry-season activities | -94.345** | 44.638 |
| Intent to sell grain | 275.516*** | 56.976 |
| Family or owned land | 50.458 | 125.298 |
| Can farm 3+ years | -114.177** | 57.969 |
| *Lambda* | .644*** | 0.258 |
| *Rho* | .947*** | 0.200 |
| *N* | 437 | |

Note: * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level

The presence of a lead farmer and sustained adopter has significant and positive effects on farmer soybean yields, and at larger magnitudes than in the OLS yield regression model. This finding indicates that producers who are lead farmers and sustained adopters have, on average, higher yields, which in turn have a positive effect on the average yields within their spatial network. Further, there is a positive and significant effect of farm size on yield in the SARAR model, yet the effect is smaller in magnitude than in the OLS regression. This finding indicates that economies of scale continue to play a role in successful soybean production when assessing their impact from a spatial perspective, but may be substituted in part by knowledge spillovers and accumulation over time.

Engagement in dry-season activities has a negative and significant effect on soybean yields when controlling for spatial dependence, which is consistent with the findings in the OLS model. Farmer intention to sell grain positively and significantly affects soybean yields in the SARAR model, which is consistent with the earlier regression results. As noted earlier, farmers who intend to sell their grain may be better integrated into commercial markets to procure yield-improving inputs, including fertilisers and high-quality seed, as well as to receive formal technical support services. Finally, farmers with a longer duration of land control have a significant and negative effect on the soybean yields of farmers within a spatial network, as seen in the OLS regression.

The estimated $\rho$ value, or the spatial error term, is also strong, significant and positive, with a value of .947, indicating that observations are related in terms of unmeasured, spatially correlated effects across farmer networks. As an example, land in a given spatial network may have inherently better soils or more desirable topographies and slope than land in another spatial network. As a result, the spatial error term may capture these types of spatially correlated characteristics related to soil, climate and topography. Furthermore, social institutions, organisational structures and policy changes that span spatial boundaries can affect farmer performance in agricultural technologies (Ward & Pede 2014). The spatial error term may also capture these effects.

In sum, there is substantial spatial dependence in yield among GROW project farmers. As such, our results show that standard OLS regressions that assume independent observations may be misleading. From a policy perspective, clustering and targeting a limited set of beneficiaries for training and lead farmer support may be more successful when rolling out long-jump technologies such as soybean. The costs per beneficiary may be higher, the raw number of beneficiaries may be lower, but the overall success rate, sustainability and impact may be greater.

## 6. Conclusion

As governments, development agencies, donors and the international community seek to identify new tools to transition African smallholders out of poverty, the cultivation of commercial crops may hold potential as an income-generating agricultural technology. It is within this context that soybean, due to the growing global demand for the crop, is seen as an agricultural technology worthwhile of investment and capable of shifting smallholders out of subsistence farming and into new opportunities for income generation. While soybean farming presents significant opportunities, it also carries with it complex challenges as a long-jump agricultural technology in that it is a non-traditional, non-staple, and new commercial crop.

This research fills a void in the existing literature by examining the adoption process for soybean as an example of a long-jump, or non-incremental, agricultural technology. Specifically, the results reveal the differences with staple crop production, in which success with soybean's long-jump nature is associated with greater scale, less diversification, crop knowledge acquisition, a commercial orientation, and commitment to the crop. Soybean production incurs fixed costs related to learning about new agronomic and production practices, making the necessary market linkages to source inputs and services, and aggregating and selling the grain. Smaller farms, and those without adequate land to allocate to soybean cultivation, may not find soybean a profitable endeavour when they are unable to spread these fixed costs over larger areas of land. Further, smaller farms may find it difficult to attract buyers who will provide a competitive price for their grain, especially if the local harvest also yields poorly.

A final key finding of the analysis centres on the importance of spatial networks and social learning in improving the performance of soybean production among smallholder farmers. This finding has important policy considerations for agricultural development programmes with respect to developing extension approaches. The results show that community-based extension models can yield positive benefits in soybean yields within a spatial network. Farmer networks can serve as a knowledge and information hub and warrant a place alongside traditional extension models that rely on visits by extension officers, who may or may not be integrated within the social network of a given farmer group, and are likely not specifically trained in soybean cultivation. Instead, providing extension information focused on soybean cultivation through a social-network, lead-farmer model may be more appropriate. In addition, in the context of female smallholder farmers, women may feel more comfortable approaching other female peers for extension information, rather than approaching government extension agents, who are predominately male.

As such, the use of soybean as a development tool must be considered within the framework of farmer networks, peer groups and social learning. Agricultural development programmes must recognise the information and knowledge flow among neighbouring smallholders and encourage responsive extension models that focus on community-based information hubs, where information sharing, resource building and aggregation opportunities can have the largest impact. In soybean production, producers are unable to rely on their tacit knowledge, norms and traditional production practices, and will look elsewhere for critical information and training on how to produce a new commercial crop. Investing in farmer networks to build these knowledge and information resources can yield sustainable extension models for farming communities.

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