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Impact of the adoption of residue retention on household maize yield in northern Zambia

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Abstract

Evaluating the impact of agricultural practices helps policymakers and farmers in their decision-making. In Zambia, most households depend on agricultural activities, in particular maize production. This paper examines the impact of the adoption of residue retention on households' maize yield in northern Zambia. We used the propensity score matching (PSM) method. By using the probit model, we also determined the factors that influence the adoption of residue retention. The results show that adopting residue retention has a positive and significant net effect on household maize yield. Residue retention traps moisture in the soil and improves soil structure. This suggests that a greater focus on this aspect is required to encourage more farmers to adopt residue retention to improve maize yield. Government policies can be structured to promote residue retention among smallholder farmers.

Key words: impact evaluation, propensity score matching, residue retention, Zambia

1. Introduction

Finding sustainable ways to alleviate poverty through improved agricultural practices should be a priority, particularly in nations where the population is highly dependent on agriculture. This is important for nations to achieve the United Nations (UN) 2030 agenda of leaving no one behind and to implement the Sustainable Development Goals (SDGs), specifically the ones that deal with poverty eradication (SDG 1) and food security (SDG 2). Because of their expected effects on the competitiveness of the agricultural sector and poverty reduction, agricultural research organisations and policymakers have a long tradition of promoting new agricultural technologies and associated practices aiming at more efficient use of external inputs (e.g. hybrid seeds, chemical inputs, mechanised equipment, etc.).

In the 1990s, increasing concerns about environmental degradation led to changes in farm management practices and a focus on those with a positive effect on food security and the environment, such as conservation agriculture (Baudron *et al*. 2007). More recently, farmers have faced new challenges posed by climate change, and new sets of practices such as climate-smart agriculture are now being promoted (Hobbs *et al*. 2008). Many of the technologies and practices have the potential to help farmers adapt to these new challenges, especially in specific conditions (Umar *et al*. 2011; Lipper *et al*. 2014). However, they present further difficulties, as they require more sophisticated understanding, often involving trade-offs between different overarching goals (such as productivity, sustainability, resilience, etc.), and have different effects, depending on the context in which they are used (Knowler & Bradshaw 2007; Läpple & Van Rensburg 2011). Apart from that, the adoption of these various practices remains low, despite obvious advantages for farmers and a number of initiatives to support them (Andersson & D'Souza 2014).

It is challenging to identify consistent factors in farmers' adoption of sustainable agricultural practices, and attempts to promote them will need to be adapted to the local social and biophysical context (Umar *et al*. 2011; Turmel *et al*. 2015; Abegunde *et al*. 2019). Among the different practices, the retention of crop residues has been promoted to farmers as a tool to build resilience and improve productivity. Residue retention entails the use of crop residues or stalks, which are the substances that are left after harvesting crops (Turmel *et al*. 2015). Mulching the retained residues will include the stalks, leaves and others parts, which are used as soil cover. Residue retention is effective in reducing soil erosion. Moreover, residue retention has the potential to improve soil organic matter. Climate change affects the spatial and temporal availability of water, i.e. rainfall, on which farmers in Zambia are dependent. Residue retention traps moisture in the soil for longer periods compared with conventional practices, thereby minimising the climate impact on crops and improving resilience. Inversely, residue retention promotes disease and pest infestation, which may affect yield as well as the occurrence of weeds (Mandal *et al*. 2004). However, there is some debate on its adaptability to and effects in various African farming contexts. As the results of the adoption and effects of this practice are likely to be context specific and related to farmers' perceptions and socio-economic conditions (Giller *et al*. 2009; Tessema *et al*. 2013; Misaki *et al*. 2018), the main research questions of this paper firstly dealt with the evaluation of the factors that influence the adoption of residue retention by maize farmers in northern Zambia, and secondly to evaluate the impact of the adoption on maize yields. Zambia is among the leading countries in Africa in the adoption of agricultural practices like residue retention, for example conservation agriculture (CA) and climate-smart agricultural practices, although there are a lack of studies that have specifically investigated the effects of residue retention (Baudron *et al*. 2007; Kaczan *et al*. 2013).

As elsewhere, the effect of agricultural practices is also a cause of debate in northern Zambia (Giller *et al*. 2009; Total LandCare [TLC] 2017). In fact, studies on the effect of adopting residue retention are based mainly on field experiments or trials (Mandal *et al*. 2004; Chivenge *et al*. 2007). They do not take into account the fact that farmers in the real-world situation face many factors that are external to production and have the potential to affect the effect of adopted practices (Ibrahim *et al*. 2008; Jat *et al*. 2019). The impact of conservation agriculture on crop production can be found in literature on the Zambian situation (Thierfelder & Wall 2010; Manda *et al*. 2016). We argue that context is important, and that focusing on specific technologies, and not treating CA practices as a package in impact evaluation studies, provides more accurate information. Moreover, farmers rarely adopt the full bundle of practices, but often opt for specific technologies under incomplete information. Therefore, this research adds to the body of knowledge on the adoption of residue retention as a CA practice by estimating the effect on farmers' total household maize yield in northern Zambia.

2. Data and methods

2.1 Study area and data sources

The study covered two provinces, the Northern Province (which includes Kasama, Mungwi, Mbala and Luwingu districts) and Luapula Province (which includes Mansa, Samfya and Kawambwa districts). The provinces are located in northern Zambia and share the same agroecological region (region III, see Figure 1). The survey was carried out by Total LandCare (TLC) Zambia as part of the Smallholder Productivity Promotion Programme (S3P), funded by the International Fund for Agricultural Development (IFAD). The S3P project was designed to address low yield and improve output and market access in the agricultural sector (TLC 2017). The survey data was collected from maize farmers in the two provinces in 2019. Data collection included key informant interviews and focus group discussions with extension officers and farmers in agricultural camps. The survey participants consisted of 306 maize farmers, who were selected from different districts in the study areas using stratified random sampling.

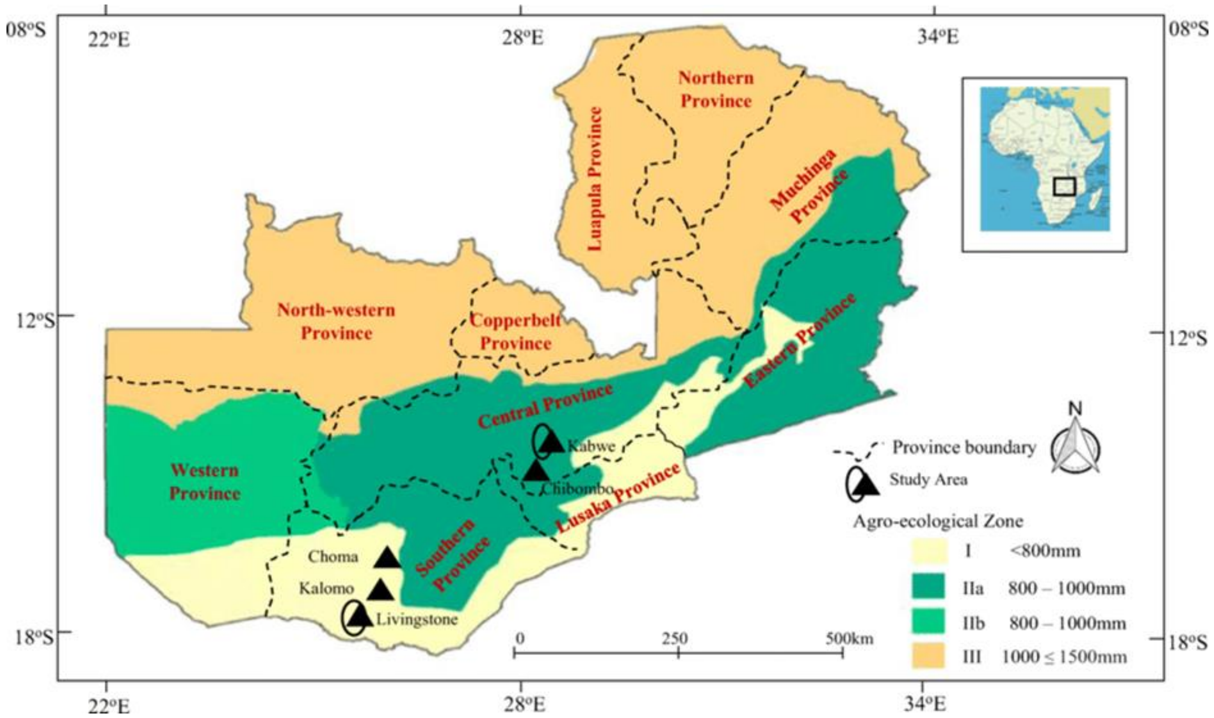

Figure 1: Agroecological zones and the study area
Source: Makondo and Thomas (2020)

2.2 Propensity score-matching procedure

The study used the propensity score matching (PSM) method to shed light on the effect of the adoption of residue retention on maize yield. Residue retention has been treated as part of climate-smart agricultural technology (CSA) in the literature because of its potential to improve farmers' adaptation and productivity. The PSM method is widely used in the impact evaluation literature, as it creates conditions similar to a randomised experiment (Rosenbaum & Rubin 1983; Mendola 2007). First, it establishes an adequate counterfactual to estimate the true causality of change. The aim is to assess what the situation of farmers would have been if they had not adopted residue retention. Second, PSM accounts for potential selection bias that may arise in adoption. Residue retention is one of the least adopted technologies in Zambia (Andersson & D'Souza 2014). Furthermore, PSM does not impose structure and assumes common support, and thus is efficient in controlling for selection bias (Heckman *et al*. 1998). Our study used observational data, thus adoption was not randomly distributed among the farmers, as they make private decisions to adopt or not to adopt, leading to self-selection problems (Abdulai 2016). The outcome variable used was maize yield in the 2018/2019 season.

Following Rubin (1974), the outcomes for non-adopting and adopting households were defined as shown in equations (1) and (2) respectively, with Y_0 representing outcomes for non-adopters and Y_1 for adopters. The X represent observable household characteristics that simultaneously influence adoption and outcome variables (maize yield). The assumption is that unobserved random errors are different; $\mu \neq \varepsilon$. Due to potential selection bias, the effect of adoption was not estimated as the difference in outcomes of adopters and non-adopters (Y_1 - Y_0), known as the average treatment effect (ATE).

$$Y_0 = B_0 X + \mu \quad (1)$$

$$Y_1 = B_1 X + \varepsilon \quad (2)$$

The existence of selection bias due to observable characteristics was tested using a t-test. The PSM method controls for selection bias by matching adopters and non-adopters with similar observed characteristics and estimating the more robust average treatment effect on the treated (ATT). The interest is to estimate the counterfactual, which is not observable. The PSM method relies on two main assumptions: (i) the conditional independence assumption (CIA); and (ii) the common support or overlap assumption, which is required to hold to estimate the treatment effect (adoption). The CIA assumption requires that adoption be random and not correlated with maize yield when the observed characteristics of farmers are controlled (Mendola 2007). The common support assumption requires that adopting farmers be similar to non-adopters in terms of observed characteristics, and be unaffected by participation (Khandker *et al*. 2009). This study assumed that only observable household characteristics affect adoption (i.e. CIA assumption), following Rosenbaum and Rubin (1983), as shown in Equation (3).

$$Y_i \perp D|X, \quad (3)$$

where D is a dichotomous dependent (treatment) variable, equal to one when farmers adopted (and zero otherwise). The "⊥" denotes independence, and the variables to the right of "|" are the conditioning variables. To be precise, the potential outcomes (Y_i) are independent of treatment assignment given the set of variables, hence would not be affected by the socioeconomic characteristics of the farmers if the only characteristics used were those that are the same for the adopters (with the treatment) and the non-adopters (without the treatment). There are, however, systematic socioeconomic differences between treatments, thus the expectation is that the potential outcome would be influenced by the differences. The study applied the probit model to estimate the propensity or probability that a farmer adopts residue retention, as shown in Equation (4).

$$P(X) = \Pr(D = 1|X) = E(D|X) \quad (4)$$

P(X) represents the estimated propensity scores. Rigorous tests ensure that all covariates that determine the adoption of residue retention are included in the propensity score equation. Covariates that influence adoption are likely to be data driven, and literature and context specific. Using the propensity scores, the region of common support was defined; this is where the distributions of the propensity score for adopters and non-adopters overlap. Adopters and non-adopters that fell outside the common support region were dropped. In addition, the estimation of the treatment effect (adoption) takes place in the region of common support. Satisfying the common support assumption ensured that households with similar observed variables have a positive probability of adopt and not adopting (Heckman *et al*. 1999; Caliendo & Kopeinig 2005). In essence, it rules out perfect predictability of the adoption state, given the observed variables as shown in Equation (5).

$$0 < P(D = 1|X) < 1 \tag{5}$$

The common support assumption needs to be satisfied so that non-adopters are matched with adopters based on the distribution of covariates, such that farmers from the two groups share similar observable characteristics (Rosenbaum & Rubin 1983). Adopters and non-adopters were matched using propensity scores. The study applied common matching methods – nearest neighbour, radius matching and kernel (Rosenbaum & Rubin 1985). The weights assigned in each matching method affect the estimation of the treatment effect. The standardised bias, t-test and pseudo-R^2 tests were used to assess the matching quality (i.e. balancing property). Matching with a good comparison group ensures that a true hypothetical mean outcome is estimated, as shown in Equation (6). For instance, the observed mean outcome for adopters is given as $E(Y_1|D = 1)$, and their hypothetical mean outcome as $E(Y_0|D = 1)$.[1] The ATT was estimated as shown in Equation (7) (Rosenbaum & Rubin 1985), such that:

$$E(Y_0|D = 1) - E(Y_0|D = 0) = 0 \tag{6}$$

$$ATT = E(\Delta|D = 1) = E(Y_1|X, D = 1) - E(Y_0|X, D = 1) \tag{7}$$

The treatment effect includes variance attributed to the derivation of propensity scores, common support region, and matching. Failure to account for this variation results in wrongly estimated standard errors (Caliendo & Kopeinig 2005). One widely used method to deal with this problem is bootstrapping (Johnson *et al*. 1991; Lechner 2002; Horowitz 2003). By bootstrapping, the results were re-estimated including the initial stages in the estimation, viz. propensity score and common support. The PSM method hinged on the CIA assumption, thus requiring sensitivity analysis to be carried out to establish how the potential existence of unobserved characteristics (hidden bias) may affect adoption. Rosenbaum bounds sensitivity analysis was adopted to check how hidden bias (unobserved influences) may affect the results of the study (i.e. the degree to which unobserved influences would require the results of the study to be questioned), as the method assumes that only observed characteristics influence the adoption of residue retention.

3. Results and discussion

3.1 Characteristics of the sampled households

Table 1 presents a summary of the characteristics of the sampled population. The mean age of the respondents was 49. The gender of the respondents was distributed between 43.14% females and 56.89% males. The educational background of the respondents showed that 3.59% had never received any formal education, 50% of respondents had primary school education, 45.75% had secondary education as their highest educational level, and only 0.65% of respondents had completed tertiary

[1] *E* is the expectation operator

education. Education is said to enable farmers to understand, acquire and interpret information that helps in decision-making. In the adoption literature, formal education is reported to improve farmers' knowledge and skills to understand the potential benefits of agricultural practices and technologies for their yield. Respondents cultivated maize on 1.24 hectares of land on average, and 69% of respondents had contact with extension officers during the 2018/2019 planting season. The data was collected at the end of the planting season.

Table 1: Descriptive statistics of sampled households for residue retention (N = 306)

Variables	Mean	Standard dev.	Percentage (%)
Age	49.2	13.136	-
Female	-	-	43.14
Male	-	-	56.86
Education			
Never	-	-	3.59
Primary	-	-	50.00
Secondary	-	-	45.75
Tertiary	-	-	0.65
Province			
Luapula	-	-	45.42
Northern	-	-	54.58
Married	0.83	0.376	-
HH size	7	2.910	-
Extension access	0.69	0.462	-
Maize area	1.24	4.339	-

Source: TLC Household Survey 2019

3.2 Awareness and reported effects of climate change on crop and livestock productivity

The lack, or limited awareness, of climate change hinders farmers' adaptation ability (see Nzeadibe *et al*. 2011). To effectively adapt to climate change, farmers must correctly perceive or observe current and future climate trends. As shown in Table 2, households reported varying effects of climate change that directly affected their welfare. About 72.88% (cumulative percentage) of farmers experienced at least one impact attributed to climate change. In addition, most farmers reported that climate variability led to a decline of 36.27% in crop production. In contrast, only 2.28% of the respondents experienced a decline in livestock production due to climate change. In this study, livestock was reported to be less affected by climate change and variability than crops. This is similar to the findings on adaptation in South Africa by Thomas *et al*. (2007), who found that smallholder farmers ceased investment in crops and rather invested more in livestock production during drought seasons and in cases of high climate and weather variability.

Table 2: Reported effects of climate change

Climate change effects	Residue retention	
	Frequency	Percentage
A decline in crop yield	111	36.27
Decline in livestock	7	2.29
Difficult to time seasons	24	7.84
Increase in yields	4	1.31
Increased diseases	35	11.44
Decrease in water availability	8	2.61
Decline crop yield and livestock	34	11.11
No consequences	83	27.12

Source: TLC Household Survey 2019

3.3 Adoption of residue retention

Most rural households in Zambia earn a living from agricultural activities. However, the progressively changing climatic conditions threaten their livelihoods. Households often would find a way to adapt to the aspects that threaten their livelihoods and their agricultural activities by employing strategies that increase their resilience to factors such as climate change. Residue retention is promoted as a sustainable practice that has the potential to improve soil fertility and trap moisture, thus improving crop yield. The data shows that 32.68% of the sample population adopted residue retention, while 67.2% did not adopt it. This confirms the assertion that adoption among smallholder farmers remains low in sub-Saharan Africa (Dinar *et al*. 2012; Shongwe 2014). Adopters are maize farmers (households) who only adopted.

3.4 Selection bias

Using the observable characteristics of the households, systematic differences were checked between adopters and non-adopters of the technologies under investigation. Checking for systematic differences between adopters and non-adopters is the first and most important step in impact evaluation and may direct the researcher on which valuation method to use. Observational studies on adoption often suffer from the existence of selection bias, causing the sample population between the two groups to be non-random or not a true representation of the whole population (Mendola, 2007; Becerril & Abdulai 2010; Kassie *et al*. 2011).

Table 3[2] shows the existence of selection bias in the adoption of residue retention. The results show that male-headed households are distributed differently between adopters and non-adopters of residue retention ($p > 0.074$). Secondly, a significant difference exists between the adopters of residue retention and the non-adopters in their awareness of climate change ($p > 0.004$). Adopters and non-adopters of residue retention are significantly different in extension contact ($p > 0.000$). Farmers who have contact with extension services are likely to adopt agricultural technologies. Other observable characteristics that are systematically different between the two groups include access to agricultural inputs ($p > 0.011$), legume cultivation ($p > 0.002$), training in running a farm as a business ($p > 0.031$), and access to market information and involvement in seed multiplication ($p > 0.000$).

3.5 Propensity score estimates

Table 4 presents the probit results in estimating the propensity scores for the adoption of residue retention. Access to extension services had a positive and significant influence on the adoption of residue retention, at $P < 0.000$. This finding is supported by Prokopy *et al*. (2015). According to Akerele (2014), the rate at which farmers adopt agricultural technologies depends on extension contact, which improves farmers' access to vital information in improving maize production. The results further show that maize farmers who grow legumes are more likely to adopt residue retention. Legumes are often intercropped with maize or rotated, the residues from legumes are also used as a soil cover (residue retention). From the results, farmers producing their seeds are likely to adopt residue retention.

[2] See the Appendix at the end for the table defining all the variables used in the study.

Table 3: Variables used in the residue retention propensity score-matching estimation

Variable	Residue retention (Yes)	Residue retention (No)	$P > T(X^2)$
Gender	0.83	0.74	0.074*
Climate change[3]	0.92	0.79	0.004***
Aware of good agricultural practices	0.80	0.72	0.148
Maize area	1.09	1.31	0.681
Extension access	0.83	0.63	0.000***
Input access	0.65	0.50	0.011**
Market access	0.94	0.87	0.076*
Livestock[4]	0.39	0.35	0.545
Treadle pump[5]	0.07	0.03	0.097*
Legumes	0.78	0.60	0.002***
Seed multiplication	0.51	0.30	0.000***
Knapsack sprayer	0.19	0.17	0.590
Farmer received training to run a farm as a business	0.86	0.75	0.031**

Source: Own calculations. * significant at 10%, ** significant at 5% and *** significant at 1%

Table 4: Probit estimates of residue retention

Variable	Coefficient	Z	P > | z |
Male	0.242	1.19	0.233
Climate change awareness	0.403	1.61	0.107
Aware of good agricultural practices	0.023	0.11	0.912
Maize area	-0.018	-0.28	0.777
Extension access	0.673	3.66	0.000***
Input access	0.249	1.42	0.156
Market access	0.144	0.48	0.630
HH had livestock	-0.065	-0.38	0.707
HH used treadle pump in farming	0.034	0.09	0.929
Farmer planted legumes	0.398	2.16	0.031**
Seed multiplication	0.423	2.35	0.019**
Knapsack sprayer	-0.116	-0.53	0.593
farmer received training to run a farm as a business	0.093	0.42	0.672
Constant	-2.118	-5.38	0.000
Summary			
Number of observations	306		
Pseudo R^2	0.115		

Source: Own calculations; * significant at 10%, ** significant at 5% and *** significant at 1%

3.6 Impact of residue retention on maize yield

The question is, what would have been the situation if the adopters of residue retention did not adopt? Alternative matching algorithms were used to this end. These included the most common matching estimator, and the nearest neighbour method (NNM) with replacement (five neighbours) (see Table 5). According to Caliendo and Kopeinig (2005), this type of NNM improves the average quality of matching and decreases bias. Other algorithms used include kernel-based and radius calliper matching. The results presented in Table 5 were consistent in all matching algorithms, with the adoption of residue retention having a positive effect on farmers' maize yields. The ATT estimates showed that adopters of residue retention were 19.5% to 25.3% better off in maize yield in the 2018/2019 season than they would have if they had not adopted. The positive effect is consistent with

[3] Climate change awareness.
[4] Livestock variable; this was coded 1 if household had cattle or goats, and 0 otherwise. Smallholder farmers practising mixed farming may feed fodder (crop residues) to livestock during dry seasons.
[5] Treadle pumps are used for irrigation.

impact evaluation studies on the effect of conservation agriculture (Hailu *et al*. 2014; Kuntashula *et al*. 2014; Nkhoma *et al*. 2017).

The Rosenbaum bounds sensitivity analysis was used for its suitability when using continuous outcome variables, viz. maize yield (Caliendo & Kopeinig 2005). As presented in Table 5, the critical gamma, Γ, ranged from 1.25 to 1.30 across matching estimators. If individuals with similar observable characteristics differed by 55% in their chances to adopt residue retention, the results would have to be revised. This percentage is fairly high, thus the results show the true effect of residue retention on welfare outcomes, as the covariates used were found to have an association with the adoption and outcome variables. Sensitivity analysis of the effect on crop income was not necessary, because it did not have any significant impact.

Table 5: Effect of the adoption of residue retention

Matching algorithm	**Adopters**	**Non-adopters**	**ATT**	**Bootstrapped standard errors**	**t-stat**	**Critical-level hidden bias** (the critical gamma, Γ)
NNM[Y]	98	161	0.253	0.137	1.84*	1.25
Radius[Y]	98	206	0.195	0.135	1.45	
Kernel[Y]	98	206	0.248	0.141	1.75*	1.30

Source: Own calculations; * significant at 10%, ** significant at 5% and *** significant at 1%

4. Conclusion

The study used smallholder farmers' data to estimate the effect of adopting residue retention on farmers' household maize yield. Farmers use technologies or practices to improve their returns in agricultural production. The study provided three important outcomes. First, residue retention was found to have a positive net effect on maize yield. Overall, the findings of this study validate the potential for residue retention in improving farmers' yields. Therefore, farmers in the study areas must be encouraged to adopt residue retention. Second, access to extension services influences the adoption of residue retention. Government policies can be structured in a way to strengthen extension services so that farmers receive context-specific information on their production. And last, the adoption of residue retention is low, with only a third of the population having adopted residue retention, despite Zambia being among the sub-Saharan countries leading in adoption.

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Appendix

Definition of variables used in the study

Variable	Definition/Codes	Adoption
Age[6]	Age of farmer in years: 1 if the age of the farmer is 18 to 35 (youth); otherwise 0	+/-
Gender	1 if the household (HH) head (farmer) is male; otherwise 0	+
Marital status	1 if HH head was married; otherwise 0	+
Education	Level of education of farmer (0 never, 1 primary, 2 secondary, 3 tertiary)	+
Household size	Number of household members	+
Maize area	Size of the maize farm cultivated, in hectares	+/-
Agribusiness	1 if the farmer received training to run a farm as a business; otherwise 0	+
Aware of GAPs[1]	1 if the farmer was aware of good agricultural practices; otherwise 0	+
Extension access	1 if the farmer received extension services; otherwise 0	+
Market access	1 if the farmer had access to market information; otherwise 0	+
Climate change	1 if farmers perceived climate change; otherwise 0	+
Input access	1 if the farmer had access to agricultural inputs (seed and fertiliser); otherwise 0	+
Legumes	1 if the farmer planted legumes; otherwise 0	+
Province	1 if the farmer was from Northern Province; otherwise 0	+
Livestock	1 if HH had livestock; otherwise 0	+/-
Manure/residue	1 if HH adopted manure or retention; otherwise 0	
Tillage	1 if HH had practised minimum tillage in the past; otherwise 0	+
Treadle pump	1 if HH used treadle pump in farming; otherwise 0	+
Knapsack sprayer	1 if the farmer used a sprayer in farming; otherwise 0	-
Seed multiplication	1 if HH was involved in seed multiplication in farming; otherwise 0	+
Maize yield	Quantity of maize produced per hectare by HH	+
Crop income	Income from maize produce sold, per hectare (ZK[2]/ha)	+

[1] Good agricultural practices
[2] Zambian Kwacha

[6] The official age range for young people (youth) in Zambia is from 18 to 35 years (Government of the Republic of Zambia [GRZ] 2020).