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Factors affecting adoption and intensity of conservation agriculture techniques applied by smallholders in Masvingo district, Zimbabwe

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ABSTRACT
This study investigates factors influencing both the use of conservation agriculture (CA) and the intensity of its uptake amongst 237 smallholders sampled in the Masvingo district of Zimbabwe. The intensity of uptake was measured using an index that accounted for the number of CA components used, their relative importance, and the rate and extent of their application. Previous studies ignore some or all of these important aspects of uptake. The determinants of use and intensity were identified using a double hurdle model. Although most smallholders applied the reduced tillage or crop rotation components of CA, few combined these practices with mulching. Farm size and experience with CA technology impacted positively on the current use of CA, while distance from town (market) and ownership of an ox-drawn plough reduced the intensity of its uptake. Sensitivity analysis showed that these results change when partial measures of CA uptake are used, emphasising the importance of establishing a comprehensive measure of intensity. Policy implications include a need for institutional change to improve smallholder access to cropland, more participatory approaches to agricultural extension, and more convenient access to farm inputs.

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1. Introduction

Conservation agriculture (CA) has been promoted in many parts of southern Africa as a means of addressing land degradation and other crop production challenges faced by smallholders (Knowler & Bradshaw, 2007; Mazvimavi, 2011; Kassie *et al.*, 2013; Andersson & D'Souza, 2014). Significant investment and resources have been channelled towards supporting and up-scaling CA technology among smallholders in developing countries (Ndlovu *et al.*, 2014; Ng'ombe *et al.*, 2017). The technology and practices associated with CA have been interpreted and defined differently in different contexts. For this study, CA is defined as a farming technique that is based on the integrated management of soil, water and biological resources through: (i) minimum disturbance of soil (limited or no-till), (ii) permanent soil cover (usually using crop residues), and (iii) crop rotation (Giller *et al.*, 2009).

Empirical studies show that the impact of CA on smallholder agricultural systems has been constrained by low rates of adoption, but findings on the reasons for low adoption are mixed (Andersson & D'Souza, 2014; Ng'ombe *et al.*, 2017). Kassam *et al.* (2014) estimated the proportions of cropland under no-till in Oceania (Australia and New Zealand), South America and North America to be approximately 69 per cent, 57 per cent and 15 per cent respectively. In Africa, the authors reported an estimate of only 0.3 per cent of arable land under no-till. Some empirical studies of CA adoption

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such as Enki *et al.* (1998) and Pedzisa *et al.* (2015a) view CA as an indivisible technology and measure its uptake as a binary variable. However, smallholders often adopt only one or two of CA's three components (Giller *et al.*, 2009; Mazvimavi & Twomlow, 2009; Pannell *et al.*, 2014; Ng'ombe *et al.*, 2017) and apply them at different levels of intensity.

Farmers choose components of CA according to their perceptions of feasibility, costs, and benefits – given external factors such as the institutional and natural environment. Adoption patterns differ from place to place owing to site-specific differences in external factors (Nakhumwa & Hassan, 2003; Giller *et al.*, 2009; Pannell *et al.*, 2014). For example, most of the farmers studied by Ngwira *et al.* (2014) in Malawi applied all three CA components, whereas farmers studied by Arslan *et al.* (2014) in Zambia were poor adopters of mulching and crop rotation. Weak adoption of mulching and crop rotation was also reported in Zimbabwe (Pedzisa *et al.*, 2015a). Studies that rely on just one component (e.g. minimum disturbance) to measure the uptake of CA ignore the reasons why farmers do not adopt the other components, or apply them at low levels. Feder *et al.* (1985) emphasised the importance of developing measures that account for different levels of uptake. Recent studies by Kassie *et al.* (2013), Arslan *et al.* (2014), Pedzisa *et al.* (2015b), and Ng'ombe *et al.* (2017) consider the adoption of different CA components but treat each component separately and do not account for their relative importance or the rate and extent of their application. This study attempts to address these issues.

The overarching goal of this study is to generate information that helps decision-makers to discern and understand factors that influence the adoption of CA and the intensity of its use by smallholders in Zimbabwe.[1] Previous empirical studies of CA uptake by smallholders, such as those conducted by Enki *et al.* (2001), Kassie *et al.* (2013) and Pedzisa *et al.* (2015a), focused largely on factors affecting the decision to adopt CA. Very little attention was given to factors that influence levels of CA uptake. Past studies of CA adoption in Zimbabwe (Mazvimavi & Twomlow, 2009; Marongwe *et al.*, 2012; Pedzisa *et al.*, 2015ab) were conducted at a time when non-government organisations (NGOs) were actively promoting CA. This research, however, was conducted after the NGOs had stopped providing free CA inputs to smallholders, thus eliminating bias introduced by subsidies. The study has three objectives. The first objective is to construct an index that measures the intensity of CA techniques applied by smallholders. The second objective is to identify factors that influence the adoption of CA techniques in a sample of Zimbabwean smallholders. The third objective is to identify factors that explain their intensity of CA uptake using a double hurdle adoption model.

2. Conservation agriculture and adoption – a review of relevant literature

Non-government organisations (NGOs) took the lead in promoting CA as a hand-hoe-based technology where farmers had to prepare planting basins during the dry season (minimum disturbance) and retain at least 30 per cent soil cover (Mazvimavi & Twomlow, 2009; Marongwe *et al.*, 2011). Crop rotation was also encouraged as part of the technology (Giller *et al.*, 2009). NGOs initially targeted vulnerable farmers, who were defined as families that faced challenges in meeting their basic livelihood needs and had difficulty acquiring inputs in a cost-effective manner (Mazvimavi & Twomlow, 2009; Andersson & D'Souza, 2014). CA reduces smallholder reliance on draught power for planting, and addresses many of the problems associated with labour availability and input use (Giller *et al.*, 2009; Mazvimavi, 2011; Kassam *et al.*, 2014).

In Zimbabwe, smallholders were initially provided with free inputs to encourage the adoption of CA technology so that its effects could be measured. Smallholders in Zimbabwe allocate most of their resources to the production of staples and consume most of the staples they produce (Johansen *et al.*, 2012). Cash earnings from the sale of surplus products tend to be trivial and, in the virtual absence of off-farm earnings, smallholders face severe liquidity constraints. This reduces their ability to invest in new technologies, particularly in cases where the technology does not provide immediate benefits (Shiferaw & Holden, 1998). In rural Zimbabwe these problems were compounded by missing input markets (Marongwe *et al.*, 2011). Many NGOs considered the temporary provision of free inputs as necessary to make the adoption of CA technologies a viable proposition. Unfortunately, this short-term 'solution' was not complemented with interventions to strengthen local markets for inputs and finance.

The promotion of CA by NGOs saw the number of farmers practising some form of CA in Zimbabwe increase from less than 20 000 households in the 2006–2007 cropping season to approximately 120 000 households in the 2009–2010 cropping season (Mazvimavi, 2011). In 2010–2011, there were approximately 300 000 households practising CA, of whom almost 40 per cent were spontaneous adopters that did not receive free inputs. Despite this impressive growth in the number of adopters, the area of crops cultivated using CA techniques was a modest 141 334 hectares, representing only 5 per cent of the area planted to maize (Marongwe *et al.*, 2012). Adoption levels started to decline after 2011 when donor-funded projects reached their maturity dates and NGOs stopped providing free inputs (FAO, 2015).

The uptake of mulching and crop rotation was particularly poor due to competing uses for crop residues and preferences for staple cereals over legumes (Mazvimavi, 2011; Pannell *et al.*, 2014; Farnworth *et al.*, 2016). The importance attached to maize as a staple food discourages crop rotation, particularly in areas where product markets are weak (as was the case in the study area). Other constraints to adoption include increased demand for labour and weed control (Nyamangara *et al.*, 2014); lack of knowledge, perceived complexity of the technology, inappropriate tools, and lack of herbicides (Johansen *et al.*, 2012); and inadequate technical support (Giller *et al.*, 2009).

Several studies conducted to identify the determinants of CA adoption or dis-adoption (Pedzisa *et al.*, 2015a) measured the use of CA techniques as a binary dependent variable scoring zero or one. However, this approach is inadequate where technology can be partially adopted as it fails to incorporate different levels of uptake (Feder *et al.*, 1985). The multinomial probit technique used by Kassie *et al.* (2013) addresses some of these shortcomings as it enables identification of factors influencing the adoption of interrelated agricultural technologies. Even so, this does not account for their relative importance, or the rate and extent of their application.

Shiferaw and Holden (1998) used farm and household characteristics to explain the levels of CA adoption by farmers in Ethiopia. They included farmer perceptions of land tenure security and soil erosion problems as explanatory variables. The decision to adopt CA was positively related to high perceptions of soil erosion and the productivity of CA technology, farmer attitudes and exposure to new technology, and farm size. Even though controlled experiments have shown that CA is most effective as an indivisible technology, farmers may see this differently given their own perceptions of benefits and costs under conditions of imperfect information and learning by doing (Feder *et al.*, 1985; Pedzisa *et al.*, 2015a). Understanding farmer perceptions of CA benefits may aid in explaining adoption patterns (Moyo *et al.*, 2012).

Many smallholders in southern Africa operate under customary land tenure arrangements that constrain exclusive land rights (Lyne, 2009; Mabuza *et al.*, 2013; Pannell *et al.*, 2014). Thomson (1996: 90) describes customary laws in KwaZulu-Natal that oblige farmers to open their fields for communal grazing after the harvest. Under CA, basins should be left visible so that farmers do not have to dig them every season, while crop residues should remain as soil-cover and not be grazed. Arguments that CA requires less effort after the first year of implementation (Mazvimavi & Twomlow, 2009; FAO, 2015) are less compelling when farmers do not have exclusive rights to their cropland. Incentives to adopt CA technology are further reduced as farmers cannot internalise the full benefits of their investment in CA (Enki *et al.*, 2001). Mabuza *et al.* (2013) identified insecure land tenure as a constraint to smallholder investment in alternative land cultivation technologies in Swaziland. However, when all smallholders are burdened with the same problem, it is difficult to measure the impact of insecure tenure owing to the absence of variation in land rights. This study attempted to elicit farmer perceptions of tenure security. Even though smallholders operate under the same tenure system, individual perceptions may differ.

Some past studies accounted for partial adoption of CA by measuring the application of CA technologies as a continuous variable. Mazvimavi and Twomlow (2009) constructed an index using the number of CA components adopted by farmers. In addition to the three main components of CA, they included other management practices such as weeding, and fertiliser and manure application, totalling eight components. Their index ranged from zero to one, with a maximum value of one for farmers who practised all eight components. The authors acknowledged the need to weight the components but argued that it was not possible at that time, as CA had been practised for only a few seasons. Moreover, their index did not account for variation within each component, and their Tobit model implicitly assumed that farmers made a single decision on adoption and the intensity of adoption (Cragg, 1971).

Arslan *et al.* (2014) adopted a latent variable approach in their Zambian study and measured CA adoption and intensity using a continuous variable. They calculated intensity as the proportion of cultivated land under different CA practices. They also treated individual CA components separately. The authors acknowledged the limited explanatory power of their model and recognised the importance of unobserved factors that influence farmer decisions, as well as factors that show little or no variation within samples, such as land tenure security. A lack of variation means that the variable cannot explain variation in adoption even though it may well be responsible for consistently low (or high) levels of adoption.

Ngwira *et al.* (2014) studied CA adoption and the extent of adoption in Malawi using a two-step Heckman procedure to address sample selection bias. Like Arslan *et al.* (2014) they measured intensity of CA uptake as the percentage of land allocated to CA techniques. However, this measure of intensity ignores the reality that farmers apply varying levels of each CA component to different areas of land. Accounting for variation in the rate and extent of application should provide accurate information about the determinants of CA adoption. Pedzisa *et al.* (2015b) attempted to measure the intensity of adoption in Zimbabwe using count regression to identify factors influencing the number of CA components practised by each farmer. Again, this approach, does not account for the relative importance of the components, or for the rate and extent of their application.

3. Research methodology

3.1 Study area, sampling design and data collection

The study was conducted in Ward 14 of Masvingo district, Zimbabwe, between October and December 2015. The ward is located 60 km southeast of Masvingo town, near Lake Mutirikwi (Figure 1). The district is predominantly semi-arid, receiving annual rainfall of 450 to 650 mm between October and April in a normal year (Moyo *et al.*, 2012). Smallholders in the study area are predominantly subsistence farmers and rely heavily on rain fed agriculture (Johansen *et al.*, 2012; Moyo *et al.*, 2012). In rare cases, they produce a marketable surplus, which may be sold or stored for future consumption. The study area is characterised by mixed farming systems, where farmers raise livestock and grow crops. Fishing is also a common off-farm activity as the study area is close to Lake Mutirikwi.

3.2 Research design

Farm households were selected using a multistage sampling technique. Ward 14 has nine villages with an estimated population totalling 1726 households. The first stage of sampling involved the selection of three villages with probability proportionate to size (PPS), where size was measured by the number of households estimated in each village. PPS controls for differences in the size of villages. The selected villages, Zano, Rukovo and Mudare, comprised 160, 135 and 305 households respectively. These households were identified and listed with the assistance of local agricultural extension personnel. In the second stage of sampling, households were selected randomly from each list at a constant rate of 40 per cent. Using PPS at the first stage of sampling, and a constant sampling rate at the second stage, generates a representative sample that can be analysed as if it were a simple random sample, as it assigns equal probability of selection to all smallholders in the

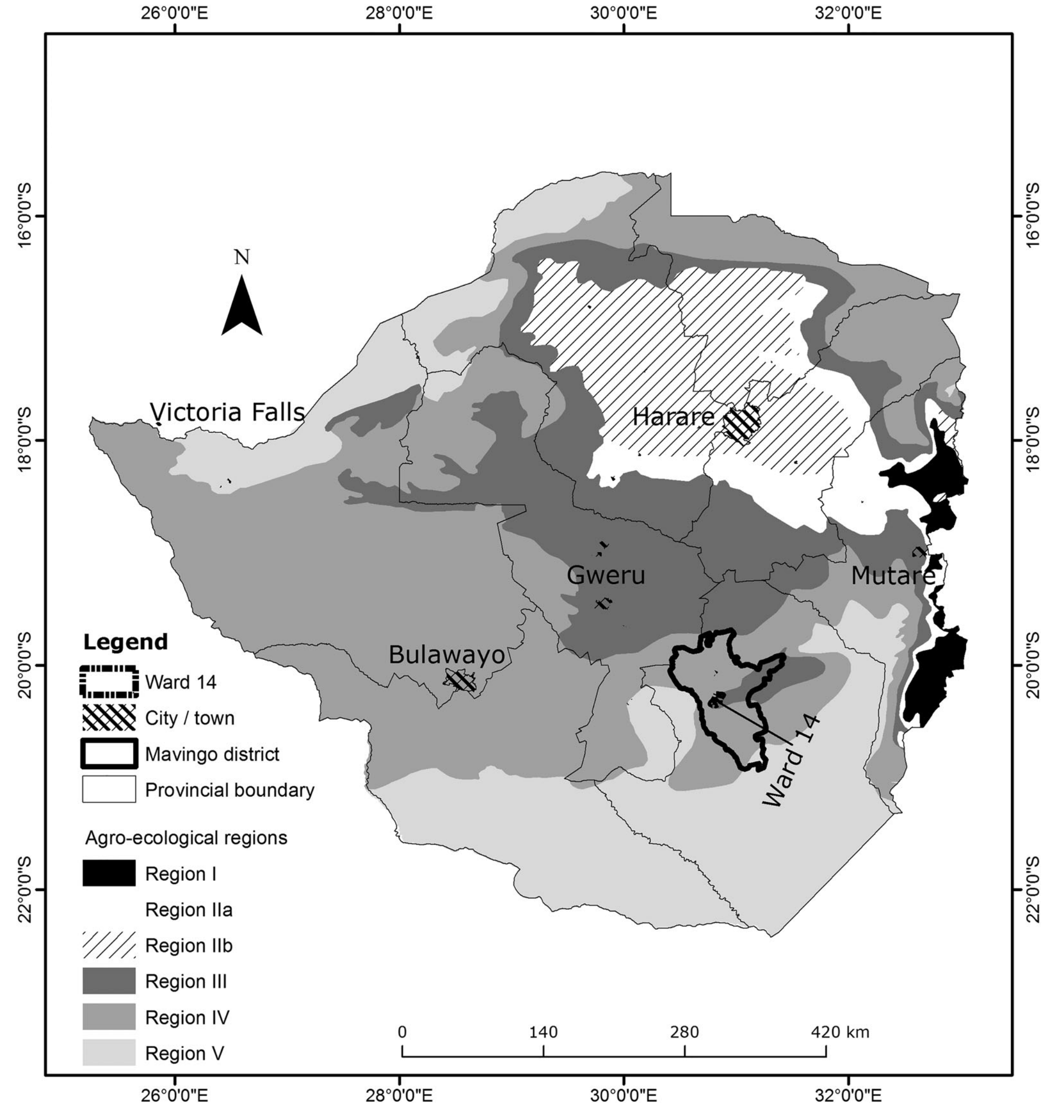

Figure 1. Map of Zimbabwe showing study area (Ward 14). Source: ICRISAT Matopos GIS unit (2015).

study area (Babbie, 2016: 216). Personal interviews were conducted with 240 farmers. A sample size of 240 households was achievable given budget and time constraints. Most of the descriptive statistics reported in Section 5 have coefficients of variation (CVs) smaller than 5 per cent, and only two have CVs larger than 16.5 per cent, indicating that the sample was large enough to generate estimates with acceptable precision (Statistics Canada, 2016: 35).

3.3 Data collection

Data were gathered using structured questionnaires, which were administered by three experienced enumerators using the local language (Shona). The enumerators were trained by the first author and familiarised themselves with the questionnaire by interviewing one another. Questions that were not clear were identified, discussed and amended to ensure consistent interpretation by the enumerators. The questionnaire was then pre-tested with a pilot group of 12 respondents and further amendments were made. Interviews were conducted with the *de jure* household head. In cases where the *de jure* head was not available, the *de facto* household head was interviewed instead.

In order to get accurate estimates of field sizes, each respondent's fields were measured by the first author using a measuring wheel. In most cases, the fields were located next to homesteads and the author was able to measure the fields and plots while the enumerators conducted the interviews. In rare cases where the fields were far from the homestead, arrangements were made with the respondents to obtain area measurements in advance of the interview. Responses were coded and then captured using SPSS v23. Of the 240 completed questionnaires, 237 were deemed usable and three were discarded as the respondents did not till any of their fields during the 2014/15 season.

4. Analytical methods

To understand the adoption of CA and the intensity of its uptake, an index was constructed to account for the number of CA components applied, their relative importance, and the rate and extent of their application.

4.1 CA intensity index (CAI)

The conservation agriculture index (CAI) was constructed from plot level data gathered at each sample household. The index was computed as:

$$CAI_i = \sum_r W_{ir} R_{ir} P_{ir} S_{ir} \tag{1}$$

In Equation (1), *CAI* denotes the conservation agriculture index score computed for the *i*th household. *W* is defined as the contribution of each CA component (or their combination) to yield, *R* is the rate at which the farmer applied the CA component (or combination of components) relative to the recommended application rate, *P* is the area of each plot relative to the total area planted by the farmer, and *S* is the area of the *r*th plot relative to largest plot in the data set. The values of *W*, *R*, *P* and *S* were computed from the sample survey data.

The yield weights, *W*, account for differences in the relative importance of CA components or combination of components. These weights could be estimated from field experiments or expert opinion, but this information was not available and the weights were estimated by regressing plot level yield data on the CA components applied by farmers in the sample. Typically, a household would have more than one plot (parcel) and would apply different CA components or combinations of CA components to each plot. Since information on the CA components applied by farmers was recorded at the plot level, it was possible to code their presence or absence using dummy variables. These dummy variables, which took a value of 1 (0) where a component or combination of components was present (absent), were regressed on yield using an ordinary least squares (OLS) regression model specified as:

$$Y_{ir} = \alpha_{0ir} + \sum_w a_{wir} X_{wir} + u_{ir} \tag{2}$$

In Equation (2), Y_{ir} represents the per hectare maize yield observed for the *r*th plot of the *i*th household. On the right-hand side of the equation, a_{0ir} is a constant, a_{wir} are estimated parameters, X_{wir} are dummy variables representing the CA components and combinations of CA components (*w*) applied to the *r*th plot by the *i*th household, and u_{ir} is an error term. Other factors that may affect yield were omitted from the regression and their effects are captured in the error term. The regression results and weights are reported in Table 1. The CA components listed in Table 1 represent all of the components and combinations of components observed in the sample. The standardised coefficients estimated by OLS regression were normalised to sum to unity, and partial effects were summed to

Table 1. Weights computed for CA components and combinations of CA components.

CA components	Standardised regression coefficient	Normalised weight	Assigned weights (W)
Reduced till only	0.248***	0.36	0.36
Crop rotation only	0.067	0.10	0.10
Reduced tillage and crop rotation	0.175***	0.26	0.36 + 0.10 + 0.26 = 0.72
Reduced tillage and mulch	0.049	0.07	0.36 + 0.07 = 0.43
All three components	0.147***	0.21	1.00
Total	0.686	1.00	

Notes: *** denotes 1% significance level.
Source: Estimated from sample survey data.

estimate the weights assigned to combinations of components. A maximum weight of 1 was assigned to plots where all three components were applied.

The rate of application (*R*) is a score based on farmer perceptions. Farmers were asked to rank themselves against the recommended rate of component use. Farmers who claimed that they applied the CA component as recommended by extension officers were assigned a weight of $R = 1$. Scores for *R* ranged from 0 to 1.

The values of *P* and *S* were computed from plot measurements. *P* is the size of the plot relative to the total area cultivated by the *i*th household in the 2014–2015 cropping season. This captures the proportion of land cultivated by the *i*th household using CA techniques. *S* is the size of the plot relative to the largest plot in the data set. This accounts for absolute differences in the extent to which households apply CA techniques. Two households could have equal values of *P* even though one of the households applies CA techniques on a much larger scale. Scale is important when the policy objective is to encourage widespread application of CA with the intention of improving long-term food security. An index based only on the number of CA components applied and their rate of application neglects scale effects and creates a misleading view of CA uptake, especially where there is a tendency for households to apply CA techniques only on their smaller plots.

The CAI improves on the measures of CA uptake used by Ngwira *et al.* (2014) and Arslan *et al.* (2014) as it considers all three CA components and combinations of components, their relative contributions to yield, the rate at which the components are applied, and the extent of their use. In addition, the CAI is a continuous variable that accommodates partial adoption and analytical techniques that cannot be used with binary or ordinal dependent variables.

4.2 Determinants of CA uptake

The computed index was used to investigate the adoption and intensity of CA techniques applied by sample households. Observed factors that were expected to affect these decisions included a number of household and farm characteristics considered by other researchers such as Shiferaw and Holden (1998), Mazvimavi and Twomlow (2009), Arslan *et al.* (2014), Ngwira *et al.* (2014) and Pedzisa *et al.* (2015a, b). In particular, this analysis included farm size, farming experience, farmer education, perceptions of tenure security, peer effects, and previous exposure to CA support services as relevant explanatory variables.

As the CAI takes positive values censored at zero, a Tobit model could be used to analyse both adoption and intensity (Cragg, 1971). However, the Tobit approach assumes that the decision to adopt and the decision relating to intensity are the same, which may not be appropriate (Cragg, 1971; Nakhumwa & Hassan, 2003). In this study, these decisions were treated as separate processes. In each season, the farmer must first make a decision to use CA techniques and then decide on the rate and extent of their use. Factors that affect the use of CA components may differ from those that affect the intensity of their application (Nakhumwa & Hassan, 2003). Garcia (2013) recommends the two-stage Heckman procedure or double hurdle approach where adoption and intensity decisions are assumed to be separate processes.

The double hurdle model assumes that individuals pass through two hurdles. The first hurdle is the decision to use or not to use CA techniques, while the second hurdle determines how much is to be applied (Cragg, 1971). The first hurdle uses a probit regression, which takes 0 as the decision not to use a technology, and 1 as the decision to use the technology regardless of how much is applied. This can be specified as:

$$P\left(w = \frac{1}{x}\right) = \varphi(x\gamma) \tag{3}$$

In Equation (3), P denotes the probability, w is a binary variable of CA adoption, φ represents the cumulative normal distribution, x is a vector of farm and household characteristics that may influence adoption, and γ represents the vector of coefficients to be estimated.

The second hurdle uses a truncated regression model to determine the factors that explain the intensity of adoption for the subset of individuals who adopt (Burke, 2009).

$$Y = x\beta + \varepsilon \tag{4}$$

In Equation (4), Y represents the vector of CA intensity levels as measured by the CAI, x is a vector of farm and household characteristics that may influence intensity levels, β is a vector of estimated parameters, and ε is a vector of error terms.

Double hurdle models assume that the error terms of the two regression models (Equations (3) and (4)) are not related. However, given the nature of the study, this assumption may not hold owing to the presence of sample selection bias. For instance, a certain class of farmers may choose to adopt a technology (Heckman, 1979; Khandker *et al.*, 2010). Consequently, there is a need to test for selection bias before estimating the double hurdle regression model. The Heckman approach addresses selection bias by including the Inverse Mills Ratio (λ) as a regressor in the second regression. If selection bias is present, λ is statistically significant and accounts for the bias (Heckman, 1979). However, if selection bias is absent (as was the case in this study), the double hurdle model is more appropriate as it produces efficient parameter estimates for both regressions and accounts for truncated data at the second hurdle (Burke, 2009).

5. Results and discussion

5.1 Household characteristics

This sub-section uses the survey data to describe an average household in the study area. It also introduces and defines variables used to analyse CA uptake. Table 2 presents a summary of key descriptive statistics computed for all households (237) in the sample. On average, each surveyed household had 5.4 members, half of whom were minors under the age of 16. Each household had approximately 3.6 adult equivalent[2] workers. Very few (12%) had hired farm labour and only 3 per cent pooled their labour with other households to share farm work. These characteristics may imply heavy reliance on family labour, including part-time contributions from school-going children.

On average, households had more than 20 years of farming experience using traditional farming methods, including the use of ox-drawn ploughs and hand hoes. Although conservation agriculture (CA) components (reduced tillage, mulching, and crop rotation) had been promoted in the study area for approximately 10 years, there was considerable variation in farmer experience with each component. The survey revealed that the average household had applied reduced tillage for approximately 5.5 years, mulching for 1.1 years, and crop rotation for 7.6 years. Longer experience with crop rotation was expected as this practice had been encouraged by extension officers prior to the introduction of CA.

Seventy per cent of the sample households had male heads, and 60 per cent had a resident male head. Overall, 88 per cent of the household heads lived on their farms. This suggests a lack of off-farm employment opportunities, and emphasises the importance of agriculture as a livelihood strategy.

Table 2. Household characteristics (n = 237).

Variable	Mean	Standard error
Household size	5.40	0.16
Number of males (adults ≥ 16 years)	1.30	0.06
Number of females (adults ≥ 16 years)	1.40	0.05
Number of children < 16 years	2.70	0.12
Family labour (adult equivalents)	3.60	0.08
Age of household head (years)	50.60	1.07
Education level of household head (years)	7.50	0.22
Education level of decision maker (years)	7.40	0.22
General farming experience of household head (years)	21.30	1.02
Experience with reduced tillage/planting basins (years)	5.50	0.27
Experience with mulching (years)	1.10	0.18
Experience with rotation (years)	7.60	0.68
Mean household annual off-farm income in US$[a]	945.61	72.44
Male-headed households (%)	70.00	3.00
Household heads that reside on the farm (%)	87.80	2.00
Household with a resident male head (%)	59.90	3.00
Households with male decision makers (%)	51.10	3.00
Household that used hired labour in 2014–2015 (%)	12.20	2.00
Households that used collective labour in 2014-2015 (%)	3.00	0.21

Notes: [a]Annual off-farm income = Cash obtained from all off-farm sources including wage income, cash from petty trading, and remittances.
Source: Sample survey data.

Males were solely responsible for crop management decisions in 51 per cent of the households sampled. This points to a significant involvement of women in crop production as managers or co-managers in 49 per cent of the households – a finding that contrasts with the view that African women provide labour for cropping activities while men make management decisions (Farnworth *et al*., 2016). Household heads and household members that were in charge of making agricultural decisions were relatively well educated with an average of 7.5 and 7.4 years of schooling, respectively. This suggests that farmers in the study area are potentially in a better position to understand and use new farming methods. On average, households earned annual off-farm incomes (mostly from non-farm enterprises and remittances) of about US$945, or US$79 per month, for an average family size of 5.4 persons. Zimbabwe's official poverty line was reported to be US$481 per month for a family of five in April 2016 (Zimbabwe National Statistics Agency, 2016). This implies that the average sample household had to harvest farm products (for own consumption or sale) worth $403 per month just to reach the official poverty line.

5.2 Land endowment, farming techniques, and crop production

The survey revealed that, on average, households had 1.6 hectares of arable land and cultivated roughly 1.2 hectares, leaving 0.4 hectares idle. Idle land was attributed to difficulties accessing inputs, a shortage of draught animals and labour constraints (Table 3). Slightly more than half, 52 per cent, of the sample households owned cattle and 44 per cent owned a mouldboard plough. Farmers that own cattle and mouldboard ploughs have a distinct advantage as they can till larger areas of land and plant early in the season, thus making better use of the limited rainfall (Mazvimavi & Twomlow, 2009). Reducing dependency on these scarce resources (draught animals and mouldboard ploughs) has been one of the major reasons for promoting CA among poor smallholders (Andersson & D'Souza, 2014). Livestock are also a store of wealth. On average, households had 2.2 tropical livestock units (TLU). A TLU is the weighted sum of large and small livestock. Cattle are assigned a weight of 0.7, while goats and sheep are assigned a weight of 0.1 (Jahnke, 1982).

Smallholders in the study area operate under a customary tenure system that may well constrain land transactions, including rental transactions. Lyne (2009) presents evidence of inefficient land rental markets in parts of KwaZulu-Natal characterised by a tenure system similar to that observed in the study area. Missing or incomplete land markets would tend to reduce the incentive to

Table 3. Farm characteristics (*n* = 237).

Variable	Mean	Standard error
Land endowment (hectares)	1.58	0.06
Area cultivated in 2014–2015 season (hectares)	1.18	0.05
Area left fallow in 2014–2015 season (hectares)	0.40	0.04
Distance from nearest town in kilometres	61.21	0.59
Distance from government extension personnel in kilometres	5.99	0.29
Livestock units (TLU)	2.21	0.20
Households owning cattle (%)	51.50	3.00
Households owning a mouldboard plough (%)	43.50	3.00
Households with fenced plots (%)	9.70	2.00
Farmers with positive perception of tenure security (%)	60.30	3.00
Farmers who perceive long term benefits of CA (%)	89.00	2.00
Farmers that received free CA inputs before 2014–2015 (%)	56.10	3.00
Farmers that received CA extension before 2014–2015 (%)	70.50	3.00
Farmers that received CA extension in 2014–2015 (%)	41.40	3.00
Farmers that received advice from social groups in 2014–2015 (%)	62.40	3.00
Households that produced maize (%)	100.00	–
Households that produced groundnuts (%)	79.00	3.00
Households that produced bambaranuts (%)	74.00	3.00
Household practising reduced tillage (%)	71.70	3.00
Household practising crop rotation (%)	56.50	3.00
Household practising mulching (%)	9.30	2.00

Source: Sample survey data.

adopt CA techniques as they have a long payback period and it may not be possible for adopters, particularly older farmers, to realise the full benefits of improved soil quality by selling or leasing their upgraded land (Place *et al.*, 1994). However, it is difficult to measure the effects of tenure arrangements when everyone operates under the same land tenure system. An alternative approach is to elicit perceptions of tenure security as individual perceptions of the breadth, duration, and assurance of land rights may differ between households depending on their social status. Respondents were asked a series of questions about risks associated with leasing land, and their ability to exercise exclusive rights to cropland. Their answers were aggregated into a dummy variable that scored 1 if tenure was perceived to be secure and 0 otherwise. Some 60 per cent of the sample households perceived tenure to be secure. Respondents were also asked questions about the long term benefits of CA. The vast majority (almost 90%) believed that CA had a positive impact on soil fertility and structure over time. It was anticipated that farmers with positive perceptions of tenure security and the long term benefits of CA would be more likely to adopt the technology.

When CA was introduced, smallholders were provided with free inputs such as fertiliser and seed to encourage adoption. NGOs gradually reduced their support after 2010 (FAO, 2015) and stopped providing free inputs to farmers in the study area from 2012. More than half (56%) of the respondents confirmed that they were given free inputs to use on their CA plots prior to the 2014–2015 season, and 70 per cent stated that they had benefitted from CA extension at that time. CA extension was delivered by both government and NGO personnel. The uptake of CA would almost certainly have been influenced by these interventions, and adoption studies conducted at that time may have suffered from this bias.

The situation was quite different when this study was conducted at the end of 2015. Farmers had to purchase inputs from suppliers in Masvingo, some 60 km from the average household. The government still offered extension support, but less than half (41%) of the sample households benefitted from this service during the 2014–2015 season. A much larger share of the households (60%) accessed information and technical advice from their social networks. These sources included neighbours, friends, relatives and religious groups.

In Zimbabwe, CA was promoted and defined as a combination of three components, namely reduced tillage, mulching and crop rotation (Giller *et al.*, 2009). The survey data gathered for this study revealed that few farmers applied all three components and that rates of uptake differed markedly between households; 72 per cent practised reduced tillage, 56 per cent crop rotation and only 9 per cent mulching. Similar findings have been reported in previous studies (Pannell *et al.*, 2014). These studies attribute the poor uptake of mulching to competing uses of crop residues as livestock feed.

5.3 Area allocation, CA components practised and crops grown

Farms in the study region are normally divided into smaller parcels (plots), so that an average 1.6 ha farm has several plots that may be managed quite differently. An individual smallholder may produce different crops on each plot using different levels of CA. Sample households had a total of 995 cultivated plots, of which approximately 53 per cent were allocated to maize, 21 per cent to ground nuts and 18 per cent to bambara nuts. Minor crops like finger millet, cowpeas, sorghum, beans and sunflowers together accounted for only 7 per cent of the cultivated plots.

Table 4 presents sample data relating to the incidence and extent of CA components applied by smallholders in the 2014–2015 season. Roughly one half (49%) of the plots observed in the sample were cultivated without any CA components. Of those farmed with CA techniques, vast majority were by characterised by either reduced tillage (42%) or crop rotation (38%). Combinations of CA components were applied to relatively few plots. Interestingly, plots farmed using all three CA components were marginally smaller than the sample average, suggesting that farmers applying all three components were either experimenting on smaller plots or that resource constraints prevented their combined use on larger plots.

It is important to measure levels of CA uptake at the plot level as they vary across the plots farmed by an individual household. However, this information would have been diluted had the CAI scores computed for plots simply been averaged or summed to produce a generalised measure of uptake at the household level. Instead, household uptake was measured by the maximum CAI score achieved by the household on any of its plots as this exploited the richness of the plot-level data.

5.4 Model specification and diagnostic tests

Table 5 shows the list of variables used in the regression and their expected signs. The selected variables were based on previous adoption studies such as Shiferaw and Holden (1998), Mazvimavi and Twomlow (2009), Arslan *et al.* (2014), Ngwira *et al.* (2014) and Pedzisa *et al.* (2015a, b). The receipt of inputs in previous years (CAinput) was expected to influence the adoption decision but not the intensity decision. On the other hand, the use of hired labour (CAlab) and access to agricultural extension (CAextcur and Advsocial) were expected to influence intensity and not adoption. This is based on the notion that the adoption decision is made before the season begins, with events occurring during the season not altering the decision to adopt.

Diagnostic tests to check for multicollinearity were carried out before estimating the double hurdle regression model. Variance inflation factors (VIFs) computed for the explanatory variables were close to unity, with a maximum value of 2.24 – a level well within limits regarded as acceptable

Table 4. Frequency of individual and combined CA component (%).

Component	% of plots (n = 995)	Mean area (Ha)	Standard error
No CA component	49.0	0.28	0.01
Reduced tillage	21.2	0.25	0.01
Crop rotation	19.4	0.30	0.02
Reduced tillage and crop rotation	8.3	0.27	0.03
Reduced tillage and mulching	0.8	0.24	0.09
All three components	1.3	0.23	0.05
All plots		0.28	0.01

Source: Sample survey data.

Table 5. Variables used in the regression model and their expected signs.

Variable	Definition	Expected sign	
		Decision to adopt CA	Intensity of CA use
Gender	Gender of decision maker (male = 1, otherwise 0)	–	–
Edudc	Education of decision maker in years	+	+
Hhresid	Household head reside on farm (yes = 1, otherwise 0)	+	+
Ttlabour	Total household labour (adult equivalent)	+	+
CAbenefit	Perception of CA long term benefits (positive = 1, otherwise 0)	+	+
tenureperc	Perception of tenure security (positive = 1, otherwise 0)	+	+
Farmexp	General farming experience (years)	+	+
Farmexpsqd	General farming experience (years)[b]	+	+
Basinyrs	Number of years practising basins	+	+
Mulchyrs	Number of years applying mulch	+	+
Rotatyrs	Number of years practising crop rotation	+	+
Landendow	Land endowment (ha)	+	+
Fence	Fences (present = 1, otherwise 0)	+	+
Plough	Ownership of ox-drawn plough (yes = 1, otherwise 0)	–	–
LU	Number of Tropical Livestock Units	+	+
Liquidity	Liquidity (US$)	+	+
Distnmkt	Distance to nearest town (km)	–	–
Distagri	Distance to government extension personnel (km)	–	–
CAinput	Free CA inputs in previous years (received = 1, otherwise 0)	+	
CAhlab	Hired labour in 2014–2015season (hired = 1, otherwise 0)		+
Advsocial	Agricultural advice from social groups in 2014–2015 (received = 1)		+
CAextcur	CA extension in 2014–2015 season (received = 1, otherwise 0)		+

Notes: [b]Farmexpsqd= Square of farming experience (years)

(Gujarati, 2003: 362; Field, 2005: 196). Sample selection bias may be present if adopters differ from non-adopters in respect of observable or non-observable characteristics. NGO's may have targeted certain types of households, and adopters may have continued to use all or some of the CA components after the NGOs withdrew their support. The double hurdle model is not appropriate when selection bias is present as it produces inefficient estimates. However, application of Heckman's two-step procedure showed no evidence of selection bias as the Inverse Mills Ratio was not statistically significant (p = 0.546). The parameter estimates were therefore expected to be efficient.

5.5 Factors determining adoption, intensity and extent of CA use

The double hurdle regression results are presented in Table 6. The regression model's Wald statistic was significant at 1 per cent suggesting a good fit. The first hurdle shows the factors that influence the decision to use CA components, while the second hurdle shows factors that influence intensity of its use.

The gender of the main decision maker had a negative impact on both the decision to implement CA components and on the intensity of its use. However, its impact was significant only for the adoption decision. This suggests that households with male decision makers are less likely to adopt CA components. This may be attributed to the fact that CA was promoted as a hand hoe technique, which is less attractive to males (Farnworth *et al.*, 2016). On the other hand, the education level of the main decision maker and the availability of the household head on farm was not statistically significant in influencing either the adoption or the intensity decision. The availability of family labour had a positive impact on both adoption and intensity, but was also not statistically significant, suggesting that it is a less binding factor for adoption and intensity in this case. Similar findings on the importance of labour were reported by Arslan *et al.* (2014). Though the use of hired labour for the 2014–20015 season had a positive impact on intensity, it was also not a statistically significant determinant of intensity. The availability of labour was expected to be an important factor given that labour constraints have been reported as one of the major reasons for the poor adoption of CA components.

Experience with CA components was expected to have a positive impact on adoption and intensity of use. Adopters are likely to gain knowledge and expertise over time. Furthermore, they are likely

Table 6. Estimated double hurdle model for factors influencing uptake of CA and level of use.

Variable	First hurdle (decision to adopt CA)	Second hurdle (intensity of CA use)
Decid	−0.8337 (−2.81)***	−0.0766 (−1.46)
Edudc	0.0173 (0.39)	−0.0106 (−1.18)
Hhresid	−0.4127 (−1.05)	0.0414 (0.53)
Ttlabour	0.1017 (1.23)	0.0165 (1.25)
CAbenefit	0.5315 (1.38)	0.0301 (0.27)
tenureperc	−0.1366 (−0.46)	−0.0067 (−0.14)
Farmexp	−0.0546 (−1.79)*	−0.0040 (−0.81)
Farmexpsqd	0.0006 (1.15)	0.0001 (1.41)
Basinyrs	0.2887 (4.66)***	0.0131 (1.66)*
Mulchyrs	−0.0505 (−0.60)	0.0116 (1.46)
Rotatyrs	0.0373 (2.23)**	−0.0036 (−1.38)
Landendow	0.4962 (2.57)**	0.0334 (1.70)*
Fence	−0.2432 (−0.50)	−0.0591 (−0.85)
Plough	−1.2923 (−3.47)***	−0.1550 (−2.16)**
LU	0.0249 (0.42)	0.0095 (1.19)
Liquidity	0.1068 (0.74)	0.0155 (0.84)
Distnmkt	0.0134 (0.80)	−0.0082 (−2.27)**
Distagri	−0.0901 (−2.52)**	0.0107 (1.51)
CAinput	0.1576 (0.4)	
CAhlab		0.0923 (1.47)
Advsocial		0.1083 (1.85)*
CAextcur		0.0797 (1.55)
Constant	−0.2185 (−0.18)	0.0440 (0.19)
Wald statistic (18)	53.76***	
Number of observations	237	

Notes: ***, ** and * denote 1%, 5% and 10% significance levels respectively. Figures in parentheses are *z*-values.
Source: Estimated from sample survey data.

to make better judgements by comparing the new technology with conventional techniques. In addition, some researchers have argued that CA becomes easier with time (Mazvimavi & Twomlow, 2009). As expected, experience with reduced tillage techniques had a positive influence on both adoption and intensity. Those who have practised reduced tillage for a long time are likely to continue practising this component. This is consistent with findings by Pedzisa *et al.* (2015a). Similarly, experience with crop rotation had a positive impact on adoption, but had an insignificant impact on intensity. General farm experience had a negative impact on adoption of CA components, but did not influence intensity. However, the negative impact diminishes with increasing experience. This may suggest that more experienced farmers are likely to stick to their traditional farming techniques.

Farmers with larger farms were more likely to adopt CA components, with regression results showing a significant positive impact on both adoption and intensity. This is consistent with findings by Nakhumwa and Hassan (2003). Farmers with larger landholdings face less risk experimenting with new technology. Larger farms also make adoption more profitable as returns to adoption are scale dependent while significant costs of adoption are not, especially information and *ex-ante* transaction costs. These fixed costs give rise to size economies even when the technology itself is highly divisible. Ownership of an ox drawn plough had a significant negative impact on both adoption and intensity. This result was expected as conventional tillage is less labour intensive than reduced tillage.

Receipt of free CA inputs in the past had no impact on current adoption decisions. This suggests that finite subsidies do not sustain ongoing use of CA technologies. In the absence of free inputs, access to inputs was measured by distance to the nearest market (Kassie *et al.* 2013). Even though access to inputs does not necessarily mean ability to buy, it can be a proxy for measuring the role of markets. The results show that distance from the nearest market (Masvingo town) was not a significant determinant of CA adoption, but had a significant negative impact on the intensity of its uptake. Farmers located further away from the market are more likely to incur higher transport costs, especially when confronted with poor physical infrastructure. Farmers may also believe that CA cannot be practised without applying fertiliser as the use of complementary inputs was emphasised when the technology was introduced (Pedzisa *et al.*, 2015b). Kassie *et al.* (2013) highlighted that complementarity affects technology productivity and adoption.

As expected, increasing distance from public extension services reduced adoption, but neither distance from government extension officers nor the delivery of public CA extension during the 2014–2015 seasons had any significant impact on the intensity of CA uptake. On the other hand, advice taken from social networks increased the intensity of CA uptake. This is consistent with findings by Kassie *et al.* (2013). In the presence of imperfect markets, social networks reduce the transaction costs associated with information acquisition. Social networks may substitute for public extension services, particularly where these services are resource constrained. Public extension usually relies on direct contact methods involving field visits or gathering farmers at a convenient centre. Training services provided by NGOs may also have displaced government extension staff.

Contrary to expectations, farmer perceptions of tenure security and the long term benefits of CA did not have a significant impact on either adoption or intensity decisions. This finding was not unexpected as there was little variation in the dummy variables used to measure farmer perceptions. Pervasive negative perceptions may well contribute to low levels of adoption and intensity even though they do not explain variation in adoption and intensity.

5.6 Sensitivity analysis – an overview of scenarios using alternative methods to measure adoption and intensity

This section attempts to show how the results change when the model is estimated using alternative measures for CA intensity. Five scenarios (Table 7) were compared with the CAI developed for this study.

The first three scenarios simply drop or modify certain components of the CAI to test alternative measures of uptake, while scenarios 4 and 5 attempt to replicate other approaches used in previous studies. Scenario 1 computes an index that omits R, the rate at which CA components were used. Scenario 2 presents an index that uses equal weights (W) for CA components. This assumes that

Table 7. Scenario analysis of alternative approaches used to measure adoption and intensity.

Variable	Complete index (CAI) $\Sigma W_{ir} R_{ir} P_{ir} S_{ir}$	Scenario 1 $\Sigma W_{ir} P_{ir} S_{ir}$	Scenario 2 $\Sigma W_{ir} R_{ir} P_{ir} S_{ir}$	Scenario 3 $\Sigma W_{ir} R_{ir} P_{ir}$	Scenario 4 $\Sigma W_{ir} R_{ir}$	Scenario 5 ΣP_{ir}
Decid	–	–	–	–	+	+
Edudc	–	–	–	–*	–	–**
Hhresid	+	+	+	+	–	+
Ttlabour	+	+	+	+	+	+
CAbenefit	+	+	+	+	+	+
tenureperc	–	–	–	+	+**	–**
Farmexp	–	–	–	–*	–	–
Farmexpsqd	+	+	+	+**	+	+
Basinyrs	+*	+	+	+**	+	+
Mulchyrs	+	+*	+**	+*	+	+
Rotatyrs	–	–	–	–	+	–
Landendow	+*	+*	+*	–*	–	–***
Fence	–	–	–	–	–	–
Plough	–**	–**	–**	–***	–	–**
LU	+	+	+	–	–	+
Liquidity	+	+	+	+	+	+
Distnmkt	–**	–**	–*	–	+*	–
Distagri	+	+	+	–	–***	+
CAhlab	+	+	+	+*	+	+
Advsocial	+*	+**	+**	+	–	+
CAextcur	+	+	+	+**	+**	+
Constant	+	–	–	+*	–	+***

Notes: ***, ** and * denote 1%, 5% and 10% significance levels respectively.
Source: Estimated from sample survey data.

all components have the same level of importance. Scenario 3 excludes the scale factor, *S*, which controls for cases where farmers could be assigned equal weights despite applying CA on different sized plots. Scenario 4 excludes altogether the area under which CA components are implemented (i.e., both *P* and *S* are dropped from the index). This has similarities to the measure used by Mazvimavi and Twomlow (2009), although in their approach they use more than three components, which were allocated equal weights and ignored variations within components. Similarly, Pedzisa *et al.* (2015b) used a count regression which merely counts the number of components used and ignored the area under CA components. Finally, scenario 5 was defined using only the proportion of area allocated to CA components, omitting *W*, *R*, and *S*. This is similar to the approach taken by Arslan *et al.* (2014) and Ngwira *et al.* (2014), which ignores the number of components used and variations in their rate of application. The results from these alternative scenarios are summarised in Table 7.

While the result of scenarios 1 and 2 were similar to those of the CAI, this was not true of scenarios 3, 4 and 5. In scenario 3, 4 and 5, scale is neglected, making it possible for farmers applying CA on very different areas to obtain the same or similar score. Moreover, in some instances, farmers who intensively apply CA on small areas can obtain higher scores than farmers who apply one or two CA components on relatively large areas. This creates a misleading view of CA uptake and distorts the influence that different factors have on intensity. The main implication of the sensitivity analysis is that alternative specifications of the CAI applied to the same dataset produce very different findings about the factors influencing intensity. This highlights the need for standardised measures that facilitate cross-contextual comparisons. The CAI used in this study improves on previous measures of CA adoption and intensity as it explicitly accounts for the number of components used, their relative importance, and the extent and level of their application.

6. Conclusions and recommendations

Decomposing CA into its components made it possible to draw informed conclusions about actual farmer practice, adoption, and intensity levels. Farmers in the study area rarely implemented CA as an indivisible technology. Most of the farmers only implemented the reduced tillage component (basin digging) of CA. There were only a few instances where sampled farmers implemented more than one component, with just 1.3 per cent of the cultivated plots in the sample using all three components.

These differences in the levels of uptake within CA components justify the computation of an index that is able to capture partial adoption. The sensitivity analysis further illustrated that using an incomplete measure of intensity (excluding other factors) yields different results. This partially explains the reason for mixed and inconsistent findings in the literature.

The double hurdle model provided useful insights to the factors influencing the adoption and intensity decisions. The regression results revealed that participation of females in decision-making, experience with technology, land endowment, and proximity to public extension officers all had positive, significant impacts on adoption. On the other hand, the intensity of adoption was positively and significantly influenced by land endowment, experience with technology, proximity of input markets, and access to informal extension support. Ownership of a mouldboard plough had a significant negative impact on both adoption and intensity.

A number of policy conclusions arise from this analysis. First, improving smallholder access to arable land might ease the land endowment constraints that reduce the uptake of CA. The survey data showed that farmers who had larger farms were more likely to be more intensive users of CA components. If land constraints were relaxed, farmers would face less risk allocating land to the production of legume crops (or practising crop rotation) and adopting more CA practices. A well-functioning land rental market would help in this regard, allowing farmers to benefit from size economies while generating rental income for neighbours that do not farm all of their land. However, land rental markets may not function well under customary tenure arrangements in rural Zimbabwe.

Second, there is also a need for greater innovation in conservation practices that accommodates the use of draught power. The results showed that farmers who owned a mouldboard plough were less likely to adopt CA components. CA technologies that include the use of ox-drawn implements may be more attractive to these farmers. Mechanised CA technologies should be developed in a participatory manner with farmers.

Third, improved access to farm inputs in local shops could encourage farmers to make greater use of CA techniques. The regression results showed that farmers located closer to input markets are more likely to be intensive users of CA components. Demand pull interventions like contract farming would encourage entrepreneurs to service local farmers, and would be more sustainable than delivering 'free' inputs to farmers as practised in Zimbabwe's initial CA projects. However, contract farming requires an economic environment that is attractive to private investors, and legal infrastructure that can be relied on to set precedents that uphold contracts.

Lastly, there is a need to re-visit the extension practices associated with CA. The regression results showed that CA adoption diminished with increasing distance from public extension services and that the intensity of CA uptake increased with access to advice from social networks. In addition, the results showed that farmers who practise CA for a long time are more likely to continue using the technology. These results suggest that farmers should have ongoing access to extension support, and that farmer-led extension via producer groups could be an effective mode of delivery. Public extension agencies and NGOs delivering outsourced extension services should facilitate this process.

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Notes

1. The research presented in this article was reported in a thesis submitted by the first author in partial fulfilment of the Master of Commerce (Agricultural) degree at Lincoln University, and supervised by the co-authors.
2. Adult equivalent = Number of adults + 0.5 (number of children (<12) + number of pensioners (>65)).

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