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Abstract

Enhancing adoption rates of climate-smart agriculture practices and their impact on livelihoods requires promotional persistence, complemented by a thorough socioeconomic analysis that recognizes the heterogeneity of smallholder farmers. Farm typologies are a useful tool to assist in understanding and un-packing the wide diversity amongst smallholder farmers to improve both up and out-scaling of climate-smart agriculture practices. Our study typifies farm households in southern Africa based on socio-economic factors prompting adoption of climate-smart agriculture practices. We use a combination of principal component analysis for necessary data reduction and cluster analysis to identify typical farm households and their socio-economic characteristics. It is evident from our results that various socioeconomic factors define clusters and can be associated with adoption and use of climate-smart agriculture practices in smallholder farming. We conclude that farm typology identification is an important step towards the promotion of climate-smart agriculture practices in smallholder agriculture. These typologies provide essential ammunition to support efforts and policies aimed at improving adoption by recognizing heterogeneities in the targeted populations. In addition, we conclude that the multivariate analysis provides useful tools suitable for identifying the important socio-economic characteristics of households influential in determining adoption of climate-smart agriculture practices.

Keywords: Climate-smart agriculture; Farm household typology, Multivariate analysis, Adoption; Southern Africa;

Background and Introduction

Climate variability and change pose a major challenge to agricultural production and rural livelihoods of smallholder farmers. Rising temperatures and changes in precipitation patterns are adversely impacting biodiversity, amplifying existing stress on water supplies, worsening vulnerability of agricultural systems especially among smallholder farmers and escalating climate-related health outcomes (IPCC 2014). Farmers in Africa adapt to climate variability and change in a multiplicity of ways (see Deressa et al. (2009); Thomas et al. (2011); Mugi-Ngenga et al. (2016)). There are significant efforts taking place to develop, deploy, and scale up climate-smart agriculture (CSA) practices (technologies and methods) to facilitate adaptation to climatic changes by farmers (Lipper et al. 2014). For example, Africa Climate-smart Agriculture (ACSA) Alliance has set a new target of twenty-five million African farmers practicing CSA by 2025 (Murray et al. 2016).

Climate-smart agriculture (CSA) as defined by FAO (2010) is agriculture that sustainably increases productivity, enhances the resilience of livelihoods and ecosystems, reduces and or removes greenhouse gases (GHGs) and enhances the achievement of national food security and development goals (Jirata, Edward, and Sebastian 2016). CSA, therefore, includes proven practical agricultural techniques such as integrated crop-livestock management, agroforestry, mulching, intercropping, crop rotations, conservation agriculture, improved grazing and improved water management. It also involves the adoption and use of innovative practices such as improved weather forecasting, early warning systems, and climate risk insurance (Murray et al. 2016). In a nutshell, CSA aims to get proven existing technologies off the shelf and into the hands of the farmers, as well as to develop new technologies such as drought-tolerant crops to meet the demands of the rapidly changing climate.

The majority of smallholder farmers in sub-Sahara Africa (SSA) cultivate small, fragmented pieces of land yet they are the key food producers (Chamberlin 2007, Wiggins 2009). This remark signifies that smallholder farmers constitute an essential part of the rural community in Africa. The significant adoption of CSA practices and their success in improving livelihoods will likely exert a noteworthy impact on the African rural communities. Smallholder farmers are, however, perceived to share certain characteristics which differentiate them from large-scale commercial farmers. These characteristics include high levels of vulnerability and low market participation, limited access to productive resources such as land, finance, and inputs (Chamberlin 2007, Kuivanen, Alvarez, et al. 2016). However, as cited in Tittonell et al. (2010) and Kuivanen, Alvarez, et al. (2016) the micro and macro-level structures, constraints and drivers of smallholder and commercial farming systems are different. It, therefore, means that not all smallholder farmers are equally resource-poor, land-constrained or market oriented. Similarly, the adoption and use of CSA technologies in smallholder farming communities cannot be perceived as homogenous. This observation implies that any efforts to develop or understand the smallholder farming sector in terms of various aspects including the adoption of climate change adaptation technologies and practices and the use of other productive inputs ought to start with an acknowledgement of this salient heterogeneity.

In the past three decades, research efforts in SSA have been targeted on the development and promotion of low-cost technologies, suitable for the smallholder farming sector (Bidogeza et al. 2009). Recently, with the need to address multiple challenges of declining yields, poor soil fertility, land degradation, food insecurity and increased agricultural risk exacerbated by climate change, the focus has shifted to promotion of significant and proven technologies that offer adaptation to climate change (Murray et al. 2016, World Bank and CIAT 2015). Several technologies in the world today are a part of this classification. These technologies include but not limited to green manure, composting, mulching systems, farm yard manure combined with other fertilizers, crop diversification, cereal-legume intercrops, agroforestry, conservation agriculture and stress tolerant crop varieties such as drought tolerant Maize. However, despite the positive effects of these technologies and or practices including improving productivity, enhancing resilience in livelihoods and ecosystems and mitigating climate change their adoption in smallholder farming remain low (Bidogeza et al. 2009, Kassie et al. 2008, Teklewold, Kassie, and Shiferaw 2013, Wollni, Lee, and Thies 2010).

Failure to recognize the heterogeneity among smallholder farming systems could be a factor constraining CSA adoption e.g. in soil fertility management strategies (Giller et al. 2011). Assuming homogeneity of smallholder farming systems in promoting and up-scaling of CSA technologies and or practices can be an important barrier to effective adoption. According to World Bank, FAO, and IFAD (2015), the knowledge, resources and capacity required to adopt a new CSA practice can be significant. Thus, scaling-up and scaling-out of CSA practices (technologies & methods), heterogeneity in farming systems in access to and control of productive resources including other socioeconomic characteristics need to be factored into the design, delivery, and diffusion of the technologies and practises. Accounting for these heterogeneities enhances our understanding of the opportunities and or constraints of CSA adoption (Murray et al. 2016). Also, enhancing the adoption rates of CSA practices and their effectiveness on the livelihoods of the population requires constant promotion of CSA practices, complemented by a thorough socioeconomic analysis that recognizes the heterogeneity of smallholder farming community (Huyer et al. 2015, Murray et al. 2016, Twyman et al. 2015).

The agriculture economics literature suggests artificially stratifying smallholder farming households into smaller and more homogenous subsets or groups as per specific criteria e.g. having the same resource base, livelihoods, opportunities and constraints (Köbrich, Rehman, and Khan 2003, Kuivanen, Alvarez, et al. 2016). The artificial stratification yields what are termed farm typologies. The choice of differentiating criteria is said to depend on a number of factors including the objective of the typology and the type of data present (Kostrowicki 1977). Results from farm typology analysis can support the implementation of a more tailored approach to agricultural development (Bidogeza et al. 2009, Kuivanen, Alvarez, et al. 2016). This remark implies that farm typology studies can be very useful in allowing proper implementation of a CSA strategy in smallholder farming. According to Chikowo et al. (2014), farm typologies are an essential tool in understanding and unpacking the diversity among smallholder farmers which helps to improve targeting of crop production intensification strategies. Farm typologies may also be useful in informing the academic study of farming system heterogeneity (Kuivanen, Alvarez, et al. 2016). For instance, they can be applied to assist in informing further exploratory studies through selection of representative farms for detailed characterization or in in-depth farming system analysis (Bidogeza et al. 2009, Kuivanen, Alvarez, et al. 2016). Modelling and simulation studies to evaluate potential effects of specific interventions of farming systems can also benefit from farm typology analysis (Andersen et al. 2007, Köbrich, Rehman, and Khan 2003). This implies that farm typology analysis can be of great importance in the assessment of the impact of climate-smart interventions on farm productivity, ecosystem resilience and livelihoods. For further appreciation of the practical relevance of farm typology analysis and its practical relevance in SSA, enthusiastic readers are referred to a review paper by Chikowo et al. (2014).

Against this background, the objective of this paper is to define farm household typologies in selected countries in Southern Africa, namely Zimbabwe, Malawi, Mozambique and Zambia with the aim of understanding if they exhibit different behaviour with regards to adoption and use of climate-smart agriculture (CSA) practices (technologies & methods). We primarily focus on socio-economic factors since they can affect CSA practices and technology adoption (Murray et al. 2016, Quisumbing and Pandolfelli 2010). Understanding why some smallholder farmers are early or heavy adopters of CSA practices is important and farm typology can provide some insights on that. Implications can be drawn on whether early or heavy adopters are those smallholder farmers who are heavily resourced (i.e. have higher levels of capital), have particular ability or power to adopt (maybe because of their education or social networking) or are motivated to change their existing practices (Murray et al. 2016). Results from the analysis are expected to produce crucial information needed in promoting, intensifying, scaling up and scaling out of CSA interventions. Precisely, information obtained will reveal key information needed to diagnose and understand the problems and opportunities for change regarding the uptake and use of CSA practices. Additionally, the results from the typology analysis can be used in further research on CSA promotion and or impact assessments.

This study is unique as it is one of a few to focus on the dynamics of CSA practices adoption precisely using the farm household typological approach. However, there are some closely related studies that have relied on the same approach in defining farm household typologies in smallholder farming based on socioeconomic characteristics that influence technologies adoption. For instance Chikowo et al. (2014) defined farm household typologies based on socioeconomic characteristics that influence adoption of nutrient management technologies and Bidogeza et al. (2009) who typified farm households based on socioeconomic characteristics that prompt adoption of new farming technologies in general. No specific study known to the researchers at the time of this research have relied on farm typologies to assess the dynamics in CSA practices adoption in studied areas, thus, making our study novel and unique.

Our empirical approach adopts multivariate statistical techniques that allow us to create farm household typologies especially when an in-depth database is available (Bidogeza et al. 2009). Specifically, we use a combination of Principal Component Analysis (PCA) for necessary data reduction and cluster analysis to identify typical farm households following studies by Gebauer (1987); Hardiman, Lacey, and Yi (1990); Solano et al. (2001); Köbrich, Rehman, and Khan (2003); Usai et al. (2006); Bidogeza et al. (2009); Tittonell et al. (2010) and Kuivanen, Alvarez, et al. (2016). Both methods have been proven to be very useful despite their potential and known weaknesses. For instance, previous research has noted that PCA leads to a loss of information (Jolliffe 2002, Lattin, Carroll, and Green 2003) while according to Alfenderfer and Blashfield (1984) Cluster Analysis has the problem of choosing the proper number of clusters (Bidogeza et al. 2009).

Main study hypothesis and research question

The main question to be answered by this research is whether farm household typologies as defined by farm and farmer socioeconomic characteristics exhibit significantly different patterns in selected CSA practices adoption. Precisely, we ought to find out whether differences in households' socioeconomic conditions can have a significant bearing on farm-level adoption of certain CSA practices. We hypothesise that CSA adoption patterns in different farmer groups (defined by socioeconomic conditions) are significantly different as farmer socioeconomic conditions might have a bearing on farm level CSA adoption decisions.

Organization of the paper

The rest of the paper is structured as follows; section 2 describes the research methods used in this article while section 3 reports the study findings and discussions. Section 4 concludes the paper and gives policy suggestions.

Materials & Methods

Study Areas description, Sampling and Data Collection

This study uses data collected from Zimbabwe's smallholder farming areas (shown in Fig.1) and some parts of the Chinyanja Triangle (CT) found in Zambia, Malawi and Mozambique (Shown in Fig. 2.). A combination of data sets obtained from different smallholder farming systems is used in the paper. Authors felt relying on a combination of data sets from smallholder farmers in slightly different geographical settings could give more reliable outcomes on the different socioeconomics conditions that prompt or constrain the uptake of different climate-smart agriculture practices in smallholder farming systems of southern Africa.

Data from Zimbabwe are drawn from surveys of smallholder producers in Zimbabwe's four districts namely; Goromonzi, Mudzi, Wedza and Guruve. About 601 smallholder farmers in the four district were interviewed. The sampling frame of smallholder farming households in the four districts was obtained based on agro-ecological potential and market access of which Goromonzi and Guruve are high potential agro-ecological zones, while Hwedza and Mudzi are in low and marginal potential zones. Brief descriptions of activities and agro-ecological conditions prevailing in the studied districts can be found in Mango et al. (2015); and Mugandani et al. (2012). Household surveys were conducted in each of the four districts by trained enumerators.

[**Insert Figure 1 Here**]

Commissioned by the International Centre for Tropical Agriculture (CIAT), the household surveys collected data on a number of characteristics including household socioeconomic characteristics, crop production, management and marketing, farming technology adoption and use, use of climate-smart agriculture practices, land use, access to information and many other social, economic, institutional and environmental characteristics associated with farming households in the four districts. Climate-smart agriculture practices covered include; conservation agriculture, crop diversification, adoption and use of improved varieties such as drought tolerant maize, and Integrated Soil fertility management methods (ISFM) (crop rotation, mulching, green manure application etc.) which are also climate-smart. The random sampling technique was used to select wards (i.e. small geographic units) in each of the four districts and individual households interviewed. Lists of households were provided by denizen agricultural extension agents. Data was collected between November and December 2011.

We also analyze a dataset collected within the Chinyanja Triangle (CT) of southern Africa. The CT is found in three southern African countries, Zambia, Mozambique, and Malawi. Data on CT was collected from the Central region of Malawi, Eastern province of Zambia and Tete province of Mozambique (see Fig. 2). Specific sites in which data were collected are shown in Fig 2 and include areas sampled for the CGIAR Research Program on Dryland Systems and Africa Research in Sustainable Intensification for the Next generation (RISING) projects. The CT is inhabited by households which share a lot in common including language (Nyanja), beliefs, and history, proposing similitude in methods to land management and resource use (Amede et al. 2014, Mapila et al. 2012). Land tenure regulations of countries within CT differs but usufruct rights at local scale are similar. Locally, chiefs are the overseers of all the land within the jurisdiction of their chiefdoms and it is shared and or reassigned mainly through a matrilineal lineage system (CGIAR 2013). Two biggest challenges within the CT are water scarcity and erratic weather or climatic conditions (CGIAR 2013). For a further description of the CT readers are referred to Myburgh and Brown (2006); Mapila et al. (2012); CGIAR (2013); and Amede et al. (2014).

Three hundred and twelve (312) households were sampled from a spatial sampling framework developed for land degradation and surveillance framework (LDSF), using multistage spatially stratified random sampling of plots in a landscape (Vågen et al. 2010). A household survey was then conducted to gather primary data used for this research. Data collected included household socio-demographic characteristics, resource endowments, crop production, management and marketing, adoption and use of climate-smart (sustainable) agriculture practices and technologies e.g. crop diversification, integrated soil fertility management, land, soil and water conservation technologies. Trained enumerators, extension personnel and research officers were involved in data collection. All the data was collected between December 2012 and June 2013.

Despite the fact that the two different data sets used were from different projects and were collected at different times, they fit under the same theme of Climate Change Agriculture and Food Security (CCAFS) and suited well in answering the main study research question. This justifies why authors relied on different data sets in this study.

[**Insert Figure 2 Here**]

Multivariate Statistical Analysis

This study examines household-level data from smallholder farmers in the CT area and from four districts in Zimbabwe namely Guruve, Mudzi, Wedza, and Goromonzi to construct farm household typologies. The multivariate techniques employed in the empirical analysis are of the type used in Makate, Makate, and Mango (2018), Makate and Mango (2017), Bidogeza et al. (2009) and many other related studies (Nainggolan et al. 2013, Carmona et al. 2010, Köbrich, Rehman, and Khan 2003, Kuivanen, Michalscheck, et al. 2016). Firstly, a Principal Components Analysis (PCA) was conducted, a technique which is necessary to summarize the data sets into smaller and non-correlated dimensions or components (Vyas and Kumaranayake 2006). Next, a two-stage Cluster Analysis technique was employed to characterize the smallholder farmers in the selected districts in Zimbabwe and the CT area. As noted in Lewis-Beck (1994), Bidogeza et al. (2009) and Makate, Makate, and Mango (2018), summarizing the data through PCA is an important step before undertaking the cluster analysis to the data set.

Prior to proceeding with the PCA approach, the Bartlett's test (Bartlett 1950) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy were performed to evaluate the appropriateness of the variables to be used as inputs to the PCA approach (Field 2009). The Bartlett's test of sphericity checks the null hypothesis that the inter-correlation matrix came from a population in which the variables to be used in the PCA are all non-collinear (i.e. an identity matrix (Field 2009). The results from this test using the survey data for Zimbabwe revealed a significant test (Chi-square = 3418.002; p-value = 0.000) suggesting that the variables are uncorrelated hence suitable for a PCA. On the other hand, the KMO test compares the correlations and the partial correlations between the variables with a small KMO suggestive of highly correlated data. Using the Kaiser (1974) characterization of the KMO values revealed that the sudy's KMO statistic of 0.719 is middling (borrowing the terminology in the STATA 2009 manual) (StataCorp 2009) and suggestive of less correlated data. Similarly, the survey data from the CT sample revealed a significant Bartlett test (Chi-squared = 2848.966; p-value = 0.000) and a KMO statistic of 0.703 which all support the appropriateness of the analysed data for the multivariate analysis procedures.

The PCA approach followed the Kaiser criterion of retaining all the components with eigenvalues greater than one. Also, to simplify the interpretability of the PCA results the components were rotated using the Kaiser's normalization applicable when the number of variables does not exceed 30 (Field 2009), which is the case with the analysed data. This approach has also been applied in recent and related studies (Bidogeza et al. 2009, Makate, Makate, and Mango 2018, Nainggolan et al. 2013). The resulting PCA components are then used as inputs to the cluster analysis to characterize the different clusters of smallholder farmers existing in the selected districts in Zimbabwe and the CT area. To better understand the farm household typologies of the smallholder farmers in these respective study areas, a commonly used hierarchical clustering technique called the Ward's procedure was employed to define the number of groups G_i (Ward Jr 1963). Furthermore, a non-hierarchical, apportioning procedure to refine the created G_i groups was employed following Hair (2010). The Ward's clustering criterion combines all the objects that result in an increase in overall within-cluster variation to the smallest degree (Mooi and Sarstedt 2010). Since there is no single procedure applicable to select the minimum number of clusters, approaches adopted in Köbrich, Rehman, and Khan (2003) Bidogeza et al. (2009) and Makate, Makate, and Mango (2018) were followed in this study and a total of six clusters were requested from the cluster analysis. To generate the optimal number of clusters, the study also utilized the dendrograms created from Ward's approach together with an expert knowledge of the study areas. The dendrogram is a pictorial depiction of the hierarchy of the nested cluster solutions (Schonlau

2002). Additionally, a one-way analysis of variance (ANOVA) was performed to identify the differences in variability between the generated clusters (Field 2009). This approach helps in identifying specific variables that contribute to the biggest differences between the clusters. All the analysis was conducted in STATA version 13.0 with the relevant cluster commands (Stata 2013).

Results & Discussions

Households characterization and use of Climate-smart agriculture practices (technologies and methods)

Descriptive statistics of all the variables used in the analysis are shown in tables 1 and 2. We give definitions for all variables used and report summary statistics (mean and standard deviation). Table 1 reports the summary statistics for variables included in the multivariate analysis for the Zimbabwean sample whilst table 2 reports the summary statistics used for the CT sample. We show them separately as the data sets used for the analysis are not 100% similar as they were collected using different research instruments (questionnaires).

[**Insert Table 1 Here**]

Socio-economic & demographic characteristics

The descriptive statistics reveal that nearly 87% of the smallholder farmers in the respective areas are full-time farmers. This could reflect high levels of commitment of farmers in the respective areas to the farming business. Farming experience can be influential in the adoption and utilization of climate-smart technologies (same with other technologies) in farming. According to Feder and Umali (1993) risk perceptions related to new technologies diminish over time through the acquisition of farming experience and information. The average years of farming experience for the farmers in our Zimbabwean and CT samples is about 20 years.

Our results also report higher proportions of married household heads (74.4%) in the Zimbabwean sample and (83%) in the CT sample which is a sign of stable family institutions. Marital status reflects the strength of the family system and can have knock-on effects on technology adoption and productivity *ceteris paribus*. Gender-linked differences in accessing complementary farming inputs can be instrumental in technology adoption (Doss and Morris 2000). In our two samples, only 24.3% of the households in Zimbabwe and 17.0% in CT were female headed.

The education of the farmer and technology adoption have a positive correlation that is well acknowledged in the adoption literature (Asfaw and Admassie 2004, Mahapatra and Mitchell 2001, Onu 2006, Tenge, De Graaff, and Hella 2004). Educated farmers are expected to relate technology adoption to the betterment of their farming activities and are also more likely to take shorter time to adopt technologies (Upadhyay et al. 2003). In the Zimbabwean sample, 47.8% of the farmers had attained at least secondary education. In the CT sample literacy rate (able to read and write) was nearly 88.5% and average years in formal education for the household head stood at 5.05 years. Regarding age, farmers from Zimbabwe are relatively older with an average age of about 51.43 years as compared to 46.59 years in the CT sample. Concerning farming experience, as the age of the household head increases, the household acquires more farming experience, becomes more risk averse and diversifies its production (Bogale and Shimelis 2009) which can increase their appetite for new technology.

Labour availability is one important variable that can influence farmers' decision to adopt agricultural technologies, practices and or inputs (Feder, Just, and Zilberman 1985). Households with larger family sizes and higher number of farm workers are expected to accomplish various agricultural tasks as noted in Deressa et al. (2008). However, a negative influence of labour can be expected as in some cases families with many members may divert or engage in off-farm activities in order to earn extra income to ease consumption pressures exerted by a larger family size (Deressa et al. 2008). Moreover, some new technologies are labour demanding while others are labor saving. For example Rusinamhodzi (2015) found that the promotion of plant basins in conservation agriculture increases labour demand in the Murehwa district of Zimbabwe, while in Mexico, a serious shortage of labour motivated new landowners to adopt new technologies (Francis and Atta-Krah 1989). Our results report mean household sizes of 5.27 and 5.87 in Zimbabwe and CT respectively. In terms of household member who are fit to provide labor results report means of 3.25 in Zimbabwe and 3.29 in the CT.

Our results report average annual incomes from farming of US$ 810.00 for the Zimbabwean sample and US 226.14 for the CT sample. In addition, engagement rate in off-farm activities was 25.1% and 32.7% for the Zimbabwean and CT samples respectively. Engagement in off-farm activities can diversify income sources for the rural population, hence a way of averting risk and uncertainty on the farm (Bidogeza et al. 2009). Income is another important determinant of technology adoption in smallholder agriculture (Bidogeza et al. 2009, Moser and Barrett 2006). Even in the economic paradigm of technology adoption, the income model take farmers as profit maximizers who adopt technologies that will increase net returns to their farming enterprises (Mansfield 1961, Upadhyay et al. 2003).

Empirical studies have found arable land size to be an important determinant of farm technology adoption (Feder and Umali 1993). For instance, Pomp (1994) found that relatively small farm sizes impede adoption and efficient use of irrigation equipment , such as pumps and tube wells. Furthermore, Nkonya, Schroeder, and Norman (1997) and Jamison and Moock (1984) demonstrated that farm size significantly and positively influenced adoption of improved maize seed and fertilizers respectively. Our results report average arable land sizes (in hectares) of 2.34 and 3.94 in Zimbabwe and CT respectively. In addition, land allocated to maize crop per season was found to be 0.83 hectares in Zimbabwe and 2.06 hectares in the CT. Maize is the main staple crop grown in the two study areas (see Myburgh and Brown (2006) for CT and Mango et al. (2015) for Zimbabwe), and therefore can have an influence on technology adoption in farming.

Agriculture extension access is another important source of information for farming communities. Agricultural extension officers link farmers with research and they decode information from researchers into a language and format that farmers can understand. In addition, they also provide feedback from farmers to the researchers. It, therefore, implies that extension access and frequency of extension services can be important determinants of technology adoption. Several studies have reported use of extension services to be an important determinant of technology adoption (see Hassan and Nhemachena (2008); Bekele and Drake (2003); Tizale (2007)). In Zimbabwe, average times each farmer has contact with agricultural extension workers per farming season was about 4.13 times.

Resource endowments (e.g. farm assets and other equipment) can influence farming technology adoption at household level (Bidogeza et al. 2009, Moser and Barrett 2006). Households who own or have access to resources are more liable to have more chances and ability to adopt new technologies. In the Zimbabwean sample, the average number of cattle owned per household was about 2.41, mean poultry units owned was 11.82, and the average number of hoes owned per household stood at 5.41 hoes. Also, ownership of oxcarts was 37.8%, 58.9% for ploughs, 49.4% for wheelbarrows, 30.8% for sprayers and nearly 78.4% owned a mobile phone. On the other hand, mean cattle owned in the CT sample was 1.46, ownership rate of poultry was at (10.6%), average number of hoes per household was 4.18, ownership rate of oxcarts was at (8.7%), plough ownership rate (12.5%), wheelbarrow (100%), sprayer (17.9%), and cell phone (42.6%).

[**Insert Table 2 Here**]

Use of climate-smart agriculture related technologies/practices

Crop diversification

We measure crop diversification as the number of crops grown in a season by the farmer in this study. Results reveal that in both Zimbabwe and the CT, farmers on average grow two or more crops per season. Crop diversification is important and considered climate-smart because it can be one ecologically feasible and cost effective way of reducing uncertainties in smallholder agriculture (Joshi 2005), increases resilience and brings spatial and temporal biodiversity on the farm (Joshi 2005, Lin 2011) improves soil fertility, controls for pests and diseases, and brings about yield stability, nutrition diversity and health (Lin 2011).

Conservation agriculture

Conservation Agriculture is a combination of soil management practices that include crop rotations, soil cover (through mulching) and reduced soil disturbance. In the Zimbabwean sample, farmers indicated whether they were practicing conservation agriculture or not at the time of the survey and (30.8%) were reported to be practicing conservation agriculture. Conservation agriculture is regarded as climate-smart mainly because it promotes water and soil conservation, facilitates carbon sinks in soils, reduces nitrogen loss in the soil and increases yields and income at farm level (World Bank and CIAT 2015).

Drought tolerant maize

Stress tolerant varieties are bred specifically to adapt to climatic change extreme events (e.g. drought) in a particular region (Asfaw et al. 2015). Drought tolerant maize is one technology meant to ease adaptation in drought prone areas of SSA. Drought tolerant maize is also considered climate-smart since it builds resilience by increasing yields and reducing vulnerability in maize–based farming systems (Rovere et al. 2014). Moreover, drought tolerant maize is said to be free from genetic modification, and have additional traits such as disease resistance to major maize diseases, high nitrogen use efficiency and high protein content (Fisher et al. 2015). In the Zimbabwean sample, about (68.7%) of the farmers had adopted drought tolerant maize at the time of the survey.

Integrated soil fertility management (ISFM) methods and irrigation

Integrated Soil Fertility Management (ISFM) is a framework that suggests the progressive adoption of a combination of practices that can maximize agronomic use efficiency of nutrients applied to the soil and improve crop productivity (Vanlauwe et al. 2010). It includes complementary effects of technologies such as improved crop varieties, good husbandry practices, and use of both inorganic and organic fertilizers. In the Zimbabwean sample, only the use of fertilizers (basal) and organic manure was captured in the data set and included in the analysis and rate of adoption is 60.1 and 46.6% respectively. Most of the other related ISFM practices are covered under the conservation agriculture bracket. In the CT area, several practices falling under ISFM were captured individually including; adoption and use of land, soil and conservation methods (e.g. water harvesting, use of contour ridges, ripping etc.) (79.2%), use of inorganic fertilizers (59.6%), crop rotation methods (50.3%), irrigation (49.4%), green manure application (42.9%), cereal-legume intercrops (31.1%), fallow (22.4%), agroforestry (14.7%), compost (14.1%), liming (3.5%) and mulching (2.6%). A combination of these practices may be beneficial at the farm level through an improvement in soil fertility, reduction in soil and land degradation, offering local climate change mitigation and adaptation, improving livelihood outcomes (income, food and nutrition security) (Vanlauwe et al. 2010), hence fits well under the climate-smart bracket.

Principal Component Analysis results and discussions

The results from the KMO and Bartlett sphericity test showed that the variables under study are related (in both cases Zimbabwe and CT), hence justifying the use of PCA. A total number of 26 variables from 601 smallholder households were included in PCA for the Zimbabwean sample (Table.1) whilst 30 variables from 312 smallholder households were used in PCA for the CT sample (Table.2). For the Zimbabwean data set the overall KMO was greater than 0.5 (0.719), while the Bartlett's sphericity test was significant (p-value = 0.000). The result for the CT was almost the same with overall KMO value at 0.698 and a significant Bartlett sphericity test (p-value = 0.000).

Principal component analysis results for Zimbabwe

Nine principal components with eigen values greater than one (1) explaining (60.20%) variability were retained for further analysis in the Zimbabwean case (Table. 3). From the results we could define each of the nine components according to the variables with which each component is most strongly associated. To ease identification of relatively larger loadings, correlations above 0.44 are indicated in bold. The first component (comp1), which explains (10.96%) of variance, is positively correlated with assets (cattle, ox-cart, hoes, plough, sprayer), household size and number of farm workers. Thus, we can say Comp1 represents assets and labor. The second component (comp2) explains about (8.34%) of the variance and is positively correlated with farming experience, age of the farmer and negatively correlated with female household headship and attainment of at least secondary education. Thus, Comp2 represents the experienced, less educated male farmers. Component 3 (comp3) represents (7.28%) of the variance and correlates negatively with household size and number of farm workers. The component thus imply that smaller families are the ones with labor shortages. The fourth component (comp4) explains (7.16%) of variability and correlate positively with the use of drought tolerant maize and basal fertilizers. This finding might possibly be suggesting that farmers who adopt drought tolerant maize are more liable to make use of basal fertilizers. The fifth component explains about (5.67%) variability and correlates positively with adoption of conservation agriculture, extension frequency and number of crops grown on the farm. This implies that farmers practicing conservation agriculture are more likely to diversify their crop production and they tend to receive extension services more frequently. The sixth component explains about (5.66%) variability and correlates positively with female household headship and ownership of cellphone. It thus implies that female household heads in that category are more likely to own a cellphone. Component 7 (comp7) correlates positively with total income from farming and full time farming. This could imply that fulltime farmers are more likely to earn higher returns from farming. The component explains about (5.62%) of the variability in the data. Components 8 (comp8) and 9 (comp9) explain nearly (9.51%) of the variability in total and correlate with farm size and use of organic manure respectively. Component 8 can thus be labeled farm size whilst component 9 can be named organic manure.

[Insert Table 3 Here]

Principal component analysis results for the Chinyanja Triangle

Ten principal components with eigen values greater than one (1) explaining (63.54%) variability were retained for further analysis in the CT sample (Table. 4). we could define eight of the ten components per the variables with which each component is most strongly associated. For easy identification of relatively larger loadings, correlations above 0.44 are indicated in bold. Component one (comp1) which explains (9.51%) variability, is positively correlated with total farm size, household size, ownership of plough, sprayer, livestock units (cattle), fallowing and crop rotations. Thus, it implies that households with relatively large farm sizes are more likely to have bigger family sizes, invest in livestock and farm implements (plough & sprayers) and practice fallowing and crop rotations. Component 2 (comp2) explains (6.82%) variability, and correlates positively with literacy, use of inorganic fertilizers, green manure and agroforestry and negatively with full-time farming and ownership of poultry units. The finding implies that the literate household heads are more liable to be part-time farmers, own no poultry units and embrace ISFM (inorganic fertilizers, green manure & agroforestry). Component 3 (comp3) correlates positively with married household heads and off-farm activities and negatively with female household headship. The component shares (6.76%) of variability and implies that, married male farmers are more likely to be engaged in off-farm activities. Component 4 (comp4) explains (6.42%) variability. The component can be named experience since it correlates positively with age and farming experience. Component 5 (comp5) correlates positively with the use of lime and compost and explains (6.24%) variability. Thus, the component could imply that farmers who apply lime are more likely to use compost manure as well. Components 6 (comp6) and 7 (comp7) explains (6 %) apiece to variance. Component 6 correlates positively with livestock units (cattle) and mulching, whilst component 7 correlates negatively with ownership of ox-carts. Thus, component 6 could imply those farmers with livestock (cattle) practice mulching. Component 7 stands for those households without ox-carts. The last three components (comp8, 9 & 10) explains (15.79 %) of variance. Only component 9 correlates highly and negatively with literacy. Component 9 is thus for the illiterate.

[**Insert Table 4 Here**]

Cluster Analysis results and discussions

The retained components from PCA were analyzed using Ward’s technique. Number of clusters retained must be realistic with respect to the empirical situation for them to be meaningful classification (Bidogeza et al. 2009). With that in mind, we requested a total number of 6 clusters from the cluster analysis. In addition to ensure we generate an optimal number of clusters, we also utilized the dendrograms created from Ward’s approach together with an expert knowledge of the study areas. Fig 3. & 4 show dendrograms for Zimbabwe and CT respectively.

[**Insert Figure 3 Here**]

The remaining six clusters for the studied areas appeared to represent close to the real situation on the ground based on the available data. We report the results from the cluster analysis including the p-values for the one-way ANOVA for each variable (equality of cluster means). Table 5 report results for the Zimbabwean sample while Table 6 reports for the CT sample. The more distinctive a variable is among the clusters (groups), the lower the p-value.

[**Insert Figure 4 Here**]

After obtaining established typologies representing smallholder farmers in the respective areas studied, we ask ourselves: what are the characteristics differentiating the obtained clusters? For the Zimbabwean sample, and judging from the p-values (shown in Table 5), factors such as total farm size, maize area, extension reception frequency, household size, number of farm workers, farming experience, off-farm activities, gender, marital status, engagement in full-time farming and asset ownership (cellphone, hoes, cattle, oxcart, plough, sprayer & poultry) seem to be significant in differentiating clusters. The same applies for climate-smart agriculture practice (methods & technology) attributes, we found the adoption of conservation agriculture, use of basal fertilizers and the adoption of stress tolerant varieties (drought tolerant maize) to be significant differentiating characteristics of the six clusters.

We obtain almost the same results for the CT sample (Table 6), factors such as farm size, and maize area, off-farm activities, number of farm workers, years of schooling and literacy, marital status, gender, fulltime farming, farming experience and age and asset ownership attributes (livestock, oxcarts, poultry, hoes, plough, wheelbarrow, sprayer) are significant in differentiating the 6 clusters defined from the CT sample. In addition, all climate-smart agriculture attributes selected (Table.6) were also significant in differentiating clusters. ISFM adoption highly explains differences across clusters. All the results imply that appropriate variables were chosen to construct the defined climate-smart agriculture practice (technology and methods) based typologies.

[**Insert Table 5 Here**]

[Insert Table 6 Here]

Description of Zimbabwean cluster characteristics

Six clusters, (Cluster 1-6) were defined from the Zimbabwean sample. Based on the dominating characteristics obtained from the one-way ANOVA results.

Cluster 1 (*Poor, Single, female household heads*), which accounts for about (23.63%) of the sample is different from others due to complete dominance of single female headed households, with the least number of farm workers, land size, cellphones and farm income. Thus, the cluster is that of possibly female household heads who are widowed or divorced. Deaths due to HIV & AIDS pandemic and other natural causes could explain the prevalence of single women in this cluster. Divorce could be attributed to worsening economic conditions in the country that has seen a lot of men migrating to nearby countries in search of greener pastures which consequently contributes to higher divorce rates. Furthermore, the cluster has below average asset ownership levels. The cluster has below average adoption rates in climate-smart agriculture practices such as conservation agriculture, crop diversification, basal fertilizer use, organic manure and use of stress tolerant maize varieties (Drought tolerant maize). In other words, the cluster communicates that single women are more likely to be vulnerable, poor and be lacking access to bigger land sizes. This finding might be suggestive of their failure to adopt climate-smart agriculture practices (technologies and methods), an observation noted by other studies (see for example Doss and Morris (2000); Bidogeza et al. (2009)). Moreover, the high labor demands associated with some climate-smart agriculture practices such as conservation agriculture (Murray et al. 2016, Rusinamhodzi 2015), and poor access to resources of women in agriculture (Murray et al. 2016) could explain the low adoption rates of climate-smart agriculture practices in this cluster.

Cluster 2 (*Rich with labor and Land*), accounts for about (10.65%) of the sample and differs from other clusters mainly because of its dominance in asset ownership, farm size and area planted to maize, family size, number of farm workers, and reception of extension services. In fact, the cluster highly dominates in cattle, oxcarts, poultry and hoe ownership. The cluster also dominates in returns from farming (farm income). Furthermore, we observe high rates of adoption and utilization of conservation agriculture, drought tolerant maize and close to average use of basal fertilizers. Overall, this cluster consists of resourceful farmers, who enjoy frequent extension visits (possibly because of their wealth), have land and obtain higher returns from it. This finding concurs with other studies from Zimbabwe. For example studies by Mtambanengwe and Mapfumo (2005); Chikowo et al. (2014) and Zingore et al. (2011) associate high resource endowment in smallholder farming systems with high rates of adoption and use of ISFM.

Cluster 3 (*minimum off-farm activities*) is that of farmers who engage the least to off-farm activities and have above average rates in asset ownership. Full-time farming is also an important characteristic but cannot distinguish cluster 3 from clusters 1, 4 & 5. The cluster accounts for nearly (10.82%) of the overall sample. Moreover, the cluster is characterized by high rates of adoption of conservation agriculture, drought tolerant maize and basal fertilizer use. This is a cluster of farmers who are at mediocre level in terms of asset wealth and possibly take farming as their main livelihood which therefore motivates them to adopt technologies which they anticipate to improve their main livelihood.

Cluster 4 (*Highly experienced*), dominates in farming experience and accounts for nearly (22.80%) of the sample. This is a group of farmers that have acquired farming experience and accumulated some assets such as cattle, oxcart, ploughs, hoes and wheelbarrows (as shown by the above average ownership rates). Adoption of conservation agriculture and use of basal fertilizers is low in this group. Adoption of drought tolerant maize is average. One would have expected high adoption rates of conservation agriculture and drought tolerant maize, and use of basal fertilizers in this group as experience weaves out perceived risks and perceptions associated with technologies (Feder and Umali 1993) but it seems that other factors could be constraining in this group as we observe below average farm sizes and frequency of extension services reception.

Cluster 5 (*Young & least experienced*), is dominated by least experienced farmers who surprisingly try to be full-time farmers at the same time dominating in off-farm activities. Moreover, most of the farmers in this category are married, which is indicative of stable families. The group is relatively poor (in terms of asset ownership), the only very common asset owned is a cellphone. Returns from farming are the lowest in this group. This cluster may perfectly suit the youthful population in Zimbabwe. The youth, because of increasing poverty levels and lack of employment opportunities in the country diversify livelihoods by venturing into more than one economic activities (farming & other off-farm activities). Adoption of drought tolerant maize and conservation agriculture is low in this group. This could be explained by the lack of resources by the youth coupled with lack of tenure security among new land owners (which include the youth) in Zimbabwe which have negatively affected investments in agriculture. A study by Zikhali (2008) found out that, land tenure insecurity created by the land reform of 2000, has adversely affected soil conservation investments among its beneficiaries in Zimbabwe.

Cluster 6 (*Male farmers*), accounts for approximately (7.82%) of the sample. The cluster is made up of part-time male farmers engaging also in off-farm activities. Moreover, asset ownership is below average (except cellphone), and they are the group with the least frequency of extension services access. In terms of climate-smart agriculture attributes, they are the least adopters of conservation agriculture, they have above average rates of basal fertilizer utilization and adoption of drought tolerant maize. The small area allocated to maize production could possibly explain the low adoption of conservation agriculture, whilst the high returns from farming could explain the above average use of basal fertilizers and drought tolerant maize varieties.

Description of CT cluster characteristics

As with the Zimbabwean sample, six clusters with distinct characteristics were defined within the CT sample.

Cluster 1 (*Educated, big area under maize*), which accounts for roughly 33.33% of the sample consists of educated and literate farmers, who allocate a large share of their land to maize production, and obtain higher returns from farming. Ownership of most assets (livestock, plough, hoe, oxcart, wheelbarrow and sprayer) is slightly below average. The cluster also features higher rates of crop diversification, and use of ISFM (use of inorganic fertilizers, liming, green manure, cereal-legume intercropping, and use of rotations, fallowing, and agroforestry). The high levels of education prevalent in this cluster could explain the high use of climate-smart agriculture. This finding is in line with the findings from several previous studies that associate the adoption of new technologies with education (Asfaw and Admassie 2004, Bidogeza et al. 2009). In addition, studies within the CT area have also shown education to be an important factor in explaining the adoption and use of ISFM practices (technologies and methods) (see for example Mponela et al. (2016) and Mapila et al. (2012).

Cluster 2 (*Aged, uneducated, single female heads*) accounts for (12.82%) of the sample and is dominated by old and mostly experienced single (widowed or divorced) female household heads with low literacy rates and least years of schooling. The cluster is also characterized by very poor (in-terms of asset ownership) members with the least number of available farm workers and farm size owned. The group is also characterized by average use of ISFM practices (except for agroforestry and rotations which are below average), crop diversification, mulching, and other land, soil and water (LSW) conservation practices. We would expect women farmers in this group to have poor use of climate-smart agriculture practices (ISFM & crop diversification) because of their characteristics, but experience seems to be an important motivating factor in this cluster. Because of experience, farmers in the cluster have tried and tested several technologies and possibly have realized their benefits, which potentially motivates them to keep on using them despite other challenges they may be confronted with. This finding aligns well with that of Mponela et al. (2016) who also found that households with older members have higher prospects of adopting ISFM practices within the CT. More so, Grazhdani (2013) found experience to be an important factor explaining the adoption of agricultural technologies. He established that households with more farming experience are more liable to adopt a combination of technologies that yield the best returns selected from a series of technology tests.

Cluster 3 (*poor, married male farmers*) is dominated by the asset-poor, married male farmers, who have above average family sizes and receive the least income from farming. The cluster accounts for about 15.71% of the sample. The cluster has very low rates of fertilizer utilization, agroforestry, adoption and use of LSW practices, green manure and cereal-grain legume intercrops. The use of practices such as compost, mulching and fallowing is zero. The farmers in this cluster also have average adoption rates of liming and crop diversification. Generally, the adoption and use of climate-smart agriculture practices is low in this cluster compared to other clusters. This observation could be because of the low incomes from farming (which do not allow re-investments in agriculture) and relatively high household sizes which may come with increased burden to support the family. Generally, households within the CT are faced with recurrent hunger and food shortages (Whiteside 2000) which then having larger families worsens the situation. A recent study by Mponela et al. (2016) found that families within the CT region with relatively large family sizes are less likely to be amongst the implementers of ISFM practices.

Cluster 4 (*young and illiterate*) accounts for nearly 11.54% of the CT sample and is characterized by young illiterate household heads who strive to engage in full-time farming while participating heavily in off-farm activities. This group has no assets to talk about except for the very low rates of cellphone ownership and slightly above average ownership of digging hoes. The use of climate-smart practice-related technology and methods is very low in this cluster. Only average use of inorganic fertilizers, crop diversification and below average use of LSW conservation practices, cereal-legume intercrops and lime is evident. Adoption of irrigation farming is surprisingly high in this cluster. The group could be involved in off-season production of other crops such as vegetables as indicated by comparably high incomes from farming. Practices such as mulching, compost, rotations and agroforestry are totally not used in this cluster. High levels of illiteracy, lack of experience and engagement in off-farm activities could explain their low utilization of climate-smart agriculture practice-related technologies and practices. The result is not surprising given the lack of interest in agriculture among the younger people in the area (CGIAR 2013) and their desire to be involved in off-farm activities such as vending at Calomue and Dedza border posts. The results here are in agreement with those of Grazhdani (2013) who observed that young farmers due to lack of experience are risk averse and more likely to adopt few agriculture technology options.

Cluster 5 (*least Maize area, farming experience and involvement in off-farm activities*) consists of a group of inexperienced farmers who have large pieces of land but put a small portion of land under maize production. The group is also least involved in off-farm activities. This cluster constitutes about 17.31% of the overall CT sample. Ownership of other assets is relatively low in this group (below average) with many farmers owning mostly hoes. In terms of climate-smart methods and technology-related attributes, they are the least crop diversifiers, and low adopters of; irrigation, rotation, legume-cereal intercrops, liming and green manure. Mulching, compost manure use and fallow are not used in this cluster. This cluster only dominates in agroforestry, use of inorganic fertilizers and other LSW conservation methods/technologies. The fact that farmers in this group allocate a small area to maize production, the main staple crop in the area (Myburgh and Brown 2006) may explain the poor adoption of technologies in this cluster. In most cases, technologies adopted in the area are meant to improve maize productivity.

For Cluster 6 (*Rich, literate & educated, married, male farmers*), which comprises of 9.30% of the households, the main distinguishing features include; highest ownership rates of assets, highest male representation and (100%) marriage rate, very educated (compared to all the other groups), (100%) literacy, aged, largest farm size. The cluster has all it takes to adopt new technologies as all the factors are favorable. Results show that, the cluster is the best in uptake and use of selected climate-smart agriculture practices (technologies & methods) considered in this study. This cluster could be ideal to lead the rest of the farmers in improving awareness and adoption of climate-smart agriculture practices (technology & methods) within the CT.

Conclusions and policy recommendations

We use a multivariate analysis approach that combines principal component analysis, and cluster analysis to clearly identify farm household typologies in smallholder farming areas of southern Africa with respect to the adoption of climate-smart agriculture practices (technologies and methods), using socioeconomic factors. Our analysis is based on two samples of data one from four districts (Guruve, Mudzi, Wedza and Goromonzi) in Zimbabwe and the other from the CT found in Mozambique, Zambia and Malawi. Data was evaluated by multivariate statistical models. Firstly, data reduction was conducted through principal component analysis to identify nine (9) components accounting for slightly more than 60% of the variability in the data. The identified components were then used to typify households in cluster analysis. The results from the cluster analysis identified six (6) different farm types in the respective areas studied.

It is evident from the results that socioeconomic factors such as gender, asset ownership, education, marital status, farm size, area put under maize farming, farming experience, extension reception frequency, availability of labour and involvement in off-farm activities, define clusters and can be associated with adoption and use of climate-smart agriculture practices (technologies and methods) in smallholder farming. Chiefly, we found single female headed households, inexperienced youths trying to mix farming and off-farm farming activities, poor male household heads with relatively big household sizes and young and illiterate farmers to be amongst the low adopters of climate-smart agriculture practices considered. On the other hand, asset-rich families with labor and large farm sizes, full-time farmers with minimal off-farm activities, married rich male farmers, farmers who put large area under maize production to be better adopters of climate-smart agriculture practices. In addition, we found that some households are into farming (fulltime farmers) but they do not regard farming as their primary source of income. Thus, such farmers may not be serious adopters of climate-smart agriculture practice as improving farm resilience and productivity may not be key to them. Also, for the youthful farmers, they may show interest in farming but lack of assets, experience, poverty and economic hardships may fail them in making meaningful investments in agriculture hence their adoption of climate-smart agriculture practices is low. Lack of land tenure security and employment opportunities amongst Zimbabwean youths is a good example.

Statistical tests carried out showed that the discriminating power of many variables used in our multivariate analysis and of the variables representing climate-smart agriculture practices (technology and methods) adoption is high. This is a good result as it indicates that the typologies we constructed can be very useful in exploring adoption and use of climate-smart agriculture practices in smallholder farming areas of southern Africa and other related areas. Our study has highlighted the salient heterogeneities of smallholder farming households with regards to adoption and use of climate-smart agriculture practices. Some households are more constrained to adopt practices as compared to others because of their inherent socioeconomic characteristics.

As a recommendation, our findings here call for segregated approaches in trying to promote adoption and use of climate-smart agriculture in smallholder farming areas of southern Africa and possibly other related areas. No single uniform approach will equally improve adoption of climate-smart agriculture practices in a heterogeneous population. It therefore means that efforts and or policies meant to improve adoption and use of climate-smart agriculture should be more focused on specific groups such as these farm typologies defined. Precisely, and as implicated by findings in this study, deliberate targeting of farm household clusters with low CSA practices adoption rates such as those characterized by single female headed households, inexperienced youths trying to mix farming and off-farming activities, poor male household heads with relatively big household sizes and young and illiterate farmers can boost CSA adoption and hence improve climate resilience in studied smallholder farming areas. Stakeholders concerned with improving climate change adaptation in smallholder farming areas in southern Africa can therefore create new or modify their existing structures for improving adoption of climate-smart agriculture practices in smallholder farming to factor in heterogeneity for them to avoid possible drawbacks that can arise by assuming homogeneity amongst smallholder farming households in southern Africa.

We conclude that defining farm typologies is an important step towards the promotion of the adoption of climate-smart technologies in agriculture practices. These typologies provide essential ammunition to support efforts and policies aimed at improving adoption of technologies/practices by recognizing the heterogeneities in the targeted populations. In addition, we conclude that the multivariate analysis (principal component analysis and cluster analysis) are useful tools suitable for identifying important socio-economic characteristics of households influential in determining adoption of climate-smart agriculture practices.

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Declarations

Authors declare no competing interests

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Figure 1

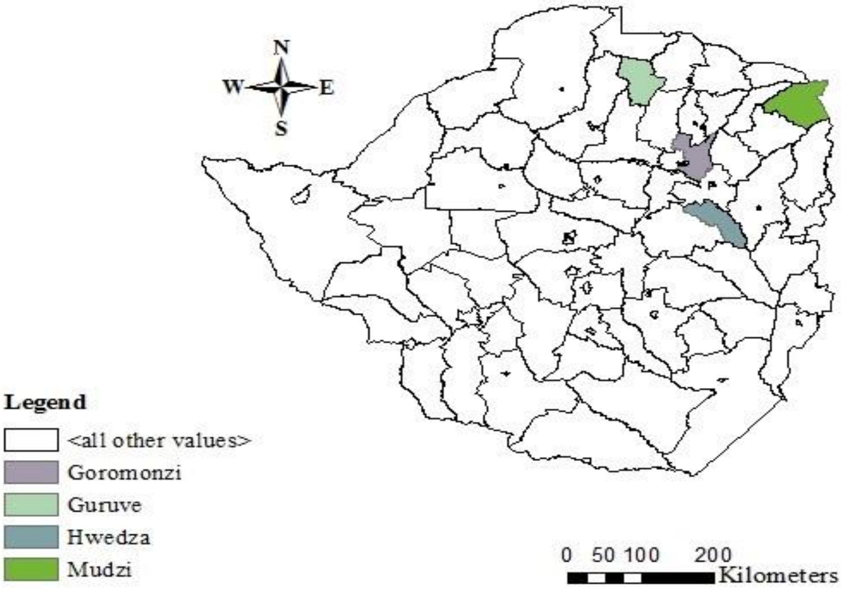

Figure 1: Map of Zimbabwe showing studied districts

Figure 2

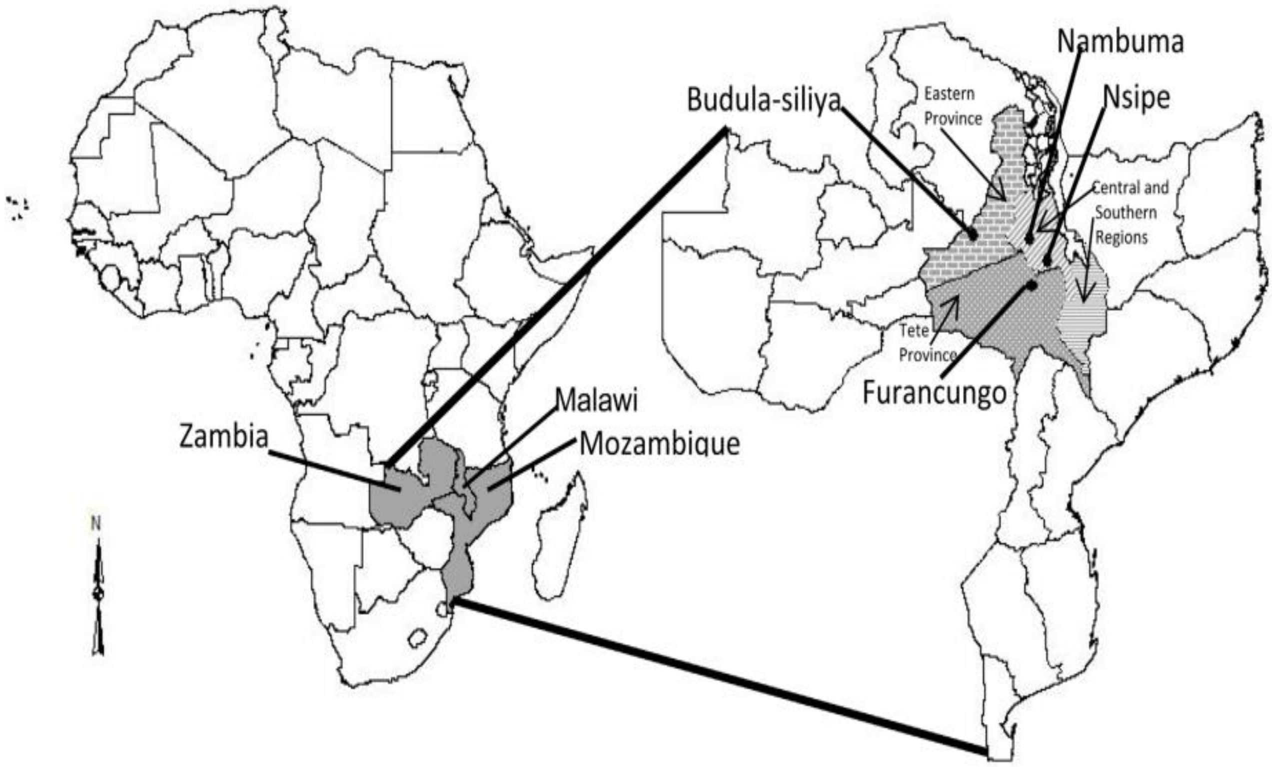

Figure 2: Map showing CT covering Tete province of Mozambique, Eastern province of Zambia and Central region of Malawi.

Figure 3.

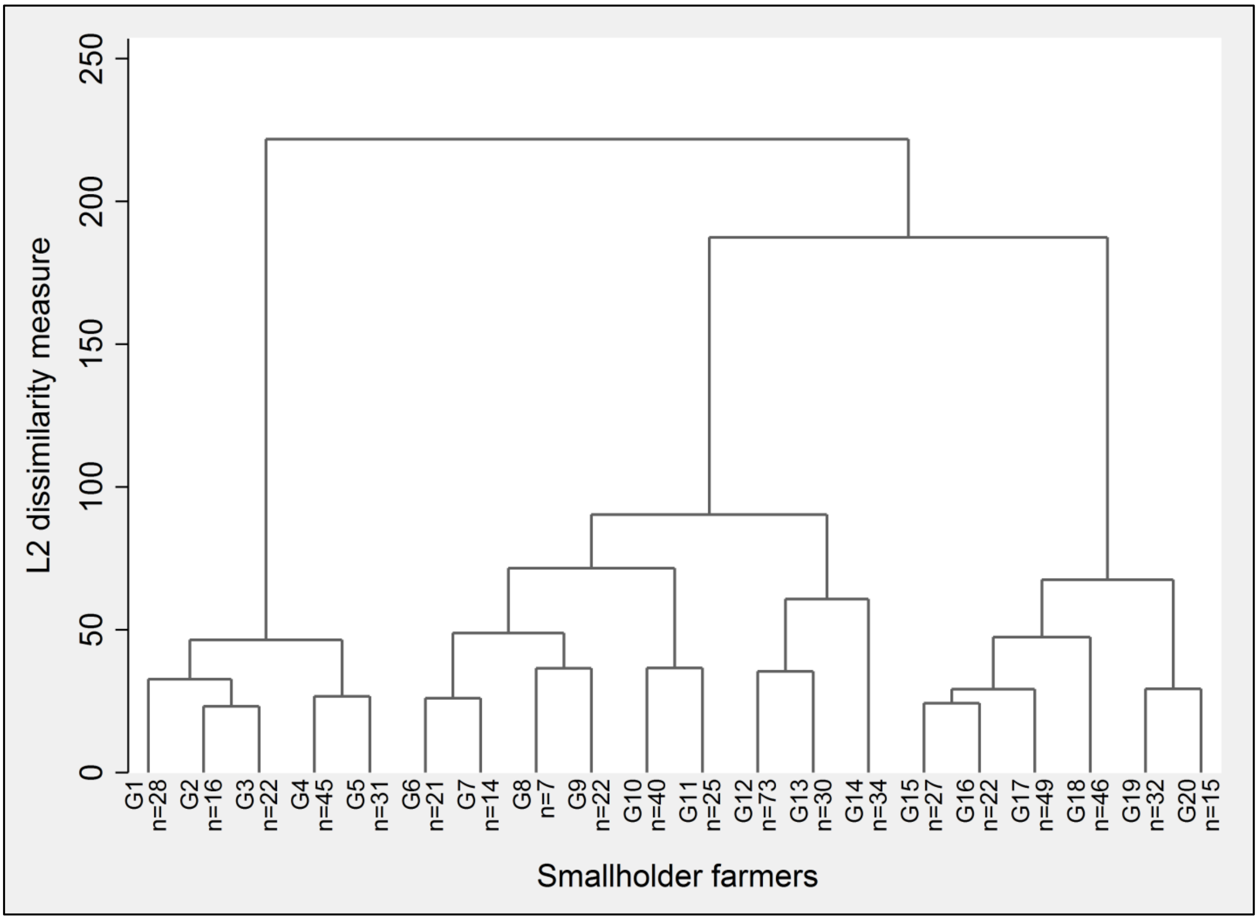

Figure 3: Dendrogram resulting from Ward's method of cluster analysis using data from Goromonzi, Guruve, Mudzi and Wedza districts in Zimbabwe. Note that, for brevity we have limited our view to the top 20 branches of the dendrogram with *cutnumber (20)*. These branches are labeled G1-G20 by default with the respective sample sizes shown beside.

Figure 4.

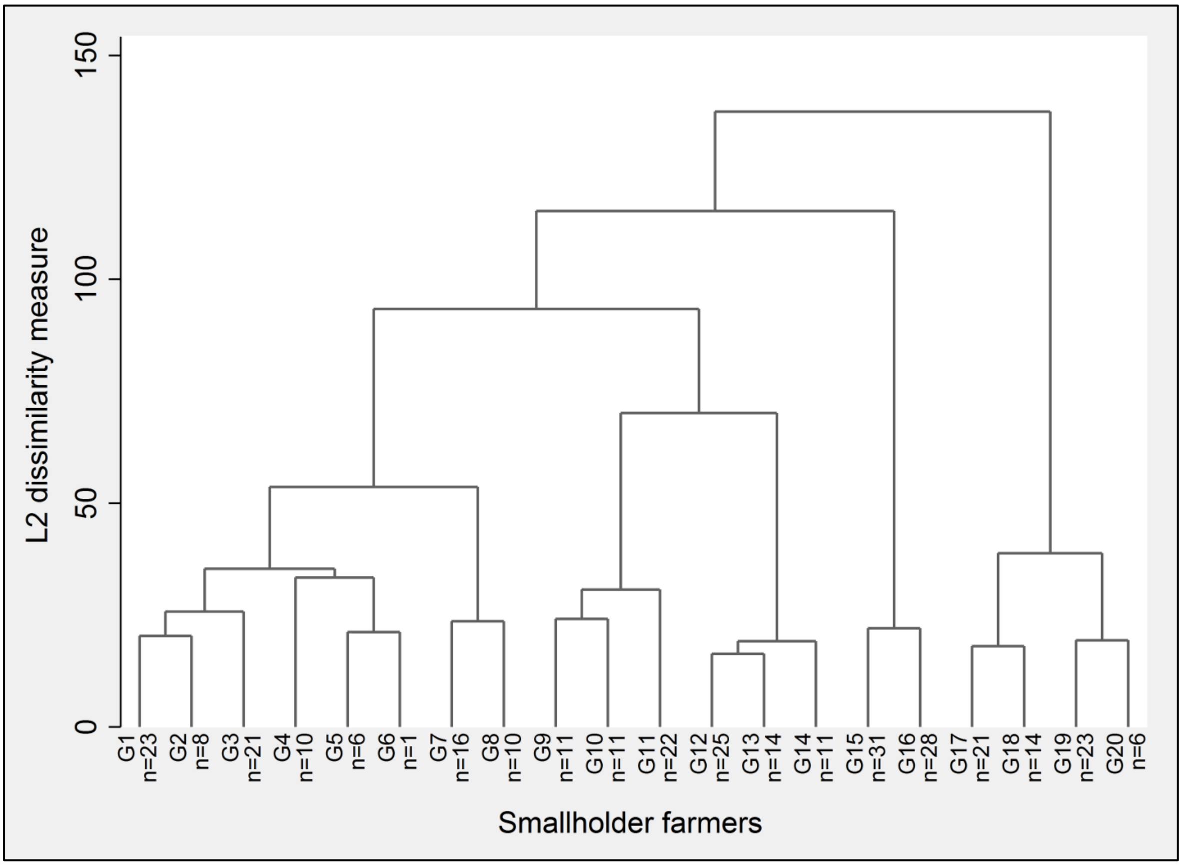

Figure 4: Dendrogram resulting from Ward's method of cluster analysis using data from smallholder farmers in CT area. Note that for brevity, we have limited our view to the top 20 branches of the dendrogram with cutnumber (20). These branches are labeled G1-G20 by default with the respective sample sizes beside.

Tables 1-6

Table 1: Descriptive statistics for the variables used in the analysis of selected districts in Zimbabwe

Variables	Definition of the variables	Mean	Std.Deviation
farmer	=1 if household is a full-time farmer; 0 otherwise	0.869	0.338
farm_exper	Years of farming experience	19.956	14.300
married	=1 if married; 0 otherwise	0.744	0.437
sex_female	=1 if female head of household; 0 otherwise	0.243	0.429
educ_sec	=1 if the farmer completed secondary education or higher; 0 otherwise	0.478	0.500
age	Age of the smallholder farmer in years	51.431	15.444
hhsize	Number of household members	5.268	2.153
farm_wkrs	Number of household members who provide farm labor	3.249	1.809
income	Total household income from farming activities in .US	810.355	1413.866
off_farm	=1 if farmer engages in off-farm activities; 0 otherwise	0.251	0.434
maize_area	Land area under maize production	0.830	0.687
farmsize	Farm size in hectares	2.344	2.661
extension_freq	Number of times the farmer receives agricultural extension advice	4.125	7.950
Climate-smart agriculture practice attributes			
num_crops	Number of crops grown	1.882	1.102
ca_farmer	=1 if farmer practices conservation agriculture; 0 otherwise	0.308	0.462
basal_fert	=1 if farmer uses basal fertilizers; 0 otherwise	0.601	0.490
organic_manure	=1 if farmer uses organic manure; 0 otherwise	0.446	0.497
dtma_maize	=1 if farmer grows drought tolerant maize varieties; 0 otherwise	0.687	0.464

Asset ownership attributes			
assets_cattle	Number of livestock (cattle) units owned by the smallholder farmer	2.411	3.417
assets_oxcart	=1 if farmer owns an oxcart; 0 otherwise	0.378	0.485
assets_chicks	Number of poultry units owned by the farmer	11.819	19.730
assets_hoes	Number of digging hoes owned by the farmer	5.408	3.504
assets_plough	=1 if farmer owns a plough; 0 otherwise	0.589	0.492
assets_wbarrow2	=1 if farmer owns a wheelbarrow; 0 otherwise	0.494	0.500
assets_sprayer	=1 if farmer owns a sprayer; 0 otherwise	0.308	0.462
assets_cellphone	=1 if owns a cell phone; 0 otherwise	0.784	0.412

Notes: Data was collected from selected smallholder farmers in Goromonzi, Guruve, Mudzi and Wedza districts of Zimbabwe.

Table 2: Descriptive statistics for the variables used in the analysis of smallholder farmers in the CT

	Definition of the variables	Mean	Std.deviation
farmer	=1 if household is a full-time farmer; 0 otherwise	0.872	0.335
farm_exper	Years of farming experience	20.218	14.318
married	=1 if married; 0 otherwise	0.830	0.376
sex_female	=1 if female head of household; 0 otherwise	0.170	0.376
educyears	Years of completed schooling	5.045	3.637
literate	=1 if farmer is literate (i.e. able to read and write); 0 otherwise	0.885	0.320
age	Age of the smallholder farmer in years	46.589	15.308
hhsize	Number of household members	5.837	2.379
farm_wkrs	Number of household members who provide farm labor	3.288	1.807
income	Annual household income from farming activities in .US$	226.139	234.520
off_farm	=1 if farmer engages in off-farm activities; 0 otherwise	0.327	0.470
maize_area	Land area allocated to maize production	2.064	7.987
farmsize	Farm size in hectares	3.940	4.976
Asset ownership attributes			
livestock_units	Number of livestock (cattle) units owned by the smallholder farmer	1.457	4.093
assets_oxcart	=1 if farmer owns an oxcart; 0 otherwise	0.087	0.282
assets_chicken	=1 if farmer own poultry units	0.106	0.308
assets_hoes	Number of digging hoes owned by the farmer	4.176	3.220
assets_plough	=1 if farmer owns a plough; 0 otherwise	0.125	0.331
assets_wbarrow	=1 if farmer owns a wheelbarrow; 0 otherwise	1.000	0.000
assets_sprayer	=1 if farmer owns a sprayer; 0 otherwise	0.179	0.384
assets_cellphone	=1 if owns a cell phone; 0 otherwise	0.426	0.495
Climate-smart agriculture practice attributes			
num_crops	Number of crops grown	2.119	0.803
sap_mulching	=1 if farmer uses mulching techniques; 0 otherwise	0.026	0.158
sap_inorgfert	=1 if farmer uses inorganic fertilizers; 0 otherwise	0.596	0.491
sap_gmanure	=1 if farmer uses green manure; 0 otherwise	0.429	0.496
sap_compost	=1 if farmer uses compost techniques; 0 otherwise	0.141	0.349
sap_lime	=1 if farmer uses lime; 0 otherwise	0.035	0.185
sap_legumes	=1 if farmer grows legumes together with cereals; 0 otherwise	0.311	0.464
sap_rotation	=1 if farmer uses rotation methods; 0 otherwise	0.503	0.501

sap_fallow	=1 if farmer uses fallowing techniques; 0 otherwise	0.224	0.418
sap_agforestry	=1 if farmer practices agroforestry methods; 0 otherwise	0.147	0.355
irrigation	=1 if farmer practices irrigation; 0 otherwise	0.494	0.501
sap_lsw	=1 if farmer adopts land/soil and water conservation technologies; 0 otherwise	0.792	0.407

Notes: Data was collected from selected smallholder farmers in CT.

Table 3

Table 3: The nine (9) components from principal components analysis including the factor loadings of the 26 variables and the cumulative proportion of the explained variance

	Components								
Variables	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7	Comp 8	Comp 9
Full time farmer	-0.006	0.338	-0.111	0.159	0.224	-0.259	**0.442**	0.316	0.382
Farming experience (in years)	0.338	**0.686**	-0.161	-0.033	-0.142	-0.008	0.026	-0.109	-0.037
Married	0.336	**-0.614**	-0.367	-0.003	-0.288	-0.379	-0.103	-0.026	-0.041
Female head of household	-0.326	**0.575**	0.364	0.036	0.274	**0.454**	0.152	0.032	-0.024
Secondary education	0.038	**-0.627**	0.233	-0.008	0.078	0.019	0.313	-0.083	0.156
Age of farmer	0.219	**0.746**	-0.207	0.006	-0.275	-0.107	-0.188	-0.037	-0.078
Household size	**0.487**	-0.074	**-0.631**	0.009	0.141	0.277	0.040	-0.043	-0.073
Number of farm workers	**0.484**	0.006	**-0.574**	0.101	0.216	0.389	0.016	-0.041	0.069
Total income	0.335	-0.223	0.358	-0.250	-0.039	0.211	-0.401	0.220	-0.120
Has income from off-farm activities	-0.167	-0.268	-0.236	-0.357	0.021	0.064	0.241	0.182	-0.122
Maize area (hectares)	0.428	-0.070	0.080	0.303	0.007	0.184	-0.352	0.337	0.228
Total farm size (hectares)	0.386	-0.035	0.028	0.072	0.391	-0.103	-0.235	**0.523**	-0.062
Frequency of extension services	0.213	0.058	0.148	-0.081	0.436	0.033	-0.194	-0.406	-0.072
Climate-smart agriculture practice attributes									
Number of crops grown	0.349	-0.057	0.122	0.042	**0.469**	-0.253	0.030	-0.275	-0.016
ca_farmer	0.328	-0.050	0.000	0.063	**0.497**	-0.287	-0.045	-0.162	-0.166
Basal fertilizers	0.097	-0.221	0.184	**0.659**	-0.030	0.122	0.128	-0.017	-0.187
Organic manure	0.166	-0.021	0.063	0.369	-0.242	0.028	-0.219	-0.375	**0.506**
DTMA maize	0.150	-0.022	0.080	**0.710**	-0.126	0.013	0.121	0.004	-0.326
Asset Ownership attributes									
Cattle (in units)	**0.590**	0.091	0.192	-0.148	-0.043	-0.110	0.075	-0.036	-0.212
Ox-cart	**0.664**	0.142	0.249	-0.060	-0.119	-0.142	0.081	0.075	-0.023

Poultry (units)	0.399	-0.064	0.201	-0.230	-0.014	0.136	-0.084	-0.025	0.355
Digging hoes (units)	**0.572**	0.001	-0.089	-0.167	-0.010	0.282	0.185	-0.133	0.025
Plough	**0.650**	0.204	0.065	0.062	-0.149	-0.144	0.212	0.178	-0.038
Wheelbarrow	0.452	0.100	0.294	-0.234	-0.290	-0.028	0.159	-0.115	-0.176
Sprayer	**0.521**	-0.084	0.182	-0.058	0.003	-0.031	0.244	0.028	0.298
Cellphone	0.218	-0.335	0.094	-0.010	-0.157	**0.457**	0.185	-0.008	-0.127
Eigen values	2.850	2.168	1.893	1.861	1.473	1.472	1.461	1.265	1.209
Cumulative proportion of explained variance (%)	10.96%	19.30%	26.58%	33.74%	39.40%	45.07%	50.68%	55.55%	60.20%

Note: Comp = component. Factor loadings 0.44 and higher are marked in bold font. Data from selected smallholder farmers in Goromonzi, Guruve, Mudzi and Wedza Districts.

Table 4

Table 4: The distribution of the ten components extracted from principal components analysis including the factor loadings of the 30 variables and the cumulative proportion of the explained variance

	Components									
Variables	Comp1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7	Comp 8	Comp 9	Comp 10
Full time farmer	0.123	**-0.466**	-0.005	0.248	0.200	-0.239	0.071	0.143	0.193	0.076
Farming experience	-0.077	0.394	-0.264	**0.629**	-0.160	-0.062	-0.059	-0.287	0.208	0.042
Married	0.289	0.123	**0.630**	-0.201	0.018	-0.195	-0.222	-0.215	0.345	-0.253
Female head of household	-0.308	-0.083	**-0.633**	0.211	-0.055	0.203	0.223	0.220	-0.346	0.188
Years of schooling	0.278	0.405	0.225	-0.371	-0.076	0.158	0.142	-0.344	-0.234	0.194
Literate	0.092	**0.454**	0.198	0.065	-0.026	-0.063	0.073	-0.190	**-0.472**	0.102
Age of farmer	0.062	0.369	-0.290	**0.657**	-0.142	0.036	-0.126	-0.165	0.236	0.031
Household size	**0.453**	0.004	0.467	0.313	-0.258	-0.210	0.274	0.133	-0.128	0.083
Number of farm workers	0.402	0.101	0.332	0.411	-0.356	-0.348	0.240	0.104	-0.108	0.007
Annual household income	-0.049	0.249	0.057	-0.278	-0.288	0.073	-0.106	0.182	0.224	0.320
Off-farm activities	-0.339	-0.215	**0.551**	0.020	0.068	0.288	0.004	0.103	0.023	0.328
Maize area	-0.047	0.176	-0.018	0.163	-0.109	0.198	-0.118	-0.142	0.314	0.429
Total farm size	**0.748**	-0.210	0.002	0.169	0.063	0.171	0.056	-0.194	-0.017	0.070
Asset Ownership attributes										
Livestock units	**0.504**	0.066	0.031	0.253	0.332	**0.441**	-0.051	-0.045	-0.015	-0.115

Oxcart	0.314	0.085	-0.069	0.116	0.296	-0.115	**-0.546**	0.287	-0.123	0.240
Poultry (in units)	-0.250	**-0.453**	0.385	0.075	-0.036	0.269	0.074	0.048	0.208	0.200
Digging hoes	0.418	-0.024	0.317	0.364	0.048	0.186	-0.006	0.329	-0.042	-0.083
Plough	**0.690**	-0.178	-0.095	0.019	0.112	0.012	-0.226	-0.056	-0.091	-0.109
Sprayer	**0.670**	-0.238	-0.187	0.018	-0.017	0.036	-0.157	0.218	-0.005	0.066
Cellphone	0.338	0.330	0.325	-0.164	-0.128	0.166	-0.198	0.127	-0.150	0.246
Climate-smart agriculture practice attributes										
Number of crops grown	-0.364	0.278	0.320	0.248	0.105	0.052	0.344	0.171	0.124	-0.065
Mulching	0.176	0.103	0.065	0.109	0.249	**0.559**	0.268	0.015	0.044	-0.251
Inorganic fertilizers	-0.228	**0.677**	0.117	0.111	0.084	-0.021	-0.224	0.106	-0.147	-0.220
Green manure	-0.091	**0.584**	-0.073	-0.007	0.146	-0.077	0.017	0.394	0.114	0.073
Compost	0.073	0.288	0.073	-0.066	**0.639**	-0.170	0.265	0.030	0.136	0.081
Lime	0.004	0.135	-0.014	0.059	**0.598**	-0.285	0.116	-0.283	-0.044	0.366
Legumes	0.329	0.310	-0.205	-0.265	0.041	-0.183	0.220	0.272	0.191	0.002
Rotation	**0.591**	0.198	-0.304	-0.322	-0.144	-0.061	0.220	0.121	0.197	-0.006
Fallowing	**0.631**	-0.106	-0.305	-0.180	-0.102	0.047	0.255	-0.150	0.121	0.172
Agroforestry	0.065	**0.560**	-0.128	-0.195	-0.107	0.353	0.009	0.042	0.130	-0.096
Eigen values	2.85378	2.04563	2.02834	1.92696	1.87277	1.80265	1.79442	1.67654	1.62705	1.43332

Cumulative proportion of explained variance (%)	9.51%	16.33%	23.09%	29.52%	35.76%	41.77%	47.75%	53.34%	58.76%	63.54%

Notes: Comp = component. Factor loadings 0.44 and higher are marked in bold font.

Table 5:

Table 5: Characteristics of chosen clusters of smallholder farmers and p-values of one-way ANOVA in Goromonzi, Guruve, Mudzi and Wedza

Variables	Cluster I	Cluster II	Cluster III	Cluster IV	Cluster V	Cluster VI	Bartlett's test of equality of variances		
							Cluster means	Cluster SD	p-value
Full time farmer	0.958	0.781	0.923	0.956	0.986	0.021	0.869	0.338	0.000
Farming experience (in years)	23.282	24.203	14.500	29.728	10.785	11.155	19.956	14.300	0.000
Married	0.063	0.891	0.938	0.934	0.993	1.000	0.744	0.437	0.000
Female head of household	0.930	0.078	0.062	0.007	0.028	0.000	0.243	0.429	0.000
Secondary education	0.303	0.359	0.800	0.234	0.757	0.574	0.478	0.500	0.458
Age of farmer	54.352	55.156	44.246	64.978	39.563	44.064	51.431	15.444	0.102
Household size	4.394	7.578	5.154	5.314	5.104	5.340	5.268	2.153	0.000
Number of farm workers	2.796	5.750	3.138	3.117	2.889	2.851	3.249	1.809	0.000
Annual household income	535.532	1918.695	969.722	718.715	526.531	1060.957	810.355	1413.866	0.000
Off-farm activities	0.197	0.281	0.108	0.124	0.451	0.340	0.251	0.434	0.000

Maize area (in hectares)	0.675	1.285	1.130	0.905	0.632	0.663	0.830	0.687	0.000
Total farm size	1.814	4.841	3.108	2.279	1.813	1.285	2.344	2.661	0.000
Frequency of extension services	3.880	9.000	8.923	2.204	2.646	1.894	4.125	7.950	0.000
Climate-smart agriculture practice attributes									
Number of crops grown	1.739	2.344	2.662	1.679	1.736	1.617	1.882	1.102	0.504
Conservation agriculture	0.211	0.531	0.600	0.248	0.292	0.128	0.308	0.462	0.042
Basal fertilizers	0.556	0.469	0.938	0.511	0.604	0.702	0.601	0.490	0.000
Organic manure	0.352	0.406	0.754	0.533	0.278	0.617	0.446	0.497	0.709
DTMA maize	0.669	0.500	0.969	0.708	0.618	0.745	0.687	0.464	0.000
Asset Ownership attributes									
Cattle (in units)	1.627	5.016	3.092	3.445	1.076	1.447	2.411	3.417	0.000
Oxcart	0.261	0.688	0.569	0.606	0.104	0.191	0.378	0.485	0.000
Poultry (in units)	9.366	29.484	12.785	10.000	8.167	10.298	11.819	19.730	0.000
Digging hoes	4.620	9.047	5.231	5.569	4.444	5.447	5.408	3.504	0.000
Plough	0.493	0.813	0.738	0.847	0.368	0.277	0.589	0.492	0.002
Wheelbarrow	0.415	0.641	0.523	0.693	0.306	0.489	0.494	0.500	0.907
Sprayer	0.183	0.641	0.615	0.299	0.208	0.149	0.308	0.462	0.040
Cellphone	0.690	0.891	0.738	0.715	0.868	0.936	0.784	0.412	0.000
Observations	142	64	65	137	144	47	601		

Notes: SD = Standard deviation, ANOVA = Analysis of variance. Data is collected from selected smallholder farmers in Goromonzi, Guruve, Mudzi and Wedza districts of Zimbabwe.

Table 6:

Table 6: Characteristics of selected clusters of smallholder farmers in the CT area

							Bartlett's test of equality of variances		
Variables	Cluster I	Cluster II	Cluster III	Cluster IV	Cluster V	Cluster VI	Cluster means	Cluster SD	p-value
Full time farmer	0.702	0.875	0.939	1.000	1.000	0.966	0.872	0.335	0.000
Farming experience	23.519	27.825	19.796	13.778	13.537	19.034	20.218	14.318	0.000
Married	0.981	0.075	1.000	0.944	0.778	1.000	0.830	0.376	0.000
Female head of household	0.038	0.925	0.000	0.056	0.185	0.000	0.170	0.376	0.000
Years of schooling	6.394	2.775	3.636	3.528	5.500	6.759	5.045	3.637	0.000
Literate	0.971	0.800	0.959	0.694	0.778	1.000	0.885	0.320	0.000
Age of farmer	50.188	51.181	43.404	37.562	43.148	50.345	46.589	15.308	0.000
Household size	5.529	4.025	6.776	5.861	5.315	8.793	5.837	2.379	0.498
Number of farm workers	3.250	2.175	3.796	2.889	2.907	5.310	3.288	1.807	0.000
Annual household income	309.801	170.811	144.625	237.582	212.113	152.064	226.139	234.520	0.156
Off-farm activities	0.308	0.225	0.388	0.972	0.037	0.172	0.327	0.470	0.000
Maize area	2.926	2.797	1.692	1.360	0.978	1.486	2.064	7.987	0.000
Total farm size	4.432	3.233	6.640	8.167	17.234	30.961	9.737	12.295	0.000

Asset Ownership attributes

Livestock units	0.840	0.634	1.123	0.748	1.225	6.676	1.457	4.093	0.000
Oxcart	0.115	0.050	0.000	0.000	0.111	0.241	0.087	0.282	0.002
Poultry (in units)	0.000	0.050	0.000	0.833	0.000	0.034	0.106	0.308	0.000
Digging hoes	3.577	2.725	4.449	4.278	3.833	8.379	4.176	3.220	0.000
Plough	0.010	0.000	0.020	0.000	0.333	0.655	0.125	0.331	0.000
Wheelbarrow	0.077	0.125	0.000	0.000	0.037	0.138	0.061	0.240	0.000
Sprayer	0.048	0.000	0.082	0.028	0.500	0.655	0.179	0.384	0.000
Cellphone	0.567	0.100	0.347	0.306	0.407	0.690	0.426	0.495	0.031
Climate-smart agriculture practice attributes									
Number of crops grown	2.298	2.275	2.388	2.389	1.463	1.690	2.119	0.803	0.022
Irrigation	0.481	0.400	0.510	0.944	0.278	0.483	0.494	0.501	0.000
Mulching	0.000	0.025	0.000	0.000	0.000	0.241	0.026	0.158	0.000
Inorganic fertilizers	0.933	0.700	0.388	0.750	0.907	0.931	0.792	0.407	0.000
Green manure	0.394	0.275	0.143	0.028	0.019	0.103	0.205	0.404	0.060
Compost	0.000	0.025	0.000	0.000	0.000	0.241	0.026	0.158	0.000
Lime	0.962	0.650	0.633	0.250	0.130	0.448	0.596	0.491	0.000
Legumes	0.750	0.550	0.245	0.139	0.130	0.345	0.429	0.496	0.000
Rotation	0.269	0.075	0.020	0.000	0.093	0.241	0.141	0.349	0.000
Fallowing	0.087	0.025	0.000	0.000	0.000	0.034	0.035	0.185	0.000
Agroforestry	0.442	0.250	0.061	0.000	0.481	0.414	0.311	0.464	0.004

LSW conservation	0.933	0.700	0.388	0.750	0.907	0.931	0.792	0.407	0.001
Observations	104	40	49	36	54	29	312		

Notes: SD is standard deviation. Data was collected from selected smallholder farmers in the CT area.