Mapping farmer perceptions, Conservation Agriculture practices and on-farm measurements: the role of systems thinking in the process of adoption

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Abstract

CONTEXT

Conservation Agriculture (CA) usage, particularly in Southern Africa, has remained low with lower yield, higher weed pressure and lower soil quality cited as reasons for 'disadoption'.

OBJECTIVE

Using a detailed case study of 50 farmers in two villages in Cabo Delgado (Northern Mozambique), this study seeks to test the hypothesis that farmers' perceptions of CA are associated with distinctly different 'mental models' and if these "ways of thinking" overlap with farmers' identified/self-identified groupings (e.g. CA users, 'disadopters' and conventional tillage users). Secondly, we examine whether these different mental models (perceptions) are associated with actual differences in on-farm measurements. Finally, we explore the hypothesis that 'systems thinking' (i.e., understanding nonlinear causal relationships and internal feedback loops that drive a complex system) and CA usage are positively associated.

METHODS

Fuzzy Cognitive Mapping (FCM) was used to elicit representations of farmers' mental models. To explore the association between farmers' mental models of CA/conventional practices and on-farm measurements we evaluated cowpea aboveground biomass, yield, weed cover, and soil quality parameters from the farmer's main plot. We drew on network analysis to measure structural metrics of cognitive maps that provide important information about a person's mental model (perceptions) of causal interdependencies of farming dynamics.

RESULTS AND CONCLUSIONS

We find evidence of two data-driven distinct clusters of farmers' mental models that are in relative alignment with farmers' identified/self-identified groupings. Cluster 1 mainly consists of conventional users and cluster 2 mainly consists of CA users/disadopters. While no significant differences in socio-demographic variables were observed, clusters of mental models were associated with key differences in on-farm measurements. Importantly, cluster 1, who tended to be conventional users, had lower yields, lower soil cover, significantly lower carbon stock and higher weed coverage than cluster 2. Soil quality indicators were higher in cluster 2 as were farmers' overall revenue per hectare. Moreover, cluster 2 had significantly higher degrees of 'systems thinking' (measured through complex network analysis of graphical mental models) than cluster 1 which had higher forms of linear thinking. We argue that higher forms of experiential learning and practice of CA relate to higher degrees of systems thinking and stronger positive perceptions of CA, even among the CA 'disadopters'.

SIGNIFICANCE

Our findings highlight the importance of systems thinking abilities and the need to consider detailed biophysical, socio-economic and mental modelling variables rather than simple binary measurements which may have led to erroneous conclusions on CA and thus has implications for how CA is understood and promoted in future.

Keywords: Conservation Agriculture; Decision-making; Mental models; Cropping systems

1. Introduction

1.1 Background and objectives

Conservation Agriculture (CA) has been promoted as a method that contributes to the sustainable intensification of smallholder farming in Africa (Pretty et al., 2011). CA is now practiced worldwide across all continents, diverse agro-ecosystems and varied farm sizes (Friedrich et al., 2012). CA is defined by three principles, namely: (i) no or minimum mechanical soil disturbance through no-till seeding; (ii) the maintenance of soil mulch cover with crop biomass, stubbles and cover crops; (iii) cropping system diversification through rotations and/or associations involving annuals and perennials, including legume crops (FAO, 2016).

In Sub-Saharan Africa (SSA), conventional tillage practice is still pervasive and usually conducted through hand-hoe or animal traction. This has resulted in widespread soil erosion and loss of soil organic matter which is further exacerbated by the practices of crop residue removal and stubble burning (Rockström et al., 2009). Despite many positive experiences across the region (e.g. Thierfelder et al., 2015; Thierfelder et al., 2016; Kassam et al., 2017), recent research (e.g. Giller et al., 2009; Giller et al., 2015; Brown et al., 2018) has suggested that CA practice in SSA (particularly in Southern Africa) remains low. Key areas of contention have surrounded yields, weeds, soil quality and labour. Studies have shown, for instance, that CA practice may contribute to a decrease in yields (particularly in the short-run) compared to those obtained under conventional tillage based agriculture, which can severely impede usage (Giller et al., 2009; Thierfelder and Wall, 2010). Giller (2009 and 2012) have also suggested that resource-poor farmers particularly in SSA, where there exists a strong crop-livestock interaction, are likely to face important trade-off decisions given that crop biomass is often fed to livestock. The challenges associated with higher weed pressure and an increase in labour requirements are also frequently cited as significant barriers to CA practice (Baudron et al., 2012; Chauhan et al., 2012; Chinseu et al., 2018). This is further compounded by arguments which have centred around the need to include agricultural inputs such as herbicides and fertilisers in the production process in order for CA to be successful (e.g. to reduce weeds and increase crop productivity) (Rusinamhodzi et al., 2011; Thierfelder et al., 2013). In addition, its agro-ecological suitability (e.g. whether suitable for drier rather wetter regions) has been an area of contention (Giller et al., 2009; Pittlekow et al., 2015). More recently, authors have questioned the role CA has in carbon sequestration due to inadequate soil sampling of soil organic carbon stock which has likely caused significant overestimates of its potential in climate change mitigation (e.g. Powlson et al., 2016). Rather research has suggested that the diversification potential of CA should be explored further and the benefits to near soil surface physical conditions as opposed to its climate change mitigation potential should be given more attention (Powlson et al., 2016).

In contrast, Baudron et al. (2015) have argued that a 'niche' exists where CA fits and this is likely to increase with time, particularly in Southern and Eastern Africa, given the predicted variation in changing climate. This is characterised by areas where the energy establishment such as labour costs are high; where yield is severely limited primarily by a lack of water availability; and where severe erosion problems exist (Baudron et al., 2015). Across Southern Africa, in recent years there has been an increase in donor and government interest in funding CA programmes. Sumberg et al. (2013) have been critical though of the blanket policy prescriptions taken by some development agencies, as it can lack contextualisation and consideration of alternate pathways.

Thus, recent research on CA and sustainable agriculture practices have also highlighted the need to consider more data to better judge the level of 'adoption' (including detailed biophysical and farmer characteristics) to track changes over time (Pannell and Claasen, 2020); the inclusion of farm-level data as opposed to on-station trials to better understand on-farm realities including opportunity costs (e.g. Pannell et al., 2014); the use of additional indicators with respect to tillage implements and farm practices (Findlater et al., 2019) and consideration of environmental threats/productivity of the soil (Knowler and Bradshaw, 2007). Dessart et al. (2019) have further highlighted the importance of considering behavioural factors (e.g. openness to new experiences, risk seeking and social pressure from key social referents) that affect the 'adoption' of sustainable agriculture practices as have Lalani et al. (2016). Similarly, Weersink and Fulton (2020) highlight 'adoption' cannot be understood in binary form (adopt/non-adopt) and involves multiple stages which need to be considered in sequence and include economic and non-economic factors. Furthermore, Levy et al. (2018) has also shown that the level of 'systems thinking' (i.e. network metrics that measure the degree of complexity, non-linearity, cyclic interdependence and feedback representation) may play a role in understanding decision-making with regards to sustainable agriculture.

Building on Lalani et al. (2016) and previous work on mental models and CA (e.g. Halbrendt et al., 2016; Levy et al. 2018), this study tests a hypothesis related to whether farmers' perceptions of CA are associated with distinctly different 'mental models' and whether these 'ways of thinking' are associated with farmers' identified/self-identified groupings a priori. Secondly, we examine whether these mental model groupings (distinct clusters of system perceptions) are associated with actual on-farm measurements. Finally, we explore the hypothesis that 'systems thinking' and CA usage are positively associated—that is, mental models generated by farmers with a higher level of experiential learning and practice of CA demonstrate higher degrees of systems thinking and stronger positive perceptions of CA, while mental models of farmers who practice conventional tillage more frequently show evidence of linear thinking.

In the next section, we describe the role of mental models in environmental decision-making and previous applications. and the study background. In section 2 we outline the case study background and our empirical framework. Results are presented in section 3, followed by discussion (section 4) and concluding section (section 5).

1.1.1 Mental models

To understand individual farmers' perceptions, we focus on their 'mental models' as they relate to CA. The notion of mental models, which was first introduced by Craik (1943), has been widely used as a construct to understand how individuals and groups understand the world and make decisions within it (see review by Jones et al. 2011). These internal models are often elicited and represented through concept or cognitive mapping. A cognitive map can be thought of as a graphical map that reflects mental processing, which is comprised of collected information and a series of cognitive abstractions by which individuals filter, code, store, refine and recall information about physical phenomena and experiences into an external representation (Vanwindekens et al., 2013; Vuillot et al. 2016; Levy et al., 2018). Therefore, understanding variation in farmer mental models, and indeed in some cases how consistent these perceptions align with measurements of external "reality", is considered to shed light on human decision-making and subsequent behavioural intentions and behaviours (Halbrendt et al., 2014)

Figure 1. Map of Mozambique showing the studied province (Cabo Delgado, in red) and district (Pemba-Metuge, in black).

2. Methods

2.1 Case study area

Cabo Delgado is the northernmost province of Mozambique and is situated on the Mozambiquan coastal plain approximate latitudes and longitudes -12.3335° S, and longitude 39.3206° E, respectively (Fig. 1). Its climate is sub-humid, moist Savanna, characterized by a long dry season spanning May to November and a rainy season commencing December and extending into April. Within greater Mozambique there exist ten different agro-ecological regions each grouped into three different agroecological categories based in large part on mean annual rainfall and degrees of evapotranspiration. A detailed explanation of the agroecological zones in Mozambique and covering Cabo Delgado province can be found in INIA (1994), Silici et al. (2015) and Salvador et al. (2014). The district under study, Pemba-Metuge, falls predominantly under the R8 classification (See Salvador et al., 2014), typified by comparatively low rainfall less than 1000mm per annum and have high evapotranspiration but the rainfall distribution is often variable with many intense dry spells and frequent heavy downpours. The predominant soil type is Alfisols (Maria and Yost, 2006), which are red clay soils notably deficient in nitrogen and phosphorous (Soil Survey Staff, 2010). Poverty is a major concern in Cabo Delgado. Indicators throughout Mozambique generally place Cabo Delgado among the poorest of provinces in Mozambique (Fox et al., 2005). In addition, there is a heavy reliance on agriculture though livestock numbers are very low; infrastructure including roads are of poor quality which significantly impede market access.

2.1.1. Conservation Agriculture in Cabo Delgado

A number of actors have participated in the promotion of CA in Cabo Delgado including a host of Non-governmental organisations (NGOs) including WWF and Umokazi. State actors (e.g. Ministry of Agriculture) have also supported its promotion as CA has formed part of the government's strategic agriculture reform (Lalani et al., 2017b). The institutional presence of the Aga Khan Foundation Coastal Rural Support Programme (AKF-CRSP) has also spearheaded promotion throughout the province (including the district under study) through the establishment of farmer field schools, within each of the districts. As of 2014, there were 266 farmer field schools in Cabo Delgado that focus on CA leading to a combined membership of 5000 members (Lalani et al., 2017b). The end of project funding in 2015, however, halted the CA project and farmer field school establishment in the district of Metuge (personal communication, Jose Dambiro, 2018). Locally adapted/context specific manual systems (e.g.

micro-pits/shallow holes similar to basins promoted elsewhere in SSA but do not require tillage each year) as well as direct seeding with use of a hand-hoe have been promoted.

2.2. Farm and field selection

In October 2017, discussions were held with farmers/key informants in two villages in Pemba-Metuge district (Nangua and Tatara) regarding their use/non-use of CA and perceptions of wealth in their respective villages. The district/villages were chosen due to their ease of access by road from Pemba (main city). Five groups of farmers were identified based on their self-identification and in consultation with key informants, familiar with CA practices, from the two villages: (i) early users of CA (1- 3 years); (ii) experienced users of CA (4 years or more); (iii) those that had stopped using CA; (iv) conventional tillage (i.e. with use of a hand-hoe) with mulch and; (v) those practicing conventional tillage (i.e. use of hand hoe) with no mulch. Key informants from both villages drew up a list of farmers/groupings (including farmers of a similar wealth strata e.g. size of the land). It was agreed that due to time constraints and resources 50 farmers (5 from each group) i.e. 25 per village would be interviewed/followed during the season. Farmers from each of the groupings were selected (from the list of farmers) and asked if they would like to participate in the study. Informed consent was gathered through explanation of a consent form in the local language. If a farmer did not want to participate in the study another farmer was contacted until the desired number was reached. 50 farmers from 2 villages (31 Males and 19 Females) were interviewed/followed in total i.e. 25 from each village (5 per group per village).

For each farmer, their main machamba (plot) cultivated with cowpea was chosen for field assessment during the 2017/2018 season as this was the crop that all 50 farmers shared in common and cultivated. All farmers cultivated a mixture of at least three crops e.g. maize, cassava, pigeonpea, sesame or peanuts/lablab. Some farmers were using micro-pits (shallow holes) with similar depths-the majority were CA farmers or those that had stopped using CA, i.e. CA left group (Appendix Table A2 and Table A3). In addition, only one farmer used compost. None of the farmers applied manure, fertiliser, pesticides or herbicides.

2.2.1 Field measurements

To explore the association between farmers' mental model predictions of outcomes of CA/conventional practices and on-farm measurements of those impacts, we evaluated cowpea aboveground biomass and yield, weed cover, and soil quality parameters from the farmer's main plot.

Aboveground biomass of cowpea and weed cover were evaluated in April 2018 in four 1 m x1 m quadrats. In each quadrat, cowpea biomass was cut at ground level and weighed as fresh biomass. It was then left to dry for 5 days on the farmer's main plot and weighed again to determine dry biomass. After removal of cowpea biomass, weed cover was determined in each quadrat using Canopeo (Patrignani and Ochsner, 2015). Total soil cover, green cover and the amount of coverage of cover plant dead residues was also assessed visually in each quadrat.

Cowpea dry yield was determined manually at harvest time, in June 2018, in four 1 m x1 m quadrats. Soil samples were taken for each field before harvest, in May 2018. For each field, five cores were taken and mixed to obtain a unique composite sample, at two different depths, 0-20 cm and 20-40 cm. Soil samples were analysed at the ARC-Institute for Soil, Climate and Water in Pretoria, South Africa. Composite samples were analysed for texture, pH (water), organic carbon (loss on ignition), total nitrogen (Kjeldhal method), available phosphorus (Bray method) and available potassium (ammonium acetate extraction).

Bulk density was determined for each field taking five undisturbed cores at two different depths. The cylinders had a diameter of 7 cm and height of 5 cm. The cores were taken in the middle of the two studied layers (i.e. between 7.5 and 12.5 cm for the 0-20 cm layer, and between 27.5 and 32.5 cm for the 20-40 cm layer). The soil contained in each cylinder was then dried at 105°C and weighed. Bulk density was obtained by dividing the dry weight by the volume of the cylinder. The median of the five cores was used to represent the field. Carbon stock for the topsoil layer was computed using the minimum equivalent soil mass approach (Lee et al., 2009). Intergroup differences between carbon stock and carbon concentration were also tested with ANCOVAs, using clay content as a covariate.

2.3. Measuring agricultural beliefs and belief based predictions

This study uses Fuzzy Cognitive Mapping (FCM) to elicit representations of farmers' mental models of the perceived causal relationships between environmental conditions (e.g. soil moisture and soil fertility), agricultural outcomes (e.g. crop yield, weed coverage, crop income), farmers' decisions (e.g. crop selection) and agricultural practices (e.g. conservation agriculture/conventional practices). For more details about FCM methodology see Ozesmi and Ozesmi (2004). FCMs are semi-quantitative forms of concept maps which allow for the mental model representations of system structure (i.e., description of how system components are interconnected) and system function (i.e., prediction of how changes in system components impact system outcomes) (Gray et al., 2015; Giabbanelli et al. 2017; Aminpour et al. 2020). FCMs represent causal relationships among factors (i.e., system components) using weighted directed graphs, where each causal link is assigned a normalized numeric weigh (e.g. between -1 to +1) or qualitative weight (e.g., low, medium, or high) that show the strength of the causal relationship (Wei et al., 2008). In addition, FCMs use aspects of fuzzy logic, neural networks, semantic networks, and nonlinear dynamic systems (Glykas, 2010) to predict system changes. These FCMs can be collected either in the form of having someone draw out their models graphically (e.g. through in-person or online interviews where individuals, with the help of facilitators, build their own maps like the process described in Cholewicki et al. 2019) or can be constructed through responses to surveys (Halbrendt et al., 2014).

2.4. Data collection

2.4.1. Survey and mental models elicitation

In May, 2018 a series of focus group interviews were conducted with farmers from the two villages in Metuge District, Cabo Delgado to ascertain an understanding of agricultural practices in these villages. The result of these focus group interviews was a list of 20 standardised concepts which represented key environmental factors (e.g. soil moisture and soil nutrients), agricultural outcomes (e.g. crop yield, weed coverage, crop income), farmers' choices (e.g. crop selection) and agricultural practices relevant to CA or conventional tillage. With the aid of an experienced field facilitator/enumerator, these list of concepts were then translated into the local dialect and a hypothetical concept map was created, such that potential causal relationships between concepts were hypothesised as + (positive influence) – (negative influence) or undecided (no influence) (Fig. 2). Using a formal household survey, which was administered in June 2018, we asked farmers to customize the hypothetical concept map based on their own perceptions of causal relationships. That is, the survey asked farmers to adjust the strength of relationships using a Likert scale. For example, survey participants were asked if improved yield influenced soil quality and to what degree using a scale from strongly negative (-1) to strongly positive (+1). These individual survey responses formed individually customised FCMs representing each individual farmer's mental model. The individual FCMs were then translated into an adjacency matrix (a mathematical representation of a directed graph) to be analysed computationally. In addition to the mental model related questions the household survey also gathered data on household demographics, farm practices, off-farm income, farm budget and wellbeing indicators. Furthermore, we conducted post-survey informal discussions (i.e., unstructured interviews) with all of the farmers surveyed to triangulate information from the household survey.

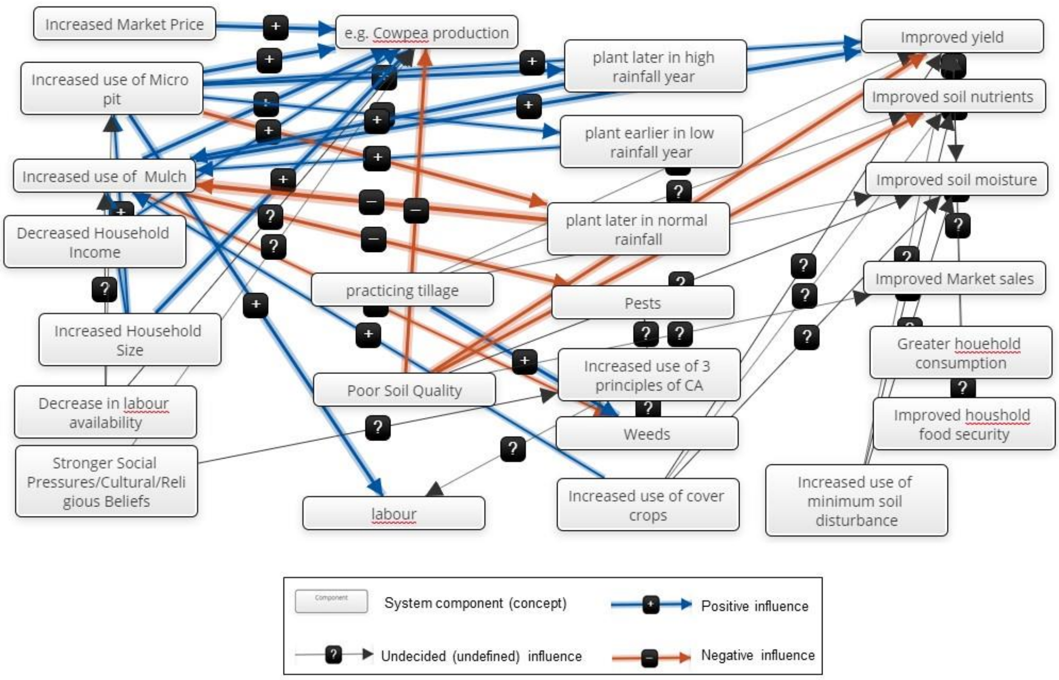


Figure 2. A hypothetical "social" cognitive map (see Ozesmi and Ozesmi 2004) created with Mental Modeler online tool (www.mentalmodeler.org). The arrows linking boxes show potential causal relationships between concepts that are hypothesised as + (blue links) – (orange links) or undecided (question mark). Each Individual farmer customised this map through survey responses to reflect their own understanding.

2.5 Data analysis

2.5.1. Farm-budget analysis

The study used gross margin (GM) analysis to compare farmers net returns among farmer practice groups. Farmers' net returns (NR) are calculated by yield per hectare multiplied by price ($y \times p$) for all crops in the specific mix less full labour costs (hired and family labour costed based on the local price of labour for a typical day/hour) per hectare (l) and opportunity cost of mulch (m) per hectare (i.e. if applicable).

$$NR = (y \times p) - (l + m) \quad (1)$$

The cost of mulch is based a crop grain to residue ratio using a 1:1 grain to residue ratio for maize and sesame and 1:1.35 for legumes (see Lalani et al., 2017; Pannell et al., 2014) i.e. cowpea and cassava is used to calculate the opportunity cost of mulch as feed.[1] These are presented in the local currency i.e. Mozambique Meticais (MZN).

2.5.1.1 Comparing means between groups/clusters

Independent samples t-tests were used to compare the means of field measurements and socio-economic variables/the main socio-demographic variables; including land-related variables, soil characteristics, and cropping management practices between farmers.

2.5.2. Mental model clustering to understand variation in "ways of thinking"

We drew on network analysis to measure structural metrics of cognitive maps that provide important information about a person's mental model (perceptions) of causal interdependencies. The network analysis metrics we used included number of connections (i.e., number of nonzero links between nodes) in each FCM, sum of the absolute value of the link strengths, centrality of five key concepts of CA (i.e., use of micro pits, mulch, cover crops, minimum soil disturbance, and tillage), total number of concepts (i.e. nodes in a graph), network density (i.e., number of nonzero links proportion to the number of all possible links), number of drivers (i.e. nodes with zero in-degree), receivers (i.e. nodes with zero out-degree), ordinary concepts (i.e. nodes with nonzero in-degree and out-degree), MacDonald hierarchy index (MacDonald 1983), and complexity score (ratio of receivers to drivers). For more details see Ozesmi & Ozesmi (2004; Table 1). We subjected these 14 metrics to a principle component analysis (PCA) to reduce the dimensions. A hierarchical clustering was then performed using Ward's minimum variance method on the Euclidian distances between points on the reduced dimensions of resultant principle components (see Appendix Table A2 and Fig. A1).

2.5.3. Scenario analysis using FCMs to understand simulated "farmer decision-making"

[1] We consider cassava under legume for the purpose of valuing the leaf residues. 'Green' in the case of cowpea refers to cassava foilage that are usually harvested mid- season before seed is harvested.

Importantly, FCMs can be used artificially to run “what-if” scenarios (Kosko 1986, Ozesmi and Ozesmi 2004). That is, FCM computation can show the relative changes in the state of system’s components given a particular input or combination of inputs (i.e. a forced manipulation in the state of the system, also known as system “activation”): when one component is activated (i.e. send signal), it triggers a cascade of changes to other system components based on how they are structurally connected. This process continues in several iterations until the initial signal has passed through the entire FCM and all components reach a steady state. By comparing the system state at the beginning and end of the process, we can assess the direction and strength of impact that changing a particular component (or combination of components) has on all other component. Such FCM simulations provide the toolset for a dynamic analysis of mental models and has been used by many researchers to represent belief-based predictions (e.g. Cholewicki et al., 2019; Halbrendt et al., 2014; Steir et al., 2017). For more information about the scenario analysis and equations (see Ozesmi and Ozesmi, 2004; Aminpour et al., 2020a and Aminpour et al., 2020b).

In this study we use FCM adjacency matrices and Python codes for computational FCM analyses developed by Aminpour (2018) (https://github.com/payamaminpour/PyFCM) to implement decision-making scenario analysis. We run two scenarios using matrix calculation to determine farmers’ perceptions of changes to the model under specified conditions: in the first scenario (*S1*), practicing tillage was artificially increased to a value of 1 to show the predicted impacts on the other model components. In the second scenario (*S2*), several conservation agriculture practices were collectively aggregated (including decreased use of practicing tillage; increased use of minimum soil disturbance; increased use of mulch; increased use of cover crops; and increased use of micro pits) to simulate the practice of 3 principles of CA.

In FCMs, there are nodes (i.e., representing system concepts) and links between them (i.e., representing how concepts are related through causal connections). These graphical maps therefore represent a person’s mental model which is his/her internal understanding about how things are connected through cause-and-effect relationships subjectively articulated by these persons through logical chains of reasoning and therefore help him/her understand/perceive something (e.g., how CA practices would influence crop production). We therefore, by collecting these FCMs, were able to measures farmers' perceptions of how the system works (i.e., how things are interconnected and influence each other), and by conducting FCM dynamic analysis (scenario analysis) we were able to measure how a person would perceive, for example, the impact of CA practice on yield or soil fertility.

2.5.4. Measuring degrees of systems thinking using network analysis

Systems thinking is an important skillset that helps us understand and manage complex systems (Senge and Sterman, 1992). The ability to define components and understand the dynamics of a system in a systematic way can improve farmers' engagement with sustainability issues which are always complex with intertwined social, environmental, and economic aspects (Aminpour et al., 2020b). Farmers with higher systems thinking might be presumed to better understand the complex dynamics of a CA system, and thus they are more likely to better predict a system's behaviour identify intervention points (Meadows, 2008), and evaluate the trade-offs between different decisions made within the system. In addition, systems thinking is thought to enable farmers to develop habits of mind that allows for reasoning about possible system outcomes and suggest actions with optimum trade-offs between ecosystem and human well-being (Gray et al., 2019). Lack of systems thinking, conversely, is associated with an inability to understand certain dimensions of complexity of the system (Senge and Sterman, 1992).

Levy et al. (2018) has shown that degree of 'systems thinking' can be measured using network analysis of mental modes that represent perceived causal structures between system components. As such, network metrics that measure the degree of complexity, non-linearity, non-hierarchical causation, cyclic (closed loop) interdependence and feedback representation may exemplify higher levels of systems thinking. We used four overarching network metrics to measure systems/linear thinking:

i. ***Complexity index*:** The ratio of the number of receiver nodes to the number of driver nodes can be used to compare cognitive maps in terms of their complexity. Larger number of receiver variables indicate that "the cognitive map considers many outcomes and implications that are a result of the system" while a large number of driver variables indicates multiple causes and more frequent top down influences (Ozesmi and Ozesmi, 2004).
ii. ***Simple cycles ratio*:** The ratio of number of simple cycles in a graph to the number of connections can be used to measure the average number of times a connection appears

in a simple cycle of any length. It demonstrates the prevalence of feedback loops and thus higher simple cycles ratio indicates higher systems thinking (Levy et al. 2018).

iii. ***MacDonald hierarchy index*****:** This hierarchy index, conceptualized by MacDonald (1983), measures the extent to which limited number of outcomes are derived by multiple causal origins. It is in fact a "measure of variance of out-degree" and is negatively correlated with complexity score (Levy et. 2018).

iv. ***Flow hierarchy index*****:** This hierarchy index is defined as the fraction of edges not participating in cycles in a directed graph (Luo et al. 2011). Flow and MacDonald hierarchy indices are both proxy measurements of top–down structure in cognitive maps conceptualized by Krackhardt (1994), showing the degree to which a cognitive map involves in leaner-thinking. Thus, lower value of these hierarchy scores indicates higher systems thinking.

3. Results

We split the results into 4 sections. First, we explore whether hierarchical clustering of farmers' mental models using their network metrics emerges into distinct clusters of cognitive maps, and then compare the composition of each cluster to examine the degree to which clusters match self-identified groupings (mentioned in section 2.2). Second, we compare farmers' beliefs and perceptions across clusters of mental models represented by their predictions of scenario outcomes under *S1* and *S2*. Third, we examine whether on-farm measurements demonstrate important differences across clusters of mental models. Finally, we use complex networks and systems theory to compare degrees of systems thinking (i.e., prevalence of network metrics that measure the degree of complexity, non-linearity, cyclic interdependence, and feedback representation) across clusters of mental models.

3.1 Clustering

Fig. 3 shows the results of the mental model clustering. As shown by the dendrograms, 50 farmers' mental models were significantly classified into two distinct clusters through hierarchical clustering based on two principle components explaining about 75% of variance in FCM structural metrics (see Appendix Fig. A1).[2] Analysis of the composition of clusters

[2] We first tried to understand if these mental models, regardless of who created them, demonstrate any emergent clusters, only based on their structural characteristics (i.e. only based on how someone articulates a network of causal relationships between concepts to develop an internal perception of the problem/system). Two clusters

based on farmers' self-identification revealed that cluster 1 was mainly (about 60%) composed of ***Conv*** farmers (those who practice conventional agriculture[3] i.e. practices more akin to conventional tillage). On the contrary, the majority of farmers (about 75%) who constituted cluster 2 were ***Cons*** farmers (those who practice/have practiced CA). These findings suggested that there may be a meaningful association between practicing CA and the structure of farmers' mental models such that farmers who received CA trainings or based on their experiences (independent of the fact that they may no longer believe they are practicing CA) developed in their minds distinct mental models that are structurally distinguishable from those who did not claim to practice CA 'officially' (i.e. conventional tillage users).

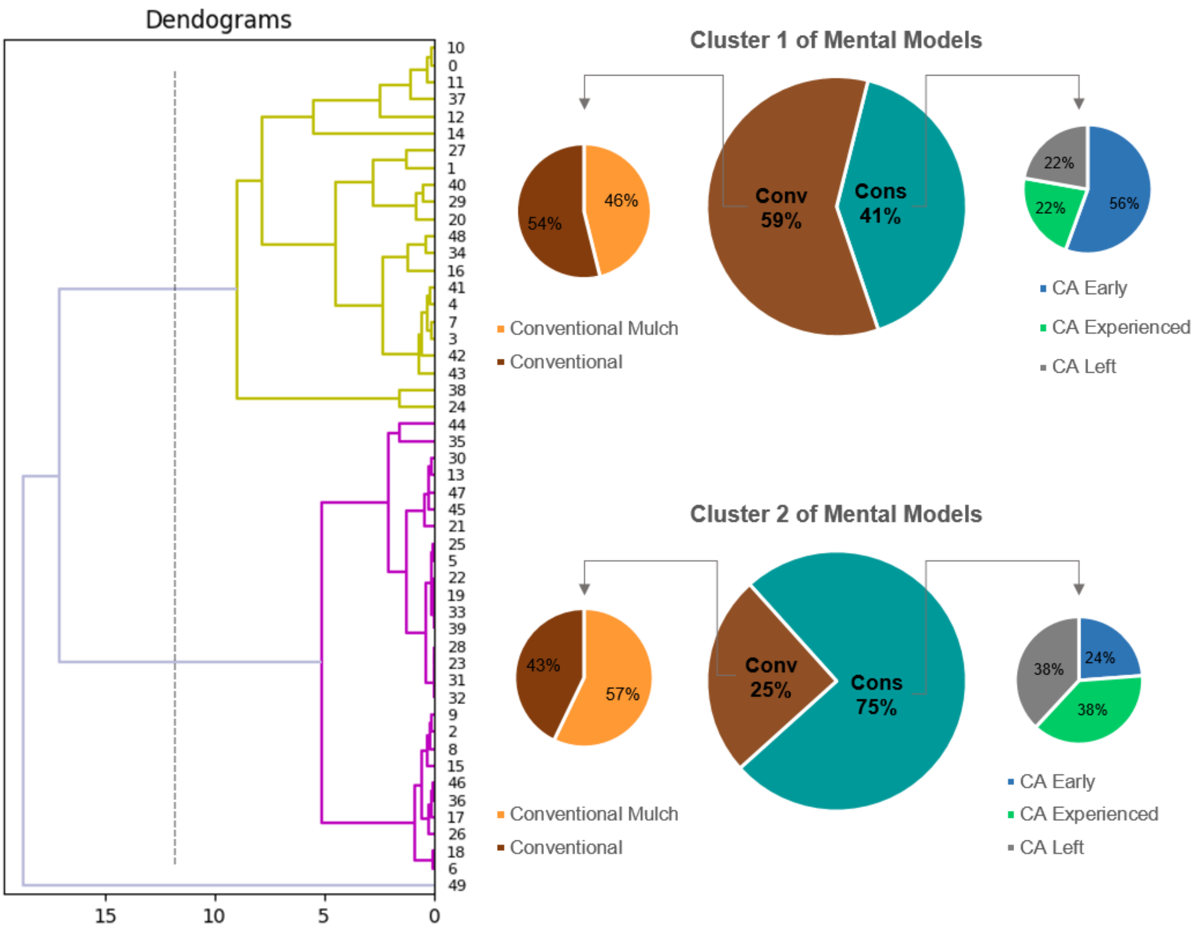


Figure 3. Farmers' mental model clustering. The dendrograms in the left side show how 50 farmers' mental models are classified into distinct clusters through hierarchical clustering using Ward's minimum variance method on the Euclidian distances between mental models. The pie

emerged, however, which suggested that clusters differ mainly due to the practice of CA or conventional agriculture (self-identification).

[3] Conventional agriculture and conventional tillage are used interchangeably

charts in the right side show the composition of clusters based on farmers' self-identification. *Cons* stands for conservation and *Conv* stands for conventional agriculture.

3.2. Scenarios analysis

Fig. 4 shows the results of scenario analysis under two artificial scenarios: (*S1*) decreased use of tillage and (*S2*) increased use of all 3 principles of CA. The boxplots in Fig. 4A show the distribution of predicted changes by clusters.[4] These results indicated that farmers in cluster 2, as opposed to cluster 1, had stronger positive perceptions of CA (e.g., they predicted stronger improvement of yield, soil moisture, soil nutrients, and reduced weed coverage). Yet, farmers of cluster 2 had stronger negative perceptions of some of the socio-economic outcomes of CA than farmers in cluster 1 (e.g. related to labour and household income).

We have also created the average map (i.e. group FCM) of each self-identified group to compare the overall predictions across those groups (Fig. 4B) which could provide one explanation for this. For example, negative perceptions of socio-economic outcomes are considered a contributor to CA 'disadoption'. Interestingly, however, all farmers in the CA left group (i.e. 'disadopters') cited a lack of adequate information/ training and support in close proximity as the main reason behind 'stopping' CA though a few farmers in informal discussions also mentioned the lack of money to hire additional labour as another reason. Similarly, farmers from the conventional tillage groups also cited the lack of access to information (assistance and training) as the primary reason for not using CA. Importantly, the main differences between conventional tillage and CA users regarding their overall group perceptions were reflected in their predictions of CA principles impacts on soil moisture, soil nutrient, and yield (e.g. on average, conventional tillage users predicted a decrease in yield and soil nutrients, while CA users and CA 'disadopters' predicted an increase in yield and soil nutrients as result of increased practice of CA principles).

[4] The figures only depict key changes for the relevant scenario. Where effects are negligible/small these are not shown.

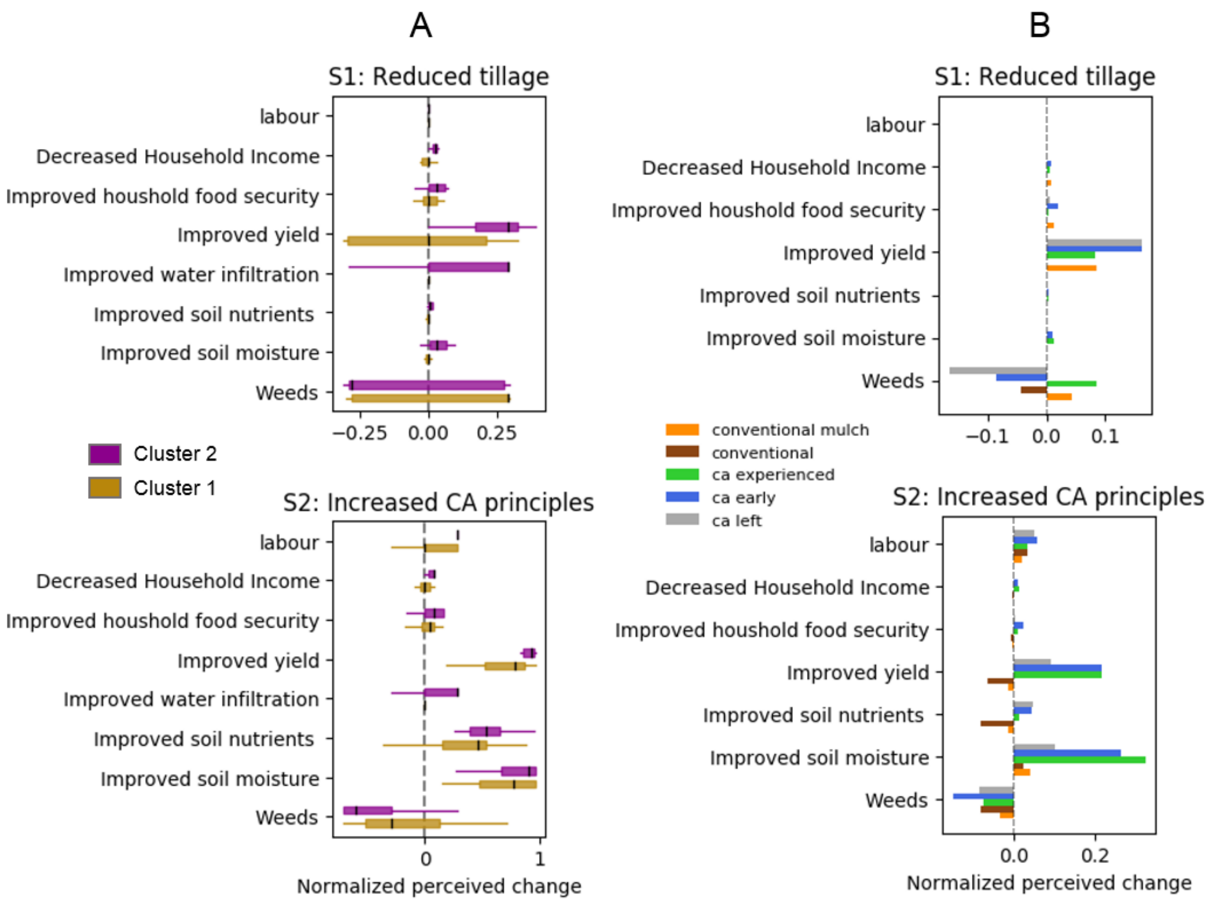


Figure 4. Predition of changes using scenario analysis. Box plots in A show the distribution of predicted changes by different clusters of mental models (cluster 1 and 2). Bar charts in B show the predicted changes by the average map of each group (i.e., an aggregated mental model where the weight of causal links are average values) based on self-identification grouping (convetional, conventinal mulch, CA experienced, CA early, and CA left).

3.3 Field (on-farm) measurements

Field measurements revealed no significant differences between clusters 1 and 2 for the main socio-demographic, land-related variables, soil characteristics, and cropping management practices (independent samples t-tests were used to compare the means). For example, similar means of age, education levels, soil type, and numbers of leguminous trees planted were observed (see Appnedix Table A2 for the full results).The statistically non-significant differences of these characteristics (i.e. covariates) across clusters increased the reliablity of clustering results—that is, clusters of farmers emerged because of their distinct mental model structures mainly driven by farmers' agricultural practices.

In addition, we measured on-farm agricultural outcomes and compared them across two clusters (Fig. 5A). Although on-farm measurements for cluster 2 revealed higher yield, higher soil cover, and lower weed cover than cluster 1, none of these differences were statisticaly significant. Cowpea yield showed huge variability across individuals, with an average of 1.9 t/ha over all fields, ranging from 1.0 t/ha to 2.5 t/ha. Mean weed cover was 57%, ranging from 8% to 49%. Similarly, no significant differences between clusters were observed for socio-economic outcomes; however, these observations suggested that farmers of cluster 2 experienced slightly lower net-benefits and higher labour usage, but better food consumption scores (Fig. 5A). In general, these trends are in high aligment with farmers perceptions (e.g. See Fig 4, farmers in cluster two percieved the practice of CA would improve household food security but percieved that it requires more labour).

Similarly, no statistically significant differences between clusters were observed for soil properties (e.g. bulk density, soil moisture at sampling, total nitrogen, available phosphorus and potassium) at 0-20 cm. Yet, mean values for these properties for cluster 2 demonstrated slightly higher soil moisture, total nitrogen, and potassium than cluster 1, while these observations revealed slightly lower phosphorus and bulk density from cluster 2 compared to cluster 1. Importantly, however, carbon stock in the first layer (48 t/ha on average for 1790 t/ha soil mass for the whole sample) was significantly different across clusters where the mean was higher in cluster 2 compared to cluster 1(Fig. 5B)

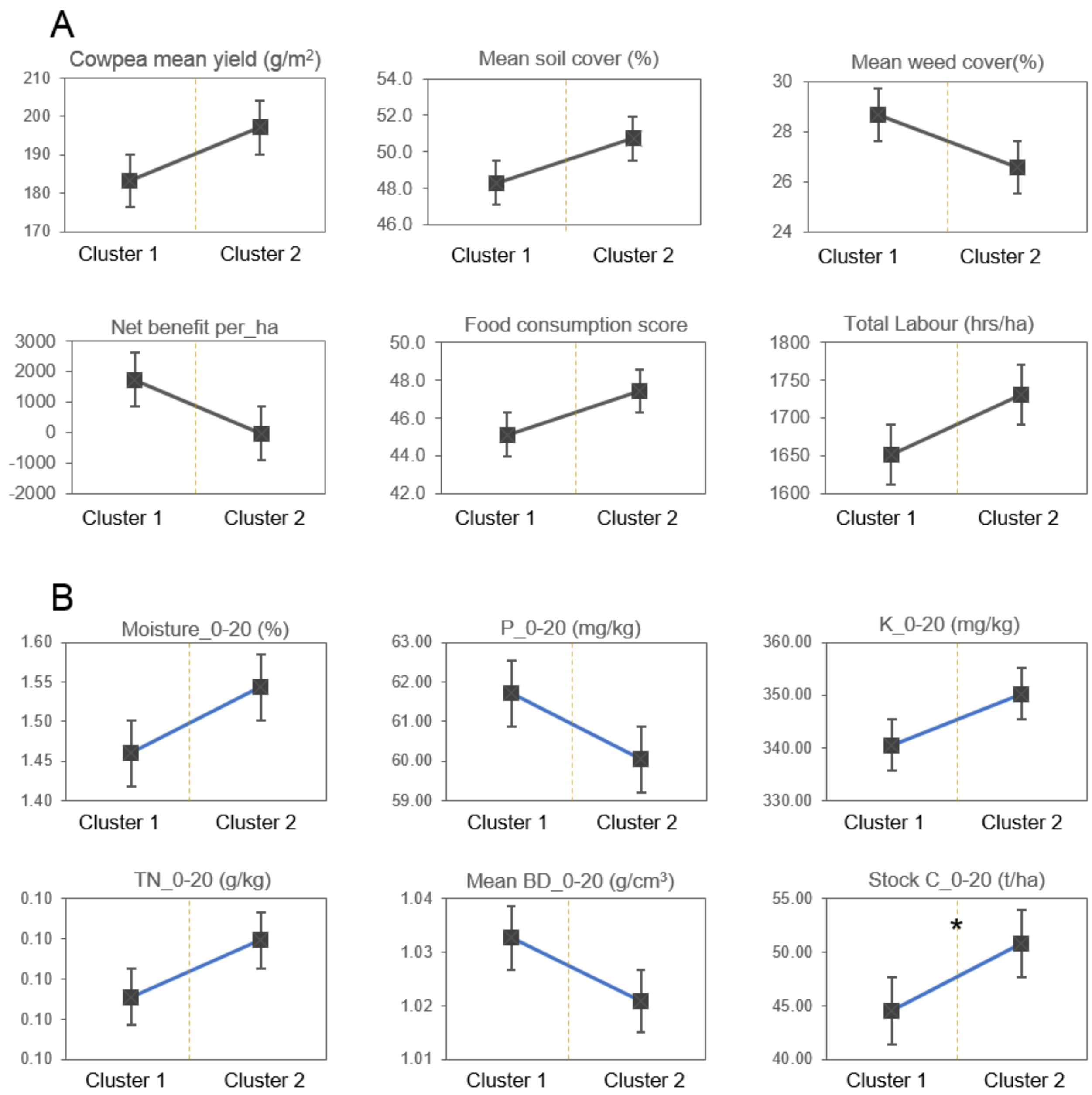


Figure 5. On-farm measurements/other indicators. Net benefit per_ha = net returns/ha in Mozambique Meticais (MZN), Total Labour (hrs/ha)= Total person hours per hectare, Food Consumption Score (FCS) represents households' dietary diversity and nutrient intake based on the frequency food items from the different food groups are consumed by the household over the past 7-days, Moisture_0_20 (%)= Soil moisture (%) (0-20 cm), K_0-20 = available potassium (0-20 cm), P_0-20 = available phosphorus (0-20 cm), TN_0-20 = total nitrogen (0-20 cm), Mean BD_0-20 = Bulk density (0-20 cm), Stock C_0-20 = carbon stock (minimum equivalent soil mass basis, 0-20 cm). Tests of significance of mean differences between the two clusters were tested using independent samples t-tests. The number of asterisks stands for the level of significance for *p*-value < 0.01, 0.05, and 0.001 respectively.

3.4. Network analysis of systems vs linear thinking

Fig. 6 shows the differences between clusters of network metrics for systems thinking and linear thinking. Comparing the distribution of these network metrics across clusters revealed that farmers' mental models in cluster 2 demonstrated significantly higher degrees of systems thinking measured by complexity score and simple cycles ratio than farmers' mental models in cluster 1 (Fig. 6A). On the contrary, mental models in cluster 2 had significantly lower degrees of linear thinking than cluster 1, measured by MacDonald and flow hierarchy indices (Fig. 6B). These results suggest that a higher level of experiential learning and practice of CA leads to higher degrees of systems thinking, even among the CA disadopters.

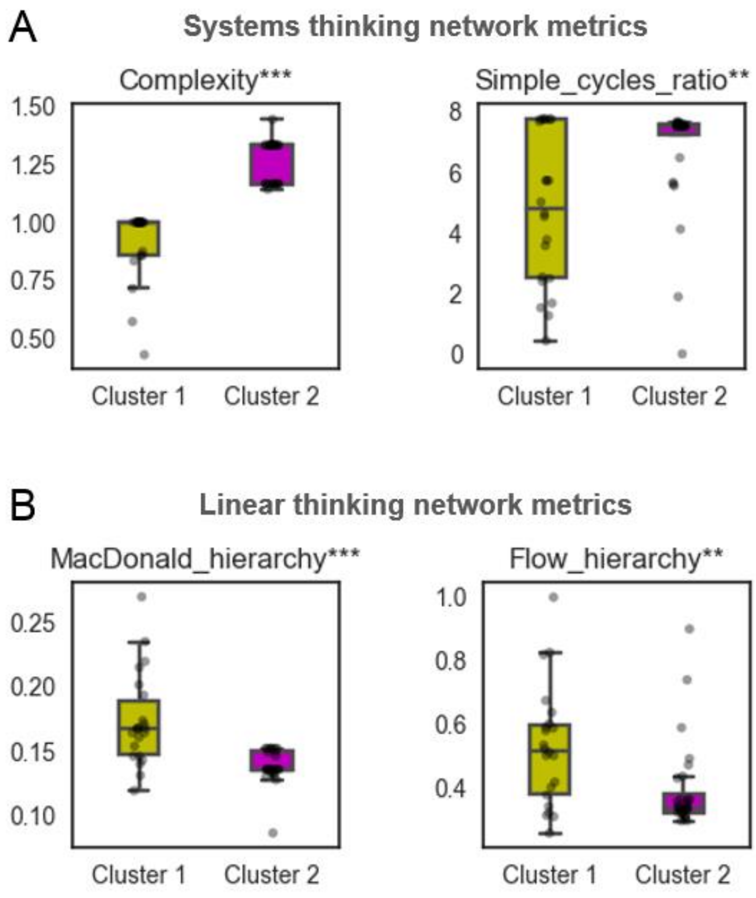


Figure 6. (*A*) Network metrics of systems thinking including the Complexity index and Simple cycles ratio. (*B*) Network metrics of linear thinking including McDonald hierarchy and Flow hierarchy indices (see section 2.4.4). Tests of significance of mean differences between two clusters were tested using independent samples t-tests. The number of asterisks stands for the level of significance for *p*-value < 0.01, 0.05, and 0.001 respectively.

4. Discussion

4.1 Farmers' perceptions

The results have demonstrated that the 50 farmers' mental models were significantly polarised into two distinct clusters which indicate a meaningful association between farmers' self-identification and the structure of farmers' mental models. For example, there are distinctly different models in cluster 2, consisting of those with more experience of using CA, compared to cluster 1: cluster 2, as opposed to cluster 1 (Fig. 1), had stronger positive perceptions of CA (e.g., they perceived higher yield, improved soil moisture/soil nutrients, and reduced weed coverage as a result of CA) (See Fig. 4). These results support previous findings about the relationship between farmers' CA perceptions, practice, and experiences. For example, Hoffman et al. (2014) identified that winegrape grower mental models of sustainability were strongly related to the adoption of sustainable agriculture practices and farmers' participation in extension programmes. Lalani et al. (2016) also found that farmers with a high intention to use CA had a higher perceived behavioural control and were motivated by key cognitive drivers such as higher yield, lower weeds, and higher soil quality. In addition, those that participated in a Farmer Field School (FFS) had stronger positive perceptions and found CA easier to use. Wuepper et al. (2019) also showed that farmers in Ghana with a significantly higher perceived self-efficacy were more likely to practice mulching and perceived the costs associated with the practice to be lower.

Interestingly, however, farmers in cluster 2 had stronger negative perceptions of some of the socio-economic outcomes of CA than farmers in cluster 1 (e.g. they predicted stronger increases in labour) (see Fig. 4). Increased labour requirements have been identified as a major contributor to CA 'disadoption' (e.g. Chinseu et al., 2018). However, all farmers in the CA left group (i.e. 'disadopters') mostly cited a lack of adequate information/ training and support as the main reason for 'disadoption whilst a lack of labour was also mentioned as a contributing factor. Whilst causes of non-usage of CA are multi-dimensional (e.g. economic, social, institutional) it has been argued that there are likely to be proximate causes such as disenchantment with advisory services and technical support (Chinseu et al., 2019). Other authors have also suggested that where the learning process is hampered or benefits may not materialise/be apparent 'non-adoption' or 'disadoption' can occur. (Kassam 2014; Weersink and Fulton, (2020)). Furthermore, Lalani et al. (2016) found for farmers in the same district under study that the perceived increase in labour and a lack of knowledge/skills were key cognitive barriers for those with a lower intention to practice CA whilst reduction in labour was considered a cognitive driver among those with high intention to CA. This being said, it should be noted that perceptions can be biased or partial. For example, Waldman et al. (2019) showed that cognitive bias can occur as farmers' perceptions of earlier rainfall onset and the physically derived onset did not match. Though, on the whole, farmers in this context are positive about CA practices which also point to the need for appropriate 'framing of costs and benefits' (Dessart et al., 2019).

4.2 On-farm measurements and socio-economic outcomes

The measurements, for the most part, in this study align with the perceptions of farmers (Fig. 5). For example, farmers in cluster 2 (mainly consists of CA users) had stronger positive perceptions of CA than cluster 1 (mainly consists of conventional users) and most of the on-farm measurements/other indicators highlighted this (even if not significant) such as higher yield, lower weeds, improved soil quality etc. (See Fig. 4 and 5). Thus, if people in one cluster perceived a stronger positive influence on yield as a result of CA practice, we also measured higher actual yield from their plots (Fig 4 and 5). Moreover, conventional users also had stronger positive perceptions of the practice of tillage (data not shown).

Though, caution should be raised regarding equating correlation with causation. For example, there are likely to be several omitted variable bias such as the quality of the field and/or self-selection bias. Other techniques have been used to account for this such as randomised control trials (RCTs) and spatial regression continuity design. For example, Wuepper et al. (2020) employ a spatial regression discontinuity design to examine erosion rates with the emphasis on comparing observations that are close to each other (similar) and controlling for all 'spatially continuously distributed confounders'.

Notwithstanding this, field measurements revealed no significant differences between the two clusters of farmers (clusters 1 and 2) for the main socio-demographics, land-related variables, soil characteristics, and cropping management practices (see Table A2). For example, similar means of age, education levels, soil type, and numbers of leguminous trees planted were observed between groups (covariates). Thus, taken together, there are some meaningful deductions that can be made for some of the outcomes. As mentioned, farmers in cluster 2 had stronger positive perceptions of CA (e.g., higher yield, improved soil moisture/soil nutrients, and reduced weed coverage). This was also reflected in on-farm measurements e.g. higher cowpea yield, lower weed coverage, higher soil moisture/soil nutrients (Fig 5and 5b). Cluster

2 also had overall higher gross revenues (cluster 1 total revenue = 30796.50 *MZN* and Cluster 2 total revenue = 35996.30 *MZN*) though the inclusion of the opportunity cost of mulch and labour resulted in lower returns compared to cluster 1 (mainly conventional farmers). Previous research in the same district (based a larger sample size/randomly selected) found benefits to labour/net returns for CA farmers (with the opportunity cost of mulch and labour accounted for) relative to conventional farmers but these were dependent on crop-mix (Lalani et al., 2017).

With respect to soil properties it is also important to note that mean values for cluster 2 demonstrated slightly higher soil moisture, total nitrogen, potassium and lower bulk density than cluster 1, though these were not significantly different (Fig. 5B). Similarly, higher soil cover, yield and significantly higher carbon stock (in the topsoil) for cluster 2 compared to cluster 1 were observed. This supports the notion that under CA systems where the amounts of biomass production are higher (retained as surface mulch), and yield is not negatively impacted, this can also lead to higher amounts of SOC (particularly in the topsoil) compared to conventional plots (Thierfelder et al., 2012; Page et al., 2020; Kassam et al., 2014). In addition, the association of higher soil cover and lower bulk density among cluster 2 is supported by previous research which also found under a no-till system that increased residue retention reduced bulk density (e.g. Shaver et al., 2002; Thierfelder et al., 2012). Furthermore, these results are in line with direct seeded CA systems (similar to those used in this region) that have shown to provide yield benefits over time due in large part to better planting arrangements, increased soil quality over time, improved soil moisture conditions for crop growth/development and less soil disturbance (Thierfelder and Wall, 2010 and 2012). The results also point to the benefits of the simultaneous application of all three principles of CA. For example, Pittelkow et al. (2015) highlight yield benefits are realised when all three principles of CA are combined. Whilst there has been some debate regarding the role CA has in carbon sequestration, mainly because of overestimation caused by inadequate sampling and a lack of understanding of what practices/processes are involved in climate change mitigation; SOC increasesdue to crop diversification will more than likely contribute to 'genuine mitigation' (Powlson et al., 2016). Thierfelder et al. (2017) has also argued that the climate change mitigation potential of CA in Southern Africa will largely depend on factors such as the duration of practice, the amount of crop residue retention and the specific cropping system. Our results also point to continued use of CA as a potential contributor to climate change mitigation and adaptation. The role of extreme weather events should also be considered as a potential driver of CA use. Ding et al. (2009) has shown, in the case of no-till, how farmers increased their use of the practice following extremely dry conditions, over several seasons, though reduced their use in extremely wet years. Knowler and Bradshaw (2007) also showed in a comprehensive review of CA studies how ‘awareness of environmental threats’ positively influenced CA use. The importance of locally adapted systems that take into consideration various agro-ecologies has also been noted. For example, Thierfelder et al. (2016) found in Mozambique and Malawi that direct seeded CA treatments led to higher yields in areas of higher rainfall and basins performed well only in dry environments compared to conventional practice. Ward et al. (2018) also showed that practicing mulching and intercropping/rotation had a ‘multiplier effect’ on usage of zero tillage among conventional tillage users in Malawi. This may explain the positive perception among conventional tillage users (with mulch) regarding reduced tillage in this study (Fig. 4). Engler et al. (2019) has pointed to the need to consider the ‘*plasticity of adoption’* which is incremental by nature as continuous change and adaptation relevant to the particular context occurs. The authors highlight how a farmer’s attitude regarding zero-tillage, for instance, can become more positive over time as more information is garnered and by learning over time/through relevant experiences.

4.3 Linear thinking and systems thinking

The network metrics for systems thinking and linear thinking showed higher degrees of complex reasoning patterns such as appreciation of feedback loops and understanding the non-linear interrelationships between multiple aspects of the system among farmers in cluster 2, while farmers in cluster 1 showed evidence of more linear, hierarchical thinking (Fig 6 a and 6b). This suggests that higher forms of experiential learning and practice of CA leads to higher degrees of systems thinking, even among the CA ‘disadopters’. This is also supported by previous research which suggests that CA is complex to practice and requires continuous adaptation based on experiential learning (e.g. Derpsch, 2008).Gray (2018) has noted the need to understand what types of experiences, interventions or training may lead to more complex reasoning patterns and thus higher degrees of systems thinking, which in turn leads to more accurate perceptions of the complex human-environment interactions and may improve the adaptation process and leverage sustainability.

We argue, therefore, that ‘systems thinking’ and the ability to perceive complex causal interrelationships is an important factor contributing to CA usage. However, informational challenges/perceived self-efficacy and barriers to active experiential learning need to be addressed through a host of methods (e.g. Wellard et al., 2014;Leeuwis 2004;Hoff and Walsh,

2018) so farmers do not feel isolated/excluded and thereby able to contribute to enhancing innovation processes. Notwithstanding this, Levy et al. (2018) also suggest that development of systems thinking can provide other benefits including stimulating social learning as it encourages receptiveness to new ideas and to a variety of causal pathways which can also be used to encourage collective problem-solving. Singer et al. (2017) showed that through participatory engagement and modelling with stakeholders how more complex cognitive maps developed regarding water quality issues and how communities were then able to better structure ideas regarding recovery and communicate with those responsible. More broadly, enhanced systems thinking ability could further strengthen community engagement (e.g. addressing sustainability problems at different scales) with respect to socio-ecological decision-making/other 'wicked problems' in similar settings (e.g. Gray et al., 2019). Policy options to encourage this and improve knowledge exchange, in general, could form part of locally constructed innovation systems that support the development of mutually reinforcing stakeholders (e.g. Lalani et al., 2017b) that account for farmers' knowledge and integrate experiential and social learning which thereby forge new relationships, trust and collective action (e.g. Tafesse et al., 2020; Kerenecker et al. 2021).

4.4 Summary and limitations

Our purpose here is to merely highlight the potential link between the degree of systems thinking, use of various CA practices and the possible association with field measurements/socio-economic outcomes. We presuppose that the significantly higher level of systems thinking found for farmers in cluster 2 is associated with a higher level of experiential learning as the clusters differ with respect to farmers' 'self-identified' experience with CA and some of the outcomes point to benefits in this regard (for those in cluster 2 in particular).[5] However, most of the differences are non-significant and longitudinal data/ econometric approaches would provide a more robust understanding of the relationship between cluster groups and outcomes.

[5] To further test the robustness of our findings and validate the findings, we ran a *power analysis*. We have two clusters (*N1=22, and N2 =28*) and the sum of sample size is 50. For this sample size (50 subjects) and for the significance level of (p<=0.05), the power analysis for an independent-sample t-test would tell us that the statistical power will be larger than 0.8 for all of the features for which we reported statistically significantly different means across two clusters (in particular, the Systems Thinking and Linear Thinking metrics in Fig 6). The desired power level is typically 80%, which means that there is a >80% probability we will not commit a type II error. Generally, a power of .80 (80 percent) or higher is considered acceptable for a study/ parametric test.

5. Conclusions

Our study advances the use of a mental modelling approach to leveraging sustainable agriculture and inform policies and management strategies regarding CA practices. Our results demonstrated that there is a link between farmers' perception of CA/non-CA, and the structure of their mental models. In addition, we showed that the elicitation of mental models of local farmers could be implemented by a certain cognitive mapping technique which was simply embedded in a survey. Our study, therefore, provides local communities, researchers, and policy makers with new forms of information about how CA users/non-users perceive the system differently, how these distinct perceptions are internally represented by farmers mental models, and how these internal representations can be elicited to inform decision-making, facilitate communication, and approach 'disadoption' or 'non-usage'. For example, in reality, the on-farm application of CA practices is often 'messy' and 'fluid' as farmers experiment and make adaptations (Hermans, 2020) We also examined whether these distinct mental models (i.e., clusters of perceptions) are associated with actual differences in on-farm measurements. We provided empirical evidence for the potential link between farmers' perceptions and their real-world on-farm measurements such as yield, weed cover, soil nutrients and soil moisture, etc. Finally, we expand upon previous research by investigating the link between the degree of 'systems thinking' and the structure of farmers' mental models. By combining a semi-quantitative cognitive mapping technique and complex network analysis we were able to measure the complexity of causal relationships in a mental model, thereby providing a practical tool for measuring the degree of systems thinking. We showed that systems thinking—as measured by quantitative network metrics such as complexity index, frequency of feedback loops, and the lower degrees of linear hierarchical causalities—is a critical component of 'successful' CA usage, and that non-usage of CA is associated with a lack of systems thinking and a stronger negative perception of the potential benefits of CA. Despite our assumption about the impact of active experiential learning, support and access to information/assistance and educational opportunities on the development of systems thinking, future research is needed to investigate what important factors and innovative strategies may foster farmers' systems thinking ability (e,g. Gray et al. 2019; Levey et al. 2018) and to what extent these abilities correspond to 'successful' CA 'adoption' and adaptation. More importantly our findings demonstrate that simple binary measurements/reductionist views on CA do not capture the nuanced nature of CA usage and underscores the importance of considering a detailed combination of biophysical, socio-economic and mental modelling related variables in order to better understand farmers' decision making, learning processes and use of practices.

References

Aminpour, P., 2018. Data From "PyFCM: Python for Fuzzy Cognitive Mapping". GitHub. Available at. https://github.com/payamaminpour/PyFCM.

Aminpour, P., Gray, S.A., Jetter, A.J., Introne, J.E., Singer, A., Arlinghaus, R., 2020a. Wisdom of stakeholder crowds in complex social–ecological systems. Nat. Sustain. 3, 191–199. https://doi.org/10.1038/s41893-019-0467-z.

Aminpour, P., Gray, S., Richardson, R., Singer, A., Castro-Diaz, L., Schaefer, M., Ramlan, M.A., Chikowore, N.R., 2020b. Perspectives of scholars on the nature of sustainability: a survey study. Int. J. Sustain. High. Educ. 21, 34–53. https://doi.org/10.1108/ijshe-05-2019-0161.

Baudron, F., Andersson, J.A., Corbeels, M., Giller, K.E., 2012. Failing to yield? Ploughs, Conservation Agriculture and the problem of agricultural intensification: an example from the Zambezi Valley, Zimbabwe. J. Dev. Stud. 48, 393–412.

Baudron, F., Thierfelder, C., Nyagumbo, I., G´erard, B., 2015. Where to target Conservation Agriculture for African smallholders? How to overcome challenges associated with its implementation? Experience from eastern and southern Africa. Environments 2, 338.

Brown, B., Llewellyn, R., Nuberg, I., 2018. Why do information gaps persist in African smallholder agriculture? Perspectives from farmers lacking exposure to Conservation Agriculture. J. Agric. Educ. Ext. 24, 191–208. https://doi.org/10.1080/1389224x.2018.1429283.

Chauhan, B.S., Singh, R.G., Mahajan, G., 2012. Ecology and management of weeds under Conservation Agriculture: a review. Crop Prot. 38, 57–65.

Chinseu, E., Dougill, A., Stringer, L., 2018. Why do smallholder farmers dis-adopt Conservation Agriculture? Insights from Malawi. Land Degrad. Dev. 30, 533–543. https://doi.org/10.1002/ldr.3190.

Chinseu, E.L., Stringer, L.C., Dougill, A.J., 2019. An empirically derived conceptual framework to assess dis-adoption of Conservation Agriculture: multiple drivers and institutional deficiencies. J. Sustain. Develop. 12, 48. https://doi.org/10.5539/jsd.v12n5p48.

Cholewicki, J., Popovich Jr., J.M., Aminpour, P., Gray, S.A., Lee, A.S., Hodges, P.W., 2019. Development of a collaborative model of low back pain: report from the 2017 NASS consensus meeting. Spine J. 19 (6), 1029–1040.

Craik, K.J.W., 1943. The Nature of Explanation. Cambridge University Press, Cambridge, UK.

Dambiro, J., (2018) Personal communication: Aga Khan Foundation (Mozambique).

Derpsch, R., 2008. Critical Steps in No-till Adoption. In: Goddard, T., Zoebisch, M.A., Gan, Y.T., Ellis, W., Watson, A., Sombatpanit, S. (Eds.), No-Till Farming Systems World Association of Soil and Water Conservation (WASWC)., Bangkok, pp. 479–495. Special Publication No. 3.

Dessart, F.J., Barreiro-Hurl´e, J., van Bavel, R., 2019. Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. Eur. Rev. Agric.

Econ. 46 (3), 417–471.

Ding, Y., Schoengold, K., Tadesse, T., 2009. The impact of weather extremes in agricultural production methods: does drought increase adoption of conservation tillage practices? J. Agric. Resour. Econ. 34 (3), 395–411.

Engler, A., Poortvliet, P.M., Klerkx, L., 2019. Toward understanding conservation behavior in agriculture as a dynamic and mutually responsive process between individuals and the social system. J. Soil Water Conserv. 74 https://doi.org/ 10.2489/jswc.74.4.74a.

FAO, 2020. URL http://www.fao.org/conservation-agriculture/en/. (Accessed 13.12.2020).

Findlater, K., Kandlikar, M., Satterfield, T., 2019. Misunderstanding Conservation Agriculture: challenges in promoting, monitoring and evaluating sustainable farming. Environ. Sci. Pol. 100, 47–54. https://doi.org/10.1016/j. envsci.2019.05.027.

Fox, L., Bardasi, Elena, Van den Broeck, Katleen, 2005. Poverty in Mozambique:

Unraveling Changes and Determinants. Africa Region. World Bank, Washington.

Friedrich, T., Derpsch, R., Kassam, A., 2012. Overview of the global spread of Conservation Agriculture. In: The Journal of Field Actions, Field Actions Science Reports Special Issue 6. http://factsreports.revues.org/1941 (Accessed 03.10.15).

Giabbanelli, P.J., Gray, S.A., Aminpour, P., 2017. Combining fuzzy cognitive maps with agent-based modeling: frameworks and pitfalls of a powerful hybrid modeling approach to understand human-environment interactions. Environ. Model. Softw. 95, 320–325.

Giller, K.E., 2012. No silver bullets for African soil problems. Nature 485, 41.

Giller, K.E., Witter, E., Corbeels, M., Tittonell, P., 2009. Conservation agriculture and smallholder farming in Africa: the Heretics' view. Field Crop Res. 114, 23–34.

Giller, K.E., Andersson, J.A., Corbeels, M., Kirkegaard, J., Mortensen, D., Erenstein, O., Vanlauwe, B., 2015. Beyond Conservation Agriculture. Front. Plant Sci. 6 https://doi.org/10.3389/fpls.2015.00870.

Glykas, G., 2010. Fuzzy Cognitive Maps: Advances in Theory, Methodologies, Tools and Applications. Springer, Berlin, Germany. https://doi.org/10.1007/978-3-642-03220-2.

Gray, S., 2018. Measuring systems thinking. Nat. Sustain. 1, 388–389. https://doi.org/10.1038/s41893-018-0121-1.

Gray, S.A., Gray, S., De Kok, J.L., Helfgott, A.E., O'Dwyer, B., Jordan, R., Nyaki, A., 2015. Using fuzzy cognitive mapping as a participatory approach to analyze change, preferred states, and perceived resilience of social-ecological systems. Ecol. Soc. 20 (2).

Gray, S., Sterling, E.J., Aminpour, P., Goralnik, L., Singer, A., Wei, C., Akabas, S., Jordan, R.C., Giabbanelli, P.J., Hodbod, J., Betley, E., Norris, P., 2019. Assessing (social-ecological) systems thinking by evaluating cognitive maps. Sustainability 11, 5753. https://doi.org/10.3390/su11205753.

Halbrendt, J., Gray, S.A., Crow, S., Radovich, T., Kimura, A.H., Tamang, B.B., 2014. Differences in farmer and expert beliefs and the perceived impacts of Conservation Agriculture. Glob. Environ. Chang. 28, 50–62. https://doi.org/10.1016/j.

gloenvcha.2014.05.001.

Hermans, T.D., Whitfield, S., Dougill, A.J., Thierfelder, C., 2020. Bridging the disciplinary gap in Conservation Agriculture research, in Malawi. A review. Agron. Sustain. Dev. 40 https://doi.org/10.1007/s13593-020-0608-9.

Hoff, K., Walsh, J., 2018. The whys of social exclusion: insights from behavioral economics. World Bank Res. Obs. 33, 1–33. https://doi.org/10.1093/wbro/lkx010.

Hoffman, M., Lubell, M., Hillis, V., 2014. Linking knowledge and action through mental models of sustainable agriculture. Proc. Natl. Acad. Sci. 111, 13016–13021. https://doi.org/10.1073/pnas.1400435111.

INIA, 1994. Zonas Agro-ecologicas de Moçambique. INIA, Maputo, Mozambique.

Jones, N., Ross, H., Lynam, T., Perez, P., Leitch, A., 2011. Mental Models: An Interdisciplinary Synthesis of Theory and Methods.

Kassam, A.H., Friedrich, T., Shaxson, F., Bartz, H., Mello, I., Kienzle, J., Pretty, J., 2014, The spread of Conservation Agriculture: policy and institutional support for adoption and uptake. Field Actions Sci. Rep. 7, 1–12. Available online at: http://factsreports.

revues.org/3720.

Kassam, A.H., Mkomwa, S., Friedrich, T., 2017. Conservation Agricutlure for Africa: Building Resilient Farming Systems in a Changing Climate. CABI, London, UK.

Kernecker, M., Seufert, V., Chapman, M., 2021. Farmer-centered ecological intensification: using innovation characteristics to identify barriers and opportunities for a transition of agroecosystems towards sustainability. Agric. Syst. 191, 103142 https://doi.org/10.1016/j.agsy.2021.103142.

Knowler, D., Bradshaw, B., 2007. Farmers' adoption of Conservation Agriculture: a review and synthesis of recent research. Food Policy 32 (1), 25–48.

Kosko, B., 1986. Fuzzy cognitive maps. Int. J. Man. Mach. Stud. 24, 65–75.

Krackhardt, D., 1994. Graph Theoretical Dimensions of Informal Organizations, pp. 89–111.

Lalani, B., Dorward, P., Holloway, G., Wauters, E., 2016. Smallholder farmers motivations for using Conservation Agriculture and the roles of yield, labour and soil fertility in decision making. Agric. Syst. 146, 80–90. https://doi.org/10.1016/j.

agsy.2016.04.002.

Lalani, B., Dorward, P., Holloway, G., 2017. Farm-level economic analysis – Is Conservation Agriculture helping the poor? Ecol. Econ. 141, 144–153. https://doi.org/10.1016/j.ecolecon.2017.05.033.

Lalani, B., Dorward, P., Kassam, A.H., Dambiro, J., 2017b. Innovation systems and farmer perceptions regarding Conservation Agriculture in Cabo Delgado, Mozambique. In: Conservation Agriculture for Africa: Building Resilient Farming Systems in a Changing Climate, pp. 100–126. https://doi.org/10.1079/9781780645681.0100.

Lee, J., Hopmans, J.W., Rolston, D.E., Baer, S.G., Six, J., 2009. Determining soil carbon stock changes: simple bulk density corrections fail. Agric. Ecosyst. Environ. 134, 251–256.

Leeuwis, C., 2004. Communication for rural innovation. In: Van den Ban, A. (Ed.), Rethinking Agricultural Extension. Blackwell Science, Oxford.

Levy, M.A., Lubell, M.N., Mcroberts, N., 2018. The structure of mental models of sustainable agriculture. Nat. Sustain. 1, 413–420. https://doi.org/10.1038/s41893-

018-0116-y.

Luo, J., Magee, C.L., 2011. Detecting evolving patterns of self-organizing networks by flow hierarchy measurement. Complexity 16, 53–61. https://doi.org/10.1002/cplx.20368.

MacDonald, N., 1983. Trees and networks in biological models. In: Wiley, J., Chichester Krackhardt, D. (Eds.), Graph Theoretical Dimensions of Informal Organizations, pp. 89–111 (1994).

Maria, R., Yost, R., 2006. A survey of soil status in four agro-ecologicial zones of Mozambique. Soil Sci. 171.

Meadows, D.H., 2008. Thinking in systems: a primer. Chelsea green publishing.

Ozesmi, U., Ozesmi, S., 2004. Ecological models based on people's knowledge: a multistep fuzzy cognitive mapping approach. Ecol. Model. 176, 43–64.

Page, K.L., Dang, Y.P., Dalal, R.C., 2020. The ability of Conservation Agriculture to conserve soil organic carbon and the subsequent impact on soil physical, chemical, and biological properties and yield. Front. Sustain. Food Syst. 4 https://doi.org/10.3389/fsufs.2020.00031.

Pannell, D., Claasen, R., 2020. The roles of adoption and behavior change in agricultural policy. Appl. Econ. Perspect. Policy. https://doi.org/10.1002/aepp.13009. In Press.

Pannell, D.J., Llewellyn, R.S., Corbeels, M., 2014. The farm-level economics of Conservation Agriculture for resource-poor farmers. Agric. Ecosyst. Environ. 187, 52–64.

Patrignani, A., Ochsner, T.E., 2015. Canopeo: a powerful new tool for measuring fractional green canopy cover. Agron. J. 107, 2312–2320. https://doi.org/10.2134/agronj15.0150.

Pittelkow, C.M., Liang, X., Linquist, B.A., Groenigen, K.J.V., Lee, J., Lundy, M.E., Gestel, N.V., Six, J., Venterea, R.T., Kessel, C.V., 2015. Productivity limits and potentials of the principles of Conservation Agriculture. Nature 517, 365–368. https://doi.org/10.1038/nature13809.

Powlson, D.S., Stirling, C.M., Thierfelder, C., White, R.P., Jat, M., 2016. Does Conservation Agriculture deliver climate change mitigation through soil carbon sequestration in tropical agro-ecosystems? Agric. Ecosyst. Environ. 220, 164–174.

https://doi.org/10.1016/j.agee.2016.01.005.

Pretty, J., Toulmin, C., Williams, S., 2011. Sustainable intensification in African agriculture. Int. J. Agric. Sustain. 9, 5–24.

Rockström, J., Kaumbutho, P., Mwalley, J., Nzabi, A.W.M., Temesgen, M.L., Mawenya, L., Barron, J., Mutua, J., Damgaard-Larsen, S., 2009. Conservation farming strategies in East and Southern Africa: yields and rainwater productivity from on-farm action research. Soil Tillage Res. 103, 23–32.

Rusinamhodzi, L., Rufino, M.C., van Wijk, M., Nyamangara, J., Corbeels, M., Giller, K.E., 2011. A meta-analysis of long term effects of Conservation Agriculture on maize grain yield under rain-fed conditions. Agron. Sustain. Dev. 31 (4), 657–673.

Salvador, E.M., Steenkamp, V., McCrindle, C.M.E., 2014. Production, consumption and nutritional value of cassava (Manihot esculenta, Crantz) in Mozambique: an overview. J. Agricult. Biotechnol. Sustain. Develop. 6 (3), 29–38.

Senge, P.M., Sterman, J.D., 1992. Systems thinking and organizational learning: acting locally and thinking globally in the organization of the future. Eur. J. Oper. Res. 59, 137–150. https://doi.org/10.1016/0377-2217(92)90011-w.

Shaver, T.M., Peterson, G.A., Ahuja, L.R., Westfall, D.G., Sherrod, L.A., Dunn, G., 2002. Surface soil physical properties after twelve years of Dryland no-till Management. Soil Sci. Soc. Am. J. 66, 1296–1303. https://doi.org/10.2136/sssaj2002.1296.

Silici, L., Bias, C., Cavane, E., 2015. Sustainable Agriculture for Small-Scale Farmers in Mozambique: A Scoping Report. IIED Country Report. IIED, London.

Singer, A., Gray, S., Sadler, A., Schmitt Olabisi, L., Metta, K., Wallace, R., Lopez, M.C., Introne, J., Gorman, M., Henderson, J., 2017. Translating community narratives into semi-quantitative models to understand the dynamics of socio-environmental crises. Environ. Model. Softw. 97, 46–55. https://doi.org/10.1016/j.envsoft.2017.07.010.

Stier, A.C., Samhouri, J.F., Gray, S., Martone, R.G., Mach, M.E., Halpern, B.S., , et al. Levin, P.S., 2017. Integrating expert perceptions into food web conservation and management. Conserv. Lett. 10 (1), 67–76.

Staff, S.S., 2010. Keys to Soil Taxonomy, 11th ed. USDA-Natural Resources Conservation Service, Washington, DC.

Sumberg, J., Thompson, J., Woodhouse, P., 2013. Why agronomy in the developing world has become contentious. Agric. Hum. Values 30, 71–83. https://doi.org/10.1007/s10460-012-9376-8.

Tafesse, S., van Mierlo, B., Leeuwis, C., Lie, R., Lemaga, B., Struik, P.C., 2020. Combining experiential and social learning approaches for crop disease management in a smallholder context: a complex socio-ecological problem. Socio-Ecol. Pract. Res. 2, 265–282. https://doi.org/10.1007/s42532-020-00058-z.

Thierfelder, C., Wall, P.C., 2010. Effects of Conservation Agriculture techniques on infiltration and soil water content in Zambia and Zimbabwe. Soil Tillage Res. 105, 217–227.

Thierfelder, C., Wall, P.C., 2012. Effects of Conservation Agriculture on soil quality and productivity in contrasting agro-ecological environments of Zimbabwe. Soil Use Manag. 28, 209–220. https://doi.org/10.1111/j.1475-2743.2012.00406.x.

Thierfelder, C., Mombeyarara, T., Mango, N., Rusinamhodzi, L., 2013. Integration of Conservation Agriculture in smallholder farming systems of southern Africa:

identification of key entry points. Int. J. Agric. Sustain. 1–14.

Thierfelder, C., Rusinamhodzi, L., Setimela, P., Walker, F., Eash, N.S., 2015. Conservation agriculture and drought-tolerant germplasm: reaping the benefits of climate-smart agriculture technologies in central Mozambique. Renew. Agric. Food Syst. 1–15.

Thierfelder, C., Matemba-Mutasa, R., Bunderson, W.T., Mutenje, M., Nyagumbo, I., Mupangwa, W., 2016. Evaluating manual Conservation Agriculture systems in southern Africa. Agric. Ecosyst. Environ. 222, 112–124. https://doi.org/10.1016/j.agee.2016.02.009.

Thierfelder, C., Cheesman, S., Rusinamhodzi, L., 2012. A comparative analysis of Conservation Agriculture systems: benefits and challenges of rotations and intercropping in Zimbabwe. Field Crops Res. 137, 237–250.

Thierfelder, C., Chivenge, P., Mupangwa, W., Rosenstock, T.S., Lamanna, C., Eyre, J.X., 2017. How climate-smart is Conservation Agriculture (CA)? – Its potential to deliver on adaptation, mitigation and productivity ON SMALLHOLDER farms in southern Africa. Food Security 9, 537–560. https://doi.org/10.1007/s12571-017-0665-3.

Vanwindekens, F.M., Stilmant, D., Baret, P.V., 2013. Development of a broadened cognitive mapping approach for analysing systems of practices in social-ecological systems. Ecol. Model. 250, 352–362. https://doi.org/10.1016/j.ecolmodel.2012.11.023.

Vuillot, C., Coron, N., Calatayud, F., Sirami, C., Mathevet, R., Gibon, A., 2016. Ways of farming and ways of thinking: do farmers' mental models of the landscape relate to their land management practices? Ecol. Soc. 21 (1), 35. https://doi.org/10.5751/ES-08281-210135.

Waldman, K.B., Vergopolan, N., Attari, S.Z., Sheffield, J., Estes, L.D., Caylor, K.K., Evans, T.P., 2019. Cognitive biases about climate variability in smallholder farming systems in Zambia. Weather Climate Society 11, 369–383. https://doi.org/10.1175/wcas-d-18-0050.1.

Ward, P.S., Bell, A.R., Droppelmann, K., Benton, T.G., 2018. Early adoption of Conservation Agriculture practices: understanding partial compliance in programs with multiple adoption decisions. Land Use Policy 70, 27–37. https://doi.org/10.1016/j.landusepol.2017.10.001.

Weersink, A., Fulton, M., 2020. Limits to profit maximization as a guide to behavior change. Appl. Econ. Perspect. Policy 42 (1), 67–79. In Press. https://onlinelibrary.wiley.com/journal/20405804.

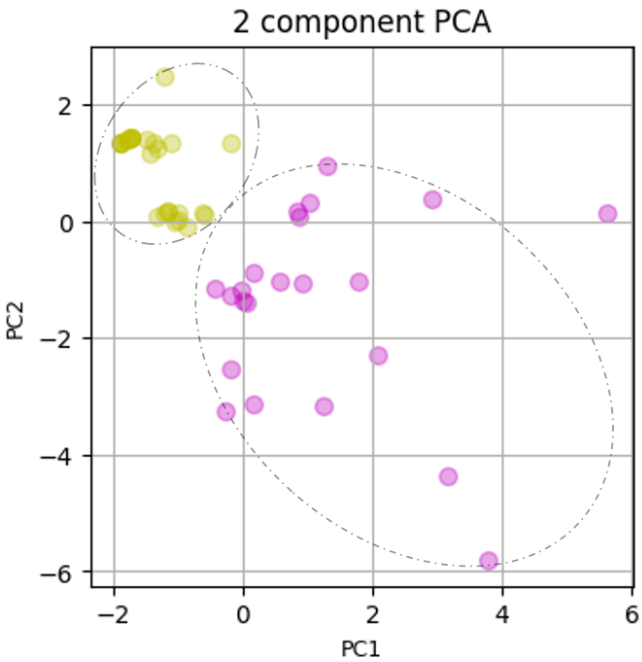
Wei, Z., Lui, L., Yanchun, Z., 2008. Using fuzzy congnitive time maps for modeling and evaluating trust dynamics in the virtual enterprise. Expert Syst. Appl. 35 (4), 1583–1592.

Wellard, K., Rafanomezana, J., Nyirenda, M., Okotel, M., Subbey, V., 2013. A review of community extension approaches to innovation for improved livelihoods in Ghana, Uganda and Malawi. J. Agric. Educ. Ext. 19, 21–35. https://doi.org/10.1080/1389224x.2012.714712.

Wuepper, D., Zilberman, D., Sauer, J., 2019. Non-cognitive skills and climate change adaptation: empirical evidence from Ghana's pineapple farmers. Clim. Dev. 12, 151–162. https://doi.org/10.1080/17565529.2019.1607240.

Wuepper, David, Borrelli, Pasquale, Finger, Robert, 2020. Countries and the global rate of soil erosion. Nat. Sustain. 3, 51–55.

Appendix A



	PC1	PC2
Variance defined	*41.3%*	*34.5%*
N_nodes	-0.178980	0.445042
N_Ordinary	-0.401078	-0.160660
N_Drivers	0.329700	0.154464
N_Receivers	0.016199	0.493092
N_edges	-0.431647	0.032269
FCM_hierarchy	0.037895	-0.464159
Complexity	-0.195300	0.413924
Density	-0.431647	0.032269
Sum_strength	-0.344533	0.089953
Cent_MicroPit	0.309140	0.267473
Cent_Mulch	0.000000	-0.000000
Cent_CoverCrops	-0.243261	-0.173848
Cent_MinSoilDist	-0.111691	0.102036
Cent_Tillage	0.000000	-0.000000

Figure A1. 14 structural metrics of fuzzy cognitive maps (FCM) were subjected to a principle component analysis (PCA) to reduce the dimensions. We used PCA with orthogonal rotation (varimax). The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = 0.8 which is well above the acceptable limit of 0.5. An initial analysis was run to obtain eigenvalues for each component in the data. Two components had eigenvalues over Kaiser's criterion of 1 and in combination explained more than 75% of the variance in FCM structural metrics. The table in the right side of this figure shows the factor loadings after rotation. Different colours in the scatter plot shows different clusters of mental models emerged as a result of a hierarchical clustering using Ward's minimum variance method on the Euclidian distances between mental models.

Table A1 The structural metrics of fuzzy cognitive maps, their definitions, and their

Mean and Standard Deviation in the sample of 50 farmers.

FCM Metric	**Details**	**Mean (*Std*)**
N_nodes	Number of concepts used	28.72 (*1.429*)
N_edges	Number of connections used	95.74 (*4.11*)
N_Drivers	Number of Driver variables	6.28 (*0.73*)
N_Receivers	Number of Receiver variables	6.96 (*1.484*)
N_Ordinary	Number of Ordinary variables	15.48 (*1.297*)
Sum_strength	Sum of connection strength	48.13 (*2.691*)
Density	Number of connections divided by total possible connections	0.1 (*0.004*)
Complexity	Number Receivers divided by number of Drivers	1.11 (*0.216*)
FCM_hierarchy	The McDonald Hierarchy index	0.15 (*0.031*)
Cent_CoverCrops	Centrality of concept "Increased use of Cover Crops"	0.56 (*0.018*)
Cent_MicroPit	Centrality of concept "Increased use of Micro Pit"	0.48 (*0.004*)
Cent_MinSoilDist	Centrality of concept "Minimum Soil Disturbance"	0.53 (*0.05*)
Cent_Mulch	Centrality of concept "Increased used of Mulch"	0.5 (*0.00*)
Cent_Tillage	Centrality of concept "Practicing Tillage"	0.5 (*0.00*)

Table A2 The results of independent samples t-tests to evaluate the differences between the cluster of farmers for the main socio-demographics, land-related variables, soil characteristics, and cropping management practices.

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Sex_HH_head	Equal variances assumed	2.553	.117	.952	48	.346	.133	.140	-.148	.414
	Equal variances not assumed			.944	43.668	.350	.133	.141	-.151	.417
AgeofHHhead	Equal variances assumed	3.565	.065	-.506	45	.615	-1.563	3.087	-7.780	4.654
	Equal variances not assumed			-.481	32.507	.633	-1.563	3.246	-8.171	5.045
Maritulstatus	Equal variances assumed	.000	.998	.105	45	.917	.033	.318	-.607	.673
	Equal variances not assumed			.104	39.057	.918	.033	.322	-.618	.684
highestlevelofeducation	Equal variances assumed	1.900	.175	-1.545	46	.129	-.936	.606	-2.155	.283
	Equal variances not assumed			-1.681	44.452	.100	-.936	.557	-2.057	.186
total number of plots (machamba)	Equal variances assumed	.058	.811	.325	48	.746	.058	.180	-.303	.420
	Equal variances not assumed			.325	45.203	.746	.058	.180	-.303	.420

size of total land (hectares)	Equal variances assumed	.013	.910	-1.367	48	.178	-.2256	.1651	-.5576	.1063
	Equal variances not assumed			-1.388	47.285	.172	-.2256	.1626	-.5528	.1015
plot1_distancefromhome	Equal variances assumed	.089	.767	-.445	45	.658	-.105	.235	-.578	.369
	Equal variances not assumed			-.447	41.597	.657	-.105	.234	-.577	.368
leguminous_trees	Equal variances assumed	1.187	.282	-1.189	46	.241	-.357	.300	-.962	.248
	Equal variances not assumed			-1.275	45.634	.209	-.357	.280	-.921	.207
soil_erosion_perception	Equal variances assumed	.487	.490	-.184	32	.855	-.035	.191	-.424	.353
	Equal variances not assumed			-.189	31.945	.852	-.035	.186	-.414	.344
plot1_compostquantity	Equal variances assumed	3.062	.087	-.843	46	.404	-1.786	2.119	-6.052	2.480
	Equal variances not assumed			-1.000	27.000	.326	-1.786	1.786	-5.450	1.878
plant_in_lines	Equal variances assumed	.250	.620	.250	44	.804	.016	.062	-.110	.141
	Equal variances not assumed			.242	34.401	.810	.016	.064	-.115	.146
soil_type	Equal variances assumed	6.294	.016	-1.188	46	.241	-.100	.084	-.269	.069
	Equal variances not assumed			-1.000	19.000	.330	-.100	.100	-.309	.109
slope_type	Equal variances assumed	.060	.808	.083	46	.934	.014	.172	-.332	.361
	Equal variances not assumed			.082	39.839	.935	.014	.174	-.337	.365
Micro_pits	Equal variances assumed	2.716	.106	.788	44	.435	.115	.146	-.179	.410
	Equal variances not assumed			.801	38.422	.428	.115	.144	-.176	.406

B1.1_frequency_meetings	Equal variances assumed	3.387	.074	-.876	37	.386	-.045	.052	-.151	.060
	Equal variances not assumed			-1.000	21.000	.329	-.045	.045	-.140	.049
B3_livestock	Equal variances assumed	8.944	.004	1.766	46	.084	.250	.142	-.035	.535
	Equal variances not assumed			1.808	44.076	.077	.250	.138	-.029	.529

Table A3 Socio-demographic variables experience with CA and cropping/management practices of farmers by type.

Type of Farmer	Mean age of farmer	Mean years of experience using CA	Mean level of education (grades of education completed)	Mean total land size (hectares)	Number of leguminous trees	Using micro-pit in 2017/2018 season (N)	Mean depth of micro-pit (cm)*
CA early	41 (2.5)	1	5 (1.1)	1.6 (0.23)	3	5	16 (1)
CA experienced	53 (2.7)	4.4 (0.6)	3 (0.74)	2.1 (0.13)	5	8	18.75 (1.8)
CA left	53 (3.2)		4 (0.41)	1.3 (0.15)	5	2	15
Conventional mulch	43 (2.9)		4 (0.59)	1.2 (0.13)	3	1	15
Conventional	47.5		3.1 (0.5)	1.2 (0.14)	5		

Std error in parenthesis * only some farmers were able to estimate depth. Blank i.e. no farmers answered or std error zero. Age and education rounded to the nearest whole number for ease of interpretation.

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