Farmers’ preferences for cropping systems and the development of sustainable intensification: a choice experiment approach

Abstract

Sustainable Intensification (SI) of farming systems aims to increase food production from existing farmland in ways that have a lower environmental impact and maintain the food production capacity over time. SI embraces a set of diverse agricultural technologies that share a common feature: their adoption is dependent on the interactions between farmers’ decision-making processes, locally specific agro-ecological conditions, and the traits of the technology itself.

There are concerns about the sustainability of the maize mono-cropping systems that are in use in Laos today. Therefore, we used Discrete Choice Experiments (DCE) to explore the potential adoption or alternative agricultural systems. We analyze the heterogeneity of farmers’ preferences and willingness to pay for different cropping system attributes using a mixed logit model and we discuss the possible drivers and barriers to the adoption of these more sustainable options. The results suggest the existence of four types of farmers: “fertility-minded”, “factor constrained”, “maximisers” and “risk-averse”. Each type of farmers was likely to react differently to the proposed sustainable intensification techniques.

Overall, the DCE appeared to be an efficient tool to elicit the diversity of farmer preferences in an agricultural region and for fine-tuning strategies for successful research and development of sustainable intensification.

1 Introduction

Increasing demand for food and growing competition for land, water, energy, and natural resources will require the agricultural sector to produce more food with fewer resources. Climate change will pose additional challenges as many current farming practices damage the environment and affect farmers’ resilience to increasingly uncertain adverse weather conditions (Campbell, et al., 2014). To deal with these challenges, a number of significant initiatives are under way to develop and promote new cropping systems under the generic goal of sustainable intensification (SI). The challenge of SI in agriculture is to increase food production from existing farmland in ways that have a lower environmental impact and which do not undermine our capacity to continue producing food in the future (Garnett, et al., 2013). As noted by these authors, SI denotes a goal, but does not specify how it should be attained, or which farming techniques should be deployed.

Many agricultural technologies researched and promoted in recent decades, such as conservation agriculture, agro-ecological agriculture, organic farming, climate smart agriculture, or even conventional intensification, can help to fulfil SI goals, at least under suitable locally-specific conditions. However, the adoption of these various techniques remains low in many areas of the tropical world, despite apparent benefits for farmers and efforts to promote them. One of the challenges, highlighted by the applied economic literature on conservation agriculture, is that it is difficult to find consistent determinants of farmers' adoption of sustainable agricultural practices, and efforts to promote them will have to be tailored to the local social and biophysical context (Knowler and Bradshaw, 2007).

There is ample literature that seeks to understand, *ex-post*, what drives the adoption of agricultural technologies (e.g., Feder, et al., 1985, Knowler and Bradshaw, 2007, Läpple, et al., 2017). While providing interesting insights into the main drivers and barriers to adoption, they require a sufficient time lapse to allow for a sufficiently large share of adopters. Another line of research has been the development of farm or farm household bio-economic models (BEM) to study, *ex-ante*, the potential adoption by farmers confronted with new technologies (e.g., Yiridoe, et al., 2006, Alary, et al., 2007, Affholder, et al., 2010, Jourdain, et al., 2014). BEMs enable *ex-ante* discussions of farmers' potential interest in new technologies by modelling how making the new technologies available affects farmers' decisions. However, BEMs are *ad-hoc* representations of farm functioning that concentrate on technical and economic aspects of farmers' decisions. Typically, they model the change in expected profits and risks when new technical opportunities appear in the farmer's choice set, given farmers' technical and resource constraints. However, unobservable risk preferences, time preferences, option values, cultural values and subjective beliefs are also very important, but difficult to include in BEM models. Stated preference methods, such as choice experiments (CE), can capture these hard-to-measure components of farmers' decisions. CEs, which were initially developed to anticipate consumer choices (McFadden, 1974) and the value of environmental goods (Adamowicz, et al., 1998), have become an increasingly important tool used to study preferences and discuss farmers' potential behaviour when offered new technologies (Duke, et al., 2012, Useche, et al., 2013, Knowler, 2015, Ortega, et al., 2016).

In this study, we used CEs to examine the adoption by farmers of alternatives to maize mono-cropping systems in an agricultural area of the Lao PDR, where the recent farming system intensification pathways have raised serious concerns about their sustainability. We explore heterogeneity in farmers' preferences and in their willingness to pay for the different attributes of these alternative cropping systems, and we use that information to discuss the potential drivers and barriers to the adoption of these more sustainable options.

The article is organized as follows: Section 2 provides a brief background of the evolution of cropping systems in mountainous areas of Southeast Asia. Section 3 describes the study area. Section 4 presents the choice experiment rationale and data analysis methodologies. Sections 5 and 6 report and discuss the results. Section 7 concludes.

2 Background

The rapid changes that have occurred in the mountainous areas of Southeast Asia in general, and in Laos in particular, provide a case in point for studying sustainable intensification. Improving infrastructures and increasing demand for animal feeds have led to a drastic increase in maize production (Vongvisouk, et al., 2016). Subsistence farming systems based on slash-and-burn rice production were converted into market-connected systems heavily dependent on the continuous cropping of hybrid maize (Castella, et al., 2012). These rapid changes occurred because the new cropping systems offered some interesting features to farmers, at least in the short term, since they required less labour and they generated cash income. As such, the introduction of maize has played a key role in lifting many households out of poverty. However, this rapid agricultural transition is also expected to increase the negative environmental impacts of farming systems. Soil erosion is expected to increase (Valentin et al. 2008), due to some detrimental ploughing practices and the long periods during which soils are left bare during the heavy rains of the monsoon months. Soil fertility is expected to decrease, since nutrient exports by crops have not been compensated for by an adequate supply of nutrients from farmers, as they saw an opportunity to use an initially abundant stock of nutrients in their soils. Siltation of lowlands, weed invasion and resistance to herbicides, along with water contamination by herbicides, are also expected to rise. Nowadays, on a farm scale, maize mono-cropping is a source of indebtedness (purchasing of seeds, herbicides, fertilizers and ploughing services) and its profitability is decreasing because of poor agronomic performance (yield), itself probably resulting from a decrease in the quality of the supporting and regulating services of the ecosystem. In addition, farm incomes are more uncertain when based on a single source of revenue. Future climate change and price instability will step up the unsustainable effects of the current maize mono-cropping systems. Climate models suggest that temperatures will rise by an average 2°C and that adverse climate events (i.e., droughts, heavy rains) will be more frequent with, in particular, increases in precipitation extremes related to the monsoon (Hijioka, et al., 2014). These changes will result in more physical damage to crops, more soil erosion and nutrient leaching, higher risks of groundwater/running water pollution, and lower agricultural yields (Hijioka, et al., 2014).

These sustainability issues can be addressed by making some adaptations to the existing maize cropping systems. Possible adaptations include 1) better management of soil fertility and weeds, by intercropping/rotation of maize with a legume crop, 2) a reduction in runoff and leaching thanks to maize direct seeding in straw mulch combined with a cover crop, 3) an increase in resource use efficiency with the use of “nitrate trap" plants intercropped with maize, which are able to extract leached nitrogen beneath the root front of maize during their coexistence and then return it for the next cycle. However, these modified maize cropping systems may negatively impact farm income in the short-term and could lead to an increase in workloads or risks (e.g., Affholder, et al., 2010). Improved pasture, or fruit trees, are other innovative systems that do not include maize, but could also be relevant. Like the former maize-based systems, this conversion may lead to an increase in workload; or in the case of improved pasture a decrease in the annual cash outflow needed, but a longer period before achieving a return on investment.

Applied studies on the adoption of such sustainable farming practices give contrasting results and highlight the importance of conducting regional studies of how factors such as labour and cash constraints affect farmers’ adoption (Knowler & Bradshaw, 2007). In our case study, questions remained regarding the extent to which farmers would adopt newly developed practices leading to sustainable intensification. Our study explored possible constraints using household surveys and choice experiments to quantify the trade-offs farmers perceived among the various attributes of cropping systems.

3 Study Area

The data used in this study came from farm household surveys conducted in the province of Xieng Khouang (XKH) located in northern Lao PDR. XKH is typical of the land use changes that occurred in Southeast Asia in the 2000s. Hybrid maize cultivation replaced traditional upland rice, gardens, orchards and also expanded into forests and fallow areas (Castella, et al., 2012). These changes are a direct consequence of the increased demand for meat products in Southeast Asia and the subsequent increased demand from the feed industry for maize.

Kham was selected as a district representative of the agricultural intensification in XKH and its consequences. Kham district has a good road network making it easily accessible (Andersson, et al., 2007). Data collected in recent years (Lairez, 2018) show that Kham district is characterised by soils ranging from sandy to clayey-loam types, with a subtropical climate (2007-2015 average annual rainfall: 1291 mm; average annual temperature: 23.7°C). The simplification of the landscape and this agricultural transition have generated negative environmental impacts, such as soil erosion, siltation of lowlands, weed invasion and water contamination with herbicides. We selected six villages of the Kham basin (Dokham, Laeng, Le, Houat, Xay and Nadou), which contrasted in terms of their ecological zone, road accessibility and village size.

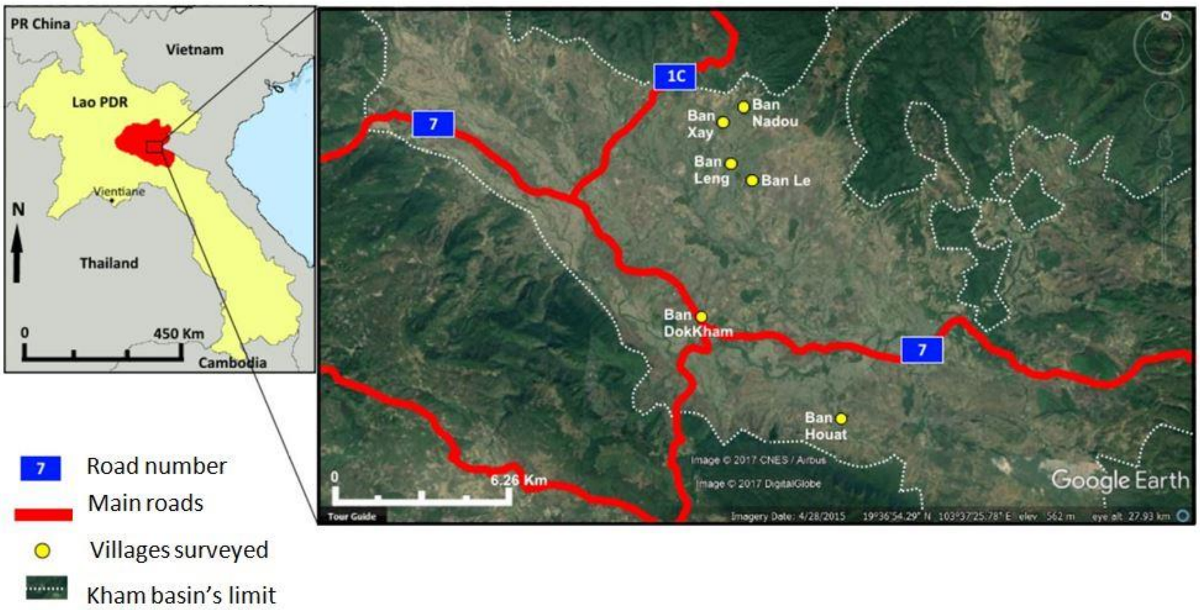

Figure 1: Study Area

Nowadays, after the transition to hybrid maize, a typical farm produces hybrid maize on the uplands (1-3 ha), lowland paddy rice on 1-3 ha, mainly for household consumption (1 cycle per year from June to October), and grows dry season vegetables on the lowlands from December to April (garlic, onions, watermelon, cucumber; around 500-1000 m^2). Many households have developed a weaving activity for their daily expenditure. Some farms also raise cattle in an extensive way: free roaming during the dry season and a natural grass cut-and-carry system during the cultivation period. Some farms are also starting to convert maize land into cultivated grasslands.

4 Designing the Choice Experiment

4.1 Elicitation of attributes

Firstly, we obtained information about the main attributes used by farmers to select their cropping systems during focus group discussions (FGD) conducted in three of the six villages. We chose the farmers in such a way as to cover the wide range of farm and household situations in terms of paddy and maize areas, family size, and the possession of farm assets. A group comprised between 12 and 15 farmers. To avoid inducing responses about attributes, we organized a game with the groups: the FGD moderator presented himself as being able to develop a new crop with the farmers that would help them, but the moderator only revealed its characteristics if asked questions to which he could answer Yes or No[1]. At the end of this first phase, questions were rearranged to avoid duplications and reformulated as attributes. The moderator then asked the farmers to rank in order of importance the attributes found by the group: three points for the most important, two for the second one and one for the third. This second phase was used to eliminate attributes that were identified by some group members, but was not seen by many farmers as an important criterion. For example, questions such as "Is it a dry season crop?", "Is it susceptible to pests?", or "Can we use it for our own consumption?" were mentioned during the game, but obtained a very low ranking during the second phase and were not adopted as attributes. To confirm and fine-tune the attributes, we discussed the focus group findings with agronomists who had working experience in the study area and we reviewed the recent literature. The final list of attributes and levels is discussed in the next section.

4.2 The attributes

The attribute "Income" corresponded to the average market value of crop products (yield x price). Other studies have also used indicators of land productivity, but usually relying on crop yields (e.g., Birol, et al., 2009, Jaeck and Lifran, 2014, Ortega, et al., 2016). We opted for income because our experiment was not specific to the crops to be grown (we told farmers that the alternatives were new upland crops, or the crop currently grown, but under a different practice). Moreover, the farmers in the study area were well connected to markets and sold most of their upland crop production (in contrast to Ortega et al., 2016). The levels used by Jaeck and Lifran (2014) were plausible average yields over a five-year period.

[1] The exact sentence used by the moderator was "*I know a perfect upland crop, what question would you like to ask me, in order to know if you would decide to grow it or not?*"

The levels used by Birol et al. (2009) and Ortega et al. (2016) were the percentage change in yields from the previous year's harvest because of the high variability of yields between farmers. Being faced with high variability, we also used a percentage change as compared to the respondents' average situation. The comparison with their average situation made more sense, as the previous year could be highly specific (e.g. drought). The levels used in the design were 80, 100 and 150, with 100 representing the base or average income from which percent changes were calculated. Potential losses (-20%) were lower than potential gains (+50%), since we expected farmers to be more sensitive to losses than to gains and likely to reject large income losses. Such asymmetries were also found in other choice experiments (e.g., Ortega et al., 2016).

The "labour requirement" and the "cash outflow" requirement attributes captured possible household labour and cash constraints, a concern expressed by farmers during the FGDs. Both attributes were expressed as a percentage change from the average labour or cash requirements of their current cropping system. The levels used in the design were 80, 100 and 150, with 100 representing the base. The two attributes, cash and labour requirements, were important criteria, as many SI cropping systems have major effects on these two attributes (Table 1). For example, using fewer herbicides (cash) usually leads to higher labour (manual weed control), or using more mechanized systems requires less labour but more cash (e.g. hiring tractorists for land preparation).

Table 1: Examples of alternative cropping systems[a] and their corresponding attributes

	Crop rotation maize-soybean	Conventional tillage, maize intercropping with rice bean	Direct seeding mulch-based cropping systems	Direct seeding/No Rotation/No Mulch
Income	+	+	+	0
Labour	++	+	++	-
Cash Outflow	0	0	-	+
Max Eco. Loss	+	+	-	++
Soil fertility	+	+	++	-

[a]: The current system corresponds to maize mono-cropping, with low fertilizer use. The zero means they are considered as the base level

The "Maximum Economic Loss" (MEL) attribute captured farmers' concerns about the possibility of a large economic loss that might jeopardize the viability of their enterprise. Since Knight (1921), many studies have focused on the effect of risk or uncertainty on farmers' decisions. The representation most commonly used to test this influence is the expected utility framework (EU), which assumes that farmers use subjective probabilities of possible events for their decisions (von Neumann and Morgenstern, 1944). Although recognized as important, risk attributes have often not been considered as an attribute in DCEs used to anticipate farmers' choices (e.g., Ortega, et al., 2016), or in a way that is not immediately connected to the EU theory (for example, Jaeck and Lifran (2014) used the number of years where yields would be below average). FGD discussions suggested that farmers tended to focus on the possibility of extreme events, such as the possibility of significant economic losses. This was consistent with earlier non-EU theories of farmers' decisions under uncertainty, such as the "*safety-first*" and "*focus-loss*" decision models that highlight the major role of extreme situations without attached probabilities in farmers' decisions (Roy, 1952, Shackle, 1961, Boussard, 1969, Roumasset, et al., 1979). More recent empirical studies based on Prospect Theory (PT) (Kahneman and Tversky, 1979) suggested that farmers use subjective probabilities, but distort those probabilities to give greater weight to extreme but low-probability events (Bocquého, et al., 2013). To be able to develop a model based on PT, some additional series of experiments would need to ascertain farmers' specific preferences as regards risk and potential losses, as in Ward, et al. (2014). However, in order to reduce farmer fatigue[2] during the interview, and as we felt that farmers were not familiar with the concept of probability, we opted for a representation of uncertainty as the possibility of an important loss of income, without considering the likelihood of its occurrence. The levels used in the design were economic losses of 200, 400, and 2,000 thousand Kip/ha, with 400 thousand Kip/ha being assigned as the current maximum economic loss.

Lastly, the attribute "impact on soil fertility" addressed an aspect of sustainability expressed by the farmers. The levels included three modalities: increased soil fertility over time, neutral, decreased soil fertility over time. To the best of our knowledge, this criterion has not been used in other DCEs.

Examples of cropping systems that could be considered by farmers in the study area, and their effects on the selected attributes are presented in Table 1. They show that farmers could relate the combination of attributes to realistic cropping systems, which was an important criterion for the validity of the experiment. (Johnston, et al., 2017)

4.3 Experimental design

The five attributes and their levels gave rise to 125 (5^3) possible scenarios in a full factorial design.We first conducted a rapid pre-survey with 10 farmers using an orthogonal design with 18 choice situations. We used these preliminary results to develop a D-efficient design with 18 choice tasks and split it into three blocks of six choice tasks each, using Ngene v.1.1.2 (Rose and Bliemer, 2009). To avoid unrealistic scenarios, we included a constraint for the generation of the sets that rejected scenarios of high income and low risk, or low income and high risk. The D-error of the final experimental design was 0.0203.

Each respondent was provided with one of the blocks, and we randomized the order of the choice sets presented to each respondent. Each choice set included two unlabelled alternatives and a status quo (See Annex A).

[2] The full survey with farmers included a Best-Worst Scaling experiment to obtain the ranking of farm-level management priorities that we do not report in this paper, and the Choice Experiment for the choice of cropping systems analysed in this paper. It was felt that another set of experiments would have generated respondent fatigue, while not providing sufficient additional information at this stage of the research project.

4.4 Survey methods

From May to July 2017, we conducted 120 face-to-face interviews with farmers selected from the population of the six selected villages. To select farmers we used the information available from previous household surveys conducted in those villages (EFICAS, 2017) and a cluster analysis that characterized the diversity of farmers based on the head of household's age, the household size, the rice and maize cropping areas, the number of head of cattle and other assets that suggested the existence of three homogeneous types of farmers. We chose farmers evenly in each cluster. The interviews were conducted at the farmers' homes. Questions were addressed directly to the heads of household (identified as the person responsible for providing the most for daily expenditure).

The interviews were organized to minimize potential biases. To minimize the differences in information or interpretation between the respondents, the concepts and purposes of the survey were thoroughly explained, with the interviewers presenting an overview of the different attributes to be compared using pictorial cards and brief descriptions, along with the terms, and a description of attributes was discussed with respondents to reach an agreement on the meaning of the attributes and the levels presented. To minimize possible bias introduced by having several interviewing styles, all interviews were conducted by only one researcher helped by one interpreter. We emphasized that responses would remain anonymous to minimize social desirability bias. No incentives were given to stimulate participation.

4.5 Data Analysis

We analysed the data using a mixed logit with error-component (ML-EC) model to analyse the diversity of preferences (Scarpa, et al., 2005, Van Loo, et al., 2014). The mixed logit model (ML) assumptions and formulation are presented in Annex B. By adding an error component (EC) specific to the current practices, the ML-EC allowed us to account for both (i) heterogeneous preferences and (ii) the additional variance of the utility of experimentally designed technologies differing from the current technology option. Participants had to select a preferred alternative from three options listed in each choice task that included two "new" technological profiles and one status quo option (keep their current technology). The current technology was actually practised by the respondents, while they could only make conjectures about the experimentally designed alternatives, so the utilities of the latter were likely to be more correlated with each other than with the current technology. The error component was a zero-mean normally-distributed random parameter assigned to the two new alternative technologies, but not to the current technology (CURR). The utility that individual $n \in (1, \dots, N)$ obtained from alternative $i \in (1, .., J)$ when confronted with choice situation $s \in (1, .., S)$ took the following form:

$$U_{njs} = \beta_{0n}.CURR_{njs} + \beta_{1n}.INCOME_{njs} + \beta_{2n}.LABOUR_{njs} + \beta_{3n}.CASH_{njs} + \beta_{4n}.MELLO_{njs} + \beta_{5n}.MELHI_{njs} + \beta_{6n}.FLO_{njs} + \beta_{7n}.FHI_{njs} + \delta.\theta.E_n + \varepsilon_{njs}$$

where *CURR* is equal to one when the current technology is chosen and zero when either of the two new technologies proposed is chosen; $E_n \sim \mathrm{N}[0,1]$ is the individual specific underlying random error component; δ is equal to one for alternatives 2 and 3 and zero otherwise; and θ is the standard deviation of the error component *E*. The other variables correspond to the attributes (MELLO, MELHI = Lower and Higher Max. Economic Loss, FLO, FHI = Lower and higher fertility). The variables MELLO, MELHI, FLO and FHI were effect-coded.

We put forward the hypothesis that all parameters would follow a normal distribution, except the parameter for Income, which would follow a Rayleigh distribution forcing the marginal utility of income to be positive, which is consistent with economic theory. Many studies use lognormal distribution, but it has been reported that the long, thick tail of the lognormal distribution produces an implausible distribution of parameters (Greene, 2016 p. N-652). We also allowed for some correlations between parameters.

We ran the ML-EC model using 700 Halton draws for the simulations of the random parameters. We compared the results of this ML-EC model to a conditional logit model (CL) that assumed a unique level of marginal utility for each attribute. The results of the CL model served as a reference base.

Using Bayes' theorem, we calculated the mean value of each parameter for each individual conditional on the observed choices (Greene and Hensher, 2003, Greene, 2016, p. 578-583). Using these coefficients, we ran a hierarchical cluster analysis with a Ward link to identify homogeneous patterns of preferences in the population[3]. To determine the number of clusters, we used the *nclusterboot* function of the R *fpc* package (Hennig, 2010). It is based on a bootstrap procedure whereby two bootstrap samples are repeatedly drawn from the data and the number of clusters is chosen by optimising an instability indicator from those pairs (Fang and Wang, 2012). Lastly, we tested possible associations of these clusters with observable farm and farm household indicators. The indicators included: the age of the head of household, the family labour available, the cultivated area, the paddy area (defined as the part of the cultivated area where irrigated rice can be grown), the ratio of paddy to cultivated area, the maize area, the size of the cattle herd, and the estimated contribution of weaving activities to income (expressed as a percentage).

5 Results

The models were estimated with 720 observations (120 farmers performing 6 choice tasks each), with three options per choice task giving a total of 2,160 alternatives to be evaluated.

5.1 Estimates of the CL model

The CL model coefficients are presented in Table 2. A likelihood ratio test indicated that the model was a significant improvement over a model with only constants. The adjusted pseudo-R^2 also showed an acceptable fit of the model. The coefficient of the *no-change* option was not significantly different from

[3] As we were looking for homogenous groups of preferences, we could use an alternative method based on a latent class logit model (LCM). However, as shown in Annex C, we did not find any compelling advantages in using the LCM. As the LCM does not take into account the additional variance potentially associated with the new alternatives (the EC), we opted for this two-step approach.

zero, suggesting that farmers were not biased towards the no-change option. All the other coefficients were significantly different from zero and of the expected signs. Increases in the expected income or soil fertility and decreases in the maximum loss had a positive effect on the farmers' utility. Increases in the labour and cash requirements, the possibility of higher revenue losses, or decreases in soil fertility, all had a negative effect on utility. Since these coefficients were defined up to an undefined scale, the magnitude of the coefficients cannot be discussed directly.

Table 2: CL coefficient estimate

Attribute	Coefficient	St. Error	Sig†
No-Change	0.219	0.253	
Expected Income	0.026	0.005	***
Labour requirement	-0.015	0.004	***
Cash requirement	-0.013	0.005	***
Max Loss (Lower)	0.880	0.191	***
Max Loss (Higher)	-0.653	0.086	**
Fertility (Lower)	-3.464	0.478	***
Fertility (Higher)	0.866	0.213	***
Log Likelihood	-578.030		
LL (constants only)	-777.860		
Pseudo R^2	0.257	(corrected 0.248)	
Likelihood ratio test	399.66		
Critical Value (chi-square)	12.600		
AIC	1172.100		

† ***, **, * indicates significance at 1%, 5%, 10% level

Using the coefficients of the CL model[4], we calculated the marginal rate of substitution (MRS) with respect to the expected income generated by the cropping system. The MRS values are presented in Table 3 (for a full description of the calculations and hypotheses, see Annex D). They can be interpreted as willingness to accept negative outcomes (e.g. WTA for increased labour or decreasing soil fertility) or as willingness to pay to obtain positive attributes (e.g. WTP for decreasing maximum loss or increasing fertility).

Table 3: Marginal Rate of Substitution with Income based on the CL model results

Attribute	MRS	Std. Error	95% Conf. Interval	
Labour	0.59	0.11	0.36	0.81
Cash outflow	0.50	0.14	0.22	0.77
Max. Economic Loss (Lower)	-43.15	9.89	-62.53	-23.76
Max Economic Loss (Higher)	16.55	9.29	-1.65	36.72
Fertility (Lower)	134.91	22.55	90.71	179.11
Fertility (Higher)	-33.74	12.46	-58.16	-9.33

For the labour requirements, the farmers would require an increase of 0.59% in their income to compensate for an additional 1% labour requirement. The increase in revenue would be 4,000 (kg/ha) x 1,300 (Kip/kg) x 0.59% x $8{,}700^{-1}$ (Kip/USD) = 3.5 USD/ha. The increase in labour requirements would be 0.5 to 0.7 days/ha. Consequently, in monetary units, the WTA ranged from 5 to 7 USD per additional labour-day required. This is very close to the average daily farm wages of 6-7 USD/day observed in the study area, suggesting that, on average, the farmers had good access to labour markets.

[4] MRS calculations using the coefficients of the mixed logit model are also included in the Table 1 of Annex D. Results showed that the MRS were of the same magnitude but higher when using the coefficients of the mixed logit model. For our discussion, we opted for the more conservative figures obtained with the CL model.

For cash requirements, the farmers would require an increase of 0.50% in their expected income for a 1% increase in cash expenses. The required additional income would be 2.96 USD/ha. The additional cash requirements would range from 2,000,000 x 1% x $8{,}700^{-1}$ = 2.3 USD/ha to 2,500,000 x 1% x $8{,}700^{-1}$ = 2.59 USD/ha. Consequently, the WTA for cash requirements would range between 1.14 and 1.28 USD per USD. This would correspond to high interest rates and suggests major cash constraints. It also suggests farmers only had access to the informal credit markets (e.g., local input dealers) where higher interest rates are usually charged.

To reduce the maximum economic loss, farmers were willing to forgo (WTP) 43% of their average income. On the other hand, they would need an increase of 16% (WTA) in the average income (but with a large standard error), in order to compensate for the possibility that the maximum loss increased. This result is not intuitive, since the WTA to increase the risk is lower than the WTP to reduce the risk. However, potential explanations could be found in Prospect Theory (PT), which anticipates that PT maximisers are expected to be mostly risk-averse in the gain domain (reducing the maximum economic loss), but mostly risk-seeking in the loss domain (Bocquého, et al., 2013). If farmers are risk-seeking for losses, it becomes rational to require less compensation for the risk of a potential high loss. However, these interpretations should be taken with extra caution, as the probabilities of these losses occurring were not part of the attribute description, and the experimental design was not made using the effect coding that we used during the analysis.

Farmers would require an increase of 135% in the current income (WTA) in order to accept some negative impact on soil fertility. On the other hand, they would be willing to decrease the expected income by 34% (WTP) to be able to obtain some positive mid-term effects on the fertility of their soil. This suggests that farmers were more concerned about the loss of fertility than with an increase in fertility. This is consistent with the literature that people give a higher value to losses than to gains (e.g., Kahneman and Tversky, 2013). Moreover, the figures show that fertility was an extremely important factor for the respondents.

5.2 Estimates of the ML-EC model

The results of this ML-EC model are presented in Table 4. The likelihood ratio tests indicated that the model was a significant improvement over a base model with only alternative specific constants, and over the CL model. The pseudo-R^2 (0.32) and the cross-tabulation of the actual versus the predicted choices showed an acceptable fit of the model (65% of choices correctly modelled). The standard deviation of the error component θ for the new technologies was statistically significant. Hence, we could not reject the hypothesis that farmers treated the current technology differently, versus the two new technologies proposed. In addition, some values below the diagonal of the Cholesky matrix $\boldsymbol{\Gamma}$ were significant, indicating some correlations between the random parameters. Overall, this confirmed that the choice of a mixed logit model with an error component for the new alternatives was appropriate.

The two coefficients (mean and deviation from the mean) used to describe the marginal utility of income in the population were significant. Using the two parameters, we were able to estimate the population mean (Greene, 2016) as $\exp\left(\beta_{INC} + 2.\sigma_{INC}.\Gamma(1 + \frac{1}{\sqrt{2}})\right) = 0.0385$. As expected, this was a positive value; it was also slightly higher than the value found with the CL model.

The coefficients for the labour requirements (both mean and deviation from the means) were significant. Given the relative magnitude of the mean and standard deviations, increased labour requirements would always decrease farmer utilities. This indicates that labour constraints were always present. The coefficients for the cash outflow requirements were also significant, but with larger measurement errors. In addition, the deviation from the mean was quite large when compared to the mean. Under the assumption of a normal distribution, the results suggested that 70% of farmers were facing cash constraints while 30% would not be bothered by increased cash investments.

Table 4: Mixed logit model with error component estimates

Attributes	Coefficient	St. Error	Sig.†
Non-Random Parameters			
No Change	0.520	0.463	
Random Parameters			
Income	-3.857	0.369	***
Labour	-0.025	0.007	***
Cash	-0.015	0.008	*
Lower Max Economic Loss	1.569	0.316	***
Higher Max Economic Loss	-1.231	0.219	***
Lower Fertility	-4.891	1.859	***
Higher Fertility	3.427	0.963	***
Standard Deviations of parameter distribution			
Income (Rayleigh)	0.330	0.105	***
Labour (Normal)	0.019	0.009	**
Cash (Normal)	0.030	0.010	***
Lower Max Economic Loss (Normal)	0.798	0.457	*
Higher Max Economic Loss (Normal)	1.082	0.635	*
Lower Fertility (Normal)	1.579	1.626	
Higher Fertility (Normal)	1.556	0.865	*
Theta	1.158	0.327	***
Log Likelihood: LLMLEC	-532.59		
LL0 (constants only)	-777.86		
Pseudo R2	0.32	(corrected: 0.288)	
Log Likelihood conditional logit (LLCL)	-578.03		
AIC	1107.20		
Percentage correctly predicted	65%		
Likelihood ratio test: 2 x (LLMLEC - LL0)	490.54	(chi-sq crit. Value: 31.4)	
Likelihood ratio test: 2 x (LLMLEC - LLCL)	90.88	(chi-sq crit. Value: 23.7)	

† ***, **, * indicates significance at 1%, 5%, 10% level

Lastly, the parameters of MEL, higher fertility and their standard deviations were significant. Again, this suggested that some heterogeneity was associated with these attributes among farmers. As for the CL model, the coefficients for the fertility attributes were much higher than the other coefficients, suggesting the real value given to that attribute. Moreover, and in agreement with the results obtained with the CL model, the farmers were more willing to avoid some degradation of fertility, than they were willing to improve fertility.

The estimated Cholesky matrix is presented in Table 5. The diagonal values of this matrix represent the standard deviation of the random parameters when the confounding effect between parameters is taken into account. The observation of these "true" standard deviation coefficients showed that, despite all the standard deviations being significant, only the Income, Labour and Cash Outflow were significantly different from zero in that matrix. This also suggested that the standard deviation parameters for Max Economic and Fertility losses were due to cross-product correlations with other random parameter estimates. This was confirmed by the fact that some of the off-diagonal elements of the Cholesky matrix were significantly different from zero.

Table 5: Cholesky matrix from MXL-EC estimates

	Income†	Labour	Cash Outflow	Lower Max Loss	Higher Max Loss	Lower Fertility	Higher Fertility
Income	0.330***						
Labour requirement	0.00	0.019**					
Cash outflow requirements	0.00	0.018	0.024**				
Lower Max Economic Loss	0.00	0.023	0.743**	0.291			
Higher Max Economic Loss	0.00	0.152	-0.844***	0.629	0.247		
Lower Fertility	0.00	0.001	0.022	0.023	0.012	1.579	
Higher Fertility	0.00	0.015	0.034	0.042	0.101	1.446**	0.574

***, **, * indicates significance at 1%, 5%, 10% level
† Correlations between normal and non-normal attributes cannot be interpreted, so we restricted the correlation between income and the other parameters to be zero (Greene, 2016, p. N557)

5.3 Cluster analysis of the individual specific estimates

Our observation of the dendrograms and the results of the bootstrap cluster analysis with 1,000 repetitions suggested the presence of four stable clusters of preferences. We present the descriptive statistics of the clusters in Table 6 and show the distribution of the preference parameters across clusters in Annex E. We did not find any links between these preference clusters and the socio-demographic variables describing farms and farm households. We present these results in Annex E.

The four clusters corresponded to distinct potential behaviours towards new technologies. The "fertility-minded farmers" (Cluster 1) showed the highest preferences for the fertility attributes, and low marginal utilities for labour and cash requirements. These farmers would be very receptive to SI techniques and would not be constrained in trying them.

Table 6: Descriptive statistics of the preference clusters

	Cluster 1 (n=29) “Fertility-minded”		Cluster 2 (n=50) “Constrained”		Cluster 3 (n=12) “Income maximisers”		Cluster 4 (n=29) “Risk-averse”		Kruskal – Wallis Test
	Median	Sd	Median	Sd	Median	Sd	Median	Sd	
Exp. Income	0.047	0.013	0.038	0.005	0.071	0.034	0.035	0.007	0.000
Labour	-0.021	0.007	-0.029	0.007	-0.015	0.017	-0.025	0.010	0.000
Cash outflow	-0.006	0.007	-0.028	0.009	-0.018	0.028	0.005	0.011	0.000
Lower Max Economic Loss	1.683	0.208	1.226	0.283	1.390	0.657	2.278	0.112	0.000
Higher Max Economic Loss	-1.374	0.312	-0.791	0.373	-0.856	0.843	-2.194	0.147	0.000
Lower Fertility	-5.386	0.229	-5.533	0.689	-3.575	0.862	-4.491	0.458	0.000
Higher Fertility	3.993	0.298	4.183	0.805	2.021	0.877	2.941	0.537	0.000

The “constrained farmers” (Cluster 2) showed the lowest preference for higher income generation and soil fertility attributes, and had the highest marginal value for lower cash or labour requirements. The coefficients associated with the maximum economic losses indicated some aversion to this risk, but lower than the “risk averse” farmers. These farmers would be mainly interested in technologies/practices that would alleviate cash and labour requirements.

The “income maximisers” (Cluster 3) showed the highest preferences for a larger income. Their median coefficient for labour requirements was lower than average. This suggested that labour constraint was less problematical for them and that they would not value technologies that would reduce labour requirements. Their median coefficients for cash suggested low concerns for cash constraints. Lastly, these farmers had lower coefficients for the maximum economic loss and fertility attributes. The farmers of these groups were therefore looking for opportunities to increase their income, without much concern over a possible risk of failure or long-term impact on their soils. As such, SI practices would only interest them if they increased their income.

The “risk averse farmers” (Cluster 4) showed the highest utility changes associated with changes in MEL (both higher and lower) and the lowest marginal utility of income. Farmers of this group also showed low marginal disutility from increased cash requirements. This suggested that they were more concerned than other members with reducing the possibility of high economic losses. Contrary to the farmers of the other groups, their coefficients for lower and higher MEL were of the same magnitude. As a result, their WTP for lower risk and their WTA for higher risk were of the same magnitude, suggesting a different attitude to risk from the other groups. Farmers of this group will probably be reluctant to try out technologies with uncertain economic consequences.

6 Discussion

The results indicated that all the cropping system attributes identified with farmers during the focus groups meetings – income, labour requirements, cash requirements, maximum economic loss and impact on soil fertility – affected the farmers’ cropping decisions, since the marginal utilities of these different attributes were all significant.

Among these attributes, the impact of cropping systems on soil fertility had the highest marginal utility, indicating that the farmers of the region were strongly concerned about this attribute. This suggested that soil conservation or enhancing technologies would raise the interest of farmers in the region, as most respondents would be ready to lose immediate income to be able to maintain their soil fertility over time, or avoid reducing it. This result was expected, since most farmers had been using continuous maize cropping systems without using organic or chemical fertilizers, and had indicated increasing problems with the fertility of their soils. However, this suggested more in-depth research is required, at least on two important dimensions.

On the first dimension, we would need to identify more clearly the reason why many farmers had a high negative WTP to avoid soil fertility losses while using techniques that induced soil fertility losses. The possible hypotheses are that farmers either a) answered strategically or some form of social bias led them to give artificially high importance to that attribute, or b) gave rational answers as they were starting to concentrate on soil fertility issues when the cost of fertility losses were becoming high (as is now the case in the survey area). In the latter case, this would suggest that the time is right for changes to occur in their cropping systems. The first hypothesis can be made since CEs are based on farmers' statements and not on real-life decisions, leaving room for bias in the answers. While this cannot be entirely discarded, it is unlikely in this research. The surveyors conducted their research on behalf of and presented themselves as belonging to an agricultural research centre. However, when presenting their activities, they did not put any particular emphasis on the technologies related to the improvement of soils, which would minimize the possibility of social bias (farmers answering what they expected the surveyors would like to hear from them). Furthermore, the reward of adoption would come as an improvement, according to the different attributes presented, and not some form of external subsidy obtained from a specific project or policy specifically presented to farmers. Again, this considerably reduced the possibility of strategic answers aimed at obtaining subsidies in the future. The second hypothesis, rational farmers, would be consistent with the soil conservation literature, as explained, for example, in Pagiola (1993): "*... observing agricultural practices that degrade soil does not necessarily imply that farmers have adopted unsustainable practices; they may simply be drawing down their soil stocks to their optimal long-run level*". Applied to our case study, the farming practices observed during the transition from traditional diversified agriculture to maize monocropping that led to the reduction in soil fertility stocks could be rational behaviour: farmers were better off making use of the substantial initial soil fertility stocks and reduce them to a level where further degradation was becoming more costly than conservation measures. When this stage was reached, farmers were ready to invest to maintain soil fertility levels. To choose conclusively between the two hypotheses, we would need to conduct additional experiments where we would identify the current soil fertility levels of the interviewed farmers and study the relation between lower current soil fertility and the value attributed to the fertility attribute. Working in contrasting areas in terms of soil fertility levels would also be useful. Additionally, we would need to seek, along with farmers, a more quantitative approach to define the “increased/decreased soil fertility” attribute in a quantitative way (as compared to the two dummies we used here). As a preliminary idea, we could define fertility loss as the expected reduction in yield (after a time horizon to be defined) if no conservation or external inputs are used during that period, but additional work on the way farmers assess soil fertility would be needed.

On the second dimension, the large marginal values obtained for the fertility attribute raised the possibility of non-compensatory behaviour towards that attribute. The most important hypothesis of CE modelling is that respondents are always ready to make trade-offs between the desirable and the undesirable aspects of each option: for example, they are always willing to give up some potential income to reduce the labour load or to maintain soil fertility. However, given the large negative marginal values associated with decreased fertility, there is a possibility that respondents were in fact not ready to make these trade-offs, at least for the fertility aspect. As further research, we could test whether some alternative choice process was used (Leong and Hensher, 2012, Hensher, 2014). Particular heuristics such as the Elimination by Aspects (Tversky, 1972) could be tested using the modelling approaches recently used in the literature (Hess, et al., 2012, Erdem, et al., 2014, Daniel, et al., 2018).

The results also indicated substantial heterogeneity in the population, which is information that will be useful for the development of new technologies. “Fertility-minded farmers” are likely to be the most receptive to technologies affecting soil fertility over time, as their marginal utility for fertility was higher than the other groups, while their marginal utility for the other aspects was lower than the other groups. “Income-maximising farmers” are another potential target for SI technologies if they can be convinced that they can build sustainable systems without compromising their income. While this is a feature of SI technologies, many of them require an adjustment period during which income is lower (as in the case of conservation tillage). In such cases, temporary payments to compensate for the losses incurred during that adjustment period would probably help convince these farmers. “Risk-averse” farmers could be reluctant to adopt new technologies since they are often perceived as more risky, at least in their early stages of development (Barham, et al., 2015). As such, convincing risk-averse farmers would require different incentives, such as insurance mechanisms linked to the adoption of SI. Lastly, “constrained farmers” will have more difficulties in adopting new technologies, as their capacity to change is limited by their labour or cash constraints. However, our results seemed to indicate more serious issues in terms of cash than in terms of labour constraints. In such a case, targeted loans with subsidized rates could be a useful policy instrument, if the SI technologies require additional labour or cash. Overall, this discussion suggests, as highlighted by Knowler (2015), that the development of SI practices in a particular area will mean developing practices and policies tailored to reflect the particular local conditions and the diversity of farmers’ preferences for the different features of the cropping systems. In that respect, our study showed that the use of DCEs provides a robust framework for ascertaining the diversity of farmers in a particular agricultural area. Besides, we did not find a strong association between socio-demographic and structural variables and the farmers’ groups of preferences. This indicated that identifying farmers' preferences is a necessary exercise, as farm and farm household structural variables alone did not seem to identify farmers' preferences clearly.

The results also showed contrasting attitudes to the possibility of large economic losses within the sampled farmers. We formulated the risk attribute as the possibility of facing high economic losses; however, this possibility was not associated with any probabilities. Thus, we implicitly assumed that the farmers would be following a safety-first approach (e.g., Roy, 1952). Since our results suggested a diversity of attitudes to economic losses, follow-up research would involve investigating possible other risk behaviours, particularly in light of Prospect Theory. This could mean designing a two-part survey to identify risk attitudes and preferences (as in Ward, et al., 2014), or designing a new survey that considers probabilities of losses as additional attributes to be able to estimate PT non-linear utility functions (Hensher, et al., 2015, Section 20.4).

Finally, in this experiment, we decided to present unlabelled technical alternatives, i.e. respondents had to choose between cropping systems that did not have names and were not linked to any specific technology. By doing so, we tried to get farmers to concentrate on the attributes of the technologies and avoid bias induced by the perceptions of particular technologies they might know, or had already tested. Such an approach enabled the calculation of the marginal utility/value of the cropping system features that did not interfere with the base value farmers were likely to give to a particular technology. In further research, we could also develop a complementary approach to test the positive/negative value farmers attach to specific technologies using an experiment with labelled options.

7 Conclusion

We used a discrete choice experiment to understand the trade-offs involved when Lao farmers choose their cropping systems. Based on data collected from a sample of 120 farmers from Xieng Khouang Province, we estimated the farmers' preferences for the attributes income, labour and cash outflow requirements, maximum economic losses and impact on soil fertility, using a mixed logit model with an error component. Soil fertility and maximum economic loss emerged as the most important attributes. The results also indicated substantial heterogeneity, with four homogenous groups of farmers who differed in terms of their constraints, their attitude to economic losses, and impact on soil fertility. Only ten percent of our sample were unconstrained profit-maximising farmers.

These results should help developers to improve their technological offer, and policy-makers to diversify incentive mechanisms to promote sustainable intensification in the region, as there is now evidence that the same technology will not work for all farmers. The identified types of farmers will be reactive to different expected impacts of the proposed techniques. However, we were not able to associate these different preferences with the socio-demographic characteristics of the households, or to structural variables of the farms, suggesting that the DCE was able to provide information that could not be easily deduced from structural typologies of farms.

However, the discussion also showed that additional research is probably needed to bring a more secure understanding of farmers' preferences. In particular, a more detailed formulation of the impact of risk or uncertainty, possibly inspired by Prospect Theory, and a more detailed description of soil fertility aspects are likely to bring a more precise understanding of farmers' potential attitudes to sustainable intensification solutions.

Overall, given the diversity of farmers, our results suggested that the transition to more sustainable farming systems will not be obtained by promoting a unique and one-size-fits-all technological solution, or by a single policy instrument. A more promising strategy might be the development of a range of techniques/practices tailored for the identified preference groups.

8 Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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