Agricultural Systems 151 (2017) 184–191

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Farmers' prioritization of climate-smart agriculture (CSA) technologies

Arun Khatri-Chhetri [a,*,1], P.K. Aggarwal [a], P.K. Joshi [b], S. Vyas [c]

[a] Climate Change, Agriculture and Food Security (CCAFS), Borlaug Institute of South Asia (BISA), International Maize and Wheat Improvement Centre (CIMMYT), New Delhi, India
[b] International Food Policy Research Institute (IFPRI), New Delhi, India
[c] CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), New Delhi, India

A R T I C L E I N F O

Article history:
Received 13 August 2015
Received in revised form 30 September 2016
Accepted 12 October 2016
Available online 17 October 2016

Keywords:
Prioritization
Climate-smart agricultural technologies
Preferences
Willingness-to-pay
Rainfall zones

A B S T R A C T

Addressing climate change impacts on agriculture is special challenge. There are number of factors that influence the extent to which farmers in a particular location adopt CSA technologies. This study applied a participatory assessment method to assess farmers' preferences and willingness-to-pay for selected CSA practices and technologies in diverse rainfall zones. The study found that farmers' preferences for CSA technologies are marked by some commonalities as well as differences according to their socio-economic characteristics and rainfall zones. The most preferred technologies by local farmers were crop insurance, weather-based crop agro-advisories, rainwater harvesting, site-specific integrated nutrient management, contingent crop planning and laser land levelling. The results also indicate that farmers' preferences and willingness-to-pay are influenced by technologies and their cost of implementation. This study shows the potential for using a participatory CSA prioritization approach to provide information on climate change adaptation planning at local level.

1. Introduction

Climate change is emerging as a major threat on agriculture, food security and livelihood of millions of people in many places of the world (IPCC, 2014). Several studies indicate that agriculture production could be significantly impacted due to increase in temperature (Lobell et al., 2012; Aggarwal et al., 2009), changes in rainfall patterns (Prasanna, 2014; Mall et al., 2006) and variations in frequency and intensity of extreme climatic events such as floods and droughts (Brida and Owiyo, 2013; Singh et al., 2013). The estimated impacts of both historical and future climate change on cereal crop yields in different regions indicate that the yield loss can be up to −35% for rice, −20% for wheat, −50% for sorghum, −13% for barley, and −60% for maize depending on the location, future climate scenarios and projected year (Porter et al., 2014). Changes in crop cultivation suitability and associated agriculture biodiversity, decrease in input use efficiency, and prevalence of pests and diseases are some of the major causes of climate change impacts on agriculture (Zabel et al., 2014; Norton, 2014). Agriculture production systems require adaptation to these changes in order to ensure the food and livelihood security of farming communities.

There are several potential adaptation options to reduce moderate to severe climatic risks in agriculture. Adaptation options that sustainably increase *productivity*, enhance *resilience* to climatic stresses, and reduce *greenhouse gas emissions* are known as climate-smart agricultural (CSA) technologies, practices and services (FAO, 2010). Broadly, CSA focuses on developing resilient food production systems that lead to food and income security under progressive climate change and variability (Vermeulen et al., 2012; Lipper et al., 2014). Many agricultural practices and technologies such as minimum tillage, different methods of crop establishment, nutrient and irrigation management and residue incorporation can improve crop yields, water and nutrient use efficiency and reduce Greenhouse Gas (GHG) emissions from agricultural activities (Branca et al., 2011; Jat et al., 2014; Sapkota et al., 2015). Similarly, rainwater harvesting, use of improved seeds, ICT based agro-advisories and crop/livestock insurances can also help farmers to reduce the impact of climate change and variability (Mittal, 2012; Altieri and Nicholls, 2013). In general, the CSA options integrate traditional and innovative practices, technologies and services that are relevant for particular location to adopt climate change and variability (CIAT, 2014). In this study, we consider a technology or practice as climate smart if it can help to achieve at least one pillar of CSA (either increases *productivity* or increases *resilience* or reduces *GHG emission*). For all adaptation options, farmers need to make ex-ante decisions under climatic risk, while making short and long-run investments depending on the extent of current climate variability and expected climate change in the future (Callaway, 2004).

The implementation of CSA technologies (hereafter CSA technologies indicate technologies, practices and services together) individually or in combination have substantial potential to reduce climate change impacts on agriculture. For example, Finger and Schmid (2007) projected that simple adaptation measures such as changes in crop

* Corresponding author.
E-mail address: a.khatri-chhetri@cgiar.org (A. Khatri-Chhetri).
[1] Mailing Address: IWMI, NASC Complex, CG Block, DPS Marg, Pusa, New Delhi 110012, India.

http://dx.doi.org/10.1016/j.agsy.2016.10.005
0308-521X/

sowing dates and adoption of irrigation technologies can result in higher yields with less variations than without adaptation. A meta-analysis of crop simulation under several climate scenarios found that farm level adaptations can increase crop yields by an average of 7–15% when compared to without adaptation (Challinor et al., 2014). Various studies show that benefits of adaptation vary with crop and with temperature and rainfall changes (Easterling et al., 2007). Similarly, several farm level studies also suggest that adoption of CSA technologies can improve crop yields, increase input use efficiency, increase net income and reduce GHG emissions (Khatri-Chhetri et al., 2016; Sapkota et al., 2014; Gathala et al., 2011).

Despite the various benefits of CSA technologies, the current rate of adoption by farmers is fairly low (Palanisami et al., 2015). There are many factors that influence extent of adoption of CSA technologies such as socio-economic characteristics of farmers, bio-physical environment of a particular location, and the attributes of new technologies (Campbell et al., 2012; Below et al., 2012; Deressa et al., 2011). The identification, prioritization and promotion of available CSA technologies considering local climatic risks and demand for technology are major challenges for scaling out CSA in diverse agro-ecological zones.

Basically, the identification and prioritization of CSA technologies support climate change adaptation planning in agriculture by designing an investment portfolio across various agro-ecological zones. When designing CSA implementation strategies at the farm level, one must consider adaptation options that are well evaluated and prioritized by local farmers in relation to prominent climatic risks in that location (FAO, 2012). Despite the importance of prioritization of CSA technologies at farm level, existing climate change adaptation programmes lack such information for better adaptation planning. Evidences on farmers' prioritization can support key stakeholders make informed decisions that are in line with government policies and institutional arrangements.

There are several prioritization approaches such as the use of simulation models, expert judgement, household and key informant surveys, participatory appraisal and hybrid methods (Mwongera et al., 2014; Taneja et al., 2014; Claessens et al., 2012). This paper describes and applies a participatory assessment method of farmers' preferences and willingness-to-pay for CSA technologies. This methodology was applied in a state of Rajasthan in India which is the most vulnerable state to climate change in the country. This state has the highest level of rural households (78.4%) dependent on agriculture (GoI, 2014). The agriculture sector contributes about 20% of total Gross Domestic Product in Rajasthan (UNDP, 2011). Frequent drought, extremely low and erratic rainfalls and very limited availability of surface water resources are major issues for climate change adaptation in Rajasthan (TERI, 2010). The state has the maximum probability of occurrence of drought in India with a 2–3 years return period (Pathak, 2011). This study uses socio-economic data and climate information of the study areas to assess farmers' preferences for CSA technologies in diverse rainfall zones and that are highly vulnerable to climate change and variability. This study area represents many similar climate change vulnerable locations in the region.

2. Sites, data and methods

2.1. Sites and data

This study was conducted in 16 villages in four diverse rainfall zones (ranging from 200 mm to 1000 mm rainfall per year) of Rajasthan in India (Fig. 1). The moderate drought probability in the selected districts (Bhilwara, Jhalawar, Jodhapur and Rajsamand) ranges from 19% to 27% and severe drought probability is above 5% (Gore et al., 2010). Rainfed agriculture is very common in the study areas which is ranges from 44% to 85% (Table 1). The major crops in Kharif (rainy season) include maize, soybean, bajra, Jawar, groundnut and sesamum. The crops grown in Rabi (winter season) include wheat, gram, mustard, lentil and barley. Maize-Wheat, Soybean-Wheat, Maize-Pulses and Pearlmillet-Wheat/Pearlmillet-Mustard are the major cropping systems.

This study has assessed a distribution of mean annual rainfall for last 30 years in the study areas. Average rainfall over last 30 years in Bhilwara district is 582 mm/year with 31–40% coefficient of variation (CV), Jhalawar 916 mm/year with 21–30% CV, Jodhapur 371 mm/year with 41–50% CV and Rajsamand 512 mm/year with 21–30% CV. This CV represents inter-annual variation in rainfall; the higher the CV, the more variable is the year-to-year rainfall.

Four villages in each district were selected to assess farmers' preferences and willingness to pay for climate-smart technologies after extensive discussion with government officials, community service organizations (CSOs) and key informants of the communities. These villages were selected by considering different rainfall zoness, high dependency on rainfed agriculture and high probability of drought prevalence. A climate change and agricultural vulnerability assessment report (Rao et al., 2013) also indicates that the agriculture in all selected districts is highly vulnerable to climate change and variability.

Data for this study was obtained through survey and group discussions with randomly selected group of 25–30 farmers in each village. The research team had interacted with the selected farmers to assess their understanding of climate change and variability, past climatic threats and their impacts on agriculture, and what adaptation options were available to them. A list of CSA technologies was developed based on a review of past studies conducted in similar study areas (Khatri-Chhetri 2016; Sapkota et al., 2015, Aryal et al., 2015; Jat et al., 2014; Sapkota et al., 2014) and in consultation with researchers in the region. We consider that any practice or technology that supports at least one of the three pillars: *productivity*, *resilience* and *mitigation* in agriculture under climate change and variability can be a CSA technology. During the discussion, detail information about existing CSA technologies suitable for local conditions were provided to all farmers (Table 2). This discussion helped to identify the most suitable CSA technologies which can minimize the climatic risks in each village. In-person interviews were also conducted with farmers to collect their basic socio-economic information.

This study used a stated preference method to analyse farmers' choice of CSA technologies in diverse rainfall zones. In the stated preference method, respondents are asked about their preferences in a list of technologies. Whereas in the revealed preference method, actual adoption of technology or related technology reveals farmers' preferences and the market value is available for that technology. The revealed preference methods can be an appropriate tool to assess farmer's preferences, but it is difficult to obtain sufficient variation in the preference data to examine all variables of interest (Kroes and Sheldon, 1988). Therefore, many studies on valuation of environmental services and consumers' preferences ranking use stated preference method. In this study, farmers' preferences for climate-smart technologies were obtained in two steps. In first step, farmers' were organized into a group of 5–6 for discussion on CSA technologies and then asked to score each technology from 0 to 3 scale (0 = no preferences, 1 = low preference, 2 = medium preference, and 3 = high preference). These values were converted to percentiles and categorized into four classes (Table 3).

In the second step, the study team conducted a bidding exercise using pseudo money for only those technologies that were highly preferred by the farmers in the scoring exercise. All selected technologies were further weighted ranging between a 0 to 100 scale based on payment schedule in terms of bidding amounts and categorized into four preference classes (poor, low, medium and high). The weight for each technology from bidding exercise was estimated based on following formula:

$$W_t = \frac{\text{Amount of bid on a technology}}{\text{Cumulative amount of bids for all the technologies}} \times 100$$

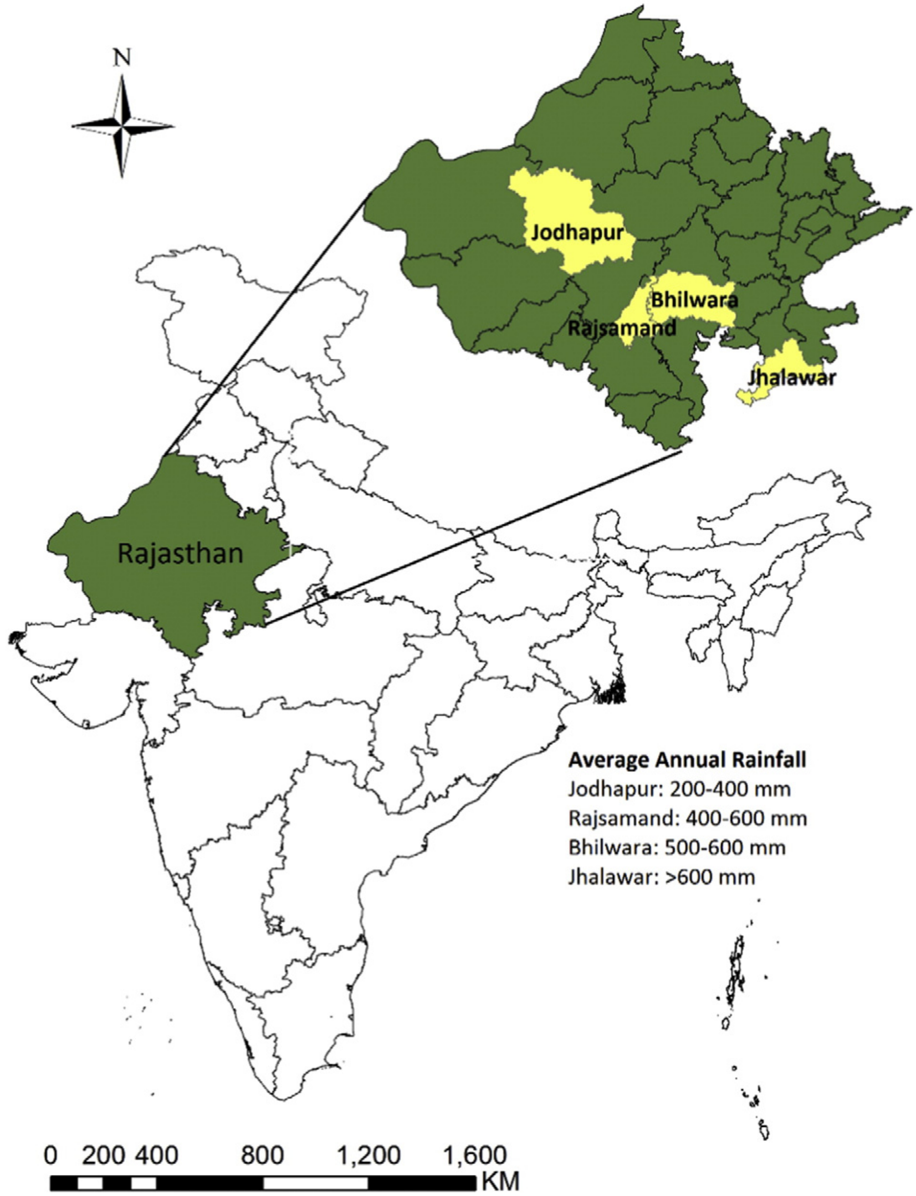

Fig. 1. Map of study area indicating Rajasthan state of India and selected districts in Rajasthan.

$$W_{tav} = \frac{\text{Sum of weights assigned by the farmers}}{\text{No.of farmers participating in the building}}$$

$$W_{tm} = \frac{100}{\text{Number of technologies included in the building}}$$

where, W_t is technology weight in bidding game, W_{tav} is average weight of technology assigned by farmers and W_{tm} represents mean weight of technologies if all technologies had same weight. Based on these weights, technologies were classified into two groups on following bases: i) high-weighted CSA technology, if $W_{tav} \geq W_{tm}$, and ii) low-weighted CSA technology, if $W_{tav} \leq W_{tm}$. These technologies were further weighed on the basis of frequency of their distribution from 0 to 100 scale and finally arranged into four groups, similar to scoring method (Table 4). The frequency of distribution represents number of farmers preference for particular technology.

The scoring and bidding methods of preferences for the technologies were statistically tested by using chi-square (χ^2) test. Total number of responses in each preference level (1 to 4) in scoring and bidding

Table 1
Percentage of rainfed agriculture and major crops in the study areas.

Districts	Percent of rainfed agriculture	Major Kharif crops (based on total area under the crop)	Major Rabi crops (based on total area under the crop)
Bhilwara	69	Maize, Jawar, Urad, Sesamum, Moog	Wheat, Gram, Mustard, Barley, Lentil
Jhalawar	77	Soybean, Maize, Urad, Sesamum, Jawar	Wheat, Gram, Mustard, Lentil
Jodhpur	85	Bajra, Moong, Jawar, Groundnut, Sesamum	Mustard, Wheat, Gram, Barley
Rajsamand	44	Maize, Jawar, Cotton, Sesamum, Groundnut	Wheat, Barley, Mustard, Gram

Table 2
Selected climate smart options to assess farmers' preferences.

Technology	Adaptation/mitigation potential
1. Water-smart	Interventions that improve water use efficiency
• Rainwater Harvesting (RH) • Drip Irrigation (DI) • Laser Land Levelling (LL) • Furrow Irrigated Bed Planting (FIBP) • Drainage Management (DM) • Cover Crops Method (CCM)	• Collection of rainwater not allowing to run-off and use for agricultural in rainfed/dry areas and other purposes on-site. • Application of water directly to the root zone of crops and minimize water loss • Levelling the field ensures uniform distribution of water in the field and reduces water loss (also improves nutrient use efficiency) • This method offers more effective control over irrigation and drainage as well as rainwater management during the monsoon(also improves nutrient use efficiency). • Removal of excess water (flood) through water control structure • Reduces evaporation loss of soil water (also adds nutrients into the soil)
2. Energy-smart	Interventions that improve energy use efficiency
• Zero Tillage/Minimum Tillage (ZT/MT)	• Reduces amount of energy use in land preparation. In long-run, it also improves water infiltration and organic matter retention into the soil
3. Nutrient-smart	Interventions that improve nutrient use efficiency
• Site Specific Integrated Nutrient Management (SINM) • Green Manuring (GM) • Leaf Color Chart (LCC) • Intercropping with Legumes (ICL)	• Optimum supply of soil nutrients over time and space matching to the requirements of crops with right product, rate, time and place • Cultivation of legumes in a cropping system. This practice improves nitrogen supply and soil quality • Quantify the required amount of nitrogen use based on greenness of crops. Mostly used for split dose application in rice but also applicable for maize and wheat crops to detect nitrogen deficiency • Cultivation of legumes with other main crops in alternate rows or mixed. This practice improves nitrogen supply and soil quality.
4. Carbon-smart	Interventions that reduce GHG emissions
• Agro Forestry (AF) • Concentrate Feeding for Livestock (CF) • Fodder Management (FM) • Integrated Pest Management (IPM)	• Promote carbon sequestration including sustainable land use management • Reduces nutrient losses and livestock requires low amount of feed • Promote carbon sequestration including sustainable land use management • Reduces use of chemicals
5. Weather-smart	Interventions that provide services related to income security and weather advisories to farmers.
• Climate Smart Housing for Livestock (CSH) • Weather based Crop Agro-advisory (CA) • Crop Insurance (CI)	• Protection of livestock from extreme climatic events (e.g. heat/cold stresses) • Climate information based value added agro-advisories to the farmers • Crop-specific insurance to compensate income loss due vagaries of weather
6. Knowledge-smart	Use of combination of science and local knowledge
• Contingent Crop Planning (CC) • Improved Crop Varieties (ICV) • Seed and Fodder Banks (SFB)	• Climatic risk management plan to cope with major weather related contingencies like drought, flood, heat/cold stresses during the crop season • Crop varieties that are tolerant to drought, flood and heat/cold stresses • Conservation of seeds of crops and fodders to manage climatic risks

Note: these technologies, practices and services directly or indirectly contribute to improve productivity, enhance resilience and reduce GHG emission. Technologies/practices that help to improve at least one component can be considered as CSA. Same technology can help to improve all three elements of CSA.

methods were used for the χ^2 test. The null hypothesis was that farmers preferences are not different on scoring and bidding methods. The comparison between two methods indicates whether the costs of technology adoption is an important constraint or not to farmers for adoption of particular CSA technology.

2.2. Empirical model

The multinomial model is used to analyse the determinants of farmer's choice of CSA technologies. The design and implementation of CSA programmes require to consider the variables that may influence farmers' investment decisions on a particular technology. Several socio-economic and climatic variables may influence a farmer's decision to invest in a particular CSA technology. This study modelled CSA adoption behaviour of farmers using discrete dependent variable with multiple choices. Some multinomial variables (e.g. preferences for CSA technology, technology ratings and opinion surveys) are inherently ordered. In these cases, although the outcome is discrete, the multinomial logit models would fail to account for ordinal nature of a dependent variable (Beggs et al., 1981; Hausman and Ruud, 1986). Thus, the ordered probit model was used to analyse the determinants of farmer's choice over CSA technologies. A multinomial ordered probit model can be represented as follow (e.g. Green, 2007):

$$\sum_{j=1}^{j} \mathrm{P_n(j)} = \mathrm{F}\left(\alpha_j - \beta_j X_n, \theta\right), \mathrm{j} = 1, \ldots\ldots\ldots\ldots \mathrm{J}-1$$

$$\mathrm{P_n(J)} = 1 - \sum_{j=1}^{J-1} \mathrm{P_n(j)}$$

where, $P_n(j)$ is the probability that farmer n (n = 1, ……, N) choices CSA technology j, α_j unknown parameter to be estimated with β_j, X_n is a vector of characteristics specific to farmers and location, β_j is a vector of

Table 3
Rating and ranking criteria to evaluate farmers' preference over CSA technologies by scoring method.

Rating scale	Level of preference	Percentile	Class/assigned value
0	No preference	0–25	Poor (1)
1	Low	26–50	Low (2)
2	Medium	51–75	Medium (3)
3	High	75–100	High (4)

Table 4
Level and value of technology preferences in bidding method.

$W_{tav} \geq W_{tm}$ Frequency ≥ 50% *High* (4)	$W_{tav} \leq W_{tm}$ Frequency ≥ 50% *Medium* (3)
$W_{tav} \geq W_{tm}$ Frequency ≤ 50% *Low* (2)	$W_{tav} \leq W_{tm}$ Frequency ≤ 50% *Poor* (1)

coefficients, and the shape of the probability distribution function, F, is determined by θ parameter. We assume that the error term is normally distributed across observations, therefore, mean and variance of error term are normalized to zero and one. In this ordered probit model, the probability of choosing a particular CSA technology can be stated as follow:

$$P_n(1) = \Phi\left(\alpha_1 - \beta_j X_n\right)$$

$$P_n(j) = \Phi\left(\alpha_j - \beta_j X_n\right) - \Phi\left(\alpha_{j-1} - \beta_j X_n\right), j = 2, \ldots\ldots\ldots, j = 1$$

$$P_n(J) = 1 - \sum_{j=1}^{J=1} P_n\left(j\right)$$

where, Φ is the cumulative standard normal distribution function. For all probabilities to be positive, we must have $0 < \alpha_1 < \alpha_1 < \ldots\ldots < \alpha_{J-1}$. Based on this function, a log-likelihood function and its derivatives can be readily estimated. This method is also used to analyse the determinants of climate change adaptation choices in agriculture in various locations (Balew et al., 2014; Gbetibouo, 2009).

The dependent variable in empirical estimation is farmer's preferences over a CSA technology from a set of technologies listed in Table 2. The explanatory variables for this study include household characteristics such as farmers' age, gender, caste, income, landholding size, farming system and locations. These explanatory variables were selected based on data availability and literature. Farmers' age and gender significantly influence the choice of technologies to climate change adaptation in agriculture (Nhemachena and Hassan, 2007; Maddison, 2006). Similarly, their economic status (e.g. income and poverty level) and their resource endowment (e.g. landholding size) also influence the adoption of CSA technologies (Deressa et al., 2011; Knowler and Bradshaw, 2007). Farmers' priorities on CSA technologies also differ based on farming systems and locations (Taneja et al., 2014). Table 5 provides a description of explanatory variables that were used for estimation of ordered probit model. The location variable represents an effect of prevailing climatic condition (rainfall zones) in farmers' priority for a particular CSA technology.

Table 5
Description of the independent variables.

Variable	Description
Experienced farmer	Experienced farmers, 1 = respondent's age > 30 years, 0 = otherwise
Gender	Gender of respondent, 1 = woman farmer, 0 = otherwise
Caste	Caste of respondent, 1 = general caste, 0 = otherwise
Income	Household income, 1 = income below 30,000/year, 0 = otherwise
Small landholders	Land holding size, 1 = landholding below 2.5 ha, 0 = otherwise
Rainfed farming	Farming system, 1 = rainfed, 0 = otherwise
Location with rainfall <600 mm/year	Study area, 1 = location with rainfall <600 mm/year 0 = otherwise

Table 6
Most preferred CSA technologies in different rainfall zones.

Rainfall < 600 mm/year	Rainfall 600–800 mm	Rainfall > 800 mm/year
Crop insurance (88%)	Weather based crop agro-advisory (86%)	Crop insurance (80%)
Rainwater harvesting (84%)	Crop insurance (86%)	Weather based crop agro-advisory (78%)
Fodder management (83%)	Laser land levelling (85%)	Climate smart housing for livestock (75%)
Weather based crop agro-advisory (80%)	Rainwater harvesting (79%)	Agro-forestry (74%)
Contingent crop planning (80%)	Agro-forestry (78%)	Site-specific integrated nutrient management (71%)

3. Results and discussion

3.1. Farmers preferences for CSA technologies

Of the 21 different CSA technologies, 13 technologies were highly preferred by farmers in scoring activity and those technologies were considered for bidding exercises. After scoring and bedding of the selected technologies, we compared farmers' overall preferences for different CSA technologies based on annual rainfall level (mean mm/year) and coefficient of variation (CV) in annual rainfall in the study area. Results indicate that farmers' preferences for CSA technologies are marked by some commonalities as well as differences. The ranking for each technology is based on average frequency of responses in scoring and bidding methods: 76–100 = high (4th rank), 51–75 = medium (3rd rank), 26–50 (2nd rank) = low, 0–25 = poor (1st rank). Table 6 presents most preferred CSA technologies in different rainfall zones. Top five preferred CSA technologies in all rainfall zone include crop insurance, rainwater harvesting, fodder management, weather based crop agro-advisory, contingent crop planning, laser land levelling, agro-forestry, climate smart housing for livestock and site specific integrated nutrient management (Table 6).

Fig. 2 presents top five CSA technologies preferred by farmers in different rainfall zoness. >80% of the farmers in low rainfall zones preferred crop insurance, rainwater harvesting and storage, fodder management, crop agro-advisories and contingent crop planning, whereas preferences for these technologies were low and varied in high rainfall zones. For instance, rainwater harvesting and crop insurance were less important for farmers in high rainfall zones.

This study also finds that farmers' preferences for CSA technologies in low annual rainfall areas and high CV of annual rainfall have commonalities. Similar results were also found in areas with high annual rainfall and low CV of annual rainfall. One of the reasons was that the level of rainfall (mm) and CV in annual rainfall (%) were negatively

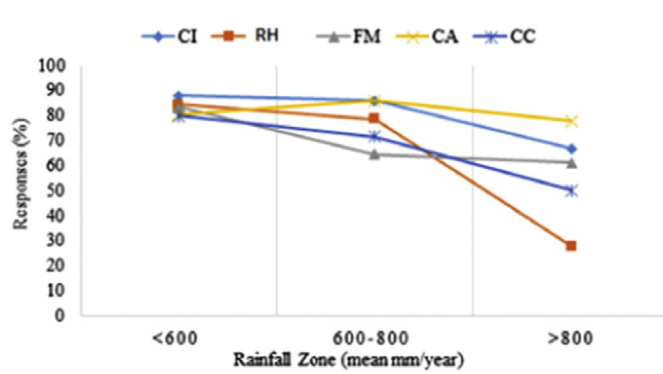

Fig. 2. Top five CSA technologies preferred by the farmers in the different rainfall zones. CI = crop insurance, RWCS = rainwater harvesting, FM = fodder management, CA = weather based crop agro-advisories, CC = contingent crop planning.

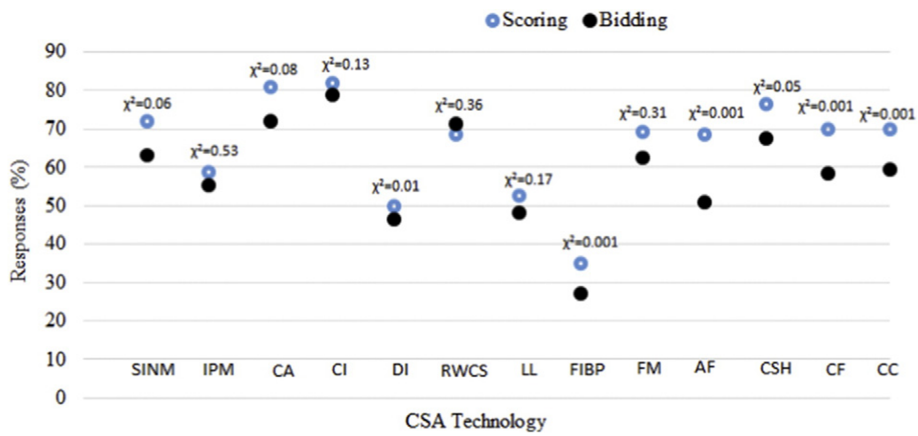

Fig. 3. Comparison between scoring and bidding methods of preferences over the CSA technologies. Abbreviations of CSA technology names can be found in Table 2.

correlated (lower the rainfall, higher the CV). Highly preferred technologies in all areas were crop insurance, weather based crop agro-advisories, rainwater harvesting, contingent crop planning, and site specific integrated nutrient management. Surprisingly, farmers in these locations have shown low levels of preference for improved crop varieties, seed and fodder banks and integration of legumes in the cropping system. The adoption of these technologies can also help to offset the impact of climate change and variability on agriculture. Our results indicate that farmers are willing to adopt some risk reduction technologies such as crop insurance, agro-advisories, and rainwater harvesting that can be supported by the government through technical and financial services.

3.2. Difference in preferences in scoring and bidding methods

We compare farmers' preferences for CSA technologies between scoring and bedding methods based on chi-square (χ^2) test. Fig. 3 presents the results of test for 13 different CSA technologies that were offered to farmers. Farmers' preferences for integrated pest management, crop insurance, rainwater harvesting, laser land levelling and fodder management are not significantly different between scoring and bidding methods. However, their preferences for site specific integrated nutrient management, weather based crop agro-advisories, drip irrigation, furrow irrigated bed planting, agro-forestry, climate smart housing for livestock, concentrate feeding for livestock, and contingent crop planning differed significantly between scoring and bidding methods. Farmers' preferences for all of these technologies in bidding were lower than in the scoring method. This result indicates that farmers' preferences and willingness-to-pay differ based on the technology and the cost of implementation. Implementation of these technologies may increase farmers' financial burden so that they might be reluctant to invest on the technologies.

3.3. Determinants of farmers' choice of CSA technologies

In the initial multinomial ordered probit model, many variables such as livestock size, family size, education, access to market and membership with farmers group were added to the model. These variables were dropped, as they were not statistically significant for all selected CSA technologies. Table 7 presents the results of ordered probit model for 8 different CSA technologies. The model for drip irrigation, furrow irrigation and bed planting, fodder management and agro-forestry did not fit well; thus they are not included in the results.

Results indicate that the age of farmer has significant effect in the ranking of CSA technologies. The choice of site specific integrated nutrient management, integrated pest management, laser land levelling, and crop insurance are positively influenced by the farmer's age. More experienced farmers are more likely to choose these technologies. However, experienced farmers are less likely to choose rainwater harvesting technologies for climate change adaptation. Female farmers prefer integrated pest management, weather based crop agro-advisories and contingent crop planning compared to male farmers. Their preference for rainwater harvesting and climate smart housing for climate change adaptation were significantly negative. Similarly, preferences for weather based crop agro-advisories and crop insurance were low for general caste farmers.

The results also indicate that low income farmers are more likely to prefer site specific integrated nutrient management, integrated pest management, laser land levelling compared to rainwater harvesting, contingent crop planning and crop insurance. Low income farmer may able to invest on these low cost technologies for adaptation to climate

Table 7
Parameter estimates of the multinomial ordered probit model.

Variable	SINM	IPM	CA	LL	RWHS	CSH	CP	CI
Experienced farmers (>30 years age)	0.358** (0.154)	0.410*** (0.157)	0.220 (0.173)	0.264* (0.163)	−0.405** (0.165)	0.152 (0.69)	0.212 (0.207)	−0.335** (0.173)
Female farmers	−0.154 (0.148)	0.287* (0.153)	0.291* (0.172)	0.195 (0.156)	−0.328** (0.159)	−0.501*** (0.160)	0.358* (0.208)	−0.120 (0.171)
Caste	−0.327 (0.283)	−0.124 (0.284)	−0.728** (0.296)	0.582* (0.322)	−0.158 (0.322)	−0.289 (0.307)	−0.288 (0.328)	−0.917*** (0.292)
Low income farmers	0.458*** (0.180)	0.421** (0.182)	−0.110 (0.204)	0.929*** (0.190)	−0.646*** (0.219)	−0.606*** (0.214)	−1.149*** (0.364)	−0.381* (0.220)
Small landholders	−0.255 (0.181)	0.237 (0.179)	0.375** (0.194)	−0.073 (0.181)	−0.259 (0.198)	0.265 (0.194)	0.456* (0.249)	0.340* (0.205)
Rainfed farming	0.223 (0.165)	0.585*** (0.171)	0.248 (0.185)	−0.304* (0.168)	0.309* (0.178)	−0.296* (0.178)	0.706*** (0.236)	0.187 (0.195)
Location with rainfall <600 mm/year	1.535*** (0.150)	1.594*** (0.153)	2.335*** (0.183)	1.875*** (0.160)	2.057*** (0.183)	2.724*** (0.335)	7.506 (138.14)	2.0476*** (0.190)
	N = 346	N = 346	N = 346	N = 346	N = 346	N = 346	N = 346	N = 346
	Log = −340	Log = −340	Log = −248	Log = −330	Log = −260	Log = −256	Log = −170	Log = −226
	R^2 = 0.15	R^2 = 0.17	R^2 = 0.32	R^2 = 0.24	R^2 = 0.26	R^2 = 0.31	R^2 = 0.45	R^2 = 0.35

, ** and * indicates significant at 10%, 5% and 1% level. Note: SINM = site specific integrated nutrient management IPM = integrated pest management, CA = weather-based crop advisories, LL = laser levelling, RWHS = rain water harvesting and storage, CSH = climate-smart housing for livestock, CP = contingent crop planning, and CI = crop insurance.*

change. The integrated pest management and contingent crop planning technologies are more preferred than other technologies by the farmers in the rainfed system. Farmers' preferences on integrated pest management, rainwater harvesting and contingent crop planning are significantly positive in rainfed areas. The model results also indicate that farmers in areas with low annual rainfall prefer site specific integrated nutrient management, integrated pest management, crop advisories, laser land levelling, rainwater harvesting, climate smart housing for livestock and crop insurance. These technologies can help to minimize the impacts of low rainfall and changes in rainfall patterns in dry areas. This result suggests that farmers' preferences on CSA technologies significantly differ according to the rainfall zones too. In low rainfall zone, more farmers are interested on CSA technologies in order to minimize the climatic risks, mostly water scarcity and droughts.

4. Conclusions and policy implications

This study provides insights into how farmers' priorities for CSA technologies are linked with prevailing climatic conditions of a particular location, socio-economic characteristics and willingness to pay for available technologies. Farmers' priorities for CSA technologies may differ according to climatic conditions and perceived risks. For instance, farmers in a location with low rainfall and high CV in annual rainfall prefer risk mitigation technologies such as crop insurance, weather-based crop agro-advisories and rainwater harvesting. Their preference for CSA technologies significantly changes in high rainfall zones. Consequently, policies and programmes aimed at promoting CSA technologies should focus on site specific technologies that are relevant to the local farmers.

This study also found that farmers' preferences and willingness to pay for CSA technologies significantly differ based on potential benefits and costs of technologies as informed to them. Even in the bidding exercise with pseudo currency, farmers' preferences for most of the CSA technologies were significantly different between the scoring and bidding methods. This result suggests that farmers may not be willing to invest on many CSA technologies even if there are foreseen benefits. Therefore, adaptation policies need to emphasize on the crucial role of providing information about available CSA technologies and creating financial resources to enables farmers to adopt various CSA technologies that are relevant for their location.

The empirical estimation based on the ordered probit model reveals that many socio-economic and location specific variables have a significant effect on farmers' preferences towards a particular CSA technology. Farmers' priorities may differ from technology to technology based on their age, gender, landholding size, income level, farming system and location. These results imply that a thoughtful and balanced policy response is required to deal with a demand for CSA technology for a particular social group in a particular location.

Finally, the prioritization method used in this study and results could have large implications to design and implement a climate change adaptation programme in agriculture. As we know that adoption of CSA technologies is largely dependent on farmers' priorities and their willingness-to-pay, participatory evaluation and prioritization of CSA technologies can provide clear guidelines for existing and new climate change adaptation policies in agriculture and allied sectors. This assessment of technology preferences is based on farmers' current level of understanding about benefits and costs of individual CSA technology. This study also indicates that farmers prefer some risk mitigation technologies such as crop insurance, agro-advisories and rainwater harvesting that can be supported by the government. Therefore, farmers' preferences for CSA technologies may differ based on their expectations of financial support from the government and other agencies. Similarly, their preferences may differ based on the combination of CSA technologies and their potential benefits for adaptation to climate change. These issues need to be further explored.

Acknowledgement

We acknowledge the support for this work provided by the numerous donors contributing to the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). The authors would like to thank BAIF Development Research Foundation, Pune, India, for the field work and data collection. We also thanks anonymous reviwers and editors for comments on an earlier version of the manuscript. The views expressed in the paper are the authors' alone.

References

Aggarwal, P.K., Singh, A.K., Samra, J.S., Singh, G., Gogoi, A.K., Rao, G.G.S.N., Ramakrishna, Y.S., 2009. Introduction. In: Aggarwal, P.K. (Ed.), Global Climate Change and Indian Agriculture. Indian Council of Agricultural Research, New Delhi, India.

Altieri, M.A., Nicholls, C.I., 2013. The adaptation and mitigation potential of traditional agriculture in a changing climate. Clim. Chang. http://dx.doi.org/10.1007/s10584-013-0909-y.

Aryal, J.P., Mehrotra, M.B., Jat, M.L., Sidhu, H.S., 2015. Impact of laser land leveling in rice-wheat systems of the north-western Indo-Gangetic Plains of India. Food Security http://dx.doi.org/10.1007/s12571-015-0460-y.

Balew, S., Agwata, J., Anyango, S., 2014. Determinants of adoption choices of climate change adaptation strategies in crop production by small scale farmers in some regions of central Ethiopia. J. Nat. Sci. Res. 4 (4), 78–93.

Beggs, S., Cardell, S., Hausman, J., 1981. Assessing the potential demand for electric cars. J. Econ. 17, 19–20.

Below, T.B., Mutabazi, K.D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., Tsherning, K., 2012. Can farmers' adaptation to climate change be explained by socio-economic household-level variables? Glob. Environ. Chang. 22 (1), 223–235.

Branca, G., McCarthy, N., Lipper, L., Jolejole, M.C., 2011. Climate-smart agriculture: a synthesis of empirical evidence of food security and mitigation benefits from improved cropland management. Mitigation of Climate Change in Agriculture Series 3. FAO, Rome.

Brida, A.B., Owiyo, T., 2013. Loss and damage from the double blow of flood and drought in Mozambique. International Journal of Global Warming 5 (4), 514–531.

Callaway, J.M., 2004. Adaptation benefits and costs: are they important in the global policy picture and how can we estimate them? Glob. Environ. Chang. 14, 271–282.

Campbell, J., Cheong, S., McCormick, M., Pulwarty, S., Supratid, R.S., Ziervogel, G., 2012. Managing the risks from climate extremes at the local level. In: Field, et al. (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A special Report of Working Groups I and II of the IPCC. Cambridge University Press, Cambridge, UK and New York, USA.

Challinor, A.J., Watson, J., Lobell, D., Howden, S.M., Smith, D.R., Chhetri, N., 2014. A meta-analysis of crop yield under climate change and adaption. Nat. Clim. Chang. 4, 287–291. http://dx.doi.org/10.1038/nclimate2153.

CIAT, 2014. Climate-smart Agriculture Investment Prioritization Framework. International Center for Tropical Agriculture (CIAT), Cali, Colombia.

Claessens, L., Antle, J.M., Stoorvogel, J.J., Valdivia, R.O., Thornton, P.K., Merrero, M., 2012. A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modelled data. Agric. Syst. 111, 85–95.

Deressa, T.T., Hassan, R.M., Ringler, C., 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. J. Agric. Sci. 149 (1), 23–31. http://dx.doi.org/10.1017/S0021859610000687.

Easterling, W., Aggarwal, P., Batima, P., Brander, K., Erda, L., Howden, M., Kirilenko, A., Morton, J., Soussana, J.F., Schmidhuber, J., Tubiello, F., 2007. Climate change 2007: impacts, adaptation and vulnerability. In: Parry, M.L., Canziani OF, Palutikof, J.P., van der Linden, P.J., Hanson, C.E. (Eds.), Cambridge University Press. UK, Cambridge, pp. 273–313.

FAO, 2010. Climate Smart Agriculture: Policies, Practices and Financing For Food Security, Adaptation and Mitigation. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

FAO, 2012. Developing a Climate-Smart Agriculture Strategy at The Country Level: Lessons From Recent Experience. Background Paper for the Second Global Conference on Agriculture. Food Security and Climate Change, Food and Agriculture Organization of the United Nations, Rome, Italy.

Finger, R., Schmid, S., 2007. Modeling Agricultural Production Risk and the Adaptation to Climate Change. Paper Prepared for Presentation at The 101st EAAE Seminar 'Management of Climate Risks in Agriculture', Berlin, Germany, July 5–6, 2007.

Gathala, M.K., Ladha, J.K., Kumar, V., Saharawat, Y.S., Kumar, V., Sharma, P.K., Sharma, S., Pathak, H., 2011. Tillage and crop establishment affects sustainability of South Asia Rice–Wheat system. Agron. J. 103 (4), 961–971.

Gbetibouo, G.A., 2009. Understanding farmers' perceptions and adaptations to climate change and variability. IFPRI Discussion Paper 00849. International Food Policy Research Institute (IFPRI), Washington DC.

GoI, 2014. Key Indicators of Situation of Agricultural Households in India. Ministry of Statistics and Programme Implementation. National Sample Survey Office, New Delhi, India.

Gore, P.G., Prasad, T., Hatwar, H.R., 2010. Mapping of Drought Areas Over India. National Climate Center, India Meteorological Department (IMD), Pune, India.

Green, W.H., 2007. Econometric Analysis. 5th edition. Parson Education, Inc., Delhi, India.

Hausman, J., Ruud, P., 1986. Specifying and Testing Econometric Models for Rank Ordered Data With an Application to the Demand for Mobile And Portable Telephone. Working Paper No. 8605, University of California, Berkeley, Department of Economics.

IPCC, 2014. Summary for policymakers. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1–32.

Jat, R.K., Sapkota, T.B., Singh, R.G., Jat, M.L., Kumar, M., Gupta, R.K., 2014. Seven years of conservation agriculture in a rice-wheat rotation of Eastern Gangetic Plains of South Asia: yield trends and economic profitability. Field Crop Res. 164, 199–210.

Khatri-Chhetri, A., Aryal, J.P., Sapkota, T.B., Khurana, R., 2016. Economic benefits of climate-smart agricultural practices to smallholders' farmers in the Indo-Gangetic Plains of India. Curr. Sci. 110 (7), 1251–1256.

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

Kroes, E.P., Sheldon, R.J., 1988. Stated preference methods: an introduction. JTEP 11–24.

Lipper, L., Thornton, P., Campbell, B.M., ... Torquebiau, E.F., 2014. Climate-smart agriculture for food security. Nat. Clim. Chang. 4, 1068–1072.

Lobell, D., Sibley, A., Ortiz-Monasterio, J.I., 2012. Extreme heat effects on wheat senescence in India. Nat. Clim. Chang. 2, 186–189. http://dx.doi.org/10.1038/nclimate1356.

Maddison, D., 2006. The Perception of and Adaptation to Climate Change in Africa. CEEPA Discussion Paper No. 10. Centre for Environmental Economics and Policy in Africa. University of Pretoria, Pretoria, South Africa.

Mall, R.K., Gupta, A., Singh, R.S., Rathore, L.S., 2006. Water resources and climate change: an Indian perspective. Curr. Sci. 90 (12), 1610–1626.

Mittal, S., 2012. Modern ICT for Agricultural Development and Risk Management in Smallholder Agriculture in India. CIMMYT. Socio-Economics Working Paper 3. CIMMYT, Mexico, D.F.

Mwongera, C., Shikuku, K.M., Winowiecki, L., Okolo, W., Twyman, J., Läderach, P., 2014. Climate Smart Agriculture Rapid Appraisal Report From the Southern Agricultural Growth Corridor of Tanzania. International Fund for Agricultural Development (IFAD), Rome, Italy.

Nhemachena, C., Hassan, R., 2007. Micro-level Analysis of Farmers' Adaptation to Climate Change in Southern Africa. IFPRI Discussion Paper No. 00714. International Food Policy Research Institute, Washington DC.

Norton, R., 2014. Combating climate change through improved agronomic practices and input-use efficiency. Journal of Crop Improvement 28 (5), 575–618.

Palanisami, K., Kumar, D.S., Malik, R.P.S., Raman, S., Kar, G., Monhan, K., 2015. Managing water management research: analysis of four decades of research and outreach programmes in India. Economic and Political Review 33–43 L (26/27).

Pathak, H.C., 2011. Drought Preparedness and Mitigation. National Academy of Agricultural Sciences (NAAS), Pusa, New Delhi.

Porter, J.R., Xie, L., Challinor, A.J., Cochrane, K., Howden, S.M., Iqbal, M.M., Lobell, D.B., Travasso, M.I., 2014. Food security and food production systems. In: Field, et al. (Eds.), Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, USA, pp. 485–533.

Prasanna, V., 2014. Impact of monsoon rainfall on the total foodgrain yield over India. J. Earth Syst. Sci. 123 (5), 1129–1145.

Rao, R.C.A., Raju, B.M.K., Rao, A.V.M.S., Rao, K.V., Rao, V.U.M., Ramachandran, K., Venkateswarlu, B., Sikka, A.K., 2013. Atlas on Vulnerability of Indian Agriculture to Climate Change. Central Research Institute for Dryland Agriculture, Hyderabad, India.

Sapkota, T.B., Majumdar, K., Jat, M.L., Kumar, A., Bishnoi, D.K., Mcdonald, A.J., Pampolino, M., 2014. Precision nutrient management in conservation agriculture based wheat production of Northwest India: profitability, nutrient use efficiency and environmental footprint. Field Crop Res. 155, 233–244.

Sapkota, T.B., Jat, M.L., Aryal, J.P., Jat, R.K., Khatri-Chhetri, A., 2015. Climate change adaptation, greenhouse gas mitigation and economic profitability of conservation agriculture: some examples from cereal systems of Indo-Gangetic Plains. J. Integr. Agric. 14 (8), 1524–1533.

Singh, G., Mishra, D., Singh, K., Parmar, R., 2013. Effect of rainwater harvesting on plant growth, soil water dynamics and herbaceous biomass during rehabilitation of degraded hills in Rajasthan, India. For. Ecol. Manag. 310, 612–622.

Taneja, G., Pal, B.D., Joshi, P.K., Aggarwal, P.K., Tyagi, N.K., 2014. Farmers' preferences for climate-smart agriculture: an assessment in the Indo-Gangetic Plain. IFPRI Discussion Paper 01337. International Food Policy Research Institute, Washington DC, USA.

TERI, 2010. Draft Rajasthan State Action Plan on Climate Change. The Energy and Resource Institute, New Delhi, India.

UNDP, 2011. India Factsheet: Economic and Human Development Indicator. United Nations Development Programme (UNDP), New Delhi, India.

Vermeulen, S.J., Campbell, B.M., Ingram, J.S.I., 2012. Climate change and food systems. Annu. Rev. Environ. Resour. 37, 195–222.

Zabel, F., Putzenlechner, B., Mauser, W., 2014. Global agricultural land resources — a high resolution suitability evaluation and its perspectives until 2100 under climate change conditions. PLoS ONE 9 (9), e107522. http://dx.doi.org/10.1371/journal.pone.0107522.