Natural Resources Forum 42 (2018) 141–158 DOI: 10.1111/1477-8947.12152

Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India

Jeetendra Prakash Aryal, Dil Bahadur Rahut, Sofina Maharjan and Olaf Erenstein

Abstract

Climate change poses a major threat to agricultural production and food security in India, and climate-smart agriculture (CSA) is crucial in addressing the potential impacts. Using survey data from 1,267 farm households in 25 villages from Bihar and Haryana in the Indo-Gangetic Plains, this study analyzes the factors that determine the probability and level of adoption of multiple CSA practices, including seeds of stress-tolerant varieties, minimum tillage, laser land leveling, site-specific nutrient management and crop diversification. We applied a multivariate probit model for the simultaneous multiple adoption decisions, and ordered probit models for assessing the factors affecting the level of adoption. The adoption of the various CSA practices is interrelated, whereas several factors, including household characteristics, plot characteristics, market access and major climate risks are found to affect the probability and level of CSA adoption. Climate-smart agriculture (CSA) adoption and its intensity also vary significantly between eastern Bihar, which is relatively poor and densely populated, and north-western Haryana. Engaging multiple stakeholders such as farmers, agricultural institutions, agricultural service providers and concerned government departments at the local level is crucial for the large-scale uptake of CSA. The study, therefore, calls for agricultural policy reforms so that most of the issues related to the uptake of CSA can be adequately addressed.

Keywords: Climate change adaptation; crop diversification; laser land leveling; minimum tillage; nutrient management; stress-tolerant varieties.

1. Introduction

The adverse impacts of climate change have increasingly become a challenge for India's agricultural systems. Extreme climatic events such as frequent floods, heat-stress and droughts can substantially reduce crop yields (Aggarwal *et al.*, 2010; Aggarwal and Rani, 2009; Singh and Pathak, 2014). Wheat production in India's northern region will face significant losses due to high temperatures (Lobell *et al.*, 2012) and by 2050, more than 50% of the Indo-Gangetic Plains may become unsuitable for wheat due to increased heat-stress (Ortiz *et al.*, 2008). This calls for climate-smart agriculture (CSA) that can increase the resilience of agriculture to climate change through better adaptation — and by reducing agriculture's contribution to global warming.

Another major agricultural challenge is to increase agricultural production whilst reducing agricultural greenhouse gas (GHG) emissions. Given the high — and growing — population and correspondingly increasingly scarce land resources, intensification of agricultural systems remains the only option to increase agricultural production that is required for ensuring food security (NAAS, 2013). This leads to more use of chemical fertilizers and energy, major sources of GHG emissions from agriculture. Hence, production systems guided by the key concerns of agricultural sustainability are required to increase food production without compromising environmental integrity (Sapkota *et al.*, 2018).

The Indo-Gangetic Plains across northern India play an important role in Indian agricultural production systems (Erenstein and Thorpe, 2011). In the northwest, the irrigated systems are resource intensive, especially in terms of energy, water and chemical fertilizer (Pingali, 2012; Singh, 2000). This justifies the pivotal role of CSA in addressing the interlinked challenges of sustainable agriculture, food security and climate change (FAO, 2010, 2013; Lipper *et al.*, 2014). Climate-smart agriculture (CSA) employs several agricultural practices that sustainably increase productivity, improve resource-use-efficiency, reduce exposure, sensitivity or vulnerability to climate variability or change, and reduce GHG emissions from agriculture

Jeetendra Prakash Aryal, Dil Bahadur Rahut, and Olaf Erenstein are at the International Maize and Wheat Improvement Center (CIMMYT), Mexico. E-mail: jeetenaryal@gmail.com; D.Rahut@cgiar.org; O.Erenstein@cgiar.org
Sofina Maharjan is at the International Maize and Wheat Improvement Center (CIMMYT), India. E-mail: sofina.maharjan@cgiar.org

(Neufeldt *et al.*, 2013). This study focuses on five CSA practices that are among the key practices promoted by the CGIAR Research Program on Climate Change, Agriculture and Food Security (CRP CCAFS) in south Asia. These CSA practices are found to have clear economic as well as climate change adaptation and/or mitigation benefits (for example, see Aryal *et al.*, 2015b, 2016; Erenstein *et al.*, 2012; Khatri-Chhetri *et al.*, 2016; Sapkota *et al.*, 2015). According to CCAFS, CSA refers to those practices that help climate change adaptation, GHG mitigation and food security (for details see Aggarwal *et al.*, 2013; www.ccafs.cgiar.org). In principle, a CSA practice must simultaneously achieve all the aims. However, in practice, farmers' decisions to adopt CSA practices usually depend on the economic benefits associated with these practices (Khatri-Chhetri *et al.*, 2016) and thus, this study gives more priority to the climate change adaptation and food security aspects of CSA rather than to GHG mitigation. But in practice, many adaptation measures with (private) economic benefits to farmers have GHG mitigation co-benefits and vice versa (FAO, 2013; Sapkota *et al.*, 2015).

Some CSA practices (for example, crop diversification) have been long-practiced, while others have only recently gained momentum in India. Relatively newer practices such as minimum tillage, laser land leveling and site-specific nutrient management are promoted by national and international agricultural development organizations. Despite the economic and climate change adaptation benefits of CSA and continued support from national and international agricultural institutions, its adoption by farmers is still varied and relatively limited (Palanisami *et al.*, 2015). Therefore, it is crucial to identify the factors that affect CSA adoption and its level of adoption by farmers. With this background, this study assesses the factors that influence the adoption of multiple CSA practices and their adoption intensity. We consider five major CSA practices, including seeds of stress-tolerant varieties, minimum tillage, laser land leveling, site-specific nutrient management and crop diversification.

Most previous CSA adoption studies emphasized a single CSA practice, ignoring the possibility of interrelationships across these practices. Farmers usually face multiple climate-related risks such as rainfall variability, declining groundwater tables, heat stress and droughts. Therefore, they may well consider applying a CSA portfolio in order to simultaneously tackle some of those risks and to exploit the possible adaptation benefits. Some CSA practices are set to complement each other. For example, laser land leveling can facilitate minimum tillage because it is easier to operate zero tillage seed drills on a laser-leveled field. Hence, enabling farmers to get both services as a package can enhance the adoption of both. This potentially also helps overcome partial adoption challenges, which often undermine the farmer's ability to achieve the full economic and environmental benefits of adoption. Complementarities among technologies thus can increase income and also stimulate further adoption (Sharma *et al.*, 2011; Yu *et al.*, 2012). In addition, technology adoption decisions can be path dependent, i.e., recent technology adoption may be partly associated with earlier technology choices. Hence, the analysis of technology adoption without properly controlling for technology interdependence can either underestimate or overestimate the influences of various factors on the adoption decision (Kassie *et al.*, 2013; Teklewold *et al.*, 2013; Wu and Babcock, 1998). Consequently, it is crucial to assess whether farmers' multiple technology adoption decisions are interrelated or not. Acknowledging these issues, this study applied a multivariate probit model to jointly analyze the decisions to adopt multiple CSA practices. The applied multivariate probit model allows the possibility of correlations between adoption decisions across different CSA practices. It also provides insights on the long-standing discussions on whether farmers adopt technology in a piecemeal way or in packages (Byerlee and Hesse de Polanco, 1986; Kassie *et al.*, 2013, 2015; Teklewold *et al.*, 2013), and helps to inform and fine tune strategies and policies to promote CSA. Indeed, farmers tend to be rational and adopt attractive technologies — be it the most attractive components first and sequentially, to combinations of components relatively simultaneously if these provide sufficient complementarities.

This study contributes to the literature in three major areas. First, it is based on survey data from 2,625 farm-plots operated by 1,267 farm households in two important yet contrasting states in the Indo-Gangetic Plains of India. The farm-plot level data allow to control for land characteristics in the analysis. Second, it acknowledges the interdependence between different CSA practices and jointly analyzes the decision to adopt multiple practices. Third, this study assesses the level of adoption, measured by the number of CSA practices adopted.

2. Econometric framework and estimation strategies

In order to model the CSA adoption decision, we applied a multivariate probit model and to estimate the intensity of CSA adoption, we used the ordered probit model. We used Stata 13.1 software for the analysis.

2.1. Multivariate probit model

A farmer's decision to adopt a CSA practice is discrete in nature and calls for qualitative choice models. Univariate logit and probit models are not appropriate and in our case, may generate biased estimates because these methods assume the independence of error terms of the different CSA practices, whereas a farmer may adopt a CSA mix and the decision to adopt one practice could be influenced by adoption decisions for other practices. Therefore, we applied a multivariate probit model, which allows for the

interrelationships among the CSA practices, i.e., the potential correlation among the unobserved disturbances in the adoption equation. Ignoring such issues leads to biased and inefficient estimates (Greene, 2003a; Wooldridge, 2002). Such biases may result in a situation where we can observe limited adoption caused by poor returns as complementary practices are not simultaneously adopted. However, we often fail to account for this because a model may not adequately correct for these complementarities. A recent study by Aryal *et al.* (2016) in the same study area found that farmers mostly practice minimum tillage in the laser-leveled plots since it is easy to operate zero tillage seed drill. Hence, unless we analyze this effect, it will not be understood that unavailability of laser land leveling can be one of the major factors limiting the adoption of minimum tillage.

Farmers often utilize information on several practices while making decisions to adopt technologies and thus, the decision to adopt one CSA practice may influence the decision to adopt another. This makes adoption decisions inherently multivariate. In such a case, using univariate techniques could exclude crucial information about interdependent and simultaneous adoption decisions (Greene, 2003a). The multivariate probit model helps us to determine possible complementarities (positive correlation) and substitutability (negative correlation) between the CSA practices.

A farmer is more likely to adopt a particular CSA practice if the benefit from its adoption is higher than non-adoption. Consider the *ith* farm household (i = 1, 2, . …, N) facing a decision on whether to adopt the *jth* CSA practice (where j denotes choice of: laser land leveling (L), minimum tillage (M), crop diversification (D), seeds of stress-tolerant variety (S) and site-specific nutrient management (O)) on its farm plot (p = 1, .. …, P). Let U_0 and U_j represent the benefits to a farmer without and with the adoption of CSA. A farmer decides to adopt the *jth* CSA practice on its farm plot p if the net benefit $\left(B^*_{ipj}\right)$ with its adoption is higher than without its adoption, i.e., $B^*_{ipj} = U^*_j - U_0 > 0$. In this case, the net benefit of CSA adoption is a latent variable, which is determined by observed household, farm plot, and location characteristics (X_{ip}), and the error term(ε_{ip}) as follows:

$$B^*_{ipj} = X'_{ip}\beta_j + \varepsilon_{ip} \quad (j = L, M, D, S, O). \tag{1}$$

Equation (1) can be presented in terms of an indicator function. In this case, the unobserved preferences in Equation (1) translate into the observed binary outcome equation for each CSA practice choice as follows:

$$B_{ipj} = \begin{cases} 1 \ if \ B^*_{ipj} > 0 \\ 0 \ otherwise \end{cases} \quad (j = L, M, D, S, O). \tag{2}$$

In the multivariate probit model with the possibility of adopting multiple CSA practices, the error terms jointly follow a multivariate normal distribution (MVN) with zero conditional mean and variance normalized to unity, i.e., $(u_L, u_M, u_D, u_S, u_O) \rightarrow^{MVN} (0, \Omega)$ and the covariance matrix (Ω) is given by:

$$\Omega = \begin{bmatrix} 1 & \rho_{LM} & \rho_{LD} & \rho_{LS} & \rho_{LO} \\ \rho_{ML} & 1 & \rho_{MD} & \rho_{MS} & \rho_{MO} \\ \rho_{DL} & \rho_{DM} & 1 & \rho_{DS} & \rho_{DO} \\ \rho_{SL} & \rho_{SM} & \rho_{SD} & 1 & \rho_{SO} \\ \rho_{OL} & \rho_{OM} & \rho_{OD} & \rho_{OS} & 1 \end{bmatrix}, \tag{3}$$

where ρ denotes the pairwise correlation coefficient of the error terms corresponding to any two CSA practices. If these correlations in the off-diagonal elements in the covariance matrix become non-zero, it justifies the application of a multivariate probit instead of a univariate probit for each individual CSA practice.

2.2. Ordered probit model

Adoption intensity is often assessed based on relative area, but the exact area under each CSA practice was challenging to assess. Following Teklewold *et al.* (2013) and Kassie *et al.* (2013), we measured the intensity of adoption by the number of CSA practices adopted in an individual farm plot as the dependent variable. In this case, the variable of interest takes integer values ranging from 0 to 5 and thus, an ordered probit model is used. The ordered probit model can be expressed as:

$$y^* = x'\beta + \varepsilon, \tag{4}$$

where y^* is unobserved and is given by:

$$\begin{cases} y = 0 \ if \ y^* \le 0 \\ \ \ = 1 \ if \ 0 < y^* \le \alpha_1 \\ \ \ = 2 \ if \ \alpha_1 < y^* \le \alpha_2, \\ \ \ \vdots \\ \ \ = J \ if \ \alpha_{J-1} \le y^* \end{cases}$$

where values of y are observed and α are unknown parameters to be estimated. We assume that ε follows a normal distribution with zero mean and unit variance. Then the probabilities of each outcome can be expressed as:

$$\begin{aligned} &\Pr(y = 0|x) = \Phi(-x'\beta) \\ &\Pr(y = 1|x) = \Phi(\alpha_1 - x'\beta) - \Phi(-x'\beta) \\ &\Pr(y = 2|x) = \Phi(\alpha_2 - x'\beta) - \Phi(\alpha_1 - x'\beta) \\ &\vdots \\ &\Pr(y = J|x) = 1 - \Phi(\alpha_{J-1} - x'\beta). \end{aligned}$$

In the ordered probit model, the marginal effects of the regressors x on the probabilities are not equal to the value of the coefficients. As it is not easy to interpret the results

directly, we have calculated the marginal effects of each outcome (for details on this, see Greene, 2003b).

We could have applied the Poisson regression model assuming that the number of CSA adopted as a count variable. However, Poisson regression assumes the equal probability of adoption of each alternative CSA. In our case, this is not a valid assumption since the likelihood of adopting the first CSA practice might differ from the probability of adopting the second and so on; and with the adoption of the first CSA practice, the farmer was exposed to information about other CSA practices.

2.3. Issues in model estimations: multicollinearity, sample size and potential endogeneity

Multiple factors can influence technology adoption. Therefore, we need to control for a number of factors while estimating the multivariate probit model. With the increase in number of explanatory variables in the multivariate probit model, we may face three problems in model estimation — multicollinearity, inadequate sample size and potential endogeneity. We used condition index for testing the multicollinearity among the explanatory variables (Belsley, 1991; Belsley *et al.*, 2005). The basic decision rule is the value of condition index. If the value of condition index is less than 30, this implies that there is no serious problem of multicollinearity, and we dropped variables having a condition index of more than 30. Sample size can become a constraining factor while estimating a multivariate probit model with many explanatory variables. As estimators are predicted based on asymptotic theory, they require sufficiently large sample sizes. We used the criterion that the number of observations should be greater than $1.5k(k+1)$, where k refers to the total number of variables used in the multivariate probit model (Behera et al., 2015; Jöreskog and Sörbom, 1993). When the sample size is less than required, the asymptotic variance-covariance matrix is unlikely to be positive definite. This is manifested in biased inference caused by poor estimates of parameter variance-covariances.

In estimating adoption models, we need to address endogeneity problems that may arise with some variables in the model specification. Endogeneity arises when an explanatory variable, such as extension services, may be jointly determined by the decision to adopt in the adoption specification (Abdulai and Huffman, 2014). To address this potential endogeneity problem, we followed the Rivers and Vuong approach (Rivers and Voung, 1988). In this, we first specified the potential endogenous variable as a function of all other variables in the adoption equation along with a set of instruments as follows:

$$T_i = \gamma X_{ij} + \psi V_{ij} + \eta_{ij}, \tag{5}$$

where T is a potential endogenous variable, X is the vector of explanatory variables as described in Equation (1), and V is an instrumental variable that is correlated with the endogenous variable but uncorrelated with error terms in adoption Equation (1). After estimating Equation (5), we include the residual term from the first stage regression of the endogenous variable as follows:

$$y^* = x'\beta + \psi V_i + R_{ij} + \varepsilon, \tag{6}$$

where R_{ij} is a vector of residual terms from Equation (5). With the inclusion of the residual term as an explanatory variable in Equation (6), the probit estimates of the potential endogenous variables in X are then consistent (Wooldridge, 2002). The distance from the nearest extension outlet is used as an instrument because it affects the access to extension services, but not the decision to adopt the technology. The result of endogeneity corrected model is presented in Appendix A. As the residual terms (variable 'extension_residual' in Appendix A) are not significant in all the models, we presented the result of the model without the residual terms.

3. Study area, data and description of variables

3.1. Study area

This study was conducted in Haryana and Bihar states of India, both located in the Indo-Gangetic Plains (Figure 1). Data for this study were collected from Karnal district of Haryana and Vaishali district of Bihar. Karnal district has a semi-arid climate with average annual rainfall of around 760 mm, while Vaishali has a semi-humid dry climate with average rainfall of about 1,150 mm. The average land holding size of the surveyed household is four ha in Karnal and 0.51 ha in Vaishali district. Rice-wheat is the dominant cropping system in both areas. Rice is grown in *Kharif* (monsoon season, June to October) and wheat in *Rabi* (winter season, November to April). Irrigation facilities are well-developed in both study areas. For irrigation, electric pumps are used in Karnal district (Aryal *et al.*, 2015c), whereas diesel pumps are used in Vaishali (Islam and Gautam, 2009). The agricultural system is relatively more resource intensive and mechanized in Karnal compared to Vaishali. These study areas were purposively chosen based on climate-related issues including frequent droughts, floods, water logging and decreasing annual rainfall in Vaishali, and erratic rainfall, declining groundwater table, and considerable dry spells in Karnal.

3.2. Sampling procedure and data

Primary data were collected through a household survey of 1,267 farm households in 13 villages in Karnal and 12 villages in Vaishali (Figure 1). Of the associated 2,625 farm plots, 2,547 farm plot level observations were used in the model estimation due to inconsistencies and

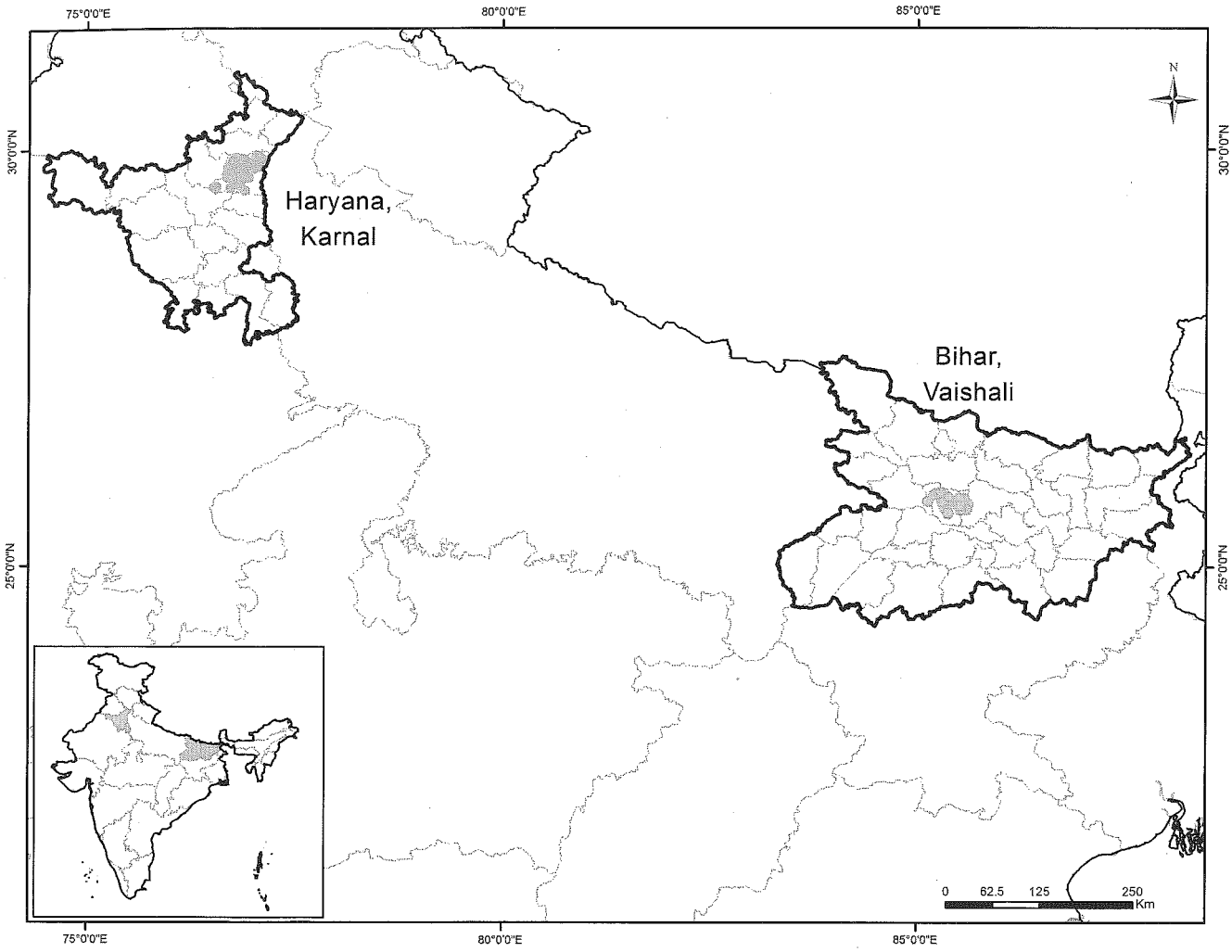

Figure 1. Map of the study area.

missing information in the remaining observations. The survey was conducted between April and November 2013. We applied a multi-stage sampling method to select the sample households. In the first stage, we randomly selected the villages within the districts under study. Then, in the second stage, a census of around 75% of households in the village was carried out to gather basic information, including the main occupation, crops grown, operational land holding, age and gender of the household head. In the third stage, the sample households were randomly selected from each village, based on the information gathered in the village census. We collected information that comprised household characteristics, farm plot characteristics, access to markets, extension services and credit, major climate risks and adaptation measures applied, and information on training received and adoption of CSA practices including laser land levelling (LLL), minimum tillage (MT), crop diversification (CD), and use of stress-tolerant varieties (STV). As rice-wheat is the main cropping system in the study areas, we focus on the rice-wheat system rather than one of the individual crops.

3.3. Explanation of variables and hypotheses

Table 1 presents the descriptive statistics and definition of dependent and explanatory variables used in the study.

3.3.1. Dependent variables

Of the several CSA practices promoted, we focus on five considering data availability, with each practice discussed below (for details on the CSA practices promoted by CCAFS, see Aggarwal *et al.*, 2013). For these CSA practices, we hypothesize that the decisions to adopt them are interdependent. This hypothesis is valid if the error terms of the multiple decision equations are significantly correlated.

Crop diversification (CD): crop diversification (CD) refers to more diverse crop rotations, including the integration of legumes and high-value crops into the cropping system. Studies show that it potentially reduces the incidence of weeds and pests, minimizes disease risk (Smith *et al.*, 2015) and improves soil fertility (Hossain *et al.*, 2016). It enhances resilience to multiple environmental stresses.

Table 1. Description of variables used in the study

Variables	Mean	S.D.	Variable Description
Dependent variables			
CD (D: Dummy)	0.19	0.38	1 if Crop Diversification is practiced and 0 if not
STV (D)	0.24	0.43	1 if seed of Stress Tolerant Variety used and 0 if not
MT (D)	0.18	0.34	1 if Minimum Tillage; 0 if conventional tillage
SSNM (D)	0.14	0.35	1 if Site Specific Nutrient Management and 0 if not
LLL (D)	0.13	0.34	1 if Laser Land Levelling is adopted, and 0 if not
Total number of CSA adopted	0.71	0.79	Intensity of adoption (# of adopted practices – CD, STV, MT, SSNM or LLL); integer value ranges from 0 to 4
Independent variables			
Household (HH) characteristics			
Male headed household (D)	0.93	0.25	1 if male and 0 if female
General Caste (D)	0.43	0.49	1 if general caste and 0 otherwise
Age of HH head (C: continuous)	51	13.29	Age of household head in years
Literate HH head (D)	0.64	0.48	1 if literate and 0 otherwise
Literate spouse of HH head (D)	0.32	0.47	1 if literate and 0 otherwise
Family size (C)	6.30	2.78	Number of family members (#)
Migrant (D)	0.27	0.44	1 if at least one member migrated and 0 otherwise
Farm land characteristics			
Tenure of plot (D)	0.79	0.41	1 if owned and 0 if rented in
Area of plot (C)	1.04	3.10	Area of plot (in ha)
Fertile soil (D)	0.58	0.49	1 if good and 0 otherwise
Deep soil (D)	0.12	0.33	1 if deep and 0 if shallow
Gentle slope (D)	0.57	0.49	1 if gentle slope and 0 if medium/steep slope
Distance to plot (C)	0.89	1.06	Distance from house to plot (in km)
Economic and social capital			
Land operated (C)	1.38	3.05	Total land operated (in ha)
Livestock owned (C)	1.49	3.15	Livestock owned (in Tropical Livestock Units, TLU)
Asset index (C)	0.094	0.57	Household asset index (0-1)
Credit Access (D)	0.39	0.49	1 if farmer has credit access and 0 otherwise
Association in group (D)	0.16	0.37	1 if membership in any association and 0 otherwise
Access to markets, agricultural extension service and training			
Distance to market (C)	3.02	2.05	Distance to local market from house (in km)
Distance to extension service (C)	4.79	3.54	Distance to agriculture extension service from house (in km)
Agricultural training (D)	0.44	0.34	Participated in at least one agricultural training
Source of information			
Farmer to farmer (D)	0.40	0.49	1 if information received from neighbor/relative farmer/ cooperative and 0 otherwise
Extension service (D)	0.43	0.20	1 if information received from government extension service/research center and 0 otherwise
ICT (D)	0.26	0.16	1 if information received from radio, newspaper, TV, mobile and 0 otherwise
Seed traders/private company (D)	0.21	0.41	1 if information received from seed traders/private company and 0 otherwise
Climate risks experienced by household over the last 5 years			
High temperatures (D)	0.69	0.45	1 if farmer experienced heat stress and 0 otherwise
Decreasing rainfall (D)	0.90	0.30	1 if farmer experienced less rainfall and 0 otherwise
Short winters (D)	0.35	0.48	1 if farmer experienced decreased winter and 0 otherwise
Total number of HH (plot)	1,258 (2,625)		

This is also important for diversified diets. Fewer yield variations and decreased risk of crop failure are major benefits of CD (Gaudin *et al.*, 2015). A recent study in India shows that CD, especially into high-value crops, can improve farmer livelihoods (Birthal *et al.*, 2015b). Similarly, legume integration in the cropping system increases income and serves as a risk-mitigating strategy (Chhatre *et al.*, 2016). Of the total plots under study, farmers practice CD in 19% of them.

Seeds of stress-tolerant variety (STV): stress-tolerant varieties (STVs) are improved crops with particular tolerance to abiotic stresses, e.g. rice varieties being submergence-tolerant while other varieties are tolerant to heat, temperature and/or drought stress. Stress-tolerant varieties (STVs) are found to have increased farmers' adaptation to climate risks such as drought, flood, heat and temperature stress (Jagadish *et al.*, 2012). Stress-tolerant varieties (STVs) were used in almost 24% of the farm plots under study.

Minimum tillage (MT): minimum tillage (MT) implies minimum soil disturbance and retaining crop residue or stubble on the farm-plot. This contributes to improvements in soil structure, carbon sequestration, soil fertility and soil water holding capacity (Aryal *et al.*, 2015c; Lal, 1997). It can also increase farmers' resilience to climate change and variability through reducing risks due to erratic rainfall. This study includes both reduced tillage and zero tillage with residue retention under MT. About 18% of the total sample plots were under MT.

Site-specific nutrient management (SSNM): this study considers the use of the leaf color chart (LCC) and use of any other software like NutrientExpert as site-specific nutrient management (SSNM). The LCC is usually used in rice, wheat and maize. It is surrogate to leaf N status and guides the application of N to maintain the required N content in the crop. The SSNM contributes to managing nutrients required by crops, thereby increasing resource use efficiency and reducing GHG emissions from agriculture. For example, in-season N management based on LCC reduce N_2O emissions and global warming potential by almost 14% from rice-wheat systems of India (Bhatia *et al.*, 2012, 2013). Site-specific nutrient management (SSNM) was applied in about 14% of the total sample farm-plots.

Laser land leveling (LLL): laser land leveling (LLL) is an improved land leveling technology, which primarily reduces irrigation water losses that occur in undulated fields. It is a climate-smart technology, which reduces irrigation water loss, enhances water use efficiency, reduces energy use for irrigation, enhances fertilizer use efficiency and increases crop yields (Aryal *et al.*, 2015b; Jat *et al.*, 2015). The quality of land leveling impacts most of the irrigated farming operations along with input use efficiency and crop yield. This saves irrigation water, nutrients and agro-chemicals and facilitates the establishment of crop stands through effective control of desirable seeding depths. Almost 13% of the total sample plots were laser levelled.

3.3.2. Explanatory variables

Inclusion of variables in the analysis and model specification are primarily based on theoretical frameworks and past empirical adoption literature (Aryal and Holden, 2011; Erenstein and Farooq, 2009; Feder and Umali, 1993; Kassam *et al.*, 2009; Kassie *et al.*, 2010, 2013; Pender and Kerr, 1998). Some literature (for example, Senyolo *et al.*, 2018) also considers technology characteristics as an important factor determining adoption, but such here was constrained by data limitations. A description of explanatory variables and a hypothesis about their effects on the dependent variable(s) is given below.

3.3.3. Household characteristics

Household characteristics include the major characteristics of the household head (such as literacy status, age, and gender), household size, literacy status of spouse, and migration. Household characteristics often influence technology adoption decisions when there is market imperfection and institutional failure (de Janvry *et al.*, 1991; Holden *et al.*, 2001). Literate household heads, i.e., with at least a primary education, are more likely to have non-farm income and a greater capacity to access and process new information. This increases an individual's ability to acquire, absorb and adopt new technology (Chander and Thangavelu, 2004). In most cases, farm technology adoption can be a part of an overall household strategy to improve livelihood and thus, the literacy status of the household head's spouse may also affect it. The direction of impact of the household head's age is indeterminate as older people, on one hand, have more experience with farming systems, with a greater accumulation of physical and social capital, while on the other hand, they are associated with short-planning horizons, loss of energy and being more risk-averse. Although migration reduces a household's labor endowment, it increases access to alternative income sources. Therefore, it is hypothesized that migration facilitates CSA adoption, especially those that save labor, such as MT and LLL, and may limit labor-intensive practices like CD.

3.3.4. Farm land characteristics

Farm plot characteristics such as plot size, tenure status, irrigation facility, soil fertility, soil depth, plot slope, and distance to plot from homestead may influence farmers' decisions to adopt technology and thus, we need to control for these factors. For example, distant plots not only cost more to transport inputs but are also difficult to monitor. Therefore, farmers may be less interested in adopting new technology in distant plots. In Bihar, land fragmentation is very high, and farmers operate multiple small plots. The small plot size can be a constraining factor for mechanization and hence, the farmers are less likely to adopt LLL and MT in such plots, while they are more likely to adopt CD and STV.

3.3.5. Economic and social capital

This study considers land owned, livestock ownership, and household labor endowment as economic capital, while membership in village institutions such as farm cooperatives or any other farm clubs/input dealers/sellers and other organizations, and caste position of the household, are taken as social capital. In order to capture the effect of wealth on CSA adoption, we constructed a household asset index using the principal component analysis.[1] We included most household assets, such as tractors, cars, televisions, water pumps, motorbikes, etc., for constructing a household asset index. Caste is one of the social capital-

[1] https://www.stata.com/manuals13/mvpca.pdf

indicating variables since it often affects access to public spheres in rural communities in South Asia (Aryal and Holden, 2012, 2013). It restricts or facilitates a household's participation in some markets, as well as access to information. In India, farmers belonging to the bottom of the social hierarchy (based on caste) have access to fewer information sources, and primarily rely on informal social networks (Birthal *et al.*, 2015a). In eastern Indian states, Yamano *et al.* (2015) found that farmers who belong to a scheduled caste group have low scores on self-perception regarding the adoption of new agricultural technologies. Therefore, we hypothesize that farmers belonging to a general caste group are more likely to adopt CSA compared to 'backward' and scheduled caste groups.

3.3.6. Markets, institutional services and training

Access to markets and other institutional services are important variables since they influence adoption through transaction costs. Distance to the village market is used as a proxy for market access, while the distance to the nearest agricultural extension service center is considered a proxy for access to institutional services. Access to institutional extension services typically plays a crucial role in enhancing adoption and innovation (Chowdhury *et al.*, 2014). Training on related topics such as soil-water management, MT, and CD also influence the farmers' likelihood to adopt those technologies. We controlled for this in the analysis.

3.3.7. Source of information

Adoption depends on access to information and training received. In India, farmers using information are found to have achieved about 12% higher net returns per hectare (Birthal *et al.*, 2015a). A recent study by Sapkota *et al.* (2018) found that farmers using modern information and communication technology to receive farm-related information have higher yields of rice, wheat and maize crops. Although farmers get information from multiple sources, including farmer to farmer communication, public extension service/research centers, information and communication technology (ICT), and private traders, they typically use one of these sources of information more frequently. Therefore, we had dummies for each separate source of information.

3.3.8. Climate risks

Agriculture is subject to several climate risks, and farmers adopt different production practices to adapt to those risks. Farmers in the study area mentioned high temperatures (heat stress and drought), less rainfall and shortened winters as three main climate risks they experienced during the last five years. We included this in our analysis because understanding the impacts of these shocks on CSA adoption is important for designing climate policies related to agriculture. We hypothesize that farmers experiencing high temperatures or less rainfall or shortened winters as major climate risks are more likely to adopt STV, MT (especially zero tillage in the case of wheat), and diversify crops.

4. Results and discussion

4.1. Determinants of multiple CSA adoption

In the study area, farmers have adopted a number of CSA practices simultaneously, indicating that there is a possibility of a correlation between their CSA choices. This is tested using pair-wise correlation coefficients across the residuals of the multivariate probit model. Of the 10 pairs of CSA practices, seven pair-wise correlation coefficients across the residuals of the multivariate probit model are statistically significant (Table 2). The results support the hypothesis that error terms of the multiple decision equations are correlated. The likelihood ratio test (chi2 (10) = 116.54; Prob > chi2 = 0.000) rejects the null hypothesis of zero covariance of the error terms across equations. Crop diversification (CD) and MT are found to be significantly and negatively associated (Table 2), implying that farmers consider these practices as either incompatible or substitutes. In our study area, this likely reflects that most of the farmers who adopted MT follow the rice-wheat system rather than the diversified one. Other CSA combinations such as MT and STV, MT and SSNM, and STV and SSNM are significantly and positively associated, implying that farmers primarily consider these as complements.

Table 3 presents the results of the multivariate probit model estimated using maximum likelihood method. Our estimates show that the model fits the data well as the Wald

Table 2. Pairwise correlation coefficients across CSA practices

Climate-smart agriculture practices	Coefficient	Standard error	P-value
Crop diversification (CD) × stress-tolerant variety (STV)	−0.092	0.061	0.131
CD × laser land leveling (LLL)	−0.073***	0.029	0.002
CD × minimum tillage (MT)	−0.199***	0.051	0.000
CD × site-specific nutrient management (SSNM)	−0.203***	0.048	0.000
STV × LLL	0.269***	0.078	0.001
STV × MT	0.214***	0.055	0.000
STV × SSNM	0.013	0.055	0.820
LLL × MT	0.192***	0.064	0.000
LLL × SSNM	−0.061	0.067	0.347
MT × SSNM	0.326***	0.044	0.000

Notes: Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho32 = rho42 = rho52 = rho43 = rho53 = rho54 = 0: $chi^2(10) = 116.54$ Prob > $chi^2 = 0.0000$.

***Refer to significant at 99% confidence level.

Table 3. Estimates of the multivariate probit model

Variables	CD	STV	LLL	MT	SSNM
Household (HH) characteristics					
Male headed HH (D: dummy)	−0.389***	−0.462***	0.219***	0.013	−0.209
	(0.133)	(0.199)	(0.086)	(0.157)	(0.146)
General caste (D)	−0.045	0.531***	0.299**	0.291***	0.341***
	(0.073)	(0.099)	(0.128)	(0.075)	(0.076)
Age of HH head (year)	0.232*	0.134	0.009	−0.261**	−0.006**
	(0.141)	(0.179)	(0.220)	(0.132)	(0.003)
Literate HH head (D)	0.390**	0.359**	0.169***	0.183**	−0.148
	(0.082)	(0.122)	(0.032)	(0.087)	(0.092)
Literate spouse (D)	−0.293***	0.006	0.162	0.223**	0.088
	(0.095)	(0.111)	(0.123)	(0.082)	(0.087)
Family size (#)	0.009	−0.048**	−0.010	−0.020	−0.049
	(0.082)	(0.021)	(0.152)	(0.080)	(0.081)
Migrant (D)	0.258***	−0.654***	−0.582***	0.197***	−0.013
	(0.071)	(0.131)	(0.168)	(0.075)	(0.080)
Farm land characteristics					
Tenure of plot (D)	0.180**	0.235**	0.069***	−0.055	0.073
	(0.082)	(0.102)	(0.023)	(0.088)	(0.090)
Area of plot (ha)	−0.267***	0.479***	0.476***	0.523***	−0.053
	(0.081)	(0.179)	(0.069)	(0.085)	(0.080)
Fertile soil (D)	0.310*	0.044	0.167	−0.392***	−0.129
	(0.083)	(0.113)	(0.200)	(0.082)	(0.081)
Deep soil (D)	0.214***	−0.571***	−0.549**	−0.637***	−0.545***
	(0.094)	(0.198)	(0.259)	(0.144)	(0.125)
Gentle slope (D)	−0.152*	0.124	0.402**	0.019	0.483***
	(0.081)	(0.111)	(0.174)	(0.082)	(0.081)
Distance to plot (km)	−0.059	0.087**	0.069	0.053*	−0.019
	(0.039)	(0.036)	(0.047)	(0.028)	(0.037)
Economic and social capital					
Land operated (ha)	−0.310***	1.142***	0.389***	0.188***	0.414***
	(0.081)	(0.181)	(0.106)	(0.056)	(0.079)
Livestock owned (TLU)	0.154***	0.197**	0.135***	0.012	−0.059**
	(0.031)	(0.039)	(0.046)	(0.029)	(0.028)
Asset index	0.028	0.632***	0.603***	0.390***	−0.123
	(0.076)	(0.116)	(0.114)	(0.081)	(0.093)
Credit access (D)	−0.182***	−0.371***	0.101	0.248***	0.426***
	(0.069)	(0.115)	(0.118)	(0.076)	(0.083)
Association in group (D)	0.409***	0.441***	0.124	−0.280**	−0.011
	(0.091)	(0.145)	(0.146)	(0.115)	(0.116)
Access to market, extension services and training					
Distance to market (km)	−0.057**	−0.120***	−0.059**	−0.094***	−0.052**
	(0.019)	(0.024)	(0.023)	(0.021)	(0.021)
Distance to extension service (km)	−0.050***	−0.028**	0.003	−0.048***	−0.007
	(0.011)	(0.015)	(0.021)	(0.011)	(0.011)
Agricultural training (D)	0.617***	0.563**	0.486***	1.073***	0.132
	(0.173)	(0.203)	(0.173)	(0.172)	(0.240)
Source of information					
Farmer to farmer (D)	0.415***	0.617***	0.031	0.263***	0.581***
	(0.071)	(0.138)	(0.159)	(0.088)	(0.084)
Extension service (D)	0.840**	0.260***	−0.124	0.483**	−0.007
	(0.337)	(0.019)	(0.288)	(0.221)	(0.231)
ICT (D)	0.533***	0.416***	−0.050	0.293	0.291**
	(0.121)	(0.149)	(0.604)	(0.258)	(0.139)
Seed traders/Private company (D)	−0.278***	0.255*	0.501**	0.378***	0.476***
	(0.094)	(0.144)	(0.253)	(0.082)	(0.085)
Climate risks faced					
High temperatures (D)	0.444***	0.362***	0.174	0.439***	0.043
	(0.078)	(0.112)	(0.111)	(0.081)	(0.082)
Decreasing rainfall (D)	0.092	0.337**	0.146***	0.142	0.018
	(0.127)	(0.149)	(0.056)	(0.113)	(0.118)
Short winters (D)	−0.099	0.422***	0.165	0.859***	0.564***
	(0.089)	(0.105)	(0.109)	(0.088)	(0.093)

Table 3. Continued

Variables	CD	STV	LLL	MT	SSNM
Other					
District dummy (Karnal)	−0.193***	0.289	0.375***	0.173***	0.322**
	(0.083)	(0.197)	(0.031)	(0.013)	(0.150)
Constant	−1.077***	−0.850***	−1.150*	−0.652***	−0.420
	(0.234)	(0.327)	(0.471)	(0.189)	(0.246)
Number of observations	2,547	2,547	2,547	2,547	2,547

Notes: Log likelihood = −3696.39; Wald $chi^2(145) = 1960.43$; Prob > $chi^2 = 0.0000$. CD: crop diversification, STV: stress-tolerant variety, LLL: laser land levelling, MT: minimum tillage, SSNM: site-specific nutrient management.
*, **, and *** refer to significant at 90%, 95% and 99% confidence level; standard errors are reported in parentheses.

test (Wald chi2(170) = 2195.17; Prob > chi2 = 0.000)) rejects the null hypothesis that all regression coefficients in each equation are jointly equal to zero. This shows the relevance of the model to account for the unobserved correlations across decisions to adopt multiple CSA practices.

Results show that effects of the explanatory variables on the probability to adopt differ substantially by the CSA type. Table 4 provides an overview of the key drivers of multiple CSA adoption to ease interpretation — highlighting only the variables that are significant for three or more CSA options and the positive or negative association.

Table 4. Summary of the key drivers of multiple CSA adoption

Variables	CD	STV	LLL	MT	SSNM
Male headed HH (D: dummy)	−	−	+		
General caste (D)		+	+	+	+
Age of HH head (year)	+			−	−
Literate HH head (D)	+	+	+	+	
Migrant (D)	+	−	−	+	
Tenure of plot (D)	+	+	+		
Area of plot (ha)	−	+	+	+	
Deep soil (D)	+	−	−	−	−
Gentle slope (D)	−		+		+
Land operated (ha)	−	+	+	+	+
Livestock owned (TLU)	+	+	+		−
Asset index		+	+	+	
Credit Access (D)	−	−		+	+
Association in group (D)	+	+		−	
Distance to market (km)	−	−	−	−	−
Distance to extension service (km)	−	−		−	
Agricultural training (D)	+	+	+	+	
Farmer to farmer (D)	+	+		+	+
Extension service (D)	+	+		+	
ICT (D)	+	+		+	
Seed traders/private company (D)	−	+	+	+	+
High temperatures (D)	+	+		+	
Decreasing rainfall (D)		+	+		
Short winters (D)		+		+	+
District dummy (Karnal)	−		+	+	+

Notes: CD: crop diversification, STV: stress-tolerant variety, LLL: laser land levelling, MT: minimum tillage, SSNM: site-specific nutrient management.

Male-headed households are more likely to go for LLL but less likely to adopt CD and STV — similar to the findings of other LLL studies in India (Gill, 2014; Jat *et al.*, 2015). Households belonging to the general caste and with a literate head are more likely to adopt the CSA options. These results corroborate the findings by Aryal and Holden (2011) and Yamano *et al.* (2015) that caste position affects farmers' investment decisions. Older household heads are more likely to adopt CD while they are less likely to adopt MT and SSNM. This may be associated with intensive tillage and crop rotation being traditional practices and thus a difficulty in changing their mindsets. In addition, older household heads are less familiar with relatively newer technologies. Migration is positively associated with the likelihood of adopting CD and MT, but less likely to adopt STV and LLL.

Some of the farmland characteristics affected the CSA adoption decisions. Land tenure affects adoption — with land owners more likely to adopt (CD, STV and LLL), consistent with earlier studies on technology adoption (for example, Feder and Umali, 1993; Kassie *et al.*, 2010, 2013). We controlled for land fragmentation using the area of an individual plot, and the larger the plot, the higher the probability of adopting STV, LLL and MT, while reducing the probability of CD. It supports our hypothesis that larger plots are more likely to receive mechanized operations like MT and LLL because such operations are easier on larger plots. Farmers with deep (and fertile) plots are more likely to adopt CD — but surprisingly, less likely to adopt the other options.

Larger farm sizes are more likely to adopt most CSA practices under study except CD, probably as most of these farmers in the study area follow the rice-wheat cropping system. Households with more livestock have a higher probability of adopting CD, STV and LLL, but a lower probability for SSNM. The probability of CSA adoption increases with a higher asset index (STV, LLL and MT, thereby again including the mechanized options). Access to credit has variable effects on technology adoption — increasing the probability of adopting MT and SSNM, while decreasing the probability of CD and STV. Farmers with access to credit may be more likely to adopt resource-saving agricultural practices, but they are less likely to go

Table 5. Estimates of the ordered probit model and marginal effects of key variable

	Marginal effects of each outcome				
CSA intensity	**Pr(Y=0|X)**	**Pr(Y=1|X)**	**Pr(Y=2|X)**	**Pr(Y=3|X)**	**Pr(Y=4|X)**
General caste (D: dummy)	−0.062***	0.040***	0.021***	0.015***	0.002**
	(0.021)	(0.014)	(0.007)	(0.005)	(0.001)
Literate HH head (D)	−0.085***	0.057***	0.027***	0.010***	0.005***
	(0.024)	(0.017)	(0.007)	(0.003)	(0.002)
Tenure of plot (D)	−0.057***	0.036***	0.023**	0.004***	0.002***
	(0.024)	(0.015)	(0.009)	(0.001)	(0.000)
Area of plot (ha)	−0.108***	0.070***	0.036***	0.003***	0.000
	(0.023)	(0.015)	(0.008)	(0.001)	(0.000)
Land operated (ha)	−0.077***	0.051***	0.026***	0.009***	0.002**
	(0.023)	(0.015)	(0.008)	(0.003)	(0.001)
Association in group (D)	−0.161***	0.088***	0.069***	0.004***	0.001***
	(0.025)	(0.012)	(0.013)	(0.001)	(0.000)
Distance to market (km)	0.020***	−0.013***	0.007***	0.001***	0.000
	(0.018)	(0.004)	(0.006)	(0.000)	(0.000)
Distance to extension service (km)	0.019***	−0.013***	−0.006***	−0.003***	−0.002**
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Farmer to farmer (D)	−0.099***	0.066***	0.032***	0.008***	0.001***
	(0.022)	(0.018)	(0.007)	(0.003)	(0.000)
Extension service (D)	−0.239***	0.186***	0.051***	0.012***	0.003***
	(0.058)	(0.051)	(0.008)	(0.004)	(0.001)
High temperatures (D)	−0.201***	0.142***	0.057***	0.003***	0.002
	(0.022)	(0.017)	(0.006)	(0.001)	(0.003)
Short winters (D)	−0.051**	0.036**	0.016**	0.001**	0.000
	(0.020)	(0.015)	(0.007)	(0.000)	(0.000)

Notes: Table 5 with all the variables is given in Appendix B. *, **, and *** refer to significant at 90%, 95% and 99% confidence level respectively; standard errors are reported in parentheses.

for more labor-intensive measures like CD. Farmers who are members of village cooperatives and groups are more likely to adopt CD and STV, while it reduced the probability of MT.

Households further away from markets and extension services are less likely to adopt CSA. This is plausible because it increases transaction costs, and in case of LLL and MT, farmers mostly used these machines on a custom hire basis, which are usually available in market centers.

Training and access to information significantly enhance the adoption of CSA. Farmers obtain information about the technologies and farming practices from different sources — with an overall positive association between each of the four information sources and different options adopted. Interestingly, the only negative association between source and option was for private sources reducing the probability of CD, probably since they largely focus on the main commercialized crops to expand their business. Many farmers in the study area reported that they receive mobile messages about the application of fertilizer and other inputs as well as weather information. Such information has contributed to the rational use of inputs; for example, applying irrigation and fertilizer on plots in accordance with rainfall information.

The climate risks experienced by households play important roles in a household's decision to adopt CSA. Farmers who experienced high temperatures over the last five years (i.e., from 2008 to 2012, inclusive) are more likely to adopt CD, MT, and STV. It is rational to adopt improved varieties that are stress-tolerant while they experience climate risks such as heat stress due to high temperatures. Similarly, CD can help adapt them to crop pest and disease that may increase due to high temperature (Lin, 2011). Minimum tillage (MT) can help them to escape the terminal heat in the case of wheat crop by facilitating early establishment (Sapkota *et al.*, 2015). Farmers who faced decreasing rainfall as a major climate risk are more likely to adopt STV and LLL. This is practical since farmers in Vaishali (Bihar) have adopted drought-tolerant varieties to cope with climate risks and LLL saves irrigation water. Farmers facing short winters are more likely to adopt STV, MT and SSNM. This could reflect the use of zero tillage wheat to escape terminal heat in the case of shorter winters (Sapkota *et al.*, 2015). Farmers in Karnal are more likely to adopt LLL, MT and SSNM, while they are less likely to adopt CD. Crop diversification (CD) was substantially reduced in Haryana after the Green Revolution, becoming one of India's major cereal producers (rice and wheat).

4.2. Factors explaining the intensity of CSA adoption

Farmers have adopted multiple CSAs in the study area, although the intensity of adoption varies. To assess the

factors explaining the CSA adoption intensity, we estimated an ordered probit model. Of the five CSA practices, the maximum number of practices applied by the same sample farm household is four. Farmers adopt specific CSA practices according to their requirements — for example, only those farmers who faced (prospects of) frequent drought would be expected to adopt STV. Therefore, we present the marginal effects when the outcome variable (number of CSA technolgies adopted) takes values 0 (i.e. no adoption), 1, 2, 3, or 4, respectively, in Table 5, with key variables, and the full model is presented in Appendix B. Since direct interpretation of the results of the ordered probit model is not easy, Table 5 presents the marginal effects for each outcome, along with the model results. The chi-square statistic for the ordered probit model is statistically highly significant (LR chi2 (34) = 1519.24; Prob > chi2 = 0.000) and rejects the null hypothesis (all slope coefficients equal to zero).

It is interesting to note that the effects of explanatory variables vary a lot over the different levels of intensity. Results show that several factors influence the number of CSA practices used. General caste and literacy are major household characteristics favoring the number of CSA practices adopted. Compared to illiterate household heads, the probability of adopting at least one, two, three or four CSA practices will be higher by 5.7, 2.7, 1 and 0.5 percentage points among the literate household heads, respectively.

Compared to rented plots, the number of CSA practices used is significantly higher in owner-cultivated plots: the probability of adopting one, two, three or four practices is higher by 3.6, 2.3, 0.4 and 0.2 percentage points in owner-cultivated plots compared to rented plots. Larger-size plots also have a positive association with the intensity of adoption, indicating that land fragmentation can be a constraining factor to CSA adoption.

Land operated has a positive effect on the number of CSA practices adopted, as does the association in groups. Access to agricultural extension service enhances the number of CSA practices used; increasing distance to extension services has a consistent negative effect, as does having received information from extension services. Farmer-to-farmer communication also enhanced the number of CSA practices used. Farmers reporting high temperatures and short winters also enhanced the number of CSA practices.

Overall, the magnitude of the impact of an individual explanatory variable declined as the level of intensity (i.e., the value of outcome variable) increased — reflecting that the number of farmers adopting numerous practices reduces with the increasing number of options in the sample.

5. Discussion: implications and policy recommendations

Farmers adopted a number of CSA practices simultaneously in our study, indicating that there are associations among the multiple CSA practices. These results corroborate with the results of other similar studies (for instance, Kassie *et al.*, 2009, 2013; Teklewold *et al.*, 2013). Farmers thereby make multiple related technology adoption decisions. Therefore, it underscores the need to acknowledge potential interdependence in multiple technology adoption decisions while identifying the factors influencing technology adoptions.

In the context that the government of India has initiated a national action plan for climate change (NAPCC), the findings of our study have several important policy recommendations:

(i). Address farmers' increasing vulnerability to future climate change through policy reformation.

Sustainable agriculture, water resource conservation, and addressing climate change are three major national missions under the NAPCC. Each state in India now has its own state-level action plan for climate change (SAPCC). Though the efforts are taken at different levels, the decision to apply the farm technology/practices addressing climate change are made at the farm household level. Therefore, the policymakers at different levels need to understand that several factors, including institutional support, farmer capacity, resource endowment, and knowledge and training, influence the adoption of CSA. Most of these factors need to be provided at the local level and therefore, achieving climate change adaptation and food security requires a local level planning that can address such issues appropriately (Aryal *et al.*, 2015a). In this context, there is a need to have spatial and stakeholder-driven decision-support approaches for better targeting of CSA (Brandt *et al.*, 2017). Enhancing the uptake of CSA at the local level also calls for the engagement of multiple stakeholders at the local level including farmers, agricultural research institutions, agricultural machinery manufacturers, service providers and relevant government departments. In most cases, institutional support is fundamental to the large-scale uptake of CSA (NAAS, 2017).

Given that larger farm plots are more likely to receive CSA practices, there is a need to address the agricultural land rental market and ensure equitable agricultural land rental contracts. The size of farm plots mostly affects the adoption of those CSA practices that require machine operation, such as LLL and zero tillage drill. The agricultural land rental contract has been distorted in several states of India due to past land-to-the-tiller policies, which create a fear of losing land among landlords when rented out (Aryal and Holden, 2013). The design of the contract can vary by state because of the level of market development and agricultural productivity. Overall, the contracts should ease property right concerns over the land for the landlord and at the same time, provide usufruct benefits to the tenants from their investment during the rental period (Aryal and Holden, 2013).

(ii). Enhance access to credit and information sources to enhance SSNM that reduces GHG emissions from agriculture.

Promotion of CSA, primarily SSNM, is essential to reduce GHG emissions from agriculture. India is the second largest producer and consumer of synthetic N fertilizers in the world (Tirado et al., 2010), and almost 6% of India's total anthropogenic emissions come from synthetic N fertilizers. This will increase further as the demand for N is more likely to increase by 25% in India (FAO, 2011). Therefore, any practices such as SSNM that increase N use efficiency can substantially reduce emissions from agriculture. The results from our analysis show that improving access to credit and sources of information such as information and communication technologies (ICT), private traders and farmer-to-farmer communication are positively associated with the decision to adopt SSNM. As suggested by Sapkota *et al.* (2018), the policymakers need to set up alternative pathways for agricultural development so that it can achieve high-yield, low-emission targets in agricultural production. Setting up such an alternative pathway needs to consider several factors, which include not only the type of agricultural technology/practices but also the socio-economic and human behavioral dimensions.

(iii). Agricultural research community and civil society to increase farmer awareness of CSA.

Coupled with the task of tackling widespread poverty and food insecurity under climate change, the task of increasing farmer awareness of the CSA practices is challenging in India. Therefore, the government needs to work together with the private sector, including farmers, private traders, agricultural machine custom hiring service providers, etc., and agricultural research institutions, to disseminate CSA practices that help farmers' uptake of these practices. Our findings add to the understanding of social drivers contributing to the adoption of multiple CSA practices. Since farmer-to-farmer communication and local private traders (i.e., local agricultural input traders, local custom hiring service providers) are key social drivers to enhance the adoption and intensity of adoption of all the CSA practices under study, engaging them properly to disseminate knowledge on CSA can be an appropriate approach to follow.

6. Conclusion

The study assessed the factors that determine the likelihood of farmers to adopt CSA practices and the adoption intensity of these practices in the Indo-Gangetic Plains of India. Our results show that farmers adopt these practices primarily as complements. Nevertheless, there is scope for promoting greater complementarities among these CSA practices. Farmers' characteristics, including gender, caste and education, social and economic capital, farmland characteristics, access to markets, extension services and training, and major climate risks experienced by the local farmers, are found to be the key factors affecting the decision to adopt CSA technologies.

Access to markets, credit and extension services and other information sources are found to play a crucial role in increasing CSA uptake. Therefore, it is important to focus on policies and plans that improve market access and enhance agricultural credit facilities and the quality of extension services. Dissemination of CSA knowledge and its role in climate risk mitigation is critical to promote it. More CSA training for farmers, government extension staff working at the local level, and use of communication tools to share and promote knowledge on CSA use to combat the global challenge of climate change are essential. Understanding barriers and enabling conditions to CSA adoption helps in designing and formulating extension messages and agricultural policies that can accelerate CSA dissemination and help safeguard agricultural production and food security in India. Another important issue of high concern is the increasing land fragmentation and its implications on CSA adoption. This has important policy implications related to the regulation of the agricultural land rental market and land tenure security — as well as the associated challenges of population growth, poverty alleviation and rural transformation. In the end, CSA can make a crucial contribution to helping address the potential impacts of climate change on India's agriculture, but wider policy and structural reforms are needed to enable accelerated CSA adoption in particular, and sustainable intensification in general.

Acknowledgements

The authors acknowledge the support of the CGIAR Research Programs (CRPs) on Climate Change, Agriculture and Food Security (CCAFS) and Wheat Agri-Food Systems (CRP WHEAT) for this study. The CRP WHEAT receives W1 and W2 support from the governments of Australia, Belgium, Canada, China, France, India, Japan, Korea, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom, United States, and the World Bank. Thanks also to all field staffs for their sincere efforts while collecting data in Bihar and Haryana states. We sincerely acknowledge the support from the farmers of Haryana and Bihar. The views expressed here are those of the authors and do not necessarily reflect the views of the funders or associated institutions. The usual disclaimer applies and the authors are responsible for any remaining errors and inferences.

References

Abdulai, A., Huffman, W., 2014. The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics*, February 1, 90(1): 26–43.

Aggarwal, P.K., Bhatta, G.D., Joshi, P.K., Prathapar, S.A., Jat, M.L., Kadian, M., 2013. *Climate Smart Villages in South Asia*. Climate Smart Agriculture Learning Platform, South Asia. Climate Change, Agriculture and Food Security (CCAFS), South Asia, New Delhi, India.

Aggarwal, P.K., Kumar, S.N., Pathak, H., 2010. Impacts of climate change on growth and yield of rice and wheat in the Upper Ganga Basin, Worldwide Fund for Nature (WWF) and Indian Agricultural Research Institute (IARI). Available at http://assets. wwfindia. org/-downloads/impacts_of_climate_change_on_growth_and_yield_of_rice_and_wheat_in_the_upper_ ganga_basin. pdf. New Delhi, India.

Aggarwal, P.K., Rani, D.N.S., 2009. Assessment of climate change impacts on wheat production in India. In: Aggarwal, P.K. (Ed.), *Global Climate Change and Indian Agriculture: Case Studies from the ICAR Network Project*. Indian Agricultural Research Institute, New Delhi. pp. 5–10.

Aryal, J.P., Holden, S.T., 2011. Caste, investment and intensity of production, 18th Annual Conference, European Association of Environmental and Resource Economists (EAERE), 29 June to 2 July 2011, Rome.

Aryal, J.P., Holden, S.T., 2012. Livestock and land share contracts in a Hindu society. *Agricultural Economics*, 43(5): 593–606.

Aryal, J.P., Holden, S.T., 2013. Land reforms, caste discrimination and land market performance in Nepal. In: Holden, S.T., Otsuka, K., Deininger, K. (Eds.), *Land Tenure Reform in Asia and Africa: Assessing Impacts on Poverty and Natural Resource Management*. Palgrave Macmillan UK, London. pp. 29–53.

Aryal, J.P., Jat, M.L., Singh, R., Gehlawat, S.K., Agarwal, T., 2015a. *Framework, Guidelines and Governance for Designing Local Adaptation Plan of Action to Mainstream Climate-Smart Villages in India*. Internantional Maize and Wheat Improvement Center (CIMMYT), New Delhi.

Aryal, J.P., Mehrotra, M.B., Jat, M.L., Sidhu, H.S., 2015b. Impacts of laser land leveling in rice–wheat systems of the north–western indo-gangetic plains of India. *Food Security*, 7(3): 725–738.

Aryal, J.P., Sapkota, T.B., Jat, M.L., Bishnoi, D.K., 2015c. On-farm economic and environmental impact of zero-tillage wheat: A case of North-West India. *Experimental Agriculture*, 51(1): 1–16.

Aryal, J.P., Sapkota, T.B., Stirling, C.M., Jat, M., Jat, H.S., Rai, M., Mittal, S., Sutaliya, J.M., 2016. Conservation agriculture-based wheat production better copes with extreme climate events than conventional tillage-based systems: A case of untimely excess rainfall in Haryana, India. *Agriculture, Ecosystems and Environment*, 233: 325–335.

Behera, B., Rahut, D.B., Aryal, J., Ali, A., 2015. Household collection and use of biomass energy sources in South Asia. *Energy*, 85: 468–480.

Belsley, D.A., 1991. A guide to using the collinearity diagnostics. *Computer Science in Economics and Management*, 4(1): 33–50.

Belsley, D.A., Kuh, E., Welsch, R.E., 2005. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. John Wiley & Sons, Hoboken, NJ.

Bhatia, A., Aggarwal, P.K., Jain, N., Pathak, H., 2012. Greenhouse gas emission from rice- and wheat-growing areas in India: Spatial analysis and upscaling. *Greenhouse Gases: Science and Technology*, 2(2): 115–125.

Bhatia, A., Jain, N., Pathak, H., 2013. Methane and nitrous oxide emissions from Indian rice paddies, agricultural soils and crop residue burning. *Greenhouse Gases: Science and Technology*, 3(3): 196–211.

Birthal, P.S., Kumar, S., Negi, D.S., Roy, D., 2015a. The impacts of information on returns from farming: Evidence from a nationally representative farm survey in India. *Agricultural Economics*, 46(4): 549–561.

Birthal, P.S., Roy, D., Negi, D.S., 2015b. Assessing the impact of crop diversification on farm poverty in India. *World Development*, 72 (August 2015): 70–92.

Brandt, P., Kvaki, M., Butterbach-Bahl, K., Rufino, M.C., 2017. How to target climate-smart agriculture? Concept and application of the consensus-driven decision support framework "targetCSA". *Agricultural Systems*, 151 (February 2017): 234–245.

Byerlee, D., Hesse de Polanco, E., 1986. Farmers' stepwise adoption of technological packages: Evidence from the Mexican Altiplano. *American Journal of Agricultural Economics*, 68(3): 519–527.

Chander, P., Thangavelu, S.M., 2004. Technology adoption, education and immigration policy. *Journal of Development Economics*, 75(1): 79–94.

Chhatre, A., Devalkar, S., Seshadri, S., 2016. Crop diversification and risk management in Indian agriculture. *Decision*, 43(2): 167–179.

Chowdhury, A.H., Hambly Odame, H., Leeuwis, C., 2014. Transforming the roles of a public extension agency to strengthen innovation: lessons from the national agricultural extension project in Bangladesh. *The Journal of Agricultural Education and Extension*, 20(1): 7–25.

Erenstein, O., Farooq, U., 2009. A survey of factors associated with the adoption of zero tillage wheat in the irrigation plains of South Asia. *Experimental Agriculture*, 45(2): 133–147.

Erenstein, O., Sayre, K., Wall, P., Hellin, J., Dixon, J., 2012. Conservation agriculture in maize- and wheat-based systems in the (sub)tropics: Lessons from adaptation initiatives in South Asia, Mexico, and Southern Africa. *Journal of Sustainable Agriculture*, 36(2): 180–206.

Erenstein, O., Thorpe, W., 2011. Livelihoods and agro-ecological gradients: A meso-level analysis in the Indo-Gangetic Plains, India. *Agricultural Systems*, 104(1): 42–53.

FAO, 2010. *Climate-Smart Agriculture: Policies, Practices and Financing for Food Security, Adaptation and Mitigation*. Food and Agriculture Organization of the United Nations, Rome.

FAO, 2011. *Current World Fertilizer Trends and Outlook to 2015*. Food and Agriculture Organization of the United Nations, Rome.

FAO, 2013. *Climate-Smart Agriculture: Sourcebook*. Food and Agriculture Organization of the United Nations, Rome.

Feder, G., Umali, D.L., 1993. The adoption of agricultural innovations: A review. *Technological Forecasting Social Change*, 43(3–4): 215–239. https://doi.org/https://doi.org/10.1016/0040-1625(93)90053-A.

Gaudin, A.C.M., Tolhurst, T.N., Ker, A.P., Janovicek, K., Tortora, C., Martin, R.C., Deen, W., 2015. Increasing crop diversity mitigates weather variations and improves yield stability. *PLoS One*, 10(2): e0113261.

Gill, G.J., 2014. *An Assessment of the Impact of Laser-Assisted Precision Land Levelling Technology as a Component of Climate-Smart Agriculture in the State of Haryana*. CIMMYT-CCAFS, Internantional Maize and Wheat Improvement Center (CIMMYT), New Delhi.

Greene, W.H., 2003a. Econometric analysis. *Journal of the American Statistical Association*, 97(457): 361–362. https://doi.org/10.1198/jasa.2002.s458.

Greene, W.H., 2003b. *Econometric Analysis*, 5th. edn. Dorling Kindersley, New Delhi.

Holden, S., Shiferaw, B., Pender, J., 2001. Market imperfections and land productivity in the Ethiopian Highlands. *Journal of Agricultural Economics*, 52(3): 53–70.

Hossain, M.S., Hossain, A., Sarkar, M.A.R., Jahiruddin, M., Teixeira da Silva, J.A., Hossain, M.I., 2016. Productivity and soil fertility of the rice–wheat system in the High Ganges River Floodplain of Bangladesh is influenced by the inclusion of legumes and manure. *Agriculture, Ecosystems and Environment*, 218: 40–52.

Islam, A., Gautam, R.S., 2009. Groundwater resource conditions, socio-economic impacts and policy-institutional options: A case study of Vaishali District of Bihar, India. In: Mukherji, A., Villholth, K.G., Sharma, B.R., Wang, J. (Eds.), *Groundwater Governance in the Indo-Gangetic and Yellow River Basins: Realities and Challenges*. CRC Press, Boca Raton, FL. pp. 105–118.

Jagadish, S.V.K., Septiningsih, E.M., Kohli, A., Thomson, M.J., Ye, C., Redoña, E., Kumar, A., Gregorio, G.B., Wassmann, R., Ismail, A.M., Singh, R.K., 2012. Genetic advances in adapting rice to a rapidly changing climate. *Journal of Agronomy and Crop Science*, 198(5): 360–373.

de Janvry, A., Fafchamps, M., Sadoulet, E., 1991. Peasant household behaviour with missing markets: Some paradoxes explained. *Economic Journal*, 101(409): 1400–1417.

Jat, M.L., Singh, Y., Gill, G., Sidhu, H.S., Aryal, J.P., Stirling, C., Gerard, B., 2015. Laser-assisted precision land leveling impacts

inirrigated intensive production systems of South Asia. In: Lal, R., Stewart, B.A. (Eds.), *Advances in Soil Science*. CRC Press, Boca Raton, FL. pp. 323–352.

Jöreskog, K.G., Sörbom, D., 1993. *LISREL 8: Structural Equation Modeling with the SIMPLIS Command Language*. Scientific Software International, Chicago, IL, US.

Kassam, A., Friedrich, T., Shaxson, F., Pretty, J., 2009. The spread of conservation agriculture: Justification, sustainability and uptake. *International Journal of Agricultural Sustainability*, 7(4): 292–320. https://doi.org/10.3763/ijas.2009.0477.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., Mekuria, M., 2013. Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological Forecasting and Social Change*, 80(3): 525–540.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., Erenstein, O., 2015. Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy*, 42: 400–411.

Kassie, M., Zikhali, P., Manjur, K., Edwards, S., 2009. Adoption of sustainable agriculture practices: Evidence from a semi-arid region of Ethiopia. *Natural Resources Forum*, 33(3): 189–198.

Kassie, M., Zikhali, P., Pender, J., Köhlin, G., 2010. The economics of sustainable land management practices in the Ethiopian Highlands. *Journal of Agricultural Economics*, 61(3): 605–627.

Khatri-Chhetri, A., Aryal, J.P., Sapkota, T.B., Khurana, R., 2016. Economic benefits of climate-smart agricultural practices to smallholder farmers in the Indo-Gangetic Plains of India. *Current Science*, 110(7): 1244–1249.

Lal, R., 1997. Residue management, conservation tillage and soil restoration for mitigating greenhouse effect by CO2-enrichment. *Soil and Tillage Research*, 43(1–2): 81–107.

Lin, B.B., 2011. Resilience in agriculture through crop diversification: Adaptive management for environmental change. *Bioscience*, 61(3): 183–193.

Lipper, L., Thornton, P., Campbell, B.M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., Hottle, R., Jackson, L., Jarvis, A., Kossam, F., Mann, W., McCarthy, N., Meybeck, A., Neufeldt, H., Remington, T., Sen, P.T., Sessa, R., Shula, R., Tibu, A., Torquebiau, E.F., 2014. Climate-smart agriculture for food security. *Nature Climate Change*, 4(12): 1068–1072.

Lobell, D.B., Sibley, A., Ivan Ortiz-Monasterio, J., 2012. Extreme heat effects on wheat senescence in India. *Nature Climate Change*, 2(3): 186–189. https://doi.org/10.1038/nclimate1356.

NAAS, 2013. Climate resilient agriculture in India. Policy Paper 65, National Academy of Agricultural Sciences, New Delhi, India.

NAAS, 2017. Innovative viable solution to rice residue burning in rice-wheat cropping system through concurrent use of super straw management system-fitted combines and turbo happy seeder. Policy Brief No. 2, National Academy of Agricultural Sciences, New Delhi, India.

Neufeldt, H., Jahn, M., Campbell, B.M., Beddington, J.R., DeClerck, F., De Pinto, A., Gulledge, J., Hellin, J., Herrero, M., Jarvis, A., LeZaks, D., Meinke, H., Rosenstock, T., Scholes, M., Scholes, R., Vermeulen, S., Wollenberg, E., Zougmoré, R., 2013. Beyond climate-smart agriculture: Toward safe operating spaces for global food systems. *Agriculture & Food Security*, 2(1): 12. https://doi.org/10.1186/2048-7010-2-12.

Ortiz, R., Sayre, K.D., Govaerts, B., Gupta, R., Subbarao, G.V., Ban, T., Hodson, D., Dixon, J.M., Iván Ortiz-Monasterio, J., Reynolds, M., 2008. Climate change: Can wheat beat the heat? *Agriculture, Ecosystems and Environment*, 126(1–2): 46–58.

Palanisami, K., Kumar, D.S., Malik, R.P.S., Raman, S., Kar, G., Mohan, K., 2015. Managing water management research: analysis of four decades of research and outreach programmes in India. *Economic & Political Weekly*, 50(26–27): 33–43.

Pender, J.L., Kerr, J.M., 1998. Determinants of farmers' indigenous soil and water conservation investments in semi-arid India. *Agricultural Economics*, 19: 13–125.

Pingali, P.L., 2012. Green revolution: Impacts, limits, and the path ahead. *Proceedings of the National Academy of Sciences*, 109(31): 12302–12308.

Rivers, D., Voung, Q.H., 1988. Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of Econometrics*, 39(3): 347–366.

Sapkota, T.B., Aryal, J.P., Khatri-Chhetri, A., Shirsath, P.B., Arumugam, P., Stirling, C.M., 2018. Identifying high-yield low-emission pathways for the cereal production in South Asia. *Mitigation and Adaptation Strategies for Global Change*, 23(4): 621–641.

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 agriculuture: Some examples from cereal systems of Indo-Gangetic Plains. *Journal of Integrative Agriculture*, 14(8): 1524–1533.

Senyolo, M.P., Long, T.B., Blok, V., Omta, O., 2017. How the characteristics of innovations impact their adoption: An exploration of climate-smart agricultural innovations in South Africa. *Journal of Cleaner Production*, 172 (January 2018): 3825–3840. https://doi.org/https://doi.org/10.1016/j.jclepro.2017.06.019.

Sharma, A., Bailey, A., Fraser, I., 2011. Technology adoption and pest control strategies among UK cereal farmers: Evidence from parametric and nonparametric count data models. *Journal of Agricultural Economics*, 62(1): 73–92.

Singh, A.K., Pathak, H., 2014. Climate sensitivity of intensive rice-wheat systems in tropical Asia: Focus on the Indo-Gangetic Plains. In: Fuhrer, J., Gregory, P.J. (Eds.), *Climate Change Impact and Adaptation in Agricultural Systems*. Chapter 4, pages 31–46. CAB International, London.

Singh, R.B., 2000. Environmental consequences of agricultural development: A case study from the Green Revolution state of Haryana, India. *Agriculture, Ecosystems and Environment*, 82(1–3): 97–103.

Smith, V.H., McBride, R.C., Shurin, J.B., Bever, J.D., Crews, T.E., Tilman, G.D., 2015. Crop diversification can contribute to disease risk control in sustainable biofuels production. *Frontiers in Ecology and the Environment*, 13(10): 561–567.

Teklewold, H., Kassie, M., Shiferaw, B., 2013. Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics*, 64(3): 597–623.

Tirado, R., Gopikrishna, S.R., Krishnan, R., Smith, P., 2010. Greenhouse gas emissions and mitigation potential from fertilizer manufacture and application in India. *International Journal of Agricultural Sustainability*, 8(3): 176–185.

Wooldridge, J.M., 2002. *Econometric Analysis of Cross Section and Panel Data*, 3rd edn. MIT Press, Cambridge, MA.

Wu, J., Babcock, B.A., 1998. The choice of tillage, rotation, and soil testing practices: Economic and environmental implications. *American Journal of Agricultural Economics*, 80(3): 494–511.

Yamano, T., Rajendran, S., Malabayabas, M.L., 2015. Farmers' self-perception toward agricultural technology adoption: Evidence on adoption of submergence-tolerant rice in Eastern India. *Journal of Social and Economic Development*, 17(2): 260–274.

Yu, L., Hurley, T., Kliebenstein, J., Orazem, P., 2012. A test for complementarities among multiple technologies that avoids the curse of dimensionality. *Economics Letters*, 116(3): 354–357.

Appendix A: Estimates of the multivariate probit model (endogeneity corrected)

Variables	CD	STV	LLL	MT	SSNM
Household (HH) characteristics					
Male headed HH	−0.386***	−0.462***	0.219***	0.013	−0.209
	(0.133)	(0.199)	(0.086)	(0.157)	(0.146)
General caste	−0.045	0.531***	0.299**	0.291***	0.341***
	(0.073)	(0.099)	(0.128)	(0.075)	(0.076)
Age of HH head	0.232*	0.134	0.009	−0.261**	−0.006**
	(0.141)	(0.179)	(0.220)	(0.132)	(0.003)
Literate HH head	0.390**	0.359**	0.169***	0.183**	−0.148
	(0.082)	(0.122)	(0.032)	(0.087)	(0.092)
Literate spouse	−0.293***	0.006	0.162	0.223**	0.088
	(0.095)	(0.111)	(0.123)	(0.082)	(0.087)
Family size	0.009	−0.048**	−0.010	−0.020	−0.049
	(0.082)	(0.021)	(0.152)	(0.080)	(0.081)
Migrant	0.258***	−0.654***	−0.582***	0.197***	−0.013
	(0.071)	(0.131)	(0.168)	(0.075)	(0.080)
Farm land characteristics					
Tenure of plot	0.180**	0.235**	0.069***	−0.055	0.073
	(0.082)	(0.102)	(0.023)	(0.088)	(0.090)
Area of plot	−0.267***	0.479***	0.476***	0.523***	−0.053
	(0.081)	(0.179)	(0.069)	(0.085)	(0.080)
Fertile soil	0.310*	0.044	0.167	−0.392***	−0.129
	(0.083)	(0.113)	(0.200)	(0.082)	(0.081)
Deep soil	0.214***	−0.571***	−0.549**	−0.637***	−0.545***
	(0.094)	(0.198)	(0.259)	(0.144)	(0.125)
Gentle slope	−0.152*	0.124	0.402**	0.019	0.483***
	(0.081)	(0.111)	(0.174)	(0.082)	(0.081)
Distance to plot	−0.059	0.087**	0.069	0.053*	−0.019
	(0.039)	(0.036)	(0.047)	(0.028)	(0.037)
Economic and social capital					
Land operated	−0.310***	1.142***	0.389***	0.188***	0.414***
	(0.081)	(0.181)	(0.106)	(0.056)	(0.079)
Livestock owned	0.154***	0.197**	0.135***	0.012	−0.059**
	(0.031)	(0.039)	(0.046)	(0.029)	(0.028)
Asset index	0.028	0.632***	0.603***	0.390***	−0.123
	(0.076)	(0.116)	(0.114)	(0.081)	(0.093)
Credit access	−0.182***	−0.371***	0.101	0.248***	0.426***
	(0.069)	(0.115)	(0.118)	(0.076)	(0.083)
Association in group	0.409***	0.441***	0.124	−0.280**	−0.011
	(0.091)	(0.145)	(0.146)	(0.115)	(0.116)
Access to market, extension services and training					
Distance to market	−0.057**	−0.120***	−0.059**	−0.094***	−0.052**
	(0.019)	(0.024)	(0.023)	(0.021)	(0.021)
Agricultural training	0.617***	0.563**	0.486***	1.073***	0.132
	(0.173)	(0.203)	(0.173)	(0.172)	(0.240)
Source of information					
Farmer to farmer	0.415***	0.617***	0.031	0.263***	0.581***
	(0.071)	(0.138)	(0.159)	(0.088)	(0.084)
Extension service	0.850***	0.260***	−0.124	0.483**	−0.007
	(0.307)	(0.019)	(0.288)	(0.221)	(0.231)
ICT	0.533***	0.416***	−0.050	0.293	0.291**
	(0.121)	(0.149)	(0.604)	(0.258)	(0.139)
Seed trader/private company	−0.278***	0.255*	0.501**	0.378***	0.476***
	(0.094)	(0.144)	(0.253)	(0.082)	(0.085)
Main climate risk faced					
High temperatures	0.444***	0.362***	0.174	0.459***	0.043
	(0.078)	(0.112)	(0.111)	(0.081)	(0.082)
Decreasing rainfall	0.092	0.337**	0.146***	0.142	0.018
	(0.127)	(0.149)	(0.056)	(0.113)	(0.118)

Appendix A. Continued

Variables	CD	STV	LLL	MT	SSNM
Short winters	−0.099	0.422***	0.165	0.859***	0.564***
	(0.089)	(0.105)	(0.109)	(0.088)	(0.093)
District dummy (Karnal)	−0.193***	0.289	0.375***	0.173***	0.322**
	(0.083)	(0.197)	(0.031)	(0.013)	(0.150)
Extension_residual	0.137	0.231	0.102	0.305	0.216
	(0.198)	(1.032)	(0.937)	(1.036)	(1.122)
Constant	−1.097***	−0.950***	−1.250*	−1.652***	−0.420
	(0.234)	(0.327)	(0.471)	(0.189)	(0.246)
Number of observations	2547	2547	2547	2547	2547

Log likelihood = −3696.39; Wald $chi^2(145) = 1960.43$; Prob > $chi^2 = 0.0000$
*, **, and *** refer to significant at 90%, 95% and 99% confidence level; standard errors are reported in parentheses.

Appendix B: Estimates of the ordered probit model and marginal effects (full model)

		Marginal effects of each outcome				
CSA intensity	**Coeff**	**Pr(Y=0|X)**	**Pr(Y=1|X)**	**Pr(Y=2|X)**	**Pr(Y=3|X)**	**Pr(Y=4|X)**
Household (HH) characteristics						
Male headed HH	−0.184**	0.069**	−0.042**	−0.033*	−0.017	−0.002
	(0.083)	(0.032)	(0.020)	(0.018)	(0.013)	(0.002)
General caste	0.163***	−0.062***	0.040***	0.021***	0.015***	0.002**
	(0.056)	(0.021)	(0.014)	(0.007)	(0.005)	(0.001)
Age of HH head	0.101	−0.040	0.027	0.013	0.001	0.000
	(0.095)	(0.036)	(0.024)	(0.012)	(0.001)	(0.000)
Literate HH head	0.221***	−0.085***	0.057***	0.027***	0.010***	0.005***
	(0.062)	(0.024)	(0.017)	(0.007)	(0.003)	(0.002)
Literate spouse	0.031	−0.014	0.009	0.004	0.001	0.000
	(0.062)	(0.024)	(0.016)	(0.008)	(0.001)	(0.000)
Family size	−0.105*	0.040*	−0.027*	−0.013*	−0.001*	−0.000
	(0.058)	(0.022)	(0.015)	(0.007)	(0.000)	(0.000)
Migrant	0.055	0.021	0.014	−0.007	−0.000	−0.000
	(0.058)	(0.022)	(0.015)	(0.007)	(0.000)	(0.000)
Farm land characteristics						
Tenure of plot	0.151***	−0.057***	0.036***	0.023**	0.004***	0.002***
	(0.065)	(0.024)	(0.015)	(0.009)	(0.001)	(0.000)
Area of plot	0.281***	−0.108***	0.070***	0.036***	0.003***	0.000
	(0.060)	(0.023)	(0.015)	(0.008)	(0.001)	(0.000)
Fertile soil	0.242***	−0.093***	0.062***	0.030***	0.001***	0.000
	(0.059)	(0.023)	(0.015)	(0.007)	(0.000)	(0.000)
Deep soil	−0.427***	0.168***	−0.123***	−0.043***	−0.002***	−0.000
	(0.082)	(0.032)	(0.026)	(0.007)	(0.000)	(0.000)
Gentle slope	0.093	−0.036	0.024	0.011	0.001	0.000
	(0.058)	(0.022)	(0.015)	(0.007)	(0.000)	(0.000)
Distance to plot	−0.092***	−0.035***	0.023***	0.012***	0.001***	0.000
	(0.022)	(0.009)	(0.006)	(0.003)	(0.000)	(0.000)
Economic and social capital						
Land operated	0.202***	−0.077***	0.051***	0.026***	0.009***	0.002**
	(0.061)	(0.023)	(0.015)	(0.008)	(0.003)	(0.001)
Livestock owned	0.036***	−0.014***	0.009***	0.007***	0.001***	0.000
	(0.007)	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)
Asset index	0.796***	−0.305***	0.199***	0.101***	0.005***	0.001
	(0.054)	(0.023)	(0.017)	(0.009)	(0.001)	(0.001)
Credit access	0.195***	−0.114***	0.076***	0.036***	0.002***	0.000
	(0.055)	(0.021)	(0.015)	(0.006)	(0.001)	(0.000)

Appendix B. Continued

		Marginal effects of each outcome				
CSA intensity	**Coeff**	**Pr(Y=0|X)**	**Pr(Y=1|X)**	**Pr(Y=2|X)**	**Pr(Y=3|X)**	**Pr(Y=4|X)**
Association in group	0.447***	−0.161***	0.088***	0.069***	0.004***	0.001***
	(0.074)	(0.025)	(0.012)	(0.013)	(0.001)	(0.000)
Access to market, extension services and training						
Distance to market	−0.053***	0.020***	−0.013***	0.007***	0.001***	0.000
	(0.047)	(0.018)	(0.004)	(0.006)	(0.000)	(0.000)
Distance to extension service	−0.050***	0.019***	−0.013***	−0.006***	−0.003***	−0.002**
	(0.008)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Agricultural training	0.418***	−0.147***	0.075***	0.069**	0.011**	0.002**
	(0.141)	(0.045)	0.015)	(0.029)	(0.02)	(0.001)
Source of information						
Farmer to farmer	0.257***	−0.099***	0.066***	0.032***	0.008***	0.001***
	(0.056)	(0.022)	(0.018)	(0.007)	(0.003)	(0.000)
Extension service/research center	0.608***	−0.239***	0.186***	0.051***	0.012***	0.003***
	(0.152)	(0.058)	(0.051)	(0.008)	(0.004)	(0.001)
ICT	0.269***	−0.166**	0.147***	0.048**	0.012***	0.001
	(0.019)	(0.087)	(0.065)	(0.024)	(0.003)	(0.002)
Seed trader/private company	0.126**	−0.110**	0.137***	0.023***	−0.001	−0.000
	(0.065)	(0.025)	(0.017)	(0.008)	(0.002)	(0.000)
Main climate risk faced						
High temperatures	0.517***	−0.201***	0.142***	0.057***	0.003***	0.002
	(0.057)	(0.022)	(0.017)	(0.006)	(0.001)	(0.003)
Decreasing rainfall	−0.063	0.024	−0.016	−0.008	−0.000	−0.000
	(0.082)	(0.031)	(0.020)	(0.011)	(0.001)	(0.000)
Short winters	0.139**	−0.051**	0.036**	0.016**	0.001**	0.000
	(0.058)	(0.020)	(0.015)	(0.007)	(0.000)	(0.000)
District dummy (Karnal)	0.967***	−0.522***	0.109***	0.363***	0.049***	0.013***
	(0.124)	(0.021)	(0.024)	(0.029)	(0.011)	(0.004)
Constant_cut1	0.432					
	(0.468)					
Constant_cut2	1.808***					
	(0.185)					
Constant_cut3	3.219***					
	(0.198)					
Constant_cut4	5.168***					
	(0.311)					
Pseudo R^2	0.321					
Log likelihood	−2058.76					
LR $chi^2(29)$	1482.54; Prob > chi^2 = 0.000					
No. of Observation	2547	2547	2547	2547	2547	2547

*, **, and *** refer to significant at 90%, 95% and 99% confidence level; standard errors are reported in parentheses.