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RESEARCH

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Climate-Smart Agriculture adoption for sustainable food systems and climate change adaptation in Northern India

Manpreet Kaur[1], DharmPal Malik[2], A. Amarender Reddy[3], Gurdeep Singh Malhi[2], Navish Kumar Kamboj[2], Elkhan Richard Sadik-Zada[4,6,7]* and Sandra Ricart[5]*

*Correspondence:
Elkhan Richard Sadik-Zada
sadikebd@rub.de
Sandra Ricart
sandra.ricart@polimi.it
[1]ICAR- Central Institute for Arid Horticulture, Bikaner, Rajasthan 334006, India
[2]Chaudhary Charan Singh Haryana Agricultural University, Hisar, Haryana 125004, India
[3]ICAR- National Institute of Biotic Stress Management, Raipur, Chhattisgarh 493225, India
[4]Institute of Development Research and Development Policy, Ruhr-University of Bochum, Bochum, Germany
[5]Department of Electronics, Information and Bioengineering, Politecnico di Milano, Via Ponzio 34/5, 20133 Milan, Italy
[6]University College, Korea University, Seoul, South Korea
[7] Center for Studies on European Economy, Azerbaijan State University of Economics, Baku, Azerbaijan

Abstract
Climate-Smart Agriculture (CSA) has emerged as a key strategy to address rising global food demand and persistent food insecurity while enhancing resilience to climate change. This study examines farmers' perceptions of climate change and the socio-economic and institutional factors influencing the adoption of CSA adoption in Haryana, India, with a focus on Climate-Smart Villages (CSVs) as a community-based approach for scaling climate-resilient strategies. Using a purposive multistage sampling design, primary data were collected from 240 farmers across two agro-climatically distinct districts—Kurukshetra and Sirsa—including both CSVs and non-CSV areas. The findings reveal pronounced regional heterogeneity in both perceptions and adoption patterns. While awareness of climate change did not differ significantly between CSV and non-CSV farmers in Kurukshetra, significant differences were observed in Sirsa, particularly in perceptions of recent temperature and rainfall variability. Multivariate analysis identifies institutional membership, crop diversification, and livestock population as key determinants of CSA adoption. Overall, adoption levels were significantly higher among CSV farmers, with target farmers exhibiting 9.7–17.3% higher adoption rates and control farmers 4.0–8.0% higher rates than non-CSV farmers, indicating substantial spillover effects. The widespread uptake of resource-efficient technologies, coupled with greater access to climate information, enhances farmers' capacity to anticipate and respond to climate risks. These adoption outcomes have important implications for food security. Higher adoption—particularly in Kurukshetra—is associated with improved yield stability, water-use efficiency, and income resilience, while lower adoption in Sirsa may constrain these gains. The results highlight the role of behavioural and institutional factors in shaping adoption decisions and underscore the effectiveness of CSV-based approaches in fostering climate-resilient farming systems. The study emphasises the need for context-specific, farmer-centred policies that integrate technological, behavioural, and institutional interventions to advance food security in vulnerable regions.

Keywords Climate smart agriculture, Climate change adaptation, Food security, Survey, Villages, India

1 Introduction

Climate change poses a growing threat to agricultural systems by increasing production uncertainty and undermining food security and rural livelihoods, particularly in underdeveloped and developing economies [74]. Altered precipitation regimes characterised by both increasing and decreasing trends [2], combined with rising global temperatures, are major drivers of declining crop yields. Under a business-as-usual-scenario, global mean temperatures are projected to exceed 1.5 °C by 2040 and may reach up to 3.5 °C by the end of the century [57]. These changes have led to pronounced disruptions in seasonal patterns, especially in India, where rainfall variability and intensity are increasing, sea levels are rising, and extreme weather events such as cyclones, heatwaves, floods, and droughts are occurring with greater frequency and severity [19]. In March and April 2022, temperatures in northwest and central India reached unprecedented extremes. April recorded the highest temperatures in 122 years, with a mean of 35.9 °C and peaks of 37.8 °C. These early and intense heatwaves were driven by persistent anticyclones over western Rajasthan in March, compounded by the absence of western disturbances. Concurrently, a declining trend in annual rainfall was observed, particularly across the Indo-Gangetic Plains and the Western Ghats, while climate projections indicate increasing interannual variability in summer monsoon rainfall throughout the twenty-first century [48, 49].

The regions of Punjab, Himachal Pradesh, Jammu and Kashmir, Haryana, Madhya Pradesh, Uttar Pradesh, and Rajasthan have experienced significant yield reductions in major field crops, including wheat (10–34%), maize (18%), chickpea (19%), and mustard (14–18%) [59]. These regional trends are closely associated with increasing climate variability, characterised by rising temperatures and erratic rainfall, which are already affecting agricultural systems in Haryana through greater production uncertainty and resource stress. Such changes are projected to alter land and water dynamics, intensifying groundwater depletion and amplifying yield instability, particularly in climate-sensitive and rainfed areas, thereby threatening agricultural productivity, food security, and rural livelihoods. At the national scale, rising temperatures could reduce crop yields by 10–40% by the end of the century [30], with modelling studies suggesting productivity declines of around 9% in the near term (2010–2039), potentially increasing to 25% in the absence of long-term adaptation [32, 43]. These projections are consistent with field-level evidence indicating that climate stressors—such as prolonged dry spells—reduce soil moisture and impair seed germination and crop establishment, ultimately constraining yield potential [9]. Together, these dynamics reinforce the link between climate variability, yield volatility, and agrarian stress, highlighting the increasing vulnerability of farming systems and rural livelihoods in the region [93].

The adoption of innovative agricultural practices—including high-yielding crop varieties, chemical fertilizers, and expanded irrigation—during the mid-1960s played a pivotal role in driving unprecedented increases in food grain production and ushered in the Green Revolution in Indian agriculture. Despite these achievements, growing concerns persist regarding the sustainability of this growth and its capacity to adequately feed the country's rapidly expanding population. According to the *Global Food Policy Report 2024* [38], nearly 17% of India's population remains undernourished, defined as habitual food consumption insufficient to meet the dietary energy requirements necessary for a healthy and active life. Similarly, the *Global Hunger Index 2024*, which assesses national nutritional status based on indicators of undernourishment, child stunting, wasting, and mortality, ranks India 105th out of 127 countries, categorizing its hunger level as *serious*, with a GHI score of 27.3. As a benchmarking tool that evaluates food security across multiple dimensions—including affordability, availability, quality and safety, and sustainability and adaptation—the *Global Food Security Index* ranks India 68th out of 113 countries, underscoring the need for strengthened efforts to build food system resilience. In response, some of the world's largest food-focused social safety net programmes have been implemented to support vulnerable populations, primarily through subsidised staple grains such as rice and/or wheat. For example, India's Public Distribution System (PDS) provides up to 25 kg of free rice and/or wheat per month to approximately two-thirds of the country's low-income households. However, while the PDS has contributed to reducing hunger and improving caloric intake, it has been less effective in ensuring access to nutritionally balanced diets among beneficiary households.

Achieving food security requires strengthening the capacity of rural households to withstand climate-related shocks and enhancing their ability to adapt to increasingly variable weather patterns. In India, nearly two-thirds of total employment is linked to agriculture, which contributes approximately 17% to the national gross domestic product [71]. Within this context, the adoption of Climate-Smart Agriculture (CSA) practices has been widely promoted in international and national policy frameworks as a viable response to climate and food security challenges [12]. Introduced in 2009, CSA has gained prominence as an overarching approach for guiding the transformation of agri-food systems toward environmentally sustainable and climate-resilient pathways, while simultaneously addressing food security, livelihood sustainability, and climate change [23]. Rather than representing a distinct set of farming technologies, CSA functions as a strategic framework aimed at identifying context-specific agricultural practices that enable farmers to adapt effectively to climate variability [39]. It encompasses a broad range of practices designed to enhance productivity, strengthen adaptive capacity, and reduce greenhouse gas (GHG) emissions concurrently [65, 85]. While CSA builds upon established agricultural knowledge, technologies, and sustainability principles, it possesses several distinguishing characteristics. First, it explicitly addresses the impacts of climate change on agricultural and food systems. Second, it emphasises the assessment and management of synergies and trade-offs among productivity enhancement, climate change adaptation, and mitigation objectives. Third, it encompasses a diverse set of practices and technologies tailored to specific agro-ecological conditions and socio-economic contexts [20, 27]. Accordingly, agricultural practices and interventions are considered climate-smart when they simultaneously advance three core objectives: ensuring food security, strengthening resilience, and promoting climate mitigation strategies [63].

Examples of CSA practices include the use of climate-resistant crop varieties, environmentally sustainable farming techniques, agroforestry and mixed farming systems, precision and targeted agricultural practices, climate-smart water management, and improved livestock management and welfare strategies [5, 37, 75]. When implemented at scale, CSA practices encompass a range of interrelated components, including weather-smart, water-smart, carbon-smart, nitrogen-smart, energy-smart, and knowledge-smart interventions [45]. Water-smart technologies include rainwater harvesting, drip irrigation, laser land levelling, furrow-irrigated bed planting, drainage management, and the use of cover crops [25]. Energy-smart technologies, such as zero tillage and minimum tillage, have demonstrated potential to reduce GHG emissions from cultivated soils in both the short and long term [24]. Minimum tillage, particularly when combined with crop residue management, also improves soil moisture retention and soil organic matter content [1]. Furthermore, when integrated with intercropping systems, these practices enhance soil organic matter and soil organic carbon stocks, thereby contributing to soil carbon sequestration [55]. Additional nutrient-smart technologies include site-specific nutrient management, green manuring, and the use of leaf colour charts to optimise fertiliser application [44].

Despite the widely recognised role of CSA in enhancing climate resilience, a more nuanced perspective has emerged, suggesting that failing to situate CSA within the broader adaptive capacity of agricultural systems may limit its effectiveness. In particular, neglecting the socio-economic and institutional contexts that render certain farmers more vulnerable to climate change can compromise CSA's ability to address the structural drivers of vulnerability and exposure to climate risks [77]. What is often lacking is a clear understanding of how specific CSA practices can be realistically adopted by farmers, given the complexity of agricultural systems and the social dynamics shaping decision-making across diverse farming contexts [90]. Consequently, the success of efforts to promote CSA depends on identifying effective engagement strategies while acknowledging the practical constraints and barriers to implementation faced by farmers [61]. Engaging directly with farmers—who are central actors in agricultural systems and possess deep contextual knowledge—offers a critical pathway for identifying both best practices and adoption challenges related to CSA. In this context, the concept of Climate-Smart Villages (CSVs) has emerged as a participatory mechanism to strengthen farmers' roles in implementing integrated, locally tailored portfolios of climate-smart practices, thereby enhancing community-level resilience to climate change [34].

This paper employs a survey-based approach to examine farmers' perceptions of climate change and their behavioural responses, focusing on levels of awareness, perceived impacts, and adaptive capacity. Specifically, the study investigates the key drivers influencing the potential adoption of CSA practices within the rural context of Haryana, India, as a pathway to enhancing climate resilience and food security. The research addresses three central questions: 1) Do farmers recognise climate change as a significant threat, and what adaptation strategies do they employ to mitigate its impacts on agricultural practices? 2) Which socio-economic factors shape farmers' perceptions and behavioural responses to climate change? and 3) What differences can be observed in outcomes between CSV and non-CSV settings? Accordingly, the study tests three main hypotheses grounded in the central role of behavioural, socio-economic, and social learning dynamics, which are increasingly emphasised in recent literature:

H1 *Farmers who perceive climate change as a significant threat are more likely to adopt adaptation strategies and CSA practices* [8], [69].

H2 *Farmers' perceptions and adaptive behaviours are influenced by socio-economic characteristics, such as gender, income, farm size, and access to resources, which significantly shape adaptation decisions and responses* [81].

H3 *Participation in CSA programmes increases awareness, adoption, and adaptive capacity, contributing to improvements in productivity, resilience, and food security* [79]. Together these research questions and hypotheses contribute to advancing CSA research in support of sustainable food systems, recognising that achieving sustainability is not reliant on a single solution but requires aligning production, consumption, governance, and behaviour under climate and resource constraints. By disentangling direct and spill-over effects of programme participation, the study aims to reveal how social learning and knowledge exchange shape farmers' perceptions, attitudes, and adaptive capacity in climate-vulnerable contexts.

The paper is organised as follows. Following the introduction, Sect. 2 presents the case study context, focusing on the districts of Kurukshetra and Sirsa, which represent two distinct agro-climatic regions. Section 3 outlines the research methodology used to analyse farmers' perspectives on climate change and the role of CSA in both CSV and non-CSV settings. Section 4 presents the empirical findings, including farmer profiles, levels of awareness, perception, and adaptive responses to climate change, as well as inter-district differences. The final section discusses the key findings and outlines implications for future research on CSA adoption.

2 Case study

The study was conducted in Haryana, a state in north-western India and a major contributor to the national food stock, supplying substantial quantities of wheat and rice to the central pool. The gross cropped area increased to 6,724,000 ha in 2021–22, representing a 35.6% rise over the past 50 years, with a cropping intensity of 191.4%. Tube wells and canals are the primary sources of irrigation, with irrigated land accounting for 93.3% of the net sown area [86] . However, significant changes in weather parameters have been observed over the last six decades, including increases in both maximum and minimum temperatures and a decline in rainfall. These trends are projected to intensify, with forecasts indicating a temperature rise of 2–6.5 °C in the region, which could adversely affect agricultural productivity. This scenario necessitates adjustments in agronomic practices, such as the adoption of stress-tolerant crop varieties and highly productive technologies, to ensure sustainable increases in crop production [16].

Haryana is divided into two agro-climatic zones characterised by variations in soil type, cropping patterns, weather parameters, rainfall, temperature, and water resource availability (Table 1). The study was conducted in two districts representing these zones:

Table 1 Main features of Kurukshetra and Sirsa districts, in Haryana*Source*: District contingency plans, [31]

Characteristics	Kurukshetra district	Sirsa district
Agro-climatic zone	Eastern Zone (HR-1)	Western Zone (HR-2)
Total geographical area (ha)	168,000	427,000
Latitude	29º57′58.9″ N	29º 31′48.00″ N
Longitude	76º49′42.79″ E	75º 01′12.00″ E
Average annual rainfall (mm/year)	645.7	391.1
Gross cropped area (ha)	266,000	710,000
Net sown area (ha)	150,000	390,000
Gross irrigated area (ha)	266,000	658,000
Net irrigated area (ha)	150,000	338,000
Rainfed area (ha)	0	52,000
Cropping intensity (%)	177	182

Kurukshetra district from the eastern agro-climatic zone and Sirsa district from the western agro-climatic zone. This selection enables an examination of location-specific contexts of awareness and the development of district-specific frameworks for climate change adaptation [82]. The districts were selected using purposive sampling based on the implementation of CSA interventions by the International Maize and Wheat Improvement Center (CIMMYT), the Indian Council of Agricultural Research (ICAR), and the Department of Agriculture, Government of Haryana.

3 Data and methods

3.1 Data collection

The study employed a purposive multistage sampling technique to capture farmers' perspectives on CSA practices in Kurukshetra and Sirsa districts. These districts were deliberately selected to represent the agro-climatic and socio-economic diversity characteristic of northern Indian agricultural systems. Kurukshetra, located in the high-productivity Indo-Gangetic Plain, represents intensively cultivated farming systems dominated by rice–wheat cropping. In contrast, Sirsa, situated in the semi-arid agro-climatic zone bordering the Thar Desert, reflects semi-arid farming conditions with greater climate vulnerability. Together, these two districts capture a broad spectrum of farming conditions that are widely representative of the heterogeneity found across northern Indian agricultural systems. In each district, two blocks with the highest number of CSVs were identified. In Kurukshetra, two blocks were selected: Pehowa (including the villages of Gumthala, Murtzapur, Usmanpur, and Bhatmajra) and Ladwa (Mehra, Khedi Dabdilan, Barna, and Gadhi). In Sirsa district, the two selected blocks were Sirsa (Kelnia, Jhotarwal, Phoolkan, and Bara Wali) and Nathusari Chaupta (Rupana Khurd, Nathusari Kalan, Chidwal, and Ali Mohammad).

These blocks together comprised 132 villages with 3615 farmers in Kurukshetra and 106 villages and 2736 farmers in Sirsa. From each selected block, two CSVs and two non-CSVs were randomly selected, resulting in a total of eight sampled villages. From each CSV, 20 farmers were selected, including 10 beneficiary farmers (CSV target) who were in direct contact with the implementing agency and 10 non-beneficiary farmers (CSV control). In addition, 10 farmers were selected from each non-CSV. Based on this classification, farmers were grouped into three categories: CSV target, CSV control, and non-CSV farmers. The selected blocks within each district had the highest concentration of CSVs, ensuring programmatic relevance, while the inclusion of both CSV and non-CSV enhances comparability. This sampling framework resulted in a total sample size of 240 farmers. The sample size was considered adequate to ensure representation of the target population while maintaining feasibility and capturing variability in CSA adoption and preferences, in line with commonly recommended thresholds for social science research involving multiple variables (see supplementary information 1 for details).

Data was collected through face-to-face interviews using a structured survey during the 2021–22 agricultural year. In Kurukshetra district, data collection was facilitated with the support of project staff from the International Maize and Wheat Improvement Center (CIMMYT), a non-profit international organization working to enhance the productivity, quality, and reliability of agricultural production systems. In Sirsa district, guidance was obtained from the Haryana Agricultural University Krishi Vigyan Kendra (KVK) to facilitate interactions with farmers. Prior contact was established with each respondent to schedule interviews at convenient locations, including farmers' fields, residencies, or village common areas. In several instances, interviews were conducted in the presence of CIMMYT or KVK staff. Each interview lasted approximately one hour. Before participation, respondents were informed about the objectives of the study, and verbal informed consent was obtained. Institutional clearance for the study was secured from the university prior to its commencement. In addition, self-reported CSA practices were verified through field-level observations. The survey instrument was organized into four sections: (i) socio-demographic characteristics, (ii) awareness and adoption of CSA practices, (iii) cost structure analysis, and (iv) constraints to CSA adoption. The questionnaire comprised a total of 36 close-ended questions, including multiple-choice, dichotomous (yes/no), and table-based response formats (see supplementary information 2 and 3 for details).

3.2 Data analysis

Statistical analyses were performed using STATA version 17, Origin Pro 2023, and Google collab (Python). Both descriptive and inferential statistical techniques were employed. Descriptive statistics were used to summarise socio-economic characteristics and agricultural attributes (independent variables), while inferential analyses were applied to examine relationships within the triple-loop framework of climate change behaviour, encompassing insights from farmers' awareness, perceived impacts, and adaptive capacity to climate change (dependent variables). Following a holistic approach, this framework was inspiring to reinforce risk assessment by tailoring farmers' decisions about the adoption of CSA practices across CSV and non-CSV settings.

Farmers' awareness was measured based on their knowledge of climate change and associated adaptation strategies. The level of awareness was assessed using a set of statements rated on a two-point scale, where a score of 1 was assigned to *Yes* responses and 0 to *No* responses. Chi-square tests were conducted to examine whether awareness levels differed significantly between CSV and non-CSV farmers within each district, with corresponding p-values reported [53]. The extent of adoption was defined as farmers' implementation of recommended CSA practices on their fields. Multiple Correspondence Analysis (MCA) was employed to assess patterns of CSA adoption and to identify underlying relationships among adoption variables [60]. Each CSA practice was treated as a nominal variable with two categories: 0 indicating non-adoption and 1 indicating adoption. A composite adoption index was constructed by aggregating these binary variables across selected CSA practices and was subsequently used for further analysis, following approaches adopted in similar studies (e.g. [28]). The CSA Technology Adoption Index was constructed and validated through a two-stage procedure. In the first stage, MCA was applied separately within functionally distinct groups of CSA technologies—categorised based on established CSA frameworks—to generate domain-specific sub-indices. MCA was preferred over conventional additive scoring approaches for methodological reasons: it is specifically designed for categorical and binary data and assigns weights based on the internal association structure of the data, thereby avoiding the arbitrary weighting inherent in summated scales.

In the second stage, the domain-specific sub-indices were aggregated into a composite adoption index, following established composite index methodologies and consistent with prior literature on binary adoption indices [13]. The categorisation of CSA technologies into functionally distinct groups ensures that the index captures multidimensional adoption behaviour, rather than collapsing conceptually distinct practices into a single undifferentiated score. Subsequently, the composite index scores were standardised to a scale of 0 to 1 using min–max normalisation, thereby facilitating meaningful interpretation and comparability of CSA technology adoption levels across sampled farmers.

Inverse Probability Weighted Regression Adjustment (IPWRA) was employed to estimate the impact of access to credit sources on technology adoption. IPWRA is a doubly robust estimator that combines inverse probability weighting with regression adjustment to estimate average treatment effect on the treated (ATET) and potential outcome means [99]. The approach accounts for selection bias by first estimating treatment assignment probabilities and then using their inverse as weights in outcome regressions. This corrects for missing potential outcomes and yields consistent ATET estimates if either the treatment model or the outcome model is correctly specified. Compared with conventional matching techniques, inverse probability weighting (IPW) retains all observations in the sample and typically produces estimates with lower variance. Weights were computed as the inverse of the estimated probability of receiving treatment and subsequently incorporated into the regression adjustment framework. The weighted regressions generated bias-corrected coefficients estimates, which were then used to derive robust ATET estimates. The doubly robust IPWRA estimation procedure was implemented in the following steps:

Step I: treatment model: Treatment assignment was modelled using multinomial logit (MNL) specification to estimate the probability of a household belonging to one of three mutually exclusive groups: beneficiaries (B), non-beneficiaries (NB), and non-CSV households, conditional on a set of observed covariates. The estimated choice probabilities served as propensity scores and were used to construct inverse probability weights for subsequent analysis. Formally, the probability of a household i receiving treatment j was defined as:

$$\hat{p}\,(D_i = d|X_i)\,\frac{\exp(Xi\widehat{d})}{\sum_{d'}\exp(Xi\widehat{d'})}$$

where, X is a multi-dimensional vector of pre-treatment covariates capturing household and farm-level characteristics as well as institutional factors, and F (.) denotes the cumulative distribution function. The estimated propensity scores were used to construct a weighted pseudo-sample in which the distribution of baseline covariates is independent of treatment assignment. For the three categories of farmers (j = 0, 1, or 2), the inverse probability weights (IPW) were defined as:

$$\mathrm{W_i} = \mathrm{T_{ij}}/\widehat{p_j}\ \ (Xi)$$

where, $\hat{p}_j(Xi)$ denotes the estimated propensity score for treatment category j for household i, based on their observed covariates Xi, and Tij is an indicator variable equal to 1 if household i received treatment j, and 0 otherwise. These weights were subsequently applied in the outcome regression to generate bias-corrected estimates of treatment effects.

Step II: outcome model: In the regression adjustment (RA) step, a linear regression model was employed for the outcome model. For each treatment group, the technology adoption score was regressed on the same set of pre-treatment covariates used in the treatment model. This procedure produced regression-adjusted predictions of technology adoption for each household under alternative credit source scenarios, allowing for the estimation of potential outcomes across treatment groups.

$$\hat{Y}_{\mathrm{i}}\left(\mathrm{d}\right) = \mathrm{X}_{\mathrm{i}}\hat{\beta}_{\mathrm{d}}$$

Step III: estimation of treatment effects: The average treatment effect on the treated (ATET) was estimated by combining the regression-adjusted predictions from the outcome model with inverse probability weights derived from the treatment model. The doubly robust property of the IPWRA estimator ensures that ATET estimates remain consistent if either the treatment model (multinomial logit), the outcome model (linear regression), or both are correctly specified. This approach yields robust estimates of the causal impact of treatment status on technology adoption while accounting for potential selection bias arising from observable confounders.

$$ATET = \frac{1}{n_d}\sum_{i=1}^{n}\left[\frac{T_{id}\left(Y_i - \hat{Y}_i\left(d\right)\right)}{\hat{p}_d\left(X_i\right)} - \left[\frac{T_{i0}\left(Y_i - \hat{Y}_i\left(0\right)\right)}{\hat{p}_0\left(X_i\right)}\right] + \hat{Y}_i\left(d\right) - \hat{Y}_i\left(0\right)\right]$$

Prior to estimation, multicollinearity among covariates was assessed using the Variance Inflation Factor (VIF), with a threshold of 5. All covariates satisfied this criterion, indicating the absence of problematic multicollinearity [66] . To ensure the validity of the IPWRA estimates, several robustness checks were conducted. First, a Heckman two-stage selection model was employed to address potential non-random selection into treatment categories [36]. The inverse Mills ratio derived from the first stage selection equation was incorporated into the outcome equation to correct for sample selection bias. Second, Rosenbaum bounds sensitivity analysis was performed to assess the robustness of the estimated treatment effects to hidden bias arising from unobserved confounders [78]. The sensitivity parameter was progressively increased to identify the threshold at which statistical significance would be undermined. Third, to address potential omitted variable bias, the Oster [70] bounding approach was applied. This involved computing the identified set for the treatment effect coefficient under the assumption that selection on unobservables is proportional to selection on observables. Fourth, to rule out reverse causality, a placebo test was conducted in which farmers' age and education—predetermined and theoretically exogenous characteristics—were regressed on treatment status. The absence of significant coefficients supports the causal interpretation of the results. Finally, for heterogeneity analysis, quantile treatment effects (QTE) were estimated at the 25th, 50th, and 75th percentiles of the adoption index distribution to examine variation in treatment effects across low, median, and high adopters, respectively [46].

4 Results

4.1 Farmers and farm characteristics

In Kurukshetra district, approximately half of the CSV target farmers were aged between 35 and 50 years, with an average family size of more than five members, although fewer

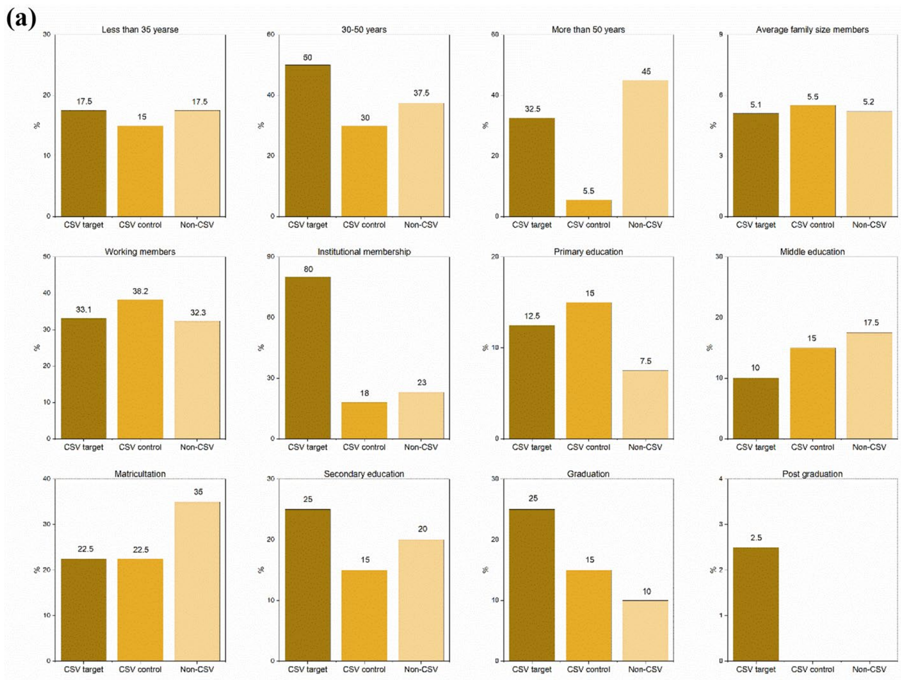

Fig. 1 **a** Socio-demographic characteristics of CSV target, CSV control, and non-CSV farmers in Kurukshetra district. **b** Socio-demographic characteristics of CSV target, CSV control, and non-CSV farmers in Sirsa district

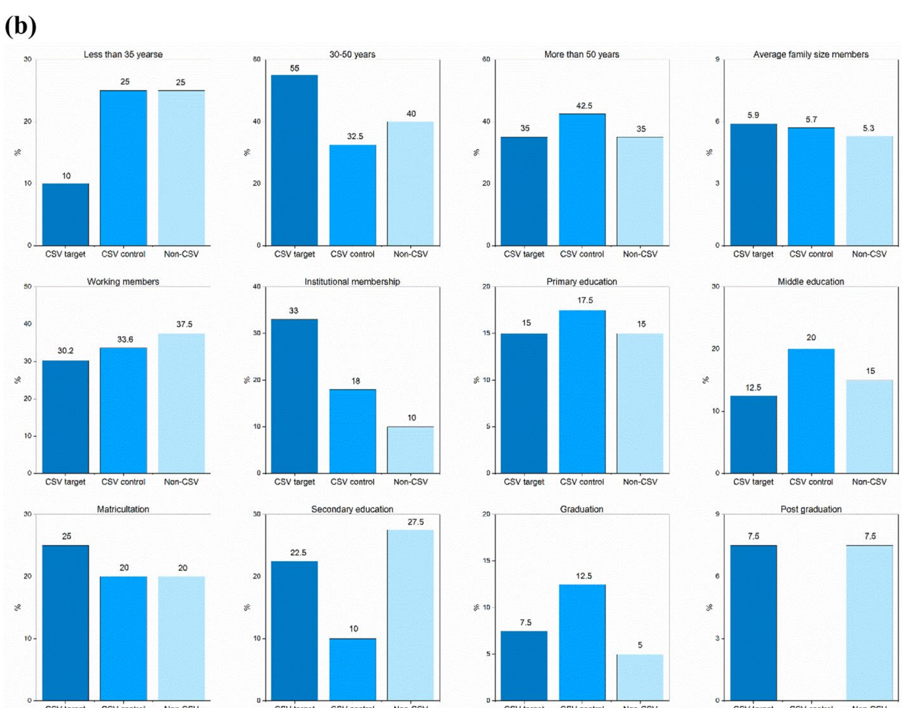

Fig. 1 (continued)

than half were actively engaged in farming activities (Fig. 1a). The literacy rate among this group was nearly universal (97%), with about one-quarter having completed senior secondary or graduate-level education. In contrast, CSV control farmers were generally older, with 55% aged over 50 years, while maintaining a similar average family size.

Literacy levels were lower in this group (82%), with most individuals having attained secondary-level education or higher. Among non-CSV farmers, the majority were also over 50 years of age. Their average family size and number of working members were comparable to those of CSV target farmers. Literacy remained relatively high (90%); however, educational attainment varied considerably, from primary to graduate levels.

In Sirsa district, CSV target farmers were predominantly aged between 35 and 50 years, with the highest average family size in the sample (nearly six members), although the number of working members was close to the overall average (Fig. 1b). The literacy rate was relatively high (90%), with secondary education being the most common level of attainment. Among CSV control farmers, although 25% were younger than 35 years, those aged over 50 years still constituted the majority. The average family size was similar to that of CSV target farmers, while the number of working members was among the highest in the sample (mean = 1.93). Literacy in this group was lower (80%), with educational attainment ranging from primary to graduate levels. Non-CSV farmers in Sirsa exhibited a socio-economic profile comparable to their counterparts in Kurukshetra, particularly in terms of average family size and literacy levels. However, the age distribution in Sirsa reflected a relatively larger proportion of younger farmers, along with a higher number of working members. Regarding institutional membership, all farmer groups across both districts exhibited moderate levels of participation (10–30%), except for CSV target farmers in Kurukshetra, where enrolment was substantially higher, reaching nearly 80%.

In Kurukshetra district, all cultivated land was irrigated, whereas in Sirsa district, CSV target and control farmers primarily cultivated irrigated land, while non-CSV farmers managed a combination of irrigated and rainfed plots. CSV target farmers in Kurukshetra had an average operational holding of 5.7 ha, with approximately half under ownership, whereas CSV control farmers held 4 ha on average, almost entirely owned (3.7 ha). Non-CSV farmers owned about 4.5 ha but leased in nearly one third of this area. Among the farmer groups, CSV target farmers were more likely to lease in land (37%), while CSV control farmers were more inclined to lease out land (15%) (Fig. 2). In Sirsa district, leasing patterns differed slightly. CSV target farmers owned 4.3 ha on average but leased in nearly half of their operated land. CSV control farmers held significantly less land that their Kurukshetra counterparts (2.5 ha) but leased a similar proportion. Non-CSV farmers in Sirsa managed an average of 3.1 ha of irrigated land and 0.2 ha of rainfed land, with approximately 0.5 ha leased in. In terms of leasing behaviour, both

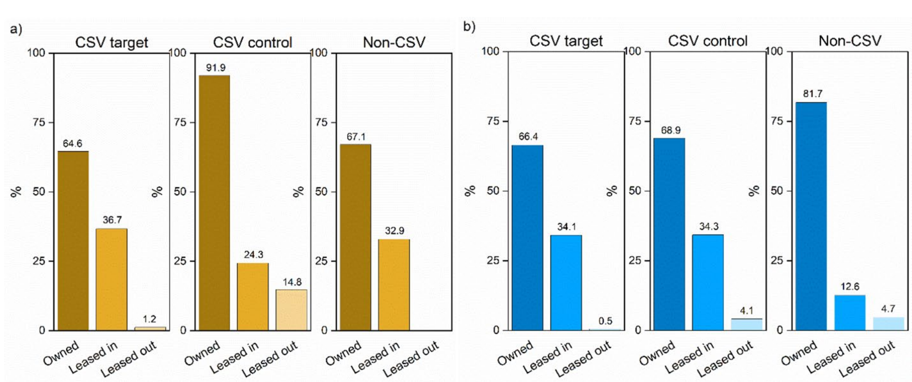

Fig. 2 Status of operational land holdings and irrigation among CSV target, CSV control, and non-CSV farmers in Kurukshetra (**a**) and Sirsa (**b**)

CSV target and control farmers leased in land at similar rates (34%), whereas leased-out arrangements were more prevalent among non-CSV farmers.

Paddy and wheat were the predominant crops cultivated by all farmer groups during the *kharif* and *rabi* seasons, respectively, in both districts (Fig. 3). Paddy was generally grown as transplanted rice, although some CSV target farmers in Kurukshetra cultivated both transplanted and direct-seeded varieties. The *kharif* season (July–October) is highly dependent on monsoon rainfall, while wheat is primarily cultivated during the *rabi* season (October–April), following the monsoon. In Kurukshetra district, CSV target farmers allocated an average of 4.5 ha to paddy cultivation, compared with 3.8 ha among both CSV control and non-CSV farmers. During the *rabi* season, wheat predominated, with CSV target farmers dedicating around 4 ha—mostly sown using the happy seeder—alongside smaller areas under potato (0.6 ha) and mustard (0.2 ha). Annual crops such as sugarcane were also cultivated on approximately 0.5 ha. CSV control farmers exhibited similar patterns, with 3.6 ha allocated to wheat, including 2.4 ha under conventional tillage and 0.9 ha using super seeder. Non-CSV farmers also prioritised wheat, with slightly higher adoption of the super seeder (1.2 ha) and marginally lower allocation to sugarcane (0.4 ha), while their overall cropping pattern closely resembled that of CSV control farmers.

In Sirsa district, CSV target farmers allocated an average of 4.2 ha to paddy, while CSV control and non-CSV farmers dedicated approximately 2 ha and 1.4 ha, respectively. Cotton was also cultivated during the *kharif* season across all groups, with average allocations exceeding 1 ha. During the *rabi* season, wheat cultivation among CSV target and control farmers was predominantly sown using super seeder, covering around 3.8 ha out of an average operational area of 5 ha. Mustard was cultivated by approximately one in ten farmers. Non-CSV control farmers cultivated slightly smaller wheat areas (3.2 ha) and allocated around 0.4 ha to mustard, with a mix of conventional tillage, happy seeder, and super seeder practices. Among non-CSV farmers, wheat cultivation was less extensive (2.8 ha), largely under conventional tillage, while the area under mustard was nearly double that of CSV farmers.

Overall, CSV target farmers in both districts tended to allocate larger areas to principal crops (paddy and wheat) and were more likely to adopt mechanised sowing methods, such as the happy seeder and super seeder. In contrast, non-CSV farmers devoted less land to wheat, with conventional tillage practices remaining more prevalent. Minor

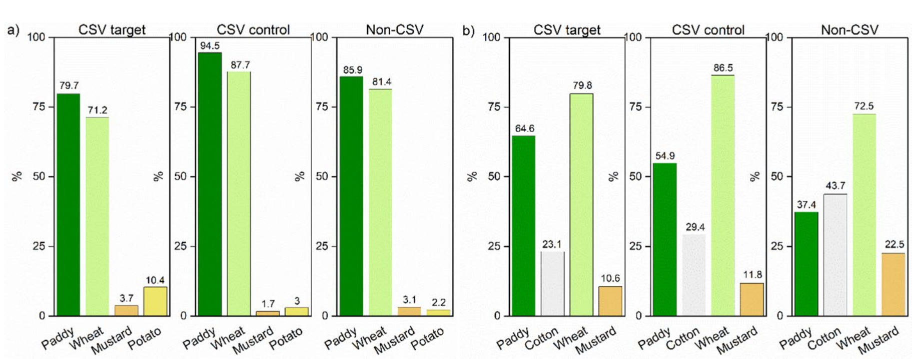

Fig. 3 Main cropping patterns of CSV target, CSV control, and non-CSV farmers in Kurukshetra (**a**) and Sirsa (**b**) during the kharif and rabi seasons

crops—including mustard, potato, sugarcane, and cotton—were cultivated across all groups but generally occupied smaller areas.

4.2 Awareness and perception

Farmers' awareness emerged as a key determinant in the adoption of CSA practices. CSV farmers in both districts demonstrated greater familiarity with the terms 'climate change' and 'global warming' compared with non-CSV farmers. In Kurukshetra district, this difference was particularly pronounced, with CSV farmers exhibiting significantly higher levels of knowledge than their non-CSV counterparts (Fig. 4). While both CSV and non-CSV farmers reported recent changes in temperature and precipitation, perception levels were higher among CSV farmers (75%) than among non-CSV farmers (60%). In terms of causation, approximately two-thirds of CSV farmers attributed climate change solely to anthropogenic activities, while an even larger share (69%) recognised a combination of anthropogenic and natural factors. Among non-CSV farmers, 45% identified anthropogenic causes, although many also acknowledged the combined influence of natural and human drivers. Deforestation, residue burning, and pollution were cited as the primary contributors by 62% of CSV farmers and 45% of non-CSV farmers. A greater proportion of CSV farmers (around three-fourths) emphasised the need to address climate change, compared with fewer than two-thirds of non-CSV farmers. In terms of impacts, CSV farmers reported higher incidences of yield reduction and greater challenges in livestock management across both districts. With respect to adaptive responses, farmers prioritised residue and water management strategies in combination with CSA technologies, with adoption rates higher among CSV farmers (77%) than non-CSV farmers (62%). More than three-fourths of CSV farmers (76%) reported improved outcomes with CSA practices in both the present and near future, and 77% indicated increased farm income. Access to climate information also differ significantly across groups. A large majority of CSV farmers (91%) utilised weather forecasting services to plan farm operations, compared with 70% of non-CSV farmers. Farmers relied on multiple information sources, including mobile messages (39%), the internet and

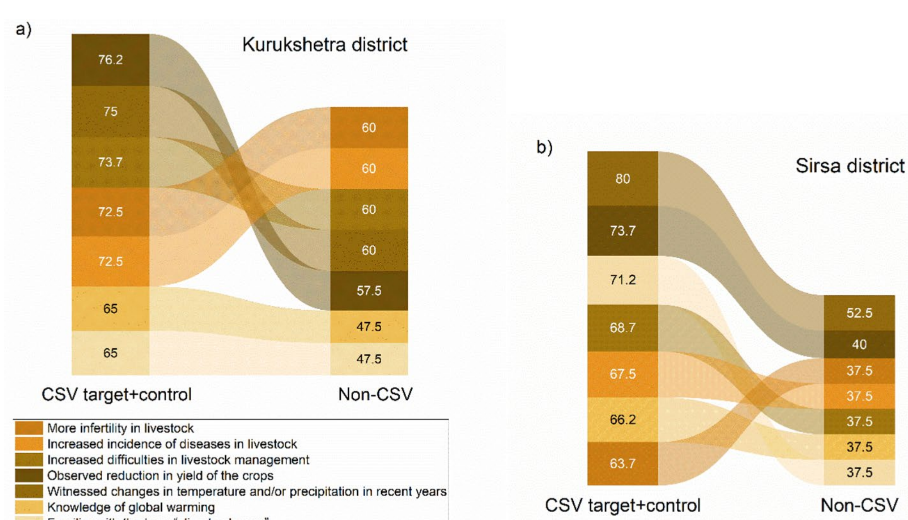

Fig. 4 Level of awareness of climate change and global warming reported among CSV (target and control) and non-CSV farmers in both district

television (67% each), and word of mouth (77%), with consistently lower usage rates among non-CSV farmers.

In Sirsa district, approximately 71% of CSV farmers were aware of concepts such as 'climate change', compared with only one-third of non-CSV farmers. Similarly, about two-thirds of CSV farmers recognised the concept of 'global warming', whereas only one-third of non-CSV farmers did. Around 80% of CSV farmers reported perceiving recent changes in temperature and precipitation, compared with roughly half of non-CSV farmers. Regarding the causes of climate change, around two-thirds of CSV farmers identified both anthropogenic and natural factors as contributors. Non-CSV farmers exhibited a similar pattern but placed greater emphasis on natural factors (45% compared with 37%). Pollution was perceived as the primary anthropogenic cause by 64% of CSV farmers, whereas non-CSV farmers more frequently cited residue burning and deforestation. Most CSV farmers (74%) acknowledged the need to address climate change and reported experiencing yield declines, while 69% also faced livestock management challenges, often related to disease. Among these farmers, 65% adopted CSA practices to mitigate climate-related impacts. In contrast, non-CSV farmers demonstrated more limited engagement with adaptation strategies, with only partial adoption of agrometeorological information (62%) and water management practices (55%).

The full set of variables used to assess farmers' awareness and perceived impacts was compared between CSV and non-CSV farmers in Kurukshetra and Sirsa districts using chi-square tests (Table 2). These tests evaluated whether the observed differences in responses between the two groups were statistically significant. Overall, differences between CSV and non-CSV farmers were more pronounced in Sirsa than in Kurukshetra, both in terms of response frequencies and chi-square values. In Kurukshetra, responses related to awareness of climate change and CSA practices were largely similar across groups, with the exception of indicators such as crop yield reduction and reliance on weather-related information, where notable differences emerged. Interestingly, the adoption of CSA practices was comparable between the two groups. In contrast, in Sirsa district, statistically significant differences were observed between CSV and non-CSV farmers across several indicators, including familiarity with the term 'climate change', knowledge of 'global warning', perception of changes in temperature and precipitation, and recognition of both natural and anthropogenic drivers of climate change, particularly residue burning and pollution. However, some areas showed convergence. Adoption of nutrient management practices and reliance on weather-related information for farm planning were similar across both groups. Likewise, access to weather-related information via the internet, television, and word of mouth was comparable between CSV and non-CSV farmers.

4.3 Adaptation

Farmers in both districts adopted a range of adaptation strategies centred on CSA technologies, including those related to carbon and energy, crops, nutrients, water, and weather (Fig. 5). Across all farmer groups, investment in improved and stress-tolerant crop varieties—a knowledge-smart technology—was universally adopted. In Kurukshetra district, CSV target farmers most frequently adopted carbon- and energy-smart technologies such as the happy seeder (97%), concentrate feeding for livestock (85%), and zero-till drills (82%). Nutrient-smart technologies were also widely implemented, with

Table 2 Comparison of awareness level of CSV and non-CSV farmers in both districts

Awareness parameters	Kurukshetra district		Sirsa district	
	Chi square	*p*-value	Chi square	*p*-value
Familiar with the term "climate change"	3.38	0.07	12.66*	0.00
Knowledge of global warming	3.38	0.07	8.98*	0.00
Witnessed changes in temperature and/or precipitation in recent years	2.86	0.09	9.76*	0.00
Possible causes of climate change				
(a) Anthropogenic activities	3.33	0.07	8.18*	0.00
Deforestation	3.33	0.07	2.82	0.09
Residue burning	3.33	0.07	4.82*	0.03
Pollution	3.33	0.07	7.42*	0.01
(b) Natural activities	2.19	0.14	4.98*	0.03
Observed reduction in yield of the crops	4.46*	0.04	12.96*	0.00
Increased difficulties in livestock management	3.25	0.07	10.71*	0.00
Increased incidence of diseases in livestock	1.93	0.17	9.82*	0.00
More infertility in livestock	1.93	0.17	7.42*	0.01
Need to face climate change	2.02	0.16	12.96*	0.00
Adopted measures to tackle climate change	0.80	0.37	18.56*	0.00
Measures of mitigating climate change				
Residue management	0.00	1.00	35.31*	0.00
Water management	1.62	0.20	6.43*	0.01
Nutrient management	0.02	0.90	3.06	0.08
Adopted technologies to face climate change	2.02	0.16	20.74*	0.00
Measures adopted resulted into better yields	3.41	0.07	9.70*	0.00
Witnessed increase in farm income due to CSA technologies	2.86	0.09	8.88*	0.00
CSA practices can also yield better in near future	2.86	0.09	8.88*	0.00
Reliance on weather information for planning farm operations	9.04*	0.00	2.02	0.16
Sources of agro-meteorological advisories				
Messages	0.89	0.35	7.37*	0.01
Internet	1.16	0.28	1.70	0.19
Television	3.46	0.06	0.02	0.89
Word of mouth	2.13	0.14	0.28	0.60

*identifies 5% level of significance

72% adopting green manuring (cover crops) and 45% using site-specific nutrient management. Among water-smart technologies, the laser land leveller was highly prevalent (92%), while raised bed planting and direct-seeded paddy were less common. Despite their awareness of changing temperature and rainfall patterns, CSV target farmers placed less emphasis on advanced irrigation methods (e.g. drip irrigation, sprinkler, or rainwater harvesting) instead prioritising weather-smart technologies such as ICT-based agro-meteorological advisories (80%). CSV control farmers in Kurukshetra exhibited a different adoption pattern, focusing primarily on concentrate feeding for livestock (82%) and zero-till drills (52%), while nutrient-smart practices such as green manuring were less widely adopted (35%). Similar to CSV target farmers, they frequently used the laser land leveller (87%); however, their adoption of weather-smart technologies was comparatively lower. Among non-CSV farmers, concentrate feeding for livestock remained the most widely adopted carbon- and energy- smart practice (75%), while water-smart technologies were again dominated by the laser land leveller (87%). Approximately half of non-CSV farmers utilised ICT-based agro-meteorological advisories, indicating moderate engagement with weather-smart technologies.

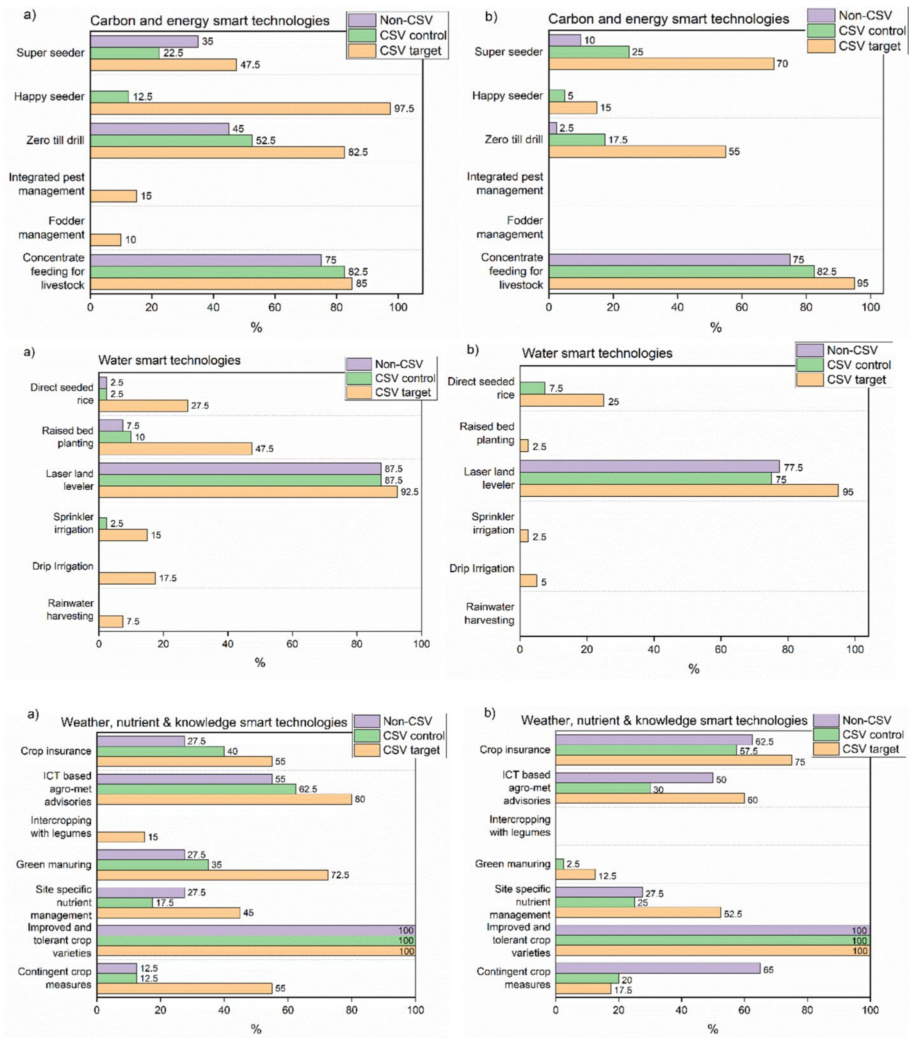

Fig. 5 Level of adoption of CSA practices among CVS target, CSV control, and non-CSV farmers in Kurukshetra (**a**) and Sirsa (**b**) districts

Among CSV target farmers in Sirsa district, concentrate feeding for livestock was the most widely adopted carbon- and energy-smart technology (95%), followed by super seeder (70%) and zero-till drill (55%). In contrast, practices such as fodder management and integrated pest management were rarely adopted. Regarding nutrient-smart technologies, site-specific nutrient management was implemented by approximately half of the farmers (52%), whereas a majority adopted water-smart technologies, with laser land leveller being the predominant choice (95%). Interestingly, crop insurance emerged as the most adopted weather-smart technology in this district. CSV control farmers exhibited slightly lower adoption rates than target farmers, with concentrate feeding for livestock (82%) and the laser land leveller (75%) as the preferred practices. Other water-smart technologies, such as drip irrigation, sprinkler systems, and rainwater harvesting, were rarely utilised. Among non-CSV farmers, the adoption pattern was broadly similar, with concentrate feeding and the laser land leveller remaining the most common technologies. Crop insurance was also the most frequently adopted weather-smart technology in this group (62%).

MCA was used to construct indices of technology adoption among farmers. For each technology group, two dimensions were identified, representing patterns of variation in respondents' adoption behaviour. The first dimension captured the greatest variation and served as the primary axis of adoption, while the second dimension reflected secondary patterns (Table 3). Together, these dimensions capture heterogeneity in farmers' adoption behaviour and provide a basis for interpretation. For the joint adoption index, constructed by combining the five individual technology indices, six eigenvalues in Kurukshetra and four eigenvalues in Sirsa were retained, explaining approximately 33–35% of the total variation. This level of explained variance is considered acceptable for index development (Fig. 6a, b). Box plots (Fig. 6c, d) illustrate the distribution of adoption indices and highlight the presence of outliers. In Kurukshetra (Fig. 6c), the median values of most indices were near to zero, indicating a balanced adoption pattern around the central tendency. The knowledge index (Index 2) exhibited the greatest variability, with a wide interquartile range. In contrast, the water index (Index 4) showed a narrow spread with several high outliers, suggesting that a small number of farmers adopted water-smart technologies at substantially higher levels than the majority. The joint adoption index displayed moderate variability, with some extreme values. In Sirsa district (Fig. 6d), the knowledge index similarly showed the highest variability, while the water index had a very narrow distribution but included a high outlier. The remaining indices—carbon, nutrient, weather, and the joint adoption index—exhibited more compact distributions, with values clustered closely around their medians.

Examination of the adoption index across farmer categories revealed that CSV target farmers (beneficiaries) exhibited higher levels of technology adoption than CSV control (non-beneficiaries) and non-CSV farmers in both districts. This pattern is illustrated through multiple visualisations, including violin plots (Fig. 7a, b), scatter diagrams (Fig. 7c, d), box plots (Fig. 7e, f), and kernel density estimates (Fig. 7g, h). Notably, even non-beneficiary (control) farmers within CSV areas demonstrated higher adoption levels than non-CSV farmers, suggesting the presence of a spillover effect from exposure to CSA interventions. These findings indicate that proximity to CSA initiatives, along with interactions with beneficiary farmers, can enhance the uptake of CSA technologies

Table 3 MCA' results by technologies and dimensions by district

Technologies	Dimensions	Kurukshetra district		Sirsa district	
		Eigenvalue	% Inertia	Eigenvalue	% Inertia
Carbon and Energy Smart technologies	1	0.24	0.65	0.23	0.60
	2	0.13	0.35	0.15	0.40
Knowledge smart	1	0.50	1.00	0.50	1.00
Nutrient smart	1	0.56	0.68	0.41	0.62
	2	0.27	0.32	0.26	0.38
Water smart	1	0.51	0.75	0.45	0.71
	2	0.17	0.25	0.18	0.28
Weather smart	1	0.64	0.64	0.56	0.56
	2	0.36	0.36	0.44	0.44
CSA	1	0.70	0.10	1	0.11
	2	0.43	0.06	2	0.08
	3	0.40	0.05	3	0.07
	4	0.37	0.05	4	0.07
	5	0.34	0.05		
	6	0.31	0.04		

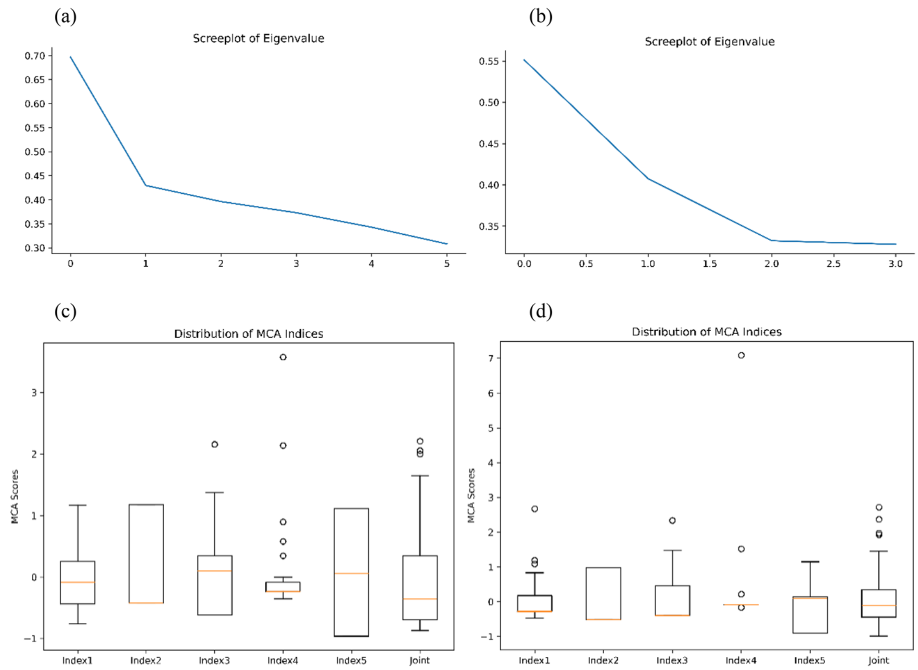

Fig. 6 Technology adoption index (based on MCA) for Kurukshetra district (**a**, **c**) and Sirsa district (**b**, **d**). Note: Index1: Carbon- and energy-smart technologies, Index2: Knowledge-smart technologies, Index3: Nutrient-smart technologies, Index4: Water-smart technologies, Index5: Weather-smart technologies, Joint index: Climate-smart technologies

among neighbouring non-beneficiaries through knowledge diffusion and peer-influenced adoption.

Inverse Probability Weighted Regression Adjustment (IPWRA) was employed to evaluate the influence of farmer category on technology adoption. Multinomial logit estimation of propensity scores (Table 4) in Kurukshetra district revealed that institutional membership and the crop diversity index were positively and significantly associated with target farmer status relative to non-CSV farmers. In contrast, the status of control farmers was significantly influenced by the number of working members in the household. In Sirsa district, CSV target farmers status was significantly associated with the number of working members in the household and operational landholding. Meanwhile, CSV control farmers were characterised by lower levels of education and smaller livestock populations, indicating that education plays an important role in farmers' assignment to a treatment category. The density distributions of propensity scores for CSV farmers (both target and control) and non-CSV were examined to assess overlap across all three categories, indicating that the groups are comparable for matching. The density plots (Fig. 8) further confirm that the common support condition is satisfied, supporting the validity of the IPWRA estimates.

Analysis of IPWRA estimates indicates that both CSV target (beneficiary) and CSV control (non-beneficiaries) farmers exhibit significantly higher levels of technology adoption than non-CSV farmers (Table 5). In Kurukshetra district, target farmers demonstrate a 17.32% higher adoption rate, while control farmers show a 4.11% higher adoption rate relative to non-CSV farmers. Similarly, in Sirsa district, adoption among target farmers is 9.79% higher, and among control farmers is 7.99% higher, compared with non-CSV farmers. These findings are further supported by Fig. 8, which shows

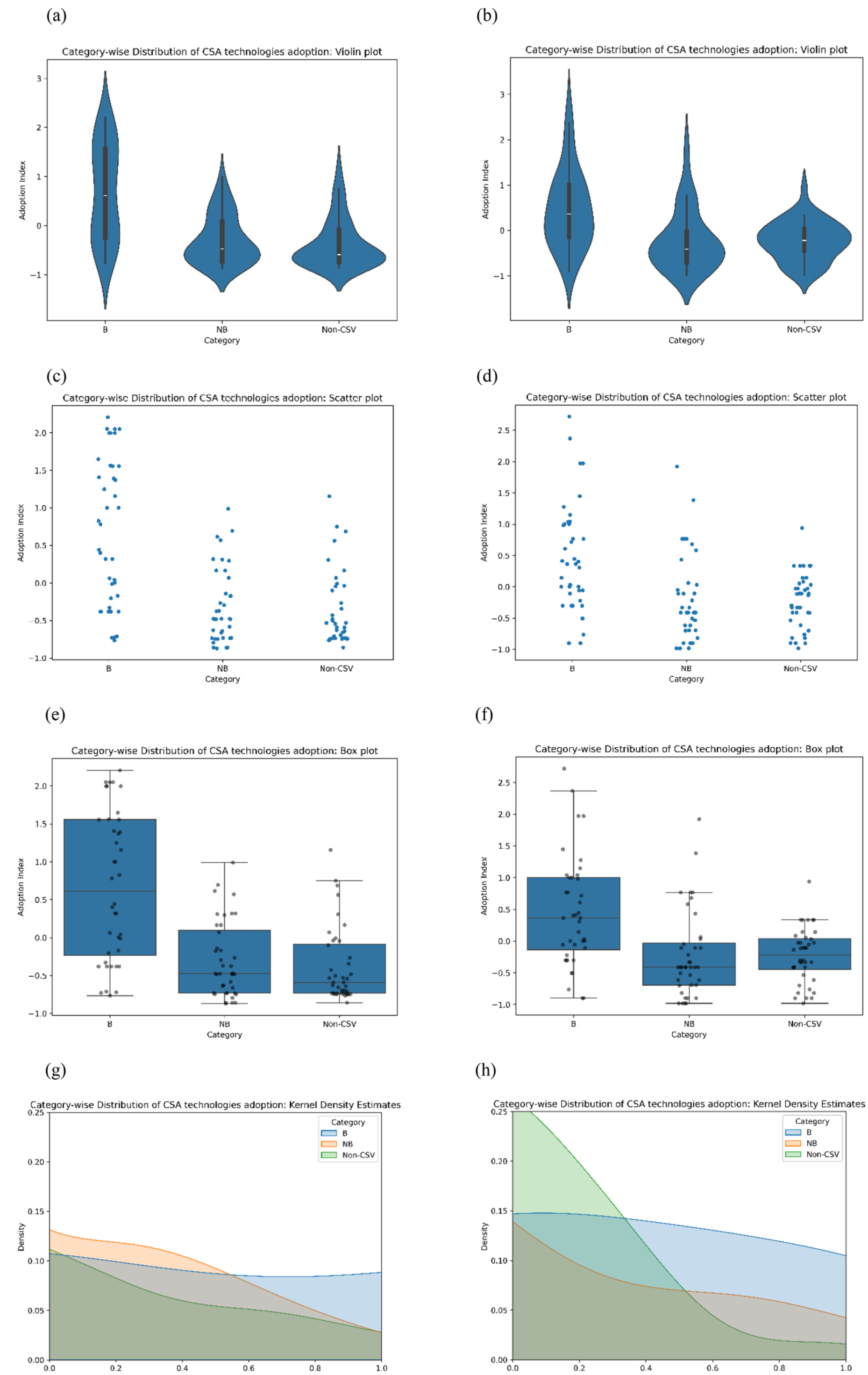

Fig. 7 Category-wise distribution of CSA practices adoption among beneficiaries (B), non-beneficiaries (NB) and CSV farmers in Kurukshetra (**a**, **c**, **e**, **g**) and Sirsa (**b**, **d**, **f**, **h**) districts

that adoption is highest among CSV target farmers, followed by CSV control farmers, and lowest among non-CSV farmers. The relatively higher adoption observed among CSV control farmers compared with non-CSV farmers provides clear evidence of a spillover effect associated with the implementation of CSVs. A series of robustness

Table 4 Multinomial logit estimation of propensity scores for generating inverse weights in both districts

Particulars	Kurukshetra district		Sirsa district	
	Target	Control	Target	Control
Age of the farmer	− 0.0213 (0.0200)	0.0022 (0.0174)	0.0213 (0.0223)	− 0.157 (0.0208)
Education of the farmer	0.0117 (0.0721)	− 0.0095 (0.0613)	− 0.0195 (0.0664)	−0.1405** (0.0644)
Family members	− 0.0679 (0.1851)	− 0.1386 (0.1497)	0.2628 (0.1612)	0.2327 (0.1569)
Working members	− 0.0762 (0.4210)	0.6499* (0.3618)	− 0.7209* (0.3871)	− 0.2465 (0.3619)
Institutional membership	0.9129** (0.4116)	− 0.2165 (0.4934)	1.0223 (0.6606)	0.7578 (0.7065)
Distance of destination for purchase/sale of inputs/produce	− 0.0002 (0.0880)	0.0479 (0.0769)	− 0.1684 (0.1326)	0.0329 (0.1529)
Operational holding	0.0176 (0.0263)	− 0.0170 (0.0266)	0.0439* (0.0265)	0.0014 (0.0293)
Livestock population	0.0262 (0.0625)	− 0.0060 (0.0906)	− 0.1397 (0.1335)	−0.3218** (0.1301)
Crop diversity index	8.8645*** (3.1309)	− 1.0604 (3.1098)	1.9014 (2.5394)	3.9085 (2.5201)
Constant	− 4.7713** (2.1025)	0.1042 (1.9657)	− 0.5308 (2.6713)	− 0.5529 (2.7488)
Number of observations	120		120	
LR Chi2	40.92		32.53	
Prob > Chi2	0.0016		0.0190	
Pseudo R2	0.1552		0.1234	
Log likelihood	− 111.3718		− 115.5674	

*10% level of significance, **5% level of significance, ***1% level of significance; σ: Standard Error. Numbers in parenthesis indicate standard error (σ)

checks confirm the validity and reliability of the IPWRA estimates. The Heckman selection model yielded an insignificant mills ratio, indicating the absence of selection bias. Reverse causality was assessed using placebo tests, in which the CSV treatment variable was regressed on predetermined characteristics such as farmers' age and education. The statistically insignificant coefficients confirm that treatment assignment does not predict these exogenous variables, thereby supporting the causal interpretation of the estimated effects. The Oster bounds test further indicated no evidence of omitted variable bias. In Kurukshetra district, the proportionality coefficient ($\delta = 2.45$) suggests that selection on unobservables would need to be 2.45 times stronger than selection on observables to nullify the estimated treatment effect. Moreover, both the observed and bounded coefficients remain positive, confirming the stability of the effect direction and ruling out sign reversal due to unobserved confounding. Similar results were obtained for Sirsa district ($\delta = 3.35$). Sensitivity to hidden bias was examined using Rosenbaum bounds. At $\Gamma = 1$, both sig + and sig- equal zero, confirming statistical significance under the assumption of no hidden bias. Importantly, even when unobserved confounders are assumed to increase the odds of CSA adoption by 2.5 times ($\Gamma = 2.5$), the estimated treatment effect remains highly significant ($p = 9.2\text{e}{-}10$) in Kurukshetra district and $p = 9.8\text{e}{-}10$ for Sirsa district), demonstrating robustness to substantial unobserved confounding. Finally, heterogeneity analysis using quantile treatment effects shows that the impact is consistent across different points of the outcome distribution.

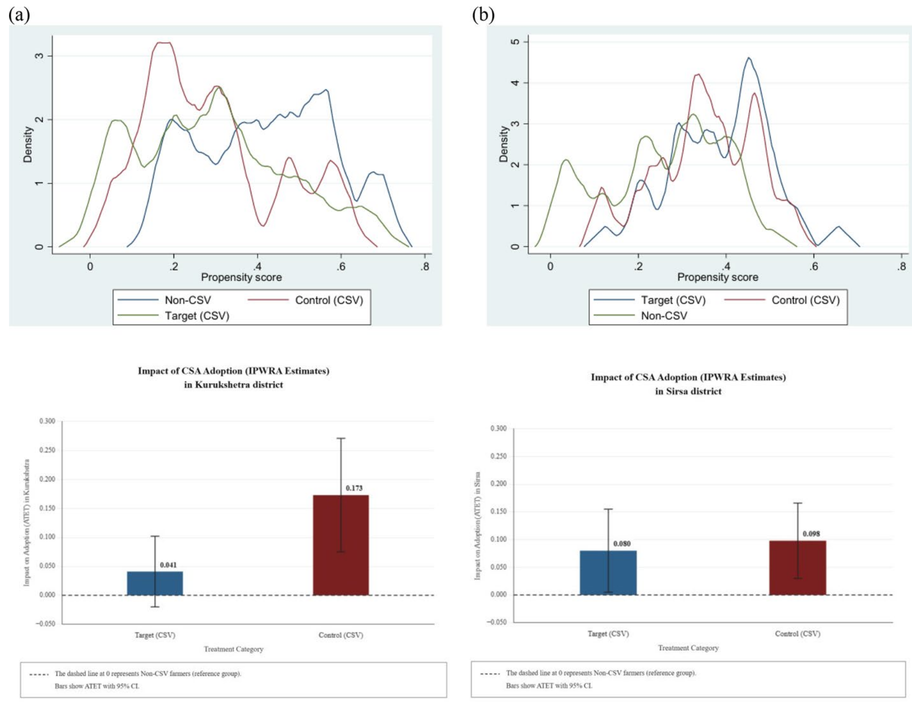

Fig. 8 Effect of farmers' assignment in a category on technology adoption for Kurukshetra district (**a**) and Sirsa district (**b**)

Table 5 Impact of farmers' category on adoption of agricultural technologies

Particulars	Kurukshetra district	Sirsa district		
	Coefficient	S.E	Coefficient	S.E
Target (CSV)	0.1732**	0.0552	0.0979**	0.0379
Control (CSV)	0.0411	0.0337	0.0799**	0.0375
Non-CSV farmers	0.1460***	0.0230	0.2471***	0.0226
Number of observations	120		120	

*10% level of significance, **5% level of significance, ***1% level of significance

5 Discussion and conclusion

By 2050, global food demand is projected to increase by 102% relative to 2009 levels [26], underscoring the urgent need for transformative agricultural innovations to address evolving climatic and socio-political challenges [97]. In India, food insecurity remains a critical public health concern, with nearly 200 million people projected to experience malnutrition [73]. Despite sustained economic growth and increased food production, these gains have not translated into proportional improvements in food security among vulnerable populations [76]. As a holistic approach, CSA has emerged as a strategic response, promoting adaptation, resilience, and food security [10, 52]. However, regional climate variability and diverse socio-economic and institutional contexts make CSA a complex, context-specific paradigm shaped by both global drivers and local dynamics [64], largely focused on policy discourse and intervention outcomes in developing-countries [51]. However, with increasing scope to combine modern and traditional adaptation strategies expand [92], a key question remains: How can governments, researchers, and rural development organisations effectively support farmers in navigating CSA complexity to enhance food security? Empirical evidence shows that CSA-aligned practices are energy- and input-efficient, improve livelihoods and food security, promote biodiversity, and enhance productivity [67, 69]. However, critiques of top-down CSA approaches highlight their limited ability to address structural inequalities in food systems [89]. Moreover, the strong focus on on-farm practices constraints mitigation potential, as the broader food system accounts for nearly one-third of global GHG emissions [17, 72]. Thus, CSA aims to support initiatives across scales that promote sustainable agricultural systems, ensure food and nutrition security, and integrate adaptation and mitigation while addressing equity and justice concerns [18].

To operationalise this ambition, three core objectives of CSA have been articulated: (i) sustainably increasing agricultural productivity to foster equitable income growth, food security, and inclusive development; (ii) reducing GHG emissions from agriculture relative to historical trajectories; and (iii) enhancing adaptation and resilience to climate change at both farm and national levels [95]. Achieving the third objective requires context-specific CSA interventions that explicitly incorporate farmers' perceptions of climate change, as well as their responses to key constraints and trade-offs. In this study, we adopt a social-learning perspective to advance the implementation and effectiveness of CSA, emphasising the inclusion of diverse farmer voices to build trust and improve outcomes [56]. Our findings provide empirical evidence that behavioural and cognitive factors play a critical role in shaping CSA adoption within a food security context. Consistent with previous studies (e.g. [33], [87]), socio-demographic characteristics such as education level and family size emerge as significant determinants of CSA adoption among treatment groups in the study area. Notably, farmers in Kurukshetra district exhibited higher overall awareness of climate change and CSA practices than those in Sirsa district. However, in both districts, CSV farmers consistently demonstrated greater awareness than non-CSV farmers, corroborating earlier findings [6, 80].

Overall, CSA practices such as the use of improved and stress-tolerant crop varieties and the laser land leveller were widely preferred across all farmer categories in both districts. The adoption of improved crop varieties is nearly universal, consistent with earlier findings [88]. Similarly, the laser land leveller—often used in combination with the happy seeder—has been adopted by more than three-quarters of farmers in both districts. This widespread uptake can be attributed to improved access to machinery and the availability of custom hiring services, along with recognised gains in water-use efficiency [14, 62]. In both districts, adoption of the laser land leveller is highest among CSV target farmers, followed by CSV control and non-CSV farmers,however, adoption rates are comparatively lower in Sirsa district. These patterns align with previous studies identifying the laser land leveller and happy seeder as part of an emerging suite of technologies promoted by national and international agencies to enhance crop productivity and indirectly mitigate food insecurity [84, 96]. In contrast, several CSA practices—including fodder management, integrated pest management, intercropping with legumes, rainwater harvesting, and drip irrigation—were adopted by only a small proportion of farmers, even among CSV target groups in Kurukshetra district. This limited uptake may reflect the strong entrenchment of existing inputs, technologies, and dominant cropping systems in the region, but also shaped by high cost and economic viability of some labour-saving technologies [3, 47]. Although the laser land leveller emerged as the dominant water-smart technology, other water management options such as drip and sprinkler irrigation and raised-bed planting remained largely negligible. Conversely, practices related to nutrient and information management—such as site-specific nutrient management, intercropping with legumes, green manuring, and ICT-based agrometeorological advisories—were more widely adopted, with significantly higher uptake among CSV target farmers than among CSV control and non-CSV farmers in both districts [7].With respect to information access, the findings underscore the importance of weather-related information disseminated through the internet, television, and interpersonal networks for both CSV and non-CSV farmers. This pattern is consistent with earlier studies highlighting the central role of mixed information channels in supporting climate-related decision-making in agriculture [68, 94].

Results from the multinomial logit estimations indicate that institutional membership emerged as a significant factor distinguishing CSV target farmers from non-CSV farmers in Kurukshetra, underscoring the importance of social and organisational linkages in programme participation [40, 42]. Crop diversity was also positively associated with target farmer status, suggesting that CSV farmers tend to maintain more diversified cropping systems. Findings from the IPWRA analysis further show that both CSV target (beneficiary) and CSV control (non-beneficiary) farmers exhibit significantly higher levels of CSA adoption than non-CSV farmers in both districts. The relatively higher adoption among CSV control farmers provides evidence of a spillover effect, whereby exposure to CSA interventions benefits farmers beyond the directly targeted. Interestingly, these findings diverge from recent studies that emphasise the role of personal norms—such as moral obligations to support collective goals like food security—in shaping farmers' acceptance of CSA practices [41, 98]. Instead, the results suggest that farmers are more likely to adopt CSA practices when they perceive tangible benefits and develop a sense of responsibility toward sustaining agricultural productivity and food security. This highlights the importance of strengthening education and training initiatives, which can play a critical role in fostering individual responsibility and long-term behavioural change. Such approaches are likely to yield more durable outcomes than strategies focused solely on financial incentives or the technical attributes of CSA practices, as they cultivate intrinsic, values-based motivation for adoption [83], [81]. However, the relatively higher adoption observed among CSV control farmers may partly reflect unobserved village-level confounders. Although key village-level characteristics were incorporated into the propensity score estimation to mitigate bias, the possibility of residual confounding cannot be entirely ruled out.

Limitations of this study should be acknowledged, which also highlight important directions for future research. First, although the empirical strategy and analytical framework establish robust associations between farmers' perspectives and CSA adoption, the cross-sectional nature of the data limits causal inference. Longitudinal studies are therefore needed to assess the sustained impacts of CSA adoption across heterogeneous farming communities [22] and to better understand how motivational factors—such as neighbourhood effects, perceived risks, and evolving policy environments—influence behavioural change over time [98]. In addition, integrating traditional farming knowledge into CSA-aligned water and land management strategies could enhance community acceptance and ensure that interventions are culturally appropriate and locally relevant [11, 21]. Second, this study focuses primarily on farmers as the central unit of analysis. However, the effective implementation of CSA practices often requires cross-sectoral and multi-actor collaboration. Future research should therefore examine how farmer heterogeneity shapes CSA adoption while incorporating perspectives from other rural stakeholders, such as union farms and irrigation districts authorities. Expanding the analytical scope in this way would provide a more comprehensive understanding of adaptive capacity and the role of CSA in fostering resilient agricultural systems, while also informing the integration of CSA trade-offs into local and regional policy frameworks. Extending research to additional villages is particularly important, as previous studies show that farmers engaged in CSA initiatives tend to exhibit higher awareness of climate variability and a greater propensity to adopt adaptive measures than non-CSV farmers [91]. Third, while this study emphasises farmers' perspectives and knowledge exchange—an approach widely recognised as critical for the co-design and scaling of CSA practices [4]—farmer-led assessments may overlook impacts beyond the farm level, such as groundwater recharge or landscape-scale environmental outcomes. Future research should therefore incorporate pre- and post-intervention assessments involving farmers alongside relevant agricultural stakeholders to better identify the drivers of systemic change at the village level. Engaging additional actors, including agricultural professionals and resource managers, is essential, as these stakeholders provide valuable insights into institutional dynamics and sectoral developments that shape the broader effectiveness and sustainability of CSA interventions [58].

Farmers have long navigated the challenges posed by weather variability; however, the increasing uncertainty associated with climate change necessitates greater adaptive capacity and more rapid response mechanisms. Strengthening resilience requires not only reducing the likelihood of food insecurity but also enhancing farmers' ability to anticipate, absorb, and respond effectively to climate-related risks. As CSA continues to evolve, future research should address existing gaps by exploring innovative financing mechanisms, improving pathways for technology dissemination, and assessing the long-term impacts of CSA practices on agricultural sustainability and food security [50, 54]. An important next step in advancing the CSA-food security nexus is to empirically examine the relationship between CSA adoption and household-level food security outcomes, particularly when considering the differences between both districts. In Kurukshetra, where higher levels of awareness and adoption were observed, the uptake of practices such as improved crop varieties, laser land levelling, and site-specific nutrient management is likely to contribute to greater yield stability, improved water-use efficiency, and reduced production risks—key dimensions of household food security. In contrast, relatively lower adoption levels in Sirsa suggest comparatively limited realisation of these benefits, potentially constraining gains in resilience and productivity. In both districts, however, the widespread adoption of resource-efficient technologies and the stronger engagement of CSV farmers with climate information services indicate improved capacity to anticipate and respond to climatic variability, thereby enhancing resilience and the reliability of food access. Moreover, the positive association between CSA adoption, crop diversification, and institutional participation highlights pathways through which adoption may support income stability and dietary diversity. These district-level differences provide indicative evidence that higher and more widespread CSA adoption—such that observed in Kurukshetra—can translate into stronger food security outcomes through productive gains, risk reduction, and enhance adaptive capacity, consisting with existing literature [15], [35].

Lastly, achieving effective climate change adaptation further requires a comprehensive approach that integrates knowledge, skills, and best management practices with technological innovation. This underscores the critical interdependence between farmers' awareness, perceived climate impacts, and adaptive capacity—factors that are shaped by supportive institutional arrangements and innovation systems [29]. In this regard, it is important to avoid one-size-fits-all strategies that risk misallocating (limited) resources, overlooking local constraints, even exacerbating existing inequalities. Instead, context-specific policy recommendations are needed to better align interventions with farmers' needs, enhance acceptability, and improve effectiveness. Key priorities include: 1) Strengthen farmer-centred extension and social learning platforms, by prioritising participatory and capacity-building programmes such as farmer field schools, peer learning groups, and demonstration plots, where peer influence and support can be reinforced, 2) Scaling up access to mechanisation services, as the widespread adoption of technologies such as laser land levellers and happy seeders highlights the importance of machinery access, for which policies should focus on expanding custom hiring centres in underserved areas—particularly in Sirsa district—to reduce barriers and promote equitable adoption; and 3) Enhancing institutional linkages and cooperation, given that institutional membership significantly influences adoption—especially in Kurukshetra district—, for which mechanisms to strengthening farmer producer organisations and cooperatives can facilitate farmer-to-farmer knowledge transfer and resource sharing. These strategies move beyond mere technology promotion by adopting integrated approaches that combine technological, behavioural, and institutional incentives, which are critical for strengthening climate resilience and enhancing food security.

Supplementary Information

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Supplementary Material 1.

Supplementary Material 2.

Supplementary Material 3.

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Author contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by M.K and D.P.M. The first draft of the manuscript was written by M.K, D.P.M and A.A.R. S.R provided guidelines on methodology, carried part of the analysis together with G.S.M. and N.K.K., and led the revision and preparation of the final draft, which was also read and approved by E.R.S.-Z. All authors commented on previous versions of the manuscript and read and approved the final version.

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Data availability

The data that support the findings of this study are not publicly available but may be shared from the authors upon reasonable request.

Declarations

Ethical approval and consent to participate

This study was reviewed by the Ethics Committee of the Department of Agricultural Economics, CCS Haryana Agricultural University, Hisar, Haryana**,** which determined that the research was observational in nature, for which a formal ethics committee approval was waived. All research procedures were performed in accordance with the ethical guidelines and regulations of the above committee and the principles outlined in the Declaration of Helsinki. Ethics compliance as per institutional policy, together with prevailing ethical guidelines for minimal-risk in social science research was ensured as the study involved adult, voluntary participation, confidentiality, anonymity of respondents, and no collection of sensitive personal data. Given the field-based nature of the study, verbal informed consent was obtained from all participants prior to their participation in the study. Participants were informed about the purpose of the research, the voluntary nature of participation, and the use of the data in publication. No sensitive data was collected, and confidentiality and anonymity were maintained throughout the study.

Consent to publication
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Competing interests
The authors declare no competing interests.

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