Does climate-smart agriculture technology improve the subjective well-being of farmers? Evidence from micro-level data

Sahoo, Dukhabandhu and Mohanty, Pritisudha and Mishra, Surbhi and Behera, Manash and Mohapatra, Souryabrata

Indian Institute of Technology Bhubaneswar, Indian Institute of Technology Bhubaneswar, Indian Institute of Technology Bhubaneswar, Indian Institute of Technology Bhubaneswar, National Council of Applied Economic Research

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Abstract

Since the global population is expected to reach 9.7 billion by 2050, food production must increase by 70% in the next 30 years to provide food security in the face of climate change. Implementing climate-smart agriculture technology (CSAT) is essential for ensuring food security and promoting economic growth in the context of sustainable agriculture. Climate change and weather patterns impact agricultural yield, necessitating the implementation of more efficient, productive, and climate-resilient techniques. However, the use of CSAT is a behavioural decision that affects the subjective well-being of the users. Using smart agricultural practices reduces climate change's impact on agricultural productivity and promotes sustainable agriculture, improving adopters' welfare. This study examines how the use of CSAT affects rural households' subjective well-being in Odisha, India. The result of the study shows that the marginal impact of CSAT use is 0.149, 0.181, and 0.144 for farmers whose intensity is 0.251-0.500, 0.501-0.750, and 0.751 and above, respectively, as compared to farmers whose intensity is 0.0-0.250. This implies greater satisfaction for farmers who engage in the moderate use of CSAT practices. Low utilization of technology may not yield benefits for farmers, while the adoption of advanced technology may not be economically viable. Additionally, CSAT is not easily available to households residing in low-lying areas, preventing them from improving their well-being. Only a small number of landowners in impoverished areas utilize CSAT. Therefore, it is necessary to evaluate government regulations regarding land and tenancy as well as develop measures for farmers to adapt to new technologies.

Keywords: Subjective well-being; Climate-smart agriculture technology; Land ownership; Beta regression

1 Introduction

The world's population is projected to grow by over 33% by 2050, necessitating significant changes to the existing agricultural system to meet the rising demand for food, according to the Food and Agriculture Organization (FAO, 2013). A recent report by FAO states that global food demand is expected to increase from 35% to 56% between 2010 and 2050 due to a shift in consumer preferences for food products (Dijk et al., 2021). Similarly, Mittal (2012) has projected India's food demand and supply up to 2026, highlighting that the surge in food demand is mainly driven by population growth and increasing per capita income. However, production is anticipated to be significantly hampered by low yield growth, posing a substantial challenge to meeting India's long-term food requirements through domestic production alone (Kumar et al., 2009). Another recent report states India's significant share of global food demand stands at 24.3%, second only to China at 16.7% (Islam et al., 2019). The United Nations' demographic projections estimate that by 2065, India's population will be about 1.718 billion, requiring 567 million tons of food. Additionally, a 60% increase in agricultural productivity is targeted to be achieved by the year 2050 for the entire globe. Hence, it is crucial to increase agricultural productivity to balance the supply and demand of food in light of the growing population and ensure food security (Fischer, 2018). However, the impact of climate change and the associated unpredictability of weather patterns make agricultural production fragile.

The mental health of the people involved in the value chain could be negatively impacted by climate change as well. Most of the time, small producers (e.g., smallholder farmers) are the ones who are forced to endure the most hardships as a result of their limited access to resources, innovative technologies, and financial capital (Badjeck et al., 2010; Shaffril et al., 2017). Climate change negatively affects people's mental health by contributing to social unrest and financial instability (Berry et al., 2010; Kam et al., 2023). This asks for a solution by which it is essential to alter the present agricultural practices to make them more efficient, productive, and less susceptible to climate change. Therefore, agricultural inputs ought to be more adaptable, and this can be brought about through the implementation of climate-smart technology by practitioners. It is a forward-thinking method of farming that lessens the impact of the unfavourable effects of climate change on agricultural production and helps move the industry closer to becoming more environmentally friendly.

In developing nations like India, the adoption of climate-smart technology has remained low. One of the probable reasons could be fear on the part of end users over the potentially negative effects of such technologies. Nevertheless, despite the huge gains in agricultural research and development, the usage of climate-smart technology remains limited in these countries. Conventional top-down and linear methods of creating and sharing agricultural innovations with end users have made little headway in encouraging technological adoption.

This is largely due to the fact that these processes are unable to recognize and support ongoing, interactive social learning and innovation processes that help farmers manage the changing complexity of their farming systems. Consequently, these procedures have demonstrated minimal advancement in encouraging the adoption of technology (Kilelu et al., 2013; Lundy et al., 2005).

A growing body of literature highlights the importance of adopting CSA worldwide. To understand the complexity of farming systems, it is important to gradually shift from a technology-focused approach to a more systems-focused one. Political influences, market infrastructure, institutional components, and interactions between the public and private sectors collectively influence the farming environment. The approach to a systems-centred one is highlighted to understand the complexity of farming systems better. (Kakzan et al., 2013; Thornton et al., 2018; Totin et al., 2018). Similarly, research indicates that the employment of CSA practices increases crop output, resource use efficiency, and farm income while simultaneously lowering greenhouse gas (GHG) emissions (Dinesh et al., 2015; Rosenstock et al., 2016; Ugochukwu and Phillips, 2018). By enhancing agricultural output and incomes sustainably, adapting to climate change, improving resilience, and reducing or eliminating greenhouse gas emissions, when practicable, the adaptation of CSA technology (CSAT) helps to achieve food and livelihood security as well as other developmental goals (FAO, 2013, 2010). Agricultural practices and technologies include minimum tillage, various crop planting techniques, irrigation, fertilizer management, and crop residue assimilation, which can increase crop yields, optimize the use of water and nutrients, and lower greenhouse gas emissions (Branca et al., 2011; Sapkota et al., 2015, 2014). According to Altieri and Nicholls (2017) and Mittal (2012), farmers can mitigate the adverse impacts of climate change and variability on agricultural operations by utilizing improved seeds, ICT-based agro-advisories, crop/livestock insurance, and rainwater harvesting. Therefore, it is assumed that CSA combines regionally relevant conventional and cutting-edge technology, practices, and services to help agriculture adjust to climate unpredictability and change so that it can enhance food security in general and the quality of life of the farmers in particular.

The quality of life, which is closely related to subjective well-being, can be understood as some non-income, social, behavioural, and demographic milestones that can be achieved by the farmers using CSAT. The importance of the economic well-being of the farmers cannot be downplayed, but too much importance given to it over subjective well-being or quality of life[1] may not be what the farmers desire. Mainstream development economics has portrayed and studied the human development index (HDI) and its components as the desired outcome variable for policy analysis and an indicator of well-being. Further, policy objectives like the enhancement of human capabilities and the reduction of absolute poverty are also given due consideration. The literature on development economics acknowledges the synergy between these policy objectives (Mehrotra and Delamonica, 2007; Mehrotra and Jolly, 2000; Mehrotra and Parida, 2021). Studies by Sen (1985, 1984) and Ranis et al. (2000) put human beings at the end and established that economic growth is important for enhancing capabilities and thus promoting human development. On the other hand, studies driven by the endogenous growth theory consider human beings as the means of economic growth (Krueger and Lindahl, 2001; Lucas, 1988; Romer, 1990).

In this context, without disregarding the contributions of the earlier studies, the current study investigates how the use of CSAT affects the subjective well-being (Quality of life) of the farmers of Odisha, India. The literature has used the concept of happiness as a strong indicator of the subjective well-being of an individual and/or household. It involves the holistic pleasure of an individual, which includes cultural, spiritual, social, political, economic, and psychological factors. This can be traced back to the days of Smith (Smith, 1776), who identified the importance of relative wealth on happiness. Subsequent thinkers like Bentham (1879)[2]and Jevons (1879) have also highlighted the importance of happiness in an individual's life, and the perspective of well-being is slowly shifting from profit to welfare (Pigou, 1912; Scitovsky, 1976; Sen, 1985). However, welfare economists had been analyzing the means of happiness (Ng, 1997) until 1972, when the 4th King of Bhutan (King Jigme Singey Wangchuck) drew the attention of the world to its new perspective of the gross national happiness (GNH) index. The idea behind this index is to maintain a balance between material, i.e., money and property, and non-material, i.e., culture, environment, spirituality, society, and community well-being of life (Gupta and Agrawal, 2017). This index gained the attention of policymakers in various countries around the world, and the United Nations General Assembly accepted happiness as an independent goal for all countries of the world in 2011. What better occasion than post-COVID-19 to make people understand the importance of happiness, which is the outcome of subjective well-being or the quality of life of

[1] Quality of life and Subjective wellbeing are used interchangeably in this study.
[2] His principle states that individuals should maximize pleasure and minimize pain.

individuals? Against this background, the research question to be addressed here is: What is the impact of the use of CSAT on the subjective well-being or quality of life of the farmers?

In order to answer the above-mentioned research question, the present study has tried to assess the impact of the use of CSAT on happiness (measured through the Index of Happiness, i.e., HI[3]). The well-being of the farmers could also have been captured in the form of economic outcomes such as farmers' income and/or food security. However, as mentioned earlier, subjective well-being or the quality of life is understood as some non-income, social, behavioural, and demographic milestones that are also affected by the culture and agroecological systems of the studied region, i.e., Odisha, India. Therefore, the HI is considered to represent the subjective well-being of the farmers and not their income and/or food security. The study used micro-level data collected from farmers using CSAT to understand the effect of its use on HI. The farmers are chosen through purposive sampling, thus making the findings limited to the sample. However, the findings of this study could be a guideline for researchers working in similar areas across the globe.

The remainder of the paper is structured as follows: Section 2 explores relevant literature, followed by the presentation of the study's methods and research design in Section 3. Section 4 delves into theoretical calculations, while Section 5 discusses the study's findings. Finally, Section 6 offers conclusions along with policy implications.

2 Related literature

It is essential to have a solid understanding of the connection between alterations in the climate and one's mental health. Easterlin (1974) presented the argument that traditional indices of well-being, such as income, cease to increase levels of happiness once a certain threshold is reached. Since then, social and economic scholars have paid greater attention to this topic. Because of this, judging someone's level of pleasure alone based on their financial circumstances is believed to be insufficient and fails to take into consideration other areas of life. Research on societal well-being has shifted towards examining subjective well-being indicators, including happiness and total life satisfaction (Rahman et al., 2022b). Since then, the evaluation of the effects of climate change has been shifted to focus on people's feelings of happiness and satisfaction. For instance, according to the findings of a study that examined

[3] Happiness is assumed as the outcome of subjective wellbeing of an individual in this study. The HI is expected to capture the subjective wellbeing of an individual.

the effects of climate change, the rise in temperature has had a negative influence on the mental health of those living in rural areas of states like Assam, Karnataka, Maharashtra, Rajasthan, Uttar Pradesh, and West Bengal of India (Pailler and Tsaneva, 2018). According to Berry et al. (2010), climate change can also affect people's mental health since it puts them in dangerous situations caused by extreme weather. According to Rehdanz and Maddison (2005), who used panel data from 67 different nations to study the topic, the effects of happiness are not uniform across all countries. This research indicates that global warming has positively influenced the happiness of people living in countries with low average winter temperatures. On the other hand, climate change has a detrimental impact on the happiness of people living in countries where the average temperature is high. In Indonesia, a recent study on the connection between climate disasters and subjective well-being conducted by Rahman et al. (2022a) showed that the effect was only significant among rural inhabitants, whereas it was insignificant among urban residents. They maintained that residents of rural areas are primarily dependent on natural resources such as agriculture and fisheries as their primary source of income, which makes them extremely susceptible to the effects of climate change. It is generally agreed that adaptation is the most effective strategy for mitigating the effects of climate change.

Researchers have attempted to identify the traits linked to individuals' subjective well-being, as scholars claim that subjective well-being is significant for human existence. However, the previous research has solely focused on how the usage of cell phones and the internet affects one's subjective well-being in the form of happiness and overall life satisfaction (Nie et al., 2021; Zheng et al., 2023a). Other studies concentrate on topics such as the influence of mobile payment adoption and online shopping (Zheng and Ma, 2022, 2021), participation in poverty alleviation programs and garbage classification (Li et al., 2023; Tang et al., 2021), options for cooking fuel (Ma et al., 2022), and working hours (Zheng et al., 2023b). However, there have been no studies that investigate the causal link between adapting to climate change through CSAT and one's subjective well-being, and this is especially true among small farmers. Further, recent research suggests that for the successful adoption of CSAT and practices, it is crucial for researchers and development practitioners to consider innovations in the agricultural systems approach.

These innovations encompass various social and economic activities that are associated with the creation, dissemination, adaptation, and utilization of new technical, institutional, and organizational knowledge and resources. This consideration is essential for the overall benefit of all stakeholders involved (Adekunle and Fatunbi, 2012; Hall, 2005; Hall et al., 2006). The concept of innovation platforms has gained recognition as a potential driver for enhancing the involvement of smallholder farmers in markets, fostering inclusive agricultural innovation, and facilitating knowledge exchange within the agricultural systems framework (Adekunle and Fatunbi, 2012; Schut et al., 2017). According to Schut et al. (2017), intellectual properties have the potential to facilitate the establishment of social networks, which can effectively promote the mobilization of essential resources for enhancing the adoption and dissemination of agricultural technology and information. This can be achieved through dynamic interactions and knowledge sharing among various stakeholders. The construction of such networks aligns with theoretical and empirical studies that see social capital as some valuable asset individuals can utilize to navigate challenges in their everyday experiences (Obaa and Mazur, 2017; Small, 2009). The relationship between well-being and climate change, as well as the adaptation of CSAT, is depicted in Figure 1.

[Figure 1 here]

The concept of social capital[4], although initially established in 1916, was later associated with economic growth and development in the year 1902 (Lollo, 2012). According to Putnam (1993), it was anticipated that social capital would play a role in enabling the establishment of a platform for attaining economic progress. Nevertheless, there exists a lack of consensus among scholars over the precise definition of social capital (Chou, 2006; Ng'ang'a et al., 2016; Sabatini, 2006), resulting in a lack of clarity surrounding the idea. The literature commonly refers to networks, norms, and trust in social interactions as key components of social capital. These elements play a crucial role in enabling individuals to collaborate and coordinate their efforts towards achieving shared objectives and reciprocal benefits (Narayan and Cassidy, 2001; Putnam, 1993). The lack of clarity surrounding the concept renders its quantitative measurement more challenging. Although there are difficulties in defining and quantifying social capital, extensive research has supported the idea that its main benefit lies in facilitating the exchange of information among individuals, thereby potentially enhancing the adoption of various processes (Läpple and Rensburg, 2011; Micheels and Nolan, 2016; Ramirez, 2013). In the study conducted by Pannell et al. (2006), it was found that the process of adoption encompasses the acquisition of knowledge and the cultivation of practical abilities. Furthermore, in relation to the discourse on the socio-cultural aspect of learning,

[4] For a detailed definition of social capital, see Claridge (2004)

Eastwood et al. (2012) assert that the incorporation of technology represents merely a superficial aspect of forthcoming transformations in management methodologies and the assimilation of novel technologies. They argue that networks and trust play pivotal roles as the main catalysts driving this dynamic process. In addition to the evident advantages associated with this sort of engagement, it is important to acknowledge the potential negative consequences that may arise. For example, instances where technological deficiencies hinder the performance of certain farmers can lead to a widespread rejection of the technology within the community. According to Agurto-Adrianzen (2009), it was observed that rural families had a stronger reaction towards the unsatisfactory performance of new technology compared to its satisfactory performance.

Numerous scholarly works have recognized the significance of integrating climate-smart technology adaptation in agriculture as a means to enhance productivity (Amertet et al., 2023; Bhavani et al., 2023; Daum, 2023; Khatri-Chhetri et al., 2017; Kiani et al., 2022; Mwongera et al., 2017; Patle et al., 2019; Rosenstock et al., 2016; Sayed et al., 2022; Senyolo et al., 2018; Zougmoré et al., 2016). Likewise, scholarly investigations have examined the determinants of climate-smart technology utilization, with Tanti (2022) delving into institutional, social, and other pertinent issues. The phenomenon of technology adoption in the agricultural sector has been extensively examined using a standard utility model, which considers the key determinants to be the characteristics of farmers (referred to as human capital) and the structure of farms (referred to as physical capital) (Abdulai et al., 2011; Abdulai and Huffman, 2014; Foster and Rosenzweig, 2010; Wossen et al., 2015). These studies fail to acknowledge the interdependence between individual decision-making and the broader societal framework (Oreszczyn et al., 2010). Moreover, this intricate social structure plays a significant role in shaping institutions that cater to the comprehensive needs of individuals, encompassing their physical, economic, and cultural aspects. As previously mentioned, this study argues that elements associated with social capital play a key role in the adoption decision-making process. Nevertheless, the manner in which the different components of social capital interact to influence the conduct of the producer remains ambiguous. Gaining an understanding of these relationships may yield valuable insights into the social capital elements that have the potential to impact decision-making processes and ultimately shape individual behaviour. This statement presents two inquiries. The inquiry pertains to the correlation between social capital and the use of technology by farmers, as well as the interrelationships among various dimensions of social capital. Hence, it is imperative to construct a Social Capital Framework (SCF) in order to comprehensively comprehend the collective influence of various forms of capital on the technology adoption process, particularly in relation to climate-smart technologies. This is particularly relevant given the evolving agricultural practices resulting from the challenges posed by climate change. The present study is an earnest attempt to contribute towards achieving this objective.

3 Material and methods

3.1 Data, sampling and analytical framework

The study employed a combination of multi-stage simple random sampling and judgmental sampling procedures. The unit of observation consists of households that are directly or indirectly engaged in agricultural and/or allied activities. Hence, this study has utilized primary data obtained from households (chosen using appropriate sampling methodology) to derive pertinent results. The current study utilized primary data obtained from rural agrarian households in Odisha, India, in October 2019. Odisha is located on the eastern coast of India, adjacent to the Bay of Bengal. It shares its boundaries with Jharkhand to the north, West Bengal to the northeast, Chhattisgarh to the west, and Andhra Pradesh to the south. The total area covered is 155,701 square kilometres. The state possesses a wide range of meteorological conditions and boasts a coastline that stretches over 480 kilometres. The climate is primarily tropical, marked by elevated temperatures, high levels of humidity, moderate to substantial precipitation, and mild winters. The annual average normal rainfall is 1451 mm, with around 75-80% of it occurring from June to September[5]. Despite the state experiencing significant levels of precipitation, it is prone to frequent occurrences of natural disasters such as droughts, floods, and cyclones. The collection of primary data was done using a self-administered, semi-open questionnaire that was specifically designed for this study. Prior to the data collection, a preliminary survey (pilot study) was conducted to verify the validity of the questionnaire.

[5] Department of Agriculture and Farmers 'Empowerment, Government of Odisha. https://agri.odisha.gov.in/

3.2 Universe of the study

The research is conducted in Odisha, which is situated in eastern India. Odisha is geographically divided into ten distinct agro-climatic zones (ACZs), as indicated in Table 1. Each ACZ is characterized by specific agro-climatic factors, making them unique and distinct from one another. In order to comprehend the correlation between social capital and the utilization of climate-smart agricultural equipment, a sample of agrarian households from all ACZs must be included.

[Table 1 here]

3.3 Selection of sample units

Each ACZ consists of varying numbers of revenue districts or portions thereof based on factors such as climate, annual rainfall, and soil type. Each ACZ can be regarded as a uniform group and, therefore, a distinct layer. In order to accurately represent the ACZs, certain districts were chosen using the proportional sampling method. For example, since the North Western Plateau ACZ is made up of two districts, Sundargarh and Deogarh, only Sundargarh was selected for the sample. On the other hand, four districts, Cuttack (P), Nayagarh, Puri, and Khurda, were selected from the East and South Eastern plateaus for the sample. This method of proportional sampling would ensure that the ACZs are represented proportionally in the final sample process (see Table 1). The current study encompasses 17 revenue districts, which represents a portion of the total 30 districts in Odisha.

Following the district selection process, one revenue block was chosen from each district in Odisha using a simple random procedure. Revenue blocks are administrative units within each district. We obtained a cumulative count of 17 blocks spread over ten administrative and civil zones in the state of Odisha. One gram panchayat (GP) was randomly selected from each income block using the lottery method of simple random sampling. After the selection of GPs, two revenue villages were chosen from each GP using a combination of judgmental sampling and a simple random sampling procedure. The process of choosing revenue villages involved gathering socioeconomic and demographic data at the village level from the 2011 census database. It has been noted that certain general practitioners have villages with a small number of families, some of which have less than 20. Thus, in this phase of the sampling procedure, a blend of judgmental sampling and simple random sampling was employed to ensure that the chosen village has a minimum of 30 households engaged in agricultural and related activities, either directly or indirectly.

In addition, the distance between the village and the GP office was considered when selecting settlements. One village was chosen in close proximity to the GP office, and another community was located at a significant distance from the GP office. This factor was taken into account, as it is believed that the village located closer to the GP office (the office responsible for managing and regulating various policy interventions and providing extension services to farmers) may receive the advantages of government policy interventions and extension services more effectively than a village located farther away from the GP office (according to the Singer-Prebish hypothesis, which relates to the relationship between the centre and the periphery). The current study encompassed a total of 34 villages, with two villages selected from each GP. Once the villages were chosen, information regarding the socioeconomic and demographic characteristics of the households was gathered from the 2011 census data. In addition, a meeting was conducted with the village leaders and the sarpanch (the elected representative of the GP) to enhance the household information gathered from the 2011 census data. A judgmental selection technique was used to pick 30 households from each village, ensuring that the selected sample households adequately represented varied degrees of landholding, asset ownership, income, education, sanitary facilities, caste, and religion. The current study includes a total of 1020 sample households for the purpose of data collection and analysis. Specifically, 30 families were selected from each of the 34 villages. Nevertheless, following a meticulous screening and purification of the data, the resulting sample size taken is 1001, which is considered to be an effective sample size.

4 Theory/calculation

As mentioned earlier, the present study tries to capture the subjective well-being of the farmers through their happiness. Therefore, CSAT uses an index of happiness (HI) to reflect the subjective well-being of the farmers. This HI was developed for the farmers adopting CSAT in Odisha in line with the studies by Lyubomirsky and Lepper (1999) and Diener et al. (1985). There are no studies that developed HI for the farmers adopting CSAT, though a few studies, like Rohit et al. (2023) and Patel (2022), used Likert scales to measure the happiness of farmers based on CSAT. However, in the present study, we have tried to modify the questions asked to the farmers to capture the different components of HI, keeping in mind the requirements of our study. A survey schedule was drafted to capture the multiple aspects of subjective well-being (happiness) of the farmers adopting CSAT (for the entire household). The responses of the farmers on various attributes of these aspects are collected on a 5-point Likert scale: 1=Strongly Disagree, 2=Disagree,3=No idea,4=Agree, and 5=Strongly Agree. The questions are: (1) In general, we consider ourselves happy; (2) Compared to my peer farmers, we consider ourselves happy; (3) In most ways, our lives are close to our ideal; (4) We are satisfied with the technology we use in our agricultural practices; (5) We are satisfied with the technology used by our peer farmers; (6) The use of CSAT has helped us to get most of the things we wanted in life; (7) The use of CSAT has helped us to get better of our counterpart; (8) The use of CSAT has stabilized our farm income; (9) Compared to our neighbours, our farm income is more stable; (10) Most people are happy in their lives irrespective of what is going on; you identify yourself (your family) as one among them. An index is constructed by using the household response to the above-mentioned questions through the principal component analysis (PCA)[6] method. The construction of the index through the PCA method is described as follows:

$$HI(PCA) = \frac{(\sum_{i=1}^{n} \lambda_i P_i)}{\sum_{i=1}^{n} \lambda_i} \tag{1}$$

where I =1, 2,10, P_i's are the Principal Components (defined as normalized linear combinations) of attributes with correlation coefficients between P_i and P_j as zero, λ_i's are eigenvalues of the correlation matrix of different dimensions, and $\lambda_1 > \lambda_2 > \ldots > \lambda_n$. Once the index is created, it is standardized as follows:

$$HI = \frac{Actual\ value - Minimum\ value}{Maximum\ value - Minimum\ value}$$

Further, the present study has identified 18 different types of CSAT practices adopted by the farmers of Odisha. Therefore, a CSAT adaptation index (CSATAI) is developed to understand the intensity of the use of CSAT by a farming household. The CSAT practices are: *1. Seed variety (climate resilient varieties); 2. Pest control (natural pest control like bio pest control); 3. Fertiliser use (organic fertilizer use); 4. Soil test; 5. Row planting; 6. Irrigation; 7. Composting (Bio composting); 8. Marketing (use of information and communication technology like online marketing); 9. Access to credit (formal credit); 10.*

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[6] For a detailed discussion on PCA see Kumar et.al. (2007)

Insurance (against any crop failure due to climate change); 11. Tractor; 12. Power tiller; 13. Seed sowing machine; 14. Sprayer; 15. Weeding machine; 16. Crop-cutting machine; 17. Fan; 18. Storage facility (like cold storage to reduce waste and market the produce where there is a dearth of supply). The CSATAI is determined using the weighted arithmetic mean approach (the weights being uniform) and is defined as:

$$CSATAI = \frac{\sum_{1}^{18} I_i}{18} \quad (2)$$

A value of "1" is assigned to households that possess and/or adapt any technology, while a value of "0" is assigned to households that do not possess any technology. The household with all the technology has CSATAI =1, and the household with no indicators have CSATAI = 0. Thus, the value of CSATAI lies between 0 and 1, i.e.,$0 \leq CSATAI \leq 1$. For empirical estimation purposes, however, there is an issue with the dependent variable being a fraction. In the present case, the Regression equation would be like this:

$$HI = (IV)\beta + \varepsilon \quad (3)$$

where "ε" is the error term assumed to satisfy all the assumptions of the CLR technique, IV is the matrix of all independent variables, including intercept, intercept dummy, and slope dummy, and β is the vector of regression coefficients. Here, the population assumption under CLR should be:

$$E(HI) \sim Normal\left((IV)\hat{\beta}, \sigma_{\varepsilon}^{2}\right) \quad (4)$$

where "σ_{ε}^{2}" is$Var(\varepsilon)$. This normality assumption of "HI" is not reasonable as it is a ratio. This gives rise to two types of problems: firstly, the problem of heteroscedasticity, which implies the variance is smaller near the extreme values. The second problem is with respect to the asymmetry of the distribution, which violates the normal assumption. Therefore, it is more acceptable to utilize a regression model that assumes that the dependent variable follows a continuous distribution supporting the value between zero and one. In the literature, such regression models are now available, known as the Beta regression model (Cepeda and Gamerman, 2005; Ferrari and Cribari-Neto, 2004; Kieschnick and McCullough, 2003; Paolino, 2001). Following Carrasco et al. (2014), the beta regression model for the present study is specified, estimated, interpreted, and discussed as follows:

$$HI = (IV)\beta + u \quad (5)$$

where $E(HI) \sim Beta\left((IV)\hat{\beta}, \sigma_u^2\right)$ and $u \sim N\{0, \sigma_u^2\}$. Further, the marginal effect of the independent variables is interpreted and compared. The estimation is done through the statistical software STATA 13.0 edition (Bruin, 2006). Table 2 displays the descriptions of the dependent and independent variables utilized in the research.

[Table 2 here]

5 Results and discussion

The overall effective number of households for the study is 1001. Table 3 displays the summary statistics for all the factors outlined in Table 2. A perusal of Table 3 reveals that the mean scores of HI, CSATAI, levels of social capital (LSC), agricultural expenditure (LAE), sanitation index (LSI), human development index of the household (HHDI) and land index (LLI) are 0.421, 0.464, 0.370, 0.052, 0.393, 0.074, and, 0.038 respectively, which is comparatively low. However, the average score of the households that have knowledge about CSAT is 0.818. This implies that a fairly good number of households have ideas about CSAT. The low adoption rate of the CSAT may be attributed to several factors.

[Table 3 here]

Figure 2 depicts the crosstab of the level of happiness with the intensity of CSATAI and agricultural expenditure. In fact, it shows that 31.17% of households with low levels of CSATAI ranging from 0.251-0.500 have low levels of happiness. Furthermore, the level of happiness is higher for households with low levels of agricultural expenditure, followed by middle expenditure groups. Further, Figure 3 shows that the level of happiness is higher in households of the age group below 60 than in households above 60 years. Similarly, people living in joint families are happier than those in nuclear families. The study revealed that happiness levels are higher in families led by males compared to those led by females.

[Figure 2 here]

[Figure 3 here]

A perusal of Figure 4 shows that the OBC category households have a higher level of happiness, followed by the SC and ST categories, whereas the general category households have the lowest level of happiness. Further, households with LSI ranging from 0.501-0.750 have higher levels of happiness in comparison to households with other levels of sanitation, and the level of sanitation is the lowest in the case of households ranging from 0.751 and above. Figure 5 shows HHDI plots that show that households with low levels of HDI have the highest level of happiness, followed by households with middle HDI group, ranging from 0.251-0. 500. The households where males make agricultural decisions are found to be happier than those in female-headed households. The level of happiness is average in the case of families where both parties make agricultural decisions. Furthermore, the level of happiness is higher for households that do not have knowledge about the CSAT than for knowledgeable households.

[Figure 4 here]

[Figure 5 here]

Figure 6 demonstrates the crosstab of the level of happiness with the level of education and land holdings. It depicts that households with secondary education have the highest level of happiness, followed by households with primary education. On the contrary, the level of happiness is lowest in households with higher education. Moreover, households with less land ownership exhibit the highest happiness levels in the land index. Table 9 shows that the level of happiness is highest for those households where women were not using CSAT due to inadequate skills. The level of happiness is lower for some women due to some socio-cultural factors. In addition to this, households with male land ownership have the highest level of happiness. On the other hand, the level of happiness is lowest for households that do not have any land ownership. Figure 7 depicts the crosstab of the level of happiness with LSC. It shows that almost half of the households (49.45%), whose LSC varies from 0.251-0.500, have the highest level of happiness. On the other hand, households with the highest LSC have a minimal level of happiness.

[Figure 6 here]

[Figure 7 here]

Table 4 displays the outcomes of the beta regression model and the impact of the independent factors on the dependent variable. A perusal of the result reveals that the adaptation of the CSAT increases farmers' happiness. The result reveals that the marginal effect of the use of CSAT on the happiness of the farmers is 0.149, 0.181 and, 0.144 for the farmers whose intensity of use of CSAT is between 0.251-0.500, 0.501-0.750 and, 0.751 and above respectively, over the farmers whose level of CSAT use is in between 0.0 to 0.250. This implies that farmers using moderate levels of CSAT are happier than otherwise. This may be due to the fact that at a lower level of technology use, the farmers may not be able to reap the benefits, and at a higher level of technology use, the cost involved may not have that effect on the farmers. The households with a moderate LSC (0.251-0.500) have a negative impact on the happiness of the farmers. The marginal effect of the LSC for these groups of farmers on their happiness is -0.047 in comparison to the farmers having a lower LSC (0.00-0.250). However, one interesting observation from the result is that with the increase in LSC among the farmers, the level of happiness is increasing (the coefficient of LSC at the level of 0.501-0.750 is positive, though significant at the 12% level). This justifies the importance of social capital in promoting happiness among farmers.

[Table 4 here]

The LAE is an indicator of the extent of use of CSAT. The beta regression result reveals that the HI increases by 0.083, 0.328 and 0.095 for a unit level change in AE 0.251-0.500, 0.501-0.750 and 0.751 and above, respectively, over the farmers whose level of AE is between 0.0 and 0.250. This shows that farmers who spend a moderate amount on their agricultural activities achieve relatively better happiness. This result is also supported by the use of CSAT. The HI increases for the tribal community (ST), though it reduces for the OBC in comparison to the SC communities. This explores some cast and community dynamics of the subjective well-being of the people. In fact, tribal communities residing mostly away from the mainland are generally happy with their limited belongings when they live with nature. Further, the result indicated that with growing age, which brings in experience, farming households tend to adopt the CSAT, which further improves their happiness. The analysis shows that the gender of the head of the home and the family type do not affect the family's satisfaction.

Further, the level of health infrastructure of the households, as indicated by the level of sanitation, shows that the marginal effect on happiness goes up by 0.108 for sanitation level 0.251-0.500, compared to families with a sanitation level of 0.0 to 0.250. The coefficients are insignificant for higher levels of sanitation. This implies that these rural households are happy with some minimal sanitation facilities. On the other hand, the effect of the level of human capital (level of HDI) on the happiness of these farming households reveals that at a lower level of human capital, people are not happy. However, the marginal effect of the HDI level (0.501-0.750) on happiness is 0.138, which implies that people are happy at a higher level of

HDI. Similarly, the marginal effect of secondary education on happiness is 0.058, whereas the effect of primary education and higher education has hardly any effect on the happiness of these people. This shows that the level of education (secondary in this case) that helps these households to adopt CSAT improves the happiness of the people; primary education does not help the use, and higher education may not be relevant to the use of CSAT by the households.

The land index is a major natural and/or physical capital for agrarian households that affects the decision of the household to use CSAT and, ultimately, their income, livelihood, and happiness. Surprisingly, the results reveal that the marginal effect of the land index is negative (-0.192) on happiness for households having a LLI in the range of 0.251-0.500, and for a higher level, the effects are insignificant. This implies that households with less land (at times fragmented land) have less opportunity to use CSAT and thus are unable to uplift their well-being. On the other hand, few landlords have kept their land barren and are indifferent to the use of CSAT. Regardless of the reasons—whether it is not women-friendly, lack of adequate skills, or socio-cultural factors—in households where women do not use the CSAT, the marginal effect on happiness is negative. This implies that if we can promote CSATs that are women-friendly, then agrarian households may be inclined to use CSATs, which ultimately raises subjective well-being. In households where females are involved in agricultural decisions, happiness increases. However, the happiness of the sample agrarian household is not affected by the ownership of the land (i.e., it does not matter whether the land is owned by the male or female members of the household).

6 Conclusions

The intensity of CSAT use as a behavioural decision in rural households can and will alter adopters' subjective well-being. The findings show that using CSAT increases farmers' happiness (HI). Farmers with moderate use of CSAT are the happiest, according to the results. This may be because farmers may not gain the benefits of technology at lower levels, and the costs might be too high at higher levels of CSAT use. Households with lower social capital have lower farmer satisfaction. One noteworthy finding is that farmers with higher LSCs are happier (although the coefficients are not significant). This shows how social capital helps farmers increase their happiness. Farmers who spend moderately on agriculture report higher-than-average satisfaction. Since they live near nature, secluded indigenous tribes are content with their little things, which make them happy. The result also showed that agricultural households are more likely to apply CSAT as people get older and more experienced, which boosts happiness. Farmers with a higher HDI are satisfied and want better health care and education for their families. However, CSAT is less accessible to households with less land or fragmented land, preventing them from improving their quality of life. Further, few landowners have kept their property undeveloped and do not employ CSAT. This requires revisiting government land and tenancy policies. The full worth of these CSATs can be determined by analyzing crop productivity, socioeconomic, and soil health data over time.

Nevertheless, the study holds significant inferences for similar regions globally, particularly in promoting the adoption of CSAT and enhancing the subjective well-being of rural households. First, it underscores the necessity for policymakers to review and potentially revise existing technology adoption policies to incentivize and facilitate the uptake of CSAT among farmers. Second, the study emphasizes the importance of customizing CSAT interventions to suit the unique contexts of different regions, highlighting the requirement for needs assessments and tailored solutions to maximize their impact on farmers' well-being. Third, it brings attention to the role of social capital in influencing farmers' happiness, indicating the significance of fostering community cohesion, promoting collective action, and strengthening social networks to support technology adoption and improve well-being. Fourth, the study underscores the challenge of land fragmentation as a barrier to CSAT adoption, calling for policy reforms to address land tenure issues and provide support mechanisms for smallholder farmers. Last, it emphasizes the importance of inclusive and equitable approaches to technology adoption, advocating for targeted interventions that reach marginalized groups such as indigenous tribes and households with limited land resources.

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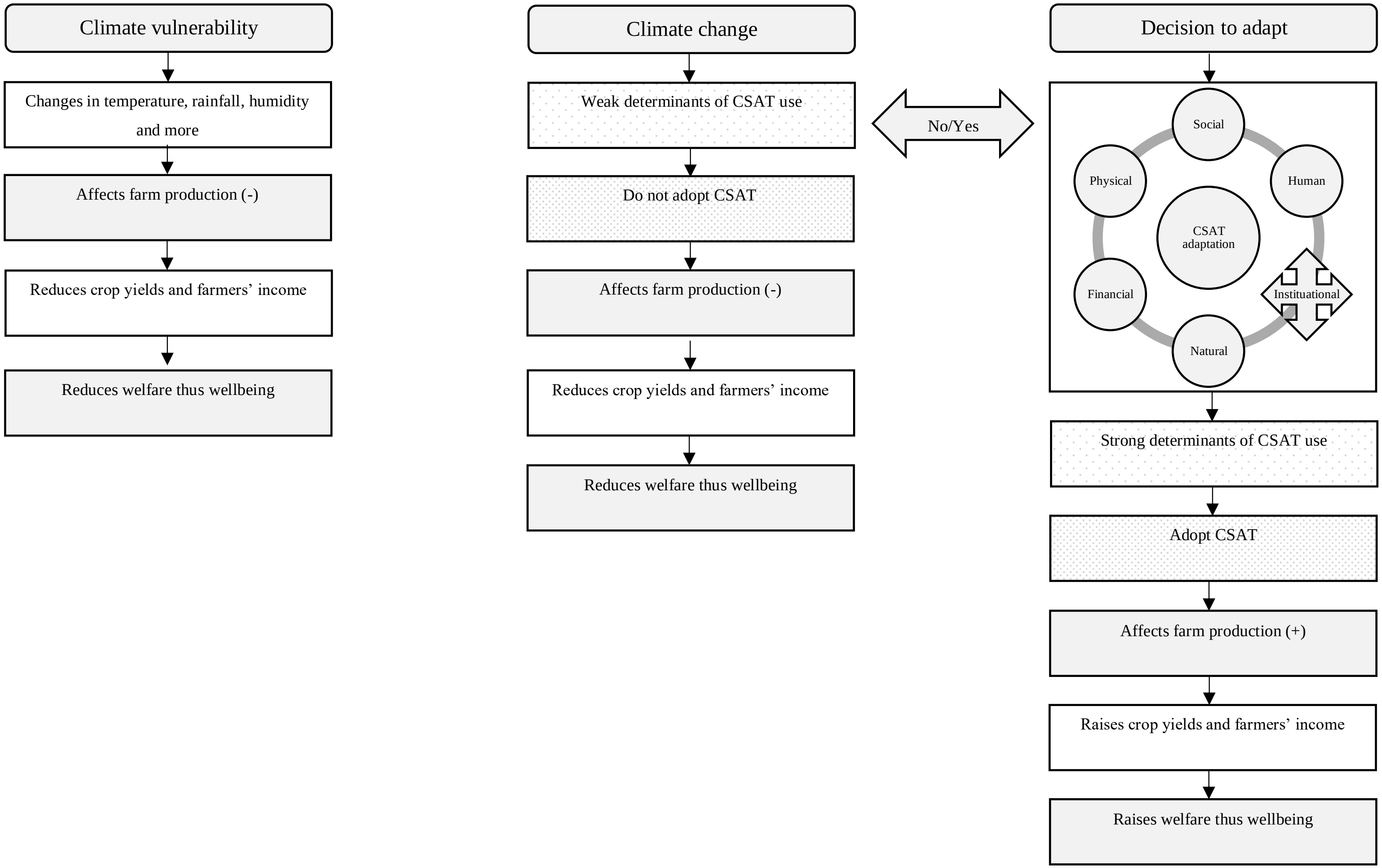
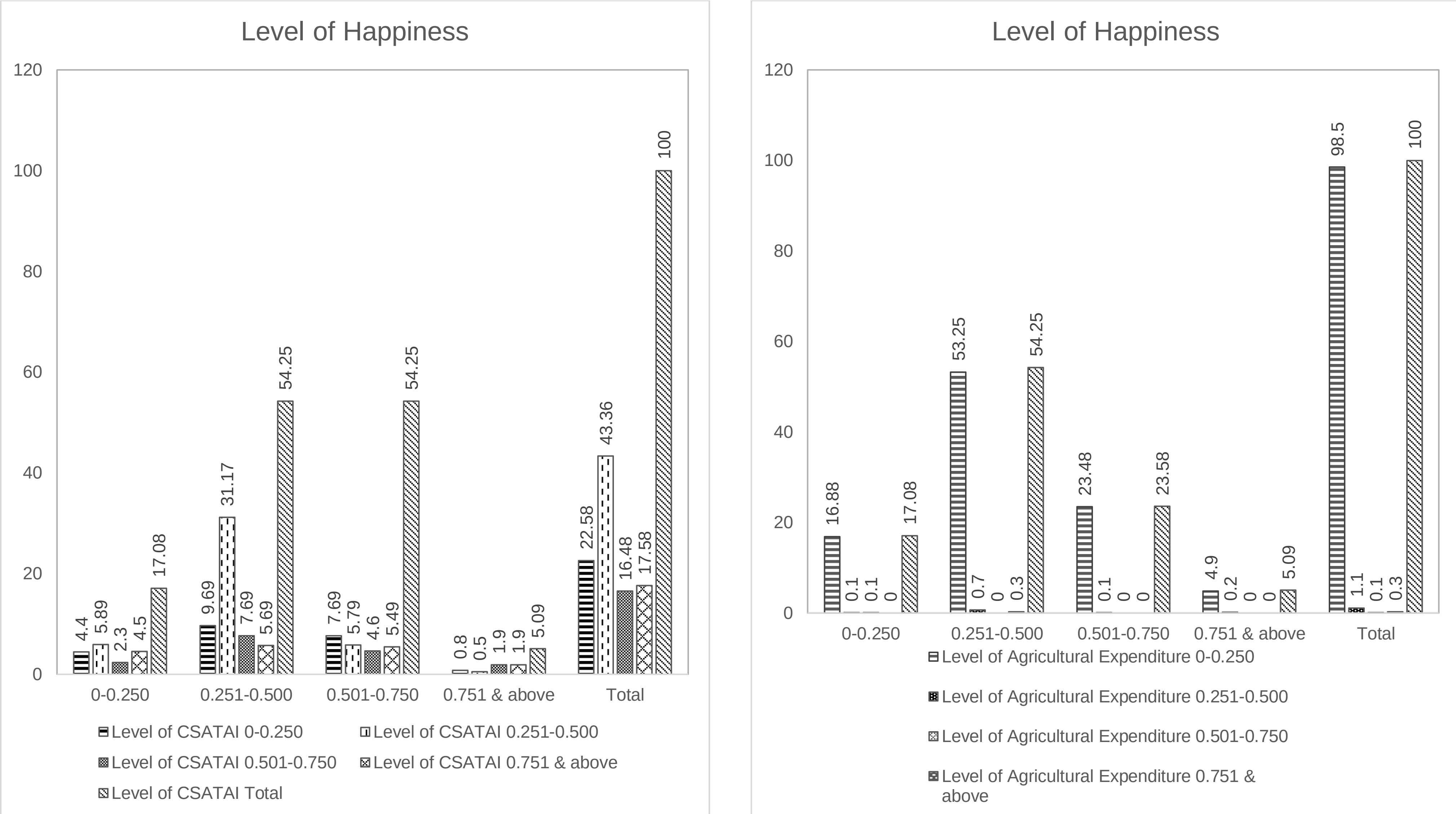
Figures

Figure 1. Conceptual framework of the relation between adaptation of CSAT and the well-being of the farmers



Source: Authors' construct.
Note: CSAT represents climate-smart agricultural technology.

Figure 2. Cross-referencing the level of happiness with the intensity of the climate-smart agricultural technology adaptation index (CSATAI) and the level of agricultural expenditure (LAE) (%)



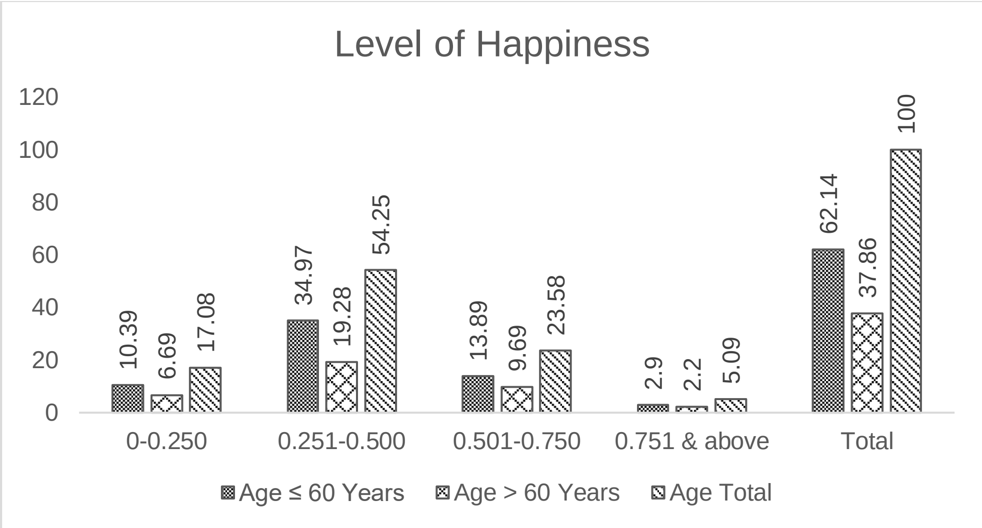
Pearson $\chi^2(9) = 134.0539^{***}$; Kendall's τ = 0.0448; ASE = 0.032

Pearson$\chi^2(9) = 12.7174$; Kendall's τ = 12.7174; ASE = 0.028

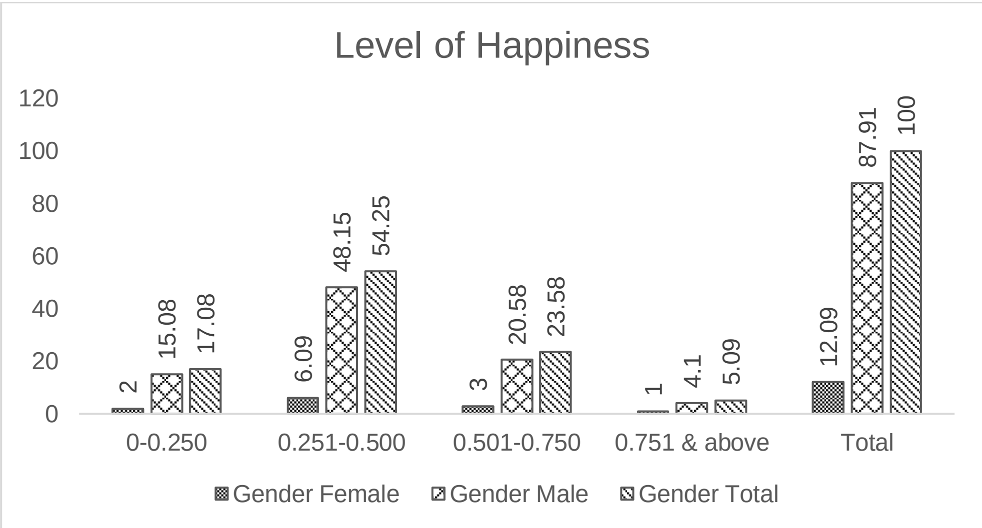
Source: Authors' construct

Note: *** denotes a 1% level of significance.

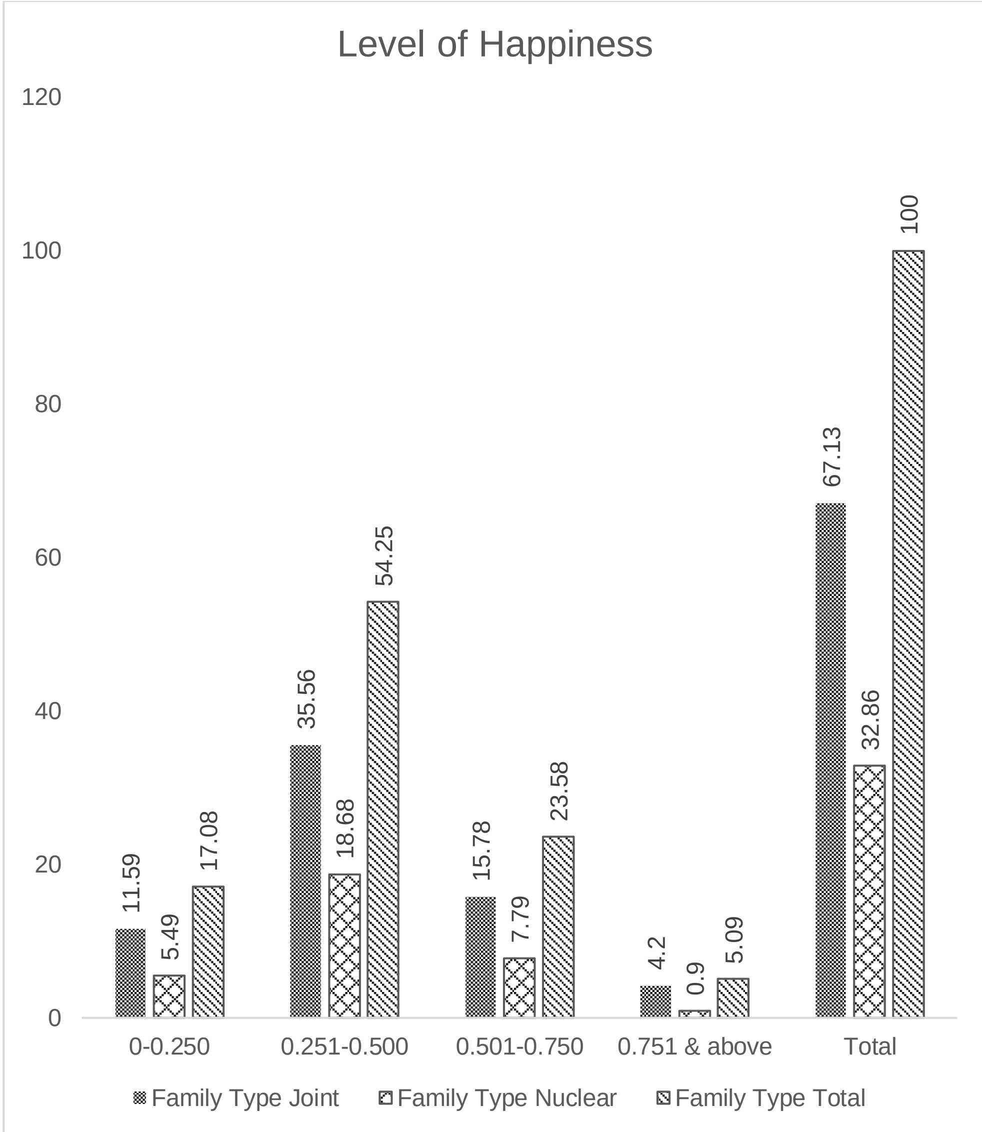
Figure 3. Cross-referencing the level of happiness with age, family type and gender (%)



Pearson$\chi^2(9)$ = 3.0235**; Kendall's τ = 0.0267; ASE = 0.030



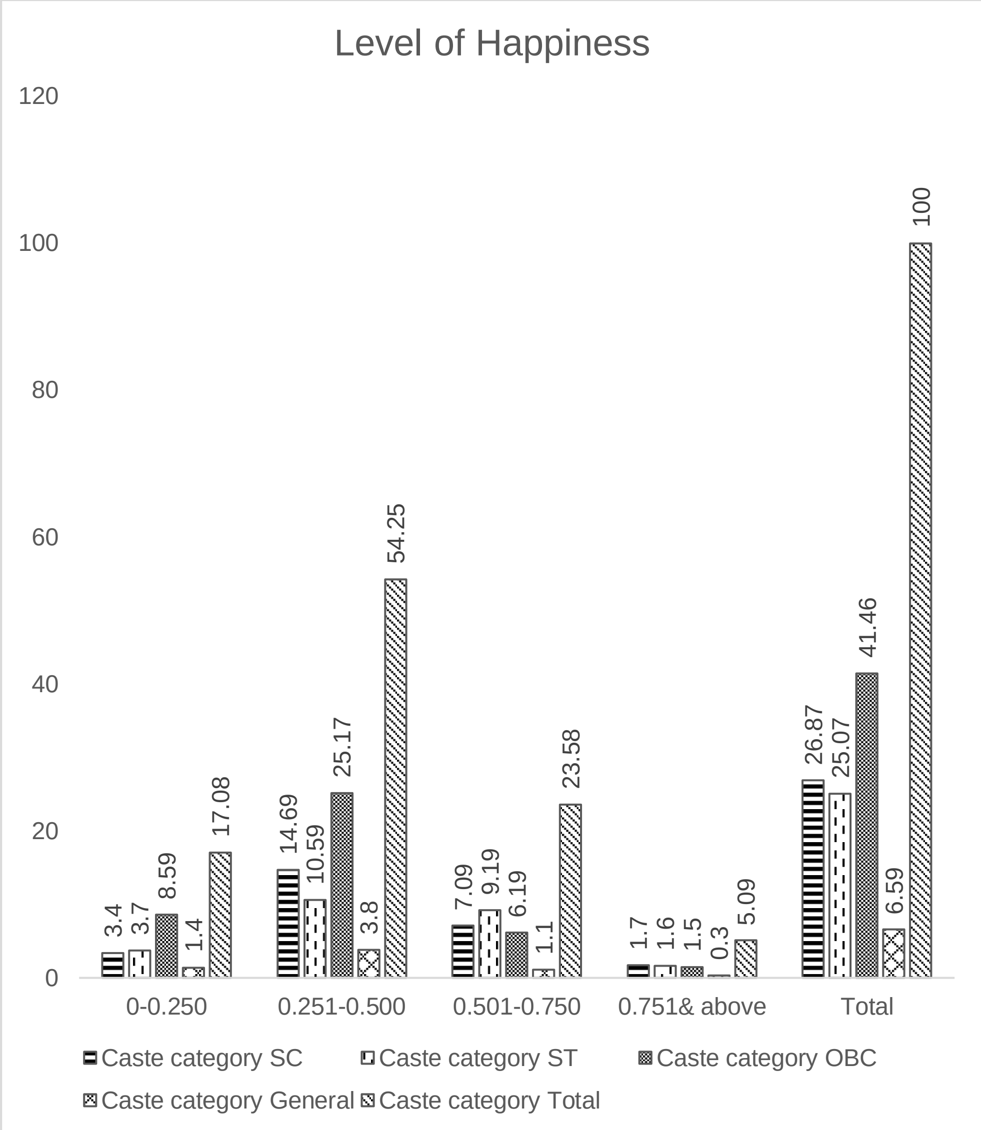
Pearson $\chi^2(9)$ = 3.1978**; Kendall's τ = -0.0315; ASE = 0.031



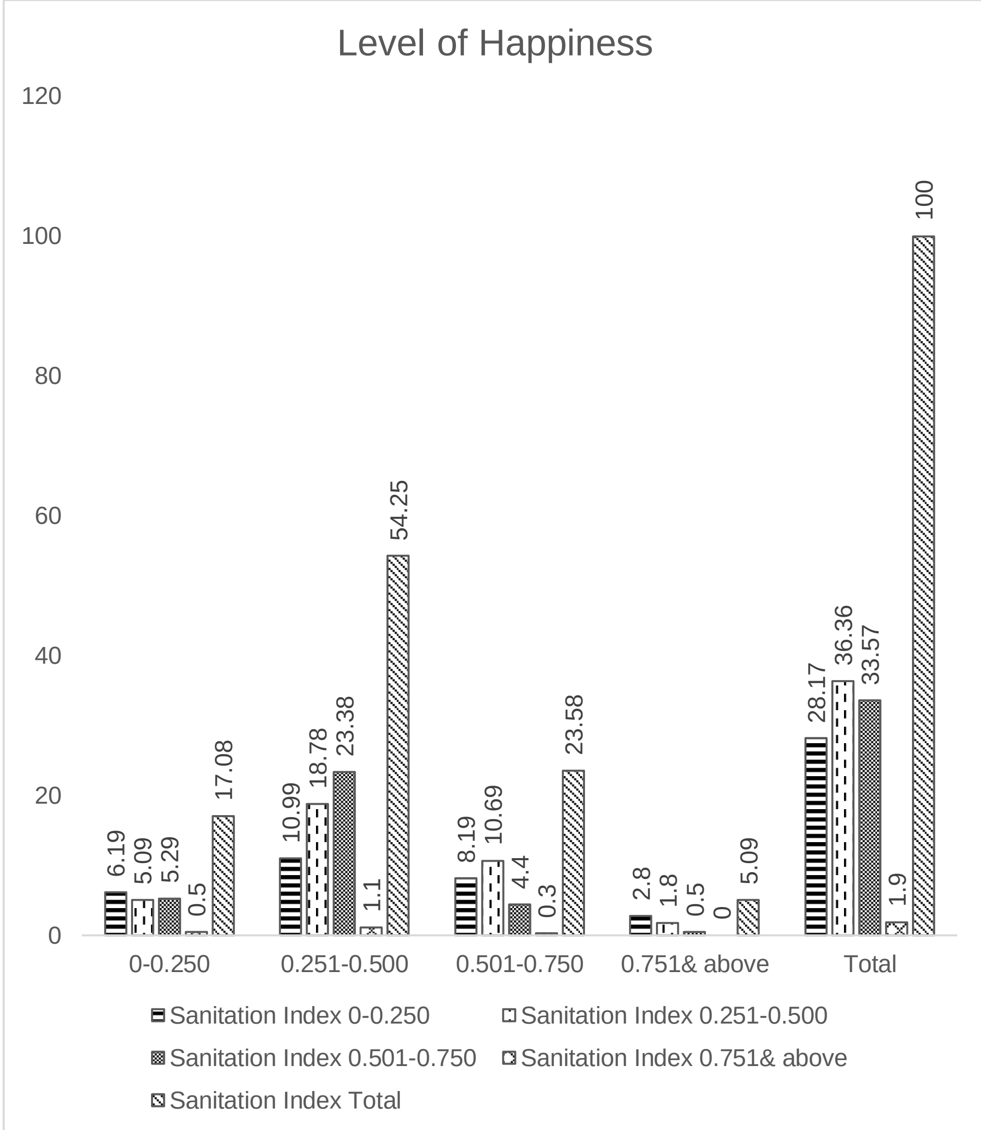
Pearson $\chi^2(9)$ = 6.0038**; Kendall's τ = 0.0270; ASE = 0.029

Source: Authors' construct
Note: ** denotes a 5% level of significance.

Figure 4. Cross-referencing the level of happiness with caste category and the level of sanitation index (%)



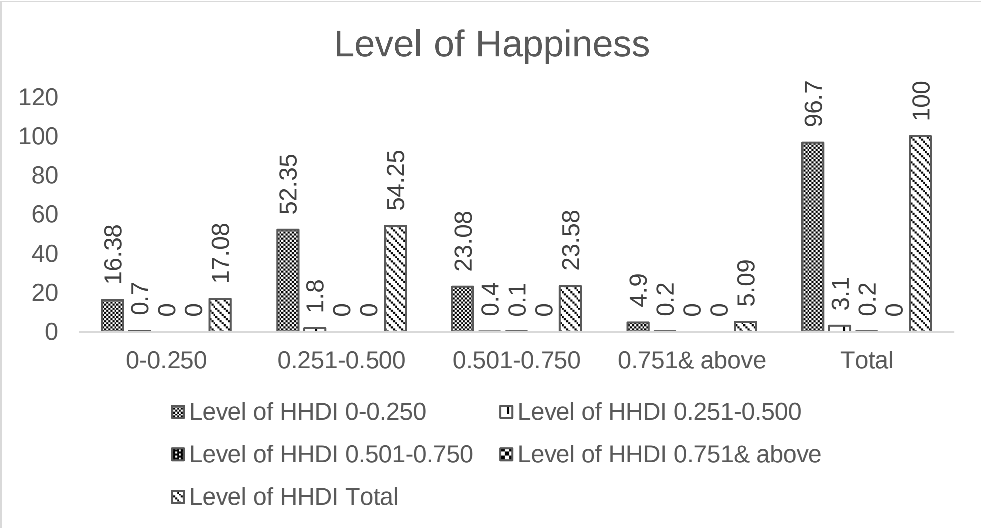
Pearson $\chi^2(9)$ = 54.8254***; Kendall's τ = -0.1405; ASE = 0.026



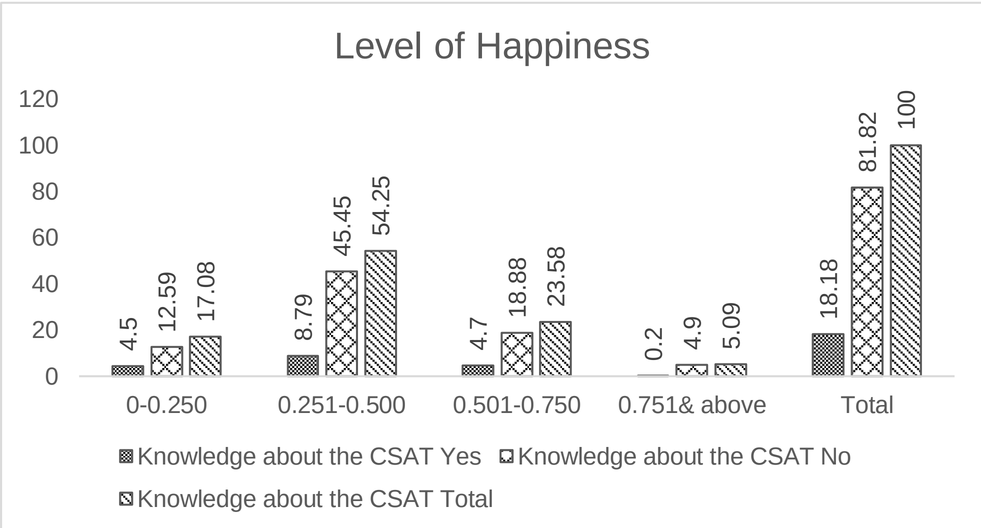
Pearson $\chi^2(9)$ = 82.0109***; Kendall's τ = -0.1280; ASE = 0.028

Source: Authors' construct.
Note: *** denotes a 1% level of significance.

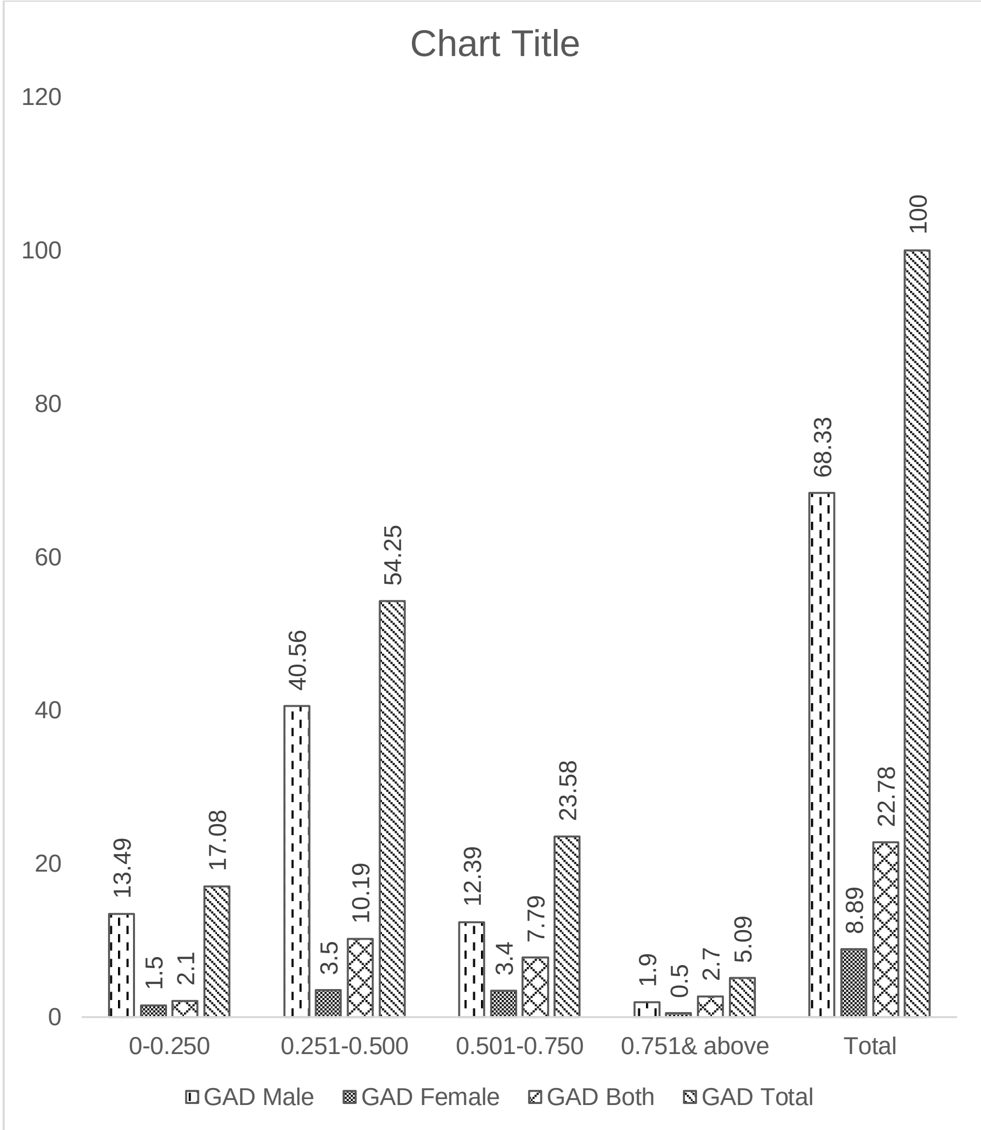
Figure 5. Cross-referencing the level of happiness with the level of human development index of the household (HHDI), gender-wise agricultural decision (GAD) and, knowledge about the climate-smart agricultural technology (CSAT) (%)



Pearson $\chi^2(9)$ =3.3336***; Kendall's τ = -0.0279; ASE = 0.029



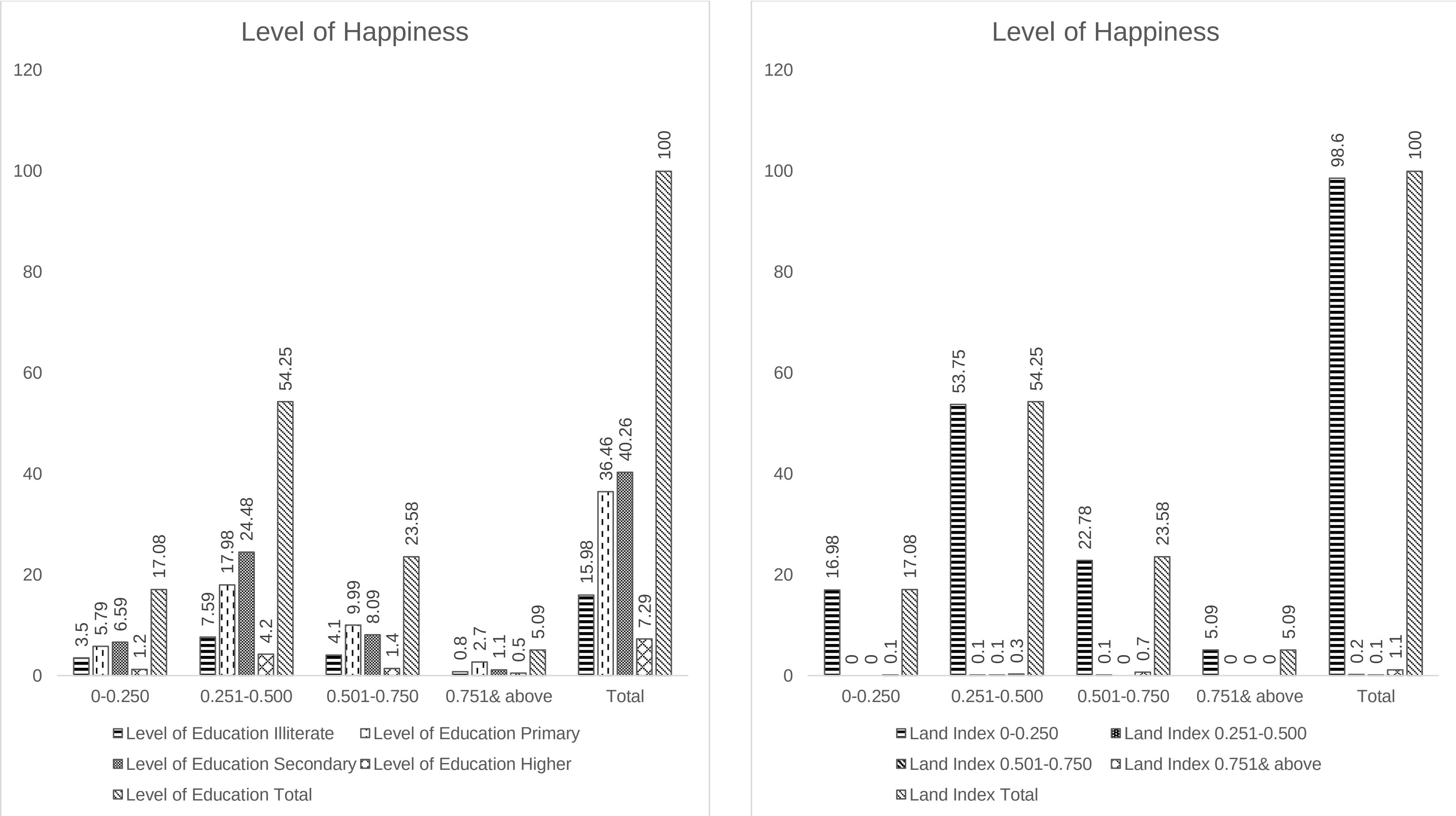
Pearson $\chi^2(9)$ = 16.4782***; Kendall's τ =0.0675; ASE = 0.031



Pearson $\chi^2(9)$ = 77.0907***; Kendall's τ =0.2238; ASE = 0.028

Source: Authors' construct.
Note: *** denotes a 1% level of significance.

Figure 6. Cross-referencing the level of happiness with the level of education and level of the land index (%)

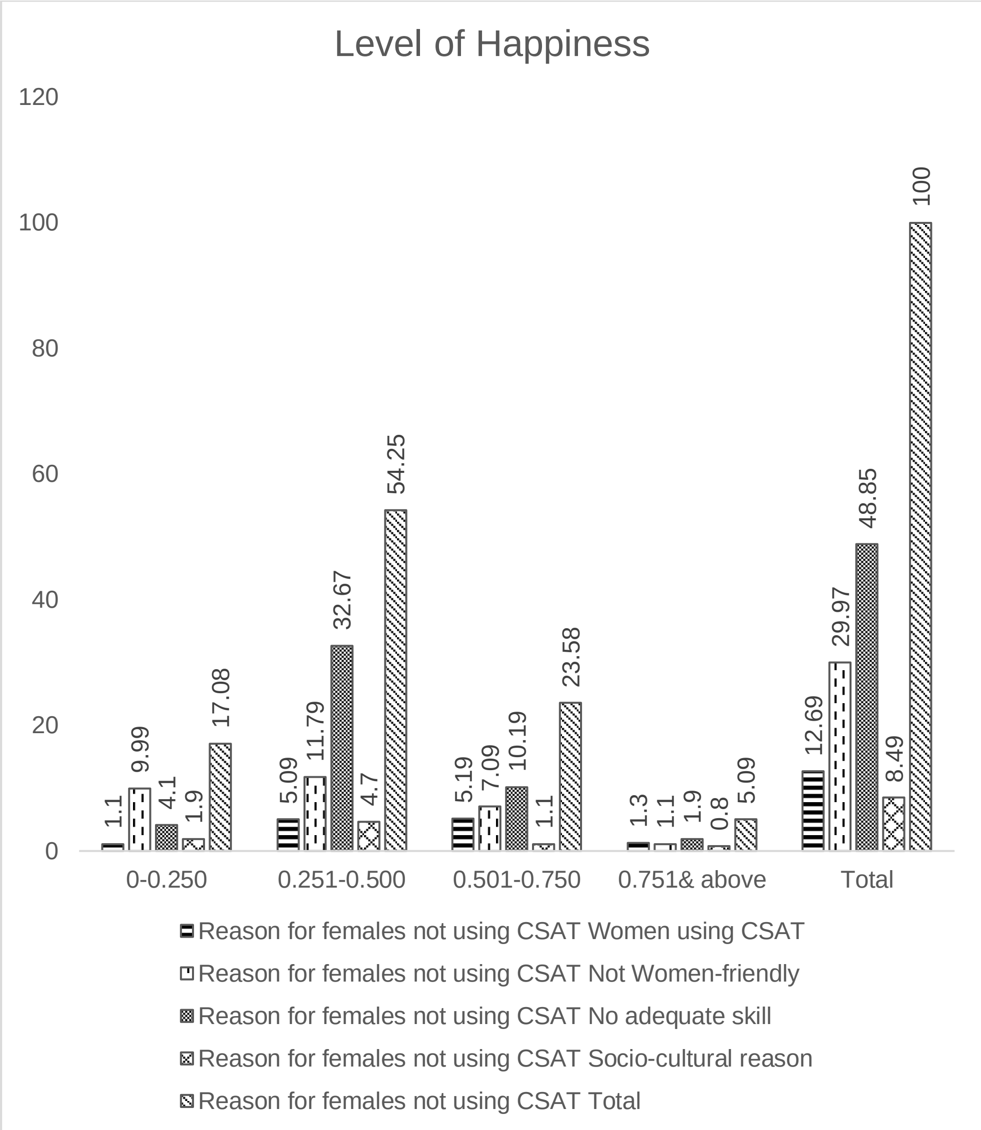


Pearson χ^2((9) = 22.7767; Kendall's τ = -0.0439; ASE = 0.028

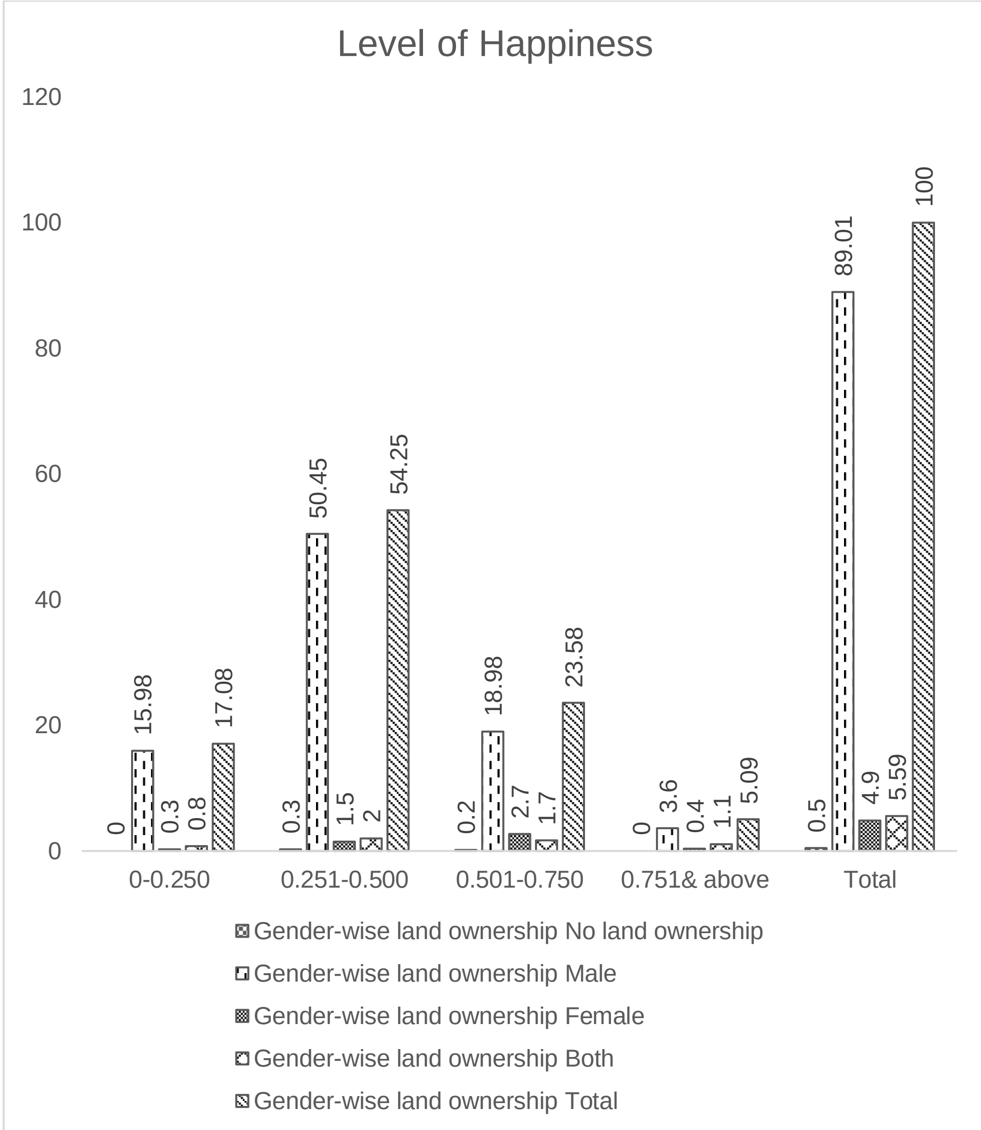
Pearson χ^2(9) = 11.9496; Kendall's τ = 0.0595; ASE = 0.028

Source: Authors' construct.

Figure 7. Cross-referencing the level of happiness with reasons for females not using the climate-smart agricultural technology (CSAT) and gender-wise land ownership (%)



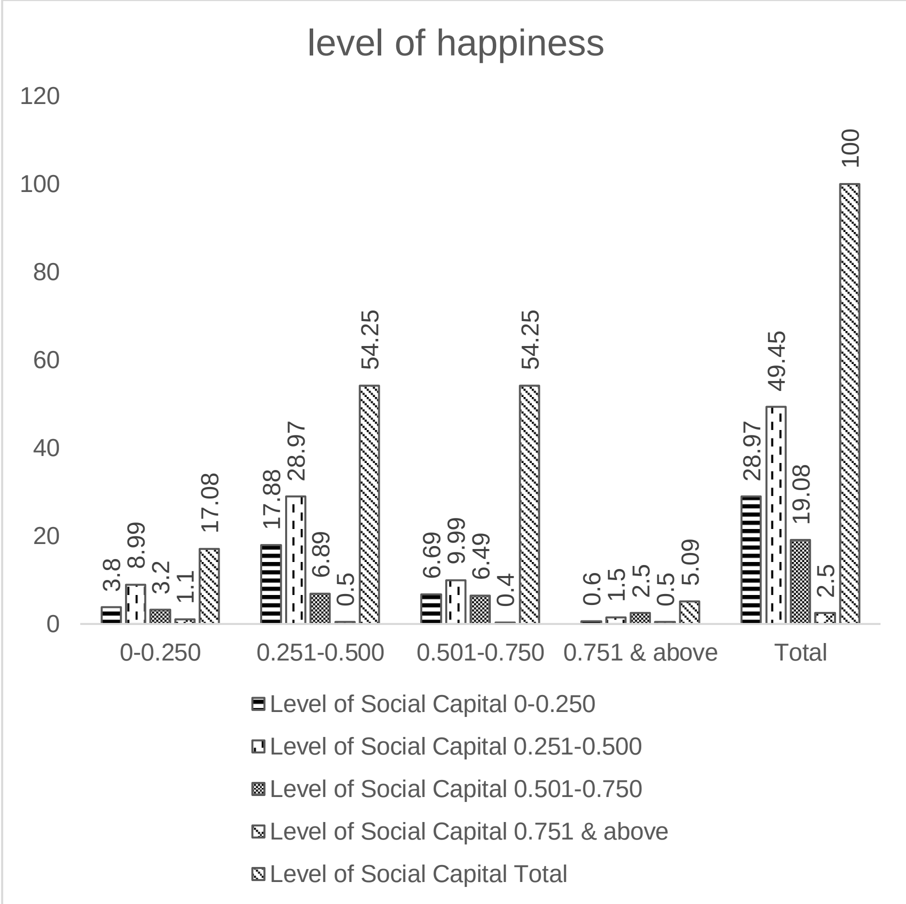
Pearson $\chi^2(9)$ = 140.1837***; Kendall's τ = -0.0332; ASE = 0.030



Pearson $\chi^2(9)$ = 65.1520***; Kendall's τ =0.1636; ASE = 0.032

Source: Authors' construct.
Note: *** denotes a 1% level of significance.

Figure 8. Cross-referencing the level of happiness with the level of social capital (%)



Pearson $\chi^2(9) = 91.4216^{***}$; Kendall's $\tau =$ 0.0688; ASE = 0.031

Source: Authors' construct
Note: *** denotes a 1% level of significance.

Tables

Table 1. Sampling process

1st Stage	2nd Stage					3rd Stage	4th Stage	5th Stage	6th Stage	7th stage
State	Argo-climatic zones					Selected District	Block	Gram panchayat (GP)	Village	Household (HH)
	Landmass	Climate	Mean annual rainfall (in mm)	Soil type	District(s)					
Odisha	North Western plateau	Warm& moist	1648	Red & Yellow	Deogarh and Sundargarh	Sundargarh	Rajgangpur	Laing	Two villages from each GP	30 HH from Village (Total 1020 HH, but effectively 1001 HH are studied here)
	North Central plateau	Warm & moist	1535	Red loamy	Mayurbhanj, Keonjhar (Except Anandapur)	Keonjhar	Ghatagaon	Patilo		
	North Eastern coastal plateau	Warm & moist sub-humid	1568	Alluvial	Bhadrak, baesorejajpur (except Sukinda), Anandapur	Jajpur (except Sukinda), Bhadrak	Dhamnagar, Jajpur	Dalanga, Khairabad		
	East & South eastern plateau	Warm & humid	1449	Coastal alluvial saline (near the coastline)	Cuttack (P), Kendrapara, Jagatsinghpur, Puri, Nayagarh, Khurda, Ganjam (P)	Cuttack (P), Puri, Nayagarh, Khurda,	Narasinghpur,Kakatpur, Nayagarh,Khurda	Jayamangala,Kakatpur, Khuntabadha,Khurda		
	North Eastern ghat	Warm& moist sub-humid	1597	Laterite and brown forest	Ganjam (P), Rayagada, Gajapati, Kandhmal, Boudh (P)	Boudh (P), Ganjam (P),	Charichhak, Sheragoda	Purunakatak, Mahupada		
	Eastern ghat high land	Hot& humid	1522	Red mixed red & yellow	Koraput (P), Nabarangpur (P)	Koraput (P)	Semiliguda	Pitaguda		
	South Eastern ghat	Hot& humid	1522	Red, mixed red & black	Malkangiri, Koraput (P)	Malkangiri	Mathili	Mathili		
	Western undulating	Hot & moist	1527	Black, mixed red and black	Kalahandi, Nuapada, Nabarangpur	Kalahandi	Golamunda	Sinapali		
	West-central tableland	Warm & moist	1527	Red, heavy textured colour	Subarnapur, Bolangir, Boudh (P), Sambalpur, Bargarh, Jharsuguda	Jharsuguda, Bargarh	Jharsuguda, Bargarh	Badmal, Khuntapalli		
	Mid-central tableland	Hot & dry sub-humid	1421	Red loamy, laterite mixed red & black	Dhenkanal, Angul, Cuttack (P) & Sukinda	Dhenkanal, Angul	Kankadahad, Pallahara	Bam, Rajdang		
Purposive	Purposive					Proportional Stratified Sampling	Simple Random Sampling	Simple Random Sampling	Judgmental Sampling and Simple Random Sampling	Judgmental Sampling and Simple Random Sampling

Source: Authors' construction.
Note: P stands for part of the district.

Table 2. Descriptions of variables with reference category

Variable	Description	Nature of variable
Dependent Variable		
Happiness index (HI)	Developed through the principal component analysis (PCA) and then converted as: $$HI = \frac{Actual\ value - Minimum\ value}{Maximum\ value - Minimum\ value}$$	Ratio: $0 \leq HI \leq 1$
Independent Variables		
Climate -smart agriculture technology adaptation index (CSATAI)	Weighted arithmetic mean (WAM) of the 18 climate- smart agriculture technology (CSAT) practices are as follows:1. Seed variety,2. Pest control, 3. Fertiliser use,4. Soil test, 5. Row planting, 6. Irrigation, 7. Composting, 8. Marketing,9. Access to credit,10. Insurance, 11. Tractor,12. Power tiller,13. Seed sowing machine,14. Sprayer, 15. Weeding machine,16. Crop-cutting machine, 17. Fan, 18. Storage facility.	Categorical: Lower = CSATAI ≤ 0.25 Moderate = 0.251 ≤ CSATAI ≤ 0.50 Higher = 0.501 ≤ CSATAI ≤ 0.75 Highest = CSATAI ≥ 0.751
Level of Social capital (LSC)	There are four levels of social capital. It is created by the PCA from eight aspects of social behaviour on a 5-point Likert scale (for the technical aspect of PCA, see Kumar et al., 2007). The PCA-generated SCI is then standardised so that 0 ≤ SCI ≤ 1. The aspects include the frequency of mobile use, attending social, cultural, religious, economic, and political meeting(s), watching television in a group and visiting relatives in the household.	Categorical: Lower = LSC ≤ 0.25 Moderate = 0.251 ≤ LSC ≤ 0.50 Higher = 0.501 ≤ LSC≤ 0.75 Highest = LSC ≥ 0.751
Level of Agricultural expenditure (LAE)	It is the total agricultural expenditure of a household divided by the maximum agriculture expenditure among all the households.	Categorical: Lower = LAE ≤ 0.25 Moderate = 0.251 ≤ LAE ≤ 0.50 Higher = 0.501 ≤ LAE ≤ 0.75 Highest = LAE ≥ 0.751
Caste category	Caste of household's head (HH): 1.scheduled caste (SC), 2. Scheduled tribe (ST), 3. Other backward caste (OBC), 4. General	Qualitative: Reference category: SC Dummy, 1= ST, 0= otherwise Dummy, 1= OBC, 0= otherwise Dummy, 1= General, 0= otherwise
Age	Age of the HH (In years):	Quantitative
Family type	1. Joint family (JF), 2. The nuclear family (NF)	Qualitative: Reference category: -Nuclear family (NF)
Gender	Gender of the HH. 1. Male, 2. Female	Qualitative: Category: -Male Dummy, 1= Female, 0 = Otherwise
Level of sanitation index (LSI)	The level of sanitation index is created by evaluating eight indicators such as: 1. residing in a permanent structure, 2. access to toilet facilities 3. access to bathing facilities 4. access to purified drinking water 5. frequency of using soap for bathing6. use of disinfectant to clean bathroom, toilet, and surfaces, 7.use of hand wash, and 8. use of detergent to clean utensils.	Ratio: The LSI is calculated by using the method WAM (the weights being uniform) and is defined as: LSI = $\frac{\sum_1^8 I_i}{8}$. Possession of an indicator by the household is assigned the value "1", and non-possession of the indicator is "0". The household having all the indicators will have LSI = 1, and having no indicators will have LSI = 0. Thus, the value of LSI will lie between 0 to 1, i.e.,$0 < \text{LSI} < 1$. Categorical: Lower = LSI ≤ 0.25 Moderate = 0.251 ≤ LSI ≤ 0.50 Higher = 0.501 ≤ LSI ≤ 0.75 Highest = LSI ≥ 0.751
Level of human development index	The level of HHDI is calculated by finding the weighted arithmetic mean using three indicators with uniform weights. The variables to be considered are total health expenditure, total education expenditure, and total income, which includes income from primary and	Ratio: The DI is calculated as:

of the household (HHDI)	secondary occupations over the past year. Dimension indices (DI) for health, education, and income are calculated by selecting minimum and maximum values as goalposts.	$\mathrm{DI} = \frac{\text{Actual value} - \text{Minimum value}}{\text{Maximum value} - \text{Minimum value}}$ The HDI is constructed as follows: $\mathrm{HDI} = \sum DI_i/3$, i= Health, Education, and Income. The value of HHDI will lie between 0 to 1, i.e., $0 \leq \mathrm{HHDI} \leq 1$. Categorical: Lower = HHDI ≤ 0.25 Moderate = 0.251 ≤ HHDI ≤ 0.50 Higher = 0.501 ≤ HHDI ≤ 0.75 Highest = HHDI ≥ 0.751
Knowledge about the CSAT	Knowledge about the CSAT by the household.	Qualitative: Dummy, 1=Yes, 0 = No
Level of education	It is the level of education that the HH has completed.	Qualitative: Reference category: - Illiterate Dummy, 1= primary (7th or less), 0 = otherwise Dummy, 1= secondary (8th to 12th), 0 = otherwise Dummy, 1= higher (above 12th), 0 = otherwise
Level of land index (LLI)	It is the total land owned by a household divided by the maximum land owned among all the households.	Ratio: 0≤ LLI ≤1 Categorical: Lower = LLI ≤ 0.25 Moderate = 0.251 ≤ LLI ≤ 0.50 Higher = 0.501 ≤ LLI ≤ 0.75 Highest = LLI ≥ 0.751
Reasons for females not using the CSAT.	The reasons for which females not using CSAT: 1. Not Women-friendly, 2. No adequate skill 3. Socio-cultural reasons	Qualitative: Reference Category: - Women using CSAT
Gender-wise agricultural decision	Agricultural decision taken by the household: 1. Male, 2. Female, 3. Both Male and Female	Qualitative: Reference Category: - Male Dummy, 1= Female, 0 = otherwise Dummy, 2= Both, 0 =otherwise
Gender-wise land ownership	Land owned by the household: 0. No land 1. Male, 2. Female, 3. Both Male and Female	Qualitative: Reference Category: - No land Dummy, 1= Male, 0 = otherwise Dummy, 2= Female, 0 = otherwise Dummy, 3= Both, 0 = otherwise

Source: Authors' construction.

Table 3. Statistical Summary

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
Happiness index	1001	0.421	0.193	0.000	0.928
CSAT adaptation index	1001	0.464	0.221	0.055	0.889
Level of social capital	1001	0.370	0.174	0.000	1.000
Level of agricultural expenditure	1001	0.052	0.072	0.000	1.000
Caste category	1001	2.278	0.933	1.000	4.000
Age	1001	45.663	11.629	17.000	84.000
Family type	1001	0.671	0.470	0.000	1.000
Gender	1001	0.879	0.326	0.000	1.000

Level of Sanitation index	1001	0.393	0.192	0.018	1.000
Level of human development index of the household	1001	0.074	0.068	0.001	0.694
Knowledge about the CSAT	1001	0.818	0.386	0.000	1.000
Level of education	1001	5.614	3.965	0.000	15.000
Level of land Index	1001	0.038	0.105	0.000	0.998
Reasons for females not using the CSAT	1001	1.531	0.821	0.000	3.000
Gender-wise agricultural decision	1001	1.544	0.839	1.000	3.000
Gender-wise land ownership	1001	1.156	0.504	0.000	3.000

Source: Authors' construction.

Note: CSAT stands for climate-smart agriculture technology.

Table 4. Estimation results of the Beta regression

Happiness index	Beta regression			Marginal effect Delta method		
	Coefficient	Standard error	P-value	Coefficient	Standard error	P-value
Level of social capital						
0.251-0.500	-0.223*	0.124	0.072	-0.047	0.027*	0.075
0.501-0.750	0.268	0.173	0.121	0.060	0.039	0.122
0.751 and above	0.259	0.257	0.313	0.058	0.058	0.317
Level of agricultural expenditure						
0.251-0.500	0.376*	0.196	0.054	0.083	0.044*	0.060
0.501-0.750	1.500***	0.217	0.000	0.328	0.040***	0.000
0.751 and above	0.444**	0.183	0.015	0.098	0.041**	0.017
Caste category						
ST	0.376***	0.143	0.009	0.084***	0.032	0.008
OBC	-0.262**	0.121	0.031	-0.055**	0.026	0.032
General	-0.326	0.225	0.147	-0.068	0.045	0.136
Age	0.166*	0.093	0.073	0.036*	0.020	0.074
Joint family	0.077	0.106	0.469	0.016	0.023	0.468
Gender	-0.020	0.136	0.881	-0.004	0.029	0.882
Level of sanitation index						
0.251-0.500	0.496***	0.117	0.000	0.108***	0.025	0.000
0.501-0.750	0.031	0.134	0.814	0.006	0.028	0.813
0.751 and above	-0.199	0.342	0.560	-0.040	0.066	0.549
Level of human development index of the household						
0.251-0.500	-0.468	0.399	0.240	-0.094	0.074	0.206
0.501-0.750	0.617**	0.280	0.028	0.138**	0.064	0.030
CSAT adaptation index						
0.251-0.500	0.746***	0.142	0.000	0.149***	0.026	0.000
0.501-0.750	0.888***	0.194	0.000	0.181***	0.039	0.000
0.751 and above	0.722***	0.209	0.001	0.144***	0.042	0.001
Level of education						
Primary	0.087	0.147	0.551	0.018	0.030	0.549
Secondary	0.271*	0.141	0.055	0.058**	0.029	0.049
Higher	0.044	0.245	0.858	0.009	0.051	0.858
Level of land index						
0.251-0.500	-1.077***	0.390	0.006	-0.192***	0.053	0.000

0.501-0.750	0.021	0.185	0.911	0.004	0.040	0.911
0.751 and above	-0.141	0.295	0.632	-0.030	0.061	0.625
Reasons for females not using the CSAT						
Not women-friendly	-1.153***	0.122	0.000	-0.249***	0.025	0.000
No adequate skills	-0.494***	0.104	0.000	-0.114***	0.024	0.000
Socio-cultural reasons	-0.603***	0.158	0.000	-0.138***	0.035	0.000
Gender-wise agricultural decision						
Female	0.491***	0.157	0.002	0.108***	0.035	0.002
Both	0.426***	0.110	0.000	0.093***	0.024	0.000
Gender-wise land ownership						
Male	-0.271	0.282	0.337	-0.059	0.063	0.347
Female	-0.159	0.371	0.669	-0.035	0.082	0.669
Both	-0.467	0.396	0.238	-0.100	0.085	0.238
Constant	1.024	0.060	0.000			
Number of observations	1001					
Wald χ^2 (33)	6695.37***					
Log pseudo-likelihood	351.814					

Source: Authors’ construction.

Note: *, **, and *** denote 10%, 5%, and 1% significance levels, respectively; CSAT stands for climate-smart agriculture technology.