CLIMATE-SMART AGRICULTURAL PRACTICES FOR CLIMATE CHANGE RISK MITIGATION IN TEMPERATE REGION OF HIMACHAL PRADESH

Thesis

by

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(ABM-2021-08-D)

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CERTIFICATE-I

This is to certify that the thesis titled **"Climate-Smart Agricultural Practices for Climate Change Risk Mitigation in Temperate Region of Himachal Pradesh"**submitted in partial fulfilment of the requirements for the award of the degree of **Doctor of Philosophy Agri-business Management** in the discipline of **Agri-business Management** to Dr. Yashwant Singh Parmar University of Horticulture & Forestry, (Nauni) Solan (HP) – 173 230 is a bonafide research work carried out by **Ms Sonaly Bhatnagar (ABM-2021-08-D)** daughter of Shri Pankaj Bhatnagar under my supervision and that no part of this thesis has been submitted for any other degree or diploma.

The assistance and help received during the course of this investigation have been fully acknowledged.

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CERTIFICATE-II

This is to certify that the thesis titled, **"Climate-Smart Agricultural Practices for Climate Change Risk Mitigation in Temperate Region of Himachal Pradesh"** submitted by **Ms Sonaly Bhatnagar (ABM-2021-08-D)** daughter of Shri Pankaj Bhatnagar to the Dr. Yashwant Singh Parmar University of Horticulture & Forestry, (Nauni) Solan (HP) – 173 230 India in partial fulfilment of the requirements for the degree of **Doctor of Philosophy Agri-business Management** in the discipline of **Agri-business Management** has been approved by the Advisory Committee after an oral examination of the student in collaboration with an External Examiner.

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Place: Nauni (Solan) **(Sonaly Bhatnagar)**
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ABBREVIATIONS USED

SD	:	Standard Deviation
ha	:	Hectare
₹	:	Rupees
msl	:	Mean sea level
H.P.	:	Himachal Pradesh
IPCC	:	Intergovernmental Panel on Climate Change
FAO	:	Food and Agriculture Organization
CSA	:	Climate-Smart Agriculture
CSAPs	:	Climate Smart Agricultural Practices
GHG	:	greenhouse gas
LVI	:	Livelihood Vulnerability Index
Sig	:	Significance
Kms	:	Kilometers
No.	:	Number
w.r.t.	:	with respect to
SDI	:	Simpson Crop Diversification Index
hhh	:	household head
VIF	:	Variance Inflation Factor
CC	:	Contingency Coefficient
FYM	:	Farmyard manure

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Chapter - 1

INTRODUCTION

Climate change is considered to be the most pressing issue, posing a serious threat to food security, livelihood of the rural population, and the sustainability of the agriculture sector at the global level (Praveen and Sharma, 2019). Climate change causes a diversity of risks emanating from changes in precipitation patterns leading to increased risk of recurrent droughts and devastating floods, rising temperatures, melting of glaciers, sea level rise, and threats to biodiversity. The primary cause of climate change is the release of greenhouse gases, such as methane, carbon dioxide, and nitrous oxide, which accumulate in the atmosphere and enhance the greenhouse effect, resulting in global warming (Hondula *et al*., 2015). Together, these gases are responsible for more than 80 per cent of the factors contributing to global temperature increases (Tang *et al*., 2021). The Intergovernmental Panel on Climate Change (IPCC) reports that a temperature increase of 1.5 ℃ above pre-industrial levels poses significant risks to both natural and human systems, including agriculture (IPCC, 2018). While the climate and agricultural production system changes will affect food security, farmers are the first to experience the blows (Datta *et al*., 2022). Farmers' livelihoods are consequently at peril across the world; climate change will probably lead to a rise in net poverty, especially in rural areas where agricultural production is economically important (Soubry *et al*., 2020). The exponential growth of population in recent decades requires serious efforts for the proliferation of agricultural produce, which will improve global food supplies, reduce food losses, and guarantee that everyone who is hungry or malnourished has access to nutritious food. A temperature increase of 2–3.5 ℃ is anticipated to decline India's net agricultural revenue by 9–25 per cent, imposing significant and cumulative impacts, particularly for smallholder farmers (Venus *et al*., 2022). Addressing local climate-related risks necessitates a comprehensive understanding of the determinants of livelihood vulnerability, which are critical for devising effective and targeted resilience-building strategies (Ghosh and Ghosal, 2020).

Agriculture is at the center of three of the greatest challenges of the 21st century – achieving food security, adapting to climate change, and mitigating climate change while critical resources such as water, energy, and land become increasingly scarce. The agricultural sector and climate change are intertwined with each other, and their relationship is particularly significant to the ever-increasing inequality of the earth's population and world

food production (Praveen and Sharma, 2019). Consequently, insufficient rainfall and its erratic distribution are the primary causes of lower agricultural yield and income. One of the most pervasive and potentially devastating impacts of climate change on agriculture is due to changing the consistency and intensity of rainfall variability (Shumetie and Yismaw, 2018). Thus, the agricultural sector is sensitive to climate change impinging considerable threats to farming systems and communities. Livelihood systems take a holistic approach, considering the vulnerabilities, assets, resources, policies, and institutions that affect the poor, as well as their responses to threats and opportunities. The sustainable livelihood approach offers a comprehensive framework for rural farmers and adaptation by addressing the multifaceted nature of livelihoods and their interplay with environmental, economic, and social factors. It recognizes the diversity of rural livelihoods and emphasizes the need to understand the opportunities and constraints that farmers face, including access to resources, institutional support, and socio-economic conditions. This approach facilitates the identification of strategies that can enhance resilience and adaptability in the face of challenges such as climate change, resource depletion, and market fluctuations. With the increasing vulnerability of agricultural systems to climate change, adaptation and adjustments in current agricultural practices are required to reduce the adverse effects of changing climate. These risks highlight the critical importance of implementing adaptive measures to safeguard food production and sustain rural livelihoods in the face of escalating climate challenges.

Adaptation is widely indicated as a plausible strategy to combat climate change and achieve sustainable development. Food and Agriculture Organization (FAO) has devised the concept of climate-smart agriculture (CSA) under which innovative and sustainable agricultural practices are urged to be deployed at the farm level (FAO, 2010). Climate-smart agricultural practices are a key concept in the present agricultural development, aiming to simultaneously achieve three objectives: sustainably intensify agriculture for better livelihoods; enhance the resilience (adaptation) of farmers; and reduce or mitigate greenhouse gas emissions (Lipper *et al*., 2014; Bhatnagar *et al*., 2024). CSAPs encompass diverse, context-specific practices rather than a single practice designed to enhance the resilience of existing farming systems while improving resource use efficiency at the farm level. Climate-smart agricultural practices and technologies demonstrate the potential to improve smallholder incomes, facilitate value chain development, enhance household food security, and bolster resilience to climate change (Mutenje *et al*., 2019). Moreover, CSA seeks to mitigate agriculture's environmental impact by reducing greenhouse gas (GHG) emissions.

The success of farming activities today in the face of the menace posed by the effects of climate change depends heavily on climate-smart agricultural practices. The adoption of climate-smart agricultural practices in a timely and effective manner is contingent upon farmers' knowledge and perceptions of climate change and its associated impacts (Haq *et al*., 2021). Adopting one practice can influence others, making it essential to study multiple practices to understand farmers' strategies for climate change mitigation and production challenges (Sardar *et al*., 2021). The intention to implement CSAPs is influenced by a range of factors, including farmers' experience, knowledge, skills, socioeconomic status, institutional and infrastructural support, and the existence of enabling policies (Ruben *et al*., 2019). Therefore, a comprehensive understanding of the determinants influencing farmers' adoption behaviour is crucial for formulating policies that effectively and sustainably enhance the adoption of CSA practices (Negera *et al*., 2022). Farmers need to develop agricultural systems and adopt new management practices with the aid of comprehensive, coherent, and forceful agricultural and climate policies.

Mountain ecosystems have unstable and complex topography with poorer economic prospects, and people in these regions are more vulnerable to the devastating impact of slight changes in the frequency and severity of climate events. Himachal Pradesh is a mostly mountainous state in the North Western Himalayas and is particularly vulnerable to climate change and its adverse effects, as 70 per cent of the population relies on agriculture for livelihood, and the agriculture sector contributing 22 per cent of the total State domestic product (State Performance Report, 2020-21). It is imperative to understand rural households' livelihood vulnerability and implement climate-smart agricultural practices to reduce farmers' vulnerability and improve their resilience. In this study, the Livelihood Vulnerability Index (LVI) framework developed by Hahn *et al*., (2009), in conjunction with the LVI-IPCC, was employed to assess the vulnerability of farming communities. This indicator-based approach is a valuable methodology for assessing vulnerabilities across spatial and temporal dimensions, identifying causative factors, and formulating strategies to mitigate impacts (Legese *et al*., 2016). This approach enables the systematic monitoring of vulnerability over time and across regions, facilitating the identification of key drivers of vulnerability. Consequently, it provides a robust foundation for developing targeted measures to reduce vulnerability and enhance resilience (Legese *et al*., 2016). Moreover, highly dynamic farming systems, i.e., climate-smart agricultural practices are needed to help farmers respond to climate change while continuing to contribute to producing sufficient food to feed the rising population. Growing concern about the potential effects of climatic change on

agriculture has motivated the current study entitled “Climate-smart agricultural practices for climate change risk mitigation in different agro-climatic zones of Himachal Pradesh”, with the following objectives:

Specifically, the main objectives of the present study are outlined below:

1. To study the livelihood vulnerability of the sample households to climate change.
2. To identify climate-smart agricultural practices adopted by farmers and factors influencing the adoption of climate-smart agricultural practices.
3. To examine the impact of climate-smart agricultural practices on livelihood vulnerability of the sample households.
4. To identify the constraints for adopting climate-smart agricultural practices among farmers.

Scope of the study

This study focuses on the role of climate-smart agricultural (CSA) practices in mitigating climate change risks in the temperate region of Himachal Pradesh. The scope of the study encompasses several critical aspects related to climate change and its impact on farmers livelihoods. The primary objective is to analyze the livelihood vulnerability of sample households to climate change, providing insights into their susceptibility and adaptive capacity. It further seeks to identify the climate-smart agricultural (CSA) practices adopted by farmers and the factors influencing their adoption, offering a comprehensive understanding of the drivers and barriers to CSA uptake. Therefore, the study examines the impact of these practices on the livelihood vulnerability of sample households, evaluating their effectiveness in mitigating climate risks and enhancing resilience. Lastly, it identifies key constraints limiting the adoption of CSA practices among farmers, highlighting areas where interventions are necessary. By addressing these objectives, the study provides valuable knowledge for policymakers, researchers, and stakeholders to develop targeted strategies for promoting sustainable agriculture and reducing livelihood vulnerabilities in the context of climate change.

Limitations of the study

The study was conducted in the high hill wet and dry temperate zones of Himachal Pradesh, a region with distinct climatic and socio-economic characteristics. Consequently, the generalizability of the findings to other regions with different contextual settings may be

limited. Primary data collection was undertaken through personal interviews using the survey method. Despite rigorous efforts to ensure data accuracy, the reliability of the information gathered may have been affected by respondent behaviour. Additionally, limitations in time, financial resources, and manpower presented challenges to both data collection and analysis. Furthermore, the reliance on self-reported data may have impacted the accuracy and objectivity of the results. These limitations underscore the need for further research in other regions of the state to assess the consistency of the observed patterns and findings. Broader and more resource-intensive studies are also essential for comprehensive validation and expansion of the results.

Outline of thesis

This thesis has been systematically organized into five chapters, each comprehensively covering various aspects of the study. The introductory chapter outlines the introduction and addresses the need, objectives, and scope of the study. The second chapter provides an extensive review of the literature relevant to the field of study. Chapter 3 details the research methodology, including the description of the study area, sampling design, data sources, and the conceptual and analytical tools and techniques used for data analysis. Chapter 4 presents the empirical results and includes a critical discussion. Finally, Chapter 5 summarizes the major findings of the research study, drawing conclusions based on the results. It discusses the policy implications of the findings, outlines the limitations of the study, and offers suggestions for future research. The references and appendices are provided at the end.

Chapter - 2

REVIEW OF LITERATURE

A review of prior studies relevant to the subject is essential in any research for several reasons. It helps define key concepts and operational terms, aids in formulating testable hypotheses, justifies the chosen methodology, guides the selection of appropriate analytical tools such as empirical models, and ensures the research objectives are effectively addressed. A livelihood comprises the capabilities, assets (both material and social), and activities that a household employs to sustain its means of living. Within the context of vulnerability, livelihoods are shaped by a household's ability to endure and adapt to various environmental, economic, and social shocks. To mitigate the effects of climate change on agricultural practices, rural producers must modify their cropping systems through Climate-Smart Agriculture (CSA) practices, which involve changes to methods, structures, and processes (Rippke *et al.,* 2016). The escalating complexities induced by climate variability necessitate the adoption of innovative and sustainable agricultural solutions (Kombat *et al.,* 2021). CSA has emerged as a critical strategy to enhance agricultural resilience; however, its adoption is influenced by various demographic, economic, and sociocultural factors (Zerssa *et al.,* 2021). Limited knowledge and capacity among farmers significantly hinder the widespread uptake of CSA, underscoring the importance of targeted training and institutional support (Nkuba *et al.,* 2020). Empirical evidence suggests that factors such as education, gender, land characteristics, social capital, and market access are essential in facilitating the adoption of CSA practices (Aryal *et al.,* 2018). Despite the proven potential of CSA practices to improve productivity and labor returns, their global adoption remains limited, highlighting a gap between their demonstrated benefits and actual implementation (Imran *et al.,* 2018). Moreover, there remains an insufficient understanding of the complex interactions between demographic, institutional, and economic factors that influence CSA adoption. The literature identifies a need for more nuanced, context-specific studies to better understand these determinants and inform the design of localized, effective policies and interventions. With this in mind, this chapter presents a review of various studies conducted by researchers both in India and abroad on aspects related to the livelihood vulnerability of farmers, the adoption of Climate-Smart Agricultural Practices (CSAPs), the determinants influencing CSAP adoption, and the impact of CSAP adoption on livelihood vulnerability. The literature review

aims to provide a comprehensive overview of the problem, identify gaps in existing research, and guide the approach and objectives of the present study, which are organized under the following broad headings:

2.1. Vulnerability of farmers due to climate change
2.2. Factors influencing the adoption of climate-smart agricultural practices
2.3. Impact of climate-smart agricultural practices

2.1. Vulnerability of farmers due to climate change

Madhuri *et al.* (2014) assessed the vulnerability of households in the district of Bhagalpur, Bihar. Data was collected from seven blocks on the basis of eight major components of LVI, namely Socio-demographic profile, livelihood strategies, Health, natural capital, social network, food, water, and natural disasters, warning, and impact. The livelihood vulnerability index (LVI) of Hahn, Riederer, and Foster was updated in accordance with the circumstances of the study area in order to identify the variability in vulnerability of affected households. The study also categorized the level of vulnerability in various blocks, which may be useful in developing and implementing various programmes to lessen the sensitivity of households in those blocks, which in turn may help them be more effective in overcoming the shock of a disaster and reestablishing their way of life. The results of the study indicated that according to LVI-IPCC, the most vulnerable blocks were Kharik, Bihpur and Ismailpur (0.06) due to more sensitivity and less adaptive capacity, whilst Naugachia (-0.07) was least vulnerable. The overall LVI-IPCC scores indicated that the households in Naugachia were comparatively less vulnerable than other blocks due to better adaptive strategy (0.29) and less sensitivity (0.27).

Panthi *et al.* (2015) conducted a study to evaluate two vulnerability assessment tools—the Livelihood Vulnerability Index (LVI) and the Intergovernmental Panel on Climate Change (IPCC) vulnerability index—in the Gandaki River Basin of central Nepal. The research surveyed 543 households engaged in mixed agro-livestock activities across three districts: Dhading, Syangja, and Kapilvastu, representing the mountain, mid-hill, and Terai (lowland) ecological zones, respectively. Data were gathered on various factors, including socio-demographics, livelihood indicators, social networks, health, food and water security, natural disasters, and climate variability, which were then incorporated into the indices. Results showed significant differences in vulnerability among the districts, with Dhading

identified as the most vulnerable and Syangja as the least. Notable variations were found across components, sub-components, and the three dimensions of vulnerability: exposure, sensitivity, and adaptive capacity. The findings of the study supported the development of site-specific strategies to mitigate the vulnerability of mixed agro-livestock smallholders to climate change.

Bhattacharjee and Behera (2018) evaluated household livelihood vulnerability and adaptive capacity in a flood-prone region of West Bengal. The study, based on primary data from two administrative blocks in Murshidabad district, focused on areas frequently impacted by floods that cause significant damage to life and property. To measure the degree of livelihood vulnerability, the researchers used both the vulnerability framework proposed by the IPCC and the Sustainable Livelihood Framework developed by the Department for International Development (DFID). A Composite Livelihood Vulnerability Index was calculated by combining household-level data, and a comparative analysis was conducted between the two blocks and at the district level. The results showed that Jiaganj block was more vulnerable than Berhampore block. The overall adaptive capacity of households was found to be lower than their exposure and sensitivity to flood events. Factors such as the age of the household head, household income, landholding size, and family size significantly influenced vulnerability elements like exposure, sensitivity, and adaptive capacity. The study identified several household coping and adaptation strategies to floods, including borrowing money from friends or relatives, money lenders, selling assets and livestock, diversifying livelihoods, migration, raising the height of houses, and preserving food and fuel stocks.

Abeje *et al.* (2019) conducted a study in the Upper Blue Nile basin of the northwestern highlands of Ethiopia. To analyze livelihood vulnerability to climate change of smallholder farmers' the IPCC-LVI construction methodology was used, which is mostly based on a sustainable livelihood framework. The two-stage sampling procedure was used to select sample households (n = 391). The Mann–Kendall (MK) test and Sen's slope estimator were applied to the time-series data from 1982 to 2016 for the three watersheds. The results of the study revealed that Guder had the highest deviation from the rainfall trend (87.1 mm), as compared to Aba Gerima (44.8 mm) and Dibatie (43.4 mm). On the basis of the aggregate score Aba Gerima (0.37) was found to be more vulnerable, followed by Dibatie (0.35) and Guder (0.34). Aba Gerima (0.14) had the highest score for the sensitivity dimension for IPCC-LVI, followed by Dibatie (0.13) and Guder (0.12). Comparing Aba Gerima (0.15) to Guder (0.14) and Dibatie (0.13), it was found that Aba Gerima had slightly higher

vulnerability due to lower adaptive capacity. This study will have practical implications for policy development in diverse agroecological zones for sustainable livelihood development and climate change adaptation programs.

Dendir and Simane (2019) assessed the vulnerability of farm households' livelihood in response to climate change in different agroecological zones of Gurage Zone, Ethiopia. The study uses a Livelihood Vulnerability Index (LVI) and Livelihood Vulnerability Index–Intergovernmental Panel on Climate Change (LVI–IPCC) method to measure the extent of vulnerability to climate change. A multi-stage sampling technique was used to collect the primary data from 357 sample households. The secondary data related to temperature and rainfall trends and seasonal variations were collected between 1983 and 2016 from the Ethiopian Meteorological Agency. Ezha woreda was more exposed (0.32) to climate change, and Ezha showed greater vulnerability in terms of the socio-demographic profile, with a weighted average score of 0.35, followed by Cheha (0.3) and Sodo (0.3). The results indicated that the differences in vulnerability to climate variability and change were associated with variations in household characteristics, lack of farm households' access to basic infrastructure, low level of diversification, and lack of available technologies. Farmers in the study areas reported that land management activities were necessary and crucial for improving natural resource use and management. Although it was suggested that poorly managed livelihood activities also weaken adaptive capacities of households and increase their vulnerability.

Huong *et al.* (2019) utilized the Livelihood Vulnerability Index (LVI) and the Livelihood Effect Index (LEI) to assess the vulnerability of three agricultural and natural resource-dependent communities in northwest Vietnam, a region predicted to experience severe climate change impacts. Using survey data and secondary climate-related information, a composite index was created, and vulnerability levels were compared across the communities. The results revealed that the "Pa Vay Su" community was the most vulnerable, particularly regarding housing, knowledge and skills, socio-demographics, health, water security, social networks, and livelihood strategies. The "Hien Luong" community showed greater vulnerability in terms of other LVI indicators, except for food security, climate variability, and natural disasters. Meanwhile, the "Moc Chau" community was more vulnerable concerning water security and socio-demographics compared to "Hien Luong." Overall, the study demonstrated that the three vulnerability assessment indices could be broadly applied to similar settings in other areas of the country, potentially serving as a

foundation for a nationally applicable index to identify and prioritize adaptation and mitigation measures for improving livelihoods.

Jamshidi *et al.* (2019) analysed smallholder farmers' vulnerability to climate change in the Hamadan province, Iran. General views and perceptions of the respondents towards climate change, climatic hazard events, and the factors contributing to vulnerability were investigated by a cross-sectional survey with a random sample of 280 smallholder farmers that was conducted in six counties of Iran's Hamadan. For vulnerability assessment, 13 factors were highly contributing, including education, income, access to infrastructure, credit, land size, etc. The coefficient weights assigned for indicators were (0.25) exposure, (0.40) sensitivity, and (0.35) adaptive capacity, respectively. On the basis of the results, the vulnerability index ranged from 0.41 (least vulnerable) to 0.59 (most vulnerable). It was found that in terms of sensitivity, Asadabad smallholder farmers were the most vulnerable group to climate change, while the most exposed to climate change impact were Malayer Farmers. Furthermore, findings showed that the majority of respondents thought vulnerability to climate change was real, and about one-third of them claimed this phenomenon to be caused by human activities. It is suggested that policymakers should strengthen the efforts to enhance farmers' adaptive capacity to climate change.

Sujakhu *et al.* (2019) aimed to investigate the impact of cultural and gender-related factors on livelihood vulnerability in indigenous farming communities in the mountainous regions of Nepal, specifically in the context of climate change. Using the Livelihood Vulnerability Index, they assessed the vulnerability of households (based on social group and gender) in farming communities within the Melamchi River Valley, Nepal. The findings revealed that female-headed households and those from disadvantaged social groups were more vulnerable and should be prioritized for policy interventions. Key factors contributing to vulnerability included higher exposure to climate extremes and hazards, reliance on natural resources, lack of financial resources, and weak social networks. The study also explored complex adaptation pathways and examined how gender and ethnicity influence the ability of households and communities to adapt to climate change.

Suryanto and Rahman (2019) conducted a study to compare farmers' livelihood vulnerability to flooding in Sukoharjo and Klaten Regency in Indonesia. Primary data was collected through interviews with 61 respondents in Sonorejo Village, Sukoharjo Regency, and 72 respondents in JiwoWetan Village, Klaten Regency. Hazard level mapping was

performed using Geographic Information System (GIS), and descriptive statistics were used to calculate the Livelihood Vulnerability Index (LVI) and the LVI-Intergovernmental Panel on Climate Change (IPCC) index. The findings indicated that farmers in Sonorejo Village faced a medium level of vulnerability to climate change, with an LVI value of 0.363 and an LVI-IPCC index value of 0.044. In contrast, JiwoWetan Village had a slightly lower vulnerability, with an LVI value of 0.344 and an LVI-IPCC index value of 0.038. Despite having similar physical characteristics and a community largely dependent on agriculture, both areas showed comparable levels of vulnerability.

Chhogyel *et al.* (2020) investigated the perception of farmers' climate change and its impacts on agricultural production, including the different coping strategies prevalent in rural communities of Bhutan. The study was conducted in six districts of Bhutan, representing high-, mid and low-altitude farming ecosystems of the country, which range between elevations of 100–2600 m above mean sea level, and randomly selected 40 farmers from each of the six study districts. A total of 240 farmers were surveyed using semi-structured questionnaires, consisting of 117 males and 123 females. In this study, a point scale of 1 and 0 was used to represent 'yes' and 'no' on the responses of the farmers. Based on these point scales, the percentage of farmers expressing various views of climate change was assessed. For assessing the values of various parameters like ANOVA, means, standard deviation, data range, and weighted mean ranking, was applied. The findings revealed that most of the farmers thought climate change to be unpredictable weather (79%), less or no rain (70%), and drying of irrigation sources (55%). Some farmers referred to climate change as the emergence of diseases and pests (45%), high-intensity rains (30%), less or no snow (24%), and shorter winters (11%). The most commonly observed adaptation strategies applied by the farmers were: the use of plant protection chemicals, improved varieties, increasing frequency of irrigation, land fallowing, off-farm works, and improved management practices.

Poudel *et al.* (2020) estimated households' livelihood vulnerability to climate change in Nepal's Lamjung district. The households in rural mountainous areas of Nepal rely on natural resources for agriculture and subsistence living, were vulnerable to climate change. Using a stratified random sampling technique, 150 households from three village development committees (VDCs) were surveyed to examine two vulnerability assessment indices: the livelihood vulnerability index and the IPCC vulnerability index. Eight key components—climate variability, natural disasters, health, food, water, socio-demographic profile, livelihood strategies, and social networks—were combined to provide descriptive

data from the survey based on 19 sub-components. The findings revealed that overall LVI was more vulnerable for Khudi VDC (0.351) as compared to the Kunchha VDC (0.310) and Ilampokhari VDC (0.309). The Khudi VDC's food vulnerability (0.1968) was likewise greater than that of Kunchha(0.1162) and Ilampokhari due to the higher average number of food-insufficient months (6.09 months) and larger percentage of households (24%) with decreased food availability (0.0737). They suggested that a micro-level analysis of vulnerability may benefit understanding the complexities and designing adaptation plans at the local level.

Rizwan *et al.* (2020) measured the risk perceptions and attitudes of rice farmers in the Punjab province of Pakistan. The equally likely certainty equivalent (ELCE) method was used to measure the attitude of rice farmers toward risks, and rice growers were asked to rank their perceptions of various risk types to severity, and frequency using a Likert scale (1=very low to 5=very high). A bivariate probit regression model was used to evaluate the impact of respondents' socio-economic and farm-level characteristics on the perception and attitude toward risk. The findings of the study disclosed that 76 per cent of growers have a risk-averse attitude toward risks and uncertainties; 72 per cent of rice farmers have risk perceptions toward flood, and 76 per cent of respondents have high risk perceptions. The results showed that crop disease risk perceptions are faced by 73 per cent of farmers, while 63 per cent perceived the high-temperature risk in the study area. Moreover, findings demonstrated that rice farmers perceived floods, high input costs, rising temperatures, and crop diseases as risks. Farmers' attitudes and perceptions of risk were influenced by a variety of socioeconomic characteristics, including age, education, the distance of their farms from rivers, and non-farm income. Overall, these findings may be useful for managing risks and sustainable farming for other crops and other developing countries.

William *et al.* (2020) conducted the study in two districts, Nsawam Adoagyiri and Keta, in the Eastern and Volta regions of Ghana, Africa. The Livelihood Vulnerability Index was used to comprehend and identify the nature and sources of vulnerability among smallholder horticulture farming households to climate variability. A total of 480 households that produce fruit and vegetables were surveyed for indicators of Livelihood Vulnerability Index components, such as socio-demographic profiles, livelihood strategies, social networking, health, food, production, water, natural disasters, and climate variability. It can be concluded that the degree of vulnerability is slightly higher for Keta households (−0.010) than for Nsawam households (−0.021). Keta was the most exposed (0.391) and most sensitive (0.379) horticulture-producing

municipality to climate impacts compared to Nsawam's exposure (0.372) and sensitivity (0.339). Further, the study indicated that Livelihood Vulnerability Index can be widely used to identify potential intervention areas and lower the vulnerability of farming communities that are specific to a given sector at both the local and global levels.

Engler *et al.* (2021) conducted a study in the Maule Region of central Chile and analyzed the relationship between individual farmer experiences regarding vulnerability and agricultural adaptation processes. Social and human resources, as well as structural factors, were used to describe the patterns of proactive and reactive adaptation behaviour. Social and human capital served as boosting elements that described proactive adaptation, while structural factors like production systems and financial capital explained the involvement in adaptation to climate change. The study suggested that policymakers should focus on future policies related to adaptation behavior and promoting proactive forms of adaptation behavior by developing and enhancing social connections and access to information, and the provision of financial schemes to enable efficient and effective adaptation within the agricultural sector.

Nguyen *et al.* (2021) analyzed and compared the livelihood vulnerability of the Dzao and Hmong of Northern Vietnam. The data was collected through a questionnaire survey and a focus group discussion of 120 respondents. Climatic data for over 55 years (1951-2016) have been collected from the Vietnam National Hydro-Meteorological Service. A formative composite index of livelihood vulnerability (LVI), Livelihood Vulnerability Index framed within the IPCC (LVI-IPCC), and Livelihood Effect Index (LEI) were constructed. Ten major components and 29 sub-components contributed equally to the overall LVI. Ten major components were sociodemographic profile; livelihood strategies; social networks and revenue; health; food; water; housing; land; and natural hazards and climate variability. Overall, aggregated components of livelihood vulnerability found that Hmong were found to be more vulnerable, with a score of 0.43, while Dzao had a relatively lower LVI with an index score of 0.34. While in the case of health, food, water, land, and housing situation of the Hmong was found to be more sensitive. Dzao had a lower sensitivity as they save crops better for other food supplies and experience better health, work, water, and arable land conditions (S(M)=0.5; S(D)=0.35). LEI comparison shows that Dzao have a higher livelihood effect index than Hmong (LEI(M)=0.34; LEI(D)=0.35).

Raihan and Hossain (2021) conducted a study to examine the livelihood vulnerabilities and adaptation strategies in response to climate change, based on empirical

evidence from wetland communities using the Livelihood Vulnerability Index (LVI) in Tanguar Haor, Sylhet, Bangladesh. The findings revealed that the people in the study area were shifting from traditional livelihood activities to alternative sources. Common adaptation strategies included crop diversification, homestead gardening, erosion-proofing, and cage aquaculture. The study identified key drivers of vulnerability such as lack of education, underdeveloped infrastructure, inadequate health facilities, and limited alternative livelihoods during extreme events. As a result, the communities living in and around the haor region require special attention. The study concluded that there is a need for policy and institutional arrangements to establish a better governance system, improve living standards, and enhance resilience to the impacts of climate variability and change.

Rana *et al.* (2021) assessed the climate vulnerability at the block scale in the Kullu district of Himachal Pradesh using a total of 108 indicators. To understand demographics, exposure, sensitivity, and adaptation in the agriculture, horticulture, and livestock sectors. primary data was collected from the farmers' survey and secondary data was collected from government revenue records and, for the weather data, from recording stations of the India Meteorological Department and the Bajaura research station of the Chaudhary Sarwan Kumar Himachal Pradesh Krishi Vishvavidyalaya (Kullu). In the study area, most of the farmers observed a trend of increasing dry spells for 6–8 months. The results of the study revealed that among different blocks of the Kullu district Banjar was highest in exposure vulnerability in the agriculture (0.909), horticulture (0.934), and livestock (0.876) sectors. The sensitivity vulnerability index was found to be highest in Anni (0.643), followed by Naggar, and lowest (0.497) in Kullu. The mountainous ecosystem of the study areas necessitates a focus on agronomically manipulated adaptations, such as adjusting planting windows, crop management techniques, cutting back on pesticide use, and balancing soil nutrient inputs.

Tran *et al.* (2021) examined the livelihood vulnerability of climate change on minority ethnic groups of Vietnam using the livelihood vulnerability index (LVI) and LVI-IPCC method. Primary data was collected by interviewing (n=240) the head of the household or the main labourer. Daily maximum and minimum temperature and precipitation data were collected from the Phu Yen meteorological station, and for over 56 years (1961-2017) have been collected from the Hydro-Meteorological Data Centre of Vietnam. In the study, LVI has eight major components, namely sociodemographic profile, livelihood strategies; social networks and finance; health; food; water; housing and productive land; and natural disasters and climate variability. The findings indicated that most households reported their areas of

agricultural land were more vulnerable to floods than droughts, except for Thai households, which were more vulnerable to droughts than floods. The most important factors that influenced the households' adaptive capacity were education level, diversity of income sources, agricultural training, and organizational membership. The study suggested that each group relied heavily on agriculture as their primary source of income. All groups have relatively low-income diversity and a heavy reliance on agriculture, which increases their exposure to climatic influences.

Nguyen and Scrimgeour (2022) investigated the impact of changes in climatic conditions on agriculture in Vietnam. The Hsiao-two step method was used for a panel of 10 years of household data, which focused on the production of 20 crops across seven areas in Vietnam. Through the study, different regions that cultivate various crop varieties have been given the opportunity to provide varying market feedback. The study has demonstrated the market shocks that have variable effects on regions growing different types of crops. The results of the study revealed that increased amount of rainfall in winter and spring was anticipated to reduce agricultural income, while increase in precipitation in the summer and autumn was beneficial for agriculture. According to the simulation marginal regional losses were ranged from 0.02 per cent to 2.6 per cent between 2030 and 2100. Cooler regions such as the Central Highlands and the Northwest were likely to experience above-average losses, and the Red River delta was shown to be minimally affected in the long run. The research provided the implicit assumption that farmers will adapt by crop switching in the changing climate.

Rai *et al.* (2022) tested the hypothesis to identify the sources of vulnerability among smallholder farming households using the Livelihood Vulnerability Index (LVI) and LVI-IPCC (Intergovernmental Panel on Climate Change) approaches in six potato-growing districts of Bhutan: Bumthang, Chukha, Gasa, Mongar, Tashigang, and Wangdue. Primary data was collected through a semi-structured sample survey of 240 households, covering seven major livelihood components: socio-demographic profiles, livelihood strategies, social networks, health, food, water, natural disasters, and climate variability. The results indicated significant differences ($p < 0.001$) in the LVI (ranging from 0.302 to 0.375) and LVI-IPCC (ranging from 0.005 to 0.030) across the districts. The Tashigang and Mongar districts were found to be less vulnerable than the other four districts according to the LVI approach, while Bumthang was identified as less vulnerable using the LVI-IPCC approach.

2.2. FACTORS INFLUENCING THE ADOPTION OF CLIMATE-SMART AGRICULTURAL PRACTICES

Aryal *et al.* (2017) highlighted the adoption of multiple climate-smart agricultural practices and analyzed the elements that affect the likelihood in the Gangetic plains of Bihar, India. A multi-stage sampling technique was employed to select the sample households (n=641). It was found in the study that farmers of large farms were more likely to adopt all CSAPs. Results from the multivariate and ordered probit models revealed that the adoption of multiple CSAPs in Bihar was not mutually exclusive. Gender of the household head, caste, literacy status of household head and migration were the major household characteristic variables affecting the intensity of CSAP adoption. The uptake of CSAPs was found to be significantly impacted by access to markets and extension services. It is suggested on the basis of the present study that it is essential to provide more training on CSAPs for farmers, increasing the number of government extension staff working at the local level, and the use of ICTs to share and promote knowledge of CSAPs.

Maguza-Tembo *et al.* (2017) examined the determinants of climate-smart agriculture technology adoption in the drought-prone districts of Malawi. Cross-sectional household data were collected from 619 farm households. Adoption decisions and interrelations between them were analyzed using a multivariate probit method. CSA technologies practiced by the respondents in the study were portfolio diversification (32%), soil and water conservation (42%), soil fertility improvement (22%), changing planting dates (17%) and irrigation/rainwater harvesting (30%). It was found that 99 per cent of the farmers were aware of changes in climate variability. Moreover, farmers who were able to foresee drought had a positive adoption effect on portfolio diversification, soil & water conservation and irrigation & water harvesting, whereas they had a negative adoption effect on soil fertility improvement technologies. Further analysis revealed that factors such as farmer type, education level, size of cultivated land, household expenditure, anticipation of disasters like drought and flooding, presence of traditional early warning system, and farmers' formal training in climate variability issues had a positive influence on farm households' decisions to adopt irrigation and water harvesting technologies; whereas farmers' livelihood status and off-farm participation had a negative impact towards irrigation & water harvesting technologies.

Shikuku *et al.* (2017) examined the attitude of smallholder farmers and also assessed the determinants of adaptation to climate risks in East Africa. A livelihood-based index was used to measure adaptation, and weights were assigned to different individual strategies

based on their marginal contributions to a household's livelihood. The result showed that at a lower level of adaptation (25% quantile), the adaptation index was positively correlated with farmers' membership groups, household size, sex of the household head, and the number of months of food shortage; Farmer group membership enhanced adaptation at intermediate (50% quantile) level whereas access to credit increased adaptation at high (75% quantile) level. However, food insecurity was negatively correlated with the likelihood of choosing individual adaptation strategies, suggesting that although households adapted to improve the food security status of their households, hunger was a barrier to adaptation.

Aryal *et al.* (2018) investigated the factors that determine the probability and level of adoption multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India. Multi-stage sampling technique was employed to collect the data from 1,267 farm households through household survey. In the study multivariate probit model was used for the simultaneous multiple adoption decisions and ordered probit models for assessing the factors affecting the level of adoption. Widely adopted CSA practices by the respondents were laser land levelling, minimum tillage, crop diversification, stress-tolerant varieties and site-specific nutrient management. Further analysis revealed that the adoption of the various CSA practices was correlated, whereas several factors, including household characteristics, plot characteristics, market access and major climate risks were found to affect the probability and level of CSA adoption. Access to markets, credit and extension services and other information sources were found to play a crucial role in boosting CSA adaptation. Therefore, the study suggested that it is essential to emphasize policies and plans that enhance market access and improve agricultural credit facilities and the quality of extension services.

Abegunde *et al.* (2019) conducted a study in South Africa and assessed the factors affecting the adoption of climate-smart agricultural practices by small-scale farming households. Most commonly adopted climate-smart agricultural practices in the study area were organic manure, crop rotation and crop diversification. For the analysis of data various tools and models such as descriptive statistics, Composite Score Index and a Generalized Ordered Logit Regression were employed in the study. The results of the study indicate that the majority (56.6%) of the small-scale farmers fell into the medium user category, while the least (17.7%) proportion fell into the high user category. Further analysis revealed that factors such as educational status, farm income, farming experience, size of farmland, contact with agricultural extension, exposure to media, agricultural production activity, membership of an agricultural association or group and the perception of the impact of climate change were

found to be statistically significant and positively associated with the level of CSA adoption. Moreover, off-farm income and distance of farm to homestead were statistically significant but negatively associated with the CSA level of adoption. Thus, the study concluded that enhancing and strengthening contact with agricultural extension agents, increased exposure to media, and raising awareness on the impacts of climate change were critical in promoting the level of adoption of CSA practices.

Makate *et al.* (2019) analysed the increasing resilience of smallholder farmers by assessing the factors explaining individual and multiple adoptions of climate change management strategies. Simple random sampling was employed to select the districts and data from 1172 smallholder farming households were collected through the International Fund for Agricultural Development-funded project. A multinomial logistic regression model was used to evaluate factors of individual and multiple adoptions of CSA innovations. Eight categories were formed from a combination of three climate-smart innovations, such as drought-tolerant maize (DTM), improved legume (IL), and conservation agriculture (CA). The following eight categories, which together make up the variable CSA, were: no adoption (the base category), CA adoption only, IL adoption only, IL and CA adoption, DTM adoption only, DTM and CA adoption, DTM and IL adoption, and DTM, IL, and CA adoption. The independence from irrelevant alternatives (IIA) assumption was formally tested using the Hausman test. The findings indicated that individual Adoption rates of DTM were overwhelmingly high sample with 34.1, 40.4 and 27.4 per cent, in the Zimbabwean sample and Malawian sample, respectively. Adoption rates in combinations, and implementation of the three innovations were highest, with 12.9 per cent, with 13.5 and 12.3 per cent in Malawi and Zimbabwe, respectively. It was found that greater access to resources enhances multiple adoptions of climate-smart innovations.

Mujeyi *et al.* (2019) examined the determinants of multiple climate-smart agriculture technologies adopted by smallholder farmers in Zimbabwe. A multistage sampling technique was employed to collect data from 386 households. Principal component analysis (PCA) was used to identify the CSA technology combinations adopted by smallholder farmers and a multinomial logistic regression model was employed to analyze the adoption of the constructed CSA technology bundles. The study identified three prominent (labour saving and soil fertility; yield and soil fertility; and dominantly traditional way of farming) technology bundles/combinations. The findings from the multinomial logistic selection model revealed that the observable household and market access characteristics influence the

likelihood of a farming household adopting any CSA technology bundle. The results showed that the gender of the household head, farm characteristics (soil type and labour size), and institutional factors (market access, information access and access to credit) were the main factors that determined the adoption of various CSA technology combinations. Therefore, the study suggested that the government should design policies aimed at enhancing farmers' knowledge with regard to CSA, including early warning systems and programmes that increase access to information, markets, and credit.

Kangogo *et al.* (2020) examined the influence of farmer entrepreneurial orientation on the adoption of climate-smart agriculture (CSA) practices. Multistage sampling was employed to collect the data from smallholder potato farmers in Kenya. Principal component analysis (PCA) was used to reduce the farmer EO statements to a small number of variables and multivariate probit model (MVP) technique was used to model the effect of farmer EO on farmers' adoption of different combinations of CSA practices. The findings revealed that risk-taking has positively influenced the adoption of irrigation, changing the cultivation calendar, use of certified seed, crop rotation and soil testing. Proactiveness was positively related to the use of irrigation, changing the cultivation calendar and use of certified seed, while it was negatively related to intercropping. The education level of the respondents was positively associated with the adoption of certified seed and soil testing, practices that require financial investment on the part of the farmer. It was also found that more proactive potato farmers do not practice intercropping because they were more market-oriented in their production decisions. This market orientation of more proactive farmers was further shown by the positive relation between proactiveness and practices such as the use of certified seed and application of irrigation. Innovativeness was found to be negatively associated with the adoption of practices that require a high intensity of financial resources. The findings revealed that measuring EO as a multidimensional rather than a unidimensional concept was more important cognitive trait of smallholder farmers that matters for their decision-making on CSA practices.

Kurgat *et al.* (2020) investigated the factors that influence the adoption of climate-smart agriculture technologies that can assist smallholder farmers to attain some of the CSA outcomes in Tanzania. Climate-smart agriculture technologies adopted in the study area were crop and livestock diversity, irrigation, application of chemical fertilizers, and agroforestry. A household survey was conducted to collect data from 821 farming households. A multivariate probit model was used to assess the determinants of adoption, allowing for examination of synergies and trade-

offs between the technologies. Results from the study revealed that 34 per cent of farmers adopted the application of chemical fertilizers, followed by 26 per cent adopting irrigation. In the study, trade-offs were observed between livestock diversity and irrigation. Major determinants of adoption were female control of farm resources, farm location, and household resources. The location dummies indicated that the adoption of CSA technologies were significantly influenced by general location factors. We consequently suggest strategies that try to enhance developing household resources as a road to better adoption of new technologies. Therefore, they recommended strategies that seek to enhance household resource building as a pathway for improved adoption of new technologies.

Opaluwa *et al.* (2020) investigated variables influencing the choice of climate change adaptation strategies among rural farming households in Kogi State, Nigeria. Multi-stage random sampling technique was used to select rural farmers (n=115). The multivariate probit model was employed to estimate the factors that determine the choice of adaptation strategies. The results of the multivariate probit model demonstrated that the decision to embrace the planting of cover crops as a strategy for adaptation was influenced by years of farming experience. The main effects of climate change that households in the study area perceived were erosion/flooding (M = 3.44), increased rainfall (M = 3.38), scarcity of resources (M = 3.24), increase in temperature (M = 3.14) and an increase in disease and pest infestation (M = 2.86) that was brought on by the increased rain. The key adaptation techniques used by the farmers in the study area were change in planting date (72.17%), change in harvesting date (67.83%), construction of drainage around homes/farms (67.83%), income diversification (64.35%), and planting cover crops (58.26%). The major barriers to climate change adaptation by farmers were the high cost of farm labour (M = 3.37), lack of finance to purchase or use an adaptation method (M = 3.25), inadequate government attention to the issue (M = 3.22), scarcity of farm inputs (M = 3.17), high cost of improved crop varieties (M = 3.12), low household income (M = 3.10), and high cost of farm inputs (M=3.09).

Zakaria *et al.* (2020) assessed the factors influencing rice farmers' adoption of climate-smart agriculture technologies using Multivariate Probit and Poisson regression models. A multi-stage sampling technique was used to solicit the primary data from 543 rice farmers using a semi-structured questionnaire. Farmers who perceived increased temperature were more likely to adopt irrigation, but less likely to adopt early maturing varieties, drought-tolerance varieties, and change planting period than farmers who did not perceive increased

temperature. Results of the MVP regression showed that the Wald $\chi 2$ of 603.30 was statistically significant at 1 per cent and justified the fitness of the MVP model for the data. It was found that seven CSATs correlation pairs were statistically significant and positively associated, indicating that rice farmers considered the CSATs to be complementary rather than substitutional technologies. Thus, rice farmers adopted multiple CSATs simultaneously. Moreover, farm size, distance between farmers' houses and farm location, location of farmers, and perceived increase in temperatures negatively influence farmers' adoption intensity of CSATs. Further, it is recommended that farmers should be sensitized to the need to adopt CSATs as a package rather than selecting single technologies to adopt. This could contribute to farmers' maximisation of the benefits of CSATs. Also, rice farmers should be educated on CSATs by agricultural extension officers, through regular training to raise their knowledge on the benefits of CSATs to foster effective CSATs adoption.

Ali (2021) examined the determinants of the choice of adaptation strategies in Northern Togo. A multistage sampling technique was used to collect data from 704 farm households. Results from zero-inflated Poisson regression and multivariate analysis revealed that the choice of adaptation technologies and the number of adopted technologies were expected to positively associate with the minimum consumption needs of the household. It was found that 85 per cent of households' heads have attended at least a primary school, followed by 63 per cent of respondents who obtained credit for farming activities, and 32 per cent of farm households were assisted by extension officers. Further analysis revealed the factors that influence households' choice of adaptation strategies were gender, household location, education level, family size, and allocated labor. The study shed light on institutional factors, i.e., market access, access to credit, and extension services were also key determinants in promoting the adoption of climate-smart practices that are environmentally friendly. Therefore, studies indicated that promoting education could boost farmers' understanding and adoption of best adaptation practices to improve productivity.

Autio *et al.* (2021) conducted a study in Southeast Kenya and determined the constraints for adopting climate-smart agricultural practices among smallholder farmers. The results also highlight the need to invest in rural public education to provide farmers with training in CSA practices and technologies after the local focus has been identified through dialogue. The findings indicated a dissonance in the perceived awareness of CSA practices and utilization of CSA technologies between state actors and farmers. State actors emphasize lack of awareness as a barrier to adoption, while farmers express knowledgeability regarding

environmental change and climate-smart practices but are confined by limitations and restrictions posed by, e.g., market mechanisms and land tenure issues.

Nyang'au *et al.* (2021) investigated smallholder farmers' perception of climate variability and change and their adaptation strategies in Masaba South Sub-County, Kisii, Kenya. A multi-stage sampling technique was employed to collect data from smallholder farmers (n=196). For the collection of data from respondents pre-tested structured questionnaire, focused group discussions, and key informant interviews were used. The results of the study revealed that most farmers perceived climate change. 88.3 per cent of respondents noted a decrease in rainfall, 79.1 per cent reported poor rainfall distribution, 88.3 per cent perceived a late onset of rainfall, and 76.6 per cent perceived an increase in temperature. The primary adopted climate-smart agriculture practices by respondents in the area were diversification of crops, change of planting time, and crop rotation/mixed cropping. The findings showed that the adoption of climate-smart agriculture practices significantly correlated with household size, monthly income, access to credit, and farmers' perception of climate change. The study suggested that the county and government development agenda should prioritize climate change to enhance the uptake of climate-smart agricultural practices.

Onyeneke *et al.* (2021) conducted a study in Ebonyi State, Nigeria, and analyzed the perception of climate change and the uptake of climate-smart agriculture in rice production. A cross-sectional household survey was conducted to collect data from 347 rice farmers in an important rice-producing area in Nigeria. For data analysis, principal component analysis, multivariate probit regression model, and descriptive statistics were employed in the study. Findings revealed that perceived climatic events include intensified rainfall, extended dry seasons, frequent floods, increasing temperature, severe windstorms, unpredictable rainfall pattern and distribution, late onset rain, and early cessation of rain. Farmers' socioeconomic, farm, and institutional characteristics influenced their perception of climate change. Farmers' perceptions of climate change were influenced by their socioeconomic, farm, and institutional characteristics. Climate-smart agricultural packages used by the farmers were crop and land management practices, climate-based services and irrigation, livelihood diversification and soil fertility management, efficient and effective use of pesticides, and planting in the nursery. The adoption of climate-smart agriculture in the production of rice was found to be hindered by high fertilizer costs, lack of access to inputs, insufficient land, insufficient capital, pests and diseases, floods, scorching sun, high labour cost, insufficient climate information, and poor extension services. Thus, it can be concluded that rice farmers should be encouraged to

use climate-smart agriculture practices to accomplish the goals of enhanced rice productivity and income, food security, climate resilience, and mitigation.

Oyetunde-Usman *et al.* (2021) evaluated determinants of the adoption of multiple sustainable agricultural practices among smallholder farmers in Nigeria. Using cross-sectional data collected from the 2015 Nigeria General Household Survey, this study examines the factors influencing the adoption of multiple SAPs, while also considering the drivers of the intensity of adoption of these practices. The methods of data analysis are based on the Multivariate probit and the ordered probit models. The SAPs considered include improved seeds, inorganic fertilizer, mixed-cropping techniques, and organic manure. The empirical results show that farmers' adoption of different SAPs and their intensity of use depend significantly on factors such as the age of the household head, gender, education, household size, access to extension services, and household wealth status.

Pello *et al.* (2021) evaluated the factors influencing the adoption of agroforestry technology in Kenya. A multistage sampling technique was used to collect data from sample households (n=239). A Probit model and K-means algorithm were employed to analyze the factors affecting farmers' agroforestry technology adoption decisions based on the sampled households' socioeconomic, demographic, and farm characteristics. The majority of female farmers were more likely to adopt agroforestry technologies as compared to their male counterparts. Further analysis revealed that the frequency of visits to extension service centers, access to markets and farm size were positively and significantly affected by the adoption of agroforestry technology. The total yield had a significant negative effect on farmers' decision to adopt agroforestry technology. The results also revealed that farmers were gradually adjusting to agroforestry to mitigate the effects of climate change. The present study suggested that the government should get more actively involved in developing policies that would increase the use of agroforestry technology and offer more generous incentives, such as providing free seedlings to farmers.

Alidu *et al.* (2022) examined the association between smallholder farmers' decision to acquire climate information and the subsequent adoption of climate-smart adaptation practices in the Northern region of Ghana. A cross-sectional survey was used to collect data from 475 smallholder farmers. The bivariate probit model was employed to assess the joint determination of the groups' access to climate change information and adoption of climate-smart adaptation practices and the related determinants of both decisions. The results

indicated that 85 per cent of the smallholder farmers adopted climate-smart adaptation practices, and 77 per cent of the smallholder farmers were males. The findings of the study revealed that factors such as gender, age, size of the farm, income from the farm, access to agricultural extension services, social group membership and assets increase the likelihood and were positively influenced by the joint decision of smallholder farmers to access climate information and adoption of climate-smart adaptation practices. The study shed light on enhancing smallholder farmers' literacy and knowledge level, including non-formal and informal educational programmes, and extension education using the farmer-field schools' method. Therefore, the study recommended to increase the income of smallholder farmers government should facilitate smallholder farmers to engage in other livelihood activities and this will consequently improve their access to climate information and adoption of climate-smart adaptation practices.

Andati *et al.* (2022) examined the factors that influence climate-smart agriculture adoption among smallholder potato farmers in Nyandarua County, Kenya. Special focus was on the role of the farmers' entrepreneurial orientation (reflected in the farmers' innovativeness, proactiveness, and risk-taking). Through a cross-sectional survey, data were collected from 350 potato farming households. Descriptive statistics, principal component analysis (PCA), and a multivariate probit regression model were used to analyze the data. Six categories of CSA practices were considered according to the sample area: soil nutrient management, crop management, crop protection, seed management, water harvesting, and crop quality improvement. The multivariate probit results showed that farmers' entrepreneurial orientation had mixed influence on CSA adoption. The average PCA scores for risk-taking, innovativeness, and proactiveness, respectively, were 0.499, 0.616, and 0.522. The findings indicated that the risk-taking behavior of the farmers was positively associated with the adoption of crop protection technologies. Farmers who participated in collective action (i.e., farmer organizations) were more likely to use CSA technologies, such as crop management and crop protection technologies, than those not participate. Thus, it is concluded from the study that EO plays a vital role and has a diverse influence on CSA adoption among potato farmers. They suggested the importance of tailoring entrepreneurial training to address the three specific dimensions − innovativeness, proactiveness, and risk-taking among potato farmers.

Anugwa *et al.* (2022) assessed the preferences of the farmer and elicited willingness to pay (WTP) for climate-smart agricultural technologies using the contingent valuation

method (CVM) in Nigeria. A multistage sampling technique was used to select sample households (n=96). Information from the respondents was elicited through surveys, focus group discussions (FGDs), and key informant interviews. During the survey questionnaire was used to collect data, comprising open and closed-ended questions on the respondents' socio-economic characteristics, CSA technologies used by them, preferred CSA technologies, WTP for the selected CSA technologies, and determinants of their WTP for the preferred CSA technologies. The respondents' preferred CSA technologies were measured on a four-point Likert scale of highly preferred, moderately preferred, slightly preferred, and no preference. The respondents' willingness to pay for their preferred CSA technologies was elicited through the single bound (referendum) CV method. The results of the study revealed that farmers use less carbon-smart, weather-smart, and nutrient-smart technologies in their rice production activities. On the basis of results, CSA technologies highly preferred by respondents improved rice variety that was flood tolerant (64.6%), crop insurance (60.4%), drip irrigation (55.0%), sprinkler irrigation (33.3%), integrated pest management (26.0%), and climate change information (22.9%), among others. The probability of WTP for nutrient-smart and carbon-smart technologies significantly decreases with the age of respondents. It was also evident that WTP, for weather-smart technology, increases significantly with the number of years respondents spent in school. On average, rice farmers were willing to pay $31.02 for water-smart, $1.85 for energy-smart, $17.97 for nutrient-smart, $17.72 for weather-smart, $6.82 for carbon-smart, and $40.25 for knowledge-smart technologies. The author suggested that policymakers should design policies aimed at strengthening agricultural extension contacts with farmers, and financial incentives should be provided to farmers, such as interest-free and collateral-free loans.

Diro *et al.* (2022) examined the adoption status of different Climate Smart Agricultural (CSA) practices and factors that influence their adoption in Ethiopia. A multistage sampling technique was used to select the respondents (n=953). A multivariate probit (MVP) model was employed to study factors that influence the adoption of climate-smart agricultural technologies, namely, manure application, minimum tillage, intercropping, use of improved forage, and physical soil and water management practices. The finding indicated that 35 per cent of farmers apply manure on their farm plots, 36 per cent of the farmers adopted minimum tillage followed by intercropping (45%) improved forages (19%), and physical soil and water management structures (47%). Therefore, the key findings revealed that there was a positive and significant effect of education, extension (access to

extension services and participation on field days), and ownership of communication devices specifically radio on the adoption of climate-smart agricultural practices. Although the study suggested that government should pay due attention to problems affecting effective farmers-extension linkage and the positive effect of radio ownership on technology adoption also recommended the need for increased accessibility of FM radio channels to farmers to be aware of climate change and innovative agricultural technologies, practices, and information that mitigate the problem.

Gikonyo *et al.* (2022) conducted a study in Nyando Basin, Kenya, to examine the influence of household savings on the adoption of climate-smart agricultural technologies. Data from 122 households was collected through a structured questionnaire using face-to-face interviews. Mostly adopted technology by the farmers in the study area was agroforestry (70%), followed by improved breeds (41%), water harvesting (30%), and greenhouse farming (8%). It was found that saving households were more formally educated as compared to non-saving households. The majority of households with savings had higher access to credit compared to non-saving households. Households located closer to the marketplace were anticipated to receive better returns on their produce due to lower transaction costs and higher savings. The findings of the study revealed that male household heads reduced the likelihood of adopting two CSA technologies by 21.5 per cent while increasing the likelihood of adopting only one by 27.6 per cent. With agricultural training, there was a 50.9 per cent decrease in the likelihood of adopting just one CSA practice, and a 42.8 per cent and a 7.2 per cent increase in the likelihood of adopting two or three practices. The adoption of CSA technologies was hampered by financial issues. Furthermore, it can be concluded that household saving and the annual interest earned in savings have the potential to increase the intensity of adopting CSA Technologies.

Kifle *et al.* (2022) assessed practices and factors affecting the adoption of climate-smart agriculture to respond to climate variability in the Siyadebrina Wayu district, Ethiopia. A simple random sampling technique was used to select sample households (n=368). Primary data was collected using a questionnaire survey, key informant interviews, and focus group discussions. The binary logistic regression model and descriptive statistics were applied to analyze the quantitative data. Binary logistic regression model was used to identify and interpret the main socio-economic and demographic factors affecting the adoption of climate-smart agriculture practices and their implications for food security. Findings revealed that widely practiced CSA technologiesadopted in the study area were crop rotation (71.7%),

cereals and legume crop intercropping (71.74%), efficient chemical fertilizer application techniques (89.4%), growing improved crop varieties (75.3%), pest-resistant crop varieties (77.5), and drought and heat tolerant high yield crops varieties (77.5%). However, adoption of conservation agriculture (25.5%), water management (8.87%), and livelihood diversification (5.7%) were very low. The adoption of integrated soil fertility management was influenced statistically significantly by on-farm ($p = 0.028$) and off-farm income ($p = 0.034$), respectively. Thus, the adoption of CSA by sample households was affected by multiple interrelated factors, mainly access to natural, financial, technological, and extension services and facilities, which require the government's attention and continuous follow-up.

Kogo *et al.* (2022) assessed farm-level adaptation responses towards climate change and their influencing factors, using a case study of western Kenya. Data from 210 maize farmers were taken through a structured questionnaire. The factors that influence farmers to implement the various adaptation strategies were analyzed using logistic and multiple linear regression models. The average perception ratings of respondents on the dangers of farming and the effects of climate change were 15.3 (SD = 2.7) and 12.6 (SD = 2.4), respectively. The key findings revealed that the majority (78.7%) of the farmers practiced early/delayed planting as a major adaptation strategy to combat the negative impacts of climate change followed by 63.3 per cent of the farmers practiced crop diversification by planting an average of two crops on their farm with a common combination i.e., inter- cropping of maize and beans in a given planting season. Further, the key determinants of adaptation strategies in the study were farm size, income, and extension training. Therefore, the study concluded that extension training should be scaled up as a key strategic activity to boost adaptation planning at the national, regional, and farm levels to maintain sustained crop yield, as they emerged as a key factor influencing farmers to adopt most of the adaptation decisions.

Mashi *et al.* (2022) examined the determinants of awareness level of CSA technologies and practices among urban farmers in Kuje town of Nigeria. A Focus Group Discussion (FGD) and Key Informant Interview (KII) sessions were conducted in the study area to collect the data from 491 farming households. The findings of the study revealed that the more educated farmers, older, have larger family sizes, income sources, and economic assets, with greater climate change experience and local knowledge, and have farmlands with better physical conditions were more aware of CSA adaptation strategies. Further analysis showed that eleven other factors such as marital status, tribal inclination, gender, religion, extension service, capacity building, security of tenure, institutional support, farmer

organizational affiliation, distance to farmlands, and availability of loans and incentives were not significantly influenced on the farmers' awareness levels of CSA adaptation strategies in the study area. Therefore, the study recommended that appropriate measures should be taken to increase the number, capacities, and capabilities of extension officials in the region so that they can better able to deliver extension services and capacity building. It also recommended that community-based organizations be encouraged to participate in extension service delivery and capacity development to the fullest extent possible.

Meshesha *et al.* (2022) investigated smallholder farmers' perceptions toward the adoption of climate-smart agriculture (CSA) in smallholder farmers in the Upper Blue Nile Highlands of Ethiopia. A cross-sectional household survey was conducted to collect the data from 424 smallholder farmers. A structured questionnaire was employed to collect primary data from the respondents. Secondary data was collected from a review of the literature and documents. Various statistical tools (T-test, $\chi 2$ test, and mean) were used for comparison tests to compare adopter and non-adopter groups with respect to farmers' perception of CSA innovations. Multivariate probit model was used in the study to examine perception factors affecting the likelihood of adopting multiple CSA innovations. Eight CSA innovations were the dependent variables, while the independent variables were crafted from the three pillars of CSA. It was found that row planting (76%), compost (66%), SWC (51%), crop residue management (46%), crop rotation (37%), improved variety (31%) and agroforestry (21%) were the most preferred and CSA innovations among smallholder farm households. Smallholder farmers perceived that CSA innovations increase productivity (91%), increase soil fertility (86%), increase income (80%), increase soil organic matter (64%) and reduce soil erosion (50%), respectively. Moreover, farmers who perceived CSA innovations were found to have an increase in productivity and were more likely to adopt improved variety, crop residue management, intercropping and agroforestry. It is suggested that by enhancing the information and communication gap of adoption of CSA innovations will have great potential to benefit from the innovations to the farmers.

Moutouama *et al.* (2022) examined farmers' perception of climate change, available CSA practices (CSAP) and the determinants of CSAP adoption in northern Benin of West Africa. A stratified random sampling technique was used to collect data from 368 farmers through face-to-face interviews. In the study, binomial generalized mixed-effect models were employed to analyze the relation between sociodemographic characteristics and the use of CSAP. Using a three-point likert scale and the frequency of agreement with the statement that

the selected practices meet the pillars of CSA were used to analyze climate-smart agricultural practices. More than 60 per cent of farmers had heard about climate change, and more than 80 per cent had observed changes in temperature, rainfall and distribution. In the study area thirty-one climate-smart agricultural practices were identified, although only 11 were known by more than 50 per cent of farmers. Out of the 12 chosen CSAP for the evaluation and assessment of adoption, seven were used by more than 50 per cent of the respondents who knew them. Therefore, a study indicated that farmers agreed with the statements that the evaluated practices increased farm productivity and adaptation to climate change but did not mitigate climate change. The study shed light on two major factors which were ethnic group and education level that significantly determined the use of the evaluated climate-smart agricultural practices.

Musafiri *et al.* (2022) conducted a study in Western Kenya and assessed the determinants for adoption of climate-smart agricultural practices among smallholder farmers. A cross-sectional survey and multi-stage sampling procedure was employed to select 300 smallholder farmers. A multivariate and ordered probit models were employed to evaluate the determinants of joint adoption of CSAPs. The CSAPs adopted in the study area included animal manure, soil water conservation, agroforestry, crop diversification, and crop livestock integrationg. Results from multivariate probit model showed that household head's gender, education, age, family size, contact with extension agents, access to weather information, arable land, livestock owned, perceived climate change, infertile soil, and persistent soil erosion influenced CSAPs adoption. Results from ordered probit model reported that gender, arable land, livestock owned, soil fertility, and constant soil erosion were crucial determinants of CSAPs adoption. Therefore, the findings of the study suggested that policymakers and relevant stakeholders should consider farmer, institutional, and biophysical factors in upscaling or promoting the adoption of CSAPs.

Negera *et al.* (2022) examined the factors that influence the adoption of climate-smart agricultural practices among farmers in the Bale-Eco region of Ethiopia. With the help of a structured questionnaire through computer-assisted personal interviews, data were collected from 404 sample households. The multivariate probit model was employed for assessing the simultaneous adoption of multiple climate-smart agricultural practices and the ordered probit model for examining the factors influencing the level of adoption. Climate-smart agricultural practices adopted by the farmers in the study area were improved agronomic practices (70%), soil and water conservation practices (87%), drought tolerant high yielding crop variety

(50%), small-scale irrigation (25%), integrated disease, pest and weed management (65%) and integrated soil fertility management (33%). Findings indicated that age and education of household heads were negatively associated with the adoption of CSA practices. Land size and farming experience have a positive effect on the adoption of CSA practices. Furthermore, it can be concluded that agricultural policies should focus on regulating agricultural land rental markets, which enables small farmers to obtain land. Enhancing the fertility of parcels is also essential to increasing the rate of CSA adoption.

Paudel *et al.* (2022) assessed the indigenous knowledge of climate change, climatic impacts, and the determinants for choosing climate change adaptation strategies and agroforestry practices. Two types of agroforestry approaches, i.e., traditional and improved agroforestry practices, were being adopted by farmers in the mid-hills of Nepal. Regression analysis, the linear probability model (LPM), probit model, and logit model were used to investigate the factors that led farmers to choose agroforestry as a form of climate change adaptation and opt for improved agroforestry practice. It was found that most of the farmers in the study areas were facing climatic difficulties, but 59.29 per cent of them acknowledged that these difficulties were brought on by climate change, and similarly, 55.24 per cent had implemented adaptation strategies. Local adaptation strategies adopted by farmers were diversifying crop production, altering farming techniques, changing occupations, and emigration. The main reasons for implementing agroforestry practices in the study area were to enhance livelihoods, generate revenue, and provide food. Most farmers viewed agroforestry as a secondary climate change adaptation strategy. The results indicated that age, education, gender, and habit of growing commercial species and generating income from tree products influenced farmers' decisions to adopt improved agroforestry as a better practice than the traditional practice. The study suggested that there is a need to further strengthen farmers through educational initiatives that link agroforestry to climate change, such as door-to-door outreach, farmer group schools, field training, and the use of technology to boost output. This will help farmers to become more aware of the importance of agroforestry practices for both coping with and mitigating climate change.

Teklu and Simane (2023) analyzed the rate, intensity, and determinants of multiple adoptions of climate-smart agriculture innovations among smallholder farmers in Ethiopia’s Upper Blue Nile Highlands.A systematic random sampling technique was employed to choose 424 respondents. Quantitative data was collected from the households through a structured survey questionnaire. CSA innovations used in the study area were improved

varieties, crop residue management, crop rotation, compost, row planting, soil and water conservation (SWC), and agroforestry. The multivariate probit model (MVP) was used to assess the factors influencing the likelihood of adopting multiple CSA innovations. The major climate-smart agriculture innovations adopted were row planting (76%), compost (66%), soil and water conservation (51%), crop residue management (46%), crop rotation (37%), improved crop variety (31%), and agro-forestry (21%). The midland with brown soil agroecosystem zone (AESZ3) adopted the highest average number of CSA innovations (4.33) due to more fertile land while the midland with black soil agroecosystem zone (AESZ2) adopted the lowest average number of CSA innovations (2.07) because it has a flat plain area more prone to flood disasters every year. Findings indicated that the correlation's overall goodness of fit was highly significant. Thirteen of the twenty-one pairs of pairwise correlations of CSA innovations were statistically significant (Wald $\chi 2$ (21) = 119; $p < 0.01$). The pairwise correlation reveals that compost adoption has a significant synergistic effect on improved variety adoption ($p < 0.01$), crop residue management ($p < 0.01$), row planting ($p < 0.01$), and agroforestry ($p < 0.1$). It was found in the study that in terms of CSA innovations, row planting has the highest intensity of adoption (0.64 ha), followed by crop residue management (0.44 ha) while agroforestry has the lowest intensity of adoption (0.002 ha). Furthermore, it is concluded that formal education, more awareness about climate change and CSA, and the ability of CSA innovations to reduce the impact of climate change risks such as rising temperatures, increased hailstorms, and increased erratic rainfall have significantly increased the likelihood of adoption.

2.3. IMPACT OF CLIMATE SMART AGRICULTURAL PRACTICES

Chhetri *et al.* (2016) conducted a study in the Indo-Gangetic Plains (IGP) of India and investigated the potential economic benefits of CSA practices adopted by smallholder farmers. The CSA practices and technologies adopted by smallholder farmers in the study area include use of improved crop varieties, laser land levelling, zero tillage, residue management, site specific nutrient management, and crop diversification. It was found that majority of the farmers prefer to use improved crop varieties, crop diversification, laser land levelling and zero tillage practice. Results of the study revealed that the average cost of adoption were +1,402, +3,037 and 1,577 INRha–1 for the use of improved crop varieties, laser land levelling and zero tillage respectively. Further analysis reported that farmers can increase net return of INR 15,712 ha 1 yr–1 with improved crop varieties, INR 8,119 ha–1 yr–1 with laser levelling and INR 6,951 ha–1 yr–1 with zero tillage in rice–wheat system.

The study concluded that the combination of improved seeds with zero tillage and laser land levelling technologies can further improve crop yields as well as net returns.

Akrofi-Atitianti *et al.* (2018) conducted a study in Ghana and evaluated the potential of climate-smart agriculture practices in comparison with conventional cocoa systems and key determinants influencing CSA practices. A mixed methods approach was employed to collect the data from the respondents (n=80). Semi-structured household questionnaires were administered and Focus Group Discussions (FGDs) were held to collect the data in the area. Logistic Regression was used for identifying factors framing CSA practices. The results of the study revealed that, according to farm budget analysis of productivity and economic performance, CSA practitioners had a 29 per cent higher income per ha than conventional farmers. The key determinants affecting CSA practices among cocoa producers included land tenure, age of farmers, location of the farm, residential status, and availability of extension services. Findings indicate that 10 per cent and 13 per cent of farmers in the conventional and CSA practices had access to farm credits, and accounting for 11 per cent of respondents had obtained access to credit. The study reported that in comparison to conventional farmers, CSA farmers had higher financial capital as evidenced by their average incomes (29% more) and hence boosted their purchasing power as observed in their average farm investments (32% more) compared to conventional farmers.

Bedeke *et al.* (2018) examined the adoption of climate change adaptation strategies by maize-dependent smallholders in Ethiopia. Household and plot-level data were collected from 252 respondents using a multi-stage sampling procedure and subsequently analysed by a multivariate probit regression model. It was found that most climate change adaptation strategies implemented by maize-dependent smallholders, were complementary. Findings of the study indicated that combining conservation tillage, mixed maize-legume cropping and terracing along with the use of drought-resistant maize varieties allows farmers to increase productivity while building resilience to climate change more than a subset of these strategies. Further analysis of the study revealed that the likelihood of adopting soil and water conservation practices, drought-resistant maize varieties and chemical fertilizers significantly increase among young and male-headed households as well as farmers having confidence in extension agents and membership in local organisations. Hence, policies should aim at further building agricultural extension agents' capacity by providing effective and continuous education and training on climate change impacts and responses. Promoting family ties and household memberships in local organisations through facilitating mutual cooperation and

communication among farming communities would help to foster adoption of climate change adaptation strategies.

Imran *et al.* (2018) studied the impact of climate-smart agriculture practices on cotton production and the livelihood of farmers in Punjab, Pakistan. A multi-stage sampling technique was employed in the study to collect the data from 198 cotton farmers. It was found that water-smart (raising crops on bed, laser land levelling, conjunctive use of water and drainage management), energy-smart (minimum tillage), carbon-smart (less use of chemicals) and knowledge-smart (crop rotation and improved varieties i.e., tolerant to drought, flood and heat/cold stresses) practices and technologies of climate-smart agriculture were adopted by the cotton farmers in the study area. Results revealed that uniform germination, higher yield and financial returns, the concentration of inputs and an increase in resource use efficiency were the main advantages of CSA. The econometric analysis showed that implementation of CSA practices and technologies such as judicious use of water and fertilizer, groundwater quality, access to extension services, and appropriate method and time of picking had a significant impact on the gross value of the cotton product (GVP). The findings of the study would be helpful for policymakers to formulate policies that can minimize farmers' financial burden to adopt CSA technologies and implement them for scaling out in Punjab and beyond.

Mango *et al.* (2018) conducted a study in the Chinyanja Triangle of Southern Africa and assessed the adoption of small-scale irrigation farming as a climate-smart agriculture practice and its influence on household income. A stratified random sampling technique was used to choose 312 households. A binary logistic and ordinary least squares regression were employed in the study. The findings showed that small-scale irrigation adoption was significantly influenced by farming off-farm employment, access to irrigation equipment, access to reliable water sources, and awareness of water conservation practices, such as rainwater harvesting. However, the adoption of small-scale irrigation farming decisions was negatively influenced by the farmer's age, distance traveled to the nearest market, and the nature of employment. The result from ordinary least squares regression revealed that the adoption of small-scale irrigation farming as a climate-smart agriculture practice has a significant positive influence on agricultural income. Furthermore, a study suggested that the government should formulate national and regional policies on small-scale irrigation farming, and farmers should be ensured that they do not suffer a total loss of their agricultural produce due to climate variability and change.

Teklewold *et al.* (2018) investigated the farmers' decisions to employ multiple climate-smart practices in the Nile Basin of Ethiopia. Multiple climate-smart agricultural practices adopted in the study were agro-forestry, water management, improved seeds, inorganic fertilizer, manure, crop diversification, soil conservation and conservation tillage. Results from multivariate probit and random effect ordered probit models revealed that there was a strong complementarity among adaptation practices. There was a positive association between crop net income and the combination of practices. They also revealed that the farm-level use of modern external inputs i.e., fertilizer and improved seeds, were less probable under low rainfall conditions. It was found that social capital, tenure security, and climatic shocks were important determinants of the choice of the type and number of adaptation practices. The study shed light on the significant role of social capital in adoption and suggested the need for establishing and strengthening local institutions to quicken the adaptation process.

Wekesa *et al.* (2018) analyzed the effect of climate-smart agricultural practices on household food security among smallholder farmers in Kenya. Multistage sampling random sampling procedure was used to select respondents (n=384). The CSA practices were clustered into 4 components (crop management, field management, farm risk reduction, and soil management practices) with the application of principal component analysis. The results of the study revealed that the greatest impact of climate-smart practices on food security was when smallholder farmers employ a larger package that contains all four categories of practices. Adopters of this package were 56.83 per cent more food secure in terms of Household Food Consumption Scores (HFCS) and 25.44 per cent in terms of Household Diversity Scores (HDDS). This package was found to mitigate the impacts of climate change as well as enhance nutrient availability in the soils for higher productivity. Further analysis revealed that the adoption of this package was positively influenced by the gender of the household head, farm size and value of productive farm assets.

Fentie and Beyene (2019) analyzed the contribution of climate-smart agricultural practice (row planting) to the welfare of rural smallholders in Ethiopia. A multistage sampling procedure was adopted to collect the data from 260 farm households. It was found that adopters of the row planting technology were more likely to be male-headed, younger, more educated, and with higher household sizes compared to non-adopters. The average educational level of the household head for adopters and non-adopters was about 4 and 3 years, respectively. Results from Propensity Score Matching revealed that row planting

technology has positive and significant impacts on per capita consumption and crop income per hectare of farming households. Results from the semi-parametric Local Instrumental Variable method revealed that the marginal treatment effect on crop income was increasing with a higher propensity to adopt the row planting technology. Further analysis of the study reported that the climate-smart agricultural practice (row planting) has the potential for the welfare improvement and resilience of farming communities. Therefore, the study concluded that research may go beyond cross-sectional data to evaluate the long-run effects of the row planting technology. Farmers can undertake multiple practices simultaneously and modeling row planting with different combinations of CSA practices that could provide a better picture of the profitability of row planting in the area.

Issahaku and Abdulai (2019) conducted a study in Ghana and analyzed the impact of adoption of climate-smart practices on farm performance (crop revenue) and risk exposure (skewness of crop yield) among smallholder farmers. A multistage sampling technique was used to select the sample of 476 households. A multinomial endogenous switching regression model was employed to account for selectivity bias due to both observable and unobservable factors. The findings of the study reported that farmers' adoption of crop choice and soil and water conservation results in increased crop revenues and decreased crop production risk, with the largest impact on crop revenues coming from joint adoption. Further analysis revealed that education of the household head, access to extension and weather information influence the likelihood of adopting these practices. Therefore, the study suggested that improving extension services and access to climate information and irrigation can narrow gaps in adoption of soil and water conservation and crop choice, considered as climate-smart practices that will eventually increase crop revenues and decrease farmers' exposure to climate-related production risks.

Makate *et al.* (2019) evaluated impacts of differential adoption regimes on farm productivity and income using a sample of 1172 smallholder farmers from Malawi and Zimbabwe. A doubly robust IPWRA estimator was adopted to evaluate impact of CSA innovations on productivity and income. No adoption group was compared to the adoption impacts of individual innovations and a combination of innovations. It was found that adopting all the CSA packages significantly influenced farm income.The full package (DTM, CA& IL) with an ATET coefficient of 0.753 which was far greater than that of other packages. Adopting innovations in combinations was found to be beneficial to the farmers more than as individual packages. The enhanced impact of adopting the innovations possibly

arise, due to the combined effect on improving soil nutrient use, soil moisture retention, fertility and adaptation of legume and cereal crops to moisture, pests and diseases stress. The study suggests that for enhanced institutional and policy efforts towards reducing constraints of adopting multiple CSA innovations in small- holder farming. Access to financial resources, education, adequate land, and effective extension services can potentially assist farmers in building resilience to climate variability and change through multiple adoptions of conservation agriculture, improved legume and drought tolerant maize.

Amadu *et al.* (2020) assessed yield effects of climate-smart agriculture aid investment in southern Malawi. Primary data was collected from a sample of 808 households. Endogenous switching regression and a control function approach was used to estimate CSA adoption and impacts on maize yield. Cobb-Douglas production function was employed in the study. Variables that positively affected CSA adoption were hired labor (82%), perception of soil fertility (73%), receipt of extension services from government and NGO sources (44%), and total extension visits (136%). Factors that negatively affected CSA adoption were the log of total number of plots (29%), the log of plot elevation (59%) signified high transaction costs of adoption. The factors that positively affected the yield of CSA adopters include plot size (42%), fertilizer used (20%), family labor (48%) per hectare, and perception of soil fertility (55%). It was found that the adoption of climate smart agricultural practices has increased maize yields by 53 per cent (controlling for potential bias in adoption and other factors). Although, it was suggested that improving competitive factor markets for smallholders in southern Malawi and beyond could boost agricultural intensification, crop yields, and potential diversification for agricultural households.

Amadu *et al.* (2020) conducted a study in southern Malawi and analyzed the maize yield impacts of agroforestry in climate-smart agriculture investments. A multi-stage sampling technique was employed to select the farm households (n= 808). A double hurdle specification with a control function approach was used in the study to account the endogeneity of CSA program participation and the intensity of agroforestry fertilizer trees. Findings of the study indicated that the participation of farmers in the CSA program had a positive and statistically significant yield effect, and the intensity of the fertilizer trees in agroforestry increased maize yields by an average of 20 per cent and 2 per cent, respectively. The study reported that incorporating agroforestry into CSA interventions could increase agricultural yields among smallholder farmers in the face of climate change which seems to be essential for achieving sustainable development goals on hunger relief and climate adaptation.

Jellason *et al.* (2020) highlighted the importance of climate-smart agriculture (CSA) practices to promote resilience against climate change in in North-Western Nigerian drylands. A mixed methods design was used with Thirty smallholders per community were chosen from a baseline study of 220 smallholders from the two research communities. A farmer participatory learning and action project involving smallholders focused on the implementation of climate-smart agricultural practices for resilience. After six months, the effects of PLA were assessed, and adoption hurdles were investigated. The study found that there was a difference in confidence in adopting some CSA practices between pre- and post-PLA training. Both communities showed greater confidence ($p < .05$) related to solving climate-related problems and the use of fertilizer. Communities differed concerning other factors that kofa exhibited improved confidence (71.4%) in solving water challenges while Zango showed greater confidence (76%) in relation to solving environmental problems. They observed that gender-responsive climate-smart agricultural practices encourage women's involvement in farming. Thus, the study concluded that the identification of climate-smart agriculture practices and their adoption highlighted the importance of participatory learning for the transformation, and empowerment of smallholders, including women, to adapt to climate change.

Ojo and Baiyegunhi (2020) analysed the impact of credit constraints on climate change adaptation strategies among smallholder rice farmers in South-West Nigeria. A multistage sampling technique was employed to select the respondents (n=360) for the study.seemingly unrelated regression (SUR) model and Generalized Method of Moments with Instrumental Variable (IV-GMM) were used to analyze the nexus between systems of credit constraints and choice of climate change adaptation. A principal component analysis (PCA) was employed to reduce the multidimensionality of the adaptation strategies and the loading with the highest eigenvalue was chosen and renamed as improved technology. The findings of the study revealed that risk-credit-constrained smallholder rice farmers were less likely to adopt climate change adaptation strategies. It was found in the quantitative analysis that the age of the household, source of credit, distance to the source of credit, interest rate, access to extension, and climate information were the determinants of credit constraint amongst the smallholder rice farmers. Although, it was suggested that to increase awareness about the working of credit market and information on the provision of climate change that would help farmers to better adapt to climate change.

Sardar *et al.* (2020) assessed the adoption of climate-smart agriculture (CSA) practices and its impact on crop yield and farm income in Punjab province, Pakistan.

Multistage sampling technique was employed to collect data from 417 farm households through pretested structured questionnaire. The study employs Ricardian model and multinomial logistic regression to examine the factors that determine the adoption of single to a full package of CSA practices. The two-stage least square (2SLS) estimation technique was used to control the endogeneity problem and to estimate the adaptation impact on crop yield and farm income. The major adoption of CSA practices were changing cropping dates, zero or minimum tillage, water management measures, improved crop varieties, and nutrient management options. The findings showed that about half of the farmers adopted one or more combi- nations of CSA practices to cope with climate change and weather shocks. Modifying cropping dates measure was predominantly adopted by farmers in Rahim Yar Khan where about half of the farmers reported changing sowing dates due to changes in climate. The average adoption rate of water management was reported about 21per cent. The low adoption of water management practice was due to the lack of knowledge about the water management options and its use at the farm level. The results indicated that adopting at least two CSA practices had a positive and significant impact to increase in the crop yield and farm income with the coefficients of 0.244, 0.354 for cotton–wheat crops, and 0.264, 0.376 for rice–wheat crops, respectively. Findings of the study suggested that effective and upscaling adoption-rate of CSA practices may demand extra financial resources and institutional support to the farmers. Additionally, subsidies should be provided on the CSA supporting technologies and should ensure the availability of certified quality seeds on the priority basis in the area where adoption rates are very few or where the farmers are still following conventional agricultural practices.

Zakaria *et al.* (2020) evaluated the adoption of climate-smart agricultural practices among farm households in Trans-Volta Togoland, Ghana and examined the role of farmer participation in training programmes. Multi-stage sampling procedure was employed to select famers(n=300). Endogenous-Switching Poisson regression model was used to determine the drivers of farmers' participation in climate change capacity building programmes and the concomitant effect of participation on adoption intensity of Climate Smart Agricultural Practices (CSAPs). The findings revealed that varying/adjusting planting date was highly practiced among the farmers (99.67%) to adapt to climate change and its related shocks, 71 per cent of the farmers adopted drought-tolerant crop varieties, while some 87 per cent practiced row/line planting. The least practiced CSAP were strip/alley farming (13.67%) and bunding (14.67%). The majority (91%) of the sampled farmers belonged to FBO groups and

found to have a positive effect on participation in climate change capacity building workshops. It was found that FBOs were the potential driver to engage farmers' participation in climate change capacity building workshops. The study suggested that climate change agricultural projects should incorporate farmer training on CSAPs in order to guide the adoption of multiple climate change adaptation practices.

Liang *et al.* (2021) assessed the factors that influence the of adoption of adaptive and mitigatory climate-smart agricultural practices in isolation and when combined, and their impacts on rice yield and rice net income in Hubei, China. The study employed three-year household-level pooled cross-sectional data. A multinomial endogenous switching regression framework was used to address the selection biases from both observable and unobservable heterogeneity. The findings of the study indicated that adopting both adaptive and mitigatory CSAPs increases rice yield and rice net income by 15.879 per cent and 19.288 per cent, respectively. Additionally, there were substantial synergies between adaptive and mitigating CSAPs to address climate change in terms of increasing production and income during extreme weather events (like the EI Nino event). Therefore, findings of the study highlighted the positive role of integrating adaptive and mitigatory CSAPs in coping with climate change challenges, and boosting household farmers' economic welfare in China, and potentially elsewhere. If synergistic effects are to be achieved, practises like implementing improved varieties, enhancing irrigation systems, and adjusting the timing of farm operations, as well as mitigation practises like zero tillage, soil testing and application of formulated fertiliser, and planting green manure, should be included in the CASPs packages. The study recommended encouraging farmers to adopt both adaptive and mitigatory CSAPs that can potentially improve farmers' resilience to climate change and promote food security.

Sedebo *et al.* (2021) conducted a study in the Lemo district of southern Ethiopia and examined the impact of smallholders' climate-smart adaptation practices on their crop production technical efficiency. Focus group discussions, experts' consultations, and household surveys were conducted to collect data from smallholder crop producers (n=600) through a three-stage sampling method. Activity-based adaptation index (AAI) of smallholder farmers' adaptation practices to climate change and Stochastic Frontier Analysis (SFA) to measure smallholder crop production efficiency were used in the study. Climate-smart agricultural practices adopted by the farmers in the study area were terracing, crop diversification, improved soil amendment practices, varying planting or harvesting schedules, and crop rotation. Results of the study indicated that education level was significantly and

negatively correlated with major crops, wheat, and teff production inefficiency. Therefore, age had a negative and significant impact on wheat production inefficiency. The study found that smallholder crop production was more efficient when adaptation to climate change impacts was taken into consideration. Moreover, the technical efficiency of smallholder agriculture might be considerably increased by the adaptation of smallholder farmers employing more climate-smart practices on a greater scale. The study suggested that there should be a policy shift to encourage smallholder farmers' adaptation to climate change through climate-smart practices for an effective response to climate change impacts while boosting technical efficiency.

Akter *et al.* (2022) examined the impact of climate-smart agriculture (CSA) adoption on yield and income in flood-prone areas of Bangladesh. Multi-stage sampling techniques were employed to select the sample(n=600) of farm households. Primary data was collected from a sample of smallholder farms and the endogenous switching regression (ESR) was applied while controlling for endogeneity issues and selection bias of CSA adoption. Six categories (residue addition and retention, non-woody plants, assisted regeneration, woody plants, physical infrastructure, and mixed measures) of CSA were considered in the study as they were consistent with the practices being promoted in the study area as well as other areas around the globe and the farm households who have maintained such CSA practices on their farms for at least four consecutive years, i.e., 2019 the data collection period plus at least three years. The production function applied in this study was Cobb Douglas. The causal effect of CSA adoption on yield and income, the endogenous switching regression (ESR) was applied. The results of the study revealed that CSA adoption significantly impacts crop yield and household income. Further, the study suggested that CSA adoption alone was not enough, but farmers need to be mindful of soil salinity as this will facilitate adoption of CSA practices that address the rising soil salinity. A crucial finding on factors affecting yield and CSA adoption was improving farm household’s perception of the soil fertility, temporal credit constraints occasioned by distance to the nearest financial leading institution, and ensuring the appropriate agricultural inputs are in place, especially the right seed conforms to the soil and environmental conditions in a given locality at a particular time. Thus, it is concluded from the study that non-adopters would greatly benefit from CSA adoption in both yield and income.

Meshesha *et al.* (2022) investigated the smallholder farmers’ perceptions toward the adoption of climate-smart agriculture (CSA) in smallholder farmers in the Upper Blue Nile

Highlands of Ethiopia. A cross-sectional household survey was conducted to collect primary data through a structured questionnaire from 424 smallholder farmers. secondary data was collected from a review of literature and documents. A multivariate probit model was used in the study to examine perception factors affecting the likelihood of adopting multiple CSA innovations. Major CSA innovations adopted by farmers in the study area were improved variety, crop residue management, crop rotation, compost, intercropping, row planting, soil and water conservation and agroforestry. CSA innovations sustainably increase productivity and income; enhance soil fertility; diversify livestock feed and energy sources; reduce soil erosion, weed infestation and crop failure; enhance soil organic matter, reduce chemical fertilizer use and rehabilitate the land. The results of the study reported farmers' positive perceptions of the benefits of CSA innovations for boosting crop productivity, reducing agricultural vulnerability to climate change, and lowering farm greenhouse gas emissions have enhanced adoption. Furthermore, it can be concluded that public extension, as well as local institutions such as farmers' training centers, needs close collaboration for the awareness of CSA. The CSA innovation scale-up strategies should emphasize farmers' perception of the benefits of CSA innovation towards food security, climate change adaption, and mitigation outcomes.

Chapter - 3

MATERIALS AND METHODS

A sound and systematic methodology is pre-requisite for a scientific enquiry. Infact, precision, reliability, validity, and acceptability of the scientific findings, and facts depend solely on the methodology adopted for the investigation of a phenomenon. The selection and application of appropriate methodology has more relevance in socio-economic studies based on sample surveys. Therefore, this chapter has been devoted to describing the methodological aspects of the present investigation. The methodology used in this study has been described under the following sub-heads.

3.1. Location of the study area
3.2. Selection of study area
3.3. Sampling procedure
3.4. Distribution of sampled farmers according to their size of land holding
3.5. Data collection
3.6. Analytical framework
3.7. Limitations of the study

3.1. LOCATION OF THE STUDY AREA

The present study was conducted on climate-smart agricultural practices for climate change risk mitigation in the temperate region of Himachal Pradesh.

3.2. SELECTION OF THE STUDY AREA

Himachal Pradesh is geographically divided into four distinct crop zones based on agro-climatic conditions: the low hill subtropical zone, mid-hill sub-humid zone, high hill wettemperate zone, and high hill dry temperate zone (DOA, 2023). This study specifically investigates the high hill wet temperate and high hill dry temperate zones of Himachal Pradesh. The high hill wet temperate zone encompasses a significant portion of Shimla (excluding Rampur tehsil) and Kullu districts, along with areas of Sirmour, Solan, Chamba, Kangra, and Mandi districts. The high hill dry temperate zone covers Kinnaur, Lahaul & Spiti districts, and the Pangi sub-division of Chamba district. These high hill zones, highly impacted by climate change, are vital agricultural areas

contributing significantly toHimachal Pradesh's economy through high-value temperate crops like apples and pears (Chand *et al.,* 2018; Rana *et al*., 2023).

3.3. SAMPLING PROCEDURE

3.3.1. Sampling design

Multistage random sampling technique was employed for the selection of sampled households. The study area was stratified into two strata, i.e., high hill wet temperate zone and high hill dry temperate zone. At each stage of the sampling process, the sample was drawn randomly utilizing the lottery method.

3.3.2. Stage 1- Selection of districts

In the first stage, a random selection was undertaken, targeting four districts, namely Shimla, Chamba, Mandi, and Kullu, from the high hill wet temperate zone, and two districts, Kinnaur and Lahaul & Spiti, from the high hill dry temperate zone. This selection was based on the greater proportion of area within these districts falling under the temperate region of Himachal Pradesh.

3.3.3. Stage 2- Selection of blocks

In the second stage of sampling, a complete list of blocks that fell under high hill wet temperate and dry zones of the selected districts were prepared, and 30 per cent of blocks were chosen randomly from each selected district (Singh and Masuku, 2014).

Table 3.1: List of the selected blocks in the study area

Zones	Selected districts	Number and name of blocks under high hill wet and dry temperate zones	Number and name of selected blocks
High hill temperate wet zone	Shimla	(09) Basantpur, Chhohara, Chopal, Mashobra, Nankhari, Narkanda, Theog, Rohru, Jubbal & Kotkhai	(03) Rohru, Jubbal & Kotkhai and Theog
	Chamba	(05) Mehla, Chamba, Tissa, Salooni, Bharmour	(02) Mehla and Chamba
	Kullu	(03) Nagar, Nirmand, Kullu	(01) Nagar
	Mandi	(03) Karsog, Seraj, Gohar	(01) Gohar
High hill temperate dry zone	Lahaul & Spiti	(02) Lahaul & Spiti	(01) Lahaul
	Kinnaur	(03) Kalpa, Nichar, Pooh	(01) Kalpa

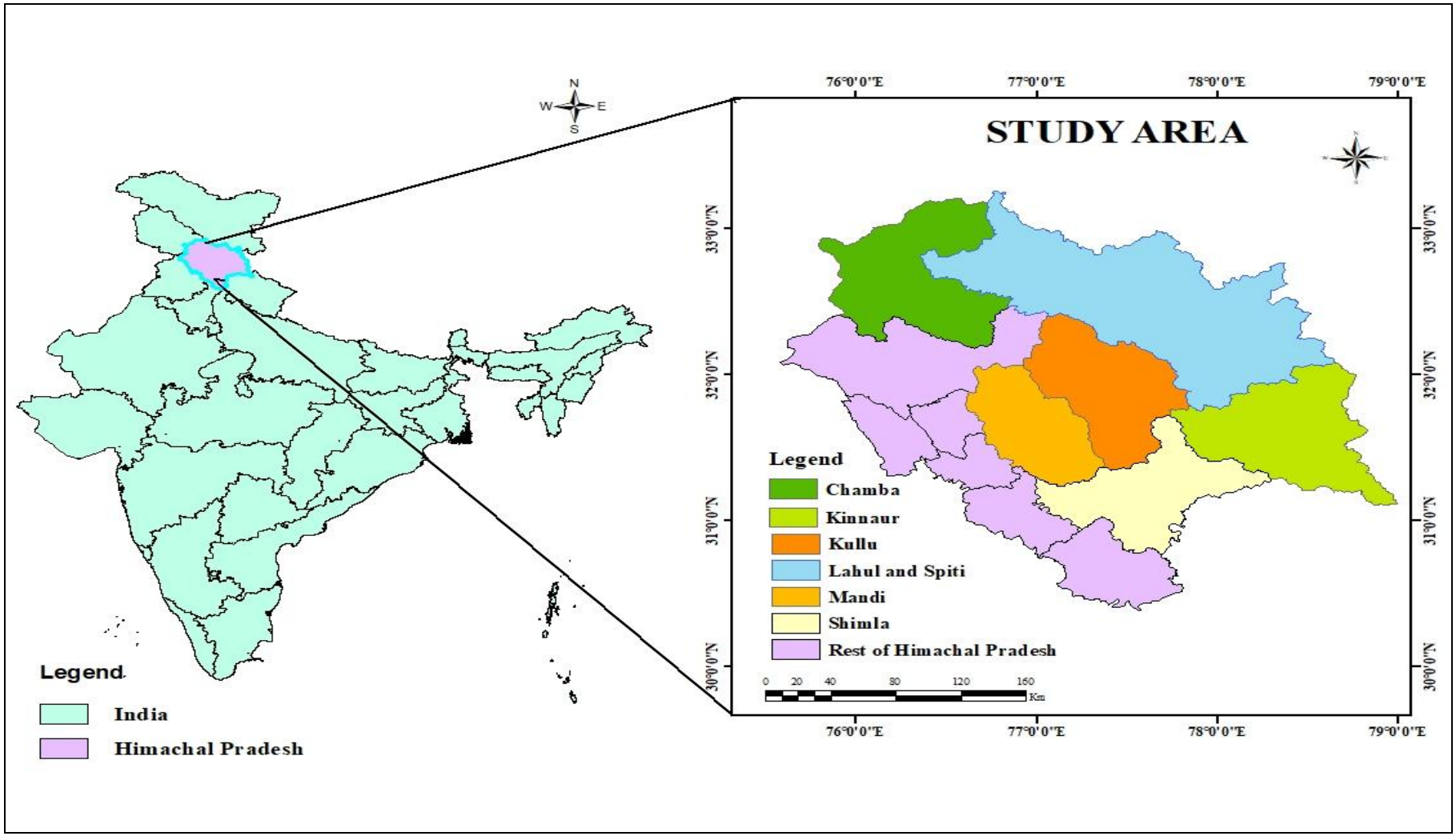


Plate 3.1: Map representing the selection of the study area

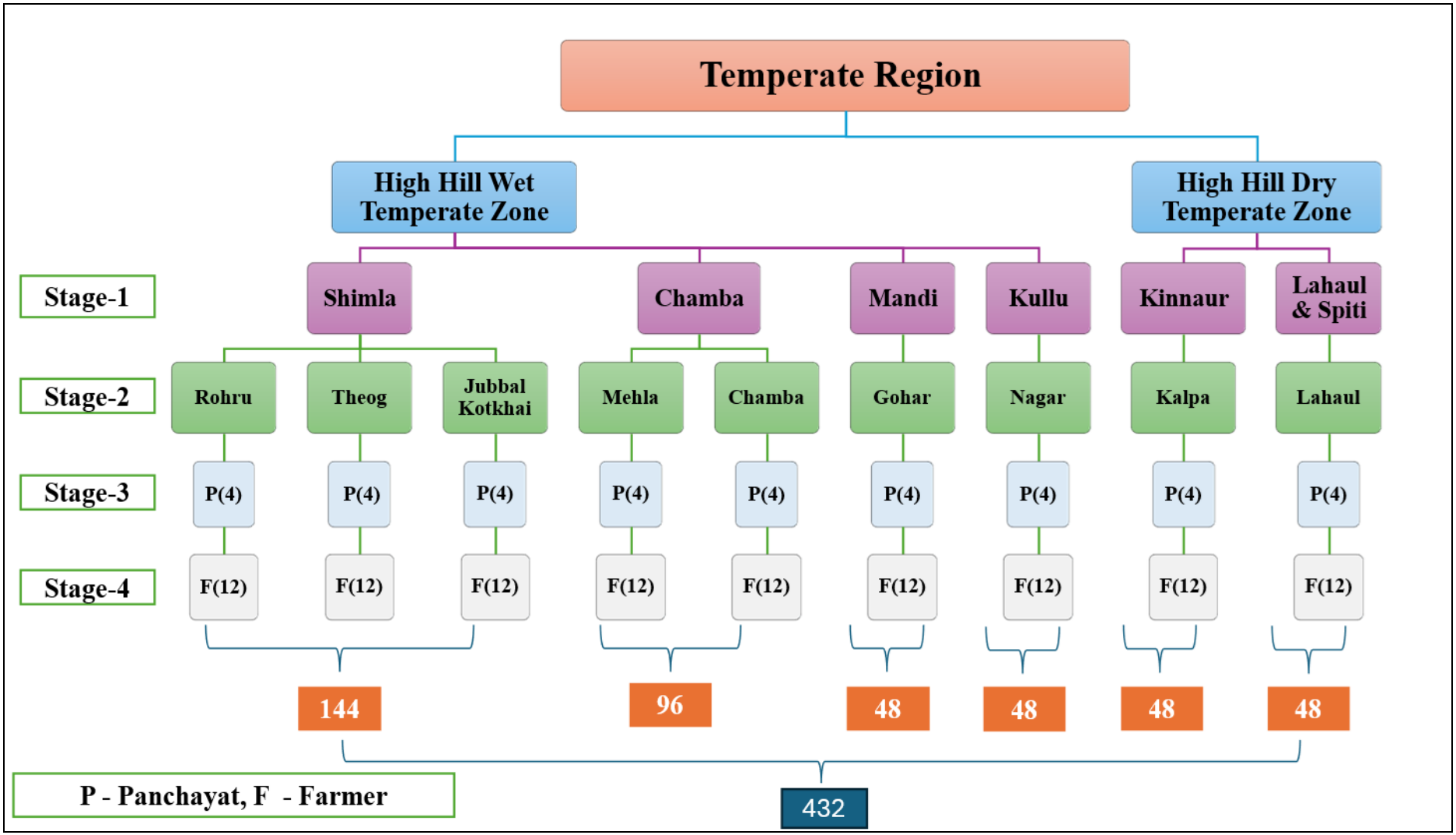


Figure 3.1: Schematic representation of sampling frame

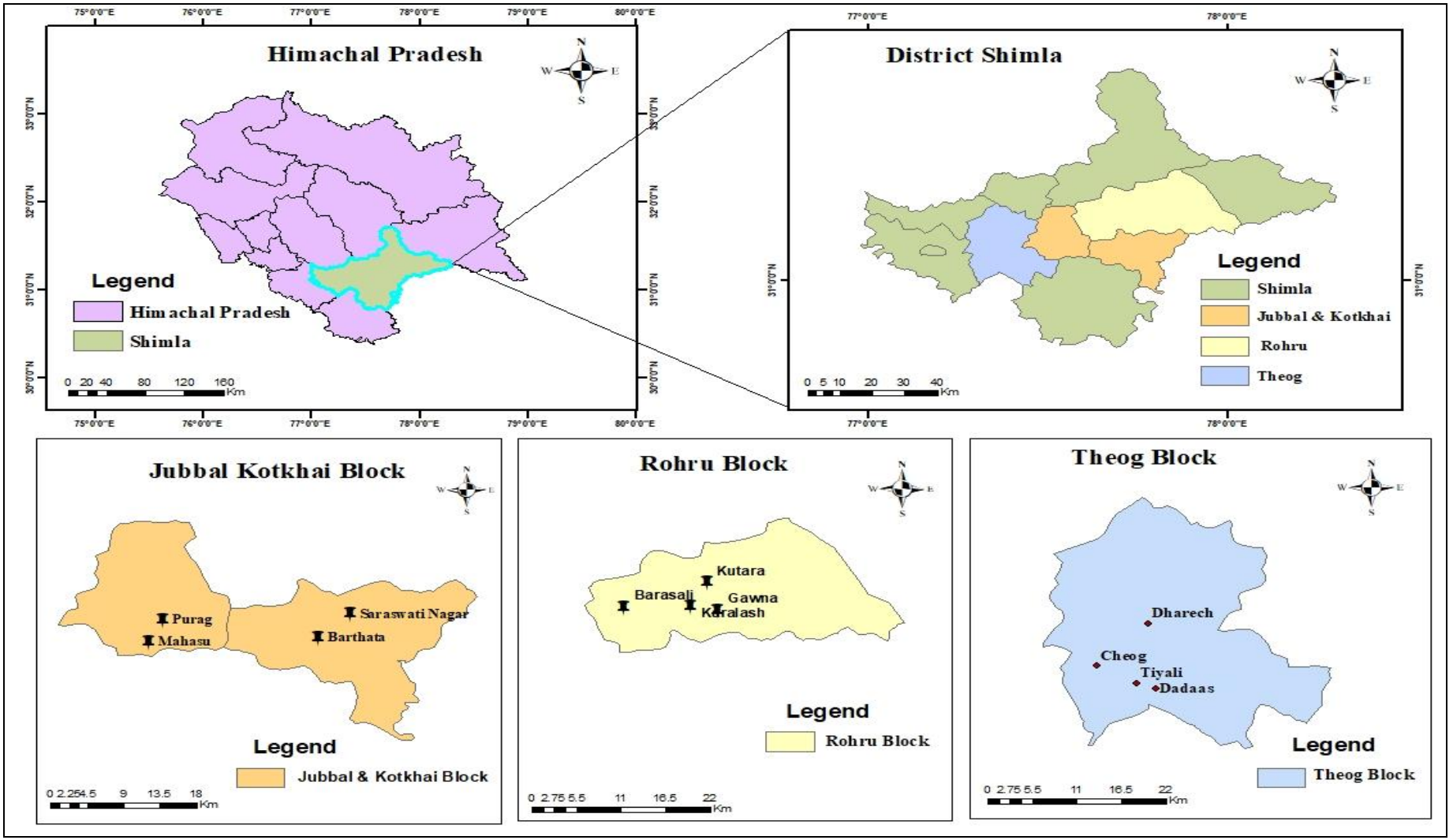


Plate 3.2: Map representing Jubbal & Kotkhai, Rohru and Theog blocks and the panchayatsof Shimla district in Temperate region of Himachal Pradesh

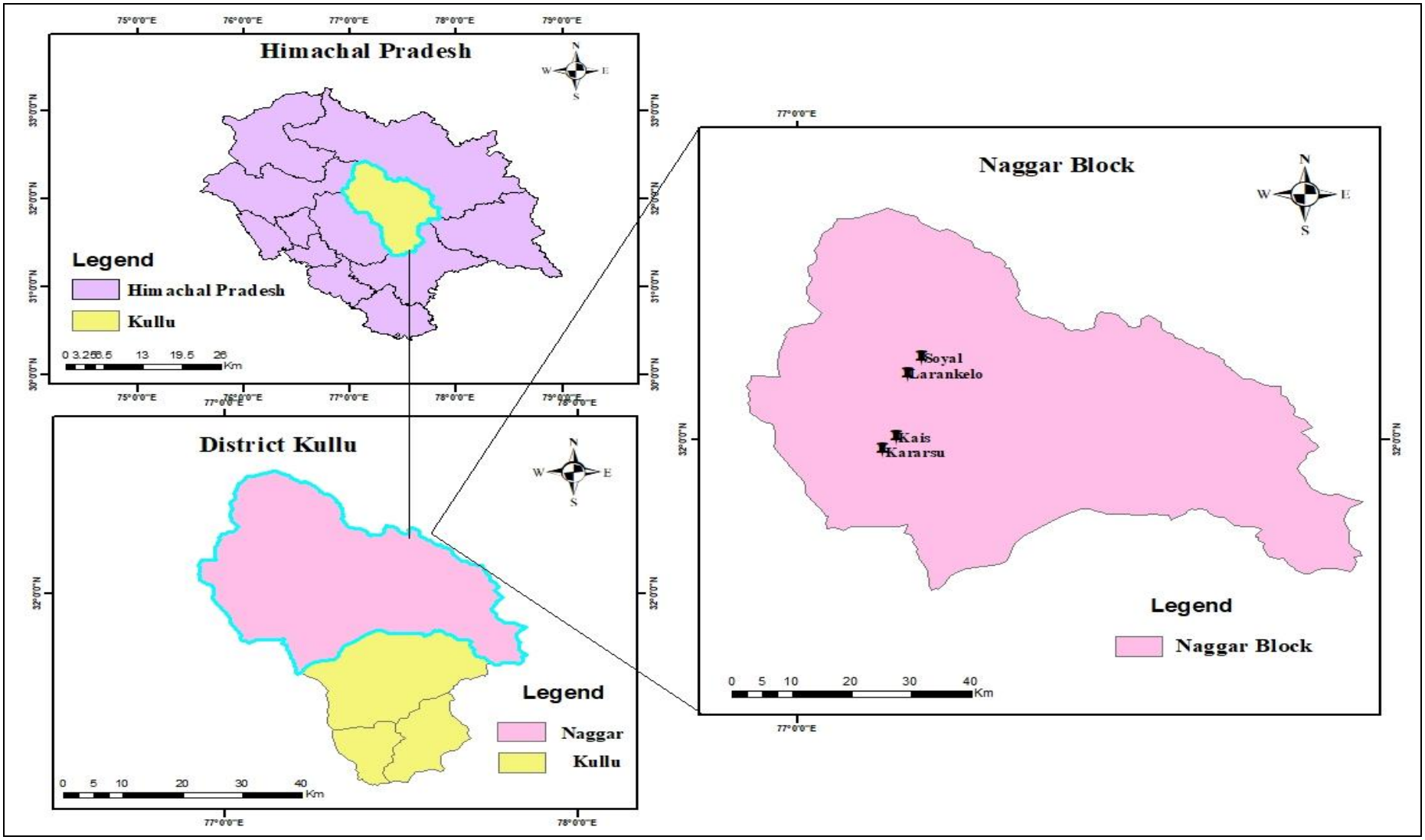


Plate 3.3: Map representing Nagar block and the panchayats of Kullu district in Temperate region of Himachal Pradesh

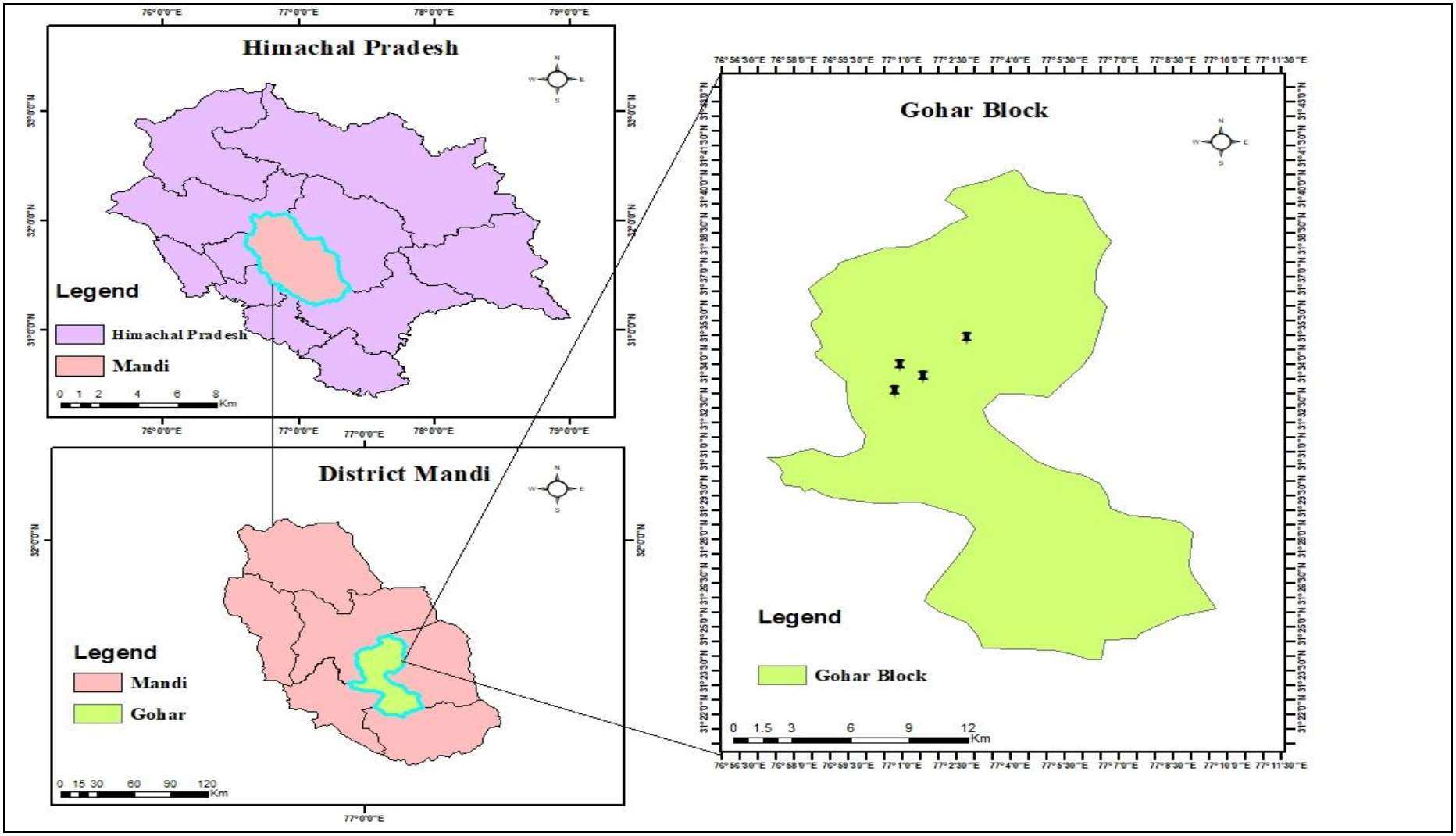


Plate 3.4: Map representing Gohar block and the panchayats of Mandi district in Temperate region of Himachal Pradesh

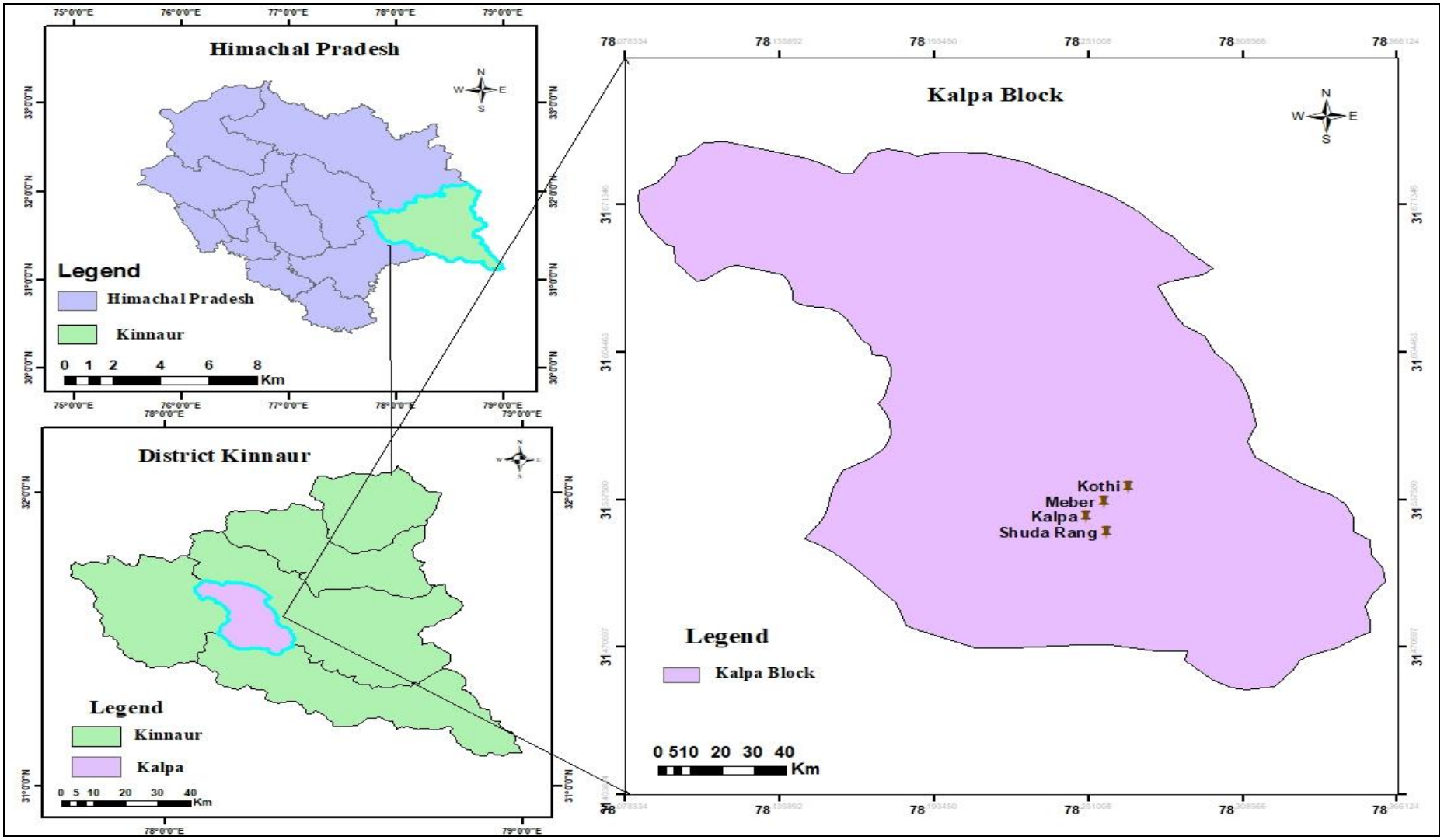


Plate 3.5: Map representing Kalpa block and the panchayats of Kinnaur district in Temperate region of Himachal Pradesh

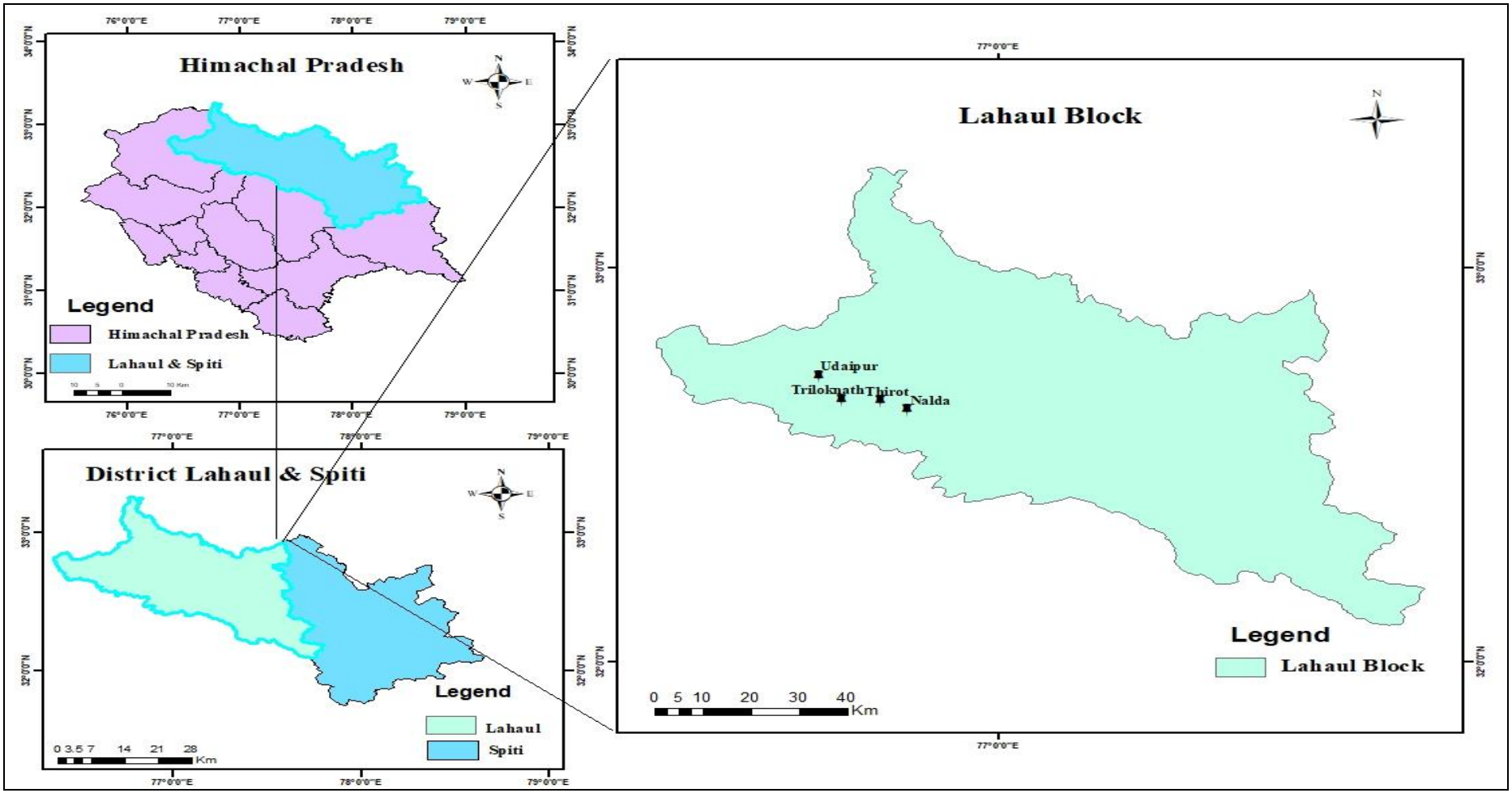


Plate 3.6: Map representing Lahaul block and the panchayats of Lahaul & Spiti district in Temperate region of Himachal Pradesh

3.3.4. Stage 3- Selection of panchayats

In the third stage of sampling, a complete list of panchayats was prepared from each selected block out of which four panchayats were selected randomly from each selected block.

3.3.5. Stage 4- Selection of sampled households

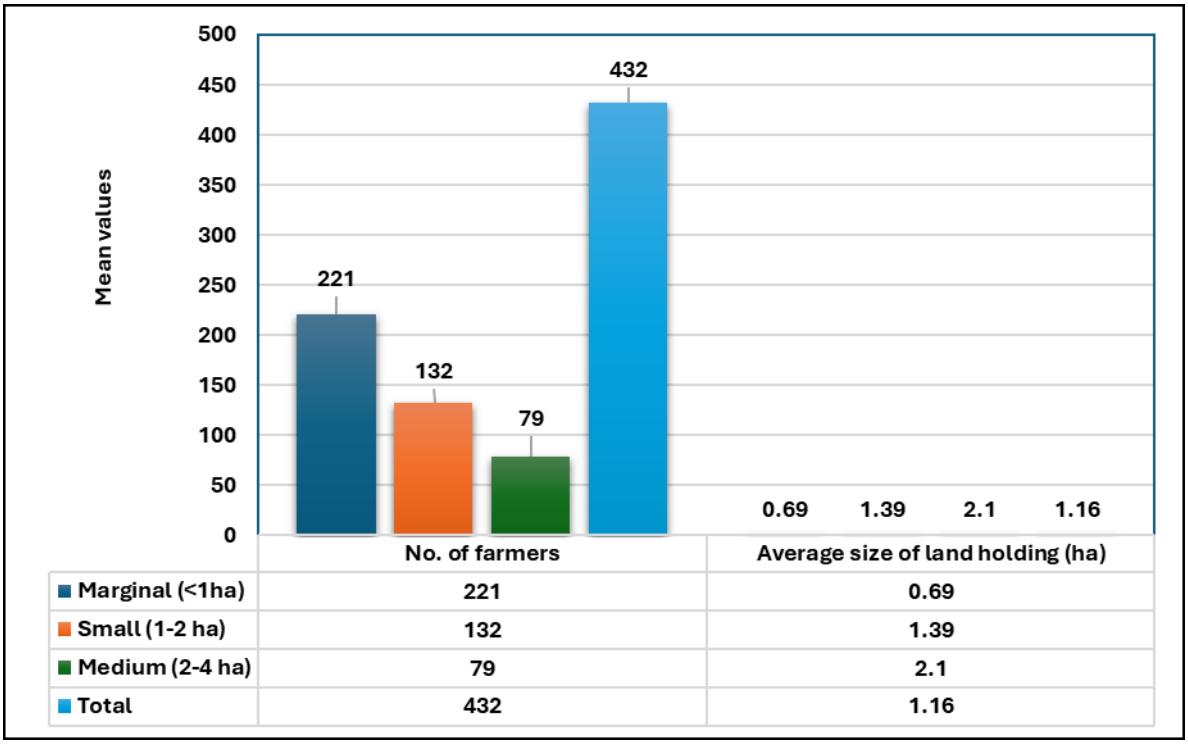
In the final stage of sampling, twelve farmers using an equal allocation method were selected from each panchayat, constituting a sample size of 144 in Shimla district, 48 in Mandi district, 96 in Chamba district, 48 in Kullu district, 48 in Kinnaur district and 48 in Lahaul & Spiti district. The equal allocation method ensures that the overall sample provides a more representative picture of the entire population, leading to more accurate conclusions. The farming practices adopted by each farmer are fairly represented within the sample. Thus, a sample size of 432 respondents was selected for the present study as shown in Figure 3.1.

3.4. Distribution of sampled farmers according to their size of land holding

For the analysis of data, the farmers were divided according to the size of their land holdings into three classes, viz., marginal (<1 ha), small (1-2 ha), and semi-medium (2-4 ha). The distribution of the sampled farmers is present in Table 3.2.

Table 3.2: Distribution of sampled households in the study area

Farm size		**Marginal (1ha)**		**Small (1-2 ha)**		**Semi Medium (>2 ha)**		**Total**	
Particular		**Number of farmers**	**Average land holding (ha)**	**Number of farmers**	**Average land holding (ha)**	**Number of farmers**	**Average land holding (ha)**		
Shimla	**Rohru**	21 (43.75)	0.72	17 (35.42)	1.46	10 (20.83)	2.12	**48**	**144**
	Theog	19 (39.58)	0.71	18 (37.5)	1.49	11 (22.92)	2.13	**48**	
	Jubbal & Kotkhai	20 (41.67)	0.74	15 (31.25)	1.52	13 (27.08)	2.2	**48**	
Chamba	**Chamba**	34 (70.83)	0.67	9 (18.75)	1.29	5 (10.42)	2.02	**48**	**96**
	Mehla	33 (68.75)	0.65	11 (22.92)	1.26	4 (8.33)	2.02	**48**	
Mandi	**Gohar**	21 (43.75)	0.61	16 (33.33)	1.31	11 (22.92)	2.07	**48**	**48**
Kullu	**Nagar**	24 (50)	0.66	14 (29.17)	1.37	10 (20.83)	2.1	**48**	**48**
Kinnaur	**Kalpa**	27 (56.25)	0.73	15 (31.25)	1.39	6 (12.5)	2.04	**48**	**48**
Lahaul &Spiti	**Lahaul**	22 (45.83)	0.76	17 (35.42)	1.31	9 (18.75)	2.09	**48**	**48**
Total number of farmers		**21**		**132**		**79**		**432**	



	No. of farmers	Average size of land holding (ha)
Marginal (<1ha)	221	0.69
Small (1-2 ha)	132	1.39
Medium (2-4 ha)	79	2.1
Total	432	1.16

Figure 3.2: Sampled farmers according to their size of land holding

3.5. DATA COLLECTION

Data collection was conducted during the agricultural year 2023-2024. A structured interview schedule was developed following an extensive review of the literature and consultations with experts in the field. Based on this review, modifications were made, and the revised schedule was pre-tested among non-sample respondents from both wet and dry temperate zones. The pre-test results informed further adjustments, leading to the finalization of the interview schedule. Consequently, both primary and secondary data were collected to meet the objectives of the present study.

3.5.1. Primary data

Primary data were collected on a well-designed and pre-tested schedule through personal interviews with the farmers by survey method on the following aspects:

- Socio-economic status of farmers.
- Information on family structure, size of the family, landholding size, number of years in farming, and literacy status,
- Information about climate-smart agricultural practices adopted by the respondent farmers to cope up with climate change and factors influencing these practices.
- Constraints faced by the farmers in adopting climate-smart agricultural practices.

Plate 3.7: Data collection during the field survey showcasing climate-smart agricultural practices and farmer interactions

Secondary data

The necessary secondary data for the present study were gathered from various sources, including publications, government departments such as the Department of Agriculture Cooperation and Farmers Welfare, the Department of Horticulture, the Directorate of Economics and Statistics, as well as books, journals, reports, Krishi-kosh, Shodhganga, CeRA (Consortium for e-Resources in Agriculture) and the India Meteorological Department (IMD), Shimla.

3.6. ANALYTICAL FRAMEWORK

To meet the specific objectives of the present study based on the nature and extent of the availability of data, appropriate mathematical and statistical tools such as mean, ratios, percentages, standard deviation, and coefficient of variance have been employed for the analysis of the data.

3.6.1. Tabular analysis
3.6.2. Livelihood vulnerability
3.6.3. Climate-smart agricultural practices
3.6.4. Impact of climate-smart agricultural practices on livelihood vulnerability
3.6.5. Constraint analysis

3.6.1. Tabular analysis

The primary data collected on the survey schedules was tabulated to work out the various socioeconomic features of sampled farmers, viz., family size, family type, educational status of family, occupational status, work force, social participation, land use pattern, cropping pattern, and investment in irrigation structure. Simple statistical tools like averages, ratios, percentages, and indices were used to compare and interpret the results. The sex ratio, literacy rate, literacy index, dependency ratio w.r.t. total workers, average family size, coefficient of variation, and cropping intensity were calculated using formulas.

a) **Arithmetic mean ($\bar{X}$):** Mean is also known as arithmetic mean, is the most common measure of central tendency.

The formula for mean is:

$$\text{Mean} = \frac{\sum x}{n}$$

where,

Σx = sum of all the sample observations
n = number of sample observations.

b) Percentage :

The formula for percentage method is:

$$P = \frac{X}{Y} \times 100$$

where;

X = Number of respondents falling in specific category

Y = Total number of respondents

c) Sex ratio: The sex ratio is the number of female per thousand males.
The formula for calculating sex ratio is:

$$\text{Sex ratio} = \frac{\text{No. of females in a family}}{\text{No. of males}} \times 1000$$

d) Literacy rate: Literacy rate is defined as the percentage of literates to the total population.

The formula for literacy rate is:

$$\text{Literacy rate} = \frac{\text{Total no. of literate farmers}}{\text{Total number of farmers}} \times 100$$

where,

W_i =Weights (0,1,2,3,4and5)for illiterate, primary, upper primary, middle, secondary, senior secondary, and graduates, respectively.

X_i = Number of persons in the respective category

e) Dependency ratio w.r.t total workers: It is a ratio of the number of dependents in the family to the total workers.

$$\text{Dependency ratio w. r. t. total workers} = \frac{\text{No. of dependents in a family}}{\text{Total workers}}$$

f) Dependency ratio w.r.t average size of family: It is a ratio of the number of dependents in the family to average size of family.

$$\text{Dependency ratio w. r. t. average size of family} \quad \frac{\text{No. of dependents in a family}}{\text{Average size of family}}$$

g) Coefficient of variation (C.V):

The formula for coefficient of variation is:

$$C.V\,(\%) = \frac{\text{Standard deviation } (\sigma)}{\text{Mean } (\bar{x})} \times 100$$

h) Cropping intensity: Cropping intensity is the number of times a crop is planted per year in a given agricultural area.

The formula for cropping intensity is

$$\text{Cropping intensity } (\%) = \frac{\text{Gross cropped area}}{\text{Net sown area}} \times 100$$

i) Normalization of livestock:

The different categories of animals maintained by farmers were converted into Adult Cattle Unit by using the following ratios as suggested by Singh (1991):

1. One buffalo equivalent to 1.30 ACU
2. One cow or bullock equivalent to 1.00 ACU
3. One young stock (buffalo/cow) equivalent to 0.75 ACU
4. One calf equivalent to 0.30 ACU
5. One sheep/goat equivalent to 0.20 ACU

3.6.2. Livelihood vulnerability

Vulnerability assessment describes a diverse set of methods used to systematically integrate and examine interactions between humans and their physical and social surroundings. Vulnerability is one of the factors that determines whether people are at risk to their livelihoods or not. According to the Intergovernmental Panel on Climate Change (IPCC, 2007), the vulnerability assessment measures the ability of the community to respond to hazards and or secure their livelihood. Therefore, the index known as the Livelihood Vulnerability Index (LVI) was developed by Hahn *et al*., (2009) for vulnerability assessment of climate change. The Livelihood vulnerability index (LVI) is a balanced weighted average approach (Sullivan *et al.*, 2002) where each subcomponent contributes equally to the overall index, even though each major component is comprised of a different number of sub-components. It has been designed to provide information to development organizations, policymakers, and public health practitioners to understand climate vulnerability and its

related components, such as demographic, social, and health (Hahn *et al*., 2009). The LVI uses multiple indicators to assess exposure to natural disasters and climate variability, social and economic characteristics of households that affect their adaptive capacity, and current health, food, and water resource characteristics that determine their sensitivity to climate change impacts. This provides a flexible approach where development planners can refine and focus their analysis to suit the needs of each geographical location.

In the present study, the Livelihood Vulnerability Index (LVI) developed by Hahn *et al*., (2009) was utilized to assess the livelihood vulnerability of the sample households to climate change. Two types of indices were used and compared based on different indicators. The first expresses the LVI as a Composite Index comprised of eight major components, while the second aggregates the eight into IPCC's three contributing factors to vulnerability—exposure, sensitivity, and adaptive capacity. As this method has flexibility, we used more relevant subcomponents to suit the local conditions based on the literature review.

3.6.2.1. Calculating the LVI: Composite index approach

The LVI comprises eight major components: socio-demographic profile, livelihood strategies, health, social networks, food, water, house and natural disaster, and climate variability. Each major component has further sub-components. Thus, these eight major components consisted of a total of thirty-six sub-components.

These were developed based on a review of the literature on each major component, as well as the practicality of collecting the needed data through household surveys. Many authors (Entwire *et al*., 2013; Shah *et al*., 2013; Aryal *et al*., 2014) have used a similar approach in various contexts because this assessment tool is accessible to a diverse set of users in resource-poor settings.

To analyze the index, the following four main steps were followed:

Step 1. Transforming measurement units: All the raw data of each subcomponent, which was collected through the survey, was transformed into appropriate standardized measurement units, such as percentages, ratios, and indices.

Step 2. Standardization of sub-components: It was first necessary to standardize each subcomponent as an index because these were measured on different scales. As many subcomponents were measured using different scales, such as numbers and percentages, each

subcomponent was standardized for comparability among them and for compiling the overall index. Equation (1) is used for the conversion, which was adapted from that used in the Human Development Index to calculate the life expectancy index, which is the ratio of the difference of the actual life expectancy and a pre-selected minimum, and the range of pre-determined maximum and minimum life expectancy (UNDP, 2010):

$$\text{Index } S_d = \frac{S_d - S_{min}}{S_{max} - S_{min}} \qquad \ldots\ldots. (1)$$

where,

S_d = the actual value of a subcomponent for farm household

S_{min} = Minimum value for each sub-component were determined using data from all the selected farm households

S_{max} = Maximum value of each sub-component were determined using data from all the selected farm households.

These minimum and maximum values were used to transform this indicator into a standardized index. For variables that were measured in frequencies, such as the "percent of households reporting conflicts over water resources in their social group," the minimum value was set at 0 and the maximum at 100. Some sub-components, such as the 'average livelihood diversification index', were created because an increase in the crude indicator, in this case, the number of livelihood activities undertaken by a household, was assumed to decrease vulnerability. In other words, we assume that a household who raises animals along with farming is less vulnerable than a household who only do farming. Herfindahl Index was used for studying livelihood diversification index, and it ranges from 0 to 1 where 1 means complete specialization and 0 means complete diversification in livelihood activities.

Step 3. Averaging of sub-components: After standardizing each indicator, the sub-components were averaged using equation (2) to calculate the value of each major component.

$$M_d = \frac{\sum_{i=1}^{n} \text{Index } S_{di}}{n} \qquad \ldots\ldots. (2)$$

where,

M_d = one of the eight major components for region d [socio-demographic profile, livelihood strategies, health, social networks, food, water, house, and natural disaster and climate variability].

Index S_{di} = sub-components, indexed by i, and n is the number of sub-components in each major component.

Step 4. Calculating final LVI score: Once values for each of the eight major components were calculated, they were averaged using Equation (3) to obtain the final LVI score. The value of each major component was the average of its sub-components.

$$LVI_d \frac{\sum_{i=1}^{8} W_{mi} M_{di}}{\sum_{i=1}^{8} W_{mi}} \ldots\ldots\ldots (3)$$

Expanded form.

$$LVI_d = \frac{W_{SDP} S_d + W_{LS} S_d + W_{SN} S_d + W_H S_d + W_F S_d + W_W S_d + W_{HS} S_d + W_{NDCV} S_d}{W_{SDP} + W_{LS} + W_{SN} + W_H + W_F + W_W + W_{HS} + W_{NDCV}} \ldots\ldots (4)$$

where,

LVI_d = Livelihood vulnerability index for study block d equals the weighted average of the eight major components.

Mdi = Major component for block indexed by i

W_{mi} = Weight of each major component

In this study, the LVI was scaled from 0 (least vulnerable) to 0.7 (most vulnerable). To further clarify the model's inference, a stepwise calculation is illustrated for one of the major components, livelihood strategies for Block-I (Rohru) in Appendix II.

3.6.2.2. LVI–IPCC approach

The LVI–IPCC index is an alternative to evaluate LVI by merging the definition of vulnerability corresponding to IPCC. Vulnerability is an action of a process that exposes and is susceptible to environmental stimuli and their adaptability to negative impacts (Shah *et al*., 2013). For the present analysis, the major components of LVI data were categorized into three groups these are adaptive capacity, sensitivity, and climate exposure (Table 3.4). Exposure was measured by the frequency of natural disasters that have occurred in the past 41 years, while climate variability was measured by the average standard deviation of the maximum and minimum monthly temperatures and monthly precipitation over a 41-year period. Adaptive capacity was quantified by the demographic profile of a block (e.g., per cent of female-headed households), the types of livelihood strategies employed (e.g., predominately agricultural, or other non-farm activities), and the strength of social networks

(e.g., per cent of households have any extension contact). Lastly, sensitivity was measured by assessing the current state of food, water security, and health status in the study area. Understanding these components can assist in assessing the nature and magnitude of climate change risk, together with the recognition of substantial sources of vulnerability.

The sub-components outlined in Table 3.3, as well as Eqs. (1) – (3) were used to calculate the LVI–IPCC. The LVI–IPCC diverges from the LVI when the major components combined. Rather than merge the major components into the LVI in one step, they were first combined according to the categorization scheme in Table 3.4 using the following equation:

$$CF_d \frac{\sum_{i=1}^{s} W_{mi} M_{di}}{\sum_{i=1}^{s} W_{mi}} \text{…….. (5)}$$

where,

CF_d = IPCC-defined contributing factors (exposure, sensitivity or adaptive capacity) for block.

Mdi = Major component for block indexed by i

W_{mi} = Weight of each major component

After calculating the exposure, sensitivity and adaptive capacity, the three contributing factors were combined using the following equation:

$$LVI - IPCC_d = (e_d - a_d)*S_d \quad \text{…… (6)}$$

where,

$LVI–IPCC_d$ = LVI for block expressed using the IPCC vulnerability framework.

e = Calculated exposure score for block (equivalent to the Natural Disaster and Climate Variability major component).

a = Calculated adaptive capacity score for block (weighted average of the Socio-demographic, Livelihood strategies, and social networks major components).

s = Calculated sensitivity score for block (weighted average of the Heath, Food, Water and House major components).

The LVI–IPCC values were scaled from -1 (least vulnerable) to +1 (most vulnerable). For illustrative purposes, a detailed example of calculating the contributing factors of LVI-IPCC for Rohru block is presented in Appendix III.

Table 3.3: Major components and sub-components comprising the Livelihood Vulnerability Index (LVI) developed for the study area

Sr. No.	Major components	Sub-components	Units	Description of sub-components
1.	Socio-demographic	Dependency ratio (Farmers)	Ratio	Ratio of the population under 15 and over 65 years of age to the population between 19 and 64 years of age.
		Female-headed households	Per cent	Percentage of households where the primary adult is female. If a male head is away from the home >6 months per year the female is counted as the head of the household.
		Average age of head of household	Years	Average age of adults as the head of household
		Per cent of illiterate household heads	Per cent	Percentage of households where the head of the household reports that they have attended 0 years of school.
		Average family size	Count	Average of household members for each family
		Average years of farming experience	Count	Average years of farming experience
2.	Livelihood strategies	Households with family members working in a different community (other than agriculture)	Per cent	Percentage of households report that at least 1 family member who works outside of the community for their primary work activity. Working in other community provides additional income, and facilitates the acquisition of knowledge, new skills, and innovative ideas, while also contributing to household expenses such as education, healthcare, and agricultural inputs.
		Households dependent solely on agriculture as a source of income	Per cent	Percentage of households that report only agriculture as a source of income.
		Average livelihood diversification index (Herfindhal Index)	Index	Herfindahl index (HI) is computed by taking sum of squares of income proportion of each income

				sources in the total number of household income sources as given by the following formula: $\mathbf{HI = \sum_{i=1}^{N} P_i^2}$ where, N is the total number of income sources and Pi represents income proportion of the ith income source. Its value is bounded by 0 and 1.
3.	**Social Network**	Average receive: give (ratio)	Ratio	Ratio of (the number of types of help received by a household in the past month + 1) to (the number of types of help given by a household to someone else in the past month + 1).
		Average borrow: lend money (ratio)	Ratio	Ratio of a household borrowing money in the past month to a household lending money in the past month, e.g., If a household borrowed money but did not lend money, the ratio = 2:1 or 2, and if they lent money but did not borrow any, the ratio = 1:2 or 0.5.
		Households that have received local government assistance in the past one year (during flood season)	Per cent	Percentage of households receiving local government assistance in the past 12 months (during flood season).
		HH does not have any extension contact	Per cent	Percentage of households did not have any extension contact.
4.	**Health**	Average time to district health facility (minutes)	Minutes	Average time it takes the households to get to the nearest health facility.
		Average distance to district hospital	Km	Average distance it takes the households to get to the nearest health facility.
		HH reporting non availability of health facilities in nearest PHC	Per cent	Percentage of households that report non availability of health facilities in nearest PHC.
		Households with family members with chronic illness	Per cent	Percentage of households that report at least one family member with chronic illness. Chronic illness was defined subjectively by the respondent.

5.	**Food**	Households that do not save crops	Per cent	Percentage of households unable to protect or recover their crops when flood strike.
		Households that do not save seeds	Per cent	Percentage of households who do not save seeds.
		Average Crop Diversification index (Herfindahl Index)	Index	Herfindahl index (HI) is computed by taking sum of squares of acreage proportion of each crop to the total cropped area as given by the following formula: $\mathbf{HI} = \sum_{i=1}^{N} \mathbf{P_i^2}$ where, N is the total number of crops and Pi represents acreage proportion of the ith crop in the total cropped area. Its value is bounded by 0 and 1.
		Average Livestock Diversity Index	Index	The inverse of (the number of animals + 1) Livestock Diversity Index = 1/ (number of livestocks +1). Diverse species of livestock reduces the risk of major losses.
6.	**Water**	Utilize natural source of water	Per cent	Percentage of households that report natural water as their primary source.
		Households reporting recent drying of water sources	Per cent	Percentage of households that report recent drying of water sources
		Households that do not have a consistent water supply for drinking	Per cent	Percentage of households that report that water is not available at their primary water source every day
		Households reporting water conflicts	Per cent	Percentage of households that report having heard about conflicts over water in their community.
		Households reporting shortage of water supply for farming	Per cent	Percentage of households that report shortage of water supply for farming
		Households storing water	Per cent	Percentage of households that store water for daily usage
		Average time to water source	Minutes	Averagetime it takes the households to travel to their primary water source.
		Inverse of the average amount (liters) of water stored per household	1/# Litre	The inverse of (the average number of liters of water stored by each household + 1).

7.	**House**	Households whose houses do not have a solid structure and are prone to damage by floods	Per cent	Percentage of households who do not have a solid structure and are more prone to damage by floods
		Flood affected households	Per cent	Percentage of households affected by floods (more than 30% damage)
8.	**Natural disasters & climate variability**	Households who were not provided with early flood warnings	Per cent	Percentage of households that were not provided with early flood warnings
		Households experienced catastrophic accidents or deaths from floods in the past five years	Per cent	Percentage of households who registered injury or death to at least one family member in the past five years due to extreme floods
		Mean standard deviation of the monthly average of average maximum daily temperature (1981-2022)	Celcius	Standard deviation of the average daily maximum temperature by month between 1981 and 2022 was averaged for each block
		Mean standard deviation of the monthly average of the average minimum daily temperature (1981-2022)	Celcius	Standard deviation of the average daily maximum temperature by month between 1981 and 2022 was averaged for each block
		Mean standard deviation of monthly average precipitation (1981-2022)	Millimeter	Standard deviation of the average monthly precipitation between 1981 and 2022 was averaged for each block

Table 3.4: Categorization of major components into contributing factors from the IPCC vulnerability definition for the calculation of the LVI–IPCC

LVI Major Components	IPCC Definition of Vulnerability (LVI-IPCC)
Exposure	Natural disaster and climate variability
Adaptive capacity	Socio-demographic profile
	Livelihood strategies
	Social networks
Sensitivity	Health
	Food
	Water
	House

3.6.3. Climate-smart agricultural practices

Climate-smart agricultural practices were assessed using a binary scale, where each practice was classified as either adopted (1) or not adopted (0) by farmers. This approach enabled a clear differentiation between farmers who had implemented specific CSA practices and those who had not.

3.6.3.1. The Composite Score

To assess the adoption of Climate-Smart Agriculture (CSA) practices among farming households, a composite scoring approach was utilized (Abegunde *et al*., 2019). This method involved using a binary scale, where a response of "Yes" (adoption of the practice) was scored as 1, and "No" (non-adoption) was scored as 0. The adoption level was measured across 12 CSA practices, with each practice contributing equally to the composite score. Consequently, the total score for a respondent could range from a maximum of 12, indicating the adoption of all practices, to a minimum of 0, representing non-adoption of any practices. Based on their scores, respondents were categorized into three groups: high adopters, who demonstratedsignificant adoption of CSA practices; moderate adopters, who showed partial adoption; and low or non-adopters, who exhibited limited or no adoption.

High adopters = respondents points fall between 12 and (M + S.D) points.
Moderate adopters = respondents between upper and lower categories.
Low adopters = respondentswhose points fall between (Mean − S.D) and 0

3.6.3.2. Ordered Logistic Regression Model

Ordinal logistic regression was used to model the relationship between an ordered multilevel dependent variable and independent variables. In the modeling, values of the dependent

variable have a natural order or ranking. They were particularly suitable for situations where the dependent variable represents levels or rankings, such as the level of adoption of Climate-Smart Agriculture (CSA) practices (e.g., low, moderate, high). The dependent variable Y_i = level of adoption of CSA practices (high adopters = 3; moderate adopters = 2; low adopters = 1).

The general form of the Ordered Logistic Regression model is:

$$\Pr(Y \leq j) = \left(\frac{\sum pr\,(Y \leq j)|X}{1-\sum pr\,(Y \leq j)|X}\right) = \alpha_j + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots + \beta_{15} X_{15}$$

where,

Y	=	Dependent variable (level of CSA adoption)
α	=	Threshold
β_1- β_{15}	=	Estimated parameters
X_1	=	Age of the household head (hhh)
X_2		Gender of the household head (hhh)
X_3	=	Education status of the household head
X_4	=	Farming experience
X_5	=	Market distance
X_6	=	Access to extension
X_7	=	Access to credit
X_8	=	Participate in training
X_9	=	Member in local area
X_{10}	=	Access to climate change information
X_{11}	=	Family size
X_{12}	=	Adult Cattle Unit (ACU)
X_{13}	=	Off-farm income
X_{14}	=	On-farm income
X_{15}	=	Farmers category

3.6.3.3. Variance Inflation Factor

To ensure the suitability of the Ordered Logistic Regression(OLR) model for investigating the effects of explanatory variables on Climate-Smart Agriculture (CSA) practices, it is essential to test for multicollinearity among the continuous explanatory variables. The Variance Inflation Factor (VIF) was used as a diagnostic measure for this purpose. The VIF quantifies the extent to which the variance of an estimated regression coefficient is inflated due to multicollinearity in the model. The VIF for each explanatory variable was calculated using the following formula:

$$\text{VIF} = \frac{1}{1-R^2}$$

where,

R^2 = coefficient of determination obtained from regressing the variable of interest on all other explanatory variables (X_i) in the model.

The value VIF is 1 if there is no collinearity between regressors. When a variable's VIF value surpasses 10, as it does when R^2 exceeds 0.90, the variable is considered to be very collinear (Gujarati, 2004).

3.6.3.4. Contingency Coefficient (CC)

To determine the degree of correlation between the dummy explanatory variables, a contingency coefficient is calculated. A score of CC ≥ 1 shows that the two variables have a stronger association. The contingency coefficient (CC) was computed as:

$$CC = \sqrt{\frac{\chi^2}{\chi^2 + N}}$$

where,

CC = coefficient of contingency

$\chi 2$ = chi-square test

N = total sample size

Table 3.5: Dependent variables of the factors influencing the adoption of climate smart agricultural practices

CSA practices	Description
Mulching	Dummy = 1 if the household adopted mulching, 0 if otherwise
Minimum/Zero Tillage	Dummy = 1 if the household adopted minimum/zero tillage, 0 if otherwise
Fruit Based Agroforestry	Dummy = 1 if the household adopted fruit-based agroforestry, 0 if otherwise
Integrating Crop Livestock Production	Dummy = 1 if the household adopted integrating crop-livestock production, 0 if otherwise
Micro Irrigation	Dummy = 1 if the household adopted micro irrigation, 0 if otherwise
Change of Planting Time (before/after onset of rainfall)	Dummy = 1 if the household changed planting time (before/after onset of rainfall), 0 if otherwise
Improved Crop Varieties	Dummy = 1 if the household adopted improved crop varieties, 0 if otherwise
Diet Improvement for Animals	Dummy = 1 if the household adopted diet improvement for animals, 0 if otherwise
Crop Insurance	Dummy = 1 if the household adopted crop insurance, 0 if otherwise
Soil Test	Dummy = 1 if the household adopted soil testing, 0 if otherwise
Use of Compost & FYM	Dummy = 1 if the household adopted the use of compost and FYM (Farm Yard Manure), 0 if otherwise
ICT Based Weather Forecast	Dummy = 1 if the household adopted ICT-based weather forecasts, 0 if otherwise

Table 3.6: Explanatory variables of the factors influencing the adoption of climate-smart agricultural practices

Variables	Description
Socio-demographic factors	
Age of the household head	Age of the household head in years
Gender of the household head	Dummy = 1 if sex of the household head is male, 0 female
Education status of the household head	The level of formal education attained by the household head: 0 = Illiterate, 1 = Primary Education, 2 = Middle Education, 3 = Secondary Education, 4 = Senior Secondary Education, 5 = Graduate and Above
Farming experience	Farming experience of the household head in years
Institutional factors	
Market distance	Distance to the nearest market in kilometers
Access to extension functionaries	Dummy = 1 if the household has access to agricultural extension services, 0 otherwise
Access to credit	Dummy = 1 if the household has access to credit, 0 otherwise
Participate in training	Dummy = 1 if the household participate in training related to climate-smart agriculture, 0 otherwise
Socio-cultural factor	
Member in local area	Dummy = 1 if the household head is a member of a social group, 0 otherwise
Climatic factor	
Access to climate change information	Dummy = 1 if the household has access to climate change information, 0 otherwise
Economic factors	
Family size	Number of family members
ACU	The total number of adult cattle units owned by the household
Off-farm income	Income generated from activities outside of farming, typically measured in monetary terms (e.g., annual income)
On-farm income	Income generated from agricultural activities, including crops, livestock, or other farm-related activities, usually measured in monetary terms (e.g., annual income)
Farmers' category	Category of farmer according to their landholding status: 1 = Marginal, 2=Small, 3=Semi medium

3.6.4. Impact of climate-smart agricultural practices on livelihood vulnerability

Multiple linear regression was used to examine the impact of climate-smart agricultural practices on livelihood vulnerability of the sample households.

3.6.4.1. Multiple linear regression

The Livelihood Vulnerability Index (LVI) of farmers was used as the response variable, while the explanatory variables included climate-smart agricultural practices, access to information on climate change, and access to training on CSA practices. The multiple linear regression model is described as follows:

$$Y = \alpha_0 + \alpha_{1X_1} + \alpha_{2X_2} + \alpha_{3X_3} + \mu$$

where,

Y = Livelihood Vulnerability Index

α_0 = Intercept

α1-α3 = Coefficients for the explanatory variables

μ = Error term

X1 = Climate smart agricultural practices

X2 = Access to information on climate change

X3 = Access to training on CSA practices

3.6.5. Constraint analysis

To achieve the final objective of identifying the constraints that hinder the adoption of climate-smart agricultural practices among farmers in the study area, mean scores were computed. Farmers were asked to respond to a series of proposed constraints using a five-point Likert scale. The mean scores for each factor were then calculated, and the most influential factors were identified based on the rankings derived from these mean scores. The factor with the highest mean score was determined to be the primary constraint faced by farmers.

3.6.5.1. Kendall's Coefficient of Concordance (W)

Kendall's W, a non-parametric test, was employed to evaluate the degree of agreement among farmers regarding the ranked constraints. This coefficient measures

concordance and ranges from 0 (no agreement) to 1 (complete agreement). The following hypotheses were tested:

Null Hypothesis (H_0) = There is no agreement among farmers regarding the constraints faced in adopting climate-smart agricultural practices.

Alternative Hypothesis (H_1) = There is agreement among farmers regarding the constraints faced in adopting climate-smart agricultural practices.

The significance of Kendall's W was determined using the formula provided by Sawant and Patil (2017):

$$W = \frac{12[T^2 - \sum \frac{(T)^2}{n}]}{nm^2n^2 - 1}$$

where,

T= sum of ranks for each constraint being ranked

m= number of ranking (Farmers)

n= number of constraints being ranked

3.7. Limitations of the study:

1. The study is based on the data collected for one year only i.e. 2023-2024 which may not necessarily hold true for other years as well.
2. Primary data were collected by a survey approach and there is a chance of biasness, although only to a limited extent.
3. During the survey, it was found that respondents were not maintaining any type of farm records; therefore, the data collected are based on their memory and experience.
4. The results of primary data may suffer from non-sampling errors although it is free from sampling errors.

Chapter - 4

RESULTS AND DISCUSSION

The results obtained through systematic analysis and interpretation of the collected data and information, along with relevant discussion have been presented in this chapter for the study area. The results are organized under the following sections.

4.1. Description of the study area

4.2. Socio-economic status of the farmers

4.3. Existing resource structure

4.4. Livelihood vulnerability

4.5. Climate-smart agricultural practices in the study area

4.6. Factors influencing the adoption of climate-smart agricultural practices

4.7. Impact of climate-smart agricultural practices on livelihood vulnerability of the sample households

4.8. Constraints faced by the adopters of climate-smart agricultural practices in the study area

4.1. DESCRIPTION OF THE STUDY AREA

Himachal Pradesh, situated in the western Himalayan range, spans a geographical area of 55,673 km² and lies between latitudes 30°22’40” to 33°12’20” N and longitudes 75°45'55" to 79°04'20” E. The state, characterized by its entirely mountainous terrain within the Himalayan belt, features altitudinal variations from 350 meters to 6,975 meters above mean sea level. It shares borders with Jammu and Kashmir to the north, Tibet to the northeast, Uttarakhand to the east and southeast, Haryana to the south, and Punjab to the southwest and west. According to the 2011 Census, the state hosts a population of 6.864 million, with a decadal growth rate of 12.94 per cent, which is considerably below the national average of 17.64 per cent. Approximately 90 per cent of the population resides in rural areas, leaving only 10 per cent in urban regions. Rural and urban populations differ substantially in employment patterns, income levels, literacy rates, poverty prevalence, and dependence on governmental aid. These disparities contribute to the socio-economic and cultural dynamics of rural communities and underscore their heightened livelihood vulnerabilities to climate change relative to urban populations. The state's territory is categorized into four distinct agro-climatic zones: Sub-Tropical Sub-Montane and Low Hill,

Sub-Humid Mid Hills, Wet Temperate High Hills, and Dry Temperate High Hills. These zones reflect the wide-ranging environmental conditions across the state. This diversity is attributed to the state's varied micro-agro-climatic regions, which support the growth of crops suited to different climatic and altitudinal requirements. The workforce distribution in Himachal Pradesh indicates a predominant reliance on agriculture and horticulture, with 58 per cent of workers engaged as cultivators and 5 per cent employed as agricultural laborers. Climatically, the state exhibits wide-ranging conditions, from hot and sub-humid tropical climates in the southern lowlands to warm temperate, cold temperate, alpine, and glacial climates in the high-altitude northern and eastern regions. This study concentrates on six districts within the temperate zone: Lahaul and Spiti, Kinnaur, Chamba, Kullu, Shimla, and Mandi. These districts are characterized by diverse agro-climatic conditions, such as wet temperate and cold dry zones, which support the cultivation of an extensive variety of crops. Major agricultural and horticultural crops include maize, wheat, paddy, barley, pulses, ginger, potato, tomato, green peas, apples, pomegranates, kiwis, almonds, cherries, apricots, millets, and oilseeds. This agro diversity highlights the region's potential for specialized agricultural practices and adaptive strategies under changing climatic conditions.

4.2. SOCIO-ECONOMIC STATUS OF THE FARMERS

Socio-economic status is a composite measure that captures both social and economic factors, determining the relative position of individuals or groups within a society. Key socio-economic characteristics include age, gender, education, family size and structure, social position, and land ownership. Understanding these characteristics, particularly in the context of farmers, is critical for analysing their decision-making processes, and the productive use of available resources. These socio-economic variables directly influence access to essential agricultural inputs, such as labour, credit, technology, and markets. For smallholder farmers, the ability to access these resources has a profound effect on food production, which ultimately determines their livelihood security and overall well-being. Furthermore, socio-economic characteristics help in predicting psychological and behavioural patterns, which are crucial in shaping farmers' access to resources, societal livelihood structures, and food security (Roy *et al.,* 2013). Therefore, a comprehensive understanding of these factors is key to improving the sustainability and productivity of smallholder farms, as well as enhancing the broader socio-economic welfare of farming communities. It is important to recognize the role these factors play in farming systems, as they help inform policies and strategies aimed at improving the well-being of farming communities. This knowledge is vital for developing

targeted interventions that enhance farm productivity and improve the livelihoods of farmers in the region. The socio-economic status of farmers, as assessed by various parameters in the study area, is outlined below.

4.2.1. Family size

Family size refers to the composition of a household, encompassing adults and children generally linked by bloodline or marriage, along with the proportion of males and females within each group. The size of a family is a key determinant of the available household labor force, particularly in agrarian contexts where family members contribute to farm activities. The data presented in Table 4.1 illustrate the family size distribution among sampled households in the study area. The perusal of the data presented in Table 4.1 showed that at an overall level, the average family size of sampled households was 5.44 with the highest family size (6.04) observed in Mehla block followed by (5.65) Rohru block and (5.60) Gohar block while the smallest average family size was observed in the (4.98) Jubbal & Kotkhai block. Analysis of age groups indicated that the majority of family members belong to the economically active age group (15-65 years), with an overall average of 2.15 males and 2.00 females in this group. Mehla block showed the highest number of males (2.35) and females (2.23) within this productive age group (15-65 years). The overall, sex ratio in the study area was found to be 896, highlighting a gender imbalance. Significant variability in the sex ratio was observed across different blocks, with the lowest ratio in Jubbal & Kotkhai (811) and the highest in Gohar (949), suggesting regional differences in gender demographics that may impact household labor dynamics and community structure.

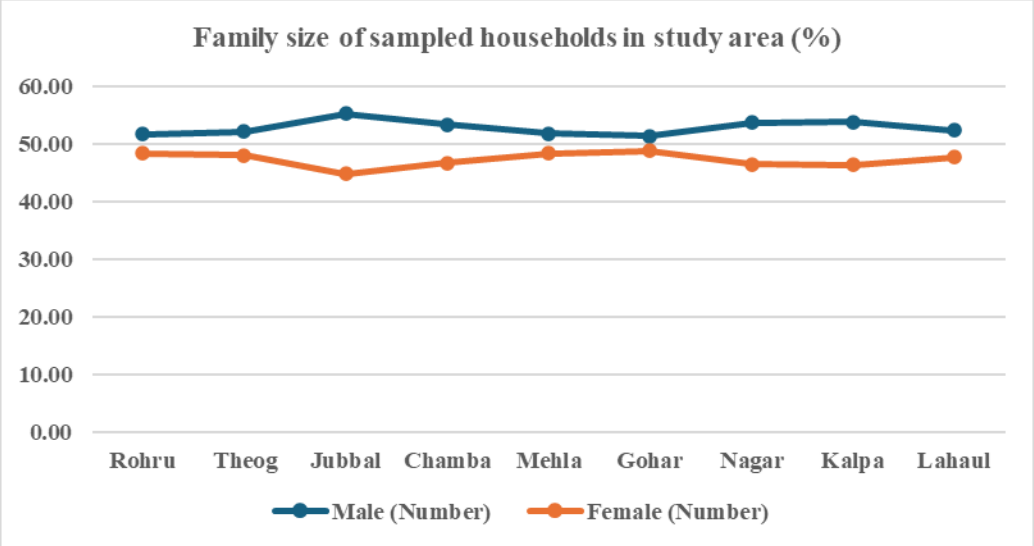


Figure 4.1: Family size of sampled households

Table 4.1: Family size of sampled households in study area

Particulars	Age Group						Average Family Size (Number)	Male (Number)	Female (Number)	Sex Ratio
	0-15		15-65		>65					
	Male (Number)	Female (Number)	Male (Number)	Female (Number)	Male (Number)	Female (Number)				
Rohru	0.44 (7.75)	0.29 (5.17)	2.13 (37.64)	2.15 (38.01)	0.35 (6.27)	0.29 (5.17)	5.65 (100.00)	2.92 (51.66)	2.73 (48.34)	936
Theog	0.40 (7.22)	0.27 (4.94)	2.15 (39.16)	2.08 (38.02)	0.31 (5.70)	0.27 (4.94)	5.48 (100.00)	2.85 (52.09)	2.63 (47.91)	920
Jubbal & Kotkhai	0.33 (6.69)	0.21 (4.18)	2.08 (41.84)	1.81 (36.40)	0.34 (6.69)	0.21 (4.18)	4.98 (100.00)	2.75 (55.23)	2.23 (44.77)	811
Chamba	0.35 (6.67)	0.27 (5.10)	2.10 (39.61)	1.96 (36.86)	0.38 (7.06)	0.25 (4.71)	5.31 (100.00)	2.83 (53.33)	2.48 (46.67)	875
Mehla	0.35 (5.86)	0.35 (5.86)	2.35 (38.97)	2.23 (36.90)	0.42 (6.90)	0.33 (5.52)	6.04 (100.00)	3.13 (51.72)	2.92 (48.28)	933
Gohar	0.5 (8.92)	0.31 (5.58)	2.02 (36.06)	2.10 (37.55)	0.35 (6.32)	0.31 (5.58)	5.60 (100.00)	2.88 (51.30)	2.73 (48.70)	949
Nagar	0.31 (5.95)	0.33 (6.35)	2.21 (42.06)	1.81 (34.52)	0.29 (5.56)	0.29 (5.56)	5.25 (100.00)	2.81 (53.57)	2.44 (46.43)	867
Kalpa	0.38 (7.06)	0.27 (5.10)	2.13 (40.00)	1.90 (35.69)	0.35 (6.67)	0.29 (5.49)	5.31 (100.00)	2.85 (53.73)	2.46 (46.27)	861
Lahaul	0.29 (5.43)	0.29 (5.43)	2.19 (40.70)	1.96 (36.43)	0.33 (6.20)	0.31 (5.81)	5.38 (100.00)	2.81 (52.33)	2.56 (47.67)	911
Overall	0.37 (6.84)	0.29 (5.30)	2.15 (39.56)	2.00 (36.71)	0.35 (6.37)	0.28 (5.22)	5.44 (100.00)	2.87 (52.77)	2.58 (47.23)	896

Figures in parentheses represent per cent to the total

4.2.2. Family type

The family, as a fundamental social institution, plays a critical role in providing social security and support to its members. Families can be broadly categorized into two primary types: nuclear families and joint families. The Table 4.2 presents the distribution of family type in the study area. It is observed from Table 4.2 that the majority of the respondents (53.24%) were members of nuclear families, while 46.76 per cent of respondents were part of joint families within the study area. The distribution of family types varied across different regions. Notably, the highest proportion of nuclear families was observed in Jubbal & Kotkhai block (66.67%), followed by Gohar block (60.42%) and Chamba block (58.33%). This trend in Jubbal & Kotkhai block suggests a shift towards smaller, nuclear family structures. Conversely, the Mehla block exhibited a higher proportion of joint families (56.25%), followed by Rohru block (54.17%), indicating a more traditional household structure, possibly influenced by cultural or agricultural practices that favor larger, extended family units for labour. Similarly, blocks like Lahaul and Theog also showed relatively balanced distributions, with joint families constituting around 52.08 per cent of households in each block, indicating a more even division between family types in these areas.

Table 4.2: Family type of sampled households in study area

Particulars	Type of family		Total
	Nuclear (Number)	Joint (Number)	
Rohru	22 (45.83)	26 (54.17)	48 (100.00)
Theog	23 (47.92)	25 (52.08)	48 (100.00)
Jubbal & Kotkhai	32 (66.67)	16 (33.33)	48 (100.00)
Chamba	28 (58.33)	20 (41.67)	48 (100.00)
Mehla	21 (43.75)	27 (56.25)	48 (100.00)
Gohar	29 (60.42)	19 (39.58)	48 (100.00)
Nagar	26 (54.17)	22 (45.83)	48 (100.00)
Kalpa	26 (54.17)	22 (45.83)	48 (100.00)
Lahaul	23 (47.92)	25 (52.08)	48 (100.00)
Overall	25.56 (53.24)	22.44 (46.76)	48.00 (100.00)

Figures in parentheses represent per cent to the total

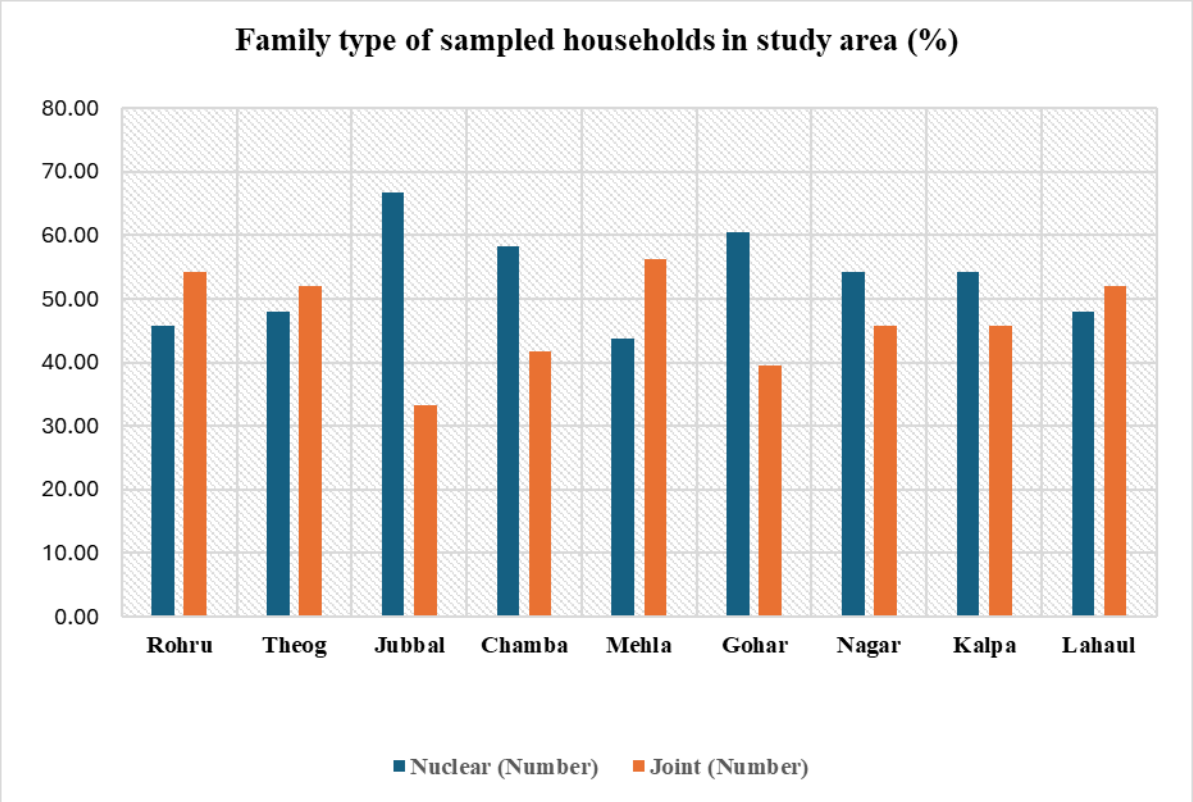


Figure 4.2: Family type of sampled households

4.2.3. Educational status of family

Education is a crucial process that facilitates the acquisition of knowledge, values, skills, morals, and personal development. It plays a pivotal role in societal advancement, serving as a key instrument for addressing issues such as poverty eradication, livelihood enhancement, gender equality, peace, and overall socio-economic development. In the context of the study area, the educational status of farmers has been analyzed and the relevant data is presented in Table 4.3. The educational status of farmers in the study area demonstrated significant regional variations in literacy levels and educational attainment. The data presented in Table 4.3 indicated that, at the overall level, a larger proportion of males (0.66%) attained education up to the senior secondary level, while the majority of females (0.57%) reached the higher secondary level.

4.2.3.1. Literacy status of sampled households

Literacy rate is a key indicator of human capital development, reflecting the overall educational attainment within a population. Higher levels of literacy contribute significantly to greater awareness, enabling individuals to make informed decisions in various aspects of life, such as health, finance, and governance. Furthermore, an educated population is better

Table 4.3: Educational status of sampled households in study area

(Number)

Particulars	Illiterate		Primary		Middle		HS		SS		G		NSG		Total	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Rohru	0.21	0.31	0.25	0.44	0.40	0.42	0.60	0.56	0.69	0.60	0.58	0.27	0.19	0.13	2.92	2.73
	(3.69)	(5.54)	(4.43)	(7.75)	(7.01)	(7.38)	(10.70)	(9.96)	(12.18)	(10.70)	(10.33)	(4.80)	(3.32)	(2.21)	(51.66)	(48.34)
Theog	0.21	0.27	0.33	0.42	0.48	0.35	0.48	0.65	0.71	0.54	0.46	0.25	0.19	0.15	2.85	2.63
	(3.80)	(4.94)	(6.08)	(7.60)	(8.75)	(6.46)	(8.75)	(11.79)	(12.93)	(9.89)	(8.37)	(4.56)	(3.42)	(2.66)	(52.09)	(47.91)
Jubbal & Kotkhai	0.21	0.21	0.46	0.25	0.42	0.35	0.35	0.67	0.69	0.40	0.48	0.25	0.15	0.10	2.75	2.23
	(4.18)	(4.18)	(9.21)	(5.02)	(8.37)	(7.11)	(7.11)	(13.39)	(13.81)	(7.95)	(9.62)	(5.02)	(2.93)	(2.09)	(55.23)	(44.77)
Chamba	0.35	0.40	0.27	0.31	0.42	0.29	0.58	0.58	0.65	0.56	0.31	0.19	0.25	0.15	2.83	2.48
	(6.67)	(7.45)	(5.10)	(5.88)	(7.84)	(5.49)	(10.98)	(10.98)	(12.16)	(10.59)	(5.88)	(3.53)	(4.71)	(2.75)	(53.33)	(46.67)
Mehla	0.42	0.52	0.52	0.58	0.56	0.46	0.48	0.58	0.77	0.48	0.21	0.15	0.17	0.15	3.13	2.92
	(6.90)	(8.62)	(8.62)	(9.66)	(9.31)	(7.59)	(7.93)	(9.66)	(12.76)	(7.93)	(3.45)	(2.41)	(2.76)	(2.41)	(51.72)	(48.28)
Gohar	0.21	0.35	0.38	0.50	0.54	0.52	0.42	0.65	0.60	0.44	0.48	0.19	0.25	0.08	2.88	2.73
	(3.72)	(6.32)	(6.69)	(8.92)	(9.67)	(9.29)	(7.43)	(11.52)	(10.78)	(7.81)	(8.55)	(3.35)	(4.46)	(1.49)	(51.30)	(48.70)
Nagar	0.27	0.31	0.31	0.29	0.40	0.44	0.63	0.60	0.67	0.48	0.44	0.19	0.10	0.13	2.81	2.44
	(5.16)	(5.95)	(5.95)	(5.56)	(7.54)	(8.33)	(11.90)	(11.51)	(12.70)	(9.13)	(8.33)	(3.57)	(1.98)	(2.38)	(53.57)	(46.43)
Kalpa	0.35	0.38	0.44	0.52	0.52	0.56	0.56	0.50	0.54	0.27	0.25	0.13	0.19	0.10	2.85	2.46
	(6.67)	(7.06)	(8.24)	(9.80)	(9.80)	(10.59)	(10.59)	(9.41)	(10.20)	(5.10)	(4.71)	(2.35)	(3.53)	(1.96)	(53.73)	(46.27)
Lahaul	0.46	0.52	0.31	0.69	0.58	0.60	0.63	0.31	0.58	0.19	0.13	0.08	0.13	0.17	2.81	2.56
	(8.53)	(9.69)	(5.81)	(12.79)	(10.85)	(11.24)	(11.63)	(5.81)	(10.85)	(3.49)	(2.33)	(1.55)	(2.33)	(3.10)	(52.33)	(47.67)
Overall	0.30	0.36	0.36	0.44	0.48	0.44	0.53	0.57	0.66	0.44	0.37	0.19	0.18	0.13	2.87	2.58
	(5.48)	(6.64)	(6.68)	(8.11)	(8.79)	(8.16)	(9.67)	(10.45)	(12.04)	(8.07)	(6.84)	(3.46)	(3.27)	(2.34)	(52.77)	(47.23)

** Figures in the parenthesis are per cent values, HS-Higher Secondary, SS- Senior Secondary, G- Graduate, NSG- Non-school going.*

equipped to adapt to new technologies, engage in higher-value economic activities, and innovate, which collectively enhance economic productivity. From the data presented in Table 4.4, it was found that the overall literacy rate in the study area was 87.16 per cent. Males were found to be more literate, with a literacy rate of 88.94 per cent, as compared to the females with a literacy rate of 85.22 per cent. The literacy rate across the regions shows that the highest literacy rates were observed in Jubbal & Kotkhai (91.19%) and Theog (90.69%), with the lowest literacy rate being recorded in Lahaul (80.74%). Among males, Rohru (92.37%) had the highest literacy rate, while Lahaul (82.95%) recorded the lowest. Similarly, for females, Jubbal & Kotkhai (90.20%) exhibited the highest literacy rate, while Lahaul (78.26%) again had the lowest. Table 4.4 showed a marked improvement in the literacy rate of the respondents, however literacy index varied between 2.03 to 2.86 among the different blocks, with an overall index of 2.56. The literacy index among the males varied between 2.35 to 3.12, with an overall index of 2.74, and in case of female it varied from 1.67 to 2.73, with an overall index of 2.35.

Table 4.4: Literacy status of sampled households

Blocks	Literacy Rate (%)			Literacy Index		
	Male	Female	Total	Male	Female	Total
Rohru	92.37	88.00	90.23	3.12	2.58	2.86
Theog	92.19	89.08	90.69	2.95	2.61	2.79
Jubbal & Kotkhai	92.00	90.20	91.19	2.88	2.73	2.81
Chamba	86.29	83.04	84.75	2.71	2.50	2.61
Mehla	85.92	81.20	83.64	2.44	2.13	2.29
Gohar	92.06	86.61	89.33	2.87	2.33	2.60
Nagar	90.00	86.49	88.38	2.89	2.52	2.72
Kalpa	86.72	84.07	85.48	2.47	2.06	2.29
Lahaul	82.95	78.26	80.74	2.35	1.67	2.03
Overall	88.94	85.22	87.16	2.74	2.35	2.56

4.2.4. Status of occupation and off-farm employment

Occupation is a fundamental aspect of livelihood, providing individuals with a means to earn income and establish their social standing. In the study area, the primary occupations were agriculture, service, and business, each contributing uniquely to the community's economic fabric. The data regarding the status of occupation and off-farm employment of the respondents in the study area were recorded and presented in Table 4.5 and Table 4.6, respectively. At the overall level, agriculture was the dominant source of livelihood, contributing 83.39 per cent of the total. This was followed by business activities, which contributed 9.01 per cent, and salaried employment, which

constituted 7.60 per cent. Among the selected blocks, the highest dependency on agriculture was observed in Kalpa block (86.39%), followed by Gohar block (85.08%) and Mehla block (85.00%). In contrast, the highest percentage of respondents involved in business activities was recorded in Jubbal block (10.43%), while the lowest was in Kalpa block (6.51%). The perusal of the data presented in Table 4.5 revealed that the maximum (10.69%) number of persons involved in the salaried sector in off-farm employment was observed in Theog block followed by Jubbal & Kotkhai block (8.59%) and Rohru block (8.09%).

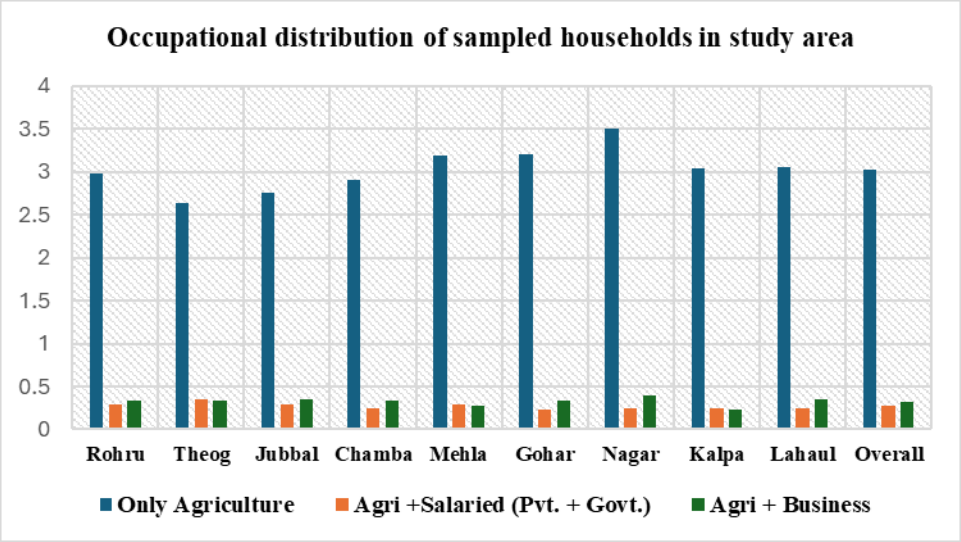


Figure 4.3: Block wise occupational distribution sampled households

Table 4.6 presents the overall average monthly income per person in salaried employment was ₹28,277.29. The average monthly income per person in salaried employment was highest (₹32738.10) in Rohru block. In contrast, the lowest (₹23611.11) average monthly income per person in salaried employment was found in Lahaul block. The variation in participation rates and income highlights regional disparities in access to salaried opportunities. Business activities, which involved a slightly higher proportion of members (54.33%), provided an overall average monthly income per person of ₹29,688.93. The average monthly income per person in business was recorded highest (₹36197.92) in the Theog block, while the lowest (₹21568.63) was observed in the Lahaul block. The data underscores the role of off-farm employment as a supplementary livelihood source, with notable regional differences in both participation rates and income levels. Business activities generally outperformed salaried employment in terms of participation, though income levels varied significantly between regions. The findings suggest a need to enhance access to better-paying salaried jobs and support for business activities to ensure more equitable off-farm income opportunities across regions.

Table 4.5: Occupational distribution of the sampled households

(Numbers)

Particulars	Rohru	Theog	Jubbal & Kotkhai	Chamba	Mehla	Gohar	Nagar	Kalpa	Lahaul	Overall
Only Agriculture	2.98 (82.66)	2.63 (79.25)	2.75 (80.98)	2.90 (83.23)	3.19 (85.00)	3.21 (85.08)	3.50 (84.42)	3.04 (86.39)	3.06 (83.52)	3.03 (83.39)
Agri +Salaried (Pvt. + Govt.)	0.29 (8.09)	0.35 (10.69)	0.29 (8.59)	0.25 (7.19)	0.29 (7.78)	0.23 (6.08)	0.25 (6.03)	0.25 (7.10)	0.25 (6.82)	0.27 (7.60)
Agri + Business	0.33 (9.25)	0.33 (10.06)	0.35 (10.43)	0.33 (9.58)	0.27 (7.22)	0.33 (8.84)	0.40 (9.55)	0.23 (6.51)	0.35 (9.66)	0.32 (9.01)
Average number of workers	3.60 (100.00)	3.31 (100.00)	3.40 (100.00)	3.48 (100.00)	3.75 (100.00)	3.77 (100.00)	4.15 (100.00)	3.52 (100.00)	3.67 (100.00)	3.63 (100.00)

Figures in parentheses are percentage to average workers

Table 4.6: Status of off-farm employment of the sampled households

Particulars	Average number of members	Salaried		Business	
		Average number of members	Average monthly income/person (₹)	Average number of members	Average monthly income/person (₹)
Rohru	0.63 (100.00)	0.29 (46.67)	32738.10	0.33 (53.33)	34114.58
Theog	0.69 (100.00)	0.35 (51.52)	32598.04	0.33 (48.48)	36197.92
Jubbal & Kotkhai	0.65 (100.00)	0.29 (45.16)	32440.48	0.35 (54.84)	31372.55
Mehla	0.58 (100.00)	0.25 (42.86)	25347.22	0.33 (57.14)	27083.33
Chamba	0.56 (100.00)	0.29 (51.85)	27678.57	0.27 (48.15)	27564.10
Gohar	0.56 (100.00)	0.23 (40.74)	27651.52	0.33 (59.26)	30208.33
Nagar	0.65 (100.00)	0.25 (38.71)	26736.11	0.40 (61.29)	29166.67
Kalpa	0.48 (100.00)	0.25 (52.17)	25694.44	0.23 (47.83)	29924.24
Lahaul	0.60 (100.00)	0.25 (41.38)	23611.11	0.35 (58.62)	21568.63
Overall	0.60 (100.00)	0.27 (45.67)	28277.29	0.32 (54.33)	29688.93

Figures in parenthesis are percentages to the total

The average monthly income per person is calculated on the basis of total number of beneficiaries only

4.2.5. Work force

The economic strength of households is significantly influenced by the number of active workers, who are the primary contributors to income and livelihood activities. The per-household distribution of both workers and dependents in the sampled households was analyzed, and the results are presented in Table 4.7. The overall average number of active workers per household in the study area was 3.63. The highest average number of workers was observed in Nagar (4.15), indicating a larger working population. While this may imply greater labor availability and potential for higher agricultural output, it could also reflect disguised unemployment—where surplus labor is engaged without a corresponding increase in productivity. This was followed by Gohar (3.77) and Mehla (3.75), which also reported relatively high numbers of active workers. In contrast, Theog (3.31) and Jubbal & Kotkhai (3.40) had the lowest averages, indicating smaller working populations in these regions.

Table 4.7: Distribution of workers and dependents of the sampled household

(Numbers)

Particulars	Rohru	Theog	Jubbal & Kotkhai	Chamba	Mehla	Gohar	Nagar	Kalpa	Lahaul	Overall
Average number of workers	3.60	3.31	3.40	3.48	3.75	3.77	4.15	3.52	3.67	3.63
Average No. of dependents (<14 & >60 years	1.38	1.21	1.08	1.25	1.46	1.48	1.23	1.29	1.19	1.29
Dependency ratio wrt total workers	0.38	0.37	0.32	0.36	0.39	0.39	0.30	0.37	0.32	0.36
Average size of family members	5.65	5.48	4.98	5.31	6.04	5.60	5.25	5.31	5.38	5.44
Dependency ratio wrt family size	0.07	0.07	0.06	0.07	0.06	0.07	0.06	0.07	0.06	0.07

4.3. EXISTING RESOURCE STRUCTURE

This section examines the existing resource structure encompassing various factors such as land, labour, cropping patterns, livestock, and farm investments. The analysis provides a block-wise breakdown of these elements, shedding light on the regional disparities and the resource utilization patterns that define agricultural practices across different blocks.

4.3.1. Land use pattern

Land is a finite and vital resource, particularly in agriculture, where its efficient utilization significantly impacts farmers' income, consumption, savings, and investments. Land use refers to the socio-economic applications of land, including agriculture, forestry, pastures, and residential purposes. Accurate land utilization statistics are critically important for effective planning and the development of agricultural policies. In Himachal Pradesh, the majority of landholdings are classified as marginal (<1 ha) and small (1–2 ha), according to the Economics and Statistics Department, Himachal Pradesh, 2020. Table 4.8 provides the distribution of agricultural input consumption among the sampled farmers, providing insights into the variability of land use practices and their associated economic impacts. Data exhibited in Table 4.8 revealed that the overall average land holding in the study area was 1.16 ha, which was subjected to different uses such as agriculture, orchard, and pasture. Out of the total land holding, 42.66 per cent of the land was used for agricultural purposes, while 46.72 per cent of the land was used as an orchard. Among the agricultural land, only 17.36 per cent was irrigated, while 19.32 per cent of the orchard area was irrigated. The remaining areas across both land uses were dependent on rain-fed

Table 4.8: Land use pattern of sampled households in study area

(in hectare)

Particulars	Land under crops (Agricultural land) (ha)			Pasture land	Orchard			Land put to non-agricultural use	Average land holding
	Irrigated	Un-irrigated	Sub-total		Irrigated	Un-irrigated	Sub-total		
Rohru	0.16 (12.26)	0.21 (16.44)	0.37 (28.71)	0.07 (5.41)	0.30 (23.79)	0.46 (35.95)	0.76 (59.74)	0.08 (6.14)	1.28 (100.00)
Theog	0.15 (11.31)	0.21 (16.19)	0.36 (27.50)	0.06 (4.60)	0.33 (24.69)	0.51 (38.63)	0.84 (63.32)	0.06 (4.59)	1.33 (100.00)
Jubbal & Kotkhai	0.17 (12.14)	0.22 (16.11)	0.39 (28.26)	0.06 (4.67)	0.40 (28.87)	0.46 (33.72)	0.86 (62.59)	0.06 (4.48)	1.38 (100.00)
Chamba	0.20 (21.36)	0.37 (39.32)	0.56 (60.68)	0.05 (5.21)	0.10 (10.41)	0.16 (17.41)	0.26 (27.83)	0.06 (6.28)	0.93 (100.00)
Mehla	0.21 (23.11)	0.34 (37.34)	0.55 (60.44)	0.05 (5.36)	0.09 (10.35)	0.15 (17.10)	0.25 (27.45)	0.06 (6.75)	0.90 (100.00)
Gohar	0.31 (26.45)	0.41 (35.08)	0.73 (61.53)	0.05 (4.53)	0.13 (11.03)	0.21 (17.68)	0.34 (28.71)	0.06 (5.23)	1.18 (100.00)
Nagar	0.13 (10.73)	0.19 (16.50)	0.32 (27.23)	0.07 (5.93)	0.32 (27.32)	0.39 (33.45)	0.71 (60.77)	0.07 (6.06)	1.17 (100.00)
Kalpa	0.13 (11.87)	0.17 (15.74)	0.30 (27.60)	0.06 (5.20)	0.27 (25.01)	0.41 (37.25)	0.68 (62.26)	0.05 (4.93)	1.10 (100.00)
Lahaul	0.32 (26.98)	0.42 (34.98)	0.74 (61.96)	0.06 (4.73)	0.15 (12.45)	0.18 (15.37)	0.33 (27.82)	0.07 (5.49)	1.20 (100.00)
Overall	0.20 (17.36)	0.28 (25.30)	0.48 (42.66)	0.06 (5.07)	0.23 (19.32)	0.33 (27.40)	0.56 (46.72)	0.06 (5.55)	1.16 (100.00)

Figures in parentheses indicate percentage to total land holding respective of total

1Biswa=40m^2; 20Biswas =1Bigha;1 Bigha =800m^2; 12.35 Bighas= 1 Hectare

conditions. This highlights the substantial reliance on rain-fed agriculture and the importance of irrigation in certain areas. Pastures constituted around 5.07 per cent of the land, with 5.55 per cent of the area left barren. The highest average landholding in the study area was recorded in Jubbal & Kotkhai (1.38 ha) block followed by Theog (1.33 ha) and Rohru block (1.28 ha). Among all the sampled blocks, Lahaul block recorded the highest (61.96%) area under agriculture, followed by Gohar block (61.53%) and Chamba block (60.68%), while the lowest (27.23 per cent) was recorded in Nagar block. The highest area under orchards was recorded in Theog block (63.32 per cent), followed by Jubbal & Kotkhai block (62.59) and Kalpa block (62.26), with a minimum (27.45 per cent) under Mehla block. Area under pastures was found highest (5.93 per cent) in Nagar block, with the lowest (4.53 per cent) for Gohar block.

4.3.2. Cropping pattern of the sampled households in the study area

Cropping pattern refers to the spatial and temporal allocation of land to various crops within a given agricultural system. It is a dynamic concept influenced by the availability of land, resources, and changing environmental and socio-economic conditions. The cropping pattern in a region is shaped by a range of factors, including geo-climatic conditions (such as physiography, climate, soil types, and water availability), socio-cultural and economic influences, as well as historical and political contexts. The physical environment, including topography, slope, temperature, and the quantity and reliability of rainfall, plays a critical role in determining the types of crops that can be grown in a particular region. Moreover, the availability of irrigation and soil fertility further affect the cropping system's diversity and intensity. Human intervention, through technological advancements, can modify these physical constraints, enabling the cultivation of crops that might otherwise be unsuitable for the region. For example, the introduction of irrigation systems or improved crop varieties can significantly alter traditional cropping patterns. Socio-economic factors, such as land tenure systems, land ownership, the size of holdings, and the size of fields, also influence cropping patterns.

Table 4.9 presents the cropping pattern followed by the sampled farms at a specific point in time. From the data, it is evident that the cropping pattern in the study area is divided across two primary agricultural seasons, namely Kharif and Rabi. This seasonal division reflects the adaptation of the local farming practices to the climatic conditions and crop suitability during these periods. The cropping pattern in the study area is influenced by the availability of water, soil fertility, and other environmental factors specific to each season, thus guiding the farmers' decisions on crop selection and cultivation strategies. It is evident from Table 4.9 that the cropping

intensity was highest in Mehla block (168.66%), followed by Chamba block (168.46%) and Gohar block (164.22%). At the overall level, the cropping intensity was calculated to be 139.65 per cent, indicating a considerable scope for increasing farm efficiency through enhanced cropping practices. By intensifying land use through practices such as crop rotation, intercropping, and adopting high-yielding varieties, farmers can increase food, feed, and bioenergy crop production. This approach not only meets the demands of a growing population but also conserves land resources and promotes sustainability. Enhanced cropping practices, therefore, contribute to better farm efficiency, economic growth, and food security. The relatively lower cropping intensity of 100 per cent in Lahaul block was primarily due to the cultivation of crops being restricted to a single cropping season, reflecting limited cropping opportunities in the area. At the overall level, the gross cropped area was 1.43.

In the Kharif season, crops such as maize, cabbage, tomato, cauliflower, pea, and potato were commonly grown across different blocks. Maize was widely cultivated across all blocks, with the highest proportion observed in Mehla (6.17%) and Chamba (5.77%). Lahaul had the lowest maize cultivation (0.59%), reflecting its limited suitability for this crop. Paddy was predominantly grown in Mehla (5.74%) and Chamba (5.36%), indicating favourable climatic and irrigation conditions in these areas. Potato was extensively grown in Lahaul (30.69%), a region known for its high-altitude suitability for tuber crops. Cabbage cultivation was highest in Lahaul (7.11%) and Gohar (4.78%). Tomato was concentrated in Gohar (5.11%) and Mehla (3.82%), suggesting these regions' potential for cash crop production. Pulses like peas, rajmash, and mash were cultivated in moderate amounts. Pea had the highest share in Lahaul (7.42%) and Gohar (6.79%). The decrease in paddy cultivation in the Rohru, Theog, and Jubbal & Kotkhai blocks can be attributed to the fact that farmers in these regions have shifted towards crops that require less water and offer higher returns, such as fruits. Paddy farming is water-intensive, and with limited irrigation resources, farmers have found it more profitable to cultivate fruits, which are better suited to the local agro-climatic conditions. This shift is also driven by the changing market demand and the growing profitability of fruit cultivation.

In the Rabi season, wheat cultivation was prominent in Mehla (16.73%) and Chamba (15.16%) blocks, reflecting a strong dependency on wheat as a staple food crop in these regions. Barley emerged as an important Rabi season crop, with substantial cultivation in Gohar (11.16%) and Chamba (10.78%). Pea cultivation during the Rabi season was notably high in Gohar (9.69%) and Rohru (8.42%) blocks, demonstrating its adaptability to both Kharif and Rabi seasons. Additionally, potato cultivation during the Rabi season was concentrated in Kalpa (10.15%) and

Table 4.9: Cropping pattern of sampled households in study area

(in hectare)

Particulars	Rohru	Theog	Jubbal & Kotkhai	Chamba	Mehla	Gohar	Nagar	Kalpa	Lahaul	Overall
Kharif										
Maize	0.02 (1.21)	0.02 (1.02)	0.02 (1.13)	0.08 (5.77)	0.08 (6.17)	0.06 (3.46)	0.03 (1.98)	0.02 (1.63)	0.01 (0.59)	0.04 (2.55)
Paddy	0.005 (0.32)	0.01 (0.36)	0.003 (0.19)	0.07 (5.36)	0.08 (5.74)	0.04 (2.39)	0.02 (1.23)	0.00 (0.00)	0.00 (0.00)	0.02 (1.73)
Cabbage	0.05 (3.14)	0.05 (3.00)	0.05 (2.89)	0.06 (4.19)	0.06 (4.21)	0.08 (4.78)	0.03 (2.38)	0.02 (1.81)	0.08 (7.11)	0.05 (3.72)
Tomato	0.04 (2.53)	0.05 (2.98)	0.04 (2.14)	0.05 (3.76)	0.05 (3.82)	0.09 (5.11)	0.03 (2.35)	0.01 (0.68)	0.00 (0.00)	0.04 (2.60)
Capsicum	0.03 (1.94)	0.03 (2.12)	0.03 (1.61)	0.04 (3.08)	0.04 (3.08)	0.06 (3.61)	0.02 (1.57)	0.03 (2.35)	0.04 (3.97)	0.04 (2.59)
Cauliflower	0.05 (3.47)	0.04 (2.78)	0.05 (3.14)	0.06 (4.54)	0.06 (4.59)	0.09 (5.14)	0.04 (2.62)	0.02 (1.78)	0.10 (9.06)	0.06 (4.12)
Potato	0.04 (2.48)	0.04 (2.50)	0.03 (1.98)	0.03 (2.18)	0.03 (2.27)	0.03 (1.55)	0.01 (1.06)	0.07 (5.36)	0.33 (30.69)	0.07 (5.56)
Pea	0.07 (4.52)	0.07 (4.50)	0.08 (4.96)	0.08 (5.66)	0.07 (5.02)	0.12 (6.79)	0.05 (4.01)	0.04 (2.84)	0.08 (7.42)	0.07 (5.08)
Rajmash	0.03 (2.06)	0.03 (1.76)	0.04 (2.27)	0.03 (2.26)	0.03 (2.49)	0.04 (2.05)	0.03 (2.51)	0.04 (3.28)	0.03 (3.14)	0.03 (2.42)
Mash	0.03 (1.76)	0.02 (1.47)	0.03 (2.02)	0.03 (2.16)	0.03 (2.23)	0.03 (1.83)	0.03 (1.87)	0.04 (3.13)	0.03 (2.56)	0.03 (2.11)
Other crops	0.02 (1.07)	0.01 (0.74)	0.02 (1.39)	0.02 (1.75)	0.02 (1.15)	0.04 (2.41)	0.03 (2.04)	0.01 (0.63)	0.05 (4.48)	0.02 (1.74)

Particulars	Rohru	Theog	Jubbal & Kotkhai	Chamba	Mehla	Gohar	Nagar	Kalpa	Lahaul	Overall
Rabi										
Wheat	0.05 (3.11)	0.05 (3.21)	0.06 (3.65)	0.21 (15.16)	0.22 (16.73)	0.21 (11.83)	0.08 (6.09)	0.05 (4.07)	0.00 (0.00)	0.10 (7.09)
Barley	0.06 (3.68)	0.05 (3.48)	0.07 (4.07)	0.15 (10.78)	0.14 (10.54)	0.19 (11.16)	0.09 (6.49)	0.04 (3.38)	0.00 (0.00)	0.09 (5.95)
Pea	0.13 (8.42)	0.12 (7.87)	0.13 (7.82)	0.10 (7.54)	0.10 (7.36)	0.17 (9.69)	0.07 (5.41)	0.06 (4.29)	0.00 (0.00)	0.10 (6.49)
Potato	0.10 (6.77)	0.11 (6.87)	0.09 (5.50)	0.06 (4.02)	0.05 (3.95)	0.06 (3.37)	0.03 (2.31)	0.13 (10.15)	0.00 (0.00)	0.07 (4.77)
Other crops	0.04 (2.51)	0.03 (1.82)	0.04 (2.69)	0.04 (3.14)	0.03 (2.13)	0.10 (5.48)	0.04 (3.33)	0.02 (1.60)	0.00 (0.00)	0.04 (2.52)
Orchard area	0.76 (50.99)	0.84 (53.51)	0.86 (52.55)	0.26 (18.66)	0.25 (18.52)	0.34 (19.38)	0.71 (52.74)	0.68 (53.00)	0.33 (30.98)	0.56 (38.93)
Gross cropped area	1.49 (100.00)	1.57 (100.00)	1.64 (100.00)	1.38 (100.00)	1.34 (100.00)	1.75 (100.00)	1.35 (100.00)	1.29 (100.00)	1.08 (100.00)	1.43 (100.00)
Net sown area	1.13	1.20	1.25	0.82	0.79	1.06	1.03	0.99	1.08	1.04
Cropping intensity (%)	132.46	130.28	131.10	168.46	168.66	164.22	130.95	130.72	100.00	139.65
Simpson crop diversification index	0.51	0.53	0.49	0.51	0.51	0.47	0.70	0.43	0.51	0.52

Figures in parentheses are percentage to gross cropped area

Theog (6.87%) blocks, signifying its role as a critical crop in the colder high-altitude areas where environmental conditions are conducive to tuber growth. Orchard areas constituted a major portion of the gross cropped area in most blocks, particularly in Theog (53.51%), Kalpa (53.00%), and Jubbal & Kotkhai (52.55%). These regions are known for fruit production, indicating a shift towards high-value horticulture.

The Simpson Crop Diversification Index (SDI), which quantifies the diversity of crops grown, ranges between 0 and 1, with higher values indicating greater diversification. In the study area, SDI values varied across blocks, reflecting differences in cropping patterns. Nagar block (0.70) exhibited the highest SDI, signifying a strong emphasis on crop diversification, likely driven by favorable ecological conditions and market opportunities. Most blocks, such as Theog (0.53), Rohru (0.51), Chamba (0.51), Mehla (0.51) and Jubbal & Kotkhai (0.49), displayed moderate diversification, balancing staple and commercial crops. However, Kalpa (0.43) showed the lowest SDI, indicating a focus on fewer crops, potentially due to climatic constraints or reliance on specific high-value crops like potatoes or orchards. The overall SDI for the study area was 0.52, reflecting a moderate level of diversification. These variations highlight the role of agro-climatic conditions, market access, and farmer preferences in shaping cropping patterns. Promoting further diversification, particularly in low-SDI regions, could enhance agricultural resilience and income stability while optimizing resource utilization.

4.3.3. Livestock status

Livestock rearing plays a vital role in the rural economy, forming an essential component of farming systems. As an integral part of agricultural practices, livestock offers numerous benefits, contributing significantly to the improvement of farmers' socio-economic conditions, especially in the hilly region. The practice of livestock rearing is influenced by various factors, including social, ecological, and economic considerations specific to the region. In the study area, the livestock primarily consists of cows, sheep, goats, and bullocks. The findings of the livestock status of sampled households in terms of Adult Cattle Units (ACU) have been summarized in Table 4.10. It is inferred from Table 4.10 that the highest adult cattle units were found in Mehla block (2.73), followed by Chamba (2.44) and Nagar (2.44). However, cow rearing was found most common in the study area, contributing a substantial portion of the total livestock holding. The highest average number of improved cows per household was reported in Gohar (47.31%), followed by Rohru (42.39%) and Theog (0.98; 42.96%), indicating a strong preference or better access to improved cattle breeds in these areas. In contrast, the lowest average number of

Table 4.10: Livestock holding of sampled households

(ACU)

Particulars		Rohru	Theog	Jubbal & Kotkhai	Chamba	Mehla	Gohar	Nagar	Kalpa	Lahaul	Overall
Cow	**Improved**	1.02 (42.39)	0.98 (42.96)	0.94 (39.86)	0.85 (34.90)	0.94 (34.42)	1.06 (47.31)	0.96 (39.28)	0.83 (41.23)	0.96 (40.89)	0.95 (40.36)
	Local	0.42 (17.30)	0.38 (16.45)	0.38 (15.94)	0.40 (16.42)	0.52 (19.04)	0.48 (21.34)	0.46 (18.79)	0.30 (14.90)	0.42 (17.78)	0.42 (17.55)
Calf		0.08 (3.11)	0.08 (3.29)	0.08 (3.45)	0.11 (4.36)	0.13 (4.58)	0.10 (4.45)	0.09 (3.84)	0.11 (5.60)	0.11 (4.53)	0.10 (4.13)
Bullock		0.79 (32.87)	0.77 (33.82)	0.83 (35.43)	0.79 (32.51)	0.81 (29.77)	0.52 (23.19)	0.77 (31.60)	0.63 (31.12)	0.63 (26.67)	0.73 (30.78)
Goat		0.08 (3.29)	0.05 (2.38)	0.08 (3.37)	0.13 (5.47)	0.16 (5.95)	0.06 (2.60)	0.10 (3.93)	0.10 (4.77)	0.12 (5.15)	0.10 (4.10)
Sheep		0.03 (1.04)	0.03 (1.10)	0.05 (1.95)	0.15 (6.33)	0.17 (6.26)	0.03 (1.11)	0.06 (2.56)	0.05 (2.49)	0.11 (4.98)	0.08 (3.09)
Total		2.41 (100.00)	2.28 (100.00)	2.35 (100.00)	2.44 (100.00)	2.73 (100.00)	2.25 (100.00)	2.44 (100.00)	2.01 (100.00)	2.34 (100.00)	2.36 (100.00)

Figures in parentheses represent per cent to the total

Table 4.11: Total milk production of livestock in sampled households

(in litres)

Particulars	Rohru	Theog	Jubbal & Kotkhai	Chamba	Mehla	Gohar	Nagar	Kalpa	Lahaul	Overall
Home consumed	142.00 (47.18)	135.00 (46.08)	142.00 (49.65)	116.00 (45.14)	142.00 (54.41)	160.00 (53.16)	138.00 (50.92)	111.00 (53.11)	108.00 (48.87)	132.67 (49.84)
Quantity sold	159.00 (52.82)	158.00 (53.92)	144.00 (50.35)	141.00 (54.86)	119.00 (45.59)	141.00 (46.84)	133.00 (49.08)	98.00 (46.89)	113.00 (51.13)	134.00 (50.16)
Total Production	301.00 (100.00)	293.00 (100.00)	286.00 (100.00)	257.00 (100.00)	261.00 (100.00)	301.00 (100.00)	271.00 (100.00)	209.00 (100.00)	221.00 (100.00)	266.67 (100.00)
Total sale Receipts per annum (Lactation period)	2146500	2133000	1944000	1903500	1606500	1903500	1795500	1323000	1525500	1809000
Average sale value per Farm	44718.75	44437.50	40500.00	39656.25	33468.75	39656.25	37406.25	27562.50	31781.25	37687.50

Figures in parentheses represent per cent to the total

improved cows were observed in Kalpa (41.23%) and Chamba (34.90%). Local cows, on the other hand, were relatively fewer, contributing 17.55 per cent to the total livestock on average. Thus, it is concluded from the study that, the proportion of improved cows (40.36%) was higher followed by bullocks (30.78%), local cows (17.55%), calf (4.13%), goat (4.10%) and sheep (3.09%) and overall adult cattle units was found to be 2.36 in the temperate region.

Dairy farming serves as a vital secondary activity across all sampled households, significantly contributing to household income in the study area. The analysis of milk production and disposal patterns is presented in Table 4.11, revealed substantial output, with Rohru and Gohar again emerging as top performers in terms of total milk production (301 liters per day). These differences in output may be influenced by factors such as the breed of livestock, feeding practices, and the local environment. The majority (50.16%) of the milk produced was sold rather than consumed at home, emphasizing the role of dairy as a key income-generating enterprise. On average, sale receipts per farm during the lactation period were estimated at ₹37,687.50, indicating moderate but vital role of dairy farming in supplementing rural household incomes. Overall, the findings highlight the critical role of dairy farming in boosting the economic resilience of farming households, with strong market linkages and efficient management practices driving increased income and socio-economic benefits.

4.3.4. Level of investment of sampled households in study area

Irrigation plays a pivotal role in enhancing agricultural productivity by ensuring consistent water availability and enabling farmers to adopt improved cropping patterns. With sufficient irrigation infrastructure, farmers can diversify their crop choices, adopt high-value crops, and achieve better yields. However, the level of investment in irrigation systems varies across households, influenced by factors such as individual needs, financial capacity, and available resources. The study identified six primary sources of irrigation: kuhls (traditional water channels), tanks, lifts, tubewell, drip systems, and sprinklers. Each system requires varying degrees of investment, depending on its complexity and efficiency. The average expenditure for the irrigation system in sampled households was analyzed and presented in Table 4.12. The analysis of average investment in irrigation structures across sampled households highlights notable regional variations and preferences for different systems, reflecting the diverse agricultural needs and financial capacities of farmers. Traditional kuhls represent a moderately cost-effective option, with investments ranging from ₹2,125 in Mehla to ₹2,937.50 in Theog, and an overall average of ₹2,553.24.

Table 4.12: Average investment on irrigation structure in sampled households

(Rupees)

Particulars	Rohru	Theog	Jubbal & Kotkhai	Chamba	Mehla	Gohar	Nagar	Kalpa	Lahaul	Overall
Kuhl	2604.17	2937.50	2729.17	2229.17	2125.00	2833.33	2416.67	2291.67	2812.50	2553.24
Tank	46354.17	51979.17	55104.17	27083.33	25833.33	46666.67	46875.00	31770.83	42083.33	41527.78
Lift	15104.17	17916.67	14062.50	14895.83	15937.50	14687.50	14687.50	15104.17	13854.17	15138.89
Sprinkler	8541.67	10208.33	10208.33	8958.33	5625.00	8333.33	8750.00	8958.33	10625.00	8912.04
Tubewell	31250.00	41666.67	26041.67	24791.67	19583.33	36458.33	20833.33	29791.67	39375.00	29976.85
Drip	27083.33	29333.33	34291.67	22208.33	20125.00	31958.33	27354.17	24125.00	34729.17	27912.04
Total Investment	130937.50	154041.67	142437.50	100166.67	89229.17	140937.50	120916.67	112041.67	143479.17	126020.84

Tanks emerge as the most expensive irrigation structure, with an average expenditure of ₹41,527.78, peaking at ₹55,104.17 in Jubbal & Kotkhai, showcasing their importance in regions with high water storage requirements. Lift irrigation exhibits relatively moderate costs, averaging ₹15,138.89, with expenditure being highest in Theog (₹17,916.67) and lowest in Lahaul (₹13,854.17). Sprinkler systems, averaging ₹8,912.04, show limited regional variation, but Lahaul records the highest spending (₹10,625), reflecting specific water distribution needs. Tube wells, with an overall average of ₹29,976.85, showed highest investments in Theog (₹41,666.67), underlining their role in areas with scarce surface water. Drip irrigation systems also represent a substantial expenditure, averaging ₹27,912.04, with the highest investment in Lahaul (₹34,729.17) block, suggesting a growing preference for water-efficient technologies in high-value cropping regions. Overall, total irrigation investments average ₹1,26,020.84, with Theog block reporting the highest (₹1,54,041.67) and Mehla the lowest (₹89,229.17). These figures indicate the critical role of irrigation in enhancing agricultural productivity, with region-specific variations shaped by water availability, crop patterns, and economic factors. The data also highlights the need for targeted support to optimize irrigation practices and improve cost-efficiency across diverse agricultural landscapes.

4.4. LIVELIHOOD VULNERABILITY

4.4.1. Livelihood Vulnerability- Composite Index Approach

Table 4.13 represents the LVI sub-component values for each block as well as the minimum and maximum values for all blocks combined. The major components and composite LVI for each block are presented in Table 4.15.

4.4.1.1. Socio-demographic profile (SDP)

The major component, Socio-Demographic Profile comprises six sub-components. In terms of the ‘dependency ratio’ subcomponent of SDP, the highest ratio was observed for the Gohar block (0.36), indicating a larger proportion of 'inactive' household members compared to the working-age population followed by Rohru, Mehla, and Kalpa blocks (each with a ratio of 0.32, while the lowest ratio was observed in Jubbal & Kotkhai block (0.28). The highest percentage of female-headed households was observed in Jubbal and Kotkhai block (20.83%), followed by Theog and Kalpa blocks (18.75%). The lowest proportion was observed in Mehla and Nagar blocks (10.42%), indicating fewer female-led households. This vulnerability arises primarily from the multifaceted responsibilities by women, encompassing both family-related obligations

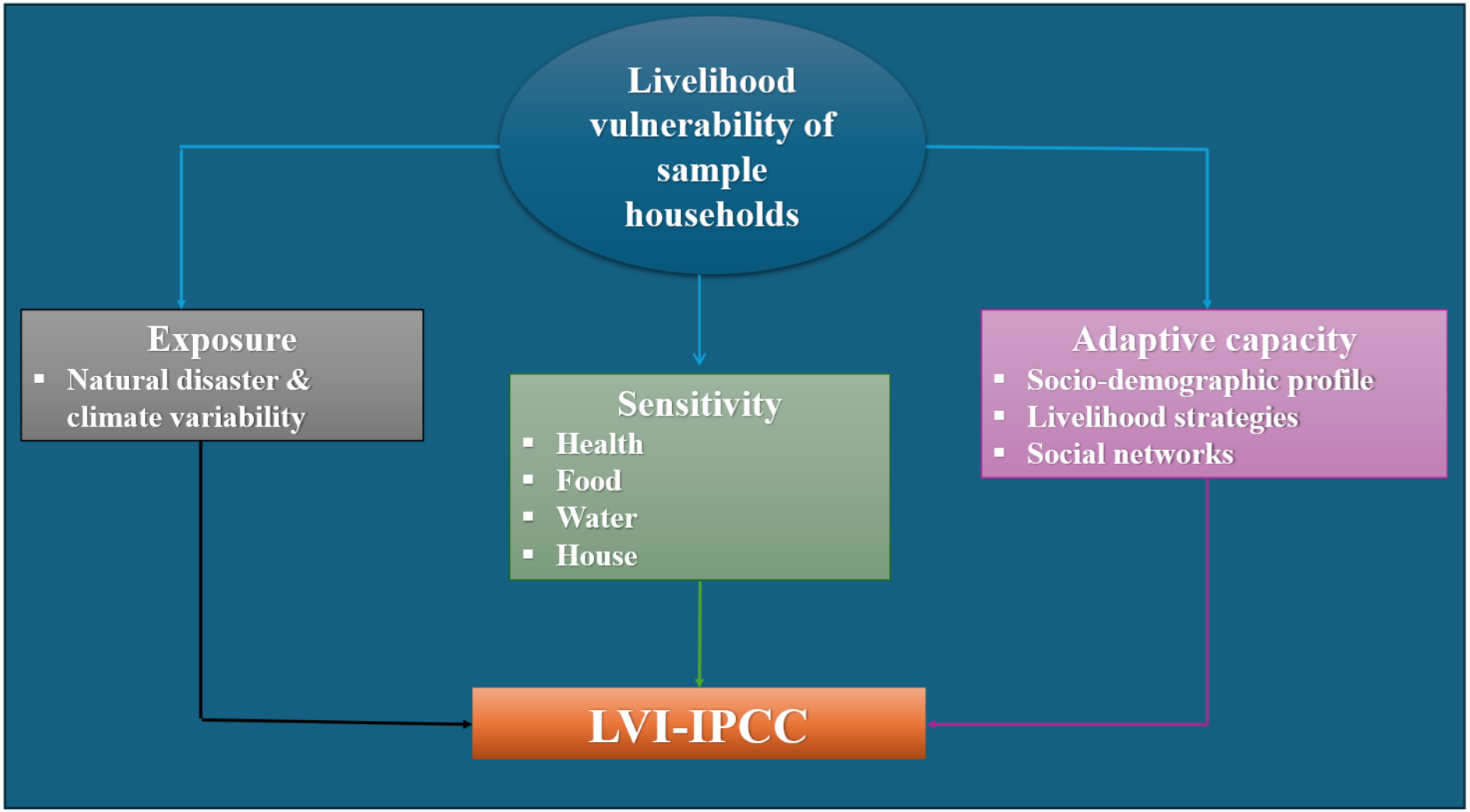


Plate 4.1:Conceptual framework to study livelihood vulnerability of the sample households

and non-agricultural concerns. Supporting evidence from Hahn *et al.*, (2009); Shah *et al*., (2013); Rai *et al.,* (2022) and Aiswarya *et al*., (2023) underscores that female-headed households were more susceptible to socio-economic challenges and environmental stressors relative to male-headed households. The average age of the household head ranged from 55.25 years in Nagar block to 59.21 years in Chamba block, suggesting that the adoption of new agricultural technologies, such as climate-smart agriculture and modern technologies, may face challenges in these regions. The highest percentage of illiterate household heads was observed in Lahaul block (31.25%), followed by Mehla and Chamba blocks (25.00%), while the lowest percentage was seen in Rohru block and Theog block (14.58%), suggesting better literacy levels in these regions. Mehla block (6.04) has been reported as the largest average family size, whereas Jubbal & Kotkhai block (4.98) has the smallest family size. It has been observed that Lahaul block (26.48%) exhibited the highest average farming experience, followed by Chamba block (26.08%) and Theog block (25.96%). Nagar block (22.94%) showed the lowest farming experience, indicating potential generational shifts in farming practices or fewer years of agricultural involvement. When the sub-components were pooled, the overall Socio-Demographic Profile (SDP) vulnerability score (Table 4.15) was found to be highest for Lahaul (with an index value of 0.303), followed by Chamba (0.294) and Mehla blocks (0.289), while the least vulnerable block was Nagar block (0.245). Lahaul block poses challenges to improving food and nutrition security, thereby increasing the vulnerability of farm households (Rai *et al.,* 2022; Tjoe, 2016).

4.4.1.2. Livelihood strategies

The major component, Livelihood Strategies, consists of three sub-components. Regarding the proportion of households with family members working in a different community, the highest percentage was observed in Theog block (68.75%), followed by Nagar and Jubbal and Kotkhai blocks (each with 64.58%). This indicated that households in Theog block exhibited a relatively higher degree of migration or external employment, suggesting a greater reliance on diversified income sources beyond the local economy. In contrast, the lowest percentage of households with family members working outside the community was observed in Kalpa block (47.92%), reflecting a more localized economy and greater reliance on local resources. While this can indicate a lower level of external dependence, it also points to reduced opportunities for income diversification and potential economic strain if local livelihoods were disrupted. In terms of households

dependent solely on agriculture as a primary income source, Kalpa block (52.08%) reported the highest reliance, followed by Mehla (43.75%), and the least was observed in Theog block (31.25%). This high dependency on agriculture in Kalpa block suggests increased vulnerability, as agriculture is inherently susceptible to environmental risks such as climate change, pest outbreaks, and market fluctuations. Such reliance on a single sector for income can amplify the block's exposure to external shocks, thereby limiting economic resilience and capacity for adaptation. In terms of the livelihood diversification index, Kalpa block showed the highest index value of 0.57, indicating the lowest levels of income diversification activities in the study area, which suggests the highest levels of vulnerability. Conversely, the lowest (0.47) value of the diversification index in Theog block reflects a higher level of diversification, potentially due to increased sources of income in the region. This development likely creates a broader range of livelihood opportunities for households, reducing their vulnerability compared to other blocks with less diversified income sources. When the three sub-components of livelihood strategies were averaged (Table 4.15), the vulnerability score was found to be highest in Kalpa block (0.523), followed by Gohar block (0.510). In contrast, the lowest vulnerability score was observed in Theog block (0.490), indicating that Theog block has relatively lower vulnerability in terms of livelihood strategies compared to the other blocks.

4.4.1.3. Social Networks

The Social Network major component comprises four sub-components, capturing the extent of household connectivity with community and institutional support systems. Lahaul block reported borrowing money more frequently and receiving more in-kind assistance from family and friends relative to the number of times they lent money or provided assistance in the past month (borrow: lend ratio: Lahaul 0.640; receive: give ratio: Lahaul 0.297). A significant proportion of households across the study area reported engaging with extension services and seeking assistance from local government or Panchayati Raj Institutions and developmental departments, either in cash or in kind. Table 4.13 indicates that Lahaul block recorded the highest percentage (56.25%) of households receiving local government assistance in the past year, particularly during the flood season. This was followed by Chamba block at 47.92 per cent and Mehla block at 45.83 per cent. Conversely, the lowest level of local government assistance was reported in Kalpa block, where only 25.00 per cent of households received support. This variability highlighted regional differences in institutional outreach and household

engagement with available support mechanisms. Limited or no engagement with extension services can have detrimental impacts on agricultural productivity and community resilience. Households that do not seek extension contact may remain uninformed about agricultural innovations, such as high-yielding crop varieties or best practices for managing pests and diseases, ultimately risking lower crop yields (Maredia *et al.,* 2014; Dendup, 2018). Further, Sujakhu *et al.,* (2019) emphasized that communities with restricted access to, or limited utilization of, support from institutions like the Agriculture and Horticulture Departments or Krishi Vigyan Kendras (KVKs) were observed to be significantly more vulnerable. These institutions play a crucial role in disseminating knowledge and providing access to agricultural innovations, which are essential for building resilience and adapting to environmental or economic challenges. Therefore, fostering awareness and ensuring equitable access to such services are vital for reducing vulnerability and enhancing agricultural sustainability. In the case of Lahaul block, a significant proportion of respondents (60.42 %) reported having no access to any form of extension contact. This was followed by Kalpa block, where 54.17 per cent of respondents lacked extension interactions, and only 47.92 per cent in Mehla block (Table 4.13). By pooling the sub-components, the overall social network vulnerability score (Table 4.15) was found to be highest for the Lahaul block (with an index value of 0.463), followed by Mehla (0.426) and Chamba blocks (0.413), while the least vulnerable block was Rohru block (0.335).

4.4.1.4. Health

The purpose of assessing the ‘health’ component was to understand the current status of household health since it is an important livelihood indicator and plays a substantial role in augmenting human development (Williams *et al.,* 2018). The time required to reach district health facilities varies significantly across the regions, with the shortest average time in Kalpa block (12.92 minutes) and the longest in Lahaul block (78.60 minutes). Kalpa block reflects better accessibility, while Lahaul block faces considerable challenges in terms of the time taken to access health services. Under this component, the highest vulnerability in terms of the average distance to reach the nearest district health unit was found maximum for Lahaul block (41.88 km), followed by Nagar block (30.45 km) and minimum in Kalpa block (4.48 km) (Table 4.13). Lahaul block indicates a significant physical barrier to accessing healthcare services. Delayed access to health facilities exacerbates health vulnerabilities among farmers, as prolonged travel or

limited healthcare availability can delay timely diagnosis and treatment. This delay not only impacts the health and well-being of farmers but also hinders their productivity and ability to work efficiently, ultimately affecting their livelihoods. Studies such as Tran *et al.,* (2021); Nair and Mishra, (2023) emphasize that easy access to health facilities was critical for maintaining the physical well-being of individuals, directly contributing to enhanced work productivity. Similarly, a study conducted by Shah *et al*., (2024) highlighted that improved proximity to healthcare services significantly reduced health-related vulnerabilities, particularly for farming communities. These findings underscore the importance of investing in accessible healthcare infrastructure to support rural livelihoods and resilience. The proportion of households reporting the non-availability of health facilities at the nearest Primary Health Center (PHC) varies significantly across the study areas, highlighting disparities in healthcare infrastructure. The highest percentage was observed in Lahaul (60.42%), indicating critical gaps in local healthcare accessibility and infrastructure, which could exacerbate health vulnerabilities for residents in this region. In contrast, Gohar reports the lowest percentage of households facing this issue, at 33.33 per cent, suggesting comparatively better availability and accessibility of PHC facilities. These findings highlighted the need for targeted interventions to address healthcare infrastructure deficiencies, particularly in regions like Lahaul, to ensure equitable access to essential health services. The prevalence of chronic illness among family members varies significantly across the study regions, with the highest levels observed in Chamba block (54.17%) and Theog block (50.00%), indicating greater healthcare needs in these areas. Conversely, Nagar block reports the lowest prevalence of chronic illnesses at 29.17 per cent, suggesting either comparatively better health conditions or a lower rate of reported cases. In Chamba block, the high prevalence of chronic diseases imposes a substantial burden on households by increasing financial liabilities through medical expenses and reducing the number of healthy workdays, which negatively impacts household income (Hahn *et al.,* 2009). When assessing overall vulnerability from Table 4.15 under the health major component, Lahaul block demonstrated the highest level of vulnerability (0.688), reflecting severe challenges in health accessibility and outcomes for its residents. This is followed by Theog block (0.475), while Gohar block (0.208) exhibited the least health-related vulnerability, indicating relatively better conditions. These findings underscore the need for focused health interventions and improved infrastructure in regions like Lahaul and Theog blocks to mitigate vulnerabilities and enhance community well-being.

Table 4.13: Livelihood Vulnerability Index (LVI) sub- component values, maximum and minimum subcomponent values for the study area

Major components	Sub components	Units	Rohru	Theog	Jubbal & Kotkhai	Mehla	Chamba	Gohar	Nagar	Kalpa	Lahaul	Maximum	Minimum
Socio-demographic	Dependency ratio	Ratio	0.32	0.29	0.28	0.32	0.31	0.36	0.31	0.32	0.29	9	0
	Female-headed households	Per cent	16.67	18.75	20.83	10.42	14.58	16.67	10.42	18.75	16.67	100	0
	Average age of head of household	Years	56.69	58.19	56.33	58.15	59.21	57.50	55.25	55.90	57.17	80	34
	Per cent of illiterate household heads	Per cent	14.58	14.58	20.83	25.00	25.00	16.67	16.67	22.92	31.25	100	0
	Average family size	Count	5.65	5.48	4.98	6.04	5.31	5.60	5.25	5.31	5.38	16	2
	Average years of farming experience	Count	24.29	25.96	23.25	25.21	26.08	25.25	22.94	23.73	26.48	44	4
Livelihood strategies	Households with family members working in a different community	Per cent	62.30	68.75	64.58	56.25	58.33	56.25	64.58	47.92	58.33	100	0
	Households dependent solely on agriculture as a source of income	Per cent	37.50	31.25	37.50	43.75	41.67	43.75	35.42	52.08	41.67	100	0
	Average livelihood diversification index (Herfindhal Index)	Index	0.48	0.47	0.51	0.49	0.49	0.53	0.50	0.57	0.49	1	0
Social Network	Average receive: give (ratio)	Ratio	1.35	1.31	1.33	1.35	1.28	1.15	1.28	1.34	1.36	4	0.25
	Average borrow: lend money (ratio)	Ratio	1.13	1.19	1.17	1.21	1.25	1.30	1.25	1.10	1.46	2	0.5
	Households that have received local government assistance in the past one year (during flood season)	Per cent	33.33	35.42	39.58	45.83	47.92	35.42	33.33	25.00	56.25	100	0
	HH does not have any extension contact	Per cent	29.17	33.33	33.33	47.92	39.58	43.75	24.00	54.17	60.42	100	0
Health	Average time to district health facility (minutes)	Minutes	21.50	46.50	25.75	27.04	24.44	13.75	57.25	12.92	78.60	84	8
	Average distance to district hospital	Km	7.63	19.85	10.05	10.07	7.35	6.53	30.45	4.48	41.88	53	2
	HH reporting non availability of health facilities in nearest PHC	Per cent	43.75	54.17	41.67	47.92	43.75	33.33	39.58	39.58	60.42	100	0
	Households with family members with chronic illness	Per cent	45.83	50.00	41.67	47.92	54.17	33.33	29.17	45.83	43.75	100	0
Food	Households that do not save crops	Per cent	64.58	56.25	66.67	47.92	43.75	52.08	62.50	58.33	47.92	100	0
	Households that do not save seeds	Per cent	56.25	58.33	72.92	56.25	50.00	52.08	64.58	52.08	50.00	100	0
	Average Crop Diversification index (Herfindahl Index)	Index	0.28	0.31	0.30	0.10	0.10	0.09	0.30	0.30	0.21	1	0
	Average Livestock Diversity Index	Index	0.35	0.36	0.36	0.25	0.28	0.37	0.35	0.37	0.32	1	0

Major components	Sub components	Units	Rohru	Theog	Jubbal & Kotkhai	Mehla	Chamba	Gohar	Nagar	Kalpa	Lahaul	Maximum	Minimum
Water	Utilize natural source of water	Per cent	43.75	50.00	54.17	83.33	72.92	58.33	56.25	62.50	70.83	100	0
	Households reporting recent drying of water sources	Per cent	43.75	41.67	45.83	47.92	52.08	45.83	58.33	52.08	60.42	100	0
	Households that do not have a consistent water supply for drinking	Per cent	56.25	43.75	45.83	58.33	60.42	41.67	47.92	43.75	54.17	100	0
	Households reporting water conflicts	Per cent	52.08	52.08	56.25	66.67	68.75	58.33	56.25	60.42	64.58	100	0
	Households reporting shortage of water supply for farming	Per cent	54.17	56.25	58.33	70.83	72.92	58.33	60.42	66.67	68.75	100	0
	Households storing water	Per cent	68.75	58.33	72.92	72.92	75.00	60.42	72.92	79.17	75.00	100	0
	Average time to water source	Minutes	13.13	9.08	13.75	26.38	17.88	15.67	11.48	10.63	15.96	36	0
	Inverse of the average amount (liters) of water stored per household	1/# Litre	0.37	0.47	0.34	0.33	0.32	0.44	0.33	0.27	0.31	1	0
House	Households whose houses do not have a solid structure and are prone to damage by floods	Per cent	39.58	35.42	47.92	52.08	56.25	41.67	33.33	60.42	56.25	100	0
	Flood affected households	Per cent	33.33	29.17	31.25	54.17	52.08	37.50	41.67	60.42	41.67	100	0
Natural disasters & climate variability	Households who were not provided with early flood warnings	Per cent	52.08	50.00	56.25	52.08	54.17	50.00	43.75	54.17	62.50	100	0
	Households experienced catastrophic accidents or deaths from floods in the past five years	Per cent	20.83	25.00	27.08	33.33	31.25	22.92	29.17	37.50	41.67	100	0
	Mean standard deviation of the monthly average of average maximum daily temperature (1981-2022)	Celcius	0.80	0.80	0.80	0.98	0.98	0.83	0.88	0.97	1.06	4.6	0.49
	Mean standard deviation of the monthly average of the average minimum daily temperature (1981-2022)	Celcius	0.67	0.67	0.67	0.90	0.90	0.67	0.89	1.21	1.36	3.92	0.48
	Mean standard deviation of monthly average precipitation (1981-2022)	Millimeter	24.18	24.18	24.18	28.97	28.97	24.71	24.96	23.57	16.36	120	9.5

4.4.1.5. Food

The Food component comprises four critical sub-components that collectively assess the food security and resilience of households. These sub-components include households that do not save crops, households that do not save seeds, the average crop diversification index, and the average livestock diversity index. The highest percentage of households not saving crops was recorded in Jubbal & Kotkhai block (66.67%), followed by Rohru (64.58%) and Nagar (62.50 %) blocks. The lowest percentages were observed in Chamba block (43.75%), Mehla and Lahaul blocks (47.92%). Households that do not save seeds were maximum in Jubbal & Kotkhai block (72.92%), followed by Nagar block (64.58%), whereas the least was observed in Chamba and Lahaul blocks (50.00%). The average crop diversification index was found to be maximum in Theog block (0.31), indicating a high level of vulnerability (Table 4.13). Whereas, in Gohar, Chamba and Mehla blocks the value of the index was found to be low in comparison to Theog block i.e. 0.09, 0.10, and 0.10 respectively, indicating high crop diversification as a result of better climatic and geographic conditions making the area suitable for cultivation of various crops in one growing season. The overall vulnerability in terms of food components was found to be maximum in Jubbal & Kotkhai block (0.514), followed by Nagar block (0.480), and Rohru block (0.460). In contrast, the lowest vulnerability score was observed in Chamba block (0.329).

4.4.1.6. Water

The major component, Water, comprises eight sub-components, as outlined in Table 4.14. The major vulnerability components depicted in Figure 4.4 illustrate the specific characteristics that predominantly influence climate change vulnerability across each block. Households' reliance on natural water sources demonstrated significant variability, with utilization rates ranging from 43.75 per cent in Rohru to 83.33 per cent in Mehla, emphasizing the critical need to protect these resources for long-term sustainability. A large percentage of households, i.e., 41.67 to 60.42 per cent, reported an increase in the drying of water sources over the past five years, with Lahaul experiencing the highest level of impact. These findings highlighted the growing vulnerability of water resources, which was closely linked to emerging issues such as the drying of water sources, water conflicts, inconsistent supply, and shortages. Inconsistent drinking water supply was another challenge, particularly in Chamba (60.42%) and Mehla (58.33%), while Gohar (41.67%) fares slightly better. Water conflicts were prevalent, with Chamba (68.75%) and Mehla (66.67%) reporting the highest levels of disputes, indicating intense competition for scarce resources. The lowest rates of

Water conflicts were noted in Rohru (52.08%) and Theog (52.08%) blocks. Respondents reported significant shortages of water for farming, with the highest prevalence observed in Chamba (72.92%) and Mehla (70.83%) blocks. In contrast, Rohru (54.17%) experienced the least impact among the surveyed areas. These disparities suggest that certain regions are more vulnerable to water scarcity, likely due to variations in local hydrological conditions, agricultural practices, and water management infrastructure. The pronounced shortages in Chamba and Mehla highlight the need for targeted interventions to improve water availability for agricultural purposes, such as enhancing irrigation systems, promoting water-efficient farming techniques, and implementing policies to address regional water stress. These challenges are indicative of the broader impacts of climate change, which exacerbate water scarcity and threaten the stability of the agricultural sector. Water shortages, in particular, compromise farming activities, directly influencing food and nutritional security by reducing crop yields and livestock productivity. The interplay between water scarcity and climate variability underscores the urgent need for adaptive management strategies, including improved water conservation practices, conflict resolution mechanisms, and the development of climate-resilient agricultural systems. Such measures are essential to mitigate the long-term effects of climate change on water availability and ensure sustainable livelihoods in the affected regions. It can be inferred from Table 4.13 that maximum water storage practices were adopted in Kalpa block (79.17%), followed by Lahaul (75.00%) and Chamba (75.00%) blocks, which help mitigate inconsistent supply of water. Households in Theog block (9.08 minutes) had the quickest access to Water Sources, while Mehla block (26.38 minutes) experienced the longest. However, the overall vulnerability of the households on the ‘water’ major component was higher for Mehla block (0.633) followed by Chamba block (0.605) and Lahaul block (0.586) while the lowest vulnerability score was observed in Theog block (0.468) Since all households in the study area rely entirely on natural water sources for both domestic use and farming, the drying up of these sources, along with water conflicts, inconsistent supplies, and shortages, poses a significant threat to agricultural activities and overall farm productivity. These challenges are likely to intensify in the future, further exacerbating the vulnerability of farming systems. To mitigate these impacts, it is crucial to implement context-specific water management strategies, including the maintenance and development of water infrastructure tailored to the unique needs of each region. This could involve improving irrigation systems, enhancing water storage capacities, and adopting water conservation techniques to ensure a more reliable and sustainable water supply for agricultural and domestic use.

Table 4.14: Indexing value of sub- components of LVI for the study area

Major components	Sub components	Units	Rohru	Theog	Jubbal & Kotkhai	Mehla	Chamba	Gohar	Nagar	Kalpa	Lahaul
Socio-demographic	Dependency ratio	Ratio	0.036	0.032	0.031	0.035	0.034	0.040	0.034	0.036	0.032
	Female-headed households	Per cent	0.167	0.188	0.208	0.104	0.146	0.167	0.104	0.188	0.167
	Average age of head of household	Years	0.493	0.526	0.485	0.525	0.548	0.511	0.462	0.476	0.504
	Per cent of illiterate household heads	Per cent	0.146	0.146	0.208	0.250	0.250	0.167	0.167	0.229	0.313
	Average family size	Count	0.260	0.249	0.213	0.289	0.237	0.257	0.232	0.237	0.241
	Average years of farming experience	Count	0.507	0.549	0.481	0.530	0.552	0.531	0.473	0.493	0.562
Livelihood strategies	Households with family members working in a different community	Per cent	0.623	0.688	0.646	0.563	0.583	0.563	0.646	0.479	0.583
	Households dependent solely on agriculture as a source of income	Per cent	0.375	0.313	0.375	0.438	0.417	0.438	0.354	0.521	0.417
	Average livelihood diversification index (Herfindhal Index)	Index	0.480	0.470	0.510	0.490	0.490	0.530	0.500	0.570	0.490
Social Network	Average receive: give (ratio)	Ratio	0.294	0.281	0.287	0.294	0.276	0.240	0.275	0.292	0.297
	Average borrow: lend money (ratio)	Ratio	0.420	0.458	0.447	0.473	0.500	0.533	0.500	0.403	0.640
	Households that have received local government assistance in the past one year (during flood season)	Per cent	0.333	0.354	0.396	0.458	0.479	0.354	0.333	0.250	0.563
	HH does not have any extension contact	Per cent	0.292	0.333	0.333	0.479	0.396	0.438	0.240	0.542	0.604
Health	Average time to district health facility (minutes)	Minutes	0.178	0.507	0.234	0.251	0.216	0.076	0.648	0.065	0.929
	Average distance to district hospital	Km	0.110	0.350	0.158	0.158	0.105	0.089	0.558	0.049	0.782
	HH reporting non availability of health facilities in nearest PHC	Per cent	0.438	0.542	0.417	0.479	0.438	0.333	0.396	0.396	0.604
	Households with family members with chronic illness	Per cent	0.458	0.500	0.417	0.479	0.542	0.333	0.292	0.458	0.438
Food	Households that do not save crops	Per cent	0.646	0.563	0.667	0.479	0.438	0.521	0.625	0.583	0.479
	Households that do not save seeds	Per cent	0.563	0.583	0.729	0.563	0.500	0.521	0.646	0.521	0.500
	Average Crop Diversification index (Herfindahl Index)	Index	0.280	0.310	0.300	0.100	0.100	0.090	0.300	0.300	0.210
	Average Livestock Diversity Index	Index	0.350	0.360	0.360	0.250	0.280	0.370	0.350	0.370	0.320

Major components	Sub components	Units	Rohru	Theog	Jubbal & Kotkhai	Mehla	Chamba	Gohar	Nagar	Kalpa	Lahaul
Water	Utilize natural source of water	Per cent	0.438	0.500	0.542	0.833	0.729	0.583	0.563	0.625	0.708
	Households reporting recent drying of water sources	Per cent	0.438	0.417	0.458	0.479	0.521	0.458	0.583	0.521	0.604
	Households that do not have a consistent water supply for drinking	Per cent	0.563	0.438	0.458	0.583	0.604	0.417	0.479	0.438	0.542
	Households reporting water conflicts	Per cent	0.521	0.521	0.563	0.667	0.688	0.583	0.563	0.604	0.646
	Households reporting shortage of water supply for farming	Per cent	0.542	0.563	0.583	0.708	0.729	0.583	0.604	0.667	0.688
	Households storing water	Per cent	0.688	0.583	0.729	0.729	0.750	0.604	0.729	0.792	0.750
	Average time to water source	Minutes	0.365	0.252	0.382	0.733	0.497	0.435	0.319	0.295	0.443
	Inverse of the average amount (liters) of water stored per household	1/# Litre	0.370	0.474	0.340	0.330	0.320	0.440	0.330	0.273	0.310
House	Households whose houses do not have a solid structure and are prone to damage by floods	Per cent	0.396	0.354	0.479	0.521	0.563	0.417	0.333	0.604	0.563
	Flood affected households	Per cent	0.333	0.292	0.313	0.542	0.521	0.375	0.417	0.604	0.417
Natural disasters & climate variability	Households who were not provided with early flood warnings	Per cent	0.521	0.500	0.563	0.521	0.542	0.500	0.438	0.542	0.625
	Households experienced catastrophic accidents or deaths from floods in the past five years	Per cent	0.208	0.250	0.271	0.333	0.313	0.229	0.292	0.375	0.417
	Mean standard deviation of the monthly average of average maximum daily temperature (1981-2022)	Celcius	0.075	0.075	0.075	0.119	0.119	0.083	0.095	0.117	0.139
	Mean standard deviation of the monthly average of the average minimum daily temperature (1981-2022)	Celcius	0.055	0.055	0.055	0.122	0.122	0.055	0.119	0.212	0.256
	Mean standard deviation of monthly average precipitation (1981-2022)	Millimeter	0.133	0.133	0.133	0.176	0.176	0.138	0.140	0.127	0.062

4.4.1.7. House

House comprises two sub-components i.e., households whose houses do not have a solid structure and were prone to damage by floods and flood-affected households. It can be inferred from Table 4.13 that the highest number of households whose houses do not have a solid structure and were prone to damage by floods was observed in Kalpa block (60.42%), followed by Lahaul block (56.25%) and Chamba block (56.25%). The highest prevalence of flood-affected households was observed in Kalpa block (60.42%), followed by Mehla block (54.17%) and Chamba block (52.08%). When assessing overall vulnerability from the Table 4.15 under the house major component Kalpa block (0.604) demonstrated the highest level of vulnerability followed by Chamba block (0.542) and Mehla block (0.531), indicating a critical need for targeted interventions in these areas whereas the lowest vulnerability score was observed in Theog block (0.323).

4.4.1.8. Natural disasters and climatic variability (NDCV)

The component, natural disasters, and climatic variability comprise five sub-components. Table 4.13 shows that the highest proportion of households not provided with early flood warnings was recorded in Lahaul block (62.50%), followed by Kalpa and Chamba (54.17%) blocks. Regarding catastrophic flood events, Lahaul block had the highest prevalence, with 41.67 per cent of households reporting such incidents, followed by Kalpa block (37.50%) and Mehla block (33.33%). Secondary data from the Indian Meteorological Department (IMD) regarding the average minimum and maximum daily temperatures, as well as average precipitation over the last several years, were collected for all nine blocks in the study area. The analysis of climatic variability revealed that the maximum standard deviation of monthly average maximum daily temperatures was highest in Lahaul block (1.06), followed by Chamba and Mehla blocks (0.98), with the lowest deviation observed in Rohru, Theog, and Jubbal & Kotkhai blocks (0.80). Similarly, the maximum deviation of monthly average minimum daily temperatures was recorded in Lahaul block (1.36), followed by Kalpa block (1.21), while the least variation was noted in Gohar, Rohru, Theog, and Jubbal & Kotkhai blocks (0.67). Regarding precipitation variability, the highest mean standard deviation of monthly average precipitation was found in Mehla and Chamba blocks (28.97), while the least variation was recorded in Lahaul block (16.36). These slight climatic anomalies or variations can have significant implications for agriculture, as they can lead to the emergence of new pests, trigger disease outbreaks, and directly affect crop yields (Chhogyel *et al.,* 2020). When considering the overall Natural Disasters and Climate

Table 4.15: Indexed value of major components and overall LVI for the study area

Major components	Rohru	Theog	Jubbal & Kotkhai	Mehla	Chamba	Gohar	Nagar	Kalpa	Lahaul
Socio-demographic	0.268	0.281	0.271	0.289	0.294	0.279	0.245	0.276	0.303
Livelihood strategies	0.493	0.490	0.510	0.497	0.497	0.510	0.500	0.523	0.497
Social Network	0.335	0.357	0.366	0.426	0.413	0.391	0.337	0.372	0.526
Health	0.296	0.475	0.306	0.342	0.325	0.208	0.473	0.242	0.688
Food	0.460	0.454	0.514	0.348	0.329	0.375	0.480	0.444	0.377
Water	0.490	0.468	0.507	0.633	0.605	0.513	0.521	0.527	0.586
House	0.365	0.323	0.396	0.531	0.542	0.396	0.375	0.604	0.490
Natural disasters & climate variability	0.199	0.203	0.219	0.254	0.254	0.201	0.217	0.275	0.300
Overall	0.364	0.381	0.385	0.419	0.409	0.361	0.393	0.396	0.468

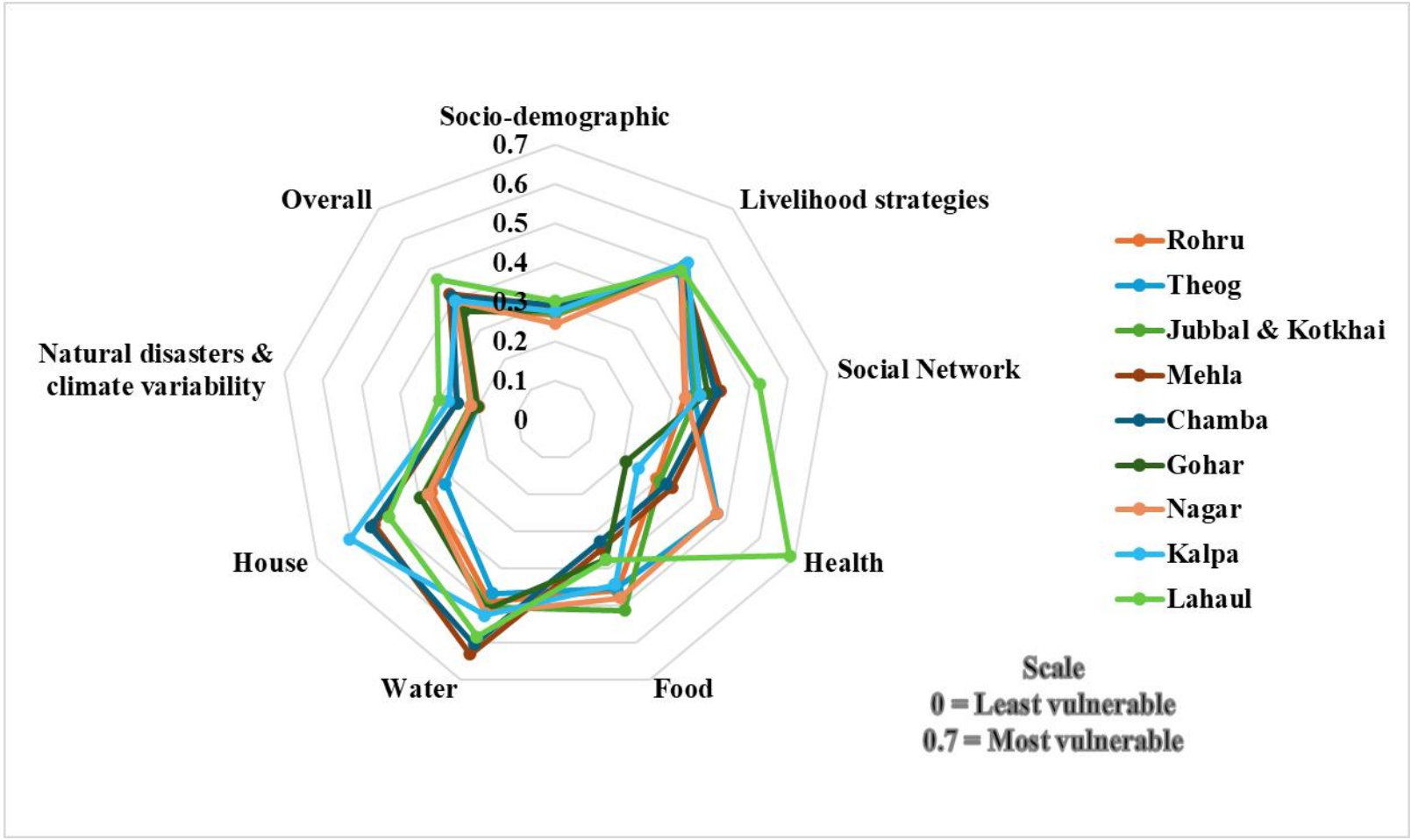


Figure 4.4: Vulnerability spider-web diagram of the major components of the Livelihood Vulnerability Index (LVI) for the study area

Variability (NDCV) vulnerability, Kalpa block exhibited the highest vulnerability score with an index value of 0.275, followed by Chamba (0.254) and Mehla (0.254) blocks. Conversely, Rohru block demonstrated the least vulnerability, with a score of 0.199, indicating a relatively lower risk of severe climate-related impacts on livelihoods in this area (Table 4.15).

The Livelihood Vulnerability Index (LVI), calculated by aggregating eight major components across nine blocks, revealed significant variations in vulnerability levels. The Lahaul block emerged as the most vulnerable, with an LVI of 0.468, followed by Mehla (0.419) and Chamba (0.409) blocks. Conversely, the Gohar block exhibited the lowest vulnerability with an LVI of 0.361. These results, presented in a spider-web diagram, demonstrated vulnerability scores ranging from 0 (least vulnerable) at the center to 0.7 (most vulnerable) at the outer edge. In terms of specific components, Lahaul block exhibited the highest vulnerability in socio-demographic profile, social network, health and, natural disasters and climate variability due to factors such as high dependency ratios, limited health access, weaker social safety nets and, susceptibility to climatic shocks Kalpa block faced severe challenges in livelihood strategies and housing, reflecting its high dependence on limited income sources. Jubbal & Kotkhai block showed the highest vulnerability in the food component. Mehla block was most vulnerable in water availability and management, with widespread reports of inconsistent water supply and drying sources. These findings underscore the need for tailored interventions to address the major vulnerabilities in each block.

Table 4.16: Block wise livelihood vulnerability index for different components in study area

Blocks	**Vulnerability index**	Rank
Rohru	0.364	VIII
Theog	0.381	VII
Jubbal & Kotkhai	0.385	VI
Mehla	0.419	II
Chamba	0.409	III
Gohar	**0.361**	**IX**
Nagar	0.393	V
Kalpa	0.396	IV
Lahaul	**0.468**	**I**

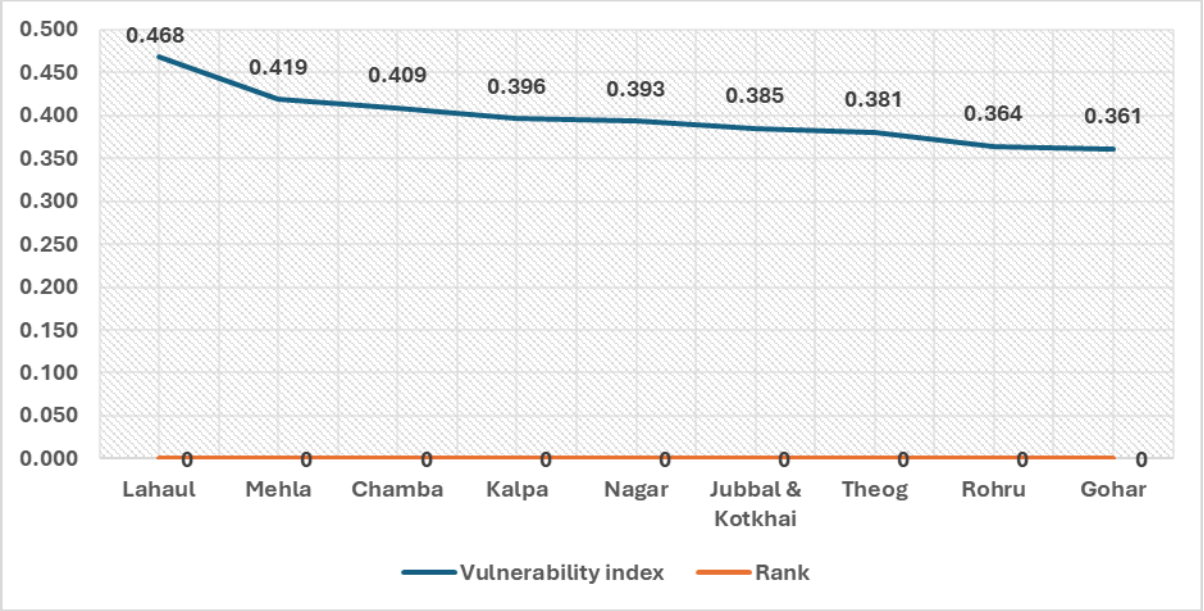


Figure 4.5: Ranking of the blocks based on Livelihood Vulnerability Index in study area

To provide the systematic characterization of the degrees of vulnerability, the blocks within the study area were classified into three categories: low, moderate and high vulnerable zones. This classification was based on range and interval size as presented in Table 4.17. The blocks with vulnerability indices range from 0.361 to 0.3967 were considered under low vulnerable zone, the blocks with the vulnerability index between 0.3967 to 0.4324 were under moderate vulnerable zone, whereas the blocks with vulnerability indices range from 0.4324 to 0.468 were taken under high vulnerable zone. It is reported that 2 blocks were categorized as low vulnerable, 5 moderate vulnerable and 2 under high vulnerable zone in the study area.

Table 4.17: Classification of different blocks in the temperate region based on vulnerability

Sr. No.	Vulnerable Zone	Lower range	Upper range	Name and number of blocks
1	Low	0.3610	0.3967	(02) Gohar, Rohru
2	Moderate	0.3967	0.4324	(05) Theog, Jubbal & Kotkhai, Chamba, Nagar, Kalpa
3	High	0.4324	0.468	(02) Mehla, Lahaul

The assessment of vulnerability levels across the study area demonstrated distinct spatial variations. One block each from Mandi and Shimla districts were categorized under the low vulnerability zone, indicating relatively lower susceptibility to adverse impacts. The

moderate vulnerability zone comprised two blocks from Shimla district and one block each from Chamba, Kullu, and Kinnaur districts, reflecting intermediate levels of susceptibility. In contrast, the high vulnerability zone included one block from Chamba district and one block from Lahaul &Spiti district. This classification underscores the spatial heterogeneity in vulnerability across the region.

Thus, it can be concluded that among all the selected districts Mandi was found to be the least vulnerable district in the temperate region followed by Shimla, Kullu and Kinnaur district as moderate vulnerable, whereas Chamba and Lahual and Spiti were found as high vulnerable districts in the temperate region of Himachal Pradesh. Table 4.18 presents the selected blocks under different categories for the present study. Thus, 2 blocks in low vulnerable, 5 in moderate vulnerable and 2 in high vulnerable zone were selected to identify climate-smart agricultural practices and factors influencing their adoption, assess their impact on livelihood vulnerability, and examine the constraints to adopting climate-smart agricultural practices among farmers.

Table 4.18: Classification of selected blocks under different degrees of vulnerability

Sr. No.	Low vulnerable (02)	Moderate vulnerable (05)	High vulnerable (02)
1	Gohar	Theog	Mehla
2	Rohru	Jubbal & Kotkhai	Lahaul
3		Chamba	
4		Nagar	
5		Kalpa	

4.4.2. LVI –IPCC approach

The LVI-IPCC framework quantifies vulnerability by grouping the eight major components into three principal contributing factors (CF): Exposure, Sensitivity, and Adaptive Capacity. Adaptive Capacity incorporates metrics from the Socio-demographic Profile, Livelihood Strategies, and Social Networks. Sensitivity is derived from indicators within the Health, Food, Water, and House components, while Exposure is exclusively represented by the Natural Disasters and Climate Variability (NDCV) component. The results from the LVI-IPCC model demonstrate notable variability across the study regions, as presented in Table 4.19. These findings are visualized using a vulnerability triangle, which plots the scores of the three contributing factors —Exposure, Sensitivity, and Adaptive Capacity—for each block (Figure 4.6). Higher CF values indicate greater vulnerability.

Negative values within the vulnerability index do not suggest an absence of vulnerability but rather indicate that the corresponding areas exhibit comparatively lower vulnerability levels relative to others in the study.

Table 4.19: LVI-IPCC contributing factors calculation for the study area

Contributing factor	Rohru	Theog	Jubbal & Kotkhai	Mehla	Chamba	Gohar	Nagar	Kalpa	Lahaul
Exposure	0.199	0.203	0.219	0.254	0.254	0.201	0.217	0.275	0.300
Sensitivity	0.426	0.450	0.452	0.494	0.474	0.402	0.485	0.454	0.552
Adaptive capacity	0.504	0.504	0.484	0.488	0.490	0.501	0.510	0.484	0.471
Overall LVI-IPCC	-0.130	-0.135	-0.120	-0.116	-0.112	-0.121	-0.142	-0.095	-0.094

Index values are interpreted as relative values to be compared within the study sample only. The LVI IPCC is on a scale from -1 (least vulnerable) to +1 (most vulnerable).

The study reported a higher Exposure to climate change and variability in Lahaul block (0.300) followed by Kalpa block (0.275), whereas least was observed in Rohru block (0.199). Due to extreme climatic conditions, Lahaul and Kalpa blocks was found to be the most exposed to the NDCV, consequently resulting as the most vulnerable under the LVI-IPCC mode. Lahaul and Kalpa blocks were predominantly characterized by high altitude, steep or rugged topography, accompanied by very low temperature with perpetual snowfall during winter months, making them more exposed and thus, more vulnerable. Further, high valleys, gorges and huge topographical surface differences often result in the significant occurrences of extreme microclimatic variation (Katel *et al.*, 2014). Accounting the sensitivity that comprises the aggregated index of health, food, water and house major components, Lahaul block (0.552) reports a higher sensitivity value to climate change followed by Mehla block (0.494) and Nagar block (0.485) (Figure 4.6). The highest sensitivity was found in Lahaul block and Mehla block due to their temperate location that has a longer chilling hour with snow coverage during winter and erratic precipitation during summer, while the Gohar block (0.402) was least sensitive. The indices of adaptive capacity within the study area had somewhat narrow range of 0.504 to 0.471 (Table 4.19), indicating similarities and high capacity to adapt to the three major components of socio-demographic profile, livelihood strategies and social networks. The overall LVI-IPCC scores indicate that households in Lahaul block (-0.094) are most vulnerable followed by Kalpa block (-0.095), than those in Rohru (-0.130) and -0.135 in Theog block (Table 4.19).

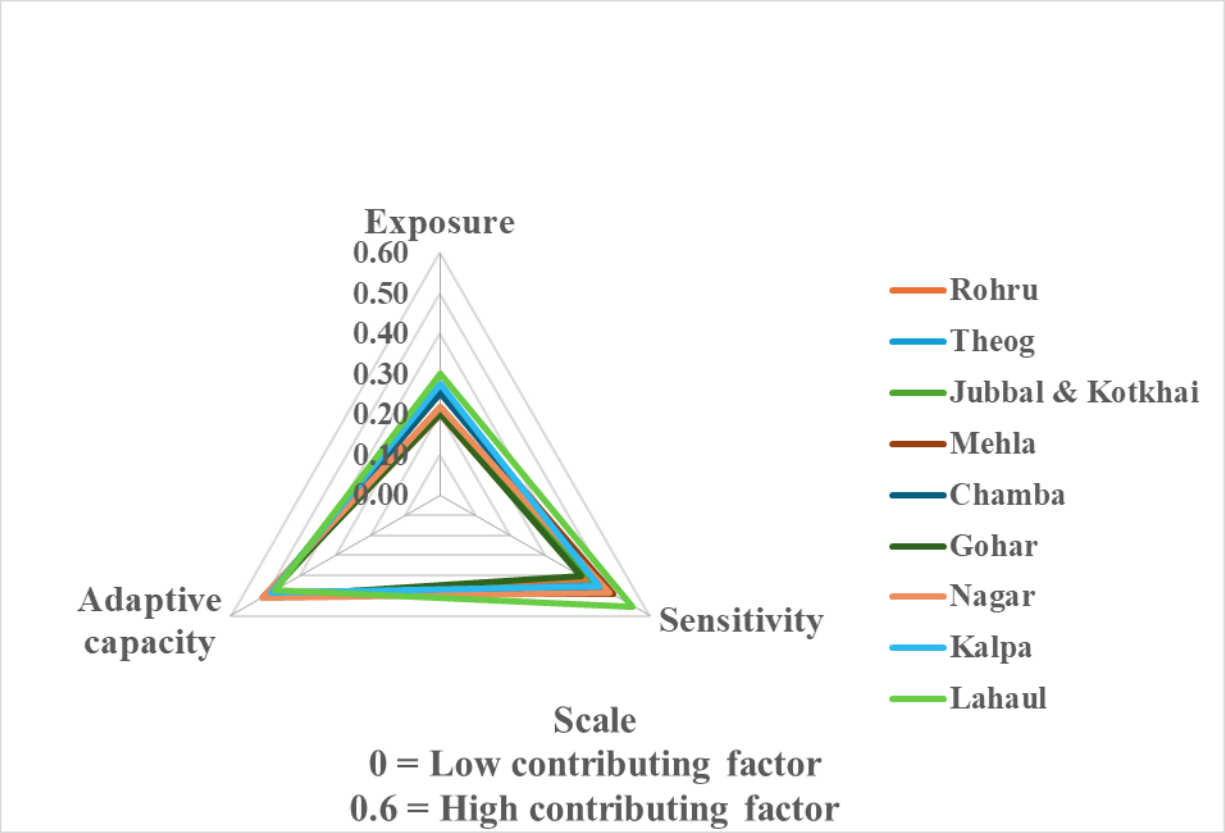


Figure 4.6: Vulnerability triangle-diagram of the contributing factors of the Livelihood Vulnerability Index (LVI-IPCC) for the study area

4.5. CLIMATE-SMART AGRICULTURAL PRACTICES IN THE STUDY AREA

Farmers in temperate regions have been adopting and implementing adaptation strategies such as climate-smart agricultural practices, either actively or passively, as a means to mitigate the impacts of climate change. The specific practices identified within the study area have been presented in Table 4.20.

4.5.1. Identification of the climate-smart agricultural practices for climate change risk mitigation in the study area

Table 4.20 presents the identification of various climate-smart agricultural practices adopted by farmers in the study area, categorized by whether they were adopted (Yes) or not adopted (No). Mulching was adopted by 72.90 per cent of farmers, with 27.10 per cent not adopting this practice. Minimum/zero tillage was adopted by 50.20 per cent of farmers, while 49.80 per cent did not implement it. Fruit-based agroforestry was adopted by 82.40 per cent of farmers, with 17.60 per cent not engaging in this practice. Integrating crop-livestock production was adopted by 81.70 per cent of farmers, while 18.30 per cent did not adopt this practice. The adoption of micro-irrigation was the

lowest, with only 35.60 per cent of farmers adopting this practice and 64.4 per cent not adopting it, likely due to the high installation costs. The practice of changing planting time was adopted by 70.10 per cent of farmers, while 29.90 per cent did not adopt it. Improved crop varieties, diet improvement for animals, and crop insurance were each adopted by 50.90 per cent of farmers, with the remaining 49.10 per cent not implementing these practices. Soil testing was adopted by 53.00 per cent of farmers, while 47.00 per cent did not adopt this practice. The use of compost and farmyard manure (FYM) demonstrated the highest adoption, with 85.90 per cent of farmers employing this practice, and only 14.10 per cent did not adopt it. ICT-based weather forecasting was adopted by 57.90 per cent of farmers, with 42.10 per cent not utilizing this practice. These findings reveal significant variation in the adoption of CSA practices, with more accessible and lower-cost practices, such as composting and mulching, achieving higher adoption rates, while more resource-intensive practices, such as micro-irrigation, exhibit lower adoption rates.

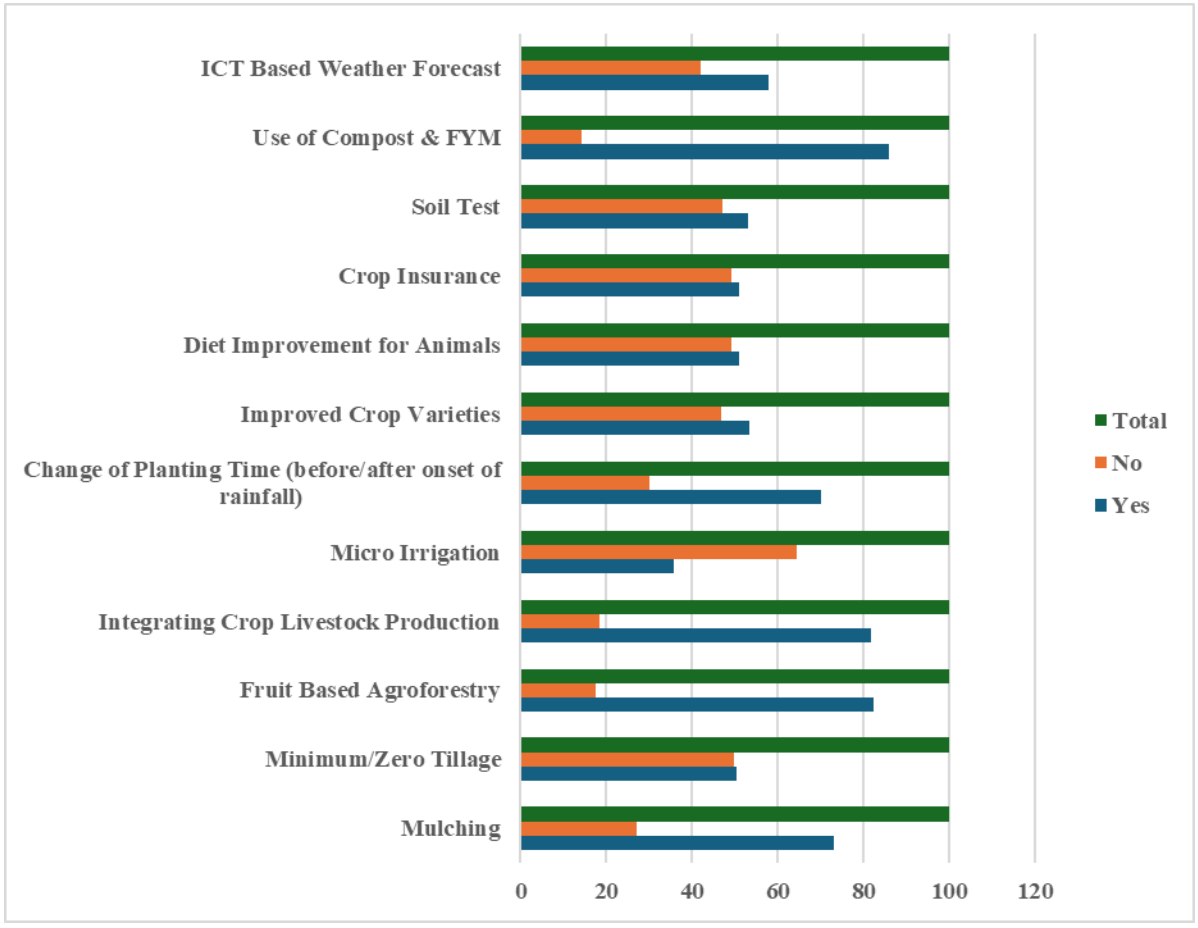


Figure 4.7: Climate-smart agricultural practices for climate change risk mitigation in the study area

Table 4.20: Identification of climate-smart agricultural practices in the study area

CSA practices	Yes		No		Total	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Mulching	315	72.90	117	27.10	432	100
Minimum/Zero Tillage	217	50.20	215	49.80	432	100
Fruit Based Agroforestry	356	82.40	76	17.60	432	100
Integrating Crop Livestock Production	353	81.70	79	18.30	432	100
Micro Irrigation	154	35.60	278	64.40	432	100
Change of Planting Time (before/after onset of rainfall)	303	70.10	129	29.90	432	100
Improved Crop Varieties	230	53.20	202	46.80	432	100
Diet Improvement for Animals	220	50.90	212	49.10	432	100
Crop Insurance	220	50.90	212	49.10	432	100
Soil Test	229	53.00	203	47.00	432	100
Use of Compost & FYM	371	85.90	61	14.10	432	100
ICT Based Weather Forecast	250	57.90	182	42.10	432	100

4.5.2. Categorization of respondents based on composite scores

The composite score was used in a binary scale to categorize respondents into three distinct groups, providing a structured framework for analyzing the extent of CSA adoption. High adopters were defined as those whose composite scores fell between 12 and the range determined by the mean plus one standard deviation (Mean + S.D). Moderate adopters included those whose scores fell between the thresholds of High and Low adopters. Low adopters were identified as respondents whose scores ranged from the mean minus one standard deviation (Mean − S.D) to a minimum of 0. This method of categorization, grounded in statistical measures of central tendency and dispersion, facilitated the identification of adoption patterns and the targeting of interventions to address barriers, enhancing the understanding of CSA practice integration among the sampled households.

Table 4.21: Category of adopters of CSA practices in the study area

Sr. No.	Category of adopters	Frequency	Percentage
1	Low adopters	173	40.00
2	Moderate adopters	132	30.60
3	High adopters	127	29.40
	Total	432	100.00

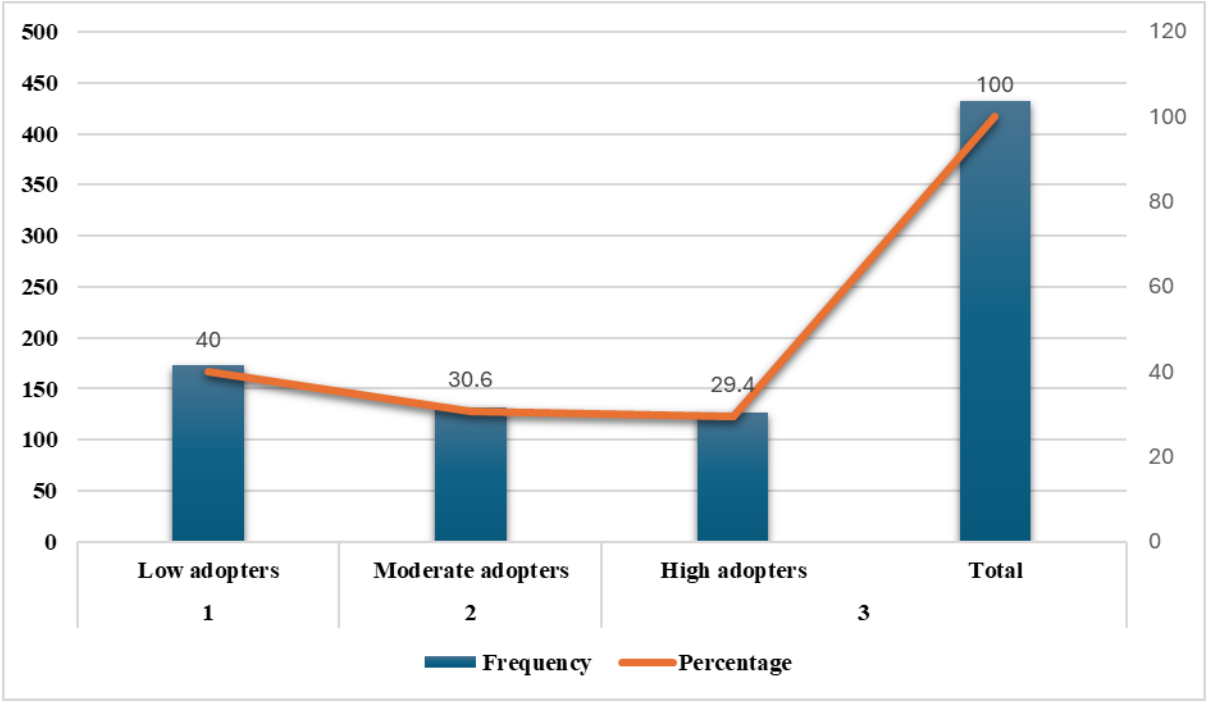


Figure 4.8: Category of adopters of CSA practices in the study area

Results (Table 4.21) from the composite score analysis revealed that the majority of respondents (40.00%) fell into the category of low adopters of CSA practices. Approximately 30.60 per cent were classified as moderate adopters, while 29.40 per cent were high adopters. These findings highlight that a significant proportion of the sampled households were either low or moderate adopters, with less than one-third exhibiting high levels of CSA adoption. This categorization underscores the need for targeted strategies to enhance the adoption of CSA practices among low and moderate adopters, thereby improving overall adoption levels in the study area.

4.5.3. Adoption level of various climate-smart agricultural practices

To assess the practice-specific adoption rates of climate-smart agricultural (CSA) practices, twelve key practices were identified through an extensive literature review and a pilot survey conducted in the study area. Each practice was evaluated using the Weighted Mean Score (WMS) method, which assigns weights to responses based on their importance and frequency of adoption within the farming community. This method provides a standardized framework for assessing the adoption levels of individual practices and ranks them according to their relative adoption levels and effectiveness.

The data analysis revealed the adoption levels and corresponding ranks of various CSA practices, as presented in Table 4.22. Fruit-based agroforestry and use of compost &fym were ranked first with a weighted mean score of 1.85 each, indicating the most impactful CSA practice. Integrating fruit trees with crops provides benefits such as improved biodiversity, soil health, and a diversified income stream. It can also help in carbon sequestration, which is crucial for climate resilience. For fruit-based agroforestry, 29.40 per cent of respondents reported high adoption, 26.16 per cent moderate adoption, and 44.44 per cent low adoption. Similarly, for compost and FYM, 28.70 per cent of respondents reported high adoption, 27.31 per cent moderate adoption, and 43.98 per cent low adoption. This practice focuses on the use of organic materials like compost and farmyard manure to improve soil fertility, structure, and moisture retention. This helps to reduce reliance on chemical fertilizers, supporting sustainable farming practices, and enhancing soil health. Mulching ranked second with a weighted mean score of 1.84, with 28.94 per cent reporting high adoption, 26.39 per cent moderate adoption, and 44.68 per cent low adoption. Mulching is a practice where organic (straw, hay, leaves) or inorganic materials (plastic film, rubber mats) are placed on the soil surface to retain moisture,

regulate temperature, and suppress weeds. It helps conserve water and improve soil health, making it a key practice for water-efficient farming. Integrating crop-livestock production ranked third with a score of 1.83, where 28.47 per cent of respondents adopted it at a high level, 25.69 per cent at a moderate level, and 45.83 per cent at a low level. ICT-based weather forecast ranked fourth with a score of 1.81, with high adoption reported by 28.70 per cent, moderate adoption by 23.15 per cent, and low adoption by 48.15 per cent. Change of planting time (before/after the onset of rainfall) ranked fifth with a weighted mean score of 1.79, where 27.55 per cent reported high adoption, 24.31 per cent moderate adoption, and 48.15 per cent low adoption. Improved crop varieties ranked sixth with a score of 1.73, with 28.70 per cent reporting high adoption, 15.97 per cent moderate adoption, and 55.32 per cent low adoption. Crop insurance and soil testing shared the seventh rank, each with a score of 1.72. Crop insurance was adopted at high levels by 27.55 per cent, moderate levels by 17.36 per cent, and low levels by 55.09 per cent. Similarly, soil testing saw 26.39 per cent high adoption, 18.98 per cent moderate adoption, and 54.63 per cent low adoption.Minimum/Zero Tillage ranked eighth with a score of 1.70, where 27.55 per cent reported high adoption, 14.58 per cent moderate adoption, and 57.87 per cent low adoption. Diet Improvement for Animals ranked ninth with a weighted mean score of 1.63, with high adoption reported by 24.31 per cent, moderate adoption by 14.81 per cent, and low adoption by 60.88 per cent. Micro Irrigation ranked tenth with a score of 1.62, with only 26.62 per cent reporting high adoption, 8.33 per cent moderate adoption, and 65.05 per cent low adoption.

It can be concluded from the Table 4.22 that practices that enhance biodiversity (agroforestry), improve soil health (compost and mulching), and provide adaptive management tools (weather forecasting, crop insurance) were considered the most critical for climate resilience in agriculture. Practices that require more infrastructure or investment, like micro-irrigation, were ranked lower, indicating challenges in their widespread adoption. Higher-ranked practices were generally those that enhance biodiversity, improve soil health, or provide adaptive tools for managing climate variability. Lower-ranked practices often face adoption challenges due to factors such as cost, infrastructure requirements, or lack of awareness. This comprehensive evaluation underscores the importance of targeted interventions to encourage the adoption of less utilized but impactful practices while leveraging the strengths of widely adopted practices to build climate resilience in agriculture.

Table 4.22: Adoption level of various climate-smart agricultural practices

CSA practices	High adoption (3)		Moderate adoption (2)		Low adoption (1)		Total weighted score	Weighted mean score	Rank
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage			
Mulching	125	28.94	114	26.39	193	44.68	796	1.84	II
Minimum/Zero Tillage	119	27.55	63	14.58	250	57.87	733	1.70	VIII
Fruit Based Agroforestry	127	29.40	113	26.16	192	44.44	799	1.85	I
Integrating Crop Livestock Production	123	28.47	111	25.69	198	45.83	789	1.83	III
Micro Irrigation	115	26.62	36	8.33	281	65.05	698	1.62	X
Change of Planting Time (before/after onset of rainfall)	119	27.55	105	24.31	208	48.15	775	1.79	V
Improved Crop Varieties	124	28.70	69	15.97	239	55.32	749	1.73	VI
Diet Improvement for Animals	105	24.31	64	14.81	263	60.88	706	1.63	IX
Crop Insurance	119	27.55	75	17.36	238	55.09	745	1.72	VII
Soil Test	114	26.39	82	18.98	236	54.63	742	1.72	VII
Use of Compost & FYM	124	28.70	118	27.31	190	43.98	798	1.85	I
ICT Based Weather Forecast	124	28.70	100	23.15	208	48.15	780	1.81	IV

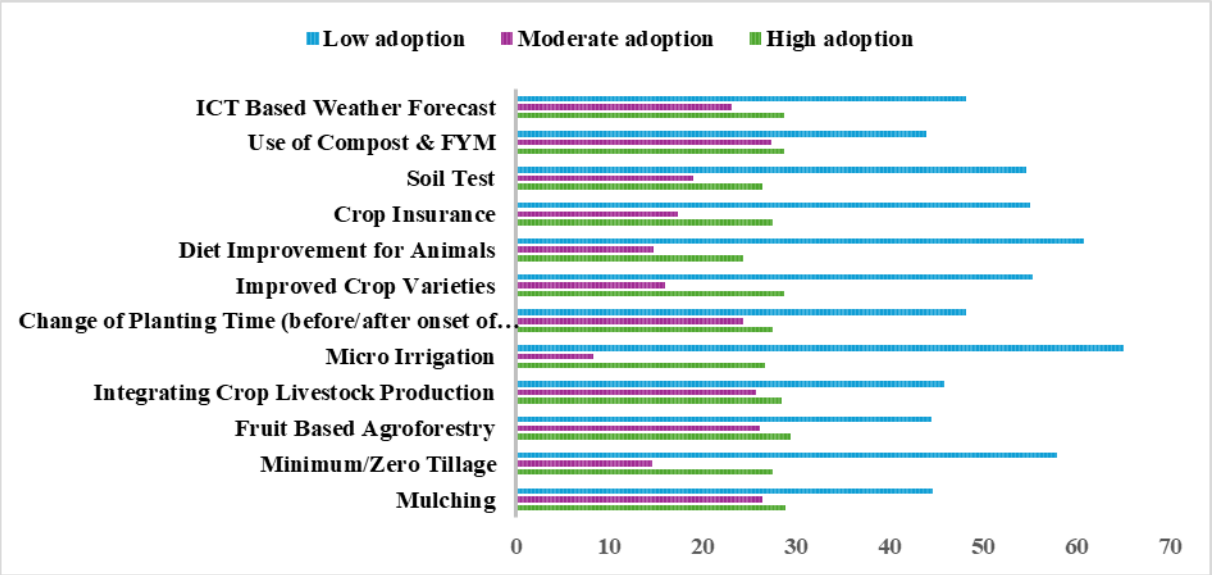


Figure 4.9: Adoption level of various climate-smart agricultural practice

4.6. FACTORS INFLUENCING THE ADOPTION OF CLIMATE-SMART AGRICULTURAL PRACTICES

An ordered logit regression model was employed to identify the determinants influencing farmers' choices in adopting climate-smart agricultural practices, which aim to mitigate the adverse impacts of climate variability and extremes. The dependent variable in the model represents the categories of adopters of climate-smart agricultural practices, classified into three levels: high, moderate, and low adopters.

The results from the Table 4.23 showed the descriptive statistics of the dependent variables as well as the independent variables. In terms of climate-smart agricultural practices, the most widely adopted practices were the use of compost and farmyard manure (FYM), with 86 per cent of respondents employing this practice; however, these were not applied up to the recommended levels, followed by fruit-based agroforestry and integrating crop-livestock production, both of which had adoption rates of 82 per cent. Conversely, practices such as micro-irrigation and crop insurance were less commonly adopted, with mean values of 0.36 and 0.51, respectively. The majority of respondents were relatively older, with an average age of 57.15 years, which corresponds to significant farming experience, as indicated by the mean of 25.54 years. The gender distribution predominantly comprises male household heads, with a mean of 0.84, suggesting a male-dominated farming population. Educational attainment was moderate, with a mean score of 2.34 on a scale of 0 to 5, indicating that most respondents have a basic to intermediate level of education. A considerable proportion of respondents also had access to institutional support, with 59 per cent reporting access to extension services and 66 per cent

having access to credit. Additionally, 60 per cent of respondents participated in agricultural training programs, highlighting the importance of capacity-building in agricultural practices. Access to climate change information was reported by 56 per cent of respondents, underlining the role of climate-related knowledge in shaping farming decisions. Economically, the respondents had relatively large family sizes, with an average of 5.44 members per household, and Adult Cattle Unit was 2.36. The mean off-farm income was 211,227, while on-farm income was considerably higher, averaging 725,801, which underscores the central role of agriculture in supporting household livelihoods. Regarding farm size, respondents were predominantly small-scale farmers, with a mean value of 1.67, which likely influences their ability to adopt more intensive or input-intensive agricultural practices.

Table 4.23: Descriptive Statistics: Factors influencing the adoption of climate-smart agricultural practices

Variables	Mean	Std. Dev.
Dependent variables		
Mulching	0.73	0.445
Minimum/Zero Tillage	0.50	0.501
Fruit Based Agroforestry	0.82	0.381
Integrating Crop Livestock Production	0.82	0.387
Micro Irrigation	0.36	0.48
Change of Planting Time (before/after onset of rainfall)	0.70	0.458
Improved Crop Varieties	0.53	0.5
Diet Improvement for Animals	0.51	0.5
Crop Insurance	0.51	0.5
Soil Test	0.53	0.5
Use of Compost & FYM	0.86	0.349
ICT Based Weather Forecast	0.58	0.494
Independent variables		
Socio-demographic factors		
Age of the household head	57.15	9.284
Gender of the household head	0.84	0.369
Education status of the household head	2.34	1.572
Farming experience	25.54	10.138
Institutional factors		
Market distance	12.03	5.939
Access to extension functionaries	0.59	0.491
Access to credit	0.66	0.474
Participate in training	0.60	0.491
Socio-cultural factor		
Member in local area	0.53	0.499
Climatic factor		
Access to climate change information	0.56	0.496

Economic factors		
Family size	5.44	1.665
Adult Cattle Unit	2.36	1.5787
Off-farm income	211227	188122
On-farm income	725801	366661
Farmers category	1.67	0.767

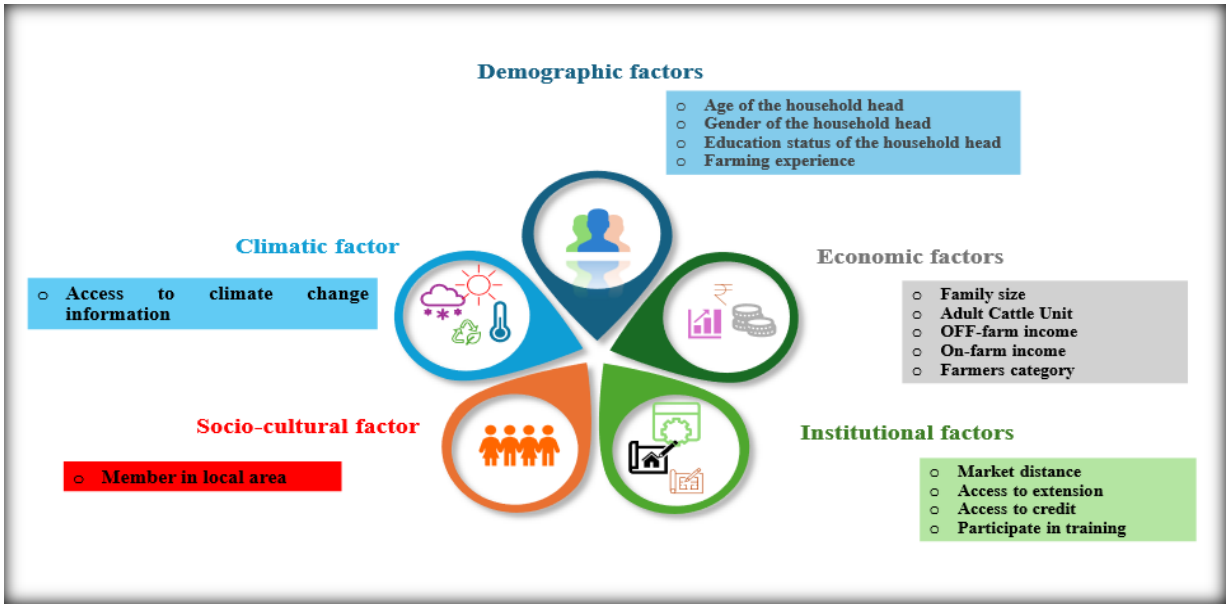


Figure 4.10: Conceptual framework for factors affecting the adoption of climate-smart agricultural practices

Diagnostic test

Before running the ordinal logistic regression model, diagnostic tests were conducted to evaluate multicollinearity among continuous variables and the degree of association among dummy explanatory variables. The Variance Inflation Factor (VIF) was used to assess multicollinearity, and the results indicated that all continuous variables had VIF values below 10, demonstrating the absence of significant multicollinearity issues. Consequently, all continuous variables were retained for inclusion in the regression model. Similarly, the Contingency Coefficient (CC) was calculated to determine the degree of association among the dummy explanatory variables (Kassa and Abdi, 2022).

In the study, the computational results of the VIF for continuous variables were found to be below 3.73, with a mean VIF of 2.16, as shown in Appendix IV. These values confirm the non-existence of a multicollinearity problem among the continuous predictor variables, allowing them to be included in the model. Moreover, the contingency coefficient values for the dummy variables were all below 0.610, which is significantly less than 0.75 (Kassa and

Abdi, 2022), indicating a weak degree of association among these variables, as presented in Appendix V. The analysis revealed weak relationships among the dummy variables, suggesting minimal overlap or redundancy. Based on these results, all continuous and dummy variables were included in the regression analysis, ensuring a reliable and unbiased estimation of the model parameters and accounting for the contributions of all relevant predictors.

An ordered logistic regression model has been applied to provide insights into the factors influencing the likelihood of adopting climate-smart agricultural practices, with the dependent variable being ordered in nature. As shown in Table 4.24 the goodness-of-fit of the models was evaluated using the pseudo-R^2 statistic, which was computed at 0.4371. This indicates that the model explains a substantial proportion of the variation in the dependent variable. Furthermore, each of the logistic regression models successfully passed the goodness-of-fit tests as recommended by Asprooth *et al*., (2023); Wimhurst *et al*., (2023), affirming the reliability and adequacy of the models for the analysis. The null hypothesis was that there is no difference in the coefficients between models. Furthermore, the model fitness was confirmed by the value of Prob > $\chi 2 = 0$, suggesting that the model was appropriate for the analysis. A test was run for the model fit for the adoption of climate-smart agricultural practices in the study area.

Several predictors showed significant positive associations with adoption of climate-smart agricultural practices. The education level of the household head significantly influences the adoption of climate smart agricultural practices (odds ratio = 0.25, p = 0.020), indicating that more educated household heads were more likely to adopt climate-smart agriculture (CSA) practices. This suggests that higher education levels enhance farmers' ability to understand, evaluate, and implement climate-smart agricultural practices, making them more receptive to adopting innovative practices. Education is statistically significant at the 5 per cent level, underscoring the importance of education in facilitating the adoption process. This finding is consistent with studies by Abegunde *et al.,* (2020); and Ojoko *et al.*, (2017), which assert that educated farmers are better equipped to integrate new agricultural technologies due to their improved decision-making and problem-solving skills. Additionally, research by Abid *et al.,* (2015), Ade and Bosede, (2016); Sebatta *et al.,* (2014); and Ume *et al.,* (2020) highlights that education has a positive effect on the adoption of modern farming practices, as it enables farmers to make informed judgments and identify opportunities for maximizing farm profitability. Therefore, the adoption of CSA practices in rural areas are

highly dependent on the educational background of farmers, which influences their willingness and ability to embrace innovations for enhanced productivity and sustainability.

Farming experience was positively associated with the adoption of climate-smart agricultural practices (odds ratio = 0.046, p = 0.048), demonstrating that experienced farmers were more likely to embrace CSA practices. This result is statistically significant at the 5 per cent level, indicating a robust relationship between farming experience and the likelihood of adoption. The accumulation of both physical and social capital through years of farming enhances the farmer's capacity to evaluate and implement new technologies. Experienced farmers possess a wealth of practical knowledge that allows them to better assess the potential benefits and challenges of new agricultural techniques. This experience contributes to more informed decision-making, increasing their confidence in adopting and sustaining new practices. Research by Abegunde *et al.,* (2019); and Onyeneke *et al.,* (2018) supports this finding, indicating that farmers with greater experience are more receptive to adopting innovations that improve productivity and sustainability. The positive relationship between farming experience and CSA adoption underscores the importance of practical knowledge gained over time in facilitating the integration of new technologies (Mujeyi *et al.,* 2021). As such, the greater the experience of farmers, the higher their likelihood of adopting CSA practices, ultimately enhancing both productivity and sustainability in farming systems. Access to extension services has a significant positive impact on the adoption of these practices (odds ratio = 1.107, p = 0.000). This indicates a strong association, with statistical significance at the 1 per cent level, demonstrating that farmers with access to extension services were notably more likely to adopt CSA practices.

Extension services play a critical role in providing farmers with essential information, technical guidance, and training, all of which facilitate the adoption of modern and sustainable farming methods. This finding is consistent with prior research, including studies by Negera *et al.,* (2022); Teklewold *et al.,* (2018); and Wekesa *et al.,* (2018), which highlight the importance of extension services in promoting agricultural innovation. Furthermore, the frequency of extension contacts is shown to significantly influence the intensity of CSA adoption among farmers as study conducted by Negera *et al.,* (2022). The positive relationship observed suggests that more frequent interactions with extension agents lead to the adoption of more intensive CSA practices. This is largely attributed to the continuous support and up-to-date knowledge provided by extension agents, which help farmers overcome barriers to adopting CSA and enhance their agricultural productivity in the face of climate challenges.

Access to credit significantly influences the adoption of climate-smart agricultural practices (CSA) (odds ratio = 1.051, p = 0.000), indicating that farmers with access to credit were more likely to adopt new practices. This result is statistically significant at the 1 per cent level, suggesting that financial resources play a crucial role in enabling farmers to invest in the adoption of innovative technologies and practices. The positive association between access to credit and CSA adoption reflects the ability of farmers to allocate funds for the purchase of inputs, training, and other resources necessary for implementing climate-smart practices. This finding is consistent with the work of Sedebo *et al.,* (2021) and Abegunde *et al.,* (2019), who observed that farmers who adopted CSA practices had greater access to financial credit and extension services. These financial resources, combined with the support of extension services, provide farmers with the necessary tools and knowledge to integrate new practices, thereby improving productivity and sustainability. Access to credit, therefore, serves as a critical enabler for the adoption of CSA practices, particularly in resource-constrained farming environments.

Participating in training programs was a significant determinant of CSA adoption, with an odds ratio of 0.603 (p = 0.016), indicating a statistically significant effect at the 5 per cent level. This suggests that farmers who engage in agricultural training were more likely to adopt new farming practices, as these programs equip them with the necessary skills, knowledge, and confidence. These results underscore the critical role of training in enhancing a farmer's capacity to integrate and apply CSA technologies effectively. Training enhances farmers' knowledge, awareness, and technical skills, which, in turn, influences their decision-making towards intensifying their agricultural practices. This finding aligns with previous studies by Theophilus *et al.,* (2019); and Vera *et al.,* (2017), all of which highlight the positive impact of agricultural training on the adoption of innovative farming techniques. Furthermore, Gikonyo *et al.,* (2022) also emphasize the importance of training in shaping the adoption and successful implementation of CSA practices among farmers.

Being a member of a local agricultural association significantly influences the adoption of climate-smart agriculture practices, with an odds ratio of 0.54 (p = 0.024), indicating statistical significance at the 5 per cent level. This suggests that farmers who were members of local agricultural groups were more likely to adopt CSA practices. Group membership provides essential social support, facilitates knowledge exchange, and offers collective access to resources, all of which promote the adoption of innovative farming techniques. Social capital, such as membership in agricultural associations, plays a crucial role in rural areas by enhancing

farmers' access to information and fostering collaboration. Research by Birthal *et al.,* (2015) and Yamano *et al.,* (2015) highlights those farmers at the bottom of the social hierarchy, who may have limited access to information and resources, are less likely to adopt new agricultural innovations. Conversely, belonging to an agricultural group enables farmers to overcome these barriers, improving their perception of CSA practices and enhancing adoption rates. This finding aligns with the work of Abegunde *et al.,* (2020), which anticipates a positive correlation between group membership and the level of CSA adoption. By leveraging the benefits of social networks, farmers gain better access to knowledge, technical support, and resources, which ultimately strengthens their capacity to adopt and implement CSA practices effectively.

Access to climate change information has a significant positive influence on the adoption of practices, as evidenced by an odds ratio of 2.462 ($p = 0.000$), indicating a highly statistically significant relationship at the 1 per cent level. This finding highlights the critical role of climate change information in shaping farmers' decisions to adopt CSA practices. Farmers who were well-informed about climate change, including its risks and potential mitigation strategies, were considerably more likely to engage in CSA practices. The provision of climate change information enhances farmers' understanding of climate-related risks, such as altered weather patterns, pests, diseases, and other environmental stressors. Furthermore, such information enables farmers to identify effective strategies for mitigating these risks, empowering them to adopt farming practices that promote resilience and sustainability. This expanded knowledge base helps farmers make informed decisions regarding the implementation of CSA practices that align with their farm's needs and environmental conditions. The dissemination of information through various media platforms not only raises awareness about the impacts of climate change but also educates farmers about the benefits of CSA practices. As such, information access becomes a key factor in influencing farmers' attitudes towards innovation and their subsequent decision to adopt or reject new farming techniques (Mujeyi *et al.,* 2019). Moreover, creating widespread awareness and distributing information about the positive impacts of CSA practices can significantly enhance adoption rates, thereby enabling farmers to better cope with the adverse effects of climate change (Negera *et al.,* 2022).

On-farm income is a significant determinant of the adoption of climate-smart agriculture practices, with an odds ratio of 3.64E-06 ($p = 0.000$), indicating a strong positive relationship that is statistically significant at the 1 per cent level. This suggests that farmers with higher on-farm income were more likely to adopt CSA practices. The availability of increased income provides farmers with the financial flexibility to invest in new agricultural technologies, which can enhance

productivity and sustainability. Higher on-farm income enables farmers to afford the initial costs associated with adopting CSA practices, such as purchasing new technologies, seeds, or inputs. Moreover, labour-saving CSA technologies like drip irrigation can further improve farm income by reducing labour costs and allowing farmers to reallocate time to other income-generating activities outside of agriculture, as suggested by Mujeyi *et al.,* (2019). This dual effect of increased income—both by reducing agricultural labour costs and creating opportunities for additional economic activities—supports the adoption of CSA practices and enhances overall household economic well-being. The relationship between on-farm income and CSA adoption aligns with findings by Abegunde *et al.,* (2019), who highlighted that higher farm income is a key driver of CSA adoption, as farmers with greater financial resources are better positioned to invest in practices that require both initial capital and long-term commitment. Therefore, increasing farm income is a critical factor in promoting the widespread adoption of CSA practices and enhancing resilience to climate change.

The category of farmers, classified according to farm size, significantly influences the adoption of climate-smart agriculture practices. The odds ratio of -0.813 ($p = 0.017$), which is statistically significant at the 5 per cent level, indicates that farm size is a critical determinant in the likelihood of adopting CSA practices. Specifically, farmers with smaller landholdings were less likely to adopt CSA practices, potentially due to limited resources or differing farming priorities. This finding is consistent with prior research, such as Kassa and Abdi, (2022); Kom *et al.,* (2020); and Teklewold *et al.,* (2013), which show a positive relationship between larger farm sizes and the adoption of CSA techniques. Larger farms generally provide more resources and space, enabling farmers to trial and implement innovative practices, thus facilitating higher adoption rates. Conversely, farmers with smaller landholdings may face challenges in adopting resource-intensive practices but may also be more inclined to adopt land-saving or labour-saving innovations. As noted by Simtowe *et al.,* (2021), smallholders are more likely to adopt technologies such as greenhouse farming or zero-grazing, which are well-suited to smaller-scale operations. However, there is evidence suggesting that farm size does not always correlate positively with CSA adoption. For example, Mujeyi *et al.,* (2019) found a negative relationship between farm size and adoption, suggesting that large farms may be less motivated to adopt input-intensive or new technologies. Instead, smaller farms may see land-conserving technologies as a more viable option to increase productivity. The impact of farm size on CSA adoption is multifaceted. While larger farms are typically better equipped to adopt CSA practices, smaller farms may adopt specific technologies that are more aligned with their resource constraints.

Table 4.24: Factors influencing the adoption of climate-smart agricultural practices

Variables	Odds ratio	Standard error	Z	P>|z|	95 % confidence interval	
					Lower bound	Upper bound
Socio-demographic factors						
Age (X1)	-0.02	0.024	-0.83	0.405	-0.068	0.027
Gender (X2)	0.078	0.327	0.24	0.812	-0.563	0.718
Education (X3)	0.25	0.107	2.33**	0.020	0.04	0.459
Farming experience (X4)	0.046	0.023	1.98**	0.048	0.001	0.092
Institutional factors						
Market distance (X5)	-0.018	0.02	-0.87	0.385	-0.057	0.022
Access to extension functionaries (X6)	1.107	0.255	4.34***	0.000	0.607	1.607
Access to credit (X7)	1.051	0.276	3.81***	0.000	0.51	1.593
Participate in training (X8)	0.603	0.25	2.41**	0.016	0.114	1.092
Socio-cultural factor						
Member in local area (X9)	0.54	0.239	2.26**	0.024	0.071	1.009
Climatic factor						
Access to climate change information (X10)	2.462	0.303	8.14***	0.000	1.869	3.055
Economic factors						
Family size (X11)	-0.004	0.087	-0.05	0.963	-0.174	0.166
Adult Cattle Unit (X12)	0.197	0.112	1.76	0.078	-0.022	0.417
Off-farm income (X13)	6.03E-07	6.83E-07	0.88	0.377	-7.35E-07	1.94E-06
On-farm income(X14)	3.64E-06	9.70E-07	3.76***	0.000	1.74E-06	5.54E-06
Farmers category (X15)	-0.813	0.341	-2.390**	0.017	-1.481	-0.146
/cut1	4.721804	1.28812		2.19713	7.24648	(Ancillary parameters)
/cut2	7.726302	1.33813		5.10363	10.349	
Number of observations	432					
LR chi2(15)	411.12					
Prob > chi2	0.00					
Pseudo R2	0.4371					
Log likelihood	-264.74074					

*Note:***,**& * represent significance at p≤0.01, p≤ 0.05 & p≤ 0.10 respectively*

Several variables were found to be statistically non-significant, suggesting their minimal or undetectable influence on the dependent variable within this study. These include age (p = 0.405), gender (p = 0.812), market distance (p = 0.385), family size (p = 0.963), adult cattle unit (p = 0.078), and off-farm income (p = 0.377). The age of the household head did not significantly impact the outcomes (p = 0.405), likely due to a threshold effect where age alone is insufficient to influence decision-making. Older household heads may face challenges in adopting new practices without exposure to modern technologies or climate change risks. Gender (p = 0.812) also showed no significant effect, suggesting that, in this context, both male and female household heads may have similar access to information and decision-making power. Market distance (p = 0.385) and family size (p = 0.963) did not significantly influence adoption behaviour, potentially because other factors like income, access to resources, and exposure to information may be more critical. The adult cattle unit (p = 0.078) showed marginal non-significance, indicating that cattle ownership may not directly impact CSA adoption, particularly in households where crop production is prioritized. Finally, off-farm income (p = 0.377) was non-significant, likely because off-farm income is less stable and less tied to agricultural decision-making, with farming practices being the primary focus for climate resilience.

4.7. IMPACT OF CLIMATE-SMART AGRICULTURAL PRACTICES ON LIVELIHOOD VULNERABILITY OF THE SAMPLE HOUSEHOLDS

The simple regression analysis was conducted to explore the relationship between climate-smart agricultural practices and livelihood vulnerability among households in the study area. The dependent variable in the model was livelihood vulnerability, which refers to the degree of susceptibility of households to the negative impacts of climate change. The key independent variable, CSA practices, was used to assess the extent to which their adoption influences vulnerability.

Table 4.25 presents the results of a regression analysis examining the impact of climate-smart agricultural practices (CSAPs), access to information on climate change, and access to training on CSA practices on the livelihood vulnerability of the sample households. The dependent variable, livelihood vulnerability, is represented by the Livelihood Vulnerability Index (Y). The constant term has a coefficient of 0.171602 with a standard error of 0.005834. The t-value of 29.41 and a p-value of 0.000 indicate that this coefficient is statistically significant, providing the baseline level of livelihood vulnerability when all other predictors are set to zero.

Table 4.25: Impact of climate-smart agricultural practices on livelihood vulnerability of the sample households

Livelihood Vulnerability Index (Y)	**Coefficient**	**Std. Error**	**t**	**P>|t|**
Constant	0.171602	0.005834	29.41	0
Climate smart agricultural practices(X1)	-0.00341	0.000996	-3.42	0.001***
Access to information on climate change (X2)	-0.01319	0.004524	-2.92	0.004***
Access to training on CSA practices (X3)	-0.01384	0.006139	-2.25	0.025**
F value	0.1646			
Prob > F	0.0000			
R^2	0.1646			
Adjusted R^2	0.1587			

*Note:***,**& * represent significance at p≤0.01, p≤ 0.05 & p≤ 0.10 respectively*

For climate-smart agricultural practices (X1), the coefficient is -0.00341, with a standard error of 0.000996 and a t-value of -3.42 (p = 0.001). This negative coefficient suggests that the adoption of CSAPs is associated with a reduction in livelihood vulnerability. Specifically, each unit increase in the adoption of CSAPs leads to a 0.00341 decrease in livelihood vulnerability. The negative sign and statistical significance indicate that CSAPs contribute to enhancing resilience and mitigating vulnerability to climate-related risks. The variable for access to information on climate change (X2) shows a coefficient of -0.01319 with a standard error of 0.004524, and the t-value is -2.92 (p = 0.004). This result suggests that access to information on climate change significantly reduces livelihood vulnerability. Households with better access to climate change information are more likely to adopt adaptive strategies, thereby decreasing their vulnerability to climate-related hazards. Similarly, access to training on CSA practices (X3) has a negative coefficient of -0.01384, with a standard error of 0.006139, and a t-value of -2.25 (p = 0.025). This indicates that training in climate-smart agricultural practices also significantly reduces livelihood vulnerability. The findings imply that the knowledge and skills gained through such training enable households to implement adaptive measures that enhance their capacity to cope with climate variability and its associated risks. The F-value for the model is 0.1646, and the associated p-value (Prob > F) is 0.0000, which confirms the overall statistical significance of the regression model. This suggests that the independent variables (CSAP adoption, access to information, and access to training) collectively have a significant impact on the livelihood vulnerability of the households. The R-squared value of 0.1646 indicates that the model

explains approximately 16.46 per cent of the variation in livelihood vulnerability, while the Adjusted R-squared of 0.1587 adjusts for the number of predictors and offers a slightly lower explanation of variance. This suggests that while the model identifies important factors influencing livelihood vulnerability, other unmeasured variables may also contribute to the variability in the dependent variable. It can be indicated that the adoption of climate-smart agricultural practices, access to climate change information, and access to training on CSA practices are significant factors in reducing livelihood vulnerability. These results underscore the importance of promoting these factors to enhance the resilience of households in the face of climate change. However, given the relatively low explanatory power of the model, further research incorporating additional variables may provide a more comprehensive understanding of the determinants of livelihood vulnerability.

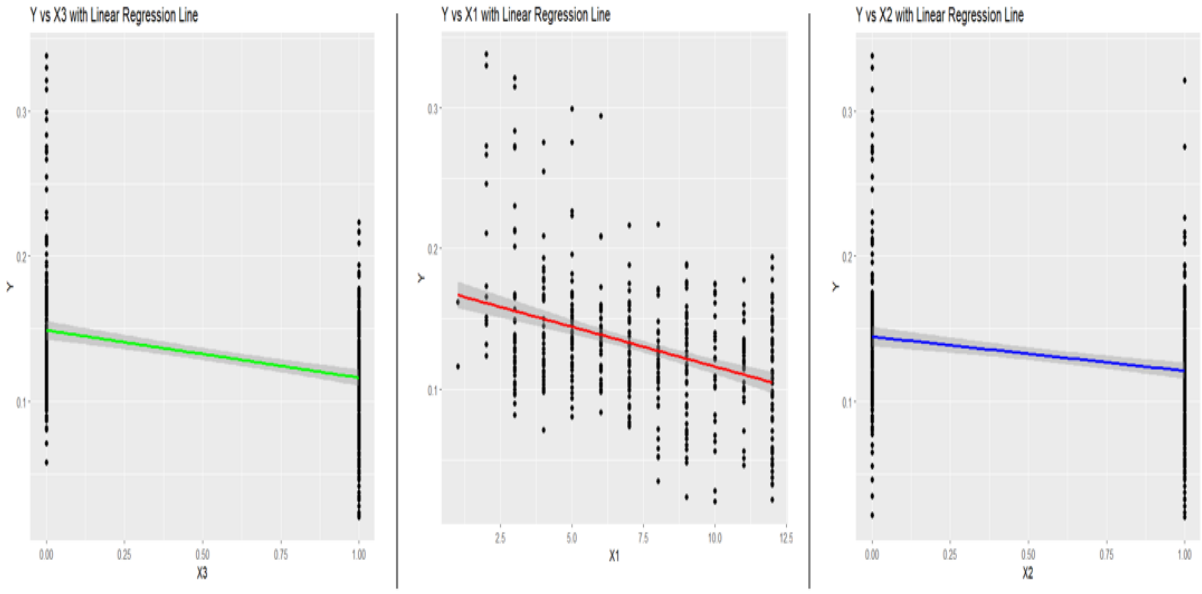


Figure 4.11: Linear graphical representation of the relationship between dependent and independent variables

4.8. CONSTRAINTS FACED BY THE ADOPTERS OF CLIMATE-SMART AGRICULTURAL PRACTICES IN THE STUDY AREA

Farmers' ability to adapt to climate change is hindered by various barriers that limit the adoption of Climate-Smart Agricultural Practices (CSAPs). The constraints faced by adopters of climate-smart agricultural practices in the temperate region were analyzed and categorized into distinct thematic areas. Kendall's W, which ranges from 0 (no agreement) to 1 (perfect agreement), revealed varying levels of concordance among different adopter groups regarding the constraints in adopting climate-smart agricultural practices. The

Kendall's 'W' values for each adopter level were calculated to assess the level of agreement among farmers on the constraints they face. The findings are summarized in Table 4.26.

The Kendall's W coefficient of concordance was found to be 0.52, 0.43, and 0.70 for low, moderate, and high adopters, respectively, and was statistically significant at the 1 per cent level. This result led to the rejection of the null hypothesis, favouring the alternative hypothesis that there is agreement among farmers regarding the constraints in adopting climate-smart agricultural practices (CSAPs). Notably, this level of agreement persisted across varied climatic conditions, suggesting that despite differences in local climates, farmers perceive similar barriers to adopting CSAPs. An overall Kendall's W value of 0.43 indicates a 43 per cent agreement across all respondents in the study area regarding the ranking of these constraints. The degree of agreement varied among adopter groups, with moderate adopters showing 43 per cent concordance and high adopters exhibiting the strongest agreement at 70 per cent. Low adopters exhibited moderate agreement (W = 0.52), indicating somewhat consistent perceptions of major challenges with some variability. Moderate adopters had lower agreement (W = 0.43), reflecting more diverse perspectives, possibly due to context-specific challenges. High adopters demonstrated strong agreement (W = 0.70), likely due to shared experiences in resource utilization and technological adoption. Overall, the agreement across all groups was moderate (W = 0.43), showing some commonality in perceived constraints but notable differences between adopter categories. These findings highlight that while farmers generally share similar perceptions of challenges, the level of agreement increases with the extent of adoption, likely reflecting the uniformity of experiences faced by high adopters of CSAPs.

4.8.1. Soil and Crop Management Constraints

An analysis of the Table 4.26 reveals that low soil fertility is consistently ranked as the most critical constraint across all adoption levels, highlighting its profound impact on agricultural productivity. With an overall mean score of 3.72, low soil fertility remains a major concern for farmers, as it directly affects crop yields and soil health. The severity of this constraint is evident across all adopter categories, although it was most pronounced among low adopters (M=3.84), who may lack access to modern inputs or technologies that can help mitigate soil fertility issues. This indicates that improving soil fertility should be a priority in promoting sustainable agricultural practices, especially for low adopters who may struggle the most with this issue. The non-availability of improved crop varieties was a significant barrier to enhancing productivity, with an overall mean of 3.44. Access to high-

yielding and resilient crop varieties is critical for farmers, especially in the context of climate change and increasing environmental challenges. Improved crop varieties not only offer higher yields but also possess traits such as drought resistance and pest resistance, which can make farming more sustainable in the long term. The relatively second high ranking of this constraint underscores the need for farmers to have better access to improved seeds that are both high-yielding and suited to the local environmental conditions. Addressing this gap in access to quality crop varieties could significantly enhance agricultural productivity and food security. Lack of adequate organic matter and higher pest & disease incidence were also identified as significant constraints faced by all adopter categories. With an overall mean score of 3.38, reflecting the critical role organic matter plays in maintaining healthy soils. Organic matter is essential for improving soil structure, enhancing moisture retention, and fostering soil microbial activity, all of which are vital for sustainable agriculture. Moreover, higher pest and disease incidences (M=3.38) were common, exacerbating productivity challenges. The increased presence of pests and diseases can reduce yields and increase the need for chemical interventions, thereby raising costs and reducing environmental sustainability. These constraints are particularly relevant for more intensive farming systems, where maintaining soil health is a continuous challenge. Lastly, lack of awareness on soil testing and soil test-based fertilizer recommendations (STBF), with an overall mean of 3.11, emerged as a notable constraint. The rankings for this constraint were relatively consistent across adopter levels, indicating that farmers across all categories may face a common challenge of limited knowledge regarding soil testing and the importance of using fertilizers based on soil health. This lack of awareness may prevent farmers from optimizing fertilizer use, leading to inefficient practices and suboptimal crop yields. Enhancing education and outreach on the importance of soil testing and the application of STBF can help farmers make more informed decisions, improving soil health and crop productivity. Overall, these constraints—low soil fertility, non-availability of improved crop varieties, inadequate organic matter, pest and disease pressures, and lack of awareness regarding soil testing—highlight key barriers to achieving sustainable agricultural practices. Addressing these challenges can significantly improve agricultural productivity, resilience, and sustainability, benefiting farmers across all adoption levels.

4.8.2. Financial Constraints

The perusal of the data presented in the Table 4.26 reveals that the lack of easy access to credit was the most pressing financial challenge for farmers across all adopter categories. With

a notable overall mean score of 3.59, this issue underscores the persistent difficulties faced by farmers in securing timely and adequate financial resources. The financial strain becomes more pronounced in the context of climate variability, which increases the demand for adaptive inputs such as drought-resistant seeds, efficient irrigation systems, and climate-smart technologies. The barriers contributing to this challenge include limited availability of institutional finance, complex documentation requirements, and protracted loan approval procedures. These factors not only delay access to funds but also impede farmers' ability to invest in modern agricultural technologies and practices, adversely impacting their productivity and economic well-being. To mitigate these challenges, it is crucial to streamline credit disbursement mechanisms, simplify procedural requirements, and implement effective outreach initiatives to enhance accessibility to institutional finance. Following this, the second-ranked constraint was the lack of provision for subsidies, which has an overall mean score of 3.53. This highlights the pivotal role of government intervention in supporting agricultural development, particularly in vulnerable and marginalized regions. Subsidies play a vital role in reducing the financial burden on farmers, enabling them to access essential inputs such as quality seeds, fertilizers, and machinery. The inadequacy or absence of robust subsidy programs limits farmers' capacity to adopt sustainable and productive climate-smart agricultural practices. Addressing this issue requires the design and execution of targeted subsidy programs tailored to meet the specific needs of the farming community. Such initiatives can boost resource availability, promote the adoption of innovative technologies, and contribute to the overall economic resilience and empowerment of farmers. Other critical constraints identified include low support from financial institutions (M=3.51), lengthy loan sanctioning processes in banks (M=3.49), high-interest rates on loans (M=3.47), and insufficient personal funds (M=3.40). These challenges collectively highlight the systemic barriers within the agricultural finance ecosystem that hinder farmers' ability to secure and utilize financial resources effectively. Addressing these constraints will require a multi-pronged approach, including improved institutional support, policy reforms, and financial literacy programs, to build a more inclusive and accessible financial infrastructure for the agricultural sector.

4.8.3. Economic constraints

The data presented in the Table 4.26 indicates that, at the overall level, high input costs emerged as the most significant constraint, with a mean score of 4.02. This observation highlights the substantial financial burden faced by farmers in procuring essential agricultural resources, including improved seed varieties such as drought-resistant seeds, efficient

irrigation systems such as drip irrigation, fertilizers, machinery, and other critical inputs for crop production. The rising costs of these inputs impede farmers' ability to adopt modern and efficient farming practices, consequently hampering productivity and operational efficiency. This constraint across different adopter categories underscores the pressing need for interventions such as cost-reduction strategies and financial assistance programs to alleviate these challenges. Regarding small landholding, the issue was identified as the highest-ranked constraint among both low adopters (M= 4.09) and moderate adopters (M= 4.02), reflecting its substantial impact on these groups. At the overall level, small landholding was ranked as the second most critical challenge, with a mean score of 4.00. The limitations associated with small and fragmented landholdings include reduced economies of scale, challenges in utilizing advanced machinery, and restrictions in implementing climate-smart agricultural practices. These limitations significantly affect the efficient use of resources and overall agricultural productivity across different adopter categories. Uncertain returns were ranked as the third most significant constraint, with a mean score of 3.50 at the overall level, and this ranking was consistent across all adopter categories. Uncertainty in returns creates financial instability, discouraging farmers from making long-term investments in innovative or sustainable farming practices. The findings suggest that small landholders face unique disadvantages, particularly in optimizing production processes or integrating advanced agricultural technologies due to constraints on space and resources. Addressing these issues necessitates targeted policy interventions, such as land consolidation programs, cooperative farming initiatives, and the provision of subsidized inputs. Such measures can significantly enhance the sustainability and productivity of agricultural systems, fostering resilience and economic empowerment for the farming community.

4.8.4. Administrative and Institutional Constraints

The analysis of administrative and institutional constraints reveals several critical barriers that hinder farmers' ability to achieve sustainable and efficient agricultural practices. Among these constraints, lack of legal and policy frameworks emerged as the most pressing issue, with an overall mean score of 3.59. This highlights a significant gap in the institutional and regulatory structures necessary to support agricultural development, particularly in regions facing unique challenges such as climate change, limited financial resources. The absence of robust legal and policy frameworks leaves farmers without clear guidelines or protections, affecting their ability to access institutional finance, adopt innovative technologies, or participate in structured markets. The lack of climate-centric policies

exacerbates vulnerabilities, as farmers lack institutional support to mitigate or adapt to climate-related challenges effectively. At the overall level second major constraint was the lengthy processes involved in loan sanctioning, which also recorded a mean score of 3.54. This reflects the procedural inefficiencies that delay access to financial resources, thereby limiting farmers' capacity to invest in timely inputs, advanced machinery, or climate-smart agricultural practices. For instance, cumbersome documentation requirements and extended approval times deter many farmers from seeking institutional credit, forcing them to rely on informal and often exploitative financial sources. Such delays are particularly detrimental during critical agricultural phases, such as sowing and harvesting, where timely financial support is essential. Equally significant is the constraint of inadequate assistance from national and local authorities in addressing climate-related issues, which also scored a mean of 3.54. This underscores the insufficient support systems available to farmers for managing the adverse impacts of climate variability, such as erratic rainfall, prolonged droughts, or pest infestations. The lack of coordinated efforts to disseminate information, provide training, or implement mitigation strategies leaves farmers ill-prepared to cope with these challenges. The absence of institutional guidance in adopting climate-smart agricultural practices further limits the resilience and sustainability of farming systems in vulnerable regions. These constraints were consistent across adopter categories, indicating systemic inefficiencies in administrative and institutional frameworks. The findings emphasize the need for targeted interventions to address these barriers. For instance, developing comprehensive legal and policy frameworks tailored to the specific needs of small-scale and climate-vulnerable farmers can provide clear operational guidelines and protections. Streamlining loan approval processes through digital platforms, reducing documentation requirements, and ensuring timely disbursement of funds can enhance farmers' access to institutional credit. Moreover, increasing institutional focus on climate-related assistance by strengthening local extension services, conducting regular climate adaptation training, and facilitating access to climate-resilient technologies can significantly mitigate the adverse impacts of climate change.

4.8.5. Knowledge and Training Constraints

The analysis of knowledge and training constraints reveals significant barriers impeding the adoption of climate-smart agricultural practices among farmers. A critical challenge identified is the lack of knowledge about adaptive practices, with an overall mean (M=3.90) indicating its severity. This constraint is most pronounced among low adopters (M=3.87) and moderate adopters (M=4.01). These findings highlight a substantial gap in farmers' understanding of

implementing climate-resilient practices, limiting their ability to make informed decisions about appropriate adaptive strategies to mitigate climate change impacts. Another key barrier is the lack of awareness regarding the latest agricultural technologies, which ranks as the second most significant constraint at an overall mean of 3.72. Low adopters rated this barrier at a mean of 3.68, while moderate adopters reported a slightly lower mean of 3.61. This underscores the necessity for targeted interventions, including structured training programs and practical demonstrations, to enhance farmers' knowledge and equip them with the competencies required for the effective adoption of innovative climate-smart practices. At an overall level lack of technical skills (M=3.68) ranked third followed by inadequate training (M= 3.53), and poor information dissemination (M=3.40) further exacerbated the problem, underscoring the need for targeted educational programs and practical demonstrations.

4.8.6. Resource Constraints

Resource constraints were another significant challenge affecting the adoption of these practices. At an overall level (M= 3.74) resource limitations, particularly water scarcity, was a major hindrance. Lack of water availability for low adopters (M=3.55), moderate adopters (M=3.77), and high adopters (M=3.98) emerged as a critical resource constraint, especially in areas prone to droughts or erratic rainfall patterns. Water scarcity limits the effectiveness of many climate-smart practices, particularly those requiring reliable irrigation systems, and thus, access to water resources is essential for the successful adoption of these practices. High costs of fertilizers and other inputs ranked as the second most severe constraint at an overall level (M=3.35). While limited land availability was less critical overall (M=3.07), it remains a significant issue for smallholder farmers, restricting their capacity to adopt CSAPs.

4.8.7. Labor and Migration Constraints

Labor and migration constraints represent significant challenges to the adoption of climate-smart agricultural practices, particularly due to labour shortages. These shortages ranked highest in this category, with an overall mean score of 3.36, reflecting the substantial impact on agricultural operations. Low adopters reported a mean score of 3.24, while moderate adopters reported a higher mean score of 3.39, indicating a more pronounced challenge among the group. The resulting labour scarcity leads to increased labour costs for agricultural activities, making it difficult for farmers to carry out essential tasks. Climate-smart practices, such as mulching, composting, and irrigation, typically require additional labour, and high labour costs become a significant financial burden, especially for resource-

constrained farmers, limiting their ability to sustain these labour-intensive practices. The situation is further aggravated by youth migration, which has an overall mean score of 3.34, diminishing the availability of skilled labour in rural areas. Migration of youth, with mean scores of 3.25 for low adopters and 3.39 for moderate adopters, depletes the local labour force and restricts the ability to implement labour-intensive climate-smart practices. This trend disproportionately affects time-sensitive farming techniques that are necessary for improving climate resilience. The migration of younger generations often leaves households with fewer labour resources, complicating the adoption of these practices, which are crucial for enhancing agricultural sustainability in the face of changing environmental conditions. In addition, high labour costs, with an overall mean score of 3.33, further strain farmers' financial resources, hindering their ability to adopt and maintain labour-intensive CSAPs. The compounded effect of labour shortages and increased labour costs underscores the urgent need for interventions that can address these barriers, facilitate labour availability, and make labour-intensive climate-smart practices more accessible to farmers.

4.8.8. Infrastructure Constraints

The most critical infrastructure constraint identified was the lack of irrigation facilities, which emerged as the highest-ranked issue across all adopter categories, with an overall mean score of 3.43. High adopters, in particular, reported the most severe impact (M = 3.54), highlighting the significant role reliable water sources play in implementing climate-smart agricultural practices (CSAPs) such as micro-irrigation and mulching. Following irrigation, poor supply of uniform electricity was the second most severe constraint, with an overall mean of 3.33. It was notably problematic for low and moderate adopters (M = 3.47 and 3.45, respectively), as unstable electricity disrupts crucial agricultural activities like irrigation and crop processing. Limited marketing access was also a significant challenge, ranking third with an overall mean of 3.35, and particularly affecting low and moderate adopters (M=3.44 and 3.48, respectively), who struggle to sell their produce at fair prices, limiting their financial capacity to invest in climate-smart technologies. The lack of transportation facilities (M=3.29) and non-availability of input on time (M=3.19) were ranked lower but still posed significant barriers, especially for low adopters. These issues hinder access to essential markets, resources, and technologies necessary for the adoption of sustainable agricultural practices. Addressing these ranked infrastructure constraints, particularly in irrigation, electricity, and marketing access, is crucial for facilitating the widespread adoption of CSAPs, requiring targeted interventions and improvements to infrastructure, policy, and resource availability.

Table 4.26: Constraints faced by the farmers in adopting climate-smart agricultural practices in the study area

Constraints	Low adopters		Moderate adopters		High adopters		Overall	
	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank
Soil and Crop Management Constraints								
Inadequate organic matter	3.32	III	3.39	III	3.46	II	3.38	III
Low fertility of the soil	3.84	I	3.78	I	3.48	I	3.72	I
Non-availability of improved crop varieties	3.39	II	3.48	II	3.45	III	3.44	II
Lack of awareness on soil testing & STBF (Soil Test Based Fertilizer Recommendation	3.01	IV	3.27	IV	3.09	IV	3.11	IV
Higher pest & disease incidence	3.32	III	3.39	III	3.46	II	3.38	III
Financial Constraints								
Insufficient Own Fund	3.53	IV	3.39	V	3.23	V	3.40	VI
No Easy Access to Credit	3.59	I	3.49	I	3.70	I	3.59	I
High-Interest Rates	3.51	V	3.39	V	3.50	III	3.47	V
Lengthy Process of Loan Sanctions in Banks	3.55	III	3.44	III	3.46	IV	3.49	IV
Low Support by Financial Institutions	3.58	II	3.42	IV	3.50	III	3.51	III
Lack of Provision of Subsidies on Planting Materials	3.55	III	3.47	II	3.57	II	3.53	II
Economic constraints								
Small landholding	4.09	I	4.02	I	3.85	II	4.00	II
Uncertain returns	3.51	III	3.44	III	3.57	III	3.50	III
High costs of inputs	3.89	II	3.86	II	4.37	I	4.02	I
Administrative and Institutional Constraints								
Too much documentation	3.42	IV	3.37	IV	3.33	III	3.38	III
Lengthy process of loan sanctions in bank	3.57	III	3.47	III	3.58	I	3.54	II
Lack of legal and policy frameworks of government	3.75	I	3.62	I	3.33	III	3.59	I
Inadequate assistance from national and local authorities with climate-related issues	3.61	II	3.59	II	3.38	II	3.54	II

Constraints	Low adopters		Moderate adopters		High adopters		Overall	
	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank
Knowledge and Training Constraints								
Lack of awareness about climate change issues	3.45	V	3.36	VI	3.33	VII	3.39	VII
Inadequate training and demonstration	3.55	III	3.47	V	3.57	IV	3.53	IV
Lack of awareness of the latest technologies	3.68	II	3.61	III	3.88	II	3.72	II
Poor information dissemination about the technologies	3.43	VI	3.34	VII	3.41	VI	3.40	VI
No extension activities about CSA Technologies	3.45	V	3.55	IV	3.57	V	3.51	V
Lack of knowledge about adaptive practices of CSA	3.87	I	4.01	I	3.83	III	3.90	I
Lack of technical skills to adopt CSAPs	3.48	IV	3.67	II	3.94	I	3.68	III
Resource Constraints								
Inadequate land holdings for adoption of CSAPs	2.99	III	3.12	III	3.13	II	3.07	III
High cost of fertilizer and other inputs	3.43	II	3.48	II	3.10	III	3.35	II
Lack of water availability	3.55	I	3.77	I	3.98	I	3.74	I
Labor and Migration Constraints								
High rate of wages for labourers	3.24	III	3.39	II	3.39	II	3.33	III
Shortage of labourers	3.45	I	3.48	I	3.10	III	3.36	I
Migration of youth	3.25	II	3.39	II	3.40	I	3.34	II
Infrastructure Constraints								
Limited marketing access	3.44	II	3.48	I	3.10	IV	3.35	II
Lack of improved communication facilities and farmers' organization	3.23	V	3.39	IV	3.39	II	3.32	IV
Lack of necessary transportation facilities	3.18	VI	3.36	V	3.35	III	3.29	V
Poor supply of uniform electricity	3.47	I	3.45	II	3.02	V	3.33	III
Lack of irrigation facilities	3.35	III	3.42	III	3.54	I	3.43	I
Non-availability of input on time	3.28	IV	3.30	VI	2.95	VI	3.19	VI
Number of observations	**173**		**132**		**127**		**432.00**	
Kendall's W	**0.52**		**0.43**		**0.70**		**0.43**	
Chi-square	**323.706***		**203.623***		**321.896***		**663.769***	
df.	**36**		**36**		**36**		**36**	

**represents significance at 1 per cent*

Chapter - 5

SUMMARY AND CONCLUSION

This chapter presents a comprehensive summary of the research study, encapsulating its key findings. It systematically outlines the policy implications derived from the conclusions drawn through a comprehensive analysis of the data. These implications are grounded in the research findings and offer valuable perspectives for policy development and decision-making.

5.1. INTRODUCTION

Climate change presents a critical global challenge, posing significant risks to food security, rural livelihoods, and the long-term viability of agriculture (Kumara *et al*., 2023). Its widespread impact, which includes erratic rainfall, frequent droughts, severe flooding, rising temperatures, melting glaciers, and the decline of biodiversity, threatens farming communities globally. Farmers, especially in rural areas where agriculture is the main economic activity, bear the brunt of these changes (Datta *et al*., 2022). The rapid growth of the global population further heightens the need for increased agricultural production to meet demand, reduce food waste, and ensure access to nutritious food for all. Agriculture and climate change are interlinked, with agriculture both contributing to and being affected by climate shifts. The sector must adapt to these changes while also taking steps to mitigate its environmental impact. This challenge is exacerbated by the growing scarcity of key resources like water, energy, and arable land. Variability in weather patterns, including temperature increases and shifts in precipitation, adversely affects crop yields, thereby impacting the livelihoods of those reliant on agriculture (Shumetie and Yismaw, 2018). Therefore, adapting agricultural practices to the changing climate is essential to protect food production and enhance resilience. One viable strategy to address these concerns is Climate-Smart Agriculture (CSA), a concept aimed at improving farming practices to address climate risks while promoting sustainability, increased productivity, and reduced greenhouse gas emissions (Lipper *et al*., 2014). CSA practices such as agroforestry, crop rotation, soil conservation, and efficient water use help to improve food security, enhance farmer incomes, and promote climate resilience (Mutenje *et al*., 2019). By integrating these practices into farming systems, farmers can manage climate risks and ensure long-term agricultural sustainability. In

mountainous regions like Himachal Pradesh, where agriculture is a key livelihood for 70 per cent of the population, climate change presents even greater risks due to the region's fragile ecosystems and challenging topography. Agriculture forms a substantial part of Himachal Pradesh's economy, making it vital to assess and mitigate the risks of climate change. Implementing CSA practices in these areas can enhance the resilience of farmers and reduce their vulnerability to climate-related risks. In consideration of the above the present study entitled “Climate-Smart Agricultural Practices for Climate Change Risk Mitigation in Temperate Region of Himachal Pradesh”, as this zone characterized by its dominance in agriculture and horticulture, prominence in agriculture and horticulture, is highly vulnerable to the detrimental impacts of climate change, which poses significant risks to both agricultural productivity and the livelihoods of the farmers. The study was carried out with the following objectives:

1. To study the livelihood vulnerability of the sample households to climate change.
2. To identify climate-smart agricultural practices adopted by farmers and factors influencing the adoption of climate-smart agricultural practices.
3. To examine the impact of climate-smart agricultural practices on livelihood vulnerability of the sample households.
4. To identify the constraints for adopting climate-smart agricultural practices among farmers.

5.2. METHODOLOGY

The present study, titled "Climate-Smart Agricultural Practices for Climate Change Risk Mitigation in the Temperate Region of Himachal Pradesh," employed a multistage random sampling technique to select respondents within the study area. The region was stratified into two zones: the high hill wet temperate zone and the high hill dry temperate zone. In the first stage, four districts from the wet temperate zone (Shimla, Chamba, Mandi, and Kullu) and two districts from the dry temperate zone (Kinnaur and Lahaul & Spiti) were randomly selected, based on the proportion of their temperate region area. In the second stage, a complete list of blocks from each selected district was compiled, and 30 per cent of blocks were randomly chosen. The third stage involved selecting four panchayats randomly from each chosen block. Finally, in the fourth stage, twelve farmers were randomly selected from each panchayat using an equal allocation method, resulting in a total sample size of 432 respondents across the six districts: Shimla (144), Mandi (48), Chamba (96), Kullu (48),

Kinnaur (48), and Lahaul & Spiti (48). This sampling procedure ensured a comprehensive representation of the region.

To meet the objectives of the present study, data collection was carried out during the agricultural year 2023-2024, incorporating both primary and secondary sources. A structured interview schedule was developed following an extensive review of relevant literature and consultations with experts in the field. After pre-testing the schedule with non-sample respondents from the wet and dry temperate zones, necessary modifications were made, and the final version was employed for data collection. Primary data were collected through personal interviews with farmers, focusing on their socio-economic status, including family structure, size, literacy level, landholding size, and years of farming experience. Additional information was gathered on the adoption of climate-smart agricultural practices, the factors influencing these practices, and the constraints faced by farmers in their implementation. Secondary data were sourced from various publications, government departments such as the Department of Agriculture Cooperation and Farmers Welfare, the Department of Horticulture, and the Directorate of Economics and Statistics, as well as academic databases and meteorological records from the India Meteorological Department in Shimla. These sources provided a comprehensive backdrop for the study's analysis.

A range of mathematical and statistical tools were employed, including measures of central tendency, ratios, percentages, standard deviation, and coefficients of variation. Tabular analysis was used to summarize socio-economic characteristics, cropping patterns, land-use patterns, and investments in irrigation infrastructure among the sampled farmers. The study aimed to assess the livelihood vulnerability of sample households to climate change using two approaches: the LVI-Composite Index Approach and the LVI-IPCC Approach. The Livelihood Vulnerability Index (LVI) developed by Hahn *et al*. (2009) was employed, utilizing a balanced weighted average approach where each subcomponent contributed equally to the overall index. To identify climate-smart agricultural practices (CSA) adopted by farmers and factors influencing their adoption, a composite scoring approach was used. Ordinal logistic regression modeled the relationship between ordered multilevel dependent variables and independent variables influencing CSA adoption. The impact of CSA practices on livelihood vulnerability was analyzed using multiple linear regression, while Kendall’s W, a non-parametric test, was employed to assess the level of agreement among farmers regarding ranked constraints to CSA adoption.

5.3. MAJOR FINDINGS OF THE STUDY

1. The average family size across all sampled households was 5.44 members. Among the surveyed blocks, Mehla recorded the highest average family size at 6.04 members, followed closely by Rohru with 5.65 members and Gohar with 5.60 members. In contrast, the smallest average family size was observed in the Jubbal & Kotkhai block, where households averaged 4.98 members.
2. The majority of family members in the surveyed households fell within the economically active age group (15–65 years), with an overall average of 2.15 males and 2.00 females per household. Among the blocks, Mehla recorded the highest number of economically active individuals, averaging 2.35 males and 2.23 females. This suggests a strong labour potential in the Mehla block, which could be advantageous for workforce-driven initiatives or development programs.
3. The overall sex ratio in the study area was 896 females per 1,000 males, reflecting a noticeable gender imbalance. Among the blocks surveyed, Jubbal & Kotkhai reported the lowest sex ratio at 811, highlighting a significant disparity. In contrast, Gohar block recorded the highest sex ratio of 949, indicating relatively better gender parity in that region.
4. A slight majority of respondents (53.24%) reported living in nuclear families, while 46.76 per cent belonged to joint families. This distribution suggests a gradual shift toward nuclear family structures in the study area, possibly influenced by factors such as urbanization, changing socio-economic dynamics, and evolving lifestyle preferences.
5. In nuclear family the highest proportion was recorded in Jubbal & Kotkhai block (66.67%), followed by Gohar block (60.42%) and Chamba block (58.33%). This trend highlights a preference for smaller family units in these regions, possibly linked to socio-economic or lifestyle changes.
6. In Joint Family Mehla block had the largest proportion of joint families (56.25%), followed by Rohru block (54.17%). This suggests traditional household structures are more prevalent in these areas, likely driven by cultural norms or agricultural labor demands.
7. A significant proportion of males (66.00%) achieved education up to the senior secondary level and the majority of females (57.00%) reached the higher secondary level, indicating a disparity in educational attainment between genders.

8. The overall literacy rate in the study area was 87.16 per cent, with males exhibiting a higher literacy rate of 88.94 per cent, compared to 85.22 per cent for females. The highest literacy rates were observed in Jubbal & Kotkhai (91.19%) and Theog (90.69%), reflecting relatively stronger educational outcomes in these blocks. In contrast, Lahaul recorded the lowest literacy rate at 80.74 per cent, indicating a potential area for focused educational initiatives and improvements.

9. Agriculture was the dominant livelihood source, contributing 83.39 per cent of the total. Business activities and salaried employment contributed 9.01 per cent and 7.60 per cent, respectively. Kalpa block had the highest reliance on agriculture (86.39%), followed by Gohar (85.08%) and Mehla (85.00%). Jubbal block had the highest proportion of respondents engaged in business activities (10.43%), while Kalpa block had the lowest (6.51%). This variation highlights regional differences in economic dependence, with Kalpa demonstrating the strongest agricultural orientation and Jubbal showing a higher inclination towards business ventures.

10. The highest participation in salaried employment was observed in Theog block (10.69%), followed by Jubbal & Kotkhai (8.59%) and Rohru (8.09%). The average monthly income for those in salaried employment was ₹28,277.29. Rohru reported the highest average income at ₹32,738.10, while Lahaul had the lowest average income at ₹23,611.11, suggesting income disparities across blocks, which could be influenced by factors such as local economic conditions and the availability of high-paying jobs.

11. The overall average number of active workers per household in the study area was 3.63. Nagar block had the highest average number of active workers (4.15), suggesting a larger working population and potentially higher economic output. Gohar (3.77) and Mehla (3.75) blocks also had relatively high numbers of active workers. Theog (3.31) and Jubbal & Kotkhai (3.40) blocks reported the lowest averages, indicating smaller working populations in these regions.

12. The overall average landholding in the study area was 1.16 hectares, with land utilized for agriculture, orchards, and pastures. 42.66 per cent of the total land was used for agricultural purposes, while 46.72 per cent was dedicated to orchards. Among agricultural land, only 17.36 per cent was irrigated, and 19.32 per cent of the orchard area was irrigated, highlighting a significant reliance on rain-fed conditions. Jubbal & Kotkhai block had the highest average landholding at 1.38 ha, followed by Theog (1.33 ha) and Rohru (1.28 ha) blocks. Lahaul block recorded the highest area under agriculture (61.96%), followed by Gohar block (61.53%) and Chamba block

(60.68%). In contrast, Nagar block had the lowest percentage of agricultural land (27.23%). Theog block had the highest area under orchards (63.32%), followed by Jubbal & Kotkhai (62.59%) and Kalpa (62.26%) blocks. Mehla block had the lowest orchard area (27.45%).

13. At the overall level, the cropping intensity was 139.65 per cent. The highest cropping intensity was recorded in Mehla block at 168.66 per cent, followed by Chamba block (168.46%) and Gohar block (164.22%). Lahaul block had the lowest cropping intensity of 100 per cent, primarily due to the restricted cultivation practices limited to a single cropping season, pointing to fewer cropping opportunities in the region.

14. The highest Adult Cattle Units were found in Mehla block with a value of 2.73, followed by Chamba (2.44) and Nagar (2.44) blocks. Cow rearing was the most common form of livestock farming in the study area. Livestock distribution varies across blocks, with improved cows dominating in Gohar (47.31%) and bullocks most common in Jubbal & Kotkhai (35.43%). Mehla has the highest share of goats (5.95%) and sheep (6.26%).

15. Traditional kuhls, gravity-fed irrigation systems prevalent in hilly and mountainous regions, were the most cost-efficient, with an average investment of ₹2,553.24. These systems are characterized by low infrastructure requirements and minimal maintenance, making them economically viable for small-scale agricultural practices. Conversely, tanks, which involve the construction of artificial reservoirs and associated infrastructure, were found to be the most capital-intensive irrigation method, with an average investment of ₹41,527.78. The investment in tanks was particularly high in the Jubbal & Kotkhai block, where the average cost reached ₹55,104.17, reflecting the higher complexity of tank construction and maintenance. Overall, total irrigation investments averaged ₹1,26,020.84, with Theog (₹1,54,041.67) having the highest and Mehla (₹89,229.17) the lowest. The findings highlight the importance of region-specific irrigation strategies to optimize agricultural productivity.

16. The composite LVI revealed significant variations in vulnerability across the blocks. Lahaul block was the most vulnerable with an LVI of 0.468, followed by Mehla block (0.419). The LVI-based assessment categorized the study area into three vulnerability zones: low (Gohar and Rohru), moderate (Theog, Jubbal & Kotkhai, Chamba, Nagar, and Kalpa), and high (Mehla and Lahaul). Blocks in the high vulnerability zone exhibited greater vulnerability, particularly in major components such as socio-

demographic factors, health, social networks, susceptibility to natural disasters and severe challenges in water availability.

17. The overall LVI-IPCC scores highlighted significant differences in vulnerability across the study area, with Lahaul (-0.094) and Kalpa (-0.095) exhibiting the highest levels of vulnerability, reflecting lower adaptive capacity and greater exposure to socio-environmental stressors. In contrast, Rohru (-0.130) and Theog (-0.135) demonstrated the lowest vulnerability scores, indicating better resilience due to higher adaptive capacity and lower sensitivity to climate-related impacts. These findings emphasize the varying levels of vulnerability, driven by a complex interplay of exposure, sensitivity, and adaptive capacity.

18. The study indicated variability in the adoption rates of CSA practices, with higher adoption observed for cost-effective practices such as composting and FYM (85.90%) and mulching (72.90%). To enhance agricultural productivity and ensure long-term food security, it is recommended that farmers adopt mulching techniques suited to their specific conditions. Mulching materials such as crop straw, plastic film, and sand help conserve soil moisture, regulate soil temperature, and reduce erosion. These practices improve soil microbiology and plant growth by creating favorable soil conditions. For instance, in regions with high temperatures, straw mulch can help cool the soil, while plastic mulch may be more effective in cooler climates for promoting early plant growth. However, factors like material availability, durability, and cost should be considered when choosing the right mulch. Prioritizing sustainable and effective mulching strategies will improve water conservation, boost yields, and support global food security. To promote sustainable agriculture and effective waste management, recycling animal waste through composting and farmyard manure (FYM) should be encouraged, as these methods enhance soil fertility and reduce environmental pollution. Ensuring the proper application dose and frequency is crucial for maximizing benefits and minimizing risks. Further research and field-level validation are necessary to optimize these practices across different agro-climatic conditions.

19. In contrast, more resource-intensive practices, including micro-irrigation, exhibited lower adoption rates, with only 35.60 per cent of respondents implementing such systems. These findings suggest that economic feasibility plays a significant role in the uptake of CSA practices, with farmers more likely to adopt low-cost, less capital-intensive methods. Targeted interventions are essential to overcome the economic

challenges faced by farmers. It is recommended that the government and NGOs focus on providing financial support mechanisms, including subsidies, low-interest credit schemes, and public-private partnerships, to make micro-irrigation systems more accessible and affordable. Furthermore, promoting low-cost, locally adaptable irrigation technologies, coupled with mobile-based advisory services, can help increase awareness and drive wider adoption. Strengthening extension services and demonstrating the long-term cost-effectiveness and yield benefits of micro-irrigation will be crucial in ensuring the sustainable scaling up of these practices.

20. The study found that 40.00 per cent of respondents were low adopters, 30.60 per cent were moderate adopters, and 29.40 per cent were high adopters of CSA practices, indicating a need for strategies to enhance adoption levels. To enhance the overall effectiveness of CSA, it is recommended to focus on raising awareness about integrating sustainable agricultural practices and improving access to training and resources. Additionally, further research should explore the impact of CSA practices on farm productivity, income, and environmental sustainability, as this will help demonstrate their long-term benefits and encourage broader adoption.

21. The analysis of factors affecting the adoption of climate-smart agricultural practices through ordered logistic regression indicates that education, farming experience, access to extension services, access to credit, participation in training, membership in local areas, access to climate change information, on-farm income, and farmer category all significantly impact adoption, with extension services, credit access, and climate information showing particularly strong effects.

22. The regression results indicate that climate-smart agricultural practices, access to information on climate change, and access to training on CSA practices significantly reduce the Livelihood Vulnerability Index (LVI). This underscores the critical role of knowledge dissemination, capacity building, and the integration of adaptive agricultural strategies in mitigating climate-related vulnerabilities and enhancing farm resilience.

23. The key constraints to adopting climate-smart agricultural practices include low soil fertility, lack of credit access, small landholdings, and inadequate water availability, with high adopters facing more significant challenges related to infrastructure and financial constraints. The overall Kendall's W values suggest moderate to strong agreement across different adopter groups, with high adopters ranking some constraints, such as access to water, more severely.

5.4. CONCLUSIONS

The findings of this study provide a comprehensive understanding of the complex challenges and opportunities faced by farmers in the region, shedding light on the diverse factors that contribute to their vulnerability to climate change and their capacity for adaptation. The socio-economic and agricultural characteristics of households in the region reveal both trends and challenges faced by the farming community. A key finding is the variation in family sizes and the changing dynamics between nuclear and joint families. This shift, especially in blocks like Jubbal & Kotkhai and Gohar, suggests a broader socio-economic transformation toward smaller family structures, which may influence labour availability, agricultural practices, and economic needs. The study also highlights the continuing dominance of agriculture as the primary livelihood source, though there is some diversification into business and salaried employment in blocks like Theog and Jubbal & Kotkhai. The reliance on agriculture, particularly in blocks like Kalpa and Gohar, underpins the importance of improving agricultural practices and ensuring efficient land use. The landholding size and crop intensity also reflect opportunities for improved farm productivity, although challenges like irrigation limitations and water availability persist, particularly in areas with lower cropping intensity. The study provides valuable insights into the vulnerability and adaptive capacities of farmers across various blocks in the region. The analysis revealed substantial variation in vulnerability levels, with Lahaul Block being the most vulnerable, followed by Mehla and Chamba. The primary drivers of vulnerability include socio-demographic factors, limited healthcare access, weak social networks, and susceptibility to climatic shocks, especially in areas exposed to extreme climatic conditions such as Lahaul and Kalpa. These areas are particularly sensitive to climate change due to persistent snowfall and low temperatures, exacerbating challenges related to food security, water availability, and livelihoods. A key finding of the study is the critical role of climate-smart agricultural practices in enhancing resilience to climate change. Practices such as fruit-based agroforestry, composting, and mulching demonstrated high adoption rates due to their positive effects on soil health, water retention, and overall farm sustainability. These low-cost and low-maintenance practices are particularly suited for smallholder farmers. Conversely, more resource-intensive practices such as micro-irrigation faced adoption barriers due to the high infrastructural costs and technical complexities associated with their implementation. The regression analysis further

supports the hypothesis that CSA adoption, CSA training, and access to climate-related information significantly reduce the Livelihood Vulnerability Index (LVI), underlining their importance in reducing vulnerability. Farmers who adopted CSA practices, received training, and had access to climate information experienced a significant reduction in vulnerability, highlighting the critical role of education and information dissemination in improving adaptive capacities. Despite the positive potential of CSA practices, several barriers hinder their widespread adoption. The most prominent constraints include soil fertility management issues, financial limitations, and institutional support. Farmers faced challenges with soil fertility, pest and disease management, and the non-availability of improved crop varieties, all of which adversely affected agricultural productivity. Financial constraints, such as limited access to credit and subsidies, further exacerbated these issues by limiting farmers' ability to invest in new technologies or sustainable practices. The study also identified economic limitations, including high input costs and small landholdings, as significant barriers to adoption. Additionally, institutional challenges, such as inefficient loan sanctioning processes and inadequate legal frameworks, hindered farmers' access to critical resources. Interestingly, the study revealed that high adopters of CSA practices experienced a more uniform experience regarding the constraints they face, suggesting that those who have adopted CSA to a higher extent encounter common challenges. This indicates that while the adoption of CSA practices brings benefits, it also requires overcoming significant barriers that can be addressed through comprehensive interventions. Thus, it can be concluded from the findings of the study that climate-smart agricultural practices have significant potential to improve resilience and reduce vulnerability among farmers. The widespread adoption of these practices requires overcoming multiple barriers. A combination of financial support, technical training, infrastructure improvement, and institutional reforms will be crucial for facilitating CSA adoption and enhancing the overall adaptive capacity of farmers in the study area.

5.5. POLICY IMPLICATIONS

- The study highlighted the need for region-specific training programs on low-cost, scalable CSA practices such as composting, mulching, and fruit-based agroforestry, with a focus on practical knowledge in improving soil health, water conservation, pest management, and climate adaptation strategies.

- Financial constraints were identified as a major barrier to CSA adoption, requiring policies aimed at improving access to affordable credit, subsidies, and loans, particularly for smallholder farmers who face challenges due to limited collateral and high interest rates.
- Expanding irrigation infrastructure is crucial for enhancing agricultural productivity, especially with limited water resources. Subsidizing micro-irrigation systems and offering technical assistance and financing options would improve adoption rates of water-efficient systems among smallholder farmers.
- Strengthening agricultural extension services, simplifying legal frameworks, and improving loan sanctioning processes are essential to streamline institutional support, making it easier for farmers to access resources that would aid in adopting CSA practices.
- Investments in research and development to provide sustainable solutions for improving soil fertility, pest management, and crop variety improvements are necessary, with a focus on organic fertilizers and biological pest control methods to facilitate the adoption of environmentally friendly practices.
- Improving access to climate information and early warning systems will help farmers make informed decisions about their agricultural practices, reducing risks associated with extreme weather conditions. Strengthening early warning systems and improving weather forecasts can enhance their planning abilities.
- Strengthening social safety nets through improved healthcare access, social insurance programs, and disaster relief mechanisms will help farmers during climatic shocks, reducing their vulnerability and providing support during adverse conditions.
- Increasing participation in CSA training programs and awareness campaigns, along with offering financial incentives such as subsidies for adopting CSA practices, can motivate farmers to adopt climate-resilient practices, especially in water and soil conservation.
- Promoting education and training opportunities, particularly for women, is critical to bridge the gender gap, empower women in decision-making roles, and equip farmers with the necessary skills to adopt new technologies and CSA practices.
- Policies should focus on making resource-intensive CSA practices, such as micro-irrigation, more affordable and accessible through subsidies and improved technology access, helping farmers overcome barriers to adopting efficient practices.

- Encouraging the diversification of livelihoods by supporting non-agricultural sectors, including skill development programs, microfinance, and local entrepreneurship, can reduce farmers' vulnerability and improve their economic resilience.
- Targeted interventions addressing specific vulnerabilities, such as socio-demographic challenges, health, and exposure to natural disasters, are necessary to reduce overall vulnerability and enhance farmers' adaptive capacity to climate change.
- Enhancing data collection and monitoring mechanisms will improve farmers' access to market information, technical knowledge, and weather patterns, helping them make better-informed decisions that boost productivity and resilience.

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DEPARTMENT OF AGRIBUSINESS MANAGEMENT

DR YS PARMAR UNIVERSITY OF HORTICULTURE AND FORESTRY NAUNI, SOLAN-173230

Interview schedule for data collection

I Sonaly Bhatnagar PhD (Agribusiness Management) student in the Department of Agribusiness Management of Dr Yashwant Singh Parmar University of Horticulture and Forestry Nauni- Solan (H.P.) working on a thesis entitled, **"Climate-Smart Agricultural Practices for Climate Change Risk Mitigation in Temperate Region of Himachal Pradesh"**. I request you kindly respond to the questions asked in the questionnaire. Your responses will be kept confidential and used only for research and academic purposes. I shall be highly thankful to you for your co-operation.

Part A

I. GENERAL INFORMATION

i. Name of respondent : ….....

ii. Residential Address

a. District : ….....

b. Block : ….....

c. Panchayat : ….....

d. Village : ….....

II. INFORMATION ON THE PROFILE CHARACTERISTICS OF THE RESPONDENTS

1. **Ageof head of the household** : ….....(years)
2. **Gender of the head of the household** : i. Male ☐ ii. Female ☐
3. **Has the head of the household attended formal school?** : i. Yes ☐ ii. No ☐
4. **If yes, what is the level of education of the head of the household (Please tick ☑)**

i.	Primary education	☐
ii.	Middle education	☐
iii.	Secondary education	☐
iv.	Senior Secondary education	☐
v.	Graduate and above	☐

5. Marital status of head of the household (Please tick ☑)

i. Married ☐ ii. Unmarried ☐ iii. Others (widow/divorced) ☐

6. Major occupation of the head of the household (Please tick ☑)

i. Fulltime Farmer ☐ ii. Agricultural labour ☐ iii. Farming and service ☐

7. Farming experience of head of the household ……...(years)

Sr No	**Farming experience**	**Please tick ☑**
i.	Less than 10 years	☐
ii.	10-15 years	☐
iii.	15-30 years	☐
iv.	Greater than 30 years	☐

8. Number of milking animals: ……...

9. Number of non-milking/ commercially kept animals (sheep/goats etc) ……

10. Total land size …….(Bigha)

Sr No	**Landholding (in hectare)**	**Please tick ☑**
i.	Marginal (0-1)	☐
ii.	Small (1 – 2)	☐
iii.	Semi-medium (2-4)	☐
iv.	Medium (4-10)	☐

11. Land inventory and land use classification

Particulars	Area (Kanals / Bighas)			Source of Irrigation	Remarks
	IR	**UIR**	**Total**		
Owned land					
Leased in land					
Leased out land					
Total land holding (1+2-3)					
Land utilization					
Cultivated area					
Orchard area					
Grassland					
Forest land					
Fallow land					
Barren Land					
Land put to nonagriculture use					
Others					

12. Family size

Sr No	No. of family members	Please tick ☑
i.	Small (1-3 members)	☐
ii.	Medium (4-6 Members)	☐
iii.	Large (> 7 members)	☐

13. Type of family : i. Joint ☐ ii. Nuclear ☐

14. Family information

Sr. No	Name	Relation to the head	Age (years)	Sex Male = 1 Female = 2	Education	Occupation

Code list for family information	
Relationship with head	**Education level**
Spouse….....1	Illiterate…..... 0
Mother/Father….....2	Primary….....1
Son/daughter….....3	Upper Primary….....2
Son/ daughter-in-law….....4	Secondary….....3
Grandson/granddaughter….5	Senior Secondary….....4
Brother/Sister….....6	Graduate and above 5
Nephew/niece….....7	
Mother/Father-in-law ….....8	

Part-B

III. LIVELIHOOD STRATEGIES

1. Please specify the right response for the following questions

Sr No	Statements	Code	Response
i.	Does any member of your family have gone outside the community to work	1-Yes 2-No	
ii.	Is your family dependent solely on agriculture as a source of income?	1-Yes 2-No	
iii.	Do you or someone else in your household raise animals?	1-Yes 2-No	
iv.	Do you or someone else in your household grow crops?	1-Yes 2-No	
v.	Do you or someone else in your household collect something from the forest, or lakes and rivers to sell?	1-Yes 2-No	
vi.	Does your family have any source of off-farm income?	1-Yes 2-No	

2. Sources of Income

Sr No	Sources	Annual income (Rs. /yr)
i.	Agriculture	
ii.	Fruits cultivation	
iii.	Forestry	
iv.	Livestock	
v.	Off-farm sources like agricultural wages/ Firewood sale/Charcoal sale/Other	
vi.	Other sources apart from agriculture & allied activities	

3. **Crop Based Livelihood**

Sr No	Name of the Crops	Production on Annual basis (Qtl/yr)	Total Quantity sold (Qtl/yr)	Annual income (Rs. /yr)
i.	Wheat			
ii.	Barley			
iii.	Maize			
iv.	Millets			
v.	Paddy			
vi.	Buckwheat (fafra)			
vii.	Pulses (Raj mash, Mash, etc.)			
viii.	Any other (Please specify)			

4. **Vegetable Based Livelihood**

Sr No	Name of the Vegetables	Production on Annual basis (Qtl/yr)	Total Quantity sold (Qtl/yr)	Annual income (Rs. /yr)
i.	Potato			
ii.	Peas			
iii.	Tomato			
iv.	Cabbage			
v.	Broccoli			
vi.	Mushrooms			
vii.	Beans			
viii.	Capsicum			
ix.	Chillies			
x.	Cauliflower			
xi.	Any other (Please specify)			

5. **Fruit Based Livelihood**

Sr No	Name of the Fruits	Production on Annual basis (Qtl/yr)	Total Quantity sold (Qtl/yr)	Annual income (Rs. /yr)
i.	Apple			
ii.	Apricot			
iii.	Peach			
iv.	Pear			
v.	Pomegranate			
vi.	Walnut			
vii.	Almond			
viii.	Any other (Please specify)			

6. **Livestock Based Livelihood**

Sr No	Name of the Animal	Number	Source of Income	Total Income Received
i.	Cows			
ii.	Buffaloes			
iii.	Sheep			
iv.	Goats			
v.	Horses/Mules			
vi.	Any other (Please specify)			

IV. HEALTH ASSESSMENT

1. Is anybody in your family chronically ill? Please tick ☑

i. Yes ☐ **ii. No ☐**

2. If yes, please specify the disease ……

Sr No	Age	Sex	Days missed

3. Who was very sick and how many days of work or school did they miss in the last 2 weeks due to illness?

4. How long does it take you to get to the nearest health facility…... Hrs…Min

V. SOCIAL NETWORK

1. How far is the nearest market from your farm?..... Kilometer

2. In the past year did relatives or friends or neighbours help you or your family?

Please specify☑?

Sr No	Type of help received or given	Received	Given
i.	Medical care or medicines		
ii.	Transportation		
iii.	Sell animal products or other goods produced by family		
iv.	Take care of children		
v.	Worked in field		
vi.	Others		

3. Please select the code of the correct option

Sr No	Statement	Code	Response
i.	Did you and your family borrow any money from relatives or friends or neighbours in the past month?	1-Yes 2-No	
ii.	Did you and your family lend any money to relatives or friends or neighbours in the past month?	1-Yes 2-No	
iii.	Has anyone from your family gone to the local government office for any assistance during the past year?	1-Yes 2-No	
iv.	Are any of your family members affiliated with any CBO/NGO in the local area?	1-Yes 2-No	
v.	Do you get access to the extension?	1-Yes 2-No	
vi.	How often do you get extension	1- No visit	

	functionaries to visit you?	2-Monthly 3-Quarterly 4-Yearly	
vii.	Do you get access to credit?	1-Yes 2-No	
viii.	Source of credit	1-Family 2-Friends 3-Bank 4-Cooperatives 5-Microfinance	
ix.	Do you participate in training/workshops on farming?	1-Yes 2-No	
x.	Was the training beneficial?	1-Yes 2-No	

VI. FOOD

Please select the code of the correct option and respond to the question.

Sr No	Statement	Code	Response
i.	Does your family save seeds to grow next year?	1-Yes 2-No	
ii.	Does your family save some of the crops you harvest to eat during a different time of year?	1-Yes 2-No	
iii.	Is your household dependent primarily or mostly on the family farm for food?	1-Yes 2-No	
iv.	Has your family found an insufficient supply of food at any time of year?	1-Yes 2-No	
v.	If yes, then how many months or a year does your family have trouble getting sufficient food?		…….

VII. WATER

Please select the code of the correct option and respond to the question.

Sr No	Statement	Code	Response
i.	Do you utilize natural water sources for drinking?	1-Yes 2-No	
ii.	Is natural water available every day	1-Yes 2-No	
iii.	Where do you collect water from?	1-River 2- Own/Public Well 3-Dam 4-Running water supply inside the house 5-Others (Specify)	
iv.	Do you store water	1-Yes 2-No	
v.	What containers do you usually store water in?	1-Metal buckets 2- Plastic buckets 3-Ceramic vessels 4-Others (Specify)	
vi.	In the past year have you heard about any conflicts over water in your community?	1-Yes 2-No	
vii.	Do you face difficulties in obtaining an ample water supply for your farm?	1-Yes 2-No	
viii.	Does your farm primarily depend on rainfall for its water supply?	1-Yes 2-No	

VIII. CLIMATE CHANGE

Please select the code of the correct option and respond to the question

Sr No	Statement	Code	Response
i.	Do you know what climate change is?	1-Yes 2-No	
ii.	Do you think the climate has changed over time?	1-Yes 2-No	
iii.	Do you have access to climate change information?	1-Yes 2-No	

IX. NATURAL DISASTER

1. **Has your area been affected by flood/drought/avalanche events in the past 5 years?**

   i. Yes ☐ ii. No ☐

2. **How many times has this area been affected by flood/drought/avalanche events in the past 5 years?**.....

3. **Did you receive any warning about the disaster before it happened?**

   i. Yes ☐ ii. No ☐

4. **Where did you get the warning from? (Please select the code)(Select only one)**

Sources	Code	Response
Weather signs	1-Yes 2-No	
Friends/Family	1-Yes 2-No	
Mobile Phone	1-Yes 2-No	
NGO	1-Yes 2-No	
Farming Association	1-Yes 2-No	
Radio	1-Yes 2-No	
Newspaper	1-Yes 2-No	
Government	1-Yes 2-No	
Others (Please specify)	1-Yes 2-No	

Part-C

X. CLIMATE SMART AGRICULTURE

1. Are you aware of climate-smart agriculture?

i. Yes ☐ ii. No ☐

2. Did you or any household member have had information/training on how to use climate-smart agriculture?

i. Yes ☐ ii. No ☐

3. What Climate Smart Agricultural Practices you have adopted to adjust to the negative impact of climate change?

S. No.	Practices	Adopted (Y/ N)
1.	Mulching	
2.	Minimum/Zero Tillage	
3.	Fruit Based Agroforestry	
4.	Integrating Crop Livestock Production	
5.	Micro Irrigation	
6.	Change of Planting Time (before/after onset of rainfall)	
7.	Improved Crop Varieties	
8.	Diet Improvement for Animals	
9.	Crop Insurance	
10.	Soil Test	
11.	Use of Compost & FYM	
12.	ICT Based Weather Forecast	

XI. Constraints for adopting climate-smart agricultural practices:

Please, state the degree of your response by ticking one of the following for each statement.

[1] = Strongly disagree; [2] = Disagree; [3] = neither agree nor disagree; [4] = agree; [5] = strongly agree.

Sr No	Statements	Agreement Scale				
		[1]	[2]	[3]	[4]	[5]
	Soil and Crop Management Constraints					
C1	Inadequate organic matter	[ ]	[ ]	[ ]	[ ]	[ ]
C2	Low fertility of the soil	[ ]	[ ]	[ ]	[ ]	[ ]
C3	Non-availability of improved crop varieties	[ ]	[ ]	[ ]	[ ]	[ ]
C4	Lack of awareness on soil testing & STBF (Soil Test Based Fertilizer Recommendation	[ ]	[ ]	[ ]	[ ]	[ ]
C5	Higher pest & disease incidence	[ ]	[ ]	[ ]	[ ]	[ ]
	Financial Constraints					
C6	Insufficient Own Fund	[ ]	[ ]	[ ]	[ ]	[ ]
C7	No Easy Access to Credit	[ ]	[ ]	[ ]	[ ]	[ ]
C8	High-Interest Rates	[ ]	[ ]	[ ]	[ ]	[ ]
C9	Lengthy Process of Loan Sanctions in Banks	[ ]	[ ]	[ ]	[ ]	[ ]
C10	Low Support by Financial Institutions	[ ]	[ ]	[ ]	[ ]	[ ]
C11	Lack of Provision of Subsidies on Planting Materials	[ ]	[ ]	[ ]	[ ]	[ ]
	Economic constraints					
C12	High costs of inputs	[ ]	[ ]	[ ]	[ ]	[ ]
C13	Uncertain returns	[ ]	[ ]	[ ]	[ ]	[ ]
C14	Small landholding	[ ]	[ ]	[ ]	[ ]	[ ]
	Administrative and Institutional Constraints					
C15	Too much documentation	[ ]	[ ]	[ ]	[ ]	[ ]
C16	Lengthy process of loan sanctions in bank	[ ]	[ ]	[ ]	[ ]	[ ]
C17	Lack of legal and policy frameworks of government	[ ]	[ ]	[ ]	[ ]	[ ]
C18	Inadequate assistance from national and local authorities with climate-related issues	[ ]	[ ]	[ ]	[ ]	[ ]
	Knowledge and Training Constraints					
C19	Lack of awareness about climate change issues	[ ]	[ ]	[ ]	[ ]	[ ]
C20	Inadequate training and demonstration	[ ]	[ ]	[ ]	[ ]	[ ]

C21	Lack of awareness of the latest technologies	[ ]	[ ]	[ ]	[ ]	[ ]
C22	Poor information dissemination about the technologies	[ ]	[ ]	[ ]	[ ]	[ ]
C23	No extension activities about CSA Technologies	[ ]	[ ]	[ ]	[ ]	[ ]
C24	Lack of knowledge about adaptive practices of CSA	[ ]	[ ]	[ ]	[ ]	[ ]
C25	Lack of technical skills to adopt CSAPs	[ ]	[ ]	[ ]	[ ]	[ ]
	Resource Constraints					
C26	Inadequate land holdings for adoption of CSAPs	[ ]	[ ]	[ ]	[ ]	[ ]
C27	High cost of fertilizer and other inputs	[ ]	[ ]	[ ]	[ ]	[ ]
C28	Lack of water availability	[ ]	[ ]	[ ]	[ ]	[ ]
	Labor and Migration Constraints					
C29	High rate of wages for labourers	[ ]	[ ]	[ ]	[ ]	[ ]
C30	Shortage of labourers	[ ]	[ ]	[ ]	[ ]	[ ]
C31	Migration of youth	[ ]	[ ]	[ ]	[ ]	[ ]
	Infrastructure Constraints					
C32	Limited marketing access	[ ]	[ ]	[ ]	[ ]	[ ]
C33	Lack of improved communication facilities and farmers' organization	[ ]	[ ]	[ ]	[ ]	[ ]
C34	Lack of necessary transportation facilities	[ ]	[ ]	[ ]	[ ]	[ ]
C35	Poor supply of uniform electricity	[ ]	[ ]	[ ]	[ ]	[ ]
C36	Lack of irrigation facilities	[ ]	[ ]	[ ]	[ ]	[ ]
C37	Non-availability of input on time	[ ]	[ ]	[ ]	[ ]	[ ]

Appendix II:Calculating the livelihood strategies major component of the LVI for Rohru block in study area

Sub-components for Livelihood strategies component	Subcomponent value for Rohru block	Maximum subcomponent value for study population	Minimum subcomponent value for study population	Index value for Rohru block	Livelihood strategies major component values for Rohru block
Households with family members working in a different community	62.3	100	0	0.623	0.493
Households dependent solely on agriculture as a source of income	37.5	100	0	0.375	
Average livelihood diversification index (Herfindhal Index)	0.48	1	0	0.48	

Step 1: (repeat for all subcomponent indicators): **Index** $_{\mathbf{LS1}\text{Rohru}} = \frac{62.3-0}{100-0} = 0.623$

Step 2: (repeat for all major components):

$$\mathbf{LS_{1\ Rohru}} = \frac{\sum_{i=1}^{n} \text{Index } S_{di}}{n} = \frac{LS_{1\ Rohru} + LS_{2\ Rohru} + LS_{3\ Rohru}}{3}$$

Step 3: (repeat for all the 9 blocks):

$$= \frac{\sum_{i=1}^{8} W_{mi} M_{di}}{\sum_{i=1}^{8} W_{mi}} = \frac{(6)(0.268)+(3)(0.493)+(4)(0.335)+(4)(0.296)+(4)(0.460)+(8)(0.490)+(2)(0.365)+(5)(0.199)}{6+3+4+4+4+8+2+5} = 0.364$$

Appendix III:Calculating the adaptive capacity major component for the LVI -IPCC for Rohru block in study area

Contributing factors	LVI Major component	Major component score	Number of sub components per major component	Contributing factor values	LVI-IPCC score
Adaptive capacity	Socio-demographic	0.497	6	0.504	-0.130
	Livelihood strategies	0.494	3		
	Social Network	0.522	4		
Exposure	Health	0.296	4	0.199	
	Food	0.460	4		
	Water	0.490	8		
	House	0.365	2		
Sensitivity	Natural disasters & climate variability	0.199	5	0.426	

Step 1: Calculate the index value for subcomponent and major component as presented in Appendix. However, we need to take the inverse of all subcomponents for the contributing factor adaptive capacity (Socio-demographic profile, Livelihood strategies and Social Network).

Step 2: (repeat for all contributing factors: exposure, sensitivity, and adaptive capacity):

$$\text{Adaptive Capacity}_{\text{Rohru}}=\frac{\sum_{i=1}^{n} W_{mi}M_{di}}{\sum_{i=1}^{n} W_{mi}} = \frac{(6)(0.497)+(3)(0.494)+(4)(0.522)}{6+3+4}$$

Step 3: (repeat for all the 9 blocks):

$$\text{LVI – IPCC}_{\text{Rohru}} = (e_{\text{Rohru}}-a_{\text{Rohru}}) * s_{\text{Rohru}} = (0.199-0.504) * 0.426 = -0.130$$

Appendix IV:Variance Inflating Factor of the continuous explanatory variable (Ordered Logit Regression Model)

Variables	VIF	1/VIF
Age	3.69	0.271198
Farming experience	3.73	0.26776
Market distance	1.05	0.954424
Family size	1.63	0.614435
ADU	2.15	0.4641
Off-farm income	1.12	0.892914
On-farm income	1.75	0.572837
Mean VIF = 2.16		

Appendix V:Contingency coefficients for dummy explanatory variables(Ordered Logit Regression Model)

Variables	Gender	Member in local area	Access to extension	Access to credit	Participate in training	Access to climate change information	Farmers category	Education
Gender								
Member in local area	0.610							
Access to extension	0.450	0.200						
Access to credit	0.450	0.161	0.290					
Participate in training	0.510	0.195	0.229	0.280				
Access to climate change information	0.430	0.206	0.354	0.343	0.243			
Farmers category	0.075	0.124	0.231	0.241	0.147	0.325		
Education	0.228	0.086	0.112	0.113	0.37	0.237	0.131	

Appendix VI:Marginal Effects Estimates (Ordered Logit Regression Model) for factors influencing the adoption of climate smart agricultural practices

Adoption status	Marginal effect (dy/dx) for low adopter	Marginal effect (dy/dx) for medium adopter	Marginal effect (dy/dx) for high adopter
Age	0.002002	4.11E-05	-0.00204
Gender	-0.00768	-0.00016	0.007836
Education	-0.02473	-0.00051	0.025242
Farming experience	-0.00459	-9.4E-05	0.004689
Market distance	0.001742	3.58E-05	-0.00178
Access to extension	-0.10962	-0.00225	0.111874
Access to credit	-0.1041	-0.00214	0.106243
Participate in training	-0.05969	-0.00123	0.060913
Member in local area	-0.05348	-0.0011	0.054575
Access to climate change information	-0.24384	-0.00501	0.248847
Family size	0.000398	8.17E-06	-0.00041
ADU	-0.01954	-0.0004	0.019943
Off-farm income	-5.97E-08	-1.23E-09	6.09E-08
On-farm income	-3.61E-07	-7.41E-09	3.68E-07
Farmers category	0.080537	0.001654	-0.08219
Number of observations	432		
LR $Chi^2(15)$	411.12		
Prob > Chi^2	0.00		
Pseudo R^2	0.4371		
Log likelihood	-264.74074		

Appendix VII:Variance Inflating Factor of the continuous explanatory variable (Multi Linear Regression Model)

Predictor	VIF Value
X1	2.18
X2	1.11
X3	2.09

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ABSTRACT

The present study has been carried out on climate-smart agricultural practices for climate change risk mitigation in temperate region of Himachal Pradesh. Multi-stage random sampling technique was used for the selection of sampled households in the study area. Primary data were collected from a sample of 432 farmers, while secondary data were collected from various publications and government departments. At the overall level, the average family size was found to be 5.44 persons, with 52.77 percent of the population being male, resulting in a sex ratio of 896 females per 1,000 males. The literacy rate and literacy index were estimated at 87.16 percent and 2.56, respectively. Agriculture emerged as the primary occupation, with 83.39 percent of the workforce engaged in farming activities across all farm categories. The average landholding size was recorded at 1.16 hectares, of which 42.66 percent was utilized as agricultural land (land under crops), while 46.72 percent was devoted to orchards. The overall cropping intensity was calculated at 139.65 percent, indicating significant potential for improving farm efficiency through optimized agricultural practices. To assess the vulnerability of rural households, the Livelihood Vulnerability Index (LVI) and LVI-IPCC approaches were employed. Based on the LVI composite index, Lahaul block (0.468) and Mehla block (0.419) were identified as highly vulnerable, while Gohar block (0.361) was found to be the least vulnerable. Similarly, using the LVI-IPCC approach, Lahaul block (-0.094) emerged as the most vulnerable, whereas Nagar block (-0.142) was determined to be the least vulnerable. The study revealed that the most widely adopted climate-smart agricultural practices were the use of compost and farmyard manure, implemented by 86 per cent of respondents, followed by fruit-based agroforestry and integrated crop-livestock production. Conversely, practices such as micro-irrigation and crop insurance were less commonly adopted by the respondents. The ordered logit regression analysis revealed that education, farming experience, access to extension services, credit, training, local organization membership, and climate change information significantly increased the likelihood of adopting climate-smart practices. On-farm income was also a strong positive predictor, while the farmer category negatively influenced adoption. The multi-linear regression analysis indicated that climate-smart agricultural practices, access to climate change information, and training on CSA practices significantly reduced livelihood vulnerability. The study highlighted key constraints in climate-smart agriculture, including small landholdings, high input costs, and limited irrigation, with varying challenges across low, moderate, and high adopters. The study concludes that climate-smart agricultural practices significantly mitigate climate change risks and reduce livelihood vulnerability in Himachal Pradesh's temperate region. It recommends improving access to resources such as credit, irrigation, and training while addressing constraints like small landholdings and high input costs to enhance the adoption of climate-smart practices.

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Title of Project in MBA	**:**	Role of women in farm activities: a study of Baijnath block
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Reseach papers	:	1
Book Chapter	:	2
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National Conference	:	1
Trainings	:	7

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