Available Online
Journal of Social Sciences Advancement
www.scienceimpactpub.com/jssa
DOI: https://doi.org/10.52223/JSSA24-050413-111

The Impact of Adoption of Climate Change Strategies on Farmers' Income: A Propensity Score Matching Approach

Sobai Majeed[1], Iqbal Javed[1], Abdul Subhan[2] and Muhammad Faisal[3]
[1]Department of Economics, University of Lahore, Sargodha Campus, Sargodha, Pakistan.
[2]Pakistan Institute of Development Economics (PIDE), Islamabad, Pakistan.
[3]Department of Economics, University of Mianwali, Pakistan.

ARTICLE INFO

ARTICLE HISTORY
Received: October 18, 2024
Accepted: December 25, 2024
Published: December 29, 2024

KEYWORDS
Adoption measure;
Climate change;
Famers income;
Propensity score matching

ABSTRACT

Globally, farmers' livelihoods and agricultural productivity face severe problems due to climate change. Pakistan is one of the country's most vulnerable to climate change. With an emphasis on comprehending the various mechanisms and results connected to adaptation strategies, this study explores how farmers' income is affected by adopting climate change strategies. The study aims to ascertain if farmers who have embraced climate change methods earn more money than those who haven't. Using a propensity score matching method, this study investigates how farmers' income is affected by their adoption of climate change initiatives based on data gathered from a sample of farmers from three agroecological zones. The factors influencing the farmers were estimated using a Poisson regression model. This study shows how several characteristics, including age, education, income, experience, family size, family system, and farm labor, influence farmers' judgments about climate change strategies. The study's findings indicate that socioeconomic characteristics positively impact the adoption of climate mitigation strategies in farming. Farmers' income from agriculture is significantly and favorably correlated with adoption. The study's policy recommendation is that the governments educate farmers on adopting climate mitigation strategies to boost their productivity and give them access to credit facilities.

Corresponding Author: Iqbal Javed (Email: iqbaljaved@gmail.com)

INTRODUCTION

Climate change is one of our day's most serious global concerns, with profound implications for ecosystems, economy, and society (Smit & Wandel, 2006). Its consequences are most severe in the agricultural sector, where farmers are at the vanguard of dealing with affecting weather patterns, changing growth seasons, and the increased vulnerabilities posed by catastrophic events such as droughts and floods (Aydinalp & Cresser, 2008). Millions of smallholder farmers' livelihoods worldwide are inextricably linked to their ability to adapt to these climate-induced issues (Makuvaro et al., 2018). The worldwide consequences of climate change are observed in the form of various phenomena, including rising temperatures, extended periods of drought, intense heat waves, reduced snow cover, rising sea levels, and extensive inundation (Thornton & Herrero, 2015). The repercussions are significantly more conspicuous in underdeveloped areas, primarily impacting nations in Asia and Africa (Mirza, 2011).

Agriculture is currently confronted with a pressing and increasing challenge posed by the constantly changing global climate, which is affecting different locations around the globe to differing degrees. In agrarian economies, particularly those that are developing and have low-income levels, the impact of climatic changes on crop cultivation is significant and detrimental, resulting in a major decrease in crop yields (Howden et al., 2008). The occurrence mentioned above is not limited solely to the agricultural sector; it has far-reaching effects on rural lives in developing nations, exacerbating farming communities' susceptibility (Abid et al., 2016).

According to numerous studies (Abid et al., 2016; Coffey et al., 2015; Hillbur, 2012; Lake et al., 2012; Porter et al., 2014; Schmidhuber & Tubiello, 2007), there is a clear correlation between climate change and food security and agriculture production in developing countries. Climate change is projected to have a negative impact on agricultural output in the country. Rising temperatures, changes in irrigation water availability, variations in rainfall patterns, and the advent of severe water-stressed situations are the principal implications for agriculture (Abidoye et al., 2017). These factors, taken together, are expected to contribute to a 6% to 18% decrease in crop output (Raza et al., 2022). Notably, the most susceptible communities in Pakistan in the face of climate change are small landowners, who account for more than 80% of the overall farming community (Shah et al., 2018). This shows that the effects of climate change may result in hunger for a more significant proportion in different regions of the globe (Thornton & Herrero, 2014).

Farmers face challenges in managing the negative impacts of seasonal temperature variations and heat stress on crops, such as wheat, which is highly sensitive to elevated temperatures (Raza et al., 2019). Despite their efforts to follow recommended input levels and crop management strategies suited for changing climates, these deleterious effects persist (Porter et al., 2014). Farmers can employ many agricultural strategies to offset the negative impact of weather variations on crop yields. These strategies include modifying planting tactics, adjusting fertilizer consumption, using irrigation techniques, selecting appropriate crop varieties, agroforestry, sustainable soil management, and managing other aspects of crop cultivation (Mubiru et al., 2018). The importance of adjusting to variations in weather conditions is in its capacity to diminish exposure and vulnerability, as emphasized by (Abid et al., 2016). A substantial body of research has consistently indicated that implementing climate-resilient strategies is associated with a notable enhancement in food productivity and farmers' income (Jamil et al., 2021). The adoption of climate change techniques within agriculture has emerged as a critical answer to the negative consequences of climate change and the requirement to guarantee food security (Ado et al., 2019). These techniques not only have the ability to strengthen agricultural systems' resilience but also to increase farmers' income and overall well-being (Abid et al., 2015). Farmers' income is affected by adopting climate change measures in various ways, with far-reaching implications for both agricultural sustainability and economic well-being (Jamshidi et al., 2019). Climate change threatens the agricultural industry, impacting crop yields, livestock production, and general farming techniques (IPCC, 2022). Farmers are increasingly adopting climate change mitigation and adaptation techniques in response to this problem (FAO, 2012).

Farmers' income can be significantly impacted by climate change policies, particularly in Pakistan, where millions of people rely heavily on agriculture for their livelihood (Kabir et al., 2016). This is a summary, with citations, of how Pakistani farmers' income can be impacted by climate change measures (Abid et al., 2016). Reduced tillage, crop rotation, and cover crops are conservation agriculture techniques that can enhance soil quality and boost crop yields, boosting farmers' incomes (Muzari et al., 2012). According to a study by Abid et al. (2016), conservation agricultural techniques in Pakistan lowered production costs by 25.4% while increasing wheat yields by 28.6%. Crop diversification can reduce the risk of crop failure brought on by climatic unpredictability and boost farmers' income by allowing them to produce a range of crops with varying characteristics (Fahad & Wang, 2018). According to a Fahad & Wang, (2018) study, crop diversification in Pakistan raised agricultural income by 15.6%. Water management, like drip irrigation and rainwater harvesting, boosts crop yields and lowers water use, boosting farmers' incomes. Drip irrigation raised cotton yields by 18% while increasing farmers' revenue by 40% (Ali et al., 2020). Integrated pest management is a multifaceted approach to controlling diseases and pests using chemical, biological, and cultural methods (Despotović et al., 2019). This technique requires fewer pesticides, which improves the environment and people's health. An investigation in Pakistan found that integrated pest management significantly reduced pesticide requirements while boosting cotton yields (Ali & Abdulai, 2010).

Additionally, implementing climate change mitigation techniques can increase production and farmers' income (Ado et al., 2019). Furthermore, sustainable farming practices can provide access to niche markets that value ecologically responsible and morally produced products. These markets frequently have higher pricing, which can help farmers' financial situation (Iqbal et al., 2018). Furthermore, agriculture credit, changes in agriculture land usage, and insect pest management can reduce the risk of income loss due to extreme weather events (Wei et al., 2020). However, there are specific adverse effects on income to consider. Many climate change adaptation strategies demand significant upfront investments in technology, infrastructure, and training, which may strain farmers' financial resources (Cavatassi et al., 2011). Furthermore, these solutions may be coupled with a learning curve, resulting in a temporary decrease in output and income while farmers adjust to new practices (Field et al., 2012). Market hurdles and a lack of acknowledgment of sustainable agricultural practices can also stymie farmers' financial gains (Greenough et al., 2001).

The decision-making process of farmers in selecting adaption techniques is influenced by multiple factors, encompassing their beliefs, risk propensity, as well as diverse socioeconomic features, institutional elements, and access to information and facilities (Nabikolo et al., 2012). A comprehensive analysis of contemporary research reveals that policymakers are actively engaged in efforts to understand the cognitive processes employed by farmers when making decisions in response to the intricate dangers posed by climate change. The comprehension of this concept holds significant importance for policymakers, as it allows them to forecast the potential reactions of farmers towards suggested policies. This, in turn, facilitates the formulation of more efficient adaptation strategies (Shah et al., 2018). While more people understand that we must move quickly to combat climate change, many countries and organizations still struggle to implement common-sense policies that could significantly reduce climate change impacts (Shah et al., 2020). In this environment, the involvement of government policies and assistance programs is critical. Policies that encourage and support the adoption of climate-resilient and sustainable farming techniques can increase farmers' incomes (Daxini et al., 2019). However, it is essential to remember that the impact of climate change measures on farmers' income might vary greatly depending on the region, kind of farming, local climate conditions, and individual techniques used (Jamil et al., 2021).

Farmers are actively engaged in the exploration of diverse adaptation measures in order to protect and ensure the continuity of their farm production. Implementing these adaptation techniques exhibits variation throughout the nation, as it is influenced by the specific environmental conditions and changes in climatic patterns unique to each locality (Faisal et al., 2021). Our research constitutes the first attempt to investigate the elements that affect the adaption process to different agro-ecological zones of Pakistan. The decision is based on recognizing that agricultural productivity in these specific agro-ecological zones is predominantly influenced by local weather patterns rather than larger-scale global shifts (Raza et al., 2019). The current study has the following objectives: to examine the sample respondents' socioeconomic characteristics. Second: To explore the implementation of climate change tactics. Third, we will estimate the impact of adopting climate strategies on farmers' income. Lastly, we will suggest policy measures.

CONCEPTUAL FRAMEWORK AND METHODOLOGY

The study's conceptual framework is explained in Figure 1.

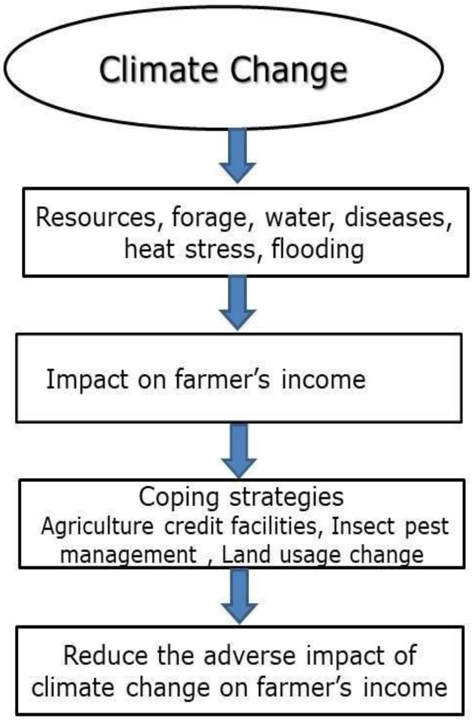

Figure 1: Conceptual Frame Work

Farmers will be considered adopters rather than non-adopters if they employ a particular strategy. Numerous studies emphasize how important it is for farmers to understand how climate change affects their operations in order to employ climate-resilient practices (Abid et al., 2016). Here, we assume that farmers will decide to implement a climate change mitigation strategy only if the anticipated total benefits surpass the associated costs. (Ali & Abdulai, 2010), For instance, it can be argued that farmers' attitudes about the issue and willingness to take action greatly influence their access to information and training on the subject.

Farmers will only adopt a climate change mitigation approach ($\beta i = 1$) if the adoption's net benefits are positive ($\beta i > 0$). If the adoption's net benefits are negative ($\beta i \leqslant 0$), they won't adopt ($\beta i = 0$). Using efficient adaptation strategies might lead to a rise in the farmer's income. However, separating adopters from non-adopters based only on welfare may be challenging. In contrast to actual biological trials, social scientific research frequently has data randomization issues, whether in the control or experiment groups. If the data were gathered using randomization and a counterfactual situation, it would be relatively straightforward to ascertain the differences between adopters and non-adopters (Ali and Behera, 2016). Our findings show that the direct effect of adaptation may be evaluated by considering the variations in the outcomes of adopters and non-adopters when cross-sectional data is unavailable to provide counterfactual information. However, this might result in calculations that are skewed and wrong. Here, the estimations are based on the equation below:

$$Yik = \alpha Xij + \delta\beta i + \varepsilon i \text{ while } \beta i = \lambda Xij + \mu i \text{ ,So } Yik = \alpha Xij + \delta(\lambda Xij + \mu i) + \varepsilon i \quad (1)$$

The error term in this case is εi, and Yik is a vector of the follow-up variable (farmer income for ith farmers). Regression coefficients α and δ are represented by Xij, the vector of independent variables, while the logistic regression coefficient and the error term are represented by λ and μi, respectively. The choice to adopt βi may be made independently, while it could be influenced by one or more unidentified factors that make up the error term εi. Additionally, εi might agree with μi, resulting in erroneous estimates due to the selection bias. Furthermore, the Poisson model was utilized to determine the variables influencing the quantity of farming techniques performed. In this model, the dependent variable was the total number of ways that farmers used. The independent factors were age, education, experience, size, family composition, income earned outside the farm, ease of market access, land holdings for operations, and use of institutional servitors.

PSM (Propensity Score Matching)

The non-random adoption of climate change strategies will be managed by applying the propensity score matching method. This entails calculating the likelihood that farmers will embrace climate change tactics based on their traits and then using comparable traits to compare farmers who chose climate change methods with those who did not. The difference-in-differences technique will be used to quantify the treatment effect of farmers' income on adopting climate change measures. In order to do this, farmers who implemented climate change measures must compare their revenue to that of farmers who did not, both before and after the methods were implemented.

An empirical study was undertaken using the Propensity Score Matching (PSM) approach to examine the potential for bias correction arising from systematic variations in farming practices across two distinct groups: adopters and non-adopters. In contrast to the limitations posed by weak instruments assumption issues, the selection of observables assumption in Propensity Score Matching (PSM) is not constrained, enabling the utilization of instrumental variables in the context of cross-sectional data. The utilization of impact assessment studies is frequently seen in the literature (Abid et al., 2016; Ali et al., 2018; Ali & Abdulai, 2010; Ali & Erenstein, 2017; Elahi et al., 2018; Khonje et al., 2015; Ali, 2017) to measure the anticipated treatment effect on the population receiving the intervention. After controlling for other variables, the correlation between farmer adoption and farmers' losses and poverty becomes insignificant and unconnected (Mendola, 2007). This is the case because Propensity Score Matching (PSM) relies on the premise of un-confoundedness, which ensures no selection bias or conditional reliance present in the randomized trial. The present study used the Propensity Score Matching (PSM) method, which posits a potential association between outcomes and relevant factors but refraining from making any assumptions about the specific functional form of this link. This approach stands in contrast to previous parametric methodologies. As discussed by Raza et al. (2022), the application of an adaptation technique reduces the dimensionality of the conditioning problem and facilitates the comparison of families with equivalent likelihoods. According to Heckman & Navarro-Lozano, (2004), the propensity score derived from the conditional probability can be utilized to identify similar families. The PSM used in this work is postulated using the following equation:

$$p(Xij) = Pr[\beta i = 1 \mid Xij] \tag{2}$$

The variable i represents climate adaptation, whereas Pr represents probability, and p represents the propensity scores of the pre-adaptation features of Xij. According to (Mendola, 2007), the conditional distribution Xij exhibits the similarity between adopters and non-adopters. The influence of adaptation techniques on outcome variables is commonly assessed using the average treatment effect on the treated (ATT) or average treatment effect (ATE), with the word "treatment" referring to adaptation. The Adoption Treatment Effects (ATE) metric quantifies the comprehensive influence of adoption on the outcome variables, considering all individuals involved in the study. Ali & Abdulai, (2010) examine the impact of adaptation on outcome variables specifically for treated respondents, following the matching process conducted by ATT. Since ATT is of more importance to us, it can be computed as follows following the calculation of propensity scores:

$$T = E\{Y1|\beta i = 1\} = E[E\{Y1 - Y0|\beta i = 1, p(X)\}] = E[E\{Y1|\beta i = 1, p(X)\} - E\{Y0|\beta i = 0, p(X)\}|\beta i = 0] \tag{3}$$

In the present situation, the variable p(X) denotes the propensity scores, T represents the average treatment effect on the treated (ATT), and Y1 and Y0 denote the values of the outcome variable. The NNM (nearest neighbor matching) approach was utilized to do matching, whereby specific examples from both groups were selected as matching partners based on their closeness. The closeness levels are evaluated by (Abid et al., 2016; Ali, 2018; Ali & Erenstein, 2017; Qi et al., 2019) for the utilization of propensity scores. By comparing the two groups, the NNM technique eliminates cases that don't match (Smith & Todd, 2005). Alternatively, we could say that ATT is acquired after determining selection bias's influence (Qi et al., 2019).

Dependent Variables

We asked farmers about their thoughts on climate change and how often they had experienced climatic shocks (droughts, floods, illnesses, etc.) in the ten years prior. According to their findings, farmers may be able to lower their chance of experiencing extreme weather events and stabilize their income by taking action against climate change. Financial resilience can be improved by diversifying sources of income through climate adaptation strategies

(Jamshidi et al., 2019). Increased income and better stability are frequently the outcomes of increased farm productivity (Mubiru et al., 2018).

1) Agriculture credit facilities are the variables that are regarded as dependent in logit analysis. (These facilities are essential for farmers to obtain the funds to invest in their farms, buy equipment, seeds, fertilizer, and cover operating expenditures. These financial services and programs are created to benefit farmers and the agricultural sector) (Linnerooth-Bayer & Hochrainer-Stigler, 2015).
2) Insect pest management (IPM): This environmentally conscious and sustainable approach to managing insect pests in agriculture, horticulture, forestry, and other areas where insects can cause economic or ecological harm integrates a variety of strategies and techniques to effectively manage insect populations while minimizing the negative impacts on the environment, human health, and non-target organisms. The main objective of IPM is to encourage the use of alternative, more ecologically friendly methods and lessen the reliance on chemical pesticides (Milgroom & Giller, 2013).
3) Land usage change: This describes modifying the purpose or function of a specific piece of land. It can involve converting natural landscapes into agricultural fields, such as agricultural (Mertz et al., 2009). The codes for dependent variables are 1 (adopted) and 0 (not adopted).

Independent Variables

The study encompassed several independent characteristics: age, education, experience, family structure and size, off-farm income, market accessibility, and the percentage of farmers' land under operation. They were included in the model for various reasons, including their predicted impact on the dependent variable or variables and learning associated with research.

Age of Farmers

Age is the most crucial factor that could significantly impact a farmer's mindset regarding adopting new technologies. At the interview, the respondents' ages were expressed in years. The count was conducted from the person's first day of existence to the interview. It was hypothesized, for instance, that elderly heads of households would be more inclined to choose traditional behaviors over methods of mitigating climate change (Abid et al., 2016; Ali & Behera, 2016).

Farmer's education

In an increasingly globalized and linked world, education is essential for success and advancement. Both individual earnings and total economic growth significantly increase. As a result, a farmer with a higher education level is anticipated to support the implementation of the suggested technology. However, because farming does not require unique expertise, farmers are a broad group of people, and most do not have a formal education. Education is crucial, particularly in challenging disciplines (Ado et al., 2019). It seems reasonable, then, to assume that knowledge would be beneficial to cattle herders who have had more formal instruction. Adoption studies show that adoption behavior and education level are highly correlated (Akhtar et al., 2021; Faisal et al., 2021); the influence of age is less well-supported (Abid et al., 2016). One other perspective on education is that it may replace experience.

Farmer's Experience

Farm labor denotes the human workforce a landowner engages to serve as laborers or servants on their estate, with the added provision of compensation for their services. Furthermore, farm labor can substitute for the machinery typically employed within the agriculture industry (Faisal et al., 2018).

Farmers Family Size

Family size encompasses the overall count of adults residing in a household, including the husband, wife, and children. In the case of an extended family, family members may also include the parents, sisters, and brothers of the husband or wife. First, the human capital available for agricultural work is measured by the number of children and adults. Because there are fewer labor shortages during peak hours, households with a bigger labor pool are likelier to adopt new technology and use it effectively (Abid et al., 2016).

Farm Labor

Farm labor is human resources that a landlord hires as servants or labor to cultivate their land. And the landlord pats their labor to do the work. Farm labor is a substitute for machinery used in agriculture (Wei et al., 2020).

Off-Farm Income

The part of farm household income that comes from sources other than the farm, such as non-farm earnings and salaries, pensions, and interest income, is called off-farm income. Other than agriculture, this revenue comes from different sources (Faisal et al., 2021).

Farmers Family System

When asked about their family structures—nuclear or blended—the respondents provided information. When just the spouse has unmarried children and lives together, the family is referred to as a nuclear family. A "joint family" describes a home that includes the husband, wife, children, and parents of either the husband or the wife, siblings, or brothers (Faisal et al., 2021).

Participants, Data Collection Technique and Climate Indicators of the Region

In order to collect primary data for the Punjab province of Pakistan's three separate zones, Toba Tek Singh, Gujrat, Rahim Yar Khan (based on geography, climate, and cropping pattern), a multistage sampling approach (District → Tehsil → Union council → Villages → Respondents) was applied. Because farmers have a low literacy rate, face-to-face interviews were conducted to ensure the accuracy of the data acquired. We queried about the list of farmers and asked the district's extension workers for assistance in gathering the data. The study's findings would help understand how climate change strategies could affect farmers' income in Pakistan's Punjab (Raza et al., 2019; Raza et al., 2019).

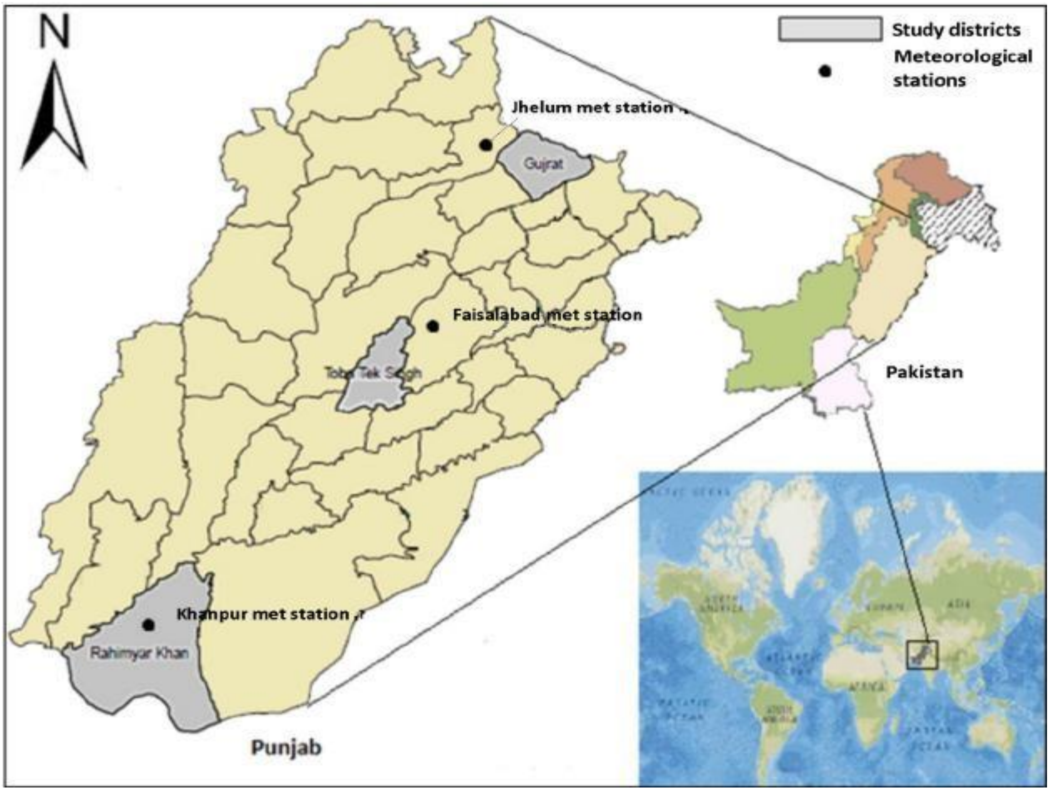

Figure 2: Study area map (World map source Punjab-Pakistan)

The study area map is shown in Figure 2. This information can be used to design the policies and interventions that support farmers in adopting climate change strategies while ensuring their income is not negatively impacted. Qualified interviewers questioned farmers.

RESULTS AND DISCUSSIONS

Descriptive Statistics

The descriptive statistics for the variables considered in our study are shown in Table 1. According to data, farmers had an average age of 36 years and 13 years of agricultural experience. This means that middle-aged farmers have a wealth of knowledge about farmer raising. Because 71% of respondents lived in a joint/extended family structure, the average number of household members was six, indicating that family size was relatively high. As declared earlier, the sampled households were engaged in the farmer-raising activities. 46% of farmers had access to agricultural credit facilities.

The questionnaire included several questions about climate change and appropriate mitigation methods. However, respondents in the study area generally adopted three strategies: First, agriculture credit facilities account for 46% of the total, which denotes the financial services and support systems provided to farmers to increase their agricultural productivity and income. The 46% indicates that it would boost the effectiveness of these credit facilities. This could involve measures such as reducing interest rates, expanding access to credit, streamlining loan approval processes, or providing farmers financial literacy and management training. The 46% shows that it would signify an ambitious effort to significantly boost the impact of these facilities on farmers' income.

Table 1: Descriptive statistics

Variable	Variable description	Mean	Std. Dev.
Age (years)	Respondent age continuous variable (Years)	36.792	12.564
Education (Years)	Respondent education continuous variable (Years)	10.758	3.318
Farming Experience (Years)	Respondent experience continuous variable (Years)	13.617	7.219
Family Members (No.)	Total no. of members	6.817	2.976
Farm Labor (No.)	No. of family members working on the farm	3.033	1.734
Off Farm Income (Rs.)	1 if the household has off-farm work, 0 otherwise	20437.50	15299.880
Family system (Nuclear/Joint)	1 if joint family, 0 otherwise	0.717	0.453
Agriculture Credit Facilities (Yes/No)	1 if farmers have access, 0 otherwise	0.467	0.501
Integrated Pest Management IPM (Yes/No)	1 if adopted, 0 otherwise	0.567	0.498
Land Usage Change	1 if adopted, 0 otherwise	0.642	0.482
Income from Agriculture	Rabi Crops in 2022 (Rupees)	56250	28723.620

Secondly, Integrated Pest Management (IPM) refers to a 56% high influence on embodies an agricultural approach for pest and disease control that seeks to optimize crop yields and income while reducing reliance on chemical pesticides. The 56% shows the importance of this variable as a precise objective aimed at augmenting the efficiency of IPM practices. This endeavor might encompass refining IPM strategies, instituting more effective pest monitoring systems, advocating for adopting biological control methods, and imparting IPM technique training to farmers. The 56% represents a substantial initiative to further enhance the benefits of IPM for farmers in terms of income augmentation. Third Land Usage Change, 64%, refers to alterations in how agricultural land is used to increase farmer income. The 64% indicates a specific goal of optimizing land utilization for more significant income generation. This might entail transitioning from low-value to high-value crops, adopting advanced farming technologies, improving soil fertility management, or exploring new income-generating activities on agricultural land (e.g., agroforestry or organic farming). The 64% represents a substantial effort to make land usage changes significantly more beneficial for enhancing farmer income. Farmers claim that the adverse circumstances have caused them to lose money.

Table 2: PSM Estimates

Poisson Regression	Coefficient	Std. Err.	z	P>z	[95% Conf.	Interval]
Age (years)	-0.044	0.009	-4.910	0.000	-0.061	-0.026
Education (Years)	0.045	0.026	1.730	0.084	-0.006	0.096
Farming Experience (Years)	0.032	0.010	3.150	0.002	0.012	0.051
Family Members (No.)	-0.024	0.028	-0.850	0.396	-0.078	0.031
Farm Labor (No.)	0.020	0.046	0.430	0.666	-0.071	0.110
Off Farm Income (Rs.)	0.000	0.000	1.080	0.282	0.000	0.000
Family system (Nuclear/Joint)	0.067	0.174	0.390	0.699	-0.274	0.409
Constant	0.994	0.446	2.230	0.026	0.119	1.868

Table 3: Adaptation 1

Dependent Variable 1 (Agriculture Credit Facilities (Yes/No))	Coefficient	Std. Err.	z	P>z	[95% Conf.	Interval]
Age (years)	-0.070	0.025	-2.770	0.006	-0.120	-0.021
Education (Years)	0.093	0.073	1.270	0.205	-0.051	0.237
Farming Experience (Years)	0.117	0.045	2.570	0.010	0.028	0.205
Family Members (No.)	-0.130	0.084	-1.550	0.121	-0.294	0.034
Farm Labor (No.)	0.217	0.141	1.540	0.125	-0.060	0.494
Off Farm Income (Rs.)	0.000	0.000	2.320	0.020	0.000	0.000
Family system (Nuclear/Joint)	0.227	0.488	0.460	0.643	-0.730	1.183
Constant	-0.912	1.354	-0.670	0.501	-3.566	1.742

Table 4: Adaptation 2

Dependent Variable 2 (Insect Pest Management (IPM)	Coefficient	Std. Err.	z	P>z	[95% Conf.	Interval]
Age (years)	-0.258	0.054	-4.780	0.000	-0.364	-0.152
Education (Years)	0.379	0.118	3.220	0.001	0.148	0.609
Farming Experience (Years)	0.200	0.072	2.780	0.005	0.059	0.342
Family Members (No.)	-0.105	0.129	-0.820	0.413	-0.358	0.147
Farm Labor (No.)	0.137	0.195	0.700	0.484	-0.246	0.520
Off Farm Income (Rs.)	0.000	0.000	1.140	0.254	0.000	0.000
Family system (Nuclear/Joint)	0.037	0.680	0.050	0.956	-1.296	1.371
Constant	2.341	1.914	1.220	0.221	-1.410	6.092

Determinants of the Number of Strategies Adopted by Farmers

The Poisson model is employed to identify the factors influencing applying different farming techniques. The model's output is presented in Tables 2, 3 and 4. The total number of agricultural techniques used was the dependent variable in this model, while the Table lists the independent factors. The age coefficient in the model, which is harmful and significant, indicates that younger farmers often employ more strategies to mitigate climate change. Experience and education have a significant and positive link, which raises the possibility that farmers with higher levels of education may employ a broader range of techniques. The joint/extended family type coefficient indicates that farmers would benefit from extra tactics; this relationship is substantial and beneficial. One possible reason for this result is that joint families need more labor than they have to maintain their land.

The results of family size, which are equally significant and beneficial, are comparable to those of family type, which show that households with more family members adopt more climate change mitigation techniques due to the availability of staff needed to maintain farms. Moreover, variables on agriculture credit services (farmers and agricultural businesses typically need to meet specific eligibility criteria and provide collateral, such as land or equipment, to secure the loans. Government agencies may also offer agricultural loan programs to support the agricultural sector and promote rural development. These programs, which typically provide beneficial terms and interest rates to assist farmers in reaching their agricultural goals, are favorable and incredibly significant, except for finance availability, which may be related to information access.

Table 5: Adaptation 3

Dependent Variable 3 (Land Usage Change)	Coefficient	Std. Err.	z	P>z	[95% Conf.	Interval]
Age (years)	-0.102	0.026	-3.960	0.000	-0.152	-0.051
Education (Years)	0.042	0.078	0.540	0.591	-0.111	0.195
Farming Experience (Years)	0.160	0.051	3.160	0.002	0.061	0.259
Family Members (No.)	-0.165	0.088	-1.860	0.062	-0.338	0.009
Farm Labor (No.)	-0.049	0.143	-0.340	0.731	-0.329	0.231
Off Farm Income (PAK Rs.)	0.000	0.000	1.120	0.262	0.000	0.000
Family system (Nuclear/Joint)	0.410	0.519	0.790	0.429	-0.607	1.428
Constant	2.482	1.484	1.670	0.094	-0.426	5.390

Propensity Score Estimates

Propensity scores for the treatment variable were assessed in addition to the matching strategy. In this instance, the logistic model was used, and the chance of implementing climate change mitigation strategies was separately regressed on each variable. The results of the propensity score estimation are presented in Tables 6 and 7. Poisson regression estimates for all three adaptation techniques mostly agree with our findings. Our dependent variables are:

1) Agriculture credit facilities (purchase equipment, seeds, fertilizers, and cover operational expenses).
2) Insect pest management (controlling insect pests in agriculture, horticulture, forestry, and other areas where insects can cause economic or ecological harm).
3) Land usage change (transforming natural landscapes into agricultural fields, urban areas, or industrial zones).

Table 6: Adaptation strategies impact on farmers' income

		Off support	On support	Total
psmatch2: Adaptation 1	Untreated	16	48	64
	Treated	1	55	56
	Total	17	103	120
psmatch2: Adaptation 2	Untreated	31	21	52
	Treated	4	64	68
	Total	35	85	120
psmatch2: Adaptation 3	Untreated	3	40	43
	Treated	8	69	77
	Total	11	109	120

Table 7: Covariates balancing indicators

Adaptation	Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias	B
1	Unmatched	0.165	27.420	0.000	30.500	31.000	96.5*
	Matched	0.018	2.710	0.910	7.300	4.200	31.6*
2	Unmatched	0.537	88.210	0.000	51.000	28.400	189.1*
	Matched	0.139	24.720	0.001	27.000	34.300	92.7*
3	Unmatched	0.207	32.340	0.000	26.600	21.800	112.0*
	Matched	0.037	7.000	0.429	11.100	7.900	45.2*

The findings show that factors impact the possibility of climate change adaptation options. The age coefficient is negative and substantial in this instance, demonstrating how young farmers adopt these techniques to lessen the effect of climate risk on farm revenue. As people develop more excellent knowledge, skills, and awareness of climate change, they are more inclined to embrace more advantageous policies. These results align with previous studies (Bryan et al., 2009; Deressa et al., 2011; Nabikolo et al., 2012; Yu et al., 2010) that support our assumptions. In strategies for maximum adaptation, institutional services have positive and significant coefficients. Off-farm income has a negative link with loan availability, though. A negative coefficient indicates that contrary to earlier study results (Iheke & Agodike, 2016), farmers are less likely to adopt these because of their limited time and access to information (Abid et al., 2016).

Unsurprisingly, the study reveals many key characteristics necessary to support the adaptation process in rural regions, particularly farmer income-related ones. These include access to institutional services, age, education, experience, and previous life conditions. Although there is a substantial association between the variables, the possibility of self-selection and heterogeneity limits our capacity to demonstrate causation. Therefore, using PSM, the model's selection bias is corrected. Propensity score estimations were used to examine how adoption techniques affected farmer income. NNM validated the matching effect based on similar propensity scores. We discovered that the propensity scores in the two groups had a similar density after PSM. The sample size for the post-matching impact research is lowered due to NNM's elimination of mismatched non-adopters during the matching procedure. If sample characteristics in the treatment and control groups are considerably similar, it will be possible to compute the average adaptation impact on farmers' income.

ATT Effect of Adaptation on Farmers' Income

Table 8: Adaption strategies impact on farmers' income

Adopted strategies	Adaptation	Observed Coefficient	Std. Err.	Z	P>|z|
1	ATT	5927.273	8680.407	0.680	0.495
	ATU	5958.333	8212.618	0.730	0.468
	ATE	5941.748	6441.652	0.920	0.356
2	ATT	22218.750	8115.719	2.740	0.006
	ATU	5904.762	15744.080	0.380	0.708
	ATE	18188.240	7883.158	2.310	0.021
3	ATT	24333.330	5417.364	4.490	0.000
	ATU	29525.000	10645.350	2.770	0.006
	ATE	26238.530	6086.122	4.310	0.000

We utilized Propensity Score Matching (PSM) analysis to highlight the disparity in farmers' income outcomes between the two groups. We employed three matching techniques to estimate the Average Treatment Effect on the Treated (ATT): Nearest Neighbor Matching (NNM), kernel-based matching, and radius matching. Table 8 summarizes the findings of the NNM. The strong ATT results show that adaptation significantly influences lowering farmer income. The result of ATT shows that farmers who adopted the agriculture credit facility had 68% higher income than those who did not embrace it. IPM gave 27% more income to farmers who adopted climate change strategies. Land usage change gave a 44% raise to farmers who adopted the strategy compared to farmers who did not adopt climate change strategies. Reduced farmer income also implies that adaptation has positively influenced the overall farmer well-being of adopters.

Balance Test between Treatment and Control Group Adaptation

The primary objective of Propensity Score Matching (PSM) is to conduct a balancing test to evaluate the matching impact within our model, ensuring equilibrium between two groups, as indicated by metrics such as mean/median absolute bias and R2 value. The findings of these balancing tests are presented in Tables 9, 10 and 11. After matching, there was a notable reduction in both the absolute mean/median bias and the R2 value, affirming the comparability of the two groups. As indicated in the results, matching effectively diminished bias, suggesting no systematic distinction in the covariate distributions between the two groups (adopters and non-adopters) after matching.

Table 9: Balance test between treatment and control group adaptation 1

Variable	Unmatched Matched	Mean		%bias	%reduct bias	t-test
		Treated	Control			
Age	U	33.321	39.828	-54.000	99.200	-2.920
	M	33.164	33.218	-0.500		-0.030
Education	U	11.750	9.891	58.800	90.200	3.180
	M	11.673	11.855	-5.700		-0.310
Experience	U	14.357	12.969	19.200	84.300	1.050
	M	13.709	13.491	3.000		0.130
Family members	U	6.839	6.797	1.400	14.300	0.080
	M	6.855	6.891	-1.200		-0.060
Farm Labor	U	3.321	2.781	31.000	86.500	1.720
	M	3.291	3.218	4.200		0.230
Off-farm income	U	24259.000	17094.000	48.100	57.200	2.620
	M	23609.000	26673.000	-20.600		-1.210
Family system	U	0.714	0.719	-1.000	-1529.100	-0.050
	M	0.727	0.655	16.000		0.820

Table 10: Balance test between treatment and control group adaptation 2

Variable	Unmatched Matched	Mean		%bias	%reduct bias	t-test
		Treated	Control			
Age	U	30.103	45.538	-150.200	92.300	-8.390
	M	29.734	28.547	11.600		1.010
Education	U	12.294	8.750	122.500	58.600	6.820
	M	12.063	13.531	-50.700		-3.120
Experience	U	13.147	14.231	-15.500	-231.600	-0.810
	M	12.188	8.594	51.400		3.430
Family members	U	6.809	6.827	-0.600	-418.000	-0.030
	M	6.797	6.891	-3.200		-0.180
Farm Labor	U	3.309	2.673	37.800	9.100	2.020
	M	3.281	2.703	34.300		2.120
Off-farm income	U	22346.000	17942.000	28.400	87.000	1.570
	M	21430.000	22000.000	-3.700		-0.300

Variable	Unmatched / Matched	Treated	Control	%bias	%reduct bias	t-test
Family system	U	0.721	0.712	2.000	-1626.600	0.110
	M	0.734	0.891	-34.400		-2.290

Table 11: Balance test between treatment and control group adaptation 3

Variable	Unmatched	Mean		%bias	%reduct bias	t-test
	Matched	Treated	Control			
Age	U	33.494	42.698	-73.900	98.100	-4.100
	M	33.232	33.406	-1.400		-0.100
Education	U	11.260	9.861	42.600	81.400	2.250
	M	11.072	11.333	-7.900		-0.460
Experience	U	14.156	12.651	21.800	66.300	1.100
	M	12.754	12.246	7.300		0.500
Family members	U	6.636	7.140	-17.100	-49.800	-0.890
	M	6.754	6.000	25.700		1.610
Farm Labor	U	3.000	3.093	-5.300	84.400	-0.280
	M	3.000	3.015	-0.800		-0.060
Off-farm income	U	21838.000	17930.000	24.300	50.100	1.350
	M	21022.000	22971.000	-12.100		-0.900
Family system	U	0.714	0.721	-1.500	-1426.800	-0.080
	M	0.725	0.623	22.300		1.270

Nevertheless, a noticeable disparity in outcomes can only be attributed to adaptation. Additionally, the significance of the findings shifts before and after the matching process, with variables losing their significance or diminishing in importance post-matching. The complete results of the balance test are displayed in Table our approach effectively mitigated selection bias and harmonized variables through informed adaptation choices.

CONCLUSION AND POLICY SUGGESTIONS

According to estimations, Pakistani farmers would suffer due to climate change. There haven't been many studies examining how farmers' income can be increased by adaptation to climate change measures. This study offers important insights for future adaptation planning and policy development. Agricultural financing facilities, insect pest control (IPM), and a shift in land use are the key adaptive methods taken in each region. In order to reduce the possibility of losses brought on by climate change, adaptations are preferable. It is important to note that there are several ways to raise farmers' income. However, the three strategies used for this study were chosen based on their high adoption rates. These policies may become ineffectual or inefficient if national climate adaptation strategies and particular actions are not adequately operationalized. One group that decides to conduct environmentally friendly production and consumption in a vast geographical area will fail if the policy does not successfully promote awareness of such possibilities on a larger scale. There is a need for appropriate frameworks for input procurement for many of the results of the most often-used mitigation measures.

However, poor societies have fewer means to invest in these desired adaptations, and institutional services also underserve them due to their remote location. PSM estimate research shows a significant opportunity to increase income by implementing these techniques, increasing farmers' productive capacity. According to the study's findings, the primary strategy for increasing farmers' income may involve more narrowly focusing research on those with few resources. In this study, we attempt to determine the counterfactual answers that are most crucial for creating beneficial policies (region-specific policies), therefore explicitly referencing the essential link between adaption techniques and farmers' financial well-being. Farmers' ability to select effective strategies to adapt to changing conditions is influenced by various factors, including their household's socioeconomic status, demographic composition, annual income from farming, market access, and climate-related information and support services.

The results have important policy implications:

1) It underscores the importance of government and non-governmental organizations providing comprehensive support for smallholder farmers in implementing their adaptation methods. This support should encompass a wide range of institutional, policy, and technological assistance, focusing on smallholder farmers.
2) In shaping future policies, there should be an emphasis on raising awareness and improving education on climate change. This can be achieved through various platforms like training sessions, conferences, and seminars.
3) Additionally, facilitating access to credit and markets, especially for adaptive technologies, can enhance smallholder farmers' capacity to diversify their adaptation strategies and the extent of their adaptation efforts.
4) Importing adaptive technologies from countries with similar socioeconomic and environmental conditions could further boost the ability of farmers in the study area to adapt effectively.
5) Furthermore, encouraging income diversification, mainly through non-farm sources less susceptible to climate change, is vital.
6) According to various adoption structures, institutional services along with farmer education should be adjusted to encourage farmers to embrace the best combinations of methods rather than relying on just one.

7) These recommendations should be adjusted due to specific conditions, and particular focus should be given to resource-poor farmers, who make up more than two-thirds of Pakistan's total farming population. Incorporating these climate change adaptation strategies into existing government structures, such as the Ministry of Agriculture and other relevant ministries, can benefit smallholder farmers.

REFERENCES

Abid, M., Scheffran, J., Schneider, U. A., & Ashfaq, M. J. E. S. D. (2015). Farmers' perceptions of and adaptation strategies to climate change and their determinants: the case of Punjab province, Pakistan. *Earth System Dynamics*, *6*(1), 225-243.

Abid, M., Schilling, J., Scheffran, J., & Zulfiqar, F. (2016). Climate change vulnerability, adaptation and risk perceptions at farm level in Punjab, Pakistan. *Science of the Total Environment*, *547*, 447-460.

Abid, M., Schneider, U. A., & Scheffran, J. (2016). Adaptation to climate change and its impacts on food productivity and crop income: Perspectives of farmers in rural Pakistan. *Journal of Rural Studies*, *47*, 254-266.

Abidoye, B. O., Kurukulasuriya, P., & Mendelsohn, R. (2017). South-East Asian farmer perceptions of climate change. *Climate Change Economics*, *8*(03), 1740006.

Ado, A. M., Leshan, J., Savadogo, P., Bo, L., & Shah, A. A. (2019). Farmers' awareness and perception of climate change impacts: case study of Aguie district in Niger. *Environment, Development and sustainability*, *21*, 2963-2977.

Akhtar, S., Abbas, A., Iqbal, M. A., Rizwan, M., Samie, A., Faisal, M., & Sahito, J. G. M. (2021). What determines the uptake of multiple tools to mitigate agricultural risks among hybrid maize growers in Pakistan? Findings from field-level data. *Agriculture*, *11*(7), 578.

Ali, A. (2017). Coping with climate change and its impact on productivity, income, and poverty: evidence from the Himalayan region of Pakistan. *International journal of disaster risk reduction*, *24*, 515-525.

Ali, A. (2018). Impact of climate-change risk-coping strategies on livestock productivity and household welfare: empirical evidence from Pakistan. *Heliyon*, *4*(10).

Ali, A., & Abdulai, A. (2010). The adoption of genetically modified cotton and poverty reduction in Pakistan. *Journal of agricultural economics*, *61*(1), 175-192.

Ali, A., & Behera, B. (2016). Factors influencing farmers′ adoption of energy-based water pumps and impacts on crop productivity and household income in Pakistan. *Renewable and Sustainable Energy Reviews*, *54*, 48-57.

Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, *16*, 183-194.

Ali, A., Rahut, D. B., & Mottaleb, K. A. (2018). Improved water-management practices and their impact on food security and poverty: empirical evidence from rural Pakistan. *Water Policy*, *20*(4), 692-711.

Ali, A., Xia, C., Jia, C., & Faisal, M. (2020). Investment profitability and economic efficiency of the drip irrigation system: Evidence from Egypt. *Irrigation and Drainage*, *69*(5), 1033-1050.

Aydinalp, C., & Cresser, M. S. (2008). The effects of global climate change on agriculture. *American-Eurasian Journal of Agricultural & Environmental Sciences*, *3*(5), 672-676.

Bryan, E., Deressa, T. T., Gbetibouo, G. A., & Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental science & policy*, *12*(4), 413-426.

Cavatassi, R., Lipper, L., & Narloch, U. (2011). Modern variety adoption and risk management in drought prone areas: insights from the sorghum farmers of eastern Ethiopia. *Agricultural Economics*, *42*(3), 279-292.

Coffey, K., Haile, M., Halperin, M., Wamukoya, G., Hansen, J., Kinyangi, J., & Tesfaye Fantaye, K. (2015). Expanding the contribution of early warning to climate-resilient agricultural development in Africa. *CCAFS Working Paper*. https://cgspace.cgiar.org/bitstream/10568/66596/1/Formatted%20Early%20warning%20FINAL.pdf.

Daxini, A., Ryan, M., O'Donoghue, C., & Barnes, A. P. (2019). Understanding farmers' intentions to follow a nutrient management plan using the theory of planned behaviour. *Land Use Policy*, *85*, 428-437.

Deressa, T. T., Hassan, R. M., & Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *The Journal of Agricultural Science*, *149*(1), 23-31.

Despotović, J., Rodić, V., & Caracciolo, F. (2019). Factors affecting farmers' adoption of integrated pest management in Serbia: An application of the theory of planned behavior. *Journal of Cleaner Production*, *228*, 1196-1205.

Elahi, E., Abid, M., Zhang, H., Cui, W., & Hasson, S. U. (2018). Domestic water buffaloes: Access to surface water, disease prevalence and associated economic losses. *Preventive Veterinary Medicine*, *154*, 102-112.

Fahad, S., & Wang, J. (2018). Farmers' risk perception, vulnerability, and adaptation to climate change in rural Pakistan. *Land use policy*, *79*, 301-309.

Faisal, M., Abbas, A., Cai, Y., Ali, A., Shahzad, M. A., Akhtar, S., ... & Batool, Z. (2021). Perceptions, vulnerability and adaptation strategies for mitigating climate change effects among small livestock herders in Punjab, Pakistan. *International Journal of Environmental Research and Public Health*, *18*(20), 10771.

Faisal, M., Abbas, A., Xia, C., Raza, M. H., Akhtar, S., Ajmal, M. A., ... & Cai, Y. (2021). Assessing small livestock herders' adaptation to climate variability and its impact on livestock losses and poverty. *Climate Risk Management*, *34*, 100358.

Faisal, M., Chunping, X., Abbas, A., Raza, M. H., Akhtar, S., Ajmal, M. A., & Ali, A. (2021). Do risk perceptions and constraints influence the adoption of climate change practices among small livestock herders in Punjab, Pakistan?. *Environmental Science and Pollution Research*, *28*, 43777-43791.

Faisal, M., Chunping, X., Akhtar, S., Raza, M. H., Nazir, A., Mushtaq, Z., & Ajmal, M. A. (2018). Economic Analysis and Production Efficiency of Dark Sun Cured Rustica Tobacco Production A Case Study of Punjab. *Pakistan. J. Soc. Sci. Hum. Stud*, *4*, 7-14.

FAO WFP, I. F. A. D. (2012). The state of food insecurity in the world 2012. *Economic growth is necessary but not sufficient to accelerate reduction of hunger and malnutrition. Rome, FAO*.

Field, C. B., Barros, V., Stocker, T. F., & Dahe, Q. (Eds.). (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change*. Cambridge University Press.

Greenough, G., McGeehin, M., Bernard, S. M., Trtanj, J., Riad, J., & Engelberg, D. (2001). The potential impacts of climate variability and change on health impacts of extreme weather events in the United States. *Environmental health perspectives*, *109*(suppl 2), 191-198.

Heckman, J., & Navarro-Lozano, S. (2004). Using matching, instrumental variables, and control functions to estimate economic choice models. *Review of Economics and statistics*, *86*(1), 30-57.

Hillbur, S. (2012). Farmer's perceptions of agroforestry: A case study about the obstacles and opportunities for agroforestry adoption in Babati, Tanzania.

Howden, S. M., Crimp, S. J., & Stokes, C. J. (2008). Climate change and Australian livestock systems: impacts, research and policy issues. *Australian journal of experimental agriculture*, *48*(7), 780-788.

Iheke, O. R., & Agodike, W. C. (2016). Analysis of factors influencing the adoption of climate change mitigating measures by smallholder farmers in IMO state, Nigeria. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural Dev*, *16*, 213-220.

IPCC. (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. Retrieved online from: https://ipcc.ch/report/ar6/wg2/.

Iqbal, M. A., Ping, Q., Abid, M., Abbas, A., Bashir, M. K., & Ullah, R. (2018). Extent and determinants of rural poverty in Pakistan: role of adopting risk management strategies. *JAPS: Journal of Animal & Plant Sciences*, *28*(6).

Jamil, I., Jun, W., Mughal, B., Raza, M. H., Imran, M. A., & Waheed, A. (2021). Does the adaptation of climate-smart agricultural practices increase farmers' resilience to climate change?. *Environmental Science and Pollution Research*, *28*, 27238-27249.

Jamshidi, O., Asadi, A., Kalantari, K., Azadi, H., & Scheffran, J. (2019). Vulnerability to climate change of smallholder farmers in the Hamadan province, Iran. *Climate Risk Management*, *23*, 146-159.

Kabir, M. I., Rahman, M. B., Smith, W., Lusha, M. A. F., Azim, S., & Milton, A. H. (2016). Knowledge and perception about climate change and human health: findings from a baseline survey among vulnerable communities in Bangladesh. *BMC public health*, *16*, 1-10.

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of adoption and impacts of improved maize varieties in eastern Zambia. *World development*, *66*, 695-706.

Lake, I. R., Hooper, L., Abdelhamid, A., Bentham, G., Boxall, A. B., Draper, A., ... & Waldron, K. W. (2012). Climate change and food security: health impacts in developed countries. *Environmental health perspectives*, *120*(11), 1520-1526.

Linnerooth-Bayer, J., & Hochrainer-Stigler, S. (2015). Financial instruments for disaster risk management and climate change adaptation. *Climatic Change*, *133*, 85-100.

Makuvaro, V., Walker, S., Masere, T. P., & Dimes, J. (2018). Smallholder farmer perceived effects of climate change on agricultural productivity and adaptation strategies. *Journal of Arid Environments*, *152*, 75-82.

Mendola, M. (2007). Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh. *Food policy*, *32*(3), 372-393.

Mertz, O., Mbow, C., Reenberg, A., & Diouf, A. (2009). Farmers' perceptions of climate change and agricultural adaptation strategies in rural Sahel. *Environmental management*, *43*, 804-816.

Milgroom, J., & Giller, K. E. (2013). Courting the rain: Rethinking seasonality and adaptation to recurrent drought in semi-arid southern Africa. *Agricultural Systems*, *118*, 91-104.

Mirza, M. M. Q. (2011). Climate change, flooding in South Asia and implications. *Regional environmental change*, *11*(Suppl 1), 95-107.

Mubiru, D. N., Radeny, M., Kyazze, F. B., Zziwa, A., Lwasa, J., Kinyangi, J., & Mungai, C. (2018). Climate trends, risks and coping strategies in smallholder farming systems in Uganda. *Climate Risk Management*, *22*, 4-21.

Muzari, W., Gatsi, W., & Muvhunzi, S. (2012). The impacts of technology adoption on smallholder agricultural productivity in sub-Saharan Africa: A review. *Journal of Sustainable Development*, *5*(8), 69.

Nabikolo, D., Bashaasha, B., Mangheni, M. N., & Majaliwa, J. G. M. (2012). Determinants of climate change adaptation among male and female headed farm households in eastern Uganda. *African Crop Science Journal*, *20*, 203-212.

Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., ... & Travasso, M. I. (2014). Food security and food production systems.

Qi, X., Jia, J., Liu, H., & Lin, Z. (2019). Relative importance of climate change and human activities for vegetation changes on China's silk road economic belt over multiple timescales. *Catena*, *180*, 224-237.

Raza, M. H., Abid, M., Faisal, M., Yan, T., Akhtar, S., & Adnan, K. M. (2022). Environmental and health impacts of crop residue burning: Scope of sustainable crop residue management practices. *International Journal of Environmental Research and Public Health*, *19*(8), 4753.

Raza, M. H., Abid, M., Yan, T., Naqvi, S. A. A., Akhtar, S., & Faisal, M. (2019). Understanding farmers' intentions to adopt sustainable crop residue management practices: A structural equation modeling approach. *Journal of Cleaner Production*, *227*, 613-623.

Raza, M. H., Bakhsh, A., & Kamran, M. (2019). Managing climate change for wheat production: An evidence from southern Punjab, Pakistan. *Journal of Economic Impact*, *1*(2), 48-58.

Schmidhuber, J., & Tubiello, F. N. (2007). Global food security under climate change. *Proceedings of the national academy of sciences*, *104*(50), 19703-19708.

Shah, A. A., Ye, J., Abid, M., Khan, J., & Amir, S. M. (2018). Flood hazards: household vulnerability and resilience in disaster-prone districts of Khyber Pakhtunkhwa province, Pakistan. *Natural hazards*, *93*, 147-165.

Shah, A. A., Ye, J., Shaw, R., Ullah, R., & Ali, M. (2020). Factors affecting flood-induced household vulnerability and health risks in Pakistan: The case of Khyber Pakhtunkhwa (KP) Province. *International Journal of Disaster Risk Reduction*, *42*, 101341.

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global environmental change*, *16*(3), 282-292.

Smith, J. A., & Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. *Journal of econometrics*, *125*(1-2), 305-353.

Thornton, P. K., & Herrero, M. (2014). Climate change adaptation in mixed crop–livestock systems in developing countries. *Global Food Security*, *3*(2), 99-107.

Thornton, P. K., & Herrero, M. (2015). Adapting to climate change in the mixed crop and livestock farming systems in sub-Saharan Africa. *Nature Climate Change*, *5*(9), 830-836.

Wei, W., Mushtaq, Z., Faisal, M., & Wan-Li, Z. (2020). Estimating the economic and production efficiency of cotton growers in Southern Punjab, Pakistan. *Custos e Agronegocio*, *16*(2), 2-21.

Wei, W., Mushtaq, Z., Ikram, A., Faisal, M., Wan-Li, Z., & Ahmad, M. I. (2020). Estimating the economic viability of cotton growers in Punjab Province, Pakistan. *Sage Open*, *10*(2), 2158244020929310.

Yu, W., Alam, M., Hassan, A., Khan, A. S., Ruane, A., Rosenzweig, C., & Thurlow, J. (2010). *Climate change risks and food security in Bangladesh*. Routledge.