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How do farm sizes and perceptions matter for farmers' adaptation responses to climate change in a developing country?

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Abstract

Farm sizes and climatic perceptions are important economic and cognitive factors for farmers' activities. However, little is known about how these factors are related to farmers' responsiveness to climate change. This research addresses what matters for farmers' responses to the climate change, hypothesizing that farm sizes, climatic perceptions and the interplay between the two are key determinants. We conduct questionnaire surveys with 1000 farmers in Nepal, collecting data on their adaptation responses, farm sizes, climatic perceptions and sociodemographic information in Nepal. With the data, the statistical analysis is conducted by employing the index to reflect farmers' effective adaptation responses. The result reveals that farmers take adaptations as the farm sizes become small or as they have good climatic perceptions & social network with other farmers. It also shows that small-sized farmers tend to adapt much more in response to their climatic perceptions than do large-sized ones. Overall, this research suggests that agriculture may be losing responsiveness to climate change, as large-sized farmers become dominant by holding a majority of land in developing countries. Thus, it is advisable to reconsider the tradeoff between productivity and responsiveness to climate change regarding farm sizes as well as how large-sized farmers can be induced to adapt through their cognition, policies, social networking and technology for food security.

Key Words: climate change; agriculture; farm sizes; adaptations; perceptions; interplay

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Nomenclature

WTP Willigness To Pay

VDC Village Development Commitee

HH Household

RA Research Assistant

AFU Agriculture and Forestry University

AdaptN Number of Adaptations

AI Adaptation Index

ha Hectare

CPI Climate Perception Index

NPR Nepali Rupees

1 Introduction

Climate change has brought several devastating consequences to the agricultural sector, posing a serious challenge to farmers' welfare (Rosenzweig et al., 2013, IPCC, 2014). There is an urgent need for farmers to take necessary adaptation responses for minimizing the consequences of climate change (McCarthy et al., 2001, IPCC, 2014).[1] In the last two decades, improvement in farmers' capacity has been recognized to be the key element at enhancing their adaptation responses in both developed and developing countries (Yohe and Tol, 2002, Smit and Wandel, 2006, Vincent, 2007, Fussel, 2007, Cinner et al., 2018). In particular, economic and cognitive factors are known to be crucial for farmers' adaptive capacity (Grothmann and Patt, 2005). This study addresses farmers' responsiveness to climate change in relation to economic and cognitive factors through studying their adaptations.

The farm size is one of the key economic factors for farmers' agricultural activities in response to climate change (Ullah et al., 2019, Kumar et al., 2020). Several studies examine adaptations in relation to farm sizes, focusing on subsistence farmers by conducting questionnaire surveys (Eitzinger et al., 2018, Ontl et al., 2017, Trinh et al., 2018, Abid et al., 2019, Khan et al., 2020, Ahmed et al., 2021). A group of studies shows positive associations between farm sizes and farmers' adaptation responses (Piya et al., 2012, Ashraf et al., 2014, Belay et al., 2017, Trinh et al., 2018). For instance, a recent study by Jiao et al. (2020) analyzes adaptation decisions and intensities, showing that farm sizes matter only for the intensities. Another group of studies reports negative associations between farm sizes and adaptation responses to climate change (Deressa et al., 2010, Uddin et al., 2014, Amare and Simane, 2017). For example, a study by Khan et al. (2020) investigates adaptation choices, and demonstrates that farm sizes inhibit farmers to choose some adaptations, such as irrigation time changes and use of short duration varieties. Overall, the literature establishes that the farm size is an influential factor for farmers' adaptation responses to climate change. However, the directions and magnitudes of the farm sizes' influences are mixed

[1] The adaptation is defined as the adjustment of agronomic practices, agricultural processes and capital investments in response to observed or expected climate change risks (Easterling et al., 2007, IPCC, 2014).

with positive and negative associations.

Past literature examines the relationship between farmers' or people's climatic perceptions and responses to climate change by conducting questionnaire surveys (Below et al., 2012, Niles et al., 2013, Abid et al., 2016, Ndamani and Watanabe, 2015, Azadi et al., 2019, Soubry et al., 2020).[2] Arbuckle Jr et al. (2013) analyze climatic perceptions and attitudes in the United States, indicating that farmers tend to display positive attitudes toward adaptations when they perceive climate change. Islam et al. (2016) analyze the relation between climatic perceptions and willingness to pay (WTP) for flood mitigations by taking a sample of 1011 people in Bangladesh, and show that people with correct perceptions tend to have higher WTP than those without them. Abid et al. (2019) examine climatic perceptions and adaptation intentions by taking 450 farmers from Pakistan as a sample, finding the positive effects of the perceptions on their intentions. Khanal et al. (2018) and Khanal and Wilson (2019) investigate adaptations by taking the Nepalese samples, showing that farmers with beliefs on climate change adapts more than the ones without such beliefs. Overall, these studies establish that farmers or people tend to take some responses to climate change when they perceive climate change or have correct perceptions to temporal trends in climate variables.

Previous studies analyze some adaptations and/or responses to climate change associated with farm sizes or climatic perceptions, mainly focusing on subsistence farmers (Below et al., 2012, Khanal and Wilson, 2019, Jiao et al., 2020). Some theoretical models of climate-change adaptations are proposed by Grothmann and Patt (2005) and Reser and Swim (2011), suggesting that people's responses to climate change shall be characterized by their cognitive and economic factors in an interactive way.[3] However, few studies have empirically examined how cognitive, economic factors and the interplay affect farmers' responses to climate change within a single framework. This research investigates what matters for farmers' adaptations as responses to climate change, hypothesizing that farm sizes, climatic perceptions and the interplay between them are the key

[2] Climatic perception is defined as a state of opinions and/or awareness toward the change in climate variables (Ruiz et al., 2020).

[3] Grothmann and Patt (2005) develop a socio-cognitive model, called "*Model of Private Proactive Adaptation to Climate Change* (MPPACC)," stating that motivations, perceptions and sociodemographic factors play roles for adaptation responses.

determinants. A novelty of this study lies in collecting the data from a wide range of farmers, not only subsistence but also large-sized commercial farmers, as well as in analyzing how such farmers' adaptation responses differ by the farm sizes and by their interaction with climatic perceptions.

2 Methodology

2.1 Study areas and data collection

The primary data were collected from the former five development regions (Eastern, Central, Western, Mid-Western and Far-Western), covering ten districts of Nepal as shown in figure 1. The districts were randomly selected for wide geographical coverage.[4] One Village Development Committee (VDC) or a municipality was randomly identified in each selected district where agriculture was the main occupation for most households. After consulting with selected VDC or municipality officers, we identified 2 to 4 wards for the study. A list of households (HHs) was obtained from the VDC office for each identified ward as a sampling frame and utilized to select HHs to be surveyed. Using a systematic random sampling method, we identified 25 - 40 HHs for each ward and collected information of a total of 1000 HHs from the study areas.

The questionnaires were prepared in the local Nepali language, pre-tested with non-sampled HHs and finally administered to the sampled HHs of the study areas. We hired graduate students from Agriculture and Forestry University (AFU) who worked as research assistants (RAs) in this study. The RAs received a one-day orientation session that covered the objectives of the study. They additionally received instructions to collect the informed consent from the HHs that ensures the anonymity of the individual information obtained in the surveys. Finally, the RAs administered the questionnaire survey and obtained the necessary information from the study areas under the direct supervision of the first author.

[Figure 1 about here.]

[4] The study areas include only Hill and Terai districts since the agricultural activities are primarily carried out in these areas.

2.2 Key variables

We ask several questions to the HH heads (hereafter, farmers), and obtain farm-related information, such as farm sizes (or land), adaptations and the land area covered by each adaptation. We also collect information related to cognitive & non-cognitive factors, such as climatic perceptions and education, and other sociodemographic variables from farmers (See table 1 for details). By following Piya et al. (2012) and Below et al. (2012), we prepare a list of adaptations to be able to ask farmers whether or not they take a particular adaptation. Since all listed adaptations might not be applied by farmers in the study areas, the list is pre-tested, revised and included in the final questionnaire. Following the list, each farmer j is asked two questions: (1) Do you adopt a particular adaptation "a_i" in your farm? and (2) To what extend the "a_i" covers your farm (or land) "w_{ij}?"

Based on these questions and answers, we calculate two outcome variables or measurements for effective adaptation responses to climate change, AdaptN and AI. The respective value of AdaptN (the number of adaptation) for the jth farmer is calculated as follows:

$$\text{AdaptN}_j = \sum_{i=1}^{n} a_{ij} \tag{1}$$

where subscript i indicates an index of adaptations for $i = 1, \ldots, n$, and a_{ij} is a dummy variable for adaptation i that takes value 1 if the jth farmer adapts; otherwise, 0. The respective value of AI (adaptation index) for the jth farmer is calculated as follows:

$$\text{AI}_j = \sum_{i=1}^{n} a_{ij} w_{ij} \tag{2}$$

where $w_{ij} = \frac{\text{Farm-size coverage of } a_{ij}}{\text{Total land of the } j\text{th farmer}}$ with $0 \leq w_{ij} \leq 1$, following Below et al. (2012) and Khanal and Wilson (2019). The theoretical values of the AdaptN_j and AI_j range from 0 to n.

Suppose that the jth farmer takes two adaptations of a_{1j} and a_{2j} with $75\,\%$ and $60\,\%$ farm-size coverages, respectively. In this case, the AdaptN_j is 2, while the AI_j is 1.35 ($= 1 \times 0.75 + 1 \times 0.60$).

Therefore, the value of AI_j depends not only on whether or not the jth farmer takes the particular adaptation (a_i) but also on to the extent to which each adaptation a_i covers his/her farm size, i.e., w_{ij}. The difference in the two measurements of AdaptN_j and AI_j lies in whether to consider a weight to each adaptation. AdaptN_j considers only the incidences of all adaptations and the associated sum by assuming that each adaptation covers an entire farm (i.e., $w = 1$). However, it is argued that it is crucial to consider a weight for each adaptation (Below et al., 2012, Khanal and Wilson, 2019). Therefore, we consider both AdaptN_j and AI_j in analyzing farmers' adaptation responses for the purposes of comparison and robustness checks.

[Table 1 about here.]

Farm size and climatic perceptions are two major independent variables in this study. To make a uniform unit of measurement, the farm size of the jth farm is first recorded in local unit (Kattha), and it is computed to hectare (ha) by multiplying it with a conversion factor of 0.0333 ($= \frac{1}{30}$).[5] Following Thapa et al. (2019) and Kumar et al. (2020), farmers are categorized into four dummies based on their farm sizes: (i) marginal farmer (farm size $< 0.16\,\mathrm{ha}$), (ii) small farmer (0.16 ha $\leq$ farm size $< 0.33\,\mathrm{ha}$), (iii) medium farmer ($0.33\,\mathrm{ha} \leq$ farm size $\leq 1.00\,\mathrm{ha}$) and (iv) large farmer (farm size $> 1.00\,\mathrm{ha}$). Hereafter, these farm-sized variables are expressed to be farm-size dummies. For climatic perceptions, we ask eight questions to farmers regarding how they have perceived the changes in eight different climate variables: summer temperature, winter temperature, drought, cold waves, hot waves, rainfall frequency, intensity and flood over the last 20 years (Manandhar et al., 2010, Below et al., 2012, Piya et al., 2012, Shrestha et al., 2019). An example of such questions is "have you noticed the changes in the pattern of summer temperature in the last 20 years?" If yes, each farmer proceeds with being asked to report his/her perception to the temporal trend as an increase or a decrease. We record farmers' replies for all eight questions and later compute each of them to be either 1 or 0. If the farmer perceives a change, i.e., either an increase or a decrease, we assign the value as 1, otherwise, 0. Finally, an aggregate CPI (climatic

[5] Note that 1 hectare $=$ 30 Katha $=$ 10000 squared meter.

perception index) is calculated to be a sum of all perception answers by the jth farmer to the eight climate variables (Below et al., 2012, Shrestha et al., 2019).

2.3 Statistical analysis

This study first calculates, analyzes and interprets the mean, median, standard deviation, minimum and maximum of the key variables. Second, it conducts some statistical analyses, such as Mann-Whitney nonparametric tests, to identify some qualitative relations between the key variables. To quantitatively examine the relationship between adaptation responses of the dependent variable and the independent ones, the Poisson and median regression models are employed. We choose the Poisson regression for characterizing AdaptN_j, because it is a variable of nonnegative integers with a relatively few observations for each count. We are interested in estimating the effect of an independent variable on AdaptN_j with the assumption that AdaptN_j follows the Poisson distribution conditional on a vector of the independent variables, $\mathbf{X}$. The likelihood function of AdaptN_j conditional on the observations of $\mathbf{X}$ is expressed as:

$$\text{Prob}(\text{AdaptN}_j = h|\mathbf{X} = \mathbf{x}_j) = \exp[-\exp(\mathbf{x}_j\boldsymbol{\alpha}')][\exp(\mathbf{x}_j\boldsymbol{\alpha}')]^h/h!, \quad h = 0, 1, 2, \ldots, n \tag{3}$$

where subscript j is the farmer's ID and $\mathbf{x}_j = (1, x_{1j}, x_{2j}, \ldots, x_{kj})$ is a vector of independent variables observed from the jth farmer, $\boldsymbol{\alpha} = [\alpha_\ell]_{\ell=0}^k = (\alpha_0, \alpha_1, \ldots, \alpha_k)$ is a vector of coefficients associated with $\mathbf{x}_j$ to be estimated and h is the number of adaptations the jth farmer takes, respectively. The estimate for each coefficient of the vector $\boldsymbol{\alpha}$ is obtained via the quasi-maximum likelihood estimation method for the Poisson regression based on equation (3) (Ramirez and Shultz, 2000, Cameron and Trivedi, 2005, Wooldridge, 2019). Each estimated coefficient can be interpreted as a percentage change with $100 \times \alpha_\ell$ (or $[\exp(\alpha_\ell) - 1] \times 100$) in $\mathbb{E}(\text{AdaptN}_j|\mathbf{X})$ when one continuous (or dummy) independent variable increases by one unit (or from zero to one), holding other factors constant.

We use median regression to analyze the relationship between AI_j and the independent variables as specified in equation (4), because the AI is identified not to follow a normal distribution by the Shapiro-Wilk tests (Kraska-Miller, 2009, Corder and Foreman, 2014). Median regression is considered more appropriate than the mean-based regression in characterizing a nonnormal dependent variable in relation to independent variables (Koenker and Bassett, 1978, Koenker and Hallock, 2001). Mathematically, median regression is expressed as follows:

$$\mathrm{AI}_j = \mathbf{x}_j \boldsymbol{\beta}' + \epsilon_j \tag{4}$$

where AI_j is the dependent variable of adaptation index for farmer j, $\mathbf{x}_j = (1, x_{1j}, x_{2j}, \ldots, x_{kj})$ is the vector of the independent variables, $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_k)$ is a vector of the coefficients associated with $\mathbf{x}_j$ to be estimated via the least absolute distance estimation method and ϵ_j is an error term, respectively. Each coefficient is interpreted as a change in AI median when one continuous (or dummy) independent variable increases by one unit (or from zero to one), holding other variables constant. The results from the Poisson and median regression models are demonstrated and compared between AdaptN and AI associated with the same set of independent variables.

3 Results

Table 2 presents summary statistics of the variables across farm sizes. The results indicate that farmers do agricultural activities on $0.83\,\mathrm{ha}$ of land (farm sizes) on average. Regarding farming experiences, farmers do not differ considerably across farm sizes, having approximately 20 years of average experiences. Farmers participate in agricultural trainings 0.34 times, and the averages are $0.28, 0.28, 0.35$ and 0.42 for marginal, small, medium and large farmers, respectively. It suggests that farmers tend to participate in agricultural trainings as farm sizes increase. Farmers generally attain formal education of 6.38 school years, and they are identified to possess 1.43 social network, such as cooperative and farm field school. The averages of education for marginal, small, medium and large farmers are $5.96, 6.97, 6.11$ and 6.63, respectively, implying that farmers tend to have high education as farm sizes increase. With respect to social network, the averages are

$1.37, 1.44, 1.47$ and 1.38 for marginal, small, medium and large farmers, respectively, demonstrating that there are no considerable differences in social networks across farm sizes.

About $50.00\,\%$ of the farmers have access to agricultural information, while the percentages are observed to be about $50.00\,\%$, $44.00\,\%$, $50.00\,\%$ and $55.00\,\%$ for marginal, small, medium and large farmers, respectively. It appears that access to agricultural information does not significantly differ among farmers. The average size of economically active family members, i.e., the labor force, is 3.43, while the averages are not substantially different across farm sizes. In the study areas, $87.00\,\%$ of the farmers are identified to be male and the percentages are similar across farm sizes. The overall average household (HH) annual income for farmers is 346 thousands NPR, and it appears that farmers' incomes become high from 271.59 to 438.76 thousands NPR as farm sizes increase. Farmers have average distances of $3.23\,\mathrm{km}$ and $2.70\,\mathrm{km}$ to reach the nearest agricultural extension service and market, respectively and the distances do not significantly differ across farm sizes. Overall, the summary statistics suggest that farmers are similar in terms of agricultural training, education, active family size, gender, distances to agricultural service and market, while they differ in terms of social network, access to information and HH annual income.

[Table 2 about here.]

Figure 2 is a bar graph to present the percentages of farmers that perceive some changes in eight climate variables over the last 20 years. A majority of farmers perceive the changes in summer temperature, winter temperature, rainfall intensity, rainfall frequency and drought, whereas about $50.00\,\%$, $38.00\,\%$ and $22.00\,\%$ of them perceive cold waves, hot waves and floods, respectively. The results suggest that climate change is perceived to be an ongoing phenomenon in the study areas, and Nepalese farmers' perceptions are consistent with previous literature (Manandhar et al., 2010, Piya et al., 2012, Khanal and Wilson, 2019, Shrestha et al., 2019). To understand how the perceptions vary across farm sizes, we calculate the perceptions to be a climate perception index (CPI) for comparison (table 2). The overall mean and median values of CPI are found to be 4.99 and 5.00, respectively, ranging between 4.82 to 5.18 across farm sizes. These values demonstrate that farmers have homogeneous climatic perceptions.

[Figure 2 about here.]

Table 2 shows that farmers take 8.00 adaptations on average with the median value of 7.00 and some variation across farm sizes. The median AdaptNs are both 6.00 for marginal and small farmers, while they are 7.00 for medium and large farmers, respectively. There is a tendency for farmers to take adaptations as farm sizes increase. The tendency is confirmed from figure 3(a) that shows boxplots of AdaptN by farm sizes. We run the Mann-Whitney test to examine distributional differences in AdaptNs across farm sizes, and apply it to every pair of different-sized farmers. The null hypothesis is that the distributions of AdaptNs between two different-sized farmers are the same. Table 3 shows that the null hypothesis is rejected only for the pair of small and large farmers at $5\,\%$ level ($P < 0.05, z = -2.017$). This implies that farmers' adaptations are not statistically identified to depend on farm sizes, while we see a tendency for large-sized farmers to take adaptations.

[Figure 3 about here.]

The value of average AI for farmers is 1.31, while the averages are $2.52, 1.62, 1.00$ and 0.79 for marginal, small, medium and large farmers, respectively (table 2). The average AIs are not only different from one another but also tend to decline when farm sizes increase, i.e., from marginal to large farmers. The results imply that farmers curb adaptation coverages as farm sizes increase. The tendency is confirmed from figure 3(b) that demonstrates the boxplots of AIs across farm sizes. We run the Mann-Whitney test to examine distributional differences in AIs across farm sizes, and apply it to every pair of different-sized farmers. The null hypothesis is that the distributions of AIs between two different-sized farmers are the same. Table 3 shows that the null hypotheses are rejected for all pairs of farmers at $1\,\%$ level, implying that AIs are statistically identified to decline with farm sizes.

[Table 3 about here.]

Table 4 report adaptations and the percentages of farmers taking them by farm sizes. The results show that farmers' adaptation responses vary across farm sizes. For example, nearly $38\,\%$

of large farmers use pump irrigation method as an adaptation, while the percentages are $65.55\,\%$, $52.40\,\%$ and $64.55\,\%$ for marginal, small and medium farmers, respectively. Only about $1.00\,\%$ of large farmers adapt mixed cropping, while more than $28.00\,\%$ of marginal, small and medium farmers take it. There are considerable differences between large and other farmers in some adaptations, such as supplement with organic/FYM or inorganic fertilizers. More than $63.00\,\%$ of marginal, small and medium farmers adapt inorganic and/or organic supplements, while only less than $36.00\,\%$ of large farmers take them. Overall, these results suggest that the kinds and actions of farmers' adaptation responses highly depend on farm sizes, indicating the possible reasons for the tendencies of AdaptN and AI observed in figure 3.

[Table 4 about here.]

Table 5 reports the estimated coefficients of the independent variables on AdaptN in the Poisson regression models 1 to 6 together with the standard errors and statistical significance. We have employed other different regression specifications to check the robustness of the results. The main results are found to remain qualitatively the same in all models. We primarily focus on reporting the effects of farm sizes, CPI, agricultural training, social network, access to information, HH annual income, agricultural service and market distances on AdaptN, because they are of particular interest in drawing implications in this research or stand statistically significant in all models.

[Table 5 about here.]

The coefficients of farm-size dummies on AdaptN are not statistically significant through models 1, 3 and 5. However, the coefficients for the medium-farmer dummy become statistically significant at $1\,\%$ to $5\,\%$ level when we include interaction terms between the farm-size dummy and CPI in models 2, 4 and 6. Model 2 demonstrates that medium farmers are likely to have additional $60.64\,\%$ AdaptN as compared to marginal farmers (base group), holding other variables fixed. The results could be due to the fact that medium farmers consist of both motivations and/or affordability to take adaptations as compared to other-sized farmers, as pointed out by previous studies (Piya et al., 2012, Jiao et al., 2020). Overall, the results suggest that farm sizes do not strongly influence farmers to take adaptations except for medium farmers through the interaction with CPI.

The coefficients of CPI are statistically significant and positive at $1\,\%$ level in models 3 and 5, and they remain so at the same level, when we include interaction terms between farm-size dummies and CPI in models 2, 4 and 6. For instance, model 3 shows that farmers tend to take additional $6.10\,\%$ AdaptN when CPI improves by one unit. Previous studies similarly find that farmers' adaptations are highly affected by their climatic perceptions (Deressa et al., 2009, Khanal and Wilson, 2019, Azadi et al., 2019, Soubry et al., 2020), suggesting that the climatic perceptions need to be improved to influence their adaptations. The results in this study also confirm that farmers' climatic perceptions are positively associated with farmers' adaptations in a consistent and robust manner.

The interaction terms between the medium-farmer (large-farmer) dummy and CPI are identified to be statistically significant at $1\,\%$ to $10\,\%$ level in models 2, 4 and 6. Since the coefficients of the interaction terms in these models are negative, the relationship between farm-size dummies and CPI appears to reflect substitutability one another. To statistically confirm the relationship, we calculate the marginal effects of CPI on AdaptN for each of medium and large farmers based on the estimated coefficients in models 2, 4 and 6. We identify that the marginal effects of CPI for medium and large farmers do not stand statistically significant, implying that farmers' adaptations in response to CPI do not practically depend on farm sizes.

Some variables, such as agricultural training, social network and agricultural service distance, show statistically consistent and positive tendencies toward AdaptN. Farmers are likely to have additional $8.00\,\%$ AdaptN when they receive one unit of agricultural training. Past studies similarly argue that trainings can help farmers to acquire adaptation-related knowledge and skills, supporting them to increase responses (Piya et al., 2012, Trinh et al., 2018, Diallo et al., 2020). The result implies that Nepalese farmers tend to adapt to climate change when trainings are given to them, being in line with the literature. Farmers are identified to take additional $11.30\,\%$ AdaptN when the social network increases by one unit. The positive effect may be due to the fact that social networks function as social devices for Nepalese farmers (i) to learn adaptations from other farmers and (ii) to receive financial supports, such as credits, enhancing their adaptation responses. The role of social network is well established in economics and sociology literature to overcome imperfect knowledge about new technologies (Foster and Rosenzweig, 1995, Bandiera and Rasul, 2006, Yamogo et al., 2018). The results suggest that social networking, such as cooperatives and farmers' field schools, are crucial for farmers' adaptation abilities and capacities. Farmers tend to have an increase in AdaptN by about $1.50\,\%$ when market distance increases by $1\,\mathrm{km}$. The result can be supported by the findings in Below et al. (2012), because farmers whose fields are away from markets diversify production methods and/or try to reduce risks associated with climate. Overall, these results suggest that farmers' adaptations are positively associated with agricultural training, social network and market distance.

Farmers with access to agricultural information tend to reduce AdaptN by $7.32\,\%$ as compared to the farmers without access. This result suggests that agricultural information is substitutability to farmers' adaptations in Nepalese contexts. Our result contradicts previous findings that show the positive influence of agricultural information on farmers' adaptations (Deressa et al., 2009, Tambo and Abdoulaye, 2011, Khanal and Wilson, 2019, Khatun et al., 2021). We conjecture that Nepalese farmers are not required to take additional adaptations when agricultural information becomes available due to geographical and/or farming practices. Farmers are likely to reduce AI by about $6.20\,\%$ when their HH annual income rises by $1\,\%$. It may imply that having high HH income does not motivate farmers to take adaptations or low-income farmers are motivated to reduce their risks by diversifying agricultural activities, as argued in Chambers (1987). Farmers tend to reduce AdaptN by about $3.50\,\%$ when agricultural service distance increases by $1\,\mathrm{km}$. We argue that farmers cultivating in close proximity to agricultural services are benefited by extension workers' frequent visits and suggestions, leading them to take adaptations. The result is consistent with past studies (Piya et al., 2012, Abid et al., 2019, Kumar et al., 2020) in that agricultural service extension is identified to be crucial for farmers' activities and productions. Overall, these results suggest that farmers' adaptations are negatively associated with agricultural information, HH annual income and agricultural service distance.

[Table 6 about here.]

Table 6 reports the estimated coefficients of the independent variables on AI in median regression models 1 to 6 along with the standard errors and statistical significance.[6] The coefficients of farm-size dummies on AI are statistically significant at $1\,\%$ level in models 1, 3 and 5 with negative signs, and the tendencies remain the same in a coherent manner, even when we include interaction terms between farm-size dummies and CPI in models 2, 4 and 6. For example, model 1 shows that small farmers take 0.776 less AI than marginal farmers, holding other variables fixed. Likewise, model 1 demonstrates that medium and large farmers tend to reduce AI by 1.480 and 1.750, respectively, as compared to marginal farmers. The results can be attributed to inflexibility of large-sized farmers to take adaptations compared small-sized ones as cumulative investments and/or efforts to do so become large (Uddin et al., 2014, Khanal and Wilson, 2019). It is also argued that large-sized farmers lack motivations and tend to overlook small cost-effective adaptations as their adaptation option (Khan et al., 2020). This argument is in line with table 3 in that large-sized farmers tend not to take small adaptations, such as mixed cropping and changes in irrigation and nutrient amendments, as compared to small-sized farmers. Overall, the results imply that farmers do not take adaptations as farm sizes become large.

The coefficients of CPI on AI are not statistically significant in models 3 and 5. However, they become statistically significant with positive signs at $1\,\%$ level, when we include interaction terms between farm-size dummies and CPI in models 2, 4 and 6. The estimated coefficients of CPI on AI range between 0.215 and 0.245, demonstrating that farmers take adaptations by $0.215 \sim 0.245$ when their CPI increases by one unit. The results in table 5 and past studies similarly find that farmers' adaptations are positively influenced by or associated with their climatic perceptions (Deressa et al., 2009, Khanal and Wilson, 2019, Azadi et al., 2019, Soubry et al., 2020). Our results with respect to CPI are considered another corroboration to establish the positive association

[6] We run different regressions as we did in the Poisson regression, finding that the main results do not differ qualitatively in all models. Therefore, we only report the effects of the main independent variables on AI.

between farmers' CPI and AI in a consistent and robust manner, and suggest that interactions between climatic perceptions and farm sizes shall be keys for characterizing farmers' adaptations.

The interaction terms between farm-size dummies and CPI are statistically significant at $1\,\%$ level in models 2, 4 and 6. Since the coefficients of the interaction terms in these models are negative, the relationship between farm-size dummies and CPI seems to reflect substitutability one another. The results can be interpreted to mean that farmers reduce adaptations in response to CPI when the farm sizes become large. For instance, model 2 shows that marginal farmers take additional 0.217 AI when their CPI increases by one unit. However, small and large farmers only take additional 0.029 $(= 0.217 - 0.188)$ and 0.038 $(= 0.217 - 0.179)$ AI, respectively, when their CPI increases by one unit. The result also shows that medium farmers even reduce AI by 0.036 $(= 0.217 - 0.253)$ when their CPI improves by one unit. The results could be again due to the relative (i) inflexibility or inability of large-sized farmers to take adaptations when they perceive climate change and/or (ii) their insensitivity toward climate variables as compared to small-sized ones. The results imply that farmers' adaptations in response to CPI significantly depend on farm sizes, demonstrating that agricultural policies must be customized for effective adaptation responses according to their climatic perceptions, sizes and the interaction.

The coefficients of some variables, such as agricultural training and social network, are statistically significant with positive signs at $1\,\%$ to $10\,\%$ level in models 3 to 6. Model 3 demonstrates that farmers take additional 0.102 AI when agricultural training increases by one unit, holding other variables fixed. Trainings may help farmers to acquire adaptation-related knowledge and skills, supporting them to increase adaptations (Piya et al., 2012, Trinh et al., 2018, Diallo et al., 2020). Model 3 shows that farmers take additional AI by 0.135 when their social network increases by one unit. We argue that social network facilitates farmers (i) to learn about adaptations from other farmers and (ii) to receive various assistance, such as credits and labor, enhancing their adaptation responses. Our results are supported by past studies that report the positive influence of social network on adopting new technologies in agriculture (Foster and Rosenzweig, 1995, Bandiera and Rasul, 2006, Yamogo et al., 2018). Overall, these findings suggest that agricultural training and social network positively influence farmers to take adaptations.

[Figure 4 about here.]

We find that the interaction terms between farm-size dummies and CPI play an important role in characterizing AI. To quantitatively clarify the interactions, we calculate and plot the median AI over CPI as prediction for different-sized farmers (holding other independent variables at the sample means) based on the estimated results in model 6 of table 6, which we call "predicted AI." Figure 4 shows the predicted AIs over CPI for marginal, small, medium and large farmers, presenting that the intercepts and the slopes are idiosyncratic across farm sizes. The slopes of the predicted AIs for the small, medium and large farmers are almost flat, meaning that these farmers generally tend not to take additional adaptations when their CPI improves, or tend to be insensitive to their own climatic perceptions. On the contrary, the slope of the predicted AI for marginal farmers is observed to be positive and steep, meaning that the marginal farmers take additional adaptations when their CPI improves or tend to be positively sensitive to their own climatic perceptions. Furthermore, the entire plot of median AI prediction is located or becomes low as the farm sizes get large, which is due to estimated differences in the interaction terms and intercept of model 6. In summary, the results graphically and quantitatively corroborate that not only farmers' AIs but also their responses to CPI are likely to decline along with farm sizes.

We finally summarize and compare the results from the two different models of Poisson and median regressions associated with AdaptN and AI in tables 5 and 6. Both regressions find that farm sizes, climatic perceptions, agricultural training and social network can be the key determinants to be positively associated with AdaptN and AI, being economically and statistically significant at least in some models. On the other hand, there are three main differences between the two regressions. First, HH income, agricultural service and market distances are found to be significant (or insignificant) for AdaptN (or AI). Second, farm sizes do not matter much for AdaptN, while they are important predictors for AI along with the interactions with farmers' climatic perceptions. Third, the AI responses to the climatic perceptions are identified to differ across farm sizes, while the AdaptN responses are not. Literature claims some potential problems to employ the number of farmers' adaptations, i.e., AdaptN, as a measurement of farmers' responses, when we study their agricultural practices under climate change (Below et al., 2012, Esham and Garforth, 2012, Niles et al., 2015, Khanal and Wilson, 2019). Building upon literature and analyses in this research, it is our belief that the results of AI median regressions are considered more plausible than those of AdaptN ones, reflecting what is going on Nepalese farmers' adaptations to climate change.

Literature suggests that economic and cognitive factors are important for farmers' adaptation responses (Brondizio and Moran, 2008, Abid et al., 2019). Two theoretical models (i) Protection Motivation Theory (Rogers, 1983, Rogers and Prentice-Dunn, 1997) and (ii) Model of Private Proactive Adaptation to Climate Change (Grothmann and Patt, 2005) argue that economic factors, cognitions and their interaction characterize people's adaptation responses. Our study identifies that farm sizes (i.e., economic factor) interact with climatic perceptions (i.e., a cognitive factor), and the interactions largely influence farmers' adaptation responses. We propose the two possible explanations for the results: (i) flexibility and (ii) sensitivity to climatic perceptions. First, large-sized farmers are generally known not to be flexible or not to be able to swiftly adjust their activities than small-sized ones due to their economic scale, since the changes often require substantial fixed efforts, investments and costs, as argued in Uddin et al. (2014). Second, large-sized farmers cannot be motivated to take or tend to ignore small-scale adaptations, inducing themselves to be insensitive to climate change, as shown in table 3, believing that such small-scale adaptations are ineffective in their large-scale farming activities, as explained in Khan et al. (2020).

The large-sized farmers hold more than $60\,\%$ of the total land area in Nepal. Similar patterns are observed in many other developing countries of Asia and Africa (Central Bureau of Statistics, 2013, Thapa et al., 2019, Government of India, 2016, Jayne et al., 2016, Anseeuw et al., 2016, Sitko and Chamberlin, 2016). Some public programs, such as land consolidations, have been taken to establish medium-sized or large-sized farm units by merging small-sized farmers' lands for the purpose of enhancing their economic scale, productivity and food security (Thapa and Niroula, 2008, Sudgen et al., 2020). However, this trend of such land consolidations for creating large-sized farmers may bring about unexpected adverse effects on agriculture in the context of climate change. This research suggests one warning, that is, agriculture may lose its abilities or capacities to swiftly or sensitively adapt and respond to climate change, irrespective of farmers' climatic perceptions. Thus, it is advisable to reconsider the tradeoff between farm productivity and responsiveness to climate regarding farm sizes as well as how large-sized farmers can be induced to adapt through their cognition, policies, social networking and technology.

4 Conclusions

This study has investigated what matters for farmers' adaptation responses to climate change, hypothesizing that farm sizes, climatic perceptions and the interplay are the key determinants for farmers' adaptation responses. We conduct questionnaire surveys with 1000 farmers in Nepal, collecting data on their adaptation responses, farm sizes, climatic perceptions and sociodemographic information in Nepal. The analyses reveal that farmers tend to take additional adaptation responses as farm sizes become small or as they have good climatic perceptions & social network with other farmers. They also show that small-sized farmers tend to adapt much more in response to their climatic perceptions than do large-sized ones, confirming insensitivity of large-sized farmers to climate change in Nepal. Overall, this research suggests that agriculture may be losing responsiveness to climate change, as large-sized farmers become dominant by holding a majority of land in developing countries. Thus, it is advisable to reconsider the tradeoff between productivity and responsiveness to climate change regarding farm size as well as how large-sized farmers can be induced to adapt through their cognition, policies, social networking and technology for food security.

We note some limitations to our research and possible directions for future studies. This study does not address the detailed processes and channels of why different-sized farmers exhibit heterogeneous responses to climatic perceptions. To address the question, future studies should closely examine farmers' cognitive factors, such as motivations, perceived risk and adaptive capacity, by farm sizes, clarifying the relation with their responsiveness and sensitivities to climatic perceptions. To this end, two approaches are suggested: (1) the neuro-psychological approach and (2) qualitative and deliberative interviews. The former one provides the collection of various cognitive scales and neuroimages to detect potential processes and channels engaged when they take adaptation responses (Wang and van den Berg, 2021, Sawe and Chawla, 2021). This approach can potentially identify a specific cognitive factor that influences different-sized farmers to take adaptations. The latter approaches have been established and adopted by several past studies (Hobson and Niemeyer, 2011, Collins and Nerlich, 2014, Shahen et al., 2020, Timilsina et al., 2021a,b). Qualitative and deliberative interviews of different-sized farmers can clarify their decision-making processes and motivations for adaptation responses. These caveats notwithstanding, we believe that this is the first study to analyze the relationship between farmers' adaptation responses and climatic perceptions along with farm sizes from subsistence or large-sized ones, and contributes to climate change and economics literature.

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Figure 1: A map of Nepal showing the study areas.

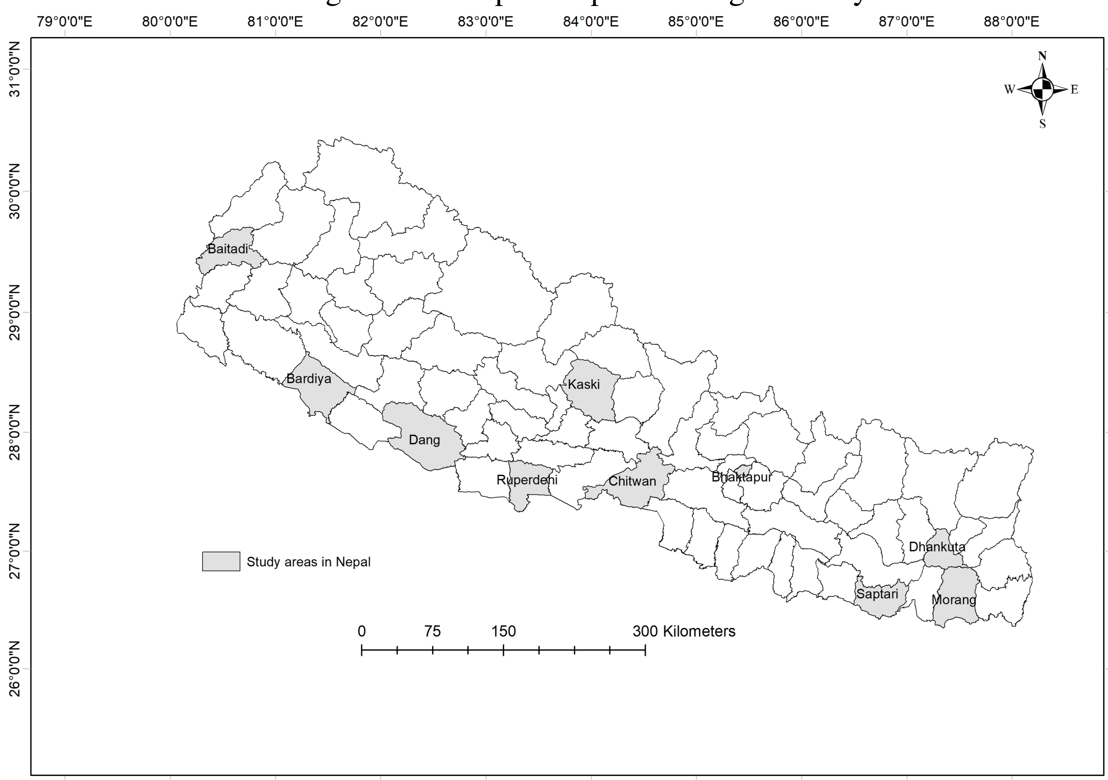

Figure 2: Bar graph of the percentage of farmers perceiving changes in climate variables.

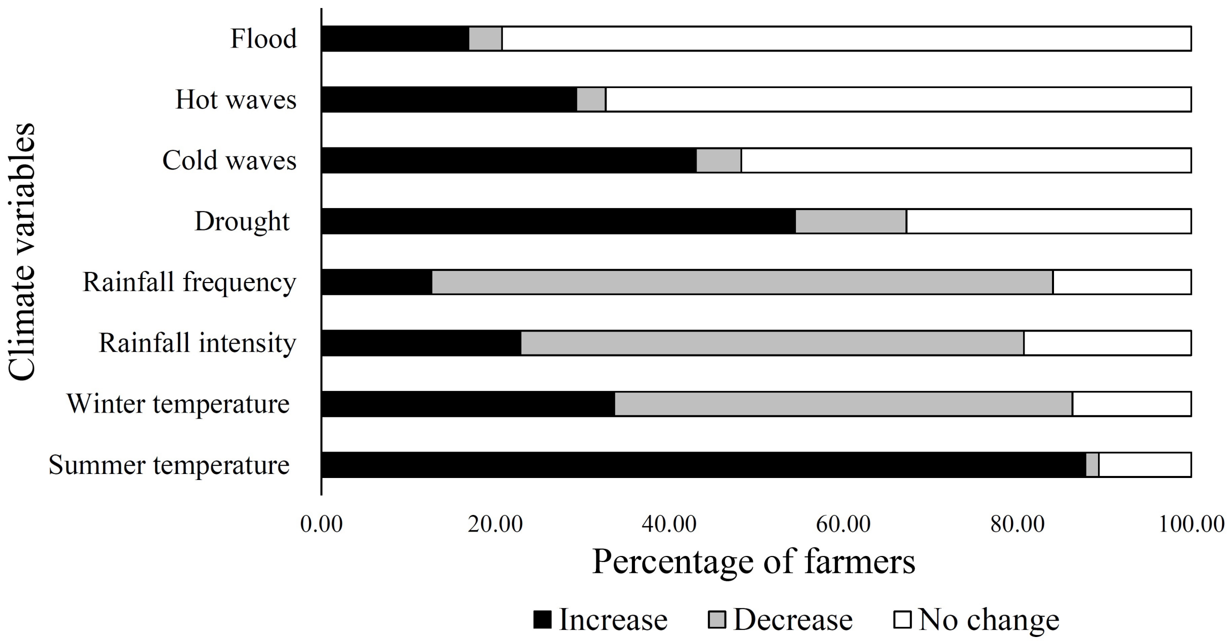

Figure 3: Box plots of (a) number of adaptations (AdaptN) and (b) adaptation index (AI) by farm sizes.

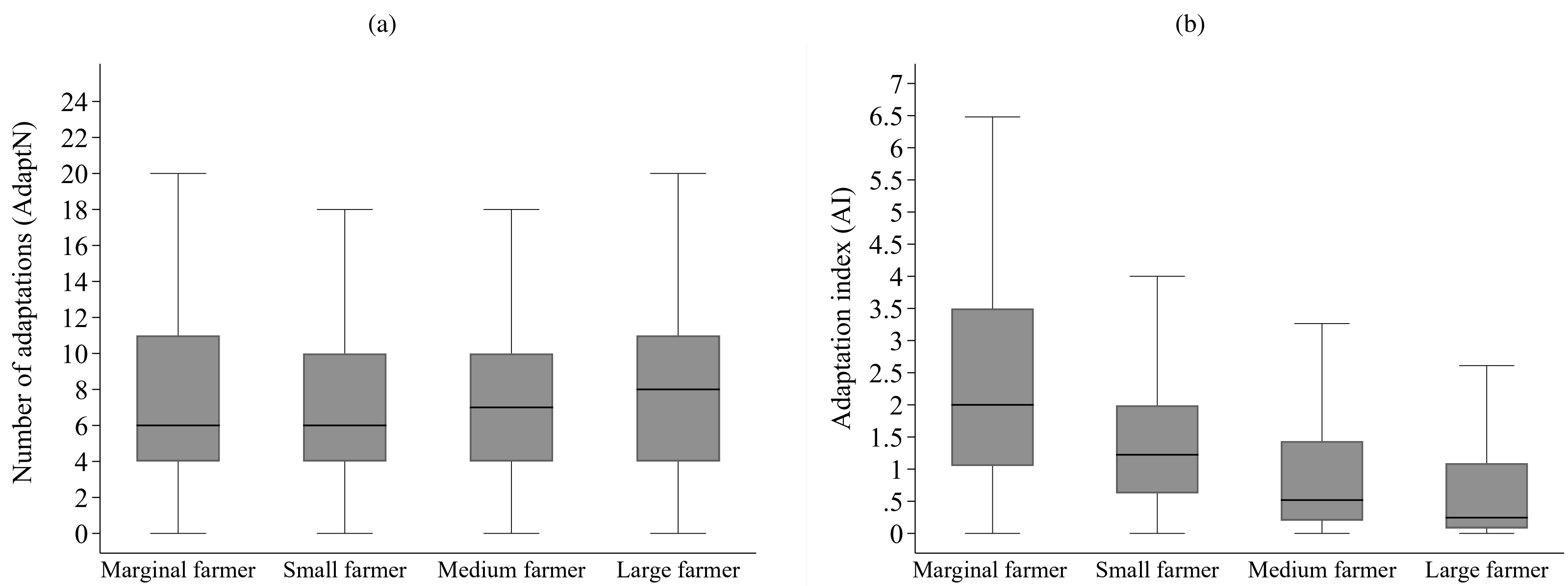

Figure 4: Predicted adaptation index (AI) over CPI (farmer's climatic perception) across farm sizes.

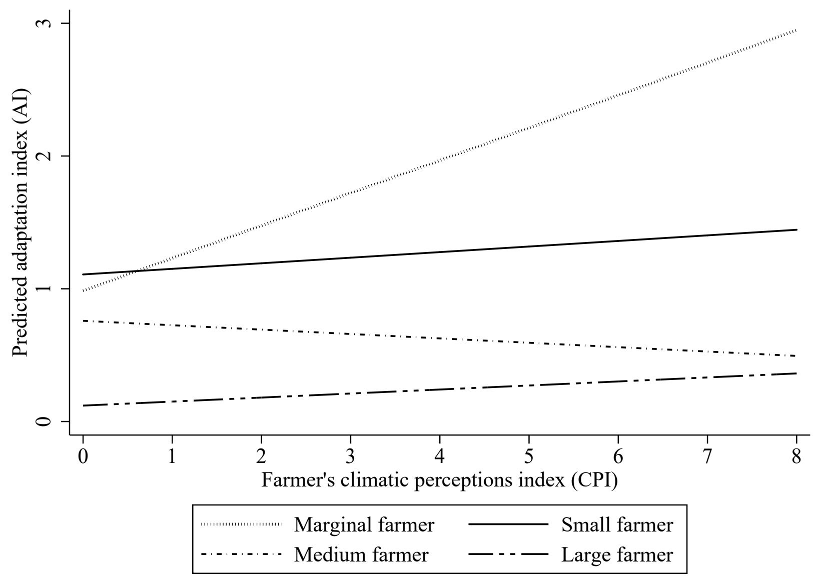

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Table 1: Definitions & descriptions of the variables.

Variables	Definitions & descriptions
Dependent variables	
# of adaptations (AdaptN)	A total number of adaptations taken by a farmer.
Adaptation index (AI)	An aggregate index value for a farmer calculated as the summation of all adaptations weighted by their respective proportion of farm-size coverage.
Independent variables	
Cognitive & non-cognitive variables	
Climate perception index (CPI)	A number of perceived changes in temperature, rainfall, drought, hot waves, cold waves and flood by a farmer within the last 20 years that ranges between 0-8.
Farming experience	Years of agricultural experience of a farmer.
# of agricultural training	A number of agricultural training taken by the farmer in last 5 years.
Education	The highest years of schooling for a farmer.
# of social network	A number of involvement in social groups for a farmer.
Access to information	A dummy variable that takes 1 if a farmer has access to agricultural information; otherwise, 0.
Sociodemographic variables	
Marginal farmer	A dummy variable that takes value 1 if the farm size of a farmer is $< 0.16\,\mathrm{ha}$; otherwise, 0.
Small farmer	A dummy variable that takes value 1 if the farm size of a farmer is $\geq 0.16\,\mathrm{ha}$ & $< 0.33\,\mathrm{ha}$; otherwise, 0.
Medium farmer	A dummy variable that takes value 1 if the farm size of a farmer is $\geq 0.33\,\mathrm{ha}$ & $\leq 1.00\,\mathrm{ha}$; otherwise, 0.
Large farmer	A dummy variable that takes value 1 if the farm size is $> 1.00\,\mathrm{ha}$; otherwise, 0.
# active family member	A number of economically active family member of a farmer.
HH annual income	An amount of monetary (NPR) earnings of farmer's family members.
Gender (base group = male)	A dummy variable that takes 1 if a farmer is male; otherwise, 0.
Agricultural service distance	Distance in kilometer (km) for a farmer to reach the nearest agricultural service center.
Market distance	Distance in kilometer (km) for a farmer to reach the nearest market.

Table 2: Summary statistics of the variables by farm sizes.

Variables	Farm-size dummy				
	Marginal farmer ($N = 147$)	Small farmer ($N = 208$)	Medium farmer ($N = 426$)	Large farmer ($N = 218$)	Overall ($N = 999$)
Dependent variables					
# of adaptations (AdaptN)					
Mean (Median)[1]	7.97 (6.00)	7.54 (6.00)	7.73 (7.00)	8.19 (8.00)	7.82 (7.00)
SD[2]	5.43	4.68	4.32	4.34	4.58
Min	0.00	0.00	0.00	0.00	0.00
Max	22.00	24.00	24.00	24.00	24.00
Adaptation index (AI)					
Mean (Median)	2.52 (2.00)	1.62 (1.22)	1.00 (0.52)	0.79 (0.25)	1.31 (0.86)
SD	2.03	1.52	1.15	1.04	1.49
Min	0.00	0.00	0.00	0.00	0.00
Max	9.91	9.50	6.95	5.00	9.91
Independent variables					
Cognitive & non-cognitive variables					
Climate perception index (CPI)					
Mean (Median)	5.07 (5.00)	5.06 (5.00)	4.82 (5.00)	5.18 (5.00)	4.99 (5.00)
SD	2.43	2.21	2.21	2.10	2.22
Min	0.00	0.00	0.00	0.00	0.00
Max	8.00	8.00	8.00	8.00	8.00
Farming experience					
Mean (Median)	21.93 (21.00)	19.07 (19.00)	19.90 ((20.00)	19.31 (18.00)	19.89 (20.00)
SD	12.07	12.13	11.40	12.00	11.80
Min	1.00	1.00	1.00	1.00	1.00
Max	50.00	50.00	70.00	60.00	70.00
# of agricultural training					
Mean (Median)	0.28 (0.00)	0.28 (0.00)	0.35 (0.00)	0.42 (0.00)	0.34 (0.00)
SD	0.86	0.72	1.02	1.03	0.94
Min	0.00	0.00	0.00	0.00	0.00
Max	5.00	5.00	15.00	10.00	15.00
Years of schooling					
Mean (Median)	5.96 (6.00)	6.97 (8.00)	6.11 (7.00)	6.63 (8.00)	6.38 (8.00)
SD	4.63	4.85	5.06	5.15	4.98
Min	0.00	0.00	0.00	0.00	0.00
Max	17.00	15.00	18.00	17.00	18.00
# of social network					
Mean (Median)	1.37 (1.00)	1.44 (1.00)	1.47 (1.00)	1.38 (1.00)	1.43 (1.00)
SD	1.09	1.09	1.11	1.11	1.10
Min	0.00	0.00	0.00	0.00	0.00
Max	4.00	4.00	5.00	4.00	5.00
Access to information					
Mean (Median)	0.50 (0.00)	0.44 (0.00)	0.50 (0.50)	0.55 (1.00)	0.50 (0.00)
SD	0.50	0.50	0.50	0.50	0.50
Min	0.00	0.00	0.00	0.00	0.00
Max	1.00	1.00	1.00	1.00	1.00
Sociodemographic variables					
# of active family member					
Mean (Median)	3.49 (3.00)	3.17 (3.00)	3.49 (3.00)	3.55 (3.00)	3.44 (3.00)
SD	2.06	1.69	1.66	1.52	1.71
Min	1.00	0.00	0.00	1.00	0.00
Max	15.00	12.00	13.00	11.00	15.00
Gender (base group = female)					
Mean (Median)	0.84 (1.00)	0.87 (1.00)	0.86 (1.00)	0.89 (1.00)	0.87 (1.00)
SD	0.36	0.34	0.35	0.31	0.34
Min	0.00	0.00	0.00	0.00	0.00
Max	1.00	1.00	1.00	1.00	1.00
HH annual income ('000)					
Mean (Median)	271.59 (229.00)	239.72 (188.50)	376.24 (240.00)	438.76 (2900.00)	346.06 (240.00)
SD	232.98	209.98	689.37	608.40	552.62
Min	0.00	0.00	0.00	0.00	0.00
Max	1480.00	1730.00	8400.00	5940.00	8400.00
Agricultural service distance					
Mean (Median)	2.99 (3.00)	3.05 (2.50)	3.52 (3.00)	2.98 (2.50)	3.23 (3.00)
SD	2.38	2.67	3.17	2.87	2.90
Min	0.00	0.00	0.00	0.00	0.00
Max	12.00	15.00	18.00	12.00	18.00
Market distance					
Mean (Median)	2.37 (1.50)	2.93 (1.50)	2.80 (1.50)	2.49 (1.50)	2.70 (1.50)
SD	2.88	3.68	3.66	3.50	3.53
Min	0.00	0.00	0.00	0.00	0.00
Max	20.00	18.00	25.00	19.00	25.00

Notes: marginal farmer (farm size $< 0.16\,\mathrm{ha}$), small farmer ($0.16\,\mathrm{ha} \leq$ farm size $< 0.33\,\mathrm{ha}$), medium farmer ($0.33\,\mathrm{ha} \leq$ farm size $\leq 1.00\,\mathrm{ha}$) and large farmer (farm size $> 1.00\,\mathrm{ha}$).

1 Median values are in parenthesis.

2 SD indicates standard deviation.

Table 3: Mann-Whitney test of a number of adaptation (AdaptN) and adaptation index (AI) by farm sizes.

	Test	
Pair of different-sized farmers	AdaptN	AI
Small vs. marginal farmer	-0.259	-4.611***
Medium vs. small farmer	1.175	-6.695***
Large vs. medium farmer	1.390	-3.939***
Medium vs. marginal farmer	0.623	-9.341***
Large vs. small farmer	2.017**	-8.083***
Large vs. marginal farmer	1.335	-9.427***

Notes: (i) *** $P < 0.01$, **$P < 0.05$ and * $P < 0.10$; and (ii) marginal farmer (farm size $< 0.16\,\mathrm{ha}$), small farmer ($0.16\,\mathrm{ha} \leq$ farm size $< 0.33\,\mathrm{ha}$), medium farmer ($0.33\,\mathrm{ha} \leq$ farm size $\leq 1.00\,\mathrm{ha}$) and large farmer (farm size $> 1.00\,\mathrm{ha}$).

Table 4: Percentage of farmers taking adaptations by farm sizes.

Adaptations	%				
	Marginal farmer ($N = 147$)	Small farmer ($N = 208$)	Medium farmer ($N = 426$)	Large farmer ($N = 218$)	Overall ($N = 999$)
Soil and water management					
Pump irrigation	65.55	52.40	64.55	37.79	64.16
Surface irrigation	25.17	38.46	37.79	17.61	35.34
Bucket irrigation	41.50	29.33	33.33	11.97	31.53
Ridge/terrace construction	44.90	38.46	41.55	24.41	20.32
Mulching	10.88	15.38	9.62	20.19	17.52
Sprinkle irrigation	3.40	8.65	10.80	6.34	9.61
Deep tillage	9.52	5.77	11.27	3.99	9.11
Growing hedges	12.24	10.10	8.22	3.05	8.71
Cover crops	4.08	6.25	7.75	2.35	6.21
Construction of reservoirs & channels	2.04	0.96	3.05	1.17	1.90
Diversion ditches	4.76	0.96	2.11	1.17	1.90
Water harvesting and/or plastic ponds	0.00	0.48	0.94	0.47	1.50
Adjustment of crop and farm management					
Supplement with inorganic fertilizers	73.47	63.46	71.83	35.68	69.87
Supplement with organic fertilizers/farm yard manure	72.11	66.35	69.01	33.57	68.17
Crop rotation	36.73	23.56	26.76	14.79	62.36
Adjustments to sowing date	17.69	28.37	41.31	20.19	34.73
Adoption of high yielding varieties	29.93	30.29	31.46	21.83	33.43
Mixed cropping	31.29	28.37	30.99	0.94	28.03
Applying nutrient amendments	31.97	26.44	19.95	9.62	24.12
Adoption of short maturing varieties	17.69	9.62	12.21	8.92	13.61
Adoption of different resistant varieties	17.69	9.62	12.21	8.92	13.62
Afforestation	14.29	16.35	11.50	4.46	12.31
Fallowing the land	17.01	5.77	6.81	5.16	8.81
Restoring degraded lands	2.04	4.33	3.52	2.11	3.60
Re-vegetation	1.36	4.33	3.99	1.41	3.40
Farm extension outside ward	2.04	2.40	2.58	1.64	2.60
Farm extension within ward	3.40	2.88	1.41	0.47	2.00
Aquaculture	0.68	0.00	1.88	2.58	2.33

Notes: marginal farmer (farm size $< 0.16\,\mathrm{ha}$), small farmer ($0.16\,\mathrm{ha} \leq$ farm size $< 0.33\,\mathrm{ha}$), medium farmer ($0.33\,\mathrm{ha} \leq$ farm size $\leq 1.00\,\mathrm{ha}$) and large farmer (farm size $> 1.00\,\mathrm{ha}$).

Table 5: Estimated coefficients of the independent variables on a number of adaptations (AdaptN) in the Poisson regressions.

	AdaptN					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Independent variables						
Farm-size dummies						
(Base group = Marginal farmer)						
Small farmer	−0.055	0.242	−0.083	0.209	−0.108*	0.173
	(0.071)	(0.203)	(0.062)	(0.197)	(0.063)	(0.185)
Medium farmer	−0.031	0.474***	−0.046	0.389**	−0.030	0.417***
	(0.062)	(0.168)	(0.054)	(0.162)	(0.056)	(0.160)
Large farmer	0.027	0.323*	−0.006	0.267	0.014	0.317*
	(0.066)	(0.189)	(0.058)	(0.181)	(0.056)	(0.179)
Climate perception index (CPI)	–	0.120***	0.061***	0.116***	0.050***	0.107***
		(0.025)	(0.008)	(0.024)	(0.008)	(0.025)
Interaction terms						
(Base group = Marginal farmer)						
Small farmer × CPI	–	−0.053	–	−0.052	–	−0.051
		(0.034)		(0.032)		(0.031)
Medium farmer × CPI	–	−0.090***	–	−0.081***	–	−0.083***
		(0.028)		(0.026)		(0.027)
Large farmer × CPI	–	−0.054*	–	−0.049*	–	−0.055*
		(0.031)		(0.029)		(0.029)
Other cognitive & non-cognitive factors						
Farming experience	–	–	−0.002	−0.002	−0.001	0.001**
			(0.002)	(0.002)	(0.002)	(0.002)
# of agricultural training	–	–	0.075***	0.076***	0.078***	0.080***
			(0.016)	(0.016)	(0.017)	(0.017)
Years of schooling	–	–	0.012***	0.012***	0.011***	0.011**
			(0.004)	(0.004)	(0.004)	(0.004)
# of social network	–	–	0.121***	0.116***	0.118***	0.113***
			(0.015)	(0.015)	(0.015)	(0.014)
Access to information	–	–	−0.090***	−0.091***	−0.075**	−0.076**
			(0.035)	(0.035)	(0.035)	(0.031)
Sociodemographic factors						
# of active family member	–	–	–	–	0.007	0.007
					(0.010)	(0.010)
Gender (base group = female)	–	–	–	–	0.01	0.086
					(0.058)	(0.058)
HH annual income	–	–	–	–	−0.063***	−0.062***
					(0.176)	(0.018)
Agricultural service distance	–	–	–	–	−0.034***	−0.035***
					(0.008)	(0.008)
Market distance	–	–	–	–	0.015***	0.015***
					(0.004)	(0.004)
Constant	2.076***	1.427***	1.575***	1.277***	2.352***	2.025***
Observations	999	999	989	964	963	963
Wald-χ^2	2.65	60.16***	181.76***	193.62***	287.23	290.56***

Note: (1) Robust standard errors are in the parenthesis; (2) *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$; and (3) marginal farmer (farm size < 0.16 ha), small farmer (0.16 ha $\leq$ farm size < 0.33 ha), medium farmer (0.33 ha $\leq$ farm size ≤ 1.00 ha) and large farmer (farm size > 1.00 ha).

Table 6: Estimated coefficients of the independent variables on the adaptation index (AI) in median regressions.

	AI					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Independent variables						
Farm-size dummies						
(Base group = Marginal farmer)						
Small farmer	−0.776***	0.083***	−0.658***	0.199	−0.730***	0.123
	(0.229)	(0.368)	(0.144)	(0.337)	(0.147)	(0.352)
Medium farmer	−1.480***	−0.303	−1.406***	−0.274	−1.438***	−0.227
	(0.216)	(0.319)	(0.127)	(0.292)	(0.130)	(0.301)
Large farmer	−1.750***	−0.937**	−1.680***	−0.842***	−1.766***	−0.865**
	(0.215)	(0.375)	(0.142)	(0.343)	(0.146)	(0.359)
Climate perception index (CPI)	–	0.217***	0.021	0.232***	0.017	0.245***
		(0.048)	(0.019)	(0.045)	(0.021)	(0.061)
Interaction terms						
(Base group = Marginal farmer)						
Small farmer × CPI	–	−0.188**	–	−0.207***	–	−0.203***
		(0.076)		(0.054)		(0.057)
Medium farmer × CPI	–	−0.253***	–	−0.256***	–	−0.278***
		(0.074)		(0.049)		(0.055)
Large farmer × CPI	–	−0.179**	–	−0.199***	–	−0.215***
		(0.072)		(0.046)		(0.054)
Other cognitive & non-cognitive factors						
Farming experience	–	–	0.004*	−0.004	0.003	0.004
			(0.004)	(0.004)	(0.004)	(0.004)
# of agricultural training	–	–	0.102**	0.108**	0.081*	0.083*
			(0.045)	(0.044)	(0.046)	(0.046)
Years of schooling	–	–	0.004	0.007***	0.005	0.001
			(0.009)	(0.009)	(0.009)	(0.009)
# of social network	–	–	0.135***	0.127***	0.101***	0.102***
			(0.038)	(0.038)	(0.049)	(0.039)
Access to information	–	–	0.093	0.063***	0.137	0.120**
			(0.085)	(0.084)	(0.088)	(0.064)
Sociodemographic factors						
# of active family member	–	–	–	–	0.027	0.025
					(0.026)	(0.027)
Gender (base group = female)	–	–	–	–	0.214	0.201
					(0.132)	(0.132)
HH annual income	–	–	–	–	−0.018	−0.016
					(0.047)	(0.047)
Agricultural service distance	–	–	–	–	−0.012	−0.007
					(0.016)	(0.016)
Market distance	–	–	–	–	−0.015	−0.015
					(0.013)	(0.013)
Constant	2.000***	1.017***	1.48***	0.613***	1.672***	0.677***
Observations	999	999	989	989	963	963
Pseudo R-squared	0.105	0.117	0.125	0.137	0.131	0.145

Note: (1) Standard errors are in the parenthesis; (2) *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$; and (3) marginal farmer (farm size $< 0.16\,\mathrm{ha}$), small farmer ($0.16\,\mathrm{ha} \leq$ farm size $< 0.33\,\mathrm{ha}$), medium farmer ($0.33\,\mathrm{ha} \leq$ farm size $\leq 1.00\,\mathrm{ha}$) and large farmer (farm size $> 1.00\,\mathrm{ha}$).