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Analyses of topical policy issues

How do farm size and perceptions matter for farmers' adaptation responses to climate change in a developing country? Evidence from Nepal

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A B S T R A C T

Farm size 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 climate change, hypothesizing that farm size, climatic perceptions and the interplay between the two are key determinants. We conduct a questionnaire survey with 1000 farmers in Nepal, collecting data on their adaptation responses, farm size, climatic perceptions and sociodemographic information. With the data, the statistical analysis is conducted by employing an index to reflect the farmers' effective adaptation responses. The results reveal that farmers take adaptations as the farm size becomes small, or when they have good climatic perceptions & social networks with other farmers. The results also show that small-sized farmers tend to adapt much more in response to their climatic perceptions than large-sized farmers. 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.

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 to minimize the consequences of climate change (McCarthy et al., 2001; IPCC, 2014).[1] In the last two decades,

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[1] 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).

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improvement in farmers' capacity has been recognized to be the key element in 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 crucial for farmers' adaptive capacity (Grothmann and Patt, 2005). This study addresses farmers' responsiveness to climate change in relation to economic and cognitive factors by investigating their adaptations.

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 size, 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 size 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 size matters only for the intensities. Another group of studies reports negative associations between farm size 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 size inhibits farmers from choosing some adaptations, such as irrigation time changes and the use of short duration varieties. Overall, the literature establishes that farm size is an influential factor for farmers' adaptation responses to climate change. However, the directions and magnitudes of the influence of farm size are mixed 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 relationship 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 who believe in climate change adapt more than those who do not. Overall, these studies establish that farmers or people tend to respond to climate change when they perceive climate change or have correct perceptions of temporal trends in climate variables.

There is a growing number of studies that indicates the negative effects of climate change on farmers in developing countries (Parry et al., 2004; Chinowsky et al., 2011; Wheeler and von Braun, 2013; Bandara and Cai, 2014). These countries possess some characteristics, that make them relatively vulnerable to climate change compared to developed countries, such as (i) clear realizations of climate change (i.e., a rise in temperature and changes in rainfall patterns), (ii) agriculture-based economies and (iii) people's limited cognitive, economic and technological capacities to adapt (Yohe and Tol, 2002; Smit and Wandel, 2006; Mertz et al., 2008). Nepal is a developing country that possesses the characteristics where agriculture has been a major source of income and employment.[3] A considerable portion of Nepalese farmers are still subsistence farmers who rely on rainfall for production, and Nepal is one of the countries most affected by climate change (Malla, 2009; Manandhar et al., 2010; Pandit et al., 2014; Practical Action, 2014; IPCC, 2014; Shrestha et al., 2019). Specifically, incidences of floods, droughts, heat and cold waves have increased over time because of climate change, suggesting that the negative impacts on agriculture can only be reduced through adaptations (Manandhar et al., 2010; Piya et al., 2012; Gentle and Maraseni, 2012; Gurung et al., 2012; Pant, 2013; Poudel et al., 2017; Khanal and Wilson, 2019; Thakuri et al., 2019; Khanal et al., 2018, 2020; Budhathoki et al., 2020; Khanal et al., 2021). Thus, it is important to investigate how farmers in Nepal, i.e., a representative country among developing ones, adapt to climate change.

Previous studies indicate that socioeconomic and cognitive factors play substantial roles in improving farmers' adaptive capacities and their responses to climate change (Piya et al., 2012; Khanal and Wilson, 2019; Budhathoki et al., 2020). However, there have been few studies on farmers' adaptations in relation to farm size and cognitive factors. Given this scarcity, we empirically investigate what matters for farmers' adaptation responses to climate change, focusing on their farm size and climatic perceptions. We conduct a questionnaire survey with 1000 farmers in Nepal, and collect data on their adaptation responses, farm size, climatic perceptions and sociodemographic information. With the data, we conduct statistical analysis by employing an index reflecting farmers' effective adaptation responses. The novelty of this study lies in (i) covering a wide range of farmers from subsistence to large-sized commercial farmers and (ii) analyzing how Nepalese farmers' adaptations differ by farm size, climatic perceptions and the interplay between them in a single empirical framework. This study contributes to the literature by addressing farmers' adaptability and their resilience against climate change in Nepal and developing countries with similar contexts, being suggestive for achieving the UN Sustainable Development Goals (SDGs) (Acuti et al., 2020; Khanal et al., 2021).

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

[3] Agriculture in Nepal contributes about 27.1% to the gross domestic product (GDP) and employs nearly 61% of the population (Ministry of Finance, 2020).

2. Theoretical framework and hypotheses

Economic theories suggest that farmers' objectives are profit (or production) maximization and cost minimization, and the associated empirical approaches, such as the profit or production function approach, are used to estimate the effects of inputs and interventions on agricultural outputs and profits (Sadoulet and De Janvry, 1995; Evenson and Pingali, 2007; Ntakyo and van den Berg, 2019). However, these approaches cannot be applied in some situations, especially when farmers vary in terms of their objectives as well as the types (or a number) of crops they grow. In Nepalese agriculture, farmers' objectives are observed to be heterogeneous in that some farmers follow cost minimization and others follow production maximization depending on the farm size and context. This study deals with a wide range of farms of different size who have distinct objectives by growing heterogeneous crops, and this poses a difficulty in applying the economic approaches for our empirical analysis. Considering these facts and contexts, we adopt sociocognitive approaches to analyze farmers' adaptation responses to climate change and combine them with some economic factors, such as farm size, agricultural training and other variables.

Literature suggests that economic and cognitive factors are important for farmers' adaptations to climate change (Brondizio and Moran, 2008; Abid et al., 2019). Two sociocognitive theoretical models, (i) protection motivation theory (Rogers, 1983; Rogers and Prentice-Dunn, 1997) and (ii) private proactive adaptation model to climate change (Grothmann and Patt, 2005), argue that economic factors, cognition and their interaction characterize people's adaptation responses. In economics, it is established that firm size and their flexibility (or adaptability) have an inverse relationship (Mills and Schumann, 1985; Fiegenbaum and Karnani, 1991; Lin et al., 2019). In agriculture, large-sized farmers are not flexible enough to adjust their activities as compared to small-sized farmers (Uddin et al., 2014; Khan et al., 2020). However, little is known about how farm size, climatic perceptions and the interplay between them affect farmers' adaptations to climate change in a single analytical framework. Given this state of affairs, we propose the following three hypotheses: (i) Hypothesis 1: Farm size influences farmers' adaptations to climate change, (ii) Hypothesis 2: Climatic perceptions induce farmers to take adaptations to climate change and (iii) Hypothesis 3: There exists an interplay between farm size and climatic perceptions on farmers' adaptations.

3. Methodology

3.1. 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 Fig. 1.[4] This study was carried out from December 5, 2013 to February 2, 2014. The districts were randomly selected for broad geographic coverage.[5] One rural or urban municipality or metropolitan city was randomly identified in each selected district where agriculture was the main occupation for most households. After consulting with selected site officers, we identified one or two wards for the study. A list of households (HHs) was obtained from the site 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 − 55 HHs for each ward and collected information of a total of 1000 HHs from the study areas (see Table A.1 in the Appendix).

The questionnaires were prepared in the local Nepali language, pre-tested with non-sampled HHs and finally administered to the sampled HHs in the study areas. We hired ten 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 study's objectives. They additionally received instructions to collect informed consent from the HHs, which ensured 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.

3.2. Key variables

We ask several questions to the HH heads (hereafter, farmers), and obtain farm-related information, such as farm size (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 engage in a particular adaptation. Since not all listed adaptations might necessarily be applied by farmers in the study areas, we pre-tested, revised the list and included it in the final questionnaire. Farmers can adjust farm activities depending on external factors, such as prices, demand, income along with climate change. Thus, we explicitly ask the farmers to report only those adjustments (i.e., adaptations) from the list that are taken in response to climate change. Following the list, each farmer j is asked two questions: (1) Have you adopted a particular adaptation "a_i" in your farm? and (2) To what extent does the "a_i" cover your farm (or land) "w_{ij}?"

[4] Nepal underwent administrative reform in 2017, where development regions were either replaced or revised to be provinces (see Table A.1 in Appendix).

[5] The study areas included only hill and terai districts since the agricultural activities are primarily carried out in such areas.

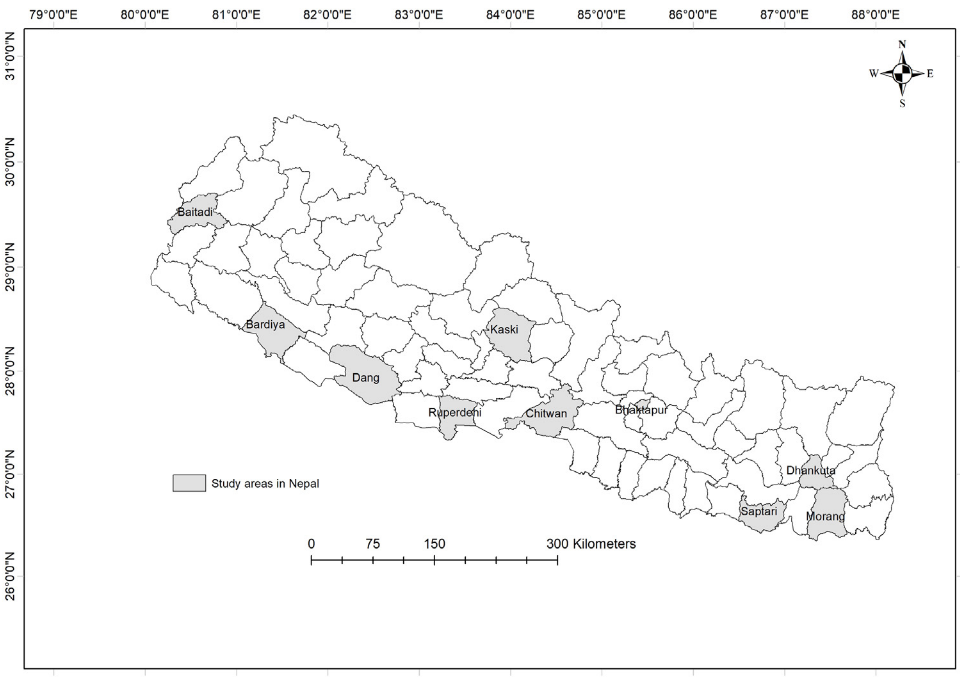

Fig. 1. A map of Nepal showing the study areas.

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 adaptations) 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 a value of 1 if the jth farmer adapts; otherwise, it takes 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 $w_{ij} = \frac{\text{Farm-size coverage of } a_{ij}}{\text{Total land of the jth farmer}}$ with $0 \le w_{ij} \le 1$, 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 engages in two adaptations of a_{1j} and a_{2j} with 75% and 60% farm-size coverage, respectively. In this case, the AdaptN_j is 2, while the AI_j is 1.35 ($= 1 \times 0.75 + 1 \times 0.60$). Thus, the value of AI_j depends not only on whether the jth farmer takes a particular adaptation (a_i) but also on 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 for 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 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.

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 the local unit (Kattha), and it is computed to hectares (ha) by multiplying it with a conversion factor of 0.0333 ($= \frac{1}{30}$).[6] Following Thapa et al. (2019) and Kumar et al. (2020), farmers are categorized into four dummies based on their farm size: (i) marginal farmer (farm size < 0.16 ha), (ii) small farmer (0.16 ha $\le$ farm size < 0.33 ha), (iii) medium farmer (0.33 ha $\le$ farm size ≤ 1.00 ha) and (iv) large farmer (farm size > 1.00 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 climate variables: summer

6 Note that 1 hectare = 30 Kattha = 10000 square meters.

Table 1
Definitions & descriptions of the variables.

Variables	Definitions & descriptions
Dependent variables	
# of adaptations (AdaptN)	A total number of adaptations taken by the farmer.
Adaptation index (AI)	An aggregate index value for the 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 the farmer within the last 20 years that ranges between $0-8$.
Farming experience	Years of agricultural experience of the farmer.
# of agricultural trainings	A number of agricultural trainings taken by the farmer in the last 5 years.
Years of schooling	The highest level of schooling for the farmer.
# of social networks	A number of social groups where the farmer is engaged in.
Access to information	A dummy variable that takes 1 if the farmer has access to agricultural information; otherwise, 0.
Sociodemographic variables	
Marginal farmer	A dummy variable that takes value 1 if the farm size of the farmer is <0.16 ha; otherwise, 0.
Small farmer	A dummy variable that takes value 1 if the farm size of the farmer is ≥ 0.16 ha & <0.33 ha; otherwise, 0.
Medium farmer	A dummy variable that takes value 1 if the farm size of the farmer is ≥ 0.33 ha & ≤ 1.00 ha; otherwise, 0.
Large farmer	A dummy variable that takes value 1 if the farm size of the farmer is >1.00 ha; otherwise, 0.
# active family members	The number of economically active family members of the farmer.
HH annual income	The amount of monetary (NPR) earnings of the farmer's family members.
Gender (base group = female)	A dummy variable that takes 1 if the farmer is male; otherwise, 0.
Distance to agricultural services	Distance in kilometers (km) for the farmer to reach the nearest agricultural service center.
Market distance	Distance in kilometers (km) for the farmer to reach the nearest market.

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 of 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, we assign it as 0. Finally, we calculate the aggregate climatic perception index (CPI) to be the sum of all perception-related answers by the jth farmer to the questions on the eight climate variables (Below et al., 2012; Shrestha et al., 2019).

3.3. 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 analysis, such as Mann–Whitney nonparametric tests, to identify some qualitative relations between the key variables. To quantitatively examine the relationship between adaptation responses as the dependent variables and the independent variables, 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 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, $\mathbf{x}_j = (1, x_{1j}, x_{2j}, \ldots, x_{kj})$ 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. 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 Eq. (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 Eq. (4) because the AI does not follow a normal distribution on 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:

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

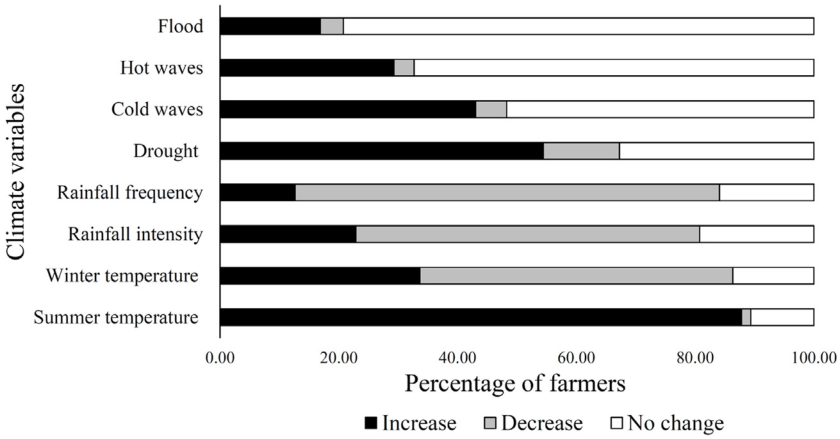

Fig. 2. Bar graph of the percentage of farmers perceiving changes in climate variables.

where AI_j is the dependent variable of the 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. Each coefficient is interpreted as a change in the 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.

4. Results

Table 2 presents summary statistics of the variables across farm size. The results indicate that farmers engage in agricultural activities on 0.83 ha of land (farm size) on average. Regarding farming experiences, farmers do not differ considerably in terms of farm size, having approximately 20 years of average experience. 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. This suggests that farmers tend to participate in agricultural trainings as farm size increases. Farmers generally attain a formal education level of 6.38 years of schooling, and they are engaged in 1.43 social networks, such as cooperative and farm field schools. The averages of schooling years for marginal, small, medium and large farmers are 5.96, 6.97, 6.11 and 6.63, respectively, implying that farmers tend to have higher education level as farm size increases. With respect to social networks, the averages are 1.37, 1.44, 1.47 and 1.38 for marginal, small, medium and large farmers, respectively, demonstrating no considerable differences in social networks across farm size.

About 50.00 % of the farmers have access to agricultural information, while the percentages are observed to be approximately 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 size. In the study areas, 87.00 % of the farmers are identified to be male and the percentages are similar across farm size. The overall average household (HH) annual income for farmers is 346 thousand NPR, and it appears that farmers' incomes rise from 271.59 to 438.76 thousand NPR as farm size increases. Farmers have average distances of 3.23 km and 2.70 km to reach the nearest agricultural extension services and the market, respectively, and the distances do not significantly differ across farm size. Overall, the summary statistics suggest that farmers are similar in terms of agricultural training, education level, active family size, gender, distances to agricultural services and the market, while they differ in terms of social networks, access to information and HH annual income.

Fig. 2 is a bar graph to present the percentages of farmers who have perceived some changes in eight climate variables over the last 20 years. A majority of farmers has perceived changes in summer temperature, winter temperature, rainfall intensity, rainfall frequency and drought, whereas approximately 50.00 %, 38.00 % and 22.00 % of them perceive cold waves, hot waves and floods, respectively. The results imply that climate change is perceived as 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 size, 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 and 5.18 across farm size. These values demonstrate that farmers have homogeneous climatic perceptions.

Table 2 shows that farmers take 8.00 adaptations on average with the median value of 7.00 and some variation across farm size. The median AdaptNs are 6.00 for both marginal and small farmers, while they are 7.00 for medium and large

Table 2
Summary statistics of the variables by farm size.

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)[a]	7.97 (6.00)	7.54 (6.00)	7.73 (7.00)	8.19 (8.00)	7.82 (7.00)
SD[b]	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 trainings					
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 networks					
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 members					
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
Distance to agricultural services					
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 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).

[a]Median values are in the parentheses.

[b]SD indicates standard deviation.

farmers, respectively. There is a tendency for farmers to take adaptations as farm size increases. The tendency is confirmed from Fig. 3(a), which depicts boxplots of AdaptN by farm size. We run the Mann–Whitney test to examine distributional differences in AdaptNs across farm size, 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 do not statistically depend on farm size, while we note a tendency for large-sized farmers to take adaptations.

The value of the 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 size increases, i.e., from marginal to large farmers. The results imply that farmers curb adaptation coverage as farm size increases. The tendency is confirmed from Fig. 3(b), that demonstrates the boxplots of AIs across farm size. We run the Mann–Whitney test to examine distributional differences in AIs across farm size, and apply it

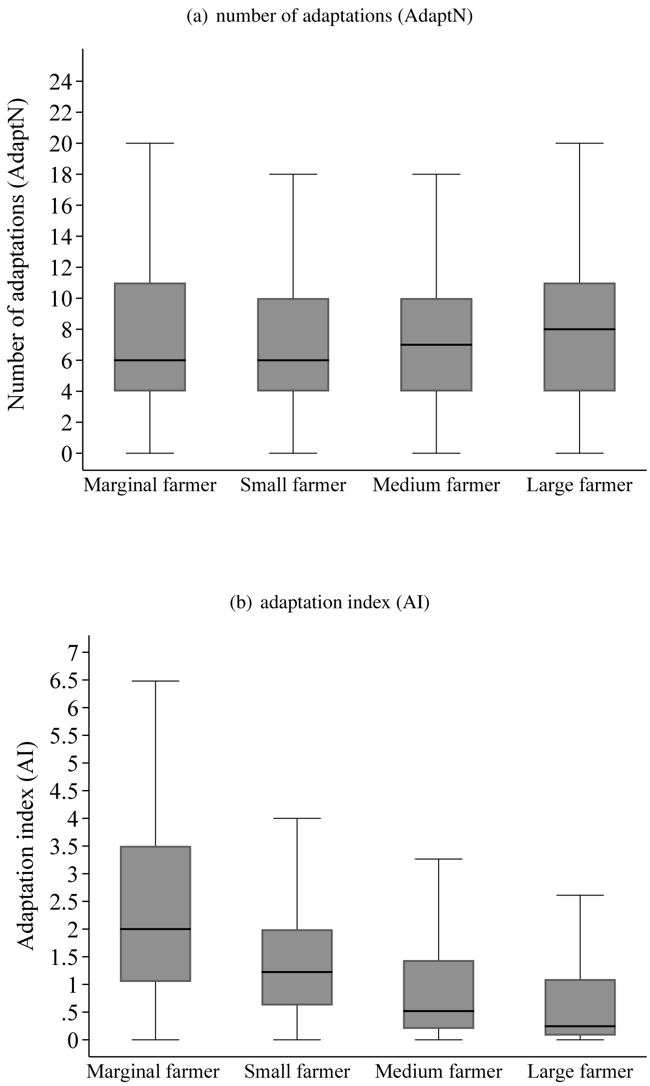

Fig. 3. Box plots of (a) the number of adaptations (AdaptN) and (b) the adaptation index (AI) by farm size.

Table 3
Mann–Whitney test of the number of adaptations (AdaptN) and the adaptation index (AI) by farm size.

Pair of different-sized farmers	Test	
	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 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).

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, suggesting that AIs statistically depend on farm size.

Table 4
Percentage of farmers taking adaptations by farm size.

Adaptations	Percentage (%)				
	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 land	2.04	4.33	3.52	2.11	3.60
Revegetation	1.36	4.33	3.99	1.41	3.40
Farm extension outside the ward	2.04	2.40	2.58	1.64	2.60
Farm extension within the 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 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 4 reports adaptations and the percentages of farmers taking them by farm size. The results reveal that farmers' adaptation responses vary across farm size. For example, nearly 38 % of large farmers use the 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 farmers and other farmers in some adaptations, such as supplementation 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 size, indicating the possible reasons for the tendencies of AdaptN and AI, as observed in Fig. 3.

Table 5 reports the estimated coefficients of the independent variables on AdaptN in the basic Poisson regression model along with the standard errors and statistical significance. Based on the basic model, other specifications as well as interaction terms are proposed 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 size, CPI, agricultural trainings, social networks, access to information, HH annual income, distances to agricultural service and the market on AdaptN, because they are of particular interest in drawing implications in this research or stand statistically significant in the models.

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 dummies and CPI in models 2, 4 and 6. Model 2 demonstrates that medium farmers are likely to have additional 60.64 % AdaptN compared to marginal farmers (the base group), holding other variables fixed. The results could be because medium farmers consist of both motivations and/or affordability to take adaptations 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 size does not strongly influence farmers to adapt, 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

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

Variables	Number of adaptations (AdaptN)					
	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 trainings	–	–	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 networks	–	–	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 members	–	–	–	–	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)
Distance to agricultural services	–	–	–	–	−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) Standard errors are in the parentheses; (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 $\leq$ 1.00 ha) and large farmer (farm size > 1.00 ha).

and Wilson, 2019; Azadi et al., 2019; Soubry et al., 2020), suggesting that climatic perceptions need to be improved to influence their adaptations. Our results also confirm that farmers' climatic perceptions are positively associated with their adaptations in a consistent and robust manner.

The interaction terms between the medium-farmer (large-farmer) dummy and CPI are 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 for one another. To statistically confirm the relationship, we calculate the marginal effects of CPI on AdaptN for 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 are not statistically significant, implying that farmers' adaptations in response to CPI do not practically depend on farm size.

Some variables, such as agricultural training, social networks and the distance to agricultural services, 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 acquire adaptation-related knowledge and skills, supporting them in increasing responses (Piya et al., 2012; Trinh et al., 2018; Diallo et al., 2020). This result implies that Nepalese farmers tend to adapt to climate change when they receive training, which is 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 because social networks function as social devices for Nepalese farmers (i) to learn adaptations from other farmers and (ii) to receive financial support, such as credits, in enhancing their adaptation responses. The role of social networks 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, is crucial for farmers' adaptation abilities and capacities. Farmers tend to have an increase in AdaptN by about 1.50 % when distance to the market increases by 1 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 networks and market distance.

Farmers with access to agricultural information tend to reduce AdaptN by 7.32 % compared to farmers without access. This result suggests that agricultural information is substitutable for farmers' adaptations in the Nepalese context. This 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 posit that Nepalese farmers do not have 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 %. This may imply that having high HH income does not motivate farmers to take adaptations, or that 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 the distance to agricultural services increases by 1 km. We argue that farmers who cultivate in close proximity to agricultural services are benefited by extension workers' frequent visits and suggestions, leading them to adapt. This result is consistent with past studies (Piya et al., 2012; Abid et al., 2019; Kumar et al., 2020) in that the extension of agricultural services 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 the distance to agricultural services.

Table 6 reports the estimated coefficients of the independent variables on AI in the basic median regression model along with the standard errors and statistical significance. Building on the basic model, other specifications as well as interaction terms are proposed for robustness check, and the results do not differ qualitatively in the models. Thus, we only report the effects of the main independent variables on AI. 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 instance, 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 support Hypothesis 1 that farm size influences farmers' adaptations to climate change. The results can be attributed to the inflexibility of large-sized farmers to take adaptations compared to small-sized farmers 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 size becomes 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. This result supports Hypothesis 2 that climatic perceptions induce farmers to take adaptations to climate change. 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 between farmers' CPI and AI in a consistent and robust manner, and suggest that interactions between climatic perceptions and farm size shall be key 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 for one another. The results can be interpreted to mean that farmers reduce adaptations in response to CPI when the farm size becomes 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. These results support Hypothesis 3 that there exists an interplay between farm size and climatic perceptions on farmers' adaptations. The results could again be 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 farmers. The results imply that farmers' adaptations in response to CPI significantly depend on farm size, demonstrating that agricultural policies must be customized for effective adaptation responses according to their climatic perceptions, farm size and interaction.

The coefficients of some variables, such as agricultural trainings and social networks, are statistically significant with positive signs at 1 % to 10 % levels in models 3 through 6. Model 3 demonstrates that farmers take additional 0.102 AI when

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

Variables	Adaptation index (AI)					
	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 trainings	–	–	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 networks	–	–	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 members	–	–	–	–	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)
Distance to agricultural services	–	–	–	–	−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 parentheses; (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).

agricultural training increases by one unit, holding other variables fixed. Training may help farmers acquire adaptation-related knowledge and skills, thereby supporting them to increase adaptation (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 networks enable farmers (i) to learn about adaptations from other farmers and (ii) to receive various forms of assistance, such as credit and labor, thereby enhancing their adaptation responses. Our results are supported by past studies that report the positive influence of social networks on adopting new technologies in agriculture (Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Yamogo et al., 2018). Overall, these findings suggest that agricultural trainings and social networks positively influence farmers to take adaptations.

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 a 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". Fig. 4 shows the predicted AIs over CPI for marginal, small, medium and large farmers, presenting that the intercepts and slopes are idiosyncratic across farm size. 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

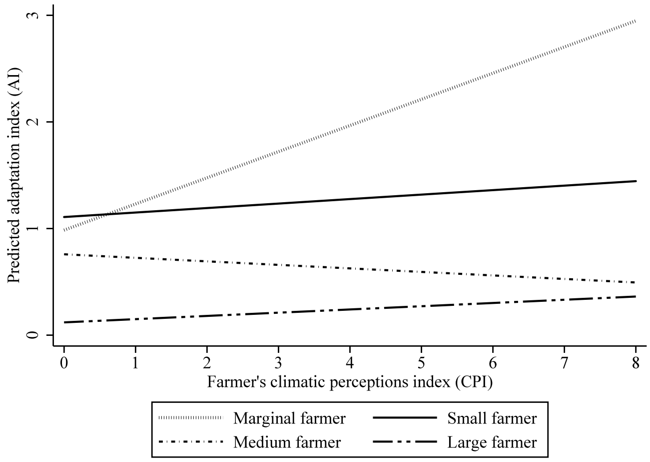

Fig. 4. Predicted adaptation index (AI) over CPI (farmer's climatic perception) across farm size.

predicted AI for marginal farmers is 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 size gets large, which is due to estimated differences in the interaction terms and intercepts 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 with farm size.

We finally summarize and compare the results from the two different models of the Poisson and median regressions associated with AdaptN and AI in Tables 5 and 6. Both regressions find that farm size, climatic perceptions, agricultural trainings and social networks can be 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, distance to agricultural services and market distance are significant (or insignificant) for AdaptN (or AI). Second, farm size does not matter much for AdaptN, while it is an important predictor for AI, in addition to interactions with farmers' climatic perceptions. Third, the AI responses to climatic perceptions differ across farm size, while the AdaptN responses do not. Literature indicates that using AdaptN has some potential problems: (i) each adaptation is assumed to be equally weighted, but farmers take adaptations at different scales (scale problem), and (ii) not all adaptation responses are uniformly important, but farmers will have different priorities (priority problem) (Below et al., 2012; Esham and Garforth, 2012; Niles et al., 2015; Khanal and Wilson, 2019). Thus, it is suggested to consider a weight of each adaptation to correct the problems (Below et al., 2012; Khanal and Wilson, 2019). Khanal and Wilson (2019) develop AI and demonstrate its importance by considering a weight of each adaptation. Building upon the literature, we believe that the results of AI median regressions are more plausible than those of AdaptN regressions, reflecting what is going with Nepalese farmers' adaptations to climate change.

Our findings provide specific countermeasures and suggestions to respond to climate change for Nepalese farmers and other developing countries with similar contexts. Since large-sized farmers are found to take adaptations less effectively in response to climatic perceptions than small-sized farmers, some policies or programs are necessary to be formulated in relation to farm size. As we posited before, large-sized farmers fail to adapt potentially because they are either overconfident or ignorant about the consequences of climate change. Therefore, it is crucial to design policies and education programs targeting large-sized farmers, and to induce them to correct overconfidence or ignorance for the purpose of enhancing their responses to climatic perceptions. Nepal has adopted an early warning system that is primarily oriented toward providing information about the changes in temperature and rainfall to farmers (Gautam and Phaiju, 2013; Cools et al., 2016; Rai et al., 2020). We suggest that the system can be further customized to include concrete information that may contain possible crop losses, the associated expected income and wealth losses by farm size. Since government and non-governmental organizations (NGOs) mostly focus only on subsistence farmers and overlook large-sized farmers, the countermeasures and suggestions by farm size can be reflected in the National Adaptation Programme of Action (NAPA) and the Local Adaptation Plan of Action (LAPA) frameworks of Nepal and other developing countries (Ministry of Environment, 2010; Gautam et al., 2018; Government of Nepal, 2014).

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; Sugden et al., 2016; Government of India, 2016; Jayne et al., 2016; Anseeuw et al., 2016; Sitko and Chamberlin, 2016; Thapa et al., 2019). Some public programs, such as land consolidation, have been implemented 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; Sugden et al., 2020). However, this trend of such land consolidation 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 ability or capacity 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 size as well as how large-sized farmers can be induced to adapt through their cognition, policies, social networking and technology.

5. Conclusion

This study has investigated what matters for farmers' adaptation responses to climate change, hypothesizing that farm size, climatic perceptions and the interplay between them are key determinants for farmers' adaptation responses. We conduct a questionnaire survey with 1000 farmers in Nepal, collecting data on their adaptation responses, farm size, climatic perceptions and sociodemographic information. The analyses reveal that farmers tend to take additional adaptation responses as farm size becomes small or if they have good climatic perceptions & social networks with other farmers. The findings also show that small-sized farmers tend to adapt much more in response to their climatic perceptions than do large-sized farmers, confirming the 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 directions for future studies. First, this study does not address the detailed processes of why different-sized farmers exhibit heterogeneous responses to climatic perceptions. Future studies should closely examine farmers' cognitive and motivational factors by farm size. Two approaches are suggested: (1) neuropsychological research and (2) qualitative and deliberative research. The former (latter) clarifies various cognitive scales and neuroimages (motivations) for farmers to adapt to climate change (Hobson and Niemeyer, 2011; Collins and Nerlich, 2014; Shahen et al., 2020; Sawe and Chawla, 2021; Timilsina et al., 2021a,b; Wang and van den Berg, 2021). Second, this study employs an area-based index to consider variations among farmers' adaptations, while some literature uses weights elicited from experts or stakeholders (Below et al., 2012; Khanal and Wilson, 2019). Because a developing country, such as Nepal, consists of heterogeneous geography and climate where wide range of agricultural practices are found, it is our view that experts or stakeholders might not be able to fully consider such heterogeneity. Rather, farmers may be the best candidates who can evaluate the differences among adaptations, and future research can consider weights by farmers for adaptations as well. These caveats notwithstanding, we believe that this is the first study to analyze the relationship between farm size and climatic perceptions to characterize farmers' adaptation responses to climate change, contributing to the economics literature and sustainability.

Table A.1
Number of sampled households by region, district, administrative unit, ward and locality.

Province (or Development Region)	District	Administrative unit	Ward number	Locality	# of HHs
Province 1 (Eastern)	Dhankuta	Dhankuta Municipality	2, 3	Bhirgaun	35
Province 1 (Eastern)	Dhankuta	Dhankuta Municipality	9, 10	Belhara	35
Province 1 (Eastern)	Dhankuta	Pakhribas Municipality	9, 10	Chumbang	30
Province 1 (Eastern)	Morang	Dhanapatan Rural Municipality	1	Nocha	25
Province 1 (Eastern)	Morang	Katahari Rural Municipality	7	Thalaha	25
Province 1 (Eastern)	Morang	Gramthan Rural Municipality	5	Tetariya	25
Province 1 (Eastern)	Morang	Belbari Municipality	5	Kaseni	25
Province 2 (Eastern)	Saptari	Chinnamasta Rural Municipality	6	Kochawakhari	55
Province 2 (Eastern)	Saptari	Rupni Rural Municipality	1	Raipur	45
Bagmati (Central)	Bhaktapur	Suryabinayak Municipality	2, 3	Balkot	34
Bagmati (Central)	Bhaktapur	Suryabinayak Municipality	1, 4	Dadhikot	30
Bagmati (Central)	Bhaktapur	Suryabinayak Municipality	5, 6	Katunje	36
Bagmati (Central)	Chitwan	Rapti Municipality	7	Birendranagar	30
Bagmati (Central)	Chitwan	Bharatpur Metropolitan City	15	Phulbari	30
Bagmati (Central)	Chitwan	Bharatpur Metropolitan City	20	Gunjanagar	40
Gandaki (Western)	Kaski	Pokhara Municipality	23	Chapakot	25
Gandaki (Western)	Kaski	Annapurna Rural Municipality	4	Bhadaure	25
Gandaki (Western)	Kaski	Annapurna Rural Municipality	2	Dhikurpokhari	25
Gandaki (Western)	Kaski	Annapurna Rural Municipality	7	Lumle	25
Lumbini (Western)	Rupendehi	Mayadevi Rural Municipality	7, 8	Hattibangai	38
Lumbini (Western)	Rupendehi	Tilottama Municipality	9	Anandaban	27
Lumbini (Western)	Rupendehi	Tilottama Municipality	5, 6	Managalpur	35
Lumbini (Mid-western)	Dang	Ghorahi Municipality	10	Narayanpur	36
Lumbini (Mid-western)	Dang	Tulsipur Municipality	16	Manpur	34
Lumbini (Mid-western)	Dang	Tulsipur Municipality	18, 19	Bijauri	30
Lumbini (Mid-western)	Bardiya	Bardiyataal Rural Municipality	5	Sorhawa	32
Lumbini (Mid-western)	Bardiya	Bardiaytaal Rural Municipality	8, 9	Kalika	30
Lumbini (Mid-western)	Bardiya	Gulariya Municipality	11	Mohammadpur	38
Sudurpaschim (Far-western)	Baitadi	Patan Municipality	8	Khodpe	52
Sudurpaschim (Far-western)	Baitadi	Dilashaini Rural Municipality	6	Gokuleshowar	48

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Appendix

See Table A.1.

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