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A study evaluating the extrinsic and intrinsic determinants of farmers' adoption of climate change adaptation strategies: A novel approach for improving farmers' health

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ABSTRACT

Small-scale farmers living in mountainous areas are particularly vulnerable to climate change. Although governments have implemented various support programs and policies to support a range of farmers to tackle climatic changes, there are still several difficulties in the implementation of these adaptation strategies. Using the survey data of 758 small-scale farmers this paper employs Multivariate Probit (MVP) and Poisson regression models to measure the effects of intrinsic and extrinsic factors affecting farmers adaptation decision in rural Vietnam. The results reveal that the extrinsic factors such as annual rainfall variations and farm size motivate farmers' adoption of their adaptations. The findings also reveal that the political connection has a significantly positive impact on the respondents' selection, while government interference such as extension training programs has a negative association with the farmers adaptation choice. Public extension programs should be simultaneously redesigned to support farmers in mitigating the impacts of climate change.

1. Introduction

Climate change is forcing many farmers around the world to adapt their agricultural systems. The specific adaptation measures are site-specific, depending on the local farming systems and changes in climate, for example, measures to cope with higher temperatures, variations in rainfall and changes in the probabilities of other extreme weather events. Farmers decisions about the adoption of adaptive measures vary sometimes for sound reasons (e.g., differences in physical conditions, such as soil types or topography) but sometimes because of differences in their knowledge or awareness [1].

Research on farmers' selections of climate change adaptation measures and their components has been widely investigated in various regions [2,3] [4]. These studies have examined changes in farmers' perceptions due to government programs, but the nexus between farmer perceptions of climate change and their farm management is weakly demonstrated. The studies of [5–7] merely conveyed the idea of how farmers' perceptions related to their adoption of climate change adaptive strategies. To fill this research gap, our study examines the role of farmers' perceptions and demographic characteristics in determining the practical drivers of farmers' selection of climate change adaptation.

Shukla, Agarwal [8] argued in a study that investigating the determinants of farmers' selection of climate change adaptation by region would triumph over the link between local effects of climate change in different geographical characteristics, implying that a local study can generalize its findings to other identical areas. By this means, our study uses northern Vietnam as a case study to fulfill our research objective. Agricultural producers in northern Vietnam are mainly smallholder farmers located in rural and mountainous regions. Farmers in mountainous areas, in particular, suffer from several climate-related hazards, including typhoons, droughts, flash floods, and landslides [9]. Furthermore, mountainous areas are home to several ethnic minorities that are

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particularly vulnerable to climate change due to their lack of access to education, financial services, and markets [10,11]. For both of these reasons, these farmers are the key targets of Vietnamese government's schemes to enhance their adaptive capacity against climate change [12].

Some governments now believe that their farmers are not adjusting effectively enough and offer initiatives to raise farmers' understanding of climate change and assist adaptation. In developing countries the objective of these schemes often include enhancement of food security and livelihood of smallholder farmers [13,14]. Even yet, farmers adoption of adaptive measures is typically limited or insufficient, necessitating further training and extension services [15]. Understanding the underlying reasons, including the elements that favor or prevent the adoption of appropriate adjustments, would assist governments in determining whether such a program is required and how it should be planned and targeted. Our latter research objective is to interpret and discuss our results, and recommend sound policies for policymakers.

2. Theoretical framework

This study constructs an adoption framework based on the idea of participation capacity paradigm from [16]. Farmers' decisions on adoptions of their adaptation strategies depend on two sets of variables, namely intrinsic and extrinsic factors. Extrinsic factors include the gradual change of rainfall or temperature, the extensive support of the government, and the constraints affecting farmers' livelihood under the context of climate change. In a study conducted in central Vietnam, Trinh, Rañola Jr. [5] found that adaptation to climate change was markedly influenced by the participation in relevant training schemes. Consistent with the general literature on the adoption of agricultural innovations, a positive relationship between farm size and uptake of adaptive practices was also found [17,18]. In a different approach, Le Dang, Li [19] conducted focus group discussions and personal interviews with Vietnamese farmers to explore the obstacles to farmers' adaptation. Their subjects reported a range of socio-economic factors that they believed holding back adaptation, including land tenure, understanding of adaptation techniques, access to markets, access to credit, access to healthcare services, and demographics. It is also apparent that farmers' limited knowledge of climate change and the available adaptations play an important role.

The second category is the farmers' perceptions of climate change and various adaptive measures (as shown in Fig. 1). Assessing the intrinsic factors is an interesting approach to understand the impact on farmers' adaptive selection. In Vietnam, Pham, Nong [1] employed farmers' perceptions to observe these impacts on the adaptations' selections of farmers in Vietnam's northern areas. Similarly, Aydogdu and Yenigün [20] used farmers' risk perceptions towards climate change in Turkey to indicate farmers' willingness-to-pay for their adaptation practices. If farmers perceive that climate has already changed, and there is an opportunity to reduce adverse impacts or amplify positive benefits resulting from the changes, then they are more likely to take on relevant adaptations [19,21,22]. In the studies of [2,5,23], intrinsic factors also include various socioeconomic factors, such as household size, age, gender, education, income, and farming experience of the household's head [24–26] as well as farmers' perceptions [27,28].

In our study, either extrinsic factors that stand for external forces affecting farmers' adaptive strategies to climate change or intrinsic factors that represents for farmers' cognitive and demographic characteristics are employed to build up our adaptations' adoption framework for small-scale farmers to understand the driving forces leading them to use their adaptive measures to cope with climate change (Fig. 1). Specifically, farmers' perceptions, supportive policies, socio-economic traits, climate variability and other constraints such as distance from farmers' house to their farms and the closest marketplace might motivate the farmers' intention to adopt their adaptations. Political connections are employed to interpret both inside and outside connectedness of the farming households in forms of family members (inside), relatives (outside) and friends (outside) that are hypothesized to encourage farmers to select or diverse their adaptations [29,30].

We define 7 adaptation strategies based on either mountainous farming households' demographics or scholarly published articles [31–33]. The adaptive measures include: (1) diversifying crops/livestock (using different types of crops and livestock, using various breeds or varieties, and crop rotations); (2) new technology application (using hybrid seeds or breeding and applying new production techniques); (3) cropping calendar adjustment (early seeding or harvesting and shortening cropping season); (4) implementation of soil preservation (bedding, reduction of pesticide usage, and canal construction); (5) cropping techniques adjustment (adjustment of fertilization and herbicides/pesticides application methods or watering timetable); (6) income diversification (having another non-agricultural job and switching from cropping to raising livestock or vice versa); and (7) household income management (enlarging production scale, increasing investment into agricultural production, and depositing money into the bank).

3. Methodology

3.1. Study area

Agriculture accounts for 20% of Vietnam's gross domestic product (GDP) and employs roughly half of the nation's labor force (Shrestha

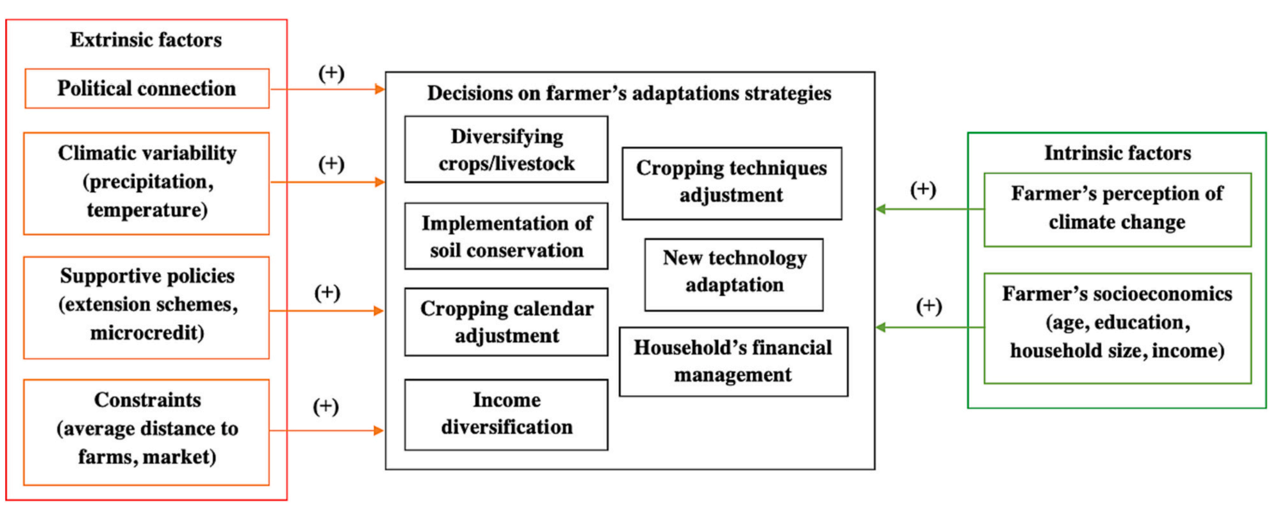

Fig. 1. Theoretical framework of the study.

et al., 2016). Agricultural production is the main income source for approximately 75% of the national population. In this study, the focus is on farmers in the northern and north-west regions (Fig. 2). These regions are the mountainous areas with the population of 11,300,000 persons consisting of 20 different ethnic groups [34]. Vietnam has had a high rate of national economic growth, however, the northern and western mountainous territories have had the slowest growth rates as well as the highest poverty rates in the country [35,36].

The main market-oriented crops in these regions are maize, cassava, and upland rice. These crops are chosen because they can be used for either household consumption or sold for cash. Thus, there is not much difference in the crops grown between subsistence farms and commercial farms. Other types of crops such as vegetables are grown in the farmers' gardens for daily consumption by the farm families.

3.2. Data sources

In this study, household-level data was collected from the rural areas of 10 provinces, namely Thanh Hoa, Hoa Binh, Quang Binh, Ha Tinh, Lao Cai, Nghe An, Ha Giang, Cao Bang, Son La, and Lai Chau, during March 2018 and December 2018. The survey was conducted with approximately 758 households in the surveyed areas through face to face interviews. Households were selected using a two-stage proportional random sampling method: (1) our first stage was to select the

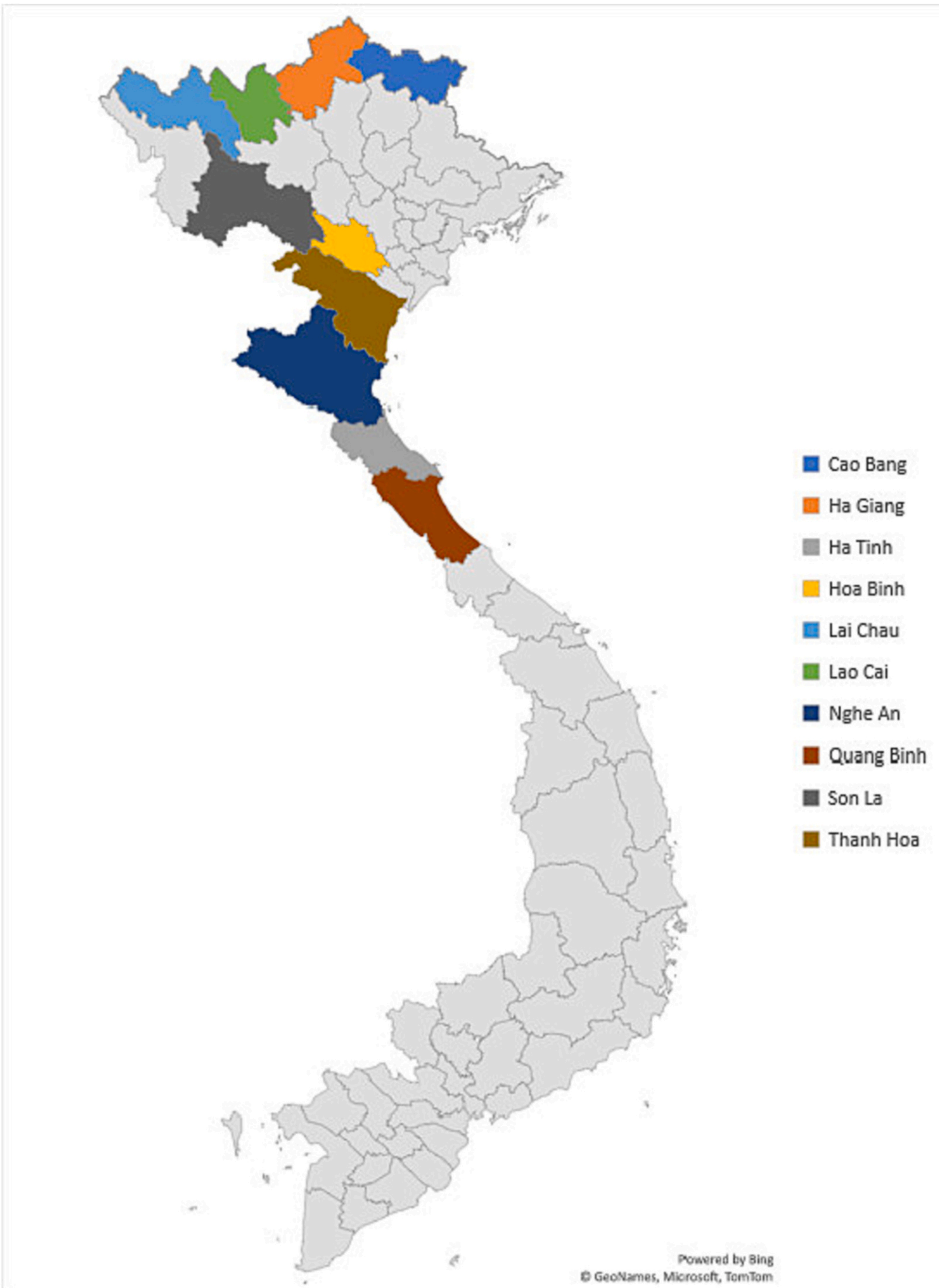

Fig. 2. Map of the study area.

impacted regions within the provinces; (2) roughly 25 farming households were randomly selected from each commune (31 communes in total), drawn from the lists of households living in the areas. After inputting the collected data, the unfinished questionnaires were eliminated, leaving us with 758 completed surveys completed by an adult member of the household who was the decision maker of the household. The questionnaire included questions to capture socio-demographic characteristics, knowledge of measures to adapt to climate change, factors affecting the uptake of these adaptations, access to extension services, access to microcredit, and receipt of aid from the government. In addition, we used climatic data retrieved from Vietnam National Center for Hydrometeorological Forecasting (NCHMF) to estimate the change in annual temperature and precipitation in the most recent 10 years at provincial level (10 surveyed provinces in Fig. 2), and spatial data from NASA's Socioeconomic Data and Applications Center (SEDAC) to calculate the distance of the farmer's house from their farms, and the distance of the farmer's house to the closest market.

The data included detailed information on farmers' perceptions regarding the existence of climate change and measures they had undertaken to adapt to these impacts. The interviewers were trained to help the respondents to distinguish between general technological changes and adaptation to climate change.

3.3. Empirical model

Nhemachena, Hassan [4] states that multivariate probit (MVP) model can be used to examine the determinants of adaptive methods. This is preferred over alternatives such as the multinomial probit model which depends on the hypothesis of independence of irrelevant alternatives (IIA). Multinomial probit also has the drawback that the correlations between adaptations' selections are prohibited. As stated by Boansi, Tambo [37], an MVP model (Eq. 1) sets up K equations, where each equation describes a latent dependent variable y_k^* that corresponds to the observed binary choice outcome (yes/no) of adopting the associated adaptation strategy y_k:

$$y_k^* = \alpha_k + x_k^{'}\beta_k + \varepsilon_k, k = 1, \dots, K$$

$$y_k = 1 \ if \ y_k^* > 0, \text{and 0 otherwise,} \tag{1}$$

where x_k is a $(p \times 1)$ vector of explanatory variables for the k_{th} equation in the MVP model, α_k is the intercept term and β_k contains a $(p \times 1)$ vector of parameters. The error term vector $(\varepsilon_1, \dots, \varepsilon_K) \sim N_K\ [0,S]$ is distributed as a multivariate normal, with zero mean and a variance-covariance matrix S. The leading diagonal elements of S are normalized to one, and the off-diagonal elements represent the unobserved correlations $\rho_{kj} = \rho_{jk}$ for $k, j = 1, \dots, K$ and $k \neq j$.

In our study, the surveyed households could choose between seven adaptation strategies ($K = 7$) for climate change mitigation that were modeled as binary dependent variables with the code '0' denoting non-adaptation and '1' for adaptation. The adoption of each adaptive measure was analyzed as a binary dependent variable and each was regressed against the same set of explanatory variables, as described in Table 1. As the MVP model hypothesizes that the choice of one adaptation strategy of a given household might affect the probability of the same household choosing another option, we tested the null hypothesis that all cross-equation correlation coefficients (rho) were simultaneously equal to zero. If the null hypothesis was rejected, the MVP specification was employed to capture the presence of unobserved factors driving the observed interconnected choices of adaptation strategies.

As mentioned above, farmers may adopt a combination of adaptation measures rather than one of these strategies individually. Besides MVP, Poisson regression is an econometric technique that analyzes the whole number of units of the dependent variable as a function of various explanatory variables [48]. Cameron and Trivedi [49] suggested applying robust standard errors to allow for the possibility that the assumption that variance equals the mean would be violated. Tambo [50] expressed the Poisson regression model in eq. (2). Over-dispersion test for Poisson is implemented to check the dispersion of estimated mean and variance.

$$y_i = \alpha X_i + \varepsilon_i \tag{2}$$

Where y_i has a Poisson distribution, $y_i \sim Poisson(\mu_i)$ for $i = 1, \dots, 7$, where the expected count of y_i is $E(y_i) = \mu$. Y_i is the number (n) of adaptive methods used by the i^{th} household. ε_i is the error term. Systematic component: X_i is a set of explanatory variables, including socio-economic, climate change, and location variables. In this study, the standard error is calculated by the sandwich estimator.

Table 1
Relevant studies - Poisson and Multivariate probit models.

Variables	Description	Reference sources
Perception		
Perception	Farmers' perceptions of the existence of climate change (0 = No/1 = Yes)	[1,19,20,38,39]
Farmer's characteristics		
Political	At least one of the family members/friends/ relatives works as a local officer (0 = No/1 = Yes)	[29]
Education	Educational level of household's head (years of schooling)	[40]
Age	Age of household's head (years)	[41]
HHsize	Total number of family members participating in labor force	[2,18];
Land	Total land used for cultivation (ha)	[1,6,38]
Agri-Incom	Earnings of the surveyed household from agricultural activities (million VND)	[42,43]
Non-Agri-Incom	Earnings of the surveyed household from non-agricultural activities (million VND)	[44]
Supportive policies		
Credit	The accessibility of the surveyed household to supportive loans fund of the government (0 = No/1 = Yes)	[25] [17]
Extension	Participation of at least one of the household members in agricultural extension training (0 = No/1 = Yes)	[45]
Constraints		
Dmarket	The distance from the respondent's house to the closest market (km)	[33]
Dfarm	The distance from the respondent's house to the farming areas (km)	[46]
Climate variability		
SDrain	Standard deviation of annual rainfall in over a recent 10-year period 2010–2019 (mm)	[47]
SDtemp	Standard deviation of annual average temperature over a recent 10-year period 2010–2019 (°C)	[38]
Rain_normal	An average of annual rainfall normals over a recent 10-year period (2010–2019) (mm)	[2,5]
Temp_normal	An average of annual temperature normals over a recent 10-year period (2010–2019) (°C)	[2,5]

4. Results

Initial inspection of the data reveals relatively high adoption rates for each of the seven adaptive measures (as shown in Table 2). Separate statistical models were estimated for each of these adaptive measures. The most widely-applied adaptation measure are diversifying crops/ livestock (96.0% of the surveyed farmers), meanwhile, households' income management is least employed (85.0% of the farmers).

Table 3 provides a summary of the data used in this study. Climate change was perceived to be occurring by 64% of the respondents. The average farm area was 8.5 ha and the average agricultural income was 3.5 million Vietnamese Dong (around US$150). The climate normals are

Table 2
Households adaptation practices.

Adaptation	Abbreviation	Percentage (%)
Diversifying crops/livestock	Diver	96.0
New technology application	Ntech	87.0
Cropping calendar adjustment	Seaso	89.0
Implementation of soil conservation	Psoil	87.0
Cropping techniques adjustment	Ptech	91.0
Income diversification	Incom	95.0
Households' income management	Finan	85.0

Table 3
Summary of descriptive statistics.

Variables	Mean	Standard error	Min	Max
Perception	0.64	0.48	0	1
Farmer's characteristics				
Political	0.62	0.48	0	1
Education	7.02	4.21	0	12
Age	43.61	11.62	15	93
HHsize	4.82	1.61	1	12
Land	8.53	1.32	3.9	11
Agri-Incom	3.51	0.82	0.5	5.9
Non-Agri-Incom	2.85	1.83	0	6.2
Supportive policies				
Credit	0.85	0.36	0	1
Extension	0.89	0.31	0	1
Constraints				
Dmarket	6.21	5.71	0.1	35
Dfarm	2.23	3.85	0.05	60
Climate variability				
SDrain	108.96	48.24	44.04	220.32
SDtemp	0.19	0.13	0.06	0.52
Rain_normal	1967.04	363.96	1455.48	2493.12
Temp_normal	23.08	1.09	21.76	25.12

represented via Table 3 and these indicators by provinces in Table A5. Specifically, the average annual temperature and rainfall in our study are 23.08 and 1967.04, respectively. In Table A5, we observe that the lowest 10-year average annual temperature and rainfall belongs to Son La province among the 10 surveyed provinces.

Interestingly, the rate of farmers connected to the political system is high, at 62% over the total of respondents. An average rural family in Vietnam connects to the local institution through three main channels: family members, extended relatives, or friends [51]. Unlike cities, rural villages in Vietnam are often prolonged and closed communities where families expand over generations and the relationship tends to be kept among insiders. Moreover, local officers are normally "villagers" elected by village residents thanks to their understanding and long-term engagement in local life. In Vietnam, it is common for one to invite his/her neighbors to attend their family funerals or weddings, hence, Tarp and Markussen [29] suggested that a family attending >15 weddings can be considered to have a good probability of gaining political connection via extended relatives. That is the reason of high rate of political connected households in rural Vietnam.

Heteroscedasticity and multicollinearity are typical issues when we deal with cross-sectional data. In our analysis, we run a Pearson correlation test for our independent variables. The results indicated that there was no collinearity problem as all coefficients were smaller than 0.3. The exception was a correlation of 0.48 between extension and credit, probably because credit and extension were both provided by government support programs. However, the correlation of all employed explanatory variables was not larger than 0.5, which signified the dependence between the aforementioned variables in the models, and thus we retained these variables in our empirical models. A robust estimate for standard errors is applied to correct the heteroscedasticity problem.

Table 4 shows the results of the multivariate probit regressions for each adaptation. Three variables stood out as being significant for almost all employed adaptations: Land, Non-Agri-Incom, and SDrain. In the literature on the adoption of new farming practices, the farm size (land area) is one of the explanatory variables that is most consistently found to influence adoption [1]. A larger farm area means that successful adoption of a beneficial practice would generate larger total benefits than on a smaller farm, so the motivation to adopt is higher. The fixed cost of learning about a new practice is lower per hectare on a larger farm, increasing the motivation for adoption. Furthermore, farmers with larger farms are more likely to have the resources available to invest in the new practice.

The increase of non-agricultural income would, on the other hand, reduce farmers' concern about potential risk of losing crops, thus, discourage them to adopt adaptive strategies. Our results indicate that this effect remains robust among 5 out of 7 strategies excluding adjusting cropping calendar and managing households' income. For these strategies, a change in income structure does not affect farmers' adopting decision, since they are fundamentally influenced by other factors such as perception or extension.

The consistent influence of rainfall variation might be because most of the adaptations were related to risk management. The higher the level of rainfall variation, the more farmers are stimulated to take actions. Our estimate is a novel contribution to indicate the recent variation in rainfall, a major source of risk in rainfed agricultural production, which significantly affects farmers' decisions about adaptive measures to adopt.

In our study, we used squared terms of climate normals variables to test the quadratic relationship between climate normal and the adoption of farmers strategies' adoption. The average temperature level (Temp_normal) and its squared term (Temp_normal^2) are shown to have a significant effect on multiple adaption measurements, except for diversifying crops, adjusting the copping calendar, and implementing soil conservation. This implies that in both cases of weather being too cold or too hot, farmers tend not to adopt these strategies, which means that there is a turning point of temperature normal at which the probability of farmers adopting strategies is highest. Yet, from the individual coefficient of Temp-normal, we can conclude that, for the current average level, farmers are still prone to use these strategies to cope with increasing temperature. SDtemp also issues significant, positive coefficient on Ntech and Incom indicate that the more temperature varies, the more likely farmers change their technology and diversify income sources. On the other hand, for soil conservation, a higher temperature deviation leads to a lower adoptability probability.

The other explanatory variables influenced the adoption of only a subset of the variables, in most cases, two or three of them. These various influences no doubt had individual explanations which are somewhat specific to the particular adaptations. For example, the age variable positively influence the application of new technologies and soil conservation but not the other adaptations. In some cases, the explanations are not obvious and need more investigation. For example, participation in extension imposes mixed effects on the likelihood of farmers adoption of adaptation strategies.

The implementation of soil conservation measures is one of the most complicated adaptations. Common forms of soil conservation in the survey areas are plowing furrows, expanding irrigation canals, forestation, and reduction of pesticide/herbicide usage. We found that adoption of these practices are less likely with larger household sizes, more likely with larger farm sizes, less likely with higher non-farm income, more likely with greater distance from market, and more likely with farmers having political connections.

Given the results for different adaptations in Table 4, we conducted a Poisson regression with several adaptations adopted as dependent variables (Table 5). After performing an overdispersion test for Poisson, the test suggests that Prob > chi2 (764) = 1.0000 and the results generated from either Poisson and Negative binomial regression (Table A4) are identical. This provided us with insights into the overall influence of the

Table 4
Parameters estimated from multivariate probit regression for each adaptive practice.

Variables	Diver	Ntech	Seaso	Psoil	Ptech	Incom	Finan
Intrinsic factors							
Perception	−0.183**	−0.227	−0.106	-0.177*	−0.328**	−0.106	−0.368***
	(0.064)	(0.138)	(0.112)	(0.105)	(0.109)	(0.067)	(0.094)
Farmers' demographic characteristics							
Education	-0.024	-0.016	0.001	0.015	0.003	0.009	-0.006
	(0.018)	(0.128)	(0.016)	(0.021)	(0.018)	(0.015)	(0.002)
Age	−0.008	-0.006	−0.008*	0.003	-0.005*	−0.003	0.001
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.008)	(0.004)
HHsize	−0.056	−0.062**	−0.059	−0.066**	−0.025**	−0.002	−0.030
	(0.038)	(0.041)	(0.022)	(0.038)	(0.037)	(0.050)	(0.054)
lnLand	0.221**	0.197***	0.091***	0.073**	0.075**	0.152**	0.214**
	(0.061)	(0.064)	(0.062)	(0.031)	(0.036)	(0.078)	(0.083)
lnAgri-Incom	0.087	0.098*	0.024	0.008	0.144**	−0.072	−0.078**
	(0.077)	(0.058)	(0.083)	(0.060)	(0.068)	(0.099)	(0.011)
lnNon-Agri-Incom	−0.056**	−0.042*	−0.004	−0.074**	−0.028***	−0.044*	−0.005
	(0.030)	(0.024)	(0.034)	(0.038)	(0.008)	(0.049)	(0.049)
Extrinsic factors							
Political	−0.057	0.042***	0.150	0.075*	0.295	0.214	0.049**
	(0.187)	(0.102)	(0.141)	(0.130)	(0.329)	(0.178)	(0.016)
Supportive policies							
Credit	0.343**	0.322	0.108	0.354	0.146*	0.078	0.466**
	(0.157)	(0.263)	(0.201)	(0.234)	(0.075)	(0.282)	(0.184)
Extension	0.031	0.085	−0.500**	0.328**	0.005	−0.413**	−0.046
	(0.199)	(0.112)	(0.265)	(0.145)	(0.181)	(0.249)	(0.224)
Constraints							
Dmarket	−0.013	0.043**	0.015	0.029**	−0.013	0.042	0.021**
	(0.011)	(0.011)	(0.014)	(0.014)	(0.010)	(0.028)	(0.011)
Dfarm	-0.011	−0.014	0.008	−0.015	0.537	0.103**	−0.023*
	(0.009)	(0.010)	(0.018)	(0.013)	(0.060)	(0.054)	(0.014)
Climate variability							
Sdrain	0.078*	0.136***	0.033	-0.039	0.091*	0.123**	0.071*
	(0.034)	(0.032)	(0.033)	(0.055)	(0.041)	(0.032)	(0.030)
Sdtemp	−0.147	0.324*	0.067	−0.442*	0.214	0.271*	−0.297
	(1.806)	(0.149)	(1.305)	(0.183)	(0.155)	(0.152)	(1.718)
Rain_normal	0.138	0.034	0.121	0.118	0.034	0.045	0.031
	(0.113)	(0.081)	(0.081)	(0.094)	(0.078)	(0.070)	(0.082)
Temp_normal	0.599	0.221**	0.101	0.652	0.244**	0.245***	0.176*
	(0.103)	(0.075)	(0.067)	(0.971)	(0.071)	(0.058)	(0.076)
$Rain\_normal^2$	-0.0004	-0.0001	-0.0003	−0.0002	-0.0001	-0.0001	-0.000
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$Temp\_normal^2$	-0.140	-0.047**	−0.029	-0.157	−0.530***	−0.528***	-0.388*
	(0.216)	(0.159)	(0.141)	(0.203)	(0.149)	(0.123)	(0.161)
Intercept	0.098*	0.146***	0.043	-0.049	0.091*	0.113**	0.061*
	(0.713)	(0.638)	(0.188)	(0.164)	(0.733)	(0.073)	(0.651)

Note: *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively; Robust standard errors are estimated using clustering analysis at village level.

various explanatory variables across the adaptations, rather than insights into the adoption of specific adaptations. Consistent with Table 5, the number of adaptations adopted are significantly and positively related to land area, standard deviation of rainfall, distance to market, and political connections, while negatively related to non-agricultural income and the squared term of temperature normal.

Tables A1 and A2 (in Appendix) describe the results of model specification tests based on the principle of parsimony. We compared the full model with alternative parsimonious specifications that eliminated one category of the explanatory factor at a time. Dupuy (2018) stated that the smaller the values of the Akaike information criterion (AIC) and Bayesian information criterion (BIC) are estimated, the better the model is. Using the AIC and BIC, the complete model with the perception of climate change and other control variables are chosen because the entire model possessed the best goodness-of-fit. In addition, we also performed a log-likelihood ratio test to statistically indicate the best model specification among the six models demonstrated in Tables A1 and A2 (in Appendix). The test results also suggested that the full models in multivariate probit models or Poisson models are the best model for our data analysis.

5. Discussion

Our analysis outcomes provide the insights that are similar with a range of prior scholars (including [25,45,52,53]. Shukla et al. [8] indicated that outcomes estimated in regional studies can be homogeneously amplified in other identical geographical regions. Based on our adaptation adoption model and analytical approach, our findings are likely to be relevant to other mountainous regions in Asian countries, potentially including Nepal and China (northern agro-pastoral ecotone), and African countries such as South Africa, Ghana, Benin, and Ethiopia.

Farmers' decision-making regarding adaptation to climate change is complex. As this research shows, it is influenced by a wide range of factors, including extrinsic and intrinsic variables. These factors variously affect the farmer's knowledge, motivation, and capacity to adapt to climate change, but the most important variables overall are cultivated land area, the weather variables (standard deviations of rainfall and temperature), and the farm's location (distance from the market). The constraints caused by distance from farmers' houses to their closest marketplace motivate them to apply the adaptations related to agricultural production because their livelihoods are highly dependent on this activity [27]. The fluctuation of annual rainfall incentivizes farmers' adaptation selection, which is also indicated in the study undertaken in a mountainous region called Bundelkhand region, India [54].

Table 5
Poisson regression model using clusters at provincial level.

Variables	Estimate	Robust SE	Lower Bound	Upper Bound
Intrinsic factors				
Perception	−0.0450***	0.0173	−0.0789	−0.0151
Farmer's characteristics				
Education	−0.0022	0.0028	−0.0078	0.0031
Age	−0.0009	0.0007	−0.0022	0.0011
HHsize	0.0021	0.0065	−0.0106	0.0171
lnLand	0.0083***	0.0036	0.0158	0.0381
lnAgri-Incom	0.0012	0.0081	−0.0146	0.0021
lnNon-Agri-Incom	−0.0072**	0.0039	−0.0121	−0.0012
Extrinsic factors				
Political	0.0228***	0.0023	0.0068	0.0831
Supportive policies				
Credit	0.0579**	0.0236	0.0116	0.1260
Extension	0.0014	0.0184	−0.0346	0.0540
Constraints				
Dmarket	−0.0031***	0.0008	−0.0046	−0.0010
Dfarm	0.0005	0.0018	−0.0031	0.0010
Climate variability				
SDrain	0.0082***	0.0076	0.0066	0.0100
SDtemp	−0.0325	0.3668	−0.7514	0.4250
Rain_normal	−0.0151	0.0133	−0.0110	0.0213
Temp_normal	0.3413***	0.0957	0.1536	0.3411
Rain_normal^2	0.0001	0.0000	0.0001	0.0000
Temp_normal^2	−0.0753***	0.0194	−0.1134	−0.0031
Intercept	2.3802	1.5801	−0.7651	5.4301

Notes: *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively. The Lower limit and Upper limit define the 95% confidence interval for the parameter estimates.

Farmland is a vital asset that decisively affects farmers' livelihood. We found that the land area of the farms had a significant positive influence on the adoption of each of the adaptations studied there (Table 5). However, in northern Vietnam and various other developing countries, land fragmentation remains a problem. Farming land rights and land ownership trading are still underdeveloped and are actively debated in some developing countries [55]. Relevant to this is the fact that several governments, such as the Vietnamese [1], Colombian [56], and Brazilian governments [57], are pursuing the same policy, which is "land accumulation". In this policy, they combine dispersed individual small-scale farmers into cooperatives. We have not specifically studied the uptake of adaptations by farmers in cooperatives, but greater adoption could be expected due to the influences of agricultural income, education, and farm size. According to Burke and Lobell [58], large-scale farmers are likely to have more confidence to invest in their farms instead of off-farm.

Regarding the interference of the government, while credits promote the uptake of several adaptive measures in response to climate change, extension is found to discourage farmers to adopt cropping calendar adjustment and income diversification. This casts doubt on the appropriateness of offering these subsidies and suggests that a cautious approach is needed when deciding on the use of subsidies in this way. The measure of extension participation was not for an extension that specifically promoted the uptake of the seven climate-change adaptations, so the lack of significant correlation in most cases was, perhaps, unsurprising. The negative correlation in two cases (calendar adjustment and diverse income) perhaps reflected that farmers who attended the extension events had other priorities rather than adapting to climate change in mind. Government subsidies were not significantly indicated in the study by [59]. When the roles of government extension or subsidies were ambiguous, the participation of private agricultural extension was essential [60]. Thus, the collaboration of the public and commercial agricultural extension sectors to adequately educate farmers in order to assist them adapt to climate change is critical.

Since we consider adaptive strategies of farmers in the context of climate change, the variation of rainfall and temperature are substantial factors. However, our results suggest that the level of precipitation does not impose any significant impact on farmers to apply their adaptive measures, while the variation of annual rainfall motivates them. Our results align with those found in the studies by [61] and [26]. The instability of precipitation causes either a water deficit and excess water that intensify crop loss. The nonsignificant relationship between annual average rainfall and farmers' strategies decision indicates that the level of rain within 2010–2019 does not make farmers concern. On the other hand, farmers are more likely to be influenced by temperature since both linear and quadratic terms of this factor issue a significant coefficient. However, the propensity to adopt of farmers only goes up to a certain level when the temperature rises. According to Table A3, when temperature falls too far from around 21 to 23 degree C in respect to each strategy, the farmers' tentation to adopt reduces. Global warming in the 2010–2019 period poses a critical threat to farming households due to significant influences on agricultural production [62]. To solve the problem in the long-run, Martinez-Feria and Basso [63] suggested that establishing a yield stability map could help to spatially and effectively implement adaptive strategies to mitigate temperature variability.

6. Conclusion

Climate change has caused various harmful outcomes, such as an increase in frequency, severity, and intensity of extreme weather events, including flash floods and heat waves that have directly impacted agricultural production. One of our contributions in this research study is to construct an adaptation adoption framework that indicates the dependence of adaptation on various intrinsic factors (e.g., farmers' perceptions of farmers and socioeconomic characteristics) and extrinsic factors (e.g., political connectedness, climate variability, and farm location) based on various academic studies in the field of adaptations to climate change. We used a multivariate probit model to find the determinants of farmer's decisions on adaptive measures to address climate change. The results indicated that farm size, household size, agricultural income, distance to the closest market, political connection, and climate variability had significant impacts on the adoption of at least some of the adaptation practices studied. Other variables having less impact or inconsistent impact were the age of the household's head, educational level of the household's head, participation in extension. The inconsistent effects of these variables might be resulting from our sample size. The annual climate temperature normal shows that farmers are more sensitive to temperature changes than rainfall. The missing monthly climatic data and seasonal variations or averages are our main drawbacks. The government has already supported these farmers in terms of extension schemes and micro-credit programs. However, the results of this research indicated that these supportive policies did not significantly encourage the motivation of adaptive measures to climate change in the northern part. Therefore, further research is needed to resolve the issues by supplementing field-trips observations and seasonal variation to observe influencing factors of farmers' decision on their adaptive strategies.

Author statement

I would like to declare on behalf of my co-author that the work described is original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part. I confirmed that no conflict of interest exists in the submission of this manuscript, and is approved by all authors for publication in your journal

Declaration of Competing Interest

All authors declare that there is no conflict of interest.

Data availability

Data will be made available on request.

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Appendix A

Table A1
AIC, BIC, and LR tests of the goodness-of-fit for multivariate probit models.

Model	AIC	BIC	LR (χ^2) *p*-value
Full model	3478.211	3972.285	
Without perception model	3429.782	3956.438	0.227
Without farmer's characteristic model	3521.745	4004.158	0.001
Without supportive policies model	3479.414	3926.356	0.033
Without constraints model	3497.662	3943.015	0.032
Without climate variability model	3509.828	3949.180	0.005

Table A2
AIC, BIC, and LR tests of the goodness-of-fit for Poisson models.

Model	AIC	BIC	LR (χ^2) p-value
Full model	3670.661	3626.361	
Without perception model	3677.719	3644.201	0.052
Without farmer's characteristic model	3678.745	3651.716	0.008
Without supportive policies model	3679.481	3638.265	0.084
Without constraints model	3679.771	3652.475	0.012
Without climate variability model	3675.843	3638.463	0.083

Table A3
Turning points of Climate Normals' variables.

Variables	Diver	Ntech	Seaso	Psoil	Ptech	Incom	Finan
Rainfall	2070.249	2040.640	2420.205	3540.478	2040.342	1306.616	2050.660
Temperature	21.393	23.116	21.205	20.764	23.019	23.201	22.680

Table A4
Negative binomial regression model using clusters at provincial level.

Variables	Estimate	Robust SE	Lower Bound	Upper Bound
Intrinsic factors				
Perception	−0.0450***	0.0173	−0.0789	−0.0151
Farmer's characteristics				
Education	-0.0022	0.0028	-0.0078	0.0031
Age	-0.0009	0.0007	-0.0022	0.0011
HHsize	0.0021	0.0065	-0.0106	0.0171
lnLand	0.0083***	0.0036	0.0158	0.0381
lnAgri-Incom	0.0012	0.0081	-0.0146	0.0021
lnNon-Agri-Incom	-0.0072**	0.0039	-0.0121	-0.0012
Extrinsic factors				
Political	0.0228***	0.0023	0.0068	0.0831
Supportive policies				
Credit	0.0579**	0.0236	0.0116	0.1260
Extension	0.0014	0.0184	−0.0346	0.0540
Constraints				
Dmarket	−0.0031***	0.0008	−0.0046	−0.0010
Dfarm	0.0005	0.0018	−0.0031	0.0010
Climate variability				
SDrain	0.0082***	0.0076	0.0066	0.0100
SDtemp	−0.0325	0.3668	−0.7514	0.4250
Rain_normal	−0.0151	0.0133	−0.0110	0.0213
Temp_normal	0.3413***	0.0957	0.1536	0.3411

(*continued on next page*)

Table A4 (*continued*)

Variables	Estimate	Robust SE	Lower Bound	Upper Bound
$Rain\_normal^2$	0.0001	0.0000	0.0001	0.0000
$Temp\_normal^2$	−0.0753***	0.0194	−0.1134	−0.0031
Intercept	2.3802	1.5801	−0.7651	5.4301

Notes: *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table A5
Average annual climate normals in 2010–2019 by provinces.

Province	Rainfall Normal	Temperature Normal
Cao Bang	1694.84	22.94
Ha Giang	2486.66	23.29
Ha Tinh	2493.07	24.77
Hoa Binh	1994.47	23.94
Lai Chau	2323.83	22.03
Lao Cai	2097.76	23.60
Nghe An	1932.88	24.39
Quang Binh	2364.95	25.13
Son La	1455.50	21.76
Thanh Hoa	2097.19	24.26

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