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Farmers' choices of climate-resilient strategies: Evidence from Vietnam

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ABSTRACT

Farmers have a long history of adapting to changing conditions, including changing climate, towards more sustainable agricultural production. In this study, we construct a unique long-duration pseudo-panel dataset from nationally representative households in Vietnam to investigate factors behind farmer's choices to adopt soil and water conservation techniques to adapt to climatic change. Since farmers' adoption decisions are inherently dynamic, a dynamic probit model was estimated. We find that weather shocks and long-run changes in temperature are significant determinants of farmers' choices. The decision to make new investments in adaptation practices in subsequent periods is confirmed to be strongly influenced by the past adoption decision. Farmer's experience, farm size, and access to weather and output price information are also associated with households that apply conservation measures. These findings suggest that policies aiming at promoting climate-resilient strategies should pay attention to farmers' adaptation behavior and the persistence of choices in farmers' decision-making processes. Policies should target improving farmers' access to information with a special focus on market- and weather-related information to enhance farmers' adaptive capacity to better cope with ongoing climatic uncertainty.

1. Introduction

Adaptation is a key strategy for reducing the adverse impacts of climate change (Deressa et al., 2009; Khanal et al., 2020). Farming households have a long history of adapting to changing production environments, including unfavorable climatic conditions. Adaptation in agriculture is manifested through a wide range of behavioral response strategies that have been identified in many empirical studies (IPCC, 2007; Masud et al., 2017). The most often quoted ones include diversification of crops and income sources, adjustment of various farm management practices, and implementation of soil and water conservation techniques. Among those, the conservation of soil and water resources has been increasingly important for the adaptation of farming systems to various stresses (Li et al., 2020; Sietz and Van Dijk, 2015). Some methods, such as terrace farming, soil bunds, and conservation tillage, have been suggested as main methods to reduce the effect of water shortages and worsening soil conditions that come as a result of climate change (Kurukulasuriya and Rosenthal, 2013; Li et al., 2021).

Most previous adaptation research has used cross-sectional datasets to investigate farmer behavior under changing climatic conditions. These micro-level studies focusing on the implementation of adaptation practices provide insights into the effects that the characteristics of farms and farmers have on their adaptation decisions (Knowler and Bradshaw, 2007). They also investigate the effects of farmers' perceptions about changing climatic conditions and explain what factors govern their decision-making process (Ali et al., 2020; Below et al., 2012; Maddison, 2007).

Sietz and Van Dijk (2015) present a meta-analysis of 63 case studies that investigate the adoption of soil and water conservation measures and confirm a multitude of factors that drive adoption decisions. Ogundari and Bolarinwa (2018) synthesis 154 studies and show that many of these studies take a snapshot of the data at a given point in time, or consider technology adoption in a static set-up. This implies that cross-sectional data are used to address an issue that is inherently dynamic and requires panel data analysis (Besley and Case, 1993; Doss, 2006; Sietz and Van Dijk, 2015). Consequently, a major obstacle to better understanding the dynamic nature of behavioral change in adopting agricultural practices conducive to adaptation to climate change has been the lack of studies based on long-duration panel datasets at the household level (Moser and Barrett, 2006). Also, there has

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been no previous work focusing on adaptation practices on farms using long-duration panel data in Vietnam. This leaves a gap in the literature that the current study is aiming to fill. While the empirical study in this paper focuses on Vietnam, the findings are relevant for many other countries, as Vietnam's agricultural development over the recent decades draws contemporary similarities to a large number of emerging and developing economies.

The paper adds value to the existing literature in several ways. We construct a long-duration panel dataset by combining data from the nationally representative sample of households in the Vietnam Living Standard Survey (VLSS) and the Vietnam Access to Resources Household Survey (VARHS) from 1992 to 2012. This allows us to work with a unique pseudo-panel data set in which data were collected over six waves, spanning twenty years across a variety of agro-ecological locations in Vietnam. The dataset is used to examine changes in agricultural practices at the farm level and to uncover the dynamic nature of farmers' behavior over a relatively long time period. Moreover, since decision-making processes on using adaptation practices are inherently dynamic, we use this dataset in a dynamic setting to examine some heretofore poorly understood dynamics of farmers' choices over time. Specifically, we assess the importance of previous adoption decisions on the current decision – the so-called state dependence – which has not been considered in sufficient detail in the climate change adaptation literature so far (Garbero and Marion, 2018). In order to present credible results, we perform robustness checks by using alternative estimators, and also control for potential sources of bias that is likely to be associated with dynamic modeling, such as the endogeneity of the adoption decision-making process and selection bias. To our knowledge, this study is among very few empirical studies globally that explain the dynamic pattern of adopting climate change adaptation practices in agriculture using a long panel dataset, and certainly is the first such study for Vietnam.

The rest of the paper is organized as follows. In the next section, we present an overview of climate change, agricultural production, and adaptation strategies in Vietnam. Section 3 describes data used in the study. In the following section, we present the conceptual framework and the empirical model. Section 5 provides and discusses the estimated results, and we draw some conclusions and policy implications in Section 6.

2. Background: climate change, agricultural production and adaptation strategies in Vietnam

2.1. Climate change and agricultural production in Vietnam

Climatic change across the country is manifesting through increasing temperatures, heavier precipitation or prolonged periods with very little or no precipitation, and through more frequent and more intense weather-related extreme events (Below et al., 2010; Nguyen et al., 2019). IPCC (2007) points out that countries with agriculture counting as a high proportion of the economy, such as Vietnam, are most susceptible to weather shocks and long-term shifts associated with climate change. Climatic variability and change are likely to be especially challenging for rice growing – a key agricultural activity in Vietnam and other developing countries in Southeast Asia – given its direct exposure to variations in temperature and precipitation. Ongoing changes in climatic conditions could impose large detrimental effects on rice production in many countries, including Vietnam, with implications for food security and household welfare (Di Falco and Veronesi, 2011).

At the national scale, Nguyen et al. (2013) note a trend of increasing average temperature over the last several decades throughout Vietnam. Besides, the variability of annual rainfall has increased dramatically across the climatic zones of Vietnam over that period (Nguyen et al., 2019).

Our study areas include six provinces (Ha Tay, Lao Cai, Nghe An, Quang Nam, Khanh Hoa, and Long An) across various agro-ecological regions that represent well the spatial distribution of climate patterns in Vietnam. At these study locations, precipitation and temperature exhibit large variations across space and within the rice-growing season. We use Growing Degree-Days (GDDs) as an indicator of temperature conditions in these locations. This indicator shows a significant increase over the period 1975–2012 (Appendix C1). We also use cumulative rainfall during the rice-growing season, which shows a declining trend in many areas (Appendix C2).

As drought is the most important extreme event that affects agriculture in Vietnam, we used the Standardized Precipitation Index (SPI) (McKee et al., 1993) to identify the variability, magnitude, and duration of drought conditions. The advantage of this index is that it can effectively represent the amount of precipitation over time by comparing the observed rainfall with the long-term average at a particular location. The index can take positive or negative values, with larger negative values indicating the greater severity of the drought. Observing the value of the SPI index over time shows that there has been increasing severity and intensity of droughts in many areas over time (Appendices C4 and C5).

2.2. Adapting to changing environmental conditions

In Vietnam, crop production is still dominated by rice as a major cash crop, using 39.8% of the total agricultural land (GSO, 2020). Rice farmers are typically smallholders and their livelihoods depend heavily on agriculture as the predominant source of income. However, rice cultivation is inherently vulnerable to climate change, because as a typical broadacre crop it is directly exposed to shifts in temperature and precipitation. In response, Vietnamese farmers are applying a broad range of strategies that allow them to adapt to changing production conditions brought about by climate change.

Climatic conditions in our study areas have changed considerably in terms of increased average temperature and an increase in the rate and magnitude of droughts. As a result, it is expected that some specific adaptation practices would have been adopted by farmers to mitigate the adverse impact of climate risks. Farmers in our study areas have been observed to use rock bunds, soil bunds, terraces, and grass lines as land conservation measures.[1] The descriptions of these methods are detailed in Appendix A. Applying these soil and water conservation practices is a key adaptation method to maintain soil moisture, alleviate the growing water-shortage and worsening soil conditions, and mitigate the negative impacts of higher temperatures and lower rainfall (Kurukulasuriya and Rosenthal, 2013). Rock and soil bunds are typically built to control surface runoff and harvest rainwater to mitigate the impact of soil erosion and increase soil moisture. Other techniques, such as building grass lines and terraces, have also been widely applied. These adaptation practices often require substantial inputs such as building materials and labor, and can therefore be quite costly to the farmer. Besides the initial investment, farmers also need to decide whether or not to continue to use the practices by investing in annual maintenance costs. The soil and water management techniques of interest have long been recommended by agricultural extension services in Vietnam, but here, we solely focus on differential adoption of those techniques in locations most impacted by climate change.

3. Data

3.1. Household data

In this study, we create a rich pseudo-panel dataset from a nationally

[1] These soil and water conservation techniques were also introduced by FAO in published technical manuals. These manuals briefly present the theoretical background and benefits of these techniques and also discuss their application at the farm level.

representative sample of households from six provinces (Ha Tay, Lao Cai, Nghe An, Quang Nam, Khanh Hoa, and Long An) across various agro-ecological regions of Vietnam (Fig. 1) by matching data.

A pseudo-panel dataset was created by combining data from two separate nationally representative surveys: the Vietnam Living Standard Survey (VLSS, 1992–1993, 1997–1998) and the Vietnam Access to Resources Household Survey (VARHS, 2006, 2008, 2010, 2012). The sample for the VLSS was selected based on a three-stage sampling strategy to represent various geographic regions of Vietnam. Further, the VARHS surveys were designed to be complementary to the VLSS and were implemented across Vietnam every two years. We use data from 2006, 2008, 2010, and 2012 waves of this survey. Commune-level data on regional input and output prices were also collected in parallel with household surveys and were deflated using the Consumer Price Index published by the Vietnam General Statistics Office.

Because adapting to changing climatic factors is an ongoing process over a long period, as is climate change itself, data with a relatively long time-frame are needed to study changes in agricultural practices applied by farmers. However, since the VARHS only provides short panel data for relatively recent years, it was necessary to match these data with observations from the earlier waves of the VLSS to create a long panel dataset. A combined panel dataset with a span of 20 years based on the two sets of surveys allows us to investigate changes in agricultural practices at the farm level over a relatively long time period, which is necessary for drawing meaningful conclusions about farmers' use of adaptation practices over time. Our 20-year, 6-wave panel is such a data set. We construct this pseudo-panel by identifying and meticulously matching households that could be treated as having been participating in both the VARHS and VLSS. However, the absence of unique and identical individual identifiers between the datasets of the two separate surveys (VLSS and VARHS) makes the simple merging of the data from the two sources impossible.

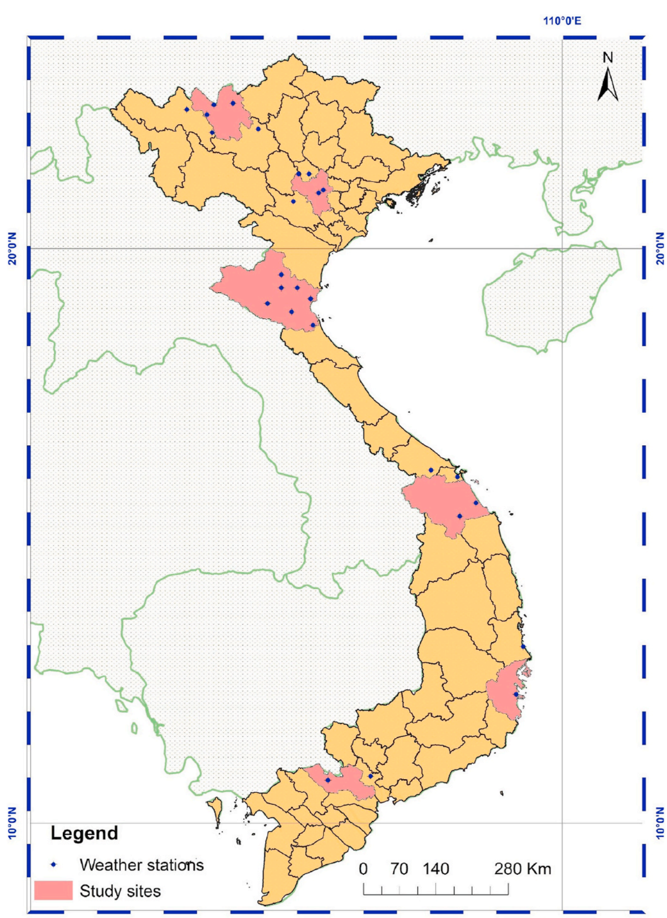

Fig. 1. Location of the study areas.

To address this problem, we use the 'probabilistic record linking' technique (Fellegi and Sunter, 1969; Jenkins et al., 2008; Newcombe, 1959). This technique has been widely applied in health, epidemiology, sociology, as well as in economics to match observations from separate surveys (Abowd et al., 2004; Kum and Masterson, 2010; Gomatam et al., 2002; Meyer and Mittag, 2019). For instance, Kum and Masterson (2010) used this method to combine two nationally representative surveys (the 2001 Survey of Consumer Finances (SCF) and 2002 Current Population Survey Annual Demographic Supplement (ADS)) into a linked dataset used to examine the distribution of income and wealth. Their matching algorithm calculates propensity scores using pre-specified segments (e.g. gender, age category, education category, race, and occupation of the household head, homeownership, family types, household size) and then matches records from the donor data file to records in the recipient data file by sorting estimated scores. Furthermore, Meyer and Mittag (2019) examined the poverty-reducing effects of the different transfer programs using linked household survey and administrative records. Their main approach is based on a probabilistic matching technique to create the Person Identification Validation System from personal data (such as address, name, gender, and date of birth) and administrative records and survey data. We apply the same technique in this study to identify likely matches of surveyed households in VARHS and VLSS to form a linked dataset across the six survey waves. The whole process of constructing the dataset is summarized below with further details in Appendix D.

Following Blasnik (2010), suppose that a 'master' dataset (in our case data collected by VARHS) has *Na* records, and a 'using' dataset (data collected by VLSS) has *Nb* records. Each of the *Nb* records in VLSS is a potential match for each of the *Na* records in VARHS. Details of the matching procedure are as follows:

(1) Create a panel dataset for VLSS. The resulting panel dataset, which is called a 'using' dataset, consists of records on 3480 households.
(2) Create a panel dataset for VARHS. The resulting panel dataset, called a 'master' dataset, consists of records on 2024 households.
(3) Perform probabilistic record linkage of households that are present in the 'using' dataset with those that are present in the 'master' dataset. The matching was performed based on a specified list of comparison variables such as location (e.g. village), same primary sampling unit (e.g. commune), having rice production activity, characteristics of the household head (e.g. age, gender, experience), and the farm (household size, farm size). All possible pairs of observations were evaluated and a matching score was computed for each pair. The pairs were then sorted by the matching score and a cut-off threshold value for the score of 0.8 was applied. Selecting the cut-off threshold value was based on a method commonly applied in the literature through the process of manually adjusting that threshold in such a way that we obtained a sample that is as representative as possible while minimizing the number of false positives and maximizing the number of false negatives (Ran et al., 2020). The matched pairs that had a matching score of 0.8 or above were then put in a 'linked' dataset. This dataset consisted of observations on 661 households from six provinces (Ha Tay, Lao Cai, Phu Tho, Nghe An, Khanh Hoa, and Long An).
(4) Consider the quality of linkages by reviewing the records for each of the 661 households in the 'linked' dataset. Wasi and Flaaen (2015) and Winkler (2006) suggest that even after matching, it is important to manually review each matched pair, especially for observations with lower matching scores. Thus, each pair of records in the 'linked' dataset was carefully checked and errors and missing data in variables of interest were identified that led to inaccurate matching. Further, we followed Sayers et al. (2016)

approach to check the quality of the linked dataset by comparison with a gold-standard sub-sample (the true panel of all survey rounds) and by comparison of linked and unlinked datasets (Appendix G). As a result, a sample of 424 matching households was identified.

(5) Merge the household-level dataset with commune-level information. It is necessary to merge these data sources to obtain a dataset including farms, households, and regional characteristics. Due to missing data at some communes, our final pseudo-longitudinal dataset consists of 316 matched households with a total of 1896 observations, for which we have data on all variables of interest. [2] Those households could be representative for both VARHS and VLSS as the main properties of key descriptor variables are highly similar to the true panel and the original nationally representative surveys (Appendix G) and the study areas are still spread across the country, as expected (Fig. 1).

The dependent variable of interest – farmers' adoption decisions to apply soil and water conservation practices – reflects new commitments, not just maintaining practices adopted earlier. This is consistent with the way the relevant question was specified in the questionnaire that was administered in the surveys: '*Has your household made any new investment in soil and water conservation improvements on plot [plotid] since [date]?*'. We also control for factors that are known to influence the decision-making process of individual farmers. Several covariates were selected for household and farm characteristics (e.g. household head experience, farm size, access to information). Commune-level information on input and output prices was also collected. The selection of these variables was based on standard practices as described in the rich literature on technology adoption in agriculture (Doss, 2006; Sietz and Van Dijk, 2015). Evidence from various sources indicates that there is a positive relationship between the number of years of experience in agriculture and the adoption of improved agricultural technologies. Moreover, Deressa et al. (2009) confirm that access to weather information and information about new techniques could facilitate the adaptation process to climatic variations and change. Information such as new agricultural practices, short-term forecasts, and seasonal forecasts may be available to farmers through the internet, radio, television, and extension agents. It is regularly hypothesized that access to credit eases the cash constraints of smallholders and allows them to invest more in farm production and management, including investing in climate change adaptation practices (Knowler and Bradshaw, 2007). In addition to household characteristics, studies on the adoption of soil and water conservation measures also pay attention to the physical features, such as farm size. The overall effect of farm size on the adoption of conservation practices has been inconclusive in previous studies (Knowler and Bradshaw, 2007).

We also control for commune-level input and output market information through labor wages and farm-gate average price variables. A set of the province- and year-specific dummy variables are also included in the model to capture location and time fixed effects and spatial heterogeneity including characteristics of biophysical farm conditions and policy variability, which are unobservable in the data.

Table 1 presents the descriptive statistics for the variables used in the study. The table shows a slight difference in the means of all variables of interest between adopters and non-adopters. This is also evident when considering the descriptive statistics across years provided in Appendix E. Table 1 shows that adopters have greater farm size, produce more output, and have longer experience in farming; they also more often access weather information, and on average receive a higher farm-gate price compared to non-adopters.

The dynamics of the aggregate new adoption decision for the period 1992 to 2012 are presented in Fig. 2.

In dynamic modeling, it is crucial to properly handle missing data in any round of the survey during the study period since we use both initial and current values of the response variable. This nature of the data could only be described and properly modeled by investigating the patterns of the missing data on the response variable (the decision to adopt conservation technologies). Table 2 presents the results of that investigation for our data set.

In the table, '1' denotes non-missing and a dot (.) denotes a missing value of the response variable for the six waves of the surveys. For example, a pattern '111111' indicates observations for which we have full responses on the adoption decision for all six waves of the surveys. As the table shows, 34.18% of the 316 observations in the 'linked' dataset have full responses. In the same vein, a pattern '111..1' indicates that there are missing data on the response variable in the fourth and fifth waves of the surveys. As suggested by Skrondal and Rabe-Hesketh (2014), it is critical to focus on observations that have at least two consecutive non-missing values across the surveyed periods. This requirement is essential to estimate a dynamic probit model, which is an adequate model for state dependency, where the influence of previous adoption decisions on current decisions is explicitly modeled. The patterns of missing values also help decide the values of the initial conditions imposed on outcome variables. Skrondal and Rabe-Hesketh (2014) suggest that observations that are preceded and succeeded by missing data should not be used in the estimation.

3.2. Weather and climate data

Baez et al. (2013) suggest that it is necessary to recognize two distinct phenomena associated with changing climatic conditions: 'shocks' and 'shifts'. Shocks are referred to as weather variability and intensity and severity of extreme events such as droughts while shifts in climate are represented by gradual changes in rainfall and temperature patterns over a longer time (Baez et al., 2013). In this study, the impacts of both 'shocks' and 'shifts' on farmers' adaptation behavior were considered with a particular focus on drought, as it directly affects soil moisture. Climatic shocks refer to the number of moderate and severe droughts that each household experienced in the two years prior to the survey. Changes in temperature were represented by Growing Degree-Days (GDDs) during the rice-growing season of the corresponding survey year.

The dataset of daily rainfall and temperature over 38 years (1975–2012) at 26 weather stations from the Vietnam National Centre for Hydro-Meteorological Forecasting was used to construct climate variables (Appendix G). These variables were constructed based on data from the weather station nearest to the surveyed household. Given the wide spatial distribution of surveyed farm households across different agro-ecological zones and the relatively long time series of observed weather data over the study period, it was possible to capture both cross-sectional and temporal variations of climate-related variables in this study (Appendices C 1, 2, 4 and 5). The conventional approach to include climate variables is to simply take a monthly or annual average of temperature or rainfall over the study period. However, agronomic studies have shown that the growth and development of plants are firmly related to the accumulation of heat and precipitation within certain thresholds during the growing season (Deschenes and Greenstone, 2007). In addition, the development of plants does not occur if the temperature at a given time is below a minimum threshold value (i.e. 8 °C for rice). Deschenes and Greenstone (2007) also argue that this method is superior for the evaluation of the impact of climatic change in the agricultural sector.

For climatic variables, GDDs represent the cumulative heat to which the rice crop was exposed within the upper (30 °C) and lower (8 °C) absorbent threshold during the entire growing season (McMaster and Wilhelm, 1997). Using daily data on temperature for the relevant survey year from the weather station closest to the surveyed farm, daily GDDs for rice were calculated during the growing season, which varies from 1

[2] The original household dataset includes 12 provinces across Vietnam. However, after matching the records over time as discussed in detail further below, we retain data from six of these provinces for further analysis.

Table 1
Descriptive statistics of outcome, explanatory and control variables.

Variable	Description	Level of observation	Full sample		Adopters		Non-adopters	
			Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Outcome variable								
Soil and water conservation	Household applied soil and water conservation techniques (yes = 1)	Households and years	0.72	0.45	1.0		0.0	
Explanatory variables								
Extreme events, climate variability and change								
SPI45 $_{(t-1)}$	Value of SPI in April and May of the previous year	Households and years	−0.41	0.77	−0.57	0.76	−0.38	0.67
Drought	Number of moderate and severe drought in the last 2 years	Households and years	1.3	1.76	1.51	3.2	0.88	2.38
GDDs	Growing degree-days: Cumulative warmth during the growing season of rice (^{0}C)	Households and years	4415.7	425.7	4364.7	412.8	4448.3	442.6
AGDDs	Average of GDDs between 1975 and a year before relevant census year (^{0}C)	Households and years	4056.5	500.3	4018.3	464.1	4076.3	551.6
Soil and water conservation $_{(t-1)}$	Lag outcome variable	Households and years	0.43	0.49	1.0		0.0	
Household and farm characteristics								
Household size	Number of family members	Households and years	4.67	0.49	4.72	1.71	4.56	1.74
Credit	Access to credit (yes = 1)	Households and years	0.59	0.49	0.61	0.48	0.58	0.49
Experience	Experience of household head in rice cultivation (years)	Households and years	13.27	5.83	13.62	5.79	12.06	6.6
Farm size	Farmland operated by household (m2)	Households and years	4053.3	8400.6	4255.9	9421.3	4089.9	7210.7
Information	Access to information on weather and climate change (yes = 1)	Households and years	0.64	0.5	0.72	0.5	0.44	0.5
Input and output information								
Labor wages$_{(t-1)}$	Average regional labor wages in previous season (1000VND/day)[a]	Regions and years	62.92	49.79	62.53	55.04	42.66	41.93
Farm-gate price$_{(t-1)}$	Average regional retail price of rice in previous season (1000VND/kg)*	Regions and years	3.29	3.52	3.32	3.94	2.15	1.49

Note.
[a] VND, Vietnamese Dong (approximately 16.015 VND/$U.S. averaged over 1992 to 2012).

Fig. 2. Percentage of households that adopted at least one of the soil and water conservation techniques (1992–2012).

Table 2
Patterns of missing data for adoption decision of conservation practices in household data.

Frequency	%	Cumulative	Pattern
108	34.18	34.18	111111
86	27.22	61.39	111..1
52	16.46	77.85	111.11
23	7.28	85.13	111 …
23	7.28	92.41	1111.1
7	2.22	94.62	1111..
6	1.90	96.52	11111.
4	1.27	97.78	111.1.
2	0.63	98.42	1..111
5	1.58	100	(others)
316		100	xxxxxx

Notes: 1 denotes non-missing and dot (.) denotes missing.

February to 30 December across various regions in Vietnam.[3] The cumulative GDDs are the sum of all daily GDDs that have occurred from the start to the end date of the rice-growing season.

For climatic shock variables, Thomas et al. (2010) recommend that an effective way to determine whether a household has been affected by extreme weather is to ask them directly because respondents know exactly what natural disasters have happened in their area. However, a drawback of the approach is that households are unable to differentiate precisely the level of intensity and severity of each extreme event. To overcome that limitation, the Standardized Precipitation Index (SPI) developed by McKee et al. (1993) which can capture the variability, magnitude, and duration of droughts was applied.[4] The index was designed to quantify the precipitation deficit for multiple timescales using long-run observed precipitation data (Svoboda et al., 2012). Positive values of SPI indicate greater than median rainfall, and negative values indicate less than median precipitation, or deficit, during the relevant period. Based on observed data from the weather station located near the households, a household-specific variable labeled SPI45 was created to capture the value of SPI in April and May of the previous year. This was justified based on the growth stages of rice, where reproductive and ripening stages take place during these months, and

[3] The formula used to calculate GDDs is provided in Appendix B.

[4] The SPI was calculated using the SPI software by the National Drought Mitigation Centre. More information is provided in Appendix B.

the rice crop is most sensitive to weather conditions, especially to droughts, during that period (Sridevi and Chellamuthu, 2015). A variable labeled 'drought' was also created to capture the intensity of the drought event using the number of moderate and severe droughts (defined by SPI < -1) experienced by households over the last two years. Climate normals were defined as 30-year averages of temperature, calculated using the long-run average of GDDs (AGDDs) between 1975 and a year before the relevant survey year. Rainfall-related variables were excluded from regression analysis due to the potential simultaneity between these covariates and the SPI, which is calculated using rainfall data.

4. Conceptual framework, empirical model and estimating strategies

4.1. Conceptual framework

To examine the dynamic patterns of farmers' decision-making process, a dynamic discrete choice model, controlling for unobserved heterogeneity and state dependence was constructed. In this study, a farmer's decision to use soil and water conservation techniques as adaptation practices is modeled as a binary choice: adoption ($y = 1$) or non-adoption ($y = 0$).

Discrete choice models are based on the random utility framework (Greene, 2003; McFadden, 1980). This framework has been used frequently in studies on the adoption of conservation practices as a part of the farmers' response to the impacts of climate-related changes (Sietz and Van Dijk, 2015). The model is based on the notion that the ith farmer faces a pair of choices: adopting (j) or non-adopting (k); and the utility associated with the two choices is U_{ij} and U_{ik}. If the farmer is observed to make choice j, then it can be assumed that the farmer perceives that choice as having higher utility than the alternative choice. An indicator function can be used with a value of 1 if $U_{ij} > U_{ik}$ and value of 0 if $U_{ij} \leq U_{ik}$ (Greene, 2003), denoted by:

$$Y_i = \begin{cases} 1 \text{ if } U_{ij} > U_{ik} \\ 0 \text{ if } U_{ij} \leq U_{ik} \end{cases} \tag{1}$$

Then, the probability that j will be chosen satisfies:

$$\Pr[Y=1] = \Pr\left[U_{ij} > U_{ik}\right] = \Pr\left[\left(v(X_{ij},\beta_j) + \varepsilon_{ij}\right) - \left(v(X_{ik},\beta_k) + \varepsilon_{ik}\right) > 0\right] = \Pr[(X'\beta + \varepsilon > 0], \tag{2}$$

where the term $\boldsymbol{X'\beta}$ collects all the observable information about the difference between the two utility functions, and ε denotes the difference between the two random errors (i.e. the unobserved factors).

In the probit model, ε_i is assumed to have a standard normal distribution and requires being independently and normally distributed. Estimation of the binary probit model is based on the method of maximum likelihood where each observation is treated as a single draw ($Y_1 = y_1$, $Y_2 = y_2 \ldots$, $Y_n = y_n$) from a Bernoulli distribution (Greene, 2003). Then, the likelihood function to be used in the estimation of the parameters is expressed as:

$$\Pr\left(Y_1 = y_1, = Y_2 = y_2, .., Y_n = y_n | X\right) = \prod_{yi=0}[1 - F(X'_i\beta)]\prod_{yi=1}F(X'_i\beta) \tag{3}$$

4.2. Empirical model and estimating strategies

Following the approach of Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014), we specify a dynamic probit model, as follows:

$$\Pr(y_{it} = 1| y_{it-1}, x_{it}, z_{it}, \varepsilon_{it}) = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \mu_i + \varepsilon_{it} \\ t = 1,2,\ldots\ldots 6; \quad i = 1,2,\ldots\ldots N, \tag{4}$$

where, y_{it-1} is the lagged choice variable; ρ is the state dependence parameter; x_{it} is a vector of explanatory variables including climatic variables such as SPI45 and temperature; z_{it} is a vector of control variables such as farm-level specific characteristics and socio-economic drivers; and μ_i is an unobserved individual-specific effect, which captures the unobserved heterogeneity. To take into account the unobserved effects, the composite error term was decomposed into an individual-specific time-invariant μ_i term, and $\varepsilon_{it} \sim N(0, \sigma_u^2)$.

Equation (4) can be alternatively written as a latent response formulation:

$$y*_{it} = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \mu_i + \varepsilon_{it} \tag{5}$$

where, ε_{it} is assumed to be independently and identically distributed over time and the observed binary choice of adoption or not of climate adaptation techniques y_{it} is:

$$y_{it} = \begin{cases} 1 & \text{if } y*_{it} > 0 \\ 0 & \text{if } y*_{it} \leq 0 \end{cases} \tag{6}$$

Estimating Equation (5) faces fundamental issues that may lead to biased results: unobserved heterogeneity (μ_i and explanatory variables may be correlated) and the 'initial condition problem' (the lagged adoption decision y_{it-1} may be correlated with μ_i).

Unobserved heterogeneity refers to those unobservable factors such as farmers' management ability and their subjective attitudes towards the adoption of conservation techniques. These factors influence the decision-making process of an individual farmer but are nearly impossible to measure or elicit. However, the panel nature of our data allows us to control adequately for time-invariant unobserved heterogeneity among respondent farmers. Mundlak (1978) proposes an approach to control for unobserved heterogeneity by allowing for correlated random effects (CRE), and this method has been further developed by Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014). We apply the CRE approach in Equation (5) by including the vectors of within-household means for the time-varying independent variables, $\bar{x}_i$ and $\bar{z}_i$.

In the presence of unobserved heterogeneity, an issue known as the 'initial condition problem' can occur in dynamic modeling (Heckman, 1981). The root of that problem lies in the potential correlation between the initial technology adoption decision y_{i0} and the unobserved effects μ_i in the estimated model. In this study, the problem arises because the start of the first adoption period of adaptation practices observed in our data (year: 1992) does not coincide with the start of the diffusion process of those practices since they may have been used by farmers some years before. If the initial condition problem is ignored, uncorrected heterogeneity not only leads to an overstatement of the state dependence effect but could also lead to an understatement of the impact of other factors influencing the decision-making process (Heckman, 1981; Moser and Barrett, 2006). Wooldridge (2005) proposes a standard approach to handle this issue in the way of modeling the unobserved heterogeneity μ_i as a function of the adoption decision y_{i0} and other explanatory variables x_i and z_i. Besides, Skrondal and Rabe-Hesketh (2014) suggest improving the Wooldridge (2005) approach by imposing initial values on all explanatory variables, x_{i0} and z_{i0}, to avoid estimation bias, especially for a panel with a limited number of survey rounds, as in our case.

Thus, to jointly allow for correlated effects, state dependence, and initial conditions, we apply the conditional approach of Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014) by way of parameterizing the individual/household effects μ_i as in the following auxiliary regression:

$$\mu_i = \alpha_{y0} y_{i0} + \alpha_{x0} x_{i0} + \alpha_{z0} z_{i0} + \alpha_{\bar{x}} \bar{x}_i + \alpha_{\bar{z}} \bar{z}_i + u_i \tag{7}$$

where y_{i0} is the initial condition; $\bar{x}_i$ and $\bar{z}_i$ are vectors of within-individual/household means for the time-varying independent variables x_{it} and z_{it}; x_{i0} and z_{i0} are the initial conditions of x_{it} and z_{it}.

Then, we substitute Equation (7) into Equation (5) to specify a latent variable model to be estimated as:

$$y*_{it} = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \alpha_{y0} y_{i0} + \alpha_{x0} x_{i0} + \alpha_{z0} z_{i0} + \alpha_{\overline{x}} \overline{x_i} + \alpha_{\overline{z}} \overline{z_i} + u_i + \varepsilon_{it} \quad (8)$$

This is a dynamic model, controlling for unobserved heterogeneity, state dependence, and correlated initial conditions. In addition to Equation (8), we estimate a pooled model (Equation (9)) and Wooldridge's estimator (Equation (10)) to show how the efficiency of estimation improves by controlling for unobserved heterogeneity, state dependence, and the initial conditions. Starting with the pooled model and moving to the Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014) estimators, each estimator has a more complex specification than the previous. Therefore, while Skrondal and Rabe-Hesketh's (2014) approach (Equation (8)) was used in estimation, a pooled model specification (Equation (9)) and Wooldridge (2005) (Equation (10)) were also reported for comparison purposes.

$$y_{it} = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \varepsilon_{it} \quad (9)$$

$$y_{it} = \beta x_{it} + \gamma z_{it} + \rho y_{it-1} + \alpha_{y0} y_{i0} + \alpha_{\overline{x}} \overline{x_i} + \alpha_{\overline{z}} \overline{z_i} + u_i + \varepsilon_{it} \quad (10)$$

5. Results and discussion

5.1. Estimation results

A dynamic model of discrete choice of adopting soil and water conservation practices, controlling for unobserved heterogeneity and state dependence was estimated (Model 3).[5] Table 3 below presents the estimation results for the probability of adoption using the Skrondal and Rabe-Hesketh (2014) estimator (Model 3 based on Equation (8)). The independent variables contain all variables listed in Table 1 plus year fixed effects. To address the initial condition problem as suggested by Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014), the means of time-varying variables and variables representing the initial conditions over time were included. For comparison purposes, the pooled probit (Model 1 based on Equation (9)) and Wooldridge's (2005) estimator (Model 2 based on Equation (10)) are also reported in the same table which allows us to assess the explanatory power of the dynamic models (Models 2, 3).

The signs of the coefficients on the estimated parameters are particularly informative. A positive (negative) sign means that any increase in the independent variable is associated with an increase (decline) in the probability of adoption of soil and water conservation technologies.

We find statistically significant evidence of the effect of climatic variability and change on farmers' behavior. The decision to adopt adaptation measures is strongly and significantly affected by weather shocks (e.g. severity and intensity of drought), and long-run changes in temperature during the rice-growing season (Models 2, 3). Farms experiencing more extreme droughts in the last two years and a lower SPI show a greater propensity to adopt these conservation technologies. In Vietnam, natural disasters such as droughts, floods, and tropical cyclones often cause considerable damage to the agricultural production system, including soil and water conservation structures. Thomas et al. (2010), using a similar dataset as ours, also point out that droughts lead to a decrease in farm productivity. As a consequence, experiencing these climate-related shocks encourages farmers to invest in conservation practices to protect their farmland and increase farm productivity.

Table 3
Estimates of the factors affecting the decision to adopt soil and water conservation techniques.

Variables	Pooled probit model (1)	Wooldridge estimator (2)	Skrondal & Rabe-Hesketh estimator (3)
SPI45 $_{(t-1)}$	0.11632	0.11161*	0.11303*
	(0.0682)	(0.0506)	(0.0495)
Drought	0.03042	0.05143*	.05143*
	(0.0237)	(0.0212)	(0.0211)
GDDs	−0.00046*	−0.00043	−0.00038
	(0.0002)	(0.0002)	(0.0003)
AGDDs	0.00005	0.00443*	0.00440***
	(0.0001)	(0.0011)	(0.0010)
Conservation techniques $_{(t-1)}$	0.16887	0.13327*	0.14199**
	(0.0895)	(0.0525)	(0.0579)
Household size	−0.00237	0.00055	0.00602
	(0.0263)	(0.0223)	(0.0195)
Credit	0.05573	0.10971	0.12623
	(0.0904)	(0.0970)	(0.1010)
Information	0.27660**	0.36956***	0.38017***
	(0.1018)	(0.0921)	(0.1067)
Experience	0.02047**	0.02315*	0.02212**
	(0.0074)	(0.0120)	(0.0111)
Farm size	0.00000	0.00001	0.00002*
	(0.0000)	(0.0000)	(0.0000)
Labor wages $_{(t-1)}$	0.00096	−0.00194	−0.00146
	(0.0024)	(0.0052)	(0.0052)
Farm-gate price $_{(t-1)}$	0.06862	0.13078***	0.14014**
	(0.0430)	(0.0216)	(0.0437)
Constant	1.70047*	1.9096*	2.91725***
	(0.6639)	(0.9424)	(0.8219)
Year dummy	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes
Continuous sequence of y	Yes	Yes	Yes
Initial condition	No	Yes	Yes
Initial values of explanatory variables	No	No	Yes
Within-household means	No	Yes	Yes
Log likelihood	−609.38	−589.79	−584.78
Number of observations	1090	1090	1090

Notes: 1. Standard errors are presented in parentheses.
2. *, **, *** significant at 10%, 5%, 1% level.

In addition, since the study considers both the temporal trend in climatic change, i.e. the increasing average GDDs over 30 years and the cross-sectional variation of household exposure to the changing climate at different study sites, we find that households with greater exposure to long-term warming and an increasing number of extreme events tend to be associated with a higher likelihood of adopting soil and water conservation techniques. Because of a noticeable increase in annual temperature and greater variations in rainfall over time in many parts of Vietnam, applying these measures could help to alleviate water shortages and soil degradation and to somewhat mitigate the adverse effects of the changing climate. Moreover, the literature reports mixed effects of the short-term shocks such as increased temperature on crop production during the growing season (Iizumi, 2017; Welch, 2010). For this study, we do not have data on rice production in greater detail such as different growth phases, so it is extremely hard to predict the expected sign of GDD. However, one possibility would be increasing in GDD (within the absorbent threshold for rice) leading to higher yield in the growing season (Iizumi, 2017); thus, by observing that farmers may notice the benefit of a short-term increase in rice yield and dismiss the adoption of conservation practices. Since the estimated coefficient of GDD is not statistically significant, it would be harder to explain the intuition behind the relationship between GDD and the adoption of conservation practices.

Based on the estimates of the coefficients on the control variables, we

[5] All models were estimated by Stata 14.0 with *xtprobit, meprobit*, and *margins* functions. The number of integration points for *meprobit* function is sensitive for achieving convergence. The more integration points, the more accurate the approximation to the log likelihood is. After several trials, we ended up with 133 integration points, which produced a robust estimation. We also re-estimated these models using GLLAMM, a user-written program developed by Rabe-Hesketh, which provided identical results.

can identify state dependence in farmers' decision to adopt soil and water conservation techniques over time. Farmers who previously applied soil and water conservation practices show a considerable tendency to reapply those practices in subsequent periods. This finding indicates that a previous adoption decision is statistically significant in explaining the contemporary choice made by individual farmers. Since analyses on state dependence in farmer behavior are relatively sparse in the literature, our study provides new evidence that state dependence drives decisions about the use of climate adaptation practices.

It is also evident that farm characteristics, such as farm size, household head's experience, and access to meteorological information are associated with households that apply soil and water conservation. Access to weather information such as rainfall and temperature forecasts has a positive and significant effect on the likelihood of implementing these conservation techniques, which can be explained by the enhancements of farmers' capacity and preparedness to cope with changing production conditions through ongoing updates of weather information (Sietz and Van Dijk, 2015). As expected, the probability of adoption increases significantly with farmers' experience in agricultural production, which reflects the important role of the household head as a decision-maker in the application of these techniques.

In dynamic modeling, the estimation may be inconsistent due to the "initial condition problem", which can result in an overstatement of the state dependence effect and at the same time an understatement of the impact of other factors influencing the decision-making process (Heckman, 1981; Moser and Barrett, 2006). In this study, we found that the pooled probit model overestimates the impact of the previous adoption decision and underestimates the effects of the other independent variables (Table 3). Consequently, the dynamic probit model (Model 3, Table 3) that we estimate shows certain advantages in controlling for potential estimation issues that are likely to be associated with dynamic modeling.

5.2. Robustness-check

The findings are reinforced when we followed robustness-check procedures specified in Appendix F to assess the dynamic models. Estimated average marginal effects from the robustness-check procedure are presented in Table 4. Moving from the pooled probit model to the Wooldridge (2005) and then to the Skrondal and Rabe-Hesketh (2014) estimators, consistent results were confirmed compared to the estimated coefficients reported in Table 3.

More specifically, the dynamic specifications (Models 2, 3, 5 and 6 in Table 4) considerably increase the explanatory power of the models. Controlling for unobserved heterogeneity and initial conditions in the dynamic models reduces the magnitude of the effect of state dependence and generally increases the magnitude of the impacts of independent variables on the probability of adoption.

Comparing the two approaches in Table 4 (Models 1, 2, and 3 to models 4, 5, and 6), it is also obvious that the approach suggested by Skrondal and Rabe-Hesketh (2014) of only using the dependent variable with a continuous sequence has some advantages in terms of explanatory power and magnitude of the marginal effects. Thus, the dynamic model allowing for unobserved effects (Model 3) presents a substantial improvement over the other models in terms of explanatory power and also has a greater statistical significance of the coefficients on the independent covariates.

Table 4
Average marginal effects of factors affecting the decision to adopt soil and water conservation techniques.

	All available data on y			Only y with continuous sequence		
Variables	Pooled probit (1)	Wooldridge estimator (2)	Skrondal & Rabe-Hesketh estimator (3)	Pooled probit (4)	Wooldridge estimator (5)	Skrondal & Rabe-Hesketh estimator (6)
SPI45$_{(t-1)}$	.03990	.04220**	.04157**	.03712	.03425*	.03493**
	(.0209)	(.0139)	(.0147)	(.0221)	(.0165)	(.0151)
Drought	.00978	.01648**	.01528*	.00970	.01578*	.01399**
	(.00072)	(.0056)	(.0062)	(.0075)	(.0062)	(.0065)
GDDs	-.00014*	-.00010	-.00009	-.00014*	-.00013	-.00011
	(.00005)	(.0001)	(.0001)	(.00005)	(.0001)	(.0001)
AGDDs	.00001	.00106**	.00104**	.00001	.00136***	.00135***
	(.00003)	(.0003)	(.0003)	(.00004)	(.0003)	(.0003)
Conservation techniques$_{(t-1)}$	.05033	.04936***	.04085***	.05318	.05006**	.04752***
	(.0274)	(.0114)	(.0107)	(.0284)	(.0143)	(.0186)
Household size	-.00139	-.00763	-.00961	-.00075	.00016	.00186
	(.0080)	(.0069)	(.0087)	(.0084)	(.0068)	(.0060)
Credit	.01678	.02670	.02818	.01779	.03367	.03901
	(.0282)	(.0384)	(.0398)	(.0288)	(.0298)	(.0312)
Experience	.00638**	.00795*	.00792*	.00653**	.00710*	.00683**
	(.0022)	(.0036)	(.0037)	(.0023)	(.0037)	(.0035)
Farm size	6.1e-07	4.2e-06	3.7e-06*	1.0e-06	5.2e-06**	5.0e-06*
	(1.3e-6)	(2.9e-6)	(1.9e-6)	(1.3e-6)	(3.0e-6)	(2.1e-6)
Information	.07050*	.08550**	.08854**	.08829**	.11342**	11750*
	(.0303)	(.0264)	(.0290)	(.0322)	(.0309)	(.0329)
Labor wages $_{(t-1)}$	.00047	-.00034	-.00033	.00030	-.00059	-.00045
	(.0005)	(.0007)	(.0006)	(.0007)	(.0016)	(.0015)
Farm-gate price $_{(t-1)}$	.02140	.03320*	.03519*	.02190	.04013***	.04331*
	(.0127)	(.0118)	(.0169)	(.0136)	(.0078)	(.0136)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Initial condition	No	Yes	Yes	No	Yes	Yes
Initial values of explanatory variables	No	No	Yes	No	No	Yes
Within-household means	No	Yes	Yes	No	Yes	Yes
Log likelihood	−652.08	−634.18	−630.37	−609.38	−589.79	−584.78
Number of observations	1177	1177	1177	1090	1090	1090

Notes: 1. Standard errors are presented in parentheses.
2. *, **, *** Significant at 10%, 5%, 1% level.

6. Concluding remarks and policy implications

The study was motivated by the ongoing changes in climatic conditions that impose detrimental effects on the agricultural sector and small-scale farmers' livelihood in many countries, including Vietnam. Our study assesses factors associated with the decisions of rice farmers to adapt to climate change by implementing various soil and water conservation technologies in a dynamic setting.

The results of the analysis reveal that there is statistically significant evidence of the effects of climate change on farmers' decision-making process. The decision to implement soil and water conservation practices is strongly influenced by weather shocks, drought intensity, and long-run changes in temperature during the rice-growing season. Thus, it is evident that farmers are constantly adapting to environmental changes to mitigate adverse impacts and increase their resilience to ongoing changes in the climate. Besides, our findings provide new empirical evidence and reinforce the common belief of the persistence in farmers' choice to implement soil and water conservation techniques over time. Farmers' past decisions to apply those adaptation practices tend to reinforce tendencies to continue to adopt in subsequent periods. Besides, access to information on the farm-gate price of rice and the weather forecast is associated with households that have decided to apply conservation techniques. Farmers' experience and farm size also foster the application of these adaptation strategies in a changing production environment.

The study provides useful insights for policymakers seeking to promote and diffuse climate-resilient strategies in Vietnam. When designing interventions to promote soil and water conservation practices, policymakers should be aware of the behavioral dimensions in farmers' decision-making processes, such as their constant adaptation to climatic change and persistence in farmers' choices of technology adoption. Providing adequate information to farmers is very important, and therefore policies should aim to improve farmers' access to information with a special focus on market- and weather-related information to enhance farmers' adaptive capacity to better cope with ongoing climatic uncertainty. Our results generate a better understanding of farmers' decision-making process and its drivers. However, there are important avenues for further research on the potential impact of the adoption of conservation practices on rural households' welfare. This study used information from a matched panel across six provinces but more comprehensive studies covering a larger geographical region and using up-to-date information could provide more robust findings. Filling those gaps could significantly increase our understanding of factors that drive farmers' decision to adopt climate-resilient strategies and how this contributes to improving their overall well-being.

CRediT authorship contribution statement

Kien Nguyen Duc: Conceptualization, Data curation, Software, Writing – review & editing, Writing – original draft, Methodology. **Tiho Ancev:** Conceptualization, Methodology, Supervision, Writing – review editing, Writing – original draft. **Alan Randall:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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