

Article

Farmers' Intention to Climate Change Adaptation in Agriculture in the Red River Delta Biosphere Reserve (Vietnam): A Combination of Structural Equation Modeling (SEM) and Protection Motivation Theory (PMT)

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Abstract: Coastal communities living in the low delta areas of Vietnam are increasingly vulnerable to tropical storms and related natural hazards of global climate change. Particularly in the Red River Delta Biosphere Reserve (RRDBR), farmers change the crop structure and diversify agricultural systems to adapt to the changing climate. The paper deals with a quantitative approach combined with behavior theories and surveyed data to analyze farmers' intention to climate change adaptation in agriculture. Based on the Protection Motivation Theory (PMT), seven constructs are developed to a questionnaire surveying 526 local farmers: risk perception, belief, habit, maladaptation, subjective norm, adaptation assessment, and adaptation intention. Structural Equation Modeling (SEM) is implemented to extract eight factors and to quantify the relationship between protective behavior factors with the adaptation intention of the surveyed farmers. Two bootstrap samples of sizes 800 and 1200 are generated to estimate the coefficients and standard errors. The SEM result suggests a regional and three local structural models for climate change adaptation intention of farmers living in the RRDBR. Farmers show a higher adaptation intention when they perceive higher climate risks threatening their physical health, finances, production, social relationships, and psychology. In contrast, farmers are less likely to intend to adapt when they are subject to wishful thinking, deny the climate risks, or believe in fatalism.

Keywords: intention; climate change adaptation; agriculture; Red River Delta Biosphere Reserve (RRDBR); Structural Equation Modeling (SEM); Protection Motivation Theory (PMT)

1. Introduction

Agriculture, a main economic sector in the tropics, is most vulnerable to climate change [1–3]. Climate change affects water resources, soils, pests and diseases, leading to significant changes in crop and livestock production; therefore, climate risk and adaptive ability to agriculture are perceived obvious by farmers [4–8]. Farmers' perceptions of climate risk are influenced by biophysical, socio-economic, political and psychological factors [9–12]. For example, drought severity, groundwater depletion, education level, farm-size, access to climate information, electricity for irrigation, and agricultural subsidies were listed as socio-economic and climate factors underlying adaptation strategies [13–15]. Agricultural extension, access to the national rural employment guarantee scheme, crop loss compensation, and access to informal credit are determinants of climate change adaptation of farms [16]. Psychological mechanisms are important to understand farmer's adaptation behavior toward climate change: efficacy beliefs were the strongest predictor of behavioral intentions, which provide reliable information for local agricultural development [17]. Agricultural experience, farm income, training, social capital, and communication to climate adaptation are listed as the most influential factors of climate change adaptation [18].

A quantitative approach combined with theories of behavior and surveyed data is used to study farmers' perception to climate change adaptation. Systematic random sampling and focus group discussions (FGDs) are used to collect data of the local perceptions on climatic change and the adaption strategies [19]. The theory of planned behavior combined with mathematic models such as logistic regression models and path analysis to assess the farmer's intention and to proposal measures for climate change adaptation [9,18,20,21]. Structural Equation Modeling (SEM) is an advanced quantitative method to analyze farmers' perception of climate change adaptation taking into account direct and indirect interactions between variables and allowing the detection of root causes of change [22]. This allows: (i) to explore the extent to which climate change scepticism prevails among dairy farmers, the factors that affected their scepticism, and the lessons that could be learned for dealing with this challenge [23]; (ii) to investigate factors influencing agricultural personnel and consultants' attitude and behavioral intention [24]; (iii) to investigate psychological motivational concepts such as farmers' knowledge and risk perception [25]; and (iv) to test the relationships between both observed and latent variables on general roundworm control [26]. SEM was combined with the protection motivation theory (PMT) to conduct questionnaire applied in the Mekong Delta of Vietnam. The results show that the adaptation intention of farmers is higher when people are aware of increasing electricity, water, and fuel prices; or when they are under pressure from other people to install adaptation measures [27].

Worldwide, Vietnam is among the countries which are most prone to climate change associated natural hazards [2,28]. Coastal communities living in the low delta areas are increasingly vulnerable to tropical storms and related natural hazards of global climate change [29–32]. Farmers along the coasts and in the lowland change the crop structure and diversify agricultural systems adapting to the changing climate. In this context, this paper aims at measuring the impacts of climate change on agriculture in a coastal area of Vietnam. Protective behavior indicators, and the way farmers intend to adapt to climate change are presented. The conceptual framework of the Protection Motivation Theory (PMT), and the Structural Equation Modeling (SEM) methodology are used to develop the indicators and to quantify the relationship between adaptation intentions with other protective behavior indicators.

2. Methodology

2.1. Study Area

The Red River Delta Biosphere Reserve (RRDBR) was first recognized as a World Biosphere Reserve by the United Nations Educational Scientific and Cultural Organization (UNESCO) in 2004. This area entails typical wetland ecosystems in the main estuary of northern Vietnam. They are the habitat of rare waterfowls and migratory birds. The RRDBR has two core zones (Xuan Thuy National

Park and Tien Hai Wetland Nature Reserve, 14,842 hectares), a buffer zone (36,951 ha), and a transition area (85,468 hectares). Six administrative districts constitute the RRDBR including Thai Thuy, Tien Hai (Thai Binh province), Giao Thuy, Hai Hau, Nghia Hung (Nam Dinh), and Kim Son (Ninh Binh) (Figure 1). In totally, over 128,000 inhabitants are living in RRDBR in 2017.

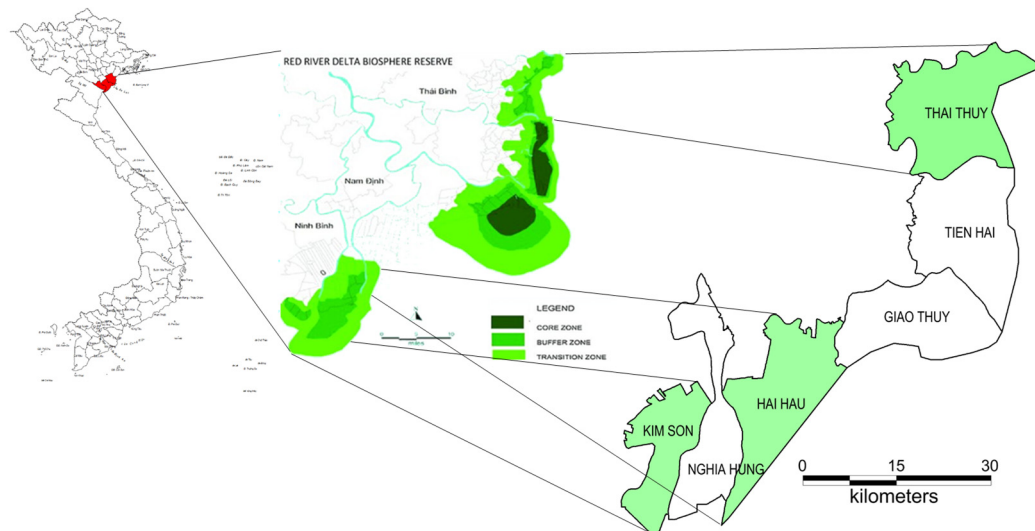


Figure 1. Location of 3 selected districts in the RRDBR, Vietnam.

Three coastal districts including Thai Thuy, Hai Hau and Kim Son are selected as study areas because they are the key agricultural areas in the RRDBR.

- The Thai Thuy district is located in the North East of the Thai Binh province. The district has a coastline of 27 km. It covers an area of 26,844 hectares. The population is about 250,000. The average annual income per capita of 1550 \$US is mainly based on agriculture, which is the main economic sector in the district (200 million \$US in 2017) [33].
- The Hai Hau district covers 22,815 hectares. The district population is 260,000. Since 2011, the district has completed the policy of land consolidation, increasing the area per plot, creating favorable conditions for farmers, applying agricultural mechanization and restructuring the agricultural economy towards industrialization and modernization. Land consolidation reduced the number of plots to 1.9 per household. This allowed gathering 321 land areas of public lands, 405 production land areas ranging from 10 to 40 ha, and the formations of 7 agricultural zones. The average rice yield reaches 12.7 tons per hectare. ‘Gao tam Hai Hau’ is high-quality rice, which is grown over 7600 hectares, and provides a yield of about 43 \$US per hectare. Shrimp and brackish water aquaculture ponds concentrate along the coast e.g., in Hai Chinh, Hai Trieu and Hai Dong. The average annual income per capita in the district is 1750 \$US [34].
- Kim Son is the only coastal district of Ninh Binh province. It covers 21,571 hectares. In 2017, the district population totaled 173,041 inhabitants. The total value of the agricultural production is 74.82 million \$US. The total annual rice yield is 95,000 tons an average 57.9 tons per hectare. The annual output of aquatic products is over 25,000 tons [35].

2.2. Protection Motivation Theory

The Protection Motivation Theory (PMT) was used guiding research on protective health risks behavior, nuclear war, water conservation, and marketing communication [36,37]. More recently PMT appeared in research on environmental risks, natural hazards, and climate change [38–40]. PMT addresses four core elements of the cognitive mediating processes: threat appraisal, coping appraisal, maladaptive coping, and protection motivation [41] (Figure 2). Regarding climate change, these elements are climate change risk appraisal, adaptation appraisal, and avoidant maladaptation [38],

risk perception of climate change, adaptation assessment, maladaptation, and adaptation intention [42]. Other concepts, as belief in climate change, adaptation incentives/disincentives, habit, and subjective norm, are hypothesized to affect the adaptation intention of farmers in response to climate change [42]. They are also incorporated and analyzed in this paper. 7 constructs were used in a questionnaire surveying farmers in the study area (Table 1).

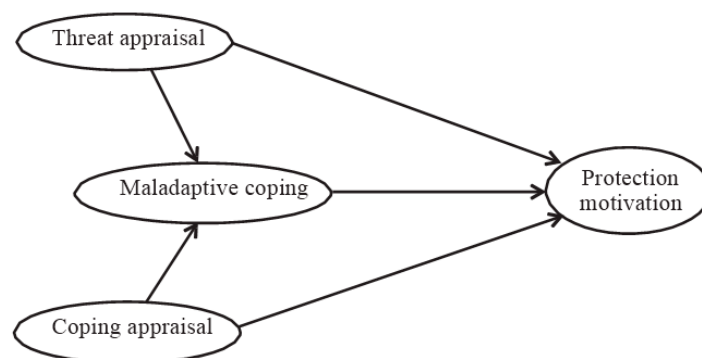


Figure 2. Path diagram of core elements in the cognitive mediating processes of PMT (Source: adapted from [41]).

Table 1. PMT's constructs and items in the questionnaire.

Construct	Selected Items	Measurement
Risk perception (PE)	- Land loss for agriculture (PE-1) - Change of traditional plant varieties (PE-2) - Increasing disease for plants (PE-3) - Reducing crop yield (PE-4) - Reduce income from agriculture (PE-5)	1–7 Likert scales (Perceived probability)
Belief (BN)	- Believe that natural disasters and climate change are actually taking place in the locality (BN-1) - Believe that cultivation is affected by natural disasters and climate change (BN-2) - Believe that the family is affected by natural disasters and climate change (BN-3)	1–7 Likert scales (disagree-agree)
Habit (PH)	- Agricultural prices affect the transformation of crop selection (PH-1) - Intention to transform crop structure when rice yield/crops decline (PH-2) - Willing to pay more to convert plant and animal selection (PH-3) - Current farming practices have been used for a long time changes are not needed (PH-4). - Willing to acquire experience to transform plant and animal selection (PH-5) - Ready to invest in machinery to change the plants and animals used (PH-6)	1–7 Likert scales (disagree-agree)
Maladaptation (NA)	- No need to change the crop structure for natural disaster mitigation and climate change adaptation because they work ineffectively (NA-1) - Difficulties in forecasting natural disasters and erratic weather impair adaptation (NA-2) - Lack of knowledge and information to conduct change (NA-3) - Lack of physical and financial resources to implement (NA-4) - Government policies limit the conversion of plant varieties and crops (NA-5)	1–7 Likert scales (disagree-agree)

Table 1. Cont.

Construct	Selected Items	Measurement
Subjective norm (ST)	- The selection of plants and animal needs changes because everyone around does so (ST-1) - Increasing crop and livestock productivity necessitates changes on selection (ST-2) - Income increase from crop and livestock production demands changes (ST-3) - It is recommended to change the structure of crops and animals because everyone around did so (ST-4) - Qualified and experienced farmers are more open to crop and livestock changes (ST-5) - Families using larger areas of crops and farms are more likely to take measures to select other crops and livestock (ST-6) - Families with access to credit services in agriculture are more likely to take measures to change crops and livestock (ST-7)	1–7 Likert scales (disagree-agree)
Adaptation assessment (LA)	- Government facilitates the replacement of plant varieties (EN-1) - Government supports purchasing agricultural products (EN-2) - Government supports disaster recovery, crop failure, agricultural subsidies (EN-3) - Government provides information and warns for natural disasters and epidemics (EN-4) - Raising awareness among residents about impacts and adaptation solutions to natural disasters and climate change (EN-5) - Improving the effectiveness of agricultural production planning (EN-6) - Construction of water supply canals for production, construction of dikes to prevent water and salt intrusion (EN-7)	1–7 Likert scales (Ineffective-effective)
Adaptation intention (AI)	- Using plant varieties adapted to temperature, rain, and natural disasters (AI-1) - Use plant varieties which have a stronger disease resistance (AI-2) - Application of effective land use measures (AI-3) - Take advantage of all kinds of land rigs and aquatic plants (AI-4) - Improve knowledge about the impacts and solutions to adapt to natural disasters and climate change (AI-5) - Invest in machinery, agricultural tools and production tools (AI-6) - Apply biotechnology, fertilizer and flexible planting (AI-7) - Seasonal changes of vulnerable crops (AI-8) - Conversion to other types of agricultural land use (AI-9)	1–7 Likert scales (not at all—very large extent)

2.3. Structural Equation Modeling

The Structural Equation Modeling (SEM) allows understanding how the core elements (factors) influence the intention of farmers' adaptation. SEM is a statistical analysis which assesses the relationship between two variables within a framework: questionnaires' items (directly measured) and factors (in-directly measured). The number of factors and items is determined according to the PMT theoretical framework. Next to validation of the framework's structure, SEM allows assessing the relationship or the relation's model between the underlying factors. In this study, SEM is structured into three steps: factor analysis, structural modeling, and bootstrapping [43–45].

2.3.1. Factor Analysis

Factor analysis is used to determine the number and the characteristics of the factors among the questionnaires' items or variables. The analysis aims to reproduce the observed relationships among a group of variables with a smaller set of factors. In case specifications are provided on the number of factors or the pattern of relationships between the factors and the variables (i.e., the factor loadings),

an exploratory factor analysis (EFA) emerges. EFA determines the appropriate number of factors, and finds out which items are reasonable variables (e.g., by the size and differential magnitude of the factor loadings). The Kaiser-Mayer-Olkin (KMO's test) and the Bartlett's test allow deciding if the sampling data qualifies for a factor analysis. The promax rotation method is based on the covariance matrix to estimate the appropriate number of items and their factors loading. When the number of factors and the pattern of items–factor loadings are estimated, a confirmatory factor analysis (CFA) will evaluate the reproducibility of the sample's covariance of items. If the EFA is typically used before in the analytical process, whereas CFA is used later after the underlying structure has been determined on prior empirical (EFA) and theoretical grounds (PMT). The results of EFA and CFA are discussed in Section 3.2.

2.3.2. Structural Modeling

The structural modeling step, handles items and factors and their relationships within a framework using two sub-models: a measurement model and a structural one. The first one specifies how to measure the factors from the observed items while the later represents the relations between these factors. An illustration of SEM is shown in Figure 3, in which the relationships of observed items or variables $X_1, X_2 \dots X_8$ and underlying factors F_1, F_2, F_3 are represented,

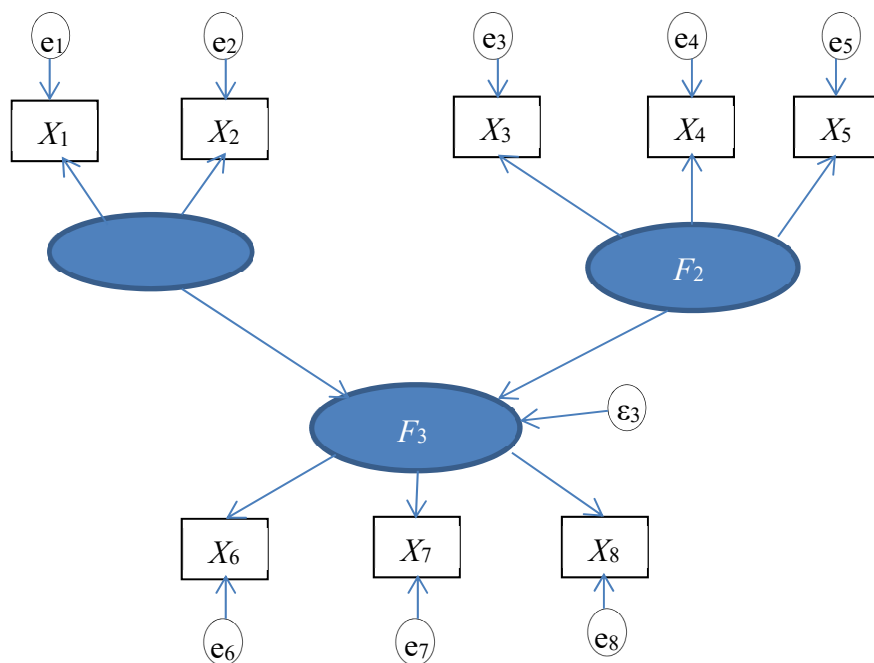


Figure 3. Relationships between observed items and underlying factors in structural modeling.

The measurement model is presented by Equations (1)–(3):

$$X_i = \lambda_i F_1 + e_i; i = \overline{1, 2} \quad (1)$$

$$X_j = \lambda_j F_2 + e_j; j = \overline{3, 5} \quad (2)$$

$$X_k = \lambda_k F_3 + e_k; k = \overline{6, 8} \quad (3)$$

where: variables X_1, X_2 and factor F_1 linearly depend on coefficients λ_1, λ_2 while e_1, e_2 are their measurement errors. Similarity, the regressions (2), (3) are the linear relationships of X_3, X_4, X_5 and F_2 , and of X_6, X_7, X_8 and F_3 .

The structural model is given by the Equation (4):

$$F_3 = \beta_1 F_1 + \beta_2 F_2 + \varepsilon_3 \quad (4)$$

where: β_1, β_2 are the regression coefficients between the factors F_1, F_2 and the factor F_3 with its potential error ε_3 .

The coefficients in SEM are also called the factor loadings.

The bootstrapping applied for the maximum likelihood estimation is required to cover this assumption. The maximum likelihood estimation (MLE) aims at producing a predicted covariance matrix $\hat{\Sigma}$ that resembles the sample covariance matrix $\bar{\Sigma}$ as close as possible. The difference between $\hat{\Sigma}$ and $\bar{\Sigma}$ is the fitting function to be minimized:

$$f_{ML} = \ln|\hat{\Sigma}| - \ln|\bar{\Sigma}| + \text{tr}\left[\bar{\Sigma}\hat{\Sigma}^{-1}\right] - p \quad (5)$$

where: p is the number of variables; the determinants and the trace summarize important information about matrices $\hat{\Sigma}$ and $\bar{\Sigma}$. The Equation (5) is solved by an iterative procedure with a selected starting value.

In addition, f_{ML} is also used in the chi-square χ^2 (test of goodness-of-fit) which measures how well the model fits the sample:

$$\chi^2 = f_{ML} \times (n - 1) \quad (6)$$

where: n is number of samples.

Under the normality assumption, an index of model fit is applied (6). Others goodness-of-fit indices commonly used are the root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR), comparative fit index (CFI), or Tucker-Lewis index (TLI). A better model means a smaller RMSEA, SRMR or a higher CFI, TLI.

2.3.3. Bootstrapping

Bootstrapping is a resampling procedure in which the original sample serves as the population [46]. Multiple samples of size n are randomly drawn from the original sample with replacement (i.e., a certain observation may be randomly selected more than once in any bootstrapped data set). All models are estimated for each data set; and the results are averaged over the data sets. The number of bootstrap samples should be sufficiently large to have a good quality of the averaged estimates (e.g., 500 samples is common). The procedure is most appropriate when the sample is small with non-normally distributed continuous indicators.

3. Results

3.1. Reliability

Totally 526 farmers in the three districts are involved in a survey organized in December 2017. Farmers were selected using a systematic random sampling to provide an even coverage of the districts' population within the sampling frame. Each farmer is considered a sampling unit. The Cronbach's Alpha coefficient tests the reliability of the scale of 9 factors with 52 observed variables. Factors attracting a Cronbach's Alpha coefficient below 0.6 are excluded from the model. Observed variables with item correlations below 0.3 do not pass the reliability test and are excluded. Table 2 shows that the results of Cronbach's Alpha for 9 factors ranged from 0.651 to 0.978 (>0.6) indicating that the scales of these 9 factors can be considered highly reliable. 16 out of 54 observed variables are excluded because their correlation coefficients are below 0.3 and the Cronbach's Alpha of one variable was higher than the Cronbach's Alpha of each factor: Belief (1 excluded observation), Maladaptation (2), Habits (1), Subjective Norm (1), Adaptation Assessment (3), Discouragement (1), and Adaptation

Intention (4). The item total correlations of the remaining observed variables were above 0.3 and the Cronbach's Alpha of one variable was below the Cronbach's Alpha of each factor. After the reliability tests, 38 observed variables are in applicable in the factor analysis (Table 2).

Table 2. Reliability of the scales.

Construct	Range of Item Total Correlation	Range of Cronbach's Alpha for Item	Cronbach's Alpha for Construct
Risk perception (PE)	[0.500, 0.642]	[0.587, 0.704]	0.708
Belief (BN)	[0.433, 0.571]	[0.622, 0.646]	0.651
Maladaptation	[0.536, 0.611]	[0.604, 0.663]	0.738
Habits	[0.339, 0.535]	[0.627, 0.672]	0.692
Subjective norm (ST)	[0.358, 0.757]	[0.634, 0.753]	0.791
Adaptation Assessment (LA)	[0.429, 0.585]	[0.638, 0.643]	0.663
Incentive (EN)	[0.429, 0.742]	[0.686, 0.765]	0.767
Discouragement (DI)	[0.484, 0.674]	[0.625, 0.746]	0.978
Adaptation Intention (AI)	[0.388, 0.759]	[0.596, 0.680]	0.943

3.2. Factor Analysis

38 variables take part in the factor analysis which includes principal axis factoring extraction, promax rotation, and KMO and Bartlett tests measuring the fit of the sample. The factor loading is at least 0.5 which assures the practical significance of the EFA.

Exploratory Factor Analysis (EFA) takes 11 rounds of qualification. The result of KMO and Bartlett test (KMO = 0.719 (>0.5) and Barley's test of sphericity is significant at a p -value = 0). This shows that data fulfill the EFA conditions. The range of the factor loadings of each variable is determined. 20 final variables loaded on 8 factors account for 82.2% of the observed variables. Table 3 shows that the factor loading coefficients of the observed variables are higher than 0.5. The observed variables of factors influencing farmers' intention to climate change adaptation correlate with each other. Factor 'Adaptation intention' (AI) highly correlates with 4 variables; factor 'Incentive' (EN) with 3 variables; factor 'Adaptation assessment' (LA) has 3 variables; and factors 'Subjective norm' (ST), 'Discouragement' (DI), 'Maladaptation' (LA), 'Risk perception' (PE), and 'Habits' (PH) correlate with 2 variables.

Table 3. Rotated factor loading in exploratory factor analysis.

Rotated Factor	Variable	Factor Loading Coefficients	Rotated Factor	Variable	Factor Loading Coefficients
Risk perception (PE)	PE-5	0.980	Adaptation Assessment (LA)	LA-7	0.977
	PE-4	0.980		LA-5	0.974
				LA-6	0.955
Maladaptation (LA)	NA-2	0.892	Incentive (EN)	EN-1	0.991
	NA-1	0.886		EN-2	0.985
				EN-7	0.974
Habits (PH)	PH-5	0.837	Discouragement (DI)	DI-3	0.979
	PH-3	0.806		DI-1	0.977
Subjective norm (ST)				AI-9	0.968
	ST-3	0.916	Adaptation Intention (AI)	AI-1	0.941
	ST-2	0.844		AI-7	0.877
				AI-2	0.739

Following the EFA implementation, the scales were further tested, using the Confirmation Factor Analysis (CFA). The purpose is to ensure more about reliability and value of scale based on known factors to limit the error in determining the factor. A set of indices to measure the goodness-of-fit of the model with the sample information is used: Chi-square (CMIN), Chi-square adjusted to degrees of

freedom (CMIN/df), Comparative Fit Index (CFI), Tucker & Lewis Index (TLI), Root Mean Square Error Approximation (RMSEA). If $1 < \chi^2/df < 3$, in some studies, two cases $\chi^2/df < 3$ (with sample $N \leq 200$) and $\chi^2/df < 5$ (with sample $N \geq 200$) were distinct the model is considered to be good. If a model attracts GFI, CFI, TLI ≥ 0.9 , $p > 0.5$, CMIN/df ≤ 3 , then the model is considered appropriate. Once the model attracts a CFI and TLI ≥ 0.9 , CMIN/df ≤ 0.2 , RMSEA ≤ 0.08 , it is consistent with the data. A confirmation factor analysis (CFA) was used to examine the 20 variables and 8 extracted factors. The first CFA results show that, based on the regression values in the standardized regression weights, the factor Discouragement (DI) has a regression value of 1.047. Because the regression values of the variables for each factor range from 0.5 to 1.0, the regression value lacks practical meaning. Therefore, the factor DI is excluded from the model.

The results of the CFA model calibration show that, the Chi-square/degree of freedom (χ^2/df) of 1672 is acceptable ($N = 526$), indicating the fitness of the model ($p < 0.0001$). Comparative indices of the model indicate the goodness of fit: both the comparative fit index and goodness-of-fit are above 0.95 (CFI = 0.993 and GFI = 0.962); the adjusted goodness-of-fit is above 0.80 (AGFI = 0.942); the root mean square residual is below 0.09 (SRMR = 0.076); the root mean square error of approximation is moderate (RMSEA = 0.036); and the PCLOSE is above 0.05 (PCLOSE = 0.997). These indices indicate that the scale model fits with the extracted data. The normalized weights are above 0.5 and the non-normalized weights are statistically significant, indicating that all the concepts have a convergent validity (Figure 4).

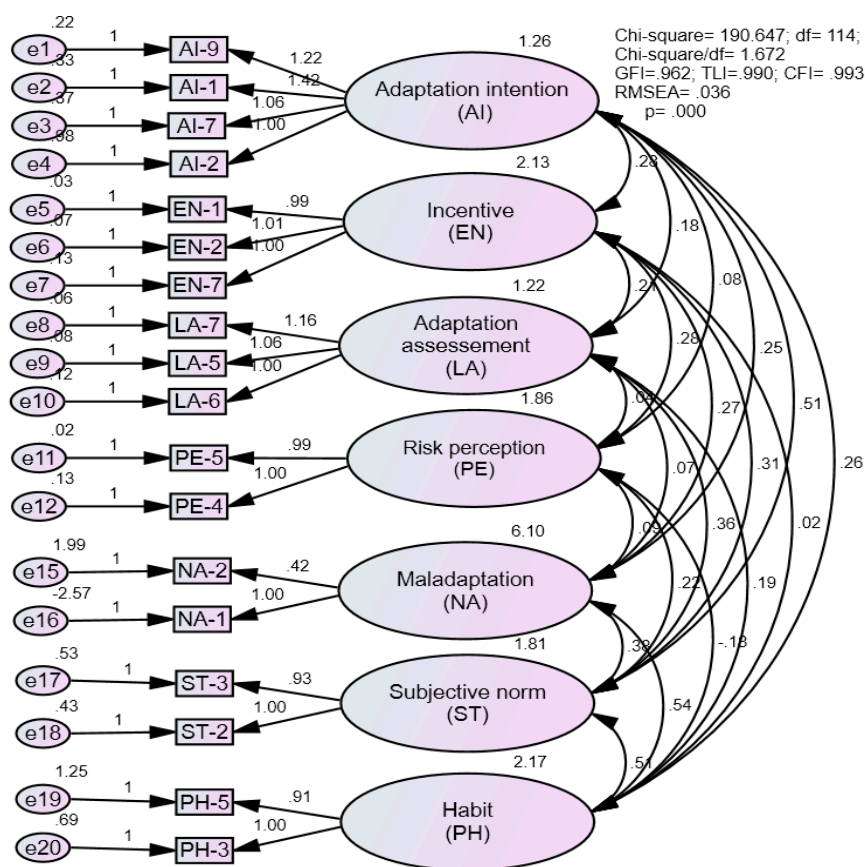


Figure 4. Calibration results of CFA model.

3.3. Structural Modelling

Figure 3 presents the significant relationships between factors. Factor 'Adaptation assessment' (LA) affects significantly and negatively the factor 'Adaptation intention' (AI) (the structural path estimation = -0.149 , $p = 0.003$). Factors 'Risk perception' (PE), 'Subjective norm' (ST) and 'Adaptation

intention' (AI) show a significant and positive relationship to each other (the structural path estimation is 0.245 (4-6) and 0.310 (5-5), and $p < 0.001$) (Table 4).

Table 4. Standardized maximum likelihood parameter estimates.

	Dimensional Impact	Estimation	S.E.	C.R.	p
AI	← EN	0.276	0.075	3.666	***
AI	← LA	0.183	0.057	3.210	0.001
AI	← PE	0.081	0.069	1.166	0.024
AI	← NA	0.254	0.089	2.839	0.005
AI	← ST	0.511	0.079	6.439	***
AI	← PH	0.259	0.084	3.075	0.002

(Note: *** $p < 0.001$).

A structural model identifies the influencing factors and the influence of each factor on the adaptation intention to climate change of the surveyed farmers. The initial model was adjusted improving the model. The results of the CFA test (with AMOS software) followed the principle of modifying the relationships that have a MI > 4 (MI-Index Modification, which corresponds to the modification of a χ^2 with a degree of freedom). This modification should fit both theoretical and practical measurements. After the modification, the CFA results showed that the Goodness-of-Fit of the theoretical model significantly improved as shown in Figure 5 ($\chi^2/\text{df} = 1.672$, GFI = 0.962, TLI = 0.990; CFI = 0.993; RMSEA = 0.036). So this model fits the data. The regression coefficients between factor AI and the influencing factors EN, LA, PE, NA, ST and PH are statistical significant. Therefore the measured factor AI with independent factors has discriminant validity.

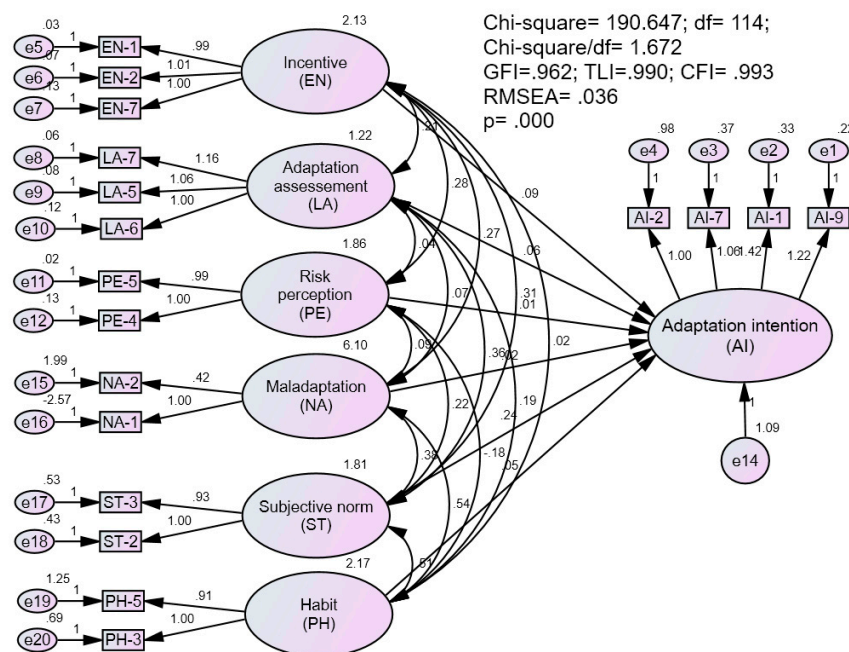


Figure 5. Structural model for climate change adaptation intention of surveyed farmer in the RRDBR, Vietnam (Loads of paths of the alternative structural model determining the composite reliability model. Source: Own elaboration using software AMOS).

3.4. Bootstrapping

Two bootstrap samples of sizes (800 and 1200) were generated to estimate the coefficients and their standard errors. Table 5 shows the results: (i) the coefficients are in Mean column; (ii) their average difference with non-bootstrap estimation are in the Bias column; and (iii) differences of standard error are in SE-Bias. The bootstrap tests whether the null hypothesis supporting Bias = 0 by calculating

the critical ratio CR. In case the value of CR is smaller than 1.96, the null hypothesis is accepted at a significance level at 5%. The test results in Table 5 confirm the estimations of the SEM model are robust. The theoretical SEM model is acceptable.

Table 5. Test of bootstrap with two bootstrap samples.

Bootstrap 800							Bootstrap 1200					
Parameter	SE	Mean	Bias	SE-Bias	CR		Parameter	SE	Mean	Bias	SE-Bias	CR
AI ← EN	0.032	0.087	0.000	0.001	0.000		AI ← EN	0.032	0.086	0.000	0.001	0.000
AI ← LA	0.042	0.058	0.003	0.002	1.500		AI ← LA	0.042	0.058	0.002	0.001	2.000
AI ← PE	0.04	0.005	0.000	0.001	0.000		AI ← PE	0.040	0.004	−0.001	0.001	−1.000
AI ← NA	0.024	0.020	0.003	0.002	1.500		AI ← NA	0.025	0.020	0.003	0.002	1.500
AI ← ST	0.053	0.238	0.001	0.002	0.500		AI ← ST	0.052	0.237	0.001	0.002	0.500
AI ← PH	0.049	0.058	0.003	0.002	1.500		AI ← PH	0.048	0.058	0.003	0.002	1.500

3.5. Multi-Group Structural Analysis

A multi-group structural analysis reviews, evaluates and compares the structural model of the impacts on the ‘adaptation intention to climate change’ of communities in Thai Thuy, Hai Hau and Kim Son districts. The analysis finds out whether they allow impacts which are different in the study areas. Using the variability method (parameters in each model are independent) and the partial invariability method (the regression weights are assumed to be equal between groups), the results show that:

- The variability methods of the multi-regional analysis of the 3 selected districts are different: the models for Hai Hau and Thai Thuy have a positive impact, while the Kim Son district shows a negative impact.
- Comparing the Chi-square of the variability model with the Chi-square of the invariability model: Chi-square of the variability model is 458.239; the Chi-square of the invariant model is 476.764; p -value = 0.000343 (<0.05). This allows rejecting H_0 . Consequently, H_1 is accepted, which indicates there is a difference between the Chi-square of the variability model and the results for the invariability model. This analysis shows a difference in Chi-square between the variability model and the invariability model. A difference among the correlation coefficients exists between the factors influencing ‘Adaptation Intention to Climate Change’, and the ‘Adaptation Intention to Climate Change’ among the selected districts.

4. Suggestions: Structural Model for Farmer’s Intention to Climate Change Adaptation in Agriculture

4.1. A Structural Model at Regional Level

The SEM result suggests a regional structural model for climate change adaptation intention of farmers living in the RRDBR, Vietnam. Figure 6 shows the positive relationships between the factors Incentive (EN), Maladaptation (NA), Risk perception (PE), Adaptation assessment (NA), Subjective norm (ST) and Habits (PH) on Adaptation Intention (AI). Risk perception has most impact on the adaptation intention (AI) next to the Incentive (EN). The higher the risk perception of farmers and the greater the incentive, the more likely their adaptation intention and vice versa. In addition, the more detailed the actual situation assessment and the practical adaptation ability in the locality, the more the adaptation intention to climate change improves.

The model shows that the habits and production customs, affecting the structure of the crop season, cause the changes of crops and the use of technological methods adapting to changing climate. This affects future solutions and adaptation intentions [47]. Climate change adaptation is the result of a long history of formation and cultivation, local production experience and knowledge, all of which helps farmers establishing local adaptation measures [48,49]. The intention also increases when habits and production are oriented towards the climate change adaptation. The model indicates that the subjective norm has the smallest impact on farmers’ intention: the adaptation intentions of farmers is

less influenced by external factors such as people around by the increased income from the crops and livestock structure. Farmers show a higher adaptation intention when they perceive higher risks of climate change and more effectiveness of the adaptation measures. Climate change threatens farmers' physical health, finances, production, social relationships and psychology [50]. In contrast, farmers less likely to adapt when they are subject to wishful thinking, deny the climate change risk, or believe in fatalism [51,52].

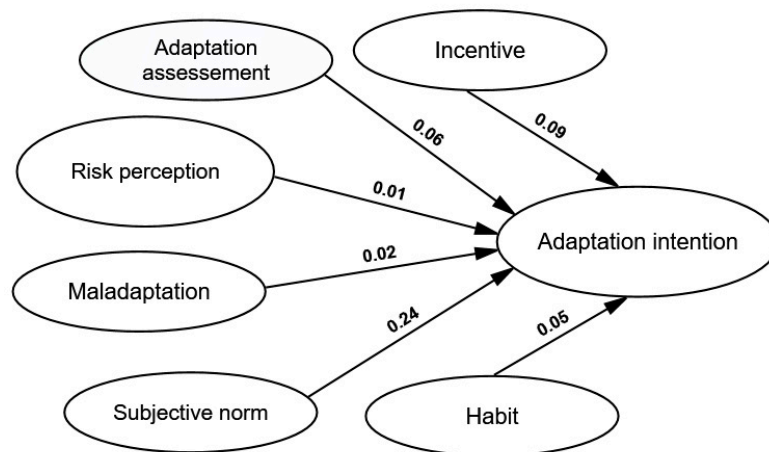


Figure 6. A regional structural model for farmer's intention to climate change adaptation in agriculture in the RRDBR, Vietnam (the figures indicate impact coefficient: value '+' show that positive relationship between factors).

4.2. Structural Models at Local Level

Figure 7 shows structural models for farmer's intention to climate change adaptation for each of the districts Thai Thuy, Hai Hau, and Kim Son.

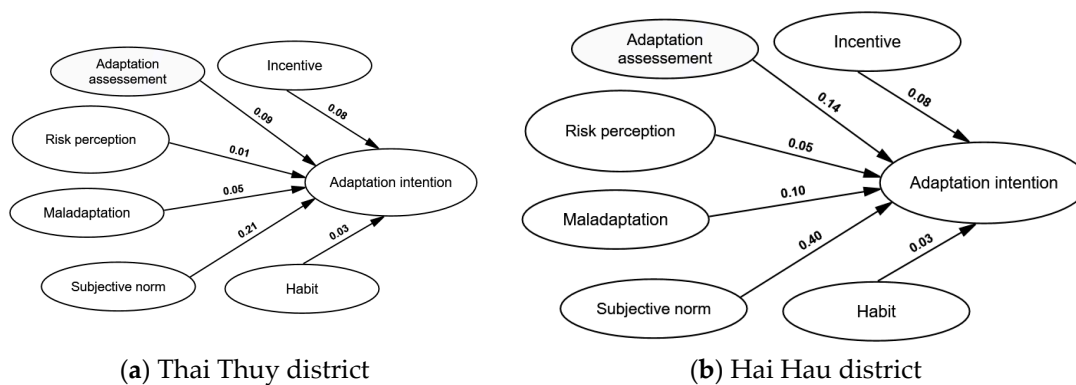
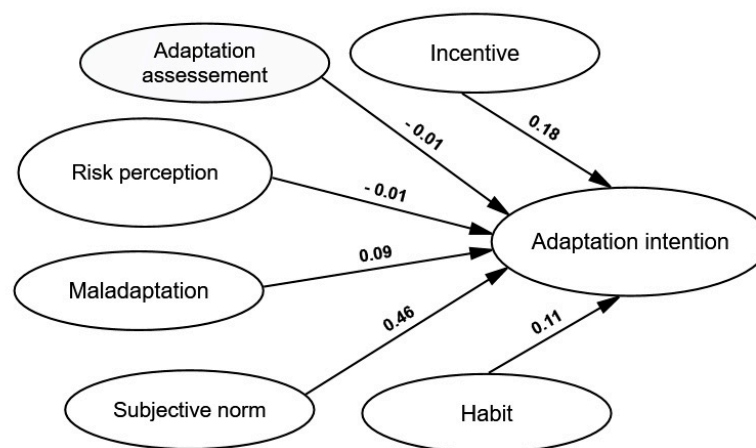


Figure 7. Cont.



(c) Kim Son district

Figure 7. A local structural model for farmer's intention to climate change adaptation in agriculture in districts of Thai Thuy, Hai Hau, and Kim Son (RRDBR, Vietnam) (the figures indicate impact coefficient between factors: value '+' show that positive relationship between factors, while value '-' show that negative relationship between factors).

For the Thai Thuy district (Figure 5a), Incentive (EN), Adaptation Assessment (LA), Risk perception (PE), Maladaptation (NA), Subjective norm (ST) and Habits (PH) on Adaptation Intention (AI) are positively related factors with the adaptation intention. If these factors improve and enhance, the adaptation intention to climate change also significantly increases and vice versa. In particular, the Subjective norm (ST) and Adaptation Assessment (LA) have the highest impact on the Adaptation Intention (AI). This means the intention to implement adaptation measures to climate change depends to a large extent on the risk perception of climate change and natural disasters. Habits (PH) of farmers have a long tradition and experience of adaptation to climate change. They contribute significantly to farmers' adaptation intentions. The incentives of policy makers are key factors affecting decision-making by farmers on implementing effective adaptation measures because they increase agricultural production. Also, Maladaptation (NA) is significant in the decision making on adaptation decisions. This demonstrates that factors such as material resources, finance, disaster warning information, and state policies for adaptation in the past were insufficient. This limited in part the formation of adaptation intentions in the study area. Similar to the overall research findings across the region, Risk perception (PE) is the least influencing factor on the adaptation intentions of farmers.

The structural model of the Hai Hau district (Figure 5b) shows that all factors have positive relationships with the adaptation intention. Adaptation Assessment (LA) is the factor with most impact, while the Habits (PH) factor has the least impact on the adaptation intention. Hai Hau has good infrastructure and establishes attractive socio-economic conditions, which contribute to the effectivity of farmers' responses to natural disasters and climate change. Adaptation assessment adds to the effective policy incentives of the local government. These latter have the most positive impact on the adaptation intentions. The ability for good adaptation, and the highly effective incentives facilitated the transformation of the crop and livestock structure. The models and solutions of climate change adaptation in the neighboring areas also contributed to the effectiveness for people's adaptation intentions in the Hai Hau district. However, to assess the extent to which new plant varieties and advanced local technologies should be carried out, complementary research is indicated. What follows is about the non-adaptation to climate change because of lack of knowledge, capacity, material resources and finances. Climate change is a long-term variation process, but only limited statistical data on specific impacts of climate change in the coastal area are available. Moreover, local people did not have access to this information, so limited knowledge on climate change also influences the adaptation intention.

The structural model for the Kim Son district (Figure 5c) shows that the Incentive, Maladaptation, Subjective norm, and Habits factors are positively correlated with the adaptation intention. This allows expecting that if these factors are improved and enhanced, the adaptation intention to climate change also increases and vice versa. Adaptation assessment and risk perception are negatively correlated with the adaptation intention. This means that increasing these factors leads to a decrease of the adaptation intention among farmers and vice versa. The farmers in the Kim Son district are migrants from other places. The increase in farming land results from the transformation of unused and abandoned land, and the expansion of sea encroachment. Farmers living in this area deal in an effective way with the risk of climate change. Local authorities support effectively dyke construction and irrigation canals. These present are affective incentive to the farmers' intentions of implementing adaptation measures to climate change in this area.

5. Conclusions

Greenhouse gas emissions from agriculture worldwide increase, driven by the food rising demand while changing farming practices provide limited mitigation opportunities. Therefore the way the farmers look in the opportunities to alleviate their contribution to the drivers of climate changes are of utmost importance.

The core of this study is finding out which adaptation intentions to climate changes farmers operating in three districts of the highly vulnerable RRDBR (Vietnam) have. The results of 526 questionnaires are subject to SEM higher adaptation intention when they perceive higher health (physical and psychological), financial, production and social relationships risks. The relative importance of these aspects is measured. This provides the basis for both regional and local structural models.

In comparison with similar studies (see [16,20,21,27,46]), lack of financial resources and access to information emerge as general barriers for farm adaptation to climate variation.

These results confirm studies that advocate awareness raising, training and education as instruments to mitigate greenhouse gas emissions in agriculture. If confirmed internationally, they also open less investigated avenues alleviating the impact of agriculture on climate change.

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References

1. Zhao, Y.; Wang, C.; Wang, S.; Tibig, L.V. Impacts of present and future climate variability on agriculture and forestry in the humid and sub-humid tropics. *Clim. Chang.* **2005**, *70*, 73–116. [[CrossRef](#)]
2. IPCC. *Climate Change 2014 Synthesis Report*; Core Writing Team, Pachauri, R.K., Meyer, L.A., Eds.; Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change; IPCC: Geneva, Switzerland, 2014; 151p.
3. Pearson, D.; Newman, P. Climate security and a vulnerability model for conflict prevention: A systematic literature review focusing on African agriculture. *Sustain. Earth* **2019**, *2*, 2. [[CrossRef](#)]
4. Reid, S.; Smit, B.; Caldwell, W.; Belliveau, S. Vulnerability and adaptation to climate risks in Ontario agriculture. *Mitig. Adapt. Strateg. Glob. Chang.* **2007**, *12*, 609–637. [[CrossRef](#)]
5. Frank, E.; Eakin, H.; Lopez-Carr, D. Social identity, perception and motivation in adaptation to climate risk in the coffee sector of Chiapas, Mexico. *Glob. Environ. Chang.* **2011**, *21*, 66–76. [[CrossRef](#)]

6. Shah, K.U.; Dulal, H.B.; Johnson, C.; Baptiste, A. Understanding livelihood vulnerability to climate change: Applying the livelihood vulnerability index in Trinidad and Tobago. *Geoforum* **2013**, *47*, 125–137. [[CrossRef](#)]
7. Takahashi, B.; Burnham, M.; Terracina-Hartman, C.; Sopchak, A.R.; Selfa, T. Climate change perceptions of ny state farmers: The role of risk perceptions and adaptive capacity. *Environ. Manag.* **2016**, *58*, 946–957. [[CrossRef](#)]
8. Douglass-Gallagher, E.; Stuart, D. Crop growers' adaptive capacity to climate change: A situated study of agriculture in Arizona's Verde Valley. *Environ. Manag.* **2019**, *63*, 94–109. [[CrossRef](#)]
9. Gandure, S.; Walker, S.; Botha, J.J. Farmers' perceptions of adaptation to climate change and water stress in a South African rural community. *Environ. Dev.* **2013**, *5*, 39–53. [[CrossRef](#)]
10. Below, T.B.; Schmid, J.C.; Sieber, S. Farmers' knowledge and perception of climatic risks and options for climate change adaptation: A case study from two Tanzanian villages. *Reg. Environ. Chang.* **2015**, *15*, 1169–1180. [[CrossRef](#)]
11. Kibue, G.W.; Liu, X.; Zheng, J.; Zhang, X.; Pan, G.; Li, L.; Han, X. Farmers' perceptions of climate variability and factors influencing adaptation: Evidence from Anhui and Jiangsu, China. *Environ. Manag.* **2016**, *57*, 976–986. [[CrossRef](#)]
12. Carlos, S.M.; Cunha, D.A.; Pires, M.V.; Couto-Santos, F.R. Understanding farmers' perceptions and adaptation to climate change: The case of Rio das Contas basin, Brazil. *GeoJournal* **2019**, 1–17. [[CrossRef](#)]
13. Ziervogel, G.; Johnston, P.; Matthew, M.; Mukheibir, P. Using climate information for supporting climate change adaptation in water resource management in South Africa. *Clim. Chang.* **2010**, *103*, 537–554. [[CrossRef](#)]
14. Alauddin, M.; Sarkerb, M.A.R. Climate change and farm-level adaptation decisions and strategies in drought-prone and groundwater-depleted areas of Bangladesh: An empirical investigation. *Ecol. Econ.* **2014**, *106*, 204–213. [[CrossRef](#)]
15. Partey, S.T.; Dakorah, A.D.; Zougmore, R.B.; Ouédraogo, M.; Nyasimi, M.; Nikoi, G.K.; Huyer, S. Gender and climate risk management: Evidence of climate information use in Ghana. *Clim. Chang.* **2018**, 1–15. [[CrossRef](#)]
16. Bahinipati, C.S.; Venkatachalamb, L. What drives farmers to adopt farm-level adaptation practices to climate extremes: Empirical evidence from Odisha, India. *Disaster Risk Reduct.* **2015**, *14*, 347–356. [[CrossRef](#)]
17. Truelove, H.B.; Carrico, A.R.; Thabrew, L. A socio-psychological model for analyzing climate change adaptation: A case study of Sri Lankan paddy farmers. *Glob. Environ. Chang.* **2015**, *31*, 85–97. [[CrossRef](#)]
18. Arunrat, N.; Wang, C.; Pumijumong, N.; Sereenonchai, S.; Cai, W. Farmers' intention and decision to adapt to climate change: A case study in the Yom and Nan basins, Phichit province of Thailand. *Clean. Prod.* **2017**, *143*, 672–685. [[CrossRef](#)]
19. Makuvu, V.; Walker, S.; Masere, T.P.; Dimes, J. Smallholder farmer perceived effects of climate change on agricultural productivity and adaptation strategies. *Arid Environ.* **2018**, *152*, 75–82. [[CrossRef](#)]
20. Tripathi, A.; Mishra, A.K. Knowledge and passive adaptation to climate change: An example from Indian farmers. *Clim. Risk Manag.* **2017**, *16*, 195–207. [[CrossRef](#)]
21. Li, S.; Juhász-Horváth, L.; Harrison, P.A.; Pintér, L.; Rounsevell, M.D.A. Relating farmer's perceptions of climate change risk to adaptation behaviour in Hungary. *Environ. Manag.* **2017**, *185*, 21–30. [[CrossRef](#)]
22. Santibáñez-Andrade, G.; Castillo-Argüero, S.; Vega-Pena, E.V.; Lindig-Cisneros, R.; Zavala-Hurtado, J.A. Structural equation modeling as a tool to develop conservation strategies using environmental indicators: The case of the forests of the Magdalena river basin in Mexico City. *Ecol. Indic.* **2015**, *54*, 124–136. [[CrossRef](#)]
23. Islam, M.M.; Barnes, A.; Toma, L. An investigation into climate change scepticism among farmers. *Environ. Psychol.* **2013**, *34*, 137–150. [[CrossRef](#)]
24. Far, S.T.; Rezaei-Moghaddam, K. Determinants of Iranian agricultural consultants' intentions toward precision agriculture: Integrating innovativeness to the technology acceptance model. *Saudi Soc. Agric. Sci.* **2017**, *16*, 280–286.
25. Wang, J.; Tao, J.; Yang, C.; Chu, M.; Lam, H. A general framework incorporating knowledge, risk perception and practices to eliminate pesticide residues in food: A Structural Equation Modelling analysis based on survey data of 986 Chinese farmers. *Food Control* **2017**, *80*, 143–150. [[CrossRef](#)]
26. Jack, C.; Hotchkiss, E.; Sargison, N.D.; Toma, L.; Milne, C.; Bartley, D.J. A quantitative analysis of attitudes and behaviours concerning sustainable parasite control practices from Scottish sheep farmers. *Prev. Vet. Med.* **2017**, *139*, 134–145. [[CrossRef](#)]

27. Dang, H.L.; Li, E.; Nuberg, I.; Bruwer, J. Understanding farmers' adaptation intention to climate change: A structural equation modelling study in the Mekong Delta, Vietnam. *Environ. Sci. Policy* **2014**, *41*, 11–22. [CrossRef]
28. IPCC. *Climate Change 2007: Impacts, Adaptation, and Vulnerability*; Parry, M.L., Canziani, O.F., Palutikof, J.P., van der Linden, P.J., Hanson, C.E., Eds.; Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change; Cambridge University Press: Cambridge, UK, 2007; 976p.
29. Dasgupta, S.; Lapla, B.; Murray, S.; Wheeler, D. *Sea-Level Rise and Storm Surges: A Comparative Analysis of Impacts in Developing Countries*; World Bank Policy Research Working Paper (42), WPS4901; World Bank: Washington, DC, USA, 2009; 41p.
30. Le, T.H.; Nguyen, A.T.; Tran, A.T.; Dao, D.C.; Luu, T.A.; Hoang, L.T.T.; Nguyen, M.H.; Tran, Q.B.; Le, V.H.; Uong, D.K.; et al. Impacts of climate change on agro-ecological landscapes in the coastal area of the Thai Binh province (Vietnam) using the Delphi technique. *Clim. Chang. Strateg. Manag.* **2015**, *7*, 222–239.
31. MONRE (Ministry of Natural Resources and Environment), UNDP. *Build Ability to Recover: Adaptation Strategies for Livelihoods in Coastal Area That Is Most at Risk Due to the Impact of Climate Change in Central Vietnam*; Report of Research Project Poverty and Environment; NARENCA Publisher: Hanoi, Vietnam, 2010. (In Vietnamese)
32. MONRE (Vietnamese Ministry of Natural Resources and Environment). *Climate Change and Sea Level Rise Scenarios for Vietnam*; NARENCA Publisher: Hanoi, Vietnam, 2016; 170p.
33. TBG (Thai Binh Provincial Government). *Socio-Economic Development Report for Thai Binh Province in 2017*; Annual Official Report; Thai Binh Provincial Government: Thai Binh, Vietnam, 2018; 39p. (In Vietnamese)
34. NDG (Nam Dinh Provincial Government). *Socio-Economic Development Report for Nam Dinh Province in 2017*; Annual Official Report; Nam Dinh Provincial Government: Nam Dinh, Vietnam, 2018; 83p. (In Vietnamese)
35. NBG (Ninh Binh Provincial Government). *Socio-Economic Development Report for Ninh Binh Province in 2017*; Annual Official Report; Ninh Binh Provincial Government: Ninh Binh, Vietnam, 2018; 62p. (In Vietnamese)
36. Floyd, D.L.; Prentice-Dunn, S.; Rogers, R.W. A meta-analysis of research on protection motivation theory. *Appl. Soc. Psychol.* **2000**, *30*, 407–429. [CrossRef]
37. Cismaru, M.; Lavack, A.M.; Hadjistavropoulos, H.; Dorsch, K.D. Understanding health behavior: An integrated model for social marketers. *Soc. Mark. Q.* **2008**, *14*, 2–32. [CrossRef]
38. Grothmann, T.; Patt, A. Adaptive capacity and human cognition: The process of individual adaptation to climate change. *Glob. Environ. Chang.* **2005**, *15*, 199–213. [CrossRef]
39. Osberghaus, D.; Finkel, E.; Pohl, M. *Individual Adaptation to Climate Change: The Role of Information and Perceived Risk*. ZEW—Centre for European Economic Research Discussion Paper, No. 10-061. 2010. Available online: <https://ssrn.com/abstract=1674840> (accessed on 22 May 2019).
40. Dang, H.L.; Li, E.; Bruwer, J.; Nuberg, I. Farmers' perception of climate variability and barriers to adaptation: Lessons learned from an exploratory study in Vietnam. *Mitigation Adapt. Strategy Glob. Chang.* **2014**, *19*, 531–548. [CrossRef]
41. Milne, S.; Sheeran, P.; Orbell, S. Prediction and Intervention in Health-Related Behavior: A Meta-Analytic Review of Protection Motivation Theory. *Appl. Soc. Psychol.* **2000**, *30*, 106–143. [CrossRef]
42. Dang, L.H.; Li, E.; Bruwer, J. Understanding climate change adaptive behaviour of farmers: An integrated conceptual framework. *Clim. Chang. Impacts Responses* **2012**, *3*, 255–272. [CrossRef]
43. Bowen, N.K.; Guo, S. *Structural Equation Modeling. Pocket Guides to Social Work Research Methods*; Oxford University Press: Oxford, UK, 2012; 217p.
44. Westland, J.C. *Structural Equation Models: From Paths to Networks*; Springer International Publishing Switzerland: Cham, Switzerland, 2015; 175p.
45. Kline, R.B. *Principles and Practice of Structural Equation Modeling*, 4th ed.; Guilford Publications: New York, NY, USA, 2015; 534p.
46. Below, T.B.; Mutabazi, K.D.; Kirschke, D.; Franke, C.; Sieber, S.; Siebert, R.; Tscherning, K. Can farmers' adaptation to climate change be explained by socio-economic household level variables? *Glob. Environ. Chang.* **2012**, *22*, 223–235. [CrossRef]
47. Efron, B.; Tibshirani, R.J. *An Introduction to the Bootstrap*; Monographs on Statistics and Applied Probability 57; Chapman & Hall/CRC: London, UK, 1993.

48. Comoé, H.; Siegrist, M. Relevant drivers of farmers' decision behavior regarding their adaptation to climate change: A case study of two regions in Côte d'Ivoire. *Mitig. Adapt. Strategy Glob. Chang.* **2015**, *20*, 179–199. [[CrossRef](#)]
49. Greaves, M.; Zibarras, L.D.; Stride, C. Using the theory of planned behavior to explore environmental behavioral intentions in the workplace. *Environ. Psychol.* **2013**, *34*, 109–120. [[CrossRef](#)]
50. Hassan, R.; Nhemachena, C. Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *Afr. J. Agric. Resour. Econ.* **2008**, *2*, 83–104.
51. Zamasiya, B.; Nyikahadzoi, K.; Mukamuri, B.B. Factors influencing smallholder farmers' behavioural intention towards adaptation to climate change in transitional climatic zones: A case study of Hwedza District in Zimbabwe. *Environ. Manag.* **2017**, *198*, 233–239. [[CrossRef](#)]
52. Trinh, T.Q.; Rañola, R.F.; Camacho, L.D.; Simelton, E. Determinants of farmers' adaptation to climate change in agricultural production in the central region of Vietnam. *Land Use Policy* **2018**, *70*, 224–231. [[CrossRef](#)]



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