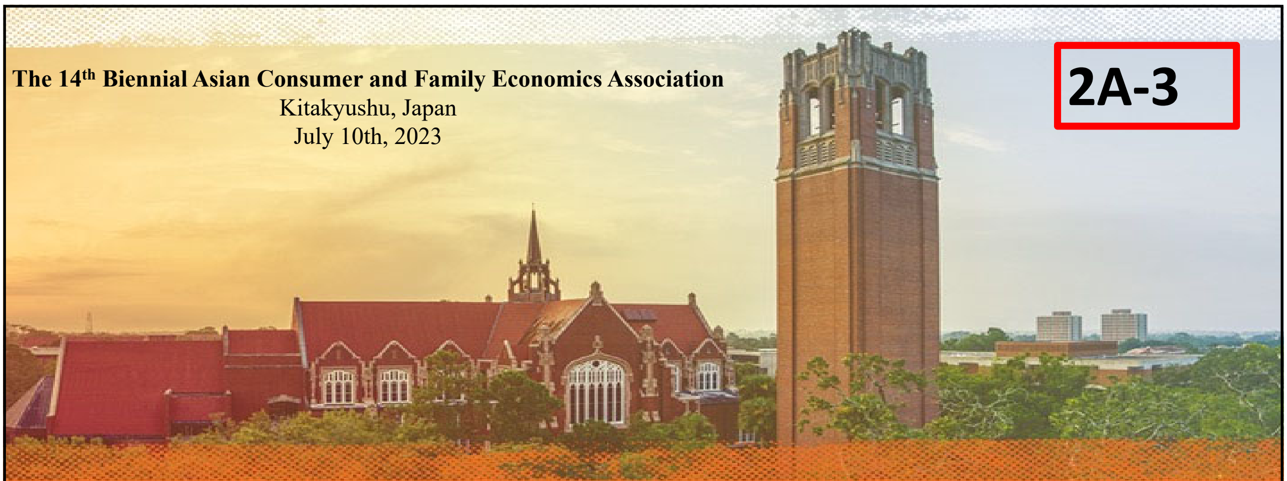

The 14th Biennial Asian Consumer and Family Economics Association
Kitakyushu, Japan
July 10th, 2023

2A-3

Exploring the Impact of Incremental and Transformative Adaptation Strategies on Smallholder Farming Households' Climate Resilience: A Machine Learning Approach

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BACKGROUND

- Adaptation and resilience are two critical concepts in the field of climate change adaptation.
- The similarities, differences, and relationships between adaptation and resilience has been discussed.
- No consensus and less empirical evidence to support their relationships.
- This study aimed to empirically examine the links between farmers' climate change adaptation and climate resilience.
- We further differentiated two categories of climate change adaptation strategies, namely, incremental and transformative adaptation, and explores the effects of these types of adaptation on climate resilience.

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Climate Change Adaptation: changes in processes, practices and structures to moderate potential damages or to benefit from opportunities associated with climate change (UNFCCC, N.D.)

Broad Definition of Resilience

- Holling (1973) originally defined resilience as the ability to persist within an ecological system in the face of change.
- There are various definitions of resilience among different disciplines.
  - The ability of a system and its parts to anticipate, absorb, accommodate, or recover from the effects of hazardous events in a timely and efficient manner (disaster risk reduction)
  - The capacity to restore or maintain economic values, such as farm income, yield, and productivity, when the economic systems encounter shocks (economic)
- We defined climate resilience as the capacity of the farming unit or agricultural system to cope with, and adapt to, the social, political, economic, and ecological challenges precipitated by a changing climate and climatic events.

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Understanding the Links among incremental, transformative, and resilience

- Folke (2006) indicated that climate resilience is not only about being persistent or robust to changing climate. It is also about the recombination of evolved structures and processes, the renewal of the system, and the emergence of new trajectories.
- Under certain circumstances, adaptation are positive for formulating resilience, however, the changes may beyond the system's ability to absorb and persist.
- Adaptation also adversely affects climate resilience.

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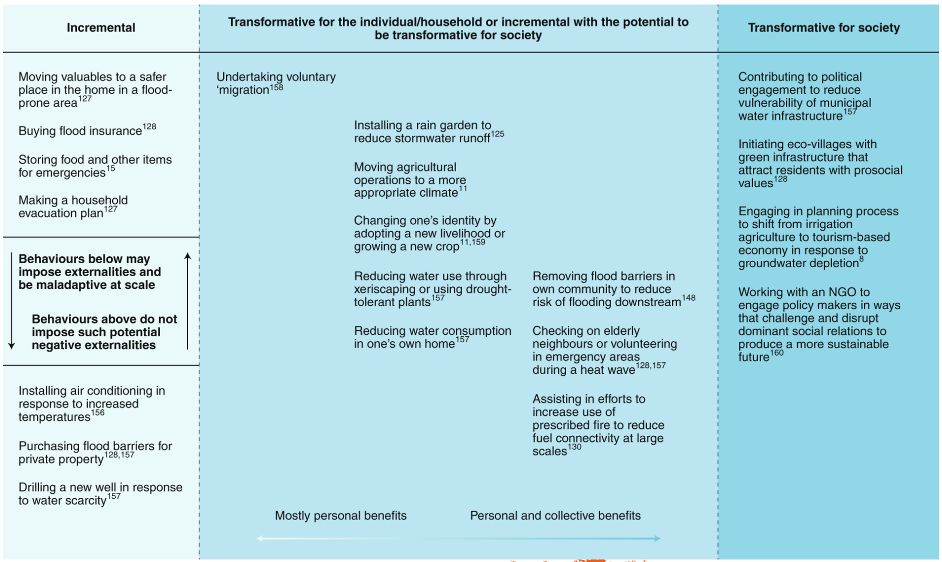


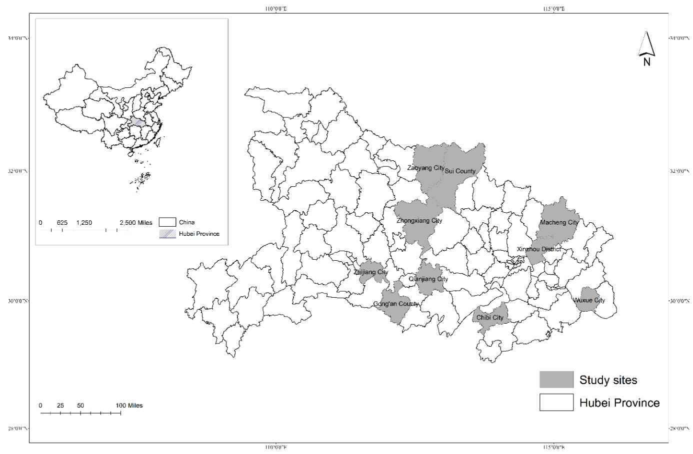
Wilson, R. S., Herziger, A., Hamilton, M., & Brooks, J. S. (2020). From incremental to transformative adaptation in individual responses to climate-exacerbated hazards. *Nature Climate Change*, *10*(3), 200-208.

DATA AND VARIABLES

Sampling and Data Collection

- 1200 rice farmers in Hubei, China, during the summer of 2016
- Ten counties
- A multi-stage random sampling method was used
  - 2-3 towns are randomly selected from each county
  - 2-3 villages are randomly selected from each town
  - 20-30 households are selected from each village
- The final sample was composed of 1115 rice farmers after examining for inconsistencies in the data and missing values.
- Research Ethical Clearance: Huazhong Agricultural University/University of Florida

STUDY SITES AND SAMPLE DISTRIBUTION



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DATA AND VARIABLES

Dependent Variable

- Climate resilience (Di Falco & Chavas, 2008; Teklewold et al., 2017; Liu et al., 2022)
  - Household income
  - Farm income
  - Technical efficiency (productivity estimated by a Stochastic Frontier Model, Lie et al., 2022).

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TECHNICAL EFFICIENCY

Following Liu et al. (2022), we measured technical efficiency by a stochastic frontier model. The general form of the stochastic frontier model can be given as (Aigner et al., 1977):

$$y_i = \boldsymbol{x\beta} + v_i - \mu_i, i = 1, \ldots, n \qquad (4\text{-}1)$$

Where, y_i is the logarithm of the output of household i. We used the per rice yield as the output variable. $\boldsymbol{x}$ is the vector of the logarithm of inputs. This equation contained six types of inputs, seeds, fertilizer, pesticides, labor, irrigation, and other inputs (e.g., electricity). $\boldsymbol{\beta}$ is the vector of unknown parameters to be estimated; v_i is the random error term with the assumed distribution of $N(0, \sigma_v^2)$. μ_i represents the inefficiency of the ith household and usually assumes μ_i to follow a one-side distribution, exponential distribution in our case. Because of these assumptions, technical efficiency can be expressed as $TE_i = E(-\mu_i)$, which ranged from 0 to 1. According to Zhu et al. (2021), we replaced TE_i with ln[TE_i /(1- TE_i)], which is not truncated.

DATA AND VARIABLES

Independent Variables

- Incremental adaptation
  - Purchasing crop insurance; Adjusting pesticide and fertilizer inputs; building or improving ridges or dikes; adjusting planting time
- Transformative adaptation
  - Using mixed crop-livestock systems; renting in or renting out large-proportion of land (more than 75%); off-farm employment; cultivating ratoon rice

Covariates

- Gender; age; educational attainment; farm experience; family size; agricultural labor; contracted land; paddy; plots
- The interactions terms of covariates
- The quadratic terms of continuous covariates

COVARIATE DEFINITIONS

Variable	Definition
Householders' gender.	A dichotomous variable that represents household heads' gender.
Householders' age	A continuous variable that captures household heads' age.
Householders' education level	A continuous variable that measures household heads' educational attainment by years.
Householders' farm experience	A continuous variable that measures household heads' farm experience by years.
Family size	The number of household members.
Agricultural labor	The number of family members who participated in agricultural production in 2015.
Contracted land	The number of contracted lands for the households.
Paddy	The number of paddy areas for the households in 2015.
Plots	A continuous variable that measures the number of rice planting plots.

Table 4-2. Summary statistics

Variable	Mean	Standard deviation	Min	Max
Household income (thousand yuan)	60.986	130.117	0	4000
Agricultural income (thousand yuan)	28.348	124.801	0	4000
Technical efficiency	0.678	0.222	0.001	0.972
Incremental adaptation	0.625	0.484	0	1
Transformative adaptation	0.430	0.495	0	1
Gender (ref. 1= Male)	0.701	0.458	0	1
Age (year)	55.578	9.129	27	83
Education (year)	6.851	3.468	0	18
Farm experience (year)	35.513	12.041	0	68
Family size (person)	4.765	1.757	1	14
Agricultural labor (person)	1.973	0.735	0	6
Contracted land (mu)	19.073	36.894	0.3	807
Paddy (mu)	14.750	37.587	0.2	807
Plots	6.622	9.405	1	150

Note: mu is not a standard unit in rural China and varies by region. In this research, we standardized this unit, i.e., 1 mu = 0.66 ha.

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EMPIRICAL STRATEGY

The Conditional Independent Assumption (CIA)

- To identify the effects of adaptation on climate resilience, we use the CIA, which indicates the outcome is independent of treatment conditional on covariates.
- If CIA holds, we can estimate the average treatment effect on the treated (ATT) by using the control group and a linear regression model to estimate the counterfactual mean outcome in the treatment.
- The CIA must satisfy one of the two conditions:
  - The regression model is correctly specified
  - The distribution of covariates must be the same in the treatment and control groups

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The CIA indicates that the outcome, i.e., climate resilience, is independent of treatment (adapting to climate change or not) conditional on covariates, which can be expressed as:

$$y_i^D \perp D_i | x_i \tag{4-2}$$

Where, y_i^D denotes the outcome variable with treatment status *D*, and *D* = {0,1}. D_i is the treatment variable. In this study, this variable represents rice farmers climate change adaptation behaviors. Moreover, x_i represents a vector of covariates.

Suppose the CIA holds in our case, then we can estimate the average treatment effect on the treated (ATT) by using the control group and a linear regression model to estimate the counterfactual mean outcome in the treatment group. That is,

$$\hat{E}[y_i^0 | D_i = 1] = \widehat{\alpha_c} + \widehat{\beta_c}\mu_t \tag{4-3}$$

Where, c denotes the model is estimated with the control group. μ_t is the mean of the covariate vector in the treatment group. $\widehat{\alpha_c}$ and $\widehat{\beta_c}$ are coefficients to be estimated.

However, the CIA must satisfy one of two conditions when estimating the ATT (Imbens, 2015): the regression model must be correctly specified, and the distribution of covariates must be the same in the treatment and control groups. If these conditions do not hold, we may have a biased estimate of the actual effect of farmers' climate change adaptation behaviors on their resilience.

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EMPIRICAL STRATEGY

Lasso algorithm and Post-double-selection (PDS) Lasso Method

- Belloni et al. (2014) suggested the single-selection lasso method produces a relatively small set of covariates.
- This study used the PDS lasso to select the covariates.

As Belloni et al. (2014b) suggested, the single-selection lasso method would produce a relatively small set of variables because it sets coefficients for weak predictors to zero, which may cause omitted variable bias and poor inference. Therefore, they proposed a novel estimation and inference method for the treatment effects of high dimensional data, named the "post-double-selection (PDS)". The PDS lasso contains three steps: Firstly, selecting a set of covariates that are useful for predicting the treatment variable. Secondly, selecting additional variables by using the control variables that predict the outcome variable. Finally, estimating the treatment effects by a linear regression model based on the outcome, treatment, and selected control variables. The double-selection procedure would increase the robustness of the estimation of impacts by reducing the problem that lasso-based covariate selection excludes covariates that are weakly correlated with treatment, the outcome, or both (Belloni et al., 2014a, 2014b; Mullally & Chakravarty, 2018; Uehleke et al., 2022).

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EMPIRICAL STRATEGY

Lasso algorithm and Post-double-selection (PDS) Lasso Method

- The least absolute shrinkage and selection operator (lasso) was used to correctly specify the functional form.

The linear lasso algorithm minimizes the mean squared error subject to a penalty on the absolute size of coefficient estimates (Ahrens et al., 2020), that is:

$$\hat{\beta}_{lasso}(\lambda) = argmin\frac{1}{n}\sum_{i=1}^{N}(y_i - \boldsymbol{x}_i'\boldsymbol{\beta})^2 + \frac{\lambda}{n}\sum_{p=1}^{P}\psi_p\,|\beta_p| \qquad (4\text{-}4)$$

Where, y_i is the outcome variable; $\boldsymbol{x_i}$ contains the *p* potential covariates. $\boldsymbol{\beta}$ is a vector of coefficients on $\boldsymbol{x_i}$. β_p is the pth element of $\boldsymbol{\beta}$. The tuning parameter λ controls the overall penalty level, and ψ_p are predictor-specific penalty loadings (Hastie et al., 2015). When λ equals to 0, equation (4-4) reduces to the OLS estimator. The number of no-zero coefficients in $\boldsymbol{\beta}$ is determined by the penalty term, $\frac{\lambda}{n}\sum_{p=1}^{P}\psi_p\,|\beta_p|$. More specifically, as λ decreases, the number of nonzero coefficient estimates increases. Therefore, the tuning parameters λ must be selected before using the lasso for prediction and model selection. The most common selection criteria used to select the tuning parameters are cross-validation (CV), the adaptive lasso, and plug-in methods. In this study, we utilized the CV method as a criterion to select the tuning parameters.

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EMPIRICAL STRATEGY

Propensity Score Matching

vs

Endogenous Switching Regression

The PDS lasso method provides a meaningful strategy for model selection, yet our identification remains challenging by the heterogeneity of rice farmers and self-selection bias. Researchers often use matching methods, such as propensity score matching (PSM), to balance the distribution of covariates in the treatment and control groups (Angrist & Pischke, 2009). However, there are several criticisms of such a method. For example, Abdulai and Huffman (2014) highlighted that the PSM approach must satisfy the CIA, indicating that the farmers' decision is random and uncorrelated with the outcome variables once the observable characteristics are controlled. Nonetheless, as Smith and Todd (2005) denoted, the outcomes of adopters and nonadopters are systematically different when farmers' selection is associated with unobserved factors. King and Nelsen (2019) also strongly criticized the PSM for its attempts to approximate an utterly randomized experiment rather than a stratified one. This method may increase imbalance, inefficiency, model dependence, and bias. As a result, this study employed an endogenous switching regression (ESR) model to correct the sample selection bias and endogeneity. As a result, we can further estimate the effects of climate change adaptation on farmers' climate resilience.

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EMPIRICAL STRATEGY

Endogenous Switching Regression

The ESR model simultaneously considered the observed and unobserved characteristics that affect rice farmers' climate change adaptation and resilience (Lokshin & Sajaia, 2004; Maddala, 1983). In general, the ESR model contains two types of equations, namely the choice equation and outcome equations. To retrieve these equations, we first assumed that all rice farmers *i* encountered two alternatives, i.e., adapt to climate change (D=1) or not adapt (D=0). In fact, only one of the choices can be selected by farmer *i* at once. Therefore, the alternatives D=1 and D=0 cannot be observed simultaneously for farmer, meaning the choice equation becomes:

$$D_i = \alpha Z_i + \mu_i \tag{4-5}$$

Where, D_i is rice farmers' decision on climate change adaptation. Z_i represents all observed covariates selected by the PDS lasso. μ_i is the error term, denoting the unobserved characteristics that affecting farmers' climate change adaptation decision-making.

And the outcome equations:

$$Y_i^1 = \beta_i^1 X_i + v_i^1 \tag{4-6}$$

$$Y_i^0 = \beta_i^0 X_i + v_i^0 \tag{4-7}$$

Equation 4-6 and 4-7 represent the outcome equations for farmers who have adapted to climate change (treatment group) and those who have not (control group), respectively. Y_i^1 and Y_i^0 denote the outcome variable of climate resilience for rice farmer *i* with and without using climate change adaptation strategies. X_i represents the factors that influences the outcome variable. Additionally, v_i^1 and v_i^0 indicate the error terms.

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The ESR model can be fitted by a two-step approach, yet this approach may be inefficient, and hard to obtain consistent standard errors (Lokshin & Sajaia, 2004). The full information maximum likelihood method (FIML) was suggested by Lokshin and Sajaja (2004) to address these issues through a simultaneous estimation of the choice and outcome equations. We can then estimate the expected outcome value for rice farmers who have adapted or have not adapted to climate change. Thus, the unbiased estimates of the average treatment effect on the treated (ATT) can be given as (Lokshin & Sajaia, 2004):

$$ATT = E(Y_1|D = 1) - E(Y_0|D = 1) \qquad (4\text{-}8)$$

An issue must be addressed before estimating the effects: At least one instrumental variable should be included in the choice equation to identify the ESR model. The valid instrumental variables need to be correlated to rice farmers' climate change adaptation decision-making (Abdulai & Huffman, 2014; Di Falco & Veronesi, 2014). In this study, two instrumental variables were selected. The first IV is farmers' climate change belief, which is measured by farmers' level of agreement with the statement that climate change is an important environmental issue. Khanal et al. (2018) utilized climate belief as an instrument when they analyzed the effects of climate change adaptation on rice yields. The second IV we chose was government extension services. We asked farmers about their frequency of receiving extension services, such as trainings. Di Falco and Veronesi (2014) argued that government extension is an important channel for farmers to obtain knowledge, information, and climate change adaptation strategies. Likewise, Shen et al. (2021) argued that extension service from the government is a valid instrument when analyzing technology adoption on farmers'

EMPIRICAL STRATEGY

Endogenous Switching Regression

- Full information maximum likelihood (FIML)
- Instrumental Variables: climate change beliefs and Government Extension

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RESULTS

The Determinants of Climate Change Adaptation and Resilience

- Demographics
- Farm characteristics
- Extension and belief

Table 4-4. The determinants of climate change adaptation and resilience

Variables	Incremental adaptation	Transformative adaptation	Household Income	Agricultural income	Technical efficiency
Incremental			0.059	0.097	-0.180
			(0.052)	(0.099)	(0.138)
Transformative			0.109**	-0.111	-0.163
			(0.053)	(0.118)	(0.152)
Family size	0.009	0.011	0.137***	-0.018	-0.069
	(0.037)	(0.039)	(0.015)	(0.026)	(0.043)
Agricultural labor	0.092	-0.008	-0.015	0.100*	0.243***
	(0.091)	(0.099)	(0.037)	(0.053)	(0.079)
Gender	0.109	1.157***	0.010	0.255**	0.436**
	(0.154)	(0.170)	(0.054)	(0.122)	(0.178)
Age	-0.022**	-0.058***	-0.029***	-0.028***	-0.027**
	(0.011)	(0.012)	(0.009)	(0.010)	(0.014)
Education	0.006	0.051**	0.011	0.021	0.009
	(0.021)	(0.023)	(0.008)	(0.014)	(0.023)
Farm experience	0.010	-0.009	0.009	0.012	-0.003
	(0.008)	(0.009)	(0.008)	(0.009)	(0.010)
Contracted land	0.006*	-0.017**	0.008***	0.016***	0.007
	(0.004)	(0.008)	(0.002)	(0.005)	(0.004)
Paddy	-0.004	0.031***	-0.002	-0.006	-0.005
	(0.003)	(0.010)	(0.002)	(0.006)	(0.004)
Plots	0.018	0.002	0.010*	0.033***	0.015**
	(0.017)	(0.011)	(0.005)	(0.011)	(0.008)
Extension	0.274***	0.171**			
	(0.074)	(0.067)			
Belief	-0.142*	0.151**			
	(0.073)	(0.076)			
Constants	1.009	1.013	11.614***	10.356***	1.607**
	(0.629)	(0.632)	(0.261)	(0.350)	(0.638)
R^2			0.242	0.165	0.043
Adjusted R^2			0.235	0.156	0.033
Pseudo R^2	0.034	0.150			
Log Likelihood	-712.490	-647.406			
F			23.023	8.065	4.542
Number of observations	1115	1115	1115	1115	1115

Note: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

RESULTS

Results of ESR models

Table 4-5. The effects of incremental adaptation on farmers' climate resilience

Variable	Household income	Agricultural income	Technical efficiency
ATT	0.172***(0.028)	0.045(0.046)	-0.137***(0.019)
Controls	Yes	Yes	Yes
$\ln\sigma_0$	-0.057(0.373)	0.377***(0.037)	1.082***(0.040)
ρ_0	-0.105(0.188)	-0.124(0.165)	2.895***(0.159)
$\ln\sigma_1$	-0.101**(0.042)	0.720***(0.031)	1.017***(0.030)
ρ_1	-1.246***(0.121)	-2.102***(0.086)	-2.599***(0.119)
LR test	27.49***	295.17***	685.55***
Log Likelihood	-2027.19	-2644.20	-2825.11
Wald chi2	79.99***	71.23***	33.96***

Note: ATT denotes the average treatment effects on the treated. Controls are selected by the PDS lasso algorithm. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4-6. The effects of transformative adaptation on farmers' climate resilience

Variable	Household income	Agricultural income	Technical efficiency
ATT	0.298***(0.028)	0.067*(0.052)	-0.206***(0.020)
Controls	Yes	Yes	Yes
$\ln\sigma_0$	-0.176***(0.029)	0.341***(0.029)	0.771***(0.029)
ρ_0	-0.082(0.169)	-0.094(0.129)	-0.092(0.165)
$\ln\sigma_1$	0.003(0.058)	0.827***(0.040)	1.142***(0.038)
ρ_1	-1.366***(0.152)	-2.178***(0.096)	-2.649***(0.115)
LR test	19.63***	226.87***	303.56***
Log Likelihood	-2036.23	-2651.18	-3041.11
Wald chi2	210.02***	205.82***	21.43***

Note: ATT denotes the average treatment effects on the treated. Controls are selected by the PDS lasso algorithm. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

RESULTS

Would Integrated Adaptations Be Better?

Table 4-7. The effects of integrated adaptation on farmers' climate resilience

Variable	Household income	Agricultural income	Technical efficiency
ATT	0.285***(0.031)	0.262***(0.050)	-0.260***(0.024)
Controls	Yes	Yes	Yes
$\ln\sigma_0$	-0.178***(0.026)	0.416***(0.026)	0.758***(0.026)
ρ_0	-0.103(0.132)	-0.105(0.106)	-0.042(0.197)
$\ln\sigma_1$	-0.005(0.076)	0.867***(0.051)	1.249***(0.047)
ρ_1	-1.323***(0.177)	-2.133***(0.116)	-2.706***(0.129)
LR test	13.35**	149.42***	219.96***
Log Likelihood	-1958.78	-2628.74	-2990.92
Wald chi2	214.66***	147.08***	26.15***

Note: ATT denotes the average treatment effects on the treated. Controls are selected by the PDS lasso algorithm. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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RESULTS

Adaptation Intensity And Climate Resilience

Table 4-8. The effects of adaptation intensity on farmers' climate resilience

Variable	Household income	Agricultural income	Technical efficiency
Adaptation intensity_IA	0.242(0.184)	0.072**(0.036)	0.002(0.050)
Adaptation intensity_TA	0.098**(0.041)	-0.065(0.079)	-0.232**(0.113)
Adaptation intensity_Total	0.030*(0.016)	0.041(0.030)	-0.030(0.043)
Controls	Yes	Yes	Yes
Number of Observations	1115	1115	1115

Note: Adaptation intensity_IA is the number of incremental adaptation strategies that farmers have adopted on their farm; Adaptation intensity_TA is the number of transformative adaptation strategies that farmers have adopted on their farm; Adaptation intensity_TOTAL is the number of adaptation strategies that farmers have adopted on their farm; Controls were selected by PDS lasso algorithm. Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

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Discussion

Table 4-9. The heterogeneous effects of different adaptation measures on the technical efficiency of rice production

Variable	IA1	IA2	IA3	IA4	TA1	TA2	TA3
ATT	0.096***	0.184***	-0.576***	0.070***	0.883***	0.258***	-0.146***
	(0.020)	(0.015)	(0.015)	(0.018)	(0.027)	(0.036)	(0.220)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\ln\sigma_0$	0.865***	0.990***	0.749***	0.835***	0.908***	0.840***	0.803***
	(0.027)	(0.028)	(0.030)	(0.025)	(0.023)	(0.023)	(0.026)
ρ_0	-0.054	2.630***	-0.029	-0.090	2.621***	2.516***	-0.089
	0.194)	(0.121)	(0.283)	(0.130)	(0.155)	(0.159)	(0.141)
$\ln\sigma_1$	0.969***	1.127***	1.135***	1.079***	0.923***	1.379***	1.173***
	(0.042)	(0.043)	(0.035)	(0.056)	(0.073)	(0.089)	(0.048)
ρ_1	-2.631***	-2.698***	-2.612***	-2.756***	-2.847***	-2.724***	-2.637***
	(0.127)	(0.124)	(0.097)	(0.168)	(0.262)	(0.264)	(0.128)
LR test	264.98***	655.60***	373.38***	193.52***	369.31***	291.93***	239.16***
LL	-3005.67	-2816.53	-3042.92	-2933.52	-2636.98	-2602.85	-2999.79
Wald χ^2	15.63***	10.22***	5.79**	7.39***	25.36***	25.93***	22.02***

Note: outcome variable is technical efficiency. TT denotes the average treatment effects on the treated. Controls are selected by the PDS lasso algorithm. Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01. IA1: purchasing crop insurance; IA2: adjusting pesticide and fertilizer inputs; IA3: building or improving ridges or dikes; IA4: adjusting planting time; TA1: using a mixed-livestock system; TA2: renting in or renting out a large proportion of land; TA3: getting an off-farm job to supplement farm income. We eliminated TA4 (cultivating ratoon rice) in our analysis because only 17 rice farmers reported adopting this practice in our sample.

- Our results indicated that both incremental and transformative adaptations significantly negatively impact farmers' technical efficiency in rice production.
- Not all adaptation strategies has positive effects on climate resilience.
- Limitations
  - Measurement of resilience
  - External validity

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CONCLUDING REMARKS

- We found that both incremental and transformative adaptation positively impact rice farmers' household and agricultural income while negatively affecting rice production's technical efficiency.
- We found that transformative behaviors have more positive and negative effects on farmers' climate resilience than incremental adjustments.
- Our results showed that not all adaptation strategies positively influence farmers' climate resilience.
- Our results suggested that the combination of incremental and transformative adaptation may be a promising scheme for rice farmers to respond to climate change in the future.

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ACKNOWLEDGMENT

- U.S. Department of Agriculture Sustainable Agricultural Research and Education-Graduate Student Grant (GS21-235)
- University of Florida International Center (Global Fellowship Award, and the UFIC Collaborative Faculty Team Project)
- U.S. Department of Agriculture/National Institute of Food and Agriculture (USDA/NIFA) Hatch Multistate project: "Cover Crops for Sustainable Southern Agroecosystems" (S1085) (FLA-FYC-005952).
- China Scholarship Council (201906760081)

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Thank you!

Questions, suggestions, and comments?

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