CLIMATE CHANGE ADAPTATION AND PRODUCTION RISKS AMONG PADDY FARMERS IN SRI LANKA

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Abstract

Production risks are unavoidable in paddy production due to unprecedented climate changes in many developing countries. This study intends to identify the production risks and farmers' decisions to adapt the climate change in paddy production. A survey was conducted, gathering cross-sectional data from 1410 farmers cultivating paddy in rural Sri Lanka. This research analyses farmers' adaptation decisions against climate change using climate-smart practices, socio-economic parameters, and household characteristics. It estimates the impact of experiencing drought and flood among adapting and non-adapting farming communities. The study uses an endogenous switching regression model to avoid endogeneity and selection bias: the study measures productivity, volatility, downside risk exposure and kurtosis between the adapters and non-adaptors. The results revealed that adaptors are sensitive to drought and flood, influencing the four production outcomes. However, the adaptors significantly reduced their volatility and risk exposure, while the non-adapters were susceptible to environmental stress experiences. Adaptation is highly influenced by climate-related variables and socio-economic and credit-related variables in the empirical analysis. The role of the extension services, access to credit, total credit, and income are prominent in the adaptation of paddy production.

JEL: *C13, C24, D12, D13, Q12, Q54*

Keywords: *Climate Smart Agriculture, Endogenous Switching Regression, Adaptation, Production Risk*

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INTRODUCTION

The impacts of environmental stress are more severe on agricultural production than ever in history. In Asia, environmental challenges, including climate change, are gradually threatening agricultural sustainability. Adapting to climate change is the process through which people reduce the adverse effects of climate on their health and well-being and take advantage of the opportunities their climatic environment provides (Burton, 1992). However, the adaption is a decision taken by the farmers in this research to the climate variations.

The agricultural sector in the Asian region supports the livelihood of over 40% of the population. It is critical to assess the impacts of climate change, including food security, poverty, water security and disaster risk management (IPCC, 2014). The study's rationale is to understand the behaviour of the farming communities in response to climate change and the factors that affect their adaptation. The climate change adaptation behaviour of the farmers is dependent upon the welfare gains due to understanding the climate variations. This study focuses on how smart climate agriculture (CSA) practices support the adaptation of paddy-cultivating farmers in Sri Lanka. Today, sustainable agriculture is essential for farmers to adapt to drought and floods with the resilience to minimise production risks. Therefore, resilience in agricultural production against environmental stress depends upon the adaptation to the technologies and innovative approaches in paddy farming adaptation in Sri Lanka.

The household decision to adapt the climate change is mostly determined by various factors in addition to the welfare gained by the adaptation decision of the farmers. These factors are essential for policymakers to make informed and evidence-based decisions. In addition to various socio-economic variables, entrepreneurial farmers tend to adapt the climate change quickly according to the adoption curve. Even though a considerable pool of studies has been conducted in various locations to estimate the impacts of climate change adaptation, robust estimation of the adaptation avoiding endogeneity and selection bias, is limited. Therefore, this study provides an avenue for understanding the factors affecting Sri Lankan farmers' climate change adaptation decisions.

This paper proceeds as follows. The second section briefly reviews existing studies on the effects of climate-smart agriculture and adaptation. Section three briefly presents the data used in the study. Section four introduces the econometric methods used to estimate the impact of adaptation. Results and discussion are included in the fifth section, while the study's conclusion is presented in the last section.

LITERATURE REVIEW

This section provides the literature on climate-smart agriculture and adaptation to climate change. Climate-smart agriculture is focused on this study whilst recognising that CSA directly impacts reducing CO2 emissions. In underpinning literature, expected utility theory has not been extensively studied for the adaptation decisions of smallholder farmers. Climate change, including drought and flood, has become more severe, has existed for a more extended period, and has happened often (Hyman et al., 2008). Mostly in developing countries, farmers are highly affected by environmental changes' impacts (Mendelsohn et al., 2006). Several researchers have studied the determinants of adaptation decisions of the farmers and their resilience (Chen et al., 2012; Deressa et al., 2009). The literature provides much empirical evidence for improving climate adaptive capacity while avoiding the negative consequences of climate change (Khanal et al., 2018 a,b). Further, it can change the environmental risks of agricultural production (Parry et al., 2004; Lobell, 2014; Schlenker and Lobell, 2010; World Bank, 2013).

The placement of the adaptation strategies is critical for the hazardous environmental stress in developing countries (Mendelsohn and Dinar 2003; Deressa et al. 2009; Di Falco and Veronesi 2013). Further, many papers studied the impact of climate change on productivity (Deressa and Hassan 2009; Di Falco et al. 2011; Di Falco and Veronesi 2013) and the determinants of adaptation (Deressa et al. 2009, 2011; Di Falco et al. 2011). However, the adaptation decision of the farmers in Endogenous Switching Regression (ESR)has not been used extensively in the literature. Thus, this analysis is based on a moment-based specification of the stochastic production function (Antle, 1983; Antle and Goodger, 1984; Chavas, 2004). Expressively, this research expects to bridge the knowledge gap in the climate change adaptation of paddy production in Sri Lanka.

Thomas et al. (2007) examined the perception of South African farmers and their response to precipitation as a climate change indicator. The farmers' perception of climate variation is also examined in the rural Sahel (Mertz et al., 2009). Eakin (2005) has studied adaptation to climate change in three rural areas in Central Mexico, focusing on understanding the effects of socio-economic and political factors on farmers' adaptive capacity and strategies for adaptation. Differences in adaptation strategies in several countries have been studied by Dinar et al. (2008). They found that one-third have not adapted to climate change even though they have perceived it. Alpizar et al. (2009) implemented a framed field experiment to analyse the adaptation to climate change of coffee farmers in Costa Rica. They found that the attitude of the farmers towards risks influences the adaptation decisions.

Adapting the CSA practices can mitigate the impacts of climate risks on developing economies' households by using new technologies in their production process. Many studies have provided evidence on adaptation to outcomes such as productivity, profit and income (Deschenes and Greenstone, 2007; Nhemachena et al., 2014; Huang et al., 2015). However, a seminal contribution to the climate change adaptation for developing countries like Sri Lanka is limited in paddy cultivation and farmers’ net returns, volatility, and downside risk exposure. Even though managing agricultural production like paddy farming under the constraints of climate change is an unavoidable choice. In Sri Lanka, harms to paddy production result in a higher loss of income and livelihood for many farmers. Reduction in agricultural productivity affects household welfare and food security (Ali and Erenstein, 2017). Even though the index insurance programme is planned to implement, it was not an alternative option for the farmers since they need to manage the risk of climate change before the loss in their production.

Therefore, the diverse nature of the literature regarding adaptation to climate change causes this study to add to the novel literature on climate change adaptation in developing countries. Thereby, the policymakers can use the research outcomes to support evidence-based decisions to improve the adaptation to climate change in the farming communities in Sri Lanka.

DATA AND METHODOLOGY

The data was obtained from a household survey conducted on a studying climate adaptation of 1410 farmers, which included 700 adaptors and 710 non-adaptors in Horowpathana, Sri Lanka. The main objective of collecting this data was to conduct an impact evaluation under the farmers' adaptation decision examining the determinants of CSA to enhance their resilience.

Figure 1: Map of Horowpathana area in Sri Lanka

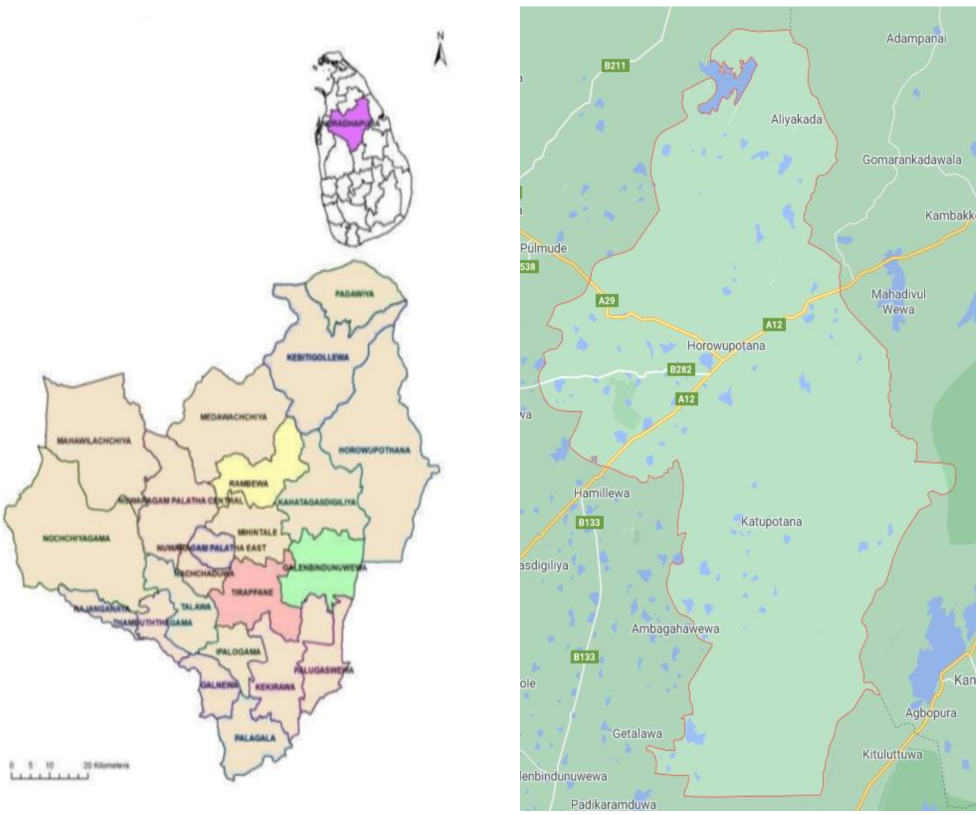

Table 1: Variable description

Dependent variables	
Adaptation decision	Dummy = 1 if farmer decided to adapt to climate variations, 0 otherwise
Production	Quantity of paddy produced per hectare (Kg)
Independent variables	
Variance	Second central movement from the production function
Skewness	Third central movement from the production function
Kurtosis	Fourth central movement from the production function
Net return	Net return from the production function
Education	Binary =1 if a farmer has at least O/L education, 0 otherwise
Btwn16and60	Number of household members aged between 16 and 60
CSA_awareness	Binary =1 if the farmer is aware of the CSA practices, 0 otherwise
CSA_practice	Binary =1 if the farmer is practicing the CSA techniques, 0 otherwise
Machinery	Binary =1 if machinery is used for the production, 0 otherwise
Animal	Binary =1 if the farmer uses animals for production, 0 otherwise
Labour	Labour use per hectare (days)
Seeds	Paddy seed usage per hectare (kg)
Fertilizer	Fertilizer usage per hectare (kg)
Manure	Manure usage per hectare (kg)
Below fifteen	Number of household members age less than fifteen, 0 otherwise
Male	Binary =1 if the household head is male, 0 otherwise
Married	Binary =1 if the head of the household is married, 0 otherwise
Age	Age of the household head (Years)
Household members	Number of people in the household
Flood	Binary =1 if the farmer experienced a flood during the last 1 years
Drought	Binary =1 if the farmer experienced a drought during the last 1 years
Off-farm jobs	Binary =1 if the farmer is doing off-farm jobs, 0 otherwise
Access to credit	Binary =1 if the farmer has access to credit, 0 otherwise
Extension from government	Binary =1 if the household head received information from government extension officers, 0 otherwise
Peer extension	Binary =1 if the household head received information from farmer-to-farmer extension, 0 otherwise
Time to town	Time (in minutes) taken to go to nearest town area
Total income	Total income of the farmers in LKR
Years in village	Number of years living in the village
Enough food	Binary =1 if the household has meals for three times a day, 0 otherwise
No food	Binary =1 if the household has no saved paddy for eating for next year, 0 otherwise
Total saved	Total savings in LKR
Total credit	Total credit obtained in LKR
Climate information	Binary =1 if extension officers provided details on rainfall and temperature, 0 otherwise
Climate info use	Binary =1 if the farmer uses climate change information, 0 otherwise
Train climate use	Binary =1 if the farmer had training in climate change, 0 otherwise
Climate comparison	Binary =1 if the farmer compares the climate change with the previous years, 0 otherwise
Crop area	Total crop area in hectares

Empirical Strategy

Based on the theoretical framework, a simple empirical approach to measure the farmers' adaptation decision for paddy cultivation is employed. The specification starts from the moment-based approach (Antle, 1983). Then it extends to the effects of adaptation, incorporating the mean, variance, risk exposure and kurtosis as the first moment, second moment, third moment and fourth moment, respectively. The paddy production function can be expressed as follows.

$y = f(C, I, X, e, w, \emptyset) + u$…………………..…………………………………... (1)

In this equation, y indicates the natural logarithm of paddy yield, and *C* refers to the adaptation to climate change. A dummy variable is assigned to take the value one if a farmer adapts to climate change; zero otherwise. *I* represent the index insurance while *X* consists of a vector for the explanatory variables such as characteristics of farmers and socio-economic variables. *w* represents the flood and drought-experiencing variables. Finally, $\emptyset$ is a vector of coefficients to be estimated and u is the disturbance term.

To get the outcomes of variability, skewness and kurtosis, the estimated errors from the above equation were squared to obtain the second moment, raised to power three to obtain the third moment and raised to power four to obtain the fourth moment of the production function. Due to the endogeneity issue in observed and unobserved characteristics between adapters and non-adapters, examining the causal inference of adaptation is biased and inconsistent. Therefore, the endogenous switching regression model is applied to account for the above bias (Lokshin and Sajaia, 2004). When the benefits from the adaptation are productive, the farmers are considered to adapt to climate change because of welfare gain (Huang et al., 2015).

Suppose that welfare gained from the adaptation to be K_i^* then K_i^*>0 indicates that the welfare gain from adaptation is higher than non-adaptation behaviour. Then, the latent variable K_i^* can be included as:

$K_i^* = f(C, I, X, e, w, n, \delta) + \mu_i \; with \; K = 1\{K_i^* > 0\}$……………..……..…………… (2)

where, *n* vector is the instruments which are the variables that affect the climate adaptation. δ is the parameters to be estimated. Accordingly, the outcomes conditional on adaptation in the model can be expressed as;

$Regime\ 1 : Y_{1i} = f(C, I, X, e, w, \beta_1) + \varepsilon_{1i} \; if \; K_i = 1$…………………….…………. (3)

$Regime\ 2 : Y_{2i} = f(C, I, X, e, w, \beta_2) + \varepsilon_{2i} \; if \; K_i = 0$……………...…………..…… (4)

where Y_{1i} the paddy production for adapters and non- adapters, and *εi* is the error term. These equations (3,4) summarise the strength of the empirical method, separately estimating the outcome variables based on the decision in adaptation and non-adaptation. As in the literature, willingness to take risks is also considered an instrument in the identification strategy (Bellemare, 2012). Therefore, it controls the unobserved heterogeneity, which affects the adaptation decision for production.

An additional feature of the ESR model is its assumption of a non-zero correlation between the error term of the adaptation function and the error term of the outcome functions. The outcome equation (3,4) tri-variate normal distribution with mean zero and covariance matrix as below.

$$\Omega = \left[\sigma_\mu^2\ \sigma_{1\mu}\ \sigma_{2\mu}\ \sigma_{\mu 1}\ \sigma_1^2\ .\ \sigma_{\mu 2}\ .\ \sigma_2^2\ \right] \text{..} (5)$$

Where, $\sigma_\mu^2 = var(\mu_i)$, $\sigma_1^2 = var(\varepsilon_i)$, $\sigma_2^2 = var(\varepsilon_2)$,$\sigma_{1\mu} = cov(\mu_{i,}\varepsilon_1)$, $\sigma_{2\mu} = cov(\mu_{i,}\varepsilon_2)$. Further, σ_μ^2 is estimable up to a scale factor and can be assumed to be equal to one (Maddala, 1983) and $cov(\varepsilon_1, \varepsilon_2)$, is not defined as Y_1, Y_2 cannot be observed simultaneously. Further, the correlation between the error term of the selection equation and the outcome equation is not zero $\left(i.e. corr\left(\mu_{i,}\varepsilon_1\right) \neq 0 \& \ corr\left(\mu_{i,}\varepsilon_2\right) \neq 0\right)$, which creates selection bias.

ESR addresses the selection bias by estimating the inverse mills ratios ($\lambda_{1i}$and λ_{2i}) and the covariance terms ($\sigma_{1\mu}$and $\sigma_{2\mu}$) and including them as auxiliary regressors. If $\sigma_{1\mu}$and $\sigma_{2\mu}$are significant, we reject the absence of selection bias. The ESR model estimates can then be used to estimate ATT (Average treatment effect on treated households) and ATU (Average treatment effect on untreated households) as follows:

$$E(Y_{1i}|K_i = 1) = f(C, I, X, e, w, \beta_1) + \lambda_{1i}\sigma_{1\mu} \text{...} (6)$$

$$E(Y_{2i}|K_i = 0) = f(C, I, X, e, w, \beta_2) + \lambda_{2i}\sigma_{2\mu} \text{...} (7)$$

$$E(Y_{2i}|K_i = 1) = f(C, I, X, e, w, \beta_2) + \lambda_{1i}\sigma_{2\mu} \text{...} (8)$$

$$E(Y_{1i}|K_i = 0) = f(C, I, X, e, w, \beta_1) + \lambda_{2i}\sigma_{1\mu} \text{...} (9)$$

The ATT and ATU are then defined as:

$$ATT = E(Y_{1i}|K_i = 1) - E(Y_{2i}|K_i = 1) \text{...} (10)$$

$$ATU = E(Y_{1i}|K_i = 0) - E(Y_{2i}|K_i = 0) \text{...} (11)$$

The above parameters of ATT estimate the effect of adaptation on mean paddy production. The equations were extended to the other outcomes, such as variance, skewness, and kurtosis. Then the evaluation outcome of the model can be estimated.

The advantage of the ESR model is that it omits the selection bias and the endogeneity. The endogeneity is one of the main reasons that hinder the robust estimation of the coefficients of the determinants in many econometric applications. However, the ESR model prevents selection bias by selecting the variables and then performing the model, which is a superior econometric approach compared to other studies.

Table 2: Summary Statistics

Variables	Mean	Standard Deviation	Observation
Age	48.11	13.44	1,410
Sex	0.59	0.49	1,410
Marital_status	0.45	0.55	1,410
Education	0.72	1.01	1,276
HH_members	4.58	5.54	1,410
Below fifteen	2.10	3.07	1,410
Btwn16 - 60 yrs	4.90	3.37	1,410
CSA_awareness	0.65	0.48	1,410
CSA_practice	0.42	0.49	1,410
Time_town	88.85	176.32	1,410
Tot_income	24,622.47	15,898.02	1,241
Years_in_village	47.26	16.08	1,410
Machinery	0.77	0.22	1,410
Animal	0.38	0.42	1,410
Flood	0.67	0.24	1,410
Drought	0.74	0.38	1,410
Off-farm jobs	0.48	0.62	1,328
Government extension	0.72	0.37	1,410
F-to-f extension	0.68	0.47	1,410
Climate_info	0.73	0.44	1,410
Climate_info_use	0.76	0.42	1,410
Train_climate_use	0.27	0.44	1,410
Climate_compare	0.88	0.31	1,410
Enough_food	0.41	0.49	1,326
No_food	0.24	0.43	1,410
Tot_saved	49,850.56	240,386.70	1,410
Access_credit	0.28	0.44	1,410
Tot_credit	217,829.60	394,357.40	1,410
Crop_area	2.45	5.00	1,410
Volatility	1.44	3.48	1,410
Skewness	-0.54	17.91	1,342
Kurtosis	14.24	97.11	1,410
Net returns	2,175.27	22,059.30	1,410

Table 3: Determining factors of adaptation and mean difference

Variables	Adaptation				Mean Difference	
	Adaptors		Non-Adaptors			
Age	47.82	(0.023)	48.40	(0.097)	-0.58	(0.910)
Sex	0.49	(0.045)	0.69	(0.672)	-0.20	(0.302)
Marital_status	0.51	(0.112)	0.49	(0.085)	0.45	(0.126)
Education	0.80	(0.190)	0.64	(0.065)	0.24***	(0.021)
HH_members	4.11	(0.100)	5.05	(0.092)	-0.94	(0.734)
Below fifteen	3.85	(0.803)	4.35	(0.005)	-0.50	(0.610)
Btwn16 – 60 yrs	5.12	(0.721)	4.68	(0.546)	0.44	(0.521)
CSA_awareness	0.84	(0.125)	0.46	(0.229)	0.38**	(0.041)
CSA_practice	0.59	(0.683)	0.25	(0.549)	0.34***	(0.000)
Machinery	0.28	(0.210)	0.26	(0.119)	0.02	(0.230)
Animal	0.71	(0.831)	0.17	(0.153)	0.54	(0.941)
Flood	0.69	(0.227)	0.41	(0.443)	0.28	(0.532)
Drought	0.72	(0.382)	0.53	(0.450)	0.19	(0.833)
Off-farm jobs	0.45	(0.237)	0.35	(0.972)	0.10	(0.083)
Government extension	0.47	(0.228)	0.32	(0.045)	0.15	(0.730)
Farmer-to-farmer extension	0.73	(0.488)	0.63	(0.196)	0.10	(0.285)
Time_town	90.01	(0.073)	87.69	(0.705)	2.32*	(0.225)
Tot_income	27,752.81	(0.626)	21,492.13	(0.553)	6,260.68**	(0.201)
Years_in_village	27.11	(0.354)	27.41	(0.115)	-0.30	(0.000)
Climate_info	0.71	(0.910)	0.75	(0.223)	-0.04	(0.012)
Climate_info_use	0.88	(0.723)	0.64	(0.345)	0.24***	(0.865)
Train_climate_use	0.26	(0.286)	0.28	(0.175)	-0.02	(0.323)
Climate_compare	0.92	(0.124)	0.84	(0.432)	0.08**	(0.930)
Enough_food	0.52	(0.183)	0.30	(0.105)	0.22**	(1.278)
No_food	0.23	(0.382)	0.25	(0.034)	-0.02	(0.553)
Tot_saved	52,735.04	(0.732)	46,966.08	(0.119)	5,768.96***	(0.066)
Access_credit	0.44	(0.390)	0.12	(0.429)	0.32***	(0.126)
Tot_credit	246,318.92	(0.172)	189,340.28	(0.064)	56,978.64**	(0.614)
Crop_area	1.46	(0.111)	1.44	(0.208)	0.02	(0.743)
Volatility	1.45	(0.162)	1.43	(0.653)	0.02	(0.016)
Skewness	0.55	(0.000)	0.53	(0.239)	0.02	(0.116)
Kurtosis	14.32	(0.693)	14.15	(0.934)	0.17*	(0.614)
Net returns	2,324.94	(0.307)	2,025.60	(0.228)	299.34**	(0.573)

Note: *Standard errors are in parenthesis.

Table 3 describes the differences in the mean between adapters and non-adapters of paddy cultivation. Generally, adopters are more educated and have more climate-smart agriculture awareness and practices than non-adopters. In addition, the total income, use of climate information, comparison of climate information, having enough food, total savings, and access to credit, total credit and net returns are significant mean differences from non-adopters. The latter part of the table provides the mean differences in the outcome of the interest of variance, skewness, kurtosis, and net returns. Table 2 depicts summary statistics of the variables.

The results show that the adopters gain higher benefits than non-adopters at a significant level. The mean differences of Kurtosis of adopters are significantly different from non-adapters at the 10% level, but the other parameters like volatility and skewness. These are mean differences but do not account for the effect of the different parameters. Thus, the decision to adapt to climate change is estimated as a selection implementing an endogenous switching regression model to capture the bias and its effects on adaptation and non-adaptation behaviour.

The following sections discuss the impact of adapting on farmers' net returns, variance, downward risk, and Kurtosis. Under this ESR model, selection and outcome equations are conjointly estimated by the full information maximum likelihood (FIML) approach. The following section explains the factors affecting the adaptation in four outcomes of interest.

Net Returns

The estimates of adapting to climate change and adaptation on net returns are presented in Table 4. The variables indicated in the climate changes, such as experience in drought, flood and CSA awareness, CSA practice, total income, received climate information, climate information usage, training to adapt to climate change, total savings, and total credits are significant predictors of the net returns of the farmers.

The adaptors of climate change are influenced by the drought and flood of the area. The adapters use several strategies for the adaptation, including farmer-to-farmer extension other than the government extension. Thereby, they are adjusting to climate change while increasing the net returns to non-adapters.

Among non-adapters of the climate change variations, marital status, the number of family members between the ages 16 – 60, having enough food, access to credit services and total credit are significant predictors of the net returns. Accordingly, these significant variables predict how farmers' adaptation to climate change varied regarding net returns. CSA awareness (0.562) and practices (0.427) are significant variables at a 5% level in adaptors implying that the use of awareness and practices of CSA is beneficial in deciding the adaptation to climate change. Because of their adaptation to climate change, the adapted farmers' total income and savings are higher at 5% significance than non-adapters.

Table 4: Determining factors of adaptation to climate change on net returns

Variables	Selection		Net Returns			
			Adaptors		Non-Adaptors	
Constant	3.225**	(0.341)	0.226	(0.834)	1.474	(0.255)
Flood	0.209	(0.106)	0.101	(0.283)	0.208***	(0.252)
Drought	0.237**	(0.392)	0.682***	(0.630)	0.461***	(0.613)
Age	0.041	(0.340)	0.912	(0.342)	0.782	(0.067)
Sex	0.923	(0.022)	0.436	(0.080)	0.487	(0.772)
Marital_status	0.213	(0.836)	0.227	(0.187)	0.362	(0.095)
Education	0.534**	(0.601)	0.702	(0.321)	0.429	(0.329)
HH_members	1.882	(0.754)	0.510	(0.112)	0.290	(0.092)
Below fifteen	0.287	(0.637)	0.190	(0.807)	0.635	(0.105)
Btwn 16 - 60 yrs	0.285***	(0.341)	0.875**	(0.903)	0.249**	(0.583)
CSA_awareness	0.228	(0.821)	0.562**	(0.128)	0.398**	(0.212)
CSA_practice	0.190***	(0.672)	0.427***	(0.732)	0.903**	(0.509)
Machinery	0.310**	(1.250)	0.201**	(0.919)	0.028**	(0.201)
Animal	0.601	(1.236)	0.108	(0.085)	0.160**	(0.471)
Off-farm jobs	0.100	(0.229)	0.401	(0.522)	0.631	(0.345)
Government extension	0.102**	(0.488)	0.313***	(0.185)	0.926**	(0.920)
Peer extension	0.129**	(0.372)	0.728**	(0.426)	0.290	(0.175)
Time_town	0.245	(0.225)	1.075	(0.043)	0.620	(0.745)
Tot_income	0.533***	(0.276)	0.198***	(0.389)	2.090***	(0.554)
Years_in_village	0.614	(0.400)	0.324	(0.955)	0.712	(0.195)
Climate_info	0.320***	(0.092)	0.289***	(0.490)	0.275***	(0.823)
Climate_info_use	0.556***	(0.845)	0.423***	(0.700)	0.357***	(0.368)
Train_climate_use	0.976	(0.223)	0.521***	(0.205)	0.304**	(0.135)
Climate_compare	0.423***	(0.990)	0.378	(0.584)	0.289	(0.452)
Enough_food	0.722	(1.478)	0.478**	(0.129)	0.673**	(0.128)
No_food	0.150	(0.533)	0.187	(0.445)	0.835	(0.634)
Tot_saved	0.812**	(0.036)	0.157***	(0.162)	0.293***	(0.649)
Access_credit	0.572***	(1.176)	0.484**	(0.300)	0.278**	(0.639)
Tot_credit	0.273	(0.664)	0.783***	(0.672)	0.489***	(0.934)
Crop_area	0.309	(0.473)	0.289	(0.311)	0.529	(0.298)
/lns1	2.987***	(0.298)				
/lns2	2.795***	(0.519)				
/r1	-0.646	(0.823)				
/r2	-12.288	(14.963)				
sigma_1	20.389	(3.666)				
sigma_2	24.508	(3.621)				
rho_1	-0.382	(0.246)				
rho_2	-1.000	(0.002)				
Wald chi2	chi2(1) = 148.72	Prob > chi2 = 0.000				
Log likelihood	61.732					
LR test of independent eqns.	4.44**					
No of observations	1,410		700		710	

Notes: The dependent variable is the natural logarithm of net return. Standard errors are in parenthesis.

***, **, * indicates the significant at 1%, 5%, and 10% level respectively.

The key factors of climate change knowledge are receipt of climate information, use of climate information and training for climate change, which are significant parameters to increase the income of the adapted farmers over non-adapted farmers. Among non-adapters, total credit is a significant variable in predicting the net returns implying that non-adapters must use more credits to increase the net returns than the adapters.

Volatility of Net Returns

Table 5 presents the estimated parameters of the volatility of net returns. The variables representing climate change, such as CSA awareness, CSA practice, education, total income, received climate information, climate information usage, training to adapt to climate change, total savings, and total credits, are significant predictors of the volatility of the farmers.

Among non-adapters of climate change, members below fifteen, having enough food and access to credit, and total credit and net returns are significant predictors of a 5% volatility level. Accordingly, both impacts of changes in net returns are influencing the farmers' adaptation decision to climate change.

The coefficients of experiencing drought and flood are negative. They are significant at 5% and 1%, respectively, among adapters indicating that by increasing the experience of flood and drought during the last year, adapters reduce the volatility of non-adapters. In adapters, the farmer-to-farmer extension is also positive and significant, implying that the sharing experiences among peers also support adapting the climate change.

Downside Risk Exposure

Downside risk exposure is also a significant risk factor affecting climate change's production risk. Therefore, understanding the downside risk is immense in the practice of CSA. According to the literature, this study estimates the impact of adaptation to climate change on skewness. Among adapters, drought (-0.66) is negatively significant at the 1% level, implying that the increasing drought condition reduces the downside risk exposure. At the same time, flood is a significant indicator for them to adapt to climate change.

Further, farmer-to-farmer extension programmes also support the adapting decision by the adapters. The adaptors of climate change have been determined by education, CSA awareness, CSA Practices, total income, climate information, climate information usage, comparison of climate information, having enough foods, and total savings. These determinants are highly significant in predicting the skewness of the net returns.

Moreover, non-adaptors are significantly predicted by the number of household members, household members aged below fifteen, CSA awareness, CSA practices, climate information, climate information usage, access to credit, and total credit obtained. These variables are also significant at the 5% level. It is observed that the skewness decreases for non-adapters implying that they experience downside risk frequently.

Table 5: Determining factors of adaptation to climate change on volatility

Variables	Selection		Volatility			
			Adaptors		Non-Adaptors	
Constant	2.456***	(2.313)	102.431**	(0.290)	112.392**	(0.252)
Flood	0.103	(0.105)	-0.129**	(0.753)	0.900	(0.125)
Drought	0.226*	(0.304)	-0.290***	(0.840)	0.230	(0.723)
Age	0.239	(0.198)	0.453	(0.962)	0.278	(0.167)
Sex	0.723	(0.129)	0.828	(0.472)	-0.298	(0.189)
Marital_status	0.208	(0.257)	0.761	(0.390)	0.673	(0.340)
Education	0.800	(0.445)	0.287**	(0.309)	0.792	(0.256)
HH_members	0.391	(2.242)	0.834	(0.623)	0.912	(0.556)
Below fifteen	0.428	(0.761)	0.482	(0.922)	0.776**	(0.444)
Btwn 16 - 60 yrs	0.822***	(0.377)	0.091	(0.765)	0.211	(0.255)
CSA_awareness	0.743	(0.609)	0.523**	(0.221)	0.552**	(0.202)
CSA_practice	0.333***	(1.352)	0.110***	(0.430)	0.239**	(0.433)
Machinery	0.290**	(0.230)	0.267**	(0.289)	0.049**	(0.734)
Animal	0.704	(0.223)	0.121*	(0.142)	0.183	(0.803)
Off-farm jobs	0.160	(0.285)	0.494	(0.572)	0.846	(0.762)
Government extension	0.129**	(0.203)	0.502***	(0.027)	0.404**	(0.478)
Farmer-to-farmer extension	0.197**	(1.426)	0.389**	(0.100)	0.073	(0.925)
Time_town	0.425**	(0.321)	1.190	(0.423)	1.103	(0.712)
Tot_income	0.432***	(0.893)	0.207**	(0.487)	0.692***	(0.911)
Years_in_village	0.397	(0.209)	0.573	(0.900)	0.372	(0.105)
Climate_info	0.328**	(0.325)	0.198***	(0.736)	0.297**	(0.883)
Climate_info_use	0.480**	(1.276)	0.255**	(0.521)	0.471**	(0.345)
Train_climate_use	0.239	(0.386)	0.552***	(0.755)	0.228**	(0.389)
Climate_compare	0.210**	(0.230)	0.411	(0.403)	0.289	(0.129)
Enough_food	0.238	(1.649)	0.238**	(0.489)	0.523**	(0.715)
No_food	0.270	(0.602)	0.222	(0.121)	0.437	(0.563)
Tot_saved	0.811**	(0.035)	0.780***	(0.138)	0.345***	(0.485)
Access_credit	0.297***	(0.155)	0.673*	(0.292)	0.382**	(0.297)
Tot_credit	0.298	(0.482)	0.593***	(0.428)	0.137***	(0.280)
Crop_area	0.231	(0.783)	0.908	(0.263)	0.273	(0.537)
Net returns	0.210**	(0.320)	0.183**	(0.237)	0.783**	(0.278)
/lns1	5.289***	(0.343)				
/lns2	4.939***	(0.248)				
/r1	-0.563	(0.501)				
/r2	-19.129	(14.865)				
sigma_1	123.422	(2.601)				
sigma_2	48.082	(2.312)				
rho_1	-0.238	(0.783)				
rho_2	-0.244	(0.962)				
Wald chi2			chi2(1) = 113.49	Prob > chi2 = 0.000		
Log likelihood	55.902					
LR test of independent eqns.	4.81**					
No of Observations	1,410		700		710	

Notes: The dependent variable is natural logarithm of volatility. Standard errors are in parenthesis. ***, **, * indicates the significant at 1%, 5%, and 10% level respectively.

Table 6: Determining factors of adaptation to climate change on downward risk exposure

Variables	Selection		Downward Risk Exposure			
			Adaptors		Non-Adaptors	
Constant	4.256***	(3.331)	10.213	(0.912)	11.893	(0.125)
Flood	0.109	(0.106)	0.132	(0.400)	0.918*	(0.273)
Drought	0.239*	(0.532)	-0.660***	(0.573)	0.063	(0.043)
Age	0.028	(0.010)	0.287	(0.232)	0.436	(0.023)
Sex	0.239	(0.052)	0.488	(0.023)	0.502	(0.042)
Marital_status	0.028	(0.387)	0.911	(0.747)	0.872	(0.735)
Education	0.852	(0.477)	0.682**	(0.381)	0.722	(0.329)
HH_members	1.398	(3.946)	0.952	(0.638)	0.892**	(0.539)
Below fifteen	-0.287	(0.397)	0.238	(0.492)	0.390**	(0.419)
Btwn 16 - 60 yrs	0.825***	(9.371)	3.099	(0.764)	1.209	(0.217)
IP_awareness	0.438	(0.662)	0.823**	(0.239)	0.794**	(0.238)
IP_practice	0.639***	(2.372)	0.127***	(0.121)	0.012**	(0.345)
Machinery	0.347**	(0.220)	0.383**	(0.103)	0.807**	(0.832)
Animal	0.651***	(0.831)	0.122*	(0.182)	0.211	(0.732)
Off-farm jobs	0.783	(0.238)	0.452	(0.627)	0.874	(0.733)
Government extension	0.039**	(0.902)	0.321***	(0.064)	0.420**	(0.672)
Peer extension	0.397**	(1.387)	0.436**	(0.392)	0.032	(0.062)
Time_town	1.245**	(0.326)	2.090	(0.023)	2.100	(0.213)
Tot_income	0.937***	(0.198)	0.298**	(0.059)	1.092	(0.923)
Years_in_village	2.164	(0.003)	0.345	(0.982)	0.776	(0.175)
Climate_info	0.227**	(0.232)	0.340***	(0.110)	0.430**	(0.490)
Climate_info_use	0.573**	(2.308)	0.213**	(0.746)	0.401**	(0.745)
Train_climate_use	1.021	(0.773)	0.571***	(0.105)	0.200	(0.111)
Climate_compare	0.543**	(1.220)	0.463**	(0.733)	0.175	(0.756)
Enough_food	0.773	(2.109)	0.226**	(0.769)	0.952	(0.775)
No_food	1.210	(2.002)	0.283	(0.874)	0.837	(0.218)
Tot_saved	0.826**	(1.035)	0.100***	(0.198)	0.242	(0.315)
Access_credit	0.288***	(2.108)	0.735	(0.202)	0.762**	(0.087)
Tot_credit	0.027	(0.762)	0.473	(0.874)	0.287***	(0.090)
Crop_area	0.003	(0.642)	0.638	(0.303)	0.893	(0.473)
Net returns	0.641**	(0.329)	0.746**	(0.863)	1.171	(0.645)
/lns1	3.177***	(0.153)				
/lns2	3.739***	(0.176)				
/r1	-0.484	(0.534)				
/r2	-16.684	(143.96)				
sigma_1	23.953	(3.673)				
sigma_2	42.053	(3.332)				
rho_1	-0.449	(0.442)				
rho_2	-1.000	(0.000)				
Wald chi2			chi2(1) = 139.63	Prob > chi2 = 0.000		
Log likelihood	53.762					
LR test of independent eqns.	3.48**					
No of Observations	1,410		700		710	

Notes: The dependent variable is natural logarithm of downward risk exposure. Standard errors are in parenthesis. ***, **, * indicates the significant at 1%, 5%, and 10% level respectively.

Kurtosis

Table 7 presents the analytical results of kurtosis. Since farmers are unwilling to the climate change events, the analysis is continued for the fourth moment of the function called kurtosis. Several factors determine the kurtosis of the net returns, and among them, drought and flood are negatively significant at a 1% level. It implies that increasing the experience of flood and drought among the adapters can reduce the kurtosis of production.

The adapters to climate change predict that the kurtosis depends on the sex of the household head, education, CSA awareness, CSA practice, the total income of the farmers, availability of climate information, usage of climate information, training to use climate change information, comparison of climate change, having enough foods, total savings, and net returns. The variables, sex, number of members aged below fifteen and between 16 to 60, CSA awareness, CSA practice, the total income of the farmers, availability of climate information, enough foods, access to credit and total credit are significant predictors of the adaptation of the non-adapters to the climate change at a 5% level.

Estimation of Average Treatment Effects on the Treated (ATT)

The estimates of ATT provide the impact of the adaptation to CSA activities on the four outcomes of interest in Table 8. Accordingly, adapting, and non-adapting farmers are statistically different. ATT estimates the selection bias in observable and unobservable parameters.

The ATT obtained from the net returns function is positive (0.212) and statistically significant at a 1% level, implying that the adapters are highly sensitive to the increased net returns, which have increased by 1.96% because of adapting to climate change. Table 8 also revealed that the adaptation significantly reduces downside risks and increases the net returns of the paddy farmers at a 1% significance level. A statistically significant (1% level) value of -0.002 of the volatility shows the counterfactual analysis in the production function that climate adaptation reduces the variance of net returns by around 12.5%. The mean skewness change is because of climate adaptation by the adapters than non-adapters.

The results also revealed that the ATT of 0.006 is statistically significant at the 1% level, indicating that adaptation to the CSA practices and other climate variables declined the downside risk exposure by about 150%. Finally, the variance is negative (-0.0002) and significant at a 1% level implying that the kurtosis value is statistically and significantly reduced by 12.5%. It means that adapting to climate change has tremendously affected the study's four primary outcomes of the adaptors and non-adaptors.

Adverse climatic conditions increase production risks, while risk-averse farmers adapt CSA practices to alleviate these conditions. Besides the farmers’ risk management strategies, they use a variety of applications to mitigate climate variations.

Table 7: Determining factors of adaptation to climate change on kurtosis

Variables	**Selection**		**Kurtosis** **Adaptors**		**Non-Adaptors**	
Constant	2.186***	(0.340)	3.108	(0.382)	1.993	(0.104)
Flood	0.101	(0.106)	-0.239***	(0.405)	0.964	(0.272)
Drought	0.219*	(0.712)	-0.637***	(0.490)	0.342	(0.633)
Age	0.408	(0.314)	0.477	(0.109)	0.209	(0.391)
Sex	0.865*	(0.107)	0.390**	(0.086)	0.398**	(0.109)
Marital_status	0.188	(0.471)	0.900	(0.728)	0.836	(0.623)
Education	0.347	(0.747)	0.843**	(0.303)	0.239	(0.333)
HH_members	1.228	(2.990)	0.489	(0.276)	0.390	(0.254)
Below fifteen	-0.227	(0.490)	0.181	(0.290)	0.223**	(0.087)
Btwn 16 - 60 yrs	0.266***	(1.189)	0.285	(0.443)	1.081**	(0.228)
CSA_awareness	0.191	(0.426)	0.109**	(0.454)	0.872**	(0.018)
CSA_practice	0.107***	(1.332)	0.623***	(0.504)	0.499**	(0.209)
Machinery	0.360**	(0.230)	0.201**	(0.138)	0.277**	(0.382)
Animal	0.728***	(0.211)	0.174*	(0.156)	0.240	(0.483)
Off-farm jobs	0.193	(0.393)	0.287	(0.949)	0.627	(0.938)
Govt_extension	0.117**	(0.198)	0.482***	(0.723)	0.024***	(0.743)
Farmer-to-farmer extension	0.134**	(1.382)	0.828**	(0.147)	0.031	(0.628)
Time_town	1.109	(0.206)	1.119	(0.473)	1.908	(0.222)
Tot_income	0.277*	(0.722)	0.673***	(0.440)	0.842***	(0.213)
Years_in_village	0.165	(0.233)	0.435	(0.952)	0.876	(0.075)
Climate_info	0.117**	(0.208)	0.320***	(0.055)	0.424***	(0.620)
Climate_info_use	0.173**	(1.318)	0.463**	(0.106)	0.001	(0.065)
Train_climate_use	0.022	(0.703)	0.473***	(0.199)	0.220	(0.151)
Climate_compare	0.223	(0.234)	0.904***	(0.203)	0.188	(0.725)
Enough_food	0.243	(0.164)	0.200**	(0.176)	0.774***	(0.715)
No_food	0.263	(2.298)	0.253	(0.454)	0.773	(0.407)
Tot_saved	0.126**	(0.015)	0.163***	(0.108)	0.222	(0.475)
Access_credit	0.118***	(3.148)	0.537*	(0.445)	0.790**	(0.117)
Tot_credit	0.227	(0.452)	0.862	(0.767)	0.198***	(0.463)
Crop_area	0.403	(0.612)	0.438	(0.633)	0.675	(0.177)
Net returns	0.632**	(0.310)	0.823**	(0.635)	0.172	(0.345)
/lns1	2.407***	(0.123)				
/lns2	2.199***	(0.731)				
/r1	-0.911	(0.783)				
/r2	-6.688	(13.90)				
sigma_1	21.900	(3.653)				
sigma_2	41.052	(2.323)				
rho_1	-0.509	(0.332)				
rho_2	-0.019	(0.010)				
Wald chi2			chi2(1) = 121.53	Prob > chi2 = 0.000		
Log likelihood	43.707					
LR test of independent eqns.	4.29**					
No of Observations	1,410		700		710	

Notes: The dependent variable is natural logarithm of Kurtosis. Standard errors are in parenthesis. ***, **, * indicates the significant at 1%, 5%, and 10% level respectively.

Table 8: Impact of adaptation on outcomes

Outcome Variables	Mean outcome			
	Adaptors	**Non-Adaptors**	**ATT**	**Change**
Farm net returns	11.248 (0.012)	10.836 (0.002)	0.212***	1.96%
Volatility	0.014 (0.002)	0.016 (0.001)	-0.002***	12.5%
Downward risk exposure	0.002 (0.001)	-0.004 (0.052)	0.006***	150%
Kurtosis	0.0014(0.000)	0.0016(0.000)	-0.0002***	12.5%

Notes: ATT= Average Treatment Effect on the Treated
*** significant at 1% level

Thus, adopting CSA practices reduces the risks, increasing net returns and paddy farmers' benefits. Even though new technology implementation has challenged to adapt CSA practices and improved access to training and extension services on these practices. The results show that credit constraints are also one of the main factors to be considered by non-adapted farmers. In contrast, adapted farmers use climatic information and use such information to increase productivity.

The measures of net returns, volatility, downside risk exposure, and kurtosis are influenced by the experience of drought and flood to adapt the climate change. Further, among many other factors, changes in drought and flood cause adaptation to the climate variations by the adaptors, increasing the net returns while reducing the volatility and risk exposure. According to the results, when appropriate, the farmers can manage the production risks in terms of net returns reducing risk exposure to climate change. Index-based insurance programmes and provision for drought-tolerant paddy varieties can be successfully implemented to mitigate the impact of severe floods and drought. Adaptation is highly influenced by climate and socio-economic and credit-related variables in the empirical analysis. The results further show that the CSA practices help reduce the paddy farmers' net returns, volatility, and downside risk exposure.

CONCLUSION AND POLICY RECOMMENDATIONS

The paper investigates determinants influencing the adaptation to climate-smart agricultural activities against climate change and the impact of adaptation of CSA practices on net returns, volatility, and skewness among paddy cultivating farmers in Sri Lanka.

The study used cross-sectional data gathered from a sample of 1410 paddy-cultivating farmers from Horowpathana area in Sri Lanka. It was found that, from a mean comparison, the differences between adapting and non-adapting farmers in terms of risk-related variables and productivity is different. However, the ESR model is applied to robustly investigate the determining factors of climate change adaptation decisions on the outcomes.

The analysis of the average treatment effect shows that drought and flood reduce the volatility of net returns by 12.5%, downside risk exposure by 150% and kurtosis by 12.5 %. Further, adaptation to climate change increases the net return by 1.96%. These findings propose that adapting to climate change can significantly increase productivity and net returns among paddy-cultivating farmers. Moreover, the factors that determine the adaptation to climate change has tremendously influenced by a set of variables, including flood and drought.

The results depicted that education level has a significant positive impact on adaptation in the selection model and farm net returns, indicating that education is an important determinant. In a summary of the model analysis, it can be predicted that the adapters are more vigilant and have strategies to manage climate change, even using climate-smart agricultural training. Further, government extension programmes are essential for adapting and non-adapting farmers even if the non-adapters are not using the strategies to overcome experiencing drought or flood.

Several policy recommendations can be derived from the study. It is vital to increase productivity and net returns among paddy-cultivating farmers through adaptation. Moreover, the factors that determine the adaptation to climate change have been tremendously influenced by a set of variables, including flood and drought—further, planning and implementation of climate change adaptation policies with the use of evidence in the research. The index insurance programme can be expedited to meet the requirements of the farmers who are in rural areas to be adapted for the climate change impacts of drought and flood.

The research outcomes suggest that education is essential to climate change adaptation. Therefore, the farmers can be provided with climate change education and related information for successful adaptation strategies. For instance, drought-tolerant varieties can be introduced in severe drought areas. Thus, agricultural extension services can tremendously affect farmer education for effective adaptation in those regions. The use of information highly influences the comparison between the adaptors and non-adaptors of climate change through government extension services and peer-learning processes. Therefore, providing accurate and timely information for the farmers can enhance the adaptation.

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