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Determinants of choice of climate change adaptation practices by smallholder pineapple farmers in the semi-deciduous forest zone of Ghana

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ABSTRACT

This paper explored the extent to which the awareness of climate change affects the choice of climate change adaptation practice by smallholder pineapple farmers. This study used a cross-sectional data collected from 150 farmers in the Nsawam Adoagyiri Municipality, Ghana. We applied the Latent Class Analysis (LCA) to identify sub-population of pineapple farmers based on their awareness levels of climate change and socioeconomic characteristics. We then used a multinomial logistic regression to examine the extent to which differences in climate change awareness influence adaptation choices. Results indicated that, smallholder pineapple farmers are well aware of climate change and perceived changes in rainfall and temperature patterns. Further, the findings revealed that smallholder pineapple farmers are implementing a host of on-farm and off-farm climate change adaptation practices including irrigation, adjusting planting time, land fragmentation, the use of agro-ecological knowledge, and seasonal migration. The LCA identified three subgroups of smallholder pineapple farmers based on their level of awareness of climate change – *strong climate change awareness* group ($n = 111$; 74%), *moderate climate change awareness* group ($n = 18$; 12%) and *poor climate change awareness* group ($n = 21$; 14%). Results showed marginal differences in the adoption rate of adaptation practices across the observed subgroups of farmers. We identified that institutional factors including the quality of climate information, quality of extension services, access to credit, education and access to extension services have a stronger effect on climate change awareness and the choice of adaptation practice compared to individual factors such as gender, marital status and farmers' age.

1. Introduction

Climate change threatens the attainment of the Sustainable Development Goals (SDGs) particularly goals relating to poverty reduction (SDG1) and food security (SDG2). This is significantly the case for many West African countries, where the majority of the people are predominantly dependent on climate sensitive sectors including agriculture and forestry. Climate change affects rain-fed agricultural systems through reduction in water resources, increasing temperature patterns coupled with high pest infestation and declining soil quality. West Africa is particularly vulnerable because of low adaptive capacity and high incidence of poverty (Mertz et al., 2011).

Ghana like many other West African countries is likely to experience increased rate of intense disasters like floods and droughts closely associated with changes in the climate (Asante and Amuakwa-Mensah, 2015) and this could affect food production especially for vulnerable communities in northern Ghana. Across Ghana, many problems relating to intra-annual rainfall inconsistency and temperature increase are further compounded by numerous political, socio-economic and ecological challenges. This has serious consequences for Ghana's growth and could undermine progress made towards eradicating poverty and hunger. The agricultural sector contributed 19.83% to Ghana's GDP in 2019, with a gross value-added growth rate ranging between 2.3% and 6.4% from 2015 to 2019 (Ministry of Finance, 2020). The sector also provides employment for significant proportion of the population; although Ghana has witnessed a drastic reduction in agriculture employment from 51.5% in 2009 to 29.2% of total employment in 2019 (Food and Agriculture Organization [FAO], 2020). Within the

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agricultural sector, horticultural production contributes significantly to the socioeconomic development of Ghana by providing employment opportunities to smallholder farmers. For instance, horticultural products contributed 82 million USD of exports in 2016 (Ghana Export Promotion Authority, 2016).

Pineapple (*Ananas comosus)* is grown in many tropical and subtropical regions of the world (Hossain, 2016; Wali, 2019). It is the most economically developed sector of the horticultural industry in Ghana (Danielou and Ravry, 2005); and particularly for the majority of farmers in the Nsawam Adoagyiri Municipality; pineapple is a major livelihood strategy (Ghana Statistical Services, 2014). Pineapple is also a major non-traditional crop that generates significant foreign exchange for Ghana (Ghana Statistical Services, 2014). Yet, pineapple production is constrained by several factors including climate change (Williams et al., 2018). Given the importance of pineapple production, it is critical to build the adaptive capacity of smallholder pineapple farmers to manage climate risks by identifying adaptation practices.

Adaptation involves adjustment in the social and economic structures by stakeholders in response to actual or expected climate and its effects (Intergovernmental Panel on Climate Change [IPCC], 2014). For resource-constrained farmers in dryland farming systems, where climate vulnerability is often high, adaptation is recognized as an essential intervention that can be used to address the threats posed by climate change and thereby increase household resilience and food security (Antwi-Agyei & Nyantakyi-Frimpong, 2021; Sonko et al., 2020; Tambo and Abdoulaye, 2013). Nonetheless, farmers' adaptation practices are closely linked to their perception of the changing patterns in rainfall and temperature (Mekonnen et al., 2018; Elum et al., 2017; Codjoe et al., 2014; Simelton et al., 2011). Farmers will only implement adaptation strategies if they can perceive changes in the climate. Therefore, perception of the long-term changes in rainfall and temperature may have its weight on decisions to initiate adaptation practices by smallholder farmers (Simelton et al., 2011).

Various studies have explored how climate change affects pineapple production. Williams et al. (2017) reported that, climate variability poses a significant challenge in the production of pineapple in Ghana. De Mondonca (2015) reported that sub-standard pineapple fruits in Essequibo Tri-Lakes Area in Guyana could be attributed to lack of rains closely linked to climate change. Whilst these studies contribute evidence on the impact of climate change on pineapple production, evidence on how pineapple farmers respond to the adverse effects of climate change based on their perception of climate change has received relatively little research attention (Wuepper et al., 2020; Williams et al., 2018). This paper addressed this research gap by exploring the extent to which the perception of climate change affects the choice of adaptation strategy by smallholder pineapple farmers in the semi-deciduous forest ecological zone of Ghana. The study answers three critical questions: (i) what is the awareness of smallholder pineapple farmers on climate change? (ii) are there variations in smallholder pineapple farmers perceptions; and (iii) to what extent does these variations influence the

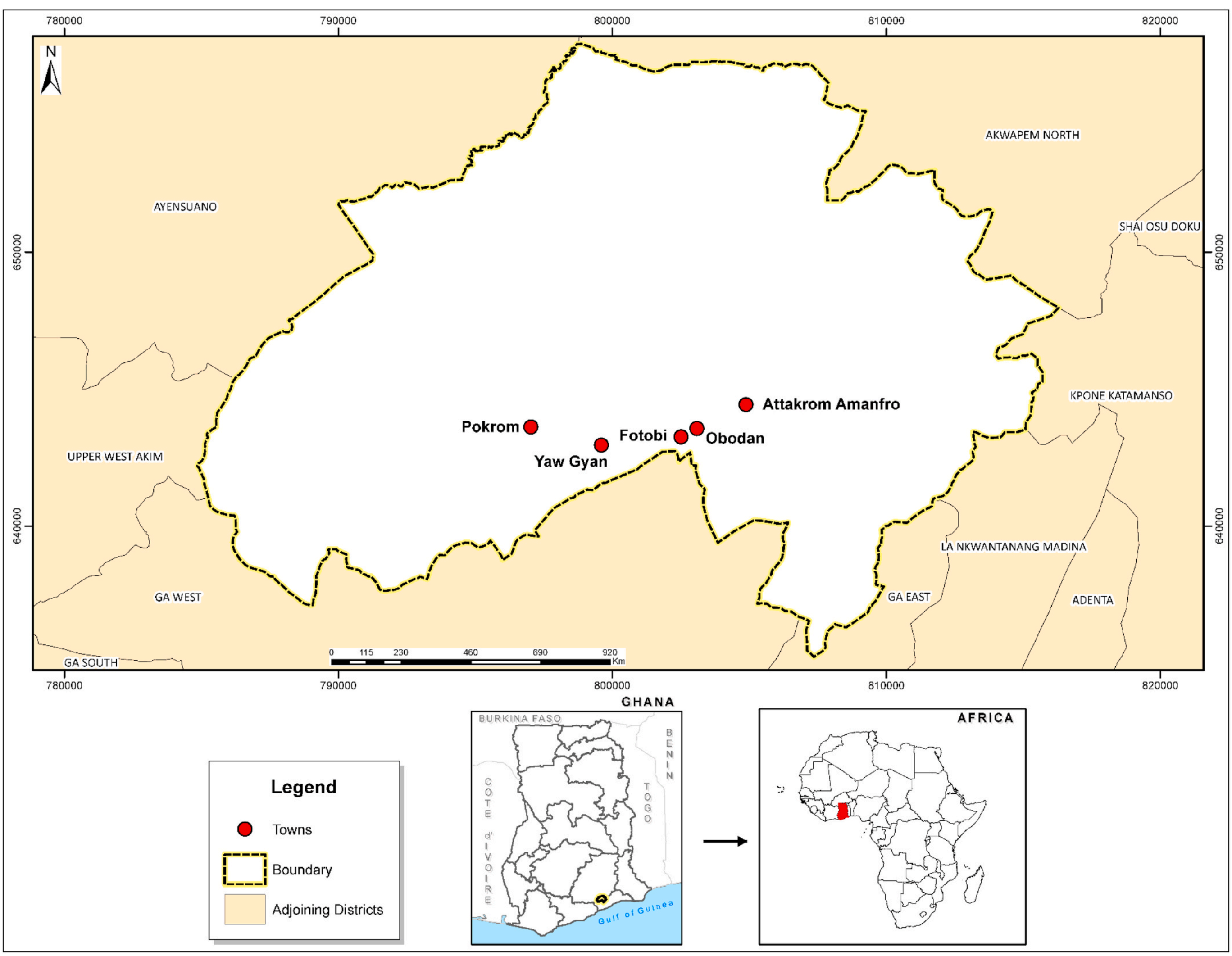

Fig. 1. Map of Nsawam Adoagyiri Municipality showing study communities.

choice of a particular climate change adaptation practice by smallholder pineapple farmers?

2. Research methodology

2.1. Description of the study area

Located between latitude 5'.45 N and 5'.58 N and longitude 0.07′W and 0.27′ W (Fig. 1), the Nsawam Adoagyiri Municipality has a total population of 86,000 (Ghana Statistical Services, 2019). Weather conditions in the municipality are warm during the day and cold at night. The Municipality records a total annual rainfall of 1250 mm–2000 mm per annum and is characterized by a mean annual temperature ranging from 26 °C to 30 °C (Ghana Statistical Services, 2014). About 90% of the municipality used to be forested (Ghana Statistical Services, 2014). However, very little of the forest cover remain today largely due to bad farming practices and uncontrolled exploitation for timber (Ghana Statistical Services, 2014).

The major crops cultivated include pineapples (*Ananas comosus*), pawpaw (*Carica papaya*), oranges (*Citrus sinensis*), and maize (*Zea mays*) among others. The economic activities sustaining the livelihoods of the residents are categorized into agriculture, commerce/trade and industry (Ghana Statistical Services, 2014). Farming is the key occupation for many in this municipality, especially those in rural areas. The municipality is best known for its production of pineapples in larger quantities for export.

2.2. Sampling process and sample size

The Nsawam Adoagyiri Municipality was purposively selected since it is a major pineapple-growing area. With the technical assistance from the Municipal Ministry of Food and Agriculture, five communities (Yaw Gyan, Fotobi, Obodan, Attakrom Amanfro and Pokrom) were purposefully selected. The selection of these communities was based on the intensive pineapple farming that is undertaken in the communities. In each community, households were randomly selected by ballot. Each household was allocated a ballot paper. A total of 30 households were selected from each of the five communities. This was done to achieve a sample size of 150 respondents intended for this study.

2.3. Data collection

A cross sectional study design was adopted to explore the perception and adaptation practices of pineapple farmers to climate variability. The respondents consisted of pineapple farmers who have lived in the selected community and have been engaged in pineapple farming for at least 15 years. The essence was to understand the past and present situations of pineapple production in relation to climate variability. The questionnaire was administered from March to April 2018, to randomly selected study respondents. Questionnaires were administered to the head of the household or the representative in the absence of the household head. A simple random sampling approach was employed for this study because it provided opportunity for all smallholder pineapple farmers in the study communities to be selected for the questionnaire administration. The respondents were briefed on the purpose and relevance of the study before the administration of the questionnaire. The questionnaire, which was pretested contained closed ended questions and covered areas including the socio-demographic characteristics of the respondents, the perception of the respondents to rainfall and temperature patterns. The other questions were related to the adaptation measures of pineapple farmers as well as the barriers to these adaptation practices. The interviews were conducted in the respondents' homes or at convenient places within the community. The consent of each respondent was sought. Further, each respondent was given the opportunity to withdraw at any point they felt uncomfortable.

2.4. Data analysis

2.4.1. Latent class model

The analysis commenced with the application of the latent class analysis (LCA) to identify sub-populations of farmers based on their socioeconomic characteristics. The latent class model is a statistical methodology that assumes that there is an underlying unobserved factor that divides a given population into mutually exclusive and exhaustive groups (Breffle et al., 2011). Group membership is however unknown but can be inferred from a set of observable data. The individual members within the same group exhibit the same characteristics but different from colleagues in alternative subgroups within the same population (Lanza and Rhoades, 2013; Peugh and Fan, 2013). The LCA has been widely applied to understand the taxonomy of behavioral outcomes and profiles (see Vaughn et al., 2013; Fox et al., 2013; Peugh and Fan, 2013).

Following Lanza and Rhoades (2013), we expressed our LCA model mathematically as a function of the probability of a farmer's awareness of changes in a climate variable, k conditioned on the probability of membership, ρ_g into a set of group, g fixed on observable socioeconomic characteristics. If r_k represent awareness r of changes in a climate variable, k and the pattern of awareness is given by y then the probability of observing a particular vector of awareness is:

$$P(Y=y)=\sum_{g=1}^{G}\rho_g\prod_{k=1}^{K}\prod_{r_k=1}^{R_k}\varphi_{k,r_k g}^{I(y_k=r_k)} \tag{1}$$

where $I(y_k = r_k)$ is an indicator variable that takes the value of 0 and 1; such that $I(y_k = r_k)$ is equal to 1 if the awareness of changes in climate variable $k = r_k$. The vector of group member probabilities is represented by ρ and expected to sum to unity and φ is the vector of climate variable awareness contingent on the group membership. To identify the optimal number of groups in the sample population, a series of latent models were compared based on equation (1). A total of 5 models were examined and the optimal model was selected based on entropy and G^2 log likelihood for each estimated model. The study also relied on the Lo-Mendell-Rubin Adjusted Likelihood Ratio Test and information statistics (AIC, and sBIC). With the selection of the optimal model, the optimal number of groups were also interrogated and individual farmers were assigned to respective subgroups based on the maximum posterior probability. This number of subgroups illustrates the classes of climatic change awareness among farmers.

2.4.2. Weighted average climate change awareness index

Weighted average of subgroup climate change awareness index was calculated based on the three subgroup latent class solution. Weighted average index (WAI) is a type of mean calculated by multiplying the weight associated with a particular event or outcome with its associated quantitative outcome and then summing all the products together. It is very useful when calculating a theoretically expected outcome where each outcome has a different probability of occurring. WAI was estimated using the equation below as employed by other authors (Ndamani and Watanabe, 2015; Uddin et al., 2014) in climate change studies.

$$\mathrm{WAI} = \frac{\sum FiWi}{\sum Fi} \tag{2}$$

where F is the frequency of farmers' climate change awareness, W is the weight of each score and i is the score. We defined the standard of strong, moderate and low climate change awareness as follows: < 0.60 = very low; $0.60 \le x \le 0.65$ = low; $0.66 \le x \le 0.70$ = moderate; $0.71 \le x \le 0.75$ = high; > 0.75 = very high.

2.4.3. Multinomial logistic regression

The multinomial logistic regression was used to examine the extent to which differences in climate change awareness influences adaptation choices. Adaptation strategies were classified in terms of on-farm and off-farm practices. The multinomial logistic regression model denotes a random variable y which takes on the values $1, 2, 3, ..., J$ conditioned on the $1 \times K$ vector of independent variable x (Deressa et al., 2009). If y is the adaptation strategies available to farmers then the probability that farmer, i will choose j out of the J number of strategies available consequent to a change in the element of x can be specified as:

$$P(y=j|x)=\pi_i=\frac{\exp\{x_i'\beta_j\}}{1+\sum_{h=1}^{J}\exp\{x_i'\beta_j\},j=1,2,3,\dots,J} \quad (3)$$

We used six options to capture the on-farm strategies and five adaptations options under off-farm methods. Because equation (3) yields parameter estimates which do not reflect the probabilities or the magnitude of change; they are only appropriately interpreted in relation to the direction of effect of the independent variables on the dependent variables (adaptation choices). Since our focus is on finding out the factors which determine the farmers' choice of climate adaptation strategy, we consider the marginal effects of the explanatory variables based on the multinomial logit model. This requires differentiating equation (3) with respect to the independent variables such that

$$\frac{\partial P(y_i=j|\boldsymbol{x}_i)}{\partial \boldsymbol{x}_k}=P_j\left(\beta_{jk}-\sum_{j=1}^{J}P_j\beta_{jk}\right) \quad (4)$$

2.4.4. Empirical strategy

At the first stage, the latent class analysis was applied to categorize the farm households into classes based on awareness of climate change. The set of awareness cohorts is then regressed on a set of covariates to determine the factors that predict group membership and by inference the awareness level of farmers. The logistic link function is used to examine the predictors that define the climatic change awareness level of sampled farmers (Dayton and Macready, 1988). The study further extends the analysis to establish the linkage between farmers' perception of climate change and adaptation choices. The probability of a farmer adopting an adaptation strategy is modeled using the multinomial logistic regression and controlling for a set of farm specific, environmental and institutional covariates; whilst observing the differential effect of awareness groups on adaptation choices among farmers. Finally, to understand the motivation for the adaptation choice, we examine constraint channels that power the choice of adaptation for each farmer group.

The basic multinomial model specified in (3) and (4) can be empirically written as follows:

$$\begin{aligned}y_i = {} & \beta_0+\beta_1 Age_i+\beta_2 Marital\_Status_i+\beta_3 Gender_i+\beta_4 Education_i\\ & +\beta_5 Household\_Size_i+\beta_6 Distance_i+\beta_7 Credit_i\\ & +\beta_8 Land\_Ownership_i+\beta_9 Literacy_i\\ & +\beta_{10} Access\_to\_Extension\_Service_i\\ & +\beta_{11} Quality\_of\_Extension\_Service_i\\ & +\beta_{12} Quality\_of\_Climate\_Information_i\\ & +\beta_{13} Awareness\_of\_Climate\_Change_i+v\end{aligned} \quad (5)$$

where y_i represents the adaptation choice selected by each individual farmer, i. v is the error term. The multinomial logistic regression was considered most appropriate for this study because it provides the advantage of examining the factors that predict the choice of an adaptation strategy with reference to a key strategy (reference category) given the set of farmer-specific characteristics and environmental attributes. The reference strategy used in this paper is "no adaptation" strategy was subsequently normalized to estimate the predictors of climate change adaptation strategies among the sampled smallholder pineapple farmers.

3. Results and discussion

3.1. Latent class model to classify farmers based on awareness of climate change

Latent models containing 1 to 5 classes were fit for the data. The models were then compared to select the best model that describes the multiple level of farmers' awareness on climate change in the study area (Table 1). The Vuong-Lo-Mendell-Rubin Likelihood Ratio Test suggests that the model with 2 subgroups solution is superior to the one-class solution ($p < 0.001$). A 3-subgroup solution was also identified to be superior to the 2-subgroup solution ($p < 0.001$). Similarly, the 4-subgroup solution was found to be a better fit compared to the 3-subgroup solution ($p < 0.001$); however, the 5-subgroup solution was not statistically different from the 4-subgroup solution ($p < 0.211$). Notwithstanding, the class size that resulted from the 4-subgroup model was considered inadequate (7 individuals, constituting 4.72% of the sample).

As noted by Hipp and Bauer (2006), a group size less than 5% of the total sample is suggestive of a spurious class. We therefore selected the 3-subgroup model solution as the best fit model. Based on the entropy value of 0.99, it was also considered that in 9 out of 10 cases the 3-subgroup model correctly assigned individual farmers to their appropriate subgroup.

Subgroup 1 which comprises 74% of the sample ($n = 111$) represents farmers who reported noticing harsh climatic conditions: rainfall, temperature and windstorms. Specifically, members of subgroup 1 perceived increased temperatures, late but reduced rainfalls and strong windstorms. We labeled this subgroup *strong climate change awareness* group. The second subgroup was labeled *moderate climate change awareness* group due to a high probability of reporting moderately harsh changes in rainfall and temperature conditions. Farmers in this group perceived an increased rainfall, increased temperature, shorter seasons, and early rainfall with moderate windstorms. The second subgroup represented 12% of the total sample ($n = 18$). Farmers in subgroup 3 represent 14% of the sample ($n = 21$) and reported a mixed perception on climate differences in the past 30 years. We labeled this subgroup *poor climate change awareness* group. Individual members perceived both increased and decreased temperatures, early rainfalls, and low windstorms.

Based on the three subgroup latent class solution, we calculated the weighted average of subgroup climate change awareness index. It was detected that farmers with strong climate change awareness have a relatively high awareness index of 0.745 with an exhibited high awareness on wind storms and rainfall pattern but moderate perception on temperature changes. The moderate climate change awareness subgroup, on the other hand obtained a weighted average awareness index of 0.679 with a reported strong perception on rainfall and temperature patterns; whereas the poor climate change awareness subgroup obtained a weighted average awareness index of 0.601 with an exhibited strong perception on rainfall patterns with a lower awareness on temperature changes. It can be inferred that changes in rainfall patterns are widely observed by farmers relative to windstorms and temperature changes,

Table 1
Diagnostics for latent class models.

	Number of classes			
	2	3	4	5
G^2	195.52 (1.00)	88.63 (1.00)	48.06 (1.00)	22.85 (1.00)
AIC	719.446	643.213	611.981	621.644
BIC	776.649	730.521	729.395	769.165
SSA-BIC	716.517	638.742	605.968	614.090
LMRT(*p*-value)	380.60 (0.001)	94.35 (0.001)	53.74 (0.001)	18.27 (0.211)
Entropy	1.000	0.999	0.999	0.999

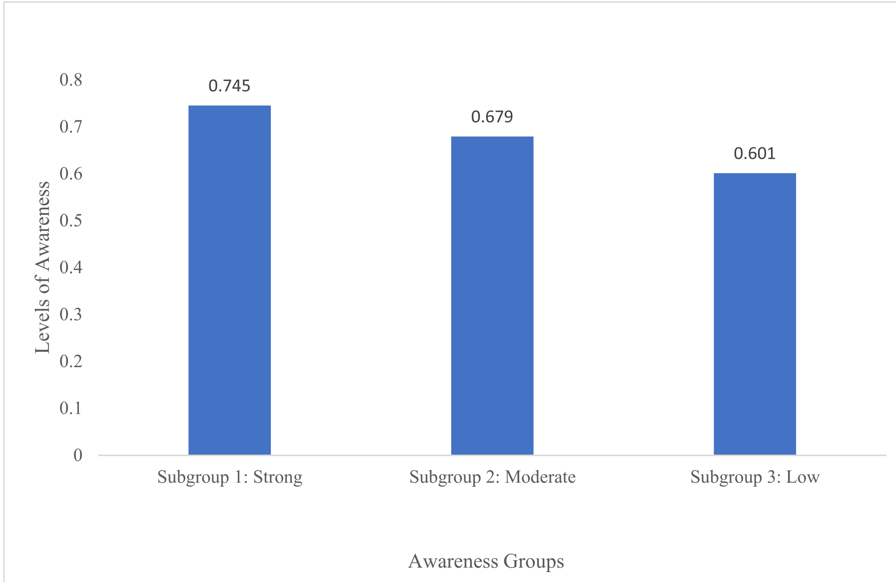

Fig. 2. Farmers climate change awareness index.

respectively. Fig. 2 provides a report of computed farmers' climate change awareness index.

3.2. Factors influencing farmers awareness of climate change

The results revealed variations in climate change awareness among farmers. Results show that farmers do not equally perceive the changes in climatic conditions. We hypothesize that the differences in perception or awareness level will influence the adaptation responses of farmers. To test this hypothesis, it is important to first find out the factors that drive the differences in awareness level among the farmers. The results of this analysis has several policy relevance; including identifying which farmers to target with climate information. The findings is also relevant for identifying gaps in existing policy efforts in improving the climate change literacy rate of farmers; with the purpose of equipping farmers with the relevant information. We compared the robustness of the OLS, multinomial and ordinal logit regressions to determine the model of best fit.

The information statistics suggested that the multinomial logit regression best fit the data; as it contained the lowest AIC and BICs [AIC = 107.211; BIC = 173.149]; compared to the OLS [AIC = 237.046; BIC = 270.016] and the ordinal logit model [AIC = 150.357; BIC = 190.353]. The log-likelihood ratio test of joint significance also suggested that the multinomial logistic model is valid [LR $\chi^2(20) = 161.33$; *p*-value = 0.001] and possesses a strong explanatory power (Nagelkerke $R^2 = 0.782$). We therefore interrogated the factors that account for differences in climate change awareness using the multinomial logistic regression. Ultimately, we assessed the factors that explain the probability of a farmer becoming a member of a climate change awareness subgroup; and by extension, the predictors of climate change awareness among farmers. We normalized subgroup 2 in the multinomial logit estimation to identify the factors that predict low and high awareness with community covariates fixed. Thus, subgroup 2 is the base category and the multinomial logistic regression results are interpreted as the average change in the probability of gaining a high or low level awareness relative to a moderate climate change awareness level due to

Table 2
Determinants of climate change awareness among farmers.

	Strong Awareness		Poor Awareness		Moderate Awareness
	Coefficient	dy/dx	Coefficient	dy/dx	dy/dx
Intercept	5.311***		5.033***		
Farmer's Age	−7.480*	−0.094	−6.615*	−0.023	0.117**
Marital Status	−1.008	−0.057	0.225	0.051	0.006
Gender	−3.878	−0.057	−3.206	−0.001	0.059
Farmer Household size	−9.368**	−0.067	−9.538**	−0.090	0.157**
Average Distance	4.270	−0.010	5.363	0.090	−0.080
Access to Credit	−9.068**	−0.214***	−5.495	0.094	0.119*
Land Ownership	1.476	0.225***	−3.894	−0.247***	0.022
Quality Extension Service	19.40***	0.079	−21.281**	−0.259**	0.338**
Inadequate Climate Info.	4.729	−0.051	6.963**	0.149***	−0.098**
Education	5.815**	0.520***	−1.803	−0.320***	−0.217***
Base Category	Subgroup 2: Moderate Climate Change Awareness				
Observations	150				
Joint Significance	LR $\chi^2(20) = 161.33$				
−2 Log Likelihood	63.211				
Pseudo (Nagelkerke) R^2	0.782				

Asterisks ***, **, * denotes parameter is significant at less than 1%, 5% and 10% significance level respectively.

a marginal change in the independent variables. The results are reported in Table 2.

The marginal effect results suggest that farmer's age predicts awareness to climate change (Table 2). Access to credit predicts climate change awareness. Access to credit increases the probability of having a moderate climate change awareness but reduces the likelihood of a farmer exhibiting a strong climate change awareness by 21.4%. Thus, if a farmer is observed to have acquired a credit facility the probability that the farmer has a strong climate change awareness level compared to a moderate climate change awareness level reduces by 21.4%.

The results also indicate that landholding conditions of a farmer increases the probability of having a strong climate change awareness by 22.5% compared to the moderate climate change awareness. Nonetheless, the probability that the farmer is a member of the subgroup with poor awareness on climate change reduces significantly by 25% relative to having a moderate climate change level. The implication is that land ownership significantly influences smallholder pineapple farmers' awareness of climate change. Results show significant influence of quality of extension service delivery on climate change awareness among farmers. An increase in quality of extension service delivery is found to reduce the probability of having a poor climate change awareness by 25.9%.

Additionally, an inadequate climate and weather forecast information increases the probability of a farmer falling in the poor climate change awareness category by 14.9%. With reference to education, farmers with high level of education are 52% more likely to have a strong climate change awareness and 32% less likely to exhibit a poor awareness on climate change relative to a moderate awareness on climate change. The heterogeneities in resource ownership and capabilities explain the observed differences in climate change awareness among farmers. Farmers with little or relatively low access to resources are less likely to build individual capacities and access information about climate change. The relatively low access to information due to inadequate resources reduces the probability of a farmer to be conscious about the variations in climatic conditions, patterns and associated consequences. This is likely to influence the level of preparedness and overall decisions on the appropriate farming methods and practices to adopt to stem the negative effect of climate change.

3.3. *Effect of climate change awareness on the choice of adaptation strategy*

To examine the extent to which the farmers' level of climate change awareness influence adaptation choices, a multinomial logit regression was employed. Adaptation practices of smallholder pineapple farmers in the study area were divided into off-farm and on-farm practices and regressed on climate change awareness levels controlling for the socio-economic conditions of farmers. Six on-farm strategic options were evaluated including irrigation, land fragmentation, adjusting planting time, planting of improved crop varieties, soil conservation and crop diversification. Five off-farm adaptation strategies were also assessed including off-farm income, seasonal migration, family and friends support, agro-ecological knowledge and government & NGOs support.

Table 3 provides a descriptive statistics of the sample data and show that the adoption rate of on-farm strategies is greater compared to off-farm practices. The descriptive report shows a wide application of

Table 3
Descriptive statistics.

	All N = 150		Subgroup 1: Strong N = 111		Subgroup 2: Moderate N = 18		Subgroup 3: Poor N = 21		Description
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	
Age	1.260	0.798	1.288	0.743	0.833	1.098	1.476	0.680	Categorical Variable: 0 = below 40 years, 1 = above 40 years
Marital Status	0.767	0.424	0.883	0.323	0.167	0.383	0.667	0.483	Categorical Variable: coded as 0 = Single, 1 = Married
Gender	0.253	0.436	0.171	0.378	0.333	0.485	0.619	0.498	Categorical Variable: coded as 0 = Male Farmer, 1 = Female Farmer
Education	1.073	0.506	1.207	0.450	0.611	0.502	0.762	0.436	Categorical Variable: coded as 0 = Never attended school, 1 = Attended school
Household Size	0.730	0.862	0.523	0.789	1.722	0.461	0.952	0.865	Categorical Variable: coded as 0 = below 4, 1 = family size above 4
Average distance to your farm	0.347	0.555	0.387	0.575	0.222	0.548	0.238	0.436	Categorical Variable: coded as 0 = 1–3 km, 1 = 4–6 km, 2 = 7 km+
Access to credit facilities	0.093	0.292	0.009	0.095	0.222	0.428	0.429	0.507	Categorical Variable: coded as 0 = No Access, 1 = With access
Type of credit formality	1.867	0.444	1.982	0.190	1.556	0.856	1.524	0.602	Categorical Variable: coded as 1 = Access to formal credit, 2 = Access to informal credit facility
Type of land ownership	0.813	0.391	0.919	0.274	0.833	0.383	0.238	0.436	Categorical Variable: coded as 0 = Inherited, 1 = Leased
Access to extension services	0.813	0.391	0.874	0.334	0.278	0.461	0.952	0.218	Categorical Variable: coded as 0 = No Access, 1 = With access
Quality of extension services	0.848	0.362	0.955	0.208	0.222	0.427	0.809	0.402	Categorical Variable: coded as 0 = Low level of perceived quality, 1 = high level of perceived quality
Quality of climate information	0.963	0.212	0.955	0.208	0.889	0.323	1.000	0.000	Categorical Variable: coded as 0 = Low level of perceived quality, 1 = high level of perceived quality
Literacy levels	0.627	0.485	0.514	0.502	0.944	0.236	0.952	0.218	Categorical Variable: coded as 0 = Low level of perceived literacy rate among farmers, 1 = high level of perceived literacy rate among farmers
Irrigation	0.178	0.384	0.099	0.300	0.389	0.502	0.471	0.514	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Land fragmentation	0.953	0.212	0.973	0.163	0.833	0.383	0.952	0.218	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Adjusting planting date	0.627	0.485	0.658	0.477	0.278	0.461	0.762	0.436	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Improved varieties	0.760	0.429	0.721	0.451	0.833	0.383	0.905	0.301	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Soil conservation	0.913	0.282	0.910	0.288	1.000	0.000	0.857	0.359	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Crop diversification	0.533	0.501	0.550	0.500	0.167	0.383	0.762	0.436	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Off-farm income	0.407	0.493	0.369	0.485	0.222	0.428	0.762	0.436	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Seasonal migration	0.133	0.341	0.027	0.163	0.222	0.428	0.619	0.498	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Relying on support from family & friends	0.713	0.454	0.793	0.407	0.278	0.461	0.667	0.483	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Agro-ecological knowledge	0.393	0.490	0.261	0.441	0.778	0.428	0.762	0.436	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted
Reliance on governmental and NGOs	0.073	0.262	0.027	0.163	0.167	0.383	0.238	0.436	Categorical Variable: coded as 0 = Not Adopted, 1 = Adopted

land fragmentation (Mean = 0.953, SD = 0.212), soil conservation (Mean = 0.913, SD = 0.282) and the use of improved varieties (Mean = 0.760, SD = 0.429).

On the other hand, the most prevalent off-farm adaptation practice is detected to be reliance on family and friends for support (Mean = 0.713, SD = 0.454). There is also observed marginal differences in the adoption rate of adaptation strategies across the observed subgroups of farmers based on awareness and perception of climate change. For instance farmers with poor awareness level are most likely to pursue off-farm income (Mean = 0.762, SD = 0.436) relative to their counterparts with strong and moderate awareness level. A large proportion of farmers who engage in soil conservation are identified to portray strong awareness and moderate awareness level, respectively.

The multinomial logit regression was subsequently conducted and results are reported in Tables 4 and 5. Table 4 focuses on the factors that determine a farmer's probability of adopting on-farm adaption strategies; whereas Table 5 presents the factors that influence the adoption of off-farm adaption strategies.

3.3.1. *Irrigation*

Irrigation is the application of controlled amounts of water to the soil or crops through various systems of tubes, pumps, and sprays at needed intervals (Knox et al., 2012). The results reveal that in spite of the level of awareness, the pineapple farmers are less likely to adopt irrigation as an on-farm adaptation strategy. The probability of applying irrigation as a climate change adaptation strategy reduces by 46% among farmers with strong awareness; but decreases by 42% among farmers with low climate change awareness (Table 4). The results also show that an improvement in the quality of climate information enhances the probability of adopting irrigation by 33.3%. Climate information is critical for meeting the adaptation needs of smallholders farmers in dryland farming systems (Antwi-Agyei et al., 2021). The level of literacy seems to have an influence on the probability of a farmer to adopt irrigation as a method of adapting to climatic changes but it is not statistically significant. It is also shown that the land ownership type and the average distance from the farm have an effect on farmers' likelihood to employ irrigation. The marginal effect estimates show that the probability of adopting irrigation decreases by 22.5%, if the distance between the farmland and the farmhouse is long. The implication is that smallholder pineapple farmers that stay close to the farms are more likely to adopt irrigation compared to their counterparts who stay a distant from their farms.

Farmers who own their farm lands through inheritance are 41.9% more likely to choose irrigation as an adaptation strategy compared to farmers who obtained the farm lands through leasing or other land tenure arrangements. It has been suggested that land tenure arrangements can greatly influence adaptation practices such as irrigation and planting of trees in the Upper East region (Antwi-Agyei et al., 2015). Irrigation facilities are expensive and farming households that have less secured forms of farmlands are usually unwilling to invest in irrigation as an adaptation option. The level of education of a farmer determines the probability of adopting irrigation as an adaptation strategy. Results indicate that institutional factors and farming conditions are the key factors influencing the choice of irrigation strategy.

3.3.2. *Land fragmentation*

Land fragmentation is a situation where a single farm or ownership consists of numerous spatially separated plots or farmers operating two

Table 4
Multinomial logistic regression estimates of the determinants of on-farm adaptation practices.

	Irrigation		Land fragmentation		Adjusting planting date	
	Coefficient	dy/dx	Coefficient	dy/dx	Coefficient	dy/dx
Intercept	0.971 (.255)***		0.116 (.160)		−0.505 (.256)*	
Farmer's Age	−0.017 (.065)	−0.027 (0.05)	−0.037 (.034)	−0.064 (0.03)*	0.105 (.055)*	0.098 (0.05)***
Marital Status	0.356 (.099)***	0.390 (0.10)	−0.012 (.062)	0.008 (0.06)	0.377 (.100)***	0.436 (0.10)***
Gender	−0.065 (.077)	−0.067 (0.08)	0.061 (.048)	0.067 (0.05)	−0.031 (.078)	−0.038 (0.07)
Education	−0.268 (.048)***	−0.284 (0.07)***	0.042 (.030)	0.018 (0.05)	0.207 (.048)***	−0.435 (0.07)***
Farmer household size	−0.115 (.069)*	0.018 (0.05)	−0.083 (.037)**	0.057 (0.03)*	−0.15 (.059)**	0.232 (0.05)***
Average distance	−0.001 (.135)	−0.225 (0.08)***	−0.026 (.084)	−0.113 (0.05)**	0.445 (.135)***	−0.325 (0.07)***
Access to credit	−0.428 (.115)***	−0.007 (0.13)	0.147 (.047)**	−0.037 (0.08)	−0.074 (.116)	0.453 (0.13)***
Land ownership type	−0.22 (.109)**	−0.419 (0.11)***	0.107 (.068)	0.160 (0.07)**	−0.143 (.10)	−0.078 (0.11)
Literacy	0.308 (.106)***	0.014 (0.04)	0.086 (.067)	−0.037 (0.03)	0.296 (.107)***	0.040 (0.04)
Access to extension services	0.036 (.039)	−0.082 (0.05)	−0.039 (.025)	−0.024 (0.03)	0.079 (.039)**	−0.012 (0.05)
Quality of extension service	−0.074 (.054)	−0.209 (0.11)*	−0.013 (.034)	0.108 (0.07)	−0.004 (.054)	−0.133 (0.104)
Quality of climate information	0.248 (.072)***	0.333 (0.10)***	0.039 (.045)	0.103 (0.07)	0.382 (.072)***	0.338 (0.10)***
Awareness [Base category: Moderate]						
1. Strong Awareness Level	−0.532 (.141)***	−0.459 (0.14)***	0.342 (.088)***	0.375 (0.09)***	0.543 (.141)***	0.643 (0.14)***
2. Low Awareness Level	−0.475 (.150)***	−0.419 (0.15)***	0.342 (.094)***	0.376 (0.09)***	0.138 (.151)	0.199 (0.15)

	Improved varieties		Soil conservation		Crop diversification	
	Coefficient	dy/dx	Coefficient	dy/dx	Coefficient	dy/dx
Intercept	0.444 (.277)		1.048 (.175)***		0.055 (.323)	
Farmer's Age	0.135 (.60)**	0.117 (0.06)*	0.097 (.038)**	0.090 (0.04)**	0.25 (.069)***	0.279 (0.07)***
Marital Status	−0.072 (.108)	−0.030 (0.11)	−0.152 (.068)**	−0.132 (0.07)*	−0.528 (.126)***	−0.592 (0.12)***
Gender	−0.091 (.084)	−0.095 (0.08)	−0.037 (.053)	−0.039 (0.052)	0.421 (.098)***	0.413 (0.09)***
Education	0.148 (.052)***	−0.184 (0.08)**	0.091 (.033)***	−0.009 (0.05)	0.181 (.061)***	0.354 (0.088)***
Farmer household size	−0.047 (.064)	0.167 (0.05)***	−0.023 (.04)	0.099 (0.03)***	0.395 (.075)***	0.222 (0.06)***
Average distance	−0.252 (.146)*	−0.120 (0.08)	−0.324 (.092)***	−0.053 (0.05)	−0.545 (.170)***	−0.662 (0.09)***
Access to credit	0.239 (.125)*	−0.235 (0.14)	0.008 (.078)	−0.31 (0.09)***	−0.105 (.146)	−0.490 (0.16)***
Land ownership	0.188 (.119)	0.228 (0.13)*	−0.097 (.075)	−0.001 (0.007)	0.164 (.138)	−0.160 (0.137)
Literacy	0.054 (.115)	0.136 (0.04)***	0.024 (.073)	0.148 (0.03)***	−0.192 (.134)	0.143 (0.048)***
Access to extension services	0.123 (.043)***	0.173 (0.06)***	0.153 (.027)***	0.064 (0.04)*	0.096 (.05)*	−0.007 (0.066)
Quality of extension service	0.166 (.059)***	0.186 (0.12)	−0.063 (.037)*	−0.100 (0.07)	−0.032 (.069)*	0.129 (0.13)
Quality of climate information	0.158 (.079)**	0.084 (0.12)	0.002 (.049)	0.038 (0.07)	0.255 (.091)***	−0.245 (0.127)*
Awareness [Base category: Moderate]						
1. Strong Awareness Level	0.247 (.153)	0.286 (0.16)*	−0.237 (.096)**	−0.225 (0.099)**	0.174 (.178)	−0.026 (0.17)
2. Low Awareness Level	0.477 (.163)***	0.490 (0.17)***	−0.303 (.103)***	−0.304 (0.10)***	0.402 (.190)**	0.216 (0.18)

Note: Standard Errors in Bracket. Asterisks ***, **, * denotes parameter is significant at less than 1%, 5% and 10% significance level respectively.

Table 5
Parameter estimates of the multinomial logit climate change adaptation (off-farm) model.

	Off-farm income		Seasonal migration		Family and friends support	
	Coefficient	dy/dx	Coefficient	dy/dx	Coefficient	dy/dx
Intercept	1.091 (0.300)***		.269 (.177)	0.268 (.176)	.283 (.237)	0.319 (.234)
Farmer's Age	.109 (.072)	0.082 (.072)	.030 (.042)	0.060 (.042)	.263 (.056)***	0.274 (.056)***
Marital Status	−.005 (126)	0.029 (.126)	-.034 (.074)	−0.030 (.074)	-.034 (.099)	−0.042 (.098)
Gender	−.059 (.099)	−0.058 (.098)	-.014 (.058)	−0.027 (.058)	.250 (.078)***	0.253 (.076)***
Education	-.067 (.063)	−0.251 (.095)	.045 (.037)	−0.120 (.056)**	-.204 (.05)***	−0.242 (.074)***
Farmer Household size	−.137 (.077)*	−0.047 (.065)	.018 (.046)	0.042 (.038)	.119 (.061)*	0.222 (.051)***
Average Distance	−.417 (.167)***	−0.194 (.100)*	.134 (.098)	−0.050 (.059)	-.432 (.132)***	−0.215 (.078)**
Access to Credit	−.424 (.151)***	−0.415 (.165)**	−.441 (.089)***	0.141 (.096)	-.168 (.119)	−0.408 (.129)***
Land Ownership	−.178 (.131)	−0.424 (.151)***	−.190 (.077)***	−0.452 (.088)***	−.343 (.103)***	−0.206 (.118)*
Literacy	.223 (.136)	0.114 (.052)**	.268 (.08)***	0.061 (.031)**	.440 (.107)***	0.155 (.041)***
Access to extension services	.118 (.051)**	0.143 (.067)**	.037 (.030)	0.078 (.039)**	.169 (.04)***	0.138 (.052)***
Quality of Extension Service	.137 (.066)**	−0.192 (.130)	.069 (.039)*	0.183 (.076)**	.129 (.052)***	0.353 (.102)***
Quality of Climate Information	.217 (.093)**	0.253 (.135)*	.113 (.055)**	0.271 (.079)***	.207 (.073)***	0.431 (.106)***
Awareness [Base category: Moderate]						
1. Strong Awareness Group	-.182 (.181)	−0.146 (.186)	-.029 (.107)	−0.004 (.109)	.004 (.142)	−0.079 (.145)
2. Low Awareness Group	.036 (.193)	0.061 (.196)	.175 (.114)	0.179 (.115)	.031 (.152)	−0.064 (.153)

	Agro-Ecological Knowledge		Government & NGOs Support	
	Coefficient	dy/dx	Coefficient	dy/dx
Intercept	.837 (.236)***	0.813 (.240)***	−.534 (.147)***	−0.517 (.145)***
Farmer's age	−.116 (.056)**	−0.087 ((.057)	.087 (.035)**	0.104 (.034)***
Marital status	.226 (.099)**	0.241 (.100)**	.043 (.062)	0.026 (.06)
Gender	.004 (.078)	−0.027 (.078)	.043 (.048)	0.049 (.047)
Education	.041 (.050)	0.268 (.077)***	-.088 (.031)***	−0.017 (.046)
Farmer household size	.110 (.061)*	0.051 (.052)	−.007 (.038)	−0.104 (.031)***
Average distance	−.206 (.131)	−0.017 (.08)	.507 (.082)***	0.038 (.048)
Access to credit	−.101 (.199)	−0.186 (.132)	.021 (.074)	0.502 (.08)***
Land ownership	.030 (.103)	−0.104 (.121)	.281 (.064)***	0.010 (.073)
Literacy	.005 (.107)	0.213 (.042)***	.127 (.066)*	0.071 (.025)
Access to extension services	.177 (.04)***	0.045 (.053)	.075 (.025)***	0.047 (.032)
Quality of extension service	.041 (.052)	0.047 (.104)	.039 (.032)	0.279 (.062)***
Quality of climate information	.280 (.073)***	0.002 (.108)	.031 (.045)	0.137 (.065)**
Awareness [Base category: Moderate]				
1. Strong Awareness Group	−.621 (.142)***	−0.550 (.148)***	.127 (.088)	0.087 (.09)
2. Low Awareness Group	.041 (.151)	0.129 (.157)	.150 (.094)	0.115 (.094)

Note: Standard Errors in Bracket. Asterisks ***, **, * denotes parameters are significant at less than 1%, 5% and 10% significance level respectively.

or more geographically separated tracts of land, taking account of the distances between those parcels (Alemu et al., 2017; Bizimana et al., 2004). The results show that the pineapple farmers' awareness of climate change has an influence on the probability of adopting land fragmentation as an adaptation strategy. However, there is no significant difference in the probability of employing land fragmentation between a farmer who has a strong awareness level (37.5%) and those with low awareness levels (37.6%). In addition, land ownership type has a positive effect on the probability of adopting land fragmentation. An increase in the farmer household size increases the probability of adopting land fragmentation by 5.7%. This result is supported by Shuhao et al. (2006) who suggested that household size and farm size had a positive impact on land fragmentation and technical efficiency.

Land fragmentation is also mostly adopted among young farmers relative to older farmers. This is in agreement with the findings of Liu and Luo (2018) suggesting that older farmers are less likely to adopt land fragmentation because older farmers with longer farming experience are more likely to employ indigenous land conservation practices. The implication is that decisions to adopt land fragmentation are influenced by awareness, farming conditions and individual factors. Institutional factors are less likely to predict the probability of adopting land fragmentation as an adaptation strategy.

3.3.3. *Adjusting planting time*

Adjusting planting time is a cultivation strategy used by farmers to change their planting time in response to the onset of the rains (Antwi-Agyei and Nyantakyi-Frimpong, 2021). The results show that albeit awareness of climate change has an effect on the probability of a farmer to adjust planting time, this adaptation strategy is mostly adopted among farmers with high climate change awareness group (Table 4). The study also suggests other socioeconomic factors influencing the probability of adjusting planting time. First, strong quality of climate information has an effect on the probability of adjusting planting time. This agrees with previous studies indicating that, farmers who have access to weather information such as seasonal forecasts make better informed adaptation decisions and have a higher probability of implementing climate change adaptation strategies (Antwi-Agyei et al., 2020; Bryan et al., 2013; Hassan and Nhemachena, 2008).

Furthermore, access to credit also has a positive influence on the decision to implement climate change adaptation such as adjusting planting time, changing cropping patterns and planting early maturing varieties of crops (Singh, 2020). Several studies including Ndamani and Watanabe (2016) and Oo et al. (2017) have reported variables such as access to credit having significant influence on climate change adaptation strategies including adjustment of planting date or time. A farmer may have substantial farming experience, but without adequate credit, the farmer will not be able to adapt well to climate change. There is also evidence to suggest that household size, farmer's age and marital status have a positive effect on the probability to adjust planting time. Previous studies have suggested that variables such as age, marital status, household size, household head, level of experience, etc., influence adoption of climate change adaptation strategies including crop diversification, soil and water conservation, etc. (Danso-Abbeam et al., 2018). In addition, the average distance and the level of education have a negative effect on the probability to adjust planting time. The implication is that farmers who reside closer to their farmlands are most likely to adjust planting time. The evidence therefore generally shows the strong influence of individual factors and farming conditions in decisions to adjusting planting time.

3.3.4. Planting of improved crop varieties

Planting of improved crop varieties involves the cultivation strategy to improve food crop production where there is the development of crops with desired traits such as high yields, disease resistance, quality product and response to fertilizers (Uduji and Okolo-Obasi, 2018). The analysis further shows that there is a positive relationship between climate change awareness and the adoption of improved seeds. The marginal effect estimate shows that the probability of adopting improved crop varieties increases by 49% among the pineapple farmers with low awareness whereas the probability of adopting improved crop varieties increases by 28.9% among farmers with strong climate change awareness. This finding is similar to previous studies suggesting that farmers are willing to adopt recommended improved crop varieties based on their awareness, perception and impacts of climate change (see Antwi-Agyei and Nyantakyi-Frimpong, 2021; Singh, 2020; Tambo and Abdoulaye, 2013; Etwire et al., 2013).

Access to extension services also positively influences a farmer's probability of adopting improved varieties. It is largely reported that access to extension services increases the likelihood of adopting several climate change adaptation strategies (Denkyirah et al., 2017). Extension officers provide sources of information on new technologies to farmers which when adopted can enhance production, incomes and livelihoods (Danso-Abbeam et al., 2018; Etwire et al., 2013). There is a positive relationship between a farmer's literacy rate and the probability of adopting improved varieties. Education has a positive influence on the adaptation strategies by the pineapple farmers and thus increases adaptation strategies significantly. This is because educated farmers are willing to adopt new technologies such as planting improved crop varieties based on their awareness of the expected benefits from the proposed technology (Hassan and Nhemachena, 2008).

Land ownership type also has a positive and significant effect on improved varieties. This is because owning land can encourage agricultural technology adoption such as planting improved varieties while renting or leasing land discourages it (Zeng et al., 2018). Abdulai et al. (2011) suggest that land ownership tend to facilitate investment in soil conservation practices including planting improved crop varieties. The evidence also portrays a positive effect of household size and farmer's age on the adoption of improved varieties.

3.3.5. Soil conservation practices

Soil conservation practices are used by the farmer to prevent soil degradation and build organic matter, increase soil structure and rooting depth (Prager & Posthumus, 2010). Results show a negative effect of climate change awareness on soil conservation practices. This is indicative of the fact that soil conservation is less likely to be practiced among farmers with strong perceptions of climatic change compared to cohorts with moderate climate change perception. This contradicts previous studies suggesting that climate change awareness and perception of climate change impacts have a positive and significant impact on the farmers' choice of adaptation options including soil conservation practices (Adger et al., 2009). Additionally, there is a positive effect of access to extension, literacy, farmer's age and household size on the probability of adopting soil conservation. Older farmers often tend to stick to their traditional ways of production and therefore less likely to adopt newly introduced technologies and adaptation practices that can enhance the productivity of the soil (Denkyirah et al., 2017). The probability of a farmer practicing soil conservation as an adaptation strategy increases by 6.4% when access to extension facilities is high. Furthermore, access to credit and marital status have a negative influence on farmers' probability of adopting soil conservation. Such findings are consistent with Denkyirah et al. (2017) who observed that marital status negatively influenced a farmer's adaptation to climate change in the Brong-Ahafo Region of Ghana. Our results suggest that institutional factors and individual characteristics are key determinants of the choice of soil conservation as a climate change adaptation strategy.

3.3.6. Crop diversification

Crop diversification involves the addition of new crops to agricultural production on a particular farm taking into account the different returns from value-added crops with complementary marketing opportunities (Pellegrini and Tasciotti, 2014). The results suggest that the level of the pineapple farmers' awareness on climatic change has a zero effect on the probability of farmer adopting crop diversification. This is contrary to previous studies suggesting that perception and knowledge of climate change issues encourage farmers to adopt climate change adaptation strategies including crop diversification (Lakhran et al., 2017). Famer's age, gender, household size and education have a positive influence on a farmer's choice of crop diversification as an adaptation strategy. This is confirmed by Kinuthia (2018) who suggested that gender, age and level of education were all significant factors that influenced the choice of adaptation strategy including crop diversification. On the other hand, marital status, average distance and access to credit have a negative effect on crop diversification. Literacy also has a positive effect on the probability to adopt crop diversification.

3.3.7. Off-farm non-agricultural income

Off-farm non-agricultural income refers to all income-generating activities except crop and livestock production (Hellin and Fisher, 2019). The results indicate that climate change awareness does not influence the choice of off-farm income. However, the quality of extension services and access to extension services have a positive effect on the reliance on off-farm income (Table 5). Access to extension services has a positive effect on the reliance on off-farm income. Furthermore, literacy rate has a positive influence on the probability of relying on off-farm income. This is because educated farmers tend to rely on other sources of non-agricultural income such as teaching to help diversify and improve their livelihoods. On the other hand, average distance, access to credit and the land ownership type have a negative influence on the probability of adopting off-farm income earning activities. Non-farm income earning activities also offer opportunities for diverse activities when agriculture becomes riskier and provides secure source of income. The pineapple farmers with non-farm income sources are therefore less likely to adopt agricultural innovations including climate change adaptation practices (Denkyirah et al., 2017; Oluwatusin, 2014). The implication is that the probability of a farmer relying on off-farm income is largely dependent on institutional conditions.

3.3.8. Seasonal migration

The results show that the pineapple farmers' awareness of climate change does not have an influence on using seasonal migration as an adaptation strategy. However, the quality of climate information, quality of extension services, access to extension services and literacy are likely to positively influence the probability of using seasonal migration as an adaptation strategy. The result is in line with that of De Brauw (2010) who suggested that, in situations where households lack access to extension services and climate change information, their productivity may rise with seasonal migration. Educational level of farmers as well as the type of land ownership have a negative influence on the likelihood of choosing seasonal migration. As the education level of the smallholder pineapple farmer improves, the probability of engaging in seasonal migration reduces by 12%.

3.3.9. Family and friends support

The level of a pineapple farmer's awareness on climate change does not have a statistically significant effect on family and friends support. However, the probability of relying on the support of family and friends is largely dependent on farmers' socioeconomic circumstances. The results suggest average distance, the level of education, access to credit and marital status have a negative influence on farmers' probability of relying on family and friends for support.

The age of farmers, household size and gender have a positive and significant effect on the probability of relying on family and friends for support. Based on the results, we can deduce that relying on family and friends support is predicted by farming conditions, institutional factors and individual characteristics; however strong access and prevalence of institutional factors reduces the probability of relying on family and friends support. For instance, access to credit facilities reduces the probability of relying on family and friends support by 40.8%.

3.3.10. Agro-ecological knowledge

Agro-ecological knowledge refers to the cumulative and evolving body of knowledge, practices, beliefs, institutions, and worldviews about the relationships between a society or cultural group and their agro-ecosystems (Calvet-Mir et al., 2018). Farmers in dryland farming systems are increasing using indigenous traditional agro-ecological knowledge to manage climate change effects (Baffour-Ata et al., 2021). The results suggest that having a strong climate change awareness level reduces the farmers' probability of relying on agro-ecological knowledge by 55%. This contradicts Kmoch et al. (2018) who reported that farmers' knowledge on increasing temperature and decreasing rainfall patterns do not hinder them from adopting traditional agro-ecological knowledge as an adaptation option. A high literacy level increases a farmer's probability of relying on agro-ecological knowledge. This is supported by the positive effect of educational level on agro-ecological knowledge. A high literacy level is positively correlated with adaptive capacity.

3.3.11. Government and NGO support

Relying on governmental and non-governmental support is an adaptation strategy where farmers receive support in terms of finances, capacity building, and agricultural inputs etc. from government or NGOs (Tahiru et al., 2019; Belay et al., 2017). The multinomial logistic regression results indicate that, awareness of climate change does not have a statistically significant effect on government and NGO support. Furthermore, the quality of climate information, quality of extension services and access to credit have a positive influence on government and NGO support. This is consistent with Antwi-Agyei and Stringer (2021), suggesting the need to build the capacity of extension agents to effectively communicate climate information. Farmers with small household sizes are most likely to receive government and NGO support. There is a positive relationship between farmer's age and government and NGO support. This implies that older farmers are more likely to rely on government and NGO support. The probability of choosing government and NGO support increases by 10.4% as the farmer's age increases.

4. Conclusions and the way forward

Our analysis showed three subgroups of smallholder pineapple farmers based on their level of awareness of climate change – *strong climate change awareness* group, *moderate climate change awareness* group and *poor climate change awareness* group. Results indicated that farmers are employing a host of on-farm climate change adaptation practices including irrigation, adjusting planting time, land fragmentation, soil conservation measures and planting improved varieties of crops. Off-farm adaptation practices include the use of agro-ecological knowledge, relying on family and friends and seasonal migration. The findings further revealed that there are differences in awareness of climate change among farmers in Ghana. The effect of variations in climate change awareness on adaptation is mixed and depends on the type of adaptation strategy. Nonetheless, it is generally identified that the effect of climate change awareness is likely to be stronger on the adoption of on-farm strategies compared to off-farm strategies. This is attributable to the fact that the likelihood of famers adopting on-farm practices is greater than off-farm strategies.

Furthermore, the results provided evidence on the effect of socio-economic factors on adaptation practices and climate change awareness among farmers. Institutional factors such as the quality of climate information, quality of extension services, access to credit, literacy and access to extension services have a superior and widespread effect on climate change awareness and adaptation practice relative to individual factors such as marital status, gender and farmers' age. The implication is that when institutional barriers confronting farmers' ability to access information and adapt to modern strategies improve, the probability of the farmer to put in measures to adapt to climatic conditions will also improve. Awareness creation on the effects of climate change should be intensified by the Ministry of Food and Agriculture and the Ministry of Environment, Science, Technology and Innovation, to help farmers better understand their vulnerability to climate risks. Adaptation policy should be informed by the various socioeconomic factors influencing the choice of climate change adaptation strategies by smallholder farmers.

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