Natural Resources Conservation and Research (2023) Volume 6 Issue 2
doi: 10.24294/nrcr.v6i2.2290

ORIGINAL RESEARCH ARTICLE

Composite effect of adaptation to climate variability, agrometeorological information, and socioeconomic and institutional factors on agricultural productivity in Kenya

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ABSTRACT

Climate variability has adversely affected agriculture and adaptation strategies are significant in enhancing resilience hence ensuring food security. Agrometeorological services are essential in decision-making and developing farmers' specific adaptive capacities mainly when variability affect agricultural productivity. This study focuses on the composite effect of adaptation to climate variability, agrometeorological information, socioeconomic and institutional factors on agricultural productivity in Kenya. Multi-stage sampling technique was used to obtain a sample size of 384 sorghum farmers. The study used an endogenous switching regression model to control for the selection problem arising from adaptation to climate variability on agricultural productivity. Results indicate that extension contacts and education level were positively significant among adapters of climate variability. Additionally, the proportion of income allocated for farming was positively significant among non-adapters. On the other hand, access to credit, gender and age of decision makers were negatively significant among adapters of climate variability. Similarly, age was negatively significant among non-adapters of climate variability. Overall, adapters to climate variability had higher sorghum output than non-adapters. This study recommends that policymakers and other key stakeholders could increase the number of extension contacts and promote education to farmers so that they can access agrometeorological information, hence adaptation to climate variability.

Keywords: adaptation strategies; agricultural productivity; Busia County; climate variability; endogenous switching regression

ARTICLE INFO

Received: 25 June 2023
Accepted: 31 July 2023
Available online: 11 September 2023

1. Introduction

Agriculture is the mainstay of many economies, contributing to food security and the employment of rural households, especially in sub-saharan Africa (SSA)[1]. The SSA region hosts about 950 million people, about 13% of the global population. The population is expected to increase to about 2.1 billion people in 2050[2]. Therefore, the demand for food keeps rising, underscoring the agricultural sector's significance in contributing to food security[3]. The agricultural sector also directly or indirectly contributes significantly to many SSA economies. On average, agriculture contributes 15% of total gross domestic product (GDP), ranging from 1.9% in botswana with the highest, 57.4% in sierra leone[4]. The agricultural sector offers employment to more than half of the total labour force in SSA. Among the rural population, it is a source of livelihood for many small-scale producers. The small-scale farmers constitute approximately 80% of all farms in SSA and employ about 175 million people[2,5]. In Kenya, agriculture contributes to about 33% of the GDP, accounts for 60% of employment and 65% of exports[6].

Climate variability and change have badly affected the agricultural sector, and the situation is expected to deteriorate in the 21st century[7]. The intergovernmental panel on climate change (IPCC) valuation report indicates that most countries will experience significant climate changes. These changes include increased average temperature, more frequent heat waves, more stressed water resources, desertification, the concentration of CO in the atmosphere and periods of heavy precipitation[8]. Climate variability and change have threatened food security through reduced production due to reduced rainfall, soil moisture and increased temperature. It also directly affects agricultural production and food security because most of the SSA population lives in rural areas with agriculture as a source its livelihood. This is worsened given that agriculture in this region is predominantly rain-fed.

The climate of SSA is warmer than it was 100 years ago, and model-based predictions of future GHG-induced climate change for the continent suggest that this warming will continue[9,10]. The projection of rainfall is less uniform. Many of the impacts of climate change will result in changes in extreme events such as droughts and floods.

Changes in rainfall patterns and shifts in thermal regimes influence local seasonal and annual water balances and affect the distribution of periods during which temperature and moisture conditions permit agricultural production. Such characteristics are common in Kenya, which relies on rain-fed agriculture. Over the last century, Africa has warmed and the average annual temperature is likely to rise by an average of 1.5–4 ℃ by 2099[11]. Since the early 1960s, Kenya has experienced extreme weather events with both minimum and maximum temperatures having risen generally by 0.7–2.0 ℃ and the maximum by 0.2–1.3 ℃, depending on the season and the region leading to loses with Kenya experiencing damages equivalent to 2.4% of gross domestic product (GDP) between 1999 and 2000 droughts[12]. Recent study on economic impacts of climate change in Kenya has estimated that annual cost of climate change impacts will be in the tune of USD 1 to 3 billion by the year 2030[12].

Access to reliable and accurate agrometeorological information can guide operational farm-level information, especially when climate change and variability are a significant threat to agriculture[13]. The information can be obtained using conventional methods and/or indigenous knowledge. Some conventional techniques include agrometeorological information from researchers, which is observed data collected in weather stations and modelled for future predictions[14]. In contrast, indigenous knowledge includes agrometeorological information validated by researchers that is passed from one generation to another among local communities[1]. Some of the indigenous agrometeorological information include observation and interpretation of plants and animal/human body conditions, various sounds by birds and other animals. Using indigenous knowledge helps farmers predict disasters caused by climate variability, and they formulate adaptation strategies to avert agricultural production losses.

Applying climate services in agriculture, specifically agrometeorological services, is a valuable innovation to assist decision-making and develop farmers' specific adaptive capacities[15]. Agrometeorological information and services have been operationally applied in farming decision-making in Kenya. The outcome showed that regular provision of agrometeorological information could help farmers to manage better risks associated with increased climate variability and change. Smallholder farmers reliant on rain-fed production systems can enhance climate resilience and coping capacity[15,16]. Seasonal climate forecasts are critical in expanding the lead-time of farmer-relevant information and contributed to a rise in the interest in applying the information to agriculture. There is a positive perception of farmers and local stakeholders toward agricultural production.

Farming in Busia County is highly dependent on rainfall, making farmers vulnerable to climate variability due to the fragile nature of the environment. The county government has identified early cessation of the long rains as the main cause of low yields in cereal crops like sorghum and maize. Variability of rainfall patterns compounded with unpredictable rainfall intensity has led to soil erosion and floods thereby affecting land preparation and food production[17]. Historical data that's there is a remarkable increase in drought frequency from every 10 years to every 2–5 years with moisture stress, increased temperature, intense rains and soil erosion being the most problematic[18]. This has contributed to high poverty level in Busia County which are higher (64.2%) than the national average of 45.9%[17]. Climate events in the county of Busia have had a profound effect on the agricultural sector and the people's livelihoods. County farmers have noted increased droughts and floods, previously unheard of between the 1940s and 1990s. These are all occurrences that occur in combination with droughts, such as the one that occurred in Teso North in 2016, which resulted in crop failures in the county, and ultimately caused a raise in food prices that the majority of residents could not afford due to the county's high poverty rate. To curb this from further escalating, development of appropriate adaptation strategies to climate variability are necessary. This will only be possible if farmers can access timely, efficient, understandable and reliable agrometeorological information.

Past studies have investigated the possible impacts of climate change on agricultural production and ways of adapting to climate change[19,20]. These studies generally indicate that farmers can overcome the negative effects of climate change by implementing adaptation measures. A lot of these studies have concentrated on a range of factors affecting the adoption of such measures by small-scale farmers with household, farm characteristics and institutional factors being indicated as the key determinants of adoption[21–23]. However, information access and utilization is becoming more important if effects of climate change are to be dealt with. This paper therefore aims to support efficient transmission of agrometeorological information and hence contribute to informing policy makers and program designers on the most efficient and reliable climate information systems and determine whether its findings will corroborate with other studies and inform farmers appropriately.

The paper is structured as follows:

- Abstract
- Keywords
- Introducton
- Literature review
- Theoritical framework
- Methodology
- Results and discussions
- Conclusions
- References

2. Literature review

Climate change is one of humanity's most critical global environmental challenges, with negative implications on agricultural productivity. This, in turn, affects poverty and food insecurity, posing a threat to achieving sustainable development goals (SDGs). Sub-saharan Africa (SSA) is highly vulnerable to negative impacts of climate variability due to its geographical location, climatic conditions, high dependence on agriculture and natural resources-driven activities and weak adaptive capacity to the threats of climate variability[24]. The trend is projected to worsen given the anticipated decline in production of the region's most important staple crops, such as maize, millet, sorghum and cassava[25]. Similarly, in Kenya, agriculture is the main contributor to Kenya's GDP and a source of raw materials for local industries. Floods, drought and increased prevalence of pests and diseases are significant climate variability effects experienced in Kenya[1]. These extreme weather events occur more regularly, meaning that seasonal climate forecasting and early warning systems will continue to be vital in planning and risk mitigation in key economic sectors, including agriculture[26].

While concerns about global warming existed decades ago, scientists worked under the auspices of the intergovernmental panel on climate change (IPCC) following its establishment in 1988 to determine the certainty of global warming due to greenhouse gases[27]. Their findings confirmed the warming of the climate system, with a 0.74 per cent increase in the global average temperature[28]. Over the last century, Africa has warmed at 0.05 per cent per decade in lockstep with global warming. The annual temperature rises from about 3 ℃ to 4 ℃, around 1.5 times the global average reaction, according to simulations in Africa's climate model under various potential emission scenarios[29].

It is therefore, imperative for stakeholders to strengthen adaptation efforts in a bid to reduce the effects of climate variability. Adapting to climate variability entails adjustments to enhance preparedness and response to current and future climate variability adversities by enriching farmers' knowledge about the risks and consequences of climate variability to better assist them in improving their adaptive capacity. This is done through availing agrometeorological information, a key prerequisite service towards adopting climate-smart agricultural practices that reduce vulnerability to climate change. Agrometeorological information services generally try to enhance smallholder farmers' ability to manage the risks of climate variability[30]. Agrometeorological information services have been growing worldwide by focusing on supporting, funding and developing capabilities for agrometeorological information by the developed nations[31]. The world meteorological organisation (WMO) has also been instrumental in driving this growth and development.

Adaptation strategies to climate variability and change are important to enhancing resilience, protecting farmer's livelihoods and ensuring food security. They are considered very effective in building resilience, especially on resource-constrained farmers. In western Kenya, climate variability and change impacts on agricultural production are evident as farmers rely on rain-fed agriculture. Some adaptation strategies that western Kenya farmers have embraced include crop diversification, change of planting dates, planting of drought-tolerant crops, planting of early maturing varieties, high-yielding varieties and agroforestry[1].

Despite adaptation strategies promising resilience to climate variability and change, there are several challenges to effective adaptation, such as poor dissemination and access to climate adaptation information, inadequate institutional measures and vague public policies on adaptation policies[32]. Effective uptake of these adaptation strategies necessitates explicit knowledge among the farmers about future climatic knowledge is likely to be. Adequate agrometeorological information is a key ingredient to the improvement of agricultural systems in all areas[32,33].

A study by Tarchiani et al.[34], show that agrometeorological information services can increase crop productivity and decrease cropping costs in inputs and working time. The study further indicates that in Mauritania's growing seasons of 2015 and 2016, sorghum yields increased by 64%, courtesy of agricultural information services. The yield increase was attributed to the choice of variety (2015–2016 seasons were shorter than average) and the sowing date, where the latter avoids failures and loss of seeds. The choice of a shorter cycle variety allowed minimizing the negative effects of an earlier normal rains cessation and avoiding pests attack at the end of the season. Saving on costs was also observed since there were minimal losses in terms of opportunity costs due to additional weedings observed among farmers who planted offseason[15,34].

3. Theoritical framework

Protection motivation theory

Rogers[35] developed protection motivation theory (PMT) as an extension of the health belief mode. According to the theory, defence motivations, like whether people take protective steps in response to perceived threats, are formed because of a detailed evaluation of threats and coping mechanisms. Assessing a person's danger involves assessing the threat's degree, which includes vulnerability and perceived severity. Perceived severity refers to the perceived seriousness of the event, whereas vulnerability refers to the perceived individual's sensitivity to the established threat[36]. In this case, perceived severity refers to the adverse effect of climate variability on smallholder sorghum farmers.

In contrast, perceived vulnerability refers to the susceptibility of smallholder farmers to adverse effects of climate variability on sorghum production. The three components of coping evaluation are self-efficacy, response efficacy and response cost. The phrase "response efficacy" refers to an individual's belief in a prescribed response's effectiveness in averting a threat. Self-efficacy is a term that refers to an individual's expected capacity to engage in a recommended coping action[37]. The phrase "response cost" refers to all perceived costs associated with preventive measures, events, or adaptation measures, including both monetary and non-monetary costs, which include effort, time and inconvenience[36].

According to Westcott et al.[38], PMT applies to "any danger for which an individual may carry out an effective recommended response." Additionally, PMT has been successfully applied to analysing smallholder farmers' pro-environmental behaviour (PEBs)[39]. Thus, the theory is relevant for this study because it considers the precautions (adaptation measures) taken by smallholder farmers in the face of potential threats posed by climate variability. Wang et al.[40] discovered that farmers' environmental conduct was highly cost-sensitive because they often lacked necessary materials and had little financial capital. As a result, response cost harmed intention. Increased risk appeals result in an increase in severity and vulnerability. Farmers who perceive climate variability as a major challenge to agricultural production and quality of life are more receptive to adaptation measures such as agroforestry, crop rotation, rainwater harvesting, cover crop planting, mulching, using organic manure, and planting drought-resistant crops such as sorghum.

4. Methodology

4.1. Description of the study area

The study was conducted in Busia County. Busia County lies between latitude 0° and 0° 45 north and longitude 34° 25 east. It covers about 1695 km^2 KNBS[41]. It is located in the western region of Kenya. It borders siaya to the south-west, Bungoma to the north, kakamega to the east, lake victoria to the south-east and uganda to the west. The mean temperature in the county is about 21–27 ℃ whereas the annual rainfall is about 750–2000 mm. The mean temperatures vary across the county, with areas near lake victoria receiving the least rainfall of about 760–1015 mm and butula and nambale receiving the highest rainfall of up to 2000 mm. The rainfall is bimodal; the long rains usually come between March and May, and the short rains are between August and October. The altitudes vary from 1140 m to 1500 m above sea level, suitable for crop farming. The major agricultural activities practised in Busia county include crop production (mainly cassava, sorghum, maize, groundnuts, sugar cane and some horticultural crops such as local vegetables and mangoes), livestock and fish farming[42]. Despite being a high agricultural potential area, the county is documented to be highly affected by climate change.

Busia is one of the top producers of sorghum in Kenya, where it is produced in smallholder farms measuring 1–2 acres throughout the county. Sorghum is high-yielding drought tolerant, which can also grow in cold semi-arid regions, moist mid-altitude areas, has high brewing quality and is resistant to smut disease.

The area under production in Busia County increased by 71%, to 13,109 ha, between 2012 and 2014[43]. This increase was driven by the high demand generated by the east African breweries limited (EABL), located in kisumu, in a program launched in 2012 to procure all of its sorghum requirements within the country. The county has sub counties namely: Teso North, Teso South, Butula, Nambale, Matayos, Samia and Budalangi. The main sorghum production areas include Teso South, Teso North, Matayos and Samia. Hence, the study was carried out in Teso South, Teso North, Matayos and Samia sub-counties.

4.2. Sampling procedure and method of data collection

The study used a multi-stage sampling technique. First, Busia County was selected purposively because of its vulnerability to climate variability and being a sorghum-growing region. Secondly, four sub-counties, Teso South, Teso North, Matayos and Samia, were selected from the seven sub-counties because they are the main sorghum production areas in the county. Finally, sorghum farming households were selected using a systematic sampling procedure in each sub-county. Households were then selected from a list of farmers generated during a pre-visit where all sorghum farmers were prequalified against the criteria of land size and period of sorghum farming.

The exact population of smallholder sorghum farmers was unknown; therefore, to determine the desired sample size, the formula specified by Cochran[44] was used as shown in Equation (1):

$$n = \frac{pqz^2}{\varepsilon^2} \tag{1}$$

where, n = sample size; z = confidence level (α = 0.05); p = proportion of the population containing the major interest; while $q = 1 - p$; and ε = allowable error. Since the proportion of the population is not known, p = 0.5, q = 1 − 0.5 = 0.5, Z = 1.96 and ε (allowable error) = 0.05 because the study allows a 95% confidence level.

$$n = \frac{0.5 \times 0.5 \times 1.96^2}{0.05^2} = 384 \tag{2}$$

The sample size in Equation (2) was adjusted upwards by 10%; therefore, the total sample size was 423 sorghum farming households. A higher sample size ensured that the minimum required sample size was retained even after dropping uncooperative respondents or any “inconsistent” responses in the collected data at the data cleaning stage. The sample size distribution per sub-county was done proportionately to the population size using the list of farmers from the sub-county agricultural offices as shown in **Table 1**.

Table 1. Sampling size distribution per sub-county.

Sub-counties	Number of households	Proportion	Adopters to climate variability	Non-adopters to climate variability
Teso North	90	0.21	74	16
Teso South	140	0.33	109	31
Matayos	85	0.20	58	27
Samia	108	0.26	54	54
Total	423	1	295	128

This study used a semi-structured questionnaire to collect primary data from smallholder sorghum farmers. A pilot study was conducted to test the validity of the questionnaire. According to Connelly[45], existing literature proposes that a pilot study sample should be 10% of the sample estimated for the main study. Hence, 42 smallholder sorghum farmers were selected for the pilot study to estimate the validity of the instrument and the time taken to complete one questionnaire. Trained enumerators experienced in agricultural and household data collection administered the questionnaires, containing open and close-ended questions. The study used a digitized questionnaire using the open data kit (ODK) application and administered through face-to-face interviews with the decision-maker in the household. Data collected included farm and farmer characteristics, institutional, production, climate and market-related factors (**Table 2**). The primary data were then entered into STATA software (version 16) for analysis.

Table 2. Table of variables used in the model.

Variables	Measurement	Expected sign
Dependent variables		
Sorghum yield produced per acre per year	Quantity of sorghum produced per acre per year	-
Independent variables		
Group membership	1 for yes, 0 otherwise	±
Frequency of extension visits	Number	±
Access to credit facilities	1 for yes, 0 otherwise	±
Distance to the market for crop produce	Kilometres	±
Gender of the key decision-maker	1 for male, 0 otherwise	±
Age of the key decision-maker	Years	±
Education level	Years	±
Owning farming land	1 for yes, 0 otherwise	±
Proportion of income allocated to farming	Kenya shillings	±
Adaptation to climate variability	1 for yes, 0 otherwise	±
Number of agrometeorological information	Quantity of agrometeorological information obtained	±
Trust in agrometeorological information	1 for yes, 0 otherwise	±

4.3. Analytical framework

The study used an endogenous switching regression (ESR) model to examine the impact of adaptation to climate variability on agricultural productivity. Lee[46], as an extension of Heckman's selection correction approach, coined the ESR model to correct for selection bias that can arise due to unobserved heterogeneity. Selection bias can arise due to unobserved factors affecting adaptation to climate variability among smallholder farmers who practice sorghum production in Busia County.

An ESR model is a two-stage model. Standard limited dependent variables methods model the adoption decision. The first stage comprises a probit model that identifies the socioeconomic factors that determine the adaptation of climate variability in agricultural productivity[47]. The estimated selection model is as follows:

$$Z_i^* = a + \gamma Q_i + \varepsilon_i \tag{3}$$

where, Z_i^* was a binary take the value 1, if the smallholder farmer adapted to climate variability and 0 otherwise; a was an intercept; Q_i was a vector of explanatory variables influencing adaptation to climate variability; γ was a vector of coefficient, and ε_i was the disturbance term with constant variance and zero mean. The error term comprises measurement error and factors not observed by the researcher but known to the farmer.

In the second stage of the ESR model, a full information maximum likelihood (FIML) model was used to account for potential selection bias. Separate regression equations are used to model sorghum productivity conditional on specified criterion functions[48]. The binary outcomes (increased sorghum productivity) conditional on adapting to climate variability were represented as switching regimes as follows:

Regime 1: if $A_i = 1$ for adapters to climate variability

$$Y_{1i} = X_{1i}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i} + u_{1i} \tag{4}$$

Regime 2: if $A_i = 0$ for non-adopters to climate variability

$$Y_{2i} = X_{2i}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i} + u_{2i} \tag{5}$$

where, Y_i represented the outcome variable (sorghum productivity) for a farmer i for each regime (1 = adopter to climate variability and 0 = non-adopter); X_i was a vector of explanatory variables that affect agricultural productivity. The variables in vectors X in Equations (4) and (5) may overlap with Q in Equation (3). However, the approach requires that at least one variable in Q that does not appear in X, β and σ were parameters to be estimated, u_{1i} and u_{2i} were independently and identically distributed error terms of the agricultural productivity estimation equation. This indicates that the ordinary least squares (OLS) estimates of β_1 and β_2 will suffer from the sample selection criterion have non-zero expected values[49]. The non-zero covariance between the error terms of the selection equation and the outcome equation showed the existence of selection bias, and the null hypothesis of the selection bias would be rejected. The inverse mills ratio (IMR) of adaptation computed from the selection Equation (1) by included in Equations (4) and (5) as a remedy for selection bias in the two-step estimation procedure (i.e., endogenous switching regression) as

$$\lambda_{1i} = \frac{\Phi(Z_i\alpha)}{\Phi(Z_i\alpha)} and \lambda_{2i} = \frac{\Phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)} \tag{6}$$

The three error terms ε_i, u_{1i} and u_{2i} are assumed to follow a tri-variate normal distribution with zero mean factor and non-singular covariance matrix as shown in the equation

$$Cov(\varepsilon_i, u_{1i}, u_{2i}) = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2 & \rho_{1e}\sigma_1 \\ \sigma_1\sigma_2 & \sigma_2^2 & \rho_{2e}\sigma_1 \\ \rho_{1e}\sigma_1 & \rho_{2e}\sigma_2 & \sigma_\varepsilon^2 \end{pmatrix} \tag{7}$$

where, ρ_{1e} and ρ_{2e} were correlation coefficients between u_{1i} and ε_i, and between u_{2i} and ε_i, respectively. If either ρ_{1e} and ρ_{2e} was significantly different from zero, the presence of selection bias would be confirmed. If $\rho > 0$, then there was negative selection bias, signifying that farmers with below-average sorghum productivity were more likely to adapt climate variability. If $\rho < 0$, a positive selection bias would indicate that farmers above average sorghum productivity would be more likely to adapt to climate variability.

The number of agrometeorological information and trust in this information were used as instrumental variables in the selection model to address the endogeneity problem. These variables influenced sorghum farmers' adaptation to climate variability but did not directly affect sorghum productivity. We selected the number of agrometeorological information because there were many information sources at the farmer's disposal depending on their level of access. Trust in agrometeorological information may have affected the sorghum farmers to adapt to climate variability if the information were reliable and consistent.

The study's main aim was to estimate the average treatment effects, the change in outcomes (increased sorghum productivity) due to adaptation to climate variability estimated as the difference between adopters and non-adopters. The average treatment effect was represented by Y_1 (sorghum productivity) as shown in the equations. The equation for the expected conditional and average treatment effects for the adopters and non-adopters to climate variability groups were given as:

The equation for the farmers practicing sorghum production in Busia County.

$$E[Y_{1i}/X, A_i = 1] = \alpha_1 + X_{1i}\beta_1 + \rho_{1i}\sigma_{1\varepsilon}\lambda_{1i} \tag{8}$$

The equation for adapters, they decided not to adapt to climate variability:

$$E[Y_{2i}/X, A_i = 1] = \alpha_2 + X_{2i}\beta_2 + \rho_{2i}\sigma_{2\varepsilon}\lambda_{2i} \tag{9}$$

The equation for non-adopters, they decided to practice sorghum production:

$$E[Y_{1i}/X, A_i = 0] = \alpha_1 + X_{1i}\beta_1 + \rho_{1i}\sigma_{1\varepsilon}\lambda_{1i} \tag{10}$$

The equation for the non-adopters, which did not adapt to climate variability:

$$E[Y_{2i}/X, A_i = 0] = \alpha_2 + X_{2i}\beta_2 + \rho_{2i}\sigma_{2\varepsilon}\lambda_{2i} \tag{11}$$

The heterogeneity effects using the expected outcomes are calculated as described in Equations (8)–(11). The base heterogeneity for adopters to climate variability was calculated as the difference between Equations (8)–(10). In contrast, the base heterogeneity of the non-adopters was calculated as the difference between Equations (9) and (11). Finally, we estimated the transitional heterogeneity ($ATT - ATU$) to understand whether the impact of sorghum productivity was larger or smaller for farmers adapted to climate variability. Thus, the estimated change in the level of sorghum productivity for farmers who adapted to climate variability (the average treatment effect of the treated households or ATT was given as

$$ATT = (a) - (b) = E[Y_{1i}/X, A_i = 1] - E[Y_{2i}/X, A_i = 1] = X_{1i}(\beta_1 - \beta_2) + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \quad (12)$$

The conditional expectations, treatment and heterogeneous effects are shown in **Table 3**.

Table 3. Conditional expectations, treatment, and heterogeneous effect.

Sub-samples	Decision stage		Treatment effects
	To adopt	Not to adopt	
Adopters	(a) $E[Y_{1i}/X, A_i = 1]$	(b) $E[Y_{2i}/X, A_i = 1]$	ATT
Non-adopters	(c) $E[Y_{1i}/X, A_i = 0]$	(d) $E[Y_{2i}/X, A_i = 0]$	ATU
Heterogeneous effects	BH_1	BH_2	TH

NB: (a) and (d) are observed outcomes, while (b) and (c) are the hypothetical unobserved outcomes (expected situations). $A_i = 1$ if farmers adopted to climate variability; $A_i = 0$ if farmers did not adapt to climate variability. ATT and ATU denotes average treatment effect on the treated and untreated. BH_1 is the effect of base heterogeneity for farmers who adapted to climate variability $(A = 1)$ and did not adopt $(A = 0)$. *TH*: transitional heterogeneity = $ATT - ATU$.

Similarly, we estimated the expected change on non-adopters farmers as the average treatment effect on the untreated farmers (*ATU*) given as:

$$ATT = (c) - (d) = E[Y_{1i}/X, A_i = 0] - E[Y_{2i}/X, A_i = 0] = X_{2i}(\beta_1 - \beta_2) + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \quad (13)$$

5. Results and discussion

The composite effect of ago-meteorological information, socioeconomic and institutional factors on adopting climate variability were analysed using the endogenous switching regression model. The results were presented in **Table 4**. ESR model is a two-step procedure in which the probit model is used as the first step, and a joint selection and outcome equation is estimated using the maximum likelihood method. A log-likelihood of -662.93418 implies that the model converges quickly. The wald chi-square statistic (*Wald chi*^{2}(9) = 42.48, *Prob* > *chi*^{2} = 0.0000) indicates that the model perfectly fits the data with strong explanatory power. The results indicate that the coefficients of variables, number of extension contacts, credit access, gender, age and education level were significant for farmers adapting to climate variability. On the other hand, age and proportion of income under farming significantly related to non-adapters to climate variability.

The number of extension contacts had a positive and significant relationship with the adoption to climate variability at 1 percent. The results explain that an increase in the number of extension contacts by one unit increases farmers' likelihood to adapt to climate variability by 11.86 percent. This is probably because extension services help disseminate innovations on the best practices of climate smart agricultural practices and build resilience capacities of the vulnerable farmers in managing the impacts of climate change. Moreover, increased extension contact is expected to lead to increased information on climate change and variability. The findings are similar to Legesse et al.[50] and Ozor and Nnaji[51], which established that access to extension services was strongly significant in adaptation to climate variability. Further, the demand for extension services builds up the need to retrain the personnel to acquire the capabilities to manage the risks associated with climate change. Ojo et al.[52] also found out that farmers' access to extension services was positive and significantly associated with the early maturing crop, reduce livestock number and irrigation adaptation strategies and attributed it to the importance of access to relevant information and other resources provided to farmers through extension service.

Table 4. Maximum likelihood estimates of endogenous switching regression model.

Variables	Selection model		Adapters to climate variability		Non-adapters to climate variability	
	Coef.	***P* > /Z/**	**Coef.**	***P* > /Z/**	**Coef.**	***P* > /Z/**
Group membership	−0.42**	0.02	−0.13	0.30	0.15	0.31
Extension contacts	0.13***	0.00	0.12***	0.00	−0.02	0.54
Credit access	1.48***	0.00	−0.30***	0.07	0.36	0.11
Market distance	0.09*	0.08	−0.00	0.96	−0.02	0.64
Gender	0.24	0.15	−0.20*	0.09	0.41	0.00
Age	0.00	0.64	−0.00***	0.86	−0.00**	0.59
Education level	−0.05**	0.03	0.04***	0.01	0.02	0.22
Income activities	0.34	0.13	−0.33	0.09	0.07	0.76
Income propo under farming	1.25*	0.09	−0.01	0.98	1.01*	0.08
Number of trainings	0.25***	0.00	0.06	0.03	−0.01	0.81
Own_farm land	0.26	0.47	−0.06	0.82	0.15	0.53
Number of agro-met	−0.27**	0.03				
Trust in agro-met infor	0.86	0.00				
_cons	−1.78***	0.00	6.68***	0.00	4.92***	0.00
Number of observations	423					
Wald chi^2(9)	42.48					
Log likelihood	−662.93					
Prob > *chi*^{2}	0.00					

*, **, *** represents 10%, 5% and 1% significance level, respectively.

Credit access had a negative and significant relationship on the adaptation to climate variability at 1 percent level. This suggests that farmers with access to credit were less likely to adapt to climate variability by 11.86 percent. The probability of credit received indicate that credit-constrained farmers were choosing adaptation strategy decreased as the amount of credit increased. This is attributed to the fact that adoption of these strategies is capital intensive with some demanding investments in the new planting materials and other technologies. Thus, farmers will find it difficult to adopt any adaptation strategy in case of inadequate credit since they might find it difficult to buy enough inputs. This confirms with Ojo and Baiyegunhi[53] that credit constraints negatively impact climate change adaptation strategies. Similarly, the financial resource is one of the key strategies used in expanding and strengthening mitigating risk strategies in the presence of threats to climate change.

Gender of the farmers was found to be negatively significant in adaptation to climate variability at 10 percent level. Female farmers were more likely to adapt to climate variability by 19.89%. This s attributed to the fact that women were more keen to implement some strategies that reduce the workload in the homestead. Thus, their willingness to implement adaptation strategies is an opportunity for introducing appropriate strategies. This is in line with the findings of Ochieng et al.[54], who note that female-headed households were more inclined to per-ceive a decrease in temperature and therefore respond faster than male-headed households. Findings by Gbetibouo[21] also corroborate that the probability to adapt of the male headed households was lower than that of the female headed households in kyuso district. However, this finding is different from Kakota et al.[55] that hold that women are more vulnerable to household food insecurity than men since they have few alternative ways to adapt.

The age of the farmer was negatively significant on adaptation to climate variability at a 1 percent level. The negative coefficient indicated that adapting to climate variability increases with a decrease in the farmer's age. Hence, older farmers were less likely to adapt to climate variability by 0.07 percent. The older people's physical strength, mobility and stamina are reduced due to their age, making it difficult to adapt to climate variability. Age is a significant factor in making an individual less or more accepting of climate variability and their willingness to adapt. Thus, it is negatively significant for both adapters and non-adapters to climate variability. In addition, as people grow older, they are reluctant to adopt new techniques; at the same time, they are unable to let go of the traditional way of doing things. The results are in line with the findings of Ndamani and Watanabe[56] who found out that the likelihood of adaptation to climate change and variability decreases in older farmers as they generally lack interest and incentive to adapt.

Education level was positively significant for the farmers adapting to climate variability at a 1 percent level. This implies that an increase in the level of education by farmers increases farmers' chances of adapting to climate variability by 3.88 percent. Education can directly improve knowledge, that is, an individual's ability to understand and process information and risk perceptions. In addition, more education has the capabilities to enhance the socioeconomic status and social capital. These are some of the important qualities and skills that are useful for coping and surviving disasters. Similar results by Ojo and Baiyegunhi[53] establish that education level increases farmers' capability to adapt to climate variability. The findings of Mutunga et al.[57] indicated that farmers with high education level were more likely to adapt as compared to farmers with low education levels since education increases the ability to receive, decode, and understand information relevant to making innovative decisions.

The proportion of income allocated for farming was found to be positively significant among non-adapters of climate variability at a 10 percent significant level. The results indicate that an increase in the proportion of income allocated for farming increases farmers' chances of becoming non-adapters of climate variability by 101.07 percent. Farmers who engage in conventional agriculture and realise high income from their farming activities do not need to adapt to new technologies since they are more comfortable with the amount of money they are receiving from farming. The farmers with higher farm incomes have less incentive to adapt than their counterparts since their farming practices might already be optimum. This is in line with the findings of Mutunga et al.[57] who found a positive relationship between farmers' off-income and their adoption of adaptation strategies to climate change and variability. However this is contrary to the findings by Fosu-Mensah et al.[58] that farm income positively influenced the decision by the farmer to adapt to climate variability other than non-adapters.

The treatments effects on sorghum yield

The results in **Table 5** show the effect of adaptation to climate variability on sorghum yield. The first step involved testing for the presence of endogeneity to ascertain whether adaptation to climate variability was endogenous or not. In order to achieve this, Durbin and Wu-Hausman were carried out and the results were as follows; Durbin (score) $chi^2(1) = 8.49397$ ($P = 0.0036$) and Wu-Hausman $F(1409) = 8.38114$ ($P = 0.0040$). Considering the P value of less than 0.05, the tests were significant; therefore, the null hypothesis that adaptation to climate variability was exogenous in the model was rejected. This shows that adaptation to climate variability was endogenous in the model. Further, the Sargan and Basman tests were conducted in testing for over-identifying restrictions, and the P values were 0.2656 and 0.2729, respectively. The P values were greater than 0.05, implying a failure to reject the null hypothesis (no over-identifying restrictions). The coefficients of the two estimated instrumental variables (number of agro-meteorological information and trust in agro-meteorological information) were jointly significant $F(2409) = 15.8779$ ($Prob > F = 0.0000$). This implies that the instruments used in the model were valid.

The values on (a) and (b) represents the observed actual sorghum output for adapters to climate variability and non-adapters to climate variability, respectively. On the other hand, values on (c) and (d) represent the counterfactual expected sorghum output for adapters to climate variability and non-adapters to climate variability, respectively. The results show that *ATT* had a negative and significant effect on sorghum output at a 1% level. The mean sorghum output of adapters to climate variability would have decreased by 0.88 had they been non-adapters. On the other hand, results on *ATU* reveal a negative and significant effect of sorghum output on adaptation to climate variability by non-adapters at a 1% level. The farmers who are non-adapters to climate variability would have earned an extra 1.37 if they had been adapters. Both adapters to climate variability and non-adapters to climate variability deserve strategies to combat climate variability since the ATE for both categories was positive. BH_1 of −0.68 implies that non-adapters to climate variability would have performed better than adapters to climate variability should they have been adapters, while BH_2 of −0.19 implies that non-adapters to climate variability would have performed better than adapters would they have been non-adapters. A negative transitional heterogeneity of −0.49 indicates that the effect on sorghum output is associated with unobserved household characteristics and not adaptation to climate variability. Adaptation to climate variability is significant to the output of sorghum farmers. This is because adapters to climate variability had higher sorghum output than non-adapters.

Table 5. Mean treatment effect on sorghum yield.

Sub-sample	**Decision**		
	Adapters to climate variability (*ATT*)	**Non adapters to climate variability (*ATU*)**	**Average treatment effects (ATE)**
Adaptation to climate variability	(a) 6.43	(c) 5.55	0.88***
Non-adapters to climate variability	(d) 7.11	(b) 5.74	1.37***
Heterogeneity effects	$BH_1 = -0.68$	$BH_2 = -0.19$	−0.49

*** significance at 1%.

6. Conclusion

This paper used a semi-structured questionnaire with a sample of 384 sorghum farmers. The specific objective of this paper was to determine the composite effect of climate variability, agrometeorological information and institutional factors on agricultural productivity in Bungoma County. The endogenous switching regression model results indicated that extension contacts and education level were positively significant among adapters of climate variability. Conversely, credit access, gender and age were negatively significant among adapters of climate variability. On the other hand, the proportion of income allocated for farming was positively significant among non-adapters of climate variability while, age was negatively significant among non-adapters of climate variability. The results of the mean treatment effect indicate that the sorghum yield was higher among adapters to climate variability compared to non-adapters. Policymakers, government institutions and non-government organizations should ensure increased extension contacts and promotion of education among farmers so that they know the various types of agrometeorological information available and the use of this information in making informed decisions on agricultural productivity. Agricultural policy seeking to enhance small-scale farmers' awareness of CSA practices, various methods of appraising and selecting the farming technologies with high returns and the uptake level of these practices should be formulated. Properly packaging agrometeorological information in a more understandable language through efficient and reliable information dissemination pathways would build confidence and trust hence make farmers to make adaptation decisions based on accurate information thereby increasing their productivity.

Author contributions

Conceptualization, GOA, EOG and KWS; methodology, GOA and EOG; software, GOA and JJM; validation, GOA, EOG, KWS and JJM; formal analysis, GOA and JJM; investigation, GOA; resources, GOA and JJM; data curation, GOA and EOG; writing—original draft preparation, GOA; writing—review and editing, GOA, EOG, KWS, JJM; visualization, GOA; supervision, EOG and KWS; project administration, GOA; funding acquisition, GOA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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