

Original Research Article

Influence of Farmers Perceptions of Climate Variability on Postharvest Technologies Adoption among the Maize Farmers in Bungoma South Sub- County, Kenya

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Abstract: Up to 30% of harvested maize is lost due to climate variability, which disrupts the drying process and creates conditions favourable for grain spoilage. Despite the availability of improved post-harvest storage technologies in the study area, their adoption remains low among maize farmers. Thus, the aim of this research was to determine farmers' perceptions of climate variability on post-harvest technologies adoption. A quasi-longitudinal research design was adopted for the study guided by Expected Utility and Diffusion theories. The unit of analysis was household maize farmers. The study encompassed the entire maize farming population of 32,137 households in Bungoma South Sub-County. Utilizing a systematic sampling technique, 400 respondents were selected from each ward, based on the proportionate share of maize farmers in each locality. The data collection was done using structured questionnaires and focus group discussions (FGDs). Secondary data was sourced from the Kenya Meteorological Departments' database and unpublished documents. Data was analyzed using means, standard deviations while qualitative done thematically. Inferential statistics was done using Chi Square and Cramer's V. The findings showed that farmers demonstrated high awareness of climate variability, with 80% perceiving temperature changes and noting increased rainfall unpredictability. The Chi-square tests showed high statistically significant influences between temperature, rainfall and rainfall duration and technology adoption for storage respectively ($\chi^2(16) = 270.77, p < 0.001$), ($\chi^2(14) = 251.468, p < 0.001$), ($\chi^2(14) = 256.244, p < 0.001$ with the effect size measured using Cramer's V of 0.850, 0.819 and 0.827 that indicated very strong influences between farmers' perception categories of temperature, rainfall and rainfall duration variations and the post-harvest technologies adopted respectively. The study concluded that farmers' perceptions of climate variability significantly influenced farmers' post-harvest storage technology choices. We recommend that farmers be guided by climate variability information when making choices on the most efficient, reliable and economical post-harvest technologies to use so as to reduce post-harvest losses during variable weather patterns, ultimately improving household food security.

Keywords: Postharvest losses, climate variability, farmers' perception, post-harvest storage technologies, post-harvest storage technology choices. Temperature variations, Rainfall variations, Rainfall duration.

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1.1 INTRODUCTION

Maize is a staple food crop in Kenya, playing a central role in national food security and rural livelihoods. In regions such as Bungoma County, maize is the most widely cultivated and consumed cereal,

forming a significant part of household diets and incomes (KNBS, 2020). However, postharvest losses (PHLs) continue to affect maize value chains, with national estimates ranging from 20% to 30%, largely due to poor

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postharvest handling, inadequate storage, pest infestation, and fungal contamination (FAO, 2020).

According to global research, the main causes of postharvest losses explored in a nutshell included pest infestation, poor storage, mechanical damage, fungal contamination (e.g., aflatoxins), climatic conditions, and infrastructural limitations. Studies carried out by Baributsa *et al.*, (2020) and Baoua *et al.*, (2021) investigated insect infestation, notably *Sitophilus zeamais* and *Prostephanus truncatus*, as primary culprits in African maize losses. A similar study done by Okonya *et al.*, (2020) established that postharvest pest pressure in Uganda led to up to 30% maize loss, especially where synthetic pesticides were improperly used or unavailable. These studies effectively identified species-level pests and their lifecycle impacts on storage losses. However, many were limited to laboratory or controlled experiments, which did not capture farmers' real-world practices such as irregular drying, overloading of storage bags among others.

Globally, many studies examining farmer perceptions of climate variability tended to focus primarily on production-related impacts, such as planting, crop yield, or irrigation decisions. For instance, Ayanlade *et al.*, (2020) explored how smallholders perceived climate variation based on rainfall and temperature changes, yet they gave little attention to how such perceptions translated into postharvest risk management strategies. This production bias led to a knowledge gap concerning how farmers interpreted climate-induced postharvest challenges, such as drying inefficiencies, pest infestation during storage, or mold due to humidity.

In Sub-Saharan Africa, while studies such as Wanjala *et al.*, (2020) and Ndegwa *et al.*, (2020) showed that farmers' exposure to climate-induced losses can shape their risk perception, however, there was limited empirical linkage between perception and actual adoption behavior regarding postharvest technologies. Much of the literature fell short of explaining why some farmers adopted technologies while others did not, even when they shared similar climate experiences. This highlighted the need to examine how perception interacted with trust, cultural norms, access to technologies, and extension services, particularly at the community level.

In Kenya, and even the study area, the key limitation was the generalized national or regional scope of most existing studies. For example, Ambuko *et al.*, (2023) assessed solar dryer adoption across several Kenyan counties but failed to differentiate findings based on localized climate impacts or community-level perception trends. Given the microclimatic diversity of areas like Bungoma South Sub-County, such generalizations may overlook crucial variation in farmer behavior. This creates a notable gap in fine-grained, sub-

county-level data that links perception of local climate events (e.g., unexpected rainfall during drying season) to technology uptake decisions that was undertaken by the current study. In addition to that, most of the reviewed literature by De Groote *et al.*, 2020, showed that climate perception was measured narrowly, often using binary survey questions (e.g., "Have you noticed changes in weather?"). Such approaches failed to capture the complexity of farmers' lived experiences with climate shocks. Similarly Ogutu *et al.*, (2023) on the other hand argued that more robust approaches such as qualitative narratives, longitudinal surveys, and perception mapping were needed to generate deeper insights.

In Bungoma County, Smallholder farmers usually dry and store their basic crops after harvesting them in order to conserve food until the following harvest. The Bungoma Development Plan 2019 stated that variations in rainfall have a significant role in the 20–30% post-harvest losses that transpire within 6 months following harvest. Mugalavai *et al.*, (2008) in their research conquered with this and postulated that, the high variability of the commencement and end of the rainy season was the reason why rainfall features, such as the length of the growing season, had always been unknown. This increases maize exposure to mold growth, aflatoxin contamination, and pest attacks (Midega *et al.*, 2020). These climatic stresses make conventional postharvest practices increasingly unreliable, creating a demand for climate-resilient postharvest technologies. In response, several modern postharvest technologies (PHTs) have been introduced in Kenya—such as hermetic storage bags (e.g., PICS and AgroZ bags), metal silos, solar dryers, and digital moisture meters—all designed to mitigate losses even under changing climatic conditions (De Groote *et al.*, 2020). While these innovations are proven to reduce losses, especially in high-risk environments, adoption rates remain low in many rural areas, including Bungoma (Affognon *et al.*, 2022). Hence the purpose of this research was to find out influence of farmers perceptions of climate variability on postharvest technologies adoption among the maize farmers in Bungoma south sub- county, Kenya.

2.0 MATERIALS AND METHODS

Study Area

The study was carried out in Bungoma County. The nine Sub-Counties that make up the greater Bungoma County are Bungoma North, Bungoma South, Webuye East, Webuye West, Bungoma Central, Bungoma West, Kimilili, Mt. Elgon, and Bumula. Bungoma South Sub-County is one of those sub-counties. It is located between latitudes 00' 28 and 10' 30 north on longitude 34'30E. It shares borders with Bungoma Central Sub-County to the north, Webuye East Sub-County to the east, and Bumula Sub-County to the west. It has a total size of 329 square kilometers. There are 14 sub-locations and 5 administrative locations inside

it. Kuywa, Nzoia, Sio, and Chwele are the rivers that supply water to the area and have permanent tributaries.

3.0 The 2014 Bungoma County Strategic Plan

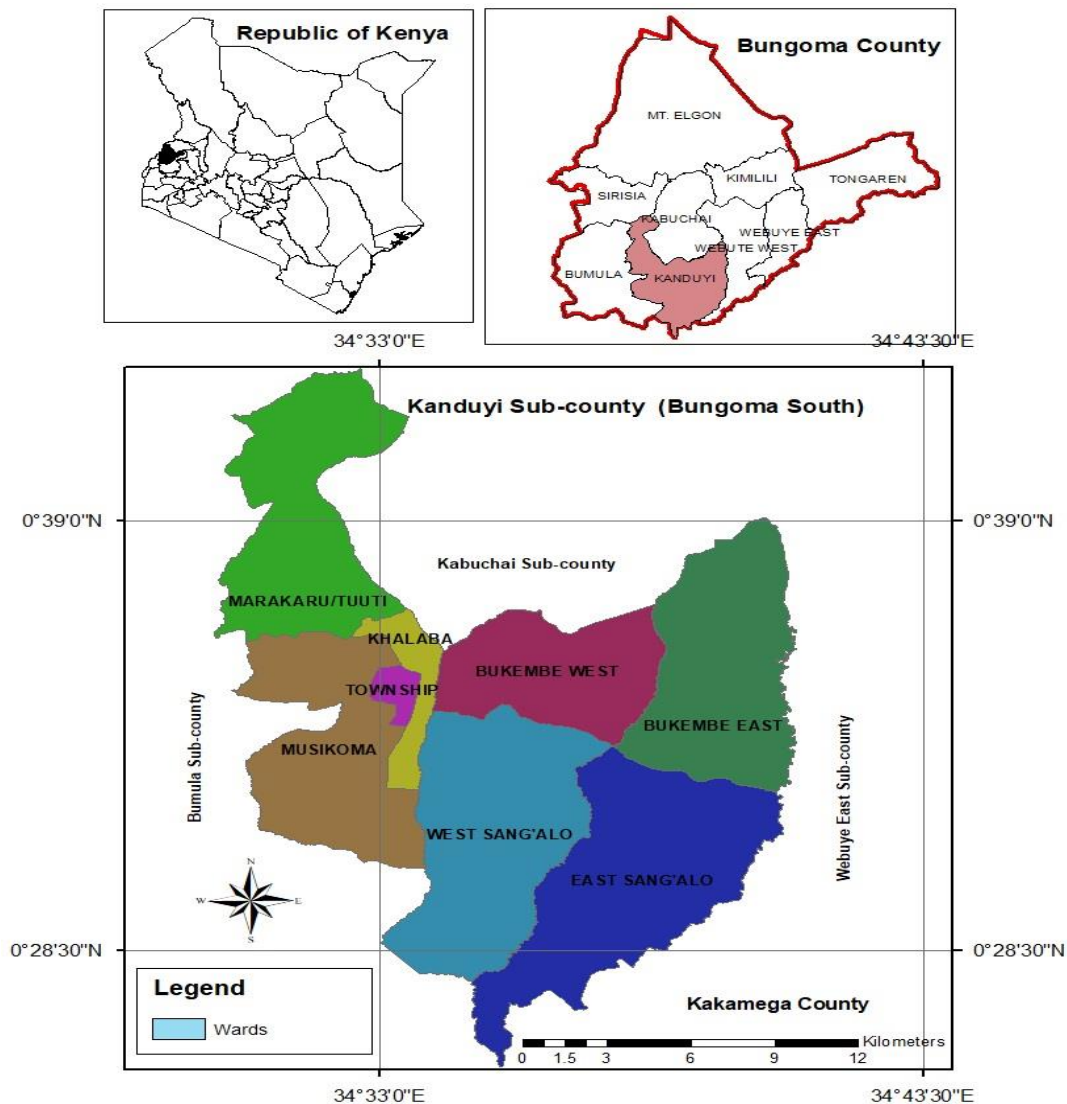


Figure 1: Study Area, (Source: GOK, 2013)

4.0 Climate of the Study Area, Climate of the Study Area

Bungoma South experiences dependable yearly rainfall in the range of 1000 mm to 1500 mm, with a bimodal pattern consisting of long rains from March to July and short rains from August to October. December, January, and February are often the months with the least amount of rainfall. The sub-County is located in the Lake Victoria Basin, with annual temperatures ranging from 21 to 25°C and elevations between 1200 and 1500 meters above sea level (A.S.L.) (GoK, 2013). The majority of farmers in the county are depended on the unpredictable and irregular rains. Low crop yields and post-harvest losses are partly caused by an increase in pest and disease events brought on by rainfall and temperature variations (County Government of Bungoma 2021).

Field Sampling

The sampling frame for the study included all maize farmers in Bungoma South Sub-County which is 32137 (Bungoma County Development Plan 2017-2022). Using Yamane (1973) the sample size was calculated to approximately 400. Systematic sampling technique was used to select the maize farmers. Using the a above sample determination formula, 400 sample respondents were picked at random from each ward using a systematic random sampling technique, with the selection process based on probability proportionate to size. However, purposive sampling was used to select key informants where one senior officer from the MOA and KMD were approached respectively. Their percentage to the overall share of households in each ward was used to calculate the sample size from each ward.

Table 3.1: Sample Households to be selected for the Study

Wards	Population	Proportion	Sample size
1. Tuuti Marakaru	3021	0.094	37
2. Khalaba	2058	0.064	26
3. Township	65	0.002	1
4. Musikoma	5463	0.17	68
5. Bukembe East	4821	0.15	60
6. Bukembe West	4177	0.13	52
7. West Sang’alo	6748	0.21	84
8. East Sang’alo	5784	0.18	72
	32,137		

Source: Author’s compilation, 2024

4.1 Data Collection

The study used a structured questionnaire as a data collection tool to collect the primary data. The questionnaire gathered information on smallholder maize farmers’ perceptions on climate variability on post- harvest maize technology adoption in Bungoma South Sub-County. The structured questionnaires utilized closed and open- ended questions covering all the areas of study.

The process of administering the survey also involved recruiting the focus group discussants. Potential focus group discussion participants were notified about a follow-up study during data collection, and they were asked whether they would be willing to participate. Focus group sessions extracted people’s thoughts and feelings regarding local viewpoints in a setting that allowed them to explore the manner in which goods or services directly impacted them (Flachs, 2019). According to Mugenda& and Mugenda, 2003, at least 10-30% of the accessible population is viable and representative enough to yield acceptable and reliable results for a generalization. Therefore, in total, 32 discussants participated in three focus groups that were

deliberately chosen from the wider group of survey participants.

Respondents were represented by three of the eight surveyed wards in the Sub-county: Township (5 discussants), Bukembe (12 discussants), and Sang’alo (15 discussants) proportional to the sample size derived from each ward. The selection process for participants included a range of perspectives, and experience in growing and storing maize. The research questions served as a guide for the focus group talks, which run roughly an hour in each case. The participant selection was aimed at obtaining varying viewpoints, gender representativeness, and maize farming & storage experience. The discussions provided a cross-sectional perspective of farmers’ experiences with and views of post- harvest maize storage technology use in their homes. The conversations contributed to the production of detailed information regarding some survey results and farmer perspectives that might not have been sufficiently gathered by the semi-structured questionnaires. The identical research questions were used in each focus group to maintain uniformity.

Table 3.2: Focus Group Discussant Breakdown

Ward	Number of Discussants
Township (township, khalaba & musikoma)	5
Bukembe (East & West)	12
Sang’alo (East & West)	15

Data on climate variables was also captured using in-depth interviews from key informants (officers from the KMD) for the last thirty-seven years' worth of records, which stretched from 1987 to 2024. Similarly, officers from the MOA were also interviewed on PHST adoption. In both cases the interview guide questions in appendixes 2 & 3 were used.

Finally, daily data for rainfall and temperature was obtained from the KMD for the period 1987-2024 so as to calculate the total mean annual rainfall & temperature variations for Bungoma South Sub-County. The rainfall and temperature figures for the Sub County were recorded in a summary check sheet and this included rainfall duration (onset & cessations) both for

short & long seasons, and rainfall& temperature variations.

4.2 Data Analysis and Results Presentation

The use of post-harvest technology by farmers was described and assessed according to the degree of agreement that respondents felt was necessary to gather data. A scale with items created specifically for this study was used to test perception. Using a Likert-type scale, the sample respondents' responses on the perception-related question was examined. As a result, the respondents' perception of the post-harvest storage technologies was measured using ratings such as strongly disagree (1), disagree (2), no opinion (3), agree (4), and strongly agree (5). The larger value (5) indicated how the farmer

believed the characteristics being presented for evaluation were being embodied, with 4,3,2, and 1 in a decreasing order. If the number was less than three, then the farmer believed the attributes being evaluated were inadequate or insufficient.

Finally, to find the relationship between farmers' perceptions of climate variability and storage technology, and other aspects of maize storage, a chi-square test with cross-tabs was employed. The effect size was measured using Cramer's V

RESULTS AND DISCUSSION

4.3 Farmers' Perceptions on the influence of Climate Variability on Post-harvest Technologies Adoption

This section presented the analysis of farmers' perceptions regarding climate variability and its influence on post-harvest technologies adoption, based on responses from 375 farmers in Bungoma South Sub-County.

Table 4.3: Farmers' responses according to levels of agreement or disagreement to statements on perceptions regarding temperature patterns and Measures of Central Tendency and Dispersion of frequencies of responses by farmers towards temperature patterns on postharvest technologies adoption(n=375)

Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Mean	SD
Temperatures have increased over past 10 years	15 (4%)	28 (7.5%)	42 (11.2%)	186 (49.6%)	104 (27.7%)	3.89	1.02
Heat waves are more frequent now	22 (5.9%)	31 (8.3%)	35 (9.3%)	195 (52%)	92 (24.5%)	3.81	1.08
Temperature variations affect maize storage	12 (3.2%)	25 (6.7%)	38 (10.1%)	178 (47.5%)	122 (32.5%)	3.99	0.98
Higher temperatures increase pest problems	8 (2.1%)	19 (5.1%)	29 (7.7%)	201 (53.6%)	118 (31.5%)	4.07	0.89

The means of 3.81 and 3.89 suggested moderate agreement, showing that farmers recognized temperature related issues as having a noticeable effect on their postharvest handling practices. The higher mean of 3.99 reflected stronger agreements, implying that this particular temperature aspect was viewed as more influential in shaping technology decisions, The highest mean of 4.09 showed the strongest consensus, indicating that farmers considered this temperature factor to be highly significant in determining whether they adopt modern postharvest technologies. Overall, the measures of central tendency revealed that farmers held generally positive and consistent perceptions regarding the influence of temperature variability on postharvest technology adoption in the study area.

In line with the above findings, related surveys showed that farmers in similar contexts perceived temperature changes clearly, with many reporting increases in temperature over recent decade and associating these changes with agricultural impacts such as crop drying and stress for instance in Kenya's Kisii region, where over 76% of farmers who noticed temperature increases(Lobell *et al.*, 2011; Thornton *et al.*, 2014; Bryan *et al.*, 2013; Porter *et al.*, 2014;

4.3.1 Central tendency and dispersion in likert scale responses to temperature patterns

Farmers' perceptions on the statements focusing on temperatures variability and its influence on maize storage and pests problems were sought. The respondents were asked to indicate the extent to which they agreed with the statements according to a five-point Likert-type scale: Strongly Agree = 5, Agree = 4, Undecided = 3, Disagree = 2 and Strongly Disagree = 1. The results are presented in Table 4.3.

In Table 4.3, the mean scores of 3.81, 3.89,3.99 and 4.07 on the perceptions of respondents about the influence of temperature on postharvest technologies adoption showed that farmers generally agreed that temperature variability affected their adoption and use of postharvest technologies. Since all the values fell between 3.50 and 4.49, they indicated a consistent level of agreement across the statements measured.

Affognon *et al.*, 2015). This reinforced our findings that mean perception scores clustered towards agreement.

Furthermore, although farmers reported agreement on temperature influence, studies showed that perception often reflected experience with climate outcomes rather than precise scientific understanding of climate trends. In the central highlands of Kenya, for example, farmers reported higher temperatures and shorter seasons, and such perceptions strongly influenced their adoption of soil and water management and other climate coping strategies ((Feder *et al.*, 1985; Meijer *et al.*, 2015; Adesina & Zinnah, 1993; Antle, 1996; Rogers, 2003).This was important because means alone do not indicate whether these agreements translated into adaptive behavior which was a key conceptual link to the current study.

Finally, the use of mean scores assumed that the survey items made a scale of related perceptions, but if items were independent or captured distinct facets of temperature impact, a simple mean would obscure important nuances (e.g some farmers may strongly agree with one item but not another). Therefore, literature suggested supplementing mean values with response

distributions, percentages of agree’’ vs strongly agree’’ as discussed in this study (table 4.3) (Porter, J. R., Xie, L., Challinor, A., Cochrane, K., Howden, M., Iqbal, M., Lobell, D., & Travasso, M. (2014).

Additionally, a standard deviation close to 1.0 was considered moderate, indicating that while there was general agreement on the issue, and farmers still differed in the strength of their opinions. The highest standard deviation of 1.08 associated with the score of 3.81 suggested that although farmers generally agreed that temperature variations affected postharvest technologies, their responses were more widely spread. This indicated that farmers had varied or differed in levels of exposure to temperature –related challenges during postharvest handling. The slightly lower standard deviation of 1.02 for the mean of 3.89 showed a similar pattern of moderate variation, implying that their perceptions were still diverse and farmers showed somewhat closer agreement on this aspect of temperature influence. Similarly, a standard deviation of 0.98 for the mean of 3.99 suggested increasing consistency among respondents, indicating that farmers views on this particular temperature related factor were more aligned. The lowest standard deviation of 0.89, linked to the highest mean score of 4.07 showed the greatest consensus among farmers. This meant that the respondents not only strongly agreed on this specific temperature influence but also held closely similar perceptions with minimal variations. Overall, the decreasing pattern of standard deviations showed that as the level of agreement increased, farmers’ perceptions became more uniform. In relation to Diffusion of Innovation Theory the variation in perceptions in our findings reflects different stages of innovation adoption, with some farmers being early adopters and others lagging behind (Rogers, 2003; Meijer *et al.*, 2015; Bryan *et al.*, 2013; Tefera *et al.*, 2011; Affognon *et al.*, 2015).

4.3.2 Distribution of Likert Scale Responses to Temperature across different categories

The results showed (Table 4.3) a clear pattern in farmers’ perceptions of temperature variations in Bungoma South Sub-County. Only 3.8% of the respondents strongly disagreed and 6.9% disagreed that temperature variability had been occurring, indicating

that very few farmers failed to recognize changes in temperature patterns. A small proportion (9.6%) remained neutral, suggesting limited uncertainty among farmers. The majority of respondents however, acknowledged noticeable temperature variations, with 50.7% agreeing and 29.1% strongly agreeing with the statement. This implied that close to 80% (agreeing and above) of the farmers positively perceived temperature variability as important climatic factor affecting farming activities. These findings had several implications on PHT adoption. The widespread perception of increasing temperatures by 80% of farmers suggested that farmers were aware of climate shifts and were now evaluating the relative advantage of modern technologies. Higher temperatures were linked with faster maize deterioration due to increased pest and fungal activity.

These findings aligned with recent studies done by Affognon *et al.*, (2015) and Mekonnen, A. B. (2024) who found that farmers perceiving climate change (especially temperature rise) were more likely to adopt modern PHTs as an adaptive response. Similarly, Bokusheva *et al.*, (2012) noted that risk perception played a central role in motivating farmers to invest in loss-reducing technologies. However, some studies (e.g., Mati, 2020) argued that even with perception of rising temperatures, lack of access to capital, low awareness and cultural attachment to traditional methods hindered adoption. This implied that perception alone wasn’t always sufficient. However, despite the observed perceptions, little empirical research existed directly correlating farmer-perceived temperature rise and actual adoption rates, most existing studies did not examine longitudinal behavior (how sustained temperature perceptions over the years influence gradual/sudden adoption of PHTs). This created a gap in understanding how perception intensity (agreed; strongly agreed) translated into actions – do stronger beliefs lead to higher investments? that necessitated this current study that filled the knowledge gap.

In addition to that, the Chi-square test of independence on the relationship between farmers’ climate variability perception of temperature and their technologies adoption was performed (Table 4.4a and Table 4.4b).

Table 4.4a: Chi-Square Test of Independence on Temperature Patterns and Technology Adoption

Chi-Square Tests	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	270.768 ^a	16	0.000
Likelihood Ratio	347.658	16	0.000
Linear-by-Linear Association	161.570	1	0.000
N of Valid Cases	375		

a. 22 cells (64.7%) have expected count less than 5. The minimum expected count is 1.22.

Table 4.4b: Cramer’s V Test Temperature Patterns and Technology Adoption

Cramer’s V test		Value	Approximate Significance
Nominal by Nominal	Phi	.850	.000
	Cramer's V	.850	.000
N of Valid Cases		375	

Table 4.4a presents the results of a Chi-Square test of independence examining the relationship between farmers’ perceptions of temperature patterns and the adoption of postharvest technologies in Bungoma South. The Pearson Chi-Square value ($\chi^2 = 270.768$, $df = 16$, $p < 0.001$) indicates a statistically significant association between perceived temperature changes and adoption behavior. Similarly, the Likelihood Ratio ($\chi^2 = 347.658$, $df = 16$, $p < 0.001$) confirms the strength of this relationship, while the Linear-by-Linear Association ($\chi^2 = 161.570$, $df = 1$, $p < 0.001$) demonstrates a positive linear trend: as farmers perceive greater temperature variability, the likelihood of adopting improved postharvest technologies increases. Although 22 cells (64.7%) had expected counts below five, the large sample size ($n = 375$) and highly significant p-values suggest that the association is robust (Field, 2013).

These results indicate that farmers’ perceptions of temperature patterns significantly influence their adoption of postharvest technologies, suggesting that climate variability serves as a critical driver of adaptive behavior. From the perspective of Expected Utility Theory, farmers evaluate adoption decisions based on the expected benefits and risks associated with innovation. When farmers perceive higher temperatures as a threat to maize quality and storage conditions, the expected utility of adopting technologies such as hermetic storage bags, metal silos, or improved drying techniques increases relative to traditional practices (Feder, Just, & Zilberman, 1985; Adesina & Zinnah, 1993). Empirical studies have shown that farmers’ risk perceptions strongly influence adaptive strategies, including investment in postharvest innovations aimed at

minimizing losses due to climatic hazards (Lobell, Schlenker, & Costa-Roberts, 2011; Deressa, Hassan, Ringler, Alemu, & Yesuf, 2009; Fosu-Mensah, Vlek, & MacCarthy, 2012).

The significant linear association observed in the analysis aligns with the Diffusion of Innovation Theory, which posits that adoption occurs through stages: knowledge, persuasion, decision, implementation, and confirmation (Rogers, 2003). Farmers who perceive temperature variability as a severe risk are likely to progress through the early stages of adoption more rapidly, moving from awareness to active implementation of improved storage technologies. Furthermore, social networks and extension services facilitate the diffusion of these innovations within communities, reinforcing the observed trend that perception of climatic risk is positively associated with adoption rates (Meijer, Catacutan, Ajayi, Sileshi, & Nieuwenhuis, 2015; Pretty, Toulmin, & Williams, 2011; Birner, Davis, Pender, Nkonya, Anandajayasekeram, Ekboir, ... Cohen, 2009).

4.3.3 Central tendency and dispersion in likert scale responses to Rainfall patterns

Farmers' perceptions on the statements focusing on rainfall patterns and its influence on maize storage and pests problems were sought. The respondents were asked to indicate the extent to which they agreed with the statements according to a five-point Likert-type scale: Strongly Agree = 5, Agree = 4, Undecided = 3, Disagree = 2 and Strongly Disagree = 1. The results are presented in Table 4.5.

Table 4.5: Farmers' Responses according to levels of Agreement or Disagreement to statements on Perceptions Regarding Rainfall Patterns and Measures o Central Tendency and Dispersion of Frequencies of Responses by farmers towards Rainfall Patterns on postharvest technologies adoption(n=375)

Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Mean	SD
Rainfall has become more unpredictable	10 (2.7%)	22 (5.9%)	31 (8.3%)	198 (52.8%)	114 (30.4%)	4.02	0.94
Long rains season has changed	18 (4.8%)	25 (6.7%)	45 (12%)	182 (48.5%)	105 (28%)	3.88	1.04
Short rains season has changed	15 (4%)	28 (7.5%)	52 (13.9%)	175 (46.7%)	105 (28%)	3.87	1.03
Rainfall affects maize drying and storage	5 (1.3%)	15 (4%)	28 (7.5%)	215 (57.3%)	112 (29.9%)	4.10	0.81

The means cores 3.87, 3.88, 4.02 and 4.10 (Table 4.5) on the likert scale indicated that farmers generally agreed with the statements measuring their perceptions of rainfall influence on postharvest technologies. Since all the mean values fell within the range of 3.50 – 4.49, they reflected a consistent perception among respondents that rainfall variability played a significant role in shaping their postharvest technology choices. The means of 3.87 and 3.88 showed moderate agreement, suggesting that farmers recognized these particular aspects of rainfall behavior – such as

timing, distribution and intensity – as influencing how the managed, stored and protected harvested maize. The slightly higher mean of 4.02 indicated stronger agreement, implying that this rainfall-related factor was perceived as more impactful on technology adoption. The highest mean score of 4.10 showed the strongest consensus among farmers, demonstrating that this specific rainfall aspect was viewed as the most influential in determining the postharvest technologies adoption. Overall, these measures of central tendency revealed that farmers held firm and consistent perceptions regarding

the importance of rainfall variability in influencing postharvest technologies adoption in Bungoma South Sub- County’.

Moreover, the standard deviations corresponding to the mean score of 3.87, 3.88, 4.02 and 4.10 were 1.03, 1.04, 0.94 and 0.89 respectively indicate varying levels of agreement among farmers regarding the influence of rainfall variability on postharvest technologies adoption. The relatively higher standard deviations of 1.03 and 1.04 suggested that while farmers generally agreed with the statements, their responses were more widely spread, pointing to differences in individual experiences with rainfall variations and their effects on postharvest handling. In contrast, the lower standard deviations of 0.94 and 0.89 reflected closer clustering of responses around the mean, implying stronger consensus among farmers that these specific rainfall related factors significantly affected their adoption and use of postharvest technologies. Overall, the decreasing trend in standard deviations suggested increasing agreement on the most influential rainfall factors that shaped postharvest technologies decisions in the study area.

These findings are consistent with prior studies that link farmers’ climate perceptions with adaptations behavior. For instance, in the central highlands of Kenya, researchers found that farmers who perceived variations in rainfall were more likely to adopt soil and water conservation practices as adaptation strategies (Tefera *et al.*, 2011). More broadly, analyses from other setting demonstrated that long-term climate risks-including rainfall variability significantly influenced the adoption of sustainable agricultural practices such as improved seeds, fertilizer use and intercropping (Feder, Just, & Zilberman, 1985; Bryan *et al.*, 2013). On the lens of EUT, these results reflected how farmers made decisions under uncertainty; When farmers perceived a sufficiently high probability that rainfall variability would adversely

affect their post-harvest outcomes, and believed that adopting postharvest outcomes ,and believed that adopting postharvest technologies would mitigate those risks, they were more likely to choose adoption-especially when their perceptions were widely shared (low standard deviation) and strongly held (high mean) (Feder *et al.*, 1985; Meijer *et al.*, 2015; Adesina & Zinnah, 1993; Antle, 1996; Rogers, 2003).

4.3.4 Distribution of Likert Scale Responses to Rainfall variations across different categories

The findings on farmers’ perceptions of rainfall variability indicated (Table 4.5) a clear pattern in the study area. Only 3.2% of the respondents strongly disagreed and 6.0% disagreed that rainfall patterns had changed, indicating that very few farmers did not recognize rainfall variability. A small proportion (10.4%) remained neutral, suggesting limited uncertainty among farmers regarding changes in rainfall trends. The majority, however, acknowledged noticeable shifts in rainfall patterns, with 51.3% agreeing and 29.1 strongly agreeing with the statements. This meant that 80% of the respondents positively perceived rainfall variability as a significant climatic challenge affecting their farming activities. On the lens of EUT, this posits that individuals make decisions by weighing potential risks and benefits under uncertainty. In this context, rainfall variability created uncertainty in maize production, drying, and storage outcomes. Farmers who perceived higher rainfall-related risks were more likely to adopt modern postharvest technologies that minimized potential losses. Thus, the high level of awareness of rainfall variability among farmers aligned with EUT as it motivates the adoption of technologies that increase expected utility by reducing climate-related risks.

Further, the Chi-square test of independence on the relationship between farmers’ climate variability perception of rainfall and the technologies adoption was performed (Table 4.6a and Table 4.6b).

Table 4.6a: Chi-Square Test of Independence on Rainfall Patterns and Technology Adoption

<i>Chi-Square Tests</i>	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	251.468 ^a	14	.000
Likelihood Ratio	326.093	14	.000
Linear-by-Linear Association	163.420	1	.000
N of Valid Cases	375		
a. 20 cells (66.7%) have expected count less than 5. The minimum expected count is .82.			

Table 4.6b: Cramer’s V Test Rainfall Patterns and Technology Adoption

Symmetric Measures		Value	Approximate Significance
Nominal by Nominal	Phi	.819	.000
	Cramer's V	.819	.000
N of Valid Cases		375	

Tables 4.6a and 4.6b present the results of Chi-Square and Cramer’s V tests examining the relationship between farmers’ perceptions of rainfall patterns and adoption of postharvest technologies in Bungoma South. The Pearson Chi-Square value of 251.468 with 14

degrees of freedom and a significance level of $p < 0.001$ indicates a statistically significant association between perceived rainfall variability and adoption behavior. Similarly, the Likelihood Ratio ($\chi^2 = 326.093, p < 0.001$) and Linear-by-Linear Association ($\chi^2 = 163.420, p <$

0.001) confirm that the observed association is robust across different measures. Although 20 cells (66.7%) have expected counts below five, the large sample size ($n = 375$) suggests that the results remain reliable, though caution is warranted when interpreting the precise chi-square values (Field, 2013).

The Cramer’s V value of 0.819 ($p < 0.001$), reported in Table 4.6b, quantifies the strength of association, indicating a very strong relationship between rainfall perceptions and postharvest technology adoption. This suggests that farmers’ views on rainfall variability are highly predictive of whether they implement technologies such as metal silos, hermetic bags, or improved drying methods to mitigate postharvest losses (Tefera *et al.*, 2011; Affognon, Mutungi, Sanginga, & Borgemeister, 2015).

According to Expected Utility Theory, farmers make adoption decisions by evaluating the benefits of a technology against the potential losses associated with non-adoption (Feder, Just, & Zilberman, 1985; Adesina & Zinnah, 1993). In the context of Bungoma South, unpredictable rainfall—including shifts in long and short rainy seasons—creates uncertainty in maize drying and storage. Farmers perceive that poor rainfall timing can increase moisture content in maize, thereby elevating risks of spoilage, mold, and pest infestation (Porter *et al.*, 2014; Tefera *et al.*, 2011).

The strong Cramer’s V value (0.819) demonstrates that farmers who recognize these risks are significantly more likely to adopt postharvest technologies. The adoption decision is consistent with maximizing expected utility: the higher the perceived risk from rainfall variability, the greater the expected benefit of protective storage innovations (Deressa, Hassan, Ringler, Alemu, & Yesuf, 2009; Fosu-Mensah, Vlek, & MacCarthy, 2012). Farmers’ strong consensus on rainfall impacts (mean scores 3.87–4.10) reinforces the notion that climatic risk perception is a key determinant of utility-driven behavior (Lobell, Schlenker, & Costa-Roberts, 2011; Maddison, 2007).

In addition to that, Diffusion of Innovation Theory posits that adoption spreads as individuals perceive a relative advantage and observe the success of peers (Rogers, 2003). The high level of agreement among farmers regarding rainfall unpredictability creates an environment where early adopters of postharvest technologies serve as models for others. When farmers adopt metal silos or hermetic storage in response to rainfall variability, they demonstrate tangible benefits, encouraging wider adoption in the community (Pretty, Toulmin, & Williams, 2011; Birner *et al.*, 2009).

Similarly, the very strong Cramer’s V value indicates that rainfall perception is not merely correlated with adoption but likely functions as a catalyst in the diffusion process. Farmers who are aware of rainfall-induced risks tend to adopt technologies earlier, accelerating technology uptake among peers. This dynamic aligns with Rogers’ emphasis on observable relative advantage, trialability, and communicability as key drivers of innovation diffusion (Rogers, 2003; Meijer, Catacutan, Ajayi, Sileshi, & Nieuwenhuis, 2015).

4.3.5 Central tendency and dispersion in likert scale responses to Rainfall Duration patterns

Information on Farmers’ Perceptions of Climate Variability of rainfall duration on post-harvest technologies adoption was sought from farmers. Their statements were anchored on a five point Likert-type scale as Strongly Agree (SA) = 5, Agree (A) = 4, Undecided (U) = 3, Disagree (D) = 2 and Strongly Disagree (SD) = 1. The respondents were asked to indicate the extent to which they agreed to the statements. The results were as indicated in table 4.7

Table 4.7: Farmers’ Responses according to levels of Agreement or Disagreement to statements on Perceptions Regarding Rainfall Duration Patterns and Measures of Central Tendency and Dispersion of Frequencies of Responses by farmers towards Rainfall Duration Patterns on postharvest technologies adoption($n=375$)

Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Mean	SD
Duration of long rains has decreased	20 (5.3%)	32 (8.5%)	48 (12.8%)	168 (44.8%)	107 (28.5%)	3.83	1.10
Duration of short rains has decreased	18 (4.8%)	35 (9.3%)	52 (13.9%)	172 (45.9%)	98 (26.1%)	3.79	1.08
Rainfall seasons start later than usual	12 (3.2%)	25 (6.7%)	38 (10.1%)	185 (49.3%)	115 (30.7%)	3.98	0.98
Rainfall seasons end earlier than before	15 (4%)	28 (7.5%)	42 (11.2%)	178 (47.5%)	112 (29.9%)	3.92	1.03

On a five-point likert scale the mean score of 3.79,3.83,3.92 and 3.98 (Table 4.7) fell within the moderate to high agreement range, suggesting that most

respondents recognized rainfall duration as an important factor affecting their postharvest management decisions. The mean scores of 3.79 and 3.83 reflected moderate

agreement implying that while farmers acknowledged the role of changing rainfall duration, some variations in perception still existed. The slightly higher mean of 3.92 showed stronger agreement, indicating that farmers considered this particular aspect of rainfall duration to have a more pronounced influence on the adoption of postharvest technologies. The highest mean of 3.98 demonstrated the strongest level of consensus that prolonged or shortened rainfall seasons significantly shaped the timing, choice and effectiveness of postharvest technologies.

In addition to that, the corresponding standard deviations of 1.08, 1.10, 1.03 and 0.98 showed a moderate level of variability in farmers' responses regarding the influence of rainfall duration. The relatively higher standard deviations for the first two items (1.08 and 1.10) indicated that while most farmers agreed, there was a widespread in opinions, suggesting differences in experience or sensitivity to variations in rainfall duration across farming households. As the means increased, the standard deviations slightly declined (1.03 and 0.98), indicating greater consensus among respondents for statements they perceived as more directly relevant to their postharvest activities. The lowest standard deviation (0.98) alongside the highest mean (3.98) suggested that this particular aspect of rainfall duration was widely shared and strongly agreed upon, reflecting a clearer, more uniform understanding of its impact on postharvest technologies adoption.

In the context of EUT, when farmers perceived unpredictable or shortened rainfall duration as a threat to postharvest operations, the expected utility of adopting modern technologies- for instance hermetic bags increased because these technologies reduced potential losses. The higher mean values, coupled with falling standard deviations, reflected situations where farmers more uniformly perceived the risks associated with rainfall duration, thus increasing the likelihood that they would choose technologies that maximized expected gains and minimized postharvest losses.

4.3.6 Distribution of Likert Scale Responses to Rainfall duration variations across different categories

The distribution of farmers' perceptions regarding rainfall duration showed a clear pattern in the study area. Only 8.7% of the respondents strongly disagree and 8.0% disagreed that rainfall duration had changed over time, indicating that relatively few farmers did not perceive any shift in the length of the rainy season. A modest 12% remained neutral, suggesting some uncertainty or mixed experiences regarding changes in how long rains lasted. However, the majority of farmers recognized changes in rainfall duration, with 46.9% agreeing and 28.8% strongly agreeing. This means that 76% of the respondents perceived rainfall duration variability as a significant climatic element that affected their farming operations.

This pattern is well explained through EUT, which argues that individuals make decisions by evaluating potential risks and expected benefits in situations of uncertainty. In this context, unpredictable rainfall duration introduced substantial uncertainty in maize production, harvesting schedules and postharvest drying processes. Farmers who perceived rainfall duration to be increasingly erratic faced higher risks of grain spoilage, drying and increased moisture related losses.

According to EUT, such farmers were more likely to adopt modern post-harvest technologies that would reduce these risks and increased expected utility by offering more reliable drying and storage outcomes. Therefore, the strong agreement levels observed in the study align with EUT, demonstrating that farmers' awareness of rainfall duration variability influenced their decision making and motivated the adoption of post-harvest technologies to manage climate related risks.

Several related studies supported this climate-perception–adoption link: Ndamani & Watanabe (2016) found that Ghanaian farmers' perception of delayed onset and shorter rain seasons significantly correlated with adoption of adaptation strategies. Makuvaro *et al.*, (2018) in Zimbabwe showed that unpredictable rainy seasons led to higher uptake of improved grain storage to mitigate losses. Komba & Muchapondwa (2012) also reported that perceived climate variability increases the probability of adopting climate-smart technologies.

However, these studies had limitations; most of the studies emphasized production-side technologies (e.g., seed varieties, irrigation) rather than postharvest systems. Despite postharvest losses contributing up to 30% of total maize loss in some Kenyan counties, few empirical studies explicitly linked rainfall onset/duration perception to postharvest technology adoption, missed a critical behavioral decision-making process and insufficient application of behavioral economic models like EUT to explain the decisions in African smallholder contexts.

Therefore, the widespread farmer perception of shorter rainy seasons and delayed rainfall onset in Bungoma South Sub-County significantly influenced the adoption of modern postharvest technologies. According to Expected Utility Theory, such technologies provided higher expected benefits under increasing climatic uncertainty. However, existing literature remained skewed toward production-focused technologies, and lacked localized, postharvest-centered studies in incorporating behavioral economic frameworks—creating a clear empirical and theoretical research gap that was undertaken by the current study.

Similarly, the Chi-square test of independence on the relationship between farmers' climate variability perception of rainfall duration and the technologies

adoption was performed and the results were as indicated in Table 4.8a and 4.8b

Table 4.8a: Chi-Square Test of Rainfall Duration and Technology Adoption for Storage Methods

Chi-Square Tests	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	256.244 ^a	16	.000
Likelihood Ratio	334.435	16	.000
Linear-by-Linear Association	166.306	1	.000
N of Valid Cases	375		

a. 20 cells (58.8%) have expected count less than 5. The minimum expected count is .41.

Table 4.8b: Cramer’s V Test of Rainfall Duration and Technology Adoption for Storage Methods

Symmetric Measures		Value	Approximate Significance
Nominal by Nominal	Phi	.827	.000
	Cramer's V	.827	.000
N of Valid Cases		375	

Tables 4.8a and 4.8b present the results of Chi-Square and Cramer’s V analyses examining the relationship between rainfall duration and farmers’ adoption of maize storage technologies in Bungoma South. The Pearson Chi-Square value of 256.244 with 16 degrees of freedom is significant at $p < 0.001$, indicating a statistically significant association between perceived rainfall duration and the choice of storage methods. The Likelihood Ratio ($\chi^2 = 334.435$, $p < 0.001$) and Linear-by-Linear Association ($\chi^2 = 166.306$, $p < 0.001$) further confirm that this relationship is robust across alternative measures. Although 20 cells (58.8%) have expected counts below five, the large sample size ($n = 375$) supports the reliability of the findings while acknowledging potential limitations in interpretive precision (Field, 2013).

The Cramer’s V value of 0.827 ($p < 0.001$) indicates a very strong relationship between rainfall duration and adoption of storage technologies. This suggests that farmers’ perceptions of shorter or irregular rainy periods are strongly associated with their choice to implement adaptive storage solutions such as hermetic bags, metal silos, or elevated storage platforms to mitigate moisture-related losses (Tefera et al., 2011; Affognon, Mutungi, Sanginga, & Borgemeister, 2015).

On the lens of Expected Utility Theory, farmers make decisions to maximize the expected benefits of adopting a technology relative to the potential losses from non-adoption (Feder, Just, & Zilberman, 1985; Adesina & Zinnah, 1993). In Bungoma South, variability in rainfall duration influences maize drying schedules and storage conditions, as prolonged wet conditions increase moisture content and vulnerability to mold and pests (Porter et al., 2014; Tefera et al., 2011).

The strong Cramer’s V value (0.827) indicates that farmers who perceive risky rainfall durations are significantly more likely to adopt postharvest storage technologies. The decision reflects risk-based behavior, as farmers assess the expected reduction in postharvest losses against the costs of adopting improved storage solutions (Deressa, Hassan, Ringler, Alemu, & Yesuf,

2009; Fosu-Mensah, Vlek, & MacCarthy, 2012). Farmers’ adoption patterns are consistent with other studies in sub-Saharan Africa showing that perceived climatic risk increases the expected utility of adaptive postharvest interventions (Lobell, Schlenker, & Costa-Roberts, 2011; Maddison, 2007).

Further, in line with the above findings on farmers’ perceptions, meetings with FGDs revealed the following common themes in their discussions; Weather Risk awareness, Efficiency of postharvest technologies, Pest Control and Ease of use.

Firstly, concerning risk awareness and technology adoption, one of the respondents reported *"We've seen more crop losses due to unpredictable weather. That's why many of us are now trying the new storage bags"*. (Female farmer from Bukembe East Ward, October 2024)

The sentiments from the farmer above showed a clear recognition of the link between weather unpredictability and crop losses and practical motivation for adopting new technologies.

Secondly, on Efficiency of postharvest technologies a respondent reported,

"We even don't know whether modern storage is better with these weather changes". (Male farmer from Tuuti Marakuru Ward, November, 2024)

This sentiment from the farmer was an indication that they were not certain about the choice of a suitable postharvest technology to adopt under varied weather conditions.

Thirdly, on pest control, a female respondent aged 40 years reported;

"We usually experience challenges when we store our maize because they are usually attacked by weevils even if we treat" (Female

farmer from Bukembe East Ward, November, 2024)

This sentiment was an indication that farmers experiences challenges when storing maize.

Thirdly, on ease of use another respondent reported; a Male farmer, 38 years said;

"Those who regularly meet with extension officers understand better how they use modern post-harvest technologies underchanging climate" (Male farmer from Khalaba Ward, November, 2024)

From the farmers' sentiments, it was evident that extension services played a crucial role in technology adoption hence the importance of farmer's regular contact with extension officers. This had an impact on the rate of adoption of postharvest technologies.

5.0 CONCLUSIONS

The findings of this study demonstrated that Farmers' perceptions of climate variability played a crucial role in technology adoption decisions. Firstly, the study found high levels of climate variability awareness among farmers, with close to 80% (agreeing and above) of the farmers positively perceived temperature, 80% of the respondents positively perceived rainfall and 76% of the respondents perceived rainfall duration variability as important climatic factors affecting farming activities. Overall, the measures of central tendency revealed that farmers held generally positive and consistent perceptions regarding the influence of temperature, rainfall and rainfall duration variability on postharvest technology adoption in the study area. Similarly, there was decreasing patterns of standard deviations which showed that as the level of agreement increased, farmers' perceptions became more uniform in each case. The Chi-square test (Table 4.4a, 4.6a,4.8a) showed a high statistically significant influence between temperature, rainfall and rainfall duration and technology adoption for storage respectively ($\chi^2(16) = 270.77, p < 0.001$), ($\chi^2(14) = 251.468, p < 0.001$), ($\chi^2(14) = 256.244, p < 0.001$). The effect size measured using Cramer's V of 0.850 (Table 4.4b), 0.819 (Table 4.6b) and 0.827 (Table 4.8b) revealed very strong influences between farmers' perception categories of temperature, rainfall and rainfall duration variations and the post-harvest technologies adopted.

From the findings, the study concluded that the high awareness levels and strong statistical relationships between perceptions and adoption choices indicated that farmers made informed decisions based on their understanding of climate variation.

6.0 RECOMMENDATIONS

Maize farmers should be guided by information on variations on temperature and rainfall when making choices on the most efficient, reliable and economical

post-harvest technologies to adopt so as to reduce post-harvest losses during unpredictable weather patterns.

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