Determinants of Smallholder Maize Productivity in Western Kenya: Evidence From a Post Harvest Plot Level Survey

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ABSTRACT

In developing agrarian economies, smallholder maize production serves as a critical pillar for rural livelihoods and national food security, yet conventional agricultural interventions consistently struggle to close persistent yield gaps. While structural policy frameworks heavily prioritize upstream input distribution, the systemic interplay between field-level management, post-harvest preservation, and empirical data accuracy remains poorly understood. Smallholder maize productivity in sub-Saharan Africa remains substantially below biological potential; Bungoma County in Western Kenya exemplifies this yield gap. This cross-sectional study examined agronomic and socio-economic factors associated with maize yield among 400 systematically sampled households using a post-harvest, plot-level survey. A thirteen-item Good Agricultural Practice (GAP) score was constructed (mean = 5.15/13; SD = 1.68) and decomposed into production and post-harvest sub-indices. Yield was measured on a six-category ordinal scale (<6 to ≥ 30 bags per acre). Ordinal logistic regression models were estimated alongside alternative specifications, including ordered probit models and wealth controls, to evaluate the robustness of identified yield determinants. Improved storage was the only predictor consistently associated with higher reported yield across all specifications. The post-harvest GAP sub-index correlated positively with yield (OR = 1.282, $p = 0.033$), whereas the production sub-index lacked statistical significance. Wealth was also positively associated with yield after adjusting for agronomic practices (OR = 1.206, $p = 0.035$). These findings suggest that post-harvest management significantly influences reported productivity in recall-based surveys. They further highlight the necessity of distinguishing between harvested production and grain retained after storage. Consequently, agricultural policy should pivot from a narrow focus on seed and fertiliser subsidies toward improving post-harvest infrastructure and localized storage technologies.

Keywords: Maize Productivity; Good Agricultural Practice; Post-Harvest Management; Yield Gap; Smallholder Agriculture

INTRODUCTION

Maize (Zea mays L.) is Kenya's principal staple and a primary source of household food security and rural income (FAOSTAT, 2023). Productivity among smallholder farmers nevertheless remains substantially below attainable levels across much of sub-Saharan Africa, a gap that perpetuates food insecurity and constrains agricultural growth (Aramburu-Merlos et al., 2024; Lobell et al., 2009). In Western Kenya, where maize is the dominant crop, productivity is hampered by a complex set of constraints, including declining soil fertility, acidity, limited access to quality inputs, inconsistent extension support, and post-harvest losses (Kisinyo et al., 2014; Tittonell & Giller, 2013).

Extensive research has identified key determinants of yield, including fertiliser application, improved seed adoption, weed management, and household resource endowments. Findings remain inconsistent across farming systems, however, reflecting both contextual variation and persistent measurement challenges. Yield estimates derived from farmer recall are particularly susceptible to confounding factors, as grain losses occurring between harvest and survey administration may distort observed relationships between management practices and reported productivity. This study examines the agronomic and socio-economic factors associated with maize yield in Bungoma County, specifically investigating how post-harvest management practices influence reported outcomes in recall-based surveys.

Statement of the Problem

Maize yields among smallholder farmers in Western Kenya remain significantly below attainable levels despite sustained efforts to promote improved agricultural technologies. While prior research has examined numerous agronomic and socio-economic determinants, including fertiliser use, improved varieties, and extension support, evidence regarding the relative importance of these factors is inconsistent. Substantial yield variation persists even among farmers operating within comparable agroecological conditions, suggests that current models do not fully account for productivity drivers.

A critical challenge involves the accuracy of yield measurement in smallholder research. Many productivity analyses rely on farmer-reported data collected after harvest, yet these quantities often reflect grain retained following initial storage rather than primary field production. In contexts where post-harvest losses are substantial, storage-related practices necessarily influence yield estimates. This potentially distorts the interpretation of productivity, as it remains unclear whether observed associations between management practices and reported output primarily reflect field-level performance, post-harvest preservation, or an intersection of both.

Empirical evidence regarding the relative contributions of production and post-harvest practices to reported yield in Bungoma County remains fragmented. This study addresses this ambiguity by evaluating the associations between agronomic management, storage technology, and reported productivity using multivariate regression analysis of household-level data.

Study Objectives

The study sought to:

1. Assess maize yield levels and agricultural practice adoption among smallholder farmers in Bungoma County.
2. Examine the association between selected agronomic and socio-economic factors and reported maize yield.
3. Assess the relative contribution of production and post-harvest management practices to reported maize productivity.
4. Evaluate the robustness of identified yield determinants across alternative model specifications and yield thresholds.

THEORETICAL FRAMEWORK

Systems Theory

This study is framed by General Systems Theory (GST), as developed by von Bertalanffy (1968), which posits that the behaviour of complex systems cannot be fully understood by examining individual components in isolation. Instead, system outcomes emerge from the interactions of interdependent elements operating within a broader environment. GST emphasises that changes in a single component can influence the performance of others; consequently, system behaviour is a product of internal relationships rather than a simple sum of independent effects (Checkland, 1999).

Applied to smallholder agriculture, Systems Theory conceptualises maize productivity as the result of interactions among agronomic practices, household resources, institutional support, environmental conditions, and post-harvest processes. Crop performance is shaped not only by the adoption of discrete technologies but also by the presence of complementary conditions. For instance, the efficacy of fertiliser often depends upon soil fertility and rainfall, while the benefits of improved seed are mediated by planting practices, nutrient availability, and pest management. Similarly, grain quantities retained after harvest are influenced by storage technology and handling practices.

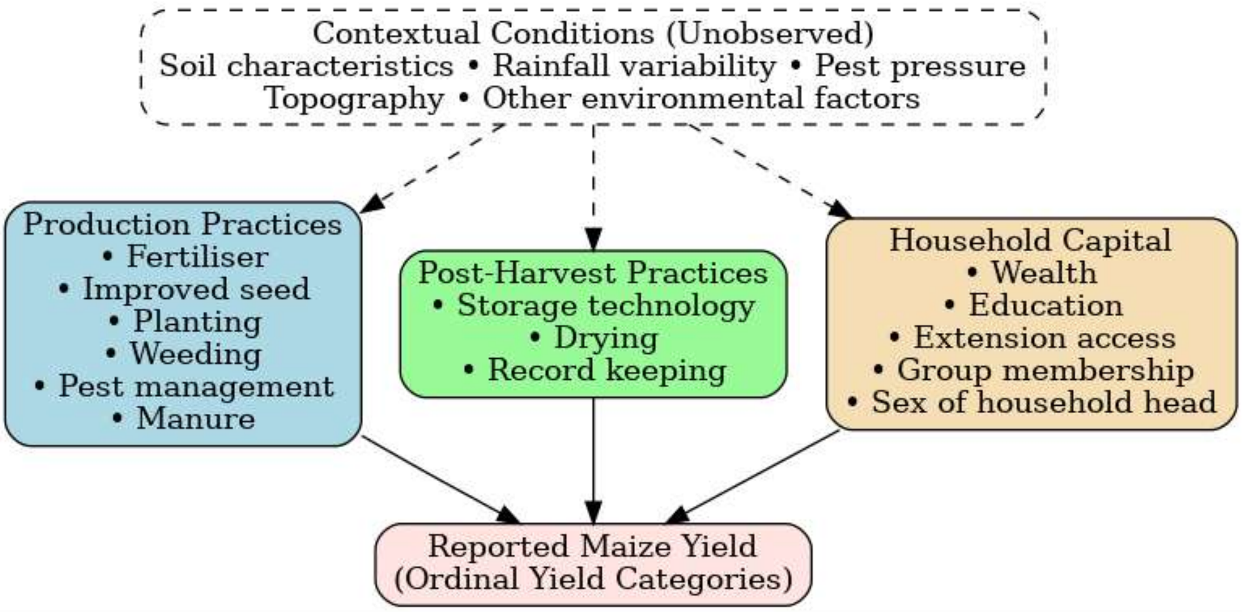
This perspective aligns with contemporary agricultural systems research, which increasingly recognises that productivity constraints are interconnected (Tittonell & Giller, 2013; Aramburu-Merlos et al., 2024). Evidence from sub-Saharan Africa indicates that combinations of complementary practices typically yield greater gains than isolated interventions, whereas household resource limitations frequently lead to selective or fragmented technology adoption (Kassie et al., 2011). Systems Theory accommodates this multidimensionality by supporting the simultaneous evaluation of production, post-harvest management, and household characteristics. By recognising that productivity results from interactions between multiple subsystems, this study views maize yield as a systemic outcome rather than the product of a single determinant.

CONCEPTUAL FRAMEWORK

Drawing upon Systems Theory, this study conceptualises reported maize yield as the systemic outcome of interactions among three interrelated subsystems: production practices, post-harvest management, and household-capital factors (Darnhofer, Bellon, and Turner, 2012). These subsystems operate within a broader biophysical and institutional environment that, while shaping productivity, is often not fully observed in cross-sectional survey data.

The production-practice subsystem comprises field-level agronomic variables, such as fertiliser application, improved seed use, and weed management. These practices are aggregated into a ‘Production GAP’ index, a construct grounded in the Food and Agriculture Organization’s (FAO, 2003) framework for Good Agricultural Practices, which emphasises soil and nutrient management as the basis for sustainable intensification (Sheahan and Barrett, 2017). The post-harvest subsystem encompasses grain drying, storage technology, and record-keeping. These factors are critical to grain preservation; following Carletto, Jolliffe, and Banerjee (2013), this study recognises that storage efficiency determines the ‘net’ yield reported in recall surveys, making the post-harvest subsystem a determinant of measured productivity rather than a post-script to it.

The household-capital subsystem reflects the human, social, and financial assets that facilitate access to technology and information (Scoones, 1998). In accordance with the Sustainable Livelihoods Framework, education (human capital), farmer-group participation (social capital), and wealth (financial capital) are conceptualised as the resources that mediate a household’s capacity to adopt production technologies (Bebbington, 1999). Surrounding these subsystems are contextual conditions, such as rainfall variability and soil pH, which constitute the external environment (Van Ittersum et al., 2013). While this study focuses on observable management factors, it acknowledges that these unobserved biophysical conditions moderate the relationship between practice adoption and yield.



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LITERATURE REVIEW

Maize Yield Gaps and Productivity Constraints

Maize systems across sub-Saharan Africa persistently operate below water-limited potential; yield gaps frequently exceed 70% despite the adoption of improved varieties and fertilisers (Aramburu-Merlos et al., 2024; Lobell et al., 2009). The persistence of these gaps suggest that productivity is governed by systemic agronomic and institutional constraints that remain unresolved by input adoption alone (Tittonell and Giller, 2013).

Recent yield-gap research emphasises that constraints rarely operate in isolation. Using farmer-managed plots across multiple countries, Aramburu-Merlos et al. (2024) demonstrated that integrated management packages, such as those combining improved seed with nitrogen application and optimal plant density, yield superior outcomes compared to individual practices. Residual gaps nonetheless remain under intensive management, pointing to the influence of unobserved soil characteristics and climatic variability. This is particularly evident in Western Kenya, where the intersection of soil acidity and nutrient depletion accounts for substantial yield variation (Munialo et al., 2020). Climate variability further complicates these dynamics, as inconsistent rainfall patterns and dry spells in major growing areas directly impede crop development and undermine management efficacy (Njeru et al., 2023).

Agronomic Determinants of Maize Productivity

While productivity research traditionally focuses on seed and fertiliser adoption, Sheahan and Barrett (2017) argue that the effectiveness of these inputs is highly contingent upon the local production environment. Fertiliser response remains heterogeneous because nutrient uptake is mediated by soil properties and management precision (Kostandini et al., 2013). In Western Kenya, soil acidity presents a critical bottleneck. Acidic conditions limit nutrient availability through aluminium toxicity and phosphorus fixation, reducing the marginal returns on fertiliser application (Kisinyo et al., 2014). Synergistic interventions, particularly those combining lime with mineral fertiliser, have shown substantially greater gains than isolated applications; this underscores the necessity of addressing multiple biophysical constraints simultaneously (Opala et al., 2018).

Smallholder systems frequently demonstrate fragmented technology adoption. Farmers may adopt improved seed but omit recommended fertiliser rates, or apply fertiliser without complementary weeding and soil amendments. This ‘partial adoption’ masks differences in management intensity and reduces the statistical signal available in aggregate indicators. Socio-economic factors further mediate these outcomes, as household wealth and market integration determine a farmer’s capacity to absorb production risks and mobilise the labour required for precise implementation (Wossen et al., 2017).

Post-Harvest Management and Measured Productivity

Although often treated as an issue of food security, post-harvest losses represent a primary constraint in Kenyan maize systems. Infestations by the larger grain borer and fungal contamination frequently reduce both the volume and quality of grain retained after harvest (De Groote et al., 2023). While hermetic technologies, such as PICS bags and metal silos, effectively mitigate these losses, storage practices remain conceptually excluded from most yield-determination models (Tefera et al., 2011). Most studies define yield strictly as grain harvested per unit area; however, this neglect of the post-harvest subsystem may distort productivity estimates in household surveys. If yield reporting occurs weeks or months after harvest, the quantities disclosed by farmers may reflect ‘retained output’ rather than ‘field production’, particularly where traditional storage methods fail to prevent grain depletion.

Measurement Challenges in Smallholder Yield Research

The measurement of productivity faces an inherent paradox: survey-based recall data remain essential for large-scale analysis but introduce significant measurement errors (Carletto et al., 2013). Discrepancies between farmer recall and objective measurements suggest that errors are not always random; instead, they may vary systematically with education or farm size (Sida et al., 2021). Furthermore, the absence of plot-level biophysical data often leaves a substantial proportion of yield variation unexplained (Hengl et al., 2021).

Consequently, observed associations between management and productivity in survey research may represent an intersection of agronomic performance and reporting bias. Current literature reflects a critical ambiguity; it remains unclear whether storage-related predictors correlate with reported yield due to their role in preserving harvest or because they serve as proxies for unobserved management quality. Testing the influence of post-harvest subsystems resolves this ambiguity by clarifying the determinants of reported productivity.

METHODOLOGY

Research Design

This study utilised a cross-sectional survey design to investigate the relationships between production practices, post-harvest management, household capital, and reported maize yield. A cross-sectional approach is appropriate for identifying associations between variables under real-world farming conditions at a specific point in time (Bryman, 2016). This design facilitates the comparison of households with varying management characteristics without the need for experimental manipulation of production practices.

Study Area

Research was conducted in Bungoma County, Western Kenya. Agriculture is the primary economic activity; maize serves as both a principal staple and a vital crop for rural households. The region experiences a bimodal rainfall pattern: long rains occur from March to July and short rains from October to December. While these conditions support intensive maize production, the area remains susceptible to soil fertility depletion, acidity, and significant post-harvest losses.

Target Population, Sampling Procedure and Sample Size

The target population comprised smallholder maize-farming households across the eight sub-counties of Bungoma. Stratified random sampling ensured geographical representation, with sub-counties acting as primary strata. Within each stratum, villages were randomly selected; subsequently, households were systematically sampled from village registers. Sample allocation was proportional to the estimated number of farming households in each sub-county. The required sample of 400 households was determined using the Yamane (1967) formula, applying a 95% confidence level and a 5% margin of error. Nineteen villages served as the primary sampling clusters for the multivariate analysis.

Research Hypotheses

The following hypotheses were tested:

H_{01}: There is no statistically significant association between Production GAP practices and reported maize yield.

H_{02}: There is no statistically significant association between Post-harvest GAP practices and reported maize yield.

H_{03}: There is no statistically significant association between household-capital factors and reported maize yield.

Data Collection Instruments and Procedures

Data were gathered using structured questionnaires administered during face-to-face interviews. The instrument captured data on socio-demographic characteristics, agronomic practices, storage technologies, and institutional support. To ensure consistency, enumerators received rigorous training on survey procedures. Data collection took place between October and November 2024, immediately following the primary harvest season. Participation was voluntary; informed consent was secured from all respondents prior to commencement.

Measurement of Variables

Dependent Variable

Reported yield was measured using a six-category ordinal scale ranging from fewer than 6 bags per acre to 30 or more bags per acre. Using categorical ranges rather than point estimates helps mitigate the impact of digit-preference bias, or 'heaping', where respondents round estimates to the nearest multiple of five or ten (Zizza and Siega-Riz, 2007). In the Kenyan context, a standard maize bag weighs 90 kg; these categories approximately correspond to metric ranges between <1.3 t/ha and ≥6.6 t/ha.

Independent Variables

Production practices were evaluated through ten binary indicators. These indicators, covering improved seed use and soil fertility management, were aggregated into a Production GAP Index (range: 0–10). This formative index construction recognizes that agricultural practices represent distinct behaviours rather than a single underlying latent trait (Bollen and Lennox, 1991). Post-harvest management was similarly assessed using a three-item GAP Index focusing on drying, record-keeping, and storage. Improved storage was strictly defined as the use of hermetic or sealed technologies, such as PICS bags or metal silos. Household capital was measured using five welfare-capability proxies. This asset-based approach provides a stable measure of economic capacity in rural settings compared to volatile income data (Filmer and Pritchett, 2001)

Data Analysis

Descriptive and inferential statistics were utilised to summarise findings and test associations. To address the ordinal nature of the dependent variable, ordinal logistic regression models were estimated using maximum likelihood with BFGS optimisation (McCullagh, 1980). Robustness was assessed through ordered probit models and binary threshold checks. Model fit was evaluated using Akaike Information Criterion (AIC) and McFadden's pseudo-R^2. Reliability for composite indicators was checked using Cronbach's alpha, acknowledging the inherent limitations of internal consistency measures for formative indexes.

Validation of Reported Yield

A limitation of this study is the absence of objective yield measurements via crop cutting to validate the reported yield data. While recall-based surveys are standard in smallholder agricultural research in sub-Saharan Africa, they are subject to measurement errors including digit-preference bias ('heaping') and potential systematic over-reporting of inputs and outputs (Gourlay et al., 2017; Sida et al., 2021). In this study, yield was captured using six ordered categorical ranges rather than point estimates, a design choice that mitigates heaping by reducing the precision required of farmer recall. Nevertheless, the quantities reported may still reflect grain retained after storage losses rather than gross field production at harvest. This distinction is central to the study's theoretical argument and is treated explicitly in the analysis. Future research should incorporate crop-cutting trials for a subsample of households — typically 10–20 per cent — to validate reported yields, assess the direction and magnitude of reporting bias, and distinguish gross harvest from net retained grain.

Validity of the GAP Index

Given that the thirteen-item GAP index exhibited a Cronbach's alpha of −0.057, indicating that the items do not reflect a single latent construct, a principal component analysis was conducted on the correlation matrix of the thirteen binary practice indicators to examine the dimensional structure and to assess whether the additive index is empirically appropriate.

Statistic	Value	Interpretation
KMO	**0.491**	Below 0.60: factor analysis not recommended

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Bartlett's test	$\chi^2(78) = 77.549$, **p = 0.493**	Not significant: items are near-independent
Factors with eigenvalue ≥ 1	**7** (out of 13)	No dominant structure
Variance explained (7 factors)	**61.2%**	Spread across many weak components
Mean inter-item $\bar{r}$	**−0.004**	Essentially zero correlation

Source: Field survey data, 2024

PCA conducted on the Pearson correlation matrix of thirteen binary GAP indicators (n = 400). KMO = 0.491; Bartlett's $\chi^2(78) = 77.549$, $p = 0.493$. Seven components retained under the Kaiser criterion (eigenvalue ≥ 1.0), explaining 61.2% of variance collectively. Mean inter-item $\bar{r} = -0.004$. Results confirm formative rather than reflective measurement structure

The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.491, which falls below the conventional threshold of 0.60 and reflects the theoretically expected pattern for a formative indicator set in which items are designed to capture conceptually distinct behaviours rather than a shared trait. Bartlett's test of sphericity was not statistically significant ($\chi^2(78) = 77.549$; $p = 0.493$), further confirming that the inter-item correlations (mean $\bar{r} = -0.004$; range: −0.146 to +0.133) are near-zero and that the correlation matrix approximates an identity matrix.

The PCA retained seven components with eigenvalues exceeding 1.0 (eigenvalues ranging from 1.293 to 1.003), collectively explaining 61.2 per cent of total variance. No dominant factor structure emerged: eigenvalues for retained components ranged narrowly from 1.003 to 1.293, with each component explaining between 7.7 and 9.9 per cent of variance. This is a distribution characteristic of near-independence among items rather than meaningful clustering. Examination of unrotated factor loadings confirmed that no item loaded predominantly on a single interpretable dimension; production-oriented items and post-harvest items cross-loaded across multiple components without a clear factor boundary. These results are entirely consistent with the formative measurement framework proposed a priori (Bollen & Lennox, 1991) and empirically validate the decision to treat the GAP index as a breadth-of-adoption count rather than a reflective psychometric scale. The a priori conceptual distinction between production and post-harvest sub-indices is therefore theoretically rather than statistically derived, reflecting the substantive distinction between pre-harvest and post-harvest farm operations, and both sub-indices are retained in the inferential models on these conceptual grounds.

RESULTS AND DISCUSSION

Socio-demographic Characteristics

Surveyed households exhibited moderate educational attainment, limited access to extension services, and small landholdings (Table 1). Fewer than one-third of respondents reported extension visits during the production season; furthermore, fewer than half participated in farmer groups. These findings suggest structural limitations in access to agricultural information and support services, which potentially constrain productivity. This reach aligns with earlier observations of extension bottlenecks in Western Kenya, where institutional support often fails to reach the most resource-constrained smallholders (Ouma et al., 2006).

Table 1: Socio-demographic Characteristics of Respondents (n = 400)

Characteristic	**Category**	**n**	**%**
Sex	Male	190	47.5
	Female	210	52.5
Age group	< 30 years	38	9.5
	30–39	112	28.0
	40–49	130	32.5
	50–59	67	16.8
	≥ 60	53	13.3
Education	No formal education	30	7.5
	Primary incomplete	75	18.8

	Primary complete	119	29.8
	Secondary	124	31.0
	College or higher	52	13.0
Household size	1–4 members	99	24.8
	5–7 members	182	45.5
	8–10 members	76	19.0
	>10 members	43	10.8
Extension visits (Yes)	—	130	32.5
Farmer group member (Yes)	—	187	46.8
Number of plots	1	197	49.3
	2	130	32.5
	3	73	18.3

Source: Field survey data, 2024.

Distribution of Yield and Agronomic Practices

Maize productivity remains generally low among the surveyed households. Nearly 40% of farmers harvested fewer than 10 bags per acre (<2.2 t/ha); only 15.2% attained yields exceeding 20 bags per acre (>4.4 t/ha). Given that maize potential in Western Kenya commonly exceeds 5 t/ha under optimal management, these results confirm a substantial yield gap.

Adoption of recommended agronomic practices was similarly modest (Table 2). The average respondent implemented approximately five of the thirteen recommended practices. Adoption was generally higher for production-oriented variables than for post-harvest management. Notably, improved storage technologies and farm record keeping were adopted by only 41% and 20.3% of households, respectively. This implementation lag in post-harvest management mirrors broader regional trends where the focus of both policy and smallholder investment remains primarily on upstream production inputs (Sheahan and Barrett, 2017.

Table 2: Distribution of Maize Yield and Agronomic Practices (n = 400)

Variable / Category	n	%	Metric equiv. (t/ha)
Maize yield (bags/acre)			
<6 bags/acre	55	13.8	<1.3
6–9 bags/acre	104	26.0	1.3–2.0
10–14 bags/acre	117	29.2	2.2–3.1
15–19 bags/acre	63	15.8	3.3–4.2
20–29 bags/acre	44	11.0	4.4–6.4
≥30 bags/acre	17	4.2	≥6.6
Seed type			—
Hybrid / certified	192	48.0	—
Improved OPV	66	16.5	—
Local / recycled	100	25.0	—
Don't know	42	10.5	—
Basal fertiliser applied	222	55.5	—
— of which: <1 bag/acre	62	28.0	—
— of which: 1 bag/acre (recommended)	122	55.0	—
— of which: >1 bag/acre	38	17.1	—
Top-dressing applied	221	55.3	—
— top-dressed at correct growth stage	212	95.9†	—
Manure / compost used	127	31.8	—
Herbicide used	106	26.5	—
Pesticide used	141	35.3	—

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Planting month			—
March or earlier	72	18.0	—
First half April (recommended)	209	52.3	—
Second half April or later	119	29.8	—
Row spacing compliance			—
Yes (full)	144	36.0	—
Partial	137	34.3	—
No	119	29.8	—
Weeding rounds			—
0–1	89	22.3	—
2	184	46.0	—
3 or more (recommended)	127	31.8	—
Pest scouting	142	35.5	—
Post-harvest drying	184	46.0	—
Improved storage method	164	41.0	—
Farm record keeping	81	20.3	—
Production GAP sub-index (0–10): mean = 4.86, SD = 1.59			
Post-harvest GAP sub-index (0–3): mean = 1.07, SD = 0.79			
Total GAP score (0–13): mean = 5.15, SD = 1.68			

Note: Percentage of top-dressers who applied at the recommended V4–V6 growth stage. Metric equivalents at 90 kg per bag, 1 acre = 0.405 ha. Source: Field survey data, 2024.

Bivariate Analysis: Chi-square Tests

Table 3 details the associations between agronomic practices and yield categories. Of the fifteen variables examined, only weeding frequency exhibited a statistically significant bivariate association with yield (χ^2 = 19.17, *df*= 10, *p* = 0.038). All other production, post-harvest, and household variables lacked statistical significance at this level. These results suggested that individual practices, when isolated, did not adequately explain productivity differences, thereby necessitating multivariate regression to control for confounding influences.

Table 3: Chi-square Tests of Association between Agronomic Practices and Yield Category

Agronomic Practice	χ^2	df	p-value	Sig.
Seed type	7.56	15	0.940	ns
Basal fertiliser	4.09	5	0.536	ns
Top-dressing	2.60	5	0.762	ns
Manure / compost	2.94	5	0.709	ns
Herbicide use	0.68	5	0.984	ns
Pesticide use	1.18	5	0.947	ns
Planting month	9.24	10	0.510	ns
Row spacing	5.84	10	0.828	ns
Weeding rounds	19.17	10	0.038	*
Pest scouting	7.91	5	0.161	ns
Post-harvest drying	1.06	5	0.958	ns
Improved storage	7.88	5	0.163	ns
Farm record keeping	1.67	5	0.893	ns
Extension visits	4.50	5	0.481	ns
Farmer group membership	4.25	5	0.514	ns

Note: $p < 0.05$; ns = not significant.

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Model Comparison Overview

Table 4 summarises the performance of six estimated specifications. Model fit remained modest across all specifications; McFadden pseudo-R^2 values ranged from <0.001 to 0.017. Model 4, which incorporated wealth proxies and plot size, achieved the highest explanatory power (McFadden R^2 = 0.017), though overall fit remained low. The consistency of findings across ordinal logit, ordinal probit, and fertiliser-intensity specifications provides a vital robustness check for the identified yield determinants. Such low pseudo-R^2 values are common in smallholder productivity studies lacking plot-level biophysical data, as unobserved soil and climatic variance typically dominate the error term (Hengl et al., 2021).

Table 4: Summary of All Estimated Models: Fit Statistics

Model specification	Predictors	AIC	McFadden R^2	LLR p	n
M1: Full ordinal logit	17 agronomic + household vars	1,348.01	0.013	0.482	400
M2: GAP score only (continuous)	1 composite score + 4 controls	1,332.53	< 0.001	0.779	400
M3: GAP sub-indices	Prod. + post-harvest sub-index + 4 controls	1,334.63	0.006	0.239	400
M4: M1 + wealth proxy + plot size	19 vars total	1,346.52	0.017	0.280	400
M5: Fertiliser intensity + top-dress timing	Replaces binary basal/topd w/ intensity	1,349.01	0.013	0.482	400
M6: Ordered probit (replication of M1)	17 vars, probit link	1,348.24	0.012	0.498	400
Storage method remains the only significant predictor across M1–M6 for yield categories ≥10 and ≥15 bags/acre.					

Note: All models estimated via maximum likelihood with BFGS optimization; n = 400 throughout.

Hypothesis Testing

H_{01}: Production GAP Practices

The first hypothesis, *H_{01},* proposed that production-oriented practices are not significantly associated with maize yield. With the exception of weeding frequency in the bivariate stage, none of the individual practices exhibited a significant association. The initial association observed for weeding (χ^2 = 19.17, p = 0.038) did not persist in the multivariate models. In the ordinal logistic regression, the Production GAP sub-index was also non-significant (OR = 0.928, p = 0.188); the corresponding Spearman correlation was similarly weak (r = –0.061, p = 0.222). The study therefore fails to reject *H_{01}*, indicating that these production practices, as measured, did not explain variance in reported yield**.**

Testing H_{02}: Post-harvest GAP Practices

Bivariate and multivariate analyses indicated that post-harvest practices were positively associated with yield outcomes. In Model 3, the Post-harvest GAP sub-index significantly increased the likelihood of reporting higher yields (OR = 1.282, p = 0.033). Improved storage emerged as the most robust individual predictor. Households using sealed technologies were significantly more likely to report higher yield categories (OR = 1.687, p = 0.005), an effect that remained stable after controlling for wealth and plot size (OR = 1.691, p = 0.005). The study rejects *H_{02}* and concludes that post-harvest management is significantly associated with reported maize productivity**.**

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Testing H_{03}: Household-Capital Factors

The associations between household capital and yield were mixed. While education, extension contact, and group membership were non-significant in the baseline model, the welfare-capability index (wealth proxy) was significant in Model 4 (OR = 1.206, $p = 0.035$). This indicates that households with greater economic capacity are more likely to achieve higher productivity categories. Consequently, H_{03} is rejected with respect to the wealth dimension.

Summary of Hypothesis Tests

Table 5 summarises the outcomes of the hypothesis tests.

Hypothesis	Finding	Decision
H_{01}: No significant association between Production GAP and yield	Production GAP not significant (p = 0.188)	Fail to reject H_{01}
H_{02}: No significant association between Post-harvest GAP and yield	Post-harvest GAP significant (p = 0.033)	Reject H_{02}
H_{03}: No significant association between Household Capital and yield	Wealth significant (p = 0.035)	Reject H_{03}

DISCUSSION

The findings of this study indicate that while most production-oriented Good Agricultural Practice (GAP) indicators lack a statistically significant association with reported maize yield, post-harvest management, specifically improved storage technology, is a robust predictor of higher yield. These results suggest that productivity outcomes in Bungoma County are shaped by post-harvest preservation as much as field-level management. This aligns with the meta-analysis by Affognon et al. (2015), which established that post-harvest losses in Sub-Saharan Africa are substantial but frequently poorly measured. By utilising systematic GAP indices, the present study addresses the deficit in empirical data quality and household-level validation noted in earlier post-harvest literature.

Production GAP Practices and Maize Yield

The study fails to reject the first hypothesis, as neither individual practices nor the composite Production GAP index demonstrated significant relationships with yield. This result is consistent with the evidence from Sheahan and Barrett (2017), who established that traditional, binary measures of fertiliser adoption often yield statistically weak results. They argued that a simple ‘Yes/No’ indicator obscures immense underlying heterogeneity in application intensity and timing. In the present sample, where over a quarter of ‘fertilisers users’ applied sub-optimal quantities, the binary metric likely masked the true marginal returns, leading to the observed statistical insignificance.

Furthermore, the statistical signal in the Production GAP subsystem was likely overwhelmed by unobserved biophysical variables. Munialo et al. (2020) observed that in Western Kenya, the effectiveness of inorganic fertilisers is frequently negated by high soil acidity and aluminium toxicity. The loss of significance for weeding frequency in the multivariate models also suggests that labour intensity may serve as a proxy for financial constraints; this confirms the observations of Kassie et al. (2011) regarding resource-poor farming strategies.

Post-harvest Management and Maize Yield

Improved storage emerged as the most consistent predictor of higher yield across all specifications. This provides empirical weight to the argument that post-harvest management determines the ‘net’ output reported in surveys.

As Bako et al. (2023) demonstrated, hermetic technologies effectively 'save' existing yield, generating benefits comparable to those achieved through production increases.

By preserving grain against insects and moisture, improved storage ensures that the quantity available for recall remains higher. This result addresses the 'recall decay' identified by Gourlay et al. (2017), who found that longer periods between harvest and survey administration often lead to systematic reporting inaccuracies. Since reported yield is often 'retained grain' rather than 'gross harvest', the post-harvest subsystem essentially acts as a filter that determines how much production is actually registered by the measurement instrument.

Selective Adoption and Household Capital

The limited internal consistency of the thirteen-item GAP index (Cronbach's alpha = –0.026) reinforces the findings of Kassie et al. (2013). Their work in East Africa proved that smallholders do not adopt technologies as uniform packages; rather, adoption is fragmented and interdependent. Farmers selectively adopt individual components based on local biophysical shocks and resource constraints. The positive influence of the wealth proxy (OR = 1.206, $p = 0.035$) supports this conclusion, suggesting that financial capital mediates the farmer's capacity to implement these 'fragmented' practices with sufficient intensity.

Implications of the GAP Index

The limited explanatory value of the composite GAP score (Cronbach's alpha = –0.026) confirms the fragmented nature of technology adoption. As Kassie et al. (2013) observed, smallholders rarely implement technology 'packages' but instead selectively adopt practices based on immediate cash flow and labour availability. The positive influence of wealth identified in Model 4 (OR = 1.206) suggests that financial capital determines the quality and timing of these adoptions. Wealthier households are better positioned to finance liming or purchase hermetic bags, both of which independently elevate productivity levels. This reinforces the systemic view that productivity is not merely an agronomic outcome but a socio-economic one.

Methodological Implications

The low McFadden pseudo-R^2 values observed (0.017) are common in cross-sectional studies lacking biophysical data (Hengl et al., 2021). These results mirror the findings of Gourlay et al. (2017), who demonstrated that recall bias can economically distort productivity metrics. In this sample, 'heaping' at salient numbers (such as 10 or 15 bags) may have attenuated the observed associations. As noted by Sida et al. (2021), systematic overreporting of inputs and outputs in recall data can mask the more subtle incremental effects of agronomic practices like planting timing or row spacing.

Generalizability and External Validity

The findings of this study are context-specific to Bungoma County, Western Kenya. The county is characterised by a bimodal rainfall pattern (long rains March–July; short rains October–December), relatively high annual rainfall exceeding 1,500 mm, altitudes ranging from approximately 1,200 to 1,800 m above sea level, and predominantly acidic soils (pH <5.5) typical of the western Kenya highlands (Kisinyo et al., 2014; Munialo et al., 2020). These agroecological conditions differ substantially from the drier, less acidic environments of Kenya's Rift Valley, Eastern, and Central regions, where annual rainfall is lower, soil properties are more variable, and temperature regimes differ. The dominance of post-harvest management as a predictor of reported yield may be particularly pronounced in high-rainfall, high-humidity contexts such as Bungoma County, where ambient moisture and pest pressure ; notably from the Large Grain Borer and Maize Weevil accelerate storage losses and thus amplify the measurement artefact identified in this study. In lower-humidity agroecological zones, storage losses may be less severe, potentially reducing the relative importance of storage as a predictor of reported yield. The study was additionally limited to a single production season (long rains 2024), and inter-seasonal variability; such as drought stress or flooding. This may alter the relative importance of production versus post-harvest practices. Multi-region, multi-season studies employing objective yield measurement are therefore recommended to assess the generalisability of these findings across Kenya's diverse agricultural environments and to separate context-specific effects from broader patterns.

Theoretical Implications for Systems-Based Interventions

Interpreted through General Systems Theory, the post-harvest subsystem appears to be 'shielding' the underlying effects of the production subsystem in recall-based survey data. This shielding effect carries significant implications for agricultural policy design and evaluation that extend beyond the present study. When a production intervention such as subsidised fertiliser or improved seed increases gross field harvest but is accompanied by inadequate storage infrastructure, the resulting post-harvest losses may offset some or all of the production gains. In a cross-sectional recall survey administered weeks or months after harvest, net retained grain would show little change, leading evaluators to conclude that the production intervention was ineffective, even if field-level productivity genuinely improved. As a concrete illustration: a 20 per cent increase in gross harvest attributable to improved fertiliser application could be entirely negated by a corresponding 20 per cent storage loss due to pest infestation or moisture damage in traditional granaries, leaving the farmer's reported yield unchanged. This mechanism implies that programme evaluations relying solely on farmer-reported yield may systematically underestimate the efficacy of production-focused interventions when post-harvest systems remain weak. The policy implication is not that production interventions are ineffective, but that their impacts are invisible to the dominant measurement instrument used in smallholder agricultural surveys. Future evaluations of agricultural programmes should therefore measure both gross harvest; ideally via crop cutting conducted immediately at harvest; and net retained grain at the time of survey administration. Longitudinal designs that track the same household across the post-harvest period would additionally enable quantification of storage losses and their attribution to specific storage technologies. A systems-based intervention framework must consequently address the entire agricultural value chain. From soil preparation and input use through to post-harvest storage, and evaluation designs must be calibrated to capture impacts at each subsystem boundary rather than at the final recall endpoint alone.

CONCLUSION

This study evaluated the relationship between Good Agricultural Practice (GAP) adoption and reported maize yield among smallholder households in Bungoma County, Kenya. The findings demonstrate that production-oriented agronomic practices, whether assessed individually or via a composite index, lack a statistically significant association with yield outcomes in the study sample. In contrast, post-harvest management practices, particularly the use of improved storage technology, exhibit a consistent and positive association with higher yield categories across all estimated specifications.

The study further established that household wealth contributes significantly to productivity, suggesting that resource endowments influence the capacity of farmers to implement management practices effectively. The significance of improved storage indicates that post-harvest management should be viewed as an integral component of agricultural productivity rather than merely a loss-prevention activity. Furthermore, the limited internal consistency of the composite GAP index reveals that technology adoption occurs in a fragmented manner; farmers selectively adopt discrete practices based on their specific circumstances rather than implementing recommendations as a unified package.

Overall, the study concludes that variance in reported maize productivity among the surveyed households is more strongly associated with post-harvest management and financial capital than with production-cycle inputs. When interpreted through General Systems Theory, the post-harvest subsystem appears to be 'shielding' the underlying effects of the production subsystem. Because storage losses are embedded in recall-based yield data, the efficiency of the post-harvest subsystem overwhelms the signal of field-level production in cross-sectional surveys.

This does not imply that the production subsystem is unimportant. Rather, it suggests that its contribution to observed productivity is masked until measurement instruments can separate gross harvest from net retained grain. A systems perspective implies that interventions to improve productivity must address the entire agricultural cycle, from soil preparation through to storage, rather than targeting isolated subsystems. These findings underscore the systemic complexity of smallholder farming and the necessity of policy interventions that balance production support with post-harvest infrastructure.

RECOMMENDATIONS

Based on the evidence presented in this study, the following policy and research interventions are recommended:

Scale post-harvest technology adoption via targeted subsidies.

The Bungoma County Ministry of Agriculture and its development partners should pivot agricultural support from purely upstream production inputs toward post-harvest infrastructure. Given that improved storage is the most robust predictor of reported yield, the county government should integrate hermetic storage technologies, such as PICS bags and metal silos, into existing subsidy and voucher programmes. This should be executed through local agricultural co-operatives to ensure technologies are accessible to resource-poor households who currently face the highest storage risks.

Implement a systems-based extension model.

Extension agencies and the State Department of Agriculture should move beyond promoting isolated agronomic practices. Extension staff should be trained to deliver integrated 'technological packages' that bundle soil health management with post-harvest handling. This systems-based approach should be operationalised through Farmer Field Schools, focusing on the complementarity between soil acidity correction and efficient grain preservation to maximise net household food availability.

Prioritise soil acidity correction in Western Kenya.

Since soil acidity is a documented 'bottleneck' that may negate fertiliser efficacy, the Bungoma County government should establish localised soil-testing hubs at the ward level. Following the testing phase, the government should facilitate the distribution of agricultural lime through private-sector partnerships, ensuring that lime is available in granular form and supported by technical advice on proper application timing.

Expand access to tailored agricultural credit.

To address the significant influence of household wealth on productivity, financial institutions and microfinance organisations should develop credit products specifically for smallholders. These should include 'asset-backed' loans for post-harvest equipment or input financing with repayment schedules aligned with the bimodal harvest cycle, thereby enabling poorer households to invest in the 'fragmented' practices they currently omit due to cash constraints.

Transition to longitudinal and biophysical research designs.

The research community and academic institutions should prioritise longitudinal panel studies that move beyond one-season cross-sectional recall. Future designs must incorporate objective measurements, including plot-level soil pH analysis and crop-cutting trials. Such designs would significantly increase model explanatory power and provide more robust evidence of the causal relationships between specific GAPs and maize productivity.

Adopt multidimensional measurement frameworks.

Scholars developing agricultural performance metrics should evaluate the dimensional structure of management indicators before constructing indices. Future research should apply item response theory or principal component analysis to identify distinct management. This would provide more reliable measures of management quality than the simple additive indices currently common in the literature.

Ethical Approval

The study involved field surveys with human participants. Informed consent was obtained from all individual participants included in the study prior to survey administration

Conflict of Interest

The authors declare that they have no financial or personal relationships that could be viewed as potential conflicts of interest.

Data Availability Statement

The dataset generated and analyzed during the current study is available from the corresponding author upon reasonable request.

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