Sustainable agricultural practice adoption and technical efficiency among smallholder maize farmers in contrasting agroecological environments of Zambia

Musowe Nsakilwa[1]
Elias Kuntashula[2]

[1]mnsakilwa@gmail.com

[1,2] The University of Zambia

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ABSTRACT

This study examines the association between Sustainable Agricultural Practice (SAP) adoption and technical efficiency among smallholder maize farmers in two contrasting agroecological environments of Zambia: Mungwi District in higher-rainfall Agroecological Region III and Senanga District in drought-prone Agroecological Region I. Using cross-sectional household survey data from 582 maize-producing households, the study estimated technical efficiency with a stochastic frontier production model. The final complete-case stochastic frontier sample comprised 482 households. A pooled Cobb-Douglas stochastic frontier with a normal/half-normal error structure was used as the main model because its inefficiency component was statistically identified. In contrast, the Translog frontier and district-specific frontiers were retained as diagnostic robustness checks. Secondary fractional logit, interaction, and propensity-score matching analyses were used to examine associations between SAP adoption and predicted technical efficiency. Mean pooled-frontier technical efficiency was 0.401, with higher average efficiency in Mungwi (0.547) than Senanga (0.258). High SAP adoption and SAP count were negatively associated with technical efficiency in pooled models. However, district-level interaction results showed that this association was concentrated in Senanga and not statistically evident in Mungwi. The findings suggest that SAP adoption counts should not be interpreted as automatic indicators of short-run resource-use efficiency. SAP promotion needs to be linked to implementation quality, agroecological suitability, complementary input and water-management support, and location-specific extension services.

Keywords: Technical efficiency; Stochastic frontier analysis; Sustainable agricultural practices; Fractional logit; Agroecological heterogeneity; Zambia

I. INTRODUCTION

Maize remains central to food security, rural livelihoods, and agricultural development in Zambia. Many smallholder households cultivate maize, which serves as both a staple food and an important source of seasonal cash income. Recent review evidence also shows that smallholder maize farming in Zambia remains constrained by climate risk, input limitations, market and institutional challenges, and uneven productivity outcomes (Malesu et al., 2024). These constraints make it important to understand not only whether farmers adopt improved or sustainable practices, but also whether they use available production resources efficiently.

The challenge of improving maize performance has become more complex amid climate variability, land degradation, and declining soil fertility. Sustainable Agricultural Practices (SAPs), including crop rotation, residue retention or mulching, and minimum or zero tillage, are promoted as part of broader sustainable intensification strategies because they may improve soil structure, conserve moisture, reduce erosion, and contribute to resilience (Pretty et al., 2011). Evidence from Zambia and elsewhere in Sub-Saharan Africa shows that such practices can improve yields, incomes, or adaptation outcomes when they are implemented well, sustained over time, and supported by appropriate input and management systems (Arslan et al., 2015; Kassie et al., 2015; Manda et al., 2016).

However, adoption of SAPs does not automatically imply efficient use of productive resources. A household may report adopting one or more conservation-oriented practices while still applying seed, fertiliser, labour, and land in ways that fall short of the best attainable production frontier. Conversely, a household may operate relatively efficiently without adopting multiple SAPs if input timing, labour organisation, and field management are well coordinated. This distinction has direct policy relevance: adoption indicators alone may overstate the productivity value of interventions if they do not capture the quality of practice, duration, plot coverage, or local agronomic suitability.

Technical efficiency analysis offers a useful framework for separating random production shocks from shortfalls in resource-use performance. Stochastic frontier analysis (SFA) is particularly relevant in smallholder agriculture because observed maize output is affected by rainfall variability, pests, soil heterogeneity, measurement error, and other factors beyond the farmer's control, in addition to management decisions (Aigner et al., 1977; Meeusen & van Den

Broeck, 1977). Estimating technical efficiency therefore helps identify whether output differences are consistent with resource-use shortfalls after accounting for stochastic noise.

This study focuses on Mungwi and Senanga because they represent sharply contrasting maize-production environments. Mungwi, in Agroecological Region III, is relatively favourable for crop production because rainfall is generally higher and more reliable. Senanga, in Agroecological Region I, is more drought-prone and experiences greater rainfall uncertainty. Comparing these districts is useful because it tests whether SAP-efficiency relationships are similar across production environments or whether the same adoption indicator has different implications under contrasting agroecological constraints.

1.1 Statement of the Problem

Zambia's promotion of sustainable agricultural practices has generated important evidence on adoption, maize yields, farm income and climate adaptation, but adoption itself is not a sufficient measure of production performance. In resource-constrained smallholder systems, the policy question is also whether farmers convert available land, seed, fertiliser and labour into maize output efficiently. Practices that conserve soil or strengthen resilience may produce benefits only after several seasons, and may initially require additional labour, changes in input timing or complementary management. Consequently, a household can adopt several SAP components without necessarily moving closer to the short-run production frontier (Arslan et al., 2015; Manda et al., 2016; Thierfelder et al., 2017).

The empirical literature in Zambia has largely developed along two separate lines. One line examines the adoption and welfare or productivity implications of sustainable practices, while another estimates technical-efficiency gaps in maize production (Chiona et al., 2014; Mwalupaso et al., 2019; Ng'ombe, 2017). Few studies directly connect these questions, and even fewer test whether the SAP-efficiency relationship varies across sharply different production environments. This omission is consequential because a common frontier may combine managerial shortfalls with technology and agroecological gaps, while a pooled SAP coefficient may conceal location-specific relationships (Ng'ombe, 2017; O'Donnell et al., 2008).

The resulting knowledge gap limits the interpretation of programme monitoring, which is based mainly on counts of practices adopted. If adoption intensity is treated as an automatic proxy for efficient production, extension programmes may overlook implementation quality, timing, plot coverage and local constraints. Conversely, interpreting lower pooled-frontier scores as purely managerial could unfairly attribute environmental or technological disadvantages to farmers. The specific problem addressed by this study is therefore the lack of evidence on whether SAP adoption is associated with technical efficiency among Zambian smallholder maize farmers, and whether that association differs between the higher-rainfall environment of Mungwi and the drought-prone environment of Senanga.

1.2 Research Objectives

i. To estimate technical efficiency among sampled maize farmers using stochastic frontier analysis;
ii. To compare pooled-frontier technical efficiency patterns between Mungwi and Senanga districts;
iii. To examine whether SAP adoption intensity and high SAP adoption are associated with predicted technical efficiency scores; and
iv. To assess whether the SAP-technical efficiency relationship differs between Mungwi and Senanga.

II. LITERATURE REVIEW

2.1 Theoretical Review

The study is anchored in production frontier theory. In this framework, the production frontier represents the maximum output attainable from a given set of inputs under the prevailing technology, while technical efficiency measures how close each farm is to that frontier. Farrell (1957) provided the conceptual foundation for measuring productive efficiency, and Aigner et al. (1977) and Meeusen and van Den Broeck (1977) introduced stochastic frontier models that decompose deviations from the frontier into two components: random statistical noise and one-sided technical inefficiency.

This distinction is particularly relevant for smallholder agriculture because observed output deviations may arise from rainfall shocks, pests, soil variability, measurement error, and other factors beyond the farmer's control. In this study, SAP adoption is not assumed to cause efficiency. Instead, SAP adoption is treated as a farm-management characteristic, and its association with predicted efficiency is examined after the production frontier has been estimated. This framing is consistent with the cross-sectional and observational nature of the data.

2.2 Empirical Review

Empirical studies on SAPs in Zambia and Sub-Saharan Africa show that farmers commonly adopt practices as portfolios rather than as isolated technologies. In Zambia, Arslan et al. (2015) linked climate-smart practices to adaptation considerations, while Manda et al. (2016) found that sustainable-practice packages were associated with maize yield and income outcomes. Kassie et al. (2015) similarly showed that adoption decisions involve complementarities and trade-offs across practices. These findings support analysing both the number of adopted components and a high-adoption threshold. However, they do not establish that a larger portfolio necessarily improves short-run resource-use efficiency.

The conservation-agriculture literature explains why performance may differ across settings and over time. Minimum tillage, residue retention and crop rotation can improve infiltration, soil cover and resilience. However, their outcomes depend on rainfall, soil conditions, weed control, labour requirements, residue availability, livestock competition and access to complementary inputs (Corbeels et al., 2020; Giller et al., 2009). Evidence from southern Africa also indicates that productivity benefits may emerge only after a transition period, with lagged gains commonly reported over several seasons (Thierfelder et al., 2017). A large Sub-Saharan African meta-analysis found only modest average short-run yield gains from conservation agriculture, with stronger results when mulching and crop diversification were combined (Corbeels et al., 2020). Thus, a simple SAP count captures breadth of adoption but not implementation quality, duration, sequencing or agronomic compatibility.

Technical-efficiency studies in Zambia consistently indicate that maize farms operate at heterogeneous distances from their estimated production frontiers. Chiona et al. (2014) reported substantial efficiency gaps among Central Province maize farmers, while Mwalupaso et al. (2019) showed that access to agricultural information and production-management conditions were associated with efficiency differences. Ng'ombe (2017) used a stochastic metafrontier approach and demonstrated that observed regional performance gaps can reflect both managerial inefficiency and differences in production technology. More broadly, a meta-analysis of African agricultural frontier studies found that efficiency estimates vary systematically with crop type, data structure and model specification, and identified education, experience, extension and credit as recurrent correlates of efficiency (Ogundari, 2014). The technology-heterogeneity issue is especially important when farms operate under contrasting agroecological conditions. Metafrontier theory distinguishes farm-specific efficiency relative to a group frontier from the technology gap between that group frontier and an overarching frontier (O'Donnell et al., 2008). Accordingly, a lower score under a pooled frontier should not automatically be interpreted as weaker management if farmers face a different attainable technology or a more adverse production environment. The evidence from Zambia therefore supports combining a pooled frontier with district-specific diagnostics and explicitly testing district heterogeneity.

Despite these two bodies of evidence, little empirical work directly examines whether adopting multiple SAP components is associated with technical efficiency across contrasting Zambian agroecological environments. Existing SAP studies principally assess adoption, yields, income, or adaptation, whereas efficiency studies generally treat management and institutional characteristics without focusing on SAP portfolios. This study bridges that gap by estimating a production frontier, deriving farm-level efficiency scores, and then examining whether SAP count and high SAP adoption have different associations with efficiency in Mungwi and Senanga. Methodologically, fractional response models are appropriate for secondary analysis of technical-efficiency scores because the scores lie between zero and one. Papke and Wooldridge (1996) developed the fractional-logit approach, while Ramalho et al. (2011) review alternative fractional-regression specifications and tests of their conditional-mean assumptions. In the present study, fractional logit is used alongside OLS as an associational robustness model rather than as a structural inefficiency equation, because the dependent variable is generated from the stochastic frontier and the cross-sectional design does not identify causal effects.

III. METHODOLOGY

3.1 Research Design, Data Sources and Sampling

The study used a cross-sectional research design based on primary household survey data. The target population was smallholder maize-producing households in Mungwi District of Northern Province and Senanga District of Western Province, Zambia. The survey collected information on household characteristics, maize production, input use, SAP adoption, institutional access, and farm-management variables. The pooled dataset comprises 582 households, including 311 from Mungwi and 271 from Senanga.

A multistage sampling procedure was used. Agricultural camps were initially selected to capture the relevance of maize production, agroecological contrast, implementation context, and field accessibility. The sampled households were drawn from 13 named agricultural camps across the two districts. In Mungwi, the camps were Mabula, Mungwi West, Chimba, Malole North, Ngulula, Kayambi West, and Mungwi East. In Senanga, the camps were Lukanda, Lui Mweemba, Lui Namabunga, Lui Wanyau, and Muweswa. Farmer lists were obtained from camp-level registers maintained through the agricultural extension system, and households were selected from these lists using random sampling procedures. Accessibility refers to the practical feasibility of reaching selected communities during fieldwork while maintaining the intended district and agroecological contrast.

The study areas were selected because they represent contrasting agroecological conditions. Mungwi is located in Agroecological Region III, which generally receives annual rainfall exceeding 1,000 mm and is relatively favourable for crop production. Senanga is located in Agroecological Region I, which generally receives less than 800 mm of annual rainfall and is characterised by recurrent drought and erratic rainfall. These differences provide a relevant empirical setting for examining whether resource-use performance and the SAP-efficiency relationship differ across production environments.

3.2 Data Audit and Estimation Samples

Before estimation, the Mungwi and Senanga datasets were cleaned, harmonised, appended, and audited for variable availability, missingness, unit consistency, extreme values, and district identifiers. Maize output was harmonised into kilograms. Production variables were screened for implausible zeros, missing values, unit inconsistencies, and extreme observations. Corrections were made only where the survey records supported them; remaining extreme values were retained rather than mechanically deleted to avoid arbitrary trimming of large but plausible farms. The stochastic frontier model required complete observations on maize output, maize area, seed, fertiliser, and labour, yielding a final SFA sample of 482 households. The secondary SAP-TE models used 481 complete observations after including covariates. The complete-case approach is reported transparently because missing-data treatment can affect inference when exclusion is not random (Little & Rubin, 2019).

Table 1

Sample construction and analysis samples

Sample item	Total	Mungwi	Senanga
Full cleaned pooled dataset	582	311	271
SFA estimation sample	482	239	243
Excluded from SFA sample	100	72	28
SAP-TE association sample	481	238	243
High SAP adopters in SAP-TE sample	111	51	60
Low SAP adopters in SAP-TE sample	370	187	183

Notes: The SFA sample requires complete, non-missing data on maize output, seed, fertiliser, labour, and maize area. The SAP-TE sample also requires complete covariate data for the secondary association models.
Source: Author's computation from survey data.

As shown in Table 1, the pooled dataset contains 582 households, but the SFA estimation sample is smaller because frontier estimation requires complete production-input information. The reduction to 482 SFA observations is substantively important because it shows that the main frontier results are based on a clearly defined complete-case sample rather than on the full survey count. The table also shows that the SAP-TE association models use 481 observations, almost identical to the SFA sample, which gives consistency between the efficiency estimates and the secondary association analysis. The distribution of high SAP adopters across districts also indicates that both districts contribute meaningfully to the SAP comparison, although the interpretation must remain sensitive to district context.

3.3 Measurement of Variables

The production frontier used maize output measured in kilograms as the dependent variable. Maize area was measured in hectares, seed quantity in kilograms, fertiliser quantity as total chemical fertiliser applied in kilograms, and labour as total person-days used in maize production. Fertiliser was treated as an aggregate input because the frontier model focuses on total fertiliser quantity rather than nutrient composition or fertiliser type. Labour was aggregated across reported household and hired labour contributions into person-days. These measurement choices make the frontier model transparent, although they do not capture differences in input quality, timing, or nutrient content.

SAP adoption was measured using three practices: crop rotation, residue retention or mulching, and minimum or zero tillage. The SAP count ranges from 0 to 3. High SAP adoption is defined as the adoption of two or more of the three practices. This definition is transparent and replicable, but it is intentionally interpreted narrowly: it captures adoption status and intensity, not implementation quality, duration, plot coverage, or agronomic complementarity. This limitation is considered when interpreting the SAP-efficiency results.

Table 2
Definition and measurement of variables

Variable	Description	Measurement
Maize output	Total maize harvested	Kilograms; transformed as ln(output) in the SFA
Maize area	Area planted to maize	Hectares; transformed as ln(area) and mean-centred
Seed quantity	Quantity of maize seed planted	Kilograms; transformed as ln(seed + 1) and mean-centred
Fertilizer quantity	Chemical fertilizer applied	Kilograms; transformed as ln(fertilizer + 1) and mean-centred
Labour	Labour used in maize production	Person-days; transformed as ln(labour + 1) and mean-centred
Technical efficiency	Predicted efficiency score	Bounded score from pooled Cobb-Douglas SFA
SAP count	Number of adopted SAP components	Count from 0 to 3: crop rotation, residue retention, minimum/zero tillage
High SAP adoption	Adoption of multiple SAP components	Dummy: 1 = two or more SAPs, 0 = fewer than two SAPs
Education	Formal education of household head	Years
Credit access	Household accessed agricultural credit	Dummy: 1 = yes, 0 = no
Cattle ownership	Household owns cattle	Dummy: 1 = yes, 0 = no
Group membership	Household belongs to a farmer group	Dummy: 1 = yes, 0 = no
District	Household location	Dummy categories: Mungwi and Senanga

The variables in Table 2 also clarify the analytical sequence used in the study. Production inputs such as maize area, seed, fertiliser, and labour are used to estimate the frontier, while SAP adoption and household characteristics are used after the TE scores are predicted. This separation prevents the discussion from confusing production-function inputs with post-estimation correlates of efficiency. The table also makes transparent that SAP adoption is measured both as a count of practices and as a high-adoption indicator, which is important because the empirical results later show that SAP effects differ by district and by how adoption is defined.

3.4 Stochastic Frontier Production Model

Following the stochastic frontier framework of Aigner et al. (1977) and Meeusen and van Den Broeck (1977), maize output was specified as a function of land, seed, fertiliser, and labour. The composed error term separates two-sided statistical noise from non-negative technical inefficiency. This modelling strategy follows standard efficiency-analysis treatments of stochastic production frontiers (Coelli et al., 2005; Kumbhakar & Lovell, 2000). A normal/half-normal error structure was used as a parsimonious baseline specification. The half-normal assumption is common in cross-sectional agricultural SFA because it imposes non-negative inefficiency while avoiding the additional distributional parameters required by more flexible alternatives. This assumption can be restrictive, so the results are interpreted with caution and supported by functional-form and district-specific diagnostic checks.

Both Cobb-Douglas and Translog frontiers were estimated. The Translog specification, originally introduced as a flexible second-order production frontier by Christensen et al. (1973), improved the log-likelihood relative to the Cobb-Douglas specification. However, the pooled Translog did not identify a statistically significant one-sided inefficiency component. Because the objective of the study is to estimate technical efficiency rather than only to improve production-function fit, the pooled Cobb-Douglas frontier was used as the main TE model. This decision also addresses the risk of overparameterisation in the Translog specification, where many higher-order terms are difficult to interpret and may not yield stable inefficiency estimates. The Translog results are retained as diagnostic evidence rather than as the main source of TE scores.

3.5 Secondary Association Models and Robustness Checks

After predicting farm-specific technical efficiency scores from the main pooled Cobb-Douglas frontier, secondary association models were estimated. OLS models were used for transparent comparison, while fractional logit models were used because technical efficiency scores are fractional outcomes bounded between zero and one. These models are interpreted as associational because the TE score is itself a generated outcome from the frontier model and because the data are cross-sectional.

The SAP-TE association was examined using both SAP count and high SAP adoption. District-interaction models were estimated to assess whether the SAP-efficiency relationship differs between Mungwi and Senanga. Propensity-score matching was used as a robustness check for high SAP adoption. District-specific frontiers were also estimated as diagnostics because a pooled frontier imposes a common technology across two agroecologically different production environments. These checks were used to guide interpretation rather than to claim causal effects.

IV. FINDINGS & DISCUSSION

4.1 Findings

4.1.1 Production Data Audit and SAP Adoption Patterns

Table 3 reports the production variables used in the stochastic frontier estimation sample. The table is included before the frontier estimates because the credibility of the technical-efficiency analysis depends on the quality and scale of the production variables used to estimate the frontier. The variables show substantial heterogeneity in production scale and input use. Mean maize output was 1,495.75 kg, but the median was only 750 kg, and the maximum was 20,500 kg. This wide dispersion in output, fertiliser, labour and maize area confirms the need to report data-audit procedures and to interpret frontier estimates with caution.

Table 3

Production variables in the SFA estimation sample

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Maize output (kg)	482	1,495.75	2,103.58	25	250	750	2,000	20,500
Maize area (ha)	482	1.47	1.20	0.05	1.00	1.00	2.00	10.00
Seed quantity (kg)	482	17.54	15.08	1	10	10	20	175
Fertiliser quantity (kg)	482	286.64	571.61	0	30	200	350	8,000
Labour (person-days)	482	234.64	263.85	0	67	120.5	270	1,357
Maize yield (kg/ha)	482	1,295.19	1,670.45	100	300	600	1,500	10,000

The data summarised in Table 3 indicate that the frontier is estimated from farms that differ substantially in production scale and input intensity. The gap between the mean and median output points to a right-skewed production distribution, while the high maximum values for fertiliser and labour underscore the need to account for outlier sensitivity in the analysis. These descriptive patterns justify the use of a stochastic frontier framework that separates random shocks from inefficiency, but they also require cautious interpretation of the estimated frontier. After establishing the structure of the production data, the analysis turns to the distribution of SAP adoption, as it is the main management variable of interest. Table 4 shows that SAP adoption patterns differed sharply by district. In the full sample, many households adopted none or only one of the three SAP components, indicating that integrated adoption remained limited. The district-level pattern is also uneven: Mungwi had more households adopting two SAP components, while Senanga had more households adopting all three practices. This uneven distribution is important because pooled SAP estimates may reflect both adoption behaviour and the production environments in which adoption occurs.

Table 4

Distribution of SAP adoption intensity in the full sample

District	0 SAPs	1 SAP	2 SAPs	3 SAPs	Total
Mungwi	94	128	64	25	311
Senanga	59	148	3	61	271
Total	153	276	67	86	582

Notes: SAP components are crop rotation, residue retention/mulching, and minimum tillage.

Source: Author's computation from survey data.

The data summarised in Table 4 show why the SAP-TE relationship cannot be interpreted as a simple dose-response process. Mungwi has a relatively larger number of households adopting two SAP components, whereas Senanga has many households adopting either one component or all three. This uneven adoption structure means that a pooled SAP coefficient may combine differences in practice intensity with differences in agroecological stress, resource constraints and implementation conditions. The next subsection therefore first establishes a defensible production frontier before interpreting SAP associations.

4.1.2 Functional Form and Frontier Diagnostics

Table 5 reports the frontier diagnostics used to decide how technical efficiency should be estimated. The Translog specification improved the log-likelihood relative to the Cobb-Douglas specification, indicating a better fit to the functional form. However, the pooled Translog model did not identify a statistically significant one-sided inefficiency component, whereas the Cobb-Douglas model did. Therefore, this study uses the pooled Cobb-Douglas frontier as the main technical-efficiency model and treats the Translog as a diagnostic robustness specification rather than as the preferred TE model.

Table 5

Frontier functional-form and inefficiency diagnostics

Model or test	**Result**	**Interpretation**
Pooled Cobb-Douglas log likelihood	-672.556	Main frontier candidate
Pooled Cobb-Douglas LR test of sigma_u = 0	chibar-square = 7.99; p = 0.002	One-sided inefficiency statistically identified
Pooled Translog log likelihood	-644.827	Flexible diagnostic model improves fit
Pooled Translog LR test of sigma_u = 0	chibar-square = 0.37; p = 0.271	Inefficiency not statistically identified
LR test: Cobb-Douglas vs Translog	chi-square(10) = 55.46; p < 0.001	Translog improves fit but is not used as the main TE because inefficiency is not identified.
Main TE model selected	Pooled Cobb-Douglas SFA	Parsimonious and statistically defensible main efficiency model

As indicated in Table 5, model choice is not determined by functional-form fit alone. Although the Translog improves the likelihood, it does not provide a statistically reliable inefficiency component in the pooled data. This distinction is important because technical-efficiency scores should be generated from a frontier that identifies inefficiency, not merely from the model with the highest likelihood. The table therefore provides the methodological bridge from the data audit to the main Cobb-Douglas frontier estimates.

4.1.3 Pooled Cobb-Douglas Stochastic Frontier Results

Having established the main frontier specification, Table 6 presents the pooled Cobb-Douglas stochastic frontier estimates. The table shows which production inputs are associated with maize output after the variables are logged and centred. Maize area, fertiliser, and labour had positive and statistically significant coefficients, while seed was positive but not statistically significant. The coefficient on maize area is the largest among the production inputs, suggesting that land allocation remains central to maize output. At the same time, fertiliser and labour also contribute positively within the observed input range. The significant LR test for the inefficiency component supports the use of SFA rather than an ordinary least squares production function.

Table 6

Main pooled Cobb-Douglas stochastic frontier estimates

Variable	**Coefficient**	**Std. Error**	**p-value**
ln(maize area), centred	0.486***	0.045	0.000
ln(seed + 1), centred	0.118	0.074	0.107
ln(fertilizer + 1), centred	0.208***	0.021	0.000
ln(labour + 1), centred	0.075**	0.038	0.049
Constant	7.817***	0.100	0.000
sigma_v	0.458		
sigma_u	1.515		
lambda	3.306		
N	482		
Log likelihood	-672.556		
Wald chi-square(4)	400.67***		0.000
LR test of sigma_u = 0	chibar-square = 7.99		0.002

*Notes: *, ** and *** denote Significance at the 10%, 5% and 1% levels.*

The coefficients in Table 6 indicate that the main frontier is economically plausible: larger maize area, greater fertiliser use and higher labour use are associated with higher maize output. Seed quantity is positive but not statistically significant, suggesting that variation in seed use alone does not explain differences in output once other inputs are controlled for. Importantly, the significant inefficiency component confirms that deviations from the frontier are not only random noise. This provides an empirical basis for predicting farm-level technical efficiency scores and comparing them across districts.

4.1.4 Technical Efficiency Distribution and District Differences

The predicted technical efficiency scores from the main pooled Cobb-Douglas frontier are summarised in Table 7. This table directly addresses the first two research questions by showing both the level of technical efficiency and the contrast between the two production environments. The overall mean TE score was 0.401, indicating a substantial shortfall from the estimated pooled frontier. Mungwi households had a higher mean TE score (0.547) than Senanga households (0.258), and the difference was statistically significant. This result indicates that households in the more favourable Mungwi environment operated closer to the pooled frontier than those in the drought-prone Senanga environment.

Table 7

Distribution of pooled-frontier technical efficiency scores by district

District	N	Mean	SD	Min	P25	Median	P75	Max
Mungwi	239	0.547	0.180	0.116	0.411	0.575	0.694	0.852
Senanga	243	0.258	0.192	0.040	0.106	0.193	0.359	0.826
Total	482	0.401	0.236	0.040	0.177	0.379	0.614	0.852

Notes: Technical efficiency scores are predicted using the main pooled Cobb-Douglas stochastic frontier model. Welch unequal-variance t-test and Wilcoxon rank-sum test both indicate a statistically significant district difference at $p < 0.001$.

The distribution in Table 7 indicates that technical inefficiency is not a marginal issue in the sample. The pooled mean of 0.401 implies that, on average, households are far below the estimated frontier given their observed inputs. The district contrast is also large: Mungwi's median TE is nearly three times that of Senanga. This difference is central to the study because it shows that agroecological context is not a background characteristic; it shapes how resource-use performance should be interpreted.

The district gap should nevertheless be interpreted carefully. Because the pooled frontier imposes a common production technology on Mungwi and Senanga, the lower Senanga scores may reflect drought-prone production conditions, technology differences, input-quality constraints, or measurement noise in addition to farmer-level management. The district comparison is therefore interpreted as a pooled-frontier performance difference rather than as a pure measure of managerial superiority in Mungwi. To move beyond the summary statistics in Table 7, the next figures examine the shape and dispersion of the technical-efficiency distribution.

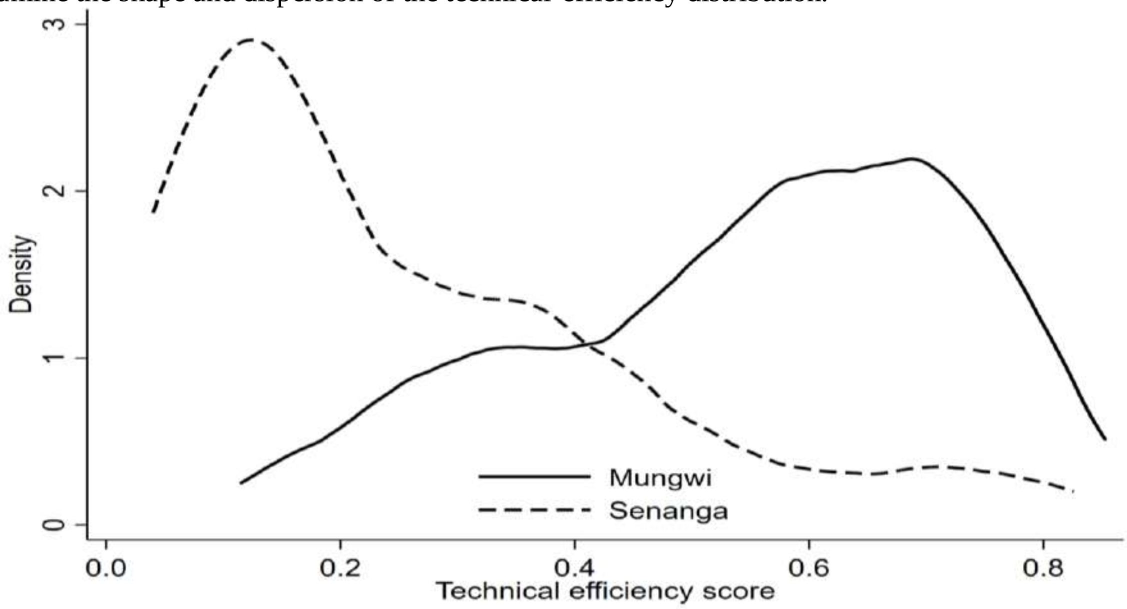

Figure 1

Kernel density distribution of technical efficiency scores by district

As illustrated in Figure 2, the district distributions are clearly separated. Mungwi households cluster toward higher TE values, while Senanga households are concentrated at the lower end of the pooled-frontier distribution. The overlap between the two curves remains important: it indicates that some Senanga households perform relatively well, while some Mungwi households perform poorly. Thus, district location is a strong correlate of efficiency, but it does not fully determine farm-level performance. Figure 3 complements this density comparison by summarising the same district difference with medians, interquartile ranges and outlying observations. Figure 3 shows whether the separation in Figure 2 is driven by the full distribution or only by a few extreme values.

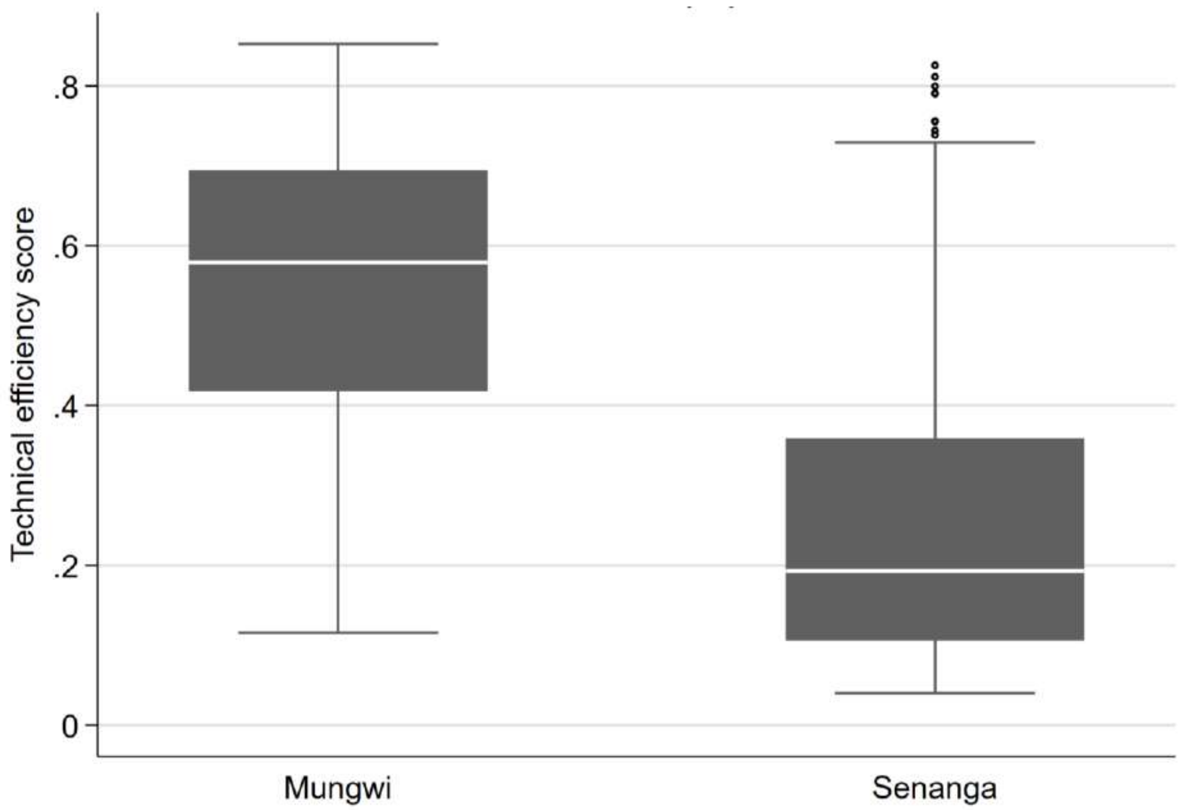

Figure 2
Technical efficiency scores by district

Figure 3 confirms the pattern suggested by the density curves. The Mungwi box is positioned higher, with a higher median and upper quartile, whereas Senanga has a lower median and a wider spread. The presence of high-efficiency Senanga outliers reinforces the point that the district gap should not be reduced to a simple story in which all farmers in one district are efficient, and all farmers in the other are inefficient. Instead, the figure highlights both the average disadvantage faced by Senanga and the within-district heterogeneity that motivates the subsequent robustness checks.

4.1.5 SAP Adoption and Technical Efficiency

Table 8 summarises technical efficiency by high SAP adoption status and by SAP count. This table provides the first descriptive answer to whether SAP adoption is associated with higher technical efficiency. High SAP adopters had lower mean TE than low SAP adopters in the pooled sample. However, the SAP-count pattern is not mechanically linear across all categories: households adopting two SAPs had relatively high mean TE, while households adopting all three SAPs had the lowest mean TE. This pattern reinforces the need to interpret SAP adoption intensity in relation to district context and implementation conditions rather than as a simple productivity ladder.

Table 8
Technical efficiency by SAP adoption status and SAP count

Group	N	Mean TE	SD	Interpretation
Low SAP adoption	370	0.425	0.230	Reference group
High SAP adoption	111	0.321	0.238	Lower mean TE; Welch test p = 0.0001
0 SAPs	124	0.422	0.234	No measured SAP component
1 SAP	246	0.427	0.228	One component adopted
2 SAPs	46	0.521	0.173	Highest observed mean TE
3 SAPs	65	0.179	0.165	Lowest observed mean TE; concentrated in Senanga

The pattern in Table 8 is important because it complicates a simple expectation that more SAP adoption should automatically correspond to higher technical efficiency. The highest mean TE is observed among households adopting two SAP components, while the lowest is observed among households adopting all three components. This suggests that adoption intensity may be entangled with district-specific production stress, implementation burden, or the tendency for more constrained households to adopt multiple practices in response to difficult conditions. Figure 4 therefore disaggregates the mean comparison by both SAP status and district.

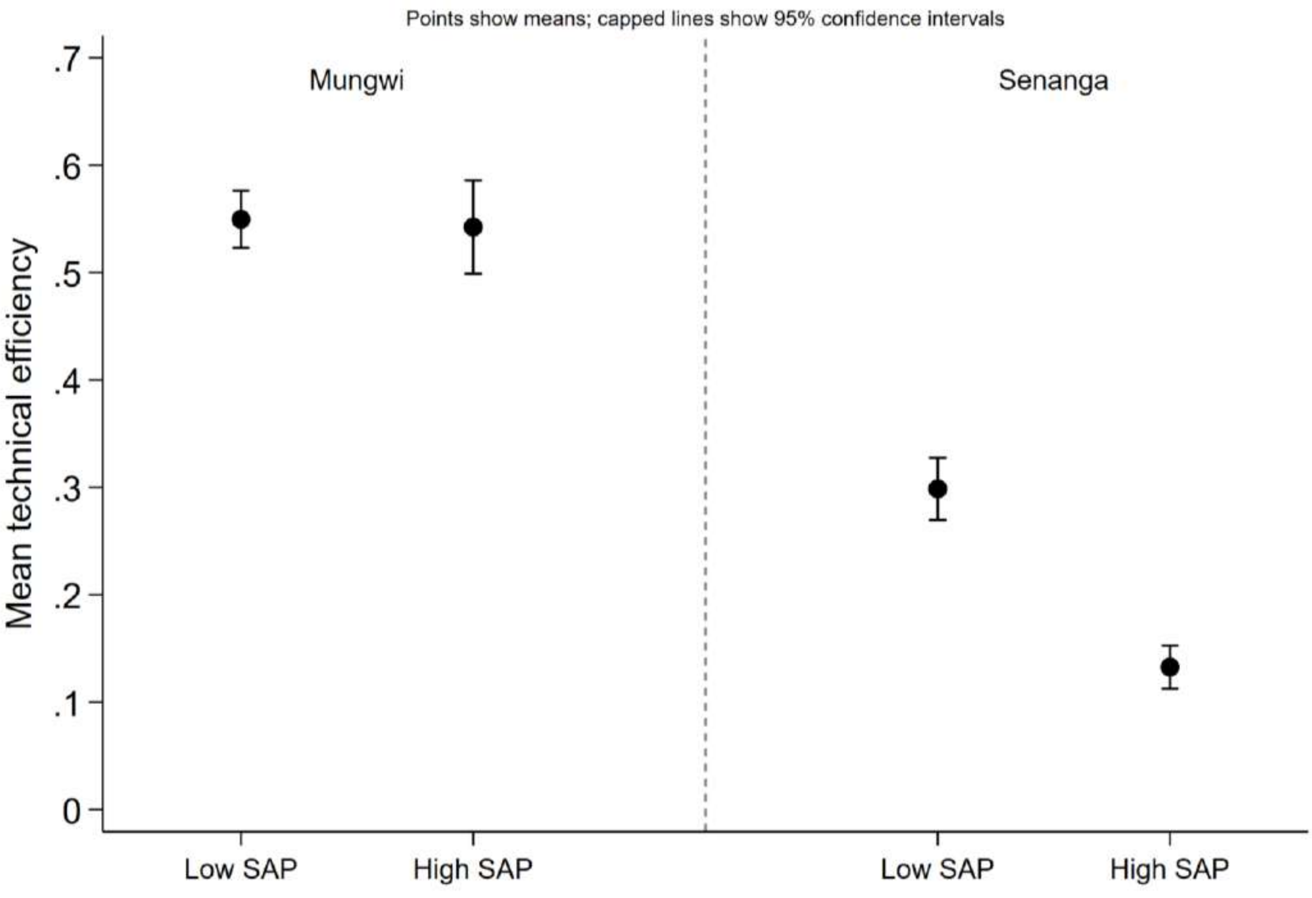

Figure 3
Mean technical efficiency by SAP adoption status and district

As illustrated in Figure 4, the high-SAP and low-SAP means are almost identical in Mungwi, but the difference is large in Senanga. This visual pattern provides an intuitive explanation for the pooled negative association: the overall result does not reflect a uniform negative association between SAP adoption and technical efficiency across districts, but rather a district-specific relationship concentrated in the more drought-prone setting. The figure therefore motivates the interaction models reported in the next subsection.

4.1.6 Multivariate SAP-TE Association Models

The descriptive comparison in Table 8 is followed by multivariate models that adjust for household, farm and district characteristics. Table 9 reports the main OLS and fractional-logit results, including district-interaction marginal effects. The multivariate results confirm that the pooled negative association between SAP adoption and technical efficiency is driven by district heterogeneity. In the pooled fractional logit model, high SAP adoption was associated with an 8.6 percentage-point lower predicted TE score. SAP count was also negatively associated with TE in the pooled model. However, the district-interaction results show that the marginal effect of SAP count was small and not statistically significant in Mungwi, but negative and statistically significant in Senanga. Similarly, the high-SAP marginal effect was not significant in Mungwi but was strongly negative in Senanga.

Table 9
SAP adoption and technical efficiency: regression and fractional-logit summary

Model/result	Estimate or AME	p-value	Interpretation
OLS: high SAP coefficient	-0.086	<0.001	High SAP associated with lower TE in pooled model
Fractional logit: high SAP AME	-0.086	<0.001	Bounded-outcome estimate consistent with OLS
Fractional logit: SAP count AME, pooled	-0.041	<0.001	Additional SAP component associated with lower TE on average
SAP count AME, Mungwi	-0.005	0.684	No statistically significant SAP-count association
SAP count AME, Senanga	-0.062	<0.001	Negative SAP-count association concentrated in Senanga
High SAP AME, Mungwi	-0.001	0.956	No statistically significant high-SAP association
High SAP AME, Senanga	-0.162	<0.001	Strong negative high-SAP association in Senanga
Crop rotation AME	-0.051	0.001	Negative component association
Residue retention AME	-0.091	<0.001	Negative component association
Minimum tillage AME	0.047	0.020	Positive component association after controls

Notes: AME = average marginal effect. All models control for district, gender of household head, education, farming experience, household size, farm size, credit, cattle ownership, and group membership where applicable.

The evidence in Table 9 refines the descriptive pattern reported in Table 8. Once controls and district interactions are included, the SAP-TE relationship is not uniform across locations. The non-significant Mungwi marginal effects suggest that SAP adoption is not associated with lower technical efficiency in the more favourable production environment. In contrast, the negative and significant Senanga effects indicate that adopting more SAP components, or crossing the high-SAP threshold, is associated with lower predicted TE in the drought-prone setting. This is the main empirical result linking SAP adoption to technical efficiency.

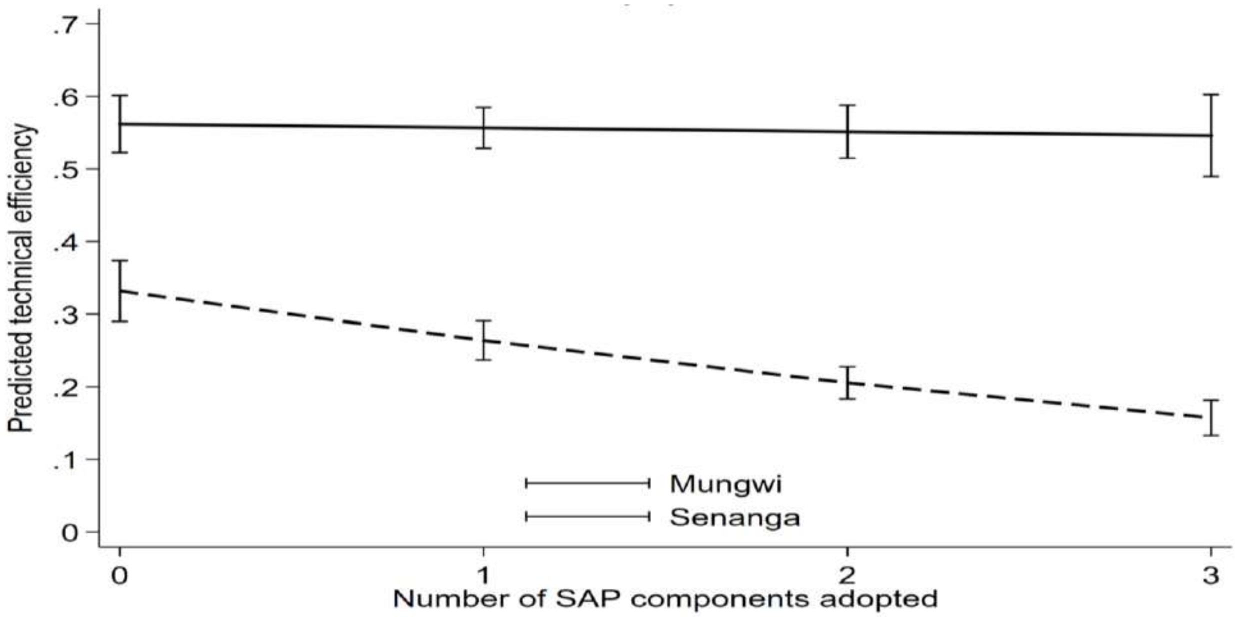

Figure 4
Predicted technical efficiency by SAP count and district

Figure 5 translates the SAP-count interaction into predicted technical-efficiency values. The Mungwi line is nearly flat across the range of 0 to 3 SAP components, indicating little predicted change in TE as the SAP count rises. By contrast, the Senanga line declines steadily as SAP count increases. This divergence is central to the paper's argument because it shows that the relationship between SAP adoption and efficiency depends on the production environment rather than on the number of practices alone.

Because policymakers often classify farmers using adoption thresholds rather than continuous counts, Figure 6 presents the same district contrast using the high-SAP indicator. This provides a more policy-facing interpretation of the interaction results.

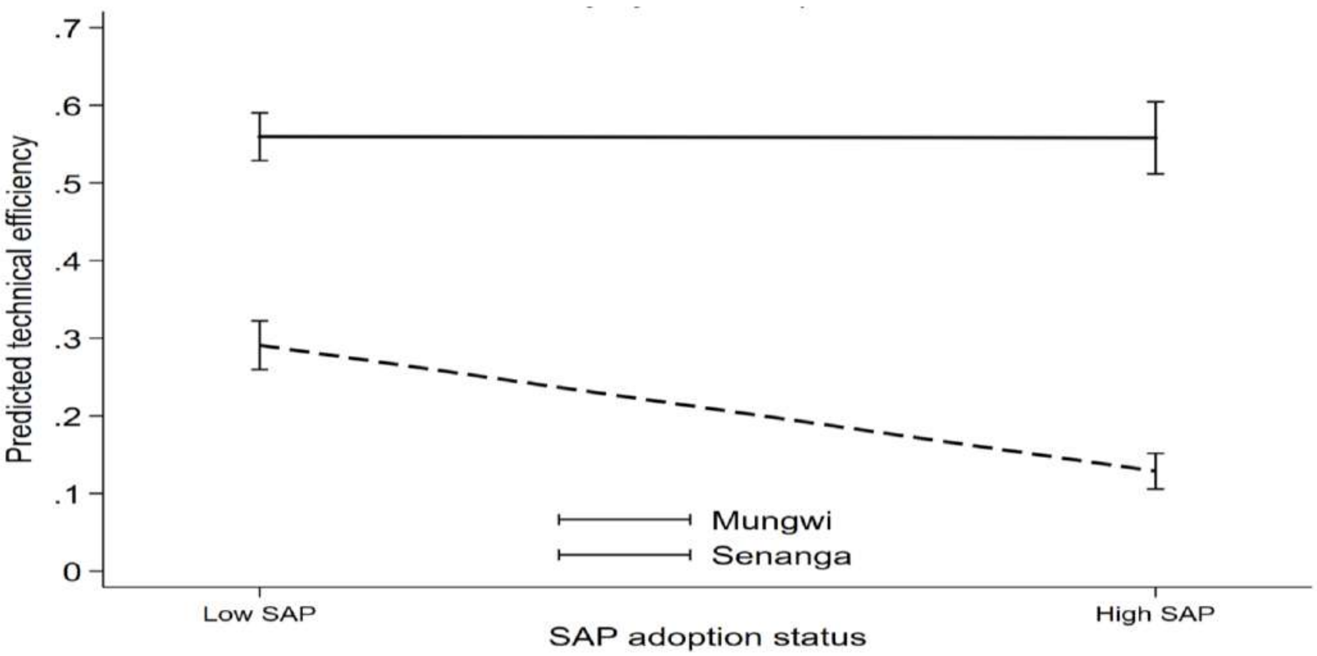

Figure 5
Predicted technical efficiency by high SAP adoption status and district

As shown in Figure 6, predicted TE remains essentially unchanged between low and high SAP adopters in Mungwi, whereas it falls sharply for high SAP adopters in Senanga. This reinforces the interpretation that the Senanga subsample drives the high-SAP association. The figure also makes clear why the policy message should not be that SAPs are inherently inefficient, but that SAP promotion in drought-prone environments requires closer attention to implementation quality, timing, complementary inputs and local constraints.

4.1.7 Propensity-Score Matching Robustness Checks

SAP adoption is observational rather than randomly assigned; therefore, propensity score matching was used as a robustness check for the high-SAP-adoption comparison. Table 10 summarises the pooled and district-specific matching estimates. The pooled ATET was negative and statistically significant. The Mungwi-only estimate was negative but not statistically significant, while the Senanga-only no-credit specification was negative and statistically significant. Credit was excluded from the Senanga-only treatment equation because it perfectly predicted treatment status in that district. These matching results support the main interpretation from Table 9: the negative SAP-TE association is concentrated in Senanga rather than being uniform across districts.

Table 10
Propensity-score matching robustness checks for high SAP adoption

PSM specification	ATET	Std. Error	p-value	Interpretation
Pooled full covariates	-0.109	0.030	<0.001	High SAP associated with lower TE
Mungwi full covariates	-0.030	0.030	0.319	Not statistically significant
Senanga no-credit specification	-0.160	0.030	<0.001	Strong negative association
Pooled no-credit robustness	-0.093	0.037	0.013	Negative association remains
Mungwi no-credit robustness	-0.052	0.032	0.108	Not statistically significant

Notes: ATET = average treatment effect on the treated. The Senanga no-credit specification excludes credit because credit perfectly predicted high SAP treatment.

Table 10 strengthens the interpretation of the regression results by showing that the same district pattern appears under a matching framework. The pooled estimate remains negative, but the district-specific results show that Mungwi does not drive this pooled association. The Senanga no-credit specification remains strongly negative even after matching treated households to comparable controls. Because the Senanga specification had to exclude credit for perfect prediction, the result is best interpreted as evidence of robustness rather than as a standalone causal estimate.

4.1.8 District-Specific Frontier Diagnostics

Table 11 reports district-specific frontier diagnostics to assess whether the pooled district gap should be interpreted as pure managerial inefficiency. District-specific frontiers were estimated because the pooled frontier imposes a common technology across two contrasting agroecological environments. The diagnostics support caution in interpreting the pooled district gap. Mungwi district-specific frontiers identified one-sided inefficiency, but Senanga district-specific frontiers did not; the Senanga TE scores degenerated near unity. This instability suggests that Senanga's lower pooled-frontier scores may partly reflect environmental constraints, technological differences, or noise structure rather than managerial inefficiency alone. For this reason, district-specific frontiers are not used as the main basis for comparing TE.

Table 11

District-specific frontier diagnostics

District	Diagnostic model	N	LR test of sigma_u = 0	Mean diagnostic TE	Implication
Mungwi	Cobb-Douglas	239	p = 0.034	Diagnostic only	Detectable inefficiency
Mungwi	Translog	239	p = 0.003	0.656	Detectable inefficiency; flexible robustness
Senanga	Cobb-Douglas	243	p = 1.000	Diagnostic only	No detectable one-sided inefficiency
Senanga	Translog	243	p = 1.000	0.994	TE degenerates near unity; diagnostic only

Notes: District-specific frontiers are not used for the main TE comparison.

The diagnostics in Table 11 explain why the study relies on the pooled Cobb-Douglas frontier for the main TE scores while interpreting district comparisons cautiously. Mungwi shows detectable one-sided inefficiency under district-specific models, but Senanga does not. The near-unity Senanga diagnostic TE from the Translog model is not substantively credible as a measure of farm performance; instead, it signals that the Senanga-only frontier cannot separate inefficiency from noise or environmental constraints in this dataset. This finding directly supports the decision to treat district-specific frontiers as diagnostics only. Therefore, the descriptive, regression, matching and diagnostic results produce a coherent narrative. Technical efficiency is low on average, Mungwi performs closer to the pooled frontier than Senanga, and the negative SAP-TE association is concentrated in Senanga. The discussion below interprets these findings in relation to the study questions, the agroecological contrast and the policy relevance of SAP promotion.

4.2 Discussion

The first major finding is that substantial technical inefficiency remains in smallholder maize production under the main pooled Cobb-Douglas frontier. The mean TE score of 0.401 indicates that observed input combinations are not consistently converted into output at frontier levels. This estimate is lower than the mean of approximately 0.50 reported for maize farmers in Zambia's Central Province by Chiona et al. (2014) and the pooled estimate reported by Mwalupaso et al. (2019), although direct numerical ranking is inappropriate because the studies use different samples, frontier specifications, variables and production environments. The broader implication is nevertheless consistent with evidence from the African frontier: important efficiency gaps persist, and their estimated magnitude is sensitive to crop, data, and model choices (Ogundari, 2014).

The frontier coefficients provide a practical interpretation of this efficiency gap. Maize area, fertiliser, and labour were positively associated with output, whereas seed quantity was positive but not statistically significant after controlling for the other inputs. The result does not imply that simply expanding land area or fertiliser use will eliminate inefficiency. Rather, the coexistence of positive input elasticities and low average TE suggests that timing, input quality, labour coordination, field operations and access to usable production information matter for how inputs are transformed into output. This interpretation accords with Zambian evidence linking extension, credit, certified seed, and agricultural information to maize farm efficiency (Chiona et al., 2014; Mwalupaso et al., 2019).

The large Mungwi-Senanga difference must be read as a pooled-frontier performance gap, not as a pure ranking of managerial ability. Mungwi farmers operated closer to the common frontier, but the Senanga-only frontier could not separate one-sided inefficiency reliably from noise. These results are not contradictory. A common frontier is useful for describing performance relative to a shared benchmark, while the unstable district frontier warns that the benchmark may embed technology and environmental differences. Metafrontier theory explicitly distinguishes between within-group efficiency and technology gaps across groups (Ng'ombe, 2017; O'Donnell et al., 2008), and Ng'ombe (2017) shows that this distinction is empirically relevant for Zambian maize production. Senanga's lower pooled scores may therefore reflect drought risk, different attainable technologies, input constraints and measurement noise in addition to management.

The central substantive result is that the SAP-TE association differs by district. In Mungwi, neither the SAP count nor the high-SAP indicator showed a statistically significant association with efficiency. In Senanga, both measures were strongly and negatively associated with predicted TE. This pattern should not be interpreted as evidence that SAPs are inherently harmful in dryland agriculture. The estimates are observational, and farmers facing more difficult soils, moisture stress, or production risk may be more likely to adopt multiple practices in response to those constraints. The SAP count also does not measure how long a practice has been used, the share of the maize area it covers, the quality of implementation, or whether complementary inputs were available.

The practice-specific results reinforce this caution. Minimum tillage was positively associated with TE after controlling for other factors, whereas crop rotation and residue retention were negatively associated. Conservation agriculture research shows that these components operate through different mechanisms and can impose distinct short-run costs. Residue retention may compete with livestock feed, minimum tillage can increase weed-management demands, and benefits from improved soil structure or moisture retention may take several seasons to emerge (Corbeels et al., 2014; Giller et al., 2009; Thierfelder et al., 2017). Meta-analytic evidence also indicates that average short-run yield gains in Sub-Saharan Africa are modest and become stronger when practices are implemented as coherent combinations with suitable complementary management (Corbeels et al., 2020). The observed associations therefore reflect implementation and context, not a universal ranking of individual SAP components.

The consistency of the district pattern across fractional-logit models, predicted margins and propensity-score matching strengthens the descriptive conclusion that the negative pooled association is concentrated in Senanga. It does not, however, convert the relationship into a causal effect. Matching addresses selection only on observed covariates, while unmeasured rainfall exposure, soil properties, field-level management, input timing and farmers' reasons for adopting may remain important. In addition, the fractional models use generated TE scores and have deliberately limited explanatory scope. They are best viewed as secondary models that identify conditional associations and heterogeneity, rather than as complete structural explanations of efficiency.

The policy implication is therefore more specific than either promoting or rejecting SAPs. Adoption counts should be supplemented with indicators of practice quality, duration, plot coverage, timing and complementarity. Evidence from Zambia shows that sustainable-practice packages can improve yields, incomes, or adaptation outcomes under appropriate conditions (Arslan et al., 2015; Manda et al., 2016), while evidence from southern Africa indicates that some benefits are lagged and depend on locally adapted combinations (Thierfelder et al., 2017). In Mungwi, extension can emphasise input coordination and the maintenance of implementation quality. In Senanga, SAP promotion should be integrated with drought-risk management, water-conservation advice, suitable rotations and varieties, residue-use planning, timely inputs and repeated field-level support. This approach recognises potential long-run soil and resilience benefits without promising automatic short-run efficiency gains.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusions

This study examined the association between SAP adoption and technical efficiency among smallholder maize farmers in Mungwi and Senanga districts of Zambia. Using pooled survey data from 582 households and a final SFA sample of 482 households, the study estimated technical efficiency using a pooled Cobb-Douglas stochastic frontier as the main model. The Translog and district-specific frontiers were retained as diagnostics because the Translog did not identify a statistically significant inefficiency component in the pooled sample and Senanga district-specific models were unstable.

The mean pooled-frontier technical efficiency score was 0.401, indicating substantial resource-use shortfalls relative to the estimated frontier. Technical efficiency was higher in Mungwi than in Senanga under the pooled frontier, but this gap should be interpreted as a difference in pooled-frontier performance rather than pure managerial inefficiency. The district-specific diagnostics suggest that agroecological constraints, technology differences, and noise structure may contribute to the lower Senanga pooled-frontier scores. SAP adoption was not uniformly associated with technical efficiency across the two districts. In the pooled model, high SAP adoption and SAP count were negatively associated with TE. However, district-interaction results showed that this negative relationship was concentrated in Senanga and was not statistically significant in Mungwi. This finding highlights the importance of context-sensitive interpretation of SAP outcomes and cautions against assuming that adoption intensity automatically translates into short-run technical efficiency gains.

5.2 Recommendations

Extension programmes should distinguish between promoting SAP adoption and improving the quality of SAP implementation. Adoption targets should be complemented by monitoring of practice duration, plot coverage, timing, residue availability, rotation quality, and integration with fertiliser and labour management. In practical terms, extension officers should not only record whether a household adopted crop rotation, residue retention, or minimum tillage. They should also assess whether these practices were applied in ways that are agronomically suitable for the local production environment.

The findings also suggest that extension messages should be more precise. Farmers should not be told that adopting more SAP components will automatically raise short-run technical efficiency. Instead, the extension should explain the distinction between long-run soil health or resilience benefits and short-run resource-use performance. This distinction is particularly important when farmers face labour constraints, drought stress, competing uses of crop residues, or limited access to complementary inputs. Agricultural support should also be location-specific. Interventions designed for the higher-rainfall Mungwi environment should not be transferred mechanically to the drought-prone Senanga environment. For Senanga, support packages may need to combine SAP promotion with drought-risk management, moisture-conservation advice, timely access to inputs, appropriate varieties, and closer field-level follow-up. For Mungwi, extension may focus more on input-use efficiency, labour organisation, and maintaining SAP quality rather than simply increasing the number of practices adopted.

Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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