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Application of Monte Carlo simulation in evaluating sunflower productivity in Tanzania: Policy Insights

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Abstract — *Sunflower (*Helianthus annuus *L.) is a key oilseed crop for Tanzania's edible-oil self-sufficiency agenda, yet national yields remain low and highly variable. This study applies a Monte Carlo–based Stochastic Simulation Approach to nationally representative data from the 2019/20 National Sample Census of Agriculture to quantify yield distributions and production risk across six farming systems distinguished by seed type and fertilizer use: (1) local seed–no fertilizer (LS_F0), (2) local seed–organic fertilizer (LS_F1), (3) local seed–inorganic fertilizer (LS_F2), (4) improved seed–no fertilizer (IMS_F0), (5) improved seed–organic fertilizer (IMS_F1), and (6) improved seed–inorganic fertilizer (IMS_F2). For each system, 500 Latin Hypercube iterations generated empirical probability density functions and Stoplight Charts to evaluate the likelihood of yields falling below 1.0 t ha^{-1} or exceeding the national target of 2.0 t ha^{-1}. Results show that low-input production dominates: 87% of farms remain in LS_F0, where more than half face yields below 1.0 t ha^{-1} and only 3% surpass 2.0 t ha^{-1}. Inorganic fertilizer significantly shifts the yield distribution upward. LS_F2 increases the probability of exceeding 2.0 t ha^{-1} to 7 %, while IMS_F2 achieves the highest mean yield (1.14 t ha^{-1}) and the greatest likelihood (16 %) of surpassing the upper target, albeit with higher variability (CV ≈ 48 %). Improved seed without adequate nutrients provides only modest gains, and improved seed with organic fertilizer underperforms. These findings demonstrate that combining improved seed with inorganic fertilizer offers the clearest pathway to Tanzania's sunflower productivity goals, though risk-management measures and region-specific strategies are essential. The analysis provides a national baseline for future agro-ecological and policy-focused research on agricultural transformation.*

Keywords— ***sunflower, productivity, Monte Carlo Simulation, improved seeds, local seeds, fertilizers, Tanzania***

I. INTRODUCTION

Sunflower (*Helianthus annuus* L.) is central to Tanzania's ambition to close its persistent edible-oil deficit and reduce dependence on costly imports (Tibamanya et al., 2022; Matekele et al., 2024). National demand for edible oil is estimated at roughly 500,000–570,000 metric tons (MT) annually, while domestic output averages only 180,000–205,000 MT, leaving a structural gap of about 320,000 MT (UNDP, 2023; Nungula et al, 2024; HAPA, 2022). Expanding sunflower productivity, therefore, offers an important pathway to import substitution, improved rural incomes, and accelerated agricultural transformation, provided that production systems remain economically and agronomically viable under variable climate and market conditions (Beteri et al., 2024; Joseph et al., 2025).

Despite the crop's strategic significance, little is known about how different combinations of seed types and fertilizer practices jointly influence sunflower productivity on a national scale. Farmers across Tanzania employ a diverse set of input regimes that reflect access to capital, risk preferences, and agro-ecological conditions. To capture this heterogeneity, the present study categorizes production into six representative farming systems: System 1 (LS_F0): Local seeds, no fertilizer; System 2 (LS_F1): Local seeds with organic fertilizer; System 3 (LS_F2): Local seeds with inorganic fertilizer; System 4 (IMS_F0): Improved seeds, no fertilizer; System 5 (IMS_F1): Improved seeds with organic fertilizer; System 6 (IMS_F2): Improved seeds with inorganic fertilizer. These groupings capture the dominant technological gradients in Tanzanian sunflower farming, seed choice, and fertilizer strategy, providing a structured lens for evaluating productivity outcomes and informing input-intensification policies.

Recent global shocks have heightened the urgency of rigorous productivity assessment. The Russia–Ukraine war disrupted Black Sea sunflower-oil exports and propelled vegetable-oil prices to historic highs in 2022 before a partial correction in 2023–2024 (Abay et al., 2023; Lin et al., 2023; Ben-Hassen & El-Bilali, 2022; Joseph et al., 2025). Because Ukraine and Russia together supply more than half of global sunflower oil exports, these disruptions have sent pronounced price signals through international edible-oil markets, directly affecting Tanzanian processors and farm-gate prices (Yanovska et al., 2025; Hussein & Knol, 2023). Studies of agricultural commodities confirm that oil price shocks propagate into broader food markets, increasing co-movement and volatility (Aizenman et al., 2024; Sharmaa et al., 2024; Goyal et al., 2024; Umar et al., 2021). Such volatility underscores the importance of quantifying productivity and yield risk across different input systems to ensure the sector's resilience.

Productivity hinges on a complex interplay of seed genetics, soil fertility, management practices, and climate. Tanzania's central corridor, Dodoma, Singida, Manyara, and neighboring regions, offers high agro-ecological suitability, but intra-seasonal rainfall variability affects planting windows, establishment, and yields (Beteri et al., 2024; Joseph et al., 2025). Evidence shows that improved seed varieties can boost yield potential, but their performance is contingent on adequate nutrient supply and timely planting (Vilvert et al., 2023; Nungula et al., 2024; Debaeke et al., 2023). Fertilizer, whether organic or inorganic, further influences yield response, soil health, and economic returns. Yet adoption rates remain uneven due to credit constraints, limited extension, and variable access to agro-dealers (Tibamanya et al., 2022; Khan et al., 2024). Understanding how these factors interact across the six defined farming systems is therefore critical for designing effective interventions.

Institutions along the value chain also shape productivity outcomes. Access to agricultural value-chain finance enables timely input purchases and can stabilize production across seasons (Matekele et al., 2024). Smallholder systems operate as complex adaptive networks that can shift abruptly under external shocks, making flexible arrangements and risk-sharing contracts essential (Orr, 2018). Quality seed systems and post-harvest handling likewise influence both yield and oil recovery: recent Tanzanian studies reveal significant differences in germination and vigor between farmer-saved and certified seed (Selemani et al., 2025). To capture these multilayered uncertainties, Monte Carlo simulation offers a robust analytical framework. Stochastic simulation integrates probability distributions of yields, prices, and input costs to estimate not only expected productivity but also the range and likelihood of outcomes (Bendato et al., 2016; Amorim et al., 2024). Such an approach is particularly valuable when market and climatic volatility are high and when multiple technological pathways, like the six farming systems identified here, must be compared under a common probabilistic framework (Aizenman et al., 2024; Umar et al., 2021).

This research is the first to apply Monte Carlo simulation to nationally representative sunflower data across Tanzania. Evaluating productivity distributions for each of the six farming systems provides a baseline for future assessments of agricultural transformation and input-intensification strategies. Specifically, the study (i) quantifies yield variability and risk profiles across input regimes; (ii) identifies productivity gains from improved seeds and fertilizer combinations; and (iii) generates policy-relevant insights on where public investment, extension, and financing can most effectively enhance resilience and competitiveness in the sunflower value chain. The findings will guide policymakers, development partners, and private investors in prioritizing interventions, such as certified seed dissemination, targeted fertilizer subsidies, and farmer credit schemes, that align with Tanzania's broader goals of achieving edible-oil self-sufficiency, raising rural incomes, and advancing agricultural transformation (UNDP, 2023). By linking detailed farming-system heterogeneity with probabilistic yield analysis, this study sets the foundation for evidence-based strategies to scale productivity and manage risk in Tanzania's sunflower sector.

II. METHODOLOGY

2.1 Study Area and Data Sources

This study covers the entire United Republic of Tanzania, encompassing both mainland regions and Zanzibar. Sunflower production is spatially heterogeneous, with the highest output concentrated in the central corridor, particularly Dodoma, Singida, Manyara, and Tabora, followed by notable production in Rukwa, Mbeya, and parts of the northern zone (Figure 1). Regional production data, illustrated on the attached map, highlight Dodoma as the leading producer (≈202,528 tonnes), with progressively lower volumes toward the coastal and southern highlands.

We used the nationally representative 2019/20 National Sample Census of Agriculture (NSCA) dataset collected by the Tanzania National Bureau of Statistics (NBS) (URT, 2021). The NSCA employed a two-stage stratified sampling design based on Census Enumeration Areas and randomly selected agricultural households, ensuring full national coverage of smallholder sunflower farmers. The dataset provides household-level information on crop production, input use, and socioeconomic characteristics, enabling robust estimation of sunflower yield distributions under different input regimes.

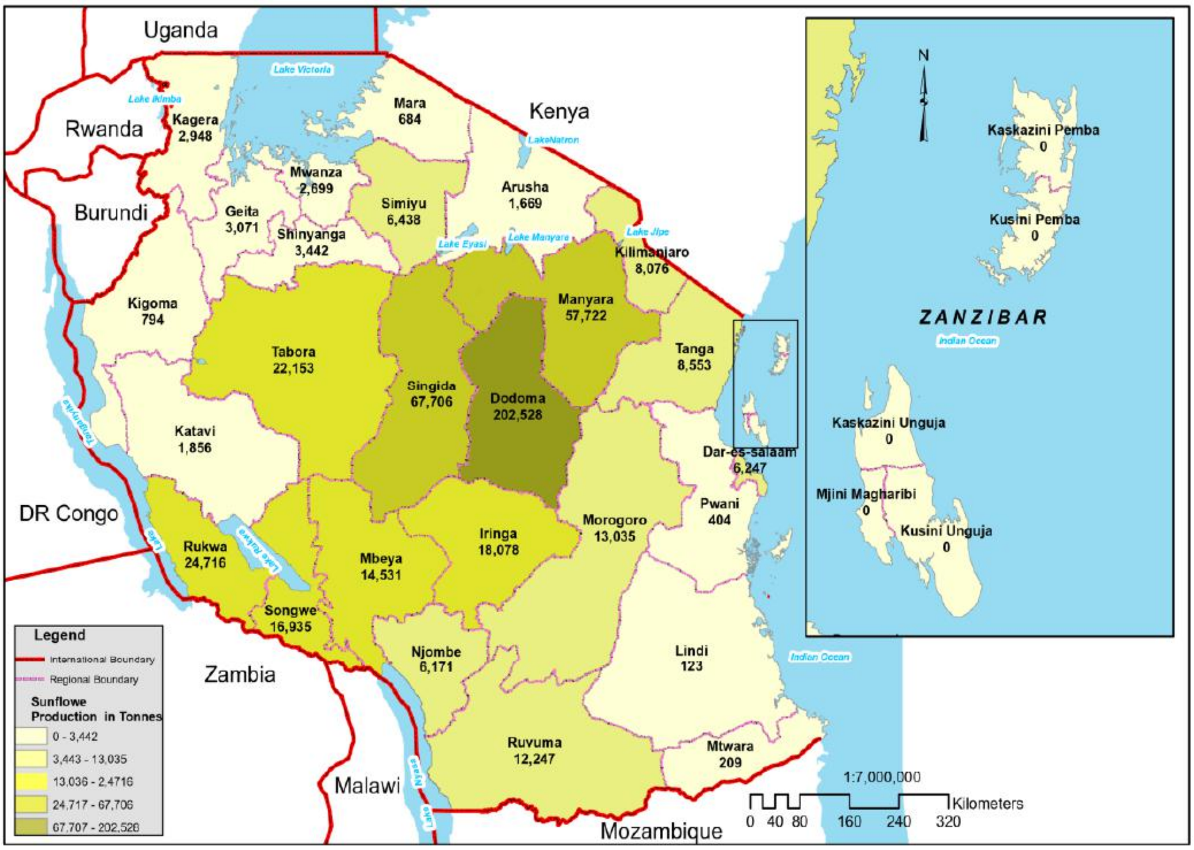


Fig.1: A Map showing the Production of Sunflowers in Tanzania by Region During the 2019/20 Agricultural Year (URT, 2021).

2.2 Farming-System Classification

To capture technological heterogeneity in sunflower production, farms were grouped into six farming systems defined by seed type (local vs. improved) and fertilizer practice (none, organic, or inorganic). Households were classified based on their reported input use during the 2019/20 production year in the nationally representative NSCA dataset. This typology reflects the principal technological gradients in Tanzanian sunflower farming and provides the basis for scenario analysis in the Monte Carlo simulations. Table 1 presents the updated distribution of observations across the six systems. Of the total 1,952 sunflower-growing households in the sample, System 1 (LS_F0), local seeds without fertilizer, dominates, accounting for 1,700 farms, or roughly 87 % of the national sample. This overwhelming share indicates that the majority of Tanzanian sunflower farmers still rely on traditional seed and minimal external inputs.

The second-largest group is System 4 (IMS_F0), improved seeds without fertilizer, with 113 households (about 6 % of the sample). Systems using local seeds with either organic or inorganic fertilizer, System 2 (LS_F1) and System 3 (LS_F2), represent about 3.6% and 2.5%, respectively. Improved seed systems that also integrate fertilizer are rare: System 5 (IMS_F1) and System 6 (IMS_F2) together comprise only 20 households, or roughly 1 % of the total. These proportions highlight two critical insights for policy and simulation design. Firstly, low input intensity, where nearly 90 % of farmers apply no fertilizer, underscores the need for improved access to both organic and inorganic nutrient sources if national yield targets are to be met. Secondly, the data reveal slow uptake of improved seed, where only about 7 % of farms use improved sunflower varieties (Systems 4–6), and an even smaller fraction combine improved seeds with fertilizer, systems often associated with the highest potential productivity.

This classification not only captures the technological diversity of Tanzanian sunflower production but also establishes the baseline scenario (System 1) against which the Monte Carlo simulations evaluate the potential productivity gains and risk profiles of the more input-intensive systems.

Table 1: Farming-System Classification by seed types and fertilizer use

System	Description	Code	Number of observations	Share of sample (%)
1	Local seeds, no fertilizer	LS_F0	1,700	87.1
2	Local seeds + organic fertilizer	LS_F1	70	3.6
3	Local seeds + inorganic fertilizer	LS_F2	49	2.5
4	Improved seeds, no fertilizer	IMS_F0	113	5.8
5	Improved + organic fertilizer	IMS_F1	9	0.5
6	Improved + inorganic fertilizer	IMS_F2	11	0.6

2.3 Data Cleaning and Variable Construction

After data cleaning, the following activities involved outlier detection, where extreme yield values (>3 SD from the regional mean) were winsorized to the 1st and 99th percentiles. Likewise, missing values or records with incomplete yield or input data were dropped (<5 % of observations). Also, yield standardization was conducted by expressing the sunflower grain yield in kilograms per hectare (kg ha^{-1}).

2.4 Monte Carlo Simulation Framework

A Stochastic Simulation Approach (SSA) grounded in non-parametric Monte Carlo techniques (Kadigi et al., 2020, 2025; Richardson et al., 2007, 2008) was used to model sunflower yield risk across the six defined farming systems. Monte Carlo simulation relies on repeated random sampling to represent systems affected by uncertainty, enabling the generation of empirical probability distributions and explicit measurement of production risk (Richardson et al., 2000). This approach is particularly appropriate for agricultural yields, which are shaped by stochastic weather, management, and market factors.

2.4.1 Stochastic Yield Specification

Observed NSCA 2019/20 sunflower yields were first expressed as deterministic yields, harvested tonnage per hectare, by farming system *i* and agro-ecological zone *ω* (Equation 1). Stochasticity was introduced by multiplying the deterministic mean ($\bar{y}_{c,i,\omega}$) by a random shock factor (ε), capturing unexplained variability (Equation 2). Equation 4 is the simplified stochastic yield expression using a multiplicative shock, indicating how the observed yield is adjusted for uncertainty using empirical distributions and simulation randomness.

Deterministic yield ($\bar{y}$)

$$yield\ (\bar{y}_{c,i,\omega}) = \frac{Tones\ harvested\ (tones)}{Hectares\ harvested\ (a)} \quad (1)$$

Stochastic yield ($\tilde{y}$)

$$\tilde{y}_{i,\omega} = \bar{y}_{c,i,\omega} * \varepsilon \quad (2)$$

$$\varepsilon = y_{i,\omega} - \bar{y}_{c,i,\omega} \quad (3)$$

$$\tilde{y}_{i,\omega} = \bar{y}_{c,i,\omega} * \left(1 + EMP\left(S_{y,i,\omega}, P\left(S_{y,i,\omega}\right), CUSD_{y,i,\omega}\right)\right) * \beta_{\tilde{y}_0} \quad (4)$$

Where:

~	=	A tilde represents a random (stochastic) variable.
i	=	Type of farming practices used (*System 1, System 2, ..., System 6*).
ω	=	Represents farms in six agro-ecological zones
a_i	=	Hectares (ha) allocated for farming practice *i*
y	=	Individual farm yield
$\tilde{y}_i$	=	Stochastic mean yield per ha for farming practice *i*
$\bar{y}_i$	=	Deterministic (mean) yield per ha for farming practice *i*
$\beta_{\tilde{y}_0}$	=	The normalization factor, which is given by $\frac{\tilde{y}_{c,i}}{\tilde{y}_{h,i}}$ and it is used to scale/adjust the 2019/20 NCSA mean yield.
$\tilde{y}_c$	=	Stochastic yield for the current survey (2019/20 NCSA)
$\tilde{y}_h$	=	Stochastic yield for the historical or previous survey (2007/08 NCSA) (URT, 2012)
S_y	=	Fraction deviations from the mean or sorted array of random yields for farming practice *i*

$P(S_y)$	=	Cumulative probability function for the S_y values
$CUSD_y$	=	Simetar function used to simulate the correlated uniform standard deviation of random variables.
$EMP()$	=	Simetar function used to simulate a stochastic variable (yield)

The simulation in Equation 4 for each farming setup employed the Latin Hypercube Sampling technique, as described by Richardson et al. (2007) and Kadigi et al. (2020, 2025). The Latin Hypercube Sampling method was chosen for its efficiency, as it ensures that a relatively small sample size (500 iterations) is sufficient to reproduce the characteristics of the parent yield distributions accurately. This approach generated a total of 3,000 simulated yields (500 iterations × 6 variables), providing a reasonable sample for comparative analysis. The larger simulated sample enhances the robustness of the analysis and facilitates a more precise evaluation of the impact of various farming practices on maize yields.

A crucial step in the process was validating the simulated yields against the historical observed yields. This was achieved using statistical tests and probability distribution functions (PDFs) to ensure close alignment between the two datasets. The validation confirmed that the stochastic model accurately captured the variability observed in the empirical data while maintaining the probabilistic characteristics introduced through Monte Carlo simulation. By matching the simulated distributions with actual historical data, the study ensured that the results are both representative and reliable for assessing the performance of various farming systems across Tanzania's agro-ecological zones. Validation outcomes are presented in the Results section.

For the six yield scenarios, covering multiple six farming systems and different production practices, the study applied an MVE distribution model as described by Richardson et al. (2000). The MVE approach is particularly advantageous in multi-variable contexts because it enables simultaneous modeling of several variables while preserving realistic outcomes, such as avoiding implausible negative yields.

Following validation, the new samples for each farming system were parameterized and simulated using the MVE model. The process involved computing residuals, defined as the percentage deviations of yields from their mean values, to derive the correlation matrix. This matrix was then applied to transform independent standard normal deviates (ISNDs) into correlated standard normal deviates (CSNDs). These CSNDs were subsequently inversely transformed into correlated uniform standard deviates (CUSDs), which were used to stochastically draw empirically ranked fractional deviates that supply the random (stochastic) component for generating simulated values. The Simetar software's built-in =*CUSD( )* function was used to simulate the correlated uniform standard deviations of the random variables.

The MVE framework effectively captured the inherent variability in yield records and reflected the probabilistic nature of maize productivity under diverse farming systems. Ultimately, this method enabled the generation of realistic, spatially explicit yield simulations that accounted for both environmental variability and management-related uncertainties. The final form of the MVE model is expressed in Equation 2.

2.4.2 MVE Validation

Model outputs were validated against historical and current NSCA observations using probability distribution functions and goodness-of-fit tests. Close agreement between simulated and empirical yield distributions confirmed that the SSA faithfully captured the variability and probabilistic behavior of sunflower productivity across Tanzania's agro-ecological zones. By combining Latin Hypercube sampling, MVE correlation structure, and rigorous validation, this Monte Carlo framework provides a robust basis for quantifying yield distributions and production risk within each farming system, forming the foundation for the study's policy-relevant analysis of sunflower productivity.

2.5 Impact Evaluation of Sunflower Yield Gaps Using PDFs and the Stoplight Function

In this analysis, Probability Density Functions (PDFs) and the Stoplight Chart were used to evaluate the yield performance of sunflower farming practices. The two approaches together provide a robust framework for assessing the entire yield distribution of each of the six sunflower farming practices. PDFs are employed to depict and compare the empirical yield distributions across all systems, enabling direct visual and statistical comparisons of spread, skewness, and central tendency. In particular, the baseline system (System 1: local seeds with no fertilizer) is contrasted against each of the other five systems (Systems 2–6) to quantify how improved seed use and fertilizer application shift the yield distribution and alter the likelihood of meeting national productivity targets.

The Stoplight Chart function was used to rank the probabilities of sunflower farms achieving the maximum yield thresholds and the probabilities of falling below the minimum values per unit area (hectares in this study). The stoplight function calculates the probabilities of (a) exceeding the upper target (green), (b) falling below the lower target (red), and (c) remaining between the two targets (yellow). The minimum and maximum yield thresholds were informed by literature and stakeholder consultations. The current National Sample Census of Agriculture (NSCA; URT, 2021) indicates that average sunflower yields in Tanzania range between 0.7 and 1.0 t ha⁻¹. Consequently, the lower target was set at 1.0 t ha⁻¹, representing the threshold for minimally acceptable productivity. The upper target was fixed at 2.0 t ha⁻¹, a level aligned with attainable yield potential and national strategic initiatives such as the Agricultural Sector Development Program II (ASDP-II; URT, 2016) and the Tanzania Seed Sector Development Strategy 2030 (Minde et al., 2024), both of which aim to double the productivity of major oil crops, including sunflower, by 2030.

By combining PDFs with the Stoplight function, the analysis identifies, for each farming system, the probabilities of yields falling below the lower target (unfavorable, red), between the lower and upper targets (cautionary, yellow), or exceeding the upper target (favorable, green) (Figure 2). These metrics provide a clear, visual summary of risk and opportunity, helping policymakers and practitioners gauge how seed–fertilizer technologies alter the likelihood of achieving national productivity goals.

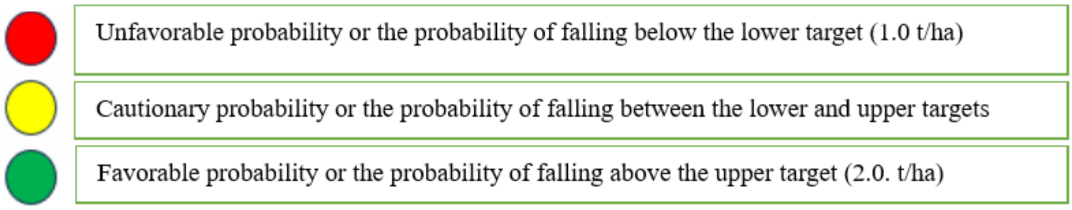


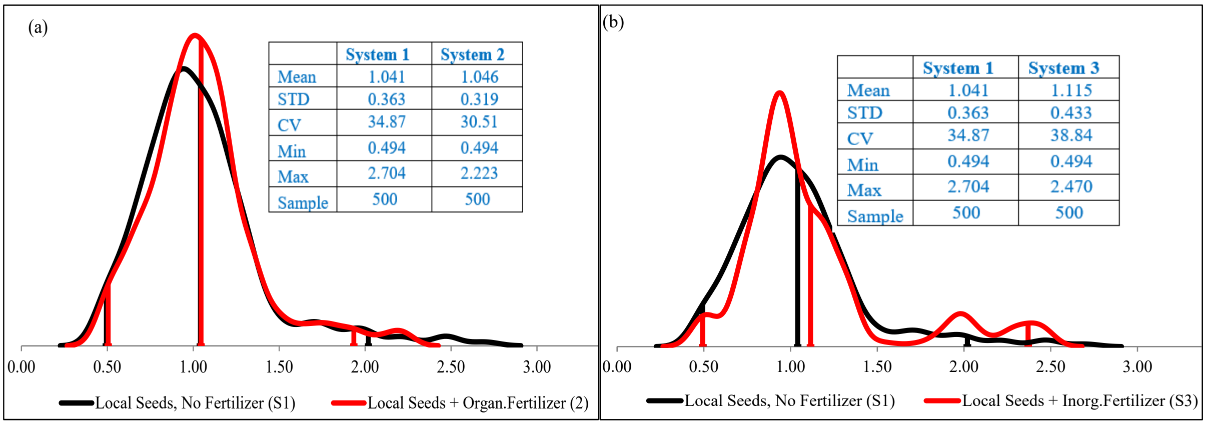
Fig.2: Stoplight chart for ranking of target probabilities

III. RESULTS

3.1 Sunflower Yield Estimation Using PDFs

Figure 3 compares the probability density functions (PDFs) of sunflower yields from the baseline System 1 (local seeds, no fertilizer) with four alternative input systems. Panel (a) contrasts System 1 with System 2 (local seeds + organic fertilizer). Their mean yields are virtually identical, 1.041 t ha⁻¹ for System 1 and 1.046 t ha⁻¹ for System 2, indicating that organic fertilizer, when used with local seeds, does not substantially raise average yields. However, System 2 displays a slightly lower standard deviation (0.319 vs. 0.363) and coefficient of variation (CV), suggesting a modest reduction in yield variability and slightly tighter clustering around the mean. Panel (b) compares System 1 with System 3 (local seeds + inorganic fertilizer). System 3 shows a higher mean yield (1.115 t ha⁻¹) and greater variability (standard deviation 0.433) than the baseline. The PDF curve for System 3 shifts rightward, illustrating a larger proportion of farms achieving yields above 1.0 t ha⁻¹. The slightly higher CV (38.84%) reflects the increased spread of outcomes associated with inorganic fertilizer use.

Panel (c) evaluates System 1 against System 4 (improved seeds, no fertilizer). System 4 records a mean of 1.066 t ha⁻¹, slightly higher than the baseline, with a similar CV (≈35%). The rightward shift of System 4's distribution is modest but evident, indicating that improved seeds alone confer a small productivity advantage while maintaining a comparable level of variability. Panel (d) contrasts System 1 with System 5 (improved seeds + organic fertilizer). System 5 yields a lower mean (0.980 t ha⁻¹) and slightly higher CV (38.06%), suggesting that combining improved seeds with only organic fertilizer provides no yield benefit and introduces marginally greater variability. Its PDF curve is slightly left-shifted relative to System 1, underscoring this decline.



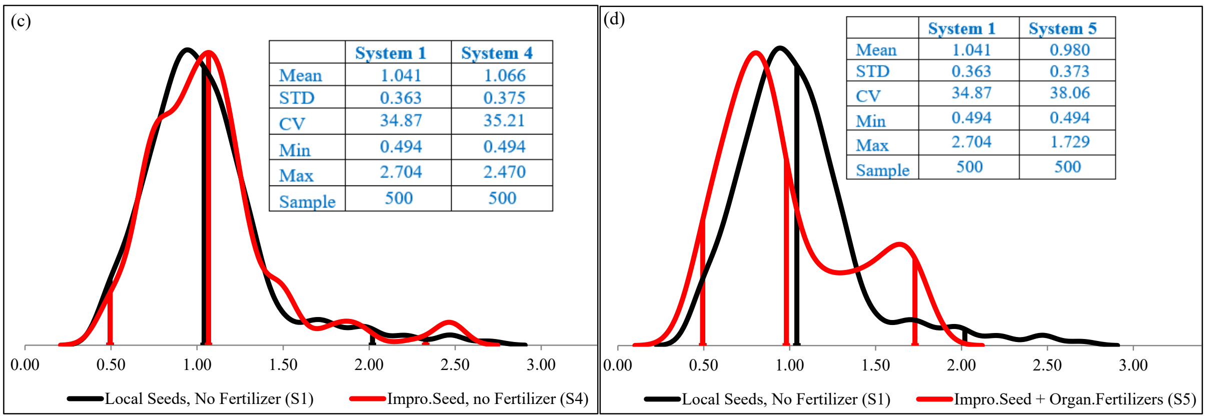


Fig.3: PDF charts showing the comparison of sunflower farms under different seed and fertilizer applications: System 1 (farms using local seeds, no fertilizer vs. System 2 (farms using local seeds with organic fertilizer), System 3 (farms using local seeds with inorganic fertilizer), System 4 (farms using improved seeds, no fertilizer) and System 5 (farms using improved seeds and organic fertilizers).

Figure 4 extends the comparison to System 6 (improved seeds + inorganic fertilizer). System 6 achieves the highest mean yield (1.138 t ha^{-1}) among all systems and displays the greatest spread, with a standard deviation of 0.548 and a CV of 48.13%. The PDF curve is noticeably right-shifted, revealing a higher probability of yields exceeding 1.5 t ha^{-1} and a distinct secondary peak near 2.0 t ha^{-1}. These results highlight the strong yield-enhancing potential of combining improved seed with inorganic fertilizer, albeit with increased yield variability. Across all panels, the baseline System 1 consistently centers near 1.04 t ha^{-1} with moderate variability. Incremental yield gains appear when either improved seed or inorganic fertilizer is used individually, while the greatest productivity occurs when the two are combined (System 6). Organic fertilizer alone (System 2) provides negligible improvement and, when combined with improved seed (System 5), may slightly depress yields. The wider distributions observed in Systems 3 and 6 point to higher production risk but also greater upside potential. Overall, the PDFs indicate that inorganic fertilizer, especially when paired with improved seed, is the primary driver of higher national sunflower yields, offering the clearest pathway to meet Tanzania's 2 t ha^{-1} target despite its larger yield variance.

3.2 Sunflower Yield Estimation Using Stoplight Charts

Figure 5 summarizes the Stoplight analysis of sunflower yield probabilities across the six farming systems. The stacked bars show the likelihood that farm productivity (i) falls below 1.0 t ha^{-1} (red, unfavorable), (ii) lies between 1.0 and 2.0 t ha^{-1} (yellow, cautionary), or (iii) exceeds 2.0 t ha^{-1} (green, favorable). These thresholds represent the minimum acceptable yield and the aspirational national target, respectively. Local seed systems (LS_F0, LS_F1, LS_F2) reveal broadly similar risk profiles. Farms using local seed with no fertilizer (LS_F0) show a 54% probability of yields below 1.0 t ha^{-1}, 44% between 1.0 and 2.0 t ha^{-1}, and only 3% above 2.0 t ha^{-1}. Adding organic fertilizer (LS_F1) reduces the low-yield probability slightly to 49% and raises the mid-range probability to 49%, but the chance of surpassing 2.0 t ha^{-1} slips to 2 %. In contrast, inorganic fertilizer with local seed (LS_F2) increases the probability of reaching the upper target to 7%, the highest among local-seed systems, though 55% of farms still risk yields under 1.0 t ha^{-1}.

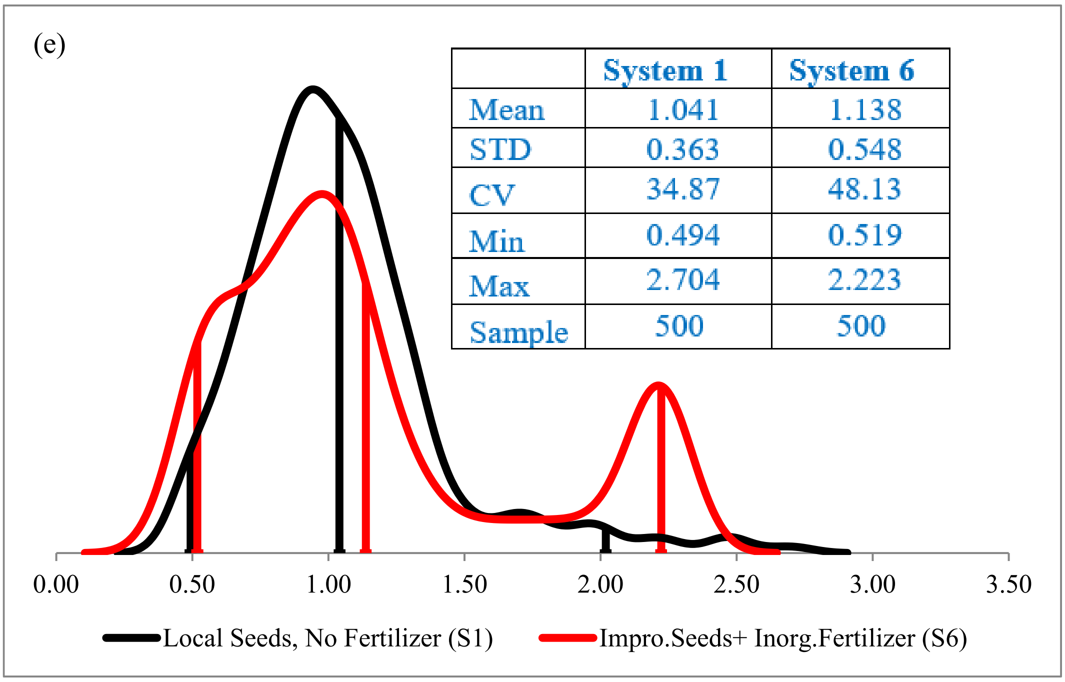


Fig.4: PDF charts showing the comparison of sunflower farms under different seed and fertilizer applications: System 1 (farms using local seeds, no fertilizer vs. System 6 (farms using improved seeds and inorganic fertilizers).

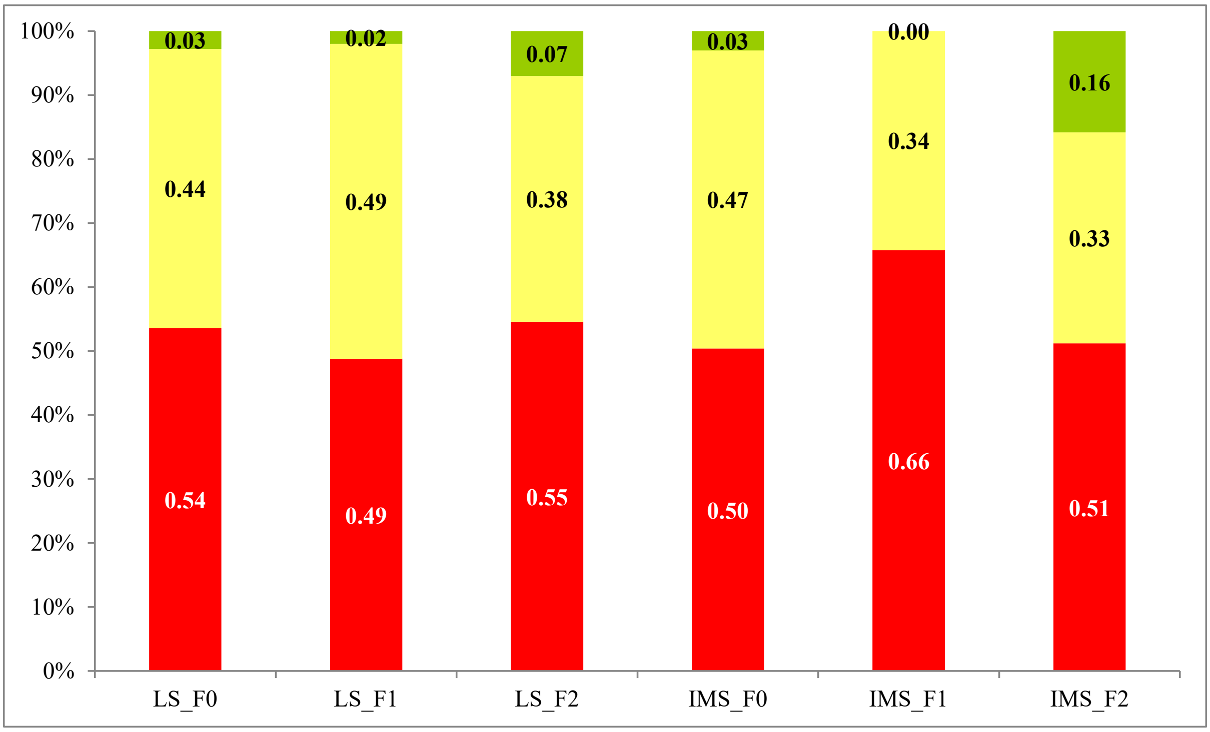


Fig.5: Probabilities of sunflower farm's productivity being greater than 2.0 t/ha (Green), less than the lower cut-off value of 1.0 t/ha (Red), and the probabilities of falling between 1.0 and 3.0 t/ha for farmers farming local seeds with no fertilizer (LS_F0), vs. those using local seeds with organic fertilizer (LS_F1), farms using local seeds with inorganic fertilizer (LS_F2), farms using improved seeds with no fertilizer (IMP_F0), farms using improved seeds with organic fertilizer (IMP_F1), and farms using improved seeds with inorganic fertilizer (IMS_F2).

Among the improved seed systems, results diverge sharply. Improved seed with no fertilizer (IMS_F0) exhibits a 50% probability of yields below 1.0 t ha^{-1} and 47% in the mid-range, with a modest 3% chance of exceeding 2.0 t ha^{-1}, slightly better than the local-seed baseline. Surprisingly, improved seed combined with organic fertilizer (IMS_F1) performs worst overall: two-thirds (66 %) of farms fall below 1.0 t ha⁻¹, and none surpass 2.0 t ha⁻¹, indicating that organic fertilizer offers no productivity advantage when paired with improved seed and may even depress yields. The most striking gains appear in System 6 (IMS_F2), where improved seed is coupled with inorganic fertilizer. Here, the probability of surpassing 2.0 t ha⁻¹ leaps to 16 %, while the share below 1.0 t ha⁻¹ drops to 51 %, and one-third of farms (33 %) achieve yields in the 1.0–2.0 t ha⁻¹ range. This system clearly provides the highest likelihood of reaching or exceeding Tanzania's national yield target.

Overall, the Stoplight results highlight three key insights. First, most sunflower farms, regardless of system, still face a ≥50 % chance of sub-1.0 t ha⁻¹ yields, underscoring persistent production risk. Second, inorganic fertilizer is the decisive input: it is the only practice, whether with local or improved seed, that consistently raises the probability of meeting or exceeding the 2.0 t ha⁻¹ benchmark. Third, combining improved seed with inorganic fertilizer (IMS_F2) delivers the strongest pathway toward national productivity goals, while pairing improved seed with organic fertilizer offers no measurable benefit and may hinder performance.

IV. DISCUSSION

4.1 Sunflower productivity

The PDF and Stoplight results indicate that sunflower productivity in Tanzania remains heavily constrained under low-input systems. Baseline farms using local seed without fertilizer (LS_F0) show a high probability (>50%) of falling below the lower threshold of 1.0 t ha⁻¹. This aligns with other studies in semi-arid regions of Tanzania, which find that nutrient limitation, particularly nitrogen deficiency, is one of the major yield-reducing factors (Vilvert et al., 2023). The predominance of low-yield outcomes in LS_F0 underscores how yield ceilings in current smallholder practice are shaped by minimal input use and perhaps suboptimal seed genetics.

Systems incorporating inorganic fertilizer (LS_F2, IMS_F2) or improved seed (IMS_F0) show marked increases in mean yield and in the probability of exceeding 2.0 t ha⁻¹, although at the cost of increased variability. This trade-off between yield gains and yield risk is well documented. For example, the study by Vilvert et al. (2023) on nitrogen management in Dodoma shows that manure (as organic fertilizer) can improve yields significantly, but beyond certain rates, water stress becomes limiting (Vilvert et al., 2023). Similarly, in Kenya, intercropping sunflowers with legumes plus fertilizer resulted in good yields and economic returns, while also affecting variation (Chappa et al., 2023). These findings mirror your System 6 results, where improved seed + inorganic fertilizer offered the strongest pathway to higher yields, but with greater spread.

Interestingly, improved seed + organic fertilizer (System 5) underperformed relative to expectations: its yield distribution is slightly left shifted compared to some local-seed + fertilizer systems, and its probability of achieving upper targets is essentially zero. This suggests that organic fertilizer alone may be insufficient to realize the benefits of improved germplasm under the agro-ecological and seasonal constraints in Tanzania. Comparable findings emerge in studies assessing organic vs. inorganic fertilizer regimes: organic inputs improve soil health but generally require higher application rates or combination with inorganic fertilizers to match yield potential (see "Assessment of Nitrogen Management on Sunflower Yield and Its Economic Response in Smallholder Farms in a Semi-Arid Region" (Vilvert et al., 2023); also in integrated fertilizer studies in other countries).

The stark contrast between Systems 2 and 3 (local seed with organic vs. inorganic fertilizer) further reinforces that inorganic fertilizer induces larger shifts in yield distribution. In many African smallholder settings, local-seed + inorganic fertilizer yields outperform those with organic fertilizer alone, particularly under constraints of timely nutrient availability and water availability (e.g., studies from sub-Saharan African sunflower farms; Nutrient Use Efficiency literature). From a risk perspective, while the highest mean yields are observed with System 6, the coefficient of variation (CV) is notably greater (>48%), indicating more inconsistency among farms. Farmers with constrained capital may find such variability risky. This is consistent with literature on yield stability: genetic diversity and stable input supply reduce year-to-year risk (Casadebaig et al., computational sunflower plasticity studies). Variance stabilization is often achieved through improved seed varieties designed for stress resilience, improved water management, or mixed fertilizer strategies (organic + inorganic) rather than reliance on one input alone.

4.2 Policy Insights

These results align with a broad body of literature: yield gains in sunflowers are maximized when improved seed is paired with inorganic fertilizers, though with increased risk. Organic fertilizers alone or improved seed without sufficient nutrients do little to shift the probability of reaching national yield goals. Policy should thus focus on enabling combinations of inputs, reducing risk through extension and finance, and tailoring interventions by agro-ecological zones to sustainably raise productivity in sunflower systems. The following is the list of policy recommendations that are highlighted by this study:

Targeted input subsidies or financing: To shift many farms from LS_F0 toward higher performing systems (particularly System 6), subsidizing or improving access to inorganic fertilizer and improved seed is likely cost-beneficial. Studies (e.g., Vilvert et al., 2023) show substantial returns when fertilizer rates are optimized even in semi-arid soils, especially in the central corridor regions of Tanzania.

Integrated soil fertility management: While organic fertilizers alone (System 2, System 5) do not significantly boost yields to target thresholds, they contribute to soil health and may buffer against risk in marginal lands. Mixing organic amendments with inorganic fertilizer (hybrid strategies) is supported in multiple contexts (SSA studies, Kenya intercropping work) as a way to balance long-term soil fertility and yield gains.

Seed variety development and deployment: Improved seed under no fertilizer (IMS_F0) gives modest gains, but its full potential is unlocked only with adequate nutrient supply (System 6). Investment in improved, stress-tolerant varieties that respond well to both organic and inorganic nutrients would help reduce yield variability (as noted in the meta-analysis of fertilization and planting strategies in China; the genetic plasticity literature).

Risk management and extension services: Given the higher variability of yield in systems using inorganic fertilizer (especially System 6), farmers require better extension, weather forecasting, access to insurance, or contract schemes to manage downside risk. Literature on yield stability emphasizes that input consistency, agronomic best practices, and support services are crucial (Drivers of adoption studies; yield gap studies).

Scaling efforts and local adaptation: Spatial heterogeneity in agro-ecological zones implies that what works in high-potential zones may perform less well in marginal zones. Models such as GGCMI (Global Gridded Crop Model Intercomparison) suggest that management and genotype–environment interactions crucially affect yield outcomes at scale (Müller et al., 2019).

4.3 Limitations and suggestions for further research

Although this study provides the first nationally representative stochastic assessment of sunflower productivity in Tanzania, several limitations warrant attention. First, the relatively small sample sizes in Systems 5 and 6, improved seeds with organic or inorganic fertilizer, may limit the precision of yield estimates and the robustness of extreme-probability calculations. These two systems represent a very small fraction of Tanzanian sunflower farmers, so their yield distributions are more vulnerable to sampling error and outlier influence. Additional field trials or targeted surveys in underrepresented systems would strengthen inference and help validate the simulation results. Second, the analysis focuses solely on yield outcomes. While yield is a critical determinant of agricultural performance, it does not capture profitability or risk from fluctuating input and output prices, labor costs, or market access. Integrating detailed cost–benefit data and modeling input price volatility would provide a more comprehensive economic feasibility picture and allow assessment of gross margins or net returns. Similarly, the study does not explicitly incorporate other key production risks such as water availability, soil fertility gradients, or pest and disease pressures, all of which can strongly influence both mean yield and variability.

Third, the analysis uses a single-year, cross-sectional dataset, limiting the ability to account for inter-annual variability due to climate fluctuations or management changes. Future work could employ longitudinal or panel data to capture year-to-year yield responses and to simulate the effects of climate change using crop-growth models. Finally, while this research analyzed the entire country as a single domain, management practices and input responses often vary across Tanzania's distinct agro-ecological zones (AEZs). Fertilizer–seed combinations that perform well nationally may be more or less effective in specific regions due to differences in rainfall patterns, soil types, and market infrastructure. Follow-up studies focusing on individual regions or AEZs would reveal whether the most productive input packages at the national scale are equally advantageous in areas such as the Central Corridor, Southern Highlands, or Lake Zone. Disaggregating the analysis in this way would help policymakers design region-specific interventions and avoid one-size-fits-all recommendations.

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