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COMPARATIVE ANALYSIS OF GENETIC ALGORITHM AND MEMETIC ALGORITHM FOR RESOURCE OPTIMIZATION AND CORN YIELD MAXIMIZATION

Henry Louis U. Tamon, Emmanuel M. Fillone, Kyrt Vincent Reyes,
Earl James T. Torrendon, Dr. Joel B. Garcera

University of San Agustin, Iloilo City, Philippines

ABSTRACT

Efficient resource management is a critical factor in modern agriculture, particularly in corn production, where maximizing yield while minimizing operational costs directly affects farm profitability and sustainability. This study investigated the effectiveness of two evolutionary optimization techniques, the Genetic Algorithm (GA) and the Memetic Algorithm (MA), in determining optimal planting density and fertilization strategies for corn cultivation. The research utilized expert-validated mathematical models representing crop yield and production cost as objective functions. Both algorithms were evaluated through nine optimization cases, with each case executed over thirty independent runs to ensure consistency, reliability, and statistical validity of the results The findings revealed that both the Genetic Algorithm and the Memetic Algorithm were capable of generating high-quality solutions that improved resource allocation and production efficiency. However, the Memetic Algorithm consistently demonstrated superior convergence behavior and solution refinement due to the integration of a local search mechanism, which enhanced its ability to explore and exploit the solution space more effectively. This resulted in faster convergence toward optimal or near-optimal solutions and greater stability across multiple runs compared to the traditional Genetic Algorithm. Despite these promising results, the study was limited by its reliance on simulated data and controlled optimization scenarios. Important real-world factors such as changing weather conditions, soil variability, pest incidence, and other environmental influences were not incorporated into the optimization models. Nevertheless, the research provides strong evidence that Memetic Algorithms offer a more effective approach for optimizing agricultural inputs than conventional optimization methods, particularly in complex decision-making environments involving multiple variables and constraints. Completed in May 2026 during Academic Year 2025–2026, this study establishes a robust foundation for the development of a data-driven agricultural decision-support framework for corn production in Iloilo. The findings contribute to the growing body of knowledge on computational intelligence applications in agriculture and highlight the need for future empirical field validation studies to evaluate algorithm performance under actual farming conditions and account for real-world variability. Such future investigations may further enhance the practical applicability and adoption of intelligent optimization systems in sustainable agricultural management.

Keywords: *Corn Yield Maximization, Decision Support System, Genetic Algorithm, Iloilo Province, Local Search, Memetic Algorithm, Meta-heuristic Algorithms, Nutrient Management, Resource Optimization*

INTRODUCTION

Corn is the second most important crop in the Philippines and plays a significant role in food security, livestock production, and rural livelihoods. It serves as a staple food for approximately 14 million Filipinos, contributes substantially to the livestock feed industry, and provides economic opportunities for around 600,000 farming households and other stakeholders involved in the agricultural value chain (Department of Agriculture MIMAROPA Region, 2024). In some agricultural areas of Iloilo Province, corn production is a substantial source of income for many small-scale farmers in which they value the quality and quantity of their yield for a better livelihood.

The corn industry remains an important agricultural subsector in Western Visayas, contributing to regional food production, livestock feed requirements, and the livelihood of farming communities through various government support programs and interventions (Department of Agriculture–Western Visayas, 2022). There was a 1.98% decline in corn production in Western Visayas, contributing to a substantial 61% sufficiency deficit in yellow corn production. This challenge is reflective of broader issues faced by smallholder corn farmers, with many experiencing production constraints that affect agricultural productivity and household livelihoods (Department of Agriculture–Western Visayas, 2022; Villaver et al., 2021). According to the Philippine Statistics Authority (2024), recurring declines in corn production continue to contribute to supply shortages in the country. This situation is particularly critical for yellow corn, which serves as a major component of livestock feed and has become a growing concern for the livestock and poultry sectors (Philippine Statistics Authority, 2024; Philippine News Agency, 2024). These production challenges are exacerbated by smallholder farmers' limited financial capacity, inadequate access to credit facilities and modern agricultural technologies, and difficulties in making data-driven decisions regarding farm inputs and resource allocation (Agricultural Credit Policy Council, n.d.; Mayo & Villarta, 2023). Such constraints hinder the adoption of improved farming practices and ultimately affect farm productivity and sustainability.

To address these challenges, there is a pressing need to improve farmers' access to quality seeds, fertilizers, and intelligent decision-support systems that can optimize the allocation of limited agricultural resources. Advances in precision agriculture and machine learning have demonstrated significant potential in enhancing farm productivity and resource efficiency through data-driven decision-making. However, many existing crop optimization models are developed within broader contexts and often fail to account for the unique microclimatic conditions, soil characteristics, and socioeconomic realities of specific localities such as Iloilo, thereby limiting their applicability and effectiveness in supporting smallholder farmers (Tlemsani et al., 2023). Developing localized computational tools presents both an urgent challenge and an opportunity to enhance productivity, sustainability, and resilience among small-scale corn farmers.

For small-scale farmers operating with limited budgets and resources, such optimization tools can be instrumental in determining the ideal mix of inputs. This enables them to achieve a critical balance between cost-efficiency and maximizing expected corn yield, thereby supporting more informed and sustainable decision-making in local farm management. This study will conduct a comparative analysis of a Genetic Algorithm (GA) and a Memetic Algorithm (MA) to determine which is more effective at recommending optimal combinations of fertilizer and seed inputs for corn farmers in Iloilo Province. The research will evaluate the algorithms based on their ability to meet specific performance metrics, including the effectiveness of their recommendations and their efficiency in adhering to farmers' budget and land constraints.

Research Objectives

The study performed a comparative analysis of a Genetic Algorithm and a Memetic Algorithm to determine which approach is more effective at optimizing corn yield and improving resource efficiency based on established performance metrics.

Specifically, this research aimed to:

1. Develop two algorithms, a Genetic Algorithm (GA) and a Memetic Algorithm (MA) and its models for comparative analysis.
2. Evaluate and compare the GA and MA based on solution quality relative to Department of Agriculture (DA) practices, computational performance, and algorithm efficiency in optimizing corn resource inputs.
3. Design and develop a website prototype that translates algorithm data into simple, actionable strategies for corn farmers.
4. Conduct user testing and evaluate the website prototype using the Post-Study System Usability Questionnaire (PSSUQ).

METHODOLOGY

Research Design and Methods

The development of the corn yield optimization system adhered to a defined software development lifecycle to ensure methodological rigor, adaptability, and consistent performance improvements. The researcher utilized the Iterative Waterfall Model to guide the system’s development.

Software Development Life Cycle

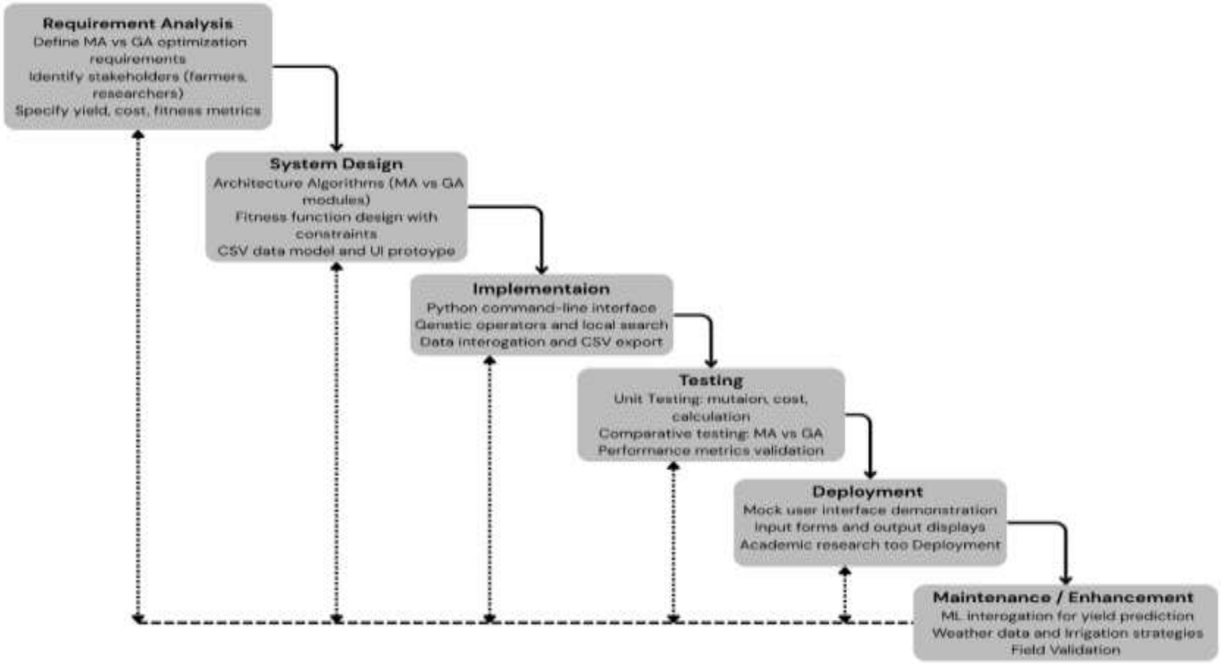


Figure 1. Iterative Waterfall Model

The Iterative Waterfall Model served as the structural foundation for this research, enhancing the traditional linear approach by enabling continuous refinement through backward feedback loops. The cycle commenced with Requirement Analysis and Planning, where the researchers identified the operational constraints of Iloilo farmers and established critical biological variables, such as NPK levels and soil pH, to target yield maximization. This transitioned into System Design and Architecture, defining a mobile-first ecosystem utilizing a Python backend for computational logic and Streamlit for the user interface. During Implementation and Development, the mathematical frameworks of the Genetic and Memetic Algorithms were coded, incorporating specialized Partial Lamarckism for enhanced local search. The Testing and Quality Assurance phase followed, involving 540 experimental runs to verify convergence and ensure recommendations remained within safe agronomic limits. The project then reached Deployment via Streamlit Cloud, providing a zero-installation web interface for immediate accessibility. Finally, the process concluded with Evaluation and Validation, where the system's usability was measured by 15 farmers using PSSUQ surveys and its scientific logic was formally vetted by Department of Agriculture (DA) experts, ensuring the prototype was both technically sound and practically impactful, allowing continuous improvement of the system. Each cycle acted as a "mini-waterfall" that ensured each iteration contributed to a more refined and optimized version of the software.

This study employed a comparative experimental design, which was a quantitative research method used to systematically compare the effectiveness of two or more approaches under controlled conditions. This design allowed the researcher to isolate the effect of the algorithms while keeping other variables like operational costs constant. The study ensured reliable and repeatable comparisons by running multiple simulations and collecting metrics like efficiency, reliability, and quality of solution (Audet et al., 2021).The controlled environment and structured evaluation made this design appropriate for testing algorithmic improvements and understanding their impact on agricultural optimization. This type of design was effective for identifying which method yielded better outcomes through direct comparison (Creswell & Creswell, 2022).

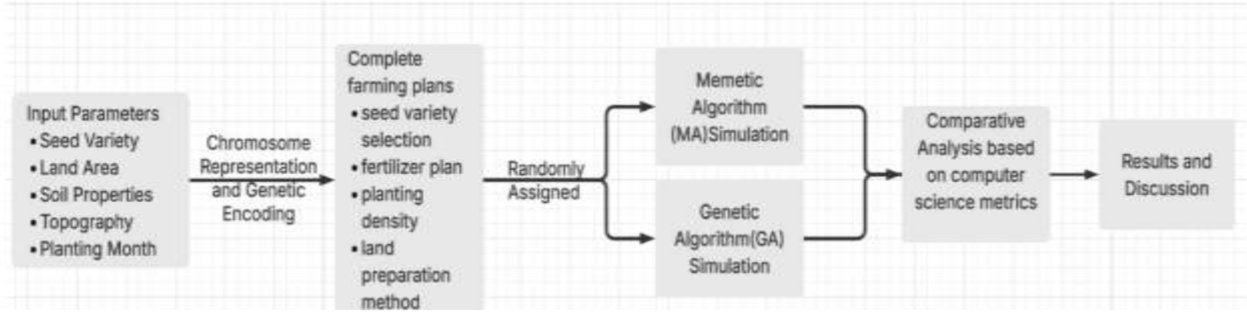


Figure 2. Experimental Diagram

Two distinct evolutionary algorithms were developed for comparative analysis: a Genetic Algorithm (GA) and a Memetic Algorithm (MA). Both algorithms shared the same core genetic representation and problem formulation but differed in their optimization strategies, allowing for a direct comparison of their effectiveness in agricultural optimization scenarios.

Core Models Implementation

The research utilized the Department of Agriculture (DA) validated penalty-based models to evaluate the solutions found by the two algorithms. This environment functioned as a decision-support framework that replicated the logic traditionally employed by agricultural extension workers and researchers. By digitizing these expert processes, the simulation provided a controlled "sandbox" where evolutionary strategies could be tested against the non-linear variables of agricultural production.

This environment was implemented upon three models: yield, cost, and fitness. The logic, parameters, and coefficients used in these models were reviewed and validated by a senior researcher from the Department of Agriculture (DA)—Regional Field Office VI (Iloilo).

Yield Model

This model estimated final yield production through a multiplicative interaction of genetic potential and environmental limiting factors. The model was defined by the following equations starting with the final yield formula:

$$\hat{Y} = Y_{base} \times NF \times DF \times SF_{soil} \times SF_{pest} \times SF_{seasonal} \times LF \times Area$$

Figure 3. Final Yield Formula

Where Ybase represents the variety-specific yield potential. NF represents the Nutrient Factor, DF stands for Density Factor, SFsoil refers to the soil and pH factor, SFpest indicates the pest factor, SFseasonal pertains to the planting month, and LF represents topography as well as the land area measured in hectares. This base potential was adjusted by factor coefficients ranging from 0.5 to 1.0, reflecting the impact of nutrient sufficiency, planting density, and site-specific conditions.

Nutrient Factor

The Nutrient Factor (NF) was modeled using an Asymmetric Multiplicative Law of the Minimum. This implementation integrated Liebig's Law of the Minimum with the Mitscherlich-Bray law of diminishing returns, establishing that while the most deficient nutrient limited overall growth, the marginal benefit of additional units decreased as the plant approached satiety. This "smooth curve" allowed the algorithms to identify the precise economic threshold where additional fertilization became a financial waste (Coggins et al., 2025). Furthermore, the model incorporated a toxicity zone for nutrient application, reflecting research indicating that excessive application resulted in a non-asymptotic, negative yield response rather than a simple plateau (Uppugunduri, 2022).

Table 1.
Asymmetric Nutrient Curve Penalties

NPK	Formula	Factor Value	Interpretation
<85%	(x / 85)0.5 * 0.5	0.0 - 0.5	Deficiency: rejected/severe penalty
85%	(x / 100)0.5	0.92	Minimum acceptable threshold
90%	(x / 100)0.5	0.95	Approaching optimal
100%	1.0	1.0	Perfect nutrient balance
105%	1.0 - (x - 100) / 15	0.67	Slight excess (33% yield loss)
110%	1.0 - (x - 100) /15	0.33	Moderate excess (67% yield loss)
>115%	-999999	0.0	Over-application: rejected

$$NF = NF_N \times NF_P \times NF_K$$

Figure 4. Nutrient Factor Formula

Density-Nutrient Synergy

Another feature of the model was the Density-Nutrient Synergy, where nutrient requirements were dynamically scaled based on the planting population. Nitrogen acted as a biological buffer, allowing higher planting densities to thrive by mitigating the competition for resources between individual plants [35]. The model utilized Department of Agriculture (DA) validated nutrients for corn production, which established a nutrient requirement of 134 kg of Nitrogen (N), 41 kg of Phosphorus (P), and 102 kg of Potassium (K) per hectare for optimal yield. These requirements were scaled synergistically:

$$N_{req} = 134 \times \frac{\text{density}}{\text{density}_{opt}}$$
$$P_{req} = 41 \times \frac{\text{density}}{\text{density}_{opt}}$$
$$K_{req} = 102 \times \frac{\text{density}}{\text{density}_{opt}}$$

Figure 5. Nutrient-Density Synergy

If a nutrient is deficient relative to this dynamic requirement, the synergy breaks down, and the plant fails to thrive regardless of the abundance of other inputs.

Density Factor

To facilitate efficient algorithmic convergence, the Density Factor (DF) was implemented using a Gaussian Optimization Function. Unlike rigid clipping or "if-else" constraints, the Gaussian curve provided a continuous gradient that functioned similarly to a Gaussian process minimization; it mapped density values to a fitness score that indicated how well the configuration fitted the variety's ideal requirements (Asset Health Center, 2021).This approach provided the Genetic and Memetic algorithms with a smooth search landscape, where they could sense gradual improvements as they moved toward the optimal peak. This ensured that variety-specific spacing was encouraged without the computational "cliffs" that often hindered evolutionary search.

$$DF = 1.0 \times \exp\left(-\frac{d^2}{2\sigma^2}\right),\ d = \frac{\text{density} - \text{density}_{opt}}{\text{density}_{opt}},\ \sigma = 0.15$$

Figure 6. Gaussian Function

Other Factors

The model incorporated fixed environmental multipliers to reduce yield based on the farm's physical and seasonal context. This prevented the algorithms from over-optimizing without considering real-world constraints.

Table 2.
Environmental Factors

Factor	Category	Multiplier	Rationale
Soil Texture	Loamy	1.00	Ideal drainage and nutrient retention.
	Clay	0.90	Potential for waterlogging/compaction.
	Sandy	0.85	High nutrient leaching and low moisture.
Soil pH	6.0 – 7.0	1.00	Optimal nutrient bioavailability.
	Deviation	-0.15	Penalty per full unit outside optimal range.
Pest	Dry Season	0.95	Lower biological stress.
	Wet Season	0.85	Increased pest/disease prevalence.
Seasonal Moisture	Irrigation	0.95	Stable moisture availability.
	No Irrigation	0.85	High risk of mid season stress
	Rain	1.0	High environmental stress/unpredictability.
Land Prep	Plain	1.0	Efficient tillage and moisture retention.
	Elevated	0.90	High runoff and operational difficulty.

The accuracy and practical relevance of these parameters were reinforced by a rigorous external review. Every baseline value, NPK requirement, and optimal planting density was formally validated by a Senior Researcher from the Department of Agriculture - Regional Field Office VI Iloilo. This verification ensured that the simulation's benchmarks and environmental penalties aligned with the latest Department of Agriculture (DA) Iloilo recommendations for local corn farmers.

Cost Model

To ensure economically viable strategies, a cost model was developed using fixed input values aligned with regional benchmarks. The approach focuses on the main variable expenses that are essential to optimization like seeds, fertilizer, and operational costs but it does not cover all overhead. This targeted approach ensures every incremental increase in plant population or nutrient input is balanced against its marginal cost.

Consequently, the algorithms are prevented from pursuing "yield at any cost" and are instead forced to prioritize the maximization of net farm income through a realistic economic lens.

Dynamic Seed and Nutrient Costing

Seed costs were modeled using a weight-based calculation that linked expenditures to planting density, seeds per hill, and farm area. This approach ensured the algorithm was penalized for every incremental increase in population, forcing high-density strategies to be economically justified by yield gains. The Department of Agriculture (DA) reports variety-specific pricing for corn seeds, retailing open-pollinated varieties at ₱556/kg and hybrids at ₱689/kg.

$$\mathbf{Seed} = \left(\frac{\mathbf{Density} \times \mathbf{Seeds/hill} \times \boldsymbol{Area}}{\mathbf{Seeds/kg}}\right) \times \mathbf{Price/kg}$$

Figure 7. Seed Cost

Nutrient expenditures were similarly treated as per-hectare variables across specific blends, with prices (₱1,737–₱2,051 per sack) aligned with DA-validated market data. To prevent biologically unsound "toxic" over-fertilization, the model enforced an agronomic cap of 12 sacks per hectare. This constraint ensured the algorithm operated within the safe and recommended saturation limits for the region, capturing the substantial financial impact of nutrient management on the total farm budget.

$$Fertilizer\_Cost = \sum (Sacks\_per\_ha \times Farm\_Area\_(ha) \times Price\_per\_Sack)$$

Figure 8. Fertilizer Cost

Site-Specific and Operational Costs

Operational costs were determined by farm topography, serving as a fixed baseline for the optimization strategy. Plain terrain required mechanized tillage at ₱6,000/ha for higher yield potential, while Elevated terrain used a ₱5,000/ha "no-till" method but incurred yield penalties. This disparity forced the algorithm to adapt its strategy based on the terrain's specific economic and productive trade-offs.

$$Total\_Operational\_Cost = Topography\_Cost[terrain] \times Farm\_Area\_(ha)$$

Figure 9. Operational Cost Formula

As stated by the Department of Agriculture (DA), herbicide application was necessary for these varieties to mitigate aggressive weed pressure and protect their high yield potential.

Dosage was adjusted for terrain-based weed diversity, ensuring the model accounted for the higher "cost of entry" associated with premium seeds.

Total Variable Cost Calculation

These variable costs were added together to provide the Total Variable Cost, which was the fitness function's main deductor from the Gross Revenue. This allowed the model to accurately replicate the decision-making environment of a rational farm.

$$\text{Total Cost} = \sum(\text{Seed} + \text{Fertilizer} + \text{Operational Costs})$$

Figure 10. Total Cost Formula

Fitness Model

The core of the optimization process was the profit-centric objective function, modeled as the farm's Gross Margin. This study utilized absolute net profit to align the algorithm’s behavior with genuine economic reality. This approach enabled the algorithms to pinpoint the Economic Optimum: the specific threshold where the cost of an additional unit of input (such as fertilizer) was exactly balanced by the marginal revenue it generated.

$$Gross\_Margin = (Total\_Yield_{kg} \times Price_{kg}) - Total\_Cost_{₱}$$

Figure 11. Gross Margin Formula

The Gross Margin was calculated by subtracting the total variable costs from the gross revenue, based on the Region 6 market benchmark of ₱17/kg (as of January 2026). This calculation serves as the primary fitness metric, establishing a rigorous standard that allows the algorithm to evaluate and rank management strategies based on their true economic viability.

Algorithm Architecture and Implementation

Chromosome Representation

The genetic structure of each solution was defined by a two-gene chromosome encapsulating planting density and fertilizer composition, with fixed parameters like topography, land preparation, and seed variety used to isolate the synergistic optimization of population and nutrients. Encoded as a hybrid data structure, the first gene was a floating-point value for planting density, dynamically constrained within 10% of the variety’s optimal range (50,000–78,000 plants/ha); the second gene was a dictionary mapping fertilizer IDs to sack counts for granular nutrient control. To ensure agronomic validity and prevent toxicity, the chromosome enforced a 12-sack total limit and a 5-sack cap per type, while maintaining internal references to farm data, yield model, and cost model for consistent population evaluation (Zhang et al., 2020; Khan et al., 2022; Wang & Hu, 2021; Majrash et al., 2020).

Algorithm Shared Configurations and Parameters

To ensure a rigorous and scientifically valid comparison, this study followed the "Total Effort" evaluation framework [20]. Both the Genetic Algorithm (GA) and Memetic Algorithm (MA) were restricted to a fixed budget of 10,000 Total Function Evaluations (TFE). While the GA utilized this budget over a longer evolutionary span of 100 generations, the MA allocated its budget more intensively, utilizing 50 generations supplemented by local search refinements. This standardization allowed for a direct comparison between long-term evolutionary progress and high-intensity local refinement within an identical computational ceiling.

Overall, the two algorithms will produce a total of 540 runs to account for the stochasticity and variability inherent in evolutionary computation (Katoch et al., 2021).This approach provided the statistical input necessary for comparative analysis, ensuring that observed performance differences were mathematically significant rather than incidental.

Table 3.
Shared Configurations and Parameters

Parameter	Value / Method	Rationale
Population Size	100	Moderate size to maintain diversity (Hassanat, 2019).
Crossover Rate	0.9	High rate to facilitate rapid trait exchange.
Mutation Rate	0.05	Standardized to prevent premature convergence.
Selection Method	Tournament (Size 3)	Provides consistent selection pressure toward optima [21].
Crossover Method	Uniform	Ensures balanced mixing of density and nutrient traits.
Mutation Method	Gaussian	Allows for controlled, small-scale variations in genes.
Elitism Count	2	Preservation of the top-performing economic strategies.
Boundary Handling	Clipping	Ensures all results remain within agricultural feasibility.

Genetic Algorithm

The Genetic Algorithm served as the population-based search engine, inspired by natural selection, to optimize the combinations between fertilizer composition and planting density. The GA facilitated an iterative evolutionary process: starting with an initial population, it evaluated each individual’s fitness, selected the strongest performers through tournament selection, and applied crossover and mutation to generate a new population. This cycle repeated for a full 100 generations, utilizing the entire 10,000 function evaluation budget to explore the search space for the most economically viable farming strategies.

Table 4.
GA-Specific Parameters

Parameter	Value	Rationale
Max Generations	100	Full budget allocation for long-term evolutionary exploration.
Mutation Step Size	0.05 (5%)	Balanced ratio for high-precision refinement and global search.
Mutation Type	Gaussian	Optimized for continuous variables (sacks and density).
Repair Method	Proportional Scaling	Ensures N:P:K ratio preservation during constraint handling.

Gaussian Mutation for Precision Refinement

The GA utilized Gaussian mutation to optimize continuous variables like fertilizer and planting density. The algorithm balanced high-precision fine-tuning (frequent small steps) with exploratory leaps (rare large steps) by applying a standard deviation of 5% to a gene's current value (Bell, 2022).This mechanism allowed the model to refine near-optimal strategies while maintaining the diversity needed to escape local optima.

Proportional Scaling Repair

Standard algorithms might simply "clipped" excessive values to a boundary; this algorithm recognized that in agronomy, the nutrient ratio (134N - 41P - 102K balance) was more vital for crop health than the absolute volume. If a chromosome's total fertilizer exceeded the 12-sack limit, the system applied a scale factor to reduce all fertilizer types simultaneously.

Memetic Algorithm

The Memetic Algorithm (MA) extended the GA by integrating a local search phase, combining global exploration with directed local refinement. While the GA followed a "Breed-Mutate-Evaluate" cycle, the MA inserted a local search step before evaluation. This hybrid approach enabled the algorithm to not only discover promising regions of the search space but also to fine-tune individual solutions within those regions, significantly accelerating convergence toward the economic optima.

Table 5.
MA-Specific Parameters

Parameter	Value	Rationale
Max Generations	50	Half the GA cycles to compensate for local search cost.
Local Search Method	Greedy Hill Climbing	Ensures directed, incremental profit improvement.
Search Strategy	Partial Lamarckism	Refines only the top 10% of offspring for efficiency.
Search Depth	10 Iterations	Prevents the search phase from becoming a bottleneck.
Search Breadth	0.05 (5%)	Fine-grained refinement within the local optima basin.

Synergy-Based Local Search

The Memetic Algorithm utilized a domain-specific neighbor generation strategy specifically designed to mitigate the complexities of epistatic interactions among variables. Recognizing that higher planting densities naturally increased nutrient demand, the local search generated neighbors that simultaneously perturbed both density and fertilizer levels (e.g., adding 500 plants/ha alongside 0.1 sack of balanced 14-14-14 fertilizer). This "synergy-based" movement allowed the algorithm to navigate the "synergy ridge" in the fitness landscape more efficiently than independent gene changes.

Adaptive Intensity via Partial Lamarckism

Following the principles of Partial Lamarckism, the local search was selectively applied only to the top 10% of the population. This targeted refinement focused computational effort on the most promising "elite" candidates, which were more likely to yield high-quality solutions. By restricting the intensive hill-climbing process to a specific subset, the MA maintained a balance between broad exploration and deep exploitation without exceeding the fixed 10,000 function evaluation budget (Cotta et al.,2025).Performance Comparison and Evaluation

Test Cases

Nine test cases representing diverse Iloilo maize farming conditions were developed, categorized by Stress Level, Biological Sensitivity, and Resource Availability validated by These scenarios encompass three distinct maize varieties: Hybrid (H1–H5), Glutinous (G1–G2), and Open-Pollinated Varieties (O1–O2). The specific parameters for these scenarios are presented in Table 8 under the Experimental Setup and Testing Results section of the Results and Discussion. These scenarios were structured into a hierarchical framework to identify optimization advantages: High Stress cases utilized sandy, acidic, nutrient-poor soil to test aggressive optimization under difficulty; Moderate Stress scenarios represented typical loamy farms to establish realistic productivity baselines; and Low Stress cases simulated optimal clay-rich environments to focus on precision and the prevention of costly over-fertilization.

Baseline Configurations

To ensure the generated plans were both practical and high-performing, these Department of Agriculture (DA) validated baselines served as the ground truth for agronomic soundness, providing evidence that the new strategies either aligned with or surpassed standard farming practices. During implementation, the yield model's density factor parametrization was refined from an initial value of 1.2 to 1.0. This adjustment was necessary to strictly enforce the agronomic constraint ensuring corn yields did not exceed the maximum theoretical threshold of 5,000 kg/ha. This refinement strengthened the model's constraint enforcement while remaining consistent with the DA-validated agricultural methodology. While the updated, refined baselines used for final analysis are presented in Table 6.

Table 6.
Baseline Values

Test Case	Planting Density	Fitness (Peso)	Yield (kg)	Cost (Peso)	NutUE (kg yield / kg nutrient)
G1	55,556	21,402.33	4,499.75	5,092.57	46.6774
G2	55,556	16,484.11	4,061.22	5,255.63	61.3477
H1	71,429	3,279.88	3,365.83	3,939.23	30.3228
H2	71,429	25,293.82	4,512.34	5,141.59	55.8458
H3	71,429	18,087.25	4,049.93	5,076.15	55.6309
H4	71,429	10,442.22	3,184.31	4,369.10	26.5359
H5	71,429	27,021.49	4,512.18	4,968.55	74.9532
O1	53,333	13,349.77	3,710.07	4,972.14	33.4241
O2	53,333	30,167.44	5,124.24	4,654.37	61.9838

While the primary metrics yield, density, and cost were used from the validation document, The nutrient Use Efficiency (NutUE) was included to provide a more comprehensive comparison of algorithm performance.

Although NutUE was not explicitly listed as a standalone column in the original signed validation, it was mathematically derived using the standard agronomic formula based on the DA-validated yield and fertilizer application data. The NutUE is calculated as follows:

$$\text{NutUE} = \frac{\text{Best Yield (kg)}}{\text{Total Nutrient Weight Applied (kg)}}$$

Figure 12. Nutrient Use Efficiency Formula

The Total Nutrient Weight is determined by summing the actual N-P-K content of the applied fertilizers:

$$\text{Total Nutrient Weight} = \sum_{i=1}^{n} \text{Sacks}_i \times 50\ \text{kg/sack} \times \frac{N\% + P\% + K\%}{100}$$

Figure 13. Total Nutrient Weight Formula

Performance Metrics

Following the comparative framework established in [20], the algorithms were evaluated through three performance metrics to determine their suitability for agricultural optimization.

Solution quality was measured by the following metrics: planting density, fitness (gross margin), yield, cost, and nutrient use efficiency (NutUE). This focus on the economic and biological viability of the results allowed for a comparison of the best fitness (gross margin) alongside total crop yield and input costs. By tracking these metrics, the study assessed how effectively each algorithm converted fertilizer into grain, ensuring that the optimization prioritized sustainable biological performance rather than just raw financial gain.

Computational Performance was based on operational speed and overhead to evaluate raw computational speed. Algorithm runtime served as the primary metric, quantifying the duration required for each algorithm process in using the full total function evaluations budget (TotalFE = 10000).

Algorithm Efficiency was quantified using Convergence Generation and the Percentage of Total Function Evaluations (FEs) required to reach an optimal state. This approach ensures that the inherent overhead of the Memetic Algorithm’s local search is fully accounted for relative to the search's progress and the economic value of the final solutions.

Statistical Analysis Framework

The statistical analysis framework utilized a rigorous experimental design with a total of 540 experiments. To prove the better algorithm's superiority with statistical rigor, this study employed normality tests to determine the distribution characteristics of the underlying data. Furthermore, to provide consistent data, the study implemented 30 independent runs per scenario, following the guidelines established in (Schloegel et al., 2024).Descriptive statistics were calculated for all performance and quality metrics across two distinct datasets: the solution quality metrics (N = 810), which compare Algorithm A, Algorithm B, and the Department of Agriculture (DA) Baseline, and the algorithmic efficiency and performance metrics (N = 540), which focus on the head-to-head comparison between the two proposed algorithms. The analysis utilized the mean to represent average performance and the standard deviation (SD) to measure the variability and consistency of the results across the 30 runs per scenario.

Normality Assessment

A normality assessment was conducted to determine the appropriate statistical tests for the experimental data. The Shapiro-Wilk and Kolmogorov-Smirnova (with Lilliefors significance correction) tests were utilized, applying a significance level ($p < 0.05$) to evaluate the null hypothesis that each metric's data followed a normal distribution [43]. The results across all key metrics indicated a non-normal distribution. Thus, non-parametric tests were selected for analysis to ensure the validity of findings.

Solution Quality

To evaluate the solution quality, the independent-samples Kruskal-Wallis H test was applied separately to each metric: planting density, fitness (gross margin), yield, cost, and nutrient use efficiency (NutUE). This test evaluates the null hypothesis that the distribution of these metrics is the same across the three groups Genetic Algorithm (GA), Memetic Algorithm (MA), and Department of Agriculture (DA) Baseline. The analysis works by ranking all observations and calculating a mean rank for each group; these ranks are then used to derive the Kruskal-Wallis H statistic [44]. A significance level of $p < 0.05$ (asymptotic significance) was used to determine if the differences between groups were statistically significant. Finally, pairwise comparisons were conducted to identify which specific pairs (e.g., MA vs. DA) showed significant differences.

Computational Performance and Algorithm Efficiency

To compare the efficiency and performance of the two proposed algorithms Genetic Algorithm (GA) and Memetic Algorithm (MA), the Mann-Whitney U Test was used. This non-parametric test was selected to evaluate whether there is a statistically significant difference between the two independent algorithm groups across three metrics [44]. Computational performance was evaluated through total runtime and algorithm efficiency was assessed using convergence generation and total function evaluations (Total FE). The test evaluates the mean ranks of the runs to determine if one algorithm consistently outperforms the other. Results are reported using the U statistic, the Z-score, and the

Asymptotic Significance (p-value). This analysis ensures a rigorous comparison of the algorithms' computational overhead and their ability to reach an optimal solution with minimal resources.

User Testing and Sampling

To validate the practical usability of the developed website prototype, a formative user testing phase was conducted using the Post-Study System Usability Questionnaire (PSSUQ). The Post-Study System Usability Questionnaire (PSSUQ) was a robust psychometric tool, and numerous studies, including the foundational work (Vlachogianni & Tselios, 2023), support its validity and widespread use. consistently demonstrate that factor analysis identified three primary, reliable subscales namely System Usefulness, Information Quality, and Interface Quality. This reliability was confirmed by consolidated research findings showing a high Cronbach's alpha coefficient that generally ranged from 0.83 to 0.96. At least 15 corn farmers were targeted from the Tigbauan Farmers Association using purposive sampling. This ensured that all participants had relevant agricultural experience and represented the actual user base for the decision-support system.

The participant profile consisted of 15 male corn farmers, all of whom were members of the Tigbauan Farmers Association residing in Cordova Norte and Sitio Intake. Every participant is the head of a household with a family. Furthermore, they are all dedicated full-time farmers, each bringing at least 5 experience in corn cultivation to the study. A study provided empirical evidence supporting the use of 10 users in certain cases. The study analyzed two real-world usability datasets and found that one dataset reached approximately 90% problem discovery with only 10 users, while the other required 20 (Majrash et al., 2020). This finding supported the notion that 10 participants can be sufficient for discovering the majority of usability issues in systems of moderate complexity, making it a suitable and resource-efficient sample size for this study.

Prototype Building Procedures

The web-based prototype was developed using an Iterative Waterfall SDLC, providing a structured yet flexible framework. This methodology ensured the delivery of a functional platform specifically designed to showcase user interactions to the algorithms.

System Design and Architecture Phase

The prototype uses a Streamlit frontend and Python backend, designed for an intuitive experience. The architecture bypasses the need for a persistent database or account creation. This allows users to jump straight into the dashboard and optimization pages, interacting with the algorithms via simple input fields without the hurdle of a login.

Implementation and Development Phase

Reactive Streamlit components were developed to handle data inputs and side-by-side visualizations. The backend houses the core models and optimization algorithms, utilizing stateless API endpoints for in-memory execution. Throughout development, Git-based version control was used to maintain code stability and the ability to seamlessly revert to previous versions if an update failed.

Testing and Quality Assurance Phase

The testing strategy employed a hybrid approach tailored for a Python and Streamlit environment. We utilized automated unit tests to validate the core algorithmic logic, while manual scenario-based testing is conducted directly within the Streamlit Cloud hosted interface. The priority was ensuring that the system manages user interactions gracefully and remains responsive, leveraging Streamlit's execution model to maintain a seamless front-end experience even during intensive back-end computations.

Deployment Phase

The application is deployed directly via Streamlit Cloud, leveraging its native integration with Python to ensure a stable, high-availability demonstration environment without the overhead of manual container management. This phase focused on seamless version control and includes the delivery of comprehensive user guides, procedures, and technical documentation to support the prototype throughout its lifecycle.

Evaluation and System Validation

Validated the prototype through internal testing to ensure it functions as a reliable decision-support tool. This confirmed the interface is intuitive for non-technical users and that the generated recommendations accurately align with experimental farm cases.

Data Gathering Methods

The primary objective of this research phase was to collect the necessary data and define the variables required to parameterize the penalty-based models for the Genetic Algorithm (GA) and Memetic Algorithm (MA).

The initial step involved a thorough review of academic literature, agronomic studies, and official reports from government agencies such as the Department of Agriculture (DA). These sources were used to validate the selection of the models as a scientifically grounded approach for simulating nutrient-to-yield relationships in corn farming. The literature also informed the appropriate ranges, thresholds, and constraints for key variables such as nitrogen (N), phosphorus (P), and potassium (K) levels, planting density, and soil pH.

To ensure local relevance, the study gathered agricultural input parameters, including seed varieties, fertilizer types, and associated costs from publicly accessible DA bulletins, regional agricultural reports, and market price databases. These inputs reflected current practices and pricing conditions in Western Visayas, particularly in Iloilo Province. Parameters related to land preparation methods, seasonal planting schedules, and typical budget ranges were also based on these official data sources.

In addition, a subject matter expert from the Department of Agriculture–Regional Field Office 6 was informally consulted to validate the realism and applicability of the chosen farming parameters. However, this expert consultation was used solely for model validation and was not treated as a formal data collection method.

Data Presentation and Analysis

The data selected from both literature and expert validation will be systematically integrated into the algorithms' models. This includes defining model parameters such as the coefficients for the yield model, soil-specific modifiers, and seasonal values to accurately simulate nutrient-to-yield relationships under Philippine conditions. Economic factors, including current market prices for seeds and fertilizers, operational costs, and typical farmer budget constraints, were used to build the cost model and fitness function, ensuring that all generated solutions are financially realistic and implementable. Lastly, practical constraints from best practices and expert recommendations, like optimal fertilizer rates and planting densities, were encoded as validation rules to ensure all solutions are agronomically sound.

The comparative analysis between the Genetic Algorithm (GA) and Memetic Algorithm (MA) was evaluated using a structured framework focusing on three key areas: solution quality, computational performance, and algorithm efficiency. Descriptive statistics, including the mean and standard deviation, were calculated across 30 independent runs per scenario to summarize average performance and measure data variability. To determine the appropriate statistical tests, normality was assessed using the Shapiro-Wilk and Kolmogorov-Smirnov tests. To evaluate solution quality, the Independent-Samples Kruskal-Wallis H Test was used to compare the GA, MA, and the Department of Agriculture (DA) baseline across metrics including planting density, fitness (gross margin), yield, cost, and Nutrient Use Efficiency (NutUE). Post-hoc pairwise comparisons were conducted to identify significant differences and specific variations between the algorithms. Computational performance and algorithm efficiency were assessed through a head-to-head comparison using the Mann-Whitney U Test.

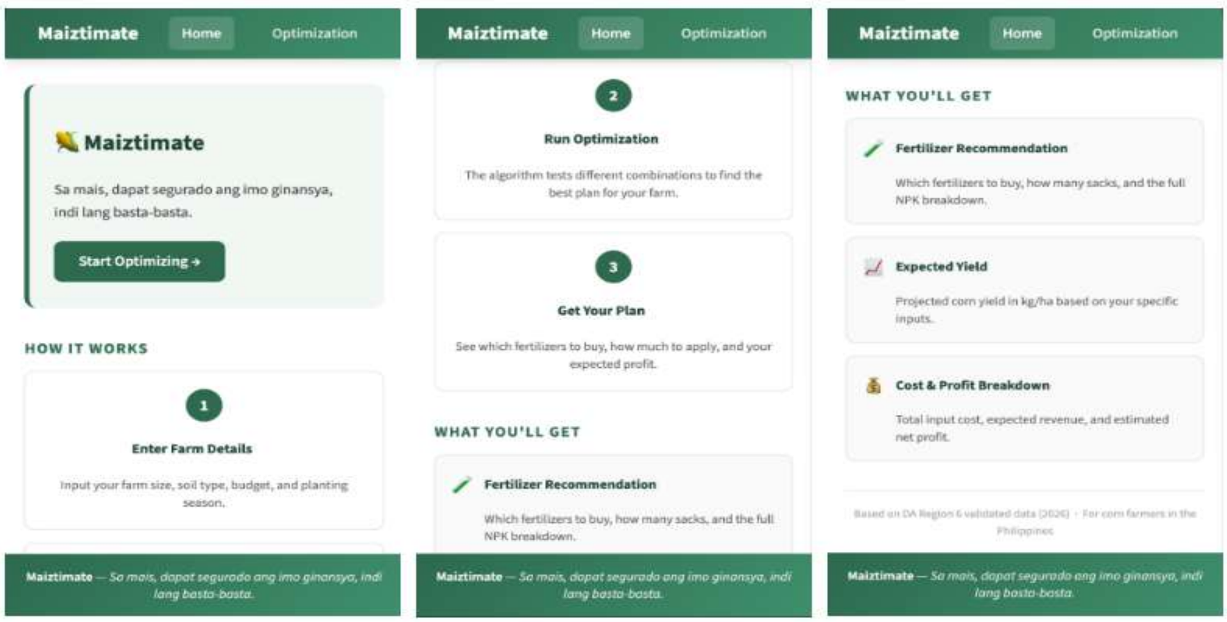
Following the comparative analysis, the superior algorithm was integrated into a functional website prototype. User testing was conducted with local farmers who were introduced and interacted with the prototype to generate localized crop recommendations and management plans. Their feedback was quantified using the Post-Study System Usability Questionnaire (PSSUQ), which measured the system across four critical dimensions: System Usefulness (navigation and task efficiency), Information Quality (relevance of agricultural data), Interface Quality (visual intuitiveness), and Overall Satisfaction regarding the likelihood of long-term adoption in their daily farming operations.

RESULTS

This study implemented a comparative analysis between a Genetic Algorithm (GA) and a Memetic Algorithm (MA) to determine which algorithm generated the better farming plan for corn resource optimization and yield maximization, with the results of that comparison to be utilized in a website prototype that took input from farmers such as farm area, soil type, soil pH, initial nutrients present, phosphorus, and potassium levels, planting month, topography, irrigation availability, and seed variety to generate an optimized farming plan helping them optimize their resource use such as fertilizers and seed based on their specific farm conditions.

The system was developed using Python as the backend and Streamlit as the frontend framework. Both algorithms operated on the same underlying agronomic model, which calculated corn yield using a multiplicative penalty-based function validated against Department of Agriculture practices, and computed total production cost by summing seed, fertilizer, and operational expenses, with the fitness of each candidate solution evaluated as total revenue minus total production cost.

All solutions were constrained to meet a nutrient adequacy range of 85% to 115% of the Department of Agriculture (DA) recommended nitrogen, phosphorus, and potassium levels of 134, 41, and 102 kg/ha respectively, ensuring that every recommended farming plan was both economically optimal and agronomically viable for corn cultivation in Region 6, Philippines.



Maiztimate

Sa mais, dapat segurado ang imo ginansya, indi lang basta-basta.

HOW IT WORKS

Enter Farm Details

Input your farm size, soil type, budget, and planting season.

Run Optimization

The algorithm tests different combinations to find the best plan for your farm.

Get Your Plan

See which fertilizers to buy, how much to apply, and your expected profit.

WHAT YOU'LL GET

Fertilizer Recommendation

Which fertilizers to buy, how many sacks, and the full NPK breakdown.

Expected Yield

Projected corn yield in kg/ha based on your specific inputs.

Cost & Profit Breakdown

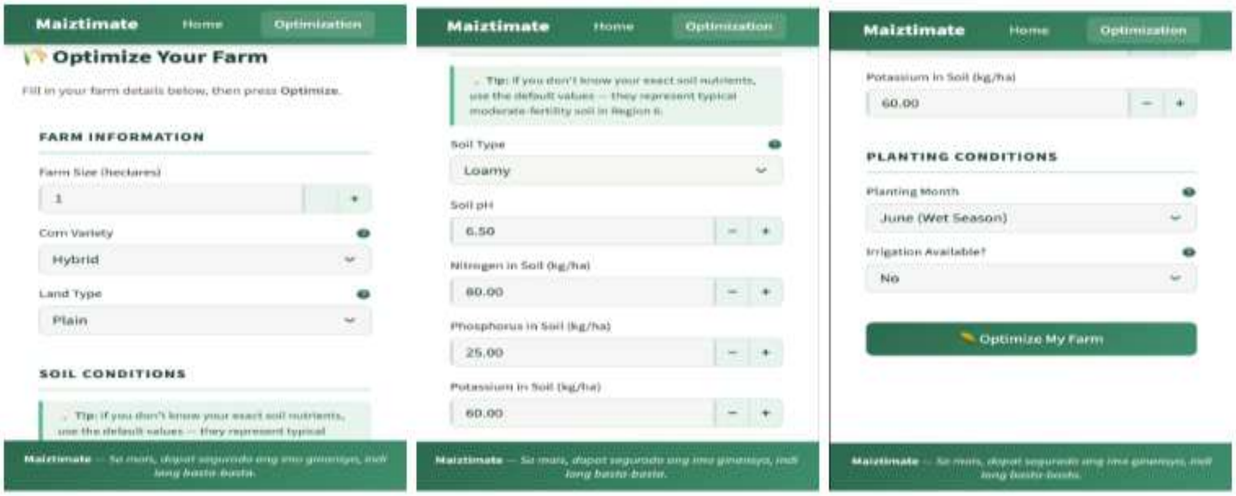
Total input cost, expected revenue, and estimated net profit.

Based on DA Region 6 validated data (2026) · For corn farmers in the Philippines

Maiztimate — *Sa mais, dapat segurado ang imo ginansya, indi lang basta-basta.*

Figure 14. Homepage: Screen Layout of Software Outputs

The Maiztimate homepage features a centralized hero section containing the "Start Optimizing" call-to-action button, serving as the primary entry point for the user. Below this, a three-step "How It Works" guide provides a procedural overview of the optimization workflow. The lower section of the interface outlines the system's primary outputs, specifically the Fertilizer Recommendations, Expected Yield projections, and a comprehensive Cost & Profit Breakdown, ensuring that the value proposition is immediately visible to the end-user.



Optimize Your Farm

Fill in your farm details below, then press Optimize.

FARM INFORMATION

Farm Size (hectares): 1

Corn Variety: Hybrid

Land Type: Plain

SOIL CONDITIONS

Tip: If you don't know your exact soil nutrients, use the default values — they represent typical moderate-fertility soil in Region 6.

Soil Type: Loamy

Soil pH: 6.50

Nitrogen in Soil (kg/ha): 80.00

Phosphorus in Soil (kg/ha): 25.00

Potassium in Soil (kg/ha): 60.00

PLANTING CONDITIONS

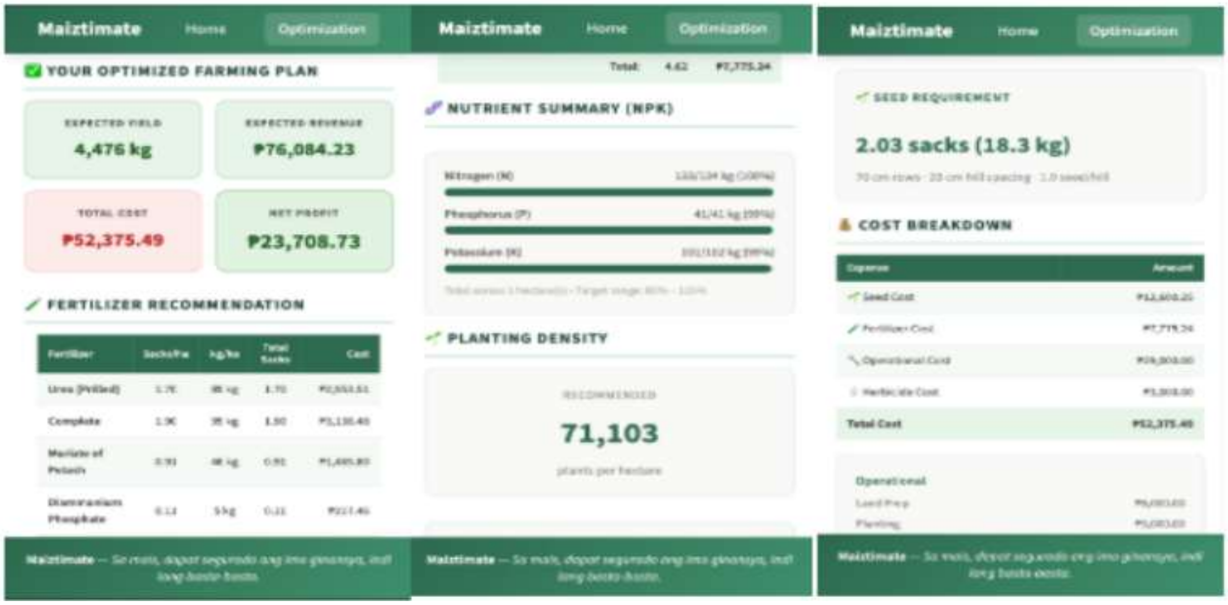
Planting Month: June (Wet Season)

Irrigation Available?: No

Maiztimate — Sa mais, dapat segurado ang imo ginansya, indi lang basta-basta.

Figure 15. Input Screen

The input interface is organized into three distinct thematic sections to ensure a systematic data collection process. The Farm Information section captures foundational parameters, including farm size (hectares), corn variety, and land topography. This is followed by the Soil Conditions module, which allows users to input critical chemical properties such as soil type, pH levels, and primary macronutrient concentrations (Nitrogen, Phosphorus, and Potassium). The final segment, Planting Conditions, gathers temporal and infrastructural data regarding the planting month and irrigation availability. The process culminates in the "Optimize My Farm" action button at the base of the interface, which triggers the backend optimization algorithm.



YOUR OPTIMIZED FARMING PLAN

4,476 kg

₱76,084.23

₱52,375.49

₱23,708.73

FERTILIZER RECOMMENDATION

Urea (Prilled)

Complete

Muriate of Potash

Diammonium Phosphate

NUTRIENT SUMMARY (NPK)

Nitrogen (N)

Phosphorus (P)

Potassium (K)

PLANTING DENSITY

71,103

SEED REQUIREMENT

2.03 sacks (18.3 kg)

COST BREAKDOWN

Seed Cost

Fertilizer Cost

Operational Cost

Herbicide Cost

Total Cost

Operational

Land Prep

Planting

Figure 16. Output Screen

The results page provides a holistic view of the optimized agricultural strategy. Key deliverables include a tailored Fertilizer Recommendation list, a Planting Density guide, and a seed requirement summary. To assist in financial planning, the system displays an itemized Cost Breakdown and a Nutrient Summary (NPK) visualization. The inclusion of the original Farm Conditions at the base of the page allows users to verify the input parameters against the generated recommendations.

Experimental Set-Up & Testing Results

The experiment was conducted to compare the performance of the Genetic Algorithm and the Memetic Algorithm across nine test cases representing simulated farm conditions in Region 6, Philippines. Each algorithm was run 30 times per test case, totaling 270 runs per algorithm and 540 runs combined. Performance was measured using three main metrics namely solution quality, computational performance, and algorithm efficiency. The results were analyzed using non-parametric tests to determine whether any observed differences between the two algorithms were statistically significant.

Test Cases

The experiment was conducted across nine test cases designed to represent diverse farm conditions in Region 6, Philippines.

Table 7.
Test cases simulating different farm conditions in Iloilo Province

Case	Description	Stress Level
G1	Moderate Stress: Loamy soil, wet season, no irrigation	Moderate
G2	Moderate Stress: Clay soil, dry season, with irrigation	Moderate
H1	High Stress: Sandy soil, low pH, wet season, no irrigation	High
H2	Moderate Stress: Loamy soil, dry season, with irrigation	Moderate
H3	Moderate Stress: Clay soil, wet season, no irrigation	Moderate
H4	High Stress: Elevated terrain, sandy soil, low pH, wet season, no irrigation	High
H5	Low Stress: Loamy soil, dry season, with irrigation	Low
O1	High Stress: Sandy soil, low pH, wet season, no irrigation	High
O2	Moderate Stress: Loamy soil, dry season, with irrigation	Moderate

Algorithm Configurations and Procedures

The compared algorithms have several shared parameters as well as unique parameter configurations. Both algorithms were constrained to exactly 10,000 function evaluations per run to ensure a fair comparison based on equal computational effort. The Genetic Algorithm (GA) consumed this budget through 100 generations of 100 individuals each, while the Memetic Algorithm (MA) used 50 generations and allocated the remaining budget to local search on the top 10% of each generation's population. Each algorithm was run 30 times per test case using a different random seed per replicate, yielding 270 runs per algorithm and 540 total runs. Thirty replicates were used to satisfy the minimum sample size requirement as highlighted in [32] to produce the necessary data for comparative analysis.

Statistical Methods

The analysis framework was summarized in Table 9. Descriptive statistics and normality tests established the foundation, while Kruskal-Wallis H and pairwise comparisons evaluated solution quality. Mann-Whitney U tests provided a head-to-head assessment of GA and MA computational performance and efficiency.

Table 8.
Summary Table for Statistical Methods Used

Statistical Method	Purpose
Descriptive Statistics (Mean, SD)	To summarize average performance and measure data variability across N=810 (Quality) and N=540 (Efficiency) samples.
Normality Assessment (Shapiro-Wilk & Kolmogorov-Smirnov)	To determine the distribution characteristics of the data.
Independent-Samples Kruskal-Wallis H Test	To compare the performance of Algorithm A, Algorithm B, and the DA Baseline across all solution quality metrics.
Pairwise Comparisons	To determine which shows specific significant differences between pairs of algorithms or baselines as a post-hoc analysis.
Mann-Whitney U Test	To perform a head-to-head comparison of Algorithm A and Algorithm B regarding computational efficiency and speed.

Summary of Descriptive Statistics for Key Metrics

This section presents an overview of the data collected across all experimental runs. Detailed descriptive statistics summarizing the solution quality metrics (N = 810), as well as the computational performance and algorithm efficiency metrics (N = 540. These summarized datasets establish the statistical foundation for the comparative analysis between the proposed algorithms and the established ground truth.

Normality Analysis

The normality of the data distribution was assessed using the Shapiro-Wilk test for all performance and efficiency metrics. T results indicated that all variables significantly deviated from a normal distribution, with p-values of less than 0.001 across the board. Because these values are substantially lower than the level of 0.05, the null hypothesis that the data are normally distributed is rejected. Non-parametric statistical methods are used for any subsequent comparative analysis.

Solution Quality

Figure 22. Mean Comparison across Solution Quality Metrics. (a) Planting Density; (b) Yield; (c) Fitness (Gross Margin); (d) Total Cost; (e) Nutrient Use Efficiency (NutUE). Error bars represent standard deviation (N = 270 per group).

As illustrated in Figure 22 (a, b, and e), while the mean values for planting density, yield, and Nutrient Use Efficiency (NutUE) generated by the Genetic Algorithm (GA) and Memetic Algorithm (MA) fall slightly below the DA baseline, they demonstrate a high degree of proximity to this standard. Specifically, the GA (Yield M = 3903.89; NutUE M = 46.03) and MA (Yield M = 3898.43; NutUE M = 46.62) produced results that closely track the DA baseline (Yield M = 4045.33; NutUE M = 49.64), having a tight margin with the baselines. Similarly, Figure 22 (c) showed GA and MA results fall short but remained close to the DA baseline (M = 18392.03, SD = 8115.51). Furthermore, the slight cost reductions observed in Figure 22 (d) for GA (M = 49621.85) and MA (M = 49416.16) relative to the DA baseline (M = 50378.64) highlight the algorithms' ability to find cost-effective balances while maintaining density levels comparable to the ground truth. Overall, the results indicate that while GA and MA remain technically below the baseline, they successfully converge toward the ground truth, providing a computationally reliable means of approximating optimized real-world agricultural scenarios.

As shown in Table 10, there were highly significant differences (p < .001) for all evaluated parameters. These suggested that the variations in the model configurations or treatments had a substantial and statistically verifiable impact on both the agronomic and economic outcomes. Specifically, the high H-statistic for Density (H = 90.07) indicated that this metric was the most sensitive to the changes across the tested groups. Because the null hypothesis was rejected for all metrics, these results justified the performance of post-hoc pairwise comparisons to identify which specific groups differed from one another.

Table 9.
Post-Hoc Pairwise Comparisons of Solution Quality Metrics

Metric	Comparison	Test Statistic	Std. Error	Std. Test Stat	Adj. Sig. (p)
Density	GA vs MA	-42.08	20.07	-2.10	.108
	GA vs DA	-181.87	20.07	-9.06	< .001
	MA vs DA	-139.79	20.07	-6.97	< .001
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Fitness	GA vs MA	-6.70	20.13	-0.33	1.000
	GA vs DA	-68.02	20.13	-3.38	.002
	MA vs DA	-61.32	20.13	-3.05	.007
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Yield	GA vs MA	2.37	20.13	0.12	1.000
	GA vs DA	-116.68	20.13	-5.80	< .001
	MA vs DA	-114.32	20.13	-5.68	< .001
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Cost	GA vs MA	11.74	20.13	0.58	1.000
	GA vs DA	-78.37	20.13	-3.89	< .001
	MA vs DA	-66.63	20.13	-3.31	.003
---	---	---	---	---	---
NutUE	GA vs MA	-14.22	20.13	-0.71	1.000
	GA vs DA	-77.78	20.13	-3.86	< .001
	MA vs DA	-63.56	20.13	-3.16	.005

The post-hoc pairwise comparisons in Table 11 revealed a consistent pattern of statistical significance. For the metrics of Yield, Cost, and NutUE, both GA and MA showed highly significant differences when compared to the DA baseline ($p < .001$). Similarly, in the Density metric, GA and MA both remained significantly distinct from DA ($p < .001$). These findings confirmed that both the GA and MA metaheuristics produced solution sets that were statistically divergent from the traditional baseline results.

In contrast, the comparisons between the two primary algorithms showed a high degree of performance parity. For Fitness, Yield, Cost, and NutUE, the adjusted significance for the GA vs. MA comparison was 1.000, indicating that there was no detectable statistical difference between the two models. Even in the Density metric, the difference between GA and MA failed to reach significance (p = .108). In summary, while both algorithms provided results that were statistically unique compared to the DA baseline, the performance of the GA and MA was statistically equivalent across nearly all evaluated parameters, suggesting that either metaheuristic could be utilized with similar expected outcomes for this specific optimization problem.

Computational Performance

Table 10.
Mann-Whitney U test result on Total Runtime

Algorithm	N	Mean Rank	Mann-Whitney U	Z-score	Adj. Sig. (p)
GA	270	135.50	0.000	-20.296	< .001
MA	270	405.50			

As shown in Table 12, the Mann-Whitney U test results for total runtime revealed a significant performance gap between the two algorithms. The Genetic Algorithm (GA) achieved a significantly lower mean rank of 135.50 compared to the Memetic Algorithm (MA), which had a mean rank of 405.50. With a U value of 0.000, a Z-score of -20.296, and an adjusted significance of p < .001, the data confirmed that the GA is statistically faster in terms of executing 10000 total function evaluations. The result indicated that MA carries a much higher computational overhead because of the local search, resulting in a significantly longer total runtime than the GA.

Algorithm Efficiency

Table 11.
Mann-Whitney U test result on Convergence Generation and Total Function Evaluations Used

Metric	Algorithm	N	Mean Rank	Mann-Whitney U	Z-score	Adj. Sig. (p)
Convergence Gen	GA	270	402.26	875.000	-19.629	< .001

	MA	270	138.74			
TotalFEs Used	GA	270	305.70	26945.000	-5.247	< .001
	MA	270	235.30			

In algorithm efficiency, a Mann-Whitney U test was performed to compare the computational performance of the Genetic Algorithm (GA) and the Memetic Algorithm (MA). The results in Table 13 indicated that the MA significantly outperformed the GA across both evaluated metrics ($p < .001$). Specifically, the MA demonstrated a substantially lower Mean Rank for Convergence Generation (138.74) compared to the GA (402.26), which indicated that the MA reached optimal solutions in significantly fewer generations. Furthermore, the MA required fewer computational resources, as evidenced by a lower Mean Rank for Total Function Evaluations (235.30) compared to the GA (305.70). These findings were supported by robust Z-scores of -19.629 and -5.247, respectively. While previous comparisons showed no significant difference in the quality of the agricultural solutions produced by either model, these efficiency data suggested that the MA provided a more computationally streamlined approach.

Implementation Results

A formal user testing phase was conducted with 15 farmers to evaluate their interaction with the platform's algorithm. Following the demonstration, participants completed the Post-Study System Usability Questionnaire (PSSUQ) to provide a standardized assessment of their experience across three dimensions: system usefulness, information quality, and interface quality. To interpret these scores verbally, a Likert scale was developed to provide a qualitative scale of the participants' numerical responses. The construction and interpretation of this scale followed methodological guidance for the effective use of Likert-type scales (South et al., 2022).

Table 12.
Verbal Interpretation of PSSUQ Likert Scale Scores

Scale	Qualitative Label	Description
1 - 1.99	Very Satisfied	The user is highly satisfied and encountered no issues.
2 - 2.99	Satisfied	The user is satisfied with the system performance.
3 - 3.99	Somewhat Satisfied	The user is generally satisfied with minor reservations.

4 - 4.99	Neutral	The user has no strong opinion or is indifferent.
5 - 5.99	Somewhat Dissatisfied	The user encountered slight difficulty or confusion.
6 - 6.99	Dissatisfied	The user is dissatisfied with this specific aspect.
7- 7.99	Very Dissatisfied	The user found the system unusable or highly frustrating.
N.A.	Not Applicable	The item was not relevant to the participant's experience.

The findings from the usability assessment are consolidated in Table 14 to provide a clear overview of participant feedback. These figures represent the mean scores across the three PSSUQ categories and the overall system satisfaction, alongside their corresponding standard deviations to indicate the consistency of the participant responses.

Table 13.
Summary of PSSUQ Survey Results

Category	Mean (M)	Std. Deviation (SD)	Verbal Interpretation
System Usefulness	1.78	0.59	Very Satisfied
Information Quality	1.78	0.63	Very Satisfied
Interface Quality	1.69	0.58	Very Satisfied
OVERALL SCORE	1.77	0.51	Very Satisfied

Based on the Post-Study System Usability Questionnaire (PSSUQ) results shown in Table 15, the system achieved a high level of user satisfaction across all three categories. The System Usefulness and Information Quality categories both yielded a mean score of 1.78, while the Interface Quality received the highest rating at 1.69. Following the 7-point Likert scale interpretation where lower scores represent higher satisfaction, all categories fall within the 'Strongly Agree' range. This indicates that the participants found the system easy to use, the information provided to be effective, and the overall interface intuitive and visually clear.

The overall standard deviation of 0.51 indicates a low variance, signifying that the majority of participants' ratings were tightly clustered around the mean. While the raw data showed occasional outliers from some participants, the low SD across all metrics confirms a strong consensus among the group.

DISCUSSION

Comparative Analysis of Solution Quality

The statistical evaluation of solution quality metrics established a clear relationship between the proposed algorithmic optimizations and the expert-derived DA baseline. The Kruskal-Wallis test results indicated highly significant differences across all groups ($H(2)=90.07$ for Density; $H(2)=43.90$ for Yield; $p<.001$), which was expected given that the DA baseline represented the manually calculated ground truth for maximum productivity. As shown in the mean comparisons, the DA baseline functioned as the performance ceiling for the study, maintaining the highest mean yield (4,045.33 kg) and planting density (63,880.33 plants/ha). Both the Genetic Algorithm (GA) and Memetic Algorithm (MA) successfully approximated this ground truth, with the GA achieving a mean yield of 3,903.89 kg and the MA reaching 3,898.43 kg. Rather than seeking to surpass the baseline, the performance of the GA and MA served to validate their capability to autonomously generate solutions that closely aligned with established agricultural standards. This proximity suggested that the metaheuristics could reliably replicate expert-level logic in a fraction of the time required for manual calculation.

In addition, the post-hoc pairwise comparisons provided a critical statistical insight: while both metaheuristics differed significantly from the DA baseline, there was no statistically significant difference between the GA and the MA across the primary solution quality metrics. For Fitness, Yield, Cost, and NutUE, the comparison between the two algorithms resulted in an adjusted significance of 1.000, indicating absolute performance parity. Even in the Density metric, the difference between GA and MA failed to reach significance ($p = .108$). This parity suggests that the inclusion of local search heuristics in the MA did not fundamentally alter the quality of the final agricultural recommendation compared to the GA. Both models successfully identified stable, near-optimal solutions that approximated the expert's manual calculations, such as the GA's mean yield of 3,903.89 kg and the MA's 3,898.43 kg relative to the DA ground truth of 4,045.33 kg. From a practical standpoint, the algorithms' ability to reach these results automatically justified their role as viable decision-support tools for small-scale farmers, providing reliable approximations of the theoretical maximum density without requiring direct expert intervention.

Economic Implications and Nutrient Use Efficiency (NutUE)

A deeper analysis of the economic and efficiency results revealed that the lower mean costs associated with the GA and MA were direct consequences of their more conservative planting densities compared to the ground truth. While the DA baseline maximized density to achieve a peak fitness (Gross Margin) of ₱18,392.03, the algorithms generated solutions with slightly lower mean fitness scores of ₱16,744.88 for GA and ₱16,856.75 for MA. This reduction in fitness was tied to a lower mean cost for GA (₱49,621.85) and for MA (₱49416.16) compared to the DA baseline cost (₱50,378.64). This finding is particularly relevant for small-scale farmers in Iloilo, who often operate under severe liquidity constraints and may prefer a lower-input strategy.

Furthermore, the Nutrient Use Efficiency (NutUE) results suggested that the algorithms maintained a highly balanced approach to resource management. While the DA baseline achieved a mean NutUE of 49.64 kg/kg, the GA and MA produced nearly identical efficiencies of 46.03 kg/kg and 46.62 kg/kg, respectively. The significant difference between the algorithms and the DA baseline ($H(2) = 16.93$, $p < .001$) indicated that the expert-calculated baseline followed a more aggressive nutrient application strategy. The algorithms' results, therefore, represented a statistically distinct "middle-ground" strategy. By offering a lower-cost entry point without a proportional collapse in efficiency, the models provide a viable alternative for farmers who lack the capital required to implement the high-input, high-density strategy recommended by the traditional DA approach.

Comparison of the Algorithms' Computational Performance and Efficiency

The analysis of computational performance reveals significant differences between the Genetic Algorithm (GA) and the Memetic Algorithm (MA). According to the Mann-Whitney U test, GA demonstrated a substantially lower runtime with a Mean Rank of 135.50 compared to MA's 405.50 ($U = 0.000$, $p < 0.001$) shown in Table 12. The Z-score of -20.296 further confirms that this difference in processing speed is statistically significant. While GA is faster in terms of raw execution time, both algorithms were found to provide solutions that were statistically distinct from the Department of Agriculture (DA) baseline across quality metrics such as yield and gross margin ($p < 0.05$). For a budget of 10000 function evaluations, GA is the better-performing algorithm in terms of raw computational speed.

Regarding algorithm efficiency, the MA demonstrated superior performance in reaching an optimal state. The results in Table 13 indicated the Mann-Whitney U test for convergence generation showed that MA achieved a mean rank of 138.74, whereas GA had a significantly higher mean rank of 402.26 ($U = 875.000$, $p < 0.001$). This indicates that the MA requires fewer generations to converge on a high-quality solution. Furthermore, the Total Function Evaluations (Total FE) for MA (Mean Rank = 235.30) were significantly lower than those for GA (Mean Rank = 305.70), with a Z-score of -5.247

($p < 0.001$). These results establish that MA is more efficient at navigating the search space to find optimal results with less overall evolutionary effort.

In summary, although the GA provides a faster runtime, the MA is more efficient due to its faster convergence and lower total function evaluations. The slower runtime of MA is attributed to the computational overhead of its local search phase, which is used to refine solutions more intensively than a standard genetic approach. It is important to note that when these algorithms are accessed through the website prototype, actual runtimes may vary depending on the user's internet connection and hardware specifications. Despite the longer processing time, the Memetic Algorithm’s ability to find higher-quality solutions more quickly in the evolutionary cycle makes it a more robust choice for complex agricultural resource optimization.

System Usability

In the user testing phase, one of the findings is the narrow variance between the three PSSUQ sub-scales, which ranged only from 1.69 to 1.78. This tight performance across System Usefulness, Information Quality, and Interface Quality suggested a balanced development cycle where no single aspect of the design lagged behind the others. The low Information Quality score (1.78) is particularly noteworthy for an algorithmic tool, as it implies the farmers viewed the output as transparent and trustworthy which is a critical factor for long-term adoption in risk-averse industries like farming.

The System Usefulness sub-scale, which achieved a mean score of 1.77, confirms that the platform is not merely a technical novelty but a functional tool that aligns with the needs of the farming community. For a user group that prioritizes efficiency and tangible outcomes, this score indicates that the system effectively facilitates the completion of tasks without unnecessary friction. This demonstrates that the tool provides the necessary utility to support agricultural decision-making, fulfilling its primary purpose as a high-value resource rather than a cumbersome administrative burden. Interface Quality emerged as the strongest dimension with a score of 1.69, suggesting that the visual hierarchy and navigational flow were optimized for the specific needs of the farmers. This peak in satisfaction reflects a successful "mobile-first" or "user-first" philosophy, where the layout facilitated, rather than hindered, the interaction with the underlying technology.

Conclusions

The comparative analysis of the Genetic Algorithm (GA) and the Memetic Algorithm (MA) for resource optimization and corn yield maximization in Iloilo Province yielded several significant findings across solution quality, computational performance, algorithm efficiency, and user acceptance.

The results demonstrated that both the GA and MA are highly effective at approximating the Department of Agriculture (DA) baseline, which served as the study’s established ground truth and performance ceiling. Both GA and MA fall within a tight proximity to the DA’s baselines. Statistical evaluation through the Kruskal-Wallis test confirmed that while the metaheuristics remain technically below the manual baseline, they reliably replicate the underlying expert-level agricultural logic. Furthermore, post-hoc pairwise comparisons revealed absolute performance parity between the GA and the MA across all primary metrics, including Yield, Fitness, Cost, and Nutrient Use Efficiency (NutUE). This indicates that both metaheuristics are equally capable of identifying near-optimal recommendations that align with established agricultural standards.

Economic and resource analysis revealed that the algorithms generated a "middle-ground" strategy particularly well-suited for small-scale farmers. By producing solutions with more conservative planting densities than the DA baseline, the GA and MA successfully reduced mean input costs. Although this resulted in a slightly lower gross margin, it offers a viable, lower-capital entry point for farmers operating under liquidity constraints. This balanced approach was also reflected in Nutrient Use Efficiency (NutUE), where the algorithms maintained stable efficiencies, providing a dependable alternative to the high-input, high-density strategies typically recommended by traditional expert methods.

Regarding computational performance and algorithm efficiency, the study identified a clear trade-off between execution speed and optimization efficiency. The Genetic Algorithm demonstrated a substantially faster raw runtime, whereas the Memetic Algorithm proved to be the more efficient optimizer within the evolutionary cycle. The MA required significantly fewer generations to converge and a lower number of Total Function Evaluations (TotalFE) to navigate the search space compared to the GA. While the slower raw runtime of the MA is attributed to the computational overhead of its local search phase, its superior convergence efficiency makes it a more efficient choice for complex resource optimization where precision and search-space navigation are prioritized over raw processing speed.

Finally, the implementation of the website prototype and subsequent user testing with 15 farmers confirmed the system's practical usability. The platform achieved an overall mean Post-Study System Usability Questionnaire (PSSUQ) score of 1.77 (where lower scores indicate higher satisfaction on a 7-point scale), placing it firmly within the "excellent" range. Interface Quality emerged as the strongest dimension (1.69), followed by System Usefulness (1.77) and Information Quality (1.78). The high degree of consistency in these scores even among participants with varying levels of technical literacy demonstrates that the prototype is an intuitive and robust decision-support tool, successfully bridging the gap between complex metaheuristic optimization and practical agricultural application.

The study successfully demonstrates that metaheuristic optimization, specifically through the integration of Genetic and Memetic Algorithms, provides a highly effective and accessible framework for corn resource optimization in Iloilo. Both the Genetic Algorithm (GA) and Memetic Algorithm (MA) were found to be effective at approximating the expert-derived Department of Agriculture (DA) baseline, which served as the performance ceiling for solution quality. Specifically, the GA and MA achieved mean outputs closely aligning with the DA’s ground truth while significantly reducing mean input costs. This identifies a critical "middle-ground" strategy that prioritizes economic sustainability and offers a viable, lower-capital entry point for small-scale farmers who operate under strict liquidity constraints.

While both algorithms showed statistical parity in terms of solution quality, the Memetic Algorithm emerged as the superior optimizer regarding search efficiency. The MA required significantly fewer generations and total function evaluations to reach stability compared to the standard GA. These findings align with rigorous theoretical frameworks established in relevant literatures, which provide formal proof that Memetic Algorithms can drastically outperform standard evolutionary components in multimodal optimization problems by effectively balancing global exploration with rapid local exploitation [48]. Such efficiency is also corroborated in other NP-hard combinatorial domains, like the cryptanalysis of Simplified Data Encryption Standard (SDES) problems, where Memetic Algorithms have been proven to perform better than classical Genetic Algorithms by utilizing local search techniques to reduce the likelihood of premature convergence [49]. Although the MA's local search phase introduced a minor computational overhead in raw runtime, this trade-off is justified by its ability to navigate the complex synergy between planting density and nutrient management more intensively. Finally, the practical viability of this approach is confirmed by the "excellent" usability score of 1.77 on the Post-Study System Usability Questionnaire (PSSUQ), proving the system is a functional tool that effectively supports agricultural decision-making for the farming community.

Recommendations

The researchers outlined necessary enhancements to further advance this prototype to be a production-ready solution. First and foremost, the researchers recommend the adoption of this system by small-scale and starting corn farmers in Iloilo Province as a foundational decision-support tool. However, it is vital to inform these beneficiaries that the current system is a prototype designed to provide "at-best" estimates. Because the model currently utilizes fixed input values, it does not reflect real-time fluctuations in market prices for fertilizers, seeds, or crop sales. Therefore, farmers should use the system’s outputs as a scientific baseline while manually adjusting for current local economic conditions to ensure financial accuracy.

On a broader scale, for the Agricultural Sector and Government to fully realize the benefits of this modernization, future research must shift from simulated environments to the use of actual field results. We recommend that local agricultural offices facilitate longitudinal studies across various microclimates to capture authentic agronomic responses. Grounding the optimization model in empirical field data, rather than purely mathematical simulations, will significantly enhance the practical trust and adoption rate among local farmers. This transition is essential for the system to evolve into a reliable tool for national food security and rural development initiatives.

Finally, for Researchers and Future System Developers, the optimization scope should be expanded to include high-resolution weather patterns, dynamic pest management, and automated irrigation. To achieve this, it is recommended to combine the Memetic Algorithm (MA) with Artificial Intelligence and Internet of Things (IoT) technologies. In this integrated architecture, IoT devices can provide real-time field data, allowing the MA to navigate the vast solution space with higher precision. From a computational perspective, further research should be directed toward refining the MA’s local search heuristics to mitigate computational overhead. By optimizing algorithmic efficiency and grounding the data in empirical results, this study serves as a vital first step toward a comprehensive system that empowers farmers to maximize productivity while maintaining sustainability.

Compliance with Ethical Standards

Purpose of the Survey. The primary purpose of the user testing survey is to evaluate the usability, interface design, and information quality of the developed corn yield optimization website prototype. The feedback will be used to assess whether the system's recommendations are clear, accessible, and practical for its intended end-users. This study utilizes 15 participants, surpassing the 10-user threshold identified as sufficient for capturing 90% of usability issues (Wang & Hu, 2021). Expected Duration of Participation. Each participant's involvement is expected to last approximately 20 to 30 minutes. This includes a brief orientation, hands-on interaction with the website prototype, and answering the Post-Study System Usability Questionnaire (PSSUQ).

Procedures to be Carried Out. During the user testing phase, participants will be invited to attend a short demonstration of the system to familiarize themselves with the website's layout and basic features. Following the orientation, they will engage in a hands-on session where they perform specific tasks using the prototype, such as inputting their farm area and budget to generate an optimized crop recommendation. Upon completing these tasks, participants will fill out the 16 item Post-Study System Usability Questionnaire (PSSUQ) to evaluate their experience with the system's usefulness, information quality, and interface. Finally, they will provide qualitative feedback specifically regarding the clarity and relevance of the agricultural recommendations, ensuring the algorithmic outputs are understandable for actual field application.

Participation. Participation is entirely voluntary. Participants have the right to decline participation or withdraw from the study at any time including during the survey without any penalty, loss of benefits, or impact on their standing within the Farmers Association. Inclusion Criteria. Participants must be active corn farmers of Tigbauan Farmers Association of Cordova Norte, must be able to read and write and also know how to use a phone to ensure the feedback is relevant to the specific agricultural models within the system. Exclusion Criteria. Farmers primarily focused on rice or vegetable production, individuals who are not members of the Tigbauan Farmers Association of Cordova Norte, those who cannot read and write, and those who are not actively farming corn are excluded from this specific testing phase to maintain the focus on corn-based decision-making and data. Risks. The study is classified as negligible or low risk to the participants, as the procedures involved do not exceed the risks encountered in daily life. There are no physical, legal, or economic risks associated with using the software prototype. To prevent any social or reputational risk, all feedback and survey responses will be strictly anonymized, ensuring that a participant's performance or opinions regarding the system cannot be traced back to them by the Farmers Association or other third parties. Benefits to the Participants. There are no monetary and non-monetary incentives that will be given to the participants of this study. However, participating in this study will help researchers identify the usability of the website prototype.

Benefits to the Local Community. This research contributes to the development of modern decision-support tools designed to enhance resource management for farmers in Western Visayas, while providing a foundational framework for future researchers to continue and expand upon this development.

Conflict of Interest. The researchers declare no financial or personal conflict of interest. The study is conducted purely for academic purposes and has not received funding from agricultural input suppliers or seed companies. Protection of Vulnerable Participants. The researchers recognize that some participants may have varying levels of digital literacy. To protect these individuals, the study will be conducted in a supportive, non-judgmental manner. Sharing of Study Results. Study findings will be disseminated through both formal academic channels and direct community engagement. A non-technical executive summary of the PSSUQ results and optimized strategies will be presented to the Tigbauan Farmers Association, while the complete thesis will be archived at the University of San Agustin Library and its digital repository. Furthermore, results may be submitted to relevant agricultural and CS conferences, with source code archived on GitHub to ensure transparency and promote future research in agricultural informatics.

Confidentiality, Anonymity, and Privacy. All PSSUQ data will be fully anonymized, ensuring no personal identifiers are linked to individual responses. To protect participant privacy, data will be stored in a secure, password-protected environment accessible only to the primary researchers. This anonymized dataset will be maintained as a permanent record for academic verification and future research, with all findings reported in aggregate form to prevent individual identification.

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Corresponding author: *jgarcera@usa.edu.ph*