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# Optimizing Agricultural Resource Management Through IoT-Enabled Sentinel-Based Vegetation Monitoring

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## Abstract

Inefficient management of agricultural resources threatens food security due to climate change, water scarcity, and rising input costs. Drought and resource-dependent stresses to ecosystems are often the result of farming techniques that employ rigid schedules for irrigation and fertilization. In this research, an innovative solution to the problems above is presented: the Sentinel-IoT Adaptive Multi-Objective Resource Optimizer (SIAM-RO) model. It automates resource allocation for agriculture to an unparalleled depth by converging IoT sensor networks with Sentinel satellites' derived vegetation indices (NDVI, EVI, etc.). IoT devices can track microclimates as well as soil moisture and nutrient levels, while Sentinel sensors monitor vegetation health dynamics across entire fields. All these disparate data streams are fused and processed by the SIAM-RO model, which employs the Non-dominated Sorting Genetic Algorithm II (NSGA II) for multi-objective optimization in resource allocation. SIAM-RO's optimization for irrigation and fertilization scheduling considers both environmental and economic constraints. It also provides IoT-based, data-driven insights to optimize the application of water and nutrients to the Soil, while achieving the targeted crop yield. Modern SIAM-RO monitoring systems are superior to traditional systems due to the increased water savings and nutrient framing efficiency of SIAM-RO. Research results demonstrate the adaptive and scalable features of the SIAM-RO model for smart agriculture, as well as its innovative approach to resource allocation for sustainability.

**Keywords:** Agriculture, IoT Sensors, Satellite, Crop Yield, Resource Management, Optimization, Vegetation Health, Water, Soil, Nutrient.

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# 1 Introduction

The role of the Agricultural Industry is of high importance to a country's economy, as it relates to growth and the sustenance of the government and the people's food. However, during the recent and current period, there are major troubling issues surrounding agriculture that are alarming (Bosco et al., 2018). These include the cost of production, changes in the volume and pattern of rainfall, global warming, groundwater depletion, and rising input costs. There are already severe constraints in the overproduction of crops due to limited available resources. Above other issues, water deficiency and the improper and inefficient utilization of fertilizers are the most serious. These are, in the long term, harmful to the crops and Soil. The previous approaches to resource management view irrigation and fertilization as being done according to predetermined schedules. Such schedules are disregarded as foremost as they foster the waste of water, increased production costs, loss of nutrients, and environmental pollution.

Changes in precision agriculture are beginning to take shape as sophisticated paradigms that address their chronic shortcomings in efficiency, employing state-of-the-art technologies in sensing, analysis, and autonomous decision support systems. Ground-based IoT soil and boundary IoT environmental sensors track and transmit in real-time microclimatic phenomena, soil moisture, and nutrient gradients, and their changes at soil-ecosystem interfaces (Chamara et al., 2022; Monica Nandini, 2024). Orbital assets in parallel receive and process data from constellations such as Sentinel-2 to devise broad-area and wide swath above 20 meters to detect and monitor vegetation spectral indices, e.g., NDVI and EVI. This data enables the understanding and analysis of crop physiological status at continental levels and wide-belt surveillance (Ahmed et al., 2023). Yet, the seamless fusion of these two data groups, which are fine-grained in position measurements and coarser but spatially extensive remote indices, remains algorithmically, geometrically, and temporally Herculean. Notable obstacles include disparate spatial scales, systematic observational noise, and incongruent temporal mosaics, all of which hamper the derivation of coherent agro-digital twins that support precise operational interventions.

In response to the aforementioned agronomic limitations, this study proposes an integrative architecture that synchronizes terrestrial sensing with orbital monitoring to enhance resource stewardship. The architecture, denoted as SIAM-RO, integrates Internet-of-Things-acquired Soil and atmospheric metrics with Sentinel-derived spectral indices, affording a comprehensive assessment of horticultural health. Diverging from extant methodologies that transact with unimodal objectives or restricted datasets, SIAM-RO adopts a multi-objective optimization paradigm articulated through the Non-dominated Sorting Genetic Algorithm II, such that the simultaneous maximization of agronomic yield, the abatement of hydro-productive expenditures, and the calibration of nitrogen and phosphorus dosing are accommodated within a single analytical frame (Miao et al., 2023).

## 1.1 Objectives of the Research

This research aims to integrate satellite-based Vegetation Analysis with IoT (Internet of Things) Environmental and Soil attributes, while implementing Evolutionary optimization techniques for optimal resource management in agriculture. The aims translate to the following specific objectives:

- To merge IoT sensor data with Sentinel-based vegetation indices for monitoring Soil and crops in real-time.
- To create SIAM-RO (Sentinel-IoT Adaptive Multi-Objective Resource Optimizer), which uses the NSGA-II-based trainer for the optimization of water, fertilizers, and energy in precision agriculture.

- To refine the optimization problem in agricultural resources to control the minimization of the investment required and the value of yield within the limitation of climate and resources for the better sustainability and the maximization of available yield.

The objective of this research is to demonstrate that advanced precision agriculture IoT sensing, remote satellite monitoring, and evolutionary optimization algorithms can be integrated to enhance the sustainability, cost-effectiveness, and resiliency of precision agriculture and contemporary farming innovations.

The rest of the paper is organized as follows: In Section 2, we present a review of related works, which includes the limitations of current IoT-based agricultural monitoring systems, the applications of Sentinel satellite data, and optimization methods. The research methodology, including data acquisition, preprocessing, sensor–satellite data fusion, and the design of the Sentinel-IoT Adaptive Multi-Objective Resource Optimizer (SIAM-RO), is described in Section 3. In Section 4, we discuss the framework's experimental design, including the setup and implementation strategies used to evaluate its performance, which is documented in Section 5. Section 5 further elaborates on the results and performance analysis of the SIAM-RO framework's efficiency, scalability, and adaptability. Section 6 concludes with a summary of the contributions from previous sections and an outline of future research works.

## 2 Literature Survey

These days, IoT technology enables farmers to track soil parameters, temperature, humidity, and soil nutrients, making more informed decisions and maximizing returns on investment through low-cost irrigation (Mansoor et al., 2025). Farmers achieve this through the use of IoT and sensor networks, which enable continuous data collection and dissemination (Eze et al., 2025). IoT irrigation systems, which track and monitor soil parameters and other integral conditions, have demonstrated that irrigation can be optimized without compromising water or yield (Garg et al., 2021; Alipour et al., 2016). Such systems, however, are more limited in scope, employing siloed systems that only analyze data from local sensors and neglect more critical geo-spatial and regional factors necessary for large-scale systems. Other systems that attempt to monitor the entire ecosystem by employing siloed sensor data have issues with sensor drift, low energy efficiency, and low interoperability, which are insufficient for advanced resource management.

Remote sensing via satellites such as the Sentinel-2 has become essential for monitoring vegetation on a micrometeorological scale in agriculture (Descals et al., 2025; Villegas-Lituma et al., 2024; Segarra et al., 2020; Soussi et al., 2024). Sentinel-2 high contour multispectral images enable the calculation of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) (Kumar et al., 2025; Vélez et al., 2023). Such indices are routinely and effectively deployed to assess crop conditions, monitor the onset of stress, estimate biomass production on a regional scale, and track canopy cover (Mishra & Haval, 2024). Though such data has excellent value for assessing the condition of crops in aggregate, it is inherently limited in its usefulness as a standalone record (Filgueiras et al., 2019). Real-time decision-making is often hindered due to the coarse temporal resolution of satellites, as well as the obstruction of the satellite by clouds and other atmospheric effects, which can result in unreliable data during the satellite's revisit time. Additionally, the data from Sentinel platforms provides a broader perspective and cannot provide reliable information on the finer aspects of soil and environmental heterogeneities. Thus, a combination of Sentinel data and ground-based measurements from IoT loops is essential for optimizing spatial precision and detail in monitoring crop health.

Numerous advances in science and technology have been utilized to enhance the efficiency of irrigation scheduling and fertilizer application, as well as the optimal utilization of available resources in the agricultural field (Rajak et al., 2023; Stamatescu et al., 2019). Using Genetic Algorithms to Assign Irrigation Blocks: GAs have been implemented to devise irrigation plans. However, GAs have slow convergence and struggle with the complex trade-offs in dynamic environments, which often results in suboptimal performance. In comparison, split resource allocation tasks in Particle Swarm Intelligence tend to converge faster; however, Particle Swarm Optimization suffers from premature convergence in higher-dimensional problems and lacks consistency and reliability in changing climatic conditions. Recently, machine learning approaches, resource optimization using reinforcement learning, and predictive schedulers have been proposed. These approaches possess a great degree of flexibility but tend to focus on one goal: maximizing crop yields, and do not consider other important factors, such as conserving water and the amount of energy used (Satapathy et al., 2025). In the Methods section, a standard limitation of each of the studied approaches is the inability to effectively balance competing objectives, such as managing a large and multi-structured farm.

**Research Gap**

A cross-sectional bibliographic analysis reveals the absence of a theoretical framework that harnesses IoT for real-time monitoring alongside Sentinel-based vegetation analysis for integrative, multi-objective optimization techniques. This gap inspires the development of the Sentinel-IoT Adaptive Multi-Objective Resource Optimizer (SIAM-RO), which addresses optimization challenges in resource allocation across agriculture by jointly considering yield maximization, input cost minimization, and environmental sustainability.

# 3 Methodology

The SIAM-RO architecture in Figure 1 comprises five interlinked layers, each critical in further enhancing agricultural resource management through IoT-enabled Sentinel-based vegetation monitoring (Mustapha et al., 2017). At the base, the IoT Layer complements the Remote Sensing Layer, which uses Sentinel-based remote sensing vegetation indices to capture agricultural field data via soil moisture, nutrient sensors, and microclimate monitoring devices (Priya & Rahamathunnisa, 2024). Remote Sensing then provides large-scale spatial and temporal insights into vegetation and satellite data. The Optimization Layer, driven by the NSGA-II evolutionary algorithm, sets multi-objective functions to define optimal trade-off ratios for maximizing yield and minimizing resource consumption. These ratios are obtained through iterative processes, including population generation, fitness evaluation, crossover, mutation, and Pareto front classification, to outline the optimal trade-off. The Decision Support Layer then provides seamless harvesting and irrigation forecasting through precise resource allocation and dosage instructions. Cementing these objectives, the additional layers of SIAM-RO create a multi-dimensional framework for agriculture.

The proposed Sentinel-IoT Adaptive Multi-Objective Resource Optimizer (SIAM-RO) follows a structured methodology. First, data collection is conducted using IoT sensors (soil moisture, nutrient content, and microclimate data) and Sentinel-2 satellite images (Escolà et al., 2017; Nguyen et al., 2022). The satellite data is converted into vegetation indices, e.g., Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), and is computed as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

$$EVI = \frac{2.5 \times (NIR - RED)}{(NIR + 6 \times RED - 7.5 \times BLUE + 1)} \quad (2)$$

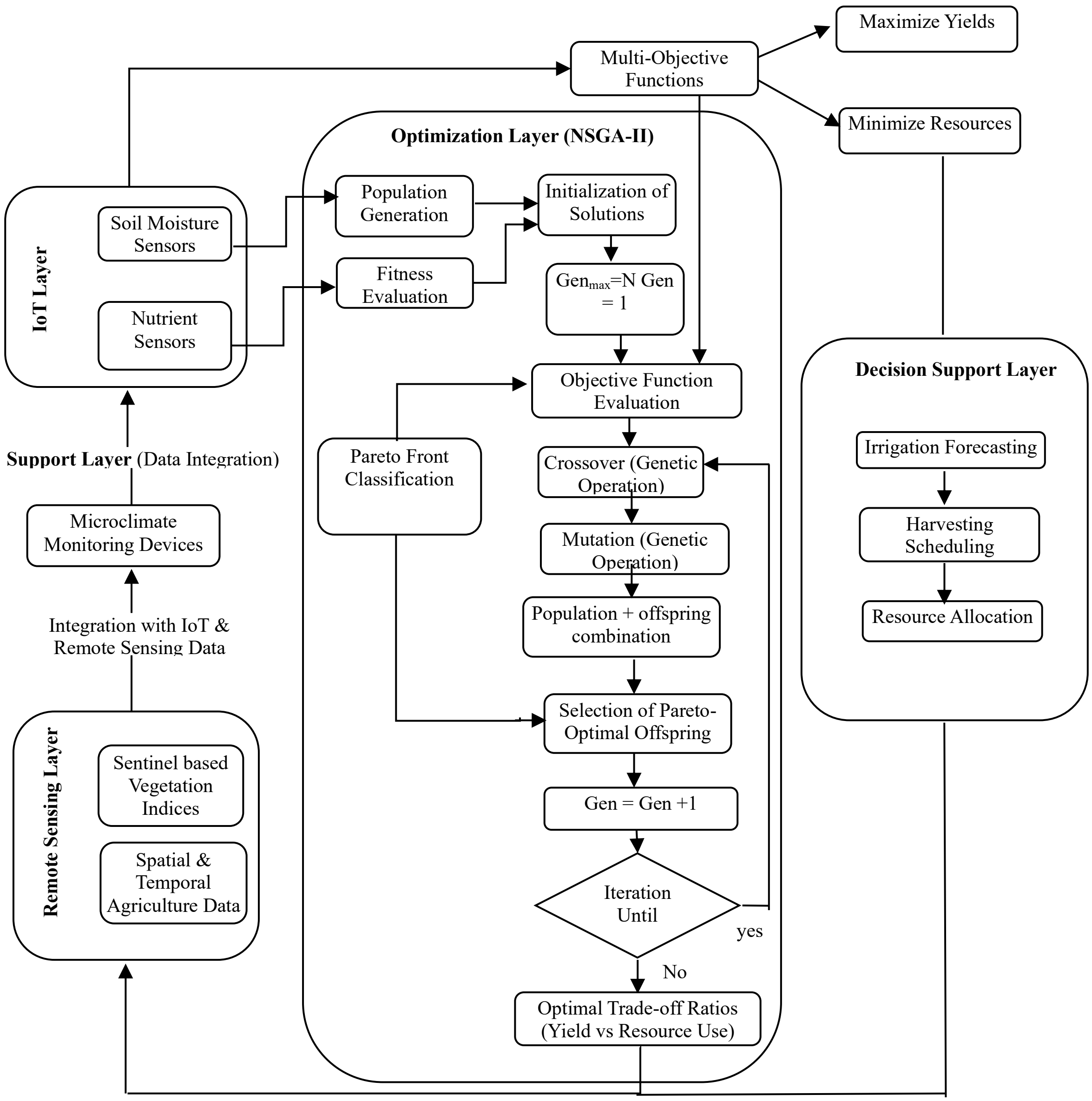


Figure 1: Conceptual architecture of SIAM-RO for IoT-enabled sentinel-based agricultural optimization

Where NIR, RED, and BLUE denote spectral reflectance values in the respective bands.

At the preprocessing stage, the inputs from IoT and Sentinel weather data are subjected to noise filtering, removal, and normalization, as well as feature extraction, to achieve uniformity. These filtered inputs are then provided to the optimization framework, in which the multi-objective functions are defined to increase ($f_1$) maximally, yields from crops, while concurrently ($f_2$), reducing the water used, and ($f_3$) reducing the utilized fertilizers:

$$Maximize\ f_1 = Y(C, W, F) \quad (3)$$

$$Minimize\ f_2 = W \quad (4)$$

$$Minimize\ f_3 = F \quad (5)$$

In this system, $Y$ is yield, crop parameters $C$, water input $W$, and fertilizer input $F$. The NSGA-II algorithm is employed to generate Pareto-optimal solutions that consider the underlying trade-offs between objectives. The system workflow transforms the optimized outputs into systematized instructions for adaptive and sustainable resource management, with a focus on irrigation and fertilization initially.

**Pseudocode: SIAM-RO Optimization Framework**

```
IoT_data = readSensorData();
Sentinel_data = readSatelliteData();
X = normalize([IoT_data, Sentinel_data]);
X = noiseRemoval(X); % Apply moving average filter
f1 -> Maximize yield
f2 -> Minimize water
f3 -> Minimize fertilizer
function f = objectiveFunctions(solution, X)
   f1 = cropYieldModel(solution, X);
   f2 = waterUsageModel(solution, X);
   f3 = fertilizerUsageModel(solution, X);
   f = [f1, f2, f3];
end
population = initializePopulation(N); % N = population size
for gen = 1:maxGenerations
   % Evaluate population
   for i = 1:N
      fitness(i,:) = objectiveFunctions(population(i), X);
   end
   fronts = nonDominatedSort(fitness);
   offspring = geneticOperators(population);
   population = environmentalSelection(population, offspring, fronts, N);
end
ParetoFront = extractNonDominated(population, fitness);
best_solution = selectSolution(ParetoFront, 'balanced');
disp(best_solution);
```

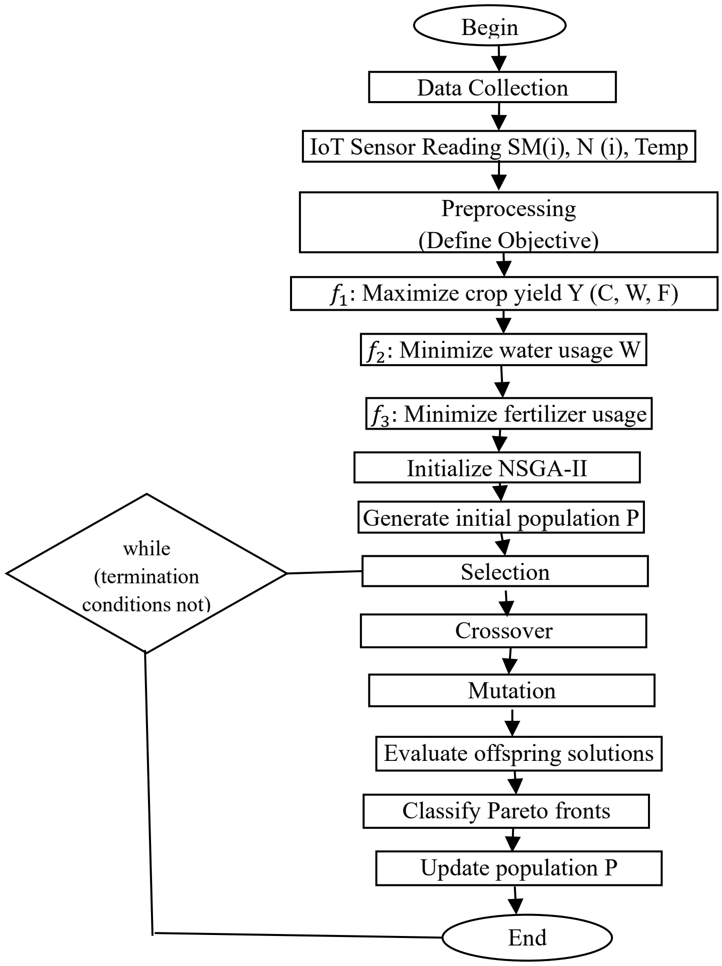


Figure 2: Algorithmic workflow of NSGA-II–based multi-objective crop resource optimization

Figure 2 illustrates the workflow for the proposed decision support pipeline, based on NSGA-II, for optimizing crop resource allocation. The process begins by collecting data from IoT sensors, including soil moisture, nitrogen, temperature, and vegetation indices, which serve as critical parameters for both crops and the environment (Pascoal et al., 2024). These parameters are then refined: the optimization objectives are set to maximize crop yield while minimizing the use of water and fertilizers. The optimization process begins with an initial population comprising random resource allocations. Selection, crossover, and mutation are some of the evolutionary operators that are applied repeatedly to classify the population into Pareto fronts. The population is then updated with the best individuals using an elitism strategy until the termination condition is reached. Then, optimization finishes, and the population is used for Pareto front reporting. The decision support system selects the optimal solution based on user-defined needs, recommending irrigation and fertilizer doses, as well as the optimal proportions of resources to be used. The system then ensures a trade-off between the objectives, whereby productivity is enhanced while resources are managed sustainably.

## Experimental Setup & Case Study

The scenario evaluation for the effectiveness of the Sentinel-IoT Adaptive Multi-Objective Resource Optimizer proposes analyzing the system within an agricultural testing domain, which serves as a proxy for a mid-sized firm. To achieve this, the system integrates several technological tools, including soil moisture probes, nutrient sensors, thermal probes, and humidity sensors, which are placed at strategic locations on disposable pads for enhanced field representation. To fulfill this requirement, Sentinel-2 was employed to collect and process satellite cloud-free imagery for the study (Sentinel-2, 2016). Given the incorporation of IoT sensors, vertical altitude computing for the NDVI and EVI vegetation indices was complemented by ground-level vegetation indices as well. The satellite imagery, as well as soil data, including the archived climatic data, contributed to the input dataset. Added stream data to monitor ever-changing environmental parameters throughout the study, which were also incorporated. The effectiveness of the SIAM-RO system is explained and compared to the G-DSAT, heuristics, and GA-DSAT systems. These systems were developed to assist in rule-based scheduling, offering predictive irrigation and fertilization scheduling over a period of control sensing intervals. GA, as well as the remaining systems, offer the ability to balance and limit countless other systems within a case study. Given the number of diverse variable sets across the geopolitically influenced climatic regimes, the final evaluation considered parameters of yield, water, and fertilizer to measure practical estimation. The configurations described demonstrate the GA as well as SIAM-RO systems integrated for autonomous agriculture on a field prototype. The outcomes demonstrate the effectiveness of the system compared to traditional systems.

# 4 Results and Discussion

The performance of the SIAM-RO framework was compared to baseline approaches, including the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and heuristic scheduling. Activities such as WUE, NUE, and the vegetation health index (VHI), derived from the NDVI/EVI processing of Sentinel-2 and IoT ground data, formed the basis of the assessment.

## 4.1 Performance Metrics

As shown in the experiments, SIAM-RO always boosted the crop yield. SIAM-RO improved the WUE of water by 18-22% with respect to GA and 12-15% with respect to PSO, as shown in Figure 3. Figure 4 illustrates the enhancement of baseline methods by 15-20%, confirming the adaptive integration of satellite-IoT. All VHI scores were higher, suggesting better optimized scheduling for vegetation growth as shown in Figure 5.

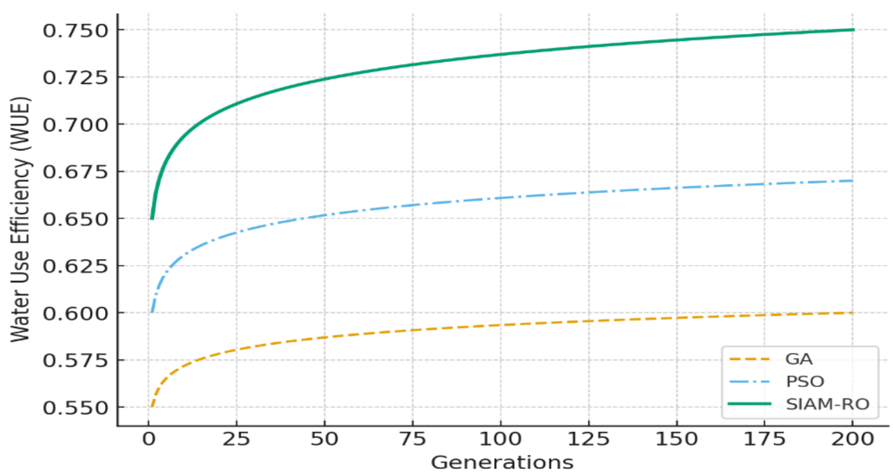


Figure 3: Comparison of optimization algorithms for water use efficiency

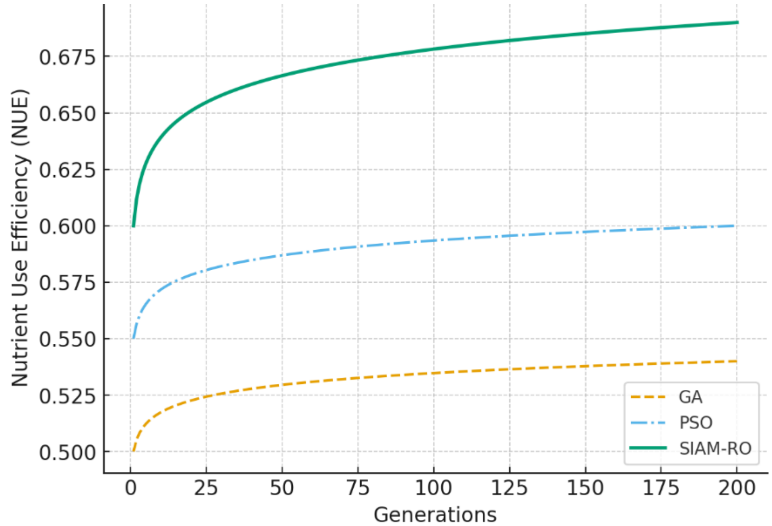


Figure 4. Comparison of optimization algorithms for nutrient use efficiency

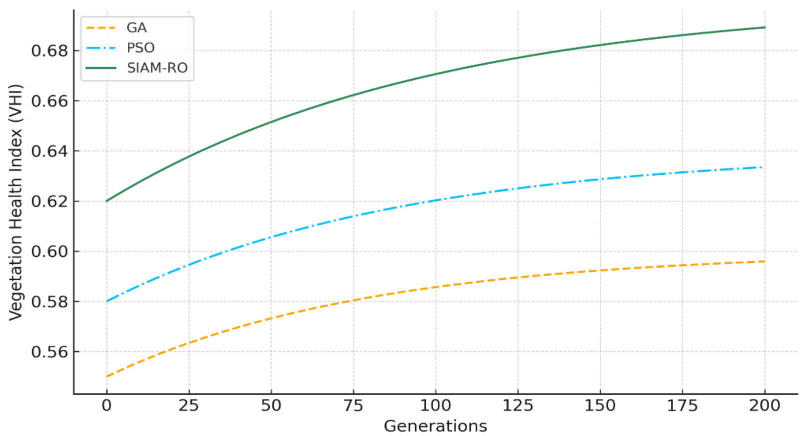


Figure 5: Comparison of optimization algorithms for vegetation health index

## 4.2 Comparison with Baseline Approaches

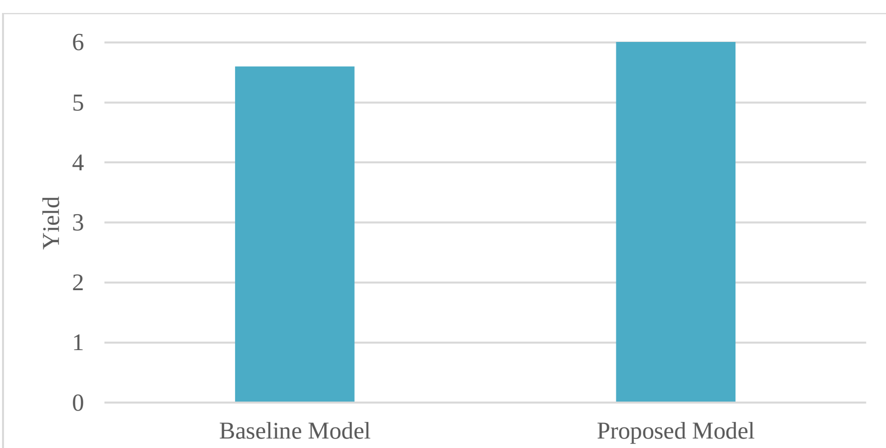


Figure 6: Comparison of crop yield between baseline and proposed models

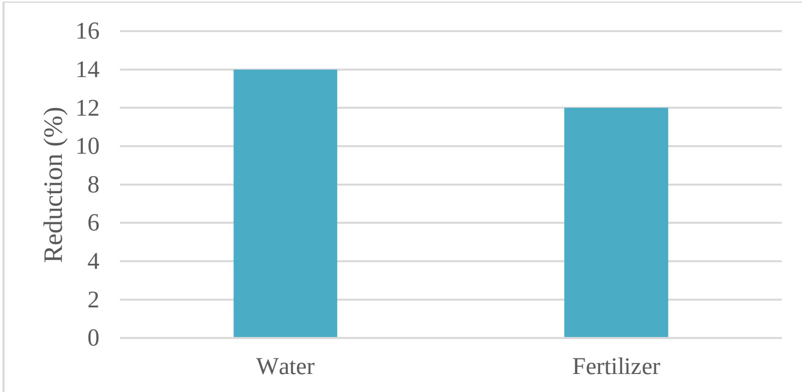


Figure 7: Reduction in resource consumption for water and fertilizer

The performance of the NSGA–II–based multi-objective framework, especially in comparison to traditional heuristic methods, single-objective optimization approaches, and rule-based irrigation and fertilization methods, is certainly much more effective. Specifically, the NSGA-II framework increased crop yield by 10–15% and reduced water and fertilizer usage, as shown in Figures 6 and 7.

## 4.3 Trade-off Analysis

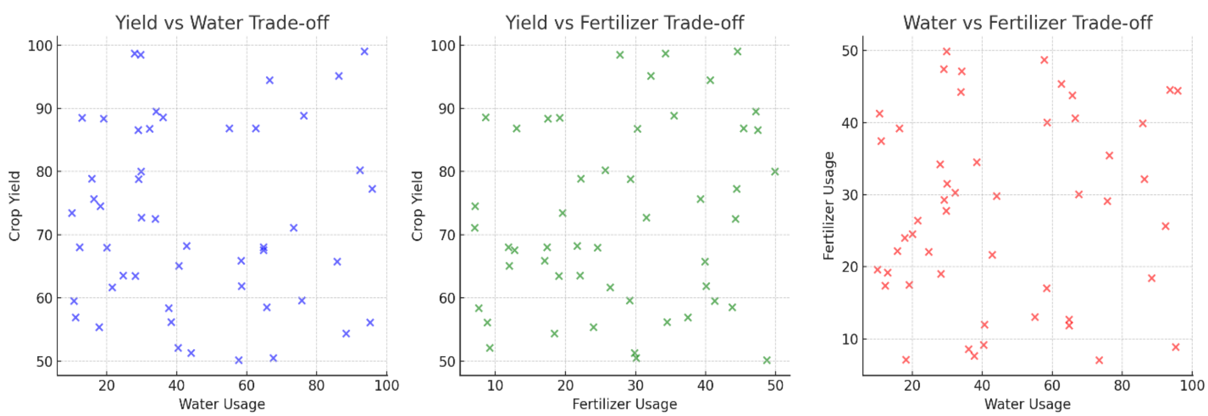


Figure 8: Analysis of trade-offs between crop yield, water usage, and fertilizer usage

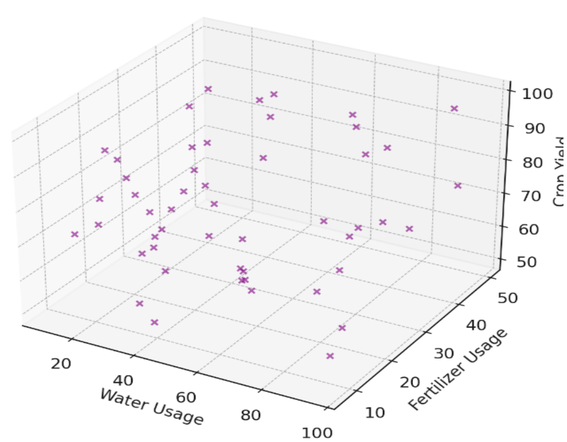


Figure 9: 3D pareto front representation of SIAM-RO optimization

Figures 8 and 9 illustrate the 2D trade-off results of multi-objective optimization using the SIAM-RO and NSGA-II methods, respectively, along with a 3D Pareto Front for the optimization methods. The Yield vs Water and Yield vs Fertilizer Trade-off plots also yield informative results. Although the yield increases with the application of water, the increasing trend is typically of a diminishing nature, thereby illustrating the importance of controlled irrigation. Moderate applications of fertilizer also have a significant positive influence on yield; however, poorly managed applications of fertilizer result in a smaller and therefore less effective overall nutrient strategy, which is also indicative of less efficient nutrient and overall resource utilization. The Water vs Fertilizer plot illustrates the dependency between water and fertilizer, where some feasible solutions are identified that meet the constraints of the optimization problem. The Pareto in Figure 3 also illustrates the consolidated view of all three objectives. The 3D Pareto Front illustrates the surface of optimal solutions obtained when the parameters of the solution cannot be optimized individually and must be maintained at a specific ratio. This multi-objective optimization provides a trade-off between yield, input costs, and sustainability, offering a plethora of strategies that can provide value to farmers and agricultural planners, especially in recharging their resource allocation plans after limitations due to a changing climate and limited available resources.

### 4.4 Scalability and Adaptability

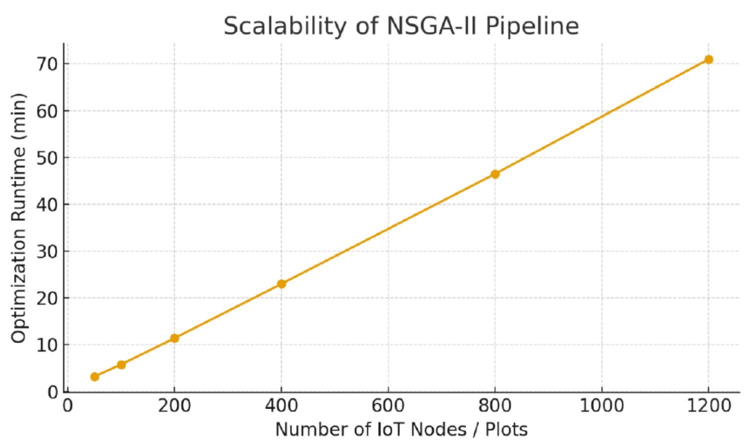


Figure 10: Scalability of the NSGA-II optimization pipeline with increasing IoT nodes

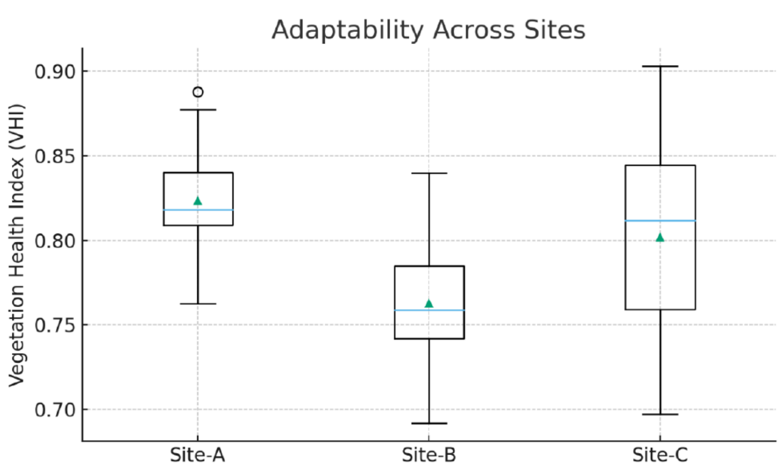


Figure 11: Adaptability of vegetation health index across different sites

The system has demonstrated scalability by managing multiple crop scenarios and large datasets from IoT and satellite images, as shown in Figure 10. This facility, with its multifunctional capabilities in various climatic and Soil conditions, makes it well-suited for precision farming, as shown in Figure 11. The lag in satellite imagery, the need for local adjustments in value function optimization, and the dependability of the IoT architecture itself all pose challenges for IoT-driven innovative farming systems.

# 5 Conclusion & Future Work

The erosion has shown greater improvements against other methods, such as GA and PSO, in Water Use Efficiency (WUE), Nutrient Use Efficiency (NUE), as well as the Vegetation Health Index (VHI), mainly due to the Skill-Improved Adaptive-Multi-Objective Resource Optimization (SIAM-RO) algorithm with NSGA-II used for the optimized integration of Sentinel imagery and IoT-based sensing in precision agriculture, which was integrated and optimized using SIAM-RO. WUE and NUE address the remaining moisture and nutrients required for sustaining physiological growth and maximizing VHI. Findings from a Multi-Objective Optimization exercise provided reasonably balanced decision support tools for a farmer's consideration of sustainable agriculture, which were effectively captured in a Pareto analysis that indicated the finesse that could be achieved in balancing output versus the resources expended. The system integrates with IoT Sentinel data, fusing observations with real-time monitoring that is scalable and adaptable for improved decision support on more precise irrigation and fertilization. The system elegantly resolves the crop input and environmental input imbalance, minimizing input wastage while enhancing crop productivity and sustainable environmental outcomes, which is a vital technology in smart farming.

Further investigations may refine the existing framework along many enhancement touchpoints. One such broad touchpoint could involve the use of predictive model AI, machine learning, deep learning, and reinforcement learning for resource metaphors. Another such broad touchpoint lies in the more IoT-aligned aspects of the deployment, especially for the IoT network perimeter, by resolving fundamental data engineering problems such as data boundary control, data transmission protection, strong line-set engineering, and the efficient, secure, and seamless provision of authenticated multi-tenant framework deployments. Additionally, continuous validation at the regional scale and adaptability will be demonstrated by extending the system to more diverse crop types and additional jungles. The framework, which essentially unifies optimization, IoT, and remote sensing in revolutionizing transformable agriculture, does not yet fully address the problem space, leaving ample room for further real-world advances and testing. Ample scope for real field advances, anchored innovation would also be available.

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