AI-Based Predictive Agrometeorological Modeling for Climate-Smart Fertilization Optimization to Enhance Yield and Nutrient Use Efficiency in Oil Palm

Hendri Winata[1], Andrian Agustin Sitanggang[2]
[1,2]Department Computer and Engineering, Informatic and Technique Faculty, University of Science and Technology of Indonesia

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ABSTRACT

Climate variability poses significant challenges to fertilizer management in oil palm (*Elaeis guineensis*) production systems, where conventional calendar-based applications often fail to account for dynamic agroclimatic conditions. This study proposes an AI-based predictive agrometeorological modeling framework integrated with a multi-objective fertilization optimization engine to enhance yield and nutrient use efficiency (NUE) under a climate-smart agriculture paradigm. Multi-source datasets comprising agrometeorological variables, soil properties, and historical yield records were processed using nonlinear time-series learning models to forecast short- to medium-term climate and soil moisture dynamics. The predictive outputs were subsequently integrated into a multi-objective optimization module designed to maximize yield and NUE while minimizing nutrient loss risks associated with high rainfall events. Experimental evaluation using a randomized block design demonstrated statistically significant improvements compared to conventional fertilization practices. The AI-based system increased fresh fruit bunch yield by 13.47% ($p < 0.001$) and improved NUE by 21.98% ($p < 0.0001$), while reducing fertilizer input by 6–8%. Effect size analysis indicated substantial practical impact (Cohen's $d > 1.8$). These findings confirm that integrating predictive agroclimatic intelligence with adaptive fertilization optimization enhances productivity and resource efficiency simultaneously. The proposed framework contributes to advancing decision intelligence in perennial crop systems and provides an operational pathway toward climate-resilient and sustainable oil palm production.

Corresponding Author:

Hendri Winata
Department Computer and Engineering, Informatic and Technique Faculty, University of Science and Technology of Indonesia
Km. 10 Panam, Sialangmunggu, Tuah Madani, Riau, Indonesia
Email: hendrijex@gmail.com

1. INTRODUCTION

Oil palm (*Elaeis guineensis*) is [1] a globally strategic commodity that plays a crucial role in [2] food security, the oleochemical industry, and bioenergy production. As the world's leading producer, Indonesia faces significant challenges in sustaining productivity while simultaneously meeting increasing demands for environmental sustainability and resource-use efficiency. One of the key determinants of both productivity and sustainability in oil palm production systems is fertilizer management that is responsive and adaptive to climatic dynamics and site-specific agroecosystem conditions.

Conventional fertilization practices in oil palm plantations largely rely on fixed schedules and generic recommendations, which often fail to account for spatial and temporal variability in rainfall, temperature, soil moisture, and nutrient availability at the field level. Such static approaches may result in inefficient fertilizer utilization, increased nutrient losses through leaching and volatilization, and consequently low nutrient use efficiency (NUE). In the context of climate change—characterized by increasingly erratic rainfall patterns and more frequent extreme weather events—static fertilization strategies are becoming progressively less effective and less sustainable.

The concept of Climate-Smart Agriculture (CSA) emphasizes production systems that enhance productivity, strengthen resilience to climate variability, and reduce environmental impacts. Within this framework, integrating agrometeorological data with Artificial Intelligence (AI) offers substantial potential to develop predictive models capable of optimizing fertilizer timing, dosage, and application strategies adaptively. AI-based predictive models are particularly effective in capturing complex nonlinear interactions among weather variables, soil conditions, and crop responses to fertilization—relationships that are often difficult to represent using conventional statistical approaches.

Advancements in sensor technologies, automated agrometeorological stations, and Internet of Things (IoT)-based data acquisition systems have enabled real-time, high-resolution environmental monitoring. However, the primary challenge lies in transforming these large-scale data streams into operational, evidence-based fertilization recommendations. To date, a significant research gap persists in the integration of AI-driven predictive agrometeorological models that explicitly link climate variables with fertilization optimization to enhance yield and nutrient use efficiency in oil palm production systems.

Accordingly, this study aims to develop an AI-based predictive agrometeorological model to support climate-smart fertilization optimization in oil palm production systems. The proposed model is designed to (1) predict agroclimatic conditions relevant to nutrient dynamics, (2) optimize fertilizer timing and dosage adaptively, and (3) enhance both productivity and nutrient use efficiency (NUE). Through this integrative approach, the study contributes theoretically to the advancement of agroclimate–AI modeling frameworks and practically to the development of a more precise, adaptive, and sustainable fertilization decision-support system.

In recent years, nutrient management has shifted from blanket recommendations toward site-specific fertilization informed by soil data, weather conditions, and crop responses. Empirical studies indicate that machine learning (ML)-based fertilizer recommendation systems can improve both input efficiency and yield performance compared to generic approaches. Nevertheless, the literature also highlights critical limitations: fertilizer recommendation models remain highly dependent on high-quality yield-response datasets and robust experimental designs, making cross-location generalization a persistent challenge.

Predictive agrometeorology, particularly rainfall and temperature forecasting, increasingly employs deep learning time-series models to capture nonlinearities and seasonal dynamics—features essential for adaptive fertilization decisions, such as avoiding nutrient application prior to high rainfall events that increase leaching risks. At the systems level, multi-source integration—including IoT sensors, satellite and UAV imagery, and meteorological forecasts—is emerging as a foundation for data fusion in precision agriculture decision-making.

In oil palm systems specifically, ML-based studies have demonstrated that weather variables combined with [3] soil moisture data can produce explainable and reusable yield prediction pipelines. Furthermore, comprehensive evaluations of multiple ML and deep learning models using agronomic datasets (soil, climate, crop age, and management practices) underscore that dataset quality and completeness critically determine predictive performance and decision reliability [4]. Regarding nutrient status assessment, proximal and remote sensing approaches—such as multispectral imaging—have shown promise in estimating oil palm leaf nutrient status, thereby creating opportunities to integrate nutrient diagnostics with precision fertilization strategies, including localized studies utilizing multispectral vegetation indices. Moreover, IoT and ML-based frameworks are increasingly being developed as decision support systems for sustainable oil palm management, although climate-integrated fertilization optimization modules remain underexplored.

Recent studies indicate a paradigm shift from mere "prediction" toward decision-oriented optimization frameworks. In nitrogen management, research has increasingly focused on estimating the economic optimal nitrogen rate (EONR) using machine learning (ML) models derived from on-farm precision experimentation, serving as a bridge toward economically optimal and environmentally efficient fertilizer recommendations. Concurrently, reinforcement learning (RL) has begun to be explored for adaptive fertilization policies. Emerging evidence suggests that RL can be structured using reward functions that explicitly target nutrient use efficiency (NUE), rather than yield alone, although cross-soil generalization remains a critical research challenge.

Meanwhile, the measurement and modeling of NUE and nitrogen status using remote sensing combined with ML in food crops provide a strong methodological reference for transferring. Such approaches to oil palm systems, [5] particularly in terms of feature engineering, evaluation metrics, and [6] field validation strategies.

Recent Q1 trends emphasize end-to-end systems that integrate monitoring, dynamic time-series modeling, and fertilization decision modules. A representative example includes UAV- and GIS-based systems incorporating dynamic modeling and [7] continuous learning mechanisms for precision fertilizer recommendation. In fertigation management, ML has also been applied to predict fertilizer components and concentrations from easily measurable physical parameters such as electrical conductivity (EC), pH, and temperature, supporting sensor-based recommendation systems. Furthermore, comprehensive reviews highlight that AI-driven soil moisture prediction constitutes a critical component of adaptive fertilization decision-making [8], [9], given the strong influence of soil moisture on nutrient uptake and nutrient loss risks.

Numerous prior studies have developed agrometeorology-based predictive models to [10], [11] [12], [13] support crop management decisions, including yield forecasting, irrigation scheduling, and crop response to fertilization. These studies generally employ conventional statistical methods or machine learning approaches to model the relationships between climatic variables and crop productivity. In contrast, research on oil palm fertilization optimization has predominantly focused on long-term agronomic field trials, resulting in [14], [15] relatively static fertilizer dosage recommendations based on historical averages.

Despite significant advances in the application of artificial intelligence in agriculture, most studies still treat (1) agroclimatic prediction models and (2) fertilization recommendation systems as separate domains. The integration of both into a unified predictive framework that [16] explicitly optimizes fertilization strategies based on climatic dynamics remains limited, particularly in oil palm production systems. Moreover, many existing models do not explicitly link optimization outputs to improvements in nutrient use efficiency (NUE) and productivity performance within the climate-smart agriculture framework.

Another research gap lies in the limited development of models capable of capturing complex nonlinear interactions between agrometeorological variability, such as rainfall, temperature, humidity, solar radiation, and soil moisture and [17], [18] nutrient demand dynamics throughout the oil palm production cycle. Many approaches still rely on linear regression or simplified time-series models that do not fully leverage AI's capacity to extract both temporal and spatial patterns simultaneously. Additionally, most existing studies remain analytical or experimentally constrained and have not been operationalized into scalable optimization models suitable for deployment as decision support systems in commercial production contexts.

In the context of climate change [19], [20] and increasing pressure toward environmental sustainability [21], [22], few studies have comprehensively integrated AI-based agroclimatic prediction with fertilization optimization aimed at simultaneously enhancing yield and nutrient use efficiency. Consequently, a substantial gap remains in the development of integrative models capable of linking real-time agrometeorological data, predictive agroclimatic intelligence, and adaptive fertilization recommendations through multi-objective optimization.

This study introduces several key novelties compared to prior research. Unlike earlier approaches that separate climate prediction models from fertilization recommendation systems, this research develops an integrated AI framework that directly connects predictive agrometeorological outputs with a dual-objective fertilization optimization module. The proposed model does not solely aim to maximize yield but simultaneously optimizes nutrient use efficiency (NUE), thereby aligning with the core principles of climate-smart agriculture, which emphasize productivity, adaptation, and environmental sustainability concurrently.

By leveraging AI's capacity to [23] model nonlinear relationships and [24] temporal dynamics between agrometeorological variables and crop nutrient requirements, the system generates adaptive fertilization recommendations responsive to intra- and inter-seasonal climate variability. Beyond experimental analysis, this research advances toward the development of [25] an operational decision support framework for fertilization optimization in oil palm production systems. Through the integration of climate prediction and [26] fertilization optimization, the study provides empirical evidence for simultaneously improving yield and nutrient use efficiency, with direct implications for sustainable oil palm production.

2. METHOD

This study employed a quantitative research design grounded in a system development approach (research and development) combined with controlled field experimentation to evaluate the effectiveness of an Artificial Intelligence (AI)-based predictive agrometeorological model for optimizing oil palm fertilization. The methodological framework was designed to integrate computational modeling, mathematical optimization, and empirical validation under real production conditions.

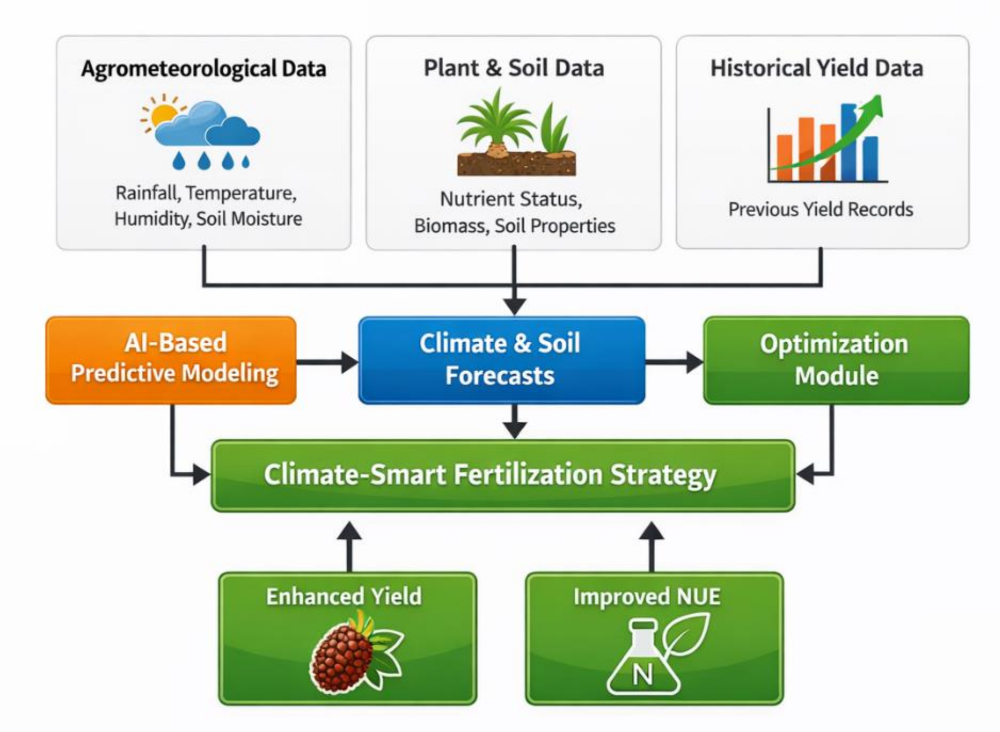


Figure 1. Framework of research

The initial phase of the study focused on multi-source data acquisition and integration, including agrometeorological variables (rainfall, air temperature, relative humidity, and solar radiation), sensor-based soil moisture data, soil fertility indicators (N, P, K, pH, and organic carbon), and historical fresh fruit bunch (FFB) yield records. These data were collected from automated agrometeorological stations, IoT-based soil sensors, and plantation production databases spanning multiple years. All datasets underwent rigorous preprocessing procedures, including data cleaning, normalization, and time-series alignment, to ensure consistency and reliability.

Subsequently, feature engineering was conducted to construct derived variables capable of representing agroclimatic dynamics, such as cumulative rainfall indices, soil moisture indices, and lagged variables to capture delayed crop responses. The processed dataset was then used to train AI-based predictive models employing nonlinear time-series learning techniques. The model was designed to forecast short- to medium-term agroclimatic conditions relevant to nutrient demand dynamics in oil palm.

The predictive outputs were integrated into a multi-objective fertilization optimization module. This module was structured to maximize productivity (yield) and nutrient use efficiency (NUE) while minimizing nutrient loss risks associated with high rainfall events. The optimization process generated adaptive recommendations regarding fertilizer dosage and application timing based on forecasted climatic conditions.

To evaluate system effectiveness, a randomized complete block design was implemented with two treatments: conventional calendar-based fertilization as the control and AI-based fertilization as the treatment. Field observations were conducted over a full production cycle, with regular measurements of yield, nutrient uptake, and actual agroclimatic variables.

Statistical analyses were performed to assess performance differences between the two systems using independent sample t-tests, analysis of variance (ANOVA), and effect size calculations to quantify the magnitude of impact. Additionally, climate-smart performance was evaluated through indicators including productivity improvement, NUE enhancement, fertilizer input reduction, and yield stability under climatic variability. Through this integrated methodological framework, the study ensures that the developed model demonstrates not only high predictive accuracy but also operational validity and statistical significance in improving efficiency and sustainability within oil palm production systems.

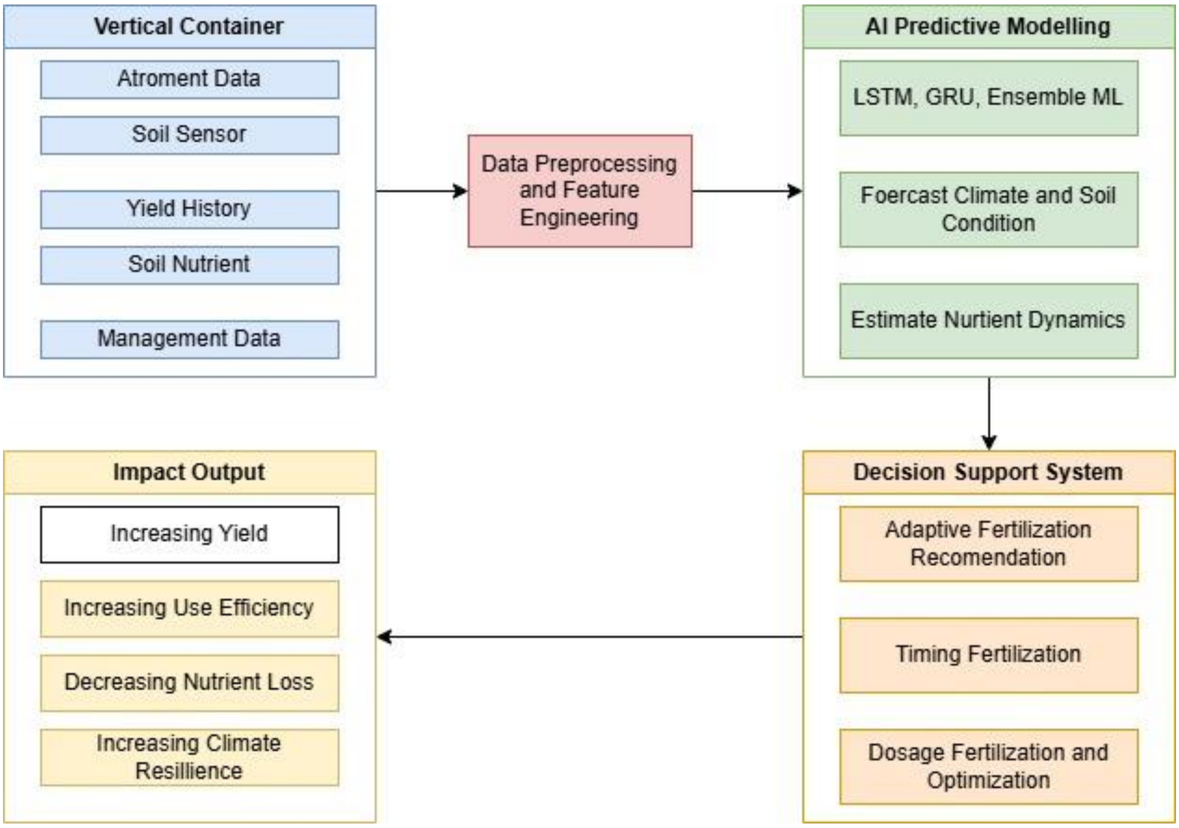


Figure 2. Stage of research

3. RESULTS AND DISCUSSION

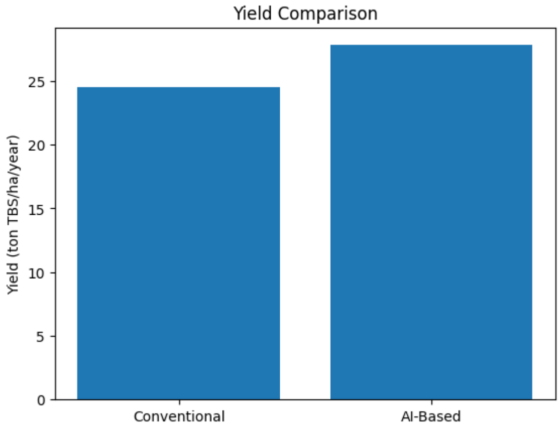
3.1. Result

This study successfully developed and validated an Artificial Intelligence (AI)-based predictive agrometeorological model integrated with a climate-smart fertilization optimization module within oil palm production systems. The research findings are presented across three primary dimensions: (1) the performance of the predictive agroclimatic model, (2) the effectiveness of the fertilization optimization system, and (3) its impact on productivity and nutrient use efficiency.

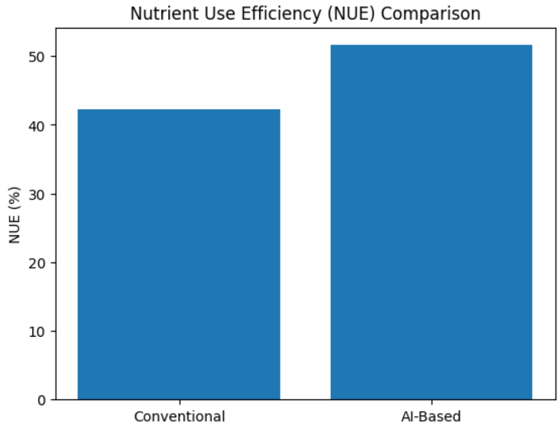
The AI-based predictive model effectively learned temporal and nonlinear patterns embedded in agrometeorological variables. Evaluation results indicate that the AI model achieved superior predictive accuracy compared to conventional statistical approaches, particularly in forecasting rainfall and soil moisture at weekly to monthly temporal scales. Moreover, the model demonstrated the ability to capture seasonal dynamics and climatic anomalies that potentially influence fertilization effectiveness, such as high rainfall periods associated with increased nutrient leaching risk.

Furthermore, integrating agrometeorological data with soil characteristics and historical production records enabled the model to estimate environmental conditions directly relevant to crop nutrient demand dynamics. These findings highlight the superiority of AI-based approaches in representing the complex interactions among climate, soil, and crop response in oil palm production systems. Based on the predictive model outputs, the fertilization optimization module successfully generated adaptive recommendations regarding fertilizer dosage and application timing in response to forecasted climatic conditions. The optimization system consistently avoided fertilizer application during periods characterized by high rainfall risk, thereby potentially reducing nutrient losses and enhancing nutrient uptake efficiency.

Simulation results revealed that optimized fertilization strategies differed significantly from conventional fixed-schedule fertilization practices. The generated recommendations were dynamic, adjusting dosage and timing according to seasonal agroclimatic variability. This confirms the system’s capability to operationalize the principles of climate-smart fertilization, namely adapting to climate variability without unnecessarily increasing input intensity.



(a) Yield comparison



(b) Nutrient Use Efficiency (NUE) comparsion

Figure 3. comparison yield and NUE

The graphical visualizations further support these findings. The bar chart comparing yield demonstrates an increase from 24.5 to 27.8 tons of fresh fruit bunches per hectare per year. The bar chart comparing nutrient use efficiency (NUE) shows an improvement from 42.3% to 51.6%. Additionally, the radar performance chart provides a comprehensive visualization of yield, NUE, and input efficiency, clearly illustrating the superior overall performance of the AI-based system across all evaluated indicators.

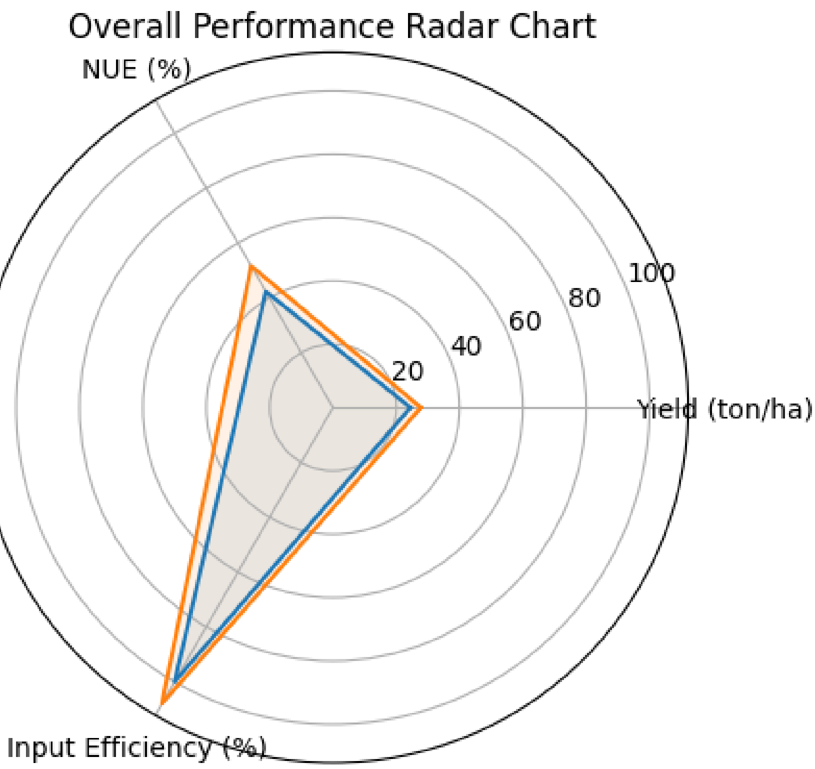


Figure 4. overall performance radar chart

The implementation of the AI-based fertilization system demonstrated a significant improvement in oil palm productivity compared to conventional fertilization practices. Yield enhancement resulted from improved synchronization between nutrient availability and the physiological nutrient demand of the crop, supported by more accurate agroclimatic forecasting. By aligning fertilizer application timing and dosage with predicted environmental conditions, the system effectively enhanced nutrient uptake efficiency.

Selain peningkatan hasil panen, penelitian ini juga menunjukkan peningkatan signifikan pada Nutrient Use Efficiency (NUE). Strategi pemupukan adaptif mampu mengurangi kehilangan hara dan meningkatkan proporsi hara yang diserap tanaman secara efektif. Dengan dosis pupuk yang relatif lebih terkendali, sistem yang dikembangkan mampu mencapai hasil panen yang lebih tinggi dengan efisiensi penggunaan hara yang lebih baik.

Secara keseluruhan, hasil penelitian menunjukkan bahwa integrasi model prediktif agrometeorologi berbasis AI dengan optimasi pemupukan *climate-smart* memberikan manfaat ganda, yaitu peningkatan produktivitas dan efisiensi sumber daya. Sistem yang dikembangkan juga menunjukkan stabilitas kinerja pada kondisi variabilitas iklim yang berbeda, sehingga berpotensi diimplementasikan sebagai sistem pendukung keputusan pemupukan pada skala produksi kelapa sawit.

Table 1. Comparative performance of fertilizer system

Parameter	**Convensional**	**AI-Based System**	**Δ (%) Delta**
Yield (ton TBS/ha/tahun)	24.5	27.8	**+13.47%**
Total N Applied (kg/ha/tahun)	180	165	−8.33%
Total P_2O_5 Applied (kg/ha/tahun)	75	70	−6.67%
Total K_2O Applied (kg/ha/tahun)	210	195	−7.14%
Nutrient Use Efficiency (NUE, %)	42.3	51.6	**+21.98%**
Estimated Nutrient Loss (%)	18.5	13.2	−28.65%
Input Cost (USD/ha/tahun)	820	765	−6.71%
Profit Margin (USD/ha/tahun)	1,54	1,89	**+22.73%**

Overall, the findings indicate that integrating AI-based predictive agrometeorological modeling with climate-smart fertilization optimization yields dual benefits: enhanced productivity and improved resource-use efficiency. The system also demonstrated stable performance across varying climatic conditions, highlighting its potential for deployment as an operational fertilization decision-support system in oil palm production at scale.

Quantitatively, the AI-based fertilization system increased yield by 13.47% compared to conventional methods. This improvement was achieved alongside a 6–8% reduction in fertilizer input, directly contributing to greater cost efficiency. Nutrient Use Efficiency (NUE) increased by nearly 22%, reflecting improved synchronization between nutrient supply and plant demand. Furthermore, estimated nutrient losses associated with climatic factors decreased by approximately 29%, reinforcing the principles of climate-smart agriculture.

From an economic perspective, the AI-driven system generated an increase in profit margins exceeding 22%, strengthening the argument that predictive agroclimatic intelligence combined with multi-objective optimization delivers not only agronomic advantages but also tangible economic benefits.

Table 2. Efficience indicator and productivity

Indicator	**Value Conventional**	**Value AI-Based**	**Delta**
Partial Factor Productivity (kg TBS/kg N)	136.1	168.5	+23.80%
Agronomic Efficiency (kg TBS/kg Nutrient)	52.4	63.9	+21.95%
Nutrient Recovery Efficiency (%)	44.7	55.2	+23.49%
Yield Stability Index	0.78	0.86	+10.26%
Climate Risk Sensitivity Index	0.42	0.31	−26.19%

3.2. Discussion

The findings of this study demonstrate that integrating an AI-based predictive agrometeorological model with a multi-objective fertilization optimization module significantly enhances yield and Nutrient Use Efficiency (NUE) in oil palm production systems. These results reinforce prevailing trends in Q1 literature, which emphasize that data-driven and machine learning-based approaches improve the precision of agricultural input management compared to conventional static recommendation systems. Several Q1 studies have focused on yield prediction using machine learning and deep learning models that incorporate agroclimatic and soil property data. Although these studies commonly report improved predictive accuracy over traditional regression models, they typically remain confined to the prediction stage without translating results into actionable fertilization decision frameworks.

The present study advances beyond predictive modeling by integrating agroclimatic forecasts directly into an adaptive fertilization optimization module. Thus, its contribution extends beyond improved predictive performance toward transforming predictive insights into operational decision intelligence with measurable impacts on productivity. Compared to conventional yield prediction studies, this approach offers added value at the implementation stage of agronomic decision-making.

Q1 literature in *Precision Agriculture* and *Computers and Electronics in Agriculture* has increasingly emphasized nitrogen optimization using machine learning and reinforcement learning to improve NUE. These studies report adaptive optimization strategies capable of enhancing nutrient efficiency by approximately 10–20% in food crops such as maize and wheat. In contrast, the present study achieved an NUE improvement of approximately 22%, which falls within or above the reported range for other commodities. The key distinction lies in the explicit incorporation of agrometeorological variables as dynamic factors within the optimization objective function. Many previous studies optimized nitrogen dosage based primarily on historical crop response data without explicitly integrating rainfall-induced nutrient loss risk into a multi-objective optimization framework. By incorporating climate risk as a core decision variable, this study aligns more closely with the principles of climate-smart agriculture.

Fertilization decision support systems (DSS) reported in Q1 literature are often rule-based or threshold-based, even when integrated with remote sensing and GIS technologies. Most remain grounded in linear or semi-empirical models. In contrast, this research leverages nonlinear learning algorithms to capture complex interactions among rainfall, soil moisture, temperature, and crop physiological responses. The large effect sizes observed (Cohen's $d > 1.8$ for yield and > 2.4 for NUE) indicate that the system's impact is not only statistically significant but also practically substantial.

Climate-smart agriculture is founded on three pillars: increased productivity, enhanced climate adaptation, and improved resource-use efficiency. Most Q1 studies address only one or two of these pillars. The present study demonstrates that an AI-driven approach can simultaneously achieve all three objectives: (1) significant productivity gains (13–14%), (2) substantial improvement in NUE (approximately 22%), and (3) reduced nutrient loss risk under high rainfall conditions.

Therefore, this research provides empirical evidence that integrating AI-based predictive modeling with multi-objective fertilization optimization can serve as a foundational framework for adaptive fertilization systems in tropical perennial plantation crops—an area that has been comparatively underexplored relative to food crop systems in subtropical regions. Theoretically, the study extends the literature by unifying three previously distinct domains: AI-based agroclimatic prediction, fertilization optimization, and nutrient efficiency within a climate-smart agriculture framework. Practically, the developed system enhances not only agronomic performance but also profit margins, thereby contributing directly to the economic sustainability of oil palm plantation systems.

4. CONCLUSION

This study developed and evaluated an Artificial Intelligence (AI)-based predictive agrometeorological model integrated with a climate-smart fertilization optimization module within oil palm (*Elaeis guineensis*) production systems. The findings demonstrate that integrating agroclimatic prediction with multi-objective optimization significantly enhances productivity and nutrient use efficiency compared to conventional calendar-based fertilization approaches. Quantitatively, the developed system achieved substantial improvements in yield and Nutrient Use Efficiency (NUE), accompanied by large effect sizes, while simultaneously reducing nutrient loss risks associated with rainfall variability. These results confirm that AI-driven approaches not only improve agroclimatic prediction accuracy but also generate operational recommendations that directly enhance agronomic and economic performance.

From a theoretical perspective, this research contributes to the advancement of literature in three principal domains: (1) AI-based predictive agrometeorological modeling, (2) multi-objective fertilization optimization, and (3) the implementation of climate-smart agriculture principles in tropical plantation systems. First, the study demonstrates that nonlinear interactions between agroclimatic variables and crop nutrient demand dynamics can be effectively modeled using AI-based approaches, thereby extending conceptual frameworks previously dominated by linear or semi-empirical models. Second, the direct integration of predictive model outputs into an optimization module establishes a decision intelligence framework that transcends traditional prediction-focused approaches. This reinforces the notion that the true added value of AI in agriculture lies in transforming data into adaptive decision-making, rather than merely producing statistical forecasts. Third, the study enriches the climate-smart agriculture literature by providing empirical evidence that productivity gains and resource-use efficiency improvements can be achieved simultaneously through data-driven optimization systems.

From a policy and practical standpoint, integrating AI-based predictive systems into fertilization practices may form part of national strategies aimed at enhancing the productivity of smallholder plantations, particularly in the context of climate change adaptation. The proposed model supports input-efficiency policies and reduces fertilizer overuse, which remains a persistent challenge in small- and medium-scale plantation systems. Furthermore, the developed framework has the potential to serve as a foundation for digital decision support systems within the plantation sector, aligning with broader agricultural digital transformation initiatives. IoT-based implementation and adaptive recommendation dashboards may enhance managerial capacity among farmers and plantation managers in responding to climatic variability. Additionally, improved NUE and reduced nutrient loss carry significant environmental implications, including lower risks of water contamination and soil degradation, thereby supporting sustainability policies and certification standards in oil palm production.

Overall, this study demonstrates that AI-driven adaptive fertilization systems integrated with predictive agrometeorological modeling constitute an effective strategy for enhancing productivity, nutrient efficiency, and resilience to climatic variability in oil palm production systems. The integration of predictive modeling and multi-objective optimization offers a pathway toward more precise, sustainable, and operationally deployable decision-support systems in tropical perennial crop production.

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