



Activating the role of Artificial Intelligence for Optimised Resource Management in light of Meta-Goal Programming for Sustainable Agriculture

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ABSTRACT

Optimising sustainable agriculture has become a vital objective for human survival, while economic progress has become the prime aim. The rapid population increase has to be faced by producing more from fewer resources. Thus, a comprehensive approach can be equipped to manage resources under-uncertainty conditions. This paper presents an integrated approach of Meta-Goal Programming with Artificial Intelligence (AI) to optimise resources in Malaysian sustainable agriculture. It has focused on rice and oil palm cultivation. Dual challenges have been addressed by this integrated approach, resource optimisation and environmental sustainability. A case study conducted to optimise resource-scarce agriculture has demonstrated significant improvements in water efficiency, crop yields, and ecological balance. This paper contributes a novel perspective to sustainable agriculture. Predictions have shown robust results which are aligned with actual data fields in terms of accuracy, 98% and 97% for rice and oil palm yield, respectively. The optimisation process has improved crop yields by reducing the usage of water and fertiliser use by 14% and 4% for rice and oil palm yield, respectively. The results validated the efficacy of the proposed approach, achieving the sustainable agriculture goals.

1. Introduction

Agriculture has a vast importance the human survival and economic progress. To face our rapid population increase with climate variability, the agriculture sector is seemingly forced to produce more with fewer resources. By 2050, the worldwide population is expected to reach over 9 billion, amplifying the demand for food by 50% compared to 2013 (FAO,

2020). Yet, agriculture stands as one of the most resource-intensive and environmentally important sectors. According to the United Nations (2019) and FAO (2021), the shrinking of freshwater resources and arable land is further stressing the delicate balance. Therefore, sustainable agriculture is an urgent solution, not a choice, securing food and sustaining the environment [8].

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Emerging modern technological advancements in agriculture, while maintaining sustainability, can address significant challenges. Integration of mathematical models using technological possibilities is reshaping the agricultural landscape. The emergence approaches of Interval Meta-Goal Programming (IMGPM) and Artificial Intelligence (AI) are transforming agroecosystem management. Uncertainties in multi-objective decision-making can be handled by applying the robust framework of IMPGM [18]. The uncertainty condition is overcome by the ability of solving real-time data-driven patterns to optimise resource allocation and enhance productivity [14].

Meta-Goal Programming and Artificial Intelligence in Agriculture

To accommodate multiple objectives in decision-making matters, Meta-Goal-Programming (MGP) is the optimum technique to be utilised for this purpose [17]. Recent studies have shed the light on the transformative role of AI. If AI models (e.g., machine learning, deep learning) emerged with MGP, the models of agricultural systems will enhance the performance, even with complex data and dynamic variables. AI models yield massive benefits, such as adaptive decision-making, improved resource use, and optimised negative environmental impacts. Introducing AI has reduced water consumption (45%), pesticide applications (50%), and post-harvest losses (40%); this AI integration has led to adaptive resource management strategies effectively [21]. This approach has illustrated a positive effect on farming aspects towards both the economy and the environment.

Applied Case Studies

The sustainable agriculture fields have benefited from integrating AI with MGP, including precision farming, pest/disease

management, and the agricultural supply chain. In precision farming, AI was employed to monitor soil health and weather patterns and to predict crop performance. Adewusi et. al. 2024 [1] and Johnson et. al. 2019, [13] employed AI models in precision farming, which helped to increase 30% in crop yield while reducing 20% of water and fertiliser usage. Further usage of AI was utilised to detect pest systems, to reduce chemical pesticide requirements, and minimise the negative impact on the environment [6]. AI has been applied in various industries, including supply chain, demand forecasting, distribution routes optimisation, and waste reduction.

Challenges

Several challenges might hinder AI and MGP's adoption, despite their significant advantages. For effective AI results, it is crucial to have accessible, accurate data [4]. In some places, a lack of internet access or insufficient computing resources forbade farmers from leveraging AI facilities [11]. This defines a resource gap in addition to a lack of the necessary knowledge to operate AI.

Applicability

Broadly, addressing the above challenges requires collaborative efforts among stakeholders, including governments and developers, with agricultural stakeholders. This leads to investing in the infrastructure and capacity-building programs [12]. Beyond the academic interest, the necessity to design sustainable agricultural frameworks means conserving our critical resources (water and soil) with better yields and fewer wastes [20, 19].

Our paper is attempting to bridge the ecological modelling and technological innovation gap. This research set sail in integrating AI with

IMGPM, covering a comprehensive approach to sustainable agricultural practices. Throughout hybridising these approaches, the paper aims to optimise resource usage, aligning with sustainability goals globally [3].

2. literature Review

It is important to discover the continuous evolution in sustainable agricultural research. Since the last century, intersections between mathematical modelling and artificial intelligence has come forth intelligibly. These crossing subjects have addressed the primary need to optimise resources and farming practices. Minimising ecological degradation leads to food security, despite globally pushed using advanced technologies. Several approaches were integrated including interval programming, meta-goal frameworks, and AI-based automation. However, calling for novel solutions to long-standing agricultural challenges has not met yet. The next section presents the related work, providing insights into gaps within this interdisciplinary field.

Related Work

This sub-section of the literature will present a concise summary of the pervious studies in agriculture including agroecosystem planning, agricultural sustainability, and technological advancements. Several studies focused on optimisation techniques and decision-support systems targeting uncertainty conditions and resource constraints. Other studies have emphasised the emerging technologies enhancing sustainable agricultural practices. Recently, the advanced interval meta-goal programming (IMGP) approach was introduced by Weerasena et. al. (2023) [26].

IMGP approach handled conflicting objectives under uncertainty conditions. Cropping patterns and resource allocation were optimised by

IMGP in regions facing water scarcity. Further work, Ramirez et. al. (2021) [22] utilised interval programming for decision-making to treat uncertainties. They have developed a robust framework to optimise multiple objectives within resource-scarce environments. A groundwork for meta-goal programming (MPG) was laid to effectively improve the decision-making process. It has integrated assorted meta-goals with competing objectives, ensuring structural priority [27]. Goal programming technique was demonstrated by Biswas, et. al. (2005) [5] and applied in an agroecosystem to balance economy, environment, and social objectives. Similarly, fuzzy goal programming was introduced by Sinha, et. al. (1988) [24] to accommodate imprecision planning in agriculture. This approach has optimised the adaptability of models in real-world conditions.

The technological advancements of AI and optimisation techniques have participated in reshaping the agriculture industry. In irrigation and pest management, AI has a significant role as report by Talaviya et al. (2020) [25]. The drones and IoT-enabled sensors were used to help improve resource efficiency and reduce labour dependency.—This key technology addressed climate variability partially and the rising food demand challenges. Precise farming techniques leveraging AI and machine learning have been explored to improve crop monitoring, yield prediction, and resource management [23]. Similarly, Liakos et al. (2018) [16] utilised advanced automation and sensing technologies to optimise productivity. By integrating GIS techniques in agricultural planning, strategies of land use and resource allocation have effectively been improved to bridge the ecological modelling with practical decision-making.

Worldwide agricultural studies have covered further challenges regarding sustainability and resource management. A strategic study reviewed sustainable cropping to balance productivity with environmental conservation (Cao et al., 2022). The review was gauging the alignment with SDG objectives, planning for long-term agricultural sustainability. Kumar, et. al. (2024) [15] targeted the arid regions, focusing on water resource management. They have explored the integration of policy interventions and technological innovations to mitigate water scarcity, enhancing irrigation efficiency. By conjugation social and environmental metrics, socio-ecological systems were analysed to build a holistic approach for agricultural interventions evaluations [2]. De Wrachien and Daniele (2003) [7] have reconnoitred planning strategies for land-use. A roadmap was achieved for balancing resource usage and sustaining agriculture for the longer term. Broad-spectrum approaches of advanced mathematical modelling and technological application, such as AI, IoT, GIS, and precision farming, can be combined to optimise sustainable agriculture. Studies above underscored the urgent need to integrate approaches addressing agricultural modern complexities, covering resource management, productivity and sustainability.

Research Gap

Despite significant efforts have been conducted by individual researchers, the outcomes of integrating IMGPM with AI remains uncharted. Actual models lack comprehensive frameworks

to jointly address the technological scalability and ecological sustainability. This research aims to fill this gap by suggesting an integrated approach for sustainable agricultural planning.

3. Methodology

Achieving research objectives has been done through integrating the Interval Meta-Goal Programming (IMGP) and artificial intelligence (AI) technologies. It equips a comprehensive approach for resource management optimising in agricultural systems under uncertainty conditions. Key aspects of the methodology are detailed as follows.

Mathematical Framework Model

The mathematical framework model is used for resource management optimisation in Malaysian agriculture. The proposed framework combines IMGPM with AI-advanced tools for precision agriculture. Framework components include IMGPM Module and Interval-based optimisation, which is used to handle uncertainties in resource allocation. The allocated resources are water, fertilisers, and labour from multiple agricultural systems. The paper's objective is to maximise productivity while minimising environmental impact.

Objective Function for Meta-Goal Programming

Meta-Goal Programming (MGP) is an extension of the normal goal programming model, but the focus is on achieving multiple conflicting goals simultaneously. The meta-goal programming objective can be represented as:

$$Maximize Z = \sum_{i=1}^n W_i G_i(x_1, x_2, \dots, x_i) - \sum_{i=1}^n \epsilon_i$$

Where:

- ♦ G1 , G2 ..., Gn are the multiple goals that need to be optimized; maximizing crop yield, minimizing
- ♦ water usage
- ♦ W1 , W2 , ..., Wn are weights associated with the importance of each goal
- ♦ ϵ_i The deviation variables for each goal
- ♦ X1 , X2 , ..., Xk are decision variables; amount of Fertiliser, irrigation, crop types

Constraints for Resource Management

To ensure that resources are allocated effectively and sustainably, we impose constraints based on available resources, environmental limits:

• **Water usage constraint:**

$$\sum_{i=1}^n a_i x_i \leq W_{max}$$

Where a_j is the water consumption rate per decision variable and W_{Max} is the maximum available water.

• **Land availability constraint:**

$$\sum_{i=1}^n b_i x_i \leq L_{max}$$

Where b_j represents the land area required for each decision variable and L_{Max} is the total available land.

• **Environmental impact constraint:**

$$\sum_{i=1}^n c_i x_i \leq E_{max}$$

Where c_j corresponds to the environmental impact (CO2 emissions) for each decision, and E_{Max} is the allowable environmental threshold.

• **Fertiliser Constraint:**

$$\sum_{i=1}^n F_i(x_i) \leq F_{max}$$

Where:

- ♦ $F_i(x_i)$ represents the amount of fertiliser
- ♦ F_{Max} is the maximum allowable fertiliser usage based on environmental regulations or sustainability targets. Alternatively, a constraint ensuring balanced nutrient supply can be formulated as:

$$N_i, P_i, K_i \leq R_i$$

Where:

- ♦ N_i, P_i, K_i are the nitrogen, phosphorus, and potassium applied to crop.
- ♦ R_i is the recommended nutrient requirement based on crop growth models.

AI-based Optimisation (Machine Learning Integration)

$$\sum_{i=1}^n c_i x_i \leq E_{max}$$

$$Q|(S_t, a_t) = R(S_t, a_t) + \gamma \max Q(S_{t+1}, a_t)$$

Where:

- ♦ $Q(st, at)$ is the quality of action at taken in state st
- ♦ γ is the discount factor that controls the trade-off between short-term and long-term rewards, $R(st, at)$ is the reward for taking action at in state st.
- ♦ $St+1$ is the next state after the action is taken.

applied to crop.

Artificial intelligence is incorporated to help aid the decision-making process through predictive modelling, clustering, or reinforcement learning. AI used to predict crop yields and optimise resource distribution, an example of using reinforcement learning (RL):

- ♦ State space (S): farm conditions (soil moisture, weather, and crop health).
- ♦ Action space (A): decisions to be made (water amount, fertiliser application).
- ♦ Reward function (R): outcomes of actions taken (profit, sustainability measure).

The RL-based decision process could be described as:

- ♦ $\|.\|^2$ is the squared error of predicted and actual values.

The equations above are integrated with the principles of goal programming utilising AI. The modelling process integrated the optimisation function to discover the best decision variables under constraints.

Data-Driven Optimisation via Neural Networks

Using neural networks, specifically, is another essential approach to predicting the optimum crop production or resource allocation. The neural network is trained using input data comprising weather, soil conditions, resource availability, and output data covering crop yield and water usage.

$$\text{Maximize } \| Y_{\text{predicted}} - Y_{\text{actual}} \|^2$$

Where:

- ♦ $Y_{\text{predicted}}$ is the predicted value
- ♦ e (crop yield)
- ♦ Y_{actual} is the actual value

A neural network is trained to approximate the function:

$$F(\theta) = \frac{1}{m} \sum_{i=1}^n (Y_{actual,i} - Y_{pred,i})^2$$

Where:

- ♦ m: Number of training examples
- ♦ Y_{actual} : Ground truth value (observed crop yield)
- ♦ $Y_{pred} = f(X; \theta)$: Neural network's prediction.

Optimisation Process: The predicted outputs, trained with the neural network, are integrated into an optimisation problem to determine optimal resource allocation or maximise crop yield.

1. Objective Function:

The optimisation modelling is seeking to maximise/minimise the problem objective as follows:

$$\sum_{i=1}^n a_i x_i \leq W_{max} x$$

Where W_i is the water requirement per unit of crop i, and W_{Max} is the total available water.

$$\sum_{i=1}^n F_i x_i \leq F_{max} x$$

Where F_i the fertiliser required per unit of crop i, and F_{max} is the maximum available fertiliser.

$$\sum_{i=1}^n A_i x_i \leq A_{max} x$$

Where A_i , is the land required per unit of crop i, and A_{Max} is the total available land.

Stochastic Optimisation with Uncertainty

Maximize $Z = \alpha Y - \beta C - \gamma E$

Where:

- ♦ $Y = f(X; \theta)$ Predicted crop yield.
- ♦ C: Resource cost (cost of water, fertiliser)
- ♦ E: Environmental impact (greenhouse gas emissions, soil degradation).
- ♦ α, β, γ : Weights assigned to yield, cost, and environmental impact.

2. Constraints:

The decision variables (X) are subject to constraints:

(a) Resource Availability Constraint:

(b) Fertiliser Usage Constraint:

3. Land Availability Constraint:

Agricultural inputs are rainfall and temperature. With ANN usage, the uncertain outputs are incorporated to predict the probability distributions. The objective of the stochastic optimisation is:

$$\text{Maximize : } E(Z) = \int ZP(X)dX$$

Where:

- ♦ P (X) Probability distribution of input features (weather conditions)
- ♦ E(Z): Expected value of the objective function

By considering variability and uncertainty, the integrated approach guarantees decisions reach the optimum outcomes for long-term, maximised objective function E(Z). Alternatively, a robust optimisation approach can minimise:

$$\text{Minimize : } \text{MaxF (X)...} X \in u$$

Where u is uncertainty set for input variables X.

Multi-Objective Optimisation

$$\text{Maximize } Z = \sum_{t=1}^T (\alpha Y_i - \beta C_i - \gamma E_i)$$

Two constraints are subject to time-dependent:

1. Resource Usage:

$$\sum_{i=1}^K W_{i,t} x_{i,t} \leq W_{max,t} \dots \forall t$$

2. Intertemporal Constraints:

$$\sum_{i=1}^K X_{i,t+1} \leq X_{i,t} \dots \forall i, \forall t$$

Where t represents the time step (planting season).

Neural Network-Informed Decision Variables

After training a neural network model, it can directly predict the optimal decision for variables X. The optimisation problem becomes:

$$F(X) = \| Y_{target} - f(X; \theta) \|^2$$

Subject to the constraints:

Oftentimes, multiple objectives that are in conflict require simultaneous optimisation. The problem can be framed as:

$$\text{Maximize : } Z = [Y, -C, -E]$$

Subject to constraints. Solutions are found using Pareto optimisation, where no single objective can be improved without worsening another. The result is a Pareto frontier, representing trade-offs between objectives.

Dynamic and Time-Dependent Optimisation

Planting schedules and irrigation planning are time-sensitive decisions; thus, the optimisation is extended for multiple time periods.

$X \in C$

Where:

- ♦ Y_{target} desired output (crop yield)
- ♦ $f(X : \theta)$ is neural network prediction
- ♦ C is a feasible region defined by constraints

4. Results

Case Study Area: Malaysia

As Malaysia is considered a main contributor to global agricultural markets, our case-study targeted its agriculture. The agricultural sector in Malaysia is evolving from traditional subsistence farming to a commercialised and mechanised system. While the most widely cultivated crops are palm oil, rubber, and rice, sustainable resource management is the primary concern. Challenges in such context can utilise advanced optimisation techniques (MGP and AI) to improve dual objectives, the economic outcomes and environmental sustainability.

Model Validation and Calibration

Integrating Artificial Intelligence (AI) with Interval Meta-Goal Programming (IMGP) in Malaysian agriculture has shown significant improvements to resources, yield, and the environment. The results are categorised into four aspects: crop yield improvement, fertiliser efficiency, water conservation, and sustainability impact. Model calibrations were performed, ensuring accurate predictions of crop yields, water usage, and fertiliser requirements aligned with actual field data. As a critical factor, model accuracy is important in determining the resource optimisation effectiveness.

Table 1: Model Calibration Accuracy

Model Component	Predicted Value	Actual Value	Accuracy (%)
Crop Yield Prediction (Rice)	5.2 tons/hectare	5.1 tons/hectare	98%
Crop Yield Prediction (Oil Palm)	18.3 tons/hectare	17.8 tons/hectare	97%
Water Usage Prediction	8000 litres/hectare	8100 litres/hectare	98%
Fertiliser Use Prediction	150 kg/hectare	160 kg/hectare	94%

Predicting Crop Yields/Rice: The Rice model has shown high accuracy of yield prediction. Less than 0.05% of difference resulted between the predicted rice yield (5.2ton/h) and actual yield (5.1ton/h). Despite AI overestimation, the AI predictive model is reliably accurate to estimate rice crop yields in cultivation.

1. **Predicting Crop Yield/Palm Oil:** The Palm oil model has also shown high accuracy of yield prediction. About 0.07% of the difference resulted between the predicted rice yield (18.3ton/h) and actual yield (17.8ton/h). An AI predictive model is slightly accurate in estimating Palm oil crop yields.
2. **Predicting Water Usage:** With less than 0.03% of deviation between the predicted (8100L/h) and the actual (8000L/h). The result of the AI model can estimate irrigation needs efficiently.

3. **Predicting Fertiliser Use:** the fertiliser use model has shown an underestimation of yield prediction (93.37%), predicted value (150 kg/h) against the actual value of 160 kg/h. Despite this slight discrepancy, the model is useful for providing an initial solution for recommendations and optimisation.

Optimisation of Resource Allocation

The Interval Meta-Goal Programming (IMGP) and Artificial Intelligence (AI) are an integrated approach to significantly enhance the efficiency of resource allocation (fertilisers, water, and energy). The optimisation model is leveraged to predict the inputs relying on real-time data, ensuring waste reduction while maintaining productivity. After calibrating the analysed results, the integrated meta-goal programming model was used to determine the impact on resource use efficiency. The breakdown of optimisation results is as follows:

Table 2: Resource Allocation Optimisation Results Per-hectare

Crop Type	Baseline Yield tons	Optimised Yield tons	Increase in Yield (%)	Water Usage Baseline/ litres	Water Usage Optimised/litres	Water Savings(%)	Fertiliser Use Baseline/kg	Fertiliser Use Optimised/kg	Fertiliser Savings (%)
Rice	5.1	5.8	14%	8000	7000	12.5%	160	140	12.5%
Oil Palm	17.8	18.5	4%	8100	7600	6.2%	160	150	6.3%

1. **Rice Crop Yield Optimisation:** The rice optimised model has shown a significant increase in the yields. Rice production increased 14% to 5.1ton/h to 5.8ton/h. Oil palm yield optimised by 4%, from 17.8 ton/h to 18.5ton/h. The model enhancements are recommended, especially beneficial for rice cultivation.
2. **Water Usage Optimisation:** The reduction of water consumption was substantially seen in both crops. Water usage for rice declined 12.5% (8000-7000 litre/h), while 6.2% reduction for oil palm (8100-7600 litre/h). The results highlight the model's ability to optimise irrigation schedules, reducing overall water consumption, thus enhancing sustainability.
3. **Fertiliser Use Optimisation:** Fertiliser application optimised for reducing cost and impacts on the environment. Rice fertilisers reduced by 12.5%, and oil palm fertiliser decreased by 6.3%. This reduction is key to promoting sustainable farming practices, preventing over-fertilisation, and minimising cost and nutrient runoff.

Sensitivity Analysis

Sensitivity analysis was conducted to understand the optimisation model responses to

various conditions and changes. This is an important model for robustness and adaptability when environmental conditions change. Three main scenarios were tested:

1. **Drought Scenario:** The integrated model predicted a slight reduction in crop yields (rice and oil palm). Rice yield dropped 22.5% (4.5 ton/h), while oil palm yield decreased 3.4% (17.2 ton/h). However, water usage is optimised, ensuring irrigation availability if needed. Comparing with the water use baseline, 10% and 8% decrease for rice and oil palm, respectively.
2. **Excessive Rainfall Scenario:** Crop yields remained comparatively stable. Both yields were close to the baseline, rice yield (5.0 ton/h) and oil palm yield (18.0 ton/h). Water usage is optimised, preventing water logging. Relative reductions in water usage were found 15% for rice and 7.4% for oil palm.
3. **Normal Conditions:** High expectations resulted in model performance. Rice crop yields achieved 5.8 ton/h and 18.5 ton/h for oil palm. As discussed previously, water usage and fertiliser application reduced correspondingly.

Table 3: Model Calibration Accuracy

Parameter	Scenario 1:Drought	Scenario 2: Excessive Rainfall	Scenario 3: Normal Conditions
Crop Yield (Rice)	4.5 tons/hectare	5 tons/hectare	5.8 tons/hectare
Crop Yield (Oil Palm)	17.2 tons/hectare	18.0 tons/hectare	18.5 tons/hectare
Water Usage (Rice)	7200 litres/hectare	6800 litres/hectare	7000 litres/hectare
Water Usage (Oil Palm)	7400 litres/hectare	7500 litres/hectare	7600 litres/hectare

Comparison with Traditional Farming Practices

The performance of the optimisation model was compared with the other traditional farming practices, quantifying the improvements in

regard to resource efficiency and crop productivity. The comparison is as follows:

1. **Crop Yield Comparison:** The integrated optimised model outperformed the

traditional practices, significantly. Rice yields improved by 14% (5.1→5.8 ton/h), while oil palm yields improved only 4%. The potential role of AI-based optimisation becomes very clear in enhancing resource optimisation in agricultural productivity.

2. **Water Usage Comparison:** The integrated optimised model has led to substantial savings in water usage compared with the traditional practices. Rice cultivation economised 12.5% of

water use, while oil palm economised 6.2%. Such reductions are essentially solving the water scarcity issue, promoting sustainable agricultural practices.

3. **Fertiliser Usage Comparison:** The integrated optimised model reduced the fertiliser use by 12.5% for rice and 6.3% for oil palm compared to traditional farming results. Reducing fertilisers mitigates serious environmental impacts.

Table 4: Comparison of Optimised Resource Management vs. Traditional Farming Practices

Parameter	Traditional Farming	Optimised Farming	Improvement (%)
Crop Yield (Rice)	5.1 tons/hectare	5.8 tons/hectare	14%
Crop Yield (Oil Palm)	17.8 tons/hectare	18.5 tons/hectare	4%
Water Usage (Rice)	8000 litres/hectare	7000 litres /hectare	12.5%
Water Usage (Oil Palm)	8100 litres/hectare	7600 litres/hectare	6.2%
Fertiliser Use (Rice)	160 kg/hectare	140 kg/hectare	12.5%
Fertiliser Use (Oil Palm)	160 kg/hectare	150 kg/hectare	6.3%

5. Conclusion

This paper presented the integration approach of Meta-Goal Programming with Artificial Intelligence (AI), optimising resources in Malaysian sustainable agriculture, focusing on rice and oil palm cultivation. The validation and calibration of the integrated model have ensured dramatic accuracy in predicting crop yields, water usage, and fertiliser requirements. The robust predictions of the integrated model are aligned with actual field data in terms of accuracy, 98% for rice yield and 97% for oil palm yield. After the optimisation process, the model improved crop yields, reduced water usage and fertiliser use. Rice production increased by 14% while oil palm production increased by 4%, water usage decreased by 12.5% for rice and 6.2% for oil palm, and fertiliser use declined by 12.5% and 6.3%, respectively.

Sensitivity analysis has expounded the model's adaptability to various conditions. Three common scenarios are considered in the case study, including drought and excessive rainfall, and normal conditions. Comparing with traditional farming practices, the modified model has outperformed both crop yields and resource efficiency in all case-scenarios.

In conclusion, combining AI with Goal Programming can offer a shining pathway to sustainable agriculture. In line with Malaysia's objectives of improving food security and conserving natural resources, the integrated model has demonstrated great capability and accuracy in improving resource allocation and reducing environmental impact.

6. Declarations

The author declares that he has no conflicts of interest.

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