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MIXED INTEGER LINEAR PROGRAMMING FOR OPTIMIZING RICE CULTIVATION RESOURCE ALLOCATION: A CASE STUDY IN PEMATANG SETRAK

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ABSTRACT

This study applies Mixed Integer Linear Programming (MILP) to optimize the allocation of rice cultivation resources in nine farmer groups in Pematang Setrak, North Sumatra. This model minimizes production costs through the allocation of seeds, fertilizers, pesticides, and labor, taking into account land area and resource availability within a single planting season. The MILP approach was chosen because it represents more realistic decision-making according to field conditions. Fertilizer and pesticide doses are determined based on safe agronomic recommendations, assumed to be in accordance with field conditions based on relevant agricultural references, and calibrated using actual data from observations and interviews with farmers, where actual data is used as the upper limit of parameter values. The model is implemented using Python and evaluated through sensitivity analysis. The optimization results reduce total production costs from 3,047,060,000 IDR to 2,845,516,500 IDR or 201,543,500 IDR (6.61%). The main savings come from the efficiency of fertilizer and pesticide allocation, while labor remains the dominant cost component. This study shows that the model is effective for use in agricultural operational planning.

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1. INTRODUCTION

Mathematical modeling represents a real-world problem using mathematical language and concepts to analyze, predict, and find solutions more systematically. In agricultural optimization, mathematical modeling plays an important role in solving production planning problems by improving resource allocation and increasing operational efficiency. Through mathematical models, farmers can determine the efficient use of land, water, fertilizer, and labor to achieve maximum yields at minimum cost. Thus, mathematical modeling can facilitate more accurate, efficient, and sustainable decision-making. For example, optimization models can systematically manage resource use in rice cultivation [1]. In Indonesia, rice cultivation is essential for meeting food demand and maintaining food availability. Rice cultivation involves land preparation, seed sowing, planting, fertilizing, water management, pest control, and harvesting, with each stage requiring various production resources, including seeds, fertilizers, pesticides, and labor [2]. Therefore, improving resource-use efficiency in rice cultivation is important for supporting agricultural productivity and food security.

Resource allocation is a common challenge in agricultural production because farmers must distribute limited inputs such as land, seeds, fertilizers, pesticides, and labor across multiple cultivation activities. In many smallholder farming systems, resource-use decisions are still commonly based on farmer habits, experience, or informal estimation, which may lead to inefficient input use [3]. This issue is also relevant in Pematang Setrak, a village located in Teluk Mengkudu District, Serdang Bedagai Regency, North Sumatra, Indonesia. The village has significant agricultural potential, particularly in rice cultivation, which is the primary source of livelihood for the local community. Agricultural activities are organized through several farmer groups under a farmer group association, but each farmer group manages a different land area and therefore requires different amounts of seeds, fertilizers, pesticides, and labor. Field observations indicate that resource allocation among farmer groups has not been supported by a formal optimization model. Thus, Pematang Setrak provides a relevant local case for developing a mathematical model that can support feasible and cost-efficient rice cultivation resource planning.

Several previous studies have applied Linear Programming (LP) to agricultural operational optimization. LP models have been used to support agricultural activity planning [4], [5], to determine optimal decisions in resource allocation problems and production planning systematically [6], and improve harvest planning while reducing losses [7]. These studies show that LP is useful for agricultural decision-making; however, most LP formulations treat decision variables as continuous and therefore may not fully represent farming decisions that involve discrete operational units. In practice, some agricultural decisions are not purely continuous but are expressed in discrete units. LP is widely used because it can systematically optimize resource allocation and minimize operational costs under multiple constraints. However, the approach relies on assumptions of linearity, deterministic parameters, and static relationships, which may limit its ability to fully represent complex real-world agricultural systems [8], [9]. Previous studies in several fields have introduced Mixed-Integer Linear Programming (MILP) as an extension of LP for optimization problems involving both continuous and integer decision variables [10], [11]. Therefore, this study develops a MILP model for rice cultivation resource allocation by combining continuous variables for seeds, fertilizers, and pesticides with integer variables for labor allocation.

Although LP and MILP models have been widely used in agricultural planning and resource allocation, several methodological gaps remain in smallholder rice cultivation contexts. First, many LP-based agricultural models assume that all decision variables are continuous, whereas some operational decisions in farming, especially labor allocation, are naturally discrete because labor is measured in whole man-days. Second, previous MILP studies have often focused on crop selection, land-use planning, production planning, or supply-chain optimization, while farmer-group-level resource allocation involving seed, fertilizer, pesticide, and labor constraints in a local rice cultivation system has received less attention. Third, the use of agronomic input parameters from previous studies is often not explicitly connected to local farming practices, creating questions about contextual validity. These gaps motivate the development of a locally calibrated MILP model for rice cultivation resource allocation in Pematang Setrak.

MILP has been implemented in various optimization contexts, including rice supply-chain cost minimization with environmental and risk considerations [12], Introducing this model for cost optimization in multi-product multi-line production scheduling [13], crop-mix selection under market-price variability and resource limitations [14], production planning in the sawmill industry [15], near-optimal solution generation for farming system design [16], and land-use planning to limit urban expansion [17], crop planting layout problems to produce optimal and sustainable land configurations in agricultural systems [18]. Agricultural planning using mathematical modeling in optimization and operations research can improve resource-use efficiency and reduce operational costs. Through optimization models, factors such as land allocation, labor, fertilizers, pesticides, and capital can be analyzed simultaneously to determine a feasible and cost-efficient combination of input use [19], [20], [21]. However, the effectiveness of such models depends on how well the decision variables, constraints, and parameters represent the actual farming system. In this study, this issue is addressed by integrating local field data, farmer-group-level constraints, bounded agronomic input parameters, and integer labor decisions into the MILP formulation. The model which takes profit, carbon footprint, and water footprint into account during optimisation [22], [23].

Therefore, this study aims to apply MILP to optimize the allocation of rice cultivation resources in Pematang Setrak. With this mathematical modeling, resource allocation can be optimized to minimize operational costs. The model is implemented based on local agronomic conditions, so the contribution of this study lies in its practical application aspect, particularly the integration of continuous variables representing seeds, fertilizers, and pesticides and integer labor variables measured in workdays, so that the MILP formulation is more realistic than the pure LP model. This model incorporates local constraints from nine farmer groups, including land area, resource availability, labor requirements, and actual farmer practices. This study is complemented by a sensitivity analysis to identify the most influential cost components. Thus, the developed model can assist farmers in decision-making for rice cultivation operations.

2. RESEARCH METHOD

This study uses a case study approach to formulate and solve a resource allocation optimization problem in rice cultivation in Pematang Setrak using the MILP approach. This model optimizes the allocation problem of seeds, fertilizers, and pesticides as continuous variables, and labor as an integer variable. Field observations and farmer interviews were used to obtain local data on land area, resource needs, and availability. Fertilizer and pesticide parameter values were determined as ranges calibrated with actual data. The model was solved using Python with the PuLP library and the CBC solver, followed by a perturbation-based sensitivity analysis to evaluate the effect of parameter changes on the objective values and solution stability.

2.1. Farm Description and Modeling Scheme

Rice cultivation in Pematang Setrak is carried out by nine farmer groups. Each group has a different land area and requires five types of fertilizer and three types of pesticides for seven agricultural activities, each handled by a number of workers. Each farmer group requires different resources. Farmers need planning to optimize resource allocation and minimize rice farming operational costs.

This study aims to develop a mathematical model using the MILP approach based on the description of agriculture in the village. The mathematical model optimizes resource allocation as input components, and minimizes operational costs as output. The mathematical modeling scheme is shown in Figure 1.

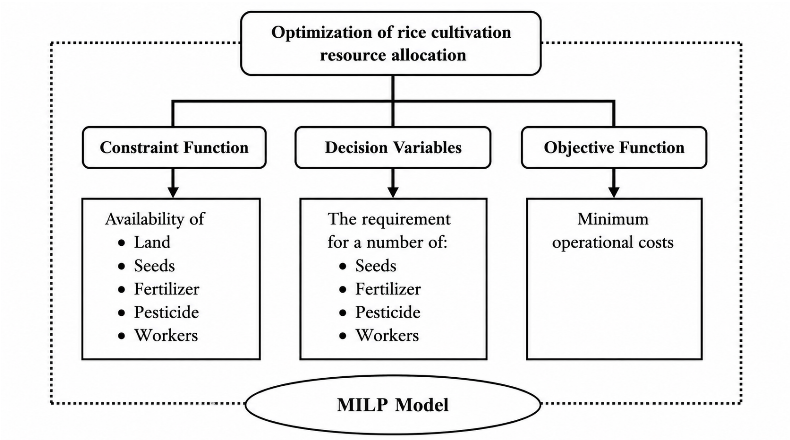

Figure 1. Scheme of Rice Cultivation Resource Allocation Optimization

MILP is a mathematical optimization model employed to solve linear optimization problems that incorporate both continuous and integer decision variables simultaneously. The general mathematical formulation of MILP can be expressed as follows:

$$\begin{aligned} \min \quad & Z = c^T x \\ \text{subject to} \quad & Ax \leq b \\ & x \geq 0, \\ & x_n \quad \text{is integer for some } n \in N \end{aligned} \tag{1}$$

2.2. Notation and Mathematical Modeling

This section presents the notation, decision variables, and parameters used in formulating the mathematical model. Agricultural activities can be carried out by farmer groups, using various types of fertilizers and pesticides in various agricultural activities, so the notation or index is introduced in Table 1.

Table 1: Indices in the Rice Cultivation Model

Symbol	Set	Description
i	I	Group of farmers
j	J	Group of fertilizers
k	K	Group of pesticides
t	T	Group of labor activities

2.2.1 Decision Variables and Parameters

Decision variables are controllable elements in the model. In this rice cultivation case, the decision variables include the number of seeds (in kilograms), fertilizer (in kilograms), and pesticide (in liters) as continuous variables, and the amount of labor (in workdays) as an integer variable allocated to nine farmer groups. These decision variables can be seen in Table 2 below:

Table 2: Decision Variables in the Rice Cultivation Model

Symbol	Type	Description	Unit
x_i	Continuous	Quantity of seeds allocated to farmer $i-$group	kg
y_{ij}	Continuous	Quantity of fertilizer $j-$type allocated to farmer $i-$group	kg
z_{ik}	Continuous	Quantity of pesticide $k-$type allocated to farmer $i-$group	L
w_{it}	Integer	Amount of labor for $t-$activity allocated to farmer $i-$group	Man-Days

The parameters used in building the MILP model include land area and its requirements for seeds, fertilizers, pesticides, and labor for each activity. The parameters used in the modeling are shown in Table 3 below:

Table 3: Parameters of Model

Symbol	Description	Unit
L_i	Land area of farmer $i-$group	ha
aB	Seed requirement for farmer $i-$group	kg/ha
aP_j	Requirement for fertilizer $j-$type for farmer $i-$group	kg/ha
aS_k	Requirement for pesticide $k-$type for farmer $i-$group	L/ha
aT_t	Labor requirement for $t-$activity for farmer $i-$group	Man-Days/ha
cB	Price of seeds	IDR/kg
cP_j	Price of fertilizer $j-$type	IDR/kg
cS_k	Price of pesticide $k-$type	IDR/L
cT_t	Labor wages for $t-$activity	IDR/Man-Days
HB	Total seed availability	kg
HP_j	Total availability of fertilizer $j-$type	kg
HS_k	Total availability of pesticide $k-$type	L
HT_t	Total labor availability for $t-$activity	Man-Days

2.2.2 The Form of the Objective Function

The optimization model is formulated with the goal of minimizing the total production costs associated with the use of various resources during agricultural cultivation. These costs include expenditures on seeds, fertilizers, pesticides, and labor wages. The optimal solution generated by this modeling approach is anticipated to be more cost-effective than actual historical expenditures. The mathematical model of this objective function can be formulated as follows:

$$\text{Min}Z = \sum_{i\in I}\left(cB\cdot x_i + \sum_{j=1} cP_j\cdot y_{ij} + \sum_{k\in K} cS_k\cdot z_{ik} + \sum_{t\in T} cT_t\cdot w_{it}\right) \tag{2}$$

2.2.3 The Form of Constraints Function

The constraints of agricultural components that must be taken into account to achieve the objectives will result in a set of constraints that includes demand constraints, availability constraints, and domain constraints. The resource requirements in the model are determined based on the characteristics of each resource. Seed and labor requirements are expressed as minimum usage thresholds based on actual condition. Meanwhile, fertilizer and pesticide requirements are determined based on standard agronomic doses and are limited to a range, with the lower limit referring to the standard dose and the upper limit adjusted to actual conditions. This range provides flexibility in determining resource allocation. Under certain conditions, when the standard dose value is equal to the actual conditions, the constraint is expressed only in the form of a minimum usage limit.

a. Seed
The seed requirement constraint in this model is designed to ensure that seed allocation to each farmer group meets the minimum requirement based on the area of land they manage. The required seed quantity is calculated by multiplying the seed usage per hectare by the area of each farmer group's land. Therefore, this constraint ensures that there is no seed shortage during rice cultivation, as follow:

$$x_i \geq aB \cdot L_i, \quad \text{for} \quad \forall i \in I \tag{3}$$

b. Fertilizer
Fertilizer requirement constraints are used to ensure that the amount of fertilizer allocated to each farmer group meets the minimum requirement based on the area of land they manage. Fertilizer requirements are determined based on the fertilizer application rate per hectare multiplied by the area of each farmer group's land. Thus, a constraint inequality is constructed based on the range of fertilizer requirements per hectare of land as follows:

$$aP_j^{(lower)} \cdot L_i \leq y_{ij} \leq aP_j^{(upper)} \cdot L_i, \quad \text{for} \quad \forall i \in I, \forall j \in J \tag{4}$$

c. Pesticide
Pesticide requirement constraints are used to ensure that the amount of pesticide allocated to each farmer group meets the minimum requirement based on the area of land they manage. Pesticide requirements are determined based on the dose range per hectare multiplied by the area of land for each farmer group. The inequality of pesticide requirement constraints is shown below:

$$aS_k^{(lower)} \cdot L_i \leq z_{ik} \leq aS_k^{(upper)} \cdot L_i \quad \text{for} \quad \forall i \in I, \forall k \in K \tag{5}$$

d. Labor
Labor requirement constraints are used to ensure that the number of workers allocated to each farmer group meets the minimum requirements for rice cultivation activities. Labor requirements are calculated based on the number of workers per hectare multiplied by the area of land requiring services. The inequality constraint is shown as follows:

$$w_{it} \geq aT_t \cdot L_i \quad \text{for} \quad \forall i \in I, \forall t \in T \tag{6}$$

The availability constraint is used to represent the limited quantity of resources available for rice cultivation. This constraint ensures that the total resource usage by all farmer groups does not exceed the available quantity. The resources in question include seeds, fertilizers, pesticides, and labor during a single growing season, ensuring that the resulting solutions remain realistic and consistent with on-the-ground conditions.

a. Seed

$$\sum_{i \in I} x_i \leq HB \quad \text{for} \quad \forall i \in I \tag{7}$$

b. Fertilizer

$$\sum_{i \in I} y_{ij} \leq HP_j \quad \text{for} \quad \forall j \in J \tag{8}$$

c. Pesticide

$$\sum_{i \in I} z_{ik} \leq HS_k \quad \text{for} \quad \forall k \in K \tag{9}$$

d. Labor

$$\sum_{i \in I} w_{it} \leq HT_t \quad \text{for} \quad \forall t \in T \tag{10}$$

These constraints ensure that the total use of each type of resource by all farmer groups does not exceed the available quantity. Thus, the model ensures that the resulting solutions remain realistic and implementable in the field, as they account for existing resource constraints. Additionally, labor availability constraints also play a significant role in the optimization process, as they limit the solution space, allowing the model to determine the most efficient resource allocation under those constraints.

In this study, the decision variables representing the use of production resources are defined as non-negative continuous variables, while the labor variable is defined as an integer as follow:

a. Continuous Variable

$$x_i, y_{ij}, z_{ik} \geq 0 \quad \text{for} \quad \forall i \in I, \forall j \in J, \forall k \in K \tag{11}$$

b. Integer Variable

$$w_{it} \in \mathbb{Z}^+ \quad \text{for} \quad \forall i \in I, \forall t \in T \tag{12}$$

2.3. Study Case in Pematang Setrak

Local data were collected through field observations and semi-structured interviews with representatives of nine farmer groups using five types of fertilizers and three types of pesticides in seven agricultural activities, as shown in Table 4. The interviews focused on land area, input use, resource availability, labor requirements, input prices, and farmer practices prevailing during the growing season. Data were collected in February 2026, during the preparation period for the first growing season in April 2026. The obtained data were cross-checked by comparing interview responses among farmer group representatives, field observation notes, and available farmer group information. Inconsistencies were clarified through further confirmation before being used as model parameters. Fertilizer and pesticide ranges from the literature were not directly adopted as fixed values; instead, they were used as agronomic reference limits and calibrated against local farmer practices, with observed farmer practices serving as the local upper limit reference. The model assumes a deterministic one-season planning setup under normal growing conditions, without explicitly modeling weather variability, pest shocks, or market price uncertainty.

Table 4: Indices of the Rice Cultivation Model in Pematang Setrak

Symbol	Set	Variety
i	Group of farmers	1 = Sri Murni I Group;
		2 = Sri Murni II Group;
		3 = Fajar Group;
		4 = Mekar Jaya Group;
		5 = Sri Murni III Group;
		6 = Sri Karya Group;
		7 = Sumber Rezeki I Group;
		8 = Sumber Rezeki II Group;
		9 = Sri Wahyuni Group
j	Fertilizer	1 = Urea;
		2 = NPK Phonska;
		3 = KCL;
		4 = SP;
		5 = ZA
k	Pesticide	1 = Insecticide;
		2 = Herbicide;
		3 = Fungicide
t	Labor Activities	1 = Land Preparation;
		2 = Nursery Preparation;
		3 = Bund Construction;
		4 = Planting;
		5 = Fertilization;
		6 = Spraying;
		7 = Harvesting

The parameter values based on field data used in the mathematical model are 262 hectares of land owned by nine farmer groups and the amount of resource requirements. In this study, the minimum range of fertilizer use and pesticide doses were added and it was assumed that the range of fertilizer amounts and pesticide doses were still in accordance with soil nutrient requirements. The range of fertilizer and pesticide reductions was determined based on literature on integrated nutrient management, integrated crop management, and site-specific nutrient management, which shows that moderate reductions in chemical inputs can be achieved through increasing nutrient use efficiency and optimizing site-specific management without significantly reducing rice productivity. Reductions in the amount of fertilizer such as: urea 20-30%, NPK Phonska 15-30%, KCL 0-20%, SP-36 25-50%, ZA 10-25% [24], [25], [26], and pesticide doses were reduced by 30% [27]. These parameters can be seen in Table 5 below:

Table 5: Parameter Values of Resource Requirements for Rice Cultivation Model in Pematang Setrak

Description	**Variety**	**Value**	**Unit**
Land area of farmer $i-$group	1 = Sri Murni I Group	30	ha
	2 = Sri Murni II Group	30	ha
	3 = Fajar Group	23	ha
	4 = Mekar Jaya Group	20	ha
	5 = Sri Murni III Group	27	ha
	6 = Sri Karya Group	30	ha
	7 = Sumber Rezeki I Group	36	ha
	8 = Sumber Rezeki II Group	33	ha
	9 = Sri Wahyuni Group	33	ha
Seed requirement for farmer $i-$group	All farmer groups	30	kg/ha
Requirement for fertilizer $j-$type for farmer $i-$group	1 = Urea	$[87.5, 125]$	kg/ha
	2 = NPK Phonska	$[175, 250]$	kg/ha
	3 = KCL	$[40, 50]$	kg/ha
	4 = SP	$[62.5, 125]$	kg/ha
	5 = ZA	$[56.25, 75]$	kg/ha
Requirement for pesticide $k-$type for farmer $i-$group	1 = Insecticide	$[1.4, 2]$	L/ha
	2 = Herbicide	$[0.7, 1]$	L/ha
	3 = Fungicide	$[0.7, 1]$	L/ha
Labor requirement for $t-$activity for farmer $i-$group	1 = Land Preparation	25	Man-Days/ha
	2 = Nursery Preparation	1	Man-Days/ha
	3 = Bund Construction	25	Man-Days/ha
	4 = Planting	25	Man-Days/ha
	5 = Fertilization	3	Man-Days/ha
	6 = Spraying	6	Man-Days/ha
	7 = Harvesting	25	Man-Days/ha

Cost parameters obtained from farmer interviews are used to indicate the exact costs incurred from the use of each type of production resource. These parameters are crucial in formulating the objective function to minimize total production costs, as presented in Table 6 below:

Table 6: Input Prices and Labor Wages Used in the Model

Description	**Variety**	**Value**	**Unit**
Price of seeds	All farmer groups	15,000	IDR/kg
Price of fertilizer $j-$type	1 = Urea	1,800	IDR/kg
	2 = NPK Phonska	1,840	IDR/kg
	3 = KCL	8,000	IDR/kg
	4 = SP	3,000	IDR/kg
	5 = ZA	4,600	IDR/kg
Price of pesticide $k-$type	1 = Insecticide	180,000	IDR/L
	2 = Herbicide	100,000	IDR/L
	3 = Fungicide	240,000	IDR/L
Labor wages for $t-$activity	1 = Land Preparation	60,000	IDR/Man-Days
	2 = Nursery Preparation	100,000	IDR/Man-Days
	3 = Bund Construction	25,000	IDR/Man-Days
	4 = Planting	60,000	IDR/Man-Days
	5 = Fertilization	150,000	IDR/Man-Days
	6 = Spraying	125,000	IDR/Man-Days
	7 = Harvesting	150,000	IDR/Man-Days

In addition, the actual resource availability parameter indicates the maximum capacity of production resources that can be utilized throughout the growing season. This parameter acts as an important constraint in the optimization model, ensuring that allocated resources are strictly limited by available supply, as shown in Table 7 below:

Table 7: Resource Availability Parameters of the Rice Cultivation Model in Pematang Setrak

Description	Variety	Value	Unit
Total seed availability	All farmer groups	7,900	kg
Total availability of fertilizer $j-$type	1 = Urea	33,000	kg
	2 = NPK Phonska	66,000	kg
	3 = KCL	13,500	kg
	4 = SP-36	33,000	kg
	5 = ZA	20,000	kg
Total availability of pesticide $k-$type	1 = Insecticide	530	L
	2 = Herbicide	270	L
	3 = Fungicide	270	L
Total labor availability for $t-$activity	1 = Land Preparation	6,600	Man-Days
	2 = Nursery Preparation	6,600	Man-Days
	3 = Bund Construction	6,600	Man-Days
	4 = Planting	6,600	Man-Days
	5 = Fertilization	6,600	Man-Days
	6 = Spraying	6,600	Man-Days
	7 = Harvesting	6,600	Man-Days

3. RESULT AND ANALYSIS

3.1. Result

All computations were performed on a standard personal computer running Windows 11 Pro with an 11th Gen Intel(R) Core(TM) i7-1165G7 processor at 2.80 GHz and 16 GB RAM. The model was implemented in Python 3.12 using the PuLP optimization library and solved with the open-source CBC solver under the default solver configuration. The computational result returned an optimal solution status with a solution time of 0.0052 seconds, an optimality gap of 0.0%, no additional branch-and-bound node exploration, and all constraints satisfied. The short solution time should be interpreted in relation to the scale of the case-study instance. The model contains 144 decision variables, consisting of 9 seed variables, 45 fertilizer variables, 27 pesticide variables, and 63 labor variables. Among these variables, 63 labor variables are integer variables. Therefore, the present case is computationally small, but the model structure remains relevant for larger applications involving more farmer groups, more resource types, multiple planting seasons, or additional policy constraints.

Table 8 shows the allocation of resources for each farmer group. The allocation represents the recommended optimization results to meet the resource requirements in rice cultivation.

Table 8: Recommended Resource Value Range for each Farmer Group

Resource	Farmer Group									Unit
	1	2	3	4	5	6	7	8	9	
Seed	900	900	690	600	810	900	1,080	990	990	kg
Urea	2,625	2,625	2,012	1,750	2,362	2,625	3,150	2,888	2,888	kg
NPK Phonska	5,250	5,250	4,025	3,500	4,725	5,250	6,300	5,775	5,775	kg
KCL	1,200	1,200	920	800	1,080	1,200	1,440	1,320	1,320	kg
SP-36	1,875	1,875	1,438	1,250	1,688	1,875	2,250	2,062	2,062	kg
ZA	1,688	1,688	1,294	1,125	1,519	1,688	2,025	1,856	1,856	kg
Insecticide	42	42	32.20	28	37.80	42	50.40	46.20	46.20	L
Herbicide	21	21	16.10	14	18.90	21	25.20	23.10	23.10	L
Fungicide	21	21	16.10	14	18.90	21	25.20	23.10	23.10	L
Labor	3,300	3,300	2,530	2,200	2,970	3,300	3,960	3,630	3,630	Man-Days

The disaggregated allocation shows that the optimized solution preserves the minimum seed requirement and selects the lower feasible agronomic bounds for reducible fertilizer and pesticide components. This explains why the total optimized allocation for urea, NPK Phonska, SP-36, ZA, and insecticide is lower than the corresponding actual or upper-bound practices. In contrast, KCL, herbicide, and fungicide remain unchanged because their lower and upper bounds are identical in the model. These results indicate that cost efficiency is achieved selectively through input components that have feasible adjustment ranges, rather than through uniform reduction of all resources.

After determining the optimized allocation for each farmer group, the total production cost under the actual farmer practice and the MILP-based optimized solution was compared. Table 9 presents the cost comparison for seeds, fertilizers, pesticides, and labor wages. This comparison is used to evaluate the economic effect of the proposed optimization model relative to the baseline allocation practice.

Table 9: Comparison of Actual and Optimization Costs

Component	**Actual and Optimal Costs**	**Optimization Cost (IDR)**
Seed Costs	117,900,000	117,900,000
Fertilizer Costs	472,910,000	326,386,500
Pesticide Costs	183,400,000	128,380,000
Labor Wages	2,272,850,000	2,272,850,000
Total Costs	**3,047,060,000**	**2,845,516,500**

As shown in Table 9, the total production cost decreased from 3,047,060,000 IDR under the actual allocation practice to 2,845,516,500 IDR under the optimized solution, corresponding to a reduction of 201,543,500 IDR or approximately 6.61%. Although this reduction may appear modest mathematically, it is economically meaningful in the farmer-group context because it was achieved within one planting season without reducing the cultivated land area or violating minimum agronomic and labor requirements. The savings were mainly obtained from fertilizer and pesticide costs, while seed and labor costs remained unchanged because they were determined by fixed land-area requirements and minimum labor activity constraints. Compared with baseline farmer practices, the result indicates that existing resource allocation was not entirely inefficient, but that specific inefficiencies existed in fertilizer and pesticide use. Therefore, the model functions not only as a cost-minimization tool but also as a diagnostic tool for identifying which resource components can be adjusted safely within feasible and locally relevant limits.

3.2. Sensitivity analysis

A sensitivity analysis was conducted to evaluate how perturbations in the main cost parameters affect the objective value and the stability of the optimal decision vector in the MILP model. The experiment consisted of 57 scenarios, comprising one baseline scenario, 16 one-at-a-time component-level scenarios, 32 item-level scenarios, and 8 combined scenarios. Each scenario was solved by re-optimising the MILP model rather than by post-processing the baseline objective value. All scenarios returned an optimal solver status.

For clarity, the results are reported in two layers. First, objective sensitivity is assessed through changes in the total optimal production cost. Second, decision sensitivity is assessed through whether the optimal allocation variables changed relative to the baseline. This separation is important because a model may be cost-sensitive while remaining stable in its decision structure.

3.2.1 Baseline cost structure

The baseline MILP solution produced an optimal objective value of 2,845,516,500 IDR. Table 10 presents the baseline cost structure, which was dominated by labor costs. Labor accounted for 79.87% of total cost, followed by fertilizer at 11.47%, pesticide at 4.51% and seed at 4.14%.

Table 10: Baseline Cost Structure of the Optimal MILP Solution.

Cost Component	**Baseline Cost (IDR)**	**Share of Total Cost (%)**
Seed	117,900,000	4.14
Fertilizer	326,386,500	11.47
Pesticide	128,380,000	4.51
Labor	2,272,850,000	79.87
Total	**2,845,516,500**	**100**

Note: Percentages are calculated relative to the baseline objective value

The baseline structure indicates that the model objective is highly exposed to labor-cost variation. Because labor forms nearly four-fifths of the total production cost, even moderate changes in labor-related parameters are expected to produce larger changes in the objective value than comparable percentage changes in other components.

3.2.2 Component-level sensitivity results

Table 11 ranks the four cost components according to the maximum absolute change in the objective value under one-at-a-time perturbations. A 30% labor-cost perturbation produced a maximum absolute delta cost of 681,855,000 IDR, corresponding to a 23.59% change in the objective value. Fertilizer ranked second, with a maximum absolute delta cost of 116,170,800 IDR, while seed and pesticide produced substantially smaller effects.

Table 11: Component-Level Sensitivity Ranking Under One-at-a-Time Perturbations.

Rank	Component	Max Absolute Delta Cost(IDR)	Max Delta Objective (%)	Sensitivity Ratio	Decision Changed
1	Labor	681,855,000	23.96	0.7987	No
2	Fertilizer	97,915,950	3.44	0.1147	No
3	Pesticide	38,514,000	1.35	0.0451	No
4	Seed	35,370,000	1.24	0.0414	No

Note: Max delta objective reports the largest absolute percentage change relative to the baseline objective value.

Figure 2 shows that the objective-value responses are approximately linear across the tested perturbation levels. The labor-cost curve has the steepest slope, indicating that changes in labor cost produce the largest proportional shift in the total optimal cost. Fertilizer shows a moderate slope, while seed and pesticide remain relatively flat. This pattern confirms that the model's objective value is not uniformly sensitive to all cost parameters. Instead, sensitivity is concentrated in the labor component because labor dominates the baseline cost structure and is constrained by minimum activity requirements.

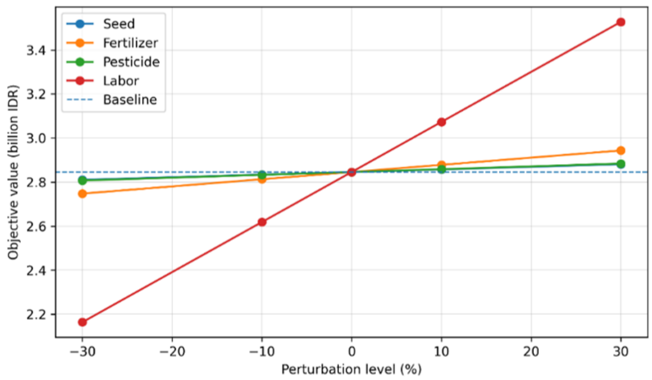

Figure 2. Objective Value Under One-at-a-Time Component-Level Sensitivity.

Figure 3 further confirms the dominance of labor in the component-level sensitivity ranking. The large gap between labor and the other components indicates that labor-cost management should be treated as the primary cost-control concern in rice cultivation planning. However, this does not imply that labor use can be arbitrarily reduced, because labor is tied to minimum cultivation activity requirements. Therefore, practical cost-control strategies should focus on labor scheduling, coordination among farmer groups, and possible mechanization, rather than simply reducing the number of required workers.

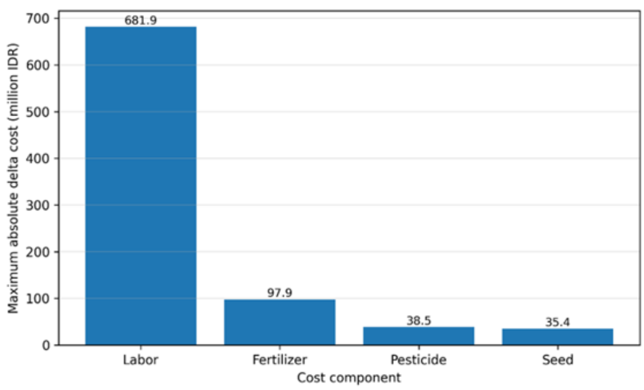

Figure 3. Component-Level Sensitivity Ranking Based on Maximum Absolute Delta Cost.

From a discussion perspective, this pattern is consistent with the baseline cost distribution. The labor sensitivity ratio of 0.7987 indicates that the objective value changed by approximately 0.7987% for every 1% change in labor cost under the tested scenario. Fertilizer showed a much lower sensitivity ratio of 0.1147, while seed and pesticide remained below 0.05. Therefore, the model is not uniformly sensitive to all input costs; its cost exposure is primarily concentrated on labor. The authors acknowledge that labor sensitivity is partly expected because labor constitutes the largest component of total production cost. Nevertheless, the sensitivity analysis still provides important operational insight by identifying labor availability as the primary bottleneck resource in the modeled rice cultivation system.

Mathematically, labor sensitivity is influenced not only by its dominant contribution to total production cost but also by the structure of the MILP model. Labor allocation is constrained by minimum labor requirements and labor availability limits $w_{it}^{\min} \leq w_{it} \leq w_{it}^{\max}$, such that the labor variable reached a binding condition at the optimal solution and could not be further reduced without violating the constraints. Constraint evaluation also showed that several labor and fertilizer constraints were binding, indicating active resource limitations rather than merely trivial lower-bound selections. In addition, integer restrictions cause small parameter perturbations to generate discrete changes in the feasible solution space. This structural property explains why labor remains the most sensitive parameter in the optimization model.

The optimization structure in this study tends to produce solutions close to the lower bounds of several agronomic inputs because the objective function is focused on cost minimization under minimum resource requirement constraints. In a linear formulation, this condition naturally drives the model to select the lowest input values that still satisfy agronomic and operational constraints. Nevertheless, the model still provides operational insight for rice cultivation planning, particularly in evaluating input-use efficiency, identifying the most influential cost components, and ensuring that resource allocation satisfies minimum cultivation requirements under local conditions. The use of agronomic constraints and discrete labor variables also produces solutions that are more realistic and consistent with operational implementation in the field. In addition to being influenced by the lower bounds of agronomic inputs, the optimal solution is also determined by the combination of land-area constraints, resource availability, labor requirements, and input bounds calibrated based on the actual practices of farmers from nine farmer groups in the village. Therefore, the proposed model can be used as a decision-support tool to improve cost efficiency and operational planning for rice cultivation at the local level.

4. CONCLUSION

The application of MILP with agronomic and labor constraints can support more efficient and operational rice cultivation planning in Pematang Setrak. Model results demonstrate decision-making in resource allocation based on the land area owned by each farmer group. The optimal solution indicates that production cost efficiency can be improved by adjusting fertilizer and pesticide allocation while maintaining constraints on land area, resource availability, agronomic dosage, and labor. Further sensitivity analysis indicates that labor is the most influential cost component because it dominates the basic cultivation cost structure and is constrained by minimum cultivation activity requirements. The model used is static and deterministic, meaning input prices, resource availability, labor requirements, and agronomic input constraints are assumed to remain constant throughout the growing season. The model also does not consider uncertainties related to weather conditions, pest intensity, input prices, and the direct relationship between input reductions and yield responses, so their impact on productivity has not been quantitatively analyzed. Furthermore, the empirical scope of this research is limited to a single local case study, requiring further validation in other agricultural contexts for broader applicability.

Future research could integrate the yield response function to agronomic inputs to evaluate the trade-off between cost efficiency and crop productivity. The relatively small computational size of the model indicates that the MILP formulation is quite simple but provides meaningful operational insights. Therefore, the model can be extended to more complex problems, such as developing a model incorporating an uncertainty-based optimization approach that can consider not only cost minimization but also yield stability and farmer income.

REFERENCES

[1] M. A. Islam, M. S. Hossain, and M. T. Rahman, "Towards sustainable resource allocation in agriculture: A systematic review on cropping pattern optimization approaches," *Applied Soft Computing*, vol. 156, p. 112360, 2024, https://doi.org/10.1016/j.asoc.2024.112360.

[2] K. P. Devkota, S. Jat, C. M. Khanda, S. J. Beebout, B. K. Mohapatra, G. R. Singleton, and R. Puskur, "Assessing alternative crop establishment methods with a sustainability lens in rice production systems of eastern india," *Journal of Cleaner Production*, vol. 244, p. 118835, 2020, https://doi.org/10.1016/j.jclepro.2019.118835.

[3] C. Wang, "Optimization allocation strategy of agricultural production resources based on ssa-bp algorithm," *Scientific Reports*, vol. 15, p. 35828, 2025, https://doi.org/10.1038/s41598-025-19747-4.

[4] I. Boninsenha, E. C. Mantovani, A. G. da Silva Júnior, and M. H. Costa, "A linear programming model for operational optimization of agricultural activity considering a hydroclimatic forecast—case studies for western bahia, brazil," *Water*, vol. 14, no. 22, p. 3625, 2022, https://doi.org/10.3390/w14223625.

[5] A. Alotaibi and F. Nadeem, "A review of applications of linear programming to optimize agricultural solutions," *International Journal of Information Engineering and Electronic Business*, vol. 13, no. 2, pp. 11–21, 2021, https://doi.org/10.5815/ijieeb.2021.02.02.

[6] A. Arenas-Calle, J. A. Mesa, and A. F. Ortega, "Optimization of agricultural resource allocation using linear programming techniques," *Agricultural Systems*, vol. 153, pp. 1–13, 2017, https://doi.org/10.1016/j.agsy.2017.01.001.

[7] N. Abdullahi, I. Bulus, H. Bukar, and H. B. Awwalu, "A systematic review of optimal resource allocation techniques in agriculture," *International Journal of Development Mathematics*, vol. 2, no. 1, pp. 251–262, 2025.

[8] G. B. Dantzig, "Linear programming," *Operations Research*, vol. 50, no. 1, pp. 42–47, 2002, https://doi.org/10.1287/opre.50.1.42.17798.

[9] K. Butterworth, "Practical application of linear/integer programming in agriculture," *Journal of the Operational Research Society*, vol. 36, no. 2, pp. 99–107, 1985, https://doi.org/10.1057/jors.1985.22.

[10] A. Dolara, F. Grimaccia, G. Magistrati, and G. Marchegiani, "Optimization models for islanded micro-grids: A comparative analysis between linear programming and mixed integer programming," *Energies*, vol. 10, no. 2, p. 241, 2017, https://doi.org/10.3390/en10020241.

[11] J. Veintimilla-Reyes, A. De Meyer, D. Cattrysse, and J. Van Orshoven, "From linear programming model to mixed integer linear programming model for the simultaneous optimisation of water allocation and reservoir location in river systems," *Proceedings*, vol. 2, no. 11, p. 594, 2018, https://doi.org/10.3390/proceedings2110594.

[12] A. I. Pratiwi, A. Mansur, and S. T. Prawibowo, "A mixed-integer linear programming model for the rice supply chain in karawang regency to minimize costs," *Jurnal Teknologi dan Manajemen Industri Terapan*, vol. 4, no. 3, pp. 993–1006, 2025, https://doi.org/10.55826/jtmit.v4i3.1083.

[13] G. Bayá, E. Canale, S. Nesmachnow, F. Robledo, and P. Sartor, "Production optimization in a grain facility through mixed-integer linear programming," *Applied Sciences*, vol. 12, no. 16, p. 8212, 2022, https://doi.org/10.3390/app12168212.

[14] C. Filippi, R. Mansini, and E. Stevanato, "Mixed integer linear programming models for optimal crop selection," *Computers & Operations Research*, vol. 81, pp. 26–39, 2017, https://doi.org/10.1016/j.cor.2016.12.004.

[15] O. Riskadayanti, M. Hisjam, and Yuniaristanto, "Mixed-integer linear programming model for production planning: A case study at sawn timber production," *Jurnal Teknik Industri*, vol. 21, no. 2, pp. 163–173, 2020, https://doi.org/10.22219/JTIUMM.Vol21.No2.163-173.

[16] D. Makowski, E. M. T. Hendrix, M. K. van Ittersum, and W. A. H. Rossing, "Generation and presentation of nearly optimal solutions for mixed-integer linear programming, applied to a case in farming system design," *European Journal of Operational Research*, vol. 132, no. 2, pp. 425–438, 2001, https://doi.org/10.1016/S0377-2217(00)00134-X.

[17] P. Kumar, J. M. Rosenberger, and G. M. D. Iqbal, "Mixed integer linear programming approaches for land use planning that limit urban sprawl," *Computers & Industrial Engineering*, vol. 102, pp. 33–43, 2016, https://doi.org/10.1016/j.cie.2016.10.007.

[18] T. Adamo, L. Colizzi, G. Dimauro, E. Guerriero, and D. Pareo, "Crop planting layout optimization in sustainable agriculture: A constraint programming approach," *Computers and Electronics in Agriculture*, vol. 224, p. 109162, 2024, https://doi.org/10.1016/j.compag.2024.109162.

[19] N. E. Caicedo Solano, G. A. García Llinás, and J. R. Montoya-Torres, "Operational model for minimizing costs in agricultural production systems," *Computers and Electronics in Agriculture*, vol. 197, p. 106932, 2022, https://doi.org/10.1016/j.compag.2022.106932.

[20] A. Rusdiansyah, S. N. Malano, F. Isnaini, and R. S. Dewi, "Optimization model of crop planning considering crop rotation with adjacency plots and nutrient cycling," *Agriculture and Natural Resources*, vol. 57, no. 4, pp. 569–578, 2023, https://doi.org/10.34044/j.anres.2023.57.4.02.

[21] B. Bilgen and T. Taşkıner, "Optimization of an integrated harvest and process planning model in the agri-food industry," *Journal of Engineering Research*, 2023, https://doi.org/10.1016/j.jer.2023.09.036.

[22] B. A. Urra-Calfuñir, C. A. Monardes-Concha, and P. A. Miranda-González, "Agri-food supply chain optimization through a decentralized production process in the olive oil industry," *Computers & Industrial Engineering*, vol. 192, p. 110185, 2024, https://doi.org/10.1016/j.cie.2024.110185.

[23] J. P. Rajakal, D. K. S. Ng, R. R. Tan, V. Andiappan, and Y. K. Wan, "Multi-objective expansion analysis for sustainable agro-industrial value chains based on profit, carbon and water footprint," *Journal of Cleaner Production*, vol. 288, p. 125117, 2021, https://doi.org/10.1016/j.jclepro.2020.125117.

[24] S. S. Girsang, R. L. Castillo, M. Syam, Z. Zaini, S. Kartaatmadja, Suyamto, J. C. Dela Torre, I. L. B. Pabuayon, R. A. Limpiada, Waluyo, Helmi, Samijan, R. Budiono, M. Hatta, Nurhayati, N. B. Kamandalu, B. Susanto, D. Parhusip, Z. Abidin, and R. J. Buresh, "Site-specific nutrient management for rice using soil properties to adjust phosphorus and potassium supply from compound npk fertilizer," *Field Crops Research*, vol. 326, p. 109864, 2025, https://doi.org/10.1016/j.fcr.2025.109864.

[25] M. F. Pampolino, I. J. Manguiat, S. Ramanathan, H. C. Gines, P. S. Tan, T. T. N. Chi, R. Rajendran, and R. J. Buresh, "Environmental impact and economic benefits of site-specific nutrient management (ssnm) in irrigated rice systems," *Agricultural Systems*, vol. 93, no. 1–3, pp. 1–24, 2007, https://doi.org/10.1016/j.agsy.2006.04.002.

[26] D. G. P. Rodriguez, "An assessment of the site-specific nutrient management (ssnm) strategy for irrigated rice in asia," *Agriculture*, vol. 10, no. 11, p. 559, 2020, https://doi.org/10.3390/agriculture10110559.

[27] J. Mariyono, "Direct and indirect impacts of integrated pest management on pesticide use: A case of rice agriculture in java, indonesia," *Pest Management Science*, vol. 64, no. 10, pp. 1069–1073, 2008, https://doi.org/10.1002/ps.1602.