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Green Economy-Based Multi-Objective Optimization Model for Agricultural Supply Chain Network Design Using Lexicographic Method

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Abstract
This Article presents a multi-objective optimization model for agricultural supply chain network design that incorporates green economy principles. The problem is formulated as a Many-to-Many Location Routing Problem (MMLRP) to address strategic decisions including Regional Food Hub site selection, commodity flow allocation between producers and hubs, distribution routing to consumer zones, and warehouse capacity planning. Two objective functions are solved hierarchically using the Lexicographic Method: maximizing demand fulfillment as the primary objective, followed by minimizing total costs comprising shipping, warehousing, and hub construction expenses. The model incorporates flow conservation constraints, capacity limits for producers and demand zones, and logical constraints linking distribution activities to hub establishment. Environmental considerations are integrated through carbon tax components and vehicle emission factors in transportation activities, enabling decision-makers to account for the environmental impact of logistics operations. Results demonstrate that the optimal network configuration identifies strategic hub locations and efficient distribution patterns characterized by short-distance delivery clusters that minimize carbon emissions, while maintaining cross-regional shipments from major production centers to satisfy demand requirements.

Keywords: *Supply Chain Network Design, Lexicographic Method, Green Economy, Many-to-Many Location Routing Problem, Carbon Tax.*

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1. Introduction

Optimization serves as a crucial instrument in managerial and technical decision-making for obtaining optimal solutions amid resource constraints [18]. The urgency of implementing optimization models becomes increasingly significant in systems with complex variables such as supply chain networks [9]. In Indonesia, rapid economic activities and urbanization have triggered substantial challenges for urban transportation and logistics systems [1]. High freight mobility volumes not only burden infrastructure but also contribute significantly to greenhouse gas emissions, adversely impacting public health and the environment [22, 7].

This condition becomes particularly critical in agricultural supply chain systems, which are now recognized as strategic distribution networks ensuring food availability and accessibility for urban populations [19]. The complexity of agricultural supply chains is characterized by extensive network structures and intricate interdependencies among distribution actors [21]. Meanwhile, environmental regulations demand integration between economic efficiency and sustainability, making adaptive distribution network design a strategic imperative [5].

However, maximizing demand fulfillment often correlates directly with increased logistics intensity, which linearly escalates operational costs and emission tax burdens [13]. Traditional deterministic approaches focusing solely on cost minimization frequently overlook environmental aspects and timeliness considerations [10]. Within the green economy framework, carbon tax policies—implemented in Indonesia through the Tax Regulation Harmonization Law with a rate of IDR 30 per kg CO_2e—necessitate explicit integration of emissions as direct cost components in optimization objective functions [2, 23].

Recent developments in multi-objective optimization for agricultural supply chain network design have explored various methodological approaches, as summarized in Table 1. Studies addressing green economy aspects include energy consumption optimization using Augmented Epsilon Constraint [9], social sustainability through Fuzzy Programming [20], and carbon emission management via Hybrid Meta-heuristics [12] or Mixed-Integer Optimization [16]. Other approaches employ Exact Solver BARON for carbon cap-and-trade [3] and Goal Programming for air quality [15]. However, a research gap persists in hierarchical multi-objective methods that explicitly prioritize demand fulfillment while incorporating carbon tax as a direct cost component in agricultural supply chains.

Table 1. State of the art research in multi-objective agricultural supply chain optimization

No	Author	Multi-objective	Green Economy Focus	Agricultural Supply Chain	Solution Method
1	[9]	✓	Energy Consumption	✓	Augmented Epsilon Constraint
2	[20]	✓	Social Sustainability	✓	Fuzzy Programming
3	[12]	✓	Carbon Emission	✓	Hybrid Meta-heuristic
4	[16]	✓	Carbon Tax & Trade	✓	Mixed-Integer Optimization
5	[3]	✓	Carbon Cap-and-Trade	✓	Exact Solver (BARON)
6	[15]	✓	Air Quality	✓	Goal Programming
7	**This Study**	✓	**Carbon Tax**	✓	**Lexicographic Method**

To address this gap, this study develops a multi-objective many-to-many location-routing problem (MMLRP) model that integrates green economy principles through explicit carbon tax incorporation. Unlike simple linear models, MMLRP effectively captures connectivity dynamics among multiple supply and demand points simultaneously within an integrated optimization framework [6]. The novelty of this research lies in employing the Lexicographic Method to hierarchically solve the multi-objective problem, where demand fulfillment maximization is prioritized over logistics cost minimization that explicitly includes carbon tax as a direct cost component. This approach aligns with Green Logistics principles by harmonizing the inherent conflict between economic cost efficiency and environmental impact mitigation in modern food distribution networks [14, 4].

The Lexicographic Method is particularly suitable for food security policy compared to Pareto-based approaches due to its non-compensatory hierarchical structure [18, 21]. In the context of food security, demand fulfillment represents a basic necessity that cannot be compromised by cost savings, as food availability must be secured before optimizing distribution costs [19, 21]. Unlike Pareto methods that allow trade-offs between objectives, the lexicographic approach treats food security as a hard constraint in accordance with regulatory requirements, ensuring that economic optimization occurs only after meeting minimum sustenance requirements [18].

2. Materials and Methods

2.1. **Linear Programming.** According to Hillier and Lieberman [8], the standard form of a linear programming model for resource allocation problems can be formulated as follows. The model aims to select the values for $x_1, x_2, \ldots, x_n$ such that:

$$\begin{aligned} \text{Maximize} \quad Z &= c_1x_1 + c_2x_2 + \cdots + c_nx_n, \\ \text{subject to} \quad a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &\le b_1, \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &\le b_2, \\ &\vdots \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n &\le b_m, \\ \text{and} \quad x_1 \ge 0, \quad x_2 \ge 0, \quad \ldots, \quad x_n &\ge 0. \end{aligned} \tag{1}$$

This formulation is referred to as the *standard form* for linear programming problems. Any situation whose mathematical formulation fits this model is classified as a linear programming problem.

The function $Z = c_1x_1 + c_2x_2 + \cdots + c_nx_n$ is called the **objective function**. The restrictions are referred to as **constraints**. The first m constraints (those with a function of all variables $a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{in}x_n$ on the left-hand side) are called **functional constraints** (or *structural constraints*). The requirements $x_i \ge 0$ are called **nonnegativity constraints** [8].

Table 2 summarizes the data structure needed for a linear programming model involving resource allocation to activities.

Table 2. Data needed for a linear programming model involving the allocation of resources to activities

Resource	**Resource Usage per Unit of Activity Activity**				**Amount of Resource Available**
	1	**2**	$\cdots$	**n**	
1	a_{11}	a_{12}	$\cdots$	a_{1n}	b_1
2	a_{21}	a_{22}	$\cdots$	a_{2n}	b_2
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
m	a_{m1}	a_{m2}	$\cdots$	a_{mn}	b_m
Contribution to Z per unit of activity	c_1	c_2	$\cdots$	c_n	

2.2. **Mixed Integer Linear Programming.** According to Hillier and Lieberman [8], Mixed Integer Linear Programming (MILP) is a linear programming problem where some variables (typically a portion of l variables) are constrained to have integer values, while other variables can take continuous values. To simplify the formulation, these variables are ordered such that the first l variables represent the integer-constrained variables, while the remaining variables have continuous values. Therefore, the general form of the problem being discussed can be expressed as follows [8]:

$$\begin{aligned} \max \quad & z = \sum_{j=1}^{n} c_j x_j \\ \text{s.t.} \quad & \sum_{j=1}^{n} a_{ij} x_j \leq b_i \quad , i = 1, 2, ..., m, \\ & x_j \geq 0 \quad , j = 1, 2, ..., n, \\ & x_j \text{ integer} \quad , j = 1, 2, 3, ..., l; \quad l \leq n. \end{aligned} \tag{2}$$

If all variables are constrained to be integer, that is when $l = n$, then the problem becomes a *pure integer programming* problem.

2.3. **Multi-Objective Optimization.** According to Rao [18], Multi-Objective Optimization (MOO) is a mathematical approach for solving problems with more than one conflicting objective function. Optimization problems with multiple objectives that have trade-off constraints can be formulated as follows [18]:

$$\begin{aligned} \min \quad & \mathbf{f}_i(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})), \quad i = 1, 2, 3, \ldots, k, \\ \text{s.t.} \quad & g_j(\mathbf{x}) \leq 0, \quad j = 1, 2, 3, \ldots, m, \end{aligned} \tag{3}$$

where in formula (3), $f_i(\mathbf{x})$ represents the objective function to be minimized, while $\mathbf{x} = (x_1, x_2, \ldots, x_n)^T$ denotes the decision variable vector. The parameter k indicates the number of objective functions to be minimized. Each or some of the functions $f_i(\mathbf{x})$ and $g_j(\mathbf{x})$ may be nonlinear. Each value of $\mathbf{x}$ that satisfies all constraints is referred to as a feasible solution, while the set of all feasible solutions is called the feasible set [18].

2.4. **Lexicographic Method.** According to Rao [18], in the *lexicographic method*, objective functions are ranked based on the importance assigned by the model developer. The optimal solution $\mathbf{x}^*$ is found by minimizing the objective function starting from the highest priority objective. The index (k) in the objective function indicates its priority. Thus, $f_1(\mathbf{x})$ and $f_k(\mathbf{x})$ represent the objective functions from the highest priority to the lowest priority, respectively. The first problem is then stated as follows [18]:

$$\begin{aligned} \min \quad & f_1(\mathbf{x}), \\ \text{s.t.} \quad & g_j(\mathbf{x}) \leq 0, \quad j = 1, 2, 3, \ldots, m, \end{aligned} \tag{4}$$

The optimal solution of equation (4) is $\mathbf{x}_1^*$ and $f_1^* = f_1(\mathbf{x}_1^*)$. Subsequently, the second problem is formulated as follows:

$$\begin{aligned} \min \quad & f_2(\mathbf{x}), \\ \text{s.t.} \quad & g_j(\mathbf{x}) \leq 0, \quad j = 1, 2, 3, \ldots, m, \\ & f_1(\mathbf{x}) = f_1^*, \end{aligned} \tag{5}$$

The optimal solution of equation (5) is $\mathbf{x}_2^*$ and $f_2^* = f_2(\mathbf{x}_2^*)$ is obtained. This procedure is repeated sequentially for subsequent priorities. In general, the problem formulation for the i-th priority (where $1 < i < k$) can be expressed as follows:

$$\begin{aligned} \min \quad & f_i(\mathbf{x}), \\ \text{s.t.} \quad & g_j(\mathbf{x}) \leq 0, \quad j = 1, 2, 3, \ldots, m, \\ & f_l(\mathbf{x}) = f_l^*, \quad l = 1, 2, 3, \ldots, i-1, \end{aligned} \tag{6}$$

such that the solution is obtained as $\mathbf{x}_i^*$ and $f_i^* = f_i(\mathbf{x}_i^*)$. The solution obtained at the final stage $\mathbf{x}_k^*$ is taken as the solution used for $\mathbf{x}^*$ from the overall problem.

2.5. **MILP Model for Supply Chain Network Design Problem.** The optimization model formulation for the supply chain problem in this study is adapted from Perdana *et al.* [17] on agricultural product distribution. The model focuses on commodity distribution flows from production centers through intermediary facilities to demand zones. The model framework employs several key sets: demand zones (I), candidate Regional Food Hub locations (J), production centers (K), and commodity types (C), denoted by indices i, j, k, and c, respectively.

This problem is formulated as a Mixed Integer Linear Programming (MILP) model. The parameters include d_{ci}, representing the demand for commodity c in zone i (tons/year), and f_{ck}, denoting the production capacity of commodity c at center k (tons/year). From an economic perspective, v_{ci} represents the selling price of commodity c in zone i (IDR/ton), b_{kj} denotes the distribution cost from producers to hubs, and b_{ji} represents the distribution cost from hubs to consumers. Additionally, h_j captures the investment cost for hub construction (IDR/facility), while q represents the warehousing/storage cost (IDR/ton).

The model incorporates two primary objective functions. The first objective aims to maximize demand fulfillment, as expressed in Equation (7):

$$\max Z_1 = \sum_{c \in C} \sum_{i \in I} v_{ci} \sum_{j \in J} w_{cji} \tag{7}$$

The second objective seeks to minimize total logistics costs encompassing investment, distribution, and storage/warehousing expenses, as stated in Equation (8):

$$\min Z_2 = \sum_{j \in J} h_j x_j + \sum_{c \in C} \sum_{j \in J} \sum_{i \in I} b_{ji} d_{ci} w_{cji} + q \sum_{c \in C} \sum_{j \in J} P_{cj} + \sum_{c \in C} \sum_{k \in K} \sum_{j \in J} b_{kj} f_{ck} y_{ckj} \tag{8}$$

The model is subject to the following operational constraints:

$$\sum_{k \in K} f_{ck} y_{ckj} = P_{cj}, \quad \forall c \in C, j \in J \tag{9}$$

$$\sum_{i \in I} d_{ci} w_{cji} = P_{cj}, \quad \forall c \in C, j \in J \tag{10}$$

$$\sum_{j \in J} y_{ckj} \leq 1, \quad \forall c \in C, k \in K \tag{11}$$

$$\sum_{j \in J} w_{cji} \leq 1, \quad \forall c \in C, i \in I \tag{12}$$

$$y_{ckj} \leq x_j, \quad \forall c \in C, k \in K, j \in J \tag{13}$$

$$w_{cji} \leq x_j, \quad \forall c \in C, j \in J, i \in I \tag{14}$$

$$x_j \in \{0, 1\} \tag{15}$$

$$y_{ckj}, w_{cji} \in [0, 1] \tag{16}$$

$$P_{cj} \geq 0 \tag{17}$$

Equations (9) and (10) ensure that RFH capacity is determined based on the balance between production and demand. Constraints (11) and (12) guarantee that proportional commodity allocations do not exceed unity, ensuring that each producer or consumer zone is assigned to at most one hub. Constraints (13) and (14) serve as logical linking constraints, ensuring that proportional allocations ($y_{ckj}, w_{cji} \in [0, 1]$) representing commodity flow distributions can only occur when the corresponding hub facility is established ($x_j = 1$).

Binary variable definitions are stated in Equation (15) and (16), while Equations (17) define proportional allocation variables and absolute throughput capacity variables (in tons), respectively.

2.6. **Green Economy and Transportation Emission Modeling.** According to Loiseau *et al.* [11], the Green Economy is defined as a system of economic activities related to the production, distribution, and consumption of goods and services designed to avoid significant environmental risks or resource scarcity. Within this framework, green logistics emerges as a critical approach focusing on reducing the negative environmental impacts of transportation activities, particularly regarding energy consumption and carbon emissions. Since transportation and warehousing activities are major contributors to greenhouse gas emissions in supply chains, emission modeling becomes an essential component in designing sustainable logistics networks.

The calculation of transportation emissions in this study employs a distance-based emission calculation approach. Total emissions are computed based on vehicle travel distance, as expressed in Equation (18):

$$E = \text{distance} \times EF \tag{18}$$

where *distance* represents the traveled distance (km) and EF denotes the emission factor per unit of transportation activity ($kgCO_2$/ton·km). This emission burden is subsequently integrated into the logistics cost minimization objective function through new emission parameter.

2.7. **Carbon Tax Integration.** Carbon tax serves as an economic instrument that assigns a price to greenhouse gas emissions to incentivize emission reductions in supply chain activities [23]. Benjaafar *et al.* [2] introduced carbon tax as a linear penalty cost proportional to the amount of emissions generated. When a company has a traditional operational cost function, the objective function incorporating carbon tax is modified as follows:

$$Z_{total} = \sum(f_t y_t + c_t q_t + h_t l_t) + \alpha \sum(\hat{f} y_t + \hat{c} q_t + \hat{h} l_t) \tag{19}$$

where f_t, c_t, h_t represent fixed costs, variable costs, and holding costs, respectively; $\hat{f}, \hat{c}, \hat{h}$ denote the associated emission coefficients; and α represents the carbon tax rate.

This optimization problem can be simplified into a pure cost minimization problem through parameter transformation into "generalized costs" as follows:

$$\bar{c}_t = c_t + \alpha\hat{c} \tag{20}$$

$$\bar{f}_t = f_t + \alpha\hat{f} \tag{21}$$

$$\bar{h}_t = h_t + \alpha\hat{h} \tag{22}$$

Equations (20)-(22) demonstrate that optimal decisions in the model are no longer based solely on the lowest financial cost, but rather on the balance between cost efficiency and emission efficiency. By substituting these generalized costs, the optimization model's objective function becomes:

$$\min Z = \sum_{t=1}^{T}(\bar{f}_t y_t + \bar{c}_t q_t + \bar{h}_t l_t) \tag{23}$$

This formulation ensures that environmental externalities are internalized into the decision-making framework, enabling supply chain managers to simultaneously optimize economic performance and environmental sustainability.

3. Results and Discussion

3.1. **Multi-Objective Optimization Model with Green Economy for MMLRP.** The modification focuses on adding the Green Economy component. The mechanism employed is carbon tax application, where greenhouse gas emissions (in this study CO_2) generated from transportation activities are monetized. This addition alters the cost minimization objective function structure (Z_2) from equation (8).

To formulate emission costs, additional parameters related to emissions are required, such as the applicable carbon tax rate, emissions from transportation activities calculated based on equation (23), and additional parameters defined in Table 3.

Table 3. Additional parameters for carbon tax application

Parameter	**Description**	**Unit**
α	Carbon tax rate set by the government	$\frac{Rp}{kgCO_2e}$
$\hat{e}_{kj}$	Transportation emission from producer k to RFH j	$\frac{kgCO_2e}{ton}$
$\hat{e}_{ji}$	Transportation emission from RFH j to consumer i	$\frac{kgCO_2e}{ton}$
$\hat{q}$	*Storage/warehousing* emission	$\frac{kgCO_2e}{ton}$

Consider equation (8) Based on the parameters in Table 3, the second objective function is modified by incorporating the carbon tax cost component, such that equation (24) is reformulated as:

$$\begin{aligned}\min Z_2 = h\sum_{j\in J} x_j &+ \sum_{c\in C}\sum_{j\in J}\sum_{i\in I} b_{ji}d_{ci}w_{cji}\\ &+ q\sum_{c\in C}\sum_{j\in J} P_{cj}\\ &+ \sum_{c\in C}\sum_{k\in K}\sum_{j\in J} b_{kj}f_{ck}y_{ckj}\\ &+ \alpha\Bigg(\sum_{c\in C}\sum_{j\in J}\sum_{i\in I}\hat{e}_{ji}d_{ci}w_{cji}\\ &\quad + q\sum_{c\in C}\sum_{j\in J} P_{cj}\\ &\quad + \sum_{c\in C}\sum_{k\in K}\sum_{j\in J}\hat{e}_{kj}f_{ck}y_{ckj}\Bigg).\end{aligned} \tag{24}$$

Subsequently, mathematical simplification is performed on equation (25) by grouping similar decision variables, resulting in the combined cost formulation as follows:

$$\begin{aligned}\min Z_2 = h\sum_{j\in J} x_j &+ \sum_{c\in C}\sum_{j\in J}\sum_{i\in I}(b_{ji}+\alpha\hat{e}_{ji})d_{ci}w_{cji}\\ &+ (q+\alpha\hat{q})\sum_{c\in C}\sum_{j\in J} P_{cj}\\ &+ \sum_{c\in C}\sum_{k\in K}\sum_{j\in J}(b_{kj}+\alpha\hat{e}_{kj})f_{ck}y_{ckj}.\end{aligned} \tag{25}$$

Thus, the final MMLRP model with Green Economy can be written comprehensively as follows:

$$
\begin{aligned}
\max Z_1 &= \sum_{c\in C}\sum_{i\in I} v_{ci}\sum_{j\in J} w_{cji},\\
\min Z_2 &= h\sum_{j\in J} x_j + \sum_{c\in C}\sum_{j\in J}\sum_{i\in I}(b_{ji}+\alpha\hat{e}_{ji})d_{ci}w_{cji}\\
&\quad + (q+\alpha\hat{q})\sum_{c\in C}\sum_{j\in J} P_{cj} + \sum_{c\in C}\sum_{k\in K}\sum_{j\in J}(b_{kj}+\alpha\hat{e}_{kj})f_{ck}y_{ckj},\\
\text{s.t.}\quad & \sum_{k\in K} f_{ck}y_{ckj} = P_{cj}, \quad \forall c\in C, j\in J,\\
& \sum_{i\in I} d_{ci}w_{cji} = P_{cj}, \quad \forall c\in C, j\in J,\\
& \sum_{j\in J} y_{ckj} \le 1, \quad \forall c\in C, k\in K,\\
& \sum_{j\in J} w_{cji} \le 1, \quad \forall c\in C, i\in I,\\
& y_{ckj} \le x_j, \quad \forall c\in C, k\in K, j\in J,\\
& w_{cji} \le x_j, \quad \forall c\in C, j\in J, i\in I,\\
& x_j \in \{0,1\}, \quad \forall j\in J,\\
& y_{ckj}, w_{cji} \in [0,1], \quad \forall c\in C, k\in K, j\in J, i\in I,\\
& P_{cj} \ge 0, \quad \forall c\in C, j\in J.
\end{aligned}
\tag{26}
$$

3.2. **Research Data.** The numerical experiment was conducted using Python programming language with the PuLP optimization library to solve the MILP model. The simulation focuses on the distribution network of rice, one of the primary agricultural commodities, comprising production centers, Regional Food Hubs (RFH), and consumer zones.

Numerical parameters input into the model are derived from secondary data processing from BPS (Statistics Indonesia) West Java for production capacity and demand volume, as well as emission standards from the Guidance on Measuring and Reporting Greenhouse Gas Emissions from Freight Transport Operations. All spatial data, including inter-location distances and operational costs, have been adjusted to reflect actual geographical conditions. Additionally, carbon tax scenarios are integrated as penalty cost components to examine the impact of environmental regulations on distribution decisions.

The distance information among production points, RFHs, and consumers serves as the basis for transportation cost calculations in the model. Therefore, a distance matrix was constructed based on actual travel distances using the OpenRouteService Application Programming Interface (API). The numerical parameters used in the experiment are presented in Table 4.

Table 4. Numerical parameters for the experiment

Parameter	Value	Unit
$v_{rice,i}$	14,500,000	IDR/ton
h	300,000,000	IDR/year
q	200,000	IDR/ton
α	30	IDR/kgCO_2
$\hat{q}$	3.4	kgCO_2e/ton

The rice commodity price ($v_{rice,i}$) represents the selling price per ton at consumer zones. The hub construction cost (h) denotes the annual investment required to establish a Regional Food Hub facility. The warehousing cost (q) covers storage operations per ton of commodity.

The carbon tax rate (α) follows the Indonesian government regulation of IDR 30 per kg CO_2e. The warehousing emission factor ($\hat{q}$) quantifies greenhouse gas emissions from storage activities. Distribution costs are calculated based on distance traveled, while the tank capacity determines the maximum load per vehicle. The emission factor for transportation accounts for fuel consumption and vehicle type in the logistics network.

3.3. **Numerical Experiment of Multi-Objective Optimization Model with Green Economy on MMLRP.** This subsection presents the numerical experiment results for rice distribution optimization in West Java Province involving 27 cities/regencies. The model applied in this case is Model (27) with the following details:

3.3.1. *First Objective Function.* In this problem, the first objective function is used to maximize demand fulfillment with constant costs based on the location specification in Table 4, formulated as follows:

$$\max Z_1 = 14,500,000 \sum_{j=1}^{27}\sum_{i=1}^{27} w_{ji}. \tag{27}$$

3.3.2. *Second Objective Function.* The second objective function aims to minimize total distribution costs, including hub construction costs, transportation, storage costs, and carbon tax. Parameters are specified in Table 4, resulting in the detailed objective function as follows:

$$\begin{aligned}\min Z_2 = 300,000,000 &\sum_{j=1}^{27} x_j + \sum_{j=1}^{27}\sum_{i=1}^{27}(b_{ji} + 30 \times \hat{e}_{ji}) d_i w_{ji} \\ &+ (200,000 + 30 \times 3.4) \sum_{j=1}^{27} p_j \\ &+ \sum_{k=1}^{27}\sum_{j=1}^{27}(b_{kj} + 30 \times \hat{e}_{kj}) f_k y_{kj}.\end{aligned} \tag{28}$$

3.3.3. *Constraints.* The hub capacity constraint is used to ensure that each hub's capacity equals the total commodity inflow from production areas and the total outflow distributed to demand areas across 27 regencies/cities:

$$\sum_{k=1}^{27} f_k y_{kj} = P_j, \quad \forall j \in \{1, 2, 3, \dots, 27\}, \tag{29}$$

$$\sum_{i=1}^{27} d_i w_{ji} = P_j, \quad \forall j \in \{1, 2, 3, \dots, 27\}. \tag{30}$$

The allocation constraint ensures that commodities shipped from production areas to RFHs do not exceed production capacity for the respective commodities, and commodities shipped do not exceed demand in West Java:

$$\sum_{j=1}^{27} y_{kj} \leq 1, \quad \forall k \in \{1, 2, 3, \dots, 27\}, \tag{31}$$

$$\sum_{j=1}^{27} w_{ji} \leq 1, \quad \forall i \in \{1, 2, 3, \dots, 27\}. \tag{32}$$

The linking constraint ensures that distribution allocation can only occur if the associated hub is constructed:

$$y_{kj} \leq x_j, \quad \forall k \in \{1,2,3,\ldots,27\}, j \in \{1,2,3,\ldots,27\}, \tag{33}$$
$$w_{ji} \leq x_j, \quad \forall j \in \{1,2,3,\ldots,27\}, i \in \{1,2,3,\ldots,27\}. \tag{34}$$

The decision variable domain specifies the type and bounds of decision variables used in the model:

$$x_j \in \{0,1\}, \quad \forall j \in \{1,2,3,\ldots,27\}, \tag{35}$$
$$y_{kj}, w_{ji} \in [0,1], \quad \forall k \in \{1,2,3,\ldots,27\}, j \in \{1,2,3,\ldots,27\}, \tag{36}$$
$$i \in \{1,2,3,\ldots,27\}, \tag{37}$$
$$P_j \geq 0, \quad \forall j \in \{1,2,3,\ldots,27\}. \tag{38}$$

Thus, the complete multi-objective optimization model for the rice supply chain in West Java is as follows:

$$\begin{aligned}
\max Z_1 &= 14,500,000 \sum_{j=1}^{27}\sum_{i=1}^{27} w_{ji},\\
\min Z_2 &= 300,000,000 \sum_{j=1}^{27} x_j + \sum_{j=1}^{27}\sum_{i=1}^{27} (b_{ji} + 30 \times \hat{e}_{ji}) d_i w_{ji}\\
&\quad + (200,000 + 30 \times 3.4) \sum_{j=1}^{27} p_j + \sum_{k=1}^{27}\sum_{j=1}^{27} (b_{kj} + 30 \times \hat{e}_{kj}) f_k y_{kj},\\
\text{s.t.} \quad & \sum_{k=1}^{27} f_k y_{kj} = P_j, \quad \forall j \in \{1,2,3,\ldots,27\},\\
& \sum_{i=1}^{27} d_i w_{ji} = P_j, \quad \forall j \in \{1,2,3,\ldots,27\},\\
& \sum_{j=1}^{27} y_{kj} \leq 1, \quad \forall k \in \{1,2,3,\ldots,27\},\\
& \sum_{j=1}^{27} w_{ji} \leq 1, \quad \forall i \in \{1,2,3,\ldots,27\},\\
& y_{kj} \leq x_j, \quad \forall k \in \{1,2,3,\ldots,27\}, j \in \{1,2,3,\ldots,27\},\\
& w_{ji} \leq x_j, \quad \forall j \in \{1,2,3,\ldots,27\}, i \in \{1,2,3,\ldots,27\},\\
& x_j \in \{0,1\}, \quad \forall j \in \{1,2,3,\ldots,27\},\\
& y_{kj}, w_{ji} \in [0,1], \quad \forall k,j,i \in \{1,2,3,\ldots,27\},\\
& P_j \geq 0, \quad \forall j \in \{1,2,3,\ldots,27\}.
\end{aligned} \tag{39}$$

3.4. **Optimal Regional Food Hub Configuration.** The numerical experiment yielded strategic decisions for RFH placement across West Java Province. the optimal solution recommends 19 RFH locations from 27 candidate sites. Figure 1 illustrates the spatial distribution of these facilities, demonstrating comprehensive coverage from northern production centers to southern urban consumption zones. This strategic placement aims to minimize transportation distances, thereby reducing carbon emissions and associated tax costs in the rice supply chain.

Figure 2 reveals significant capacity differentiation among selected RFHs. Indramayu handles the largest volume at 870,215 tons annually, followed by Karawang (725,710 tons) and Subang (532,174 tons). These facilities correspond to West Java's primary rice production

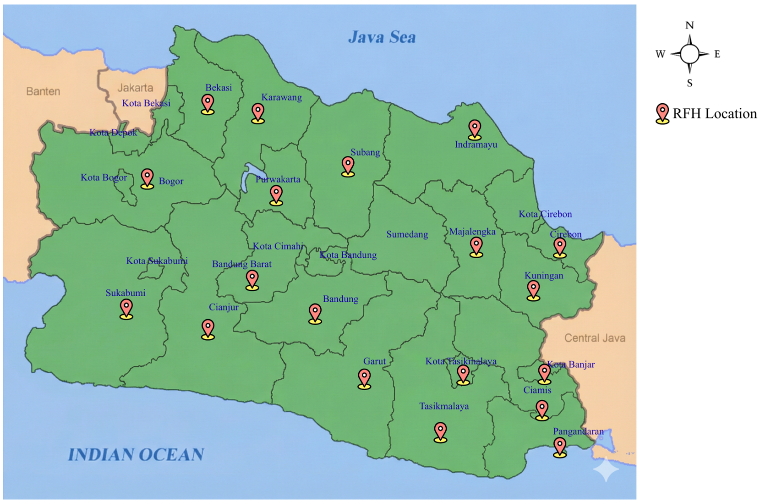

Figure 1. Spatial distribution of optimal RFH locations in West Java Province

zones, functioning as critical aggregation points for local supply before redistribution. The model generates a 42:1 capacity ratio between the highest (Indramayu) and lowest (Kota Bandung) facilities, demonstrating adaptive scaling based on local supply-demand characteristics.

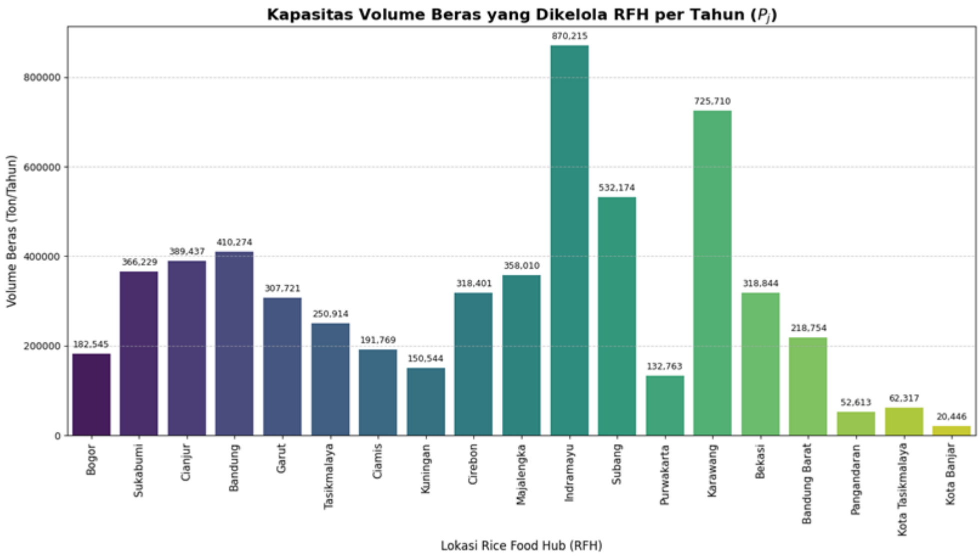

Figure 2. Annual rice handling capacity by RFH location (P_j in tons/year)

3.5. **Demand Fulfillment Analysis.** The primary objective function prioritizes demand maximization. Based on 2024 data, West Java faces a supply deficit with total production capacity of 5,859,679.13 tons against demand of 6,130,329.40 tons. Consequently, 100% fulfillment is infeasible. The optimal solution is thus defined by the model's ability to distribute all available supply efficiently.

Table 5 presents the demand fulfillment analysis across consumer zones. The model achieves 95.59% overall fulfillment ratio, distributing 5,859,679.13 tons of available supply to meet 6,130,329.40 tons of demand. Most regencies achieve 100% fulfillment, while urban centers experience partial fulfillment due to local production deficits.

Table 5. Aggregate demand fulfillment analysis

Description	Total Demand (Ton)	Fulfilled Demand (Ton)	Fulfillment Ratio (%)
West Java Province	6,130,329.40	5,859,679.13	95.59

3.6. **Distribution Network Configuration.** Figure 3 illustrates inbound flows from production zones to RFHs. The model optimizes local sourcing, with most RFHs receiving supply from their respective regencies, minimizing transportation distances. Major production areas along the northern coast (Indramayu, Subang, Karawang) serve as primary suppliers, reflecting their role as national rice granaries.

Figure 3. Rice distribution flows from production zones to RFH locations

Figure 4 presents outbound distribution from RFHs to consumer zones. While the model predominantly forms short-distance delivery clusters, notable exceptions occur in long-haul shipments from Indramayu RFH to metropolitan areas (Kota Depok, Kota Bekasi, Kota Bogor). This pattern indicates local production deficits in densely populated urban regions.

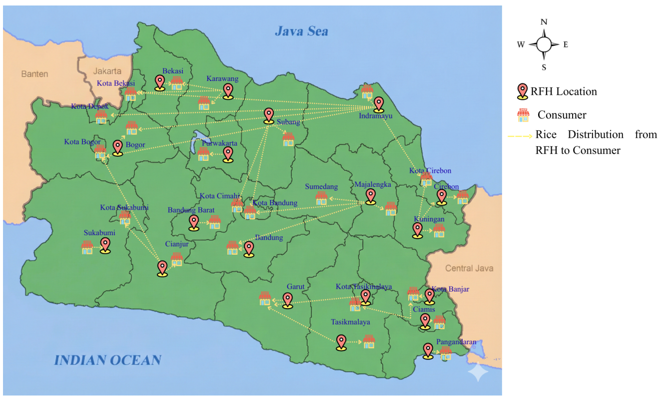

Figure 4. Rice distribution flows from RFH locations to consumer zones

The model identifies insufficient production capacity in western regions to satisfy local demand, necessitating cross-regional supply from Indramayu as the primary production center. In this context, the model prioritizes demand fulfillment over distance minimization, reflecting the practical reality of food dependency in the Jakarta metropolitan area and surroundings on West Java's agricultural regions. This hierarchical objective structure ensures food security takes precedence while simultaneously minimizing logistics costs and environmental impacts where feasible.

4. Conclusion

This study successfully formulated a multi-objective optimization model for agricultural supply chain network design incorporating green economy principles using the Lexicographic Method, as presented in equation (27). The model hierarchically prioritizes demand fulfillment maximization followed by logistics cost minimization with integrated carbon tax components and emission factors. The integration of carbon tax into generalized costs ensures that the optimal network configuration is inherently more environmentally sustainable. By monetizing emissions as direct operational costs, the model naturally generates short-distance delivery clusters that minimize carbon footprint while maintaining food security objectives, providing decision-makers with solutions that align economic efficiency with environmental responsibility.

Numerical experiments using actual rice distribution data in West Java Province demonstrate the model's effectiveness in generating efficient network configurations through Regional Food Hub intermediaries. The optimal solution achieves 95.59% demand fulfillment while minimizing carbon-inclusive distribution costs. The model identifies 19 strategic RFH locations from 27 candidates, with capacity differentiation ranging from 20,446 to 870,215 tons annually, reflecting adaptive scaling based on local supply-demand characteristics. The resulting distribution network prioritizes short-distance delivery clusters to minimize carbon emissions while maintaining necessary cross-regional shipments from major production centers (Indramayu, Karawang, Subang) to metropolitan consumption zones, ensuring food security in densely populated areas.

This research demonstrates that integrating carbon tax mechanisms into supply chain optimization effectively balances economic efficiency with environmental sustainability, providing a practical framework for implementing green logistics in agricultural distribution systems. The Lexicographic Method proves particularly suitable for this context, as it explicitly prioritizes food security objectives while simultaneously addressing environmental concerns through penalty cost mechanisms.

Future research could enhance realism by incorporating inequality constraints or slack variables to account for safety stock requirements, storage capacity buffers, and commodity spoilage in perishable supply chains.

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