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Application of Transportation Models for Biopharmaceutical Crops Harvest Optimization

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ABSTRACT

Transportation models are typically used to optimize shipping costs for products, however, their application in agricultural harvest planning remains limited. The purpose of this study is to explore the use of transportation models for optimizing biopharmaceutical crop harvest production. The research method is a quantitative optimization approach by transforming harvest production and land allocation data into a transportation model matrix. The matrix of the transportation model for the harvest of biopharmaceutical crops is adjusted to address the existing problems. In this model, sub-districts were treated as sources, crop types as destinations, and average harvest yield per square meter as the optimization parameter. The model that has been formed is then simulated and solved using POM-QM software with Vogel's Approximation Method (VAM). The model solution shows that the harvest of all biopharmaceutical crops is 4,187,642 Kg. This means that the simulation results of the transportation model are 136,697 Kg (3.37%) more than the data in 2023. These findings indicate that the transportation model can effectively support harvest production planning.

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1. INTRODUCTION

Applied mathematics bridges theoretical mathematics and practical implementation through mathematical modeling, optimization, and computational analysis [1]. One important branch of applied mathematics is operations research, which focuses on analytical decision-making and optimization under resource constraints. Operations research provides a range of quantitative techniques to support planning and management systems, including linear programming, dynamic programming, queuing theory, inventory theory, assignment models, and transportation models [2]. Since its early development by Hitchcock [3] and further expansion through linear programming theory by Dantzig [4], operations research has become an essential approach in solving complex allocation and optimization problems in many sectors.

Among the various methods in operations research, the transportation model is one of the most widely studied optimization techniques. Traditionally, transportation models are designed to determine the optimal allocation of goods from several sources to multiple destinations while minimizing total transportation costs and satisfying supply-demand constraints [5]. The classical transportation problem uses a matrix-based representation, making it computationally efficient for handling large-scale allocation systems. In addition to minimizing costs, transportation models can also support resource balancing, scheduling, and strategic planning. Previous studies have demonstrated the effectiveness of transportation models in solving distribution and logistics problems, particularly product delivery systems [6], [7], [8], [9], [10]. However, modern operations research literature shows that transportation models are not limited to logistics and goods distribution. The model has evolved into a flexible optimization framework applicable to workforce planning, inventory management, warehouse systems, agricultural supply chains, and production allocation problems [11]. Transportation applied concepts to manpower planning in public hospitals [12], transportation models integrated with warehouse and inventory optimization [13]. Transportation-based linear programming also can support human resource allocation efficiently [14]. These developments indicate that transportation models possess broader analytical capabilities beyond conventional shipping problems.

The growing complexity of agricultural systems further underscores the need for optimization methods to support production planning and resource allocation. Land availability, harvesting schedules, labor allocation, demand fluctuations, and environmental conditions strongly influence agricultural production systems. Consequently, mathematical optimization methods are increasingly utilized to improve agricultural productivity and decision-making efficiency. Optimization and planning models play a crucial role in modern agri-food supply chains, particularly in coordinating production, harvesting, storage, and distribution activities [15]. Agricultural system planning also requires data-driven approaches supported by computational models and analytics [16]. Several studies have applied optimization methods to agricultural production and harvesting problems. Quadratic programming to optimize coconut production [17], Quadratic modeling approaches for rice harvest analysis [18], Singular Value Decomposition (SVD) combined with Ant Colony Optimization (ACO) [19], Goal Programming [20], and multi-objective optimization methods to improve agricultural production systems [21]. More recent studies have explored integrated optimization frameworks in crop planning and agricultural supply chains [22], [23]. Optimization approaches can effectively support harvest scheduling operations in agricultural industries [24]. These studies confirm that optimization models significantly improve the efficiency and productivity of agricultural planning.

Although many optimization approaches have been implemented in agricultural production planning, the application of transportation models specifically for harvest production optimization remains relatively limited. Most previous studies involving transportation models still focus on product distribution and logistics systems rather than production allocation or harvest planning. Compared with other optimization methods, transportation models offer several advantages, including simpler computational procedures, a flexible matrix representation, and easier interpretation for practical decision-making. This creates a research gap because harvest planning fundamentally involves allocation decisions similar to transportation systems, such as determining optimal quantities across multiple categories, locations, periods, or production capacities. Transportation models possess several advantages for such problems, particularly their matrix structure, computational simplicity, and ability to handle large-scale allocation data efficiently.

Furthermore, transportation models can provide practical and interpretable solutions for decision-makers compared with more mathematically complex optimization methods. Recent developments in optimization and mathematical programming also indicate increasing interest in adapting classical transportation frameworks into broader planning systems [25], [26], [27]. Therefore, exploring transportation models in nontraditional contexts represents an important contribution to the development of applied operations research. Preliminary work related to the application of transportation models in biopharmaceutical crop production has been previously presented by the authors [28].

Based on these considerations, this study proposes the application of a transportation model to optimize harvest production planning for biopharmaceutical crops in Majalengka Regency, Indonesia. Biopharmaceutical crops, commonly known as herbal plants, include commodities such as ginger, galangal, turmeric, aromatic ginger, cardamom, and lime. These crops possess high economic value because they are widely used as food ingredients, traditional medicines, cosmetics, and health supplements [29]. Increasing demand for herbal products requires effective production planning to ensure efficient harvest management and optimal resource utilization. In this study, the harvest production problem is transformed into a transportation model matrix and solved using Vogel's Approximation Method (VAM). Sub-districts are represented as sources, crop types as destinations, and average harvest yields per square meter as optimization parameters within a transportation model matrix. This study aims to explore the applicability of transportation models in agricultural harvest optimization and to evaluate their effectiveness in improving biopharmaceutical crop production planning. The novelty of this research lies in adapting a classical transportation optimization framework to harvest production systems rather than conventional logistics distribution problems. This study also contributes to expanding the practical implementation of transportation models in real-world optimization problems beyond conventional transportation contexts. Therefore, the findings of this study are expected to make theoretical contributions to operations research and to have practical implications for agricultural production planning and decision-making systems.

2. METHOD

This study employed a quantitative research approach, using an optimization modeling method, to examine the application of transportation models in biopharmaceutical crop-harvest planning. The research focused on harvest data from Majalengka Regency, Indonesia. Secondary data were obtained from agricultural statistical reports and related government publications for the year 2023. The collected data included harvest quantities

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and land-use constraints for several biopharmaceutical crops, including ginger, turmeric, galangal, aromatic ginger, cardamom, and lime.

The research procedure began by identifying the harvest planning problem and transforming it into a transportation model. Crop production data were represented as sources, while land allocation requirements were represented as destinations. The transportation matrix was then formulated mathematically with the objective of optimizing harvest allocation under supply and demand constraints as follows:

$$Maximize\ Z = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} \quad (1)$$

Subject to

$$\sum_{j=1}^{n} x_{ij} = s_i, \qquad i = 1,2,\dots,m \quad (2)$$

$$\sum_{i=1}^{m} x_{ij} = d_j, \qquad j = 1,2,\dots,n \quad (3)$$

$$x_{ij} \geq 0 \quad (4)$$

Where

c_{ij} represents the average harvest yield per square meter, computed using equation (5)

$$c_{ij} = \frac{Biopharmaceutical\ Corps\ Production}{Biophamaceutical\ Corps\ Harvested\ Area} \quad (5)$$

x_{ij} represents the harvested land allocation from sub-district i to crop type j

s_i represents the total harvested land area in sub-district i

d_j represents the harvested land requirement for crop type j

The model was solved using POM-QM for Windows software with the Vogel's Approximation Method (VAM) through POM-QM for Windows software. VAM was selected because it is computationally efficient and capable of generating near-optimal initial solutions. The research procedure can be summarized as follows:

1) Collect harvest production and land-use data.
2) Construct the transportation matrix model.
3) Formulate the objective function and constraints.
4) Input the model into the POM-QM software.
5) Solve the model using VAM.
6) Compare the optimization results with the actual 2023 harvest data.

The effectiveness of the model was evaluated by comparing optimized harvest results with actual harvest production data to assess the potential application of transportation models in agricultural production planning.

3. RESULTS AND DISCUSSION

Transportation models are typically used to calculate the cost of shipping goods from multiple sources to multiple destinations. This study applies the transportation model to another field, namely, to calculate the amount of biopharmaceutical crop harvest. The data used are data on the harvest area and production of biopharmaceutical crops in Majalengka Regency. Data taken from the website of the Central Statistics Agency of Majalengka Regency in 2023. The harvest area indicates the area of land used for cultivating biopharmaceutical crops (m^2), and biopharmaceutical crop production is the harvest of biopharmaceutical crops (kg). The biopharmaceutical crop data taken in this study are data on ginger, galangal, aromatic ginger, turmeric, lime, and cardamom plants. This study is limited by the following assumptions:

1) The harvest area or available land can be planted with any type of biopharmaceutical crop.
2) Other factors that affect the harvest are not considered in this model.

3.1. Results

The transportation model consisted of 26 sub-districts as sources and 6 biopharmaceutical crop types as destinations. In this model, the objective function is to maximize the harvest of biopharmaceutical plants. The initial data set is shown in Figure 1.

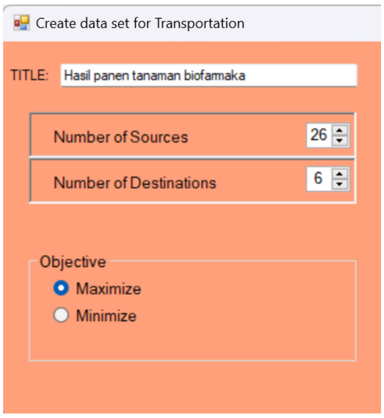

Figure 1. Initial Data Set

The initial data is displayed in the form of a table. This table shows the transportation model matrix. The empty transportation model matrix will look like Figure 2. The rows in the matrix indicate the source filled with the names of sub-districts in Majalengka Regency, and the columns in the matrix indicate the destination filled with the names of biopharmaceutical plants.

	Lime (1)	Turmeric (2)	Cardamom...	Ginger (4)	Galingale (...	Aromatic ...	SUPPLY
Argapura (1)	0	0	0	0	0	0	0
Banjaran (2)	0	0	0	0	0	0	0
Bantarujeg (3)	0	0	0	0	0	0	0
Cigasong (4)	0	0	0	0	0	0	0
Cikijing (5)	0	0	0	0	0	0	0
Cingambul (6)	0	0	0	0	0	0	0
Dawuan (7)	0	0	0	0	0	0	0
Jatitujuh (8)	0	0	0	0	0	0	0
Jatiwangi (9)	0	0	0	0	0	0	0
Kadipaten (10)	0	0	0	0	0	0	0
Kasokandel (11)	0	0	0	0	0	0	0
Kertajati (12)	0	0	0	0	0	0	0
Lemahsugih (13)	0	0	0	0	0	0	0
Leuwimunding (14)	0	0	0	0	0	0	0
Ligung (15)	0	0	0	0	0	0	0
Maja (16)	0	0	0	0	0	0	0
Majalengka (17)	0	0	0	0	0	0	0
Malausma (18)	0	0	0	0	0	0	0
Palasah (19)	0	0	0	0	0	0	0
Panyingkiran (20)	0	0	0	0	0	0	0
Rajagaluh (21)	0	0	0	0	0	0	0
Sindang (22)	0	0	0	0	0	0	0
Sindangwangi (23)	0	0	0	0	0	0	0
Sukahaji (24)	0	0	0	0	0	0	0
Sumberjaya (25)	0	0	0	0	0	0	0
Talaga (26)	0	0	0	0	0	0	0
DEMAND	0	0	0	0	0	0	

Figure 2. The Empty Transportation Model Matrix

The supply column is usually filled with the amount of stock of goods at the source, but in this transportation model, the supply column is filled with the area of biopharmaceutical crops per sub-district. The area of land per sub-district is the sum of all the land planted with all types of biopharmaceutical crops in the sub-district. The demand row is usually filled with the quantity of goods needed at the destination, but in this transportation model, it is filled with the area of biopharmaceutical plants per plant type. The area of land per type of plant is the sum of all the land for planting one type of biopharmaceutical plant in each sub-district. The calculation of the harvested area is shown in Table 1.

Table 1. The Calculation of The Harvested Area

Sub-District	**Harvested Area**						**Harvested Area/Sub district**
	Lime (Jeruk nipis)	**Turmeric (Kunyit)**	**Java Cardamon (Kapulaga)**	**Ginger (Jahe)**	**Galanga (Laos)**	**East Indian Galangal (Aromatic ginger)**	
Argapura	0	15.000	0	15.000	0	0	**30.000**
Banjaran	0	4.000	0	33.000	0	0	**37.000**
Bantarujeg	0	0	0	50.000	0	0	**50.000**
Cigasong	0	12.500	0	0	11.250	0	**23.750**
Cikijing	0	0	0	110.000	0	0	**110.000**
Cingambul	0	0	0	5	0	0	**5**
Dawuan	0	0	0	0	0	0	**0**
Jatitujuh	0	0	0	0	0	0	**0**
Jatiwangi	0	0	0	0	0	0	**0**
Kadipaten	0	400.000	0	0	0	0	**400.000**
Kasokandel	0	14.000	0	0	0	0	**14.000**
Kertajati	0	0	0	0	0	0	**0**
Lemahsugih	0	0	50.000	70.000	0	0	**120.000**
Leuwimunding	0	0	0	0	2.500	0	**2.500**
Ligung	0	0	0	0	0	0	**0**
Maja	0	11.000	0	55.000	0	0	**66.000**
Majalengka	0	270	0	0	0	0	**270**
Malausma	0	0	0	0	0	0	**0**
Palasah	1.500	0	0	0	0	0	**1.500**
Payingkiran	0	0	0	300	0	25	**325**
Rajagaluh	350	7.500	5.400	0	0	0	**13.250**
Sindang	253	205.925	8.210	52.250	34.705	0	**301.343**
Sindangwangi	97	2.800	0	0	6.300	0	**9.197**
Sukahaji	0	9.825	2.450	5.125	7.500	0	**24.900**
Sumberjaya	0	0	0	0	0	0	**0**
Talaga	0	0	0	70.000	0	0	**70.000**
Harvested Area/ Crop Type	**2.200**	**682.820**	**66.060**	**460.680**	**62.255**	**25**	**1.274.040**

The transportation matrix coefficients were calculated using the ratio between crop production and harvested land area using equation (5). These productivity values became the optimization parameters in the transportation model because the objective of the study was to maximize total harvest production. The data is then entered into the transportation model matrix as shown in Figure 3.

	Lime (1)	Turmeric (2)	Cardamom...	Ginger (4)	Galingale (...	Aromatic ...	SUPPLY
Argapura (1)	0	3	0	3.5	0	0	30000
Banjaran (2)	0	2.8	0	2.83	0	0	37000
Bantarujeg (3)	0	0	0	2.4	0	0	50000
Cigasong (4)	0	3.2	0	0	5.57	0	23750
Cikijing (5)	0	0	0	4	0	0	110000
Cingambul (6)	0	0	0	3.6	0	0	5
Dawuan (7)	0	0	0	0	0	0	0
Jatitujuh (8)	0	0	0	0	0	0	0
Jatiwangi (9)	0	0	0	0	0	0	0
Kadipaten (10)	0	3.07	0	0	0	0	400000
Kasokandel (11)	0	3.2	0	0	0	0	14000
Kertajati (12)	0	0	0	0	0	0	0
Lemahsugih (13)	0	0	5.9	1.43	0	0	120000
Leuwimunding (14)	0	0	0	0	1.2	0	2500
Ligung (15)	0	0	0	0	0	0	0
Maja (16)	0	2.5	0	3	0	0	66000
Majalengka (17)	0	1	0	0	0	0	270
Malausma (18)	0	0	0	0	0	0	0
Palasah (19)	29.6	0	0	0	0	0	1500
Panyingkiran (20)	0	0	0	3.56	0	2.04	325
Rajagaluh (21)	20.73	1.75	2.39	0	0	0	13250
Sindang (22)	8	2.5	1.4	3	4	0	301343
Sindangwangi (23)	5	2.4	0	0	2.81	0	9197
Sukahaji (24)	0	2.95	3.27	2.87	3.12	0	24900
Sumberjaya (25)	0	0	0	0	0	0	0
Talaga (26)	0	0	0	4.57	0	0	70000
DEMAND	2200	682820	66060	460680	62255	25	

Figure 3. Transportation Model Matrix

The transportation model matrix is solved using Vogel's Approximation Method through the POM-QM for Windows software. The transportation model solution is shown in Figure 4.

solution value = $4187642	Lime (1)	Turmeric (2)	Cardamom (3)	Ginger (4)	Galingale (5)	Aromatic Ginger (6)
Argapura (1)				30000		
Banjaran (2)		37000				
Bantarujeg (3)				50000		
Cigasong (4)					23750	
Cikijing (5)				110000		
Cingambul (6)				5		
Dawuan (7)		0				
Jatitujuh (8)		0				
Jatiwangi (9)		0				
Kadipaten (10)		400000				
Kasokandel (11)		14000				
Kertajati (12)		0				
Lemahsugih (13)			66060	53940		
Leuwimunding (14)		2475				25
Ligung (15)		0				
Maja (16)				66000		
Majalengka (17)		270				
Malausma (18)		0				
Palasah (19)	1500					
Panyingkiran (20)				325		
Rajagaluh (21)	700	12550				
Sindang (22)		182428		80410	38505	
Sindangwangi (23)		9197				
Sukahaji (24)		24900				
Sumberjaya (25)		0				
Talaga (26)				70000		

Figure 4. Transportation Model Solution Matrix

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The transportation model solution is shown by the matrix in Figure 4. The entries in the matrix indicate the land area in the sub-district used to plant the types of biopharmaceutical plants in the column. Argapura Sub-district must use 30,000 m^2 of land to plant ginger, while Lemahsugih Sub-district must use 66,060 m^2 to plant cardamom and 53,940 m^2 to plant ginger. The land area listed in the solution matrix will provide maximum yields for all types of biopharmaceutical plants. This is indicated by the solution value of $4,187,642, which, in this transportation model, is interpreted as the total harvest from all biopharmaceutical plants, 4,187,642 Kg. The model solution shows 136,697 Kg more than the data in 2023. This shows that using land to plant biopharmaceutical plants according to the solution matrix will yield the maximum harvest.

3.2. Discussion

3.2.1. Comparative Interpretation of Optimization Results

The optimization results produced by the transportation model indicate that the proposed allocation system can potentially increase total biopharmaceutical crop production compared with the actual production data reported by the Central Statistics Agency (BPS) of Majalengka Regency in 2023. Production harvest per crop type is shown in Figure 5

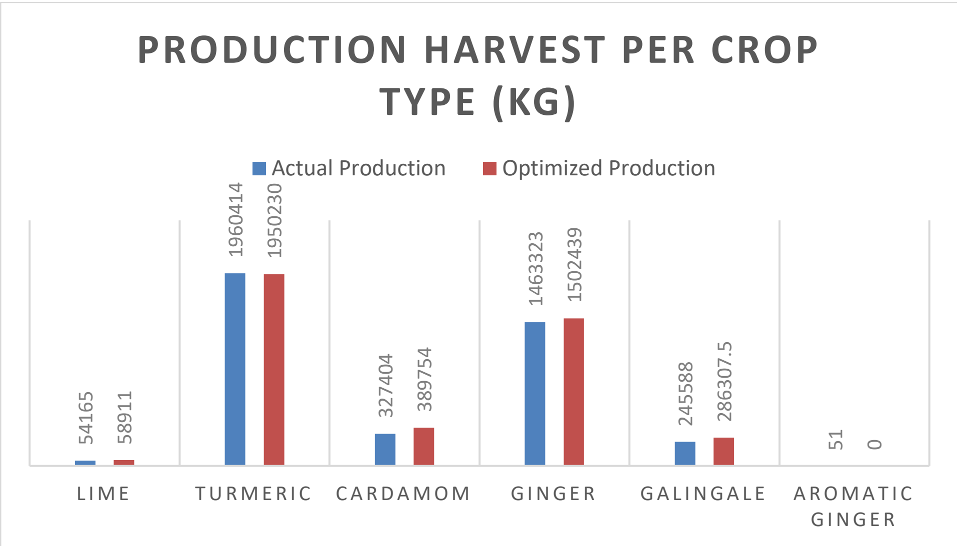

Figure 5. Production Harvest per Crop Type

The results indicate that the optimization model did not increase production uniformly across all crop types. Instead, the model selectively reallocated harvested land toward crops with higher productivity potential, resulting in a more efficient production structure. The largest increase occurred in ginger production, which increased from 1,463,323 kg to 1,502,439 kg, representing an additional 39,116 kg. This finding suggests that ginger possesses a high productivity contribution within the transportation model and that reallocating land toward ginger cultivation can significantly improve total harvest output. A substantial increase was also observed for cardamom, whose production increased from 327,404 kg to 389,754 kg, corresponding to an increase of 62,350 kg. This indicates that cardamom cultivation may be underutilized under the existing allocation pattern and offers considerable potential for productivity improvement. Moderate increases in production were observed for galangal and lime. Galangal production increased from 245,588 kg to 286,307.5 kg, while lime production increased slightly from 54,165 kg to 58,911 kg. Although these increases are smaller than those observed for ginger and cardamom, they still demonstrate the model's ability to identify more productive allocation strategies across different crop types.

In contrast, turmeric production decreased slightly, from 1,960,414 kg to 1,950,230 kg. This result suggests that the transportation model identified greater overall production gains by reallocating a portion of turmeric land to other crops with higher marginal productivity contributions. Therefore, maximizing total harvest production does not necessarily imply increasing the production of every crop individually. Instead, the model seeks the combination of crop allocations that produces the highest aggregate output. A particularly interesting result can be observed for aromatic ginger (kencur). While the actual production recorded by BPS was 51 kg, the optimized model allocated land to a subdistrict that has zero harvest yield per square meter, resulting in zero production. This outcome indicates that, under the assumptions of the model, aromatic ginger contributes minimally to the objective function compared with other crops. Consequently, the optimization process prioritized crops with higher productivity coefficients. However, this finding should be interpreted cautiously, as real-world agricultural planning often considers factors beyond productivity alone, including market demand, crop diversification, cultural preferences, and food security.

Overall, the crop-level comparison shows that the transportation model increases total production primarily by reallocating land toward higher-return crops, particularly ginger and cardamom. The total optimized production reached 4,187,642 kg, exceeding the actual production of 4,050,945 kg by 136,697 kg (3.37%). This result confirms that the proposed transportation model can identify more productive allocation patterns while maintaining the same overall land resources.

Although the optimization model achieved a higher total harvest output, the results should not be interpreted as a direct recommendation for replacing existing cropping patterns. Agricultural systems are inherently multidimensional, involving economic, environmental, and social considerations. The model optimizes production solely based on land allocation and productivity coefficients, without accounting for market prices, farmers' preferences, crop rotation requirements, climate variability, irrigation availability, labor constraints, or soil suitability. Therefore, the optimized allocation should be viewed as a theoretical benchmark that illustrates the maximum production potential under simplified conditions rather than a complete operational plan for agricultural implementation.

3.2.2. Sensitivity Analysis

A sensitivity analysis was conducted to evaluate the robustness of the transportation model across different productivity and land allocation scenarios. The analysis examined how changes in crop productivity and land constraints affected the optimization results. The scenarios included productivity increases of 10% for each crop type and reductions of 10%

in land supply and in land allocation between crop types. The results of the sensitivity analysis are presented in Table 2.

Table 2. Sensitivity Analysis Result

Scenario	Optimization Result (Kg)	Difference from Baseline
Baseline Model	4,187,642	-
Lime Productivity +10%	4,193,531	+5,889
Turmeric Productivity +10%	4,385,552	+197,910
Cardamom Productivity +10%	4,226,618	+38,976
Ginger Productivity +10%	4,337,935	+150,293
Galangal Productivity +10%	4,216,344	+28,702
Aromatic Ginger Productivity +10%	4,187,642	0
Land Supply -10%	2,843,578	-1,344,064
Land Demand -10%	3.941,151	-246,491
Land Supply and Demand -10%	2,774,198	-1,413,444

The sensitivity analysis reveals that the transportation model is highly responsive to changes in crop productivity, particularly for turmeric and ginger commodities. A 10% increase in turmeric productivity generated the highest optimization result, increasing total harvest production by 197,910 kg. Similarly, increasing ginger productivity by 10% increased total production by 150,293 kg. These findings indicate that turmeric and ginger are dominant commodities within the optimization structure because they possess relatively high productivity coefficients and allocation proportions. In contrast, increasing aromatic ginger productivity by 10% produced no change in the optimization result. This suggests that aromatic ginger has a limited influence on overall harvest optimization, given its relatively small harvested area and lower contribution to the allocation matrix. The result also indicates that not all commodities contribute equally to the optimization objective, and some crops have stronger leverage effects on total production outcomes.

The land allocation scenarios demonstrate even stronger sensitivity effects. A 10% reduction in land supply caused total production to decrease significantly to 2,843,578 kg, while simultaneous reductions in land supply and demand reduced production further to 2,774,198 kg. These results confirm that land availability is one of the most critical factors affecting the optimization of agricultural production. Even relatively small reductions in available land can substantially decrease total harvest output.

From a practical perspective, the sensitivity analysis highlights the importance of maintaining agricultural land availability and improving crop productivity through cultivation technology, irrigation improvement, and agricultural management strategies. The results also suggest that productivity enhancement programs focused on turmeric and ginger may have a larger impact on regional agricultural production than programs focused on other crop types. Nevertheless, the sensitivity analysis also reflects the limitations of deterministic optimization models. The scenarios were simulated under fixed assumptions and did not account for uncertainty factors such as climate variability, seasonal changes, market instability, or unexpected agricultural disruptions. Therefore, although the transportation model demonstrates strong responsiveness to parameter changes, future studies should integrate stochastic or multi-objective optimization approaches to improve model realism and adaptability in complex agricultural environments.

4. CONCLUSION

This study demonstrates that the transportation model can be adapted as an alternative optimization framework for agricultural harvest planning beyond its conventional application in logistics and distribution systems. By representing harvested land allocation as a transportation problem, the model provides a structured approach for identifying more efficient allocation patterns among biopharmaceutical crops and production areas. The findings indicate that transportation-based optimization can support decision-making in agricultural resource management and improve production efficiency through data-driven allocation strategies.

However, the proposed model is subject to several limitations. The optimization framework was developed using harvested land area and productivity data as the primary decision variables, while important agricultural factors such as climate variability, irrigation systems, labor availability, soil characteristics, market conditions, and crop suitability were not incorporated. Consequently, the model should be interpreted as a simplified representation of agricultural systems intended to explore the applicability of transportation models in harvest optimization rather than as a complete operational planning tool.

Future research may extend this work by integrating environmental, economic, and geographical variables into the optimization framework. The incorporation of Geographic Information Systems (GIS), stochastic optimization, multi-objective programming, or artificial intelligence-based approaches could improve model realism and support more comprehensive agricultural planning. This study contributes to the development of applied operations research by demonstrating the flexibility of classical transportation models in addressing agricultural allocation problems and providing a foundation for future optimization studies in sustainable agricultural management.

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