

Article

A MILP-Based Two-Echelon Logistics Network Design Model Under Uncertainty: Application to a Perishable Banana Supply Chain

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Abstract

Background: Perishable agri-food supply chains require logistics networks that remain economically viable despite fluctuations in demand, transportation costs, and market prices. This study develops and evaluates a two-echelon logistics network for the banana supply chain in Magdalena, Colombia. **Methods:** A mixed-integer linear programming model was formulated to maximise daily profit by jointly determining collection-centre activation and product flows among 14 producers, five candidate collection centres, and two commercial buyers. The deterministic solution was complemented by sensitivity analysis and 1000 Monte Carlo optimisation scenarios incorporating variability in demand, transportation costs, and selling prices. **Results:** Under nominal conditions, all five collection centres were activated, the full demand of 42,000 kg/day was served, and the optimal profit was USD 3093/day. Centres C1–C4 operated at full capacity, whereas C5 reached 42.9% utilization. Under uncertainty, the mean profit decreased to USD 1955.70/day, the mean unmet demand was 954.03 kg/day, and shortages occurred in 72.3% of scenarios. C1–C4 remained the network core, while C5 acted as a flexible contingency facility. **Conclusions:** The proposed framework reveals an efficiency–resilience trade-off overlooked by deterministic optimisation. Demand growth and capacity reductions are the principal operational risks, supporting investment in collection capacity and proactive demand management.

Keywords: logistics network design; mixed-integer linear programming (MILP); Monte Carlo simulation

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1. Introduction

Over the past decade, the focus on incorporating social and environmental considerations into the agri-food supply chain process has shifted from the periphery to the centre of research and management [1]. Efficient decisions regarding resource allocation within the agricultural supply chain network for perishable goods affect operating costs, product quality, and overall environmental implications [2]. The presence of severe supply chain management challenges linked to the agro-industrial sector—the main driver of develop-

ment and export competitiveness—tends to affect developing countries with greater infrastructure deficiencies and higher climate risk [3].

Colombia's banana sector is a high-value agroindustrial sector, accounting for 2.5% of agricultural GDP and 60,000 direct jobs. The department of Magdalena produces locally grown bananas, providing financial support to banana-farming communities. However, they suffer from poor infrastructure, costly transportation and logistics, and rising international standards for quality and sustainability. The harvesting, consolidation, and distribution of bananas using a balanced approach would nearly eliminate severe post-harvest losses, currently estimated at 15% to 25% of total production [4]. In rural banana-growing regions, these inefficiencies significantly affect supply chain performance.

Supply chain network design problems have received significant analytical attention in the context of deterministic mixed-integer linear programming (MILP) methods [5]. These methods enable the analysis and optimisation of facility location, capacity allocation to these facilities, and transportation flows. On the other hand, deterministic MILP methods use fixed values for the modelled parameters and, as a result, assume that demand, transportation costs, and market prices remain unchanged. This assumption does not hold in the context of agri-food supply chains, which are generally subject to climate variability, price changes, and disrupted transport logistics [6].

Several approaches exist for dealing with uncertainty, largely based on stochastic programming, robust optimisation, and, more recently, simulation [7]. While both stochastic and robust optimisation offer rigorous theoretical foundations, their limited applicability stems from the large amount of data required to build the respective models, their high computational complexity, and their relatively low interpretability for end users. On the other hand, Monte Carlo simulation provides the flexibility and transparency needed to evaluate the robustness of optimisation solutions by sampling model parameters and obtaining probabilistic performance estimates [8].

Although significant advances have been made in logistics network design and uncertainty modeling, most studies still focus on deterministic optimization of facility location and transport planning, or on developing exact solution methods and advanced metaheuristics. Furthermore, systematic literature reviews have highlighted the critical role of resilience, risk management, and uncertainty in contemporary supply chains, especially in agri-food systems where unpredictable and volatile operating conditions exist.

On the other hand, research on the behavior of optimal logistics network configurations when uncertainty is incorporated into the decision-making process has received little attention. Most studies focus on identifying optimal solutions under specific operating conditions, and far less on analyzing the robustness of the optimal solution against changes in demand, transport costs, and market prices. This is of particular interest when dealing with agricultural supply chains, as these systems contain significant uncertainty in their production and distribution processes.

In this context, a two-stage logistics network design model for banana supply chains is proposed. It consists of mixed-integer linear programming to determine the optimal opening of collection centers and the optimal flow of products from producers to collection centers and to commercial buyers. The proposed model combines deterministic optimization with the Monte Carlo method. Within this framework, the mixed-integer linear programming model is solved for each uncertainty scenario. The proposed optimization-simulation approach enables the simultaneous evaluation of economic performance and solution robustness under uncertainty, providing a practical decision-support tool for agricultural logistics planning and contributing to the development of more resilient agri-food supply chains.

The main contribution of this study is the development of an integrated optimization-simulation framework for the design of agricultural logistics networks in contexts of

uncertainty. Based on mixed-integer linear programming and Monte Carlo scenario simulation, the developed framework identifies optimal logistics network configurations and evaluates their robustness under variations in demand and transportation costs, sales prices, and collection center capacities. Thus, it offers decision-makers the means to evaluate the economic and operational aspects of perishable agricultural supply chains.

2. Literature Review

2.1. Logistics Network Design and Facility Location

Logistics network design is a strategic problem in supply chain management because it interprets the spatial configuration through which products move from origin nodes to consumer markets. Determining the location of inputs, capacity, and product flows impacts transportation costs, responsiveness, and network efficiency. In this context, input location serves as an analytical model for long-term logistics planning. As noted by [5], modern supply chain network design models increasingly integrate facility location with other relevant decisions such as production, inventory, and distribution, thereby reflecting the interconnected nature of real logistics systems.

Within this stream, capacitated multi-echelon formulations are particularly relevant because they capture the role of intermediate facilities in consolidating and redirecting flows. Liu et al.[9] classifies such models under the broader family of facility location–network design problems, emphasising that capacity constraints and multi-echelon structure are decisive for cost and service trade-offs in distribution networks. In agro-logistics, where producers are geographically dispersed, and intermediate collection centres play a critical role in structuring the outbound distribution process, this multi-echelon view is essential [10]. Therefore, the present study is positioned within the family of two-echelon logistics network design models, in which facility activation and product allocation decisions are determined simultaneously under capacity constraints [11].

The literature on logistics network design contains ample evidence of the applicability of both exact and metaheuristic methods to addressing the two-stage transportation problem with fixed costs. This problem involves the complex combination of decisions regarding facility location, transportation, and routing. To this end, many researchers have proposed using genetic and hybrid optimisation approaches as evolutionary heuristics [12,13]. Matheuristics, hybrid algorithms, and parallel approaches have been developed to address facility opening and transportation routing decisions based on the presence of route-dependent fixed costs [14,15]. Other methods, such as ant colony optimisation, have also been effective for two-stage supply chain network design [16]. Although these methods have improved the effectiveness of network design, most studies focus on network design efficiency, leaving a gap in evaluating the solution's robustness. This lack of attention is particularly true regarding the stochastic nature of supply chain components and the associated costs. This research aims to fill that gap by evaluating the robustness and cost of the logistics design of a two-level supply chain for perishable bananas. This will be achieved by using a two-level supply chain and a Monte Carlo simulation with scenario analysis.

2.2. Agro-Food Supply Chains

Agro-food supply chains differ from many conventional logistics systems because products are often highly perishable, seasonally produced, and sensitive to delays in transportation and handling. For this reason, logistics decisions in agricultural systems must consider not only cost minimisation but also the ability to move products rapidly and reliably across the network. Ahumada and Villalobos [17] show that planning in agro-food supply chains requires coordination across production, distribution, and market al-

location, particularly in systems based on fresh agricultural crops. Their review summarises perishability and harvest time as two key aspects used to categorise these networks as distinct from traditional industrial supply chains.

In a recent study, Yavari and Geraei [18] proposed a two-layer network design model for a closed, resilient, and environmentally friendly supply chain for perishable dairy products, considering both cost and environmental objectives, as well as disruption risks. Similarly, Eskandarpour et al. [19] presented a multi-level, multi-period model for the distribution of perishable foods that considers shelf life and environmental factors. These studies highlight the need to design agri-food logistics networks that balance profitability, overall product quality, and environmental considerations.

In particular, de Keizer et al. [6] show that the design of logistics networks for perishable products is influenced by heterogeneous quality deterioration. Their findings show that quality deterioration affects product allocation, as well as the design and profitability of the logistics network. Although this study does not focus specifically on quality deterioration, product perishability determines the application's contextual scope, rather than a specific model feature.

In this respect, this study supports the existing literature on perishable agri-food logistics networks, which emphasises the need for network design to ensure the timely and efficient consolidation and transport of products [20].

2.3. Uncertainty in Logistics Network Design

A major limitation for logistics networks is the assumption that input parameters remain constant. Demand, transportation costs, and sales prices are just a few of the many parameters that can fluctuate during network and market disruptions. Consequently, many researchers have investigated supply chain design under uncertainty. Oliveira et al. [21] provide a comprehensive review in this area and highlight the dominance of stochastic, robust, and scenario-based methodologies. While their review focuses on uncertainty regarding network design, it is important to note that uncertainty permeates the strategic, tactical, and operational design of networks at multiple levels.

In agri-food logistics, uncertainty is particularly significant because even minor changes in demand or transportation conditions can affect the profitability of an optimal transportation configuration. According to Liu et al. [9], in perishable food supply chains, demand uncertainty and disruption risks significantly alter the economic viability of multi-level network designs. In networks operating near capacity, fluctuating demand alters the roles of intermediaries and the flow of products. Hasani and Khosrojerdi [22] conclude that demand and capacity uncertainties compel network configuration designers to consider multiple robust options and, therefore, backup alternatives. Thus, assessing the robustness of the logistics network is as essential as evaluating the nominal optimum. This research addresses the uncertainties in transportation, demand, and product prices that impact logistics performance in agri-food distribution systems.

2.4. Monte Carlo Simulation for Robustness Assessment

In theory, optimisation models that incorporate uncertainty are quite rigorous. However, uncertainty in probability distributions or limitations in function approximations that decision-makers may not fully understand can make implementation problematic. Under these conditions, evaluating the robustness of potential deterministic solutions can be done using simulation-based methodologies. In particular, the Monte Carlo simulation approach can be useful, especially when the primary purpose is to understand the configuration provided by the deterministic optimisation solutions (or model) and how it behaves in the face of frequent stochastic fluctuations in the constraint and decision variables.

This logic is consistent with the broader literature on simulation-enhanced optimization and simheuristics. Juan et al. [23] explain that simulation-based evaluation is a valuable complement to optimization methods in stochastic combinatorial problems because it enables the analysis of solution stability and risk exposure under uncertain conditions. In supply chain and logistics applications, Monte Carlo simulation can therefore be used to generate empirical distributions of key performance measures, such as profit, facility utilisation, and service coverage, without sacrificing the interpretability of the underlying optimisation model [5].

In this paper, Monte Carlo simulation is implemented as a scenario-based optimization framework. Instead of evaluating a single deterministic solution, the MILP model is re-solved for each stochastic realisation of uncertain parameters. This approach allows the analysis of both optimal decision variability and system performance under uncertainty, providing a unified optimisation–simulation framework [8]. This optimisation–simulation logic provides a practical bridge between deterministic network design and stochastic performance evaluation in perishable agro-food supply chains, aligning with recent work that couples MILP models with Monte Carlo sampling to appraise the robustness of logistics network designs [24].

The literature provides strong foundations for facility location, agro-food planning, and uncertainty-aware network design. However, fewer studies explicitly combine a two-echelon logistics network design model for a perishable agricultural product with a Monte Carlo-based robustness assessment focused on facility activation and flow stability. Existing work frequently emphasizes either deterministic optimization [18] or more complex stochastic formulations such as robust or stochastic programming [25,26].

By contrast, the present study proposes a tractable optimization–simulation framework that preserves the transparency of a deterministic MILP model while incorporating stochastic evaluation of network performance under realistic operating variability. This gap is consistent with the need identified in the literature to better connect network configuration decisions with uncertainty-aware performance assessment [27]. The present work, therefore, contributes to this emerging line by adapting the MILP + Monte Carlo paradigm to a perishable banana supply chain, explicitly analyzing how uncertainty in demand, transport costs, and prices affects facility activation patterns and flow stability, in line with recent work on probabilistic and Monte Carlo-based analysis of logistics networks [28].

3. Materials and Methods

3.1. Deterministic MILP Model

This study considers a two-echelon logistics network composed of producers $i \in I$, collection centers $j \in J$, and commercializers $k \in K$, handling different types of banana products $p \in P$. The network structure connects producers to intermediate facilities and subsequently to final buyers. The objective is to determine the optimal activation of collection centres and the allocation of product flows across the network in order to maximise total profit, while satisfying supply, demand, and capacity constraints.

All flows and capacities are expressed in kilograms per day (kg/day).

3.2. Sets

Table 1 describes the set of variables and indexes representing the main elements in the model.

Table 1. Sets used in the model.

Set	Description
$i \in I$	Set of banana producers
$j \in J$	Set of candidate collection centers
$k \in K$	Set of commercializers
$p \in P$	Set of banana types

3.3. Parameters

Table 2 shows the descriptions of all the parameters implemented in the model.

Table 2. Model parameters.

Parameter	Description	Units
c_{ip}	Production cost of product p at producer i	USD/kg
f_j	Fixed cost of opening collection center j	USD
t_{ij}	Transport cost from producer i to center j	USD/kg
t_{jk}	Transport cost from center j to commercializer k	USD/kg
d_{kp}	Demand of product p at commercializer k	kg
s_{ip}	Production capacity of producer i for product p	kg
u_j	Capacity of collection center j	kg
r_p	Selling price of product p	USD/kg

3.4. Decision Variables

Table 3 describes the mathematical explanation for each decision variable.

Table 3. Mathematical notation of the decision variables.

Variable	Description
y_j	Binary variable equal to 1 if collection center j is opened
x_{ijp}	Quantity of product p transported from producer i to center j
z_{jkp}	Quantity of product p transported from center j to commercializer k

3.5. Objective Function

The objective of the model is to maximize the total profit of the supply chain, considering revenues from sales and subtracting production, transportation, and facility opening costs. The full description of the constraint is presented in Table 4.

$$\max Z = \sum_{j \in J} \sum_{k \in K} \sum_{p \in P} r_p z_{jkp} - \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} t_{ij} x_{ijp} - \sum_{j \in J} \sum_{k \in K} \sum_{p \in P} t_{jk} z_{jkp} - \sum_{i \in I} \sum_{p \in P} c_{ip} \sum_{j \in J} x_{ijp} - \sum_{j \in J} f_j y_j \quad (1)$$

The model is subject to the following constraints.

$$\sum_{j \in J} x_{ijp} \leq s_{ip} \quad \forall i \in I, \quad p \in P \quad (2)$$

$$\sum_{i \in I} x_{ijp} = \sum_{k \in K} z_{jkp} \quad \forall j \in J, \quad p \in P \quad (3)$$

$$\sum_{i \in I} \sum_{p \in P} x_{ijp} \leq u_j y_j \quad \forall j \in J \quad (4)$$

$$\sum_{j \in J} z_{jkp} = d_{kp} \quad \forall k \in K, \quad p \in P \quad (5)$$

$$x_{ijp} \geq 0 \quad \forall i \in I, \quad j \in J, \quad p \in P \quad (6)$$

$$z_{jkp} \geq 0 \quad \forall j \in J, \quad k \in K, \quad p \in P \quad (7)$$

$$y_j \in \{0,1\} \quad \forall j \in J \quad (8)$$

Table 4. Description of model constraints.

Constraint	Description
(2)	Ensures that the quantity supplied by each producer does not exceed its production capacity for each banana type.
(3)	Represents the flow conservation at collection centers. The total quantity received must equal the quantity shipped to commercializers.
(4)	Guarantees that the total flow handled by a collection center does not exceed its storage capacity and that the center operates only if it is activated.
(5)	Ensures that each commercializer's demand for each banana type is satisfied.
(6)	Defines the non-negativity condition for flows from producers to collection centers.
(7)	Defines the non-negativity condition for flows from collection centers to commercializers.
(8)	Defines the binary nature of the facility activation decision variable.

Constraints (2)–(5) define the operational feasibility of the logistics network, guaranteeing supply availability, demand satisfaction, and flow balance within the system. Constraints (6)–(8) define the mathematical domain of the decision variables.

3.6. Solution Approach

The proposed MILP model was implemented in R (Version 4.6) using the packages *ompr*, *ompr.roi*, *ROI*, and *ROI.plugin.glpk*. The optimization problem was solved using the GLPK solver, which is appropriate for mixed-integer linear formulations of moderate size.

The solution procedure determines the optimal activation of collection centers and the corresponding product flows between producers, intermediate facilities, and commercializers. The deterministic MILP solution is used as the baseline configuration for the subsequent robustness assessment under uncertainty.

Although the model size in the present case study is computationally manageable, the problem belongs to the class of combinatorial optimisation problems due to the presence of binary facility activation variables. Consequently, computational complexity may increase significantly as the number of nodes, products, or planning periods expands.

Commercial solvers such as CPLEX and Gurobi may provide faster computational performance for large-scale instances. Nevertheless, the GLPK solver was sufficient to obtain optimal solutions for the case-study instances considered in this research. The objective of this work is not to compare optimisation solvers but rather to evaluate the proposed optimisation–simulation framework under uncertainty.

3.7. Monte Carlo Simulation Framework

To evaluate the robustness of the logistics network design, we describe the implementation of a scenario-based Monte Carlo optimisation framework. Within this framework, the MILP model is solved separately for each realisation of the stochastic parameters. Therefore, the evaluation is not limited to a single deterministic design but rather

comprises the empirical distribution of optimal solutions obtained under stochastic conditions.

In the proposed framework, it is resolved for each stochastic realisation, resulting in a scenario-based optimisation framework. This approach does not rely on a single deterministic configuration, but instead generates an empirical distribution of optimal solutions across stochastic scenarios.

The simulation included stochastic parameters comprising each customer's demand for all banana varieties, transportation costs between producers and collection points, transportation costs between collection points and marketers, and market prices for banana products. These parameters were modelled using a normal distribution centred on their deterministic mean values. Stochastic demand in the r replication was modeled as follows:

$$D_{kp}^{(r)} \sim \mathcal{N}(d_{kp}, \sigma_{D_{kp}}) \quad (9)$$

where d_{kp} is the nominal demand of product p at commercializer k , and $\sigma_{D_{kp}}$ is set equal to 10% of the nominal demand. Similarly, transportation costs are modeled as

$$T_{ij}^{(r)} \sim \mathcal{N}(t_{ij}, \sigma_{T_{ij}}) \quad (10)$$

$$T_{jk}^{(r)} \sim \mathcal{N}(t_{jk}, \sigma_{T_{jk}}) \quad (11)$$

where the standard deviation is fixed at 8% of the nominal transportation cost. The selling prices are generated according to:

$$R_p^{(r)} \sim \mathcal{N}(r_p, \sigma_{R_p}) \quad (12)$$

where σ_{R_p} corresponds to 5% of the nominal selling price. In all cases, negative sampled values are truncated to zero in order to avoid infeasible or economically meaningless realizations.

3.7.1. Unmet Demand Representation

Under stochastic conditions, realized demand may exceed the available supply and processing capacity of the logistics network. To ensure feasibility of each replication and to quantify service level deviations, an unmet demand variable $u_{kp}^{(r)}$ is introduced.

The demand balance constraint is reformulated as:

$$\sum_{j \in J} z_{jkp}^{(r)} + u_{kp}^{(r)} = D_{kp}^{(r)} \quad (13)$$

$$u_{kp}^{(r)} \geq 0 \quad (14)$$

Unmet demand is penalized in the objective function through a cost parameter π_{kp} , allowing the model to capture the trade-off between profitability and service level under uncertainty.

3.7.2. Statistical Analysis

The expected profit is estimated as:

$$\bar{Z} = \frac{1}{R} \sum_{r=1}^R Z^{(r)} \quad (15)$$

The variability is measured using:

$$\sigma_z = \sqrt{\frac{1}{R-1} \sum_{r=1}^R (Z^{(r)} - \bar{Z})^2} \quad (16)$$

Additionally, empirical percentiles are computed:

$$P_q = \text{quantile}(Z^{(r)}), q \in \{0.05, 0.50, 0.95\} \quad (17)$$

To evaluate structural robustness, the activation frequency of each collection center is defined as:

$$AF_j = \frac{1}{R} \sum_{r=1}^R y_j^{(r)} \quad (18)$$

and the average utilisation is computed as:

$$\bar{U}_j = \frac{1}{R} \sum_{r=1}^R U_j^{(r)} \quad (19)$$

The integrated system uses a Monte Carlo framework in conjunction with a deterministic optimization model to analyze system performance. Under normal conditions, the Mixed Integer Linear Programming (MILP) model determines the optimal configuration. The simulation then determines the configuration's capacity under flexible conditions and the potential variations in profitability, facility consumption, and service levels.

This combined optimisation and simulation framework models a realistic, practical, and decision-support system for analysing the logistics network of agri-food supply chains. Table 5 describes the stochastic parameter implemented in the Monte Carlo Simulation.

Table 5. Stochastic parameters used in the Monte Carlo simulation.

Parameter	Distribution	Mean	Standard Deviation
Demand	Normal	d_{kp}	10% of nominal demand
Producer-to-center transport cost	Normal	t_{ij}	8% of nominal cost
Center-to-buyer transport cost	Normal	t_{jk}	8% of nominal cost
Selling price	Normal	r_p	5% of nominal price

To determine the levels of variability selected for moderate operational uncertainty, expert judgment and the typical variability observed in agricultural logistics systems were used. Demand was considered the most variable factor due to seasonality, market changes, and fluctuations in production. Transportation costs were considered to have moderate variability due to fuel costs, road conditions, and other operational factors, while selling prices were considered comparatively stable over the planning horizon. These assumptions provide a realistic representation of uncertainty while maintaining the interpretability of the simulation results. The implementation setting for the Monte Carlo simulation are presented in Table 6.

Table 6. Monte Carlo simulation settings.

Setting	Value
Number of replications	1000
Software	RStudio
Solver	GLPK

To enhance reproducibility and clarity of the simulation framework, the Monte Carlo procedure is summarized in Algorithm 1.

Algorithm 1. Scenario-Based Monte Carlo Optimization Procedure

Input: Nominal parameters $d_{kp}, t_{ijp}, t_{jkp}, r_p, a_{ip}, C_j, f_j$; penalty parameter π_{kp} ; number of replications $R = 1000$.

Output: Profit distribution, facility activation frequencies, average utilization, and unmet demand indicators.

1. Initialize storage structures for $Z^{(r)}, y_j^{(r)}, U_j^{(r)}$, and $u_{kp}^{(r)}$.
2. **For** $r = 1, \dots, R$ **do**:
3. Generate stochastic demand:

$$D_{kp}^{(r)} \sim \mathcal{N}(d_{kp}, \sigma_d), \sigma_d = 0.10 d_{kp}$$
4. Generate stochastic transportation costs:

$$C_{ijp}^{(r)} \sim \mathcal{N}(c_{ijp}, \sigma_c), C_{jkp}^{(r)} \sim \mathcal{N}(c_{jkp}, \sigma_c), \sigma_c = 0.08 c$$
5. Generate stochastic selling prices:

$$R_p^{(r)} \sim \mathcal{N}(r_p, \sigma_r), \sigma_r = 0.05 r_p$$
6. Truncate negative sampled values to zero.
7. Replace nominal parameters with sampled scenario values.
8. Solve the MILP model for scenario r , including unmet demand variables $u_{kp}^{(r)}$.
9. Record optimal profit $Z^{(r)}$.
10. Record facility activation decisions $y_j^{(r)}$.
11. Record product flows $x_{ijp}^{(r)}$ and $z_{jkp}^{(r)}$.
12. Compute utilization:

$$U_j^{(r)} = \frac{\sum_i \sum_p x_{ijp}^{(r)}}{C_j}$$

13. Record unmet demand $u_{kp}^{(r)}$.

3. **End For**

4. Compute summary statistics:

- Mean and variance of $Z^{(r)}$
- Activation frequency of y_j
- Average utilization U_j
- Probability and magnitude of unmet demand

5. Return robustness indicators and performance metrics.
-

In each iteration of the Monte Carlo method, samples are drawn from the set of uncertain parameters, and the MILP model is optimized again. Therefore, this method provides a distribution of optimal solutions rather than the performance of a deterministic solution in the presence of uncertainties.

The proposed methodology incorporates an ordered simulated optimization process. The process begins by solving the deterministic MILP model to determine the optimal configuration of the logistics network. The next step is a sensitivity analysis in which selected key parameters are varied (the most relevant being demand, transportation costs, sales prices, and collection center capacity). In the final step, a Monte Carlo simulation is used, where uncertain parameters are drawn from designated probability distributions, and the MILP model is re-optimized at each iteration. The result is a range of optimal solutions from which the impacts of uncertainty on the network can be analyzed.

4. Case Study

4.1. Study Area and Logistics Context

The proposed optimization–simulation framework was applied to a banana logistics network located in the Magdalena Department, Colombia. This region is one of the main

banana-producing areas in the country and is characterized by the presence of geographically dispersed farms, intermediate collection processes, and downstream commercial distribution channels. From a logistics perspective, the regional supply chain exhibits a typical two-echelon structure in which multiple producers must be connected to a limited number of candidate collection centers before products are delivered to commercializers.

The objective of this case study was to construct a plausible logistics configuration for the regional banana sector. The formulated network comprises 14 producers, 5 prospective collection centers, and 2 market agents. The study analyzed two types of banana products: traditional bananas and exported bananas. The case was designed to analyze the implications of product flow distribution and the intervention of intermediate-layer nodes on the profitability and resilience of the logistics network.

The solution developed in this case study is a spatial configuration of logistics centers that allows for the consolidation of the product from the producers' dispersed farms to the final market buyer, taking into account production constraints and market demand. A deterministic MILP model was used to derive the optimal node configuration, and Monte Carlo simulation was used to evaluate the configuration's performance, considering the stochastic nature of demand, transportation costs, and sales prices.

4.2. Data Description

The numerical data used in the case study represent the main operational components of the logistics network: producer supply capacity, collection center capacity, buyer demand, transportation costs, production costs, fixed opening costs, and selling prices.

4.2.1. Producer Supply Capacity

The numerical data compiled for this case study represent a realistic configuration of a banana supply chain in the Department of Magdalena, Colombia. The parameter values were constructed using a combination of publicly available sectoral information, regional agricultural statistics, and expert knowledge regarding typical operational conditions in the banana industry. Official sources such as Agronet, the Colombian Rural and Agricultural Information Observatory [29], provide production and sectoral statistics that can serve as reference information for the calibration of real-world applications. While some parameters were defined based on representative production and market conditions, others were established to construct a logistics network that is both realistic for analytical purposes and internally consistent. Consequently, the case study should be interpreted as a representative application of the proposed framework rather than as the exact reproduction of a specific company's operations.

Table 7 reports the daily production capacity of the 14 producers. The total available supply in the system is 44,500 kg/day, distributed between conventional and export bananas according to the proportions defined in the model inputs.

Table 7. Production capacity of banana producers.

Producer	Capacity (kg/day)
P1	2800
P2	3500
P3	2200
P4	4100
P5	3000
P6	2600
P7	3300
P8	3700

P9	2400
P10	3100
P11	2800
P12	3400
P13	2600
P14	3000

4.2.2. Collection Center Capacity

Table 8 presents the handling/storage capacities of the candidate collection centers. The total available center capacity is 46,000 kg/day, which slightly exceeds total available supply and allows the optimization model to select the most convenient subset of facilities.

Table 8. Capacity of candidate collection centers.

Collection Center	Capacity (kg/day)
C1	12,000
C2	10,000
C3	9000
C4	8000
C5	7000

Capacities in Table 8 are expressed in kilograms per day (kg/day).

4.2.3. Buyer Demand

Table 9 shows the demand of the two commercializers. Total nominal demand in the deterministic scenario is 42,000 kg/day, distributed across conventional and export banana categories.

Table 9. Demand of commercializers.

Commercializer	Conventional Banana (kg/day)	Export Banana (kg/day)	Total Demand (kg/day)
B1	13,000	9000	22,000
B2	12,000	8000	20,000
Total	25,000	17,000	42,000

Values in Table 9 are expressed in kg/day.

4.2.4. Selling Prices and Production Costs

The model considers two banana categories with differentiated production costs and selling prices. Table 10 summarizes these values.

Table 10. Product prices and production costs.

Product	Selling Price (USD/kg)	Production Cost (USD/kg)
Conventional banana	0.68	0.35–0.36
Export banana	0.82	0.42–0.43

4.2.5. Cost description for collection centers.

Table 11 presents the daily fixed operating cost associated with activating each candidate collection center. These costs were included to avoid the trivial solution of opening all centers without considering their economic impact.

Table 11. Fixed opening costs of collection centers.

Collection Center	Fixed Cost (USD/day)
C1	1500
C2	1300
C3	1100
C4	1000
C5	900

4.2.6. Transportation Cost Structure

Transportation costs were defined for each origin–destination pair in the two logistics echelons: producer-to-center and center-to-buyer. Since the complete matrices are extensive, only their structure is summarized in the main text. Producer-to-center costs vary approximately between USD 0.05/kg and USD 0.11/kg, while center-to-buyer costs range between USD 0.07/kg and USD 0.11/kg. Table 12 provides a compact summary.

Table 12. Summary of transportation cost ranges.

Route Type	Minimum Cost (USD/kg)	Maximum Cost (USD/kg)
Producer to collection center	0.05	0.11
Collection center to commercializer	0.07	0.11

4.2.7. Uncertainty Settings

In the Monte Carlo simulation stage, demand, transportation costs, and selling prices were treated as stochastic inputs. The uncertainty structure was defined around the nominal values presented above. Demand was generated with a standard deviation equal to 10% of nominal demand, transportation costs with 8% of nominal cost, and selling prices with 5% of nominal price. These assumptions were selected to reflect moderate but operationally meaningful variability in the logistics system.

4.3. Network Representation

Figure 1 shows the structure of the banana logistics network analyzed in this study. The system is represented as a two-echelon network in which bananas move from producers to candidate collection centers and from collection centers to final buyers. This representation is consistent with the structure of the MILP model and the operational organization of the case study.

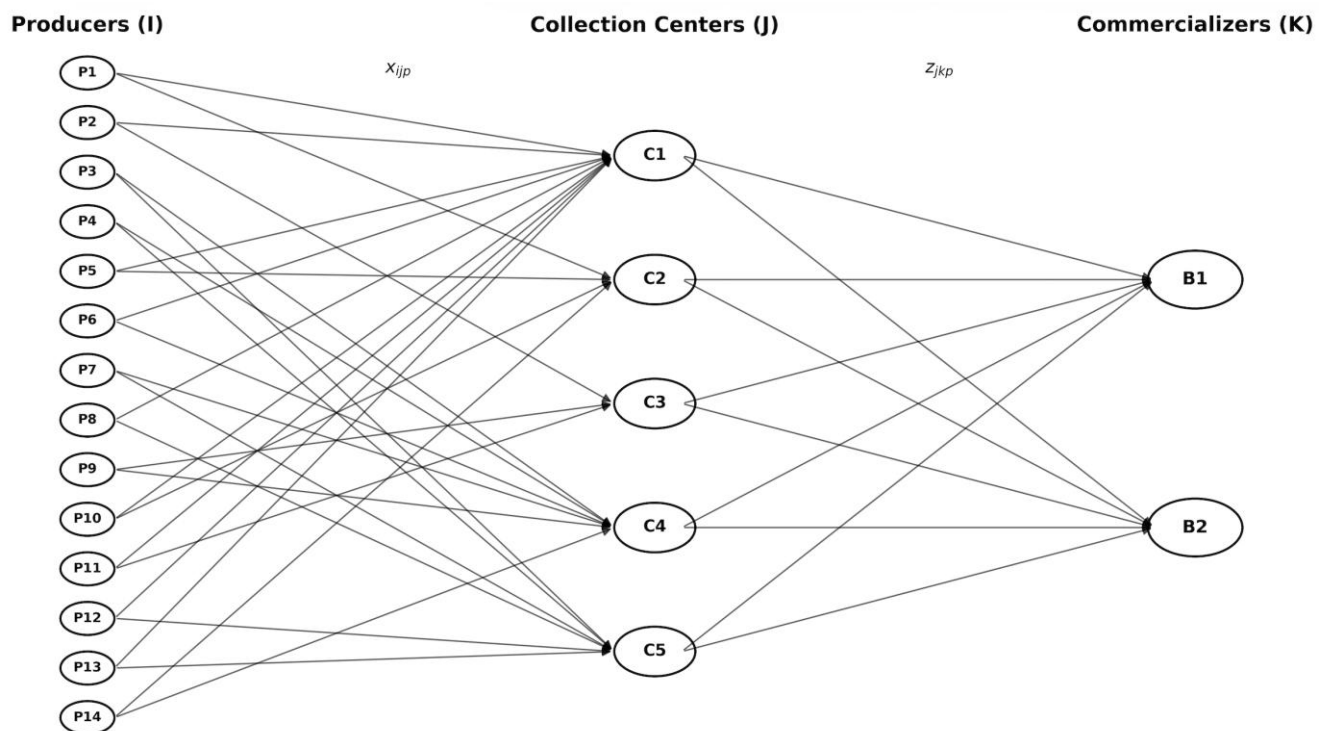


Figure 1. Distribution network graph for the banana supply chain.

Figure 1 illustrates the distribution network considered in this study. Producers supply banana products to intermediate collection centers, which consolidate and dispatch the flows to downstream commercializers. The graph highlights the two-echelon structure of the system and the role of facility activation and flow allocation decisions in the proposed optimization model. The above data define the deterministic baseline used in the optimization model and the nominal parameter values used in the Monte Carlo simulation framework. Based on this case configuration, the next section presents the deterministic optimization results followed by the robustness analysis under stochastic variability. P1–P14 represent banana producers, C1–C5 denote candidate collection centers, and B1–B2 correspond to commercial buyers.

4.4. Deterministic Optimization Results

The deterministic MILP model was solved using the GLPK solver, yielding an optimal profit of USD 3093 per day, as summarized in Table 13. The optimal solution activates all five candidate collection centers, indicating that the available supply and demand levels justify the utilization of the full intermediate logistics infrastructure.

Table 13. Optimal objective value and network configuration.

Metric	Value
Optimal profit (USD/day)	3093
Activated collection centers	5
Total demand served (kg/day)	42,000
Total inbound flow (kg/day)	42,000
Total outbound flow (kg/day)	42,000

The network processes a total of 42,000 kg/day, with a complete balance between inbound and outbound flows. All buyer demands are fully satisfied (See Table 14), confirming the feasibility and internal consistency of the model formulation.

Table 14. Activation and capacity utilization of collection centers.

Collection Center	Activation Status	Inflow (kg/day)	Capacity (kg/day)	Slack (kg/day)	Utilization (%)
C1	1	12,000	12,000	0	100.0
C2	1	10,000	10,000	0	100.0
C3	1	9000	9000	0	100.0
C4	1	8000	8000	0	100.0
C5	1	3000	7000	4000	42.9

Capacity utilization was computed as the ratio between the total inflow assigned to a collection center and its available handling capacity. The activation of all five collection centers is economically justified by the structure of the optimal solution. Although center C5 operates with substantially lower utilization than the remaining facilities, its activation increases the network's effective handling capacity and provides additional flexibility for balancing product flows. The fixed cost associated with opening C5 is compensated by the operational benefits derived from satisfying demand requirements and reducing transportation inefficiencies. Consequently, the deterministic solution identifies C1–C4 as the core infrastructure of the network, while C5 acts as a supporting facility that enhances system feasibility and operational flexibility.

The network configuration for these capacity utilization results is best described as fully utilized, as the capacity of centers C1, C2, C3, and C4 is fully utilized. They form the logistical backbone of this system. This is also the only instance where full capacity is achieved in the backbone. The operating center C5 has a utilization rate of only 42.9%, with considerable unused capacity. The first four centers are fully utilized, while the collection center C5 serves to fill gaps in demand and provides sufficient means to meet the system's demand constraints. Flexibility, albeit limited, is evident in the unused capacity of C5. Table 15 shows the relation between aggregated production and collection center.

Table 15. Aggregated producer-to-center flows by product.

Collection Center	Conventional (kg/day)	Export (kg/day)	Total Inflow (kg/day)
C1	6100	5900	12,000
C2	6680	3320	10,000
C3	4620	4380	9000
C4	5580	2420	8000
C5	1800	1200	3000
Total	24,780	17,220	42,000

The distribution shows a consistent and economical allocation of products across the collection centers. Conventional bananas represent almost 59.0% of the total product flow, while the remaining 41.0% comprises export bananas.

All buyer demands are fully satisfied, with zero unmet demand across both product categories (See Table 16). This confirms that the deterministic solution is feasible and demand-compliant, ensuring complete service coverage under nominal conditions. Regarding the collection centers, C1 and C2 are the key consolidation centers, as they handle the highest product volumes. Collection centers C3 and C4 are the next most important consolidation centers. Center C5 acts as a last resort, as evidenced in Table 17, by the minimal product flow directed to it.

Table 16. Buyer demand satisfaction and outbound flows.

Buyer	Product	Served (kg/day)	Demand (kg/day)	Gap
B1	Conventional	13,000	13,000	0
B1	Export	9000	9000	0
B2	Conventional	12,000	12,000	0
B2	Export	8000	8000	0

Table 17. Main producer assignments to collection centers.

Collection Center	Main Assigned Producers	Total Inflow (kg/day)
C1	P1, P2, P6, P7, P12	12000
C2	P3, P5, P7, P10	10000
C3	P4, P6, P8, P13	9000
C4	P4, P9, P11	8000
C5	P14	3000

Although one partially occupied centre, C5, shows some flexibility, the distribution exhibits almost lethal flexibility due to clustering and a tight equilibrium.

4.5. Sensitivity Analysis

To further evaluate the robustness of the proposed logistics network, a sensitivity analysis was conducted by systematically varying key model parameters while keeping all remaining inputs fixed at their baseline values. Unlike the Monte Carlo simulation presented in the following section, this analysis examines the isolated effect of individual parameters on network performance. Four parameter groups were considered: demand levels, transportation costs, selling prices, and collection center capacities. For each scenario, the MILP model was re-solved and the resulting profit, facility activation pattern, average capacity utilization, and unmet demand were recorded.

The objective of this analysis is to identify the factors that exert the greatest influence on the economic and operational performance of the banana logistics network and to provide additional managerial insights regarding the stability of the optimal solution.

4.5.1. Demand Sensitivity

Demand growth is one of the most important sources of operational pressure in agricultural supply chains. To assess its impact, total demand was varied by −20%, −10%, +10%, and +20% relative to the baseline scenario.

The results indicate that the logistics network performs satisfactorily under moderate demand reductions, maintaining positive profitability while requiring fewer activated collection centers. However, demand increases rapidly generate capacity shortages. A 10% increase in demand produces 3700 kg/day of unmet demand, while a 20% increase generates 7900 kg/day of unmet demand and leads to negative profitability due to shortage penalties. These findings indicate that the baseline network operates close to its effective handling capacity.

Figure 2 illustrates the rapid deterioration of profitability once demand exceeds the nominal capacity of the network. The results confirm that demand growth constitutes the most significant operational risk affecting the system.

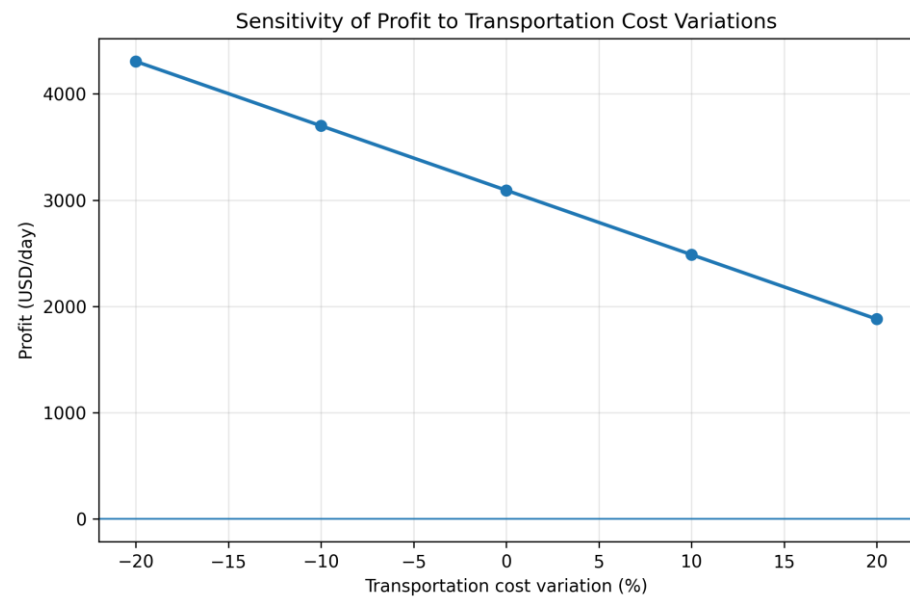


Figure 2. Impact of demand variations on profit and unmet demand.

4.5.2. Transportation Cost Sensitivity

Transportation costs were varied between -20% and $+20\%$ to evaluate their influence on logistics performance.

As expected, profitability decreases almost linearly as transportation costs increase. A 20% reduction in transportation costs increases profit to USD 4305.8/day, whereas a 20% increase reduces profit to USD 1880.2/day (See Figure 3). Nevertheless, the optimal facility activation pattern remains unchanged across all scenarios, indicating that transportation costs primarily affect economic performance rather than network structure.

These results suggest that transportation efficiency initiatives may improve profitability, although they are unlikely to alter the fundamental configuration of the logistics network.

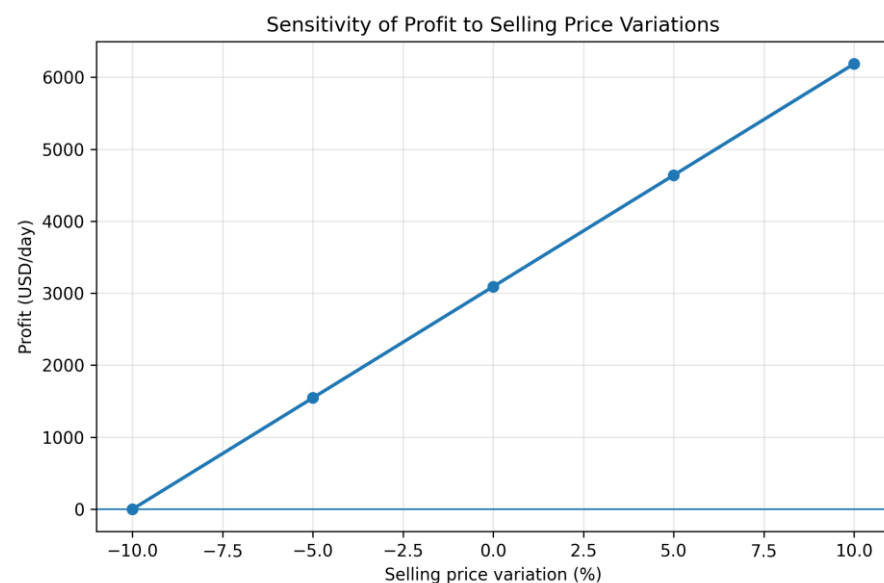


Figure 3. Sensitivity of profit to transportation cost variations.

4.5.3. Selling Price Sensitivity

Selling prices directly determine the revenue generated by the supply chain and therefore represent a key economic parameter.

The results reveal a strong relationship between selling prices and profitability. A 10% reduction in selling prices reduces profit to approximately zero, while a 10% increase raises profit to USD 6187/day (See Figure 4). Despite these substantial economic changes, the network configuration remains stable throughout all evaluated scenarios.

This behavior highlights the dependence of the banana supply chain on market conditions and export price fluctuations, which directly affect economic viability without necessarily modifying logistics decisions.

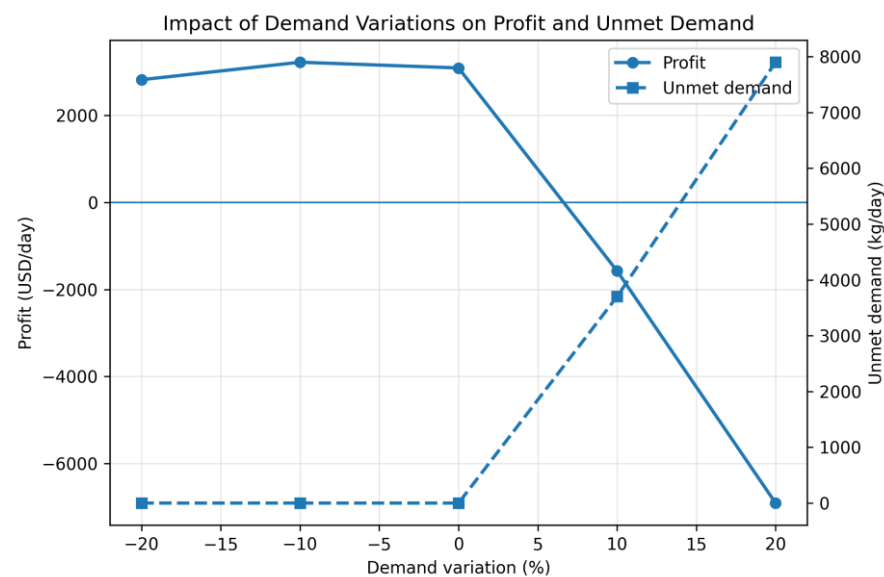


Figure 4. Sensitivity of profit to selling price variations.

4.5.4. Capacity Sensitivity

Collection center capacities were varied between −20% and +20% to evaluate the operational flexibility of the network.

The results indicate that capacity reductions significantly deteriorate system performance. A 20% reduction in collection center capacity produces 5200 kg/day of unmet demand and negative profit values, revealing the operational fragility of the network under constrained conditions. Conversely, increasing capacity improves profitability while reducing utilization levels, thereby providing additional operational flexibility.

Figure 5 confirms that additional handling capacity reduces congestion and increases operational resilience. These results suggest that strategic investments in collection center expansion could provide substantial long-term benefits.

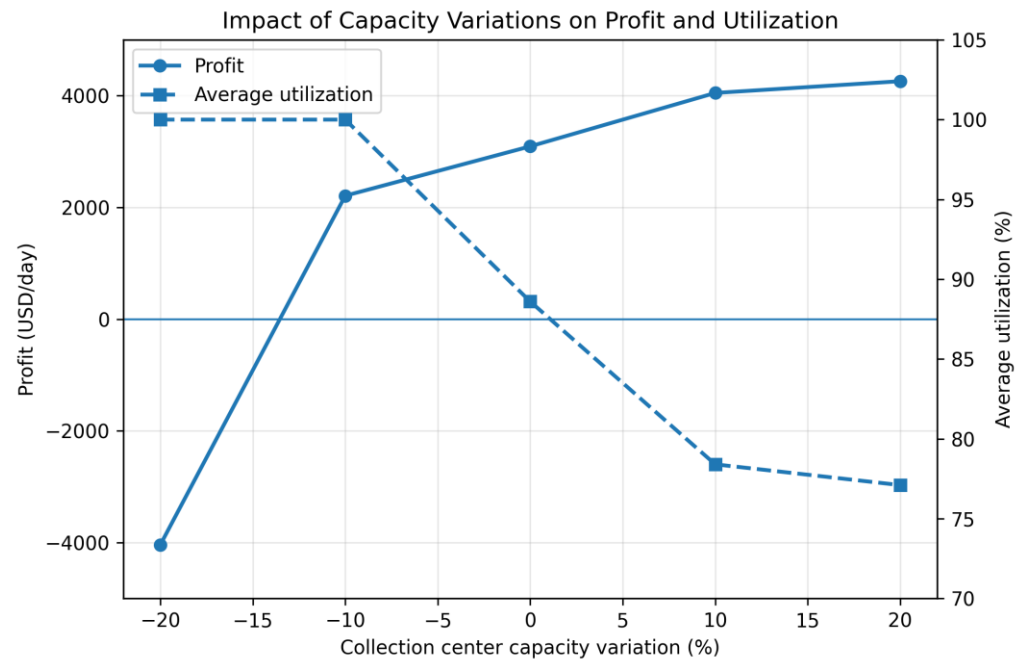


Figure 5. Impact of capacity variations on profit and utilization.

While the sensitivity analysis examines the individual influence of selected parameters, actual supply chain environments are characterized by the simultaneous occurrence of multiple uncertain factors. To capture these interactions and obtain a probabilistic assessment of network performance, the next section presents the results of a Monte Carlo simulation based on 1000 stochastic scenarios involving demand, transportation costs, and selling prices.

4.6. Monte Carlo Simulation Results

To evaluate the robustness of the proposed logistics network, a Monte Carlo simulation with 1000 replications was conducted. Uncertainty was incorporated into three key parameters: demand ($\pm 10\%$), transportation costs ($\pm 8\%$), and selling prices ($\pm 5\%$). This approach allows assessing system performance under realistic variability conditions beyond the deterministic baseline. Table 18 presents the main statistics of the profit distribution obtained from the simulation.

Table 18. Impact of demand variations on network performance.

Demand Variation	Profit (USD/day)	Unmet Demand (kg/day)	Open Centers
−20%	2823	0	4
−10%	3225	0	4
Base	3093	0	5
10%	−1573	3700	5
20%	−6909	7900	5

Tables 19 and 20 shows significant variability in economic performance. While the profit gained using deterministic modeling is USD 3093 per day, the profit obtained under conditions of uncertainty drops to USD 1955.70 per day. This means that deterministic modelling increases the system's profit compared to reality.

Table 19. Impact of collection center capacity variations on network performance.

Capacity Variation	Profit (USD/day)	Unmet Demand (kg/day)	Average Utilization (%)
−20%	−4042	5200	100.0
−10%	2209	600	100.0
Base	3093	0	88.6
10%	4049	0	78.4
20%	4259	0	77.1

The negative profit results show a potential economic loss of USD 6693.18 per day (See Table 20), supporting the claim that deterministic modelling produces worse optimisation solutions. The percentile results show that the expected results, from worst to best, likely outcomes, are highly predictable. This asymmetric distribution of results generates highly variable outcomes.

Table 20. Mean profit for the simulated scenario

Statistic	Value (USD/day)
Mean	1955.70
Standard deviation	1709.73
Minimum	−6693.18
5th percentile	−1155.83
Median	2159.64
95th percentile	4402.53
Maximum	5959.40

The activation frequencies show a consistent structural pattern. Collection centers C1, C2, and C3 are activated almost every time, and C4 also has a fairly high activation rate. However, as observed in Table 21, C5 is activated in only 83.6% of cases, suggesting that its role in the network is more that of a flexible or contingency facility, rather than a core component. This shows the same results as the deterministic model and, furthermore, highlights the strengthening of the distinction between essential and auxiliary infrastructure due to uncertainty.

Table 21. Activation frequency of collection centers under uncertainty.

Collection Center	Activation Frequency
C1	1.000
C2	0.999
C3	0.999
C4	0.992
C5	0.836

The utilization levels reinforce the structural interpretation of the network. Each of the centers C1–C4 has consistently operated at near-saturation levels, suggesting they are the operational core of the network. On the other hand, C5 has been processing at an average of 35.04%, much lower than the other centers, meaning its utilization is significantly lower (See Table 22).

Table 22. Average utilization of collection centers under uncertainty.

Collection Center	Mean Utilization (%)
C1	97.90
C2	99.22

C3	99.89
C4	98.34
C5	35.04

This disparity indicates that there is reserve capacity that is not needed in all situations but is useful under certain demand or cost scenarios. This suggests a balance between efficiency and flexibility.

Unmet demand reveals a fundamental weakness in the system. During the study, we found that demand is unmet by an average of 954 kg/day, leading to supply shortages in 72.3% of the “what if” scenarios tested. This demonstrates that the company’s logistics network is not flexible enough to absorb the inevitable variations in demand and the resulting costs. Most of the time, demand will remain unmet to a small to moderate degree, but there is a risk of minor service disruptions, and in the most extreme cases, this could reach up to 8263 kg/day (See Table 23).

Table 23. Unmet demand statistics under Monte Carlo simulation.

Metric	Value
Mean unmet demand (kg/day)	954.03
Maximum unmet demand (kg/day)	8263
Probability of unmet demand	0.723

The distribution of unmet demand (Figure 6) is right-skewed, with a concentration of low shortages and a tail of high-impact scenarios. Overall, the Monte Carlo simulation demonstrates that the deterministic solution corresponds to a highly efficient but fragile configuration. Although the system performs optimally under nominal conditions, it is highly sensitive to parameter uncertainty. The results highlight three key insights:

1. Overestimation of performance: Deterministic optimisation overstates expected profitability and ignores downside risk.
2. Structural dependence on core facilities: Collection centers C1–C4 are consistently critical, while C5 provides flexibility under uncertainty.
3. Efficiency–resilience trade-off: High utilization levels improve cost efficiency but reduce the system’s ability to handle variability.

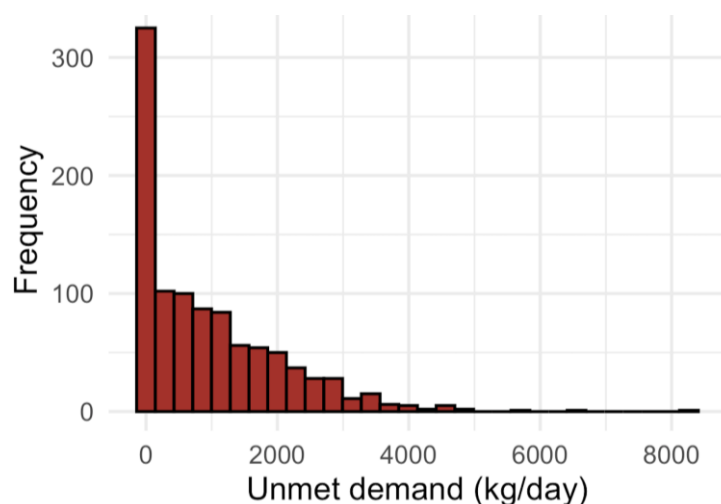


Figure 6. Distribution of total unmet demand.

These results highlight the need for robustness analysis when designing logistics networks, especially for perishable agri-food supply chains where uncertainty is the norm.

Deterministic optimization combined with sensitivity analysis and Monte Carlo simulation provides a comprehensive view of how the solution's robustness is affected by different operating conditions.

Overall, the deterministic optimization, sensitivity analysis, and Monte Carlo simulation results show that the network operates very close to its effective capacity limits. The greatest performance concerns are capacity reductions and demand growth. Profitability is most affected by transportation costs and sales prices. However, these constraints/reductions represent a much lesser concern for the network's viability. Therefore, capacity planning and demand management are key concerns for maintaining service levels under both deterministic and stochastic operating conditions.

The strong correlation shown in the deterministic optimization, sensitivity analysis, and Monte Carlo simulation results provides an additional layer of analysis to validate the robustness of the proposed computational framework. The convergence of these different analyses offered complementary perspectives and confirmed that the prevailing constraints on the network remain valid under both stochastic and deterministic operating conditions.

5. Conclusions and Future Research

This study developed an integrated optimization framework to design and evaluate a two-tier banana logistics network in the Department of Magdalena, Colombia. The framework incorporates mixed-integer linear programming (MILP) and Monte Carlo simulation, enabling it to address the strategic concerns of logistics managers regarding the design of banana collection centers and the allocation of banana product flows. The optimization findings demonstrate that, from a profit-maximization perspective, the logistics network configuration must include all five collection centers to serve the entire market. Furthermore, the results indicate that four collection centers operate at near full capacity, suggesting that the logistics network operates under baseline conditions with a high degree of capacity constraint.

To assess the stability of the network configuration, various scenarios were tested for transportation costs, selling prices, and collection center capacity, in addition to demand. The most limiting factors for network performance were demand and capacity. Transportation costs and selling prices affect the network's profitability, but demand and capacity determine the network's ability to serve the market. Increasing demand and reducing capacity resulted in unmet demand and significant profit losses, indicating that the system is operationally fragile under adverse conditions. Monte Carlo simulation improved understanding of the logistics network's behavior when combined with uncertainty. The network was found to be economically sustainable in many of the stochastic cases.

However, profitability becomes variable, and unmet demand occurs with adverse combinations of demand, transportation costs, and market prices. Statistics on the frequency with which transport links were activated and how much of their capacity was utilized confirmed the importance of large collection centers to the network. For management purposes, the results showed that demand and capacity management were the most important elements of the banana supply chain. The analysis indicated that building additional capacity at collection centers is likely a better investment for improving service reliability and network robustness than reducing transportation costs. Therefore, logistics managers should focus on the capacity of collection centers and routes if demand grows.

The consistency observed across the deterministic optimization results, the sensitivity analysis, and the Monte Carlo simulation outcomes provides additional evidence regarding the reliability and robustness of the proposed computational framework. Theoretically, this study contributes to the literature on logistics network design by integrating a robustness assessment technique that combines deterministic optimization with simu-

lation, all within a single decision-support framework. While most studies focus on designing optimal network configurations, the methodology presented here describes how those configurations perform in the presence of uncertainty. As a result, the framework builds upon existing models of facility location and flow assignment, providing a structured assessment of operational robustness within agricultural supply chains.

From a managerial perspective, the results identify several key logistics drivers of business performance, including demand forecasting and capacity planning. The results of the sensitivity analysis indicated that increases in demand and reductions in capacity have a more significant negative impact on profitability and service levels. Consequently, expanding collection centers and improving supporting infrastructure can offer superior service levels and greater service resilience compared to investments that address only improvements in transportation costs.

From a social perspective, improved performance and increased robustness of logistics systems reduce post-harvest losses, improve producers' access to markets, and help strengthen the economic viability of rural communities. Potential improvements in logistics in banana-producing areas, such as Magdalena, could foster competition among producers, increase agricultural employment, and improve the region's overall economic well-being.

The new optimization–simulation framework constructs a logistics system for an agricultural supply chain within the limits of current computational capabilities. Although this work focused on the Magdalena banana supply chain, the framework can be adapted to other perishable agricultural supply chains with decentralized production systems and capacity-constrained logistics networks. Future research can build upon this work by integrating the effects of spoilage, refrigerated transport, carbon footprints, and vehicle routing decisions across multiple time periods. These improvements would offer a better approximation of agricultural logistics systems.

Another limitation of the framework concerns scalability. While the framework efficiently solves the case study as developed, larger network designs incorporating more producers, collection centers/stations, additional products, and longer planning periods may result in prohibitively high computational effort. In such cases, research should focus on heuristic, commercial, and optimization solutions to address large-scale problems.

Future research may also extend the proposed framework by incorporating explicit perishability constraints, multi-period planning horizons, environmental performance indicators, and resilience considerations under supply chain disruptions.

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