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RESEARCH PAPER

Designing a Sustainable Closed-Loop Supply Chain Network for Agricultural Products under Uncertainty with a Focus on Water Consumption Reduction

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Abstract

As global population growth accelerates, demand for agricultural products has surged, leading to higher production, rising costs, increased water use, and food shortages. This study proposes a sustainable agricultural supply chain network that prioritizes water conservation while meeting customer needs. A mathematical model optimizes a closed-loop supply chain, maximizing demand for agricultural products and compost. The model minimizes costs, maximizes customer satisfaction, and reduces water consumption, ensuring sustainability. A stochastic programming approach manages supply and demand uncertainties through scenarios. Results show that increasing customer satisfaction raises costs and water use. For example, increasing the customer importance factor from 0.2 to 0.8 increases total costs by 4.53% and water use by 43.75%, highlighting the sensitivity of water use to customer satisfaction. Reducing processing center capacity decreases water use but increases costs and reduces customer satisfaction. A 50% reduction in capacity raises costs by 56.41%, decreases customer satisfaction by 4.44%, and reduces water use. Water use reductions vary by stage: a 50% reduction in agricultural production cuts total water use by 32.33%, while similar reductions in processing and composting yield smaller decreases of 17.86% and 28.32%, respectively. This underscores agricultural production as the most water-intensive phase. The model's effectiveness is demonstrated through numerical examples and sensitivity analyses. Metrics such as the Number of Pareto Fronts (NPF) and Maximum Spread Index (MSI) are used to compare solutions. This study emphasizes aligning sustainable production, resource conservation, and customer needs to create a resilient agricultural supply chain.

Keywords:
Agricultural Supply Chain (ASC), Augmented ε-Constraint Method, Closed-Loop, Sustainability, Water Consumption Optimization

Introduction

The agricultural products supply chain has evolved not only to address recycling, the sale of organic products, and the reduction of environmental pollution but also to incorporate social aspects, such as water conservation. Over recent decades, corporate attention to environmental issues and the need to comply with governmental regulations have given rise to the concept of

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sustainable development. Sustainable development encompasses three key dimensions: economic, social, and environmental sustainability, integrated within the supply chain (Carter & Rogers, 2008). Notably, the seventh goal of the Sustainable Development Goals (SDGs) specifically targets the reduction of food waste and losses (Cordova & Celone, 2019).

In response to environmental challenges, such as carbon dioxide emissions and pollution, as well as social concerns like customer satisfaction, job creation, and energy consumption optimization, a new paradigm known as the sustainable supply chain has emerged. This approach simultaneously addresses environmental, economic, and social considerations (Waltho et al., 2019). Among these, environmental issues are of paramount importance, second only to economic factors. Governments have mandated producers to collect and manage recyclable goods to reduce CO_2 emissions, leading to the integration of reverse supply chain management with traditional supply chain practices (Bagheri Tofighi et al., 2024). The reverse supply chain focuses on managing the flow of goods returned by customers. The combination of these two supply chains, along with sustainability principles, has given rise to the concept of the sustainable closed-loop supply chain. This framework not only addresses sustainability dimensions but also enables the reuse of returned products (Kazemi et al., 2019).

The sustainable closed-loop supply chain has been applied across various industries, including automotive parts, electronics, manufacturing, and perishable goods. Among these, agricultural products are particularly significant, especially when considering factors such as water consumption optimization. The sustainable agricultural supply chain is designed to produce and distribute food in an environmentally and socially responsible manner. It encompasses processes that minimize environmental harm, conserve natural resources, promote fair labor practices, and comply with government regulations (Routroy & Behera, 2017). Key components of this supply chain include agricultural practices, efficient transportation, packaging and waste management, standards, farmer collaboration, local and fair trade, and consumer awareness. Managing these components requires a systematic approach that optimizes economic, social, and environmental aspects while addressing water consumption management (Mashreghi et al., 2023).

Rapid population growth in recent decades has significantly increased the demand for agricultural and food products. To address food security concerns, production within the agricultural supply chain has intensified. However, this increase in production has also led to higher levels of waste, necessitating the adoption of closed-loop supply chains for recycling and reusing waste materials (Alidadi Talkhestani et al., 2023).

Moreover, the overproduction of agricultural products contributes to issues such as greenhouse gas emissions and excessive water consumption on agricultural lands. These challenges create ripple effects throughout the supply chain, impacting intermediaries at subsequent network levels. Water plays a critical role in agricultural supply chains, as it is essential for food security and crop production. Currently, over 70% of global freshwater is used for agriculture, primarily for irrigation. Asia, accounting for approximately 2.17 trillion cubic meters of water annually, is the largest consumer of water in the agricultural sector, highlighting the sector's economic importance on the continent (Russo et al., 2014). By 2050, the global population is projected to exceed 10 billion, leading to a 50% increase in demand for agricultural products and a 15% rise in freshwater requirements for production.

Climate change and excessive water consumption have caused freshwater shortages in many regions worldwide, making water conservation a critical priority. This study proposes a sustainable closed-loop supply chain network for agricultural products under uncertain conditions. The network includes producers, processing centers, distribution centers, collection centers, compost centers, and primary and secondary customers. Primary customers demand processed products, while secondary customers demand compost products. The model incorporates three objective functions: (1) minimizing total network costs (economic sustainability), (2) maximizing customer satisfaction (social sustainability), and (3) minimizing water consumption (environmental sustainability).

In today's volatile markets, parametric uncertainty significantly impacts optimization problems, particularly in strategic decision-making contexts such as Supply Chain Network Design (SCND). Agricultural supply chains are inherently complex and vulnerable due to the perishable nature of the products. Uncertainty permeates all levels of the supply chain, from suppliers to end customers. However, many optimization models in the literature assume deterministic parameters, which is unrealistic in practice.

Our proposed supply chain network accounts for uncertainties in both customer demand and product supply. These uncertainties arise from external factors such as public health crises, shifts in customer preferences, or droughts. Managing demand uncertainty is crucial, as it can lead to increased costs, excess inventory, surplus production capacity, and intangible costs such as reputational damage and reduced customer satisfaction. Since customers are the ultimate endpoint of the supply chain, meeting their demand is critical for overall satisfaction.

To address uncertain demand and supply parameters, we employ stochastic programming, utilizing historical data to manage uncertainty. Given the complexity of supply chain network design problems, we adopt an exact solution method. Specifically, we use the Augmented Epsilon Constraint method to solve the multi-objective model, which includes minimizing total costs, maximizing customer satisfaction, and reducing water consumption. This method is well-suited for handling multi-objective optimization and generating efficient solutions.

While sustainable closed-loop supply chain networks have been applied to various goods, including perishable and non-perishable items, their application to agricultural products with inherent demand and supply uncertainties remains underexplored. Furthermore, existing research on sustainable closed-loop supply chains for agricultural products has not adequately addressed water consumption reduction, a critical issue for societies. Our study aims to fill these gaps and advance the field. The key innovations of this research are summarized as follows:

1. **Holistic Sustainability Approach**: The study integrates all three dimensions of sustainability—economic, social, and environmental—within the closed-loop supply chain network for agricultural products, ensuring a balanced approach to decision-making.
2. **Handling Uncertainty:** Unlike deterministic models, this research incorporates demand and supply uncertainty using stochastic programming, enhancing the robustness of decision-making under real-world conditions.
3. **Water Consumption Reduction:** The study explicitly addresses water consumption minimization, contributing to environmental preservation and societal well-being.

Literature Review

The agricultural product supply chain plays a pivotal role in managing the production and distribution of agricultural goods to customers. Numerous studies have explored this field, addressing both deterministic and uncertain parameters such as demand, supply, and transportation costs. However, most studies have overlooked the issue of agricultural waste. While a few studies have examined this issue within the context of closed-loop supply chain networks, these investigations have typically been conducted in isolation. This section provides a review of the most significant contributions in the existing literature.

Deterministic Models of Agricultural Product Supply Chain Networks

This section examines deterministic models of agricultural product supply chain networks. Zhao and Duo (2011) proposed a mixed-integer programming model to determine optimal facility locations, select production capacities, and choose transportation modes with the aim of minimizing total costs in the food-agricultural supply chain. Due to the complexity of the optimization problem, the authors developed a Particle Swarm Optimization (PSO) approach, which outperformed binary PSO in solving the problem. Accorsi et al. (2016) proposed a linear programming model to balance logistics costs and carbon emissions in the agricultural-food ecosystem, highlighting the interdependence of infrastructure, production, distribution, and environmental resources.

De Keizer et al. (2017) investigated the design of a logistics network for perishable products with a quality decline period. The operational period of logistics, as well as environmental conditions during these operations, significantly affect the performance of the logistics network for fresh agricultural products. Orjuela-Castro et al. (2022) addressed the major challenges in modeling the perishable food supply chain, including delivery time, specific food biophysical conditions, food losses, etc. The authors proposed a multi-objective, multi-echelon, and multi-product model for designing logistics networks for perishable food. Finally, the authors applied it in a case study concerning the perishable fruit supply chain. Goodarzian et al. (2023) developed a mixed-integer linear programming model for the sustainable production-distribution-routing problem in an agricultural supply chain considering CO_2 emissions. Their objective was to minimize total costs, minimize water consumption, and maximize social impacts. For this purpose, four metaheuristic algorithms were chosen to solve the problem, and the results showed that the Simulated Annealing (SA) and the PSO algorithms provide more acceptable results within a reasonable time frame. Fathi et al., (2024) proposed a multi-stage model for sustainable supply chain network design. After an overview of operations research methods for sustainable supply chain network design, this study proposed a hybrid method based on multi-criteria decision-making (MCDM) and optimization techniques in operations research. Modak et al., (2024) designed a two-step fresh agricultural products supply chain with only one retailer and one producer. The fresh agricultural products are produced and processed by the manufacturer, who then supplies it to the retailer. The manufacturer simultaneously operates an online/e-tail channel to sell its product.

Uncertain Models of Agricultural Product Supply Chain Networks

Uncertain models of agricultural supply chain networks are examined in this section. Motevalli-Taher et al. (2020) proposed a multi-objective model to minimize total costs and water consumption while maximizing job opportunities. They used Goal Programming to consolidate the objectives and addressed demand uncertainty for wheat flour through simulation. Jouzdani and Govindan (2021) developed a multi-objective model to optimize costs, energy consumption, and traffic density. They modeled product lifetime uncertainty as a Weibull random variable and considered refrigerated trucks as a decision variable to influence food spoilage. Their results show that focusing on economic aspects can increase environmental impact by up to 120% for highly perishable products and social impact by up to 51% in congested road networks.

Baghizadeh et al. (2022) proposed a mathematical model for designing a sustainable supply chain of highly perishable agricultural products (strawberries). This model is a multi-objective and multi-product Mixed Integer Nonlinear Programming (MINLP) that considers economic, social, and environmental objectives to cover all aspects of sustainability. The authors used the robust fuzzy approach to control uncertain parameters. Additionally, the authors utilized the epsilon-constraint method for simultaneous optimization of three objective functions. Gholian-Jouybari et al. (2023) investigated metaheuristic algorithms for a sustainable agricultural supply chain considering marketing strategies under uncertainty. To achieve this, the authors developed a multi-objective two-stage stochastic programming model, the effectiveness of which was validated through a case study on saffron trade using the LP-Metric method. To address the complexity of the problem, the authors utilized a modified version of the Keshtel algorithm as a metaheuristic approach. Daneshvar et al. (2023) presented a distribution network model for agricultural products with high perishability to corruption under conditions of uncertainty. The proposed model consists of three levels: suppliers, distribution centers, and retailers, where suppliers can fulfill retailers' demands directly or indirectly. The authors controlled the uncertain demand using the robust fuzzy approach and showed that with increasing uncertainty, the costs of supply, distribution, holding, and ordering increased. Rahbari et al., (2024) investigated the closed-loop supply chain of canned food in uncertain conditions. One of the main features of the problem is to use the canned food waste to increase profitability during the COVID-19 pandemic. In addition, the Robust Probabilistic Chance Constrained Programming (RPCCP) approach is presented to face the uncertainty of the problem.

Closed-Loop Models of Agricultural Product Supply Chain Networks

These models include a cycle from production to consumption, and then recycling or reusing waste. Jabarzadeh et al. (2020) proposed a multi-objective sustainable closed-loop supply chain for agricultural products. The authors defined production, distribution, and customer levels to meet customer demand, as well as composting centers and compost markets to better utilize returned products. The proposed model attempted to minimize the total cost of the sustainable closed-loop supply chain, increase responsiveness to customer demand, and minimize CO_2 emissions. This study utilized deterministic data. Chouhan et al. (2021) proposed a mathematical model for a multi-echelon closed-loop supply chain for the sugarcane industry. Their main objective was to optimize the total costs of the agricultural supply chain network using heuristic algorithms.

Alinezhad et al. (2022) presented a bi-objective, multi-period, multi-product, and multi-echelon supply chain network model for the food industry. Their aim was to simultaneously maximize the profit of the supply chain network and the customer satisfaction. Due to the uncertainty of the mathematical model, the authors used fuzzy programming to control uncertain data. Additionally, the authors utilized the LP-Metric method to form the Pareto front and achieve efficient solutions. Seydanlou et al. (2022) designed a multi-objective optimization model for a closed-loop supply chain network for the olive oil industry and utilized hybrid metaheuristic algorithms to solve the problems. Their objectives were to minimize total costs, minimize carbon dioxide emissions, and maximize job opportunities. For this purpose, the authors analyzed the mathematical model using the epsilon-constraint method for small-scale numerical examples and employed different algorithms to solve large-scale problems. Salehi-Amiri et al. (2022) examined an optimization model for the avocado supply chain. In this study, only two aspects of sustainability, economic and social, were considered, and the environmental aspect was not taken into account. The authors also aim to increase job opportunities in this research.

Rajabi-Kafshgar et al. (2023) developed a new mixed integer linear mathematical model for an agricultural supply chain network to minimize the total fixed and variable costs of the closed-loop supply chain. To address the proposed model, the authors employed both traditional and recent efficient and well-known metaheuristic algorithms. The results showed that the genetic algorithm is more efficient than other algorithms. Gholipour et al. (2024) designed a sustainable closed-loop supply chain for pomegranates. The authors were able to return pomegranate peels and discarded pomegranates into the supply chain for recycling using reverse logistics. Gholian-Jouybari et al., (2024) proposed a new mixed-integer linear programming model to propose an agri-food supply chain network design for the coconut industry under sustainable terms. This study mainly aims to solve a multi-objective closed-loop supply chain, considering both forward and reverse product movements. The model attempts to manage the net present value of total cost for specific planning horizons while monitoring environmental pollution and job opportunities within the network.

Table 1. Summary of the agricultural supply chain network design studies

Authors	Objective Functions (Sustainability Dimensions)			Closed-loop	Multi-product	Multi-period	Uncertainty	Case Study	Water Consumption Reduction	Solution Approach
	Economic	Social	Environmental							
Jabarzadeh et al. (2020)	Minimizing total cost	Maximizing customer satisfaction	Minimizing CO_2 emissions	✓		✓	D	Fruit		LP-metric
Motevalli-Taher et al. (2020)	Minimizing total cost	Maximizing Job opportunity	Minimizing Water consumption				S	Wheat	✓	GP
Chouhan et al. (2021)	Minimizing total cost			✓			D	Sugarcane		GA-SA-RDA-KA
Alinezhad et al. (2022)	Maximizing profit	Maximizing customer satisfaction		✓	✓	✓	FP	Food		LP-metric
Seydanlou et al. (2022)	Minimizing total cost	Maximizing Job opportunity	Minimizing CO_2 emissions	✓		✓	D	Olive		SA-GA-EMA-VCS
Baghizadeh et al. (2022)	Minimizing total cost	Maximizing Job opportunity	Minimizing CO_2 emissions		✓	✓	FP - RO	Strawberry		ε-constraint
Salehi-Amiri et al. (2022)	Minimizing total cost	Maximizing Job opportunity		✓	✓	✓	D	Avocado		Exact
Daneshvar et al. (2023)	Minimizing total cost						FP - RO	Agricultural product		GA-AOA-WOA
Rajabi-Kafshgar et al. (2023)	Minimizing total cost			✓	✓		D	Agricultural product		GA-SA-PSO
Goodarzian et al. (2023)	Minimizing total cost	Maximizing customer satisfaction	Minimizing Water consumption				D	Agricultural product	✓	GA-SA-PSO-KA
Gholian-Jouybari et al. (2023)	Maximizing profit	Maximizing customer satisfaction	Minimizing Water consumption				TSSP	Saffron	✓	LP-Metric MOKA
Gholipour et al. (2024)	Minimizing total cost	Maximizing customer satisfaction	Minimizing supply risk	✓		✓	D	Pomegranate		NSGA-II MOPSO GAMS
Fathi et al., (2024)	Minimizing total cost	Maximizing customer satisfaction	Minimizing CO_2 emissions		✓	✓	D	Agricultural product		LP-Metric
Modak et al., (2024)	Maximizing profit				✓	✓	D	Agricultural product		Exact
Gholian-Jouybari et al., (2024)	Minimizing total cost	Maximizing customer satisfaction	Minimizing CO_2 emissions	✓	✓	✓	D	coconut		NSGA-II
Rahbari et al., (2024)	Minimizing total cost			✓	✓	✓	RO	Canned product		Exact
This Study	**Minimizing total cost**	**Maximizing customer satisfaction**	**Minimizing Water consumption**	✓		✓	**SP**	**Agricultural product**	✓	**Augmented ε-constraint**

Abbreviations: " D: Deterministic ; S: Simulation ; FP: Fuzzy Programming ; RO: Robust Optimization ; SP: Stochastic Programming ; TSSP: Two-Stage Stochastic Programming ; GP: Goal Programming ; GA: Genetic Algorithm ; SA: Simulated Annealing ; KA: Keshtel Algorithm ; RDA: Red Deer Algorithm ; EMA: Electromagnetism-like Algorithm ; VCS: Virus Colony Search Algorithm ; WOA: Whale Optimization Algorithm ; PSO: Particle Swarm Optimization ; MOPSO: Multi-Objective Particle Swarm Optimization ; AOA: Arithmetic Optimization Algorithm ; MOKA: modified Keshtel Algorithm ; NSGA-II: Non-Dominated Sorting Genetic Algorithm of kind II "

Table 1 summarizes key studies on agricultural supply chain network design. While many papers have explored agricultural supply chains, few have specifically addressed closed-loop or reverse logistics for agricultural products. Moreover, the literature reveals a limited focus on sustainable closed-loop supply chain networks tailored for agricultural products.

In recent years, researchers have increasingly directed their attention toward integrating sustainability aspects (economic, social, and environmental) within closed-loop agricultural supply chains. On the other hand, it is essential to recognize that although many papers across various industries have discussed reducing water consumption as a critical dimension of sustainability, no cases have explicitly considered this issue within a closed-loop agricultural supply chain. Surprisingly, even in the agricultural sector, where water scarcity is a pressing concern, addressing and effectively meeting the challenge of reducing water consumption remains insufficient. Despite this, three studies by Motevalli-Taher et al. (2020), Goodarzian et al. (2023), and Gholian-Jouybari et al. (2023) stand out. However, none of these studies specifically incorporated the objective of reducing water consumption in a sustainable closed-loop supply chain for agricultural products, especially considering the uncertainty associated with demand and supply parameters. Additionally, stochastic programming methods were not utilized to manage uncertainty in these investigations.

Problem Definition

The proposed model in this study represents a sustainable closed-loop supply chain for agricultural products. The network comprises the following key components:

1. Agricultural Producers: These include orchards, farms, and other sources of agricultural products.
2. Processing Centers: These facilities add value to raw agricultural products through sorting, packaging, and other processing activities.
3. Distribution Centers: Responsible for wholesaling and retailing both processed agricultural products and compost.
4. Collection Centers: These centers collect agricultural waste from various stages of the supply chain.
5. Compost Centers: Transform agricultural waste into enriched fertilizer for reuse.
6. Final Customers: The endpoint of the supply chain, consisting of primary customers (demanding processed products) and secondary customers (demanding compost).

Figure (1) illustrates the structure and flow of this sustainable closed-loop supply chain network. The process begins with agricultural producers, who supply raw products. Healthy products suitable for processing and sale are transferred to processing centers, while agricultural waste is sent to collection centers. At the processing centers, the healthy products are sorted and processed, though some waste may still occur due to perishability or packaging issues. The processed products are then sent to distribution centers, where they are sold to primary customers. However, some processed products may also be wasted at this stage.

In the reverse supply chain, collection centers gather waste from producers, processing centers, and distribution centers. This waste is transported to composting centers, where it is converted into compost. The final products—processed goods for primary customers and compost for secondary customers—are distributed through the distribution centers.

This sustainable closed-loop supply chain optimizes resource utilization, minimizes waste, and enhances both environmental and economic sustainability by integrating forward and reverse logistics.

In the agricultural supply chain network, both customer demand for processed products and compost, as well as the supply of agricultural products by producers, are subject to uncertainty. Supply uncertainty arises from factors such as drought, low rainfall, and other environmental conditions, while demand uncertainty can be influenced by market fluctuations and consumer behavior. These uncertainties significantly impact network design decisions, making it essential to account for them in the model.

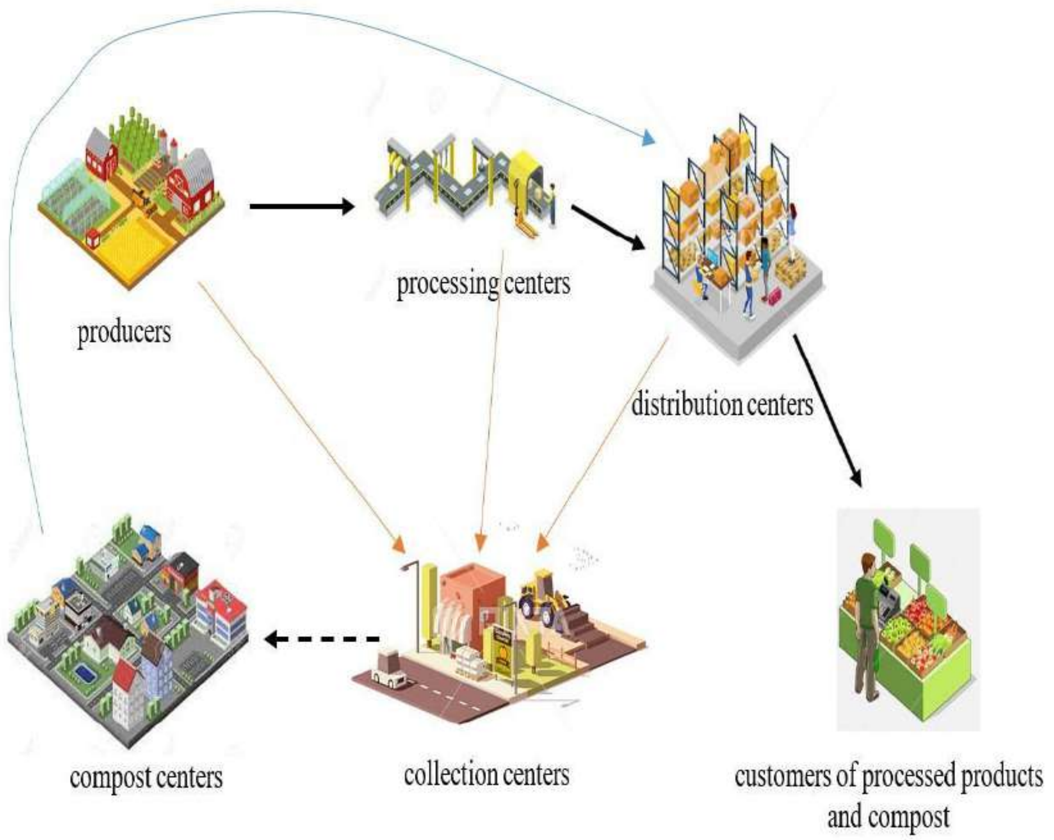

Figure 1. schematic of the sustainable closed-loop supply chain of agricultural products.

To address the uncertainty in demand and supply, this study employs stochastic programming. Each scenario is assigned a probability of occurrence, which is incorporated into the problem formulation. Additionally, the model is based on the following key assumptions:

1. The mathematical model is single-product and multi-period.
2. Multiple vehicles are available for transporting products between different levels of the supply chain.
3. The quantities of agricultural product demand and supply are uncertain.
4. The locations of customers, production centers, composting centers, and distribution centers are fixed, with predefined capacities.
5. Both processed agricultural products and compost can be stored at distribution centers.
6. Water consumption during transportation is considered negligible.
7. Primary and secondary customers are assigned different importance coefficients to reflect their varying priorities.

Given the above assumptions, the considered model for the sustainable closed-loop supply chain of agricultural products aims to optimize three objective functions. These objective functions include, minimizing total costs, maximizing customer satisfaction by reducing unmet demand, and minimizing water consumption in the production, processing, and composting stages, respectively. It is important to note that reducing the volume of production, processing, and composting of agricultural products directly correlates with lower water consumption. This indicates that water usage is inherently dependent on production levels. However, the second objective function introduces a trade-off, as it aims to maximize customer satisfaction by minimizing product shortages, which may require higher production volumes.

In contrast, the first objective function involves decisions related to facility location and inventory management, making it difficult to establish a clear linear relationship between the first and third objective functions. This highlights the complexity of balancing economic, social, and environmental objectives within the model.

The simultaneous optimization of the three objective functions is designed to support decision-making regarding the location variables of processing and collection centers, as well as tactical decisions such as production quantities, the volume of products transported between network levels using various vehicles, and the quantities of processed and composted products stored in distribution centers. To model the problem, the following elements are defined: indices, parameters, and decision variables.

Table 2. Sets and indices.

Indices	Definition
i	Set of producers; $i = 1,2,\dots,I$
j	Set of processing centers; $j = 1,2,\dots,J$
k	Set of distribution centers; $k = 1,2,\dots,K$
c_1	Set of primary customers; $c_1 = 1,2,\dots,C_1$
c_2	Set of secondary customers (compost market); $c_2 = 1,2,\dots,C_2$
c	Set of total customers; $C_1 \cup C_2 \in C$
l	Set of composting centers; $l = 1,2,\dots,L$
o	Set of collection centers; $o = 1,2,\dots,O$
t	Time periods; $t = 1,2,\dots,T$
r	Set of vehicles; $r = 1,2,\dots,R$
s	Scenarios; $s = 1,2,\dots,S$

In this study, a scenario represents fluctuations in the supply and demand of agricultural products within the supply chain. These fluctuations may arise due to factors such as droughts, changes in imports/exports of agricultural products, and other external influences. The time period considered in this study is structured on a monthly basis.

Table 3. Parameters.

Parameter	Definition
fe_j	Fixed cost of processing center $j \in J$ ($)
fm_o	Fixed cost of collection center $o \in O$ ($)
d_{cts}	Demand of customer $c_1 \in C_1$ for processed products in period $t \in T$ under scenario $s \in S$ (Tons)
d'_{cts}	Demand of customer $c_2 \in C_2$ for compost products in period $t \in T$ under scenario $s \in S$ (Tons)
ρ	Importance coefficient of primary customers of agricultural products
α_{it}	Waste percentage of agricultural products during harvesting by producer $i \in I$ in period $t \in T$
β_{jt}	Waste percentage of agricultural products during processing by processing center $j \in J$ in period $t \in T$
γ_{kt}	Waste percentage of agricultural products during distribution and storage by distribution center $k \in K$ in period $t \in T$
cp_{its}	Supply amount of agricultural products from producer $i \in I$ in period $t \in T$ under scenario $s \in S$ (Tons)
cd_{jt}	Maximum processing capacity of agricultural products at processing center $j \in J$ in period $t \in T$ (Tons)
cr_{kt}	Maximum distribution capacity of processed agricultural products and compost products at distribution center $k \in K$ in period $t \in T$ (Tons)
cs_{ot}	Maximum collection capacity of wasted agricultural products at collection center $o \in O$ in period $t \in T$ (Tons)
ct_{lt}	Maximum composting capacity of wasted agricultural products at compost center $l \in L$ in period $t \in T$ (Tons)
tx_{ijr}	Transportation cost from producer $i \in I$ to processing center $j \in J$ by vehicle $r \in R$ ($)
ty_{jkr}	Transportation cost from processing center $j \in J$ to distribution center $k \in K$ by vehicle $r \in R$ ($)
tz_{kcr}	Transportation cost from distribution center $k \in K$ to customer C by vehicle $r \in R$ ($)
tw_{ior}	Transportation cost from producer $i \in I$ to collection center $o \in O$ by vehicle $r \in R$ ($)
tu_{jor}	Transportation cost from processing center $j \in J$ to collection center $o \in O$ by vehicle $r \in R$ ($)
tp_{kor}	Transportation cost from distribution center $k \in K$ to collection center $o \in O$ by vehicle $r \in R$ ($)
tn_{olr}	Transportation cost from collection center $o \in O$ to compost center $l \in L$ by vehicle $r \in R$ ($)
th_{lkr}	Transportation cost from compost center $l \in L$ to distribution center $k \in K$ by vehicle $r \in R$ ($)
h_k	Holding cost of processed products at distribution center $k \in K$ ($)
h'_k	Holding cost of compost products at distribution center $k \in K$ ($)
wo_{it}	Water consumption volume for agricultural product production by producer $i \in I$ in period $t \in T$ (thousand of liters per ton)
we_{lt}	Water consumption volume required for composting products at compost center $l \in L$ in period $t \in T$

	(thousand liters per ton)
wj_{jt}	Water consumption volume required for processing products at processing center $j \in J$ in period $t \in T$ (thousand liters per ton)
p_s	Probability of scenario occurrence

Table 4. decision variables.

Variable	**Definition**
E_j	1 If processing center j is opened; 0 Otherwise
M_o	1 If collection center o is opened; 0 Otherwise
X_{ijrts}	Quantity of products shipped from producer $i \in I$ to processing center $j \in J$ by vehicle $r \in R$ in period $t \in T$ under scenario $s \in S$
Y_{jkrts}	Quantity of processed products shipped from processing center $j \in J$ to distribution center $k \in K$ by vehicle $r \in R$ in period $t \in T$ under scenario $s \in S$
Z_{kcrts}	Quantity of processed products shipped from distribution center $k \in K$ to customer $c_1 \in C_1$ by vehicle $r \in R$ in period $t \in T$ under scenario $s \in S$
Z'_{kcrts}	Quantity of compost products shipped from distribution center $k \in K$ to customer $c_2 \in C_2$ by vehicle $r \in R$ in period $t \in T$ under scenario $s \in S$
W_{iorts}	Quantity of waste shipped from producer $i \in I$ to collection center $o \in O$ by vehicle $r \in R$ in period $t \in T$ under scenario $s \in S$
U_{jorts}	Quantity of waste shipped from processing center $j \in J$ to collection center $o \in O$ by vehicle $r \in R$ in period $t \in T$ under scenario $s \in S$
P_{korts}	Quantity of waste shipped from distribution center $k \in K$ to collection center $o \in O$ by vehicle $r \in R$ in period $t \in T$ under scenario $s \in S$
N_{olrts}	Quantity of waste shipped from collection center $o \in O$ to composting center $l \in L$ by vehicle $r \in R$ in period $t \in T$ under scenario $s \in S$
H_{lkrts}	Quantity of compost products shipped from composting center $l \in L$ to distribution center $k \in K$ by vehicle $r \in R$ in period $t \in T$ under scenario $s \in S$
Q_{kts}	Quantity of processed products stored at distribution center $k \in K$ at the end of period $t \in T$ under scenario $s \in S$
Q'_{kts}	Quantity of compost products stored at distribution center $k \in K$ at the end of period $t \in T$ under scenario $s \in S$

Given the notations defined above, the multi-objective mathematical model for a sustainable closed-loop supply chain network for agricultural products under uncertainty conditions, with a focus on reducing water consumption, is as follows:

$$
\begin{aligned}
MinOB_1 = & \sum_{j\in J} fe_j E_j + \sum_{o\in O} fm_o M_o + \sum_{r\in R}\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\sum_{s\in S} p_s tx_{ijr} X_{ijrts} \\
& + \sum_{r\in R}\sum_{j\in J}\sum_{k\in K}\sum_{t\in T}\sum_{s\in S} p_s ty_{jkr} Y_{jkrts} + \sum_{r\in R}\sum_{k\in K}\sum_{c\in C_1}\sum_{t\in T}\sum_{s\in S} p_s tz_{kcr} Z_{kcrts} \\
& + \sum_{r\in R}\sum_{k\in K}\sum_{c\in C_2}\sum_{t\in T}\sum_{s\in S} p_s tz_{kcr} Z'_{kcrts} + \sum_{r\in R}\sum_{i\in I}\sum_{o\in O}\sum_{t\in T}\sum_{s\in S} p_s tw_{ior} W_{iorts} \\
& + \sum_{r\in R}\sum_{j\in J}\sum_{o\in O}\sum_{t\in T}\sum_{s\in S} p_s tu_{jor} U_{jorts} + \sum_{r\in R}\sum_{k\in K}\sum_{o\in O}\sum_{t\in T}\sum_{s\in S} p_s tp_{kor} P_{korts} \\
& + \sum_{r\in R}\sum_{o\in O}\sum_{l\in L}\sum_{t\in T}\sum_{s\in S} p_s tn_{olr} N_{olrts} + \sum_{r\in R}\sum_{l\in L}\sum_{k\in K}\sum_{t\in T}\sum_{s\in S} p_s th_{lkr} H_{lkrts} \\
& + \sum_{k\in K}\sum_{t\in T}\sum_{s\in S} p_s h_k Q_{kts} + \sum_{k\in K}\sum_{t\in T}\sum_{s\in S} p_s h'_k Q'_{kts}
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
MaxOB_2 = 100 * (\rho & \sum_{r\in R}\sum_{k\in K}\sum_{c\in C_1}\sum_{t\in T}\sum_{s\in S} p_s Z_{kcrts} \Big/ \sum_{c\in C_1}\sum_{t\in T}\sum_{s\in S} p_s d_{cts} \\
& + (1-\rho)\sum_{r\in R}\sum_{k\in K}\sum_{c\in C_2}\sum_{t\in T}\sum_{s\in S} p_s Z'_{kcrts} \Big/ \sum_{c\in C_2}\sum_{t\in T}\sum_{s\in S} p_s d'_{cts})
\end{aligned}
\tag{2}
$$

$$MinOB_3 = \sum_{r\in R}\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\sum_{s\in S}\frac{p_s wo_{it} X_{ijrts}}{(1-\alpha_{it})} + \sum_{r\in R}\sum_{i\in I}\sum_{o\in O}\sum_{t\in T}\sum_{s\in S}\frac{p_s wo_{it} W_{iorts}}{\alpha_{it}} + \sum_{j\in J}\sum_{k\in K}\sum_{r\in R}\sum_{t\in T}\sum_{s\in S}\frac{p_s wj_{jt} Y_{jkrts}}{(1-\beta_{jt})} + \sum_{j\in J}\sum_{o\in O}\sum_{r\in R}\sum_{t\in T}\sum_{s\in S}\frac{p_s wj_{jt} U_{jorts}}{\beta_{jt}} + \sum_{l\in L}\sum_{k\in K}\sum_{r\in R}\sum_{t\in T}\sum_{s\in S} p_s we_{lt} H_{lkrts} \tag{3}$$

$s.t$:

$$\sum_{r\in R}\sum_{k\in K} Z_{kcrts} \le d_{cts}, \quad \forall c\in C_1, t\in T, s\in S \tag{4}$$

$$\sum_{r\in R}\sum_{k\in K} Z'_{kcrts} \le d'_{cts}, \quad \forall c\in C_2, t\in T, s\in S \tag{5}$$

$$Q_{kts} = (1-\gamma_{kt})Q_{k,t-1,s} + (1-\gamma_{kt})\sum_{r\in R}\sum_{j\in J} Y_{jkrts} - \sum_{r\in R}\sum_{c\in C_1} Z_{kcrts}, \quad \forall k\in K, t\in T, s\in S \tag{6}$$

$$Q'_{kts} = Q'_{k,t-1,s} + \sum_{r\in R}\sum_{l\in L} H_{lkrts} - \sum_{r\in R}\sum_{c\in C_2} Z'_{kcrts},, \quad \forall k\in K, t\in T, s\in S \tag{7}$$

$$\sum_{r\in R}\sum_{k\in K} Y_{jkrts} = \sum_{r\in R}\sum_{i\in I} X_{ijrts} - \sum_{r\in R}\sum_{i\in I}\beta_{jt} X_{ijrts}, \quad \forall j\in J, t\in T, s\in S \tag{8}$$

$$\sum_{r\in R}\sum_{j\in J} X_{ijrts} \le (cp_{its} - \alpha_{it} cp_{its}), \quad \forall i\in I, t\in T, s\in S \tag{9}$$

$$\sum_{r\in R}\sum_{o\in O} W_{iorts} \le \alpha_{it} cp_{its}, \quad \forall i\in I, t\in T, s\in S \tag{10}$$

$$\sum_{r\in R}\sum_{o\in O} U_{jorts} = \sum_{r\in R}\sum_{i\in I}\beta_{jt} X_{ijrts}, \quad \forall j\in J, t\in T, s\in S \tag{11}$$

$$\sum_{r\in R}\sum_{o\in O} P_{korts} = \sum_{r\in R}\sum_{j\in J}\gamma_{kt} Y_{jkrts}, \quad \forall k\in K, t\in T, s\in S \tag{12}$$

$$\sum_{r\in R}\sum_{i\in I} W_{iorts} + \sum_{r\in R}\sum_{j\in J} U_{jorts} + \sum_{r\in R}\sum_{k\in K} P_{korts} = \sum_{r\in R}\sum_{l\in L} N_{olrts}, \quad \forall o\in O, t\in T, s\in S \tag{13}$$

$$\sum_{r\in R}\sum_{o\in O} N_{olrts} = \sum_{r\in R}\sum_{k\in K} H_{lkrts}, \quad \forall l\in L, t\in T, s\in S \tag{14}$$

$$\sum_{r\in R}\sum_{l\in L} H_{lkrts} = \sum_{r\in R}\sum_{c\in C_2} Z'_{kcrts}, \quad \forall k\in K, t\in T, s\in S \tag{15}$$

$$\sum_{r\in R}\sum_{i\in I} X_{ijrts} \le cd_{jt} E_j, \quad \forall j\in J, t\in T, s\in S \tag{16}$$

$$\sum_{r\in R}\sum_{j\in J} Y_{jkrts} + \sum_{r\in R}\sum_{l\in L} H_{lkrts} \le cr_{kt}, \quad \forall k\in K, t\in T, s\in S \tag{17}$$

$$\sum_{r\in R}\sum_{i\in I} W_{iorts} + \sum_{r\in R}\sum_{j\in J} U_{jorts} + \sum_{r\in R}\sum_{k\in K} P_{korts} \le cs_{ot} M_o, \quad \forall o\in O, t\in T, s\in S \tag{18}$$

$$\sum_{r\in R}\sum_{o\in O} N_{olrts} \le ct_{lt}, \quad \forall l\in L, t\in T, s\in S \tag{19}$$

$$E_j, M_o \in \{0,1\} \tag{20}$$

$$X_{ijrts}, Y_{jkrts}, Z_{kcrts}, Z'_{kcrts}, W_{iorts}, U_{jorts}, P_{korts}, N_{olrts}, H_{lkrts}, Q_{kts}, Q'_{kts} \ge 0 \tag{21}$$

Equation (1) represents the total cost objective function of the supply chain, encompassing location, transportation, and holding costs for processed and composted products at distribution centers. Equation (2) maximizes social responsibility by focusing on customer satisfaction, aiming to meet the maximum demand of customers. Equation (3) addresses the environmental aspect of sustainability by minimizing water consumption at production, composting, and processing centers. Equations (4) and (5) ensure that the demands of primary and secondary customers for processed and compost products, respectively, are met as much as possible. Equations (6) and (7) specify the quantities of processed and compost products that can be stored in distribution centers for use in subsequent periods. Equations (8) and (9) determine the quantities of products transferred to distribution and processing centers, accounting for waste generated at processing and production centers.

Equations (10) to (12) represent the percentage of waste generated at production, processing, and distribution centers, which is sent to collection centers for composting. Equations (13) to (15) balance the flow of compost products: Equation (13) ensures all collected waste is transferred to composting centers for fertilizer production, while Equations (14) and (15) specify the quantities of composted products sent to distribution centers and secondary customers, respectively. Equations (16) to (19) represent capacity constraints for processing, distribution, collection, and composting centers. Notably, processing and collection centers must be established before operations can begin, meaning no product transfer or waste collection can occur until they are built.

Finally, Equations (20) and (21) define the binary and non-negativity constraints for the decision variables, ensuring the model adheres to logical and practical limitations.

Solution Approach

The purpose of this section is to describe the approach used to solve the mathematical model. Various methods are used to solve multi-objective models. Due to the research gap and the efficiency of the augmented ε-constraint method in solving supply chain network design problems, this method has been used to solve the proposed model in this paper. The augmented ε-constraint method was chosen over other multi-objective optimization techniques, such as the weighted sum method and goal programming, due to its distinct advantages. The weighted sum method, while simple, requires predefined weights, introducing subjectivity and potentially missing Pareto solutions. Goal programming relies on specific targets, which may not always be feasible or representative of the full trade-off space. In contrast, the augmented ε-constraint method ensures Pareto optimality for all objectives, avoids subjective weightings, and systematically explores the entire Pareto front. This method is particularly suited to our study, as it effectively balances economic, environmental, and social objectives in designing a sustainable closed-loop supply chain network for agricultural products. By providing a comprehensive and unbiased analysis of trade-offs, the augmented ε-constraint method enables decision-makers to identify optimal solutions that align with sustainability goals under uncertainty.

Chankong and Haimes (1983) introduced the ε-constraint method, which optimizes one objective function while constraining the others within specified bounds. By varying these bounds, the method generates a set of efficient solutions. Mavrotas (2009) later proposed the augmented ε-constraint method to address limitations of the original approach. This enhanced method uses the lexicographic technique to compute the payoff table for each objective function, ensuring efficient and non-dominated solutions. It transforms inequality constraints related to secondary objectives into equality constraints by introducing slack or surplus variables. Additionally, the augmented ε-constraint method incorporates these variables into the main objective function, improving its ability to handle multi-objective optimization problems. The decision-maker ranks the objective functions based on their importance, guiding the optimization process.

The augmented ε-constraint method involves several key steps: (1) selecting a high-priority objective function and determining its optimal value, (2) constructing the payoff table to identify the best and worst values for other objective functions, (3) converting inequality constraints into equality constraints using slack or surplus variables, and (4) integrating these variables into the main objective function. To validate the three-objective mathematical model, a small-scale numerical example is examined, and the augmented ε-constraint method is applied to solve it.

Numerical Analyses

In this section, we first analyze a small-scale numerical example to validate the model. Following this, sensitivity analysis is conducted on the small-scale example to investigate the impact of various parameters on the objective function values. Subsequently, several larger-scale numerical examples are designed and solved using the augmented epsilon-constraint method to evaluate its effectiveness and scalability in handling more complex instances of the problem.

Small Problem Instance

The model presented in this study is a multi-objective optimization model designed for the sustainable closed-loop supply chain of agricultural products. To validate the model, a small-scale numerical example was employed, consisting of 3 producers, 3 processing centers, 2 distribution centers, 2 collection centers, 2 composting centers, and 4 customers. The problem is structured over 2 time periods, utilizes 4 vehicles, and considers 2 scenarios. Table (5) provides the parameter values for the small-scale numerical example across these two scenarios.

Table 5. Defined range of parameters for the small problem.

Parameter	Levels		Unit
fe_j, fm_o	$\sim U(8000{,}9000)$		\$
ρ	0.6		-
$\alpha_{it}, \beta_{jt}, \gamma_{kt}$	$\sim U(0.05{,}0.1)$		-
cd_{jt}	$\sim U(500{,}600)$		Ton
cr_{kt}	$\sim U(350{,}450)$		Ton
cs_{ot}	$\sim U(300{,}400)$		Ton
ct_{lt}	$\sim U(150{,}200)$		Ton
tx_{ijr}, ty_{jkr}	$\sim U(5{,}6)$		\$
tz_{kcr}	$\sim U(1{,}2)$		\$
$tw_{ior}, tu_{jor}, tp_{kor}, tn_{olr}, th_{lkr}$	$\sim U(1{,}3)$		\$
h_k	$\sim U(10{,}12)$		\$
h'_k	$\sim U(2{,}4)$		\$
wo_{it}	$\sim U(200{,}250)$		Thousand liters per ton
we_{lt}	$\sim U(180{,}220)$		Thousand liters per ton
wj_{jt}	$\sim U(100{,}150)$		Thousand liters per ton
	$s = 1$	$s = 2$	
p_s	0.5	0.5	
d_{cts}	$\sim U(200{,}300)$	$\sim U(150{,}200)$	Ton
d'_{cts}	$\sim U(70{,}100)$	$\sim U(50{,}70)$	Ton
cp_{its}	$\sim U(600{,}700)$	$\sim U(700{,}800)$	Ton

In the table above, it is important to note that water consumption varies across different stages: production, processing, and composting of agricultural products. These values are expressed in thousand liters per ton. Specifically, water consumption ranges from 200 to 250 thousand liters per ton for production, 180 to 220 thousand liters per ton for processing, and 100 to 150 thousand liters per ton for composting.

Scenario 1 (50% probability) simulates high demand and low supply (conditions like drought), while Scenario 2 (50% probability) simulates low demand and high supply (conditions like heavy rainfall and import competition). The probabilities for scenario 1 and scenario 2 were initially set to 0.5 each, reflecting an equal likelihood in the absence of historical data or expert opinions specific to our problem context. This assumption allowed us to explore the trade-offs between the two scenarios without introducing bias. To ensure the robustness of our results, we conducted a sensitivity analysis by varying the probabilities of scenario occurrences, as shown in Table 8. In this small-scale numerical example, the minimum customer satisfaction rate is set to 70%. Efficient solutions are investigated using the augmented epsilon-constraint method. In this approach, the third objective function—minimizing water consumption—is assigned the highest priority, followed by the objective functions of total cost minimization and customer satisfaction maximization, respectively.

The augmented epsilon constraint method assigns the highest priority to objective function $OB_1(x)$, finding its optimal solution OB_1^*. To optimize the second objective function, the constraint $OB_1(x) = OB_1^*$ is added, retaining the optimal solution for the first objective. The value OB_2^* is then calculated to optimize the next priority objective function. The following equation is generally used to optimize multi-objective problems:

$$\begin{aligned} & Min\ OB_1 - \delta\left(\frac{s_2}{r_2} + \frac{s_3}{r_3}\right) \\ & s.t.: \\ & \quad OB_2 - s_2 = \varepsilon_2 \\ & \quad OB_3 + s_3 = \varepsilon_3 \end{aligned} \tag{22}$$

In the above equation r_i for $i = 2, 3$ represent the domain of the objective functions, ε_i for $i = 2, 3$ represent the obtained solutions from each iteration, and δ is a small positive number. The coding and solving were performed in the GAMS software, and the obtained results are presented below.

Table 6 represents the payoff table. In this table, the best and worst values of each objective function obtained using the individual optimization method are shown.

Table 6. Payoff table of the small size numerical example.

Objective function	Value of objective function 1	Value of objective function 2	Value of objective function 3
First objective	**23160.73**	70	1023113.45
Second objective	28818.74	**100**	10321128.07
Third objective	35062.28	70	**411825.63**

Based on this and using the augmented epsilon constraint method, 29 efficient solutions were obtained according to Table 7.

Table 7. The set of pareto solutions for the small size numerical example.

Solution	Value of objective function 1 ($)	Value of objective function 2 (%)	Value of objective function 3 (thousand liters per ton)
1	27106.96	71	418198.2
2	27251	72	424200
3	27395.01	73	430208.1
4	27539.02	74	436216.3
5	27811.26	75	442224.5
6	28054.74	76	448469.2
7	28132.51	77	465636.7
8	28169.28	78	483866.3
9	28207.39	79	502095.2
10	28245.5	80	520325.5
11	28283.61	81	538555.1
12	28191.99	82	556784.7
13	28230.1	83	575014.3
14	28268.21	84	593243.9
15	28451.67	85	614454.8
16	28490.17	86	636872.3
17	28529.22	87	659289.9
18	28569.23	88	681707.4
19	28609.25	89	704125
20	28649.26	90	726542.5
21	28689.27	91	748960.1

22	28729.29	92	771377.6
23	28729.88	93	794915.2
24	28806.45	94	817431.7
25	28882.31	95	842630.2
26	28929.9	96	867876.4
27	28972.84	97	896961.4
28	29019.1	98	927263.2
29	29185.44	99	958048.3

Table (7) demonstrates that an increase in the volume of processed products leads to a corresponding rise in composted products. This results in higher costs across production, processing, composting, transportation, and other supply chain network activities. Additionally, increased production enhances customer satisfaction, as more customer demand is met. However, the higher production, processing, and composting volumes also lead to greater water consumption. Consequently, as the value of the first objective function (total cost) increases, the values of the second (customer satisfaction) and third (water consumption) objective functions also rise. Figure 2 illustrates the Pareto front obtained for the small-scale instance problem.

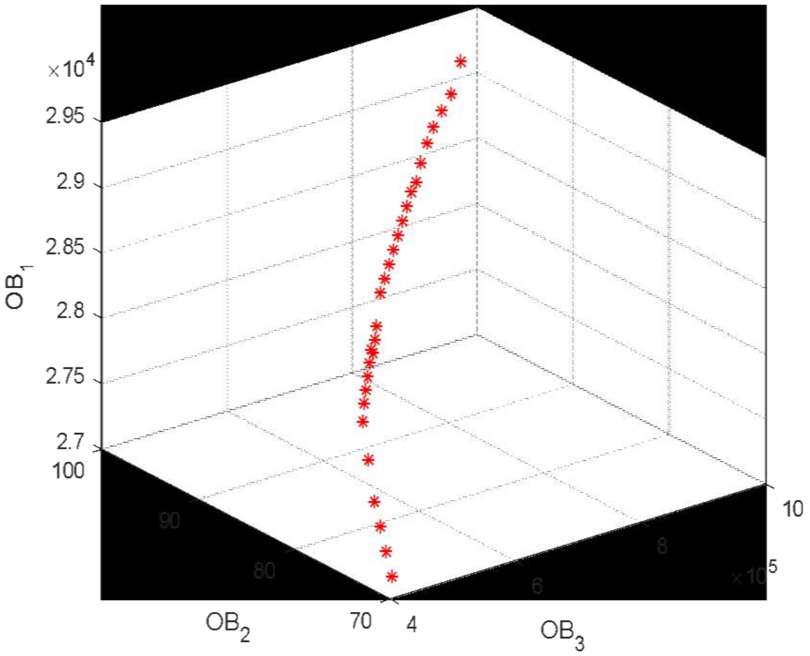

Figure. 2. The Pareto front for the numerical example in small size.

Figure 2 demonstrates that as customer satisfaction increases, water consumption in the network also rises. This occurs because production, processing, and composting centers increase their output to fully meet customer demand. Consequently, higher production and processing volumes lead to greater water consumption across the supply chain network.

The Pareto front in Figure 2 provides supply chain managers with a range of efficient solutions balancing cost, customer satisfaction, and water consumption. Decision-makers can select solutions based on their priorities. For example, Solution 1 minimizes cost (27,106.96) but results in lower customer satisfaction (71%), and water consumption (958,048.3 thousand liters per ton), suitable for businesses prioritizing customer loyalty. Solutions with lower water consumption (e.g., Solutions 1–5) are preferable in water-scarce regions, even if they entail slightly higher costs or lower satisfaction.

Practically, managers must weigh these trade-offs based on their operational context. In water-scarce areas, reducing water consumption might justify higher costs or lower satisfaction.

In competitive markets, maximizing customer satisfaction could outweigh increased costs and water usage. Cost-sensitive operations might prioritize minimizing expenses, even with slight compromises on satisfaction or sustainability. By leveraging the Pareto front, managers can make informed, data-driven decisions that align with their strategic goals and environmental responsibilities.

Sensitivity Analysis on Small Problem Instance

In this section, sensitivity analysis is conducted on the presented numerical example. Given the equal probability of scenario occurrences, sensitivity analysis is first performed on the probabilities of these scenarios.

Sensitivity Analysis on the Probability of Scenario Occurrences

Scenario one represents higher demand and lower supply, while scenario two represents lower demand and higher supply. By varying the probability of each scenario, the average efficient solutions of the problem are calculated and presented in Table (8).

Table 8. Changes in the average objective functions with different probabilities of scenario occurrences.

Probability of Scenario 1	Probability of Scenario 2	Average Total Cost ($)	Average Customer Satisfaction (%)	Average Water Consumption (thousand liters per ton)
10	90	26876.07	85.24	532567.38
20	80	27324.52	85.21	558855.62
30	70	27666.07	85.16	585559.72
40	60	27966.86	85.10	611681.21
50	50	28349.31	85.00	637361.90
60	40	28911.00	84.89	661712.38
70	30	29340.17	84.78	685755.21
80	20	29743.28	84.67	709903.45
90	10	30107.28	84.55	734168.28

The results in Table 8 show that as the probability of Scenario 1 (higher demand and lower supply) increases, customer satisfaction decreases due to the inability to fully meet demand. To address this, the supply chain network increases production levels, leading to higher total costs. Additionally, increased production generates more waste, resulting in greater water consumption in the production and composting sectors.

Sensitivity Analysis on Customer Importance Coefficient

In a separate analysis, the impact of changes in customer importance coefficients on the objective function values was examined. In the baseline analysis, the importance coefficient for customers demanding processed products was set to 0.6, while for customers demanding compost products, it was 0.4. The higher importance coefficient for processed products reflects factors such as greater market demand, higher revenue potential, and direct customer benefits. In contrast, compost products provide indirect benefits, such as improved soil health and waste reduction, which may not be as immediately visible or valued by customers. Table (9) presents the variations in the average objective function values for different customer importance coefficients.

Table 9 Changes in the average objective function values for different customer importance coefficients.

Customer Importance Coefficient	Average Total Cost ($)	Average Customer Satisfaction (%)	Average Water Consumption (thousand liters per ton)
0.2	27396.17	81.25	513927.21
0.4	27525.28	83.34	617303.28
0.6	28349.31	85.00	637361.90
0.8	28638.41	88.11	738808.62

The results in Table (9) show that as the customer importance coefficient increases, maximum demand fulfillment is achieved. This leads to higher total costs, increased customer satisfaction, and greater water consumption. Specifically, increasing the customer importance factor from 0.2 to 0.8 results in a 4.53% rise in average total costs, an 8.44% increase in average customer satisfaction, and a 43.75% increase in average water consumption. This analysis highlights that water consumption is more sensitive to changes in the customer importance factor compared to total costs.

Sensitivity Analysis on the Capacity of Processing Centers

In another analysis, the impact of changes in the capacity of processing centers on the average objective functions is investigated. Table (10) presents the results for scenarios where the capacity of processing centers is reduced by **10%**, **30%**, and **50%**, respectively.

Table 10. Changes in the average objective function values for different capacities of processing center

Percentage Change in Processing Center Capacity	Average Total Cost ($)	Average Customer Satisfaction (%)	Average Water Consumption (thousand liters per ton)
0	28349.31	85.00	637361.90
10% Reduction	36414.28	84.26	617473.62
30% Reduction	36935.90	83.27	610881.34
50% Reduction	44343.72	81.22	609913.28

The results in Table (10) show that reducing the capacity of processing centers leads to fewer products being processed, resulting in lower customer satisfaction. Additionally, the decreased capacity necessitates the construction of more processing centers to meet demand, increasing total costs. However, the reduction in capacity also reduces the volume of processed products, leading to lower water consumption.

This analysis reveals that a 50% reduction in the capacity of agricultural processing centers increases average total costs by 56.41%, while decreasing customer satisfaction by 4.44% and water consumption by 4.30%, as production decreases proportionally.

Sensitivity Analysis on Water Consumption Parameters

A key focus of this study is examining water consumption across three echelons of the supply chain: production, processing, and composting. The third objective function captures the parameters related to water consumption. In this section, the impact of changes in water consumption volumes at each echelon on the value of the third objective function is analyzed. Table (11) presents these changes.

Table 11. Changes in the Average Water Consumption value in different scenario

Scenario (Reduction the Water consumption volume)	Production center	Compost center	Processing center
0	637361.90	637361.90	637361.90
10%	603128.48	612434.67	603314.67
30%	623428.67	584754.46	531667.68
50%	431254.24	523497.49	456847.66

The results in Table (11) show that a 50% reduction in water consumption in the agricultural production sector reduces the total water consumption in the supply chain by 32.33%. In contrast, a 50% reduction in water consumption in the processing and composting sectors reduces total water consumption by 17.86% and 28.32%, respectively. These findings highlight that the largest share of water consumption in the supply chain occurs during the production of agricultural products, followed by processing.

Large Problem Instances

After analyzing the small-scale numerical example and conducting sensitivity analysis, several larger-scale numerical examples were solved. Table (12) presents the parameter values for these instances, while Table (13) outlines the sizes of the numerical examples at different scales.

Table 12. Parameter Values of the Numerical Example at Larger Scales.

Parameter	Levels	Unit
fe_j, fm_o	$\sim U(8000{,}9000)$	$
ρ	0.6	-
$\alpha_{it}, \beta_{jt}, \gamma_{kt}$	$\sim U(0.05{,}0.1)$	-
cd_{jt}	$\sim U(500{,}600)$	Ton
cr_{kt}	$\sim U(350{,}450)$	Ton
cs_{ot}	$\sim U(300{,}400)$	Ton
ct_{lt}	$\sim U(150{,}200)$	Ton
tx_{ijr}, ty_{jkr}	$\sim U(5{,}6)$	$
tz_{kcr}	$\sim U(1{,}2)$	$
$tw_{ior}, tu_{jor}, tp_{kor}, tn_{olr}, th_{lkr}$	$\sim U(1{,}3)$	$
h_k	$\sim U(10{,}12)$	$
h'_k	$\sim U(2{,}4)$	$
wo_{it}	$\sim U(200{,}250)$	Thousand liters per ton
we_{lt}	$\sim U(180{,}220)$	Thousand liters per ton
wj_{jt}	$\sim U(100{,}150)$	Thousand liters per ton
p_s	$1/\lvert S\rvert$	
d_{cts}	$\sim U(150{,}300)$	Ton
d'_{cts}	$\sim U(50{,}100)$	Ton
cp_{its}	$\sim U(700{,}800)$	Ton

The sizes of the numerical examples were selected randomly to evaluate the problem-solving time using the augmented epsilon-constraint method.

Table 13. Sizes of numerical examples in larger scales.

Test problems	i	j	k	C	o	l	t	v	s
1	3	3	4	5	2	2	2	4	2
2	3	4	4	6	3	3	2	4	2
3	4	4	5	7	3	3	2	4	2
4	5	5	6	9	4	4	3	5	2
5	6	6	8	12	5	5	3	6	3
6	7	7	10	15	6	6	3	6	3
7	7	7	11	16	6	6	3	6	3
8	8	8	12	18	6	6	4	6	4
9	9	9	14	20	8	8	4	8	4
10	10	10	15	22	9	9	4	8	4

After solving numerical examples of varying sizes, the average values of the objective functions—total cost, customer satisfaction, and water consumption—derived from the average efficient solutions are presented in Table (14). Additionally, Table (14) includes the average problem-solving time using the augmented epsilon-constraint method.

Table 14. Average Objective Function Values and Problem Solving Time.

Test problems	Average Total Cost ($)	Average Customer Satisfaction (%)	Average Water Consumption (thousand liters per ton)	Solving Time (Seconds)
1	38810.58	85.21	862127.52	171.82
2	39008.65	85.25	893233.06	215.88
3	42745.10	85.13	1031247.58	316.55
4	54081.03	85.23	1613246.19	646.85
5	62415.38	85.12	2234532.58	1157.68
6	74953.29	84.97	2946535.68	1756.37
7	98639.56	85.31	3568415.97	2536.64
8	124457.38	85.24	4394653.31	3348.61
9	156674.38	85.06	4969793.00	4325.61
10	186862.32	85.67	5544932.68	5408.63

The results in Table 14 demonstrate that the computational time increases exponentially with problem size, highlighting the NP-hard nature of the model. While the augmented epsilon-constraint method effectively generates Pareto-optimal solutions for small- to medium-scale instances, its application to larger-scale problems becomes computationally intensive. This exponential increase in solving time is primarily attributed to the multi-period structure of the model and the complexity of balancing the three objectives: cost, customer satisfaction, and water consumption. As problem size grows, the computational resources required to explore the solution space expand significantly, underscoring the challenges of scaling exact optimization methods to larger, real-world supply chain networks. Figure (3) illustrate the average values of the first to third objective functions and the problem solving time in various numerical examples.

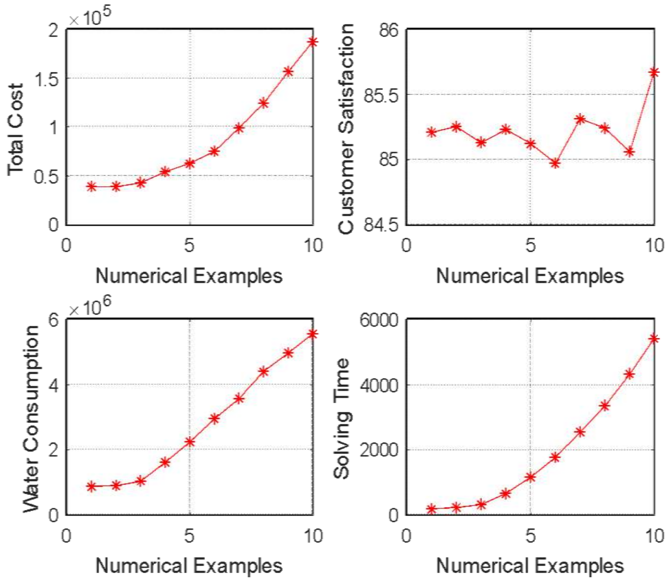

Figure 3. Average objective function values in different numerical examples.

Additionally, due to the presence of multiple efficient solutions in the numerical examples, three metrics—Number of Pareto Front (NPF), Maximum Spread Index (MSI), and Space Metric (SM)—have been used to compare the results across the numerical examples. Figure (4) illustrates these metrics for the efficient solutions in the different numerical examples.

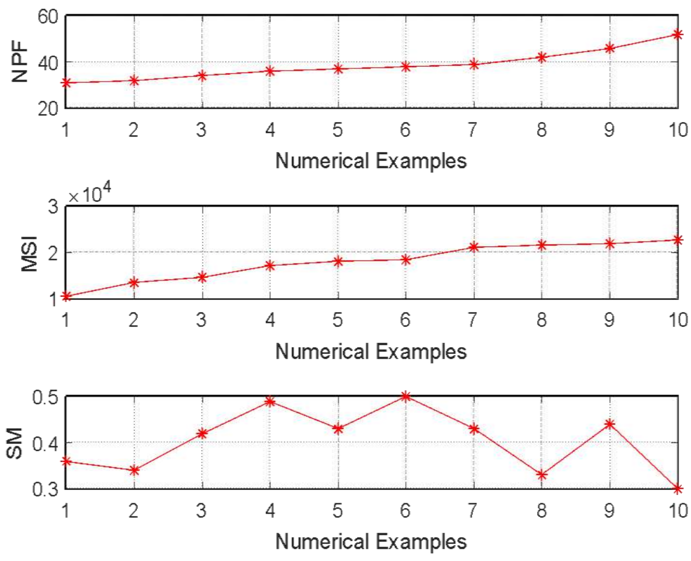

Figure 4. The indexes of the effective solutions in the different numerical examples.

Figure (4) shows that as the size of the numerical examples increases, the number of customers also rises, resulting in a greater number of Pareto solutions. This aligns with the expectation that larger problem instances yield more Pareto solutions. Additionally, Figure (4) demonstrates that the Maximum Spread Index (MSI) increases with the size of the numerical examples and the number of efficient solutions, indicating that decision-makers have more flexibility and better decision-making opportunities in larger-scale problems. Finally, the Space Metric (SM) does not follow a specific trend across the numerical examples, with the best value achieved in numerical example 10.

Conclusion

This study introduces a novel multi-objective optimization model for designing a sustainable closed-loop agricultural supply chain, explicitly addressing uncertainty and prioritizing the minimization of water consumption. The model integrates key components of the agricultural supply chain, including agricultural production, processing facilities, distribution networks, collection centers for agricultural waste, composting facilities, and customer demand points. It simultaneously optimizes three conflicting objectives: (1) minimizing total supply chain costs, (2) maximizing customer satisfaction (defined as fulfilling demand and ensuring product quality), and (3) reducing overall water consumption across the supply chain.

The model incorporates strategic decisions such as the optimal location and capacity of processing and collection centers, as well as the efficient allocation of processed agricultural products and compost derived from agricultural waste. A distinctive feature of the model is its differentiation between primary customers (who receive processed products) and secondary customers (who utilize compost products). To address uncertainties in agricultural supply and customer demand, a scenario-based stochastic programming approach is employed, enabling robust decision-making under fluctuating conditions.

Analysis of a representative numerical example and the resulting Pareto front revealed inherent trade-offs between the objectives. For instance, improving customer satisfaction through increased production to meet higher demand led to higher costs in production, processing, and composting activities, thereby increasing overall supply chain costs. Additionally, increased production volumes directly correlated with higher water consumption, underscoring the importance of balancing customer service levels with efficient resource utilization.

Sensitivity analysis further explored the impact of uncertainty and key model parameters. An increased probability of a high-demand, low-supply scenario reduced customer satisfaction due to unmet demand, highlighting the need for resilient supply chain planning. Conversely, prioritizing demand fulfillment through increased production significantly raised total costs and waste generation, subsequently increasing water consumption in production and composting centers. This emphasizes the critical role of waste minimization strategies.

The analysis of the customer importance coefficient—a parameter reflecting the weight placed on customer satisfaction—revealed a clear relationship between customer focus, costs, and water consumption. Increasing the customer importance factor from 0.2 to 0.8 resulted in a 4.53% increase in average total costs, an 8.44% increase in average customer satisfaction, and a substantial 43.75% increase in average water consumption. This indicates that water consumption is more sensitive to changes in customer importance than total supply chain costs.

Further analysis showed that reducing processing center capacity decreased water consumption due to lower production volumes but also increased total supply chain costs and reduced customer satisfaction. Specifically, a 50% reduction in processing center capacity led to a 56.41% increase in average total costs, a 4.44% decrease in customer satisfaction, and a 4.30% decrease in water consumption.

Finally, examining changes in water consumption under different scenarios revealed the significant impact of water use in agricultural production. A 50% reduction in water consumption in the agricultural production sector reduced total water consumption by 32.33%, while similar reductions in the processing and composting sectors resulted in reductions of 17.86% and 28.32%, respectively. This demonstrates that agricultural production is the most water-intensive stage in the supply chain, followed by processing and composting.

Although the augmented epsilon-constraint method effectively generates efficient solutions for the proposed multi-objective model, its computational demands for larger-scale problems pose a significant challenge. To overcome this limitation, future research could explore heuristic or metaheuristic algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), or Simulated Annealing (SA), which are capable of solving large-scale problems within practical timeframes. Additionally, decomposition techniques like Benders Decomposition and the use of parallel computing frameworks could further improve computational efficiency. These advancements would enhance the model's scalability and enable its application to more complex, real-world supply chain scenarios, offering decision-makers valuable insights for balancing cost, customer satisfaction, and water consumption. When combined with fuzzy programming methods, advanced production technologies, and perishability considerations, these strategies could significantly broaden the model's applicability and impact in addressing real-world supply chain challenges.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon request.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. No part of this work has been influenced by personal or financial relationships with other people or organizations. The authors have no affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter or materials discussed in this manuscript.

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