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Addressing climate change impacts on food supply chain operations: An integrated framework for sustainable optimization

Shayan (Shawn) Mirhosseini (M.Sc., PMP®, P.Eng.)[1,*]

[1] Department of Biosystems Engineering, University of Manitoba, Canada

*Corresponding author: shawnnmir@gmail.com

Abstract: Climate change exerts significant and multifaceted impacts on food supply chains, disrupting operations from production to consumption. This study investigates how climate-related vulnerabilities such as extreme weather events and climatic variability affect the efficiency, cost structure, and overall resilience of food supply chains, with a particular emphasis on disruptions that pose risks to the stability of food supply under uncertain climate conditions. These dimensions remain insufficiently explored in the current literature. To address this gap, a novel multi-objective optimization model is developed, incorporating Climate Vulnerability Indices (CVI) into the strategic planning of food supply chain networks. The model is formulated and solved using GAMS with the CPLEX solver, drawing on parameters derived from prior research in sustainable supply chain management. Results illustrate that integrating the CVI into supply chain decision-making enhances the model's ability to account for climate-related risks, enabling more informed trade-offs among economic, environmental, and social objectives. Moreover, through its adaptive structure, the model promotes the long-term sustainability of food supply chains and supports continuity under climate-induced operational challenges. This study offers an innovative, resilience-focused modeling framework that supports sustainable and adaptive supply chain configurations. The findings underscore the critical need for climate-aware optimization approaches to enhance the resilience and sustainability of food systems amid escalating climate risks.

Keywords: Climate change; Food supply chain resilience; Sustainable supply chain; Climate vulnerability; Supply chain optimization

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1 Introduction

Climate change is increasingly recognized as a critical threat to the stability and performance of global food supply chains. Rising temperatures, extreme weather events, and fluctuating precipitation patterns have significant impacts on agricultural productivity, transportation systems, and the overall resilience of supply networks (Vermeulen et al., 2012; Wheeler & Von Braun, 2013).These climate-induced disruptions amplify existing vulnerabilities and pose serious risks to food security, particularly in regions heavily reliant on climate-sensitive agricultural systems. Food supply chains represent complex, multi-tiered systems encompassing production, processing, distribution, and consumption. Climate change introduces profound challenges to these systems, including supply disruptions, increased operational costs, reduced production efficiency, and compromised food quality and safety. These effects undermine not only logistical reliability but also the ability to ensure a consistent and secure food supply. This study explores the interconnected impacts of climate vulnerability on food supply chain performance. Climate vulnerability, in this context, refers to the degree to which supply chain elements are exposed and sensitive to climatic stressors, including rising temperatures, extreme weather events, and shifts in precipitation. It is a function of exposure, sensitivity, and adaptive capacity capturing the likelihood that food production, processing, transportation, and distribution operations are adversely affected by changing climate conditions (Godde et al., 2021; Wiebe et al., 2019).

Traditional supply chain management approaches often lack the flexibility to respond effectively to dynamic and uncertain risks such as those induced by climate change. Consequently, there is an increasing need for robust and adaptive optimization strategies that explicitly account for climate vulnerability. While previous studies have addressed aspects of climate change adaptation in agriculture and logistics, relatively few have integrated climate vulnerability indices into the mathematical optimization of food supply chains. Food supply chains are increasingly vulnerable to climate-induced disruptions, yet systematic and quantitative modeling frameworks that address this vulnerability remain scarce. Many existing models emphasize economic performance while underrepresenting critical aspects of environmental uncertainty and long-term sustainability. Systems that are more sensitive to external stressors tend to experience greater variability in performance. In contrast, adaptive capacity, defined as the ability of a system to respond effectively to changing conditions, plays a pivotal role in minimizing disruptions and reducing losses. A supply chain with strong adaptive capacity is inherently more resilient to the adverse impacts of climate variability and extreme weather events (Tchonkouang et al., 2024). In recent years, the design of supply chain networks has garnered increasing attention in the field of optimization, as it is a key factor in reducing costs related to infrastructure development, production, and logistics while enhancing overall system efficiency (Shishebori & Babadi, 2018). Food supply chain networks span the full range of activities from food production and processing to distribution and final consumption. These networks involve diverse stakeholders, including farmers, processors, logistics providers, and retailers. The complexity of these systems stems from the need to balance supply and demand efficiently, ensure food quality, reduce waste, and maintain consistent delivery timelines. Any disruption in one segment can have cascading effects across the entire network, reinforcing the importance of robust logistical management (Mogale et al., 2023; Pishvaee et al., 2011). As environmental challenges and climate risks continue to escalate, the integration of sustainability considerations into supply chain network design has become increasingly important. The perishable nature of food products necessitates timely delivery before spoilage or expiration, making the resilience and sustainability of food supply chains especially urgent. These systems frequently face uncertainties in both demand and distribution, along with various operational, economic, and quality related constraints. Moreover, external shocks such as extreme weather events often manifest in the short term, creating further planning complexities. Growing environmental awareness has driven a shift toward sustainable and green supply chain practices, including the adoption of cleaner production methods, energy efficient logistics, and environmentally responsible management systems. Within this context, food supply chains are particularly vulnerable to climate-related disruptions across all stages of the product life cycle. As a result, sustainable supply chain management is increasingly recognized as a holistic approach that transcends internal operations, encompassing the entire supply network, from raw material sourcing and processing to distribution and final consumption (Abdi et al., 2021; Ahi & Searcy, 2013). Such an integrated approach is vital for managing the energy-intensive and capital-heavy processes that define modern food supply chains, especially under the growing pressure of climate change.

Recent studies have increasingly recognized the need for supply chain models that move beyond purely economic considerations to address environmental and social dimensions, particularly in light of the growing influence of climate-related disruptions. While the literature highlights the importance of sustainability, adaptability, and responsiveness in food systems, there remains a gap in models that holistically integrate these elements into a unified optimization framework. In response, this study presents a comprehensive approach that incorporates climate vulnerability indices into supply chain planning, enabling the evaluation of operational costs, carbon emissions, and employment generation under diverse weather scenarios. The model is structured around predefined facility locations and estimated input conditions, allowing for a tractable yet meaningful analysis of supply chain performance. By embedding these interconnected objectives within a scenario-based multi-period model, the proposed framework supports more informed and adaptive decision-making, contributing to the development of food supply chains that are better aligned with long-term sustainability goals. This study presents a novel mathematical optimization model that integrates climate vulnerability indices into the strategic planning and operational management of food supply chains. The model is designed to improve operational performance while enhancing the system’s adaptability to climate-related disruptions. Developed using the General Algebraic Modeling System (GAMS) and solved with the CPLEX solver, the framework accommodates complex, scenario-based data to support decision-making under uncertainty. By embedding climate vulnerability directly into the supply chain design, the proposed model offers a practical tool for mitigating adverse impacts while promoting sustainability and food security objectives. The study also highlights the role of transportation planning as a key factor in minimizing environmental impacts and increasing the flexibility of supply chain operations (Crainic et al., 2018). Through this integrated approach, the research contributes to bridging the gap between operational efficiency and environmental considerations, advancing current efforts in climate-aware supply chain management. The findings underscore the importance of proactive, data-informed strategies in building more resilient and responsive food systems under increasing climatic uncertainty.

2 Literature review

2.1 Climate change and food supply chains

In recent years, the sustainability of supply chains has emerged as a critical concern for planners and decision makers, largely driven by the escalating impacts of climate change. Disruptions in the food supply chain, whether localized or spanning long distances can cause systemic challenges, undermining food availability and accessibility at various scales. The literature underscores the value of establishing operational coordination centers across supply chain nodes to enhance adaptability and resilience (Wiebe et al., 2019). These centers can serve as focal points for strategic oversight, enabling timely responses to disruptions and maintaining service continuity. Core capabilities recognized as essential for supply chain resilience include robustness, agility, waste minimization, and flexibility. These principles support systems in withstanding shocks and adapting rapidly to changing environmental or logistical conditions. In particular, eliminating nonvalue adding activities and reducing inefficiencies are seen as critical steps toward improving supply chain performance in a sustainable manner. In a comprehensive review titled it was shown that the lack of adaptive strategies is a major limitation in supply chains. More recent theoretical developments include the study in a comprehensive review of the food supply chain literature, categorized the challenges and shortcomings and pointed out the lack of adaptive strategies for the impacts of climate change (Yadav et al., 2022). Similarly, inflation and variable times was emphasized in the optimization of perishable food supply chains and demonstrated the importance of dynamic adaptability in mathematical modeling (Agarwal & Badole, 2021). A number of studies advocate for adaptation strategies that prioritize improved resource management, access to timely climate information, and the continuous training of supply chain personnel. These strategies are vital to supporting regional food security under climate-related stressors. Comprehensive analyses of climate change impacts on food systems often involve investigating multiple facets, including agricultural productivity, distribution reliability, and consumer access. Moreover, different food products demonstrate varying sensitivities to climatic stressors, necessitating nuanced understanding and tailored mitigation strategies (Wiebe et al., 2019).

Weather variability, manifesting through altered precipitation patterns, increased frequency of droughts and floods, and intensified extreme events, has both direct and indirect implications for food production and logistics. Recognizing this, scholars have called for the integration of environmental and climatic considerations into the structural design of resilient food supply chains (Yuan et al., 2024). Enhancing responsiveness, boosting robustness, and embedding flexibility into system design are viewed as key levers for improving performance and ensuring long-term sustainability. Developing a comprehensive resilience framework anchored by these indicators can significantly aid supply chain managers in anticipating, monitoring, and mitigating the effects of climate induced volatility. In general, seasonal, perishable, and time-sensitive goods constitute the core raw materials of the food supply chain industry. Ensuring the timely provision and distribution of these products requires efficient coordination with farmers, processing facilities, and suppliers within specific and typically short time windows. The inherent vulnerability of agricultural, livestock, and dairy products, commonly regarded as staple commodities presents one of the foremost operational challenges within food supply chains. Climate change further compounds this challenge by threatening the stability and security of recipient centers and end consumers. In response, targeted adaptation strategies are essential to strengthen the resilience of such systems. Observed climate trends have indicated consistent shifts in average temperatures and precipitation patterns, confirming the evolving nature of climatic stressors (Godde et al., 2021; Hahn et al., 2009). In the seafood sector, climate induced vulnerabilities are expected to introduce new chemical and biological risks. These include elevated levels of toxic metals, residues of organic chemicals, algal toxins, and the proliferation of marine and human pathogens. Importantly, different seafood categories exhibit varying sensitivities to climate stressors, necessitating product specific adaptation strategies. The safety of public food supplies especially seafood is likely to face growing scrutiny as consumer trust becomes increasingly contingent upon robust quality assurance mechanisms in a warming climate (Marques et al., 2010). Climate change also imposes significant operational challenges on logistics infrastructure. Extreme weather events can damage storage facilities, disrupt production and distribution activities, and degrade transportation infrastructure. These disruptions can delay delivery schedules, reduce system reliability, and increase operational costs through the need for infrastructure repairs, route modifications, or emergency interventions. Moreover, weather-induced disruptions often trigger unpredictable shifts in inventory levels, resulting in either shortages or surpluses across various points in the supply chain. Extreme weather conditions can stress transportation infrastructure and global supply chains, leading to production interruptions and increased prices (Cevik & Gwon, 2024). Despite a growing body of research highlighting the intersection of climate change and supply chain management, the integration of resilience and adaptability into food supply chain optimization models remains limited. While conceptual frameworks and empirical assessments have begun to explore vulnerability and adaptation pathways (Vermeulen et al., 2012; Wheeler & Von Braun, 2013), few studies have operationalized these considerations through rigorous mathematical modeling or integrated them into real-time decision support tools. This gap presents a critical opportunity to advance the field through robust, climate-aware supply chain optimization frameworks.

A growing body of literature has documented the direct and indirect impacts of climate change on agricultural production systems, highlighting reductions in crop yields, quality degradation, and disruptions to logistical operations. These disruptions propagate across the entire food supply chain, affecting transportation, processing, and retail functions. While the broader implications of climate change for food security and supply chain functionality are increasingly acknowledged, many existing supply chain models do not adequately account for the uncertain and dynamic nature of climate risks. To address this gap, vulnerability assessment frameworks have been developed to evaluate the exposure, sensitivity, and adaptive capacity of supply chain systems (Adger, 2006; Nelson et al., 2009). These frameworks often utilize climate vulnerability indices, quantitative constructs that integrate climatic, socioeconomic, and infrastructural variables, to assess the degree of risk within specific regions or systems. Despite their analytical potential, the integration of such indices into operational optimization models remains limited. Most existing applications rely on qualitative assessments or scenario-based planning rather than embedding these indices directly into mathematical formulations. Consequently, the advancement of proactive, data-informed analytical frameworks for mitigating climate-related risks within supply chain systems remains in its nascent stages.

2.2 Optimization models in food supply chains

Mathematical optimization techniques such as linear programming, mixed-integer programming, and stochastic programming have long been employed to enhance the efficiency of food supply chains (Ahumada & Villalobos, 2009; You et al., 2012). These models commonly aim to minimize costs, optimize resource utilization, or maximize profits while satisfying a variety of logistical and operational constraints. However, relatively few optimization models explicitly incorporate climate-related disruptions or systematically integrate vulnerability indicators into their formulations (Rajeev et al., 2017). Recent research emphasizes the importance of resilience-oriented strategies in mitigating the effects of climate variability on supply chains. These strategies include flexible sourcing arrangements, decentralized storage systems, and adaptive transportation networks designed to withstand unexpected disruptions. Concurrently, green logistics approaches such as optimizing transport modes, minimizing fuel consumption, and redesigning supply routes have shown promise in enhancing environmental performance while reducing greenhouse gas emissions (Sarkis, 2012; Sbihi & Eglese, 2010). Nonetheless, comprehensive optimization models that jointly address economic efficiency, environmental sustainability, and climate resilience remain relatively underdeveloped. Although advances have been made in both climate science and supply chain optimization, further research is needed to integrate these dimensions into decision-making frameworks. Few studies have systematically embedded climate vulnerability metrics into quantitative optimization frameworks tailored to food supply chains. This limitation hampers the operationalization of resilience strategies and restricts their applicability in real-world planning contexts. This study seeks to address this shortfall by proposing an innovative mathematical model that directly incorporates climate vulnerability indices into supply chain planning. In doing so, it contributes to bridging the gap between theoretical constructs and practical applications, offering a robust decision support tool to enhance the adaptability, flexibility, and sustainability of food supply chains under increasing climatic uncertainty.

3 Methodology

3.1 Model overview

This section presents the methodological framework employed to formulate and solve the proposed optimization model for climate-resilient food supply chain management. The approach integrates climate vulnerability indices (CVI) within a multi-objective mixed-integer linear programming (MILP) model. The aim is to enhance supply chain adaptability, operational efficiency, and sustainability in the face of climate-related uncertainties. This study develops a multi-objective optimization model designed to capture the interdependencies among economic, environmental, and social dimensions of a food supply chain while embedding climate vulnerability considerations directly into its structure. The model is constructed as a MILP formulation that supports strategic and tactical decision-making across a network comprising production, processing, distribution, and retail nodes affected by climate variability. The supply chain network is characterized by multiple echelons including production and supply centers, processing facilities, distribution hubs, and retail outlets. Decision variables oversee the flow of goods, facility siting, transportation modes, under uncertainty. The proposed model simultaneously optimizes three key objectives, reflecting the economic, environmental, and social dimensions of sustainable supply chain design. Economically, it aims to minimize total operational costs, including expenses related to production and processing stages, transportation, and facility establishment. From an environmental perspective, the model seeks to reduce carbon emissions associated with production, processing, and transportation activities. It explicitly accounts for climate-induced disruptions, which may lead to rerouting or inefficient resource utilization, thereby increasing emissions. On the social front, the model promotes employment across supply chain facilities by recognizing that regions with higher climate vulnerability (as measured by the Climate Vulnerability Indices) often require additional labor to manage disruptions and sustain service levels. This added workforce demand reflects the human effort necessary for adaptation in more vulnerable areas. At the same time, the model balances the social benefits of job creation against the associated economic and environmental trade-offs, enabling decision-makers to identify employment strategies that enhance resilience without undermining overall supply chain efficiency. Through balancing these objectives, the model enables decision makers to identify trade-offs among cost efficiency, environmental impact, and social benefits. It also serves as a decision support tool to strengthen supply chain resilience in climate vulnerable regions.

3.2 Climate vulnerability indices

Climate Vulnerability Indices (CVI) are integrated into the model as key parameters influencing supply chain performance under climate uncertainty. These indices represent aggregated exposure to climatic disruptions, accounting for risks such as extreme weather frequency, infrastructure sensitivity, and the adaptive capacity of supply chain components. By embedding CVI into the optimization framework, the model reflects how varying levels of climate-related stress influence operational parameters such as production output, transportation reliability, and inventory stability. Higher CVI values indicate increased exposure to climate-related disruptions, resulting in greater delays, reduced productivity, and elevated logistical and operational costs. These impacts are systematically reflected in the model's constraints and objective functions to evaluate their influence on cost, carbon emissions, and employment outcomes. Performance metrics are assessed across different levels of climate vulnerability, allowing for a detailed analysis of trade-offs and adaptation strategies under a range of climate impact conditions.

3.3 Mathematical formulation

The proposed model is formulated as a multi-objective Mixed-Integer Linear Program (MILP) to optimize supply chain operations under climate-related uncertainty. The network consists of suppliers, processing facilities, distribution zones, and retail centers, considered across multiple time periods. The formulation includes a structured set of indices and variables representing supply chain entities (e.g., suppliers, processing centers, distribution hubs, and retail locations) across multiple time periods and climate scenarios. It incorporates key parameters such as production and transportation costs, carbon emission rates, employment coefficients, facility capacities, retail demands, and climate disruption intensities derived from Climate Vulnerability Indices (CVI). The decision variables capture the product flows between network nodes, binary activation of facilities, and corresponding employment levels required under each scenario and planning period. To construct a realistic and tractable optimization model, several assumptions were adopted regarding network structure, climate vulnerability, and operational dynamics. The supply chain network is structured across four echelons, suppliers, processing centers, distribution centers, and retail outlets, connected through deterministic transport links. The average distances between these nodes are assumed to fall within practical, regionally plausible ranges: 100-150km from suppliers to processing centers, 50-80km from processing to distribution centers, and 20-60km from distribution to retail locations. These distance assumptions inform both transportation costs and associated carbon emissions. CVI values are introduced as a scalar representation of climate risk, ranging from 0.1 to 1 under normal or favorable weather conditions, with 1 denoting moderate vulnerability. CVI values above 1 up to 2 represent increasingly severe weather conditions, affecting transportation delays, facility availability, and cost escalations. The model is developed based on the assumption of fixed facility locations and centralized decision-making, utilizing estimated operational parameters such as demand levels, emission coefficients, and cost structures. It further relies on simplified relationships between climate vulnerability and operational outcomes, enabling manageable analysis and facilitating meaningful optimization insights. Compared to conventional supply chain models that primarily focus on economic performance or rely on deterministic assumptions, this formulation adopts a more holistic perspective by incorporating environmental and social dimensions through the integration of climate vulnerability indices. While the model provides a comprehensive framework, it does not currently capture more complex system behaviors, such as dynamically shifting weather conditions, adaptive decision-making processes, or real-time operational responses. These features suggest avenues for future research to enhance the realism and practical relevance of climate-resilient supply chain strategies.

The three sustainability-oriented objectives introduced earlier are optimized using the ε-constraint method, allowing for a structured exploration of trade-offs. In this study, the ε-constraint method was selected to address the multi-objective nature of the proposed supply chain optimization model, which seeks to minimize operational cost while considering carbon emissions and employment generation. The method is particularly effective for problems involving discrete decision variables, as it maintains computational tractability within a mixed-integer linear programming (MILP) framework. Compared to alternative methods like goal programming, which may depend heavily on subjective weightings and can lead to non-Pareto solutions, the ε-constraint approach systematically explores the trade-offs between objectives by optimizing one while bounding the others. This allows for a clearer understanding of the interdependencies among economic, environmental, and social outcomes. Additionally, the ε-constraint method is compatible with widely used solvers such as CPLEX and enables the generation of a set of efficient solutions, which is beneficial for conducting sensitivity analysis and scenario comparison. Its structured formulation and ability to generate diverse solution sets make it a suitable and practical choice for the proposed model (Mavrotas, 2009). The model incorporates core constraints that ensure the feasibility and realism of the supply chain configuration. These include demand fulfillment constraints to guarantee that customer requirements are met at retail centers, capacity limitations at supplier, processing, and distribution facilities to reflect operational boundaries, and flow balance equations to maintain the continuity of product movement across network stages. Additionally, the model includes climate-adjusted constraints that dynamically modify transportation reliability and production efficiency in response to varying Climate Vulnerability Indices (CVI) levels, thereby capturing the disruptive effects of weather uncertainty on supply chain operations.

3.4 Model development, solution approach and sensitivity analysis

The proposed MILP model is developed and implemented in the General Algebraic Modeling System (GAMS), with solution procedures carried out using the CPLEX solver, which efficiently handles large-scale linear and integer programming problems. To address the model's multi-objective nature, the ε-constraint method is employed to optimize one primary objective while systematically constraining the others, allowing the generation of a Pareto-optimal front that reflects trade-offs among economic, environmental, and social goals. A scenario-based framework is incorporated to capture varying degrees of climate impact across the supply chain, using the Climate Vulnerability Indices (CVI) as a key parameter that influences transportation reliability and operational performance. The model's input values, including demand profiles, capacity limits, and cost structures, are based on a combination of literature insights and representative assumptions consistent with supply chain planning practices. Particular emphasis is placed on the role of CVI in shaping the operational landscape under different weather severity conditions.

Model development is guided by aligning the model structure and outputs with reference scenarios found in the literature to ensure logical consistency. Sensitivity analysis is subsequently applied to assess the influence of critical parameters, particularly Climate Vulnerability Indices values on total cost, carbon emissions, and employment levels. This process helps assess the model's responsiveness and supports iterative refinement by testing how shifts in parameter values affect overall performance. The results are interpreted with respect to baseline scenarios, enhancing both the robustness and practical relevance of the proposed framework. Key inputs, including CVI scores and operational costs, are systematically varied to observe their effect on the optimal configuration and behavior of the supply chain. This integrated methodological framework enables a comprehensive evaluation of climate-resilient strategies for optimizing food supply chains in the face of increasing environmental uncertainties. The parameters are approximated based on insights from related studies in food supply chain management, environmental logistics, and labor economics. This allows for a reasonable and illustrative exploration of system dynamics. Sensitivity analysis also serves to validate model performance and explore how climate vulnerability shapes trade-offs among economic, environmental, and social objectives. The overall structure of the supply chain network, comprising suppliers, processing centers, distribution hubs, and retail outlets, is illustrated in Figure 1.

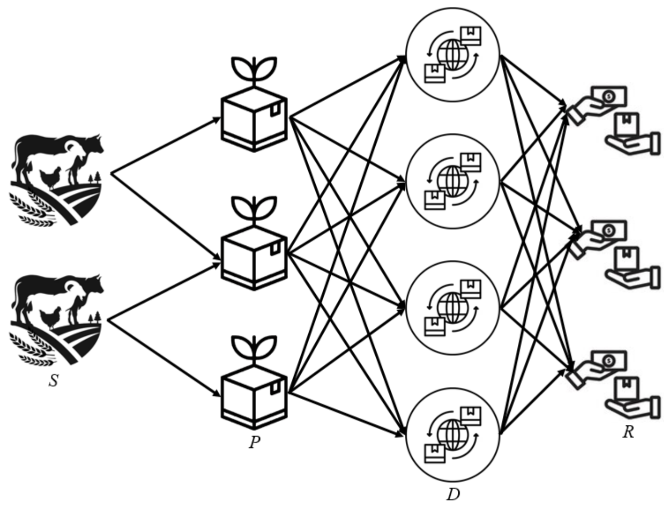

Figure 1: The supply chain network

To facilitate understanding of the mathematical formulation, the model's core structural and operational elements are first introduced. These include the sets used to define the supply chain structure, the parameters that represent key operational, environmental, and social (employment-related) factors, and the decision variables that drive the model's optimization logic. A summary of these components is provided in Table 1, supporting the structure and interpretation of the formulation presented in the following section.

Table 1: Summary of sets, parameters, and variables

Symbol	Description
Sets	
S	Suppliers (production centers) in the supply chain network.
P	Process centers where raw food products are converted into finished goods.
D	Distribution centers that act as intermediary transfer hubs.
R	Retail centers where food products reach end consumers.
K	Climate scenarios representing varying levels of weather.
T	Time periods defining the planning horizon.
Parameters	
d_{ij}	Parameters denoting the distances (km) between respective supply chain nodes *i* and *j* where $\forall(i,j) \in \{(s,p),(p,d),(d,r)\}$.
cv_{ij}^{kt}	Climate vulnerability indices representing the severity of climate risk along the transportation route (*i,j*), aggregated for each scenario *k* and time period *t*.
ce_{ij}^{kt}	Carbon emission coefficients for food transport along route (*i,j*) under scenario *k* and time period *t*.
em_i^{kt}	Employment impact factors at supply chain facility *i* where $\forall i \in \{s,p,d,r\}$ under scenario *k* and time *t*.
$prob_k$	Probability of occurrence for climate scenario *k*.
$prod_{cap_{st}}$	Production capacity of supplier *s* during time *t*.
$proc_{cap_{pt}}$	Processing capacity of processing center *p* during time *t*.
$dist_{cap_{dt}}$	Distribution capacity of distribution center *d* during time *t*.
$demand_r^{kt}$	Demand at retail center *r* under scenario *k* and time *t*.
System Variables	
x_{ij}^{kt}	Decision Variables representing the number of food units transported within supply chain nodes under scenario *k* at time *t*, where $\forall(i,j) \in \{(s,p),(p,d),(d,r)\}$.
y_i^{kt}	Binary Variables, indicating whether facility *i* ($\forall i \in \{s,p,d,r\}$) is active (1) or inactive (0) under scenario *k* and time period *t*.
y_{ij}^{kt}	Binary Variables indicating whether the transportation route between nodes *i* and *j* is active (1) or inactive (0) under scenario *k* and time *t*, where $\forall(i,j) \in \{(s,p),(p,d),(d,r)\}$.

As described earlier, the proposed model aims to optimize three key objectives: minimizing total operational cost, minimizing carbon emissions, and maximizing employment under climate uncertainty. These objective functions are summarized in Equations (1) to (3), and the associated constraints are presented in Equations (4) to (12) as follows.

$$\begin{aligned} min.: Z_1 = & \sum_{s\in S}\sum_{p\in P}\sum_{k\in K}\sum_{t\in T}(x_{sp}^{kt} \times d_{sp} \times cv_{sp}^{kt} \times prob_k \times t) \\ & + \sum_{p\in P}\sum_{d\in D}\sum_{k\in K}\sum_{t\in T}(x_{pd}^{kt} \times d_{pd} \times cv_{pd}^{kt} \times prob_k \times t) \\ & + \sum_{d\in D}\sum_{r\in R}\sum_{k\in K}\sum_{t\in T}(x_{dr}^{kt} \times d_{dr} \times cv_{dr}^{kt} \times prob_k \times t) \\ & + \sum_{s\in S}\sum_{k\in K}\sum_{t\in T}(y_{s}^{kt} \times cv_{s}^{kt} \times prob_k) + \sum_{p\in P}\sum_{k\in K}\sum_{t\in T}(y_{p}^{kt} \times cv_{p}^{kt} \times prob_k) \\ & + \sum_{d\in D}\sum_{k\in K}\sum_{t\in T}(y_{d}^{kt} \times cv_{d}^{kt} \times prob_k) \end{aligned} \tag{1}$$

$$\begin{aligned} min.: Z_2 = & \sum_{s\in S}\sum_{p\in P}\sum_{k\in K}\sum_{t\in T}(x_{sp}^{kt} \times ce_{sp}^{kt} \times d_{sp} \times cv_{sp}^{kt} \times prob_k \times t) \\ & + \sum_{p\in P}\sum_{d\in D}\sum_{k\in K}\sum_{t\in T}(x_{pd}^{kt} \times ce_{pd}^{kt} \times d_{pd} \times cv_{pd}^{kt} \times prob_k \times t) \\ & + \sum_{d\in D}\sum_{r\in R}\sum_{k\in K}\sum_{t\in T}(x_{dr}^{kt} \times ce_{dr}^{kt} \times d_{dr} \times cv_{dr}^{kt} \times prob_k \times t) + \sum_{s\in S}\sum_{p\in P}\sum_{k\in K}\sum_{t\in T}(y_{sp}^{kt} \times ce_{sp}^{kt} \\ & \times cv_{sp}^{kt} \times prob_k) \\ & + \sum_{p\in P}\sum_{d\in D}\sum_{k\in K}\sum_{t\in T}(y_{pd}^{kt} \times ce_{pd}^{kt} \times cv_{pd}^{kt} \times prob_k) \\ & + \sum_{d\in D}\sum_{r\in R}\sum_{k\in K}\sum_{t\in T}(y_{dr}^{kt} \times ce_{dr}^{kt} \times cv_{dr}^{kt} \times prob_k) \end{aligned} \tag{2}$$

$$\begin{aligned} max.: Z_3 = & \sum_{s\in S}\sum_{k\in K}\sum_{t\in T}(y_{s}^{kt} \times em_{s}^{kt} \times cv_{s}^{kt} \times prob_k) \\ & + \sum_{p\in P}\sum_{k\in K}\sum_{t\in T}(y_{p}^{kt} \times em_{p}^{kt} \times cv_{p}^{kt} \times prob_k) + \sum_{d\in D}\sum_{k\in K}\sum_{t\in T}(y_{d}^{kt} \times em_{d}^{kt} \times cv_{d}^{kt} \times prob_k) \\ & + \sum_{r\in R}\sum_{k\in K}\sum_{t\in T}(y_{r}^{kt} \times em_{r}^{kt} \times cv_{r}^{kt} \times prob_k) \end{aligned} \tag{3}$$

***S.t.*:**

$$\sum_{p\in P} x_{sp}^{kt} \le prod_{cap_{st}} \ \forall s \in S, \forall k \in K, \forall t \in T \tag{4}$$

$$\sum_{d\in D} x_{pd}^{kt} \le proc_{cap_{pt}} \ \forall p \in P, \forall k \in K, \forall t \in T \tag{5}$$

$$\sum_{r\in R} x_{dr}^{kt} \le dist_{cap_{dt}} \ \forall d \in D, \forall k \in K, \forall t \in T \tag{6}$$

$$\sum_{d\in D} x_{dr}^{kt} \ge demand_{r}^{kt} \ \forall r \in R, \forall k \in K, \forall t \in T \tag{7}$$

$$\sum_{s\in S} x_{sp}^{kt} \geq \sum_{d\in D} x_{pd}^{kt} \ \forall p \in P, \forall k \in K, \forall t \in T(8) \tag{8}$$

$$\sum_{p\in P} x_{pd}^{kt} \geq \sum_{r\in R} x_{dr}^{kt} \ \forall d \in D, \forall k \in K, \forall t \in T \tag{9}$$

$$\sum_{p\in P} x_{sp}^{kt} \leq y_s^{kt} \times prod_{cap_{st}} \forall s \in S, \forall k \in K, \forall t \in T \tag{10}$$

$$\sum_{d\in D} x_{pd}^{kt} \leq y_p^{kt} \times proc_{cap_{pt}} \ \forall p \in P, \forall k \in K, \forall t \in T \tag{11}$$

$$\sum_{r\in R} x_{dr}^{kt} \leq y_d^{kt} \times dist_{cap_{dt}} \ \forall d \in D, \forall k \in K, \forall t \in T \tag{12}$$

The application of the ε-constraint method enables the exploration of trade-offs by iteratively adjusting bounds on secondary objectives. Through this structured approach, a spectrum of non-dominated solutions can be identified, offering decision-makers greater clarity on the implications of emphasizing one sustainability dimension over others within the supply chain context. By systematically varying the constraint levels applied to the secondary objectives, the model produces a diverse set of optimal solutions that reflect different combinations of economic, environmental, and social outcomes. This process supports a more informed and balanced decision-making framework, allowing the selection of solutions aligned with strategic priorities under climate uncertainty, and reinforcing the model's capacity to capture sustainability-oriented trade-offs in a rigorous and operationally relevant manner. Using the ε-constraint method, the problem is reformulated by retaining Z_1 as the primary objective and introducing the following constraints.

$$Z_2 \leq \varepsilon_2 \tag{13}$$
$$Z_3 \geq \varepsilon_3 \tag{14}$$

Also, the domains of the decision variables are defined as follows, ensuring clarity in their roles within the optimization model:

$$x_{ij}^{kt} \geq 0 \ \forall (i,j) \in \{(s,p),(p,d),(d,r)\}, \forall k \in K, \forall t \in T \tag{15}$$
$$y_i^{kt} \in \{0,1\} \ \forall i \in \{s,p,d,r\}, \forall k \in K, \forall t \in T \tag{16}$$
$$y_{ij}^{kt} \in \{0,1\} \ \forall (i,j) \in \{(s,p),(p,d),(d,r)\}, \forall k \in K, \forall t \in T \tag{17}$$

Equations 1, 2, and 3 collectively define the model's multi-objective framework. Equation 1 seeks to minimize total operational costs across the supply chain network, factoring in transportation and facility-related expenses under various climate scenarios. Equation 2 focuses on minimizing carbon emissions associated with product flows, incorporating scenario-dependent emission coefficients to reflect environmental impact. Meanwhile, Equation 3 aims to maximize employment opportunities across supply chain facilities, supporting the model's social sustainability dimension by encouraging employment generation across the supply chain facilities. Constraint 4 ensures that the total quantity of goods transferred from supplier s to all processing centers p, under climate scenario k and time period t, does not exceed the available production capacity of supplier s in that time period. It enforces feasibility in supply by aligning outbound flows with the supplier's production limitations, thereby maintaining realistic operational bounds in the model. Constraint 5 ensures that the total amount of products sent from processing center p to all downstream distribution centers d in scenario k and time period t does not exceed the processing capacity of that center at that time. The purpose is to enforce capacity limits of processing facilities so they do not handle more than their maximum operational capability during any time period. Constraint 6 ensures that the total quantity of products distributed from distribution center d to all retail centers r, in scenario k and time frame t, does not exceed the capacity of that distribution center at that time. Constraint 7 illustrates that the total amount of products delivered to retail center r from all distribution centers d, in scenario k and time period t, meets the retail center's demand for that period. The purpose of this constraint is to guarantee customer satisfaction and ensure service level by fulfilling the required demand at each retail location under all climate scenarios and time periods. Constraints 8 and 9 ensure that the total inflow of products from all suppliers s to every processing center p in scenario k and time period t is at least equal to the total outflow from processing center to all distribution centers d, and the total inflow to each distribution center d from all processing centers p, is at least equal to the total outflow from distribution center to all retail centers r. Constraints 10, 11, and 12, link facility activation decisions (binary variables y) with their respective capacity limits. They ensure that no product flow can occur through a facility unless it is activated, and when activated, the flow cannot exceed the facility's capacity. These constraints impose logical consistency, operational realism, and capacity compliance within the supply chain network under each scenario k and time period t.

4 Results and discussion

The proposed multi-objective optimization model was applied to a multi-tier food supply chain network comprising production, processing, distribution, and retail centers over several planning periods. Climate vulnerability indices, reflecting transportation disruption risks across the supply chain route, were embedded into model parameters to influence production capacity, transportation reliability, and overall operational viability. Using the ε-constraint method, the model was solved with cost minimization as the primary objective, while carbon emissions and employment levels were constrained within acceptable thresholds. The optimization results revealed notable structural reconfigurations of the supply chain in response to varying levels of climate vulnerability. Facilities situated along routes with high CVI values exhibited reduced utilization or were excluded from the optimal configuration. In contrast, supply chain segments with lower vulnerability were favored for production and distribution operations, reflecting an adaptive strategy to maintain continuity in the face of disruption risks. The model effectively minimized total operational costs within the limits imposed by environmental and social constraints. Compared to a baseline model that did not incorporate climate considerations, the climate-informed model exhibited a marginal increase in total costs. This increase is attributed to the inclusion of redundancy, alternative routing, and reliance on more resilient (but sometimes higher cost) transportation links. These results underscore the inherent trade-off between cost efficiency and operational resilience. Moreover, carbon emissions were significantly influenced by rerouting strategies, as longer but more stable transportation paths were sometimes preferred. Employment levels also responded dynamically to changing CVI conditions;

under higher climate stress, certain supply chain functions required greater labor input, balancing operational continuity with regional employment opportunities.

These findings highlight the importance of integrating climate risk into operational planning. The model provides supply chain managers with a practical tool to balance competing sustainability objectives while enhancing adaptability under uncertain climatic conditions. Across all climate scenarios, carbon emissions remained within the predefined threshold, affirming the model's effectiveness in maintaining environmental performance under varying risk conditions. The optimization consistently favored shorter, more reliable transportation routes and prioritized energy-efficient processing centers. Regions with lower average climate vulnerability demonstrated reduced emissions due to fewer delays, minimized spoilage, and more stable logistics operations. On average, emissions were notably reduced compared to the baseline configuration that excluded climate considerations, highlighting the value of climate-responsive routing and facility selection in lowering the supply chain's environmental footprint. Employment levels across all scenarios surpassed the minimum threshold established within the model's constraints. Notably, the model strategically activated a broader set of facilities particularly in medium risk regions to maintain operational efficiency while promoting job creation. This distributed activation pattern enhanced geographical employment diversity, contributing to regional resilience and aligning with social sustainability goals. By balancing labor allocation with efficiency and risk exposure, the model supports community-based adaptation strategies that mitigate localized vulnerabilities and strengthen socio-economic resilience in vulnerable areas. Scenario analysis was performed by systematically varying CVI levels to examine the model's responsiveness to changes in climate risk. Results revealed a non-linear increase in operational costs as CVI values rose, driven by the need for adaptive strategies such as redundancy and rerouting. Carbon emissions exhibited an initial spike under moderate climate stress primarily due to the use of longer but more stable transport routes but subsequently stabilized as the network adjusted. Employment levels remained relatively stable across scenarios due to the proactive activation of facilities in less vulnerable regions, demonstrating the model's built-in social robustness. These trends underscore the necessity of dynamic supply chain design and forward looking planning under climate uncertainty. Through integrating CVI into the decision-making process, the model effectively balances economic, environmental, and social objectives. The results confirm that enhancing climate resilience does not inherently compromise performance; rather, it requires informed trade-offs and flexible resource allocation strategies that optimize across multiple dimensions.

4.1 Model implementation and baseline scenario

The climate vulnerability indices, serving as a representation for the severity of weather-related disruptions in the model, directly influences supply chain operating costs. Defined for each planning scenario, the Climate Vulnerability Indices (CVI) captures the compounded effects of climate-induced transportation and infrastructure challenges across the network. Higher CVI values are associated with increased operational difficulties, such as transportation delays, rerouting needs, reduced facility efficiency, and occasional closures. As the CVI increases, the total operational cost calculated by the primary objective function rises accordingly. This cost escalation is primarily driven by climate-related inefficiencies and disruptions, which demand more resilient (and often costlier) logistical arrangements. In high vulnerability scenarios, the growth in operational cost becomes more pronounced, reflecting the compounding effects of environmental stressors. Conversely, in low vulnerability scenarios, the network operates more efficiently, and total costs decrease due to smoother logistics and higher supply chain stability.

These trends are visualized in Figure 2, which illustrates the relationship between CVI values and the corresponding total operational cost. The figure highlights a clear upward trajectory, demonstrating how increased climate stress leads to higher expenditures in the food supply chain. Notably, the cost rises from approximately 71,000 at CVI ≈ 0.2 to over 640,000 at CVI ≈ 1.9, indicating a nearly ninefold increase across the evaluated scenarios. A relatively non-linear escalation trend is observed between CVI values of 0.9 and 1.3, where the slope steepens, suggesting potential threshold effects that intensify the system's vulnerability. This pattern reflects how rising CVI levels lead to greater disruptions, logistical rerouting, or penalty costs within the system. The figure underscores the sensitivity of the cost objective function to climate risk variations and reinforces the importance of adaptive planning. Proactively managing supply chains in anticipation of adverse weather conditions can significantly mitigate financial impacts and support sustainable operational performance.

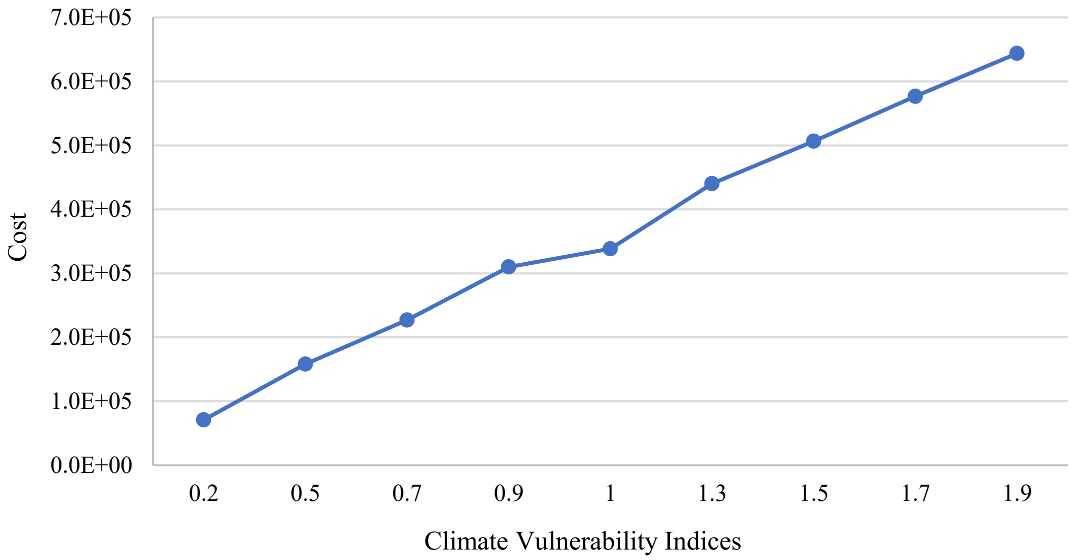

Figure 2: Sensitivity analysis of climate vulnerability impacts on total cost

Figure 3 illustrates the impact of varying demand levels at retail centers on total supply chain costs under normal weather conditions. As demand increases from 1,296 units to 3,888 units, the total cost rises steadily from approximately 158,000 to over 475,000, revealing a strong positive correlation. This increase reflects the compounded operational requirements such as expanded production, processing, and transportation that accompany larger volumes of food distribution. The trend suggests a near-linear or slightly exponential growth in cost, indicating that the supply chain scales predictably in the absence of climate disruptions. As demand intensifies, additional supply chain facilities may need to be activated or expanded, contributing to higher operating expenditures. This sensitivity analysis underscores the cost implications of demand fluctuations and supports proactive infrastructure and resource planning to accommodate future growth.

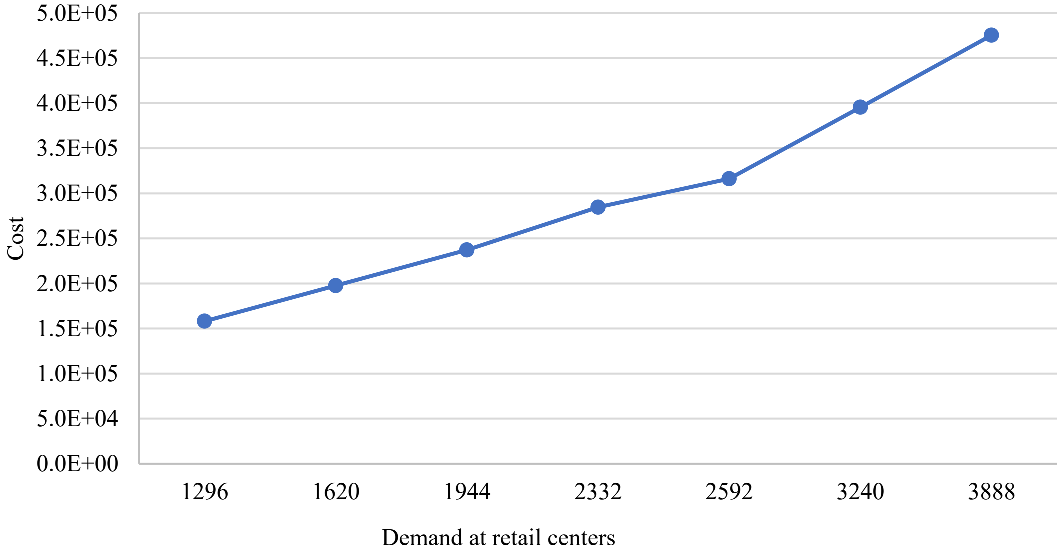

Figure 3: Cost vs. demand at retail centers under normal weather conditions

The below chart (Figure 4) demonstrates as the percentage of demand at receiving centers increases, the cost function increases in the production-to-processing, processing-to-distribution, and distribution-to-receiving paths, respectively. The production to processing stage bears the heaviest cost increase, likely due to fixed capacities being stretched or the need for expedited or additional procurement. Distribution to retail observes the smallest increase, possibly indicating higher existing flexibility or less sensitivity to demand surges. A 100% increase in demand at different stages of the chain has resulted in an approximately twofold increase in costs. This trend is maintained with a 200 to 300% increase in demand at receiving centers. Moreover, at lower demand levels, supply chain performance effectively leads to cost reduction. As demand rises, the corresponding cost values exhibit a steeper upward trend, reflecting the additional resource requirements, expanded capacity needs, and heightened transportation efforts necessary to meet increased demand.

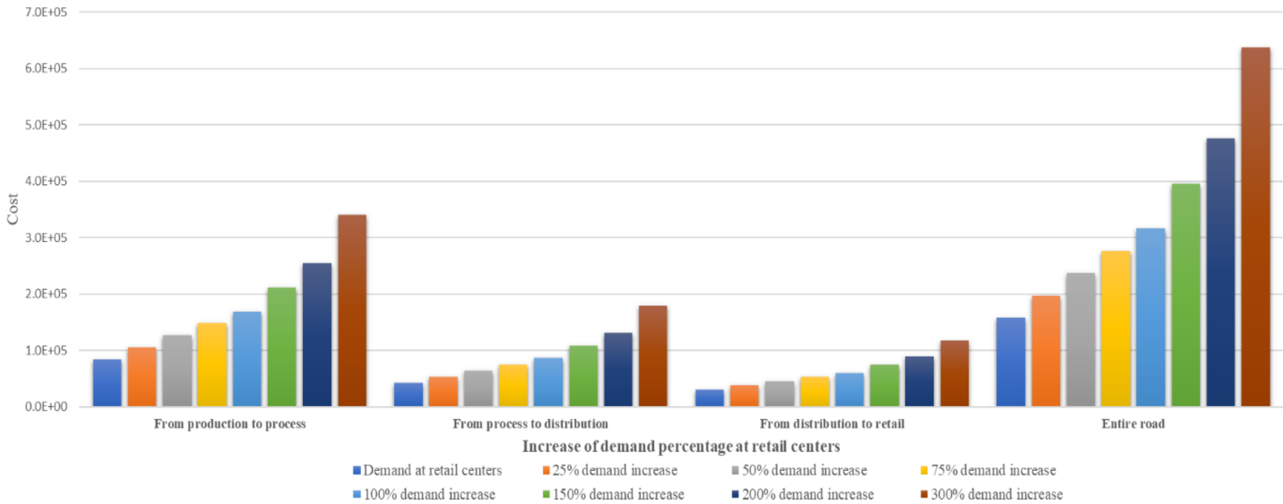

Figure 4: Cost vs. increase of demand percentage within retail centers under normal weather conditions

Figures 5 and 6 present the sensitivity analysis of the objective function based on the total demand at the receiving centers and the impact of the percentage increase in demand on the optimized total cost of the supply chain under severe weather conditions. They show a significant escalation in total operational costs as retail demand increases.

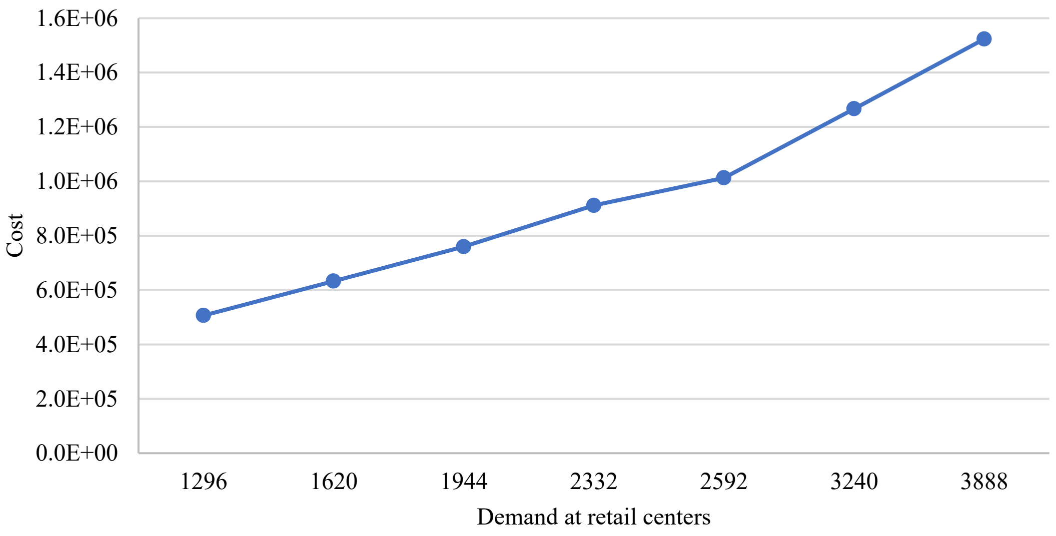

Figure 5: Cost vs. demand at retail centers under severe weather conditions

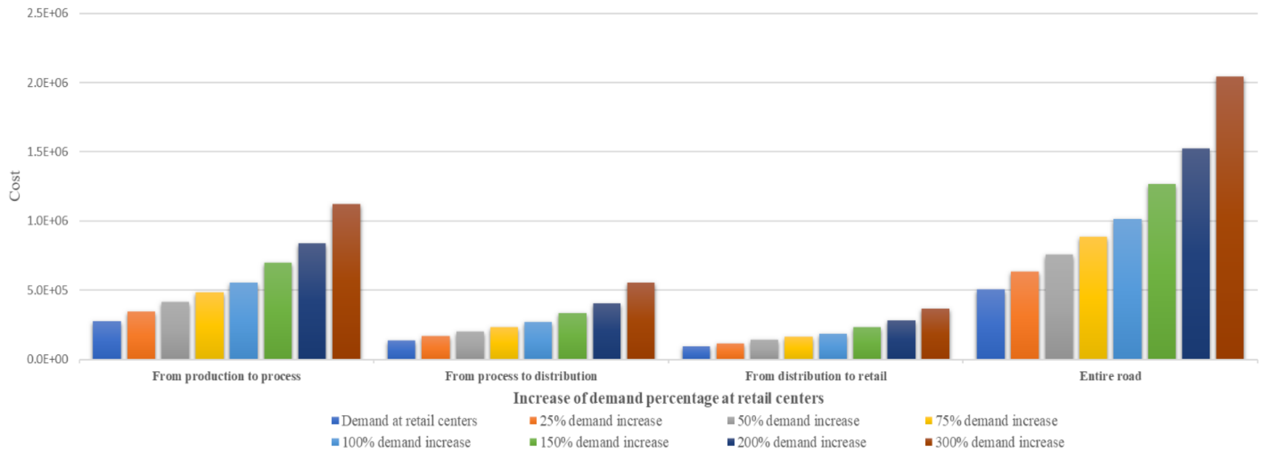

Figure 6: Cost vs. increase of demand percentage within retail centers under severe weather conditions

As shown in Figure 5, when demand rises from 1,296 to 3,888 units, the corresponding cost surges from approximately 506,000 to over 1.5 million, a slightly more than threefold increase compared to the cost levels observed under normal weather conditions. This sharp escalation highlights the amplified operational burden imposed by severe climate stressors, where disruptions and penalties associated with environmental instability significantly raise costs. Figure 6 further reinforces this trend by illustrating the cost trajectory relative to the percentage increase in demand, revealing a highly sensitive and nonlinear cost response. Collectively, these results emphasize the critical importance of climate-adaptive planning and resource allocation, especially when managing supply chains exposed to uncertain and worsening climate scenarios. The analysis underscores the need to strengthen infrastructure and contingency measures to ensure continuity and sustainability under rising demand and environmental risk.

Figure 7 presents the variation in total operational cost across different transportation time periods under normal weather conditions. As the duration of transport increases, the total cost of the supply chain rises approximately steadily. This trend highlights the influence of time-sensitive logistics, where extended travel durations contribute to additional operational burdens, including higher energy use, longer vehicle deployment, and scheduling complexities. A sharper increase in cost is observed beyond the five-hour threshold, suggesting that certain temporal limits may introduce additional constraints or inefficiencies that elevate expenses. Figure 8 depicts how transportation time periods affect operational cost under severe weather conditions. Similar to the normal scenario, costs increase with longer transport durations; however, the rise is more pronounced in this case. The graph reflects how adverse climatic events can exacerbate logistical challenges, such as route disruptions, delays, or reduced vehicle availability. As with Figure 7, the cost escalation becomes more significant beyond the five-hour mark, indicating the compounding effect of time in environments exposed to higher climate risk.

This analysis emphasizes the importance of incorporating time-period variability into the supply chain optimization model. Incorporating this temporal dimension provides strategic flexibility, allowing decision-makers to adapt operations in response to shifting climate conditions, evolving demand at retail centers, and capacity constraints. Such time-sensitive planning enhances the supply chain's responsiveness and overall resilience in the face of increasing environmental disruptions.

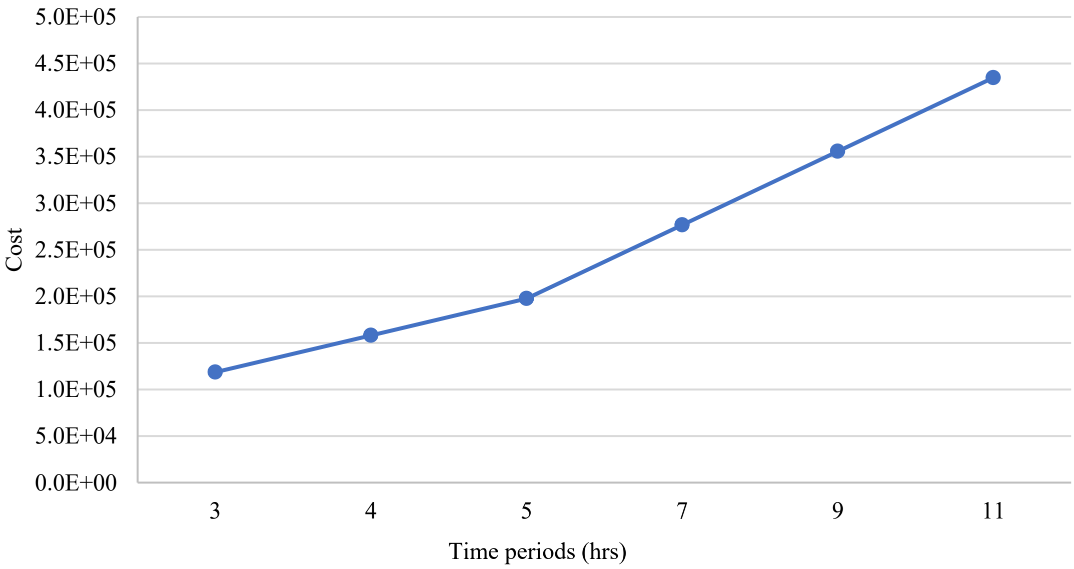

Figure 7: Cost vs. time periods under normal weather conditions

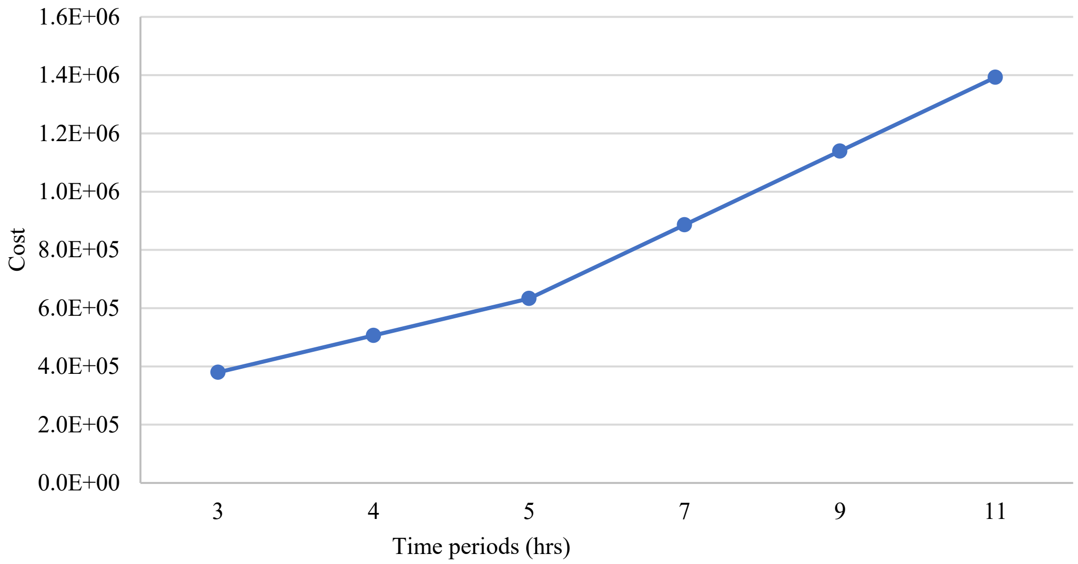

Figure 8: Cost vs. time periods under severe weather conditions

Time flexibility in the model allows for reactive adjustments to be made based on the actual conditions of each time period. For example, if demand exceeds forecasts in one period, the model can compensate by increasing production and transportation in subsequent periods. This feature allows the model to manage operating and transportation costs more evenly, predictably, and better over time.

Figure 9 indicates the sensitivity analysis of climate vulnerability impacts on total carbon emissions (Z_2). The results clearly indicate a linear and positive relationship between climate vulnerability indices and carbon emissions. As the climate vulnerability indices increases from 0.2 to 1.9, carbon emissions escalate proportionally from approximately 7,500 to nearly 69,000. This strong upward trend suggests that climate-induced disruptions significantly worsen the environmental performance of the food supply chain. The increase in emissions can be attributed to the factors including detours and longer transport routes are needed due to regional vulnerability, which increases fuel consumption. Operational inefficiencies tend to increase under adverse conditions, such as when additional energy is required to maintain refrigeration or heating in warehouses and vehicles. Moreover, under these conditions, the system often becomes more reliant on alternative suppliers or facilities that are either farther away or less environmentally efficient.

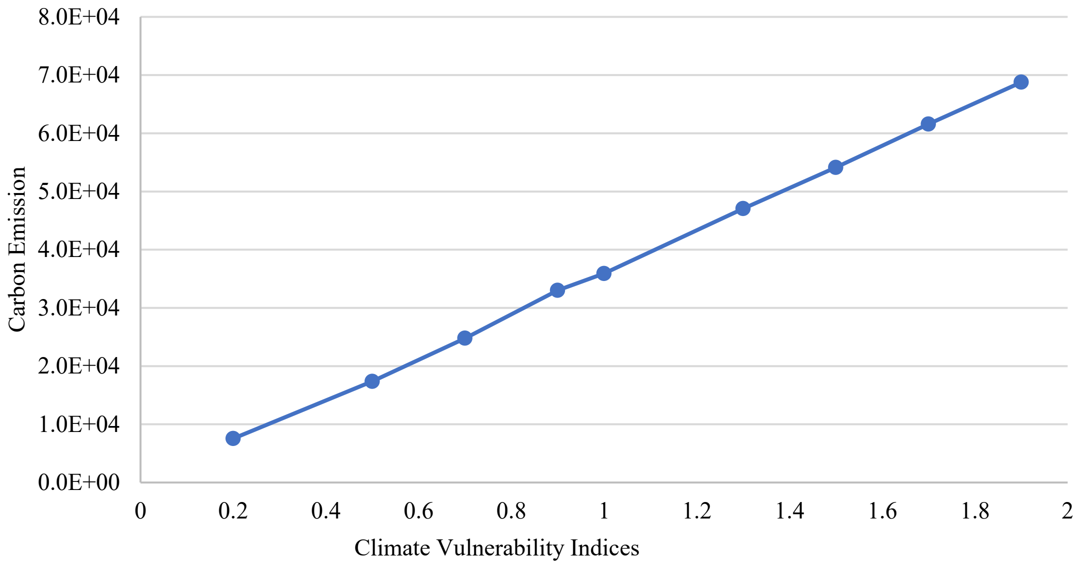

Figure 9: Climate vulnerability impacts on carbon emission within the supply chain network

The model incorporates climate vulnerability weights in the emission calculations, amplifying the carbon impact under vulnerable scenarios. This reflects the realistic interdependence between climate sensitivity and logistics emissions, especially in complex supply networks. These findings underscore the importance of integrating climate risk adaptation strategies into low-carbon supply chain planning. Effective measures may include:

- Deploying resilient and energy efficient transport infrastructure.
- Incorporating carbon-sensitive routing algorithms that adapt to real-time climate data.
- Shifting towards renewable-powered transport and processing technologies in high-risk areas.

Ultimately, this analysis highlights that climate vulnerability not only threatens supply chain reliability but also significantly affects environmental sustainability, reinforcing the necessity for resilient and green planning in future supply chain networks.

Figure 10 presents the relationship between climate vulnerability indices and total employment within the sustainable food supply chain network. Unlike typical assumptions that climate stress would reduce employment, the results indicate a strongly positive correlation: as the climate vulnerability index increases from 0.2 to 1.9, total employment also rises. This trend can be interpreted through the structure of the model and how operations adjust in response to risk; higher vulnerability in supply routes and regions often leads to greater labor engagement, such as manual rerouting, increased inspections, or decentralized processing, all of which demand more workforce. Climate-induced disruptions may necessitate parallel logistics strategies or redundancies, requiring additional staff in distribution, transport, and handling. Certain vulnerable areas might receive priority investment in localized employment schemes as part of adaptive sustainability planning.

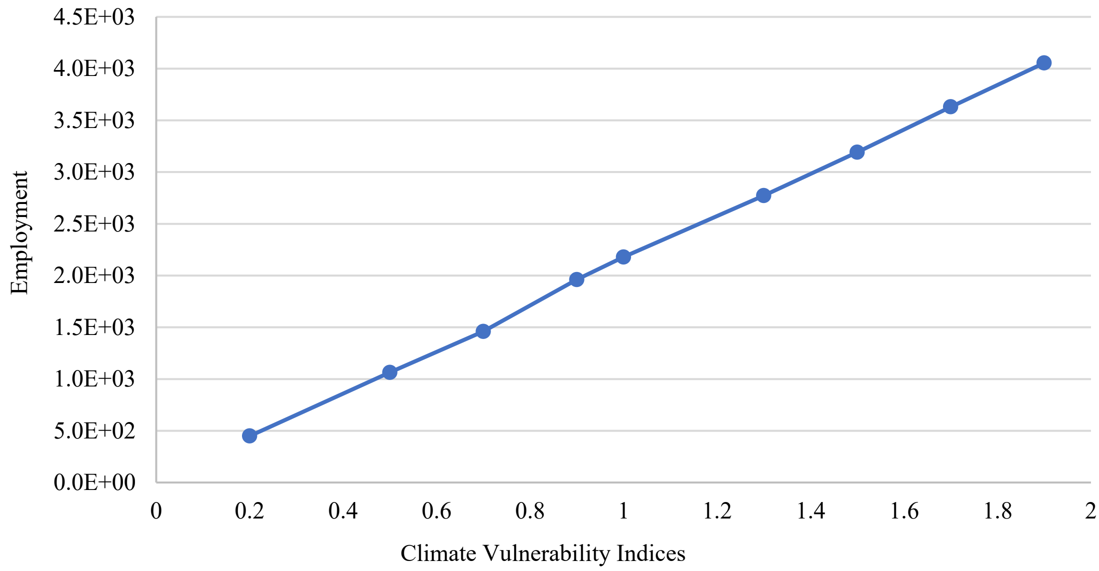

Figure 10: Climate vulnerability impacts on total employment within the supply chain network

A sensitivity analysis further highlights the model's robustness by illustrating clear numerical trends across varying Climate Vulnerability Indices (CVI). The results of the proposed model illustrate clear trends in how climate vulnerability affects supply chain performance. As CVI increases from 0.2 to 1.9, the total operational cost rises significantly from approximately 71,000 to over 640,000, reflecting a near ninefold increase. Carbon emissions also increase steadily, growing from around 7,500 at CVI ≈ 0.2 to approximately 69,000 at CVI ≈ 1.9. Employment levels show a similar upward trend, increasing from 450 workers at low CVI to about 4,050 workers under the highest CVI condition to maintain service levels and local engagement. Even in simplified network settings (e.g., two suppliers, processors, distributors, and retailers), the model consistently prioritizes routing through lower-risk nodes and activates facilities in a way that balances service continuity with resource efficiency. These outcomes demonstrate the model's practical utility in guiding strategic decision-making under uncertain climate conditions and offering valuable insights for developing more adaptive, resilient, and data-driven supply chain networks. From a sustainability perspective, the findings offer important insight. As climate vulnerability intensifies, operational costs and carbon emissions tend to rise; yet this trend may also be accompanied by an increase in employment, particularly in areas related to logistics adaptation and system maintenance. This suggests that, with targeted strategies and investment, climate adaptation efforts can be aligned with job creation goals, especially in vulnerable or underserved areas. This reinforces the importance of integrating employment objectives within climate resilience planning, rather than viewing them as separate trade-offs.

In conclusion, while climate vulnerability introduces operational challenges, it may also open avenues for broader socio-economic participation when strategically addressed. The findings highlight the complex nature of sustainability-oriented supply chain planning, where heightened climate stress can simultaneously escalate costs and emissions while fostering increased workforce involvement. As CVI levels rose, the model captured compounding disruptions including reduced process efficiency, extended lead times, and the activation of additional facilities to sustain service reliability which contributed to the consistent growth in total operational cost (Z_1). For example, at a CVI level of 1.5, total cost exceeded 500,000, compared to just over 71,000 at a low CVI of 0.2. The second objective, carbon emissions (Z_2), exhibited a steady upward trajectory under higher climate vulnerability. As the network adapted by expanding delivery routes and utilizing less efficient transport modes, emissions rose significantly. For instance, emissions increased from roughly 24,000 at CVI ≈ 0.7 to nearly 61,000 at CVI ≈ 1.7, illustrating the environmental cost associated with deteriorating operational conditions. Conversely, the third objective, employment activation (Z_3), increased alongside rising CVI levels. At moderate vulnerability levels (CVI ≈ 1.0), the number of workers engaged reached around 2,200, and exceeded up to 4,000 under the most severe scenario. This trend reflects greater reliance on human resources in tasks such as logistics coordination, facility operation, and contingency handling. Through capturing this dynamic, the model underscores the potential for reinforcing social resilience through expanded workforce engagement in the face of climate uncertainty. Figure 11 illustrates the three dimensional relationship between the model's objectives, cost (Z_1), carbon emissions (Z_2), and employment rate (Z_3) as the Climate Vulnerability Index varies from 0.2 (low vulnerability) to 1.9 (high vulnerability). Each plotted point represents an optimized supply chain configuration under a specific CVI level, solved using the ε-constraint method.

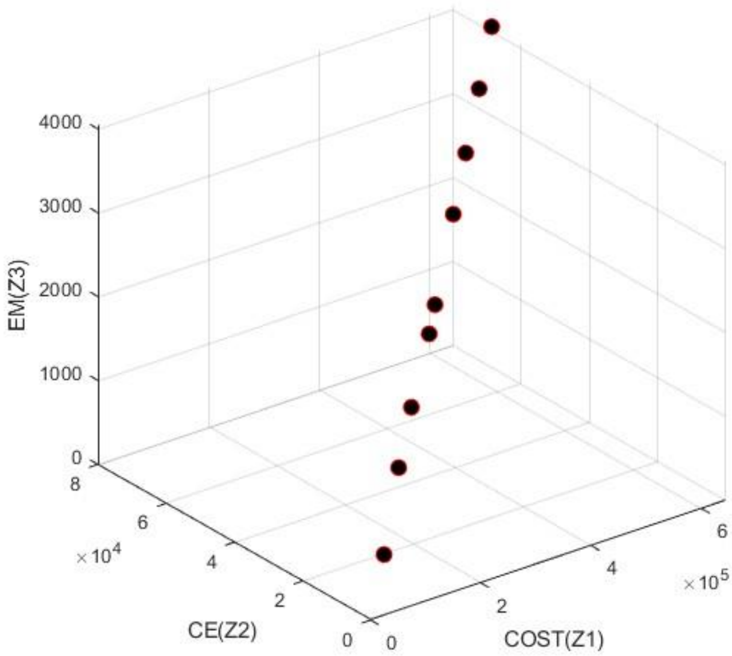

Figure 11: Graphical analysis of multi-objective trade-offs under climate vulnerability

The graph reveals a nonlinear trade-off pattern among the three objectives. Cost (Z_1) and carbon emissions (Z_2) increase substantially as CVI rises. This behavior reflects the added challenges and resource demands of operating under more severe climate conditions. Higher CVI scenarios likely necessitate rerouted transportation, increased buffer capacities, or costlier logistics to ensure continuity, leading to elevated expenditures and emissions. In contrast, employment rate (Z_3) improves consistently with increasing CVI. This is primarily due to the model's embedded resilience strategy, which promotes labor-intensive practices such as local sourcing, decentralized warehousing, and adaptive manual interventions in vulnerable areas. These practices enhance social sustainability but often come at a higher operational cost. The path seen in the plot reflects the model's strength in balancing competing priorities. As climate vulnerability intensifies, the model adapts by accepting increased costs and emissions to support employment, a key resilience and sustainability indicator. This behavior aligns with the theoretical expectation that resilient and socially inclusive supply chains may incur higher short term economic and environmental costs, especially under weather stress conditions. However, the long-term benefits, such as improved adaptability and reduced systemic risk, justify these trade-offs. The plot also supports the effectiveness of this method in providing a spectrum of feasible solutions under various climatic scenarios, enabling supply chain managers to select trade-offs aligned with their sustainability priorities. The results demonstrate that incorporating climate vulnerability considerations entails a multi-objective trade-off, as cost increases significantly with rising climate stress, and carbon emissions also escalate due to operational complexities such as longer transport routes and increased energy usage. However, employment improves, reinforcing local socio-economic capacity and system resilience. This trade-off highlights the value of CVI-informed planning. While the system incurs additional costs and emissions to preserve functionality under adverse conditions, the increase in employment contributes positively to social sustainability and long-term supply chain robustness. From a strategic standpoint, the findings suggest that moderate increases in operational cost represent justifiable investments to ensure continuity of supply under climate stress, preserve food system reliability, and strengthen local workforce engagement.

4.2 Managerial implications

The integration of climate vulnerability indices (CVI) into supply chain optimization offers actionable insights for decision makers aiming to enhance resilience and sustainability. The model results suggest several key strategies:

- Investing in infrastructure resilience: Prioritizing infrastructure upgrades in high risk areas can reduce operational disruptions and long-term costs.
- Contingency planning: Developing transportation contingency protocols in vulnerable zones enhances operational continuity under adverse weather conditions.
- Flexibility through diversification: Diversifying suppliers and logistics options strengthens adaptability and reduces reliance on climate sensitive routes.

These strategies support the development of agile and climate-resilient supply chains that are better prepared for future environmental uncertainties. This study demonstrated how incorporating CVI into multi-objective supply chain planning influences cost, carbon emissions, and employment outcomes. The quantitative results, while illustrative, underscore the practical feasibility of balancing economic efficiency with environmental and social goals. Importantly, the slight increase in operational cost is offset by meaningful gains in emission reductions and employment preservation, reinforcing the economic rationale for investing in resilience. The ε-constraint method proved effective in navigating trade-offs among conflicting objectives. Through allowing decision-makers to set flexible bounds on emissions and employment while optimizing for cost, the approach supports adaptive decision-making. This flexibility is crucial in contexts where climate risks are dynamic and regulatory requirements are evolving. The findings contribute to the growing discourse on climate-resilient and socially responsible supply chains. For decision makers, the results emphasize the value of incentivizing sustainable infrastructure investments and supporting regional employment in less vulnerable areas. Collectively, these insights advance both academic understanding and practical implementation of sustainable supply chain management under climate change.

5 Conclusion & future research

This study presented an integrated optimization framework for enhancing the resilience and sustainability of food supply chains under climate change impacts. This research contributes to the literature by bridging the gap between theoretical vulnerability assessments and practical optimization applications in food supply chain management. It highlights the necessity of integrating environmental risk factors into quantitative models to support more informed, robust, and adaptive supply chain strategies. Through incorporating climate vulnerability indices into a multi-objective mixed-integer linear programming model and applying the ε-constraint method, the model effectively balanced economic, environmental, and social objectives, demonstrating the critical importance of embedding climate risk considerations into supply chain design and management. Results illustrated that climate-adaptive supply chain configurations could minimize operational costs, reduce carbon emissions, and promote employment, even under increased climate risks. The findings underscore that achieving sustainability within food supply chains is feasible without sacrificing economic viability. The slight increase in cost associated with enhanced resilience is outweighed by the significant environmental and social benefits, contributing to long-term food security and supply chain stability. Furthermore, the study confirms the strategic importance of climate-aware decision-making in optimizing supply chain design, facility location, and transportation planning.

While the proposed model provides valuable insights, several avenues for future research are proposed. First, extending the model to consider dynamic climate change scenarios over longer planning horizons would capture progressive risk evolution, enabling more adaptive, time-phased supply chain strategies. Second, incorporating additional sustainability criteria such as water usage or biodiversity impact, would provide a more comprehensive sustainability assessment and a deeper understanding of risk under uncertainty. Applying the model to real-world case studies, across different regions and food products, would further indicate its applicability and enhance its practical relevance. Finally, integrating uncertainty modeling techniques, such as stochastic or robust optimization, could additionally enhance the model's applicability in highly volatile climate environments. Addressing these research directions would further strengthen the development of climate-resilient food supply chains, contributing significantly to global efforts in ensuring food security and sustainability amid escalating climate challenges. The results reveal that incorporating CVI into decision-making processes leads to a more resilient supply chain configuration, capable of maintaining high service levels despite increased operational costs. In particular, the model demonstrates that strategic reallocation of resources toward less vulnerable regions, investment in flexible logistics networks, and proactive adaptation measures significantly bolster system resilience and food security under adverse climate scenarios. Although a trade-off exists between cost efficiency and resilience, the relatively modest cost increase is justified by substantial gains in supply chain reliability and long-term sustainability.

These findings confirm that climate-adaptive configurations enabled through CVI-informed strategies can sustain service levels and strengthen food security despite elevated operational burdens.

The modest increase in cost is justified by significant gains in robustness, demand fulfillment, and job creation, reinforcing the notion that sustainable supply chains are both achievable and strategically advantageous. This study makes a novel contribution by bridging the gap between theoretical climate risk assessments and quantitative supply chain optimization. It emphasizes the strategic value of climate-aware planning for facility location, resource allocation, and transportation design. Moreover, it demonstrates that a cost-resilience-sustainability trade-off can be effectively managed through informed modeling, leading to better preparedness against future climate uncertainties. Ultimately, the study illustrates that integrating climate considerations into supply chain planning enables more adaptive and forward-looking strategies. Through balancing operational efficiency with environmental and social priorities, such models support the development of supply chains that are not only responsive to disruption but also aligned with broader sustainability goals. This integrated approach offers a practical foundation for informed decision-making in increasingly uncertain and dynamic conditions.

Contributor Statement

Shayan (Shawn) Mirhosseini was responsible for the conceptualization, methodology, model definition, formal analysis, writing of the original draft, review and editing of the manuscript, and visualization.

Use of AI

No AI tools were used.

Conflict Of Interest (COI)

There is no conflict of interest.

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