Academic Journal of Management and Social Sciences
ISSN: 2958-4396 | Vol. 17, No. 2, 2026

Disruption and Recovery Strategies for Fresh Agricultural Product Supply Chains under Extreme Heat: A System Dynamics Study

Zhang Xiang

School of Management, Chongqing University of Technology, Chongqing, China

Abstract: Extreme heat events increasingly threaten fresh agricultural product supply chains (FAPSC), whose vulnerability stems from product perishability, timeliness requirements and heavy cold chain reliance. This paper establishes a logistics provider-only inventory model fitting fresh produce's low-inventory operation, and builds a system dynamics-based disruption and recovery model for a four-echelon FAPSC. It explores the nonlinear evolution, risk transmission and recovery paths of extreme heat-induced supply chain (SC) disruptions. Results reveal extreme heat's disruption impact features nonlinear amplification and an obvious threshold effect. Equal downstream disruptions harm overall SC performance more severely than upstream ones. While expedited supply facilitates disruption recovery, it brings rising marginal costs. Logistics inventory buffers supply volatility and eases terminal shortages, yet incurs profit losses from extreme heat damage.

Keywords: Fresh Agricultural Product Supply Chains; System Dynamics; Supply Chain Disruption and Recovery; Extreme Heat.

1. Introduction

As a vital component of the global food system, the stable operation of the FAPSC is directly related to livelihood security and economic stability [1]. However, fresh agricultural products exhibit inherent characteristics, including seasonal production, perishability, strict freshness requirements, significant price volatility, rigorous food safety standards, and high dependence on cold chain logistics, which render their SC systems notably vulnerable and highly susceptible to external shocks such as extreme weather events [2]. In recent years, the frequency of extreme heat has increased substantially, posing an unprecedented threat to the FAPSC. Extreme heat not only directly affects the yield and quality of agricultural products but also severely disrupts the stability of cold chain logistics, thereby triggering disruption risks across the entire chain from production to consumption of fresh agricultural products. According to the (IPCC, 2023) report, the global average temperature has risen by approximately 1.1 ℃ since the pre-industrial era, and the frequency of extreme heat has increased 2.8-fold [3]. For the FAPSC, the effects of extreme heat are cross-node, nonlinear, and highly complex: upstream in the SC, heat stress induced by heatwaves inhibits the photosynthetic efficiency of crops; for instance, when the temperature exceeds 15℃, wheat yield decreases by an average of 6% for every 1 ℃ rise in air temperature [4]. Downstream in the SC, high-temperature environments significantly accelerate microbial growth and respiration in agricultural products. Taking strawberries as an example, their shelf life at 30℃ is 75% shorter than that at 0℃, and the decay rate shows a marginally increasing trend with rising temperature [5]. Thus, the disruptive impact of extreme heat on the FAPSC is characterized by complex multi-channel transmission dynamics and nonlinear evolution [6], making traditional linear risk analysis inadequate to capture its internal mechanisms and evolutionary paths.

As an effective method for analyzing the dynamic behavior of complex systems, system dynamics (SD) provides a useful analytical framework for examining disruption mechanisms in the FAPSC under extreme heat conditions. By constructing causal feedback loops, this method enables the quantification of relationships among variables in production, logistics, distribution, consumption, and other segments, simulates the dynamic impacts of changes in parameters (such as extreme high-temperature intensity and duration) on the overall stability of the SC, and further identifies critical intervention nodes. Existing studies have applied SD to analyze SC disruptions in manufacturing under natural disasters, revealing typical phenomena such as the bullwhip effect[7]. Nevertheless, when applying SD to the study of the FAPSC, current research mostly focuses on single-node disruption scenarios, and four-echelon SC disruption models targeting the specific trigger of extreme heat remain underdeveloped.

Against this background, this study develops an SD-based disruption and recovery model for a four-echelon FAPSC consisting of producers, logistics providers, distributors, and consumers. It examines the formation mechanisms, transmission paths, and performance consequences of disruptions under extreme heat and proposes corresponding recovery strategies. Specifically, this study aims to answer the following key questions:

Q1: How does extreme heat trigger disruptions in the FAPSC?

Q2: How does SC performance evolve dynamically during SC disruption and recovery?

Q3: What are the differences in the responses of key performance indicators when disruptions occur in upstream versus downstream of the SC?

To address these questions, this study develops a four-echelon SC model in which only logistics providers hold inventory. This model specification offers the following advantages: (1) It better aligns with the practical characteristics of low-inventory operations in the FAPSC. Traditional models assume that producers, logistics providers, and distributors all maintain inventory, which essentially originates from the logic of general manufacturing SC.

However, the short shelf life, high spoilage rate, and fast turnover of fresh agricultural products mean that SC entities generally adopt low-inventory or zero-inventory operation models. Therefore, the specification that only logistics providers hold inventory is more consistent with the operational reality of fresh agricultural product supply chains. (2) It simplifies model complexity and focuses on core contradictions. The core focus of this study is SC disruption and recovery under extreme heat. Traditional multi-inventory models introduce numerous redundant variables, complicating the model structure and obscuring the critical logic of logistics providers' inventory serving as the core buffering mechanism against high-temperature disruptions. (3) It highlights the core buffering role of logistics providers' inventory. The core contradiction of FAPSC disruptions under extreme heat lies in insufficient upstream supply and unmet downstream demand, and logistics providers' inventory serves as the only effective short-term buffering instrument. Traditional multi-inventory models divert attention from this core contradiction and may lead to an overestimation of SC resilience. (4) It improves the targeting of strategy outputs. The ultimate goal of this study is to provide actionable disruption response strategies for all SC entities. Traditional multi-inventory models lead to scattered strategies and obscure the core strategies of each participant. With only logistics providers holding inventory, strategies can be concentrated on the core functions of each entity, enhancing their targeting and operability.

This study is conducted based on the following assumptions:

Assumption 1: Expedited supply is activated after a disruption occurs. Under partial disruption, it can be initiated immediately, whereas under full disruption, it is activated after a delay[8].

Assumption 2: Consumer demand is stable and follows a random normal distribution, RANDOM NORMAL (780, 820, 800, 10, 1), with no sudden surges.

Assumption 3: Disruptions may occur in the upstream segment, the downstream segment, or both simultaneously.

Assumption 4: The thresholds for full disruption in the upstream and downstream of the SC are 0.7 and 0.5, respectively[9].

Assumption 5: The occurrence time of extreme heat is fixed, without considering earlier or later onset or changes in duration.

2. Literature Review

2.1. Impact of Extreme Weather on the Fresh Agricultural Product Supply Chain

Against the backdrop of global climate change, extreme weather events such as droughts and rainstorms have occurred with increasing frequency and intensity, posing severe threats to the stability and sustainability of the FAPSC. Due to their inherent perishability, strong timeliness, and high dependence on cold-chain logistics, fresh agricultural products exhibit high sensitivity to the natural environment throughout the entire chain from farm to table. Therefore, accurately understanding how extreme weather triggers disruption in the FAPSC and designing forward-looking and operable recovery strategies have become key research topics addressed jointly by academia and industry.

Scholars have conducted in-depth investigations into this issue. Amanda (2016) applied an agricultural sector model combined with quarterly data on drought conditions in the United States to assess the long-term economic impacts of drought on the U.S. beef SC. The study found that drought not only raises feed costs and leads to early cattle slaughter in the short run but also causes structural increases in beef prices and declines in cattle inventories over the long term, revealing the profound lagged effects of extreme weather on the livestock SC[10]. Haque (2020) employed an ordinary least squares regression model to examine the impacts of extreme weather events on the yield of subtropical fruits in Australia. The results indicated that extreme weather events exerted moderate effects on the yields of selected fruit varieties, and significant differences existed in temperature sensitivity across different fruit types[11]. Chanda (2021) adopted an interdisciplinary conceptual model to analyze innovative strategies adopted by the tomato industry in Florida to maintain sustainable production under extreme weather challenges by combining cultivar improvement, planting time adjustment, and insurance mechanisms[12]. Rahman (2022) took the potato SC in Idaho as a case study and used agent-based modeling to construct a multi-echelon SC simulation model involving five types of agents. The findings revealed heterogeneous impacts of droughts and blizzards on different agents and product categories within the SC: upstream producers bear the brunt of the shocks, while downstream distributors experience distinct delayed effects[13].

Regarding digital applications, Wang (2024) explored the challenges of extreme weather to agricultural production and SC management for smallholder farmers in developing countries based on field survey data of fresh agricultural products in rural China. The study innovatively proposed that SC risks induced by heatwaves could be mitigated by shifting sales channels from offline to online, thereby opening a new pathway for smallholder farmers to improve profits[14]. Akdemir (2025) compared three distinct multi-objective evolutionary algorithms and linear programming methods to optimize biomass cultivation decisions in the U.S. Corn Belt under extreme weather conditions, providing quantitative tools for climate adaptation at the agricultural production stage[15]. Using a two-stage instrumental variable estimation procedure, Yim (2025) found that the impacts of drought were not confined to the regions where they occurred but also generated cross-industry spillover effects[16]. Fuerzas (2025) employed qualitative research methods to analyze the impacts of extreme weather on SC vulnerability in major coffee-producing regions of the Philippines, revealing that extreme events such as typhoons cause disruptions to production cycles, reduce yields, and lower farmers' incomes[17]. Based on climate models and multiple weather scenarios using actual soil data from California, Hernandez-Cuellar (2025) conducted a case study on the cold-chain food SC in California with strawberries as the representative crop. The results showed that scenarios with increased rainfall during the growing season conversely lead to higher yields, uncovering divergent effects of different types of extreme weather on specific crops[18].

Although existing studies have yielded substantial findings concerning the impacts of extreme weather on agricultural product SC, the research objects are relatively less sensitive to meteorological factors such as extreme heat. In view of this, this paper focuses on fresh agricultural products, which are most significantly affected by extreme heat, to deeply investigate their SC disruption mechanisms and recovery strategies. It aims to provide more targeted theoretical support and practical guidance for risk management of FAPSC under extreme weather conditions.

2.2. Application of System Dynamics in Supply Chain Resilience Assessment and Enhancement

As a simulation methodology for investigating the structural, behavioral, and strategic interactions of complex systems, SD has become a powerful tool for modeling dynamic SC problems due to its strength in handling multiple feedbacks, time delays, and nonlinear relationships[6]. Since Forrester founded industrial dynamics in 1958, SD has undergone decades of development in SC management, and its application, particularly in disruption and recovery research, has become well-established. The classic “beer game” model by Sterman (1989) vividly revealed the bullwhip effect in SC caused by information delays and decision feedback, providing a theoretical foundation for modeling the dynamics of orders, inventory, and deliveries among nodes[19].

In SC disruption modeling, Wilson (2007) was among the first to apply SD to simulate the recovery process of manufacturing SC following natural disasters, pioneering the use of SD in disruption management [20]. Since then, the integration of SD and risk analysis has deepened progressively, with research scenarios expanding from manufacturing to resources and energy, pharmaceuticals, agricultural products, and other sectors.

In the field of resource and energy SC, Shao (2020) developed a SD model incorporating price dynamics and supply–demand relationships to evaluate the resilience of China’s lithium SC under the dual pressures of growing new energy vehicle demand and supply disruption risks. The study identifies excessive upstream resource concentration as the primary vulnerability and proposes improvements such as diversifying import sources and enhancing recycling rates[21]. Munikhah (2021) applied SD to construct a conceptual model of Indonesia’s nickel pig iron SC and developed a quantitative stock-flow diagram model. Through multi-policy scenario simulations, the study analyzed the impacts of government export control policies on SC resilience and proposed strategies to enhance disruption response capabilities[22]. Liu (2023) established a SD model consisting of four subsystems (i.e., price, production capacity, supply, and demand) to assess the evolutionary resilience of China’s cobalt SC amid expanding electric vehicle demand and geopolitical supply risks, identifying critical intervention points [23]. Ma (2025) focused on the Sino-Russian timber SC, constructed a four-dimensional SD model, and combined it with the entropy-weight TOPSIS method for resilience assessment, providing differentiated strategies of “strengthening logistics in the short run and expanding demand in the long run” to improve resilience in cross-border resource SC [24].

In pharmaceutical and emergency SC, Zhu (2025) targeted the drug SC in Hebei Province and developed a resilience evaluation framework based on “impact factors, capabilities, and resilience”. SD simulations revealed that risk tolerance was the dominant factor affecting pharmaceutical SC resilience, surpassing reserve capacity and coordination capability[25].

In manufacturing SC, Ekinci (2024) used SD to simulate national SC behavior during the COVID-19 pandemic. The results showed that learning effects and SC agility helped reduce system complexity during the second wave of infections, and accumulated crisis response experience could be transformed into endogenous drivers of resilience improvement[26]. Fleisch (2024) conducted an in-depth case analysis of the semiconductor industry and found that forecasting accuracy and organizational inertia represented major barriers to SC resilience, while information technology capability and vertical integration served as core enablers[27].

Although SD was adopted relatively late in agricultural and food SC, several valuable studies have emerged. Piewthongngam (2014) integrated factors across breeding stages in a hog SC into a SD model, enabling managers to visualize dynamic changes in the production chain and better respond to environmental shifts and SC disruptions[28]. Singer (2022) employed SD to analyze the impacts of the COVID-19 pandemic on Austria’s milk SC. The findings indicated that the SC remains relatively stable under pandemic shocks, and she proposed recommendations to enhance resilience, including improving cold chain flexibility and optimizing inventory policies[29].

In summary, the application of SD in SC resilience research has formed a relatively mature methodological framework. Research contexts have expanded from early manufacturing to resources and energy, pharmaceuticals and emergency supplies, agricultural products and food, and other sectors. Research perspectives have evolved from single disruption types to multi-scenario comparative analyses, and research objectives have advanced from phenomenological description to strategy optimization. Nevertheless, existing literature still exhibits the following limitations. First, research on fresh agricultural products as a distinctive category remains limited, and their core characteristics, including perishability, timeliness, and high cold chain dependence, have not been fully incorporated into modeling. Second, there is relatively little targeted research on extreme heat as a specific inducing factor. The negative impacts of heatwaves on fresh agricultural products exhibit complex characteristics such as nonlinearity and marginal increase, which require specialized modeling and analysis. Third, insufficient attention has been paid to simultaneous multi-node disruption scenarios, which limits the ability to address the realistic challenges of compound disasters and cross-regional transmission under the normalization of extreme weather. Accordingly, this paper introduces SD into the study of disruption and recovery strategies for the FAPSC under extreme heat, aiming to address the gaps in existing research.

2.3. Transmission Mechanism and Recovery Strategies for Supply Chain Disruptions

The transmission and diffusion of supply chain disruptions, together with targeted recovery strategies, form the core of ensuring that supply chain systems can resist risks and recover rapidly. Existing studies have revealed the laws governing disruption propagation and established a full-process recovery framework covering five major dimensions: modeling of disruption transmission mechanisms, resilience inference and assessment, cascading failure prevention and control, intelligent risk prediction and strategy optimization, and post-crisis tail risk governance.

At the level of supply chain disruption transmission mechanisms, supply chain opacity and supplier risk correlation act as key drivers of endogenous network vulnerability. Andrea (2024) verified, using a vertical production network game model, that supply chain information opacity reduces the marginal benefit of diversified procurement for firms, leading to a lower level of corporate diversification than the socially optimal level. While complete information lowers the probability of individual disruptions, it increases the overall vulnerability of the network[30].

For complex supply chain resilience inference, hypergraph neural networks effectively overcome the limitation that traditional graph models cannot capture high-order dependencies. Shen (2025) formalized the supply chain resilience inference problem and developed the SC-RIHN model. This model represents multi-agent interactions via a firm–product–firm hyper edge structure and enables resilience prediction without explicit dynamic equations by incorporating inventory time-series data. Its prediction accuracy on the test data set is markedly superior to that of traditional models, supporting early warning of disruption risks[31].

From the perspective of cascading failures, supply chain disruptions are accompanied by dual failure modes of overload and underload, and node heterogeneity and adaptive regulation are central to enhancing invulnerability. Hu (2026) refined the load–capacity model by integrating dual failure modes, used a nonlinear function to characterize firm heterogeneity, and built a strategic framework that combines active adaptation and passive risk recovery. Simulations indicate that the coordination of these two strategies can significantly suppress cascading failures [32].

In the domain of disruption emergency recovery, emergency procurement represents the mainstream response strategy, whose effectiveness is highly sensitive to disruption types and parameter settings. Thomas (2020) performed dynamic simulations using system dynamics and control engineering approaches to analyze two disruption categories: high-frequency short-duration and low-frequency long-duration. Their results show that a trade-off exists between service level and long-term revenue for the former, whereas the latter requires balancing emergency preparedness and recovery actions. The optimal response time of backup suppliers was also identified, providing quantitative support for strategy configuration[33].

Regarding the complex risks of cross-border supply chains, intelligent fusion algorithms enable accurate risk prediction and dynamic optimization. Xi (2026) constructed a dynamic risk assessment framework by integrating LightGBM, multi-scale graph attention networks, and temporal convolutional networks, achieving identification of risk transmission paths and real-time early warning. The model achieves a prediction accuracy of 92.5%, and when combined with a reinforcement learning strategy engine, response time can be reduced to 15 minutes, effectively reconciling risk control and cost control objectives[34].

In summary, existing studies cover the full chain of theoretical transmission mechanisms, intelligent resilience assessment, cascading failure prevention and control, emergency strategy simulation, and cross-border intelligent optimization for supply chain disruptions. They form a complete research system of "mechanism characterization – quantitative inference – strategy design – effect verification". This body of work not only reveals the core drivers of disruption propagation but also offers scenario-based and implementable recovery strategies, providing theoretical and methodological support for the full-cycle management and control of supply chain disruptions.

2.4. Research Gaps and Contributions

Existing studies have achieved significant progress in the field of disruption and recovery of the FAPSC under extreme weather. At the theoretical level, a basic framework has been established covering risk identification, transmission paths, and recovery strategies. At the methodological level, various tools such as SD, Bayesian networks, fuzzy mathematics, and agent-based modeling have been integrated to effectively address the challenge of processing uncertain information under extreme weather. At the practical level, a response logic has been formed that shifts from single-segment optimization to whole-chain coordination, and a complete strategy system of prevention, response, and recovery has been proposed, which exhibits strong practical guiding value.

However, deficiencies exist in the existing literature. First, the research perspectives are relatively limited, with most studies focusing on partial segments. For example, although Olivares-Aguila (2020) and Wilson (2007) considered SC disruptions at two nodes, they only examined scenarios of independent disruptions without addressing simultaneous multi-node disruptions or cross-regional risk transmission, which makes it difficult to adapt to the realistic trend of normalized extreme weather and compound disasters [8] [20]. Second, in modeling the SC recovery process, expedited supply costs are set as fixed constants without dynamic adjustment according to different disruption ratios and the gradual recovery of the SC. In practice, the more severe the disruption, the higher the unit emergency transportation cost, and this nonlinear relationship has not been reflected in existing models. Third, existing studies treat the delay time following different disruption levels as identical, which is clearly inconsistent with reality. In practice, compared with partial disruptions, full disruptions usually require longer periods to restart production, repair logistics, and allocate resources, whereas most existing models adopt fixed delay assumptions, leading to deviations from actual conditions.

Accordingly, this study fully considers multiple scenarios in which disruptions of varying degrees occur separately and simultaneously in the upstream and downstream of the SC. By introducing an emergency supply cost function and a delay time function that vary with disruption severity, a more realistic and explanatory SD model is constructed to improve the model's real-world fitness and strategic guidance value, thereby providing more accurate theoretical support and decision-making basis for the FAPSC to cope with extreme weather risks.

3. Construction of System Model for Supply Chain Disruptions

This study mainly draws on and extends the work of Thomas (2020) and Olivares-Aguila (2020). Thomas constructed a dynamic simulation model for emergency sourcing strategies under supply chain disruptions. Using a system dynamics and control engineering framework, he established a two-echelon supply chain model with an emergency backup supplier and examined the impacts of disruptions on long-term profitability and backlogs[33]. Olivares-Aguila (2020) developed a four-echelon supply chain model consisting of second-tier suppliers, first-tier suppliers, plants, and distribution centers. They systematically investigated the dynamic evolution of key supply chain performance indicators when disruptions occurred at the first-tier supplier and the plant, respectively

[8]. Partial and full disruption scenarios were set separately at these two nodes, and an expedited supply strategy above the normal level was activated immediately after disruptions to accelerate the recovery process of the supply chain.

Inspired by their studies, this paper introduces system dynamics into the field of FAPSC research and constructs a four-echelon supply chain structure covering four major stakeholders: producers, logistics providers, distributors, and consumers, as shown in Figure 1. Given that distributors and consumers are usually geographically close, the supply chain between them is relatively less affected by extreme weather. Therefore, this paper focuses on the evolutionary characteristics of key supply chain indicators under extreme heat shocks across the three core segments: producers, logistics providers, and distributors.

On the basis of existing research, this paper further expands the research boundary by investigating the response differences and linkage effects of key performance indicators for the overall supply chain and its participants when disruptions occur simultaneously in the upstream and downstream of the supply chain [35]. The model is specified as follows: when a supply chain disruption occurs, each stakeholder can adopt an expedited supply strategy to meet downstream demand and facilitate supply chain recovery. The activation timing of expedited supply varies with the severity of disruption. Specifically, under partial disruption scenarios, expedited supply can be activated immediately; whereas under full disruption scenarios, a certain delay is required before activation due to blocked information transmission in the supply chain. This delay time is determined by the full disruption coefficient and exhibits a positive correlation: the larger the full disruption coefficient, the longer the delay in information feedback and response. In addition, expedited supply is usually realized through unconventional means such as overtime production or additional rental of transportation equipment, whose unit transportation cost is significantly higher than that of normal supply. Moreover, it shows a marginally increasing nonlinear positive correlation with the disruption coefficient [36]; that is, the deeper the disruption, the faster the unit expedited cost rises. This setting is more consistent with the typical characteristics of resource scarcity and surging emergency costs in real-world situations.

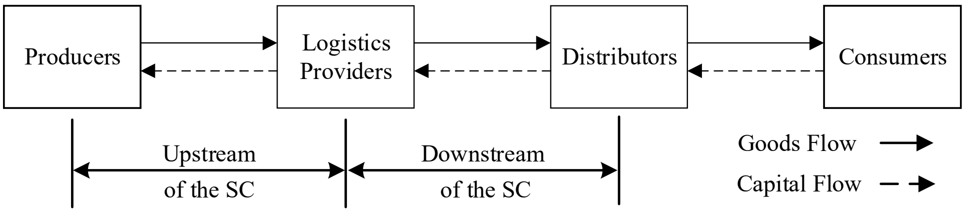


Figure 1. Goods flow and capital flow of the FAPSC

For the convenience of research, corresponding parameters are assigned to each variable in the model. Table 1 summarizes all adopted parameters together with their definitions.

3.1. Expedited Supply Module

When a disruption occurs in the FAPSC, it is necessary to restore the supply capacity of the SC to a normal level within a specified time period to meet the demand of downstream entities. At this point, expedited supply is adopted to recover SC capacity, and the decision to initiate expedited supply follows Equation (1). With the launch of expedited supply, the FAPSC recovers continuously, and the recovery progress is expressed in Equation (2). Within a given time frame, a larger disruption coefficient imposes a higher requirement on expedited supply, resulting in a greater volume of expedited shipments. The volume of expedited shipments varies continuously with SC recovery according to Equation (3), leading to higher expedited transportation costs. The unit cost of expedited transportation exhibits a marginally increasing trend with the SC disruption ratio, as shown in Equation (4).

$$ESQ_i=\begin{cases}1 & RP_j>=0,\ Time>=ST_{ew}+UDT_j \\ 0 & else\end{cases} \tag{1}$$

$$RP_j=MIN\{1,\left[Time\text{-}\left(ST_{ew}+UDT_j\right)\right]/30\} \tag{2}$$

$$ESQ_i=\begin{cases}ESC*OQ_{i+1}*DR_j*RP_j & US_j=1 \\ 0 & US_j=0\end{cases} \tag{3}$$

$$EUTC_i=ETC_i+BFC+MCC*DR_J^2,\ j=1,2 \tag{4}$$

3.2. Loss Rate Module

As the sole participant holding inventory in this FAPSC, logistics providers face losses arising from agricultural product spoilage. When logistics providers are impacted by extreme heat, the spoilage they incur exceeds that under normal temperatures. In this case, the agricultural product spoilage rate of logistics providers is jointly affected by extreme heat and product accumulation caused by SC disruptions, with the specific influence formulated in Equation (5).

$$AR=BAR+IC*(IR_1+DR_2)+TIC*MAX(0,\ A_t\text{-}S_t) \tag{5}$$

3.3. Procurement and Sales Volume Module

In the absence of SC disruptions, the order quantities placed by each SC entity to its upstream stage and the sales volumes delivered to its downstream stage are deterministic. When a SC disruption occurs, the order and sales volumes among entities vary with the disruption coefficient and the gradual recovery of the SC driven by expedited supply. Meanwhile, the order and sales volumes between SC entities are constrained by the cash flow of each entity, as specified in Equations (6)-(9).

$$PQ_2=MIN\left(PQ_3/IC_2,\ MPQ_2\right) \tag{6}$$

$$PQ_3=MIN\left(CDQ,\ MPQ_3\right) \tag{7}$$

$$MPQ_i=CF_i/SP_{i-1},\ i=2,\ 3 \tag{8}$$

$$LSV=MIN\left(LPI+NSQ_1+ESQ_1,\ PQ_3\right) \tag{9}$$

3.4. Price Module

The sales price of producers in the FAPSC is determined by the base production cost and the markup rate, as shown in Equation (10). The sales prices of logistics providers and distributors are determined by the sales price of the upstream stage and their own markup rates, as shown in Equation (11).

$$SP_1=UPC*(1+PM_1) \quad (10)$$

$$SP_i=SP_{i-1}*(1+PM_i),\ i=2,3 \quad (11)$$

Table 1. parameters and definitions.

Parameters	Definitions	Parameters	Definitions
I	*i=1,2,3 represents producers, logistics providers, and distributors.*	*PPC*	*Producers Production Cost*
J	*j=1,2 represents the occurrence of disruption in the upstream and downstream of the SC.*	*PO*	*Producers Output*
TC_i	*Total Cost*	*ASV*	*Actual Shipment Volume of Producers*
TP_i	*Total Profit*	NSQ_i	*Normal Shipment Quantity*
TC_t	*Total Cost on day t*	TP_t	*Total profit on day t*
CF_i	*Cash Flow*	ESQ_i	*Expedited Shipment Quantity*
IA_i	*Investment Amount*	PQ_i	*Purchase Quantity*
ICF_i	*Initial Cash Flow*	*LSQ*	*Logistics providers Sales Quantity*
II	*Initial Inventory*	PC_i	*Procurement Cost*
UPC	*Unit Production Cost*	*IQ*	*Logistics providers Inventory Quantity*
PM_i	*Profit Margin*	*LQ*	*Logistics providers Loss Quantity*
PCR	*Procurement Capacity Ratio*	*IC*	*Logistics providers Inventory Cost*
IR_i	*Investment Ratio*	*LC*	*Logistics providers Loss Cost*
UTC_i	*Unit Transportation Cost*	MPq_i	*Maximum Purchase Quantity*
UIC	*Unit Inventory Cost*	PQ_i	*Purchase Quantity*
BDQ_i	*Basic Demand*	*CDQ*	*Consumer Demand Volume*
BAR	*Basic Loss Rate*	SP_i	*Selling Price*
ILC	*Disruption Loss Coefficient*	IC_j	*Disruption Coefficient*
BIR_j	*Basic Disruption Ratio*	US_j	*Expedited Activation*
CIT_j	*Full Disruption Threshold*	DT_j	*Delay Time*
BEC	*Basic Expedited Cost*	EST_j	*Expedited Supply Time*
MCC	*Marginal Expedited Cost Coefficient*	t_j	*Recovery Time*
ST_{ew}	*Start Time of Extreme Weather*	$EUTC_i$	*Expedited Unit Transportation Cost*
ESC	*Expedited Supply Coefficient*	*LS*	*Logistics providers Loss Rate*
DR_j	*Disruption Ratio*	CV_i	*Cost Volume*
SR_i	*Sales Revenue*	PV_i	*Profit Volume*
TC	*Total SC Cost*	TP	*Total SC Profit*
ETC_i	*Expedited Transportation Cost*	RP_j	*Recovery progress*

3.5. Fresh Agricultural Product Producers Subsystem Module

In the producers subsystem of the FAPSC, producers' profit consists of producers' sales revenue, production cost, and transportation cost, as shown in Equation (12). Producers' sales revenue is determined by the logistics providers' purchase quantity and the producers' selling price, as presented in Equation (13). Producers' harvest quantity is jointly determined by the logistics providers' purchase quantity and the producers' upstream disruption coefficient, as given in Equation (14). Producers' production cost is determined by the unit production cost and the producers' output, as specified in Equation (15).

Producers' transportation cost is related to whether a disruption occurs in the SC. When no SC disruption occurs, producers' transportation cost is determined solely by the producers' normal transportation cost, and the producers' delivery quantity is determined by the logistics providers' purchase quantity. When a SC disruption occurs, producers incur an expedited transportation cost, as shown in Equation (16). In this case, the producers' delivery quantity is jointly determined by the logistics providers' purchase quantity and the producers' upstream disruption ratio, as presented in Equation (17). To fulfill the logistics providers' procurement demand as soon as possible, producers adopt expedited supply. The quantity of producers' expedited shipments during this period is given in Equation (18). Throughout this process, producers' profit accumulates continuously, as expressed in Equation (19).

$$PV_1=SR_1\text{-}MPC\text{-}TC_1 \tag{12}$$

$$SR_1=PQ_2*SP_1 \tag{13}$$

$$\mathrm{MO}=\mathrm{PQ}_2/\mathrm{IC}_1 \tag{14}$$

$$MPC=UPC*MO \tag{15}$$

$$TC_1=NSQ_1*UTC_1+ESQ_1*UUDC_1 \tag{16}$$

$$NSQ_1=PQ_2*(1\text{-}DR_1) \tag{17}$$

$$ESQ_1=\begin{cases} ESC*PQ_2*DR_1*RP_1 & (US_1=1) \\ 0 & (US_1=0) \end{cases} \tag{18}$$

$$CF_1=\int_0^{Time}(DV_1\text{-}IA_1)dt+ICF_1 \tag{19}$$

3.6. Logistics Providers Subsystem Module

Within the FAPSC, logistics providers not only store fresh agricultural products but also participate in transactions between upstream and downstream entities in the SC, which differs from traditional logistics providers. Accordingly, logistics providers' costs include traditional inventory costs and deterioration costs, as well as procurement costs paid to fresh agricultural product producers. To reduce their inventory costs and deterioration costs, logistics providers procure fresh agricultural products from producers following Equation (21).

$$CV_2=PC_2+IQ*LR_{tp}+LQ*SP_2 \tag{20}$$

$$PQ_2=MIN\left(PQ_3/IC_2\,,\,MPQ_2\right) \tag{21}$$

The total cost and total profit of logistics providers accumulate continuously as shown in Equations (22) and (23), while the cash flow accumulates continuously in accordance with Equation (24) and determines the maximum procurement capacity of logistics providers.

$$TC_2=\int_0^{Time}CV_2\,dt \tag{22}$$

$$TP_2=\int_0^{Time}PV_2\,dt \tag{23}$$

$$CF_2=\int_0^{Time}PV_2\,dt+ICF_2 \tag{24}$$

Logistics providers' cost is composed of procurement cost, inventory holding cost, and deterioration cost. Logistics providers' profit consists of sales revenue and total cost. The equation for calculating logistics providers' cost is given by Equation (25), and the equation for calculating their profit is presented in Equation (26).

$$CV_2=PC_2+IC_{tp}+LPLC \tag{25}$$

$$PV_2=SR_2\text{-}CV_2 \tag{26}$$

3.7. Fresh Agricultural Products Distributors Subsystem Module

Given the significant perishability of fresh agricultural products, it is assumed in the model construction that distributors follow a buy-and-sell immediately rule to reduce their inventory deterioration risk. Distributors' cost consists of procurement cost and transportation cost, while distributors' profit is determined by sales revenue and total cost. The equations for calculating distributors' cost, profit, total cost, and total profit are given by Equations (27) to (30), respectively.

$$CV_3=PC_3+TC_3 \tag{27}$$

$$PV_3=SR_3\text{-}CV_3 \tag{28}$$

$$TC_3=\int_0^{Time}CV_3\,dt \tag{29}$$

$$TP_3=\int_0^{Time}PV_3\,dt \tag{30}$$

3.8. Model Validation

Validity testing of the SD model is a critical procedure to ensure that the model can genuinely reflect the operational laws of the real-world system. For the four-echelon FAPSC model affected by extreme heat, we need to examine the model validity from four dimensions: structural validity, parameter validity, behavioral validity, and practical validity. To ensure unit consistency, the built-in tools in Vensim are used to check model units.

In this study, structural validity testing includes examinations of the rationality of causal loop diagrams, consistency of flows and stocks, and reasonableness of system boundaries. Parameter validity is achieved through continuous calibration of parameters during repeated simulation analyses. Behavioral validity testing is implemented via boundary behavior tests and extreme scenario tests, accompanied by fitting simulations using relevant historical data. Practical validity is verified through goal-matching tests and reviews by industry experts.

According to the scenario test results, it is found that the changes in the dynamic behavior patterns of the model correspond to the existing knowledge regarding FAPSC operations. Therefore, it is concluded that the model is applicable for policy evaluation.

4. Numerical Simulation

4.1. Scenario Setup and Simulation Results

Compared with ordinary industrial products, fresh agricultural products exhibit prominent perishability. For this reason, the simulation time horizon in this study is shorter than those in traditional studies on industrial SC disruptions, which typically range from 800 to 1000 days [20]. The full SC simulation period is set to 60 days, with a minimum simulation step of 1 day.

In contrast to Olivares-Aguila (2020), who set the delay time under full disruption as a fixed value [8], the innovation of this study lies in the following: to better reflect real-world conditions, the expedited delay time under full disruption is treated as a dynamic variable. The length of the delay depends on the severity of extreme weather, the greater the extreme weather intensity, the more severe the obstruction to information transmission and response, and the longer the corresponding delay, which is set to range from 5 to 10 days. To ensure a speedy recovery of the SC, it is stipulated that full recovery must be achieved within 30 days after the onset of disruption, regardless of whether a partial or full disruption occurs.

Table 2 presents the scenario settings and simulation results used to investigate the impacts of disruptions in the upstream and downstream segments of the FAPSC under extreme heat shocks. The first row of Table 2 lists the core parameter configurations for simulating disruption events and expedited supply. Taking Scenario S_1 as an example, this scenario assumes an upstream disruption ratio of 0.3, meaning that the upstream supply capacity of the SC decreases by 30%, followed by a 30-day expedited supply period until the SC is fully restored.

Table 2. Scenario setting and simulation results of SC disruption

Scenario	α_1	t_1	DT_1	α_2	t_2	DT_2	TC_{20}	TC_{50}	TP_{20}	TP_{50}
S_0	0	0	0	0	0	0	942778	2280290	167519	502887
S_1	0.3	30	0	0	0	0	~	2360100	~	362188
S_2	0.5	30	0	0	0	0	~	2498860	~	180042
S_3	0.7	20-25	5-10	0	0	0	~	2765310	~	-129801
S_4	0.9	20-25	5-10	0	0	0	~	3234420	~	-642297
S_5	0	0	0	0.1	30	0	~	2377160	~	432801
S_6	0	0	0	0.3	30	0	~	2621420	~	256114
S_7	0	0	0	0.5	20-25	5-10	~	2970590	~	3095.92
S_8	0	0	0	0.7	20-25	5-10	~	3508420	~	-387037
S_9	0.3	30	0	0.3	30	0	~	2702160	~	175382
S_{10}	0.3	30	0	0.5	20-25	5-10	~	3068540	~	-94852.4
S_{11}	0.3	30	0	0.7	20-25	5-10	~	3632850	~	-511469
S_{12}	0.7	20-25	5-10	0.3	30	0	~	3203870	~	-379413
S_{13}	0.7	20-25	5-10	0.5	20-25	5-10	~	3662020	~	-703525
S_{14}	0.7	20-25	5-10	0.7	20-25	5-10	~	4379260	~	-1257880
S_{15}	0.5	30	0	0.3	30	0	~	2869610	~	-8497.01
S_{16}	0.5	30	0	0.7	20-25	5-10	~	3881630	~	-760249

4.2. Analysis of Simulation Results

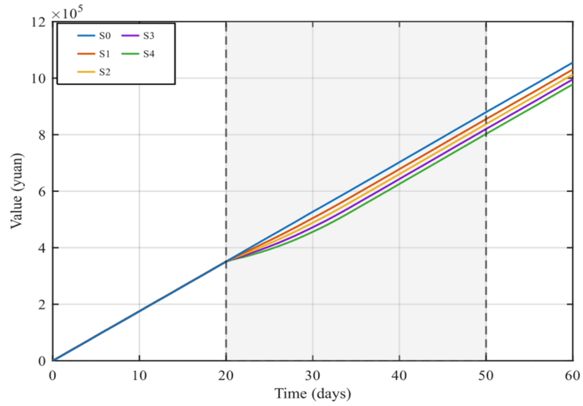
4.2.1. Analysis of Disruptions Occurring Independently in the Upstream and Downstream of the Supply Chain

(a)Analysis of upstream disruptions

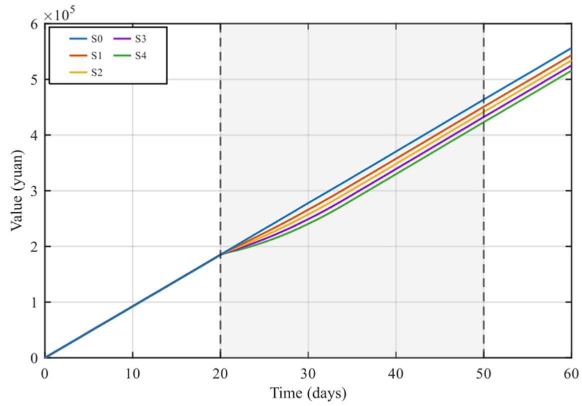
This section simulates the scenario where disruptions occur only in the upstream segment of the FAPSC, covering Scenarios S_1, S_2, S_3, and S_4, with a comparative analysis against the baseline scenario S_0. The simulated total cost and total profit of distributors are presented in Figure 2(a) and Figure 2 (b). We found that although the impact of upstream disruptions propagates downstream along the SC, its impact on distributors' total cost and total profit is negligible. The underlying reason is that, as the sole inventory holder in the model, the logistics providers can continue supplying distributors from their inventory even if the upstream producers temporarily suspend supply. Consequently, impacts on the distribution sector are extremely limited under upstream disruption scenarios.

Notably, Table 2 demonstrates that upstream disruptions exert a significant impact on the SC's total cost and total profit, with particularly sharp fluctuations in total profit. This is because upstream disruptions directly impair the regular sales of producers and the procurement activities of logistics providers. During disruptions, producers are unable to deliver products normally, and the transportation costs incurred by expedited supply are substantially higher than under regular operations. Under this dual pressure, the total profit of the SC declines significantly, and the profit reduction widens continuously as the disruption coefficient increases. Notably, across all simulated scenarios, the total profit of the SC remains above zero, indicating that the SC as a whole is still profitable.

(b) Downstream disruption analysis



(a) Total cost of distributors

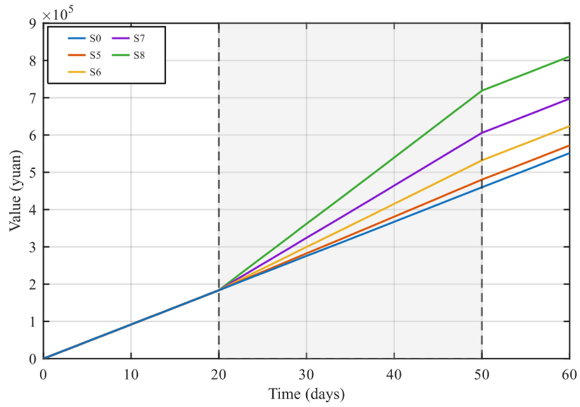


(b)Total profit of distributors

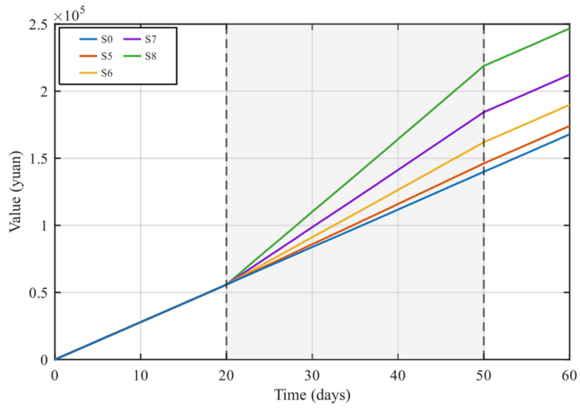
Figure 2. Impact of upstream disruption on the SC.

This section simulates the scenario where disruptions occur only in the downstream segment of the FAPSC. Scenarios S_5, S_6, S_7, and S_8 are investigated sequentially and compared with the baseline scenario S_0.

The simulated total cost and total profit of producers are illustrated in Figure 3 (a) and Figure 3 (b). It is found that the impact of downstream disruptions propagates in the upstream direction along the SC and imposes a significant shock on producers' total cost and total profit. This result is in sharp contrast to Figure 2 (a) and Figure 2 (b), where upstream disruptions exert only a weak influence on distributors, revealing the asymmetry of the disruption transmission effect between upstream and downstream.



(a)Total cost of producers



(b)Total profit of producers

Figure 3. Impact of downstream disruption on the SC

Meanwhile, the simulation results in Table 2 further indicate that the total cost and total profit of the SC are also significantly affected. Critically, in the scenario where $\alpha_2 = 0.7$, the SC profit eventually falls below zero after suffering the disruption shock, implying an overall loss for the SC. This phenomenon stands in stark contrast to the result that the SC remains profitable under all upstream disruption scenarios. By comparing the limited impact of upstream disruptions on distributors' profit with the severe shock of downstream disruptions on producers' profit, an important conclusion can be drawn: downstream disruption imposes a far greater impact on the overall system than equivalent disruption intensity in the upstream. This finding suggests that in SC planning and the design of disruption recovery strategies, priority should be given to the optimization and recovery of downstream segments, so as to more effectively curb risk diffusion and safeguard system stability.

4.2.2. Analysis of Simultaneous Disruptions in The Upstream and Downstream of The Supply Chain

This section further investigates the complex scenario where simultaneous disruptions occur in both the upstream and downstream of the SC. For ease of comparative analysis, the simultaneous disruption scenarios are categorized into four types: (a) partial upstream disruption combined with downstream disruption; (b) full upstream disruption combined with downstream disruption; (c) partial downstream disruption combined with upstream disruption; (d) full downstream disruption combined with upstream disruption.

(a) Partial upstream disruption and downstream disruption

This section simulates Scenarios S_9, S_{10}, and S_{11}, in which the upstream experiences a partial disruption ($\alpha_1 = 0.3$) while the downstream suffers disruptions of varying intensities. A comparison is conducted with Scenario S_1, the baseline case of partial upstream disruption, to examine the superimposed impact of downstream disruption severity on the total cost and total profit of the SC.

As shown in Table 2, the simulation results reveal that the total cost and total profit of the SC change significantly with the increase in the downstream disruption coefficient, and the rate of change exhibits a marginally increasing characteristic. Compared with the scenario involving only downstream disruptions occur, the SC incurs a higher total cost and achieves a lower total profit under the combined disruptions. This is attributed to the additional partial upstream disruption ($\alpha_1 = 0.3$), whose dual shocks intensify the pressure on the system.

(b) Complete upstream disruption and downstream disruption

This section simulates Scenarios S_{12}, S_{13}, and S_{14}, where the upstream suffers a full disruption and the downstream experiences disruptions of varying degrees. These scenarios are compared with the baseline scenario S_3 of complete upstream disruption to analyze the superimposed impact of downstream disruption severity on SC performance. The simulation results are presented in Table 2. We find that the total cost and total profit of the SC fluctuate significantly with changes in the downstream disruption coefficient, and the rate of change shows a marginally increasing characteristic. Compared with scenarios involving partial upstream disruption plus downstream disruption, the SC under complete upstream disruption plus downstream disruption incurs a higher total cost and yields a lower total profit, indicating that the impact of complete upstream disruption is stronger than that of partial upstream disruption. More importantly, the marginal variation ranges of total cost and total profit in the latter case are larger than those in the former. This reveals that upstream disruption not only directly shocks the overall SC but also amplifies the negative impact of downstream disruption, and such a superimposed effect increases marginally with the rise of the upstream disruption coefficient.

(c) Partial downstream disruption and upstream disruption

This section focuses on Scenarios S_9, S_{12}, and S_{15}, where the downstream experiences a partial disruption ($\alpha_2 = 0.3$) and the upstream undergoes disruptions of varying degrees. These scenarios are compared with the baseline scenario S_6 of partial downstream disruption to investigate the superimposed impact of upstream disruption severity on SC performance. The simulation results are shown in Table 2.

Against the backdrop of partial downstream disruption, changes in the upstream disruption coefficient exert a significant impact on the total cost and total profit of the SC, and the magnitude of such impact increases marginally as the disruption coefficient rises. However, relative to scenarios with simultaneous partial upstream and downstream disruptions, the variation ranges of total cost and total profit are narrower when only partial downstream disruption is coupled with upstream disruption. This indicates that, given partial downstream disruption, the impact intensity of upstream disruption is weaker than that of downstream disruption. This finding further corroborates the conclusion presented in Section 4.2.1 that downstream disruptions have more destructive effects.

(d) Complete downstream disruption and upstream disruption

This section simulates Scenarios S_{11}, S_{14}, and S_{16}, in which the downstream undergoes a full disruption and the upstream experiences disruptions of varying degrees. A comparison is made with the baseline scenario S_8 of complete downstream disruption to analyze the superimposed impact of upstream disruption severity on SC performance. The simulation results are presented in Table 2.

Even under the extreme condition of complete downstream disruption, the total cost and total profit of the SC still fluctuate significantly with changes in the upstream disruption coefficient. However, compared with scenarios involving complete upstream disruption coupled with downstream disruption, the variation ranges of total cost and total profit are narrower under scenarios of complete downstream disruption coupled with upstream disruption. This again verifies that the impact of upstream disruption remains weaker than that of downstream disruption even when a full disruption occurs in one segment.

This finding strengthens the core conclusion drawn earlier: the downstream segment constitutes a critical bottleneck in the SC resilience system and should be prioritized in disruption early warning and the optimization of recovery strategies.

4.3. Management Recovery Strategies

Based on multi-scenario simulation comparisons of upstream and downstream disruption ratios from the logistics providers perspective, and combined with core output indicators of each agent in the model, including capital flow, costs, and supply shortages, targeted SC management and recovery strategies can be derived from the viewpoints of the three core participants: producers, logistics providers, and distributors. These strategies are all formulated based on the typical characteristics exhibited in the simulation results under scenarios with different disruption ratios.

4.3.1. Producers: Enhancing Upstream Supply Resilience Through Tiered Response and Cost Optimization

As the source of the SC, the disruption rate at the producers level directly determines actual shipment volumes. Recovery priorities vary significantly depending on the severity of disruption:

(a) Develop a tiered inventory mechanism based on upstream disruption ratios to accurately balance supply security and inventory costs

The simulated results of the producers' actual delivery volume are depicted in Figure 4. When $\alpha_1 \leq 0.5$, the actual delivery volume can still be maintained at a minimum of 65% of the planned volume, and the logistics providers' initial inventory is sufficient to absorb short-term supply shortages. In this case, excessive inventory stocking is unnecessary to avoid cost inefficiency resulting from inventory backlog. When $\alpha_1 \geq 0.7$, the actual delivery volume plummets to below 50% of the planned volume, the logistics providers' inventory is depleted within 3-5 days, and the terminal supply gap widens to more than 40%. Under such circumstances, expedited supply should be launched immediately, priority should be given to securing highly stable transportation routes, and the risk of total supply disruption when the disruption ratio reaches 0.9 must be strictly prevented.

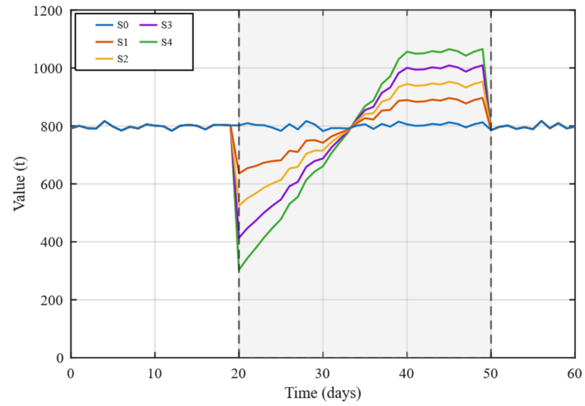


Figure 4. Actual shipment volume of producers.

(b) Optimizing the transportation cost allocation mechanism to alleviate cost pressures under high disruption rates

As shown in Figure 5, when α_1 rises from 0.3 to 0.9, the producers' marginal expedited unit transportation cost surges from 0.0107 kUSD per ton per day to 0.1360 kUSD per ton per day, representing 92% reduction in cost. Moreover, the cost growth rate increases markedly when α_1 exceeds 0.5. It is recommended to sign transportation agreements with logistics providers that are linked to the disruption ratio: settle at normal unit prices when $\alpha_1 \leq 0.5$; negotiate and implement bulk transportation discounts when $\alpha_1 \geq 0.7$ to prevent unit costs becoming uncontrolled. Meanwhile, producers should integrate transportation demand from other producers in the region and adopt a carpooling cold-chain mode to reduce empty-load rates.

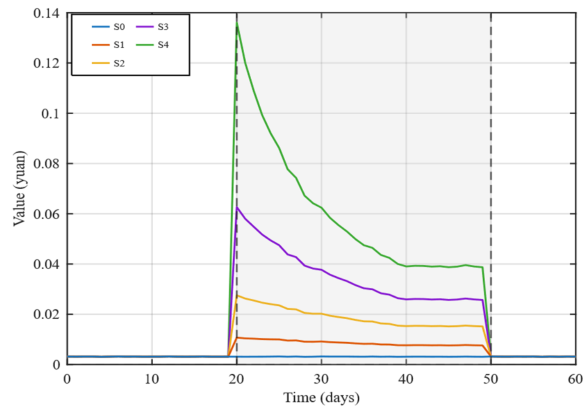


Figure 5. Marginal unit transportation cost of producers expedited supply

(c) Establish an upstream disruption early warning and information-sharing mechanism to secure response buffer time for downstream operations

The simulation results of logistics providers' inventory are shown in Figure 6. The transition period during which α_1 rises from 0.3 to 0.5 serves as a critical window for downstream logistics providers to adjust their inventory. By using Internet of Things devices to monitor in real time the impact of extreme heat on production and transportation, information can be shared with logistics providers 2-3 days in advance when an upstream disruption ratio exceeding 0.5 is predicted. This helps them adjust inventory turnover rhythms ahead of time and prevents the downstream from being put at a disadvantage due to information delays.

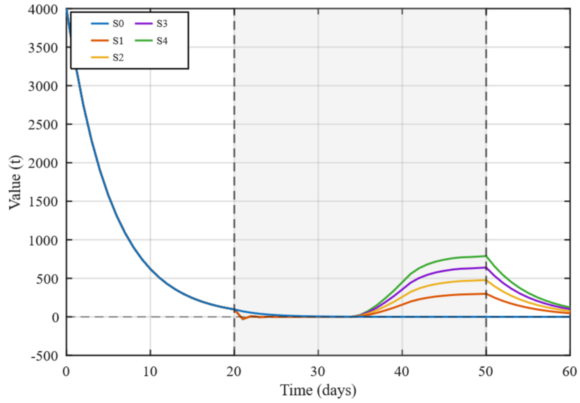


Figure 6. Inventory of logistics providers

4.3.2. Logistics Providers: Coordinating Inventory, Losses, and Expedited Orders to Balance Supply Continuity and Cost Control

As the intermediate hub of the SC, logistics providers must address both upstream and downstream disruption risks simultaneously, and serve as the only entity responsible for inventory management in the model. Simulations indicate that downstream disruptions exert a more significant impact on their operational pressure.

(a) Dynamically adjusting safety stock levels to match upstream and downstream disruption risk combinations

Under different combinations of disruption ratios, the inventory consumption rate of logistics providers varies significantly, requiring targeted safety stock strategies: for the low-risk combination ($\alpha_1 \leq 0.3$, $\alpha_2 \leq 0.3$): The average daily inventory consumption is approximately 100 units, and a safety stock equivalent to 3 days of average daily demand is sufficient. For the medium-risk combination ($0.3 < \alpha_1 < 0.7$, $0.3 < \alpha_2 < 0.5$): Inbound inventory decreases by 50%, while outbound inventory increases due to expedited demand, raising the average daily inventory consumption to 250 units. The safety stock should be increased to 7 days of average daily demand. Meanwhile, batch-based outbound delivery should be implemented to prioritize core distributors. For the high-risk combination ($\alpha_1 \geq 0.7$, $\alpha_2 \geq 0.5$): Inbound inventory plummets to 30%, and expedited outbound demand surges, resulting in inventory depletion within 2 days. Temporary inventory redistribution from surrounding regions is required, supply to non-core distributors should be suspended, and priority should be given to ensuring terminal livelihood demand.

(b) Strengthen control over high-temperature losses to reduce inventory deterioration loss during power outages

As shown in Figure 7, under extreme heat, the spoilage rate of logistics providers increases exponentially with the rise in temperature deviation, i.e., the disruption ratio. In particular, when $\alpha_2 \geq 0.5$, inventory turnover slows down and storage duration lengthens, leading to a nearly hundredfold increase in deterioration volume compared with normal conditions. In this case, low-temperature preservation upgrades should be implemented. For instance, lowering the preservation temperature from 5℃ to 2℃ can reduce the spoilage rate from 8% to 3%, generating an overall net cost saving of approximately 15%, despite a slight increase in unit preservation cost. When $\alpha_2 = 0.5$, the "ambient-temperature preservation plus rapid turnover" mode can be adopted to keep the spoilage rate below 1%. When $\alpha_1 \geq 0.7$, $\alpha_2 \geq 0.5$, and inventory overstock exceeds 5 days, near-expiry products should be promptly discounted to avoid total loss.

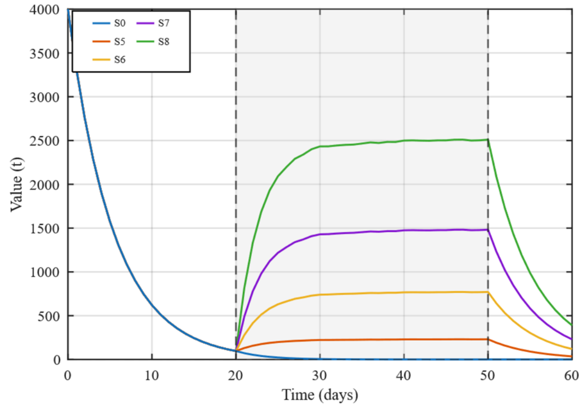


Figure 7. Inventory of logistics providers.

(c) Refine the trigger thresholds for expedited supply to prevent cost escalation caused by indiscriminate expediting

As shown in Figure 8, when α_2 rises from 0.3 to 0.7, the unit expedited transportation cost increases from 2.42 kUSD/ton to 4.3 kUSD/ton, representing an increase of 87%. It is recommended to adopt a tiered expediting strategy based on the downstream disruption ratio: When $\alpha_2 \leq 0.3$, expedited transportation is unnecessary, as demand can be satisfied through inventory buffering; When $0.3 < \alpha_2 < 0.5$, partial expediting is activated to balance supply and cost; When $\alpha_2 \geq 0.5$, full expediting is implemented, with priority given to temporarily hiring local vehicles to shorten response time.

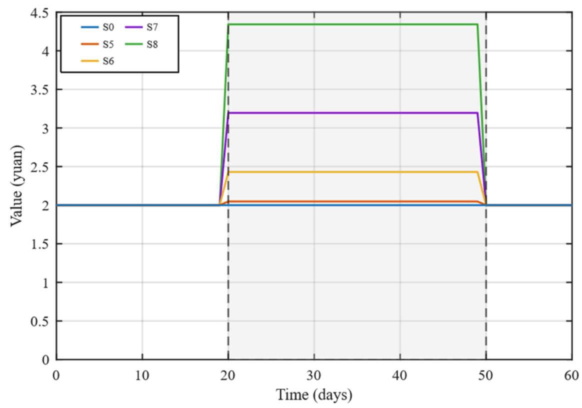


Figure 8. Unit expedited transportation cost of distributors

4.3.3. Distributors: Focus on Demand Fulfillment and Cost Control, Using Flexible Responses and End-User Coordination to Minimize Profit Losses

As an intermediary linking logistics providers and consumers, distributors' supply gap and expediting costs are directly determined by the downstream disruption ratio. Simulations indicate that their profit is most significantly affected by the downstream disruption ratio, and the following countermeasures can be adopted:

(a) Develop a joint decision-making strategy based on the downstream disruption rate and expedited shipping cost thresholds to avoid unnecessary expedited deployment

As shown in Figure 9, the downstream disruption ratio exhibits a marginally increasing relationship with the distributors' expedited transportation cost. When α_2 rises from 0.5 to 0.7, the distributors' steady-state daily expedited transportation cost increases from 1,327 kUSD to 2,526 kUSD, representing a surge of 90%, leading to a sharp decline in profit. It is recommended to set a tolerance threshold for expediting costs, for instance, limiting daily expediting costs to no more than 30% of normal profit. When $\alpha_2 \geq 0.7$ and expediting costs exceed the threshold, reliance on expedited supply should be avoided, and demand diversion measures should be activated instead. Specifically, substitutes can be recommended to non-priority consumers, while rationing can be implemented for essential customers. This approach not only safeguards basic demand but also reduces dependence on expedited transportation.

(b) Establish a collaborative disruption response mechanism with logistics providers to reduce information delay windows

In this study, the delay time of expedited supply under full disruption varies between 5 and 10 days depending on the disruption ratio, and information delay is a critical factor contributing to the widening supply gap. It is recommended to establish a real-time disruption information sharing platform with logistics providers: When logistics providers detect that the downstream disruption ratio is about to exceed 0.3, an early warning should be sent to distributors in real time, allowing distributors to issue supply alerts to consumers two days in advance (e.g., informing them that relevant products may be rationed in the next three days). When α_2 exceeds 0.5, both parties should jointly launch an emergency response team to communicate inventory status and expedited progress on a daily basis, thus avoid the dilemma of distributors still facing stockouts even though logistics providers have already arranged expedited shipments due to information asymmetry.

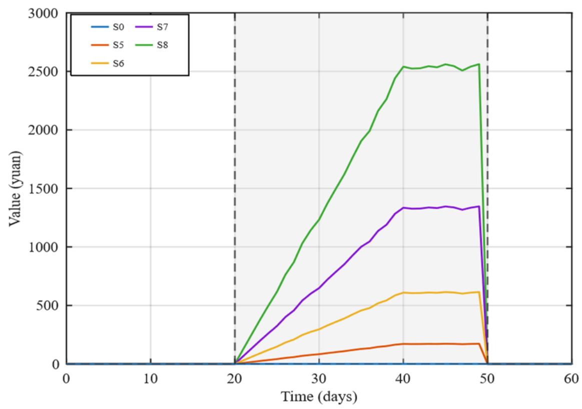


Figure 9. Cost of expedited transportation for distributors

4.3.4. Implications For Cross-Entity Collaboration: Establishing a Shared Disruption Risk System to Enhance Overall Supply Chain Resilience

Responses from a single entity are insufficient to withstand systemic risks caused by simultaneous upstream and downstream disruptions. Taking the scenario where $\alpha_1 = 0.9$ and $\alpha_2 = 0.7$ as an example, simulations show that the overall SC profit under this condition decreases by 65% compared with the normal state. Cross-entity collaboration is urgently needed to mitigate the impact, and the following countermeasures can be adopted:

(a) Establish a disruption risk-sharing fund

Producers, logistics providers, and distributors contribute to the fund based on a fixed proportion of their annual revenue, which is used for emergency redistribution, preservation upgrades, and subsidies for expediting costs during high-disruption periods. For instance, the fund subsidizes 30% of producers' inventory stocking costs when $\alpha_1 \geq 0.7$, and subsidizes 20% of distributors' expediting costs when $\alpha_2 \geq 0.5$.

(b) Develop a graded disruption response plan

Classify risk levels as low, medium, and high based on combinations of upstream and downstream disruption ratios, and clarify the responsibilities of each participant at each level. Under low risk, prioritize supply assurance for producers; under medium risk, optimize logistics providers' inventory; and under high risk, implement tripartite coordinated emergency response to avoid chaotic reactions.

In summary, the management implications for all stakeholders should be closely tied to the thresholds of disruption ratios: focus on cost optimization under low-risk conditions, emphasize the balance between inventory and supply during moderate disruptions, and prioritize emergency coordination and risk sharing in severe disruption scenarios. Only in this way can the dynamic balance between supply continuity and economic viability of the FAPSC be achieved under the new normal of frequent extreme heat events.

5. Conclusion

Based on a SD model of the capital flow within a four-echelon FAPSC, this paper incorporates the marginally increasing effect of extreme heat on the SC and the dynamic response mechanisms of various stakeholders. It systematically reveals the evolutionary characteristics of disruptions, risk transmission laws, and recovery paths of FAPSC under extreme heat, thereby providing theoretical support and practical implications for enhancing SC resilience. The core findings of this study are summarized as follows:

First, the impact of extreme heat on SC disruption exhibits nonlinear amplification. When the temperature deviates slightly from the optimal range, the disruption ratio increases moderately, resulting in only partial SC disruptions with slow impact diffusion. In contrast, when the temperature deviates severely from the suitable interval, the disruption ratio rises exponentially, and the SC rapidly deteriorates from partial disruption to full disruption, indicating clear tipping-point behavior. This finding warns that the threat of extreme heat is not linearly cumulative but presents a significant threshold effect.

Second, the disruption occurring in the downstream of the SC exert a far greater impact on the overall system than equal-proportion disruption in the upstream. The study indicates that downstream disruption is more likely to trigger the paralysis of the entire SC, which stems from the structural differences in disruption thresholds between the upstream and downstream, leading to a "downstream amplification" effect in risk transmission. A 70% disruption ratio is required in the upstream to induce full disruption, and initial inventories can buffer short-term shortages; however, merely a 50% downstream disruption ratio directly causes terminal supply gaps, exposing the vulnerable position and critical bottleneck of downstream segments in the SC resilience system.

Third, expedited supply serves as a key lever for SC disruption recovery, yet its application involves a profound trade-off between costs and benefits. Expedited supply can significantly improve the demand fulfillment rate and effectively alleviate terminal shortage pressures. Nevertheless, as the disruption ratio increases, expediting costs exhibit a marginally increasing trend, sharply squeezing the profit margins of producers and distributors. This finding uncovers the core contradiction in emergency response, namely the dynamic balance between efficiency improvement and cost control, which requires prudent consideration in strategy design.

Fourth, logistics providers' inventories play a dual buffering role. On the one hand, they can provide a short-term buffer of approximately 3-4 days against upstream supply fluctuations, mitigating the transmission of production-side shocks to the midstream. On the other hand, they can delay the emergence of terminal gaps and buy valuable time for downstream responses. However, the spoilage rate of logistics providers' inventories rises sharply under high-temperature conditions, directly eroding their profit margins, which places logistics providers under dual challenges of "buffering capacity" and "operational pressure" in SC resilience construction.

In summary, research on the disruption and recovery of FAPSC under extreme heat should focus on three core issues: precise early warning of downstream disruptions, dynamic control of expediting costs, and collaborative optimization of logistics providers' inventories. By setting differentiated disruption response thresholds, establishing a multi-stakeholder cost-sharing mechanism for expedited supply, and strengthening inventory preservation technologies under high-temperature environments, the resilience of FAPSC can be systematically improved, enhancing their adaptability in the context of frequent extreme weather events.

This study has limitations in model construction and conclusion derivation owing to data availability and other constraints, model simplification requirements, and focused research objectives. Specifically, the application of SD in FAPSC disruption research still faces challenges including difficult parameter calibration, oversimplification of real-world complexity, and simplified dynamic mechanisms. Based on the existing four-echelon SC SD model, future research can be deepened and expanded in the following directions: first, expanding research scenarios by incorporating complex contexts such as the superposition of multiple types of extreme weather and cross-regional SC linkages; second, refining variable dimensions by introducing dynamic factors including price fluctuations, demand anomalies, and policy interventions; third, elaborating action mechanisms by depicting the nonlinear evolution of delay times and cost functions under different disruption levels; fourth, integrating diverse methods by combining SD with optimization algorithms, game models, machine learning, and other approaches to improve the model's explanatory power and prediction accuracy.

Through continuous exploration in the above directions, it is expected to gradually break through the simplifying assumptions of existing models, make the research framework closer to the complex reality of FAPSC, and enhance its application value in corporate decision-making and policy formulation. Ultimately, the dual improvement of academic research depth and practical empowerment breadth can be achieved.

Disclosure Statement

This manuscript is the authors' original work, has not been published previously, and is not under consideration for publication elsewhere in whole or in part. All authors have approved the submission and agree to be accountable for all aspects of the work. The authors declare no conflicts of interest.

References

[1] Myo, M. A., & Yoon, S. C. (2014). Temperature management for the quality assurance of a perishable food supply chain. Food Control, 40(1), 198-207.

[2] Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review, 136, 101922. https://doi.org/ 10.1016/ j. tre. 2020. 101922.

[3] Gustavsson, J., Cederberg, C., Sonesson, U., van Otterdijk, R., & Meybeck, A. (2011). Global food losses and food waste: Extent, causes and prevention. Food and Agriculture Organization of the United Nations.

[4] Calvin, K. (2023). Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Core Writing Team, H. Lee & J. Romero, Eds.). Intergovernmental Panel on Climate Change. https://doi.org/10. 59327/IPCC/AR6-9789291691647.

[5] Asseng, S., & Ewert, F. (2015). Rising temperatures reduce global wheat production. Nature Climate Change, 5(2), 143-147. https://doi.org/10.1038/nclimate2470.

[6] Bayer, S. (2004). Business dynamics: Systems thinking and modeling for a complex world. INFORMS Journal on Applied Analytics, 34(4), 324-326.

[7] Ivanov, D. (2017). Simulation-based ripple effect modelling in the supply chain. International Journal of Production Research, 55(7), 2083-2101. https://doi.org/10.1080/ 00207543. 2016. 1218438.

[8] Olivares-Aguila, J., & ElMaraghy, W. (2021). System dynamics modelling for supply chain disruptions. International Journal of Production Research, 59(6), 1757-1775. https:// doi. org/ 10.1080/00207543.2020.1760370.

[9] Simchi-Levi, D., Schmidt, W., & Wei, Y. (2014). From superstorms to factory fires: Managing unpredictable supply-chain disruptions. Harvard Business Review, 92(1-2), 96-.

[10] Carter, A. M., Lusk, P. L., & Gallegos, J. L. (2016). Dynamic effects of drought on the U.S. beef supply chain. Agricultural and Resource Economics Review, 45(3), 459-484. https:// doi. org/ 10.1017/are.2016.22.

[11] Haque, S., Akbar, D., & Kinnear, S. (2020). The variable impacts of extreme weather events on fruit production in subtropical Australia. Scientia Horticulturae, 262, 109050. https:// doi.org/10.1016/j.scienta.2019.109050.

[12] Chanda, S. L., Bhat, M., Shetty, K. G., & Jayachandran, K. (2021). Technology, policy, and market adaptation mechanisms for sustainable fresh produce industry: The case of tomato production in Florida, USA. Sustainability, 13(11), 5933. https://doi.org/10.3390/su13115933.

[13] Rahman, M. M., Nguyen, R., & Lu, L. (2022). Multi-level impacts of climate change and supply disruption events on a potato supply chain: An agent-based modeling approach. Agricultural Systems, 201, 103469. https://doi.org/10. 1016/j. agsy. 2022.103469.

[14] Wang, Y. J., & He, Z. Q. (2024). Online or offline: High temperature, sales channel adjustment, and agricultural profit. International Journal of Production Economics, 269, 109153. https://doi.org/10.1016/j.ijpe.2024.109153.

[15] Akdemir, E. A., Kern, J., Smith, J. P., Limb, B. J., & Quinn, J. C. (2025). Multi-objective optimization of sustainable aviation fuel production pathways in the U.S. Corn Belt. Biomass and

Bioenergy, 193, 107590. https://doi.org/10. 1016/j. biombioe. 2025. 107590.

[16] Yim, H., & Dall'erba, S. (2025). Impact of extreme weather events on the US domestic supply chain of food manufacturing. Proceedings of the National Academy of Sciences of the United States of America, 122(41), e2424715122. https://doi.org/ 10. 1073/ pnas.2424715122.

[17] Fuerzas, I. V., Delina, L. L., & Tam, K.-P. (2025). "Crisis in the cup:" Unveiling the hazards and vulnerabilities of the Philippine coffee supply amidst emerging risks. Sustainable Development, 33(6), 9426-9443. https://doi.org/10. 1002/ sd. 70172.

[18] Hernandez-Cuellar, D., Castillo-Villar, K. K., & Castillo-Villar, F. R. (2025). Optimizing cold food supply chains for enhanced food availability under climate variability. Foods, 14(15), 2725. https://doi.org/10.3390/foods14152725.

[19] Sterman, J. D. (1989). Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. Management Science, 35(3), 321-339. https:// doi. org/ 10.1287/mnsc.35.3.321.

[20] Wilson, M. C. (2007). The impact of transportation disruptions on supply chain performance. Transportation Research Part E: Logistics and Transportation Review, 43(4), 295-320. https:// doi. org/10.1016/j.tre.2005.09.008.

[21] Shao, L., & Jin, S. (2020). Resilience assessment of the lithium supply chain in China under impact of new energy vehicles and supply interruption. Journal of Cleaner Production, 252, 119624. https://doi.org/10.1016/j.jclepro.2019.119624.

[22] Munikhah, I. A. T., Ramdhani, A. Y., & Pratama, A. Y. (2022). Scenario analysis of Indonesian ferronickel supply chain resilience with system dynamics. Jurnal Teknik Industri, 24(2), 129-140. https://doi.org/10.9744/jti.24.2.129-140.

[23] Liu, W., Li, X., Liu, C., et al. (2023). Resilience assessment of the cobalt supply chain in China under the impact of electric vehicles and geopolitical supply risks. Resources Policy, 80, 103183. https://doi.org/10.1016/j.resourpol.2022.103183.

[24] Ma, C. L., Zhang, L., Gao, X. R., et al. (2025). Modelling and evaluating wood supply chain resilience factors based on system dynamics. Scientific Reports, 15(1), 16207. https:// doi. org/ 10.1038/s41598-025-00873-6.

[25] Zhu, Y., Yang, Z., & He, Q. (2025). Simulation of pharmaceutical supply chain resilience in Hebei Province: An impact factor-capability perspective. Alexandria Engineering Journal, 122, 436-452. https://doi. org/ 10.1016/j. aej. 2025. 122.436-452.

[26] Ekinci, E., Mangla, S. K., Kazancoglu, Y., et al. (2022). Resilience and complexity measurement for energy efficient global supply chains in disruptive events. Technological Forecasting and Social Change, 179, 121634. https://doi.org/ 10. 1016/j. techfore.2022.121634.

[27] Fleisch, L., & von Dzengelevski, O. (2024). Supply chain resilience and international manufacturing strategy: A case study from the semiconductor industry. Journal of Manufacturing Technology Management, 35(6), 1151-1174. https: //doi.org/10.1108/JMTM-04-2023-0159.

[28] Piewthongngam, K., Vijitnopparat, P., & Pathumnakul, S., et al. (2014). System dynamics modelling of an integrated pig production supply chain. Biosystems Engineering, 127, 24-40. https://doi.org/10.1016/j.biosystemseng.2014.07.011.

[29] Singer, J., Kummer, Y., Weber, C., et al. (2022). Analysis of the impacts of the COVID-19 pandemic on the drinking milk supply chain in Austria by means of a business process modelling and system dynamics approach. Bodenkultur, 72(2), 73-82. https://doi.org/10.2478/boku-2022-0008.

[30] Toma, A. (2024). Endogenous fragility in opaque supply chains [Preprint]. arXiv (Cornell University). https://arxiv.org/ abs/ 2402. 14321.

[31] Sun, Z., Wang, H., Chen, J., et al. (2026). Resilience inference for supply chains with hypergraph neural network. Proceedings of the AAAI Conference on Artificial Intelligence, 40(46), 39259-39267. https://doi.org/10.1609/aaai.v40i46.32142.

[32] Hu, X. Q. (2026). Adaptive and risk recovery strategies for enhancing supply chain network resilience: A cascading failure perspective. Annals of Operations Research, 1-45. https://doi. org/ 10.1007/s10479-026-05287-8.

[33] Thomas, V. A., & Mahanty, B. (2020). Assessment of emergency sourcing strategy of a supply chain through dynamic simulation approach. Journal of Industrial and Production Engineering, 37(1), 56-69. https://doi.org/ 10. 1080/ 21681015.2019.1686044.

[34] Xi, D. (2026). Application of the LightGBM algorithm in cross-border supply chain risk management: Prediction and mitigation strategy development. Scientific Reports. https://doi. org/ 10.1038/s41598-026-47821-9.

[35] Zhang, Q., Johnson, D., & Smith, A. (2024). Heatwave impacts on U.S. lettuce supply chain: A 10-year empirical analysis. American Journal of Agricultural Economics, 106(2), 543-562. https://doi.org/10.1111/ajae.12472.

[36] Georgiadis, P., Vlachos, D., & Iakovou, E. (2005). A system dynamics modeling framework for the strategic supply chain management of food chains. Journal of Food Engineering, 70(3), 351-364. https://doi.org/10. 1016/j. jfoodeng. 2004. 06. 030.