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Partial Disruptions and Recovery Strategies in Vegetable Supply Chains under Heavy Rainfall: The Role of Irrational Purchasing Decisions

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Abstract: Heavy rainfall may impair a vegetable supply chain without shutting down the market. This paper studies that partial state and the part played by non-routine purchasing during disruption and recovery. The system dynamics model follows vegetables through farmers, distribution centers, and retailers. Rainfall-related losses in production and transport enter the same structure as deterioration, inventory adjustment, price, and demand. We compare seven scenarios. They cover normal operation, two disruption intensities, and excessive or suppressed purchasing at each intensity. Capacity falls and the supply gap grows as the rainfall shock becomes more severe; operating cost rises and total profit declines. Purchasing behavior does not change realized production capacity in the model. It changes when and how much consumers demand, which then affects prices and the supply-demand balance. Advance purchasing creates a sharp short-run gap. Suppressed purchasing reduces that pressure, although lower sales and narrower margins may reduce profit. The recovery implication depends on the source of the imbalance. Production protection and transport coordination address the physical shock, while inventory rules and consumer communication address the response to it. The model therefore adds a behavioral demand channel to operations-research analysis of climate-related disruption in perishable food systems.

Keywords: Heavy Rainfall; Vegetable Supply Chains; Partial Disruptions; Irrational Purchasing Decisions; System Dynamics.

1. Introduction

Extreme precipitation has become a recurring operational problem for vegetable supply chains. These chains often cover long distances, pass through several handling points, and carry products with short shelf lives. Heavy rainfall can therefore reduce harvests and block transport at the same time; the remaining inventory offers only a limited buffer. The temporary shortages of tomatoes and cucumbers in the United Kingdom in February 2023 illustrate this combination. Poor weather in Spain, Morocco, and other supply regions disrupted harvests, while transport constraints tightened availability and led several supermarkets to limit purchases (Reuters 2023). UK grocery price inflation had already reached 16.7% in January 2023 (Kantar 2023), adding to the pressure on food markets. China presents a different scale but a similar operational exposure. Production is concentrated in major growing regions, while much of the demand lies in large and medium-sized cities, so cross-regional transport connects spatially separated supply and consumption. Rain that affects fields, harvesting, and roads can quickly appear as an urban shortage or price change. During prolonged rainfall in 2021, for example, prices for several vegetables rose sharply in Beijing wholesale markets, including Xinfadi (Reuters 2021; Xinhua 2021).

Rainfall enters the chain at several points. Waterlogging, damaged facilities, and interrupted harvesting reduce farm output and make short-run production less predictable. Road restrictions and cold-chain delays then slow deliveries and increase losses before produce reaches the market. Consumers face incomplete information about both availability and quality, so their purchasing may also change. The disruption is consequently physical and behavioral: production and logistics determine what can be supplied, while demand responses feed back into orders, inventories, and prices.

Purchasing during a sudden shock need not follow normal demand patterns. Sheth et al. (2020) link crisis conditions to greater uncertainty and concern about access to resources. Some consumers buy early or in unusually large quantities because they expect shortages or price increases. Others postpone purchases because travel is difficult, product quality is uncertain, or household income is under pressure. The two responses move demand in opposite directions, but both weaken the usual information conveyed by price and inventory. Advance purchasing concentrates demand in a short period and may create an acute supply gap. Delayed purchasing slows turnover; for perishable vegetables, this can increase waste and handling cost even as the immediate shortage recedes. These are not necessarily one-day effects. Orders, inventory, perceived scarcity, and prices can reinforce one another, allowing a modest rainfall shock to persist or grow after the initial disturbance.

Song et al. (2021) used system dynamics to study Singapore's urban vegetable supply chain during COVID-19, with production contraction and consumer stockpiling as major sources of shortage. Heavy rainfall creates a different problem: capacity loss, congested logistics, and deterioration develop together, yet the chain may continue to function. Research has also said relatively little about why rainfall-related risk produces either excessive or suppressed purchasing, or how the two responses alter recovery. We address three questions:

RQ1 asks how a partial disruption travels through a vegetable supply chain during heavy rainfall and which links are most exposed.

RQ2 asks how the disruption changes production capacity, the supply gap, total cost, and total profit.

RQ3 asks whether excessive and suppressed purchasing change that process and what the differences imply for recovery.

The analysis connects three elements that are often modeled separately: rainfall damage, perishability, and purchasing behavior. Their interaction is represented in one three-tier system dynamics model. Scenario comparisons then trace production capacity, the supply gap, cost, and profit as disruption intensity and demand behavior change. The same comparisons show managers where shared information or coordinated decisions may curb a demand surge or prevent excess perishable inventory.

2. Literature Review

2.1. Risks in Vegetable Supply Chains Under Extreme Weather

Work on weather risk in vegetable supply chains has developed unevenly. Cross-country studies first established broad links between disasters and agricultural output. Lesk et al. (2016), for instance, found detectable national yield losses from droughts and heat waves in long-run data. Evidence for heavy rainfall is thinner, and output correlations alone say little about what happens after crops leave the field. A chain-level account must also consider quality loss, transport, and recovery.

Crop research supplies part of the explanation. Bisbis et al. (2018) linked changing precipitation to yield, quality deterioration, and postharvest loss. Parajuli et al. (2019) placed production inputs, handling, and cold-chain management in the same analytical frame. Dumitru et al. (2023) found relatively few studies devoted specifically to vegetables and called for closer attention to rainfall-related variation in yield, quality, and safety. Evidence from supply-chain participants points in the same direction. Thompson et al. (2023) observed nonlinear loss increases and longer recovery after floods. Tchonkouang et al. (2024) noted that research still concentrates on production shocks. We therefore examine production and transport together with sales.

Distribution studies show why farm output is only one part of the problem. Flooded roads can leave produce physically available but inaccessible to buyers (Wiśniewski et al. 2020). Esmalian et al. (2022) found that congestion and recovery also vary across locations and that static access measures miss this variation. Retail operations may remain impaired after roads reopen: Rosenheim et al. (2024) recorded shorter opening hours and suspended fresh-food sales after disasters. Demand can move at the same time. Yu et al. (2022) attributed changes in price and transaction volume during heavy rainfall to both reduced supply and changing demand, with warnings influencing expectations. Beatty et al. (2019) likewise found that forecasts brought emergency purchases forward into a short period.

Existing evidence links heavy rainfall to crop damage, obstructed transport, and volatile retail markets. It says less about how these changes develop together while the chain remains partly operational. Demand studies document forecast-driven advance purchasing, but seldom include that behavior, or suppressed purchasing, in the feedback among supply gaps, inventories, and prices for perishable vegetables. A system dynamics model can represent these relationships and their delays over time.

2.2. System Dynamics-Based Research on Supply Chain Disruptions

System dynamics (SD) represents stocks and flows together with delays and feedback (Sterman et al. 2015). That structure suits a setting in which inventory, production capacity, and demand continue to move throughout disruption and recovery. A static or single-period model cannot trace the same sequence directly. Scenario runs make it possible to compare responses while keeping the assumptions fixed. Hosseini et al. (2016) caution that resilience has several dimensions. We therefore report the performance drop and later system behavior separately instead of compressing them into one measure.

The ripple-effect literature shifted attention from an isolated failure to its movement through a network. Ivanov et al. (2014) described how a disturbance passes through supply, production, and distribution and exposes trade-offs between efficiency, flexibility, and resilience. Ivanov (2017) then used simulation to trace the path, duration, and losses of a disruption, including partial and complete failures and emergency actions. The COVID-19 application in Ivanov (2020) showed that closure timing, lead times, and delayed feedback affect losses as much as disruption duration. Ghadge et al. (2022) reached a similar conclusion for simultaneous disturbances in supply, demand, and logistics: propagation depends on both the individual risks and their combination.

Later studies used dynamic models to test operational responses. Rahman et al. (2023) combined agent-based modeling and optimization to compare capacity, raw-material, transport, and inventory measures during COVID-19. Their results favored coordinated adjustment over reliance on one lever. In disaster logistics, Peng et al. (2014) modeled how uncertainty and response choices shape inventory and recovery after earthquakes. Katsoras et al. (2022) used SD in a closed-loop chain with recycling and reprocessing. Although these settings differ from vegetable distribution, they show how a model can connect an external shock to several operating stages and compare policy responses over time.

Perishable products add deterioration to the usual shortage problem. Song et al. (2021) modeled an urban vegetable chain in which hoarding and supply constraints changed both the supply gap and waste. In some runs, hoarding produced a larger gap than a supply contraction of similar size. Alzubi et al. (2023) examined citrus and compared labor deployment, reverse logistics, and loss reduction. These studies imply that adding capacity or inventory is not always enough. Short shelf lives make turnover, loss control, and demand management part of the recovery decision.

Vegetable chains exposed to heavy rainfall present a specific modeling problem. They can lose capacity, incur higher costs, and distribute more slowly without suffering a complete supply failure. Few models describe this intermediate condition explicitly. Purchasing is also commonly imposed as an external demand shock, which omits the feedback among perceived scarcity, orders, inventory, and price. The present model includes both the physical disruption and the demand response so that excessive and suppressed purchasing can be compared at two rainfall intensities.

2.3. Research on Consumers' Irrational Purchasing Decisions

Research first documented unusual buying during crises and later tried to define it more carefully. Sheth (2020) associated crisis purchasing with reduced access, greater perceived risk, and channel switching. In a review of COVID-

19 panic buying, Billore et al. (2021) found that the literature had moved beyond isolated stockpiling toward explanations involving product categories, emotions, and expectations of scarcity. Lindell (2024) questioned the broad label 'panic buying' and distinguished precautionary stocking from disordered or excessive behavior. This distinction matters because an unusual purchase is not necessarily irrational.

Explanations of excessive purchasing draw on several mechanisms. Lehberger et al. (2021) linked stockpiling to attitudes, subjective norms, and concern about future availability. Naeem (2021) described how social media can spread fear, uncertainty, scarcity cues, and conformity pressure. Omar et al. (2021) connected uncertainty, perceived severity, scarcity, and anxiety to attempts to regain control through purchasing. Bentall et al. (2021) added individual differences and psychological distress. The studies differ in emphasis, but all treat purchasing as a response to information and perceived risk rather than a fixed demand increase.

The operational consequence is an altered order stream. Wang et al. (2016) showed that demand variation can grow as orders travel upstream, the familiar bullwhip effect. A crisis makes the initial change sharper. In the vegetable model of Song et al. (2021), consumer stockpiling caused shortages more severe than a moderate supply contraction and could produce shortage and waste at the same time. Purchasing therefore belongs inside the inventory-order-price feedback, not outside the supply chain as a one-off disturbance.

Demand may also fall. Consumers can delay a purchase when access is poor, quality is uncertain, or a substitute is available. Tarabashkina et al. (2025) found that consumers often avoided climate-affected produce when an equally priced substitute was offered; preferences, price sensitivity, and empathy toward farmers influenced the choice. Heavy rainfall can thus produce either advance buying or suppressed demand. Both forms are included in our scenarios.

Crisis-purchasing research has moved from documenting unusual behavior to explaining its psychological and informational causes and, later, its effects on supply chains. Vegetable studies still emphasize excessive purchasing more than delayed or suppressed demand. Consumer behavior is also often placed outside the operational model. Here, excessive and suppressed purchasing enter the demand feedback directly, allowing their effects on supply, inventory, and price to be compared.

2.4. Synthesis and Research Gaps

Weather damage, disruption propagation, and crisis purchasing are well established as separate topics. Their interaction in a vegetable chain that remains partly operational has received less attention. Most of the available models concern pandemics or general disasters, and few examine heavy rainfall together with perishability and opposing demand responses. Our model narrows the question to the joint movement of production loss, transport delay, inventory, demand, and price.

3. Model Description

We use a three-tier structure grounded in two earlier descriptions. Song et al. (2021) represented Singapore's largely import-dependent urban system with suppliers, retailers, and consumers. Zhang et al. (2019) described a comparable Chinese chain in which farmers sell through collectors to vendors, with some direct family links. For the present model, these roles are expressed as farmers, distribution centers, and retailers. Parameter choices draw on the National Agricultural Product Cost and Revenue Data Compilation 2025 (National Development and Reform Commission Price Department and National Development and Reform Commission Price Cost and Certification Center 2025).

Figure 1 sets out the causal loops used in the model. Rainfall reduces supply, but the resulting path is not one-way: constrained availability changes perceived scarcity and demand, while orders and inventory adjustments feed back into distribution and recovery.

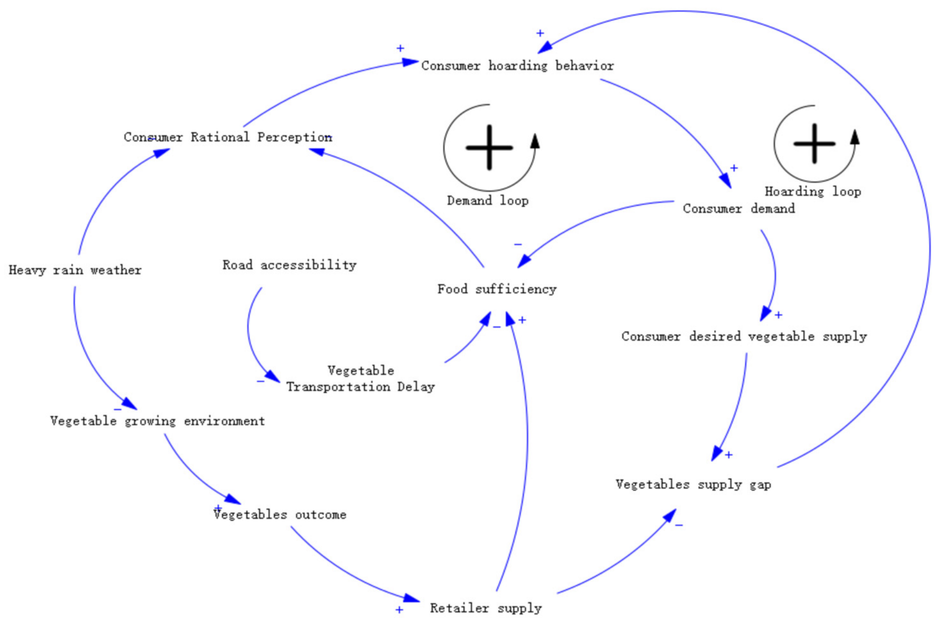

Fig 1. Causal Loop Diagram

The first effect of heavy rainfall is a reduction in effective supply through lower production capacity, slower transport, and greater loss. Market availability falls and uncertainty rises. Demand may nevertheless increase when consumers interpret limited information as evidence of scarcity or future price increases. Retail orders transmit that response upstream, creating a feedback channel through which purchasing behavior can enlarge the original disruption.

Excessive purchasing brings orders forward and raises the load on inventory and transport during the period when capacity is already constrained. Higher perceived risk increases demand; tighter supply can then strengthen the same perception. Suppressed purchasing follows a different route. Lower sales slow inventory turnover and may increase deterioration, reallocation, and unit cost. It can therefore ease the immediate supply gap while making recovery less efficient.

Purchasing behavior is thus modeled as part of the disruption process, not simply as an external response. Demand and inventory feedback can turn a mild rainfall shock into a more severe operating state. The causal loop diagram provides the structure for testing that proposition quantitatively.

Table 1. Symbol definitions

Variable *Type*	*Parameter*	Indices	*Numeric*	Unit
Subindex	*Tier*	j	*Represent respectively Farmers, Distribution Centers, Retailers*	*dmnl*
	Time	t		*days*
State Variable	*Order Transit*	O_{jt}		*t*
	Inventory	I_{jt}		*t*
	Cumulative Total Cost	TC_{jt}		¥
	Cumulative Total Profit	TP_{jt}		¥
Constant	*Simulation Time*	ST		*days*
	Disruption Start Time	$Sday_j$	*40*	*days*
	Disruption End Time	$Fday_j$	*60*	*days*
	Delay Time	DT	*1*	*days*
	Step Size	$Step$	*1*	days
	Vegetable Planting Area	VPA	*150*	*mu*
	Unit Labor Cost	ULC	*¥1,845*	*¥/mu*
	Unit Material and Service Cost	$UMSC$	*3313*	*¥/mu*
	Incremental Production Cost Rate	EIR	*0.2*	*dmnl*
	Natural Loss Rate	$VPOE$	*0.1*	*dmnl*
	Vegetable Input-Output Coefficients	I_{j0}	*1*	*dmnl*
	Initial Inventory	TRC	*1500/1500/1500*	*t*
	Truck Capacity	TFU	*20*	*t*
	Cost Per Truck	$PICR$	*100*	*¥/truck*
	Price Growth Rate	PGR_j	*3*	*dmnl*
Auxiliary Variable	*Additional Loss Rate*	EIR		*dmnl*
	Vegetable Production Inputs	VPI		¥
	Vegetable Output Fluctuation Coefficient	VDC		*dmnl*
	Weather Impact Coefficient	WSC		*dmnl*
	Market Demand	MD_t		*t*
	Irrational Purchase Coefficient	IBC		*dmnl*
	Consumer Demand Coefficient	CDC		*dmnl*
	Number of Trucks	TRn_{jt}		*truck*
	Transportation Cost	TC_{jt}		¥
	Transportation Delay Penalty Coefficient	$TDPC$		*dmnl*
	Base Unit Cost	BUC_{jt}		¥
	Procurement Cost	PC_{jt}		¥
	Selling Price	P_{jt}		¥
	Irrationality Price Coefficient	$IBPC$		*dmnl*
	Inventory Cost	IC_{jt}		¥
	Maintenance Cost Rate	MCR		*dmnl*
	Supply Gap	VSG		*t*
	Weather Price Coefficient	$WPAC$		*dmnl*
Rate Variable	*Order Inflow*	OI_{jt}		*t*
	Order Delivery	OD_{jt}		*t*
	Vegetables Produced by Farmers	Q_t		*t*
	Delivered Vegetables	DV_{jt}		*t*
	Total Cost	CV_{jt}		¥
	Total Revenue	IE_{jt}		¥
	Total Profit	PV_{jt}		¥

3.1. System Dynamics Model of Supply Chain Disruption

Assumptions:

(1) Farmers' production processes have constant returns to scale: the output elasticities in the Cobb-Douglas production function sum to 1. Song et al. (2021) use the same assumption.

(2) The market places orders with retailers each day, following the operating pattern for perishable-goods retail described by Huber et al. (2021).

(3) In the study setting, transportation costs are borne by the receiving party, following the common settlement practice of payment upon delivery.

The full stock-and-flow diagram for each supply chain tier and the overall supply chain is provided in Appendix A (Fig. A1).

3.2. Mathematical Formulations

This section presents detailed equations, with each variable assigned a corresponding symbol. All symbols and their definitions are listed in Table 1.

3.2.1. Market Demand Module

Market demand on day t fluctuates around its baseline and is modified by the purchasing-behavior coefficient in Eq. (1). The order subsystem converts this demand into tier-level orders. Farmers and distribution centers receive the upstream demand signal; distribution centers and retailers receive shipment volumes through the logistics flow. Equation (2) gives the order balance for each tier.

$$MD_t = CDC*\left(1+IBC\right) \tag{1}$$

$$O_{jt} = \begin{cases} OI_{(j+1)t} & j=1,2 \\ MD_t & j=3 \end{cases} \tag{2}$$

3.2.2. Production Module

Song et al. (2021) used a constant-returns Cobb-Douglas function for Singapore's local vegetable output, with labor, capital, land, and total factor productivity as inputs. We retain that functional form but parameterize it with cultivated area and vegetable-specific unit costs for labor, materials, and services. Equations (3) and (4) give output and input expenditure, respectively.

$$Q_t = OC*VPI^{VPIOE}*WSC \tag{3}$$

$$VPI = VPA*\left(ULC+UMSC\right) \tag{4}$$

3.2.3. Inventory Module

Inventory at each tier follows the stock balance in Eq. (5), beginning from the initial levels needed for routine operation. Natural deterioration depends on storage conditions; rainfall-related changes in temperature and humidity add further loss. Purchasing deviations can also require reallocation or additional dispatch. Shipments take time, so a flow delay represents the lead time between tiers. Equation (6) defines the farmers' final daily delivery.

$$I_{jt} = I_{j0} + \left(1-NIR-EIR\right)*\int_0^t \left(OI_{jt} - OD_{jt}\right)dt \tag{5}$$

$$DV_{jt} = \begin{cases} DelayFlxed\left(OI_{jt},1,0\right) & j=1,2 \\ MD_t & j=3 \end{cases} \tag{6}$$

3.2.4. Transportation Module

Equation (7) converts delivery volume into the required number of trucks using the rated safe payload. Whenever the load exceeds that payload, the model assigns another vehicle.

$$TRn_{jt} = \begin{cases} 0, & \dfrac{OD_{jt}}{TRC} = 0 \\ 1, & 0 < \dfrac{OD_{jt}}{TRC} < 1 \\ ceil\left(\dfrac{OD_{jt}}{TRC}\right), & \dfrac{OD_{jt}}{TRC} - floor\left(\dfrac{OD_{jt}}{TRC}\right) > 0.01 \\ floor\left(\dfrac{OD_{jt}}{TRC}\right), & O.W. \end{cases} \tag{7}$$

Truck numbers determine the main transport cost at each tier. Purchasing deviations can add tasks: excessive purchasing raises peak shipment loads, whereas suppressed purchasing may generate returns or exchanges. Equation (8) represents these tasks through a higher transport delay-penalty coefficient.

$$TC_{jt} = TRn_{jt}*(1+TDPC) \quad j=2,3 \tag{8}$$

3.2.5. Supply Chain Performance Module

Costs, prices, and profit are calculated at each tier. Following Olivares-Aguila et al. (2021), Eq. (9) defines base unit cost as the tier's primary cost component multiplied by its incremental cost rate.

$$BUC_{jt} = \begin{cases} VPI*(1+PICR_j) & j=1 \\ PC_{jt}*PICR_j & j=2,3 \end{cases} \tag{9}$$

The procurement cost at each tier is specified in Eq. (10).

$$PC_{jt} = P_{j\text{-}1}*OD_{j\text{-}1t} \quad j=2,3 \tag{10}$$

At each tier, the sales price is calculated as the product of the corresponding base unit cost and the price growth rate. Under heavy rainfall, however, consumers' irrational purchasing decisions can distort pricing dynamics; the resulting price formulation is given in Eq. (11).

$$P_{jt} = BUC_{jt}*(1+PGR_j+IBR_j) \tag{11}$$

The inventory cost is specified in Eq. (12), and the total cost is defined in Eq. (13).

$$IC_{jt} = I_{jt}*BUC_{jt} \tag{12}$$

$$CV_{jt} = \begin{cases} VPI+IC_{jt} & j=1 \\ PC_{jt}+IC_{jt}+TC_{jt} & j=2,3 \end{cases} \tag{13}$$

At each tier, revenue is calculated as the product of the corresponding delivered volume and sales price. Profit at each tier is defined in Eq. (14).

$$PV_{jt} = IE_{jt} - CV_{jt} \tag{14}$$

3.3. Model Validation

Model checking covered structure and behavior. For the structural check, we traced every link among production, distribution, and consumption against ordinary supply-chain operations. We then reviewed rate equations, stock equations, variable bounds, and the definitions in Table 1 for consistency with one another and with vegetable-chain practice.

The behavioral check uses profit reduction. Simulated changes are compared with public observations from major production areas, distribution actors, and markets during the 2021 Zhengzhou and 2024 Chongqing rainfall events, including Shouguang in Shandong and Wanbang in Henan. Table 2 reports the comparison.

Table 2. Behavioral Validation

Verification Metric	Mild Actual Value	Mild Simulation Value	Error Rate	Severe Actual Value	Severe Simulation Value	Error Rate
Profit reduction	19%-22%	19.8%	±4%	37%-40%	37.6%	±2.1%

Table 2 places the simulated profit reductions beside the real-event reference values. The difference is below 5% for both disruption levels. The model therefore reproduces the observed direction and approximate size of rainfall-related profit loss closely enough for the scenario comparisons used here.

4. Numerical Study and Results Analysis

The numerical study begins with three runs that hold purchasing behavior constant. S0 is normal operation, S1 is a mild rainfall disruption, and S2 is a severe disruption. Their trajectories isolate how rainfall moves through the chain and changes the four performance measures.

Four further runs add consumer behavior. S3 and S5 impose excessive purchasing under mild and severe disruption; S4 and S6 impose suppressed purchasing at the same two levels. Parameter ranges draw on historical rainstorm disturbances, with the July 2025 Beijing event used as the reference case. Beijing issued its highest rainstorm alert, while road, electricity, and communication interruptions in mountainous and northern areas constrained logistics and regional supply (Xinhua 2025; Beijing Municipal Government 2025).

The event did not shut down the whole market. Xinfadi received about 19,000 tons of vegetables per day, average prices moved only slightly, and overall supply remained broadly stable (People's Daily Online 2025; Beijing Business Today, 2025). Local blockages alongside continued market operation match the partial-disruption setting used here. Vensim runs the model for 90 days at a one-day time step.

4.1. Partial Disruptions in the Vegetable Supply Chain under Heavy Rainfall

4.1.1. Scenario parameter settings

S0 supplies the no-rainfall baseline. S1 and S2 then apply different shock intensities so that the transmission path can be compared under mild and severe conditions.

S1 represents a typical heavy-rainfall event. The empirical settings are a 30% loss of production capacity, a 15% additional loss rate, a 30% maintenance cost rate, and a 150% transport delay penalty.

S2 represents rainfall accompanied by flooding and road disruption. Production capacity falls by 60%, the additional loss rate is 30%, the maintenance cost rate is 60%, and the transport delay penalty is 250%.

All three runs place the disruption on days 40-60. Table 3 lists the remaining settings.

Table 3. Scenarios for Analyzing the Impact of Partial Disruptions

Scenario	Scenario Name	Production Capacity Loss Rate	Additional Loss Rate	Maintenance Cost Rate	Transportation Delay Penalty Rate	Downtime
S0	Normal Scenario	-	-	-	-	-
S1	Mild Disruption	30%	15%	30%	150%	40-60
S2	Severe Disruption	60%	30%	60%	250%	40-60

4.1.2. Quantitative Analysis of Core Supply Chain Metrics Under Partial Disruptions

Day 50 is used for the cross-scenario comparison in Table 4. By then the rainfall shock has taken effect, but recovery has not started. Cost and profit are cumulative values produced by the simulation, not observed market totals.

Table 4. Comparison of Core Indicators Under Different Disruption Scenarios (Day 50)

Scenario	Vegetable Production Capacity (t)	Supply Gap (t)	Total Supply Chain Cost ($\times10^{17}$ CNY)	Total Supply Chain Profit ($\times10^{17}$ CNY)
S0	710.3	-205.9	2.1	3.4
S1	497.2	1456.0	2.7	2.8
S2	284.1	2522.5	3.3	2.2

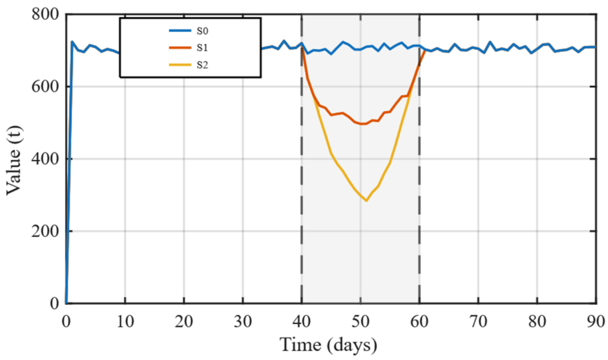

Fig 2. Vegetable Production Capacity under Partial Disruption Scenarios

Figure 2 separates the three capacity paths after day 40. S0 remains near its normal level. By day 50, S1 has fallen to 497.2 t and S2 to 284.1 t. Capacity begins to recover after day 60 in both disrupted runs. The ordering of the paths follows the imposed loss rates.

The supply gap in Figure 3 responds more strongly as the shock increases. At day 50 it is 1,456.0 t in S1 and 2,522.5 t in S2. S0 remains negative, meaning supply still exceeds demand. The difference between S1 and S2 comes from the combined loss of capacity and slower transport.

Figure 4 reports cumulative cost of 2.7×10^{17} CNY in S1 and 3.3×10^{17} CNY in S2 at day 50. Extra deterioration and transport-delay penalties account for the increase. Rainfall worsens storage conditions, raises cold-chain requirements, and forces detours.

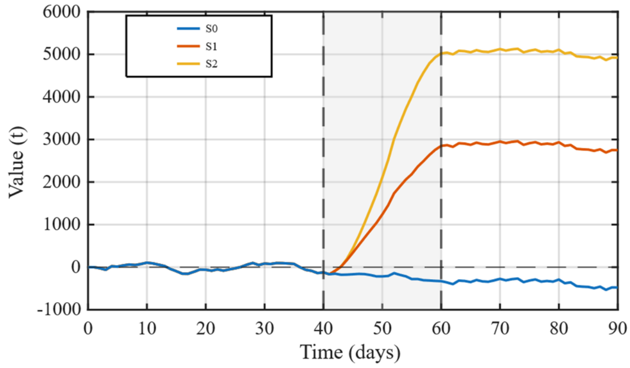

Fig 3. Supply Gap under Partial Disruption Scenarios

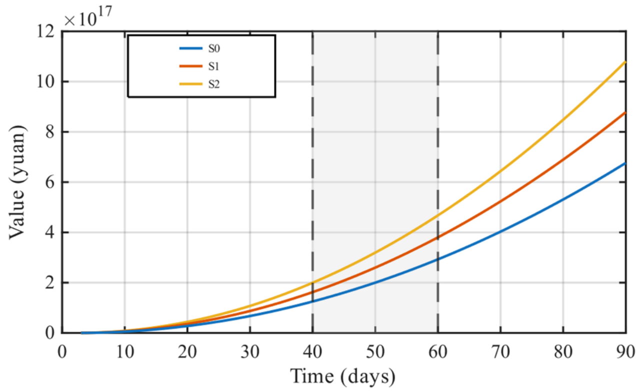

Fig 4. Total Cost under Partial Disruption Scenarios

Profit moves in the opposite direction (Fig. 5). It falls to 2.8×10^{17} CNY in S1 and 2.2×10^{17} CNY in S2 at day 50. Lower capacity and higher cost therefore appear downstream as a reduction in total supply-chain profit.

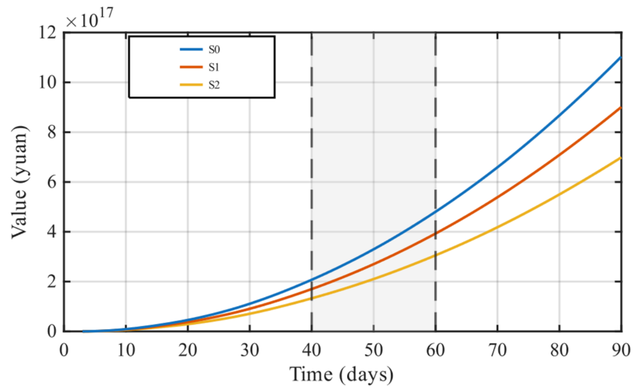

Fig 5. Total Profit under Partial Disruption Scenarios

The baseline runs keep purchasing behavior fixed. Rainfall first reduces production capacity and slows distribution. The supply gap then grows, deterioration and delay add cost, and profit falls. S2 shows a larger change than S1 in each measure. These trajectories provide the reference case for the purchasing experiments.

4.2. Effects of Irrational Purchasing Decisions on Partial Disruptions

4.2.1. Scenario Parameter Settings

The behavior experiment adds four runs to the rainfall baseline. S3 and S4 pair mild disruption with excessive and suppressed purchasing. S5 and S6 apply the same demand responses under severe disruption.

Excessive-purchasing runs raise both the demand coefficient and price growth rate by 50%. Suppressed-purchasing runs lower both by 50%. These values represent comparative shifts reported in earlier work and observed cases; they are not a calibration to one event. Table 5 gives the complete settings.

Table 5. Scenarios for Analyzing the Impact of Irrational Purchasing Decisions

Scenario	Scenario Name	Consumer Demand Coefficient	Price Growth Rate	Disruption Duration
S1	Mild Disruption + Rational Purchasing	-	-	40-60
S2	Severe Disruption + Rational Purchasing	-	-	40-60
S3	Mild Disruption + Excessive Purchasing	+50%	+50%	40-60
S4	Mild Disruption + Suppressed Purchasing	-50%	-50%	40-60
S5	Severe Disruption + Excessive Purchasing	+50%	+50%	40-60
S6	Severe Disruption + Suppressed Purchasing	-50%	-50%	40-60

4.2.2. Analysis of Core Supply Chain Metrics under Irrational Purchasing Decisions

Table 6 again uses day 50, after the shock is established and before recovery. This timing makes the demand responses easier to compare. Cost and profit remain simulated cumulative monetary values.

Table 6. Comparison of Core Indicators Under Irrational Purchasing Decisions (Day 50)

Scenario	Vegetable Production Capacity (t)	Supply Gap (t)	Total Supply Chain Cost ($\times10^{17}$ CNY)	Total Supply Chain Profit ($\times10^{17}$ CNY)
S1	497.2	1456.0	2.7	2.8
S2	284.1	2522.5	3.3	2.2
S3	497.2	3093.0	2.7	2.9
S4	497.2	-514.7	2.6	2.8
S5	284.1	3952.1	3.4	2.3
S6	284.1	650.4	3.3	2.1

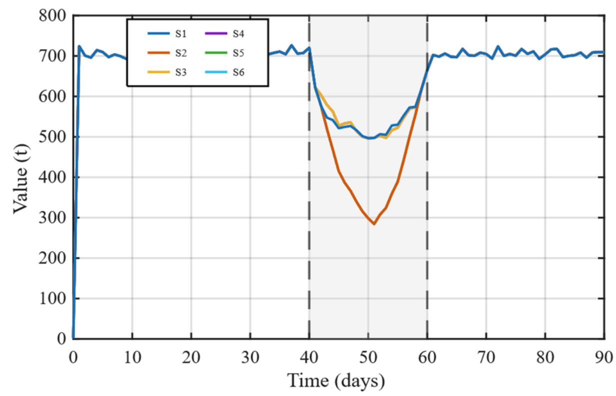

Fig 6. Vegetable Production Capacity under Irrational Purchasing Scenarios

Production capacity in Figure 6 depends on rainfall severity, not the purchasing coefficient. S3 and S4 coincide with S1, while S5 and S6 coincide with S2. Under the model assumptions, purchasing changes demand, distribution, and inventory but does not alter output already realized during the disaster.

Demand behavior separates the supply-gap paths in Figure 7. At day 50, excessive purchasing raises the gap to 3,093.0 t in S3 and 3,952.1 t in S5. Suppressed purchasing produces -514.7 t in S4 and 650.4 t in S6. The contrast occurs even though capacity is identical within each rainfall pair.

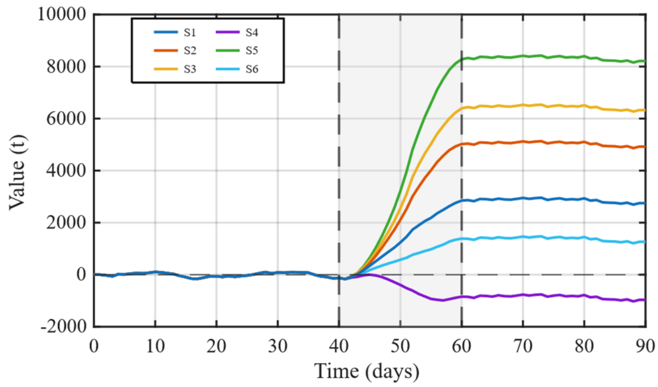

Fig 7. Supply Gap under Irrational Purchasing Scenarios

Cost does not move in one direction across the four behavior runs (Fig. 8). Excessive purchasing adds modestly to cost, especially when severe rainfall has already tightened logistics. Suppressed purchasing can reduce cost under mild disruption, but under severe disruption slow turnover and deterioration offset part of the demand reduction. The cost response therefore depends on both behavior and rainfall intensity.

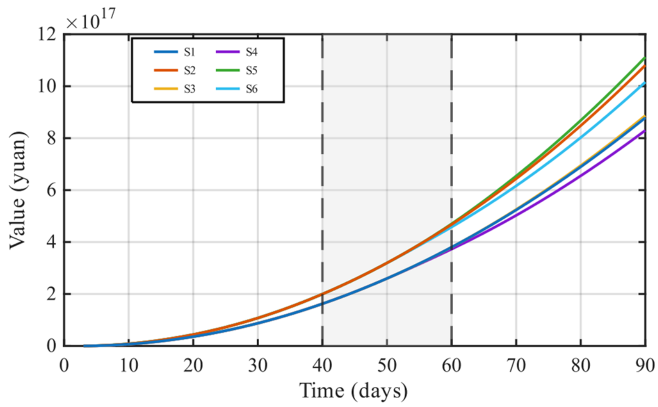

Fig 8. Total Cost under Irrational Purchasing Scenarios

Figure 9 shows the corresponding profit paths. Excessive purchasing increases sales volume and price pressure, so S3 and S5 exceed their rational-demand counterparts. Suppressed purchasing reduces volume and price, narrowing margins; S6 reaches 2.1×10^{17} CNY at day 50.

The behavior runs leave production capacity unchanged within each rainfall pair, but their demand paths diverge. Excessive purchasing concentrates orders; suppressed purchasing reduces them. Price, logistics, and inventory then adjust to those different demand paths, producing distinct supply gaps, costs, and profits.

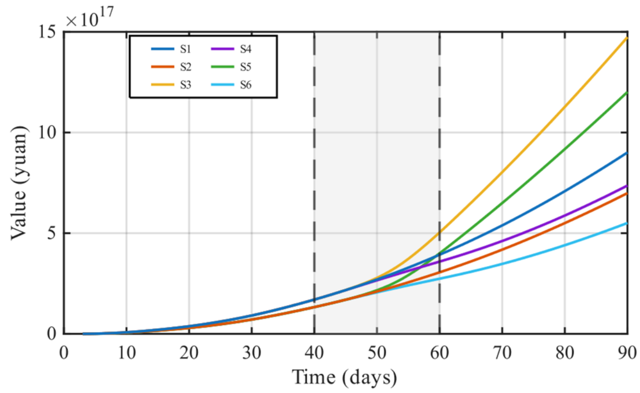

Fig 9. Total Profit under Irrational Purchasing Scenarios

5. Conclusion

The system dynamics model represents farmers, distribution centers, and retailers in a vegetable chain that continues to operate under rainfall damage. Seven scenarios separate disruption intensity from excessive and suppressed purchasing. The findings below correspond to the propagation paths and performance measures used to answer the three research questions.

5.1. Key Findings

(1) The disruption begins with lost production capacity and becomes more severe when transport is congested. The resulting supply gap and added operating cost pass downstream and reduce retail availability and total supply-chain profit.

(2) In the simulations, heavier rainfall produces a larger fall in capacity and profit and a larger increase in the supply gap and operating cost.

(3) Purchasing behavior works through demand and price rather than production capacity. Excessive purchasing brings demand forward, enlarging the short-run shortage and raising prices. Suppressed purchasing narrows that shortage but reduces sales and may compress margins.

5.2. Management Implications

No single intervention covers the entire disruption. Production protection addresses the initial capacity loss, while transport allocation and perishable-inventory rules affect the movement of available supply. Consumer information and pricing act on the demand response. The measures need to be coordinated because a decision at one tier changes conditions at the next.

Farmers and local agricultural managers can act first on upstream capacity. Once output falls, the model shows a rapid widening of downstream gaps and higher costs. Drainage maintenance, facility reinforcement, adjusted harvesting schedules, and rapid field recovery should begin when warnings are issued. Complete loss prevention is unlikely during severe rainfall. A more practical aim is to limit the capacity reduction enough to reduce later transport pressure, shortage peaks, and lost profit.

Distribution centers need different inventory and dispatch rules for mild and severe events. A buffer can smooth a short interruption, but additional stocks of perishable vegetables become costly when delivery and turnover both slow. Under mild disruption, regular turnover and stable delivery frequency take priority. Under severe disruption, managers should revise inventory ceilings and dispatch priorities as conditions change, assigning scarce cold-chain and transport capacity first to products with shorter shelf lives and more urgent demand.

Retailers need to identify why sales have changed. Excessive purchasing can enlarge the supply gap even when production is unchanged. Publishing inventories and expected arrivals, staggering replenishment, or imposing a temporary purchase limit may reduce that concentration. When consumers delay purchases, information on product quality and substitutes can support turnover; selective discounts or bundled sales offer additional options.

Information is most useful across tiers near the disruption peak. Farmers, distribution centers, and retailers need current reports on crop damage and road access alongside delivery, inventory, and demand data. Managers can then assign transport and stock according to shelf life, urgency, and local shortage instead of routine schedules. During recovery, coordinated orders and pricing reduce the chance of a second fluctuation caused by delayed deliveries, over-ordering, or a sudden reversal in demand.

Recovery begins by limiting the production loss and keeping perishable inventory moving. It also requires action on abrupt demand changes and the reallocation of transport capacity as conditions evolve.

5.3. Research Limitations and Future Directions

The model's scope imposes four limitations. It covers heavy rainfall but not heatwaves, droughts, or compound hazards. Common decision rules represent farms and distribution channels, leaving differences in actor size and arrangements such as platform distribution outside the model. Consumer behavior is limited to excessive and suppressed purchasing and does not vary with access to information or communication channels. Most parameters come from scenario assumptions and empirically plausible ranges; full calibration against a large observational dataset was not possible.

Further research could apply the framework to other weather hazards and supply-chain structures. Survey or transaction evidence would permit a more detailed behavioral module, while production and logistics records would strengthen calibration. Econometric, optimization, or agent-based components could provide additional forms of external validation.

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Disclosure Statement

The authors report there are no competing interests to declare.

Data Availability Statement:

The data that support the findings of this study are available from publicly available sources cited in the article. Further processed data are available from the corresponding author upon reasonable request.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT (GPT-5.5 Thinking, OpenAI) for language editing, grammar checking, formatting assistance, and manuscript submission preparation. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the manuscript.

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Appendix A. Stock-and-Flow Diagram of the Vegetable Supply Chain

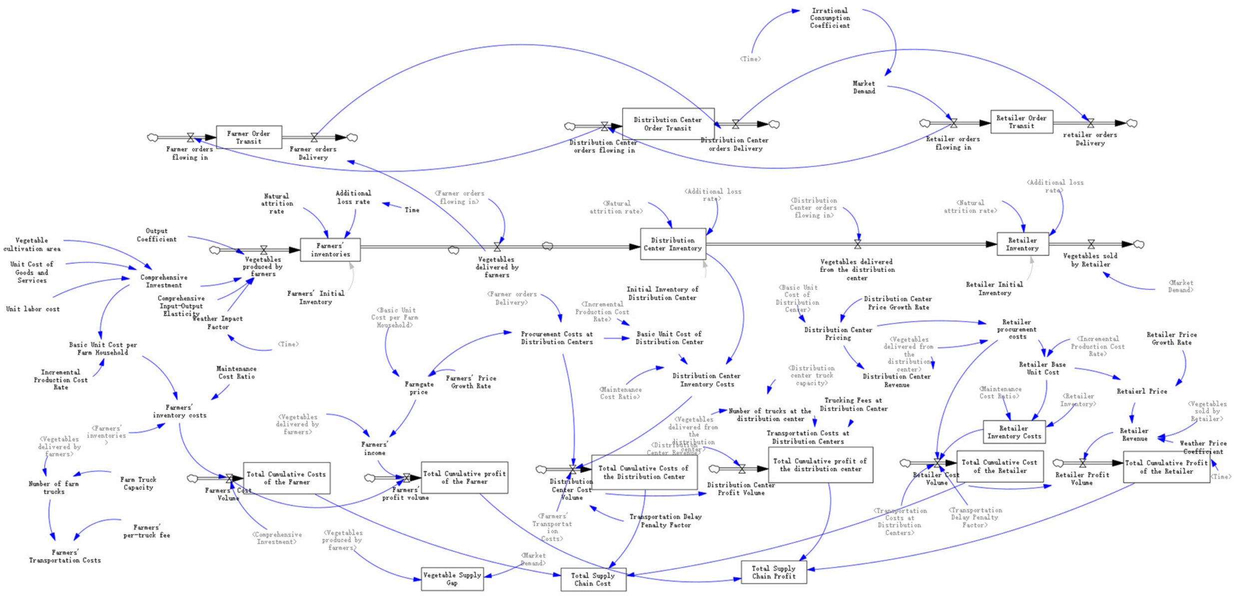

Fig A1. Stock-and-flow diagram of the vegetable supply chain.