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# AI-Driven Risk Forecasting for Strengthening the United States Food Supply Chain Resilience: Case Study: A National AI-Enabled Food Supply Chain Risk Forecasting Framework and a Data Analytics Approach to Predicting Disruptions

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## Abstract

The United States food supply chain is one of the most complex and interconnected systems in the world, spanning agricultural production, processing, transportation, storage, and retail distribution. While this complexity enables efficiency and scale, it also increases vulnerability to disruptions caused by climate change, labor shortages, geopolitical shocks, transportation failures, cyber threats, and public health crises. Conventional risk management methods, often reactive and siloed, have proven inadequate in predicting and mitigating systemic shocks that have become frequent occurrences in today's world. This article examines how artificial intelligence (AI) and data analytics can transform risk forecasting in U.S. food supply chains by enabling real-time adaptive, predictive, and prescriptive decision-making. Leveraging machine learning, predictive analytics, and integrated data ecosystems, the paper examines the various stages of the food supply chain, key drivers of disruption, analytical models, data sources, and the benefits of AI-driven risk forecasting. The study concludes that AI-driven risk forecasting offers a powerful pathway toward building a more resilient, transparent, and sustainable U.S. food system.

**Keywords:** Food Supply Chain; Artifical Intelligence; Risk Forecasting; Predictive Analytics; Supply Chain Resilience; Machine Learning

## 1. Introduction

Food supply chains are critical to national security, economic stability, public health, and environmental sustainability in the United States. The U.S. food system supplies over 330 million people with food and supports an estimated 21.5 million jobs, representing roughly 10% of the national workforce, across agriculture, food processing, transportation, warehousing, and retail. According to the U.S. Department of Agriculture(USDA) Economic Research Service(ERS), agriculture, food, and related industries contributed $1.537 trillion to U.S. GDP in 2024 (USDA ERS, 2024).

Despite its scale, the U.S. food system has shown significant vulnerability in recent years, with events such as the COVID-19 pandemic, extreme weather events, animal disease outbreaks, and geopolitical instability, including the Russia-Ukraine conflict, exposing significant fragilities in the system. Traditionally, food supply chain risk management has relied on backward-looking metrics, manual assessments, and localized contingency planning. However, these approaches often fail to capture the dynamic, nonlinear, and interconnected nature of modern supply chains. Disruptions in a single node, such as farm input shortages or trucking delays resulting from a ransomware attack crippling a logistics provider, can affect the entire system, leading to price volatility, food waste, shortages, and

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unavailability of food in extreme cases. Climate-driven extreme weather events resulted in over $21 billion in crop losses in the U.S. in 2023 (Munch, 2024), making reactive decision-making no longer a viable strategy.

Artificial intelligence (AI) and advanced data analytics, leveraging data from multiple points along the supply chain, present an opportunity to transition from reacting to crises to proactive risk forecasting. By leveraging large-scale, real-time data from satellites, weather models, IoT sensors, market indicators, and predictive modeling, AI systems can identify early warning signals, simulate disruption scenarios, and support faster, more informed decision-making. This article explores how AI-driven risk forecasting can strengthen U.S. food supply chains, focusing on analytical frameworks, practical use cases, and the strategic implications for policymakers, industry leaders, and national security planners.

## 2. The Structure and Vulnerabilities of U.S. Food Supply Chains

### 2.1. Overview of the U.S. Food Supply Chain

The United States food supply chain is a highly complex, multi-tiered system that transforms agricultural inputs into food products delivered to consumers across the nation and global markets. It is characterized by geographic dispersion, high specialization, technological intensity, and strong interdependence across the various stages of the supply chain. While this structure supports scale, efficiency, and affordability, it creates systemic vulnerabilities that allow disruptions across the entire supply chain with greater speed and intensity. The five primary stages of the U.S. food supply chain are outlined below.

#### *2.1.1. Input supply (seeds, fertilizers, feed, labor):*

The input supply stage provides the foundational resources for agricultural production, including seeds (both conventional and genetically modified), fertilizers, pesticides, animal feed, machinery, energy, and labor. Many of these inputs are produced by a relatively small number of domestic and global suppliers, creating concentration risk. Research from the International Food Policy Research Institute (IFPRI) shows that market concentration has increased across multiple agricultural input sectors, with a handful of multinational firms dominating seeds, agrochemicals, and fertilizer production (Hernandez et al., 2023). The USDA's Agricultural Marketing Service similarly reports that consolidation in the seed industry has reduced competition and limited farmer choice, contributing to higher input costs and reduced resilience during supply disruptions (USDA, 2023).

**Key Characteristics are**

- Heavy reliance on global supply chains for fertilizers, chemicals, and equipment
- Increasing dependence on advanced seed technologies and data-driven farming inputs
- Seasonal and migrant labor, critical to planting and harvesting

**Vulnerabilities***:*

- Disruptions in fertilizer and chemical supply due to geopolitical tensions or trade restrictions
- Volatility in energy and fuel prices affecting input costs
- Labor shortages driven by immigration policy, demographic shifts, and workforce aging
- Limited domestic production capacity for certain critical inputs

Disruptions at this stage can significantly increase production costs or delay planting cycles, with downstream effects on food availability and prices

#### *2.1.2. Agricultural production*

Agricultural production involves the cultivation of crops and the raising of livestock across diverse climatic and geographic regions. The U.S. is a global leader in agricultural output, supported by advanced mechanization, precision agriculture, and data-driven farm management. According to the USDA Economic Research Service, precision agriculture technologies have expanded dramatically over the past two decades, with autosteering systems used by 52% of midsize farms and 70% of large-scale crop farms in 2023, and yield monitors, yield maps, and soil maps used on 68% of large-scale farms (USDA ERS, 2024). A 2024 assessment by the U.S. Government Accountability Office further highlights that precision agriculture tools such as GPS-guided equipment, automation, and livestock activity monitors improve efficiency, reduce fertilizer runoff, and enhance animal health monitoring (US GAO, 2024). These technologies, combined with data-driven farm management systems that integrate satellite imagery, soil analytics, and real-time sensor data, enable producers to optimize planting decisions, input use, and herd management. As a result, U.S. agriculture continues to maintain high productivity despite challenges such as labor shortages, rising input costs, and climate variability.

**Key Characteristics are:**

- Regional specialization (e.g., corn and soybeans in the Midwest, fruits and vegetables in California)
- High productivity supported by technology and scale
- Extensive use of contract farming, especially for poultry and crops such as potatoes

**Vulnerabilities:**

- Climate-related risks such as droughts, floods, hurricanes, and extreme heat
- Crop diseases and livestock epidemics (e.g., avian influenza)
- Water scarcity and soil degradation
- Financial pressures on small and mid-sized farms

Since agricultural production is highly sensitive to environmental conditions, disruptions at this stage often represent the earliest and most impactful shocks to the U.S. food supply chain.

#### *2.1.3. Processing and manufacturing*

Processing and manufacturing sit at the center of the food supply chain because they transform raw agricultural products into consumable food items through activities such as milling, canning, packaging, and preservation. This stage adds significant economic value by converting perishable goods into stable, transportable, and higher-margin products, supporting a vast network of food manufacturers ranging from grain millers and meat processors to dairy plants and beverage producers. It also plays a critical role in ensuring food safety and regulatory compliance, as processors must meet federal standards for sanitation, food handling, hazard control, and traceability. Modern processing facilities increasingly rely on automation, cold-chain technologies, and digital quality-control systems to maintain consistency and reduce contamination risks. Many food categories, such as meatpacking, dairy processing, and grain milling, are dominated by a small number of large firms, and as a result, supply chain disruptions at this stage can have enormous impacts on national food availability and pricing.

***Key Characteristics are:***

- High levels of automation and capital intensity
- Significant consolidation, particularly in meat and poultry processing
- Strict regulatory oversight for food safety and quality

***Vulnerabilities:***

- Concentration of processing capacity in a limited number of large facilities
- Labor-intensive operations, vulnerable to workforce disruptions
- Equipment failures and cybersecurity threats
- Regulatory shutdowns following safety or health incidents

A disruption at a single major processing facility can have nationwide impacts, as demonstrated during the COVID-19 pandemic. In April 2020, Cargill's Hazleton, Pennsylvania plant was forced to shut down after some of its workers tested positive for COVID-19, removing a key source of beef and pork from the U.S. supply chain (Reuters, 2020). The closure of this plant and similar plants across the country contributed to broader national shortages and heightened pressure on other processing plants already struggling to maintain output.

#### *2.1.4. Transportation and distribution*

Transportation and distribution connect producers, processors, and markets through a network of trucking, rail, waterways, ports, and cold-chain logistics. This stage is essential for maintaining food freshness, minimizing waste, and ensuring timely delivery. Of the four major modes of transporting food commodities, trucking remains the dominant mode for domestic food movement, accounting for **70.5%** of U.S. food transportation, followed by rail (17%), ship (8%), and air (4.5%) (Kan-Haul, 2013). Together, these transportation systems form the backbone of national food distribution, and disruptions—whether from labor shortages, low water levels, port congestion, or freight bottlenecks can quickly ripple across supply chains, affecting availability, prices, and food quality.

***Key Characteristics are:***

- Heavy reliance on trucking for domestic food movement
- Increasing use of just-in-time inventory strategies
- Dependence on fuel availability and transportation infrastructure

***Vulnerabilities***

- Driver shortages and labor constraints
- Port congestion and rail bottlenecks
- Weather-related disruptions such as floods and snow to roads and waterways
- Rising transportation and fuel costs

Transportation disruptions can quickly lead to spoilage, inventory shortages, and price spikes, particularly for perishable goods.

#### *2.1.5. Retail and food service*

The final stage includes grocery stores, wholesalers, restaurants, institutional food services, and food assistance programs. The U.S. food retail sector is one of the largest in the world, shaped by shifting consumer behavior and rapid growth in online grocery sales. This stage directly interfaces with consumers and plays a critical role in food accessibility and affordability. The retail and food service sector collectively determines how effectively food reaches consumers, particularly low-income households, and how resilient communities are during economic or supply-chain disruptions.

***Key Characteristics are:***

- High-volume, low-margin operations
- Demand-driven inventory management
- Increasing reliance on digital platforms and e-commerce

***Vulnerabilities***

- Sudden shifts in consumer demand and purchasing behavior
- Supply shortages and inventory imbalances
- Inflationary pressures affecting affordability
- Unequal access to food in low-income and rural communities

#### *2.1.6. Mapping Risks Across the Five Stages of the U.S. Food Supply Chain*

The table below maps key risk categories to each stage of the U.S. food supply chain, highlighting disruption sources, impacts, and how AI-driven analytics can be applied for early warning and mitigation.

**Table 1** Risk Mapping Across the U.S. Food Supply Chain Stages

| Supply Chain Stage | Key Activities | Major Risk Categories | Examples of Disruptions | Potential Impacts | AI & Data Analytics Applications |
|---|---|---|---|---|---|
| 1. Input Supply | Seed production, fertilizer manufacturing, feed supply, labor provisioning | Geopolitical risk, price volatility, labor shortages, energy dependence | Fertilizer shortages, fuel price spikes, migrant labor constraints | Increased production costs, delayed planting, reduced yields | Predictive price modeling, supplier risk scoring, labor availability forecasting |
| 2. Agricultural Production | Crop cultivation, livestock raising | Climate risk, biological risk, water scarcity, financial stress | Droughts, floods, pest infestations, livestock disease outbreaks | Yield losses, income instability, upstream supply shocks | Climate forecasting models, satellite-based yield prediction, disease outbreak detection |

| | | | | | |
|---|---|---|---|---|---|
| 3. Processing & Manufacturing | Slaughtering, milling, packaging, food preservation | Capacity concentration, labor risk, equipment failure, cyber threats | Plant shutdowns, food safety incidents, cyberattacks | National supply shortages, price spikes, food waste | Anomaly detection, capacity utilization forecasting, predictive maintenance |
| 4. Transportation & Distribution | Trucking, rail, ports, cold-chain logistics | Infrastructure risk, fuel costs, congestion, weather disruption | Port delays, driver shortages, refrigeration failures | Spoilage, inventory shortages, delivery delays | Route optimization, delay prediction models, real-time shipment tracking |
| 5. Retail & Food Service | Grocery retail, restaurants, institutional food service | Demand volatility, inflation, inventory imbalance | Panic buying, supply shortages, price inflation | Food insecurity, public health impacts | Demand forecasting, dynamic inventory optimization, consumer behavior analytics |

**Table 2** Cascading Risk Effects Across Supply Chain Stages

| Originating Stage | Initial Shock | Downstream Effects | National-Level Consequences |
|---|---|---|---|
| Input Supply | Fertilizer shortage | Reduced crop yields higher feed costs | Food price inflation, export instability |
| Agricultural Production | Severe drought | Lower processing throughput | Supply shortages, increased imports |
| Processing & Manufacturing | Major plant shutdown | Distribution bottlenecks | Regional food shortages, price volatility |
| Transportation & Distribution | Port congestion | Retail stockouts | Reduced food access in urban areas |
| Retail & Food Service | Demand surge | Upstream inventory strain | Public health and food security risks |

A linear flow diagram showing the five stages of the food supply chain, overlaid with bidirectional data flows feeding into a centralized AI risk forecasting platform. The platform integrates climate, market, logistics, and labor data, generating early-warning alerts and prescriptive actions that feed back into each stage.

The above tables and conceptual diagrams demonstrate how risks emerge, propagate, and amplify across the U.S. food supply chain, reinforcing the need for AI-driven forecasting systems that provide system-wide visibility rather than siloed monitoring.

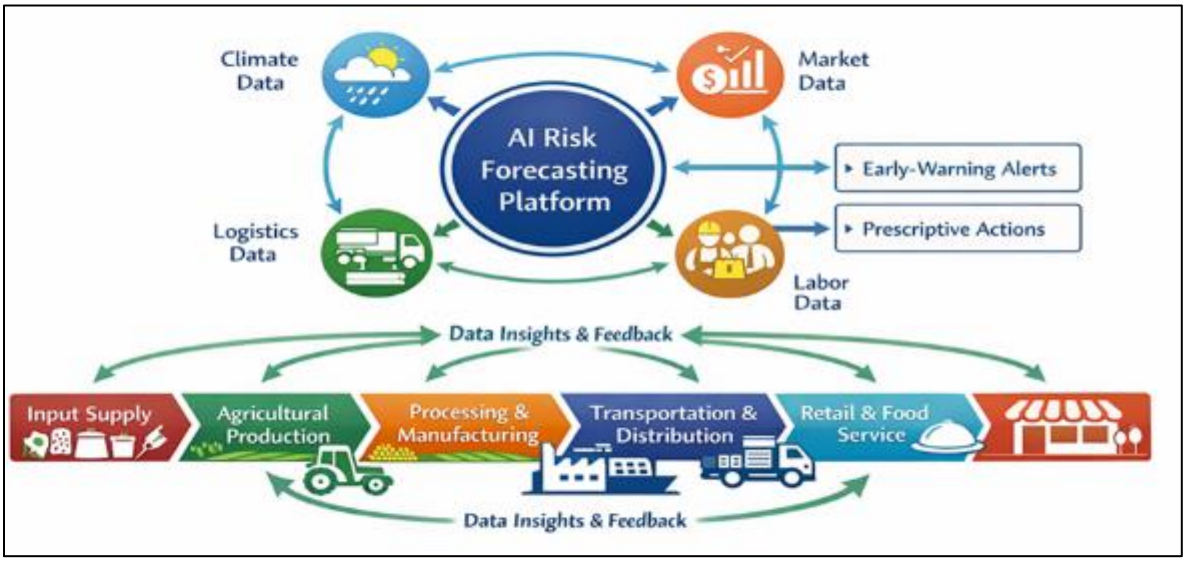


**Figure 1** AI-Enabled Risk Flow Across the U.S. Food Supply Chain

Disruptions at this stage can result in immediate social and public health impacts, with disproportionate effects on vulnerable and food-insecure populations, especially given the highly specialized, geographically dispersed nature of the U.S. food supply chain. Although this specialization enhances efficiency and scale, it also increases reliance on just-in-time logistics and concentrated processing capacity. For example, meat processing in the United States is dominated by a small number of large facilities, creating systemic vulnerability when disruptions occur. Due to the five stages being deeply interconnected, they are highly exposed to shocks that rarely remain confined to a single stage. Disruptions originating in input supply or agricultural production can rapidly propagate through processing, transportation, and retail channels, amplifying their impact across the national food system. Therefore, a comprehensive understanding of the structure and vulnerabilities at each stage is critical for developing AI-driven risk forecasting systems capable of identifying early warning signals and enabling proactive, coordinated intervention.

### 2.2. Key Sources of Disruption

U.S. food supply chains are increasingly exposed to a wide range of interconnected, systemic, and often unpredictable disruptions. These risks span environmental, biological, operational, economic, and technological domains, and their combined effects have intensified due to globalization, climate change, and increased system complexity. Understanding these disruption drivers is critical to developing effective AI-driven risk forecasting models that anticipate shocks and mitigate cascading impacts.

**Major disruption drivers in U.S. food supply chains include:**

- **Climate and environmental risks:** These risks represent one of the most significant and growing threats to U.S. food supply chains. Extreme weather events such as droughts, floods, hurricanes, heatwaves, and wildfires directly affect agricultural productivity and the reliability of infrastructure. Prolonged droughts in the Midwest and Western states reduce crop yields and strain water resources, while floods in river-based transportation corridors disrupt barge traffic critical for grain exports. Hurricanes along the Gulf Coast frequently damage ports, processing facilities, and transportation infrastructure, while wildfires in agricultural regions threaten both production and labor availability. In 2024, the United States experienced 27 separate billion-dollar weather and climate disasters according to the National Oceanic and Atmospheric Administration (NOAA), and the American Farm Bureau Federation estimates that crop and rangeland losses exceeded $20.3 billion, driven by drought, flooding, hurricanes, and wildfires across multiple regions (Munch, 2025). Apart from unpredictability, climate risks are particularly challenging because they are increasing in coverage, frequency and severity, often affecting multiple supply chain stages simultaneously (Food and Agriculture Organization [FAO], 2021). These risks underscore the importance of AI-enabled climate modeling and early-warning systems that integrate weather forecasts, satellite data, and historical patterns.

- **Biological risks:** These include plant diseases, pest infestations, and livestock epidemics that can rapidly spread and cause severe supply disruptions. Crop diseases, such as fungal infections, or invasive pests, can significantly reduce yields, while livestock diseases, such as avian influenza or swine fever, can result in large-scale culling and processing shutdowns. These risks are exacerbated by high-density farming practices and global trade, which accelerate the spread of biological threats. Biological disruptions often trigger regulatory responses, including quarantines and trade restrictions, amplifying their economic impact. AI-driven disease surveillance systems can analyze veterinary data, trade flows, and environmental conditions to predict outbreak risks before they escalate.

- **Labor risks:** Labor availability is a critical yet often underappreciated component of food supply chain resilience. The U.S. food system relies heavily on seasonal, migrant, and specialized labor across farming, processing, and transportation. Workforce shortages caused by demographic changes, immigration constraints, health crises, or labor disputes can significantly disrupt operations. For example, shortages of agricultural workers during planting and harvesting seasons can lead to crop losses, while labor disruptions in meat processing facilities can reduce national supply. AI-driven labor forecasting models can help anticipate shortages by analyzing demographic trends, policy changes, and regional labor market data, enabling proactive workforce planning. By integrating real-time hiring patterns, wage movements, and regional supply–demand imbalances, AI tools allow producers, processors, and distributors to adjust recruitment strategies, allocate labor more efficiently, and prepare contingency plans that reduce the risk of disruptions across the food supply chain.

- **Transportation risks:** Transportation and logistics risks arise from the food supply chain's dependence on fuel, infrastructure, and coordinated multimodal networks. Fuel price volatility directly affects transportation costs, while congestion at ports and rail hubs can delay shipments and increase spoilage, particularly for perishable goods. The USDA reports that **trucks account for about 83%** of agricultural freight movements by tonnage, (USDA AMS, 2020), meaning even modest increases in diesel prices can significantly raise transportation costs, disrupt the supply chain, and ultimately increase consumer prices. Aging infrastructure, equipment failures, and extreme weather events further exacerbate these vulnerabilities.

  Transportation disruptions often amplify localized shocks, transforming them into national supply shortages. A port closure can delay thousands of containers, disrupt inventory cycles, and trigger price spikes and shortages across multiple food categories. AI-powered logistics analytics can predict delays, optimize routing and fuel consumption, and improve inventory positioning, reducing the impact of transportation-related disruptions.

- **Economic and geopolitical risks:** Stemming from global market volatility, trade policies, and international conflicts, these risks can abruptly alter supply and demand dynamics for key commodities such as grains, fertilizers, and animal feed. Commodity price shocks driven by global supply imbalances or speculation can increase food prices and strain household budgets.

  The U.S. is both a major food exporter and importer of key inputs and geopolitical disruptions can have significant domestic consequences. According to the World Bank, fertilizer prices "increased sharply during 2022 Q1, following an 80% surge in 2021," driven by high energy costs, supply disruptions, and geopolitical trade constraints (harber G & Koh, 2022). AI-driven market analytics can monitor global trade flows, policy developments, and price signals to anticipate economic shocks and inform strategic responses.

- **Cyber and data risks:** As U.S. food supply chains become increasingly digitized, cyber threats such as zero-day exploits, denial-of-service attacks, malware, and ransomware have emerged as a critical concern. Cyberattacks targeting logistics providers, processing facilities, data systems, or systems related to the food supply chain can disrupt operations, raise food commodity prices, compromise food safety, and erode trust. Ransomware attacks on food processors and transportation companies have also demonstrated the potential for cyber incidents to cause physical supply disruptions. In 2021, a ransomware attack on JBS, the world's largest meat processor, caused it to temporarily shut down plants in the U.S., Canada, and Australia and cost the company $11 million in ransom. Also, in 2021, a cyberattack on Colonial Pipeline disrupted 45% of fuel supplies on the East Coast and caused widespread transportation delays, affecting food distribution networks. In addition, data integrity risks, including inaccurate or incomplete data, can also undermine decision-making and forecasting accuracy. AI systems must therefore be supported by robust cybersecurity measures and data governance frameworks to ensure resilience and reliability.

These disruption drivers rarely occur in isolation as climate events can exacerbate labor shortages, biological outbreaks can trigger trade restrictions, and cyber incidents can severely affect transportation networks. The compounding nature of these risks highlights the shortcomings of traditional risk management approaches. It emphasizes the need for AI-driven forecasting systems capable of modeling complex interactions, detecting early warning signals, and supporting coordinated, proactive intervention across the U.S. food supply chain.

## 3. AI and Data Analytics in Risk Forecasting

### 3.1. From Descriptive to Predictive and Prescriptive Analytics

Historically, descriptive and diagnostic analytics have been the foundation of supply chain risk management in the United States. Descriptive analytics focus on summarizing past events, such as production volumes, shipment delays, or price fluctuations, while diagnostic analytics aim to explain why those events occurred by identifying correlations and root causes. Although these approaches provide valuable retrospective insights, they are inherently reactive and limited in their ability to anticipate future disruptions in complex and rapidly changing food supply chains. Artificial intelligence (AI) and advanced data analytics enable a fundamental shift from reactive analysis toward **predictive** and **prescriptive** decision-making. This transition is particularly critical for U.S. food supply chains, where delays in response can lead to food shortages, price inflation, and public health risks.

*AI enables the transition to:*

**Predictive analytics:** Predictive analytics leverage historical data, real-time inputs, and machine learning algorithms to estimate the likelihood and potential impact of future events. In the context of food supply chains, predictive models can forecast disruptions across multiple stages, including input supply, agricultural production, processing, transportation, and retail. AI-driven predictive models can identify patterns and nonlinear relationships that traditional statistical methods often miss. For example, machine learning algorithms can combine weather forecasts, satellite imagery, commodity prices, and logistics data to predict crop yield variability or transportation delays weeks or months in advance. These forecasts allow stakeholders to act early rather than respond after disruptions have already occurred.

*In U.S. food systems, predictive analytics can be used to:*

- Anticipate climate-related yield losses
- Forecast labor shortages during critical harvesting periods
- Predict port congestion and transportation delays
- Estimate price volatility for key commodities

By transforming uncertainty into probabilistic forecasts, predictive analytics provide a powerful early-warning mechanism for decision-makers.

**Prescriptive analytics:** Predictive analytics not only answers the question of what is likely to happen but can also recommend optimal actions to take in response. Prescriptive analytics use optimization models, simulations, and AI-driven decision rules to recommend actions that minimize risk, cost, or disruption severity.

*In food supply chains, prescriptive analytics can suggest:*

- Alternative sourcing strategies when suppliers are at risk
- Inventory repositioning to prevent shortages
- Rerouting of shipments in response to forecasted delays
- Timing of policy interventions such as strategic reserve releases

These recommendations are generated by evaluating multiple scenarios and constraints, including cost, capacity, regulatory requirements, and service levels. AI systems can simulate thousands of potential outcomes in real time, enabling decision-makers to select the most effective response in the face of uncertainty.

#### *3.1.1. Continuous Learning and Adaptive Intelligence*

A strategic advantage of AI-driven analytics is its ability to learn and adapt continuously. Unlike static models, machine learning systems update their parameters as new data becomes available, improving forecast accuracy over time- which is particularly valuable in food supply chains, where conditions such as climate, global politics, government policy and customer demand evolve rapidly. For example, an AI model forecasting transportation risk can refine its predictions as new data on fuel prices, weather patterns, or infrastructure performance are introduced. Similarly, demand forecasting models can adapt to changes in consumer behavior, such as shifts between food service and retail consumption. This adaptive intelligence allows AI-driven risk forecasting systems to remain relevant and effective in dynamic environments, reducing reliance on outdated assumptions.

#### *3.1.2. Strategic Implications for U.S. Food Supply Chains*

The shift from descriptive to predictive and prescriptive analytics has profound implications for the resilience of U.S. food supply chains. It enables stakeholders to move beyond crisis response toward proactive risk management, improving coordination across public and private sectors. For policymakers, predictive and prescriptive insights support evidence-based interventions that stabilize markets and protect vulnerable populations, while for industry participants, these tools enhance operational efficiency, reduce waste, and improve profitability. Ultimately, AI-driven predictive and prescriptive analytics transform data into actionable intelligence, providing the foundation for a more resilient, transparent, and adaptive U.S. food supply chain.

### 3.2. Core AI Techniques Used in Risk Forecasting

AI-driven risk forecasting in U.S. food supply chains relies on a combination of advanced analytical techniques designed to process large, heterogeneous datasets and uncover complex patterns that traditional methods cannot capture. These techniques enable early detection of emerging risks, assessment of cascading impacts, and support for proactive decision-making across all stages of the supply chain

*Key AI and data analytics techniques include:*

**Machine learning (ML):** This is the foundation of AI-driven risk forecasting and is achieved by creating models that refine their internal parameters as new information becomes available, allowing them to capture nonlinear relationships and emerging trends that traditional statistical models often miss, without explicit programming. Commonly used ML models include random forests, gradient boosting algorithms, and neural networks, each offering distinct advantages.

Random forests and gradient boosting models are particularly effective for structured data, such as production volumes, transportation metrics, and price indicators. These models excel at handling nonlinear relationships and interactions among multiple risk factors, making them well-suited for predicting climate risks, inventory imbalances, yield variability, supplier reliability, and cost fluctuations. In addition to prediction, they excel at **classification, ranking, feature importance, and anomaly detection** across structured datasets. Neural networks, including deep learning architectures, can model highly complex relationships across multiple data sources, such as combining weather data with fuel prices, logistics and market signals. Their ability to learn hierarchical representations enables them to detect subtle patterns, such as how extreme heat interacts with transportation bottlenecks to affect delivery times, or how global commodity price movements propagate through domestic supply chains. As a result, neural networks are increasingly used for high-resolution yield prediction, demand forecasting, and early detection of systemic risks that emerge from the interplay of environmental, economic, and logistical factors. In U.S. food supply chains, ML models are increasingly used to forecast crop yields, assess supplier risk, predict processing capacity constraints, customer demand, and estimate the probability of supply interruptions under varying conditions.

**Time-series forecasting (ARIMA hybrids, LSTM models):** Time-series forecasting models analyze sequential data to identify trends, seasonality, and temporal dependencies. Traditional statistical approaches such as ARIMA (AutoRegressive Integrated Moving Average) models, remain useful for stable, linear patterns, while hybrid models combine these techniques with machine learning to improve accuracy.

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, are particularly effective for capturing long-term dependencies and complex temporal dynamics. LSTM models are well-suited for forecasting demand fluctuations, price volatility, transportation delays, and climate-driven production risks. In food supply chains, time-series forecasting enables decision-makers to anticipate seasonal disruptions, align inventory strategies with demand cycles, and adjust procurement plans in advance of anticipated shocks. LSTMs are “adept at capturing intricate temporal dependencies” (Suddala, 2024) in volatile demand patterns, while outperforming classical models for food forecasting, especially when data exhibit nonlinear or climate-driven variability.

A 2024 study shows that combining ARIMA with LSTM "achieves superior predictive accuracy and robustness in real-world supply chain data" (Suddala, 2024), and that hybrid ARIMA–LSTM models further improve forecasting accuracy for supply chain demand and inventory optimization.

**Natural language processing (NLP):** Natural language processing (NLP) allows AI systems to extract meaningful insights from unstructured text data, including news articles, regulatory announcements, weather reports, and social media content, that often contain early warning signals long before disruptions appear in operational data. NLP models can identify emerging risks by analyzing media coverage of labor disputes, disease outbreaks, port congestion, or geopolitical developments affecting agricultural inputs. This capability is very important in supply chain analytics, as over 80% of global data is unstructured (Harbert, 2021), and critical supply chain risk indicators often emerge first in narrative form rather than in structured datasets. Sentiment analysis and topic modeling techniques help assess the severity and potential implications of these events. In the U.S. context, NLP-driven insights enable faster recognition of policy changes or localized disruptions, improving situational awareness and response times.

**Graph analytics:** Graph analytics model supply chains as interconnected networks of suppliers, processors, distributors, and retailers. Nodes represent entities, while edges represent relationships such as material flows, contracts, or transportation links. This approach is particularly valuable for understanding interdependence and identifying critical nodes whose failure could trigger cascading disruptions. Graph-based AI models enable analysts to assess network resilience by simulating node or link failures and evaluating their downstream effects. In highly concentrated sectors such as meat processing, graph analytics help identify systemic risks and support diversification and contingency planning.

For U.S. food supply chains, network modeling provides insights into supplier concentration, regional dependencies, and potential bottlenecks that are not visible through linear analysis.

**Anomaly detection:** Anomaly detection techniques identify deviations from normal patterns that may signal emerging disruptions. These techniques are especially useful for detecting early-stage risks that have not yet produced obvious impacts. *Examples include* unexpected drops in crop health indices, sudden changes in transportation lead times, unusual price movements, or irregular equipment performance at processing facilities. Unsupervised learning methods, such as clustering and autoencoders, are commonly used to detect anomalies without requiring labeled data. In practice, anomaly detection serves as an early-warning system, alerting decision-makers to potential issues before they escalate into major disruptions that require costly interventions.

#### *3.2.1. Integrated Impact: Detecting Weak Signals Early*

When combined, these AI techniques provide a powerful, multi-layered risk forecasting capability. Machine learning identifies complex relationships, time-series models capture temporal dynamics, NLP extracts qualitative signals, graph analytics reveal systemic vulnerabilities, and anomaly detection flags early deviations. Together, these tools enable organizations to detect weak signals such as abnormal yield patterns, labor instability, or transportation delays early enough to implement proactive mitigation strategies. This integrated AI-driven approach is essential for managing the complexity and uncertainty inherent in U.S. food supply chains.

## 4. Benefits of AI-Driven Risk Forecasting

The integration of AI-driven risk forecasting into food supply chains offers transformative benefits for both private industry and public policymakers. By leveraging predictive and prescriptive analytics, organizations can move from reactive management of disruptions to proactive, informed decision-making. These benefits extend across operational efficiency, supply chain resilience, transparency, sustainability, and social welfare.

**The adoption of AI-driven risk forecasting delivers several strategic benefits:**

**Early warning capabilities:** One of the most significant advantages of AI-driven risk forecasting is the ability to detect weak signals and anticipate disruptions before they materialize. In transportation networks, anomaly detection can identify bottlenecks by analyzing deviations in freight movement, dwell times, or route performance, a priority area highlighted in federal assessments of supply-chain vulnerabilities. By providing early warnings, AI enables stakeholders to implement mitigation measures such as rerouting shipments, adjusting planting schedules, implementing inventory management measures or securing alternative suppliers before a localized problem escalates into a systemic crisis. This proactive capability reduces the frequency and severity of food supply disruptions, enhancing operational stability across the United States.

**Improved resilience:** AI-driven forecasting enhances overall food supply chain resilience by identifying vulnerabilities and simulating the ripple effects of potential disruptions across the system. Graph analytics and network modeling enable organizations to map supplier dependencies, processing concentration, and transportation bottlenecks, giving them the advantage of diversifying suppliers, prepositioning inventory, and implementing contingency plans that minimize the impact of shocks. In sectors such as meat processing and perishable produce, where a single facility disruption can affect national supply, AI-driven resilience planning ensures that vulnerabilities are addressed before they compromise the broader system.

**Cost efficiency and Waste reduction:** Operational efficiency is enhanced through AI-enabled optimization of inventory, transportation, and production processes. Predictive analytics allow retailers and processors to anticipate demand fluctuations and align procurement and stocking strategies accordingly, reducing overproduction and spoilage. Dynamic logistics scheduling, informed by AI forecasts, reduces fuel consumption, lowers overtime labor costs, and prevents losses associated with perishable products. In the long term, these efficiencies contribute to lower operating costs, improved profit margins, and more stable consumer pricing.

**Enhanced Transparency and Supply Chain Visibility:** AI systems provide comprehensive visibility across the supply chain, integrating data from suppliers, food producers, logistics providers, processors, and retailers. This transparency allows organizations to monitor real-time performance metrics, detect emerging risks, and coordinate responses across multiple stakeholders. For example, visibility into transportation flows can identify bottlenecks before they impact retail delivery, while supplier monitoring can flag disruptions in input availability. Greater transparency supports trust, accountability, and more informed decision-making, particularly in complex, multi-tiered perishable goods supply chains such as those for fruits, vegetables, and meat.

**Sustainability and Optimized Resource Use:** By reducing waste, greenhouse gas emissions, optimizing transportation, and improving production planning, AI-driven forecasting contributes to environmental sustainability. Precision agriculture models informed by AI can optimize water, fertilizer, and energy use, while logistics optimization reduces greenhouse gas emissions associated with fuel consumption. Sustainable practices not only improve environmental outcomes but also reduce operational costs and enhance brand reputation. In a sector where climate variability is increasingly a risk factor, integrating sustainability into risk management further strengthens resilience.

**Policy and Public Sector Benefits:** AI-driven risk forecasting provides strategic value to corporate organizations, policymakers as well as public agencies. Predictive insights enable evidence-based interventions to stabilize food markets, manage price volatility, and ensure equitable access to essential food supplies. During extreme events such as hurricanes, droughts, or supply chain shocks, AI models can inform the allocation of emergency food reserves, optimize distribution logistics for nutrition assistance programs, and prioritize support for vulnerable populations. By anticipating disruptions, policymakers can proactively mitigate economic and social consequences, thereby enhancing national food security.

The adoption of AI-driven risk forecasting represents a paradigm shift in food supply chain management. Early warning capabilities, improved resilience, cost efficiencies, transparency, sustainability, and policy support collectively enhance the robustness and adaptability of the U.S. food system. As climate volatility, labor constraints, and market uncertainties increase, these benefits are essential for maintaining stable, secure, and efficient food supply chains that serve both economic and societal objectives.

## 5. Conclusion

With rapid advances in digital technology, AI-driven risk forecasting is increasingly playing a vital role in managing U.S. food supply chain disruptions. Rather than rely solely on historical trends or manual reporting, stakeholders such as farmers, food processors, and policy makers can leverage advanced data analytics, machine learning, natural language processing and integrated multi-source data ecosystems to anticipate risks, mitigate shocks, and enhance the resilience, efficiency and sustainability of the nation's food system. Beyond optimizing food supply chain operations, AI in agriculture can enable predictive and prescriptive analytics. For example, AI tools can be used to identify unusual crop-stress signals from satellite imagery or sensor networks, patterns that often precede yield losses or disease outbreaks —allowing producers to intervene earlier and avoid shortages that could disrupt the food supply chain. AI can also be used for scenario analysis to detect vulnerabilities caused by climate shocks, geopolitical tensions, or market volatility that would otherwise remain hidden until they disrupt the broader supply chain. These predictive and prescriptive capabilities are essential for proactive decision-making that ensures supply continuity and public welfare, especially in an era of increasing climate volatility, geopolitical uncertainty, and complex logistics.

The role of federal agencies, including the USDA, Food and Drug Administration (FDA), Department of Homeland Security (DHS), Department of Transportation (DOT) and related bodies, is central to guiding AI adoption in alignment with national food security objectives. By providing leadership, regulatory frameworks, technical support, and coordinated policy guidance, the federal government can ensure that AI deployment enhances both efficiency and equity across the food system. Public-private partnerships, investment in digital infrastructure and governance standards form the core of a coordinated strategy to operationalize AI-driven forecasting at scale.

Ultimately, the full potential of AI in U.S. food supply chains will be realized only through integrated action across technology, infrastructure, policy, and human capital domains. The strategic adoption of AI not only improves supply chain performance but also strengthens national food security, ensuring that the system remains robust, adaptive, inclusive and efficient. As disruptions grow in complexity due to natural and human factors, AI-driven predictive intelligence will become an essential tool for building a food supply network that can withstand disruptions, support vulnerable populations, and promote a resilient, sustainable, and equitable food system for the nation.

## Compliance with ethical standards

*Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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