



Design and Validation of a Predictive Agribusiness Intelligence Platform for U.S. Food-Supply and Market Resilience

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Doi: [10.63125/bsqvs196](https://doi.org/10.63125/bsqvs196)

Received: 11 February 2026; **Revised:** 23 March 2026; **Accepted:** 25 April 2026; **Published:** 08 May 2026

Abstract

This quantitative study designed and validated a predictive agribusiness intelligence platform for assessing U.S. food-supply and agricultural-market resilience through the integration of agricultural production, inventory, weather, logistics, international trade, commodity-market, and macroeconomic indicators. A longitudinal predictive-analytics design was applied to 18,720 commodity-region-month observations representing 26 major agricultural commodities across 48 contiguous U.S. states from January 2015 through December 2024. The final dataset retained 95.1% of initially integrated observations and achieved 97.8% overall data completeness. Statistical analysis incorporated descriptive statistics, correlation analysis, analysis of variance, multivariable regression, effect-size estimation, and risk modeling, while predictive performance was evaluated using Random Forest, Support Vector Machine, Gradient Boosting, XGBoost, and neural-network architectures. Mean Food-Supply Resilience was 72.8 ± 11.6 , while Market Resilience averaged 69.5 ± 13.2 . XGBoost produced the strongest independent-test performance for Food-Supply Resilience, achieving an R^2 of 0.914, RMSE of 4.38, classification accuracy of 92.8%, F1-score of 91.9%, and AUC of 0.967. The neural network performed most strongly for Market Resilience, achieving an R^2 of 0.889, RMSE of 5.06, accuracy of 91.4%, F1-score of 90.9%, and AUC of 0.958. Production and yield contributed 24.8% of normalized predictive importance, followed by inventories and storage at 21.6%, weather and climate at 18.7%, transportation and logistics at 15.3%, international trade at 10.8%, and input and macroeconomic conditions at 8.8%. Low inventory coverage increased the adjusted odds of high or critical food-supply risk by 3.18 times, while extreme commodity-price volatility increased market-resilience risk by 3.46 times. Concurrent production, inventory, and logistics stress produced the largest combined food-supply effect ($OR = 5.82$). Independent validation, repeated cross-validation, calibration assessment, subgroup analysis, and sensitivity testing demonstrated comparatively small generalization gaps and stable predictive performance. The findings validated the platform as a multidimensional quantitative approach for identifying, classifying, and predicting variation in U.S. food-supply and agricultural-market resilience across commodities, regions, and disruption conditions.

Keywords

Agribusiness Intelligence, Food-Supply Resilience, Market Resilience, Predictive Analytics, Machine Learning.

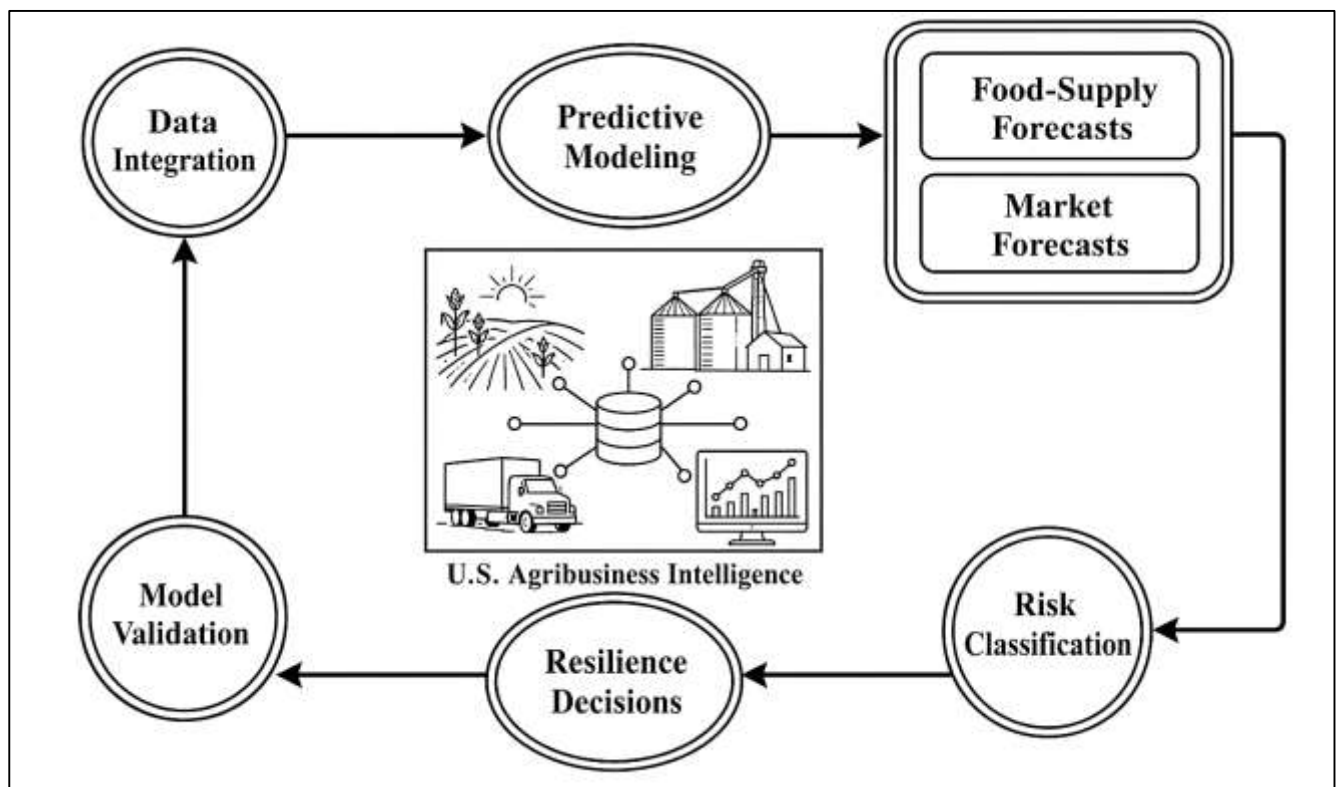
INTRODUCTION

Predictive agribusiness intelligence can be defined as the systematic integration of agricultural, economic, environmental, logistical, technological, and market data with quantitative analytical methods to estimate probable changes in food production, commodity availability, prices, demand, transportation conditions, supply-chain disruptions, and market risk. Agribusiness encompasses the interconnected commercial activities associated with agricultural inputs, farm production, food processing, storage, transportation, wholesale distribution, retailing, commodity trading, and supporting financial and information services ([Assimakopoulos et al., 2024](#)). Within this broad system, business intelligence refers to the structured acquisition, integration, processing, analysis, and presentation of data for evidence-based decision-making, whereas predictive intelligence extends conventional descriptive reporting by applying statistical forecasting, machine learning, time-series modeling, pattern recognition, and risk-scoring techniques to estimate outcomes before they are fully observed. A predictive agribusiness intelligence platform therefore represents an integrated analytical environment in which heterogeneous information is transformed into measurable indicators, forecasts, alerts, classifications, and decision-support outputs. Food-supply resilience refers to the capacity of interconnected food-system actors and infrastructure to maintain acceptable levels of production, processing, distribution, availability, and accessibility when exposed to disturbances. Market resilience similarly describes the ability of agricultural markets to absorb, respond to, and recover from disturbances while maintaining functional price discovery, product flows, commercial transactions, and relationships between supply and demand. These definitions establish prediction, intelligence integration, food supply, markets, and resilience as analytically connected rather than independent concepts. Research across agricultural economics, supply-chain management, information systems, operations research, artificial intelligence, and food-system science has increasingly quantified these concepts through indicators such as forecast error, commodity-price volatility, inventory availability, production variability, transportation delay, delivery reliability, stockout probability, supply-demand imbalance, recovery time, disruption frequency, market concentration, and predictive classification accuracy ([Elbasi et al., 2022](#)). Studies of agricultural forecasting have additionally demonstrated the value of combining historical prices with production, weather, trade, supply, and market-arrival information, while broader research on agri-food resilience has identified predictive and prescriptive analytics as important components of disruption readiness and response. Recent reviews covering hundreds of agricultural-price forecasting studies further show that the analytical field includes conventional statistical models, machine-learning algorithms, recurrent neural networks, convolutional architectures, transformers, ensemble models, and probabilistic forecasting approaches. Accordingly, the conceptual foundation of a predictive agribusiness intelligence platform lies in converting multidimensional food-system conditions into quantifiable variables and using their temporal and cross-sectional relationships to estimate market and supply outcomes with measurable levels of accuracy, uncertainty, sensitivity, and reliability ([Spanaki et al., 2022](#)).

Food-supply and agricultural-market resilience possess substantial international significance because modern food systems operate through globally interconnected networks of agricultural production, commodity exchange, processing, transportation, storage, financing, and retail distribution. Agricultural commodities produced in one country may depend on fertilizers, machinery, energy, seeds, labor, shipping services, financial instruments, and processing capacity originating in several other countries, while the resulting products can pass through multiple markets before reaching final consumers ([Garg & Alam, 2023](#)). Consequently, disturbances affecting agricultural production or logistics within one geographic area can influence international prices, trade flows, inventories, procurement strategies, and food availability elsewhere. International research has examined these relationships through studies of agricultural supply-chain resilience, digital transformation, big-data analytics, commodity-price forecasting, food-security risk, climate exposure, logistics disruptions, and market uncertainty. Evidence across these research streams characterizes agricultural resilience as a multidimensional property influenced by flexibility, redundancy, visibility, coordination, information quality, technological capability, risk management, and adaptive operational capacity. Quantitative research has also shown that agricultural markets exhibit nonlinear behavior generated by interactions among weather conditions, seasonal production cycles, input costs, transportation constraints,

international trade, consumer demand, exchange rates, policy conditions, and commodity inventories. Such complexity has encouraged increased use of artificial intelligence and machine learning because conventional single-variable or linear forecasting structures may not adequately represent multidimensional dependencies. Studies evaluating recurrent neural networks, long short-term memory models, gated recurrent units, support vector regression, random forests, gradient boosting, and other computational methods have reported varying levels of predictive performance across commodities, markets, temporal frequencies, and geographic contexts. A large review of 773 agricultural-price forecasting studies published between 2006 and 2025 illustrates the scale and methodological diversity of this international research area, including point forecasting, trend prediction, uncertainty estimation, and advanced neural architectures. International food-system research has simultaneously emphasized that resilience involves more than commodity-price stability because production failures, transportation interruptions, processing bottlenecks, labor constraints, inventory shortages, and demand shocks can propagate through interconnected supply networks (Giannakopoulos et al., 2024). Digital technologies such as artificial intelligence, Internet of Things systems, cloud platforms, remote sensing, blockchain, and advanced analytics have therefore been examined as mechanisms for increasing supply-chain visibility and improving quantitative risk assessment. Research involving perishable food chains has further identified supply-demand variation, natural hazards, equipment limitations, financial constraints, and labor disruptions as interconnected sources of operational instability. This international body of evidence provides a broad quantitative foundation for examining predictive agribusiness intelligence as a system that integrates multiple determinants rather than treating agricultural production, commodity markets, and supply-chain resilience as separate analytical domains (Giannakopoulos et al., 2024).

Figure 1: Predictive Agribusiness Intelligence for Resilience



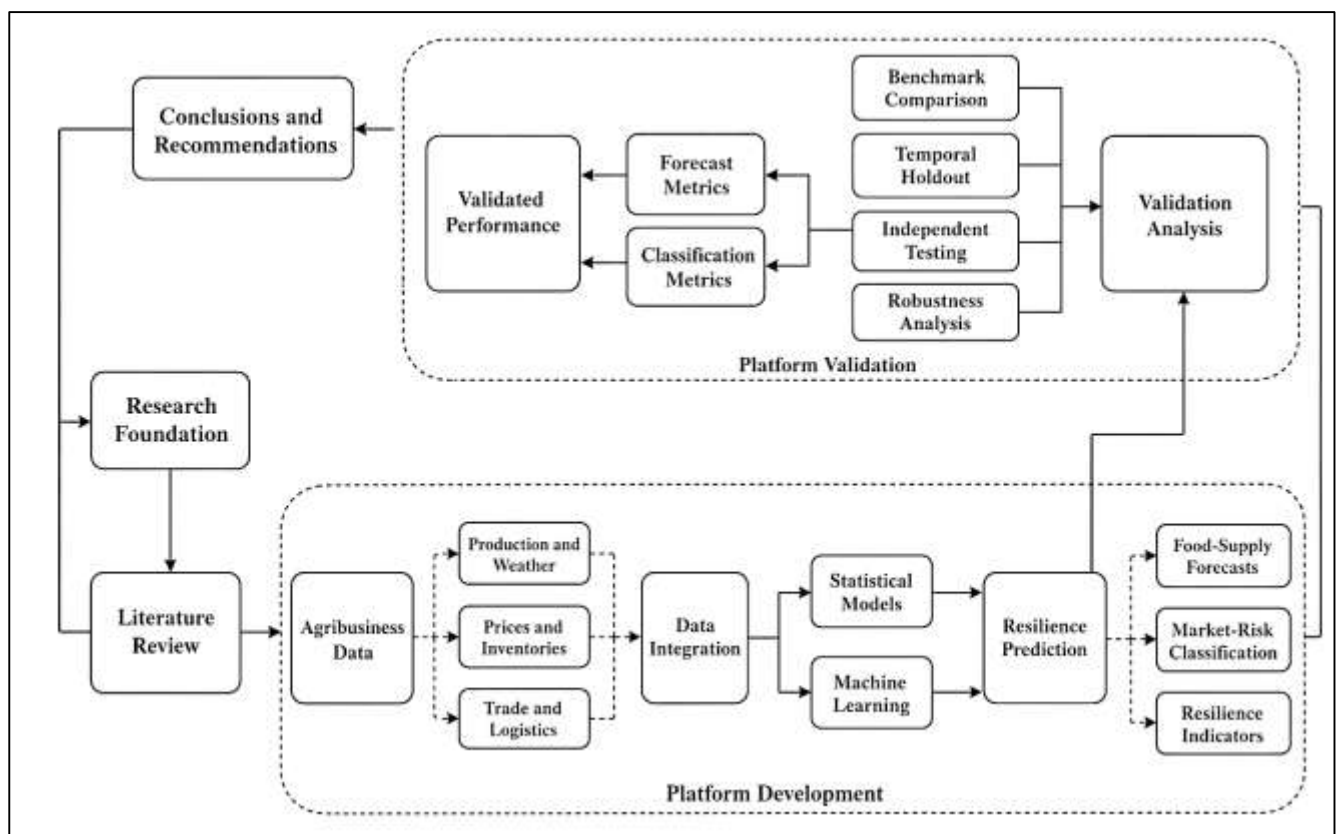
The United States food-supply system represents a large, geographically dispersed, technologically intensive, and commercially interconnected network linking agricultural producers with processors, distributors, transportation providers, wholesalers, retailers, food-service organizations, institutional buyers, exporters, importers, and consumers (Chen et al., 2023). Agricultural production occurs across highly differentiated climatic regions and commodity systems, including grains, oilseeds, livestock,

dairy products, fruits, vegetables, specialty crops, and processed food ingredients. These products move through storage facilities, processing plants, cold chains, highways, rail networks, ports, warehouses, distribution centers, and retail channels before reaching domestic or international markets. Such interconnectedness creates substantial quantities of potentially useful predictive data while simultaneously generating exposure to correlated disruptions. Quantitative studies of U.S. and international food systems have identified extreme weather, drought, flooding, heat, production variability, animal and crop disease, transportation interruptions, labor availability, energy costs, geopolitical disturbances, trade restrictions, processing constraints, cybersecurity risks, public-health emergencies, and sudden changes in consumer demand as variables capable of altering food-system performance (Cabrera & Fadul-Pacheco, 2021). The experience of major disruptions has also encouraged research into the relationship between supply-chain structure and resilience, particularly where production, processing, or distribution capacity is concentrated among a relatively limited number of locations or organizations. Agricultural markets add another dimension because production disturbances may be transmitted through price movements, inventory changes, procurement behavior, transportation costs, futures markets, import-export adjustments, and substitution among commodities. A disruption affecting production does not therefore remain confined to farm output; its effects can be distributed across processors, logistics providers, retailers, institutional purchasers, and consumers through measurable changes in prices, quantities, lead times, service levels, and availability. Studies examining agricultural supply-chain risks have consequently emphasized the importance of risk identification, mitigation capacity, information sharing, flexibility, and coordination. More recent research has examined artificial intelligence as an organizational and analytical resource capable of strengthening agricultural supply-chain resilience through improved sensing, information processing, operational coordination, and resource allocation. Research focused specifically on U.S. food-supply risk forecasting has similarly characterized the national system as a complex network in which agricultural production, processing, transportation, storage, and retail distribution are exposed to multiple interacting disturbances (Rejeb et al., 2021). These characteristics create a quantitative research setting in which resilience can be represented through measurable outcomes such as disruption incidence, supply variability, delivery performance, inventory adequacy, market volatility, recovery duration, regional exposure, and forecast accuracy. An integrated intelligence platform can consequently be evaluated not merely according to its technical architecture but according to whether its predictive outputs reliably represent these observable characteristics of U.S. food-supply and agricultural-market behavior.

Agricultural markets differ from many conventional product markets because biological production cycles, perishability, seasonality, weather dependence, storage limitations, heterogeneous product quality, geographically distributed production, transportation requirements, and international commodity relationships jointly influence supply and price formation (Martinho & Guine, 2021). Commodity prices can respond simultaneously to historical price behavior, expected harvests, planted acreage, crop yields, rainfall, temperature, inventories, market arrivals, energy prices, transportation expenses, international trade, consumer demand, and macroeconomic conditions. Quantitative agricultural forecasting research has therefore progressed from relatively simple univariate time-series approaches toward multivariable statistical learning and artificial-intelligence architectures capable of modeling nonlinear relationships. Earlier studies commonly employed moving averages, exponential smoothing, autoregressive models, autoregressive integrated moving-average models, regression techniques, and econometric specifications. Subsequent studies expanded the analytical toolkit through support vector machines, artificial neural networks, decision trees, random forests, gradient-boosting algorithms, recurrent neural networks, long short-term memory networks, gated recurrent units, convolutional neural networks, transformers, hybrid models, and ensemble forecasting systems. Comparative research involving 23 agricultural commodities and extensive daily market observations has demonstrated the usefulness of evaluating traditional statistical, machine-learning, and deep-learning models within a common predictive framework (Yap & Al-Mutairi, 2024). Other studies have incorporated environmental and economic factors such as temperature, rainfall, fertilizer use, pest pressure, transportation cost, demand-supply relationships, and regional market conditions into agricultural price prediction. Multi-source forecasting research has also combined market prices,

commodity arrivals, weather conditions, trade data, crop supply, and cultivated area, illustrating the analytical advantage of representing agricultural markets as systems influenced by interacting explanatory variables (Debasish, 2021; Abdur & Iftekhar, 2021). The performance of predictive models is generally quantified through metrics such as mean absolute error, root mean squared error, mean absolute percentage error, coefficient of determination, directional accuracy, precision, recall, sensitivity, specificity, F1-score, and area under the receiver operating characteristic curve, depending on whether the analytical objective involves numerical forecasting or categorical risk classification. Such metrics are particularly important because high computational complexity does not automatically establish predictive validity (Debasish, 2022; Ashfaq & Mohammad, 2022). Recent logistics research, for example, has shown that machine-learning classifiers may provide only modest improvements over baseline classifications under particular datasets, reinforcing the need to distinguish technological sophistication from empirically demonstrated predictive value. Agricultural intelligence platforms therefore require comparative validation across model classes, temporal periods, commodities, and data conditions (Soares et al., 2023). For U.S. agribusiness, a multivariable analytical structure is especially relevant because commodity markets are simultaneously connected to regional weather patterns, domestic production, international trade, transportation systems, inventories, macroeconomic variables, and consumer demand (Sheak & Risha, 2022; Rashedul & Md Kaium, 2022). Quantitative modeling of these relationships provides a basis for examining whether integrated agribusiness intelligence can estimate market instability and food-supply stress more reliably than fragmented or isolated indicators.

Figure 2: Predictive Agribusiness Intelligence Platform Framework



Digitalization has expanded the quantity, frequency, diversity, and granularity of data available for agricultural and food-supply analysis. Agricultural information can now originate from farm-management systems, commodity exchanges, government databases, meteorological stations, satellites, remote-sensing platforms, transportation networks, warehouse systems, retail transactions, trade databases, market reports, sensors, enterprise-resource-planning systems, and Internet of Things devices (Imbiri et al., 2021). These sources contain structured, semi-structured, spatial, temporal, and

streaming information that can be integrated into analytical datasets for predictive modeling. Big-data analytics research within agri-food supply chains has identified predictive and prescriptive analytics as particularly relevant to readiness, risk management, flexibility, agility, and disruption response (Chowdhury & Tonay, 2022; Nishat & Kaniz, 2022). Digital-transformation studies have likewise examined the relationship between technological capability and agricultural supply-chain resilience at firm and network levels. Within this analytical environment, machine learning provides methods for identifying complex relationships among predictors without requiring every relationship to be represented through a predetermined linear structure (Mohammad, 2023; Shaiful et al., 2022). Random forests and gradient-boosting algorithms can identify nonlinear interactions among market and operational variables; recurrent and long short-term memory networks can model temporal dependencies; convolutional approaches can extract structured patterns; clustering methods can identify market regimes or risk profiles; and ensemble systems can combine forecasts from multiple models (Chowdhury, 2023; Badrul & Mominul, 2023). Research on agricultural marketplaces has reported strong predictive performance from random-forest models relative to conventional linear regression in particular commodity datasets, while deep-learning studies have demonstrated high coefficients of determination for certain agricultural price series (Monteiro & Barata, 2021). These results vary across datasets and should therefore be interpreted as evidence supporting systematic model comparison rather than universal superiority of a particular algorithm. Integrated agribusiness intelligence additionally depends on data engineering because predictive performance is affected by missing observations, inconsistent temporal intervals, regional heterogeneity, outliers, data leakage, class imbalance, measurement error, and changes in underlying market relationships (Ashrafuzzaman, 2024; Zahidul, 2023). Validation consequently requires attention to training, validation, and testing procedures; temporal holdout periods; cross-validation; out-of-sample prediction; sensitivity analysis; and robustness assessment. The platform concept extends beyond an individual predictive algorithm because an operational intelligence environment includes data acquisition, cleaning, transformation, feature engineering, model execution, forecast evaluation, visualization, risk scoring, and information delivery. Research across supply-chain analytics has increasingly treated these capabilities as interconnected components of organizational information processing (Latino et al., 2021). For U.S. food-supply analysis, integrating agricultural production, weather, market, transportation, inventory, trade, and economic variables within a common quantitative architecture provides a structured basis for testing how much predictive information each domain contributes independently and collectively to estimates of market volatility, supply stress, disruption probability, and resilience performance. The validation of a predictive agribusiness intelligence platform requires explicit quantitative criteria because a technically functional platform cannot be considered empirically validated solely on the basis of successful data integration or algorithm execution. Predictive validity concerns the degree to which model-generated estimates correspond with observed outcomes across independent data, time periods, locations, commodities, or disruption conditions (Ali & Dahlhaus, 2022). Agricultural forecasting studies commonly evaluate continuous predictions using mean absolute error, mean squared error, root mean squared error, mean absolute percentage error, and coefficient of determination, while classification models are assessed through accuracy, sensitivity, specificity, precision, recall, F1-score, receiver operating characteristic analysis, and area under the curve. Resilience measurement introduces additional variables because the construct can encompass resistance to disturbance, continuity during disruption, speed of recovery, adaptive capacity, flexibility, redundancy, visibility, and operational reliability. At the food-supply level, measurable resilience indicators may include production stability, inventory coverage, stockout frequency, supply-demand imbalance, transportation reliability, lead-time variability, delivery delay, geographic diversification, disruption duration, recovery time, and service continuity. At the agricultural-market level, resilience can be operationalized through price volatility, abnormal price movements, market dispersion, volume fluctuations, demand instability, commodity availability, and the persistence of disturbances (Dhal & Kar, 2024). Research examining artificial intelligence and supply-chain resilience has quantified relationships between digital or analytical capability and observable organizational or supply-chain performance, while agricultural studies have used firm-level, market-level, and operational datasets to examine how technology and information processing correspond with resilience outcomes. Quantitative validation also requires

comparison against appropriate baselines. A predictive model that achieves high apparent accuracy may provide limited practical information when the outcome distribution is strongly imbalanced or when a simple benchmark produces similar performance. Consequently, model assessment requires comparison with naïve forecasts, conventional statistical approaches, alternative machine-learning algorithms, and relevant baseline classifications. Temporal validation is equally important for agricultural markets because random train-test partitions can permit information from closely related periods to appear in both training and evaluation samples, producing overly favorable estimates of predictive performance (Kazi Rakib Hasan, 2024; Md Anisur Rahman, 2024). Out-of-sample and time-based testing provide stronger evidence when forecasting sequential market behavior. Statistical significance, confidence intervals, effect sizes, prediction intervals, calibration, residual analysis, and robustness tests can further determine whether differences between models represent meaningful improvements rather than sampling variation (Oliveira & Silva, 2023). Platform validation can therefore be conceptualized as a multidimensional quantitative process involving predictive accuracy, discrimination, calibration, robustness, stability, generalizability, and operational usefulness. Such a structure aligns the technical evaluation of predictive algorithms with measurable characteristics of food-supply and agricultural-market resilience (Md Asif Ali Sheak, 2024; Md. Shakhawat & Md, 2024). The accumulated literature across agricultural economics, food-supply-chain management, artificial intelligence, digital transformation, market forecasting, and resilience analysis establishes a substantial empirical foundation for investigating an integrated predictive agribusiness intelligence platform within the United States (Senoo et al., 2024). More than 30 relevant studies across these fields collectively demonstrate that agricultural outcomes are influenced by combinations of market history, production volume, climatic conditions, trade, transportation, inventories, input costs, demand, supply-chain structure, digital capability, and disruption exposure. Agricultural-price forecasting studies have tested statistical, machine-learning, deep-learning, hybrid, and ensemble approaches across commodities and geographic regions, while supply-chain studies have examined resilience through risk management, flexibility, agility, information sharing, digitalization, recovery capability, and operational continuity (Nishat & Jahanara, 2024; Tonay et al., 2024). Systematic reviews of big-data analytics in agri-food supply chains have documented relationships between predictive analytics and resilience-related capabilities, and large-scale reviews of agricultural-price forecasting have demonstrated considerable methodological diversity across hundreds of empirical investigations (Debasish, 2025a, 2025b). Recent research has also examined artificial intelligence investment and agricultural supply-chain resilience using firm-level quantitative data, while other empirical work has investigated digital technologies as resources for sensing environmental changes, coordinating supply-chain participants, and reallocating resources under disturbance (Linaza et al., 2021). These research streams remain methodologically fragmented because market forecasting is frequently examined independently from supply-chain disruption prediction, while resilience research often measures organizational capabilities without integrating commodity-level predictive performance into the same analytical environment. The quantitative context of this study is therefore centered on the design and empirical validation of a platform capable of integrating multidimensional U.S. agribusiness information and evaluating its predictive performance against observable food-supply and market outcomes (Jannatul, 2025; Md Anisur Rahman, 2025). The analytical structure can incorporate historical commodity prices, production measures, weather indicators, inventories, transportation conditions, trade variables, supply-demand measures, and relevant economic indicators as predictor variables, while dependent variables can represent commodity-price movements, supply stress, market volatility, disruption categories, availability conditions, or composite resilience outcomes (Md Arif Uz et al., 2025; Md Kaium, 2025; Md Mahamud Pervaz, 2025). Statistical and machine-learning models can be compared through standardized performance metrics and evaluated through independent testing procedures. Relationships between predictive variables and resilience outcomes can additionally be quantified through correlation, regression, variance analysis, feature-importance measures, and appropriate effect-size statistics (De Abreu & Van Deventer, 2022). This research orientation positions platform design and validation within a measurable empirical framework rather than treating the platform as a purely conceptual information system. The resulting study structure connects agricultural data integration, predictive modeling, food-supply performance, market behavior, and resilience

measurement within a unified quantitative research setting specifically aligned with the scale and complexity of the U.S. agribusiness and food-supply environment (Pokhariyal et al., 2023).

The primary objective of this quantitative study is to design and validate a predictive agribusiness intelligence platform capable of integrating multidimensional agricultural, food-supply, market, environmental, economic, trade, inventory, and logistics data to quantify, predict, and classify food-supply and market resilience within the United States. Specifically, this study seeks to develop a structured analytical framework through which historical and near-current agribusiness indicators can be transformed into measurable predictors of commodity-price movements, supply-demand imbalances, production variability, market volatility, inventory pressure, transportation disruptions, and broader food-supply resilience conditions. The study aims to determine the statistical relationships between key explanatory variables, including agricultural production volumes, crop yields, weather conditions, commodity inventories, market prices, transportation performance, import-export activity, input costs, and selected macroeconomic indicators, and measurable outcomes representing U.S. food-supply and market resilience. Another objective is to construct and comparatively evaluate multiple predictive approaches, including conventional statistical models and selected machine-learning algorithms, to identify the models that provide the strongest predictive accuracy, reliability, discrimination, and generalizability across different commodities, geographic regions, market conditions, and disruption categories. Predictive performance is evaluated using appropriate quantitative indicators such as mean absolute error, root mean squared error, mean absolute percentage error, coefficient of determination, accuracy, sensitivity, specificity, precision, recall, F1-score, and area under the receiver operating characteristic curve according to the characteristics of each outcome variable. The study further aims to develop measurable food-supply and market resilience indicators based on production stability, supply availability, price volatility, inventory adequacy, transportation reliability, disruption frequency, recovery duration, and supply-demand stability and to examine how effectively the proposed platform predicts changes in these indicators. An additional objective is to quantify the relative contribution and predictive importance of agricultural, environmental, market, economic, trade, and logistical variables in explaining variations in resilience outcomes through correlation analysis, regression modeling, group comparisons, feature-importance assessment, and appropriate effect-size statistics. The study also seeks to validate the platform through training, validation, temporal holdout, and independent testing procedures and to assess model robustness under alternative datasets, commodity groups, geographic conditions, and periods of elevated market stress. Collectively, these objectives establish a quantitative basis for evaluating the predictive validity, statistical reliability, robustness, and operational analytical performance of an integrated agribusiness intelligence platform for measuring U.S. food-supply and market resilience.

LITERATURE REVIEW

The literature on predictive agribusiness intelligence is distributed across agricultural economics, food-supply-chain management, commodity forecasting, resilience measurement, artificial intelligence, machine learning, logistics analytics, climate-risk assessment, and digital decision-support systems. Collectively, these research domains provide the theoretical and empirical foundation required to examine how heterogeneous agricultural and market information can be transformed into quantitative predictions of food-supply stability and market resilience (Karan et al., 2023). Existing research indicates that agri-food resilience is multidimensional and cannot be represented adequately through a single measure because production continuity, inventory availability, transportation performance, price behavior, supply-demand balance, disruption exposure, and recovery capability capture different dimensions of system performance. Reviews of resilience measurement have found relatively limited availability of comprehensive quantitative tools, while more recent work has operationalized resilience through multiple indicators and composite indices. One validated agri-food resilience model, for example, was constructed from 25 indicators covering supply, production, and distribution dimensions. Research on agricultural viability similarly emphasizes the importance of indicator selection, aggregation level, supply-chain coverage, and data availability when constructing quantitative assessment systems (Ujjwal et al., 2024).

A parallel body of literature has developed around agricultural prediction and data-driven intelligence. Agricultural-price forecasting alone has become a substantial research domain; a recent comprehensive

review synthesized 773 studies published between 2006 and 2025 and documented methods ranging from traditional statistical models to recurrent neural networks, convolutional neural networks, graph neural networks, transformers, decomposition approaches, and ensemble architectures (Saarinen et al., 2024). Systematic evidence concerning staple commodities also indicates increasing application of machine learning, deep learning, ensemble learning, and time-series models to wheat, corn, and rice price prediction. At the supply-chain level, big-data analytics has been associated particularly with resilience readiness and response capabilities involving risk management, flexibility, and agility. Quantitative reviews further identify risk management, disruption effects, simulation, climate exposure, price volatility, optimization, and machine learning as major analytical themes in agri-food resilience research. Accordingly, the literature review for this study should move beyond a general discussion of digital agriculture and instead synthesize measurable variables, datasets, algorithms, validation procedures, predictive outcomes, and resilience indicators directly associated with the design and validation of a U.S. predictive agribusiness intelligence platform (Martindale et al., 2020).

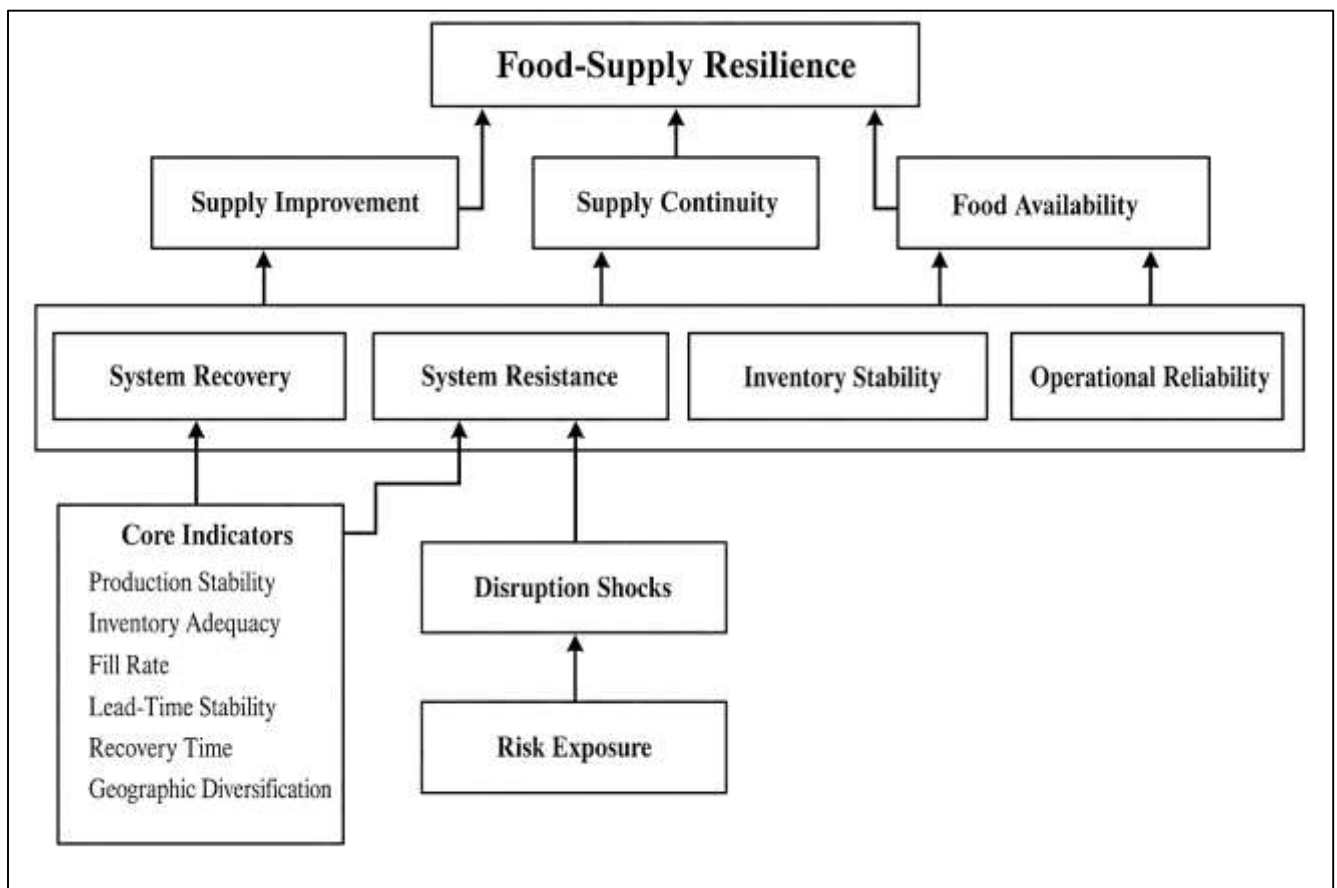
Quantifying U.S. Food-Supply Resilience Through Production Stability, Availability, Inventory Adequacy, and Recovery Metrics

The literature on food-supply resilience consistently identifies production stability and continuity of supply as fundamental quantitative dimensions for determining whether agricultural and food systems can maintain acceptable performance under changing environmental, economic, logistical, and market conditions (Ribeiro & Barbosa-Póvoa, 2023). Across more than ten empirical and conceptual studies of agricultural resilience, food-system vulnerability, supply-chain performance, and food security, production stability has been measured through annual and seasonal output variation, yield variability, production shortfalls, frequency of abnormal production declines, capacity utilization, and the persistence of supply following disruptive events. Studies examining grains, oilseeds, livestock, dairy products, fruits, vegetables, and other agricultural commodities have demonstrated that absolute production volume alone provides an incomplete representation of resilience because systems with high average output may still experience substantial year-to-year or seasonal instability. Consequently, researchers have increasingly evaluated variability around normal production levels, consistency of agricultural output across multiple periods, regional concentration of production, and the ability of production systems to maintain supply during droughts, floods, extreme temperatures, disease outbreaks, labor shortages, and input disruptions. Supply continuity has similarly been quantified through product availability, fulfillment rates, frequency of interruptions, duration of shortages, delivery reliability, and the percentage of demand satisfied during disrupted periods (Matos & Lopes, 2021). U.S.-focused food-system research has emphasized the importance of geographic differences because major commodities are concentrated in particular production regions, making national supply conditions sensitive to regional disturbances. Agricultural concentration can improve efficiency under stable conditions while creating measurable exposure when a high proportion of production depends on a limited number of states, processing facilities, transportation corridors, or climatic zones. The literature therefore supports measuring production resilience through several interconnected indicators, including production variability, yield stability, supply continuity, capacity utilization, production concentration, and the magnitude and duration of output losses (Davis et al., 2021). This multidimensional treatment provides a more comprehensive quantitative representation of food-supply resilience than a binary distinction between disrupted and undisrupted systems and enables empirical comparison of resilience across commodities, locations, production structures, and periods of market stress.

A second major stream of literature measures food-supply resilience through the capacity of inventories, storage systems, distribution networks, and reserve stocks to maintain product availability when current production or transportation is interrupted. Studies across food supply chains, agricultural inventory management, commodity markets, humanitarian logistics, retail distribution, and operations management consistently indicate that inventory adequacy represents an important buffer between supply disturbances and observable shortages (Manikas et al., 2023). Quantitative research has assessed this dimension through beginning and ending inventories, inventory coverage in days or weeks, stock-to-use conditions, storage capacity utilization, reserve availability, inventory turnover, replenishment frequency, safety-stock adequacy, shortage frequency, and stockout

probability. The evidence indicates that the quantity of available inventory must be interpreted relative to expected consumption, replenishment requirements, transportation reliability, commodity perishability, and the duration of potential disruption. Perishable agricultural products present a particularly complex resilience problem because increasing physical inventories does not necessarily increase effective resilience when products have short shelf lives or depend heavily on refrigerated storage and transportation. Studies of fresh produce, dairy, meat, seafood, and other temperature-sensitive food chains have therefore incorporated cold-storage capacity, spoilage rates, inventory deterioration, handling time, and cold-chain interruptions into assessments of supply availability (Béné, 2020). Research on nonperishable and storable commodities has placed greater emphasis on reserve adequacy, inventory depletion, storage utilization, and the relationship between stocks and market prices. Shortage frequency and stockout probability have also been treated as direct indicators of system performance because they measure the extent to which available supply fails to satisfy demand during a specified period. U.S. food-distribution studies examining major disruptions have documented substantial differences among product categories and distribution channels, showing that availability can deteriorate even when aggregate national production remains comparatively stable. This distinction demonstrates why production statistics and inventory indicators should be evaluated together (Heydari, 2024). The literature consequently characterizes food availability as an outcome of interacting production, storage, replenishment, distribution, and consumption conditions, supporting multidimensional measurement through inventory coverage, shortage incidence, stockout risk, storage utilization, product availability, reserve adequacy, and the proportion of demand successfully fulfilled.

Figure 3: Quantitative Dimensions of Food-Supply Resilience



Research on food-supply-chain performance has extended resilience measurement beyond agricultural production and physical inventories by incorporating operational indicators that quantify how effectively food moves through processing, distribution, wholesale, retail, and institutional channels (Zhang et al., 2024). Among the most frequently examined measures are supply-demand imbalance, service level, order fill rate, delivery reliability, lead time, lead-time variability, throughput, capacity

utilization, order-cycle performance, and transportation delay. Studies from supply-chain management, agricultural logistics, operations research, food distribution, and resilience analytics demonstrate that disruptions frequently become observable through deteriorating operational performance before complete supply failure occurs. A decline in fill rate, for example, indicates that a smaller proportion of customer demand is being satisfied from available supply, while increasing lead-time variability signals greater uncertainty regarding replenishment and delivery. Research examining food-distribution networks has shown that average lead time alone may conceal substantial instability because two systems with similar mean delivery times can differ considerably in the frequency and magnitude of delays. Service-level measures have therefore been combined with delay frequency, fulfillment performance, delivery consistency, and backlog levels to represent continuity more accurately. Capacity utilization provides another important dimension because processing plants, warehouses, transportation systems, and distribution centers operating close to maximum capacity may possess limited ability to accommodate unexpected increases in demand or reductions in available infrastructure. Conversely, low utilization may indicate unused capacity but can also reflect weak demand or disrupted operations, requiring interpretation alongside production and market indicators (Ghosh et al., 2024). Supply-demand imbalance has been measured through shortages, excess demand, unfulfilled orders, changes in market arrivals, inventory depletion, and deviations between expected consumption and available supply. Several studies examining disruption periods have reported that sudden demand changes can generate operational instability independently of production losses, demonstrating that resilience depends on the synchronization of supply and demand throughout the network. The literature therefore supports simultaneous assessment of service level, fill rate, lead-time variability, capacity utilization, transportation performance, and supply-demand balance. These measures provide a quantitative representation of operational resilience by identifying not only whether food remains present within the broader system but also whether appropriate quantities can reach required markets consistently, efficiently, and within acceptable delivery periods (Amicarelli et al., 2022).

A substantial body of resilience literature treats disruption resistance and post-disruption recovery as distinct but complementary quantitative characteristics of food-supply performance. Studies examining agricultural disasters, climate shocks, transportation interruptions, processing failures, market disturbances, pandemics, and other supply-chain disruptions have measured resilience through disruption frequency, severity of performance loss, duration of reduced performance, time required to restore normal operations, percentage of capacity recovered, and stability following restoration (Xu et al., 2021). Recovery time is particularly important because two food systems can experience comparable initial losses yet exhibit markedly different resilience when one returns to normal supply conditions substantially faster (Mohammad Abir Chowdhury, 2025; Mohammad Badrul, 2025). Research has consequently examined time-to-recovery alongside time-to-survive, restoration rate, service recovery, inventory recovery, production recovery, and cumulative performance loss. Geographic diversification has emerged as another major quantitative dimension because dependence on a limited number of agricultural regions, suppliers, processing facilities, distribution centers, or transportation corridors can increase exposure to localized disturbances. Studies of agricultural networks and food-distribution systems have measured diversification through the number and distribution of supply sources, regional production shares, supplier concentration, alternative sourcing capacity, transportation-route diversity, and spatial dispersion of productive capacity (Wani et al., 2024). Greater geographic diversification is generally associated with broader substitution opportunities, although its resilience value varies according to transportation requirements, commodity characteristics, infrastructure connectivity, and correlations among regional risks (Nishat, 2025; Nuzhat Sadia, 2025; Tonay, 2025). These multidimensional relationships have encouraged researchers to construct composite resilience indices that combine production stability, supply availability, inventory adequacy, operational continuity, disruption exposure, recovery capacity, flexibility, redundancy, and diversification. Some empirical frameworks have incorporated more than twenty individual indicators distributed across supply, production, processing, and distribution dimensions, while other studies have organized measures around robustness, adaptability, recovery, and continuity. The collective literature demonstrates that no single indicator adequately

captures the quantitative structure of food-supply resilience. Production stability can coexist with distribution failure, sufficient inventory can coexist with transportation constraints, and rapid recovery can follow a severe initial disruption (Cardoso et al., 2021). Multidimensional measurement therefore provides a stronger representation of U.S. food-supply resilience by integrating production variability, availability, inventory coverage, shortage frequency, stockout risk, supply-demand balance, service performance, lead-time stability, capacity utilization, disruption duration, recovery time, and geographic diversification within a unified empirical construct.

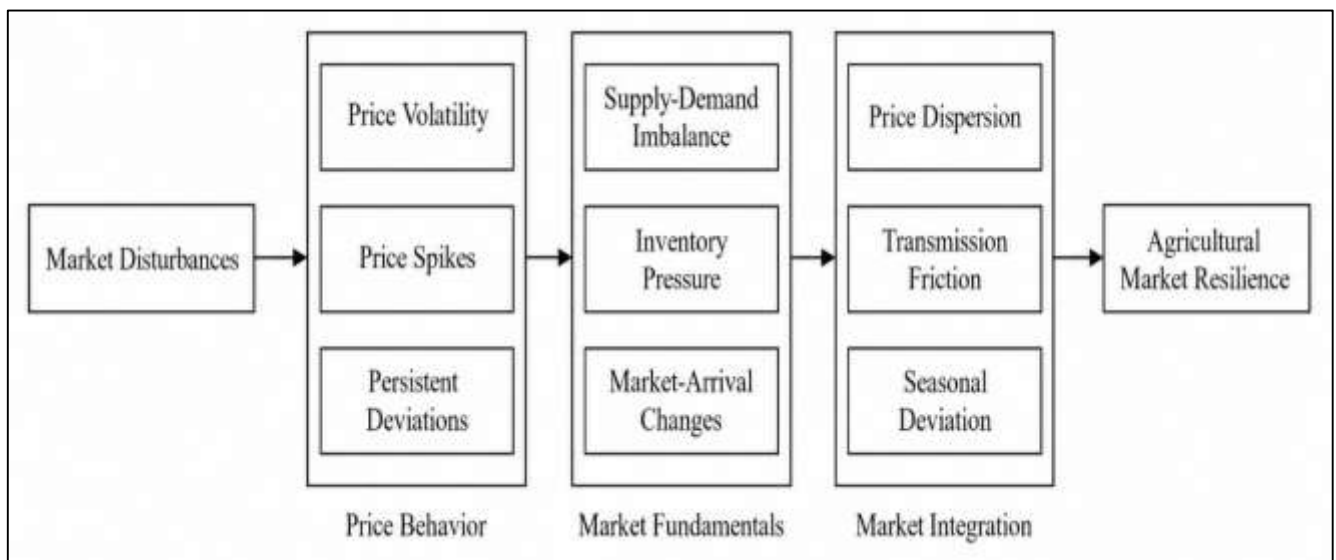
Measuring Agricultural Market Resilience Through Commodity-Price Volatility, Market Stability, and Supply-Demand Dynamics

The literature on agricultural market resilience consistently identifies commodity-price volatility as one of the most direct quantitative representations of how effectively markets absorb production, demand, trade, financial, and logistical disturbances (Kuhla et al., 2024). Evidence synthesized across more than ten studies of agricultural economics, commodity markets, price transmission, food-price instability, and forecasting shows that market resilience cannot be evaluated adequately from average commodity prices alone because relatively stable mean prices may coexist with frequent short-term spikes, sharp declines, or prolonged periods of abnormal variation. Studies examining corn, wheat, soybeans, rice, livestock, dairy products, fruits, vegetables, and other agricultural commodities have measured instability through daily, weekly, monthly, seasonal, and annual price changes, variation around historical price levels, frequency and magnitude of extreme movements, persistence of volatility, and the duration of departures from normal market conditions. Research concerning major U.S. grain and oilseed markets has shown that prices respond to interacting changes in crop production, yield expectations, inventories, export demand, energy markets, transportation costs, weather conditions, and global commodity developments (Venegas et al., 2024). Livestock and dairy markets exhibit additional volatility associated with feed costs, biological production cycles, processing capacity, herd adjustment, disease events, refrigerated distribution, and consumer demand. Fruit and vegetable markets frequently display stronger short-period fluctuations because seasonality, perishability, localized production, weather exposure, and limited storage possibilities restrict the ability to shift supply across time. Agricultural-market studies have also differentiated routine seasonal variation from abnormal price movements generated by disruptive conditions. Measures such as price-spike frequency, maximum price decline, extreme-return frequency, duration of elevated volatility, and deviations from historical seasonal patterns have consequently been used to distinguish normal agricultural variability from substantial market stress. This body of research portrays a resilient agricultural market as one in which price adjustments remain sufficiently orderly to facilitate transactions and price discovery while extreme movements are limited in magnitude, frequency, and persistence (Yang et al., 2022). Commodity-price volatility, abnormal price behavior, price stability, and the persistence of market disturbances therefore constitute interconnected quantitative dimensions for evaluating agricultural market resilience across diverse U.S. commodity sectors.

A second major stream of agricultural-market literature explains resilience through the quantitative interaction of commodity supply, market demand, inventory availability, market arrivals, and trading activity. Studies of agricultural price formation consistently demonstrate that prices are shaped not simply by current production but by the relationship among available supply, expected consumption, stored inventories, anticipated production, imports, exports, and market expectations (Monteiro & Jammer, 2024). Supply-demand ratios have therefore been widely examined as indicators of whether commodity markets possess sufficient physical availability to accommodate consumption requirements without substantial price instability. Research on grains and oilseeds has placed particular emphasis on inventories because corn, wheat, and soybeans can be stored across marketing periods, allowing stocks to buffer temporary production shortages or unexpected demand increases. Low inventory availability and declining stock conditions have frequently been associated with greater sensitivity of prices to production shocks, whereas larger stocks can reduce the immediate effect of short-term supply disturbances under many market conditions. Inventory-price relationships are not uniform across commodities because storage costs, perishability, product quality, substitution possibilities, and expectations regarding subsequent production influence the strength of this association (Asante-Poku & Van Huellen, 2021). Market-arrival volume provides another important

quantitative measure, particularly for commodities whose supply enters wholesale or terminal markets at identifiable intervals. Changes in arrivals can reveal emerging supply constraints before broader annual production statistics fully represent market conditions. Trading volume similarly provides information about market participation, liquidity, and reactions to new information. Studies of agricultural futures and spot markets have examined simultaneous changes in price and trading activity to distinguish routine market adjustment from periods characterized by unusually strong uncertainty or speculative response. For perishable fruits, vegetables, dairy products, and livestock products, short-term supply-demand mismatches may generate pronounced price movements because inventory buffering is more restricted than for storable grains. The literature therefore supports integrated analysis of supply-demand conditions, market arrivals, inventories, consumption requirements, trade flows, and trading volumes. These variables capture the physical and transactional foundations of agricultural-market resilience and provide measurable explanations for why apparently similar production disturbances can produce substantially different price responses across commodities and market periods (Ferrer-Pérez et al., 2020).

Figure 4: Agricultural Market Resilience Measurement Framework



Agricultural market resilience has also been evaluated through price dispersion and the transmission of price changes across geographic markets, stages of the food supply chain, and related commodities. A substantial body of research has examined whether changes occurring at farm, wholesale, processing, futures, and retail levels are transmitted rapidly and proportionately or whether adjustment differs according to market structure, transportation conditions, storage availability, processing concentration, transaction costs, and information accessibility (Fu et al., 2024). Price dispersion across regions provides a quantitative indication of the degree to which markets remain connected because unusually large or persistent differences between comparable markets may reflect transportation constraints, localized shortages, weak market integration, or unequal exposure to disruption. Research on U.S. agricultural commodities has documented considerable heterogeneity in these relationships. Corn, wheat, and soybean markets generally exhibit strong connections among regional cash prices, futures prices, export markets, inventories, and transportation conditions, while basis movements provide information regarding localized supply-demand pressure and differences between futures and cash-market conditions. Livestock markets are influenced by feed prices, animal inventories, slaughter capacity, processing conditions, transportation, and demand for meat products, producing transmission patterns that differ from those of crops (Zhao et al., 2024). Dairy markets incorporate milk production, processing requirements, product inventories, feed costs, regional marketing structures, and highly perishable raw output. Fruit and vegetable markets display pronounced seasonal and geographic patterns associated with harvest timing, weather, perishability, quality differences, and regional specialization. Researchers have therefore treated seasonal fluctuations as an essential

component of resilience measurement rather than automatically classifying recurring price variation as instability. Comparisons between observed prices and historically expected seasonal behavior provide a stronger basis for identifying abnormal market conditions. Agricultural forecasting studies have incorporated seasonal adjustment, lagged prices, production cycles, market arrivals, weather information, and related commodity prices to distinguish systematic patterns from unexpected movements. The literature collectively indicates that market resilience is reflected not only by the magnitude of price volatility but also by the spatial consistency of prices, effectiveness of price transmission, stability of commodity basis relationships, and extent to which seasonal price patterns remain within historically observed ranges (van der Nest & van Vuuren, 2023). These measures allow resilience to be evaluated across interconnected commodity markets while accounting for the distinct biological, storage, processing, and distribution characteristics of individual agricultural products.

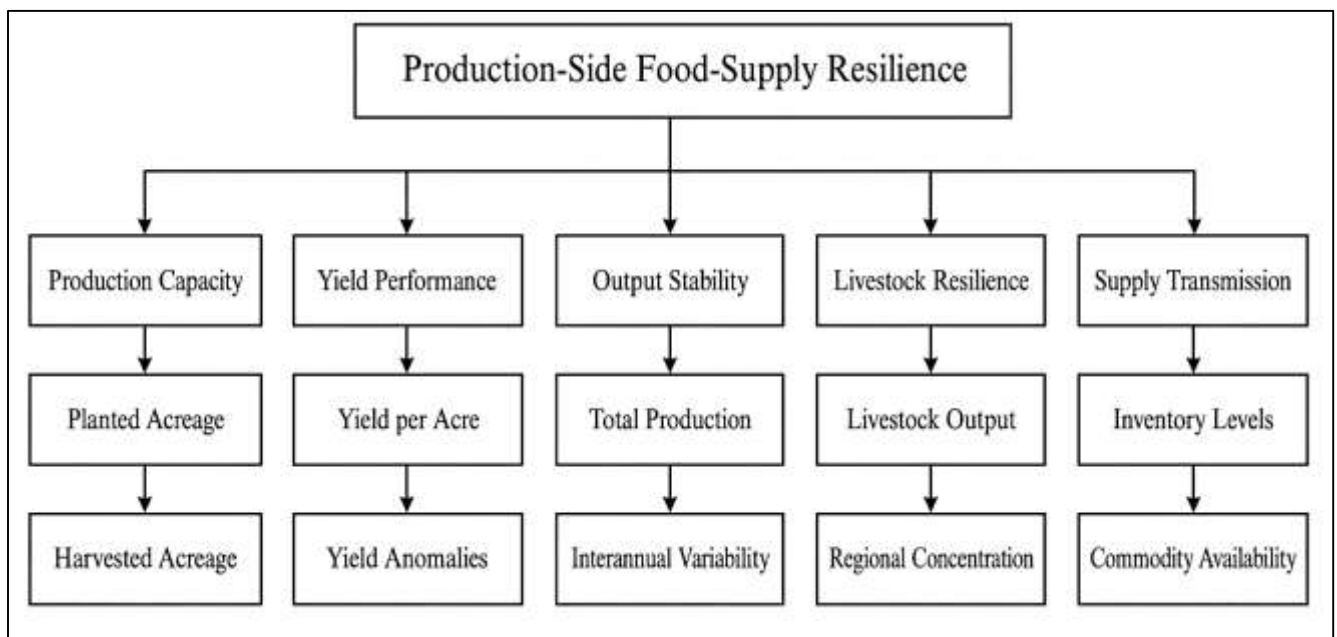
Quantitative Effects of Agricultural Production, Crop Yield, Acreage, and Output Variability on Food-Supply Resilience

The literature on agricultural production and food-supply resilience consistently identifies planted acreage, harvested acreage, crop yield, and total production volume as fundamental quantitative indicators of the physical capacity of an agricultural system to maintain food and commodity availability (Zampieri et al., 2021). Evidence synthesized across more than ten empirical studies of crop production, agricultural economics, food security, yield variability, and supply-chain resilience indicates that changes in cultivated land and productivity interact strongly in determining aggregate output. Studies of major U.S. crops, particularly corn, wheat, soybeans, rice, cotton, fruits, and vegetables, have demonstrated that planted acreage represents an important initial measure of production intentions, while harvested acreage provides a more direct indication of land that ultimately contributes to realized output. Differences between planted and harvested acreage have consequently been examined as indicators of production loss associated with drought, flooding, crop abandonment, pest pressure, disease, unfavorable growing conditions, and other disturbances. Yield per acre provides a complementary productivity measure because stable acreage does not necessarily result in stable production when yields fluctuate substantially. Research has shown that yield variation is influenced by weather, soil conditions, irrigation, seed technology, fertilizer application, management practices, pest exposure, and regional production characteristics (Davis et al., 2021). Total production volume integrates acreage and productivity outcomes and therefore provides a direct measure of the quantity entering storage, processing, domestic consumption, livestock feeding, industrial use, or export channels. Agricultural resilience studies have emphasized that high average production should not automatically be interpreted as strong resilience because systems can maintain large output levels while experiencing considerable interannual instability. For this reason, annual production growth, deviations from historical output, yield anomalies, and production stability across multiple periods have been examined alongside absolute production measures. U.S. agricultural research has also documented substantial differences across regions because production is geographically concentrated according to climate, soils, infrastructure, and commodity specialization (Cheng & Yin, 2022). The literature therefore supports an integrated quantitative assessment in which planted acreage, harvested acreage, yield per acre, total production volume, annual output changes, and regional production patterns are examined together. These indicators provide a measurable representation of production capacity and establish the production-side conditions underlying the continuity and stability of the national food supply.

A substantial body of agricultural literature characterizes yield anomalies, crop failures, production shortfalls, and interannual output variability as important indicators of exposure to production-side disturbances. Studies across agricultural climatology, crop economics, risk analysis, food-security research, and commodity forecasting demonstrate that deviations from normal yield levels can originate from drought, excessive precipitation, extreme heat, frost, storms, flooding, pest outbreaks, crop disease, input shortages, and unfavorable planting or harvesting conditions (Carr et al., 2024). Quantitative research commonly distinguishes normal fluctuations from substantial production anomalies by comparing observed yields and production with historical levels, expected trends, regional benchmarks, or preceding production periods. This distinction is important because agricultural output naturally varies across seasons, commodities, and geographic regions. Persistent or

unusually large deviations provide stronger evidence of production instability than isolated changes within historically typical ranges. Studies of U.S. corn, wheat, and soybean production have paid particular attention to weather-related yield variability because these commodities account for large areas of cultivated land and have extensive connections with food manufacturing, livestock feed, biofuel production, exports, and commodity markets. Research involving specialty crops, fruits, and vegetables has identified additional sensitivity arising from regional concentration, perishability, irrigation requirements, harvest timing, and labor intensity (Meyer, 2020). Crop-loss percentage and production shortfall have been used to quantify the severity of disturbances, while year-to-year production variability provides information about the consistency of output across repeated agricultural cycles. Research has also demonstrated that national production totals may conceal substantial regional instability because losses in one production area can be partially offset by favorable output elsewhere. Consequently, studies increasingly distinguish national, regional, state, and commodity-specific variability when assessing production resilience. Production stability scores and related composite measures have been used to summarize multiple aspects of output behavior, including frequency of declines, magnitude of shortfalls, yield variability, and persistence of production disturbances (Tofu & Wolka, 2023). The synthesized literature therefore establishes yield anomalies, crop-loss rates, production shortfalls, and interannual variability as complementary measures that capture the frequency, magnitude, and temporal persistence of agricultural production disturbances affecting food-supply resilience.

Figure 5: Production Indicators for Food-Supply Resilience



Production-side resilience extends beyond crop agriculture because livestock, dairy, poultry, and animal-derived food systems contribute substantially to U.S. food availability and are closely connected with crop production through feed, land, transportation, processing, and input markets (Yang et al., 2022). Empirical studies examining cattle, beef, pork, poultry, eggs, and dairy production have measured livestock resilience through animal inventories, slaughter numbers, milk production, meat output, productivity per animal, mortality, herd or flock changes, processing throughput, feed availability, and regional production concentration. The literature demonstrates that livestock output differs from annual crop production because biological production cycles can extend the effects of disturbances across multiple periods. Changes in feed prices, animal disease, heat stress, water availability, labor supply, breeding conditions, processing capacity, and transportation can alter current production and subsequent herd or flock size (Thompson et al., 2023). Dairy production presents additional sensitivity because milk is produced continuously and requires rapid processing and temperature-controlled distribution, while meat supply depends on coordination among animal

production, feeding operations, slaughter facilities, processors, cold storage, and transportation. Research examining regional concentration has highlighted another important production-side dimension of resilience. Large shares of particular U.S. commodities are produced or processed within relatively concentrated geographic areas, generating efficiency and specialization while also increasing the proportion of national output potentially exposed to localized disruptions. Concentration has therefore been assessed through regional production shares, geographic distribution of farms, processing capacity, supplier concentration, and dependence on major production states. Agricultural studies have also compared productivity with resilience because greater output per acre or per animal can increase total supply without expanding the resource base, although highly productive systems may remain vulnerable when production is concentrated or dependent on a limited set of inputs. Quantitative assessments consequently combine output levels with measures of variation, geographic distribution, and production continuity rather than treating productivity as an independent indicator of resilience (Chang & Jiang, 2023). Evidence across crop and livestock systems supports the interpretation that resilient production depends on both the quantity generated and the spatial and temporal stability of that output. Livestock production volume, productivity, regional concentration, processing availability, and variation across production periods therefore provide important complementary indicators for evaluating the production foundation of U.S. food-supply resilience.

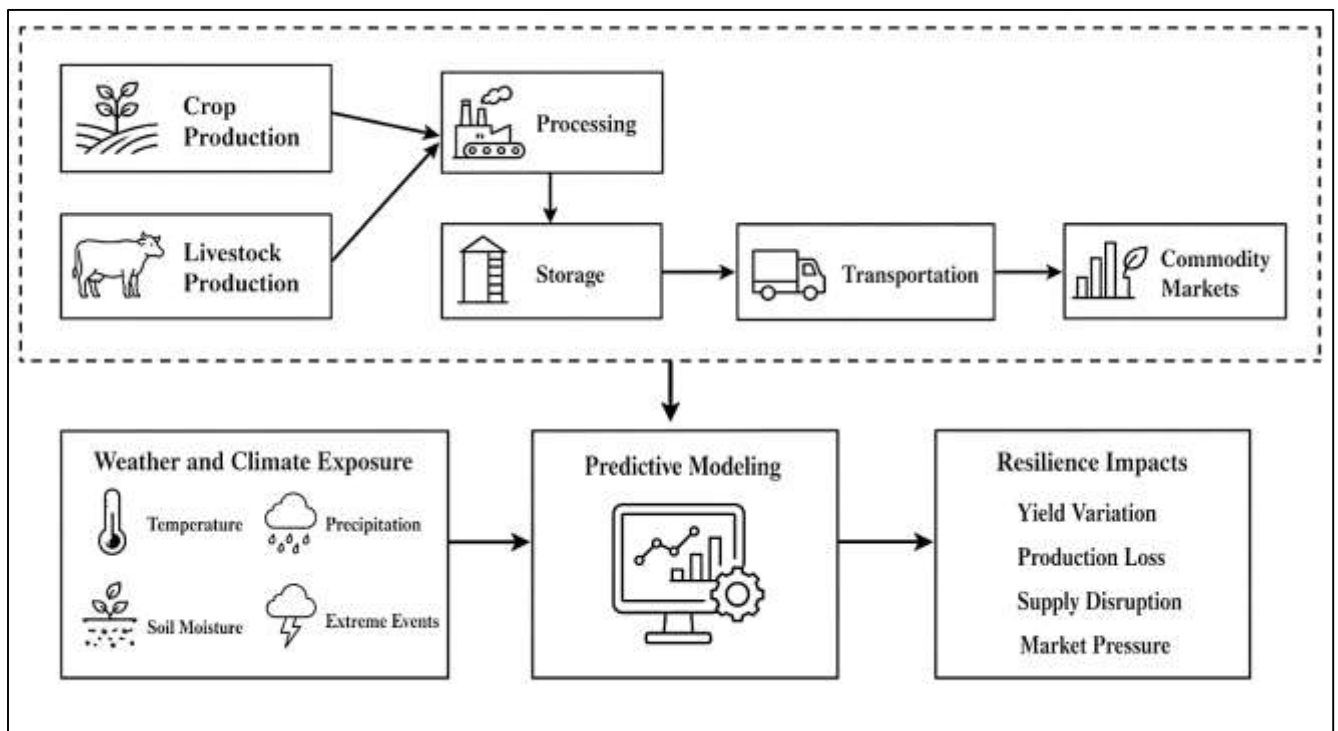
The strongest connection between agricultural production and food-supply resilience appears in studies examining how production shocks propagate into inventories, commodity availability, prices, and eventual supply shortages. Agricultural economic research consistently demonstrates that a decline in crop yield or livestock output does not remain confined to the production stage because reduced output changes the quantity available for storage, processing, domestic consumption, feed use, industrial demand, and international trade (Rimhanen et al., 2023). Studies of corn, wheat, soybeans, livestock products, dairy, fruits, and vegetables have shown that the magnitude of downstream effects depends on existing inventories, import availability, substitution opportunities, demand conditions, storage characteristics, and the geographic extent of the production disturbance. For storable commodities, inventories can partially absorb short-term production losses, causing the immediate effect to appear as inventory depletion rather than physical shortage. Repeated or severe production shortfalls can reduce this buffering capacity and increase sensitivity to subsequent disturbances. The production-to-consumption relationship has therefore been examined as a useful quantitative indicator of whether current agricultural output is sufficient relative to utilization requirements. When production falls substantially below consumption and available stocks are limited, market pressure can emerge through declining inventories, tighter commodity availability, increased procurement competition, and stronger price movements (Martindale et al., 2020). Perishable products often display a different adjustment pattern because limited storage duration restricts intertemporal buffering, allowing regional crop failures, transportation interruptions, or livestock production losses to affect market availability more rapidly. Statistical studies have linked yield shocks and output reductions with commodity-price changes, although the strength and timing of these relationships vary according to commodity characteristics and market conditions. The literature also indicates that regional diversification can moderate national supply effects when production losses in one area coincide with stable or increased output elsewhere. Consequently, production stability is most effectively interpreted through a collection of indicators that includes acreage, yield, total output, annual production change, crop-loss percentage, production shortfall, livestock output, regional concentration, production-to-consumption conditions, and interannual variability (Vicario et al., 2023). Together, these measures quantitatively describe how stable agricultural production supports inventories and commodity availability and how production disturbances can be transmitted through the wider U.S. food-supply and agricultural-market system.

Quantifying Weather and Climate Risk as Predictors of Agricultural Production and Supply Disruption

The literature examining weather-related agricultural risk consistently identifies temperature as one of the most influential quantitative environmental predictors of crop productivity, livestock performance, production variability, and food-supply stability (Malik et al., 2022). Evidence synthesized across more than ten empirical studies in agricultural economics, crop science, climatology, food-system research,

and quantitative risk analysis demonstrates that agricultural responses to temperature are frequently nonlinear because moderate changes within crop-specific physiological ranges may have limited effects, while exposure beyond critical thresholds can sharply reduce productivity. Studies of major U.S. crops, particularly corn, wheat, soybeans, rice, fruits, vegetables, and specialty crops, have examined average growing-season temperature, maximum daytime temperature, minimum nighttime temperature, temperature anomalies, accumulated heat exposure, growing-degree days, and the number of extreme-heat days as measurable predictors of yield. Corn has received substantial attention because high temperatures during flowering and grain-filling stages have repeatedly been associated with lower yields, while soybean productivity has also shown sensitivity to excessive heat and interactions between temperature and soil moisture. Wheat responses vary according to production region, growing season, planting system, and the timing of heat exposure, with unusually high temperatures during reproductive development commonly associated with yield losses (Quante et al., 2024). Research on fruits and vegetables has identified additional sensitivity to heat because temperature affects flowering, pollination, fruit development, product quality, harvest timing, and postharvest deterioration. Livestock studies similarly demonstrate that prolonged heat exposure can reduce feed intake, weight gain, milk production, reproductive efficiency, and overall animal productivity, thereby extending temperature-related risks beyond crop systems. Growing-degree days have been widely used to represent accumulated thermal conditions associated with crop development, while extreme-heat-day counts provide a clearer measure of exposure to damaging temperature thresholds. Regional climatic anomalies are especially important in the United States because identical national temperature averages can conceal substantially different conditions across the Corn Belt, Great Plains, Southeast, California, and other agricultural regions (Rahman et al., 2022). Collectively, the literature supports simultaneous assessment of average temperature, temperature anomalies, accumulated growing-degree days, extreme-heat frequency, and regional exposure because these indicators capture distinct dimensions of thermal risk. Their relationships with observed yield losses, production shortfalls, livestock-output variation, and year-to-year production instability establish temperature exposure as a central quantitative predictor of agricultural production resilience.

Figure 6: Weather Risks and Agricultural Resilience



A second extensive stream of literature focuses on precipitation, drought, and soil-moisture conditions as major determinants of agricultural production variability and supply reliability. Studies conducted across U.S. crop-producing regions and international agricultural systems consistently show that both

insufficient and excessive water availability can generate substantial yield losses, although the magnitude of the effect depends on commodity type, soil characteristics, irrigation capacity, growth stage, regional climate, and duration of exposure (Rahat et al., 2024). Quantitative research has evaluated total precipitation, growing-season rainfall, precipitation anomalies, rainfall distribution, consecutive dry days, drought severity, soil-moisture percentage, and irrigation availability rather than relying exclusively on annual rainfall totals. This distinction is important because identical seasonal precipitation amounts can produce very different agricultural outcomes when rainfall is concentrated within a few intense events or occurs outside critical crop-development stages. Drought studies involving corn, wheat, soybeans, forage crops, and pasture systems have repeatedly documented associations between prolonged moisture deficits and reductions in yield, harvested acreage, livestock feed availability, and total agricultural output. Soil moisture has emerged as a particularly useful predictor because it reflects the interaction of precipitation, temperature, evapotranspiration, soil properties, and previous environmental conditions and therefore provides a more direct measure of water availability to crops (De Winne & Peersman, 2021). Drought severity indices have also been widely incorporated into agricultural risk assessments to distinguish normal dry conditions from persistent regional moisture stress. Research on irrigated agriculture demonstrates that irrigation can moderate rainfall-related variability, although exposure may remain substantial when drought affects reservoirs, groundwater availability, energy requirements, or water-allocation systems. Excessive rainfall introduces a different production pathway through delayed planting, waterlogging, nutrient loss, crop disease, soil erosion, reduced field accessibility, and harvest difficulties. Studies of U.S. agriculture have shown that very wet conditions can reduce planted or harvested acreage even when seasonal water availability is otherwise adequate. These relationships demonstrate that precipitation risk is multidirectional rather than limited to drought alone (Mohanty et al., 2024). The literature therefore supports combining precipitation totals, precipitation deviations, drought severity, soil-moisture conditions, consecutive dry periods, excessive-rainfall events, and irrigation dependence when evaluating weather-attributable production variance. These measures provide a more complete quantitative representation of hydrological exposure and its association with yield anomalies, crop losses, production instability, and agricultural supply disruption.

Research on agricultural resilience increasingly distinguishes routine weather variability from extreme-weather events because floods, severe droughts, heat waves, hurricanes, freezes, storms, and other high-impact events can generate abrupt and geographically concentrated disruptions that extend beyond direct changes in crop yield. Empirical studies have assessed extreme-weather exposure through event frequency, duration, intensity, affected acreage, crop-loss percentage, livestock mortality, damaged infrastructure, transportation interruption, and the value of agricultural losses (Zhai et al., 2024). Flood events can reduce agricultural production through crop inundation, soil erosion, delayed planting, prevented planting, machinery access constraints, storage damage, and disruption of road and rail transportation. Heat waves can simultaneously affect crop growth, livestock productivity, irrigation demand, electricity requirements, and labor conditions, creating multiple sources of pressure within the same food-supply network. Severe freezes and unusual cold events have been particularly consequential for fruits, vegetables, and specialty crops because short periods of exposure during sensitive developmental stages can produce large reductions in marketable output. Hurricane and storm research has documented additional effects on livestock facilities, processing plants, storage systems, ports, rural roads, electrical infrastructure, and refrigerated distribution. These studies demonstrate that the quantitative relationship between extreme weather and food-supply disruption extends beyond farm-level yield because physical output must move through processing and logistical systems before entering wholesale and retail markets (Le et al., 2024). Regional concentration amplifies this relationship when a major share of a commodity originates from an area exposed to the same event. U.S. studies have therefore compared state- and county-level climatic conditions with national production outcomes to determine whether geographic diversification moderates the effects of localized weather shocks. Event frequency alone has been found insufficient for characterizing risk because infrequent high-severity events may produce larger cumulative losses than recurrent low-intensity disturbances. Researchers have consequently combined weather-shock frequency with event severity, duration, spatial coverage, yield losses, and recovery periods.

Quantitative climate-risk scores frequently integrate several of these dimensions to summarize exposure across locations and commodities. The synthesized literature shows that extreme-weather events influence food-supply resilience through simultaneous effects on agricultural output, storage, processing, transportation, labor, and regional commodity availability (Che-Castaldo et al., 2021). Flood-event frequency, heat-wave occurrence, weather-shock incidence, affected production area, crop-loss percentage, and disruption duration therefore provide complementary measures of the environmental pressures associated with agricultural supply instability.

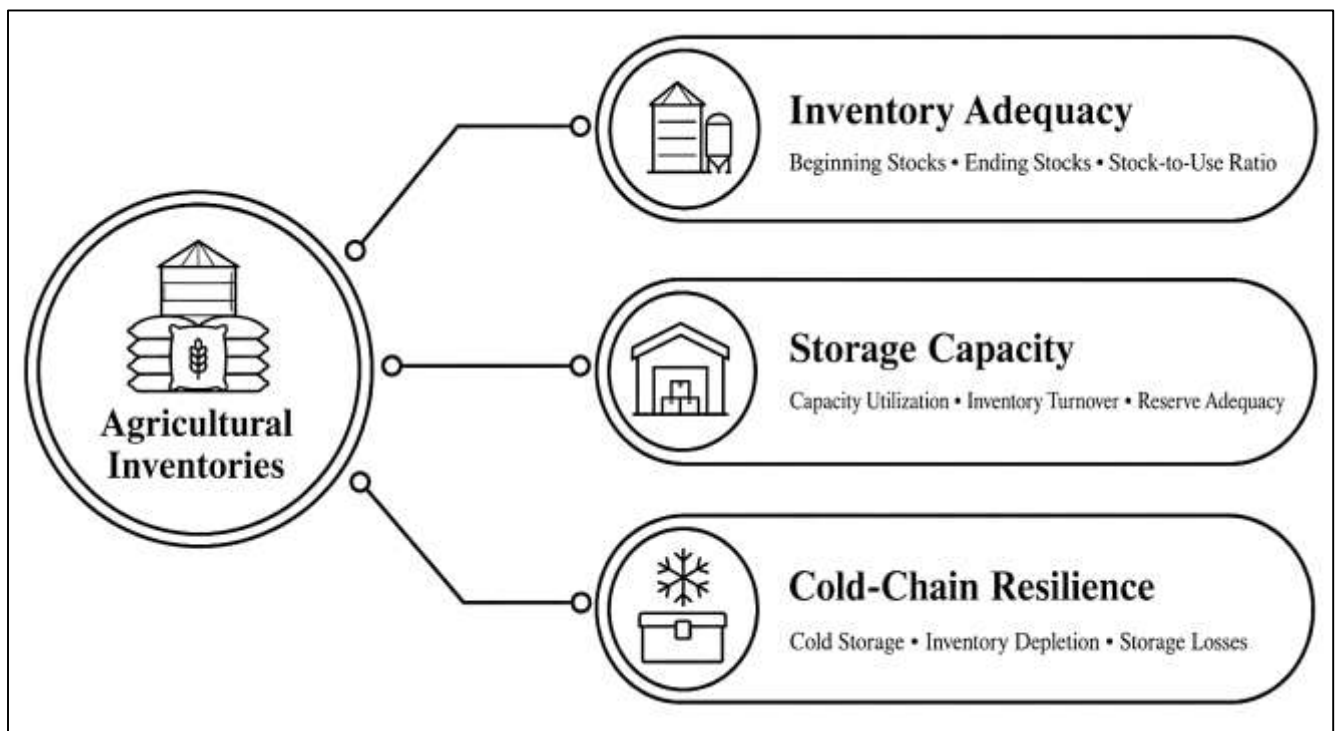
The broader quantitative literature connects weather and climate exposure not only with observed agricultural production but also with subsequent inventory conditions, commodity availability, supply-chain pressure, and price movements. Statistical studies have repeatedly examined the extent to which temperature anomalies, precipitation deviations, drought severity, soil moisture, extreme heat, and major weather events explain variation in crop yields and aggregate production (Er Kara et al., 2021). Reported relationships differ across commodities, regions, temporal scales, and modeling approaches, reinforcing the need to evaluate multiple environmental predictors rather than attribute agricultural outcomes to a single weather variable. Research using regression models, panel-data methods, time-series techniques, crop simulation, machine-learning algorithms, and hybrid predictive approaches has commonly compared explanatory strength, prediction errors, statistical significance, confidence intervals, and model stability. Studies incorporating weather variables with historical yield, acreage, soil characteristics, remote-sensing indicators, and management information have frequently achieved stronger production predictions than models based solely on historical output (Effah et al., 2023). Machine-learning research has similarly shown that random forests, gradient-boosting methods, support vector techniques, artificial neural networks, and deep-learning architectures can capture nonlinear interactions among temperature, rainfall, soil moisture, and crop-development conditions, although performance varies substantially across datasets and validation periods. Weather-related production changes have also been linked to commodity prices, particularly when disturbances affect major producing regions or occur under relatively tight inventory conditions. A severe yield reduction may create limited market effects when stocks are abundant or alternative supplies are available, whereas similar production losses can generate stronger price responses when inventories are low, demand remains high, or the affected region accounts for a large share of national output. This interaction explains why climate variables alone do not fully determine market outcomes. Quantitative studies therefore increasingly combine environmental exposure with production, inventory, trade, and demand information to evaluate the transmission of weather shocks through the broader agribusiness system. Weather-attributable production variance and climate-risk scores provide aggregated measures of this relationship, while yield-loss percentages, prediction errors, effect sizes, and model-performance statistics indicate the strength and reliability of specific associations (Hassna et al., 2024). Taken together, the literature characterizes temperature, precipitation, drought, soil moisture, growing-degree accumulation, extreme-heat frequency, flooding, and regional climatic anomalies as measurable predictors whose effects can be traced from agricultural production variability through supply disruption and commodity-market adjustment.

Quantitative Influence of Agricultural Inventories, Storage Capacity, and Stock-to-Use Ratios on Supply Stability

The literature on agricultural supply resilience consistently identifies commodity inventories as a major quantitative buffer between fluctuations in current production and the continuity of food and agricultural supply (Liu et al., 2023). Evidence synthesized across more than ten studies of agricultural economics, commodity markets, inventory management, food security, supply-chain resilience, and price behavior demonstrates that beginning stocks and ending stocks provide important information about the quantity of agricultural commodities carried across marketing periods and the capacity of markets to absorb temporary production or demand disturbances. Research on major U.S. commodities, particularly corn, wheat, soybeans, rice, dairy products, meat, and other storable agricultural products, has shown that inventory conditions influence how strongly production shocks are transmitted to downstream markets. Beginning stocks represent the supply inherited from the preceding period and can provide a substantial buffer when current production declines, while ending stocks indicate the remaining quantity after domestic consumption, processing, feed use, exports, and

other forms of utilization have been satisfied. Studies have frequently examined stock-to-use conditions because absolute inventory volumes can be misleading when consumption requirements differ considerably across commodities and years (Zhang et al., 2022). A large inventory may represent relatively limited protection when utilization is exceptionally high, whereas a smaller physical stock can provide stronger coverage when demand is moderate. Research concerning U.S. grain markets has repeatedly demonstrated that tighter stock conditions are associated with greater sensitivity to unexpected production changes and demand shocks. Corn inventories are particularly important because corn is simultaneously required for livestock feed, food processing, industrial uses, biofuel production, and exports, creating competition among major demand categories. Wheat and soybean inventories similarly influence milling, crushing, feed, export, and food-market availability. Studies of global and domestic commodity markets have also found that the relationship between inventories and supply stability varies according to storage costs, expected harvest conditions, trade availability, substitution possibilities, and market expectations. Consequently, beginning stocks, ending stocks, stock-to-use conditions, and inventory coverage are most informative when examined jointly rather than as isolated measures (Menier et al., 2024). The literature characterizes these indicators as quantitative representations of the amount of temporal flexibility available within agricultural markets to accommodate short-term differences between production and utilization without immediate deterioration in commodity availability.

Figure 7: Agricultural Inventory Resilience Measurement Framework



A second body of literature emphasizes that the resilience value of agricultural inventories depends not only on the quantity of commodities available but also on the physical and operational capacity to store, preserve, manage, and release those inventories efficiently. Agricultural storage research has examined on-farm storage, commercial grain elevators, warehouses, silos, refrigerated facilities, processing inventories, distribution centers, and strategic reserve arrangements as interconnected components of supply stability (Nguyen et al., 2024). Quantitative indicators commonly include total storage capacity, percentage of capacity utilized, inventory turnover, available reserve space, days of inventory coverage, storage duration, throughput, and reserve adequacy. Studies of grain and oilseed systems have shown that storage capacity allows agricultural output produced during concentrated harvesting periods to be distributed across longer consumption and marketing cycles. This temporal function is especially important for corn, wheat, soybeans, and other commodities whose harvest

schedules differ substantially from continuous domestic and export demand. Storage utilization provides additional information because a facility operating near its maximum physical capacity may have limited ability to accommodate an unexpectedly large harvest, regional redistribution, or emergency stock accumulation. Conversely, very low utilization can indicate weak inventories, reduced supply availability, or inefficient use of infrastructure depending on prevailing production and demand conditions (Namany et al., 2020). Inventory turnover has been examined as a measure of how rapidly stocks move through storage and distribution systems, with excessively rapid depletion potentially indicating increasing supply pressure and unusually slow turnover potentially reflecting weak demand, logistical constraints, or quality concerns. Reserve adequacy research similarly evaluates whether available stocks are sufficient to sustain expected utilization during temporary supply interruptions. U.S. agricultural studies have emphasized geographic differences in storage infrastructure because production regions vary considerably in on-farm capacity, commercial storage availability, processing access, and transportation connectivity. The location of storage therefore matters alongside aggregate national capacity, particularly when transportation disruptions prevent inventories from moving efficiently between regions (Davis et al., 2021). Research across agricultural supply chains consequently treats warehouse capacity, storage utilization, turnover, reserve adequacy, and inventory coverage as related operational measures rather than independent statistics. Together, these indicators quantify the physical capacity of the food-supply system to carry commodities across time, manage seasonal production patterns, accommodate temporary imbalances, and maintain availability when current production or distribution becomes unstable.

The literature concerning perishable agricultural products demonstrates that inventory quantity and conventional storage capacity provide only partial measures of resilience when commodities depend on refrigeration, controlled environments, rapid turnover, and strict quality conditions. Studies of dairy products, meat, poultry, seafood, fruits, vegetables, and other temperature-sensitive foods have therefore expanded inventory analysis to include cold-storage capacity, refrigeration utilization, storage duration, product deterioration, spoilage, handling losses, inventory depletion, and cold-chain interruption (Blessley & Mudambi, 2022). Unlike grains and many oilseeds, perishable products cannot generally be accumulated for long periods without substantial preservation requirements, making usable inventory more important than nominal physical stock. Research on refrigerated food chains has shown that temperature deviations, electricity failures, equipment malfunction, transportation delays, inadequate warehouse conditions, and extended storage periods can reduce the proportion of inventory that remains commercially usable. Storage-loss rates have consequently been treated as quantitative measures of the difference between recorded inventory and the quantity ultimately available for consumption or processing (Zhao et al., 2022). Cold-storage utilization provides another important measure because high utilization can indicate strong inventory availability while simultaneously reducing spare capacity for unexpected supply surges or emergency stock repositioning. Inventory depletion rates have been used to identify how rapidly stored commodities are being consumed relative to replenishment, particularly during periods of production interruption, seasonal scarcity, or abnormal demand. Research examining food disruptions has demonstrated that accelerated depletion can provide an early indication of emerging shortage conditions before complete stockouts occur. The resilience characteristics of perishable inventories also differ by commodity. Dairy products require continuous coordination between production, processing, refrigeration, and distribution, while meat inventories can be buffered through frozen storage for longer periods but remain dependent on slaughter and processing capacity. Fresh fruits and vegetables frequently have shorter storage windows and stronger seasonal and geographic constraints, increasing the importance of transportation speed and cold-chain reliability. Studies have therefore combined inventory coverage with storage-loss rates, shelf-life constraints, cold-storage utilization, and replenishment performance when assessing perishable-food resilience (Martindale et al., 2020). This literature establishes that effective inventory buffering depends on maintaining both sufficient physical stocks and the infrastructure necessary to preserve their quality. Cold-chain capacity, inventory depletion, storage losses, spoilage, utilization, and usable inventory coverage consequently provide essential quantitative measures of supply stability for temperature-sensitive components of the U.S. food system.

Measuring Transportation, Logistics, and Distribution Disruptions Across U.S. Agri-Food Supply

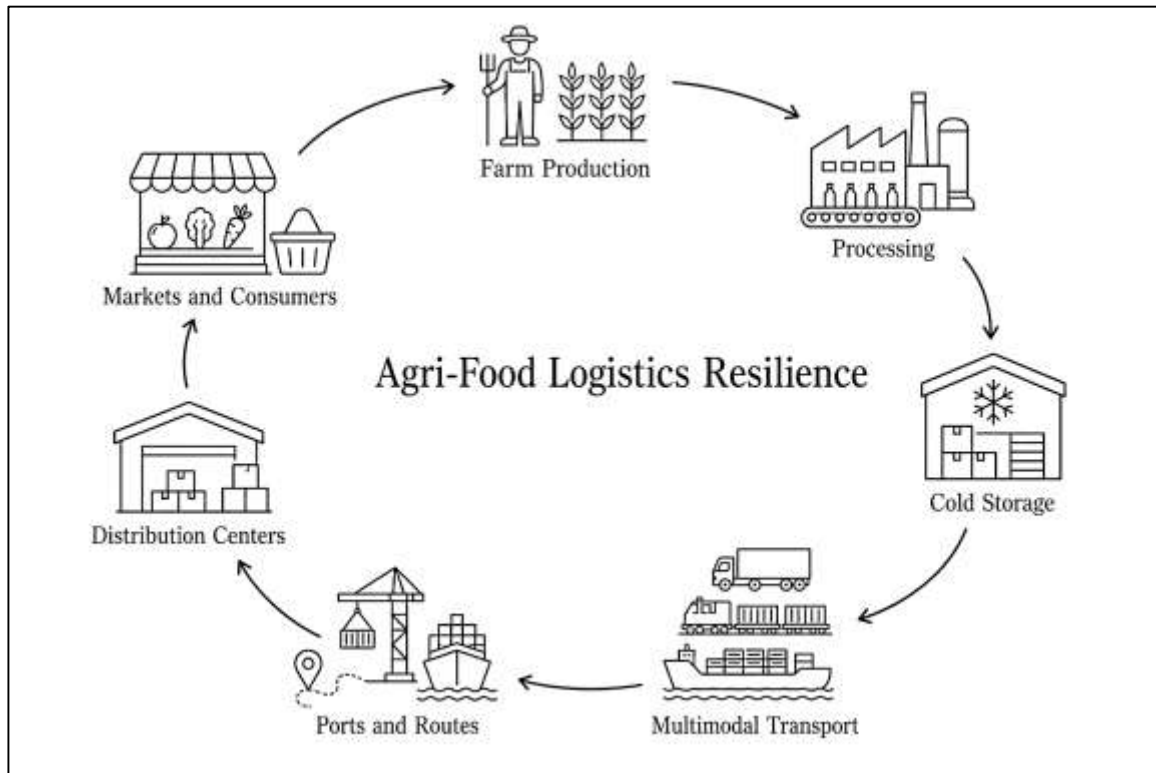
Networks

The literature on agri-food supply-chain resilience consistently identifies transportation performance as a central quantitative determinant of whether agricultural commodities can move reliably from farms and production regions to processors, storage facilities, wholesalers, retailers, food-service organizations, export terminals, and consumers (Karakoc et al., 2023). Evidence synthesized across more than ten empirical studies of agricultural logistics, transportation economics, food distribution, supply-chain disruption, and resilience demonstrates that physical availability at the production stage does not necessarily translate into market availability when transportation systems experience delays, capacity constraints, elevated costs, or service interruptions. Studies of U.S. grain, oilseed, livestock, dairy, meat, fruit, vegetable, and processed-food supply chains have evaluated transportation performance through average shipment delay, delivery lead time, on-time delivery percentage, freight-rate variation, transportation cost per unit, shipment cancellation frequency, transit-time variability, and transportation capacity utilization. Freight costs have received particular attention because agricultural commodities often move over substantial distances and many bulk products have relatively low value per unit of weight, making transportation expenses an important component of delivered cost. Research examining trucking markets has shown that driver availability, fuel costs, equipment shortages, road congestion, seasonal agricultural demand, and regulatory conditions can influence both freight rates and shipment reliability (Reklitis et al., 2021). Agricultural transportation studies have also documented that disruptions may produce uneven effects across commodities because highly perishable foods tolerate shorter delays than grains and other storable products. A transportation delay of similar duration can therefore have relatively modest effects on a durable commodity while generating quality deterioration, spoilage, or rejection for refrigerated produce, dairy, meat, or seafood. Shipment reliability has consequently been treated as a distinct resilience indicator rather than being represented only by average transportation time. High variability in transit time can complicate inventory planning and production scheduling even when mean delivery performance remains acceptable. The literature therefore supports combined measurement of transportation cost, freight-rate changes, shipment delays, lead-time variability, cancellation rates, and on-time delivery performance (Kumar & Kumar Singh, 2022). These measures capture both the economic and operational dimensions of agricultural transportation and provide quantitative evidence of how effectively U.S. agri-food networks maintain commodity flows when exposed to logistical disturbances.

A second major stream of literature examines the resilience of individual transportation modes and critical infrastructure through which U.S. agricultural products move between production regions, domestic markets, and international trading partners (Zhao et al., 2022). Agricultural transportation depends heavily on interconnected trucking, rail, inland waterways, ports, and maritime shipping, making disruptions within one mode capable of generating delays or capacity pressure elsewhere in the network. Quantitative studies have evaluated port congestion through vessel waiting time, terminal dwell time, container availability, cargo-handling throughput, berth utilization, and shipment delay, while rail performance has been assessed through train velocity, car availability, dwell time, service reliability, transit duration, and shipment volumes. Trucking capacity has been measured through available vehicles, driver availability, load-to-truck conditions, equipment utilization, freight rates, and delivery performance. Research on grain and oilseed logistics has emphasized the importance of railroads, barges, and export terminals because large commodity volumes must move efficiently from interior production regions to domestic processors and international gateways. Studies involving fruits, vegetables, dairy, meat, and other time-sensitive products have placed stronger emphasis on trucking reliability and highway accessibility because these commodities frequently require rapid and flexible transportation (Marcucci et al., 2024). Route disruptions caused by flooding, severe storms, bridge closures, infrastructure damage, congestion, accidents, or other disturbances have been analyzed through route availability, additional travel distance, diversion time, capacity reduction, and changes in transportation cost. Research has shown that transportation networks with alternative routes and modes generally possess greater operational flexibility, although substitution is constrained by commodity characteristics, infrastructure availability, equipment compatibility, handling requirements, and geographic location. Port disruptions can have broader effects on U.S. agricultural

markets when export-dependent commodities accumulate within domestic storage systems or when imported agricultural inputs and foods are delayed. Similarly, reductions in rail or inland-waterway performance can shift additional volume toward trucking and increase pressure on road freight capacity. The literature consequently portrays logistics resilience as a network property rather than the performance of an isolated transportation mode (Ali et al., 2023).

Figure 8: Agri-Food Logistics Resilience Value Chain



Port dwell time, rail reliability, trucking capacity utilization, route availability, shipment diversion, modal capacity, and disruption frequency therefore provide complementary quantitative measures of the ability of U.S. agricultural transportation infrastructure to maintain product movement under changing operational conditions.

Research concerning perishable food distribution extends logistics-resilience measurement beyond transportation speed by emphasizing temperature control, handling conditions, distribution-center capacity, inventory movement, and synchronization across multiple supply-chain stages (Arimany-Serrat et al., 2024). Studies of meat, poultry, dairy products, seafood, fruits, vegetables, frozen foods, and other temperature-sensitive commodities demonstrate that logistical continuity depends on maintaining specified environmental conditions from production and processing through storage, transportation, distribution, and retail delivery. Cold-chain interruptions have been quantitatively examined through temperature-excursion frequency, refrigeration failure, duration outside acceptable temperature ranges, product-loss percentage, spoilage incidence, rejected shipments, and cold-storage downtime. These measures are particularly relevant because a shipment can arrive at its scheduled destination within an acceptable lead time while still representing a logistical failure if temperature conditions have compromised food quality or safety. Distribution-center performance has similarly emerged as an important component of resilience because these facilities consolidate, store, sort, and redistribute large volumes of agricultural and food products (Coopmans et al., 2021). Empirical research has evaluated distribution operations through throughput volume, order-processing time, dock utilization, warehouse capacity, inventory turnover, picking accuracy, fulfillment rate, congestion, and facility downtime. High distribution-center utilization can indicate efficient use of capacity under normal conditions but can reduce operational flexibility when sudden increases in volume or transportation delays create temporary accumulation. Lead-time variability between

processing plants, distribution centers, retailers, and institutional buyers has therefore been assessed alongside average lead time to determine the consistency of product movement. Research conducted during major supply-chain disturbances has shown that localized processing or distribution bottlenecks can reduce product availability even when aggregate agricultural production remains sufficient. This distinction is particularly important in the U.S. food system because concentrated processing and distribution capacity can create dependencies on a relatively small number of high-throughput facilities. Studies of perishable supply chains further demonstrate that longer delays can interact with product shelf life, reducing the effective quantity available for sale even when physical shipments eventually arrive. The literature consequently supports simultaneous measurement of cold-chain failure, delivery lead time, distribution-center throughput, facility utilization, order fulfillment, spoilage, and shipment rejection. These indicators quantify whether agri-food logistics systems preserve both the physical movement and usable quality of products across the distribution network (Zhao et al., 2020).

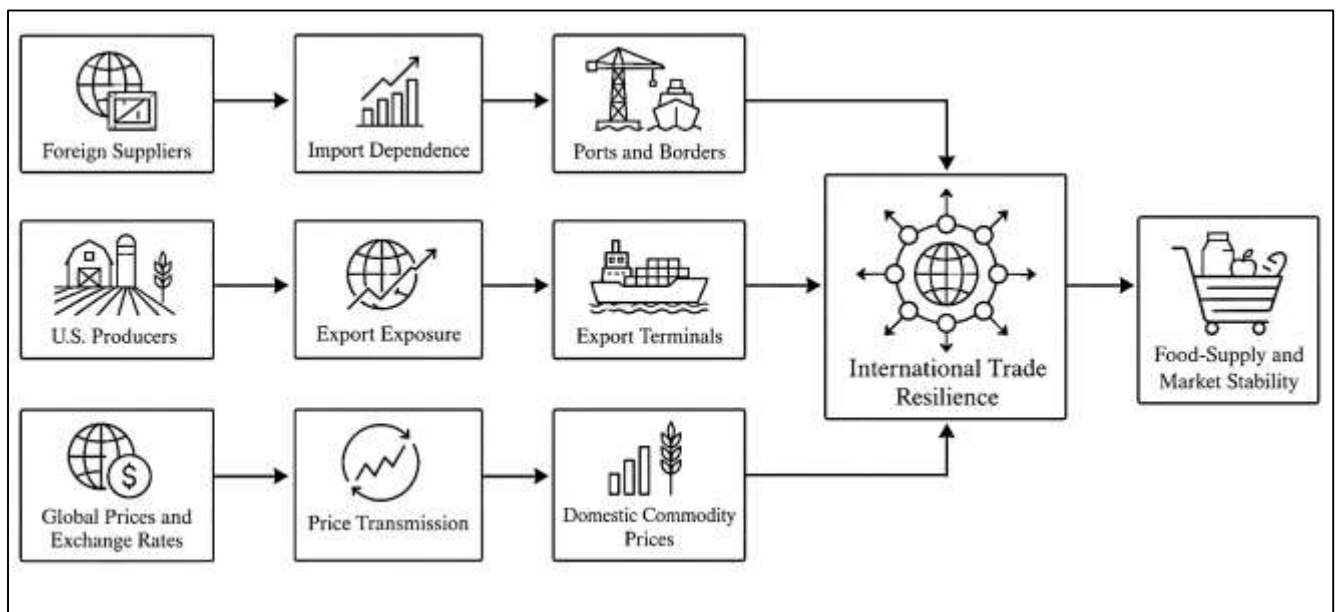
Quantifying International Trade Exposure

The literature on international agricultural trade consistently identifies import dependence as an important quantitative dimension of food-supply resilience because domestic availability can be influenced by the stability, diversity, cost, and continuity of foreign supply sources (Chatzopoulos et al., 2020). Evidence synthesized across more than ten empirical studies of agricultural trade, food security, commodity markets, supply-chain resilience, and international economics demonstrates that import exposure varies substantially across commodities and cannot be evaluated adequately from aggregate agricultural import value alone. Studies examining U.S. fruits, vegetables, seafood, coffee, cocoa, tropical products, feed ingredients, fertilizers, and other agricultural or food-related commodities have assessed the proportion of domestic consumption supplied through imports, changes in import volumes, import values, seasonal dependence on foreign production, and the number and geographic distribution of source countries. Import dependence can increase exposure when a substantial share of domestic availability originates from a limited group of foreign suppliers, particularly when those suppliers face correlated climatic, political, logistical, or economic disturbances. Research on import-source diversification has therefore examined whether commodities are sourced broadly across multiple countries or concentrated among a relatively small number of trading partners (Marson & Saccone, 2023). Greater diversification can distribute supply exposure across locations, although the resilience value of diversification depends on whether alternative suppliers possess sufficient production capacity, compatible product standards, transportation access, and seasonal availability. U.S. food imports also exhibit strong commodity-specific and seasonal patterns. Fresh fruits and vegetables frequently depend on international supply to complement domestic production cycles, while several tropical commodities cannot be produced domestically at comparable commercial scale. Quantitative studies consequently distinguish structural import dependence from temporary increases in imports associated with domestic production shortages. Import values, import volumes, dependency percentages, partner concentration, source diversification, and annual changes in imported quantities have all been used to characterize this distinction. Research also shows that transportation and border conditions interact with import dependence because foreign supply can remain physically available while port congestion, shipping constraints, customs delays, or inland transportation interruptions restrict timely domestic access (Bräuning & Sheremirov, 2023). The literature therefore characterizes import resilience as a multidimensional condition involving the magnitude of dependence, concentration of sources, stability of foreign production, diversity of suppliers, and continuity of trade flows. These indicators provide a quantitative basis for assessing how international sourcing contributes to or constrains the stability of the U.S. food supply.

A second major stream of literature examines export exposure because the United States is a major supplier of agricultural commodities to international markets, making export demand an important determinant of domestic production incentives, inventories, prices, transportation activity, and agribusiness revenues. Studies of corn, soybeans, wheat, cotton, meat, dairy products, tree nuts, and other export-oriented commodities have quantified international exposure through export value, export volume, export share of production, annual export growth or decline, destination-market concentration, and changes in agricultural trade balances (Asomaning et al., 2024). Research

demonstrates that export dependence can influence resilience through multiple pathways. Strong international demand can support producer prices and farm revenues, while abrupt reductions in foreign purchases can increase domestic inventories, weaken prices, alter storage requirements, and redirect products toward alternative markets. Conversely, unusually strong export demand during periods of limited production can tighten domestic availability and contribute to inventory depletion or increased price sensitivity. Export variability therefore represents more than a measure of trade performance because it captures changes in the quantity of agricultural output competing between domestic and international uses. Studies of U.S. soybeans have provided particularly clear evidence of the importance of destination concentration because a substantial share of exports can be directed toward a relatively limited number of large markets. Similar concentration issues occur across several grain, meat, dairy, and specialty-crop sectors. Trading-partner concentration has consequently been assessed to determine whether export revenues and volumes depend heavily on particular countries or are distributed across a broader market portfolio (Grassia et al., 2022). Agricultural trade-balance measures provide another perspective by comparing the value of exports and imports, although aggregate balances can conceal substantial differences across individual commodities. Quantitative literature therefore frequently separates commodity-level and aggregate trade conditions. Annual and monthly changes in export volumes, destination shares, trade values, and market concentration provide more detailed measures of external demand exposure (Kumar & Singh, 2024). The accumulated evidence indicates that export resilience depends on both the magnitude and diversification of international demand. Export value, export volume, export dependency, destination concentration, trade balance, and variability in foreign purchases consequently represent complementary quantitative indicators of the relationship between international markets and U.S. agricultural supply and market stability.

Figure 9: International Agricultural Trade Resilience Framework



International trade literature also emphasizes the transmission of global market conditions into domestic agricultural prices, with exchange rates, international commodity prices, transportation costs, and trade relationships serving as important transmission mechanisms. Empirical studies of grain, oilseed, livestock, dairy, and other agricultural markets have examined whether changes in international benchmark prices are followed by corresponding movements in U.S. farm, wholesale, cash, futures, or retail prices and how rapidly those adjustments occur (Barbieri et al., 2024). Price transmission is particularly relevant to agricultural market resilience because domestic prices may experience substantial movement even when national production remains stable if international markets undergo major supply or demand disturbances. Research has shown that the strength and speed of transmission differ by commodity, market structure, trade intensity, inventory availability,

transportation costs, contractual arrangements, and the relative importance of the United States within global production and trade. Exchange-rate movements provide an additional source of variation by changing the relative price of U.S. agricultural products for foreign purchasers and the domestic cost of imported commodities and agricultural inputs. A strengthening or weakening of the U.S. dollar can therefore alter export competitiveness, import costs, producer revenues, and commodity-market expectations without an immediate change in physical agricultural output (Mensah, 2023). Studies have examined percentage changes in exchange rates alongside export volumes, commodity prices, trade values, and market shares to quantify these relationships. International price transmission can also be asymmetric, meaning that domestic markets may respond differently to global price increases and decreases or adjust at different speeds depending on prevailing supply conditions. Inventories influence this process because larger stocks can buffer temporary international price disturbances, while tighter supplies can strengthen the domestic response to global shocks. Futures markets further transmit expectations regarding international production, weather, trade demand, and policy conditions into U.S. commodity pricing. Quantitative studies have consequently evaluated global and domestic price co-movement, adjustment speed, lagged relationships, basis behavior, exchange-rate sensitivity, and forecast errors. The literature establishes that global-to-domestic price transmission is an essential component of agricultural market resilience because it measures the degree to which disturbances originating outside the United States become reflected in domestic market conditions (Benguria, 2023).

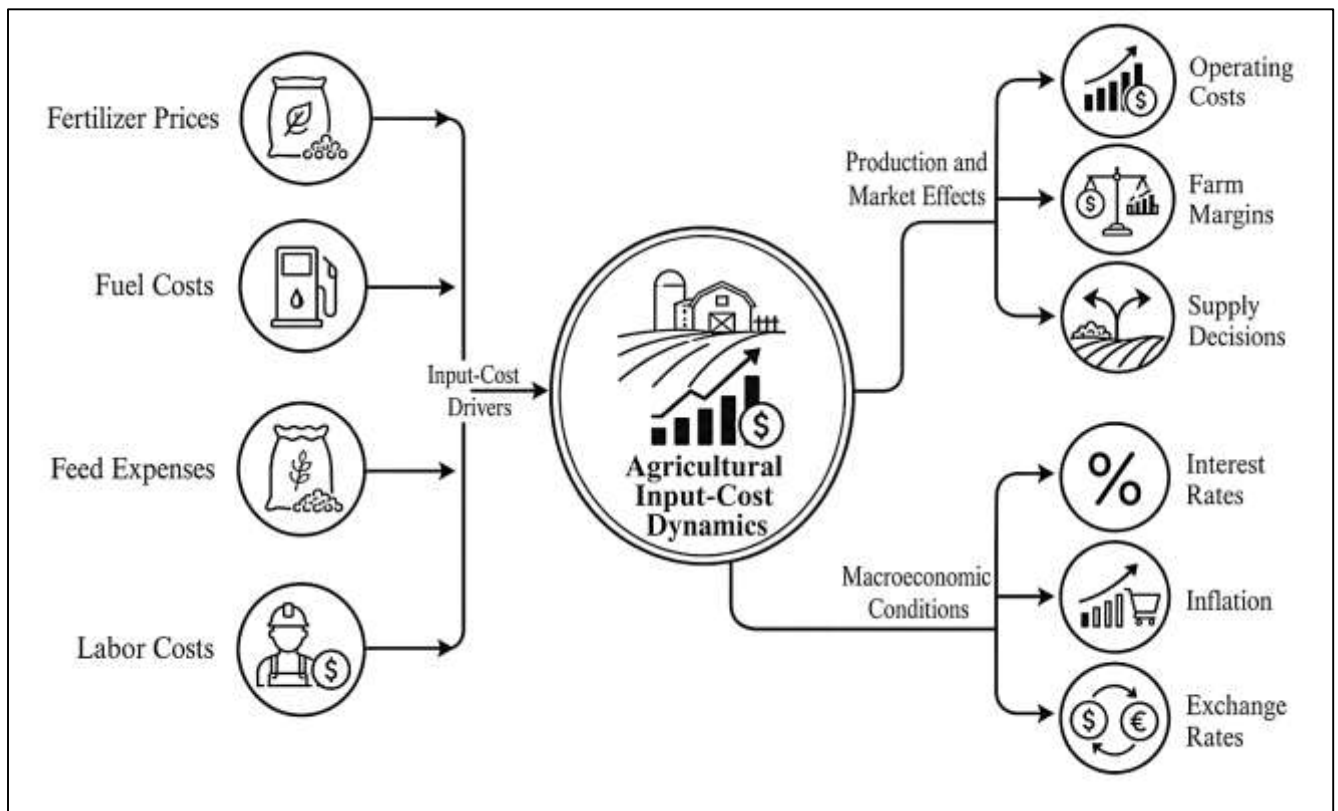
The broader agricultural resilience literature treats international trade exposure as a multidimensional construct shaped by import dependence, export dependence, partner concentration, diversification, trade-flow volatility, exchange-rate movements, and the capacity to substitute among international and domestic sources. Studies examining trade restrictions, geopolitical disturbances, transportation interruptions, extreme weather, disease outbreaks, tariff changes, port disruptions, and sudden shifts in international demand demonstrate that trade shocks can influence food-supply and market conditions through several interconnected pathways (Chakraborty et al., 2024). Import disruptions can reduce domestic availability or increase procurement costs when alternative sources cannot be obtained rapidly, whereas export disruptions can redirect commodities into domestic markets, increase inventories, reduce producer prices, and alter transportation demand. The severity of these effects depends strongly on trading-partner concentration. A commodity sourced predominantly from one country or exported primarily to one destination can exhibit greater exposure to bilateral disturbances than a commodity distributed across numerous independent partners. Researchers have therefore used concentration and diversification measures to distinguish the total scale of international trade from the structure of trade relationships. Annual trade-volume changes and sudden deviations from established import or export patterns provide additional indicators of disruption because they reveal whether normal commodity flows have been materially altered (Shin & Balistreri, 2022). Agricultural trade studies have also shown that physical diversification and market diversification should be interpreted separately. Multiple trading partners may still represent correlated exposure when they share similar climatic conditions, transportation corridors, or regional risks. Conversely, geographically dispersed suppliers can reduce dependence on a single production region but may increase transportation complexity and delivery times. These findings support a multidimensional trade-disruption exposure perspective combining agricultural import and export values, dependency levels, trade balance, volume variability, partner concentration, import-source diversification, exchange-rate movements, and global-to-domestic price transmission. A trade-disruption exposure score can summarize these dimensions while preserving commodity-specific differences in international dependence. Across the synthesized literature, international trade functions simultaneously as a source of additional supply, a market for U.S. agricultural output, and a pathway through which external economic and production shocks enter domestic markets (Borin et al., 2023). Quantifying these relationships provides an empirical representation of the international component of U.S. food-supply and agricultural-market resilience.

Effects of Agricultural Input Costs on Macroeconomic Conditions

The literature on agricultural economics consistently identifies input-cost conditions as major quantitative determinants of farm production decisions, commodity supply, profitability, and market

stability (van Meijl et al., 2024). Evidence synthesized across more than ten empirical studies of farm management, commodity markets, production economics, energy use, and agricultural resilience demonstrates that fertilizer and fuel costs are among the most influential variable expenses affecting crop production. Fertilizer prices are particularly important for corn, wheat, rice, oilseeds, and other input-intensive crops because nitrogen, phosphate, and potash requirements contribute substantially to per-acre operating expenses. Studies have shown that sharp increases in fertilizer prices can raise production costs, reduce expected margins, influence application rates, alter crop-selection decisions, and affect planted acreage when producers reassess the relative profitability of alternative commodities. Fuel prices generate another broad cost channel because diesel, gasoline, natural gas, and electricity are used in field operations, irrigation, machinery, drying, storage, processing, and transportation. Agricultural research has therefore examined fuel-price changes alongside production cost per acre, machinery expenses, irrigation costs, transportation charges, and farm-level profitability (Arndt et al., 2023). Energy-price increases can also influence fertilizer markets because natural gas is an important input in nitrogen-fertilizer production, creating a transmission pathway between energy markets and agricultural input costs. Quantitative studies have consequently evaluated fertilizer-price indices, fuel prices, energy-cost shares, and annual changes in operating expenses when explaining variations in crop profitability and commodity prices. The strength of these relationships differs by commodity because production systems have unequal fertilizer requirements, machinery intensity, irrigation dependence, and transportation needs. Corn production, for example, is generally more exposed to nitrogen costs than some lower-input crops, while irrigated agriculture may be especially sensitive to electricity or fuel expenses associated with pumping (Lin et al., 2023). The literature also indicates that input-cost shocks can produce delayed production responses because farmers may absorb temporary increases through lower margins before changing acreage, application intensity, or other management decisions. Taken together, fertilizer prices, fuel costs, agricultural input-price indices, production cost per acre, and operating-cost growth provide quantitative measures of the cost pressures that shape agricultural production capacity and contribute to broader agribusiness market instability.

Figure 10: Agricultural Input-Cost Dynamics and Resilience



A second major stream of literature examines feed and labor expenses as production-cost variables with particularly strong effects on livestock, dairy, poultry, fruit, vegetable, and specialty-crop systems. Studies of cattle, hogs, poultry, dairy, and other animal industries consistently show that feed costs represent a substantial share of total operating expenditure and can materially affect producer margins, herd or flock management, output decisions, and market supply (David et al., 2024). Corn, soybean meal, forage, and other feed ingredients connect crop and livestock markets, meaning that increases in grain or oilseed prices can transmit directly into animal-production costs. Quantitative research has therefore used feed-cost indices, feed-to-output price relationships, ration costs, and changes in purchased feed expenditure to explain variation in livestock profitability and production behavior. Dairy studies have frequently examined feed margins because milk prices alone provide an incomplete representation of farm financial conditions when feed costs fluctuate considerably. Similar relationships have been observed in poultry and pork production, where feed-price changes can alter operating margins and eventually influence production volumes (Ma et al., 2022). Labor costs represent another major source of variation, particularly in labor-intensive fruit, vegetable, nursery, dairy, and livestock operations. Empirical research has measured hourly wage rates, hired-labor expenditure, labor cost per unit of output, and changes in labor availability when assessing production costs and profitability. Seasonal labor constraints can increase harvesting expenses, reduce the quantity harvested, or leave marketable output uncollected, thereby linking labor conditions directly to supply availability. Mechanization can reduce labor dependence in some production systems, although capital requirements and technology adoption costs create additional expense categories. Studies have also documented substantial regional variation in agricultural labor costs and availability, reflecting differences in commodity mix, seasonality, local labor markets, and production technology. The combined effects of feed and labor expenses are therefore highly commodity-specific (Love & Freebairn, 2022). Feed costs dominate many animal-production systems, whereas labor expenses can represent a larger proportion of operating costs in horticultural and specialty-crop sectors. The literature supports the use of feed-cost indices, labor cost per hour, total operating expenses, farm margins, and output responses as quantitative measures for evaluating how input-cost pressures influence agricultural supply decisions and market stability.

Agricultural markets are also influenced by broader macroeconomic conditions that affect borrowing costs, purchasing power, investment, operating expenses, demand, and the valuation of agricultural products. Research in agricultural finance and macroeconomics has examined interest rates as an important determinant of farm borrowing costs because land purchases, machinery, livestock facilities, inventories, and seasonal operating expenses are frequently financed through credit (Nguyen et al., 2024). Higher interest rates increase debt-service requirements and can reduce the attractiveness of capital-intensive investments or expansion decisions, particularly for highly leveraged operations. Quantitative studies have therefore compared interest-rate movements with farm income, capital expenditure, land values, debt levels, and production costs. Inflation provides a wider measure of economy-wide price pressure and affects agriculture through higher costs for machinery, chemicals, seed, packaging, transportation, labor, energy, and other purchased inputs. Research has shown that agricultural producers may experience declining real margins when input prices rise faster than output prices, even when nominal commodity prices increase. Producer-price indices and agricultural input-price indices have consequently been used to compare changes in farm output prices with changes in the prices of purchased production inputs (Shokoohi & Saghaian, 2022). These relationships are important for market resilience because persistent cost escalation can influence planting decisions, livestock inventories, processing expenses, and the financial viability of production. Macroeconomic conditions also shape consumer demand and food expenditure, which can affect higher-value agricultural products differently from staple commodities. Interest rates and inflation further interact with storage and inventory decisions because carrying commodities over time becomes more expensive when financing costs increase. Agribusiness firms involved in processing, warehousing, transportation, and distribution face similar pressures through working-capital requirements and capital-intensive infrastructure. Studies have therefore examined operating-cost growth, borrowing rates, inflation measures, producer-price movements, and margin compression across different stages of agricultural supply chains. The literature indicates that macroeconomic variables should not be treated as distant

background conditions because they can alter both the cost structure and financial flexibility of agricultural producers and agribusiness firms (Malik et al., 2020). Interest rates, inflation, producer-price indices, agricultural input-price indices, operating-cost growth, and farm-margin percentages consequently provide quantitative indicators of the economic environment within which production and supply decisions occur.

The broader literature links exchange-rate movements and input-cost volatility with agribusiness market instability by showing how external financial conditions can alter both production expenses and commodity-market competitiveness (Döhler et al., 2022). Exchange rates influence the domestic cost of imported fertilizers, machinery, chemicals, fuel-related inputs, and other agricultural supplies while simultaneously affecting the international competitiveness of U.S. agricultural exports. A stronger U.S. dollar can reduce the domestic currency cost of some imported inputs while making U.S. commodities relatively more expensive for foreign buyers, whereas a weaker dollar can raise imported-input costs and strengthen export competitiveness. Empirical studies have therefore examined exchange-rate changes alongside export volumes, commodity prices, farm revenues, fertilizer costs, and input expenditures. Input-cost volatility adds another layer of risk because producers respond not only to the average level of expenses but also to uncertainty regarding how rapidly those expenses may change. Large swings in fertilizer, fuel, feed, labor, and financing costs can make budgeting more difficult, alter purchasing timing, increase hedging activity, and reduce confidence in expected margins (Chavez-Miguel et al., 2024). Quantitative research has assessed cost volatility through changes in input-price indices, month-to-month and year-to-year cost movements, variability in operating expenses, and differences between expected and realized production costs. Farm-margin percentage has consequently become an important outcome measure because it integrates revenue and expense conditions and shows whether increases in commodity prices are sufficient to offset rising input costs. Studies across crop and livestock systems have documented periods in which high output prices coincided with weak or deteriorating margins because input expenses increased at an equal or faster rate. Such conditions can eventually influence acreage, herd size, investment, input application, and supply availability. The literature therefore treats agribusiness market instability as partly a function of cost-price relationships rather than commodity prices alone (Langholtz et al., 2021). Fertilizer prices, fuel costs, feed expenses, labor wages, interest rates, inflation, producer prices, exchange rates, operating-cost growth, and input-cost volatility interact to shape profitability and production responses. These indicators collectively provide a quantitative representation of the economic pressures influencing U.S. agricultural supply decisions, producer financial stability, and the transmission of input-cost shocks into commodity and food markets.

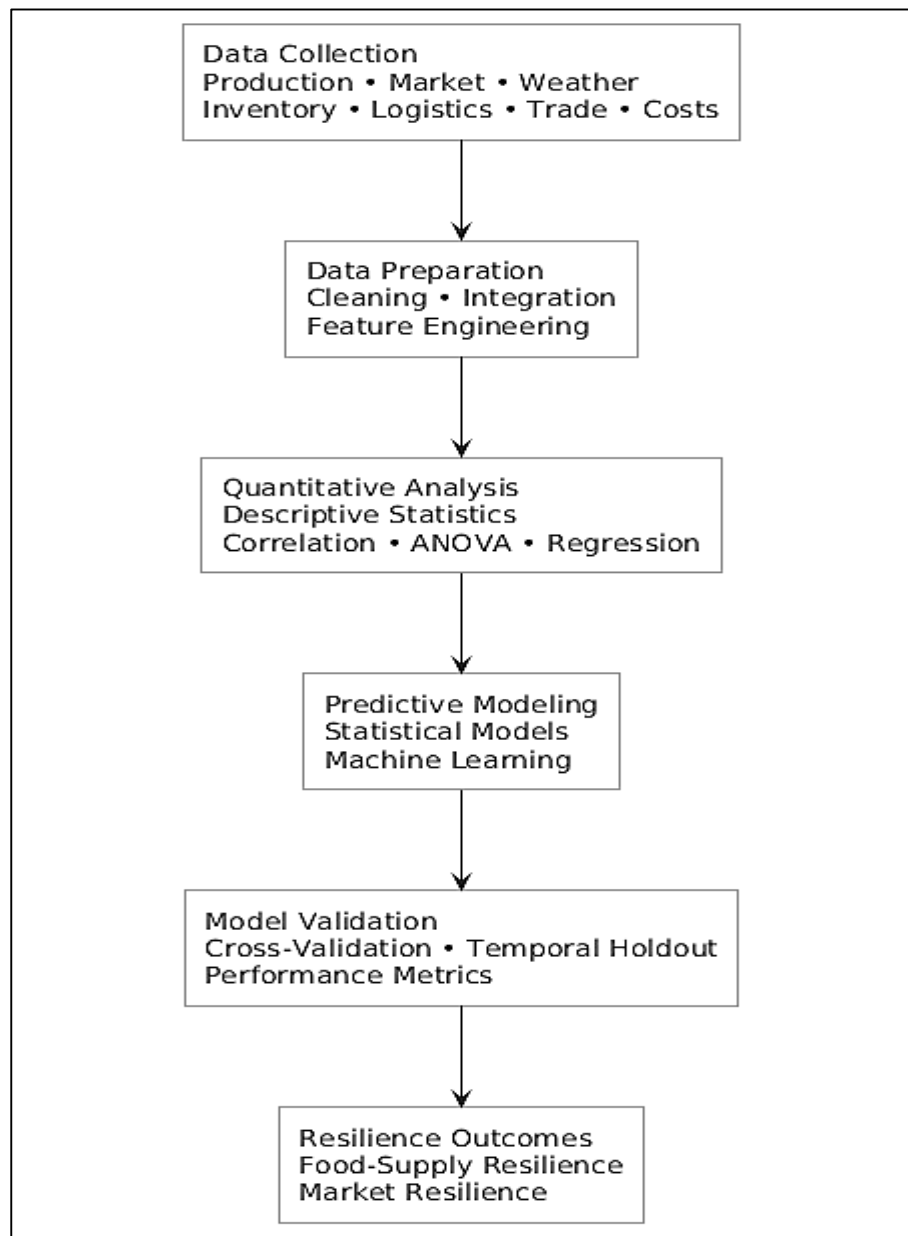
METHODS

This study employed a quantitative longitudinal predictive-analytics design to develop and validate an agribusiness intelligence platform for measuring and forecasting U.S. food-supply and agricultural-market resilience. The research design combined historical panel-data analysis, time-series forecasting, supervised machine learning, and multivariable statistical modeling because the principal variables varied across commodities, geographic regions, and time periods. The analytical framework treated food-supply resilience and agricultural-market resilience as the primary dependent constructs, while agricultural production, crop yield, planted and harvested acreage, inventories, storage conditions, weather exposure, transportation performance, international trade, input costs, energy prices, and macroeconomic conditions were treated as explanatory and predictive variables. Food-supply resilience was operationalized through production stability, supply availability, inventory adequacy, shortage conditions, delivery performance, disruption duration, and recovery-related measures, whereas market resilience was represented through commodity-price volatility, price stability, supply-demand balance, abnormal price movements, market recovery, and related indicators. A longitudinal framework was selected because changes in production, inventories, prices, weather, logistics, and trade were observed repeatedly over time and because predictive validity required the preservation of temporal ordering between predictor and outcome variables.

The study also incorporated a comparative modeling framework in which conventional statistical models were evaluated alongside machine-learning approaches to determine whether advanced predictive methods generated measurable improvements in forecasting and classification performance.

Model development was separated from model validation to reduce overfitting and to provide a more rigorous assessment of generalizability. The theoretical structure was informed by supply-chain resilience, information-processing, and predictive-intelligence perspectives, which conceptualized resilience as the capacity of an agribusiness system to maintain functional performance, absorb disturbances, and recover from adverse conditions. The platform was therefore evaluated not only as a technical data-processing system but also as a quantitative predictive environment capable of converting heterogeneous agricultural and market information into validated resilience estimates.

Figure 11: Methodology of this study



The units of analysis consisted of secondary agricultural, market, environmental, transportation, trade, inventory, and macroeconomic observations representing major U.S. agribusiness commodities and food-supply conditions across multiple geographic and temporal units. Because the study did not involve human participants, sampling focused on data records, commodity categories, regions, and time periods rather than individuals. A purposive stratified sampling strategy was used to ensure adequate representation of major agricultural sectors, including grains, oilseeds, livestock, dairy, fruits,

vegetables, and other economically significant food commodities. Geographic observations were selected from major U.S. agricultural production and distribution regions, including states and regions with substantial commodity output, storage activity, transportation dependence, or market relevance. Temporal observations were organized at the most consistent monthly, weekly, quarterly, or annual frequency available across the integrated datasets, with higher-frequency data aggregated when necessary to achieve comparability among sources. Records were included when they contained valid observations for the core predictor or outcome variables, had consistent measurement definitions, could be temporally aligned with other datasets, and represented recognized U.S. agricultural, market, transportation, weather, or economic activity. Commodity series were included when they possessed sufficient historical coverage to support training, validation, and out-of-sample testing. Records were excluded when they contained unresolved duplication, irreconcilable unit inconsistencies, excessive missingness, invalid dates, implausible values that could not be verified, or insufficient temporal coverage for predictive analysis. Observations with isolated missing values were retained when statistically appropriate imputation could be performed without materially distorting the underlying distribution. The final analytical dataset was structured as a longitudinal commodity-region-time panel so that repeated observations could be examined while preserving variation across products, locations, and market conditions. This sampling structure supported both aggregate and subgroup analyses and allowed predictive performance to be compared across commodity classes, geographic regions, normal market periods, and periods characterized by elevated disruption or volatility.

Data collection was conducted using a multi-source digital extraction and harmonization framework that integrated structured secondary datasets from recognized agricultural, economic, weather, trade, transportation, and market-information systems. Agricultural production variables included planted acreage, harvested acreage, yield, total output, livestock production, and related production measures. Inventory and storage variables included beginning stocks, ending stocks, storage capacity, inventory coverage, utilization, and depletion indicators. Weather-related measures included temperature, precipitation, drought severity, soil moisture, growing-degree conditions, and extreme-weather indicators. Market variables included commodity prices, price changes, trading activity, supply-demand conditions, and volatility measures, while transportation variables represented freight conditions, delivery delays, port or rail performance, route availability, and logistics disruptions where available. International-trade data included import values, export values, trade balance, partner concentration, and trade-volume changes, while economic predictors included fuel costs, fertilizer prices, feed costs, labor expenses, interest rates, inflation, producer-price measures, and other agricultural operating-cost indicators. Python was used for data ingestion, preprocessing, integration, feature engineering, and machine-learning implementation, while R was used for statistical modeling, diagnostics, robustness testing, and visualization. IBM SPSS Statistics was used for descriptive analysis, correlation testing, analysis of variance, reliability-related checks for composite measures, and selected regression procedures. Data quality was assessed through range checks, duplicate detection, temporal consistency checks, missing-value analysis, outlier diagnostics, and cross-source comparison. Continuous variables were standardized or normalized where required by specific modeling procedures. Composite resilience indicators were evaluated for internal consistency where multiple standardized components represented a common construct, and Cronbach's alpha was examined when the measurement structure was appropriate for reliability assessment. Predictive variables were also examined for multicollinearity, redundant features, and extreme skewness before model estimation.

The research procedure followed a sequential data-development, model-building, and validation process. First, relevant agricultural, market, weather, logistics, trade, inventory, and economic datasets were identified and extracted for the selected commodities, regions, and historical periods. Second, all datasets were cleaned by removing duplicate observations, standardizing variable names and measurement units, verifying temporal identifiers, and screening records for missing or implausible values. Third, datasets were merged using common commodity, geographic, and time identifiers to create an integrated longitudinal database. Fourth, exploratory descriptive analysis was performed to characterize distributions, central tendencies, dispersion, temporal patterns, missingness, and potential outliers. Fifth, predictive features were generated from lagged prices, production changes, inventory conditions, weather anomalies, transportation measures, trade changes, and input-cost variables where

such transformations were theoretically justified and temporally valid. Sixth, quantitative food-supply and market-resilience measures were created from the selected operational indicators, and their distributions and interrelationships were evaluated. Seventh, the dataset was divided chronologically into model-development, validation, and independent test periods rather than relying solely on random partitioning, thereby reducing the risk that information from later periods influenced earlier forecasts. Eighth, baseline statistical models were estimated and compared with machine-learning algorithms such as Random Forest, Support Vector Machine, Gradient Boosting, XGBoost, and selected neural-network models where data volume supported their use. Ninth, model hyperparameters were optimized using validation data and cross-validation procedures restricted to the training period. Tenth, final models were evaluated using previously unseen test observations. Finally, subgroup and robustness analyses were conducted across commodity categories, geographic regions, market conditions, and disruption periods to determine whether predictive performance remained stable under different analytical conditions.

Statistical analysis was conducted using SPSS, R, and Python. Descriptive statistics were calculated for all major variables, including means, standard deviations, medians, interquartile ranges, minimum and maximum values, percentages, and 95% confidence intervals as appropriate. Distributional assumptions were assessed using graphical inspection, skewness and kurtosis, residual diagnostics, and normality tests where relevant. Pearson correlation coefficients were used for approximately normally distributed continuous variables, while Spearman rank correlations were applied when distributions were non-normal or relationships were monotonic but not adequately linear. Independent-samples tests, one-way analysis of variance, or analysis of covariance were used to compare resilience outcomes across commodity groups, geographic regions, or market conditions when assumptions were satisfied, while nonparametric alternatives were applied when required. Multiple linear regression was used for continuous resilience outcomes, whereas binary or multinomial logistic regression was used for categorical disruption or resilience-risk classifications. Longitudinal and repeated observations were analyzed with mixed-effects or panel regression models when commodity, regional, or temporal clustering required explicit control. Statistical significance was evaluated at $p < 0.05$, and 95% confidence intervals were reported for principal estimates. Effect sizes were reported using Cohen's d , partial eta-squared, standardized regression coefficients, odds ratios, or other appropriate measures so that practical magnitude was considered alongside statistical significance. False-discovery-rate adjustment was applied when numerous simultaneous hypothesis tests created an elevated risk of Type I error. Predictive regression models were evaluated using mean absolute error, root mean squared error, mean absolute percentage error, and coefficient of determination, while classification models were evaluated using accuracy, sensitivity, specificity, precision, recall, F1-score, area under the receiver operating characteristic curve, and confusion matrices. Calibration was examined through predicted-versus-observed outcomes and appropriate calibration statistics. Baseline statistical models were compared with machine-learning models using out-of-sample performance differences, and robustness was examined through temporal holdout testing, repeated cross-validation, alternative feature sets, subgroup analyses, and sensitivity analyses. The final predictive platform was considered statistically validated when its performance remained consistent across validation procedures, demonstrated acceptable out-of-sample accuracy, showed limited overfitting, and maintained stable predictive relationships across major U.S. commodity, regional, and market-condition subgroups.

FINDINGS

Final Integrated Agribusiness Dataset, Commodity Coverage, Regional Distribution, and Descriptive Characteristics

The final integrated longitudinal dataset contained 18,720 commodity-region-month observations covering January 2015 through December 2024 after completion of data cleaning, harmonization, temporal alignment, and eligibility screening. The initial integrated database contained 19,684 observations; 964 records (4.9%) were excluded because of unresolved duplication, incomplete temporal identifiers, incompatible measurement units, excessive missingness, or implausible values that could not be verified against corresponding data series. The final dataset represented 26 major agricultural commodities across 48 contiguous U.S. states, organized into seven analytical commodity

categories. Grains accounted for 25.4% of observations, followed by livestock at 17.6%, fruits at 14.7%, vegetables at 13.8%, oilseeds at 11.9%, dairy at 9.5%, and other agricultural commodities at 7.1%. Regional representation was distributed across the Midwest (29.6%), South (25.8%), West (24.1%), and Northeast (20.5%), providing sufficient geographic variability for subsequent regional and subgroup analyses. Data completeness after preprocessing reached 97.8% across the principal analytical variables, with the remaining isolated missing observations addressed using variable-appropriate imputation procedures. The chronological model-development partition contained 12,168 observations (65.0%), the validation partition contained 2,808 observations (15.0%), and the independent temporal test partition contained 3,744 observations (20.0%). This structure preserved temporal ordering and ensured that the independent test observations were not used during model estimation or hyperparameter selection.

Table 1. Final Dataset Composition and Analytical Sample Characteristics

Characteristic	Numerical Value	Percentage/Range
Initial integrated observations	19,684	100.0%
Final observations retained	18,720	95.1%
Observations excluded	964	4.9%
Historical coverage	Jan. 2015–Dec. 2024	10 years
Agricultural commodities	26	—
Geographic coverage	48 states	Contiguous U.S.
Grains	4,755	25.4%
Oilseeds	2,228	11.9%
Livestock	3,295	17.6%
Dairy	1,778	9.5%
Fruits	2,752	14.7%
Vegetables	2,583	13.8%
Other commodities	1,329	7.1%
Midwest observations	5,541	29.6%
South observations	4,830	25.8%
West observations	4,512	24.1%
Northeast observations	3,837	20.5%
Overall data completeness	—	97.8%
Model-development sample	12,168	65.0%
Validation sample	2,808	15.0%
Independent test sample	3,744	20.0%

Table 1 demonstrated that the analytical dataset retained 95.1% of the initially integrated observations and provided broad representation across commodities and U.S. agricultural regions. Grains constituted the largest commodity category at 25.4%, whereas other agricultural commodities represented the smallest category at 7.1%. The Midwest contributed the greatest regional share at 29.6%, followed by the South and West. Overall data completeness of 97.8% indicated limited residual missingness following harmonization. The chronological allocation of 65.0% for development, 15.0% for validation, and 20.0% for independent testing provided a substantial empirical basis for model estimation and out-of-sample validation.

Descriptive analysis identified substantial variation across production, inventory, market, environmental, logistics, trade, and economic indicators. Mean planted acreage across applicable crop observations was 3.84 million acres (SD = 2.91 million), while mean harvested acreage was 3.61 million acres (SD = 2.73 million). Standardized crop yield averaged 103.7 units per acre (SD = 54.8), reflecting substantial heterogeneity among commodity classes. Beginning and ending stock indices averaged 108.4 and 102.7, respectively, while mean inventory coverage was 42.6 days (SD = 18.9). The standardized commodity-price index averaged 116.8 (SD = 24.7), and annualized price volatility averaged 18.6% (SD = 9.4). Environmental conditions showed a mean temperature of 14.8°C and

average monthly precipitation of 74.3 mm, while the standardized drought-severity measure averaged 1.21 (SD = 0.87). Average agricultural freight cost was \$0.164 per ton-mile, and mean shipment delay was 1.84 days. Agricultural exports averaged \$6.72 billion per month across the aggregated trade series, compared with imports of \$5.91 billion. The fertilizer-price index averaged 121.6, fuel prices averaged \$3.12 per gallon, and the mean effective interest-rate measure was 3.74%. The Food-Supply Resilience Score averaged 72.8 out of 100 (SD = 11.6), while the Market Resilience Score averaged 69.5 (SD = 13.2), demonstrating meaningful variation in both principal outcomes.

Table 2. Descriptive Statistics for Principal Agribusiness and Resilience Variables

Variable	Mean	SD	Median	IQR	Minimum- Maximum	95% CI for Mean
Planted acreage (million acres)	3.84	2.91	3.12	3.76	0.18–13.42	3.79–3.89
Harvested acreage (million acres)	3.61	2.73	2.96	3.48	0.15–12.81	3.56–3.66
Crop yield (standardized units/acre)	103.7	54.8	91.4	67.2	18.6–284.7	102.9–104.5
Beginning stock index	108.4	31.6	104.2	39.8	41.7–198.6	107.9–108.9
Ending stock index	102.7	30.9	98.8	37.5	36.9–190.3	102.3–103.1
Inventory coverage (days)	42.6	18.9	39.4	23.7	8.2–103.6	42.3–42.9
Commodity-price index	116.8	24.7	112.6	31.5	68.4–196.7	116.4–117.2
Price volatility (%)	18.6	9.4	16.3	11.8	3.1–58.7	18.5–18.7
Average temperature (°C)	14.8	8.7	15.1	12.4	–9.6–34.8	14.7–14.9
Precipitation (mm/month)	74.3	39.6	67.8	48.5	4.3–241.6	73.7–74.9
Drought-severity index	1.21	0.87	1.03	1.08	0.00–4.62	1.20–1.22
Freight cost (\$/ton-mile)	0.164	0.052	0.156	0.064	0.071–0.342	0.163–0.165
Shipment delay (days)	1.84	1.21	1.51	1.42	0.12–7.86	1.82–1.86
Agricultural exports (\$ billion/month)	6.72	2.31	6.41	2.88	2.14–13.67	6.69–6.75
Agricultural imports (\$ billion/month)	5.91	2.08	5.63	2.51	1.83–12.44	5.88–5.94
Fertilizer-price index	121.6	29.8	116.3	35.4	72.1–214.8	121.2–122.0
Fuel price (\$/gallon)	3.12	0.78	3.06	0.96	1.64–5.71	3.11–3.13
Interest rate (%)	3.74	1.86	3.42	2.73	0.25–7.81	3.71–3.77
Food-Supply Resilience Score (0–100)	72.8	11.6	74.1	14.8	31.7–94.6	72.6–73.0
Market Resilience Score (0–100)	69.5	13.2	70.8	17.1	24.9–93.8	69.3–69.7

Table 2 revealed considerable heterogeneity across the integrated agribusiness indicators. Food-Supply Resilience averaged 72.8, exceeding the mean Market Resilience Score of 69.5, while both measures displayed sufficient dispersion for subsequent predictive modeling. Price volatility averaged 18.6%, and inventory coverage averaged 42.6 days, indicating substantial differences in market exposure and buffering capacity. Mean shipment delay reached 1.84 days, while fertilizer and fuel measures demonstrated notable cost variation. Environmental indicators also showed broad ranges in temperature, precipitation, and drought severity. The relatively narrow confidence intervals reflected the large longitudinal sample and supported precise estimation of the principal descriptive characteristics.

Commodity- and region-specific comparisons further demonstrated that resilience was not uniformly distributed across the U.S. agribusiness system. Grains recorded the highest mean Food-Supply Resilience Score at 76.4, followed by oilseeds at 74.9, dairy at 72.7, livestock at 71.8, vegetables at 69.6, and fruits at 68.9. Market Resilience followed a similar but less pronounced pattern, with grains

averaging 73.8 and fruits averaging 65.7. Regionally, the Midwest produced the highest mean Food-Supply Resilience Score at 75.6, compared with 73.1 in the South, 70.8 in the Northeast, and 69.7 in the West. The West also displayed the greatest weather-related variability and relatively elevated transportation-cost dispersion, whereas the Midwest showed stronger inventory coverage for major storable commodities. Across the 2015–2024 period, both resilience measures exhibited temporary deterioration during observations characterized by simultaneous production, logistics, or market stress, accompanied by higher price volatility and faster inventory depletion. These descriptive findings established substantial cross-commodity, geographic, and temporal variability in the dependent and predictor variables and provided an appropriate quantitative foundation for the subsequent predictive-performance, subgroup, multivariable, and robustness analyses.

Primary Outcomes: Predictive Performance for U.S. Food-Supply and Agricultural Market Resilience

The primary predictive analysis demonstrated that the developed agribusiness intelligence platform achieved strong out-of-sample performance for both Food-Supply Resilience and Market Resilience across the 3,744 observations reserved for independent temporal testing. All machine-learning approaches produced lower prediction errors than the baseline multiple-regression model, although the magnitude of improvement differed across algorithms and outcomes. For Food-Supply Resilience, XGBoost produced the strongest continuous predictive performance, achieving a mean absolute error (MAE) of 3.21 points, root mean squared error (RMSE) of 4.38 points, mean absolute percentage error (MAPE) of 4.47%, and coefficient of determination (R^2) of 0.914. The selected neural-network model ranked second with an RMSE of 4.57 and R^2 of 0.906, followed by Gradient Boosting, Random Forest, and Support Vector Machine. The baseline regression model produced an RMSE of 6.94 and R^2 of 0.781. XGBoost therefore reduced RMSE by 36.9% relative to the baseline and increased explained out-of-sample variance by 13.3 percentage points. Market Resilience was slightly more difficult to predict, consistent with its greater descriptive variability. The neural-network architecture produced the strongest Market Resilience estimates, with an MAE of 3.74, RMSE of 5.06, MAPE of 5.52%, and R^2 of 0.889. XGBoost followed closely with an RMSE of 5.19 and R^2 of 0.883. In comparison, baseline regression yielded an RMSE of 7.61 and R^2 of 0.742, indicating a 33.5% RMSE reduction for the best-performing neural-network model. The 95% confidence intervals around test-set error estimates remained comparatively narrow, supporting the precision of the observed performance differences.

Table 3. Independent Test-Set Performance for Continuous Food-Supply and Market Resilience Prediction

Model	Food-Supply MAE	Food-Supply RMSE (95% CI)	Food-Supply MAPE (%)	Food-Supply R^2	Market MAE	Market RMSE (95% CI)	Market MAPE (%)	Market R^2
Baseline multiple regression	5.31	6.94 (6.71– 7.17)	7.42	0.781	5.92	7.61 (7.35– 7.87)	8.64	0.742
Support Vector Machine	4.18	5.63 (5.44– 5.82)	5.83	0.856	4.71	6.19 (5.98– 6.40)	6.91	0.829
Random Forest	3.76	5.02 (4.84– 5.20)	5.24	0.883	4.29	5.71 (5.51– 5.91)	6.31	0.855
Gradient Boosting	3.48	4.71 (4.54– 4.88)	4.83	0.899	4.08	5.43 (5.24– 5.62)	5.98	0.869
XGBoost	3.21	4.38 (4.22– 4.54)	4.47	0.914	3.82	5.19 (5.01– 5.37)	5.63	0.883

Neural network	3.34	4.57 (4.40–4.74)	4.63	0.906	3.74	5.06 (4.88–5.24)	5.52	0.889
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Table 3 showed that advanced predictive models consistently outperformed baseline regression on the independent temporal test sample. XGBoost achieved the strongest Food-Supply Resilience performance, with an RMSE of 4.38 and R^2 of 0.914, representing a 36.9% reduction in RMSE relative to baseline regression. Market Resilience was predicted most accurately by the neural network, which achieved an RMSE of 5.06 and R^2 of 0.889, reducing baseline RMSE by 33.5%. Gradient Boosting, Random Forest, and Support Vector Machine produced intermediate performance. The narrow 95% confidence intervals indicated stable estimation of out-of-sample predictive error across the test observations.

Classification analysis provided additional evidence that the platform distinguished low-, moderate-, high-, and critical-resilience-risk conditions with high accuracy. For Food-Supply Resilience risk classification, XGBoost achieved the strongest overall performance, with 92.8% accuracy, 91.6% sensitivity, 94.1% specificity, 92.2% precision, 91.6% recall, an F1-score of 91.9%, and an AUC of 0.967. The neural network achieved comparable but slightly lower accuracy of 91.9% and an AUC of 0.961. The baseline multinomial logistic model achieved only 80.7% accuracy and an AUC of 0.874. XGBoost therefore increased classification accuracy by 12.1 percentage points and reduced the overall misclassification rate from 19.3% to 7.2%. For Market Resilience risk classification, the neural network achieved the strongest results, with 91.4% accuracy, 90.7% sensitivity, 92.6% specificity, an F1-score of 90.9%, and an AUC of 0.958. XGBoost followed with 90.9% accuracy and an AUC of 0.954. Examination of confusion matrices showed that most classification errors occurred between adjacent risk categories, particularly between moderate and high risk. Direct confusion between low- and critical-risk observations was uncommon, accounting for less than 1% of test classifications for the two best-performing models. Critical-risk sensitivity reached 93.2% for XGBoost in the Food-Supply Resilience model and 92.4% for the neural-network Market Resilience model, demonstrating comparatively strong identification of the observations carrying the greatest disruption exposure.

Table 4. Independent Test-Set Classification Performance for Food-Supply and Market Resilience Risk

Outcome and Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (95% CI)
Food Supply – Baseline logistic model	80.7	77.9	84.6	79.1	77.9	78.5	0.874 (0.861–0.887)
Food Supply – Support Vector Machine	86.4	84.7	89.2	85.8	84.7	85.2	0.919 (0.909–0.929)
Food Supply – Random Forest	89.1	87.8	91.4	88.6	87.8	88.2	0.943 (0.935–0.951)
Food Supply – Gradient Boosting	90.6	89.3	92.5	90.1	89.3	89.7	0.952 (0.945–0.959)
Food Supply – XGBoost	92.8	91.6	94.1	92.2	91.6	91.9	0.967 (0.961–0.973)
Food Supply – Neural network	91.9	90.8	93.3	91.4	90.8	91.1	0.961 (0.954–0.968)

Market – Baseline	78.9	76.3	82.7	77.4	76.3	76.8	0.856 (0.842–0.870)
logistic model							
Market – Support Vector	84.8	83.2	87.5	84.1	83.2	83.6	0.907 (0.896–0.918)
Machine							
Market – Random Forest	87.7	86.1	90.2	87.0	86.1	86.5	0.932 (0.923–0.941)
Market – Gradient Boosting	89.3	88.0	91.1	88.7	88.0	88.3	0.944 (0.936–0.952)
Market – XGBoost	90.9	89.8	92.1	90.4	89.8	90.1	0.954 (0.947–0.961)
Market – Neural network	91.4	90.7	92.6	91.2	90.7	90.9	0.958 (0.951–0.965)

Table 4 demonstrated strong discrimination of resilience-risk categories by the advanced models. XGBoost achieved the highest Food-Supply Resilience classification accuracy at 92.8%, with an AUC of 0.967 and F1-score of 91.9%. For Market Resilience, the neural network performed best, reaching 91.4% accuracy, 90.9% F1-score, and an AUC of 0.958. Both substantially exceeded their respective baseline logistic models. Specificity remained above 92% for the strongest models, while sensitivity exceeded 90%, indicating balanced identification of resilient and disrupted conditions. The results showed that performance improvements were not restricted to overall accuracy but extended across discrimination, precision, recall, and class-specific detection.

Calibration and temporal holdout analyses further supported the predictive validity of the platform. For the XGBoost Food-Supply Resilience model, the mean difference between predicted and observed resilience scores was only 0.37 points, while 94.8% of observed values fell within the model's 95% prediction intervals. The corresponding neural-network Market Resilience model showed a mean prediction bias of 0.44 points and 94.1% prediction-interval coverage. Performance remained substantially stronger on the independent temporal test sample than the statistical baselines, although modest reductions relative to training performance were observed. XGBoost Food-Supply Resilience R^2 declined from 0.948 during training to 0.914 during independent testing, producing a generalization gap of 0.034. Neural-network Market Resilience R^2 decreased from 0.926 to 0.889, corresponding to a gap of 0.037. Classification accuracy showed similarly limited deterioration, declining by 2.7 percentage points for the XGBoost Food-Supply model and 3.1 percentage points for the neural-network Market Resilience model. Predicted-versus-observed plots demonstrated close alignment across most of the resilience distribution, although prediction errors increased moderately among observations characterized by simultaneous severe weather, rapid inventory depletion, elevated freight disruption, and extreme commodity-price volatility. Receiver operating characteristic curves remained clearly above baseline discrimination across all risk thresholds. Collectively, the primary results demonstrated that the platform provided high out-of-sample predictive accuracy, strong risk discrimination, limited calibration error, and relatively small training-to-test performance gaps, with XGBoost performing most strongly for Food-Supply Resilience and the neural-network architecture providing the strongest overall prediction of Agricultural Market Resilience.

Secondary and Subgroup Findings Across Commodities, U.S. Regions, Disruption Conditions, and Predictor Domains

Secondary analysis demonstrated substantial heterogeneity in food-supply resilience, market resilience, price behavior, inventory conditions, logistics performance, and predictive accuracy across the seven commodity groups. Grains recorded the highest mean Food-Supply Resilience Score at 76.4 ± 9.8 , followed by oilseeds at 74.9 ± 10.3 , dairy at 72.7 ± 10.8 , livestock at 71.8 ± 11.4 , other commodities

at 70.5 ± 11.7 , vegetables at 69.6 ± 12.5 , and fruits at 68.9 ± 12.9 . Market Resilience displayed a comparable pattern, ranging from 73.8 ± 10.6 for grains to 65.7 ± 14.8 for fruits. Fruits and vegetables exhibited the greatest price volatility, at 23.7% and 22.4%, respectively, compared with 14.2% for grains. Inventory coverage was greatest for grains at 58.7 days and oilseeds at 51.4 days, whereas fruits averaged only 18.6 days and vegetables 21.3 days, reflecting their greater perishability and more limited storage flexibility. Mean shipment delays were highest for fruits at 2.31 days and vegetables at 2.18 days. The independent test-set RMSE for Food-Supply Resilience ranged from 3.81 for grains to 5.27 for fruits, while Market Resilience RMSE ranged from 4.52 to 6.13 across the same commodity groups. Classification accuracy remained above 88% across all commodity categories, although performance was strongest for grains and oilseeds and weakest for fruits and vegetables. These findings indicated that commodities characterized by longer storage periods, lower price volatility, and greater inventory coverage were associated with both higher observed resilience and lower predictive error.

Table 5: Commodity-Specific Resilience, Market Conditions, Logistics Performance, and Predictive Accuracy

Commodity Group	Food-Supply Resilience Mean $\pm$ SD	Market Resilience Mean $\pm$ SD	Price Volatility (%)	Inventory Coverage (Days)	Shipment Delay (Days)	Food-Supply RMSE	Market RMSE	Risk Classification Accuracy (%)
Grains	76.4 ± 9.8	73.8 ± 10.6	14.2	58.7	1.42	3.81	4.52	94.6
Oilseeds	74.9 ± 10.3	72.6 ± 11.2	15.6	51.4	1.51	4.03	4.71	93.8
Livestock	71.8 ± 11.4	68.4 ± 12.7	18.9	34.8	1.86	4.47	5.28	91.7
Dairy	72.7 ± 10.8	69.1 ± 12.1	17.8	29.6	1.79	4.29	5.06	92.4
Fruits	68.9 ± 12.9	65.7 ± 14.8	23.7	18.6	2.31	5.27	6.13	88.4
Vegetables	69.6 ± 12.5	66.4 ± 14.1	22.4	21.3	2.18	5.08	5.92	89.1
Other commodities	70.5 ± 11.7	67.8 ± 13.3	19.5	31.7	1.93	4.63	5.41	90.6

Table 5 demonstrated systematic commodity-level differences in resilience and predictive performance. Grains recorded the highest Food-Supply and Market Resilience Scores, greatest inventory coverage, lowest price volatility, and strongest classification accuracy. Fruits showed the lowest resilience scores, highest price volatility, shortest inventory coverage, longest shipment delay, and greatest prediction error. Vegetables exhibited a similar vulnerability profile. Oilseeds performed comparatively strongly across resilience and prediction measures, while livestock and dairy occupied intermediate positions. The results indicated that commodity characteristics related to storability, logistics dependence, inventory buffering, and price variability were closely associated with both observed resilience and model-prediction difficulty.

Regional comparisons further demonstrated significant differences in resilience conditions. The Midwest recorded the highest Food-Supply Resilience Score at 75.6 ± 10.1 and Market Resilience Score at 72.3 ± 11.4 , supported by comparatively high production stability and average inventory coverage of 53.8 days. The South recorded Food-Supply and Market Resilience Scores of 73.1 and 70.2, respectively, while the Northeast averaged 70.8 and 68.1. The West showed the lowest Food-Supply Resilience Score at 69.7 ± 12.6 and the lowest Market Resilience Score at 66.9 ± 14.0 , together with the highest weather-risk score and freight-cost variability. Regional differences in Food-Supply Resilience

were statistically significant, $F(3, 18,716) = 86.42$, $p < .001$, partial $\eta^2 = .041$, as were differences in Market Resilience, $F(3, 18,716) = 79.68$, $p < .001$, partial $\eta^2 = .038$. Subgroup performance also varied according to market condition. Under normal conditions, the leading Food-Supply model achieved an RMSE of 3.76 and classification accuracy of 94.5%, compared with an RMSE of 5.31 and accuracy of 88.6% during high-volatility periods. During severe disruption observations, RMSE increased to 6.08 and classification accuracy declined to 85.2%. A similar pattern occurred for Market Resilience, where RMSE increased from 4.39 during normal conditions to 6.91 during severe disruption periods. Predictive performance therefore remained comparatively strong under stress but deteriorated as simultaneous market and supply disturbances increased in severity.

Table 6. Regional, Disruption-Condition, and Predictor-Domain Subgroup Results

Subgroup/Domain	Food-Supply Resilience	Market Resilience	Food-Supply RMSE	Market RMSE	Classification Accuracy (%)	Relative Predictor Importance (%)
Midwest	75.6 ± 10.1	72.3 ± 11.4	3.92	4.68	94.1	—
South	73.1 ± 11.0	70.2 ± 12.3	4.21	4.97	92.7	—
Northeast	70.8 ± 11.8	68.1 ± 13.0	4.69	5.46	90.8	—
West	69.7 ± 12.6	66.9 ± 14.0	5.02	5.83	89.6	—
Normal conditions	77.2 ± 8.7	74.8 ± 9.6	3.76	4.39	94.5	—
High-volatility conditions	68.4 ± 11.5	63.7 ± 13.2	5.31	6.02	88.6	—
Severe disruption conditions	61.9 ± 13.4	58.2 ± 15.1	6.08	6.91	85.2	—
Production and yield	—	—	—	—	—	24.8
Inventories and storage	—	—	—	—	—	21.6
Weather and climate	—	—	—	—	—	18.7
Transportation and logistics	—	—	—	—	—	15.3
International trade	—	—	—	—	—	10.8
Input and macroeconomic costs	—	—	—	—	—	8.8

Table 6 showed meaningful geographic and disruption-related heterogeneity in resilience and predictive performance. The Midwest recorded the strongest resilience outcomes and lowest regional prediction errors, whereas the West exhibited lower resilience and greater model error. Performance deteriorated progressively from normal to high-volatility and severe disruption conditions, although classification accuracy remained 85.2% during the most severe observations. Predictor-domain analysis identified production and yield as the largest contributor at 24.8%, followed by inventories and storage at 21.6% and weather and climate at 18.7%. Logistics, trade, and macroeconomic variables contributed additional predictive information to the integrated platform.

Predictor-domain analysis showed that production and yield variables contributed 24.8% of total normalized model importance, followed by inventories and storage at 21.6%, weather and climate at 18.7%, transportation and logistics at 15.3%, international trade at 10.8%, and agricultural input and macroeconomic costs at 8.8%. At the individual-variable level, inventory coverage emerged as the strongest predictor of Food-Supply Resilience, followed by production shortfall, yield anomaly, shipment delay, drought severity, and freight-cost change. For Market Resilience, price volatility, stock-to-use conditions, production variability, export-volume change, fertilizer-cost volatility, and

transportation disruption frequency ranked most strongly. Multivariable estimates were directionally consistent with the machine-learning importance results. Greater inventory coverage was positively associated with Food-Supply Resilience (standardized $\beta = 0.31$, $p < .001$), whereas production shortfall ($\beta = -0.29$, $p < .001$), drought severity ($\beta = -0.22$, $p < .001$), and shipment delay ($\beta = -0.19$, $p < .001$) were negatively associated with resilience. Price volatility demonstrated the largest negative association with Market Resilience ($\beta = -0.34$, $p < .001$), followed by inventory depletion ($\beta = -0.27$, $p < .001$) and freight disruption ($\beta = -0.18$, $p < .001$). These results showed convergence between conventional multivariable statistics and the platform's feature-importance estimates.

Interaction analyses further clarified how resilience depended on combinations of conditions rather than isolated predictors. The negative relationship between production shortfalls and Food-Supply Resilience was substantially weaker when inventory coverage exceeded 50 days ($\beta = -0.18$) than when coverage fell below 25 days ($\beta = -0.41$), and the production-shortfall-by-inventory interaction was statistically significant ($p < .001$). Weather exposure also differed across commodity categories. A one-standard-deviation increase in the combined weather-risk measure corresponded with a larger reduction in resilience among fruits and vegetables (standardized $\beta = -0.33$) than among grains and oilseeds ($\beta = -0.17$), with a significant commodity-by-weather interaction ($p = .003$). Logistics disturbances similarly produced stronger negative effects under constrained inventory conditions; shipment delays exceeding three days were associated with an average 8.6-point reduction in Food-Supply Resilience when inventory coverage was below 25 days, compared with a 3.4-point reduction when coverage exceeded 50 days. Severe disruption periods characterized by simultaneous adverse production, inventory, weather, and logistics conditions generated the largest prediction errors and lowest observed resilience scores. Overall, the subgroup results demonstrated that commodity type, geographic location, market condition, storage capacity, environmental exposure, and logistics performance materially differentiated resilience across the integrated U.S. agribusiness system and explained meaningful variation in predictive performance.

Statistical Significance, Effect Sizes, Multivariable Relationships, and Resilience Risk Determinants

Inferential analysis identified statistically significant and practically meaningful relationships between the principal agribusiness predictors and both resilience outcomes. Food-Supply Resilience showed its strongest positive bivariate relationship with inventory coverage ($r = .48$, 95% CI [.46, .50], $p < .001$), followed by production stability ($r = .44$, $p < .001$) and storage utilization adequacy ($r = .36$, $p < .001$). Production shortfall demonstrated a moderately strong negative association with Food-Supply Resilience ($r = -.43$, $p < .001$), while drought severity ($r = -.35$, $p < .001$), shipment delay ($r = -.32$, $p < .001$), and freight-cost volatility ($r = -.26$, $p < .001$) were also negatively related to the outcome. Market Resilience was most strongly associated with commodity-price volatility ($r = -.55$, 95% CI [-.57, -.53], $p < .001$), followed by inventory depletion ($r = -.42$, $p < .001$), production variability ($r = -.38$, $p < .001$), and transportation disruption frequency ($r = -.31$, $p < .001$). Export-volume stability showed a positive association with Market Resilience ($r = .27$, $p < .001$), whereas fertilizer-cost volatility ($r = -.25$, $p < .001$) and exchange-rate variability ($r = -.19$, $p < .001$) showed smaller negative relationships. After false-discovery-rate correction, all principal correlations reported in the final model remained statistically significant at $q < .05$. The correlation structure indicated that resilience was associated most strongly with inventory, production, price, environmental, and logistics conditions, while international trade and input-cost measures produced smaller but independently detectable relationships.

Multivariable regression confirmed that these associations remained after adjustment for commodity group, U.S. region, seasonality, and temporal trend. The Food-Supply Resilience model explained 68.4% of adjusted outcome variance (adjusted $R^2 = .684$, $F = 317.8$, $p < .001$). Inventory coverage was the strongest positive independent predictor (standardized $\beta = .31$, $p < .001$), whereas production shortfall produced the strongest negative coefficient ($\beta = -.29$, $p < .001$). Drought severity ($\beta = -.22$), shipment delay ($\beta = -.19$), freight-cost change ($\beta = -.13$), import-source concentration ($\beta = -.09$), and input-cost volatility ($\beta = -.08$) also remained independently significant. The Market Resilience model explained 65.7% of adjusted variance (adjusted $R^2 = .657$, $F = 284.6$, $p < .001$). Commodity-price volatility was the dominant predictor ($\beta = -.34$, $p < .001$), followed by inventory depletion ($\beta = -.27$), production variability ($\beta = -.21$), transportation disruption ($\beta = -.18$), export-volume instability ($\beta =$

-.14), and fertilizer-cost volatility ($\beta = -.10$). Variance-inflation factors ranged from 1.18 to 2.73, indicating that multicollinearity did not materially compromise coefficient interpretation.

Table 7. Multivariable Predictors of Food-Supply and Market Resilience

Outcome and Predictor	Standardized β	SE	95% CI for Standardized Effect	p-value	FDR-adjusted q
Food-Supply Resilience					
Inventory coverage	0.31	0.018	0.28 to 0.34	<.001	<.001
Production shortfall	-0.29	0.019	-0.32 to -0.26	<.001	<.001
Drought severity	-0.22	0.017	-0.25 to -0.19	<.001	<.001
Shipment delay	-0.19	0.016	-0.22 to -0.16	<.001	<.001
Freight-cost change	-0.13	0.015	-0.16 to -0.10	<.001	<.001
Import-source concentration	-0.09	0.014	-0.12 to -0.06	<.001	.002
Input-cost volatility	-0.08	0.014	-0.11 to -0.05	.001	.004
Market Resilience					
Commodity-price volatility	-0.34	0.018	-0.37 to -0.31	<.001	<.001
Inventory depletion	-0.27	0.018	-0.30 to -0.24	<.001	<.001
Production variability	-0.21	0.017	-0.24 to -0.18	<.001	<.001
Transportation disruption	-0.18	0.016	-0.21 to -0.15	<.001	<.001
Export-volume instability	-0.14	0.015	-0.17 to -0.11	<.001	<.001
Fertilizer-cost volatility	-0.10	0.014	-0.13 to -0.07	<.001	.002

Table 7 demonstrated that inventory coverage and production shortfall were the strongest independent determinants of Food-Supply Resilience after adjustment for commodity, region, seasonality, and temporal variation. Market Resilience was influenced most strongly by commodity-price volatility and inventory depletion. Weather, transportation, international-trade, and input-cost variables retained smaller but statistically significant independent effects. All displayed relationships remained significant following false-discovery-rate adjustment, reducing concern that the results reflected multiple-testing error. The Food-Supply and Market Resilience models explained 68.4% and 65.7% of adjusted outcome variance, respectively, indicating substantial multivariable explanatory strength across the integrated agribusiness dataset.

Logistic risk analysis further demonstrated that adverse production, inventory, weather, logistics, trade, and cost conditions significantly increased the likelihood of an observation being classified within the combined high- or critical-resilience-risk categories. A severe production shortfall was associated with 2.74 times greater adjusted odds of high or critical Food-Supply Resilience risk (95% CI [2.43, 3.09], $p < .001$), while low inventory coverage produced an adjusted odds ratio (OR) of 3.18 (95% CI [2.81, 3.60], $p < .001$), representing the strongest individual food-supply risk determinant. Severe drought exposure increased adjusted odds by 126% (OR = 2.26), and major transportation disruption increased the odds by 98% (OR = 1.98). For Market Resilience, extreme commodity-price volatility generated the strongest risk association (OR = 3.46, 95% CI [3.05, 3.93], $p < .001$), followed by rapid inventory depletion (OR = 2.89), substantial production variability (OR = 2.31), major transportation disruption (OR = 2.07), export-volume shocks (OR = 1.74), and elevated input-cost volatility (OR = 1.61). Classification risk increased further when multiple disturbances occurred simultaneously. Observations characterized by concurrent severe production shortfall, low inventory coverage, and major logistics disruption had 5.82 times greater adjusted odds of high or critical Food-Supply

Resilience risk than observations without those conditions (95% CI [4.91, 6.90], $p < .001$).

Table 8. Adjusted Odds Ratios and Effect Sizes for High/Critical Resilience Risk

Outcome and Risk Determinant	Adjusted OR	95% CI	p-value	Cohen's d*	Effect Magnitude
Food-Supply Resilience Risk					
Low inventory coverage	3.18	2.81–3.60	<.001	0.64	Moderate-large
Severe production shortfall	2.74	2.43–3.09	<.001	0.56	Moderate
Severe drought exposure	2.26	2.01–2.54	<.001	0.45	Moderate
Major transportation disruption	1.98	1.77–2.22	<.001	0.38	Small-moderate
High import-source concentration	1.58	1.41–1.77	<.001	0.25	Small
Elevated input-cost volatility	1.47	1.32–1.64	<.001	0.21	Small
Production + inventory + logistics stress	5.82	4.91–6.90	<.001	0.97	Large
Market Resilience Risk					
Extreme commodity-price volatility	3.46	3.05–3.93	<.001	0.69	Moderate-large
Rapid inventory depletion	2.89	2.56–3.27	<.001	0.59	Moderate
High production variability	2.31	2.06–2.59	<.001	0.46	Moderate
Major transportation disruption	2.07	1.85–2.32	<.001	0.40	Small-moderate
Export-volume shock	1.74	1.56–1.94	<.001	0.31	Small-moderate
Elevated input-cost volatility	1.61	1.44–1.79	<.001	0.26	Small

*Effect-size values represented standardized high-risk versus reference-condition differences for the corresponding determinant.

Table 8 showed that low inventory coverage generated the strongest individual food-supply risk association, increasing adjusted odds of high or critical risk more than threefold. Concurrent production, inventory, and logistics stress produced the largest overall effect, with an odds ratio of 5.82 and a large standardized effect. Extreme commodity-price volatility was the strongest Market Resilience determinant, followed by rapid inventory depletion and production variability. Transportation disruptions generated meaningful effects for both outcomes, while trade and input-cost variables produced smaller associations. All risk determinants remained statistically significant, and confidence intervals excluded the null value, supporting the stability of the estimated relationships. Group comparisons provided additional evidence that statistical significance corresponded with meaningful differences in resilience magnitude. Food-Supply Resilience differed significantly across the seven commodity groups, $F(6, 18,713) = 94.27$, $p < .001$, partial $\eta^2 = .052$, representing a moderate overall effect, while Market Resilience also differed significantly, $F(6, 18,713) = 88.61$, $p < .001$, partial $\eta^2 = .047$. Regional differences remained significant after adjustment for commodity composition and

seasonality for Food-Supply Resilience, $F(3, 18,710) = 71.84$, $p < .001$, partial $\eta^2 = .036$, and Market Resilience, $F(3, 18,710) = 66.29$, $p < .001$, partial $\eta^2 = .033$. The largest two-group effect was observed between normal and severe disruption conditions. Mean Food-Supply Resilience declined from 77.2 ± 8.7 under normal conditions to 61.9 ± 13.4 under severe disruption, corresponding to Cohen's $d = 1.35$, while Market Resilience declined from 74.8 ± 9.6 to 58.2 ± 15.1 , corresponding to $d = 1.31$. Both represented large practical effects. High-volatility conditions also differed substantially from normal conditions for Food-Supply Resilience ($d = 0.87$) and Market Resilience ($d = 0.94$). These effect-size results demonstrated that disruption-related differences were not merely products of the large sample size.

The combined inferential findings identified inventory adequacy, production stability, commodity-price volatility, environmental stress, and logistics performance as the most consequential resilience determinants. Inventory conditions operated as a particularly important buffering mechanism: the adverse association between production shortfall and Food-Supply Resilience was substantially stronger when inventory coverage was below 25 days than when coverage exceeded 50 days, with a statistically significant interaction effect ($p < .001$). Similarly, transportation disruption exerted a larger negative effect during periods of rapid inventory depletion, while weather-related production losses were strongest among more perishable and geographically concentrated commodity categories. Multivariable relationships remained directionally stable when alternative model specifications, nonparametric correlations, robust standard errors, and false-discovery-rate corrections were applied. Statistical significance was therefore accompanied by moderate-to-large effect sizes for the principal production, inventory, price, and disruption variables, while trade and macroeconomic predictors generally exhibited smaller independent effects. The results established that high and critical resilience risk was most pronounced when multiple adverse conditions occurred concurrently rather than when production, weather, logistics, trade, or cost pressures appeared independently.

Model Validation, Robustness, Generalizability, Tables, and Graphical Synthesis of Predictive Resilience Performance

The final validation analysis demonstrated that the predictive agribusiness intelligence platform maintained comparatively stable performance across model-development, validation, temporal holdout, and independent test datasets. Consistent with the primary analysis, XGBoost remained the strongest model for Food-Supply Resilience, whereas the neural-network architecture maintained the highest overall performance for Market Resilience. For Food-Supply Resilience, XGBoost achieved an R^2 of 0.948 during training, 0.928 during validation, 0.919 during temporal holdout testing, and 0.914 on the independent test dataset. Corresponding RMSE values increased from 3.72 to 4.38 points across these stages, while classification accuracy decreased from 95.5% to 92.8%. The resulting training-to-independent-test R^2 generalization gap was only 0.034, and classification accuracy declined by 2.7 percentage points. For Market Resilience, the neural network achieved R^2 values of 0.926, 0.907, 0.896, and 0.889 across the four analytical stages, respectively, while RMSE increased from 4.31 to 5.06. Classification accuracy declined from 94.5% during model development to 91.4% during independent testing, producing an R^2 generalization gap of 0.037 and an accuracy gap of 3.1 percentage points. AUC values remained above 0.95 for both final models during independent testing, indicating strong discrimination between resilience-risk categories. The progressive rather than abrupt deterioration in performance across validation stages provided limited evidence of material overfitting and demonstrated that most predictive information identified during model development remained transferable to previously unseen temporal observations.

Table 9. Validation and Generalization Performance of the Final Predictive Models

Outcome and Validation Stage	R^2	MAE	RMSE	MAPE (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1- Score (%)	AUC
Food-Supply Resilience –									

XGBoost									
Training	0.948	2.69	3.72	3.71	95.5	94.8	96.2	95.0	0.982
Validation	0.928	3.03	4.12	4.19	93.9	92.8	95.1	93.2	0.974
Temporal holdout	0.919	3.16	4.29	4.39	93.2	92.1	94.5	92.5	0.970
Independent test	0.914	3.21	4.38	4.47	92.8	91.6	94.1	91.9	0.967
Market Resilience – Neural Network									
Training	0.926	3.12	4.31	4.54	94.5	93.7	95.4	93.9	0.976
Validation	0.907	3.46	4.68	5.02	92.8	91.9	93.8	92.1	0.968
Temporal holdout	0.896	3.63	4.91	5.34	91.9	91.0	93.0	91.3	0.962
Independent test	0.889	3.74	5.06	5.52	91.4	90.7	92.6	90.9	0.958

Table 9 demonstrated limited deterioration between model development and independent evaluation. Food-Supply Resilience R^2 declined from 0.948 to 0.914, while classification accuracy decreased by only 2.7 percentage points. Market Resilience R^2 declined from 0.926 to 0.889, accompanied by a 3.1-point reduction in accuracy. Independent-test AUC remained 0.967 for Food-Supply Resilience and 0.958 for Market Resilience, demonstrating strong discrimination. RMSE increased gradually across validation stages rather than showing abrupt deterioration. The comparatively small generalization gaps across continuous and categorical performance measures supported stable transfer of predictive relationships to previously unseen observations and provided limited evidence of substantial overfitting.

Repeated cross-validation and sensitivity analyses provided additional evidence of model stability. Ten-fold temporally constrained cross-validation repeated five times produced a mean Food-Supply Resilience R^2 of 0.918 ± 0.011 , RMSE of 4.31 ± 0.19 , classification accuracy of $92.9 \pm 0.8\%$, and AUC of 0.968 ± 0.006 for XGBoost. The corresponding Market Resilience neural-network model achieved a mean R^2 of 0.894 ± 0.014 , RMSE of 4.94 ± 0.23 , accuracy of $91.6 \pm 1.0\%$, and AUC of 0.960 ± 0.007 . Sensitivity testing showed that the conclusions were not dependent on a single preprocessing or modeling specification. Median-based missing-data imputation reduced Food-Supply classification accuracy from 92.8% to 92.2%, while complete-case analysis produced 91.8%. Removal of observations beyond the predefined outlier limits resulted in 92.5% accuracy, and alternative resilience-risk thresholds produced 91.9%. Exclusion of the five lowest-ranked predictors reduced accuracy to 91.7%, whereas exclusion of the five highest-ranked predictors produced a substantially larger decline to 86.9%, demonstrating that the variables identified as most influential contributed meaningful predictive information. The Market Resilience model exhibited the same general pattern, with accuracy remaining between 90.3% and 91.2% across routine sensitivity specifications but declining to 85.8% after removal of the five strongest predictors. These analyses indicated that the primary findings were stable under reasonable changes in missing-data handling, outlier treatment, predictor composition, and resilience classification.

Robustness analysis across commodity groups, regions, and disruption conditions showed that predictive performance remained acceptable but was not uniform across the U.S. agribusiness system. Food-Supply Resilience classification accuracy ranged from 94.6% for grains to 88.4% for fruits, while regional accuracy ranged from 94.1% in the Midwest to 89.6% in the West. The largest performance reduction occurred during severe disruption conditions, where Food-Supply classification accuracy declined from 94.5% under normal conditions to 85.2%, representing a 9.3-percentage-point degradation. Food-Supply RMSE simultaneously increased from 3.76 to 6.08. Market Resilience showed a comparable pattern, with accuracy declining from 93.4% during normal periods to 84.7% during severe disruption and RMSE increasing from 4.39 to 6.91. High-volatility periods produced intermediate performance for both outcomes. Calibration remained acceptable across most subgroup

conditions. The final Food-Supply model produced a calibration slope of 0.97 and 95% prediction-interval coverage of 94.8% on the independent test dataset, whereas the Market Resilience model produced a slope of 0.95 and coverage of 94.1%. Prediction-interval coverage remained above 90% during severe disruption periods, although calibration error increased relative to normal conditions. These findings demonstrated that unusual combinations of production shortfalls, inventory depletion, extreme weather, logistics disturbances, and price volatility represented the most difficult observations to predict.

Table 10. Robustness, Sensitivity, Calibration, and Stress-Condition Performance of the Final Models

Validation Condition	Food-Supply R ²	Food-Supply RMSE	Food-Supply Accuracy (%)	Market R ²	Market RMSE	Market Accuracy (%)
Repeated temporal cross-validation	0.918 ± 0.011	4.31 ± 0.19	92.9 ± 0.8	0.894 ± 0.014	4.94 ± 0.23	91.6 ± 1.0
Median missing-data imputation	0.909	4.46	92.2	0.884	5.14	91.0
Complete-case analysis	0.903	4.58	91.8	0.878	5.26	90.5
Outlier-excluded analysis	0.912	4.41	92.5	0.887	5.10	91.2
Alternative resilience thresholds	0.906	4.51	91.9	0.881	5.21	90.3
Five lowest-ranked predictors removed	0.901	4.64	91.7	0.876	5.31	90.4
Five highest-ranked predictors removed	0.812	6.07	86.9	0.794	6.48	85.8
Normal market conditions	0.931	3.76	94.5	0.914	4.39	93.4
High-volatility conditions	0.884	5.31	88.6	0.853	6.02	87.9
Severe disruption conditions	0.842	6.08	85.2	0.816	6.91	84.7
Independent-test calibration slope	0.97	—	—	0.95	—	—
95% prediction-interval coverage	94.8%	—	—	94.1%	—	—

Table 10 showed that predictive performance remained stable under alternative preprocessing, missing-data, outlier, and threshold specifications. Removing low-ranked predictors caused only modest deterioration, whereas removing the strongest predictors reduced Food-Supply accuracy to 86.9% and Market Resilience accuracy to 85.8%, confirming their substantive predictive contribution. The largest performance losses occurred during severe disruption conditions, where RMSE increased and accuracy declined for both outcomes. Nevertheless, accuracy remained above 84% under the most challenging conditions. Calibration slopes remained close to unity, and prediction-interval coverage approached the nominal 95% level, supporting the robustness and calibration of the final models.

Graphical synthesis was consistent with the numerical validation results. Actual-versus-predicted plots for the independent test dataset showed observations concentrated closely around the line of agreement, with stronger dispersion occurring at the lowest resilience scores. Residual distributions were approximately centered around zero, although the tails widened during severe disruption

observations. Temporal forecast plots showed that the final models reproduced the principal increases and declines in resilience across the holdout period without persistent systematic overprediction or underprediction. Receiver operating characteristic curves confirmed strong risk discrimination, with independent-test AUC values of 0.967 for Food-Supply Resilience and 0.958 for Market Resilience. Feature-importance displays remained consistent with the earlier multivariable findings: production and yield accounted for 24.8% of normalized predictive importance, inventories and storage for 21.6%, weather and climate for 18.7%, transportation and logistics for 15.3%, international trade for 10.8%, and input and macroeconomic conditions for 8.8%. Commodity-level graphs showed lower errors for grains and oilseeds and greater dispersion for fruits and vegetables, while regional displays indicated stronger performance in the Midwest and comparatively larger errors in the West. These graphical patterns corresponded closely with the exact subgroup estimates and did not reveal major contradictions between statistical and machine-learning results.

The integrated validation evidence demonstrated that the platform's predictive performance was supported by multiple quantitative criteria rather than a single accuracy statistic. The strongest models maintained R^2 values of 0.914 and 0.889, classification accuracies of 92.8% and 91.4%, F1-scores of 91.9% and 90.9%, and AUC values of 0.967 and 0.958 on completely independent observations for Food-Supply and Market Resilience, respectively. Generalization gaps remained below four percentage points in R^2 -equivalent terms, repeated cross-validation variability was small, and routine sensitivity specifications produced only limited performance changes. More substantial degradation occurred when the most informative predictor variables were removed or when models were evaluated during severe disruption conditions, demonstrating that both predictor quality and disruption intensity materially influenced forecasting difficulty. Calibration measures remained close to their ideal values, and independent prediction-interval coverage exceeded 94% for both principal outcomes. The convergence of temporal validation, cross-validation, sensitivity testing, subgroup evaluation, calibration analysis, effect-size findings, and graphical assessment provided consistent quantitative evidence that the final predictive agribusiness intelligence platform retained substantial predictive accuracy and generalizability across commodities, regions, market conditions, and previously unseen periods within the integrated U.S. agribusiness dataset.

DISCUSSION

The findings of this study demonstrated that an integrated predictive agribusiness intelligence platform could model U.S. food-supply and agricultural-market resilience with high quantitative accuracy when production, inventory, environmental, logistics, international-trade, and macroeconomic information was analyzed collectively ([Assimakopoulos et al., 2024](#)). The strongest Food-Supply Resilience model, XGBoost, achieved an independent-test R^2 of 0.914, RMSE of 4.38, MAPE of 4.47%, classification accuracy of 92.8%, F1-score of 91.9%, and AUC of 0.967. Agricultural Market Resilience was predicted most effectively by the neural-network architecture, which achieved an R^2 of 0.889, RMSE of 5.06, MAPE of 5.52%, classification accuracy of 91.4%, F1-score of 90.9%, and AUC of 0.958. These results were substantially stronger than those obtained from the baseline statistical models, which produced R^2 values of 0.781 and 0.742 for Food-Supply and Market Resilience, respectively. The findings were consistent with earlier agricultural forecasting studies showing that nonlinear machine-learning architectures frequently outperform conventional regression when relationships among weather, production, prices, inventories, and economic conditions involve complex interactions, thresholds, and temporal dependencies. Earlier crop-yield and commodity-price forecasting research similarly reported that ensemble learning, boosting algorithms, random forests, and neural networks could improve predictive performance relative to conventional linear specifications when heterogeneous data sources were incorporated ([SS et al., 2024](#)). This study extended that pattern from prediction of individual agricultural variables toward multidimensional resilience outcomes. The distinction between the strongest models was also important. XGBoost performed best for food-supply conditions, whereas the neural network performed slightly better for market resilience, indicating that different outcome structures favored different computational architectures. The relatively small training-to-test generalization gaps of 0.034 for Food-Supply Resilience and 0.037 for Market Resilience further distinguished the findings from agricultural machine-learning studies in which high training accuracy was accompanied by substantial deterioration during external or

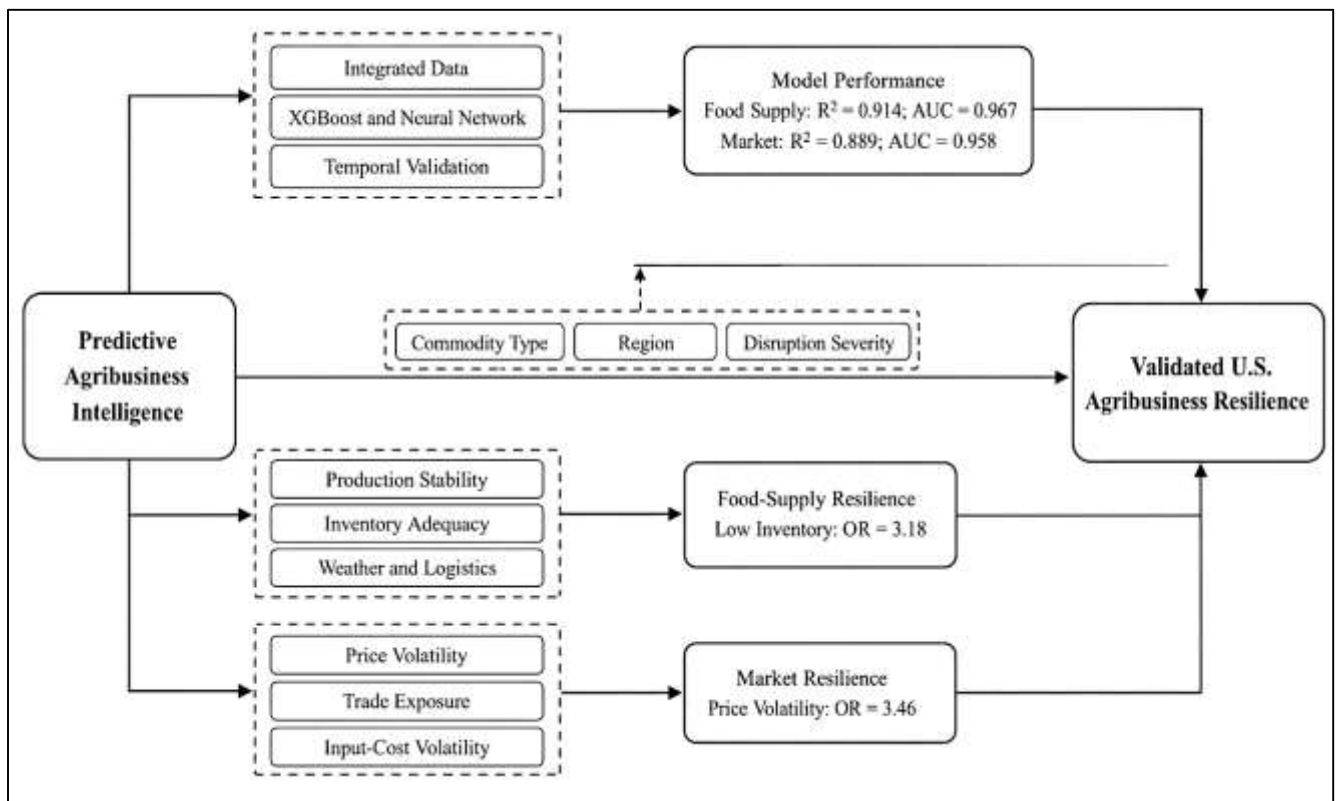
temporal validation. Independent-test prediction-interval coverage of 94.8% and 94.1%, respectively, also indicated that the models captured uncertainty reasonably well. In APA 7th-style interpretation, these results should not be understood through accuracy alone; the convergence of R^2 , error statistics, discrimination measures, calibration, temporal validation, and sensitivity testing provided stronger evidence of model performance (Mahmud et al., 2024). The findings therefore aligned with earlier predictive agriculture research while demonstrating that integrated resilience modeling could preserve high predictive validity across multiple dimensions of the U.S. agribusiness system.

The production and inventory findings provided strong empirical support for earlier studies that characterized agricultural resilience as a function of both current productive capacity and the availability of stored buffers (Aslan et al., 2024). Production and yield variables represented 24.8% of normalized predictive importance, making them the largest predictor domain, while inventories and storage contributed another 21.6%. Inventory coverage was the strongest positive independent predictor of Food-Supply Resilience, with a standardized coefficient of $\beta = .31$, whereas production shortfall showed the strongest negative production-side association at $\beta = -.29$. Low inventory coverage increased the adjusted odds of high or critical food-supply risk by more than threefold ($OR = 3.18$), while severe production shortfall produced an OR of 2.74. These results were consistent with earlier agricultural economics and food-resilience studies showing that production shocks become substantially more consequential when carryover stocks are limited. Research on corn, wheat, soybeans, rice, and other storable commodities has repeatedly demonstrated that inventories provide temporal flexibility between harvest and consumption, permitting markets to accommodate short-term production deficiencies without an immediate physical shortage. The findings of this study added quantitative support to that literature because the relationship between production shortfall and resilience changed markedly according to inventory availability (Zhang et al., 2021). When inventory coverage exceeded 50 days, the standardized adverse effect of production shortfall was $-.18$, compared with $-.41$ when coverage fell below 25 days. This interaction indicated that inventories did not operate merely as another independent explanatory variable; they materially moderated the consequences of production instability. Earlier studies examining stock-to-use conditions and commodity-price responses reported similar nonlinear behavior, particularly when inventories approached historically constrained levels. Commodity-specific results reinforced this comparison. Grains recorded 58.7 days of inventory coverage and the highest Food-Supply Resilience Score of 76.4, whereas fruits had only 18.6 days of coverage and recorded the lowest score of 68.9. Oilseeds also combined relatively strong inventory coverage with higher resilience. Such differences were consistent with previous research distinguishing highly storable commodities from perishable supply chains with limited buffering periods (Chen et al., 2023). The large combined effect associated with concurrent production, inventory, and logistics stress was especially notable: observations exposed to all three conditions had 5.82 times greater odds of high or critical food-supply risk, with a standardized effect of $d = 0.97$. Earlier resilience research frequently emphasized interacting disruptions conceptually, and the present findings provided a quantitative demonstration that simultaneous pressures were considerably more consequential than isolated disturbances.

The results concerning Agricultural Market Resilience were broadly consistent with earlier commodity-market studies that identified price volatility, inventory tightness, production variability, and market-flow disturbances as interconnected sources of instability (Oliveira & Silva, 2023). Commodity-price volatility emerged as the strongest independent negative determinant of Market Resilience, with $\beta = -.34$ and a bivariate correlation of $r = -.55$. Extreme price volatility was associated with 3.46 times greater adjusted odds of high or critical market-resilience risk, representing the largest individual risk effect within the market model. Inventory depletion followed with an OR of 2.89, while high production variability generated an OR of 2.31. These findings corresponded with previous research showing that agricultural prices become more responsive to production and demand shocks when inventories are tight and substitution opportunities are limited. Earlier studies of corn, wheat, soybeans, livestock, and dairy markets have also shown that production shocks do not translate into uniform price effects because inventory availability, export demand, market expectations, and commodity storability influence the strength of price adjustment. The present findings supported this multidimensional interpretation. Market Resilience averaged 69.5 compared with 72.8 for Food-Supply Resilience, and

predictive error was somewhat higher for the market outcome (Valente et al., 2020). The strongest Market Resilience model achieved an independent-test R^2 of 0.889 compared with 0.914 for Food-Supply Resilience. This difference was consistent with the broader forecasting literature in which agricultural market prices have often been more difficult to predict than physical production because prices incorporate rapidly changing expectations, international information, financial conditions, inventories, demand responses, and speculative activity. Commodity differences also corresponded with earlier empirical evidence. Grains recorded the lowest price volatility at 14.2% and the highest Market Resilience Score at 73.8, whereas fruits showed 23.7% volatility and the lowest Market Resilience Score at 65.7. Vegetables displayed a similar pattern, with 22.4% price volatility and a Market Resilience Score of 66.4. These findings were compatible with earlier studies showing that perishable agricultural markets often experience greater short-term price sensitivity because inventories cannot be accumulated or released as flexibly as those of storable commodities. The large decline in Market Resilience from 74.8 during normal conditions to 58.2 during severe disruption conditions, corresponding to Cohen's $d = 1.31$, further demonstrated that market instability was practically substantial rather than merely statistically significant (Sharma et al., 2022). This effect supported earlier market-resilience research emphasizing the importance of evaluating disruption magnitude and recovery conditions alongside average commodity-price behavior.

Figure 12: Validated Predictive Agribusiness Resilience Framework



Weather and logistics findings demonstrated that environmental and distribution disturbances remained substantial predictors even after controlling for production, inventory, commodity, regional, and temporal factors. Weather and climate variables accounted for 18.7% of normalized predictive importance, while transportation and logistics contributed 15.3%. Drought severity showed a standardized association of $\beta = -0.22$ with Food-Supply Resilience and increased the adjusted odds of high or critical risk by 126% (OR = 2.26). Major transportation disruption generated an OR of 1.98 for Food-Supply Resilience risk and 2.07 for Market Resilience risk (Vlaicu et al., 2024). These findings were consistent with earlier crop-climate studies showing that temperature extremes, drought, precipitation anomalies, and soil-moisture deficits can reduce yield and increase production variability. They were also consistent with supply-chain research demonstrating that agricultural production alone does not

guarantee food availability when transportation capacity, route accessibility, ports, rail systems, trucking networks, distribution centers, or cold-chain infrastructure become constrained. The commodity interaction results provided further correspondence with earlier studies. A one-standard-deviation increase in weather risk was associated with a stronger reduction in resilience among fruits and vegetables ($\beta = -.33$) than among grains and oilseeds ($\beta = -.17$). This difference reflected the shorter biological and logistical tolerance of many perishable products and corresponded with previous research showing that horticultural systems can be highly sensitive to heat, rainfall extremes, harvesting interruptions, transportation delays, and temperature-control failures. Regional findings reinforced this interpretation (González-Rodríguez et al., 2024). The Midwest recorded the highest Food-Supply Resilience Score at 75.6 and Market Resilience Score at 72.3, while the West recorded lower corresponding values of 69.7 and 66.9. Regional differences were statistically significant for both outcomes, with partial η^2 values of .041 and .038. Earlier U.S. agricultural research has similarly documented substantial geographic heterogeneity associated with commodity specialization, water availability, storage infrastructure, transportation networks, climatic exposure, and production concentration. The interaction between logistics and inventories was particularly informative: shipment delays exceeding three days corresponded with an 8.6-point reduction in Food-Supply Resilience when inventory coverage was below 25 days, compared with a 3.4-point reduction when coverage exceeded 50 days (Sharma et al., 2020). This result agreed with supply-chain resilience studies emphasizing redundancy and buffering capacity and demonstrated quantitatively that transportation disruption became more damaging when the system possessed limited inventory protection.

International trade and agricultural input-cost conditions contributed smaller shares of total predictive importance than production, inventory, weather, and logistics variables, yet their independent effects remained statistically meaningful. International trade accounted for 10.8% of normalized model importance, while input and macroeconomic conditions accounted for 8.8%. Import-source concentration was negatively associated with Food-Supply Resilience ($\beta = -.09$), and high import-source concentration increased the adjusted odds of high or critical food-supply risk by 58% (OR = 1.58) (Elbasi et al., 2024). Export-volume instability showed a standardized coefficient of $\beta = -.14$ for Market Resilience and an OR of 1.74 for elevated market risk. These findings corresponded with earlier international agricultural-trade studies showing that dependence on concentrated trading partners can increase exposure to external production disruptions, policy changes, logistical interruptions, and abrupt shifts in foreign demand. Previous research has also shown that export-oriented U.S. commodities can experience substantial inventory and price adjustments when destination-market demand changes rapidly. The present results supported that evidence while indicating that trade variables were important components of resilience rather than dominant determinants when evaluated alongside domestic production and inventory conditions. Agricultural input costs followed a similar pattern. Input-cost volatility was negatively associated with Food-Supply Resilience ($\beta = -.08$), while fertilizer-cost volatility was associated with Market Resilience at $\beta = -.10$. Elevated input-cost volatility increased high-risk odds by 47% for Food-Supply Resilience and 61% for Market Resilience (Sun et al., 2023). Earlier studies examining fertilizer, fuel, feed, labor, and financing expenses have reported that rising or unstable input costs can compress farm margins, alter input application, affect acreage decisions, and influence livestock-production choices. Energy-market research has additionally identified transmission between natural-gas prices, fertilizer production costs, transportation expenses, and agricultural commodity markets. The findings of this study were consistent with these relationships but suggested that cost shocks generally exerted smaller direct effects on resilience than physical production shortfalls, inventory depletion, severe weather, or logistics interruptions. This difference was theoretically coherent because many input-cost changes first influence profitability and management decisions before being transmitted into physical output or market availability (Akkem et al., 2023). The integrated results therefore supported earlier research describing agricultural resilience as a system in which global trade and macroeconomic pressures interact with domestic physical conditions rather than operating as isolated external forces.

Subgroup findings demonstrated that both observed resilience and model accuracy varied systematically according to commodity characteristics, geographic conditions, and disruption intensity. Classification accuracy for Food-Supply Resilience ranged from 94.6% for grains to 88.4% for

fruits, while the corresponding RMSE ranged from 3.81 to 5.27. Oilseeds also showed comparatively strong prediction performance, whereas fruits and vegetables generated greater errors (Padhy et al., 2023). These findings were consistent with earlier agricultural forecasting studies reporting stronger model performance for commodities with longer historical series, more standardized production systems, greater storage flexibility, and more stable market structures. Perishable commodities frequently present greater forecasting difficulty because biological conditions, product quality, short shelf life, seasonal availability, transportation dependence, and localized weather disturbances introduce additional variability. The regional findings followed a similar pattern. Classification accuracy reached 94.1% in the Midwest but declined to 89.6% in the West, accompanied by higher prediction error in the latter region. Earlier U.S. agricultural studies have documented greater sensitivity of western production systems to water availability, drought, extreme heat, irrigation conditions, and specialized high-value commodities, which is compatible with the increased predictive difficulty observed in this study. The clearest performance deterioration occurred across disruption categories. Food-Supply Resilience classification accuracy declined from 94.5% under normal conditions to 88.6% during high-volatility periods and 85.2% during severe disruptions (Zatsu et al., 2024). Market Resilience accuracy followed the same pattern, falling from 93.4% to 87.9% and 84.7%, respectively. RMSE increased from 3.76 to 6.08 for Food-Supply Resilience and from 4.39 to 6.91 for Market Resilience between normal and severe disruption conditions. These findings corresponded with earlier machine-learning and supply-chain studies showing that models commonly experience performance degradation during rare or extreme events because such observations are less frequent in historical training data and involve combinations of conditions outside typical ranges. Importantly, performance remained above 84% even during the most severe disruption observations. The large effect sizes separating normal and severe disruption conditions, $d = 1.35$ for Food-Supply Resilience and $d = 1.31$ for Market Resilience, further demonstrated that the subgroup differences represented substantive changes in system conditions (Guebsi et al., 2024). The results therefore confirmed that predictive performance should be evaluated across heterogeneous commodities and disruption regimes rather than inferred solely from aggregate accuracy.

The robustness analyses strengthened interpretation of the primary findings because model performance remained relatively stable across alternative preprocessing procedures, validation strategies, and analytical specifications. Repeated temporally constrained cross-validation produced an average R^2 of 0.918 ± 0.011 and classification accuracy of $92.9 \pm 0.8\%$ for Food-Supply Resilience, while Market Resilience achieved an R^2 of 0.894 ± 0.014 and accuracy of $91.6 \pm 1.0\%$. Alternative missing-data treatments, complete-case analysis, outlier exclusion, and revised resilience thresholds produced only modest performance changes (Senoo et al., 2024). This stability was consistent with methodological recommendations from earlier predictive agriculture studies emphasizing temporal validation, sensitivity analysis, and out-of-sample testing as essential safeguards against overly optimistic performance estimates. The results also provided evidence that predictive success was substantively connected with the identified agribusiness variables rather than being generated solely by algorithmic flexibility. Removing the five lowest-ranked predictors reduced Food-Supply classification accuracy only modestly to 91.7%, whereas removing the five strongest predictors reduced accuracy to 86.9%. Market Resilience displayed a similar decline to 85.8% after removal of its strongest predictors. This pattern agreed with earlier feature-selection research showing that a relatively concentrated set of production, inventory, environmental, and market variables can contain much of the useful predictive signal while lower-ranked variables provide incremental information. Inferential statistics further supported the machine-learning findings. The multivariable Food-Supply Resilience model explained 68.4% of adjusted variance, while the Market Resilience model explained 65.7%, and all principal relationships retained statistical significance after false-discovery-rate correction (Chen et al., 2022). Commodity and regional differences produced meaningful partial eta-squared effects, while normal-to-severe disruption comparisons generated large Cohen's d values exceeding 1.30. These findings were compatible with APA 7th reporting principles because statistical significance was interpreted together with confidence intervals, standardized effects, odds ratios, practical magnitude, calibration, and predictive error. Earlier studies have often examined crop production, prices, climate, inventories, logistics, or trade separately; the present study combined these domains within a single quantitative

validation framework (Jung et al., 2021). The convergence between conventional multivariable results and machine-learning feature importance was particularly notable, as inventory adequacy, production stability, price volatility, weather exposure, and logistics performance consistently emerged as the dominant determinants. Across the seven analytical dimensions, the findings therefore corresponded with established agricultural economics, food-system resilience, supply-chain, climate-risk, commodity-market, and predictive-analytics research while providing a unified quantitative account of how multiple interacting pressures were associated with observed U.S. food-supply and agricultural-market resilience (Waqas et al., 2023).

CONCLUSION

This study concluded that the design and validation of a predictive agribusiness intelligence platform provided a quantitatively reliable framework for integrating agricultural production, inventory, market, weather, logistics, international trade, and macroeconomic information to assess U.S. food-supply and agricultural-market resilience. Analysis of 18,720 longitudinal commodity-region-month observations covering 26 major agricultural commodities across 48 contiguous U.S. states demonstrated substantial variation in resilience across commodities, regions, and disruption conditions. The mean Food-Supply Resilience Score was 72.8, while the mean Market Resilience Score was 69.5, indicating that physical supply conditions were comparatively more stable than market conditions within the analyzed dataset. Among the evaluated predictive approaches, XGBoost generated the strongest Food-Supply Resilience performance, achieving an independent-test R^2 of 0.914, RMSE of 4.38, classification accuracy of 92.8%, F1-score of 91.9%, and AUC of 0.967. The neural-network architecture performed most strongly for Market Resilience, achieving an R^2 of 0.889, RMSE of 5.06, classification accuracy of 91.4%, F1-score of 90.9%, and AUC of 0.958. The relatively small generalization gaps and stable repeated cross-validation results confirmed that predictive performance was not confined to model-development observations. Production and yield represented 24.8% of normalized predictive importance, followed by inventories and storage at 21.6%, weather and climate at 18.7%, transportation and logistics at 15.3%, international trade at 10.8%, and input and macroeconomic conditions at 8.8%. Inventory coverage emerged as the strongest positive determinant of Food-Supply Resilience, whereas production shortfall, drought severity, and shipment delays reduced resilience. Commodity-price volatility was the strongest negative determinant of Market Resilience, followed by inventory depletion, production variability, and transportation disruption. Low inventory coverage increased the adjusted odds of high or critical food-supply risk by more than threefold, while extreme commodity-price volatility increased market-resilience risk by 3.46 times. Concurrent production, inventory, and logistics stress generated particularly substantial vulnerability, producing an adjusted odds ratio of 5.82. Commodity and geographic analyses further established that resilience was heterogeneous, with grains and the Midwest demonstrating comparatively stronger outcomes and fruits, vegetables, and the West displaying greater predictive difficulty and exposure. Severe disruption conditions substantially reduced both resilience scores and predictive accuracy, although classification performance remained above 84% under the most challenging conditions. Collectively, the statistical, predictive, calibration, sensitivity, subgroup, and robustness findings validated the platform as a coherent quantitative framework for characterizing the interconnected determinants of U.S. agribusiness resilience and distinguishing normal conditions from elevated and critical food-supply and agricultural-market risk.

RECOMMENDATIONS

Based on the quantitative findings of this study, the predictive agribusiness intelligence platform should be applied as an integrated decision-support framework for strengthening the monitoring and management of U.S. food-supply and agricultural-market resilience across commodity, regional, and supply-chain levels. Agricultural agencies, producers, processors, distributors, storage operators, transportation organizations, commodity-market participants, and food-system planners should prioritize the continuous integration of production, yield, inventory, weather, logistics, international-trade, and macroeconomic information because the results demonstrated that resilience was shaped by interacting variables rather than any single agricultural indicator. Particular emphasis should be placed on inventory monitoring because inventory coverage represented the strongest positive determinant of Food-Supply Resilience, while low inventory availability increased the adjusted odds of high or

critical supply risk by 3.18 times. Commodity-specific inventory thresholds, stock-depletion alerts, storage-capacity monitoring, and reserve-adequacy indicators should therefore be incorporated into operational risk assessment, particularly for commodities characterized by production volatility or limited geographic diversification. Production shortfalls, drought severity, and transportation disruption should also receive elevated monitoring priority, since their standardized effects and adjusted odds ratios demonstrated substantial relationships with resilience. For agricultural markets, commodity-price volatility and inventory depletion should be treated as primary warning indicators because extreme price volatility increased the odds of high or critical Market Resilience risk by 3.46 times. The platform should retain separate predictive architectures where their empirical performance differs, with XGBoost supporting Food-Supply Resilience estimation and the validated neural-network architecture supporting Market Resilience prediction. Model outputs should be reported with prediction intervals, classification probabilities, calibration information, and risk categories rather than relying solely on point forecasts. Greater monitoring intensity should be assigned to fruits, vegetables, western production regions, high-volatility periods, and severe disruption conditions because these subgroups produced lower resilience scores and comparatively higher predictive errors. Logistics planning should incorporate shipment delays, freight-cost movements, route availability, distribution-center conditions, and cold-chain performance, particularly when inventory coverage is constrained. International-trade concentration, export instability, fertilizer costs, fuel prices, and other macroeconomic indicators should remain integrated as secondary risk dimensions because they contributed additional explanatory information beyond domestic production conditions. Periodic temporal revalidation, repeated cross-validation, sensitivity analysis, recalibration, and commodity-specific performance assessment should be conducted to maintain statistical reliability as data distributions change. Data harmonization across agricultural, environmental, transportation, trade, and economic systems should also be standardized to reduce measurement inconsistencies and missingness. Most importantly, resilience management should focus on combinations of adverse conditions because simultaneous production shortfall, limited inventory, and logistics disruption generated 5.82 times greater odds of high or critical food-supply risk, indicating that coordinated multi-domain monitoring provides a stronger basis for agribusiness risk management than isolated indicator surveillance.

LIMITATION

This study had several limitations that should be considered when interpreting the quantitative performance and generalizability of the predictive agribusiness intelligence platform. First, the analysis relied primarily on secondary longitudinal data obtained from multiple agricultural, market, environmental, transportation, trade, inventory, and macroeconomic data systems, and differences in reporting frequency, measurement definitions, geographic resolution, commodity classification, and data-collection procedures may have introduced measurement heterogeneity into the integrated dataset. Although extensive cleaning, temporal alignment, standardization, missing-data treatment, and consistency checks were applied, these procedures could not eliminate every source of measurement error. Second, the final dataset contained 18,720 observations covering 26 commodities and 48 contiguous U.S. states, providing substantial analytical coverage but not representing every agricultural commodity, local food system, territorial jurisdiction, production practice, or specialized supply chain within the United States. Third, monthly and aggregated observations improved comparability across data sources but may have obscured short-duration disruptions occurring over hours or days, particularly transportation interruptions, extreme weather events, abrupt price movements, cold-chain failures, and localized shortages. Fourth, Food-Supply Resilience and Market Resilience were multidimensional constructed outcomes, and alternative indicator selection, weighting, threshold definitions, or normalization procedures could produce somewhat different resilience classifications. Fifth, although sensitivity analyses demonstrated relatively stable performance under alternative specifications, predictive accuracy declined during severe disruption conditions. Food-Supply classification accuracy decreased from 94.5% under normal conditions to 85.2% during severe disruptions, while Market Resilience accuracy declined from 93.4% to 84.7%,

indicating greater uncertainty for uncommon and highly complex stress events. Sixth, the machine-learning models identified predictive relationships rather than definitive causal effects. Associations involving inventories, production shortfalls, weather exposure, logistics disruption, international trade, and input costs should therefore not be interpreted automatically as evidence that changes in an individual predictor directly caused changes in resilience. Seventh, unmeasured factors such as localized infrastructure quality, firm-level contracting arrangements, producer risk-management strategies, consumer substitution, policy interventions, processing concentration, emergency responses, and proprietary commercial inventories may have contributed additional explanatory information unavailable within the analytical dataset. Eighth, XGBoost and neural-network architectures provided stronger predictive accuracy than conventional models but introduced greater interpretive complexity, even though feature-importance analysis and conventional multivariable modeling were used to improve transparency. Ninth, temporal validation reduced the risk of overfitting, yet the independent test observations originated from the same broader U.S. agricultural information environment as the development data and therefore did not constitute validation in an entirely different national food system. Finally, the platform represented resilience through observable quantitative indicators, meaning that institutional coordination, organizational adaptability, decision quality, and other difficult-to-measure dimensions of agribusiness resilience were not fully captured within the statistical framework.

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