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forecasting

Review

Transforming Agricultural Productivity with AI-Driven Forecasting: Innovations in Food Security and Supply Chain Optimization

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Abstract: Global food security is under significant threat from climate change, population growth, and resource scarcity. This review examines how advanced AI-driven forecasting models, including machine learning (ML), deep learning (DL), and time-series forecasting models like SARIMA/ARIMA, are transforming regional agricultural practices and food supply chains. Through the integration of Internet of Things (IoT), remote sensing, and blockchain technologies, these models facilitate the real-time monitoring of crop growth, resource allocation, and market dynamics, enhancing decision making and sustainability. The study adopts a mixed-methods approach, including systematic literature analysis and regional case studies. Highlights include AI-driven yield forecasting in European hydroponic systems and resource optimization in southeast Asian aquaponics, showcasing localized efficiency gains. Furthermore, AI applications in food processing, such as plasma, ozone and Pulsed Electric Field (PEF) treatments, are shown to improve food preservation and reduce spoilage. Key challenges—such as data quality, model scalability, and prediction accuracy—are discussed, particularly in the context of data-poor environments, limiting broader model applicability. The paper concludes by outlining future directions, emphasizing context-specific AI implementations, the need for public–private collaboration, and policy interventions to enhance scalability and adoption in food security contexts.

Keywords: AI-driven forecasting; food security; machine learning; hydroponics and aquaponics; pulsed electric field; resource optimization

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1. Introduction

The issue of global food security is a highly urgent concern in the 21st century, which is influenced by several parameters including population expansion, climate change, limited resources, and geopolitical instability [1]. Given the projected world population of 9.7 billion by 2050, there will be a significant surge in the need for food, which will exert enormous strain on agricultural systems [2]. Concurrently, climate change poses a danger to agricultural output by giving rise to severe weather phenomena, altering the timing of growing seasons, and deteriorating natural resources like soil and water. These variables particularly affect developing regions, where access to affordable and nutritious food remains a significant challenge.

Building on the transformative potential of these technologies, this study specifically examines how forecasting models can be utilized to enhance both conventional and alternative agricultural systems. By exploring their role in optimizing food processing and supply chain management, the study aims to identify how such models can contribute to the resilience and sustainability of global food systems.

However, while the study aims to address global food security, it is essential to acknowledge a critical limitation: the availability of data and research predominantly focus on localized or regional applications of AI technologies. These regional implementations are designed to improve agricultural production efficiency in specific contexts, but they may not always directly translate to global-scale impacts. This limitation presents a challenge in assessing the broader, international implications of AI-driven forecasting technologies, as the current research often lacks comprehensive datasets from diverse regions needed to support the development of globally applicable models. Addressing these gaps will require international collaboration and significant advancements in data-sharing frameworks to achieve a truly global perspective on food security.

To guide this investigation, the following key research questions are raised:

1. How can forecasting models improve the efficiency and sustainability of conventional and alternative agricultural systems in the context of global food security?
2. What role do forecasting technologies play in enhancing food processing and supply chain management for greater resilience in global food systems?
3. In what ways can the convergence of forecasting technologies, alternative agricultural practices, and food processing innovations contribute to addressing the complex challenges of global food security?

The remainder of this paper comprehensively explores the transformative potential of AI-driven forecasting models across various dimensions of global food security. The methodology section provides an analytical approach to understanding how advancements in AI, ML, and big data analytics can revolutionize agricultural systems, food processing, and supply chain management while also emphasizing how these forecasting models can build resilience and sustainability in global food systems.

In the section on defining food security and the need for forecasting models, the four dimensions of food security—availability, access, utilization, and stability—are analyzed in the context of forecasting models. This section highlights how AI-driven models can predict and address food security challenges through informed decision making.

The overview of the forecasting models section delves into various approaches, including time-series, ML, DL, and hybrid models, illustrating their roles in predicting crop yields, climate impacts, and disruptions to supply chains.

Following this, the paper investigates the applications of forecasting models in traditional and alternative agriculture, showcasing their contributions to yield prediction, resource optimization, climate forecasting, and market forecasting across different agricultural systems.

The section on forecasting models in food processing and supply chains then examines how predictive models can improve food processing techniques, minimize waste, and enhance operational efficiency, providing early warnings and optimize logistics in food supply chains.

Finally, the paper concludes with a discussion on the challenges and limitations of forecasting models, outlining the obstacles related to data quality, scalability, and model accuracy while emphasizing future directions for these models in the pursuit of global food security.

2. Methodology

This review paper, titled "Transforming Agricultural Productivity with AI-Driven Forecasting: Innovations in Food Security and Supply Chain Optimization", adopts a comprehensive analytical approach to explore the integration of AI-powered forecasting models in addressing key challenges related to global food security. The methodology focuses on how advancements in AI can revolutionize agricultural systems, food processing, and supply chain management. Each component of the diagram (Figure 1) is examined in detail to highlight the role of data-driven methods in improving global food systems.

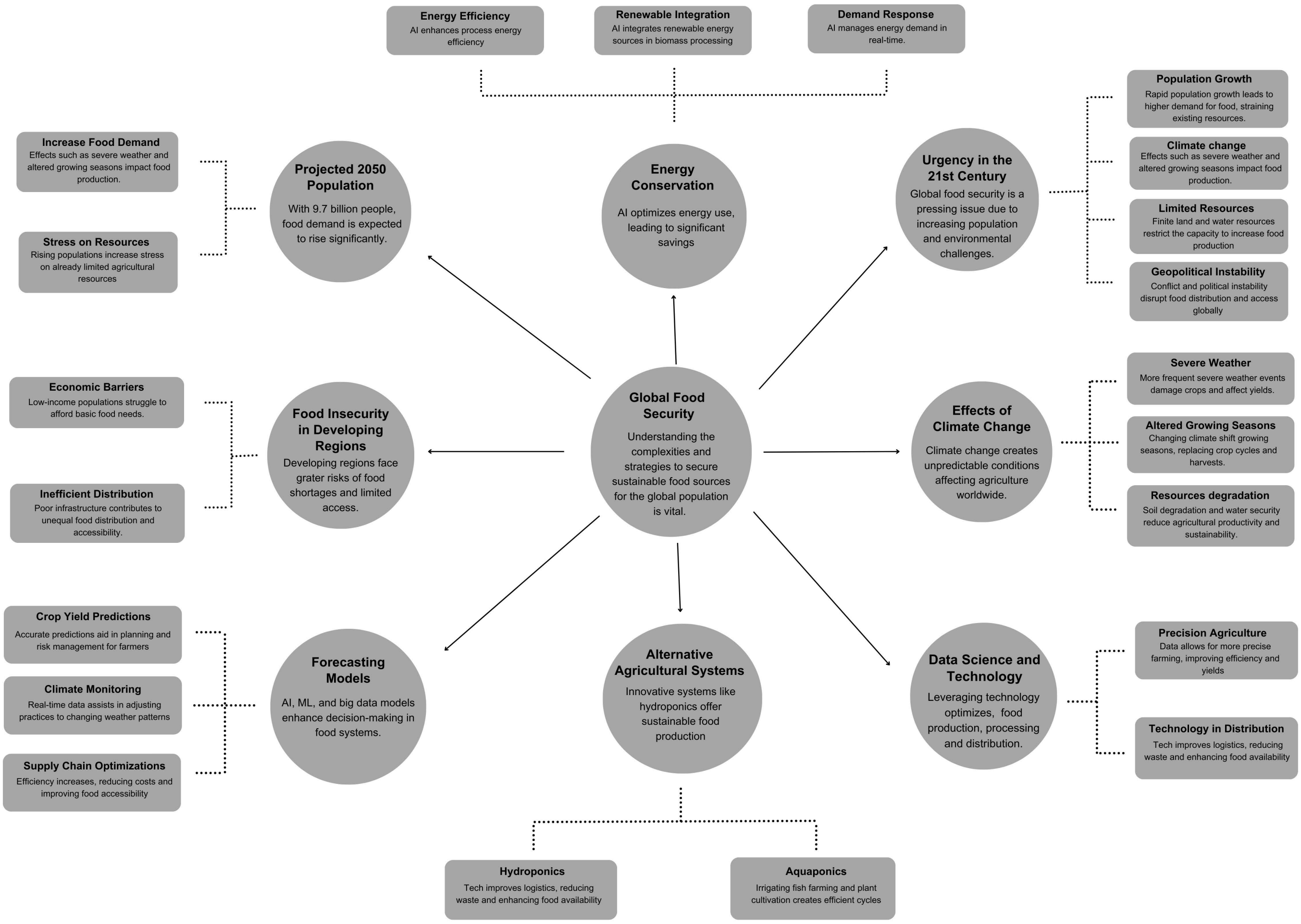

Figure 1. Schematic diagram providing a comprehensive review of global food security challenges and limitations.

2.1. Global Food Security Framework

The study begins by establishing the context of global food security. As the world population is projected to surpass 9 billion by 2050, the need for innovative solutions to meet the growing food demand becomes critical [3]. This section evaluates the urgency of food security in the 21st century, particularly in light of the following:

- Projected Population Growth and Food Demand: The methodology examines how AI-driven forecasting models can be used to predict and plan for the increased food demand due to rapid population growth, especially in developing regions [4].
- Challenges in Developing Regions: The study explores how economic barriers and inefficient food distribution systems exacerbate food insecurity in low-income regions and how AI-driven models can offer potential solutions [5,6].

2.2. Key Challenges to Global Food Security

The review identifies and investigates several core challenges to achieving global food security:

- Population Growth: Rapid population expansion continues to place immense pressure on agricultural resources. By 2050, the world's population is expected to grow to 9.7 billion, necessitating an increase in food production by approximately 70% to meet global demand [7]. This study analyzes how AI can predict and manage resource allocation for food production to meet this escalating demand.
- Climate Change: Climate change significantly affects growing seasons, weather patterns, and agricultural productivity. The increasing frequency and intensity of extreme

weather events, such as droughts, floods, and heatwaves, have a direct impact on crop yields and food availability [8,9]. Additionally, climate change disrupts the phenology of crops, altering the growth cycle and reducing the viability of traditional farming systems [10]. Several peer-reviewed studies have documented the adverse effects of climate variability, demonstrating reductions in crop yields and increased food insecurity, particularly in vulnerable regions [11,12]. To address these challenges, this study evaluates how AI-driven climate models can provide accurate forecasting and support decision-makers in mitigating the negative impact of these environmental changes.
- Limited Resources: The scarcity of critical agricultural inputs, such as water, arable land, and nutrients, poses a major threat to global food production [13]. Increasing competition for water resources and the degradation of arable land due to intensive farming practices further threaten agricultural sustainability [14,15]. This paper assesses how precision agriculture, supported by AI technologies, can optimize the use of limited resources to enhance sustainability and improve productivity through targeted interventions such as precision irrigation and nutrient management.
- Geopolitical Instability and Resource Distribution: Political conflicts and geopolitical instability have substantial implications for global food security, often leading to disruptions in food supply chains and inequitable access to food [16]. Regions experiencing conflict or political turmoil face greater barriers to both importing essential agricultural inputs and exporting their produce, resulting in reduced food availability and heightened risk of famine [17]. This section reviews how forecasting technologies can predict disruptions arising from instability and support stakeholders in developing proactive strategies to mitigate the impact of these disruptions on food distribution.

2.3. AI-Driven Technological Interventions

The study explores the impact of advancements in AI and data science technologies on improving food security through accurate forecasting, optimization techniques, and the proactive management of food production and supply:

- Precision Agriculture: The study delves into how AI can support precision farming, offering detailed analysis of soil, weather, and crop data to improve yield prediction, minimize waste, and reduce costs. These improvements are not just localized but have a far-reaching effect in stabilizing food production globally by ensuring efficiency and reducing overuse of resources, which contributes to a sustainable global food supply chain. Predictive models help optimize input use, ensuring higher yields with lower environmental impact, which is essential for global food security efforts.
- Technological Advancements in Food Distribution: AI-driven logistics and distribution technologies are reviewed for their capacity to minimize food waste, improve supply chain efficiency, and enhance food accessibility on a global scale. AI is applied to analyze and predict supply chain disruptions—like those seen during the COVID-19 pandemic—helping to ensure that food can be distributed effectively to areas experiencing scarcity [18]. The integration of AI in logistics enhances the resilience of the food distribution network, especially for temperature-sensitive products, by forecasting potential disruptions and optimizing cold chain logistics, which prevents spoilage during transit across multiple borders.
- Alternative Agricultural Systems: The study examines alternative and AI-enhanced farming systems such as hydroponics, aquaponics, and vertical farming. These systems utilize data-driven techniques and have proven highly effective in meeting food production challenges, especially in resource-constrained environments. For example, real-time sensor data used in aquaponics help regulate nutrient concentrations, improving yield and contributing to food security, even in urban areas where traditional farming is not feasible [19]. Beyond their local utility, these alternative systems are emerging as global solutions, enabling food production in environments that previ-

ously lacked sufficient agricultural potential, ultimately contributing to greater global food availability.

- Global Climate and Market Monitoring: AI-based platforms like the World Food Programme's Hunger Map use satellite imagery, economic data, and local reports to provide the real-time monitoring of food insecurity levels across the globe [20]. These platforms make use of AI to predict food shortages and direct aid proactively to regions where it is needed the most, enhancing global food security. By analyzing climate patterns like El Niño and La Niña, AI models offer insights that help farmers and policymakers prepare for global-scale climate events, further ensuring the resilience of international food systems.

2.4. AI-Driven Forecasting Models

The study focuses on the potential of AI-driven forecasting models to improve decision making across agriculture, food processing, and supply chain management:

- Crop Yield Predictions: AI models can predict crop yields with greater accuracy, enabling better planning and risk management [21,22]. This section reviews the application of AI and big data in forecasting crop performance and assessing the impact of environmental variables.
- Climate Monitoring and Real-Time Data: AI-powered climate models help monitor and respond to changing weather patterns, offering farmers real-time insights to adjust their practices [23]. The study evaluates the role of these models in enhancing resilience against climate variability.
- Supply Chain Optimization: AI-driven models provide optimization solutions for food supply chains by reducing inefficiencies, minimizing costs, and improving food accessibility [24]. The methodology assesses how these models can improve the entire supply chain from production to distribution.

The methodology of this review paper provides a structured exploration of how AI-driven forecasting models, powered by ML and big data analytics, can address the complex challenges of global food security. By focusing on the intersection of technology, agriculture, and food processing, the study highlights the transformative potential of AI in building more resilient, efficient, and sustainable global food systems.

3. Defining Food Security and the Need for Forecasting Models

Food security is a complex and multifaceted concept, as depicted in Figure 1, which outlines the main dimensions under threat from various global challenges, such as population growth, climate change, and resource depletion. The four key dimensions of food security—availability, access, utilization, and stability—are under increasing pressure due to these factors.

Addressing the challenges associated with these dimensions is crucial for ensuring food security, and AI-driven forecasting models have become essential tools in identifying and mitigating vulnerabilities in global food systems. By leveraging AI, these models offer data-driven insights that empower decision making in areas like agricultural production, food processing, and distribution. Through such predictive capabilities, these models help ensure global food security even under difficult and unpredictable conditions.

3.1. Dimensions of Food Security

As highlighted in Figure 1, the four critical dimensions of food security are directly impacted by global challenges such as climate change, geopolitical instability, and resource degradation. Forecasting models address vulnerabilities within these dimensions by predicting outcomes and helping stakeholders respond effectively.

- Availability: Refers to the physical availability of sufficient quantities of food. This depends on agricultural output, production systems, and trade. Forecasting models are used to predict agricultural yields, simulate environmental factors like rainfall and temperature, and detect potential food shortages or surpluses [25].
- Access: Involves both the economic and physical means to obtain food. AI-driven forecasting models help predict market dynamics, food prices, and potential supply chain disruptions, ensuring food access for economically disadvantaged and vulnerable groups [26].
- Utilization: Encompasses how food is used, focusing on food safety, nutritional quality, and proper storage. Forecasting models in food processing help predict optimal storage conditions, shelf life, and nutritional degradation, ensuring the efficient and safe use of food resources [27].
- Stability: Refers to the ability to maintain a stable food supply over time, particularly in the face of shocks like natural disasters or economic downturns. Forecasting models play a crucial role in creating early warning systems for crises, enabling proactive responses to stabilize food systems in the long term [28].

3.2. Leveraging Forecasting Models to Tackle Food Security Challenges

As seen in Figure 1, climate change, population growth, and geopolitical instability continue to threaten global food security. Forecasting models, highlighted in this section, are integral to predicting and mitigating the risks associated with these global challenges. This section focuses on how different types of forecasting models contribute to food security:

- Climate Forecasting Models: The effects of climate change, as shown in Figure 1, such as altered growing seasons and severe weather, are significant risks to agricultural production. Climate forecasting models predict these shifts in weather patterns and environmental changes, helping farmers adjust their practices to prevent crop failures and make more efficient use of resources [29].
- Crop Yield Forecasting Models: As depicted in Figure 1, the increase in food demand driven by population growth places immense pressure on agricultural systems. Crop yield forecasting models use data on soil quality, rainfall, and temperature to predict yields, allowing for better planning and timely interventions to prevent shortages, ensuring food security [30].
- Supply Chain Forecasting Models: According to Figure 1, inefficient distribution contributes to significant issues in food supply chains. AI-driven supply chain forecasting models are critical in predicting customer demand, identifying logistical bottlenecks, and optimizing food transportation from producers to consumers, improving the operational efficiency of food distribution systems [31].

3.3. The Evolving Role of Alternative Agriculture and Food Processing

As depicted in Figure 1, alternative agricultural systems such as hydroponics and aquaponics, along with advanced food processing technologies, are becoming increasingly vital for sustainable food production. This subsection explores the application of forecasting models in optimizing these systems:

- Hydroponics and Aquaponics: These soilless farming systems rely on the precise control of environmental factors like water, nutrients, and light. Forecasting models help predict the ideal nutrient levels, water conditions, and energy use to optimize plant and fish growth, ensuring efficiency and yield consistency [32–37].
- Vertical Farming: In highly urbanized areas, vertical farming offers a sustainable solution for food production, but it is energy-intensive. Forecasting models help balance energy use, optimize harvest cycles, and predict plant growth rates to enhance sustainability [38,39].
- Advanced Food Processing Techniques: In food processing, forecasting models, driven by real-time data from Internet of Things (IoT) devices and automation, help improve product quality and safety. These models predict spoilage rates, optimize energy

consumption, and ensure efficient processing workflows, leading to enhanced food preservation and reduced waste [40,41].

In summary, forecasting models (Figure 2) are essential to modern food security strategies, offering vital support to both traditional and alternative agricultural systems. These models optimize food production by providing predictive insights into plant development, resource needs, and environmental factors, ensuring the efficient and sustainable operation of systems like hydroponics and aquaponics. They also enhance food processing by predicting spoilage rates, optimizing storage conditions, and reducing post-harvest losses, improving the preservation and transformation of food products. By stabilizing supply chains and enabling real-time monitoring and decision making, forecasting models are pivotal in addressing the complex challenges of food insecurity in an increasingly dynamic world.

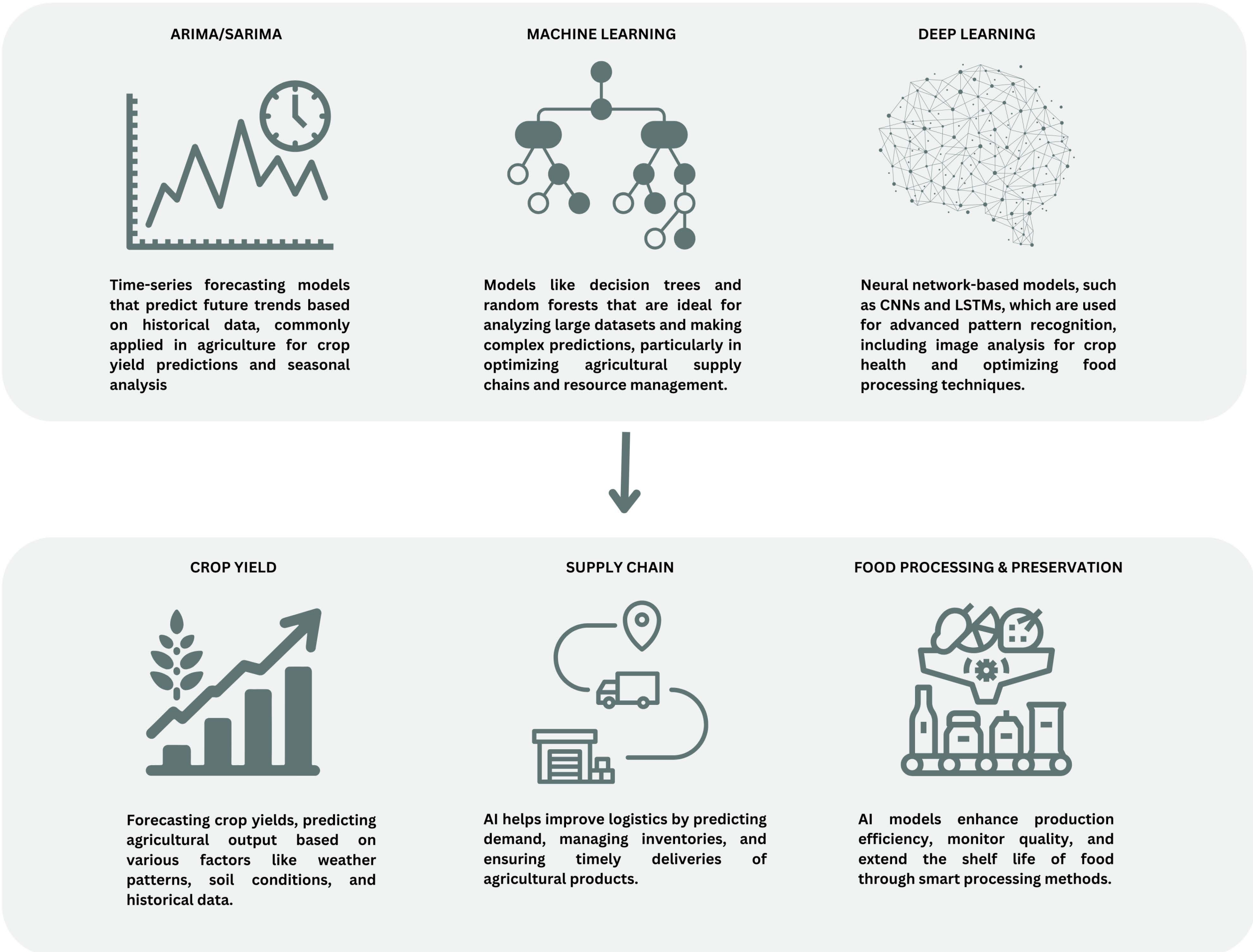

Figure 2. Applications of AI-Driven forecasting models in agriculture, supply chain, and food processing.

4. Overview of Forecasting Models Used in Food Security

This section presents findings from the literature review, focusing on four core dimensions of food security: availability, access, and utilization and stability. The role of forecasting models in addressing these dimensions is examined in both traditional and alternative agricultural systems as well as in advanced food processing and supply chains. The review explores forecasting methods—time-series models, ML, DL, and hybrid models—that optimize agricultural productivity, manage resources, predict market dynamics, and ensure supply chain efficiency.

4.1. Dimensions of Food Security and Forecasting Models

The four dimensions of food security—availability, access, utilization, and stability—are critical for maintaining global food security (as depicted in Figure 1). Forecasting models provide essential predictive insights into each of these dimensions, helping decision-makers mitigate risks and manage food systems more effectively.

- Availability: The availability of food is influenced by agricultural output, environmental conditions, and market forces. Time-series models such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) have proven effective in predicting crop yields and market prices by analyzing historical data and detecting trends and cycles. These models help farmers and policymakers in resource planning and yield forecasting [42,43].
- Access: Access to food is shaped by economic and physical factors. ML models, such as Random Forests (RF) and Support Vector Machines (SVMs), are used to predict market dynamics and price fluctuations. These models help farmers and distributors optimize production schedules, improve market access, and mitigate supply chain disruptions [44–46].
- Utilization and Stability: The proper use of food, its safety, and its stability over time are crucial aspects of food security. DL models, such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs), are used to predict long-term environmental impacts, supply chain interruptions, and post-harvest quality, providing early warnings of food shortages or processing bottlenecks [47–51].

4.2. Key Forecasting Models for Climate, Yield, and Supply Chain Optimization

Various forecasting models are applied to tackle food security issues, particularly those related to climate variability, yield prediction, and supply chain optimization. These models are classified into three broad categories:

4.2.1. Time-Series Models

ARIMA and SARIMA are commonly used for yield and price forecasting in agriculture. These models analyze historical data to predict trends and cycles, helping farmers and policymakers make informed resource allocation decisions [52–56]. These models also extend to processing schedules to ensure that food products are distributed optimally to minimize waste [57–59]. As detailed in Table 1, these models are summarized alongside their key applications, offering a clearer view of how they play a vital role in both forecasting and resource optimization.

4.2.2. ML Models

ML models, including RF and SVMs, excel at handling complex, non-linear relationships among climate, soil quality, and market conditions. These models are widely used for yield forecasting and market prediction, providing robust insights into market dynamics and resource optimization [60–64]. Table 2 summarizes the key applications of these ML models, highlighting their effectiveness in improving agricultural productivity and decision-making processes.

4.2.3. DL Models

- LSTMs, a type of Recurrent Neural Network (RNN), analyze sequential data, such as long-term weather patterns, enabling accurate predictions of environmental impacts on agricultural systems [65,66].
- CNNs process spatial data, such as satellite imagery, to monitor crop health and predict supply chain disruptions, providing real-time insights into potential bottlenecks [67,68].
- The integration of LSTMs and CNNs in hybrid models enhances prediction accuracy by combining spatial and temporal data, particularly in advanced yield prediction and supply chain management [69–76].

Table 3 summarizes these applications, showcasing the capabilities of LSTMs, CNNs, and their hybrid combinations in improving agricultural predictions and supply chain efficiency.

Table 1. Applications of time-series models in food security.

Model	Application	Description	References
ARIMA	Yield Forecasting	Predicts future crop yields by analyzing historical data, identifying trends, cycles, and seasonal variations. Supports optimal resource use and reduces risks.	[52,53]
SARIMA	Price Forecasting	Captures seasonal patterns in agricultural commodity prices, improving financial planning and market prediction for agricultural economies.	[54–56]
ARIMA/SARIMA	Processing and Distribution	Forecasts processing schedules and distribution needs by analyzing historical production and demand data. Minimizes waste by timely food processing.	[57–59]

Table 2. Applications of ML models in food security.

Model	Application	Description	References
RF	Yield Prediction	Analyzes data on soil quality, climate conditions, and crop health to predict crop yields. Handles non-linear relationships robustly.	[62]
SVMs	Market Dynamics	Predicts market trends and price fluctuations based on historical market data, supporting planning and strategy development.	[64]

Table 3. Applications of DL models in food security.

Model	Application	Description	References
LSTMs	Agricultural Ecosystems	Predicts long-term effects of environmental factors on agricultural systems by analyzing sequential data like weather patterns and rainfall.	[69,70]
CNNs	Supply Chain Prediction	Analyzes spatial data from satellite imagery to predict disruptions in agricultural supply chains, including transportation and infrastructure.	[71,72]
LSTM + CNN	Advanced Yield Prediction	Combines temporal and spatial data for crop yield forecasting, integrating historical weather, soil conditions, and land use data	[73–75]

4.3. The Evolving Role of Hybrid Models in Food Security

Hybrid models combine various forecasting methods, such as ML, DL, and time-series models, to improve prediction accuracy in food systems. These models are particularly valuable for addressing complex agricultural challenges.

4.3.1. Time Series + ML

Combining time series with ML provides a comprehensive understanding of agricultural trends, enhancing forecasting accuracy in yield and price predictions [77,78].

4.3.2. ML + DL

Hybrid models that combine ML for feature selection with DL for long-term predictions are especially effective in forecasting complex risks such as pest outbreaks, extreme weather events, and supply chain failures [79–81].

4.3.3. Clustering + ML

Recent research highlights the application of clustering algorithms with traditional ML models for enhanced sales prediction in retail environments. This same approach can be adapted to agriculture to group farms with similar environmental and economic characteristics [82].

Table 4 provides a detailed summary of the applications of these hybrid models, illustrating their effectiveness in improving prediction accuracy across various aspects of agricultural productivity and risk management.

Table 4. Applications of hybrid models in food security.

Model	Application	Description	References
Time Series + ML	Yield and Price Forecasting	Combines historical trend analysis of time-series models with ML's ability to handle complex, non-linear relationships, improving yield and price forecasts.	[77,78]
ML + DL	Advanced Risk Prediction	Integrates ML for feature selection and DL for long-term predictions, improving the accuracy of forecasting risks like pest outbreaks or climate extremes.	[79–81]
Clustering + ML	Sales and Demand Prediction	Combines clustering with traditional ML models to enhance sales and demand forecasting, grouping similar regions or entities for better prediction accuracy	[82]

4.4. Applications in Traditional and Alternative Agriculture

Forecasting models are used extensively across both traditional and alternative agriculture systems to optimize productivity, align production with demand, and improve resource efficiency:

4.4.1. Traditional Agriculture

Forecasting models for climate and price prediction help determine planting schedules and mitigate risks by providing accurate environmental forecasts, thus assisting farmers in planning resources efficiently [83,84].

4.4.2. Hydroponics and Aquaponics

These soilless farming systems require precise control over water, nutrients, and light. Forecasting models like DL (LSTMs and CNNs) use sensor data to optimize growth conditions and nutrient cycles, ensuring efficient resource use and yield consistency [85–88].

4.4.3. Alternative Agriculture

Methods such as vertical farming and advanced processing benefit from market and processing forecasting models, which align production with demand, reduce post-harvest losses, and improve resource efficiency [89–91].

4.4.4. Food Valorization

The process of valorizing agri-food waste is becoming crucial for sustainability. Forecasting models help identify optimal uses for by-products, such as extracting bioactive compounds from food waste. Studies like Yadav et al. discuss recent trends and future sustainable challenges related to valorization, underlining the importance of predictive tools in transforming waste into value-added products [92].

Table 5 summarizes the applications of forecasting models in these various agricultural systems, showcasing their role in improving productivity, resource efficiency, and sustainability.

Table 5. Applications of forecasting models in alternative agriculture.

Area	Application	Description	References
Traditional Agriculture	Climate and Price Forecasting	Predicts environmental impacts on crop yields and forecasts market prices, assisting in resource allocation and financial planning.	[83,84]
Hydroponics and Aquaponics	Environmental Control and Resource Optimization	Adjusts water, nutrients, and light for optimal plant growth, maintains balanced nutrient cycles, and aligns production with market demand.	[85–87]
Alternative Agriculture	Market and Processing Forecasting	Aligns production with demand trends and optimizes processing schedules to reduce post-harvest losses and improve resource efficiency.	[88–90]

4.5. Supply Chain Disruption Forecasting and Early Warning Systems

Supply chain disruptions, such as delays in shipping and issues within cold chain logistics, pose significant risks to food quality and availability, particularly for perishable goods treated with advanced processing methods like PEF, ACP, or ozone treatments [93–97]. Forecasting models are crucial for identifying potential disruptions and providing early warnings, allowing stakeholders to take proactive measures to maintain product quality, reduce waste, and ensure continuity in food supply chains [98–102]. Table 6 provides a detailed summary of the applications of forecasting models in maintaining food processing efficiency, emphasizing their importance in predicting disruptions, optimizing cold chain logistics, and extending the shelf life of perishable products.

Table 6. Applications of forecasting models for food processing efficiency.

Area	Application	Description	References
PEF	Predicting Optimal Electric Field Processing Time	Forecasts the best timing for PEF based on food type, microbial load, and shelf-life requirements, extending product freshness.	[98,99]
Plasma and Ozone Treatment	Microbial Inactivation and Preservation	Predicts plasma and ozone treatment timings for microbial inactivation without altering food quality, improving shelf life.	[100,101]
Food Valorization	By-Product Optimization for High-Value Products	Forecasts the best uses for food by-products (e.g., skins, seeds) to convert waste into high-value products based on market demand.	[102]

AI and predictive models analyze real-time data on transportation, infrastructure, and environmental conditions to anticipate disruptions in food distribution. These models can identify bottlenecks, such as delays or infrastructure issues, and recommend adjustments to routes, storage conditions, or transportation methods to prevent spoilage and maintain food quality [103].

Cold chain logistics are particularly vital for transporting temperature-sensitive products, especially those processed with plasma, ozone, or electric field technologies. Predictive models monitor variables like temperature fluctuations, transportation durations, and environmental factors, ensuring that perishable items are preserved during transit. By optimizing cold chain logistics, these models help extend the shelf life of food products and maintain their safety throughout the distribution process [104,105].

Forecasting models serve as integral components of early warning systems, predicting potential food shortages by evaluating factors such as agricultural productivity, weather patterns, transportation disruptions, and geopolitical risks. These early warnings enable stakeholders to secure alternative suppliers, adjust inventory levels, and implement other preemptive strategies to mitigate the impact of shortages [106,107]. Table 7 summarizes the applications of forecasting models in detecting supply chain disruptions, optimizing cold chain logistics, and providing early warnings of food shortages, highlighting their importance in ensuring food quality and availability.

Table 7. Forecasting models for detecting supply chain disruption and early warning systems.

Area	Application	Description	References
Disruption Forecasting	Predicting Supply Chain Bottlenecks	AI models forecast potential disruptions in food distribution, enabling corrective actions to prevent spoilage.	[103]
Cold Chain Optimization	Monitoring and Timing for Perishable Goods	Predicts optimal transportation conditions to maintain food quality during transit, particularly for temperature-sensitive products.	[105]
Early Warning Systems	Food Shortage and Processing Chain Bottlenecks	Provides early warnings of potential food shortages and identifies bottlenecks in processing and distribution to optimize operations	[106,107]

4.6. Limitations of Forecasting Models

While forecasting models offer significant value in predicting agricultural outcomes and optimizing food security, each type of model has inherent limitations that impact its applicability. This section details these limitations to provide a more balanced perspective.

4.6.1. Limitations of ARIMA Models

- Sensitivity to Non-Stationary Data: ARIMA models require data to be stationary, meaning that statistical properties like mean and variance must remain constant over time. Agricultural data, such as climate patterns and yield estimates, are often non-stationary, making ARIMA less effective without substantial pre-processing [108–110].
- Limited Ability to Handle External Variables: ARIMA models struggle to incorporate external influencing factors, such as market shifts or unexpected climate events, that can significantly impact agricultural productivity. This limits their effectiveness in dynamic and complex agricultural environments [111,112].

4.6.2. Limitations of Random Forest Models

- Interpretability: RF models, while powerful for predicting yields and market dynamics, are inherently complex, making them difficult to interpret. This "black-box" nature is a drawback for agricultural stakeholders who need understandable insights to make informed decisions [113,114].
- Risk of Overfitting: RFs can overfit small datasets, capturing noise instead of meaningful trends. Given the limited availability of high-quality agricultural datasets in certain regions, this overfitting risk reduces the reliability of predictions for smallholder farms [115,116].
- Computational Requirements: The need for multiple decision trees makes RFs models computationally expensive, which can be a constraint for low-resource settings that lack access to high-performance computing infrastructure [117,118].

4.6.3. Limitations of Neural Networks

- High Computational Cost: Neural Networks, including LSTMs and CNNs, are computationally intensive and require significant hardware resources. The high cost of computation makes it challenging for smaller farms, particularly in developing regions, to adopt these models [119–121].
- Data Requirements: Neural Networks generally require large volumes of high-quality labeled data for effective training. In agriculture, especially in smallholder settings, the lack of comprehensive datasets is a major barrier [122,123].
- Difficulty in Understanding Outputs: The complex architecture of Neural Networks leads to difficulties in understanding how the model reaches a particular prediction. This lack of transparency reduces user trust and may limit the widespread adoption of these models in agriculture, particularly where farmers and stakeholders prefer interpretable models [124–126].

The limitations of different forecasting models used in agriculture are stated in Table 8.

Table 8. Summary of the limitations of the various forecasting models.

Model Type	Limitation	Description	References
ARIMA	Non-Stationarity and Sensitivity	Struggles with non-stationary data typical of climate and agricultural variables.	[108–110]
	External Variable Handling	Limited capacity to account for unexpected market or environmental changes.	[111,112]
Random Forest	Interpretability	Difficult for non-experts to understand the reasoning behind predictions.	[113,114]
	Overfitting	Risk of overfitting with small datasets.	[115,116]
	Computational Requirements	Requires considerable computing power for training and analysis	[117,118]
Neural Networks	High Computational Cost	Expensive to implement, particularly in resource-limited settings.	[119–121]
	Large Data Requirements	Requires a substantial amount of high-quality, labeled data for effective training.	[122,123]
	Output Interpretability	Complex model structure makes it difficult to explain how results are generated.	[124–126]

5. Case Studies

Forecasting models have demonstrated their ability to enhance agricultural productivity across various real-world settings. The following detailed case studies illustrate their applications:

5.1. Aquaponics Systems in the Netherlands

AI-based forecasting models are used to analyze real-time sensor data, such as water quality, nutrient concentration, temperature, and humidity. The models help optimize nutrient cycling and resource utilization, which in turn improves crop development and fish health. Aquaponics farms in the Netherlands utilize these models to predict growth rates, enabling proactive adjustments to maintain resource balance and minimize waste. By implementing these predictive approaches, farms have reported a consistent yield improvement of approximately 15–20% while also enhancing resource efficiency [127].

5.2. Hydroponics in Sweden

In Sweden, predictive models are used to manage water and nutrient usage more efficiently in hydroponic systems. These models collect dynamic data from sensors to adjust irrigation and nutrient dosing automatically, ensuring that plants receive optimal growth conditions at every stage. By doing so, Swedish hydroponic farms have achieved up to a 30% reduction in water and fertilizer use and a 25% increase in yield. The integration of forecasting models has also allowed for better energy optimization and contributed to Sweden's reputation as a leader in sustainable urban agriculture [128].

5.3. Aquaponics in Southeast Asia

In southeast Asia, aquaponic systems face challenges due to climate variability, which impacts the interaction between fish and plants. Here, climate prediction models are utilized to forecast fluctuations in environmental conditions such as temperature and rainfall. These models inform precise adjustments to feeding schedules, nutrient delivery, and environmental control measures to maintain equilibrium in nutrient cycling. Consequently, farms have reported improved system resilience, consistent fish and plant production despite extreme weather conditions, and reduced reliance on manual adjustments [129,130].

5.4. Vertical Farming in the US and Europe

Vertical farming in urban areas has adopted AI-based forecasting models to enhance resource management, production cycles, and market forecasting. These models are utilized to optimize energy-intensive activities, such as LED lighting schedules and temperature control, ensuring that crops receive precisely what they need for growth without excess energy consumption. This has led to a 20% reduction in energy expenses alongside a 15% boost in productivity. Furthermore, models used for market demand prediction ensure that vertical farms produce the right crops at the right time, reducing waste and ensuring financial sustainability [131,132].

5.5. Food Processing in North America

In North America, AI-based forecasting models are extensively used to predict the optimal processing times for perishable food items, such as vegetables and dairy products. These models analyze product attributes, storage conditions, and processing requirements to determine the best processing schedules. This has led to significant improvements in reducing food spoilage with up to 30% reductions reported in food waste. The models are also integrated into the supply chain management process to predict disruptions (e.g., transportation delays, labor shortages), allowing processors to adjust schedules proactively and maintain supply chain continuity [133].

6. Challenges and Limitations of Forecasting Models

While forecasting models hold great promise for improving agricultural productivity, optimizing food processing, and enhancing supply chain efficiency, they face significant challenges and limitations. This section discusses these issues, including insights derived from real-world case studies, and suggests opportunities for future improvements as depicted in Figure 3.

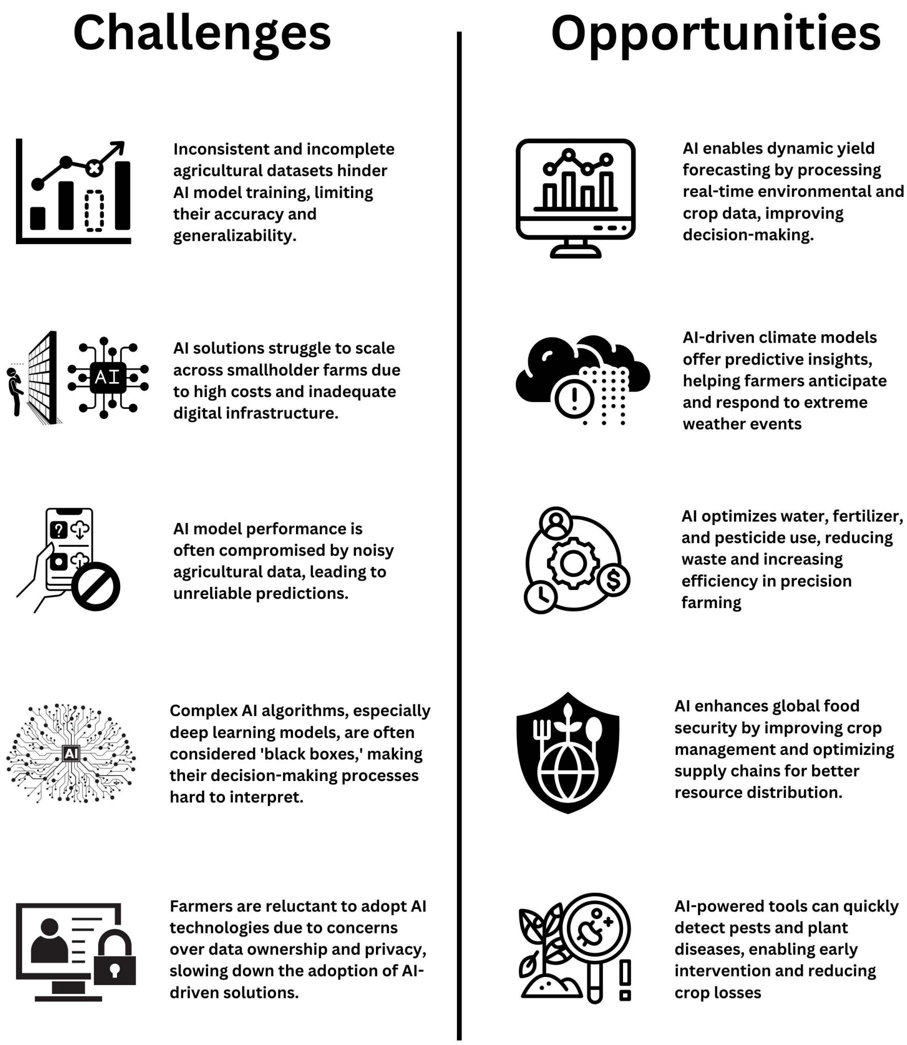

Figure 3. Challenges and opportunities for AI forecasting technologies in agriculture.

6.1. Data Availability and Quality

The availability and quality of data are crucial to developing effective forecasting models. Unfortunately, these aspects often present significant challenges—especially for smallholder farms and emerging agricultural systems such as hydroponics and aquaponics [134].

6.1.1. Inconsistent and Incomplete Data

The efficacy of forecasting models largely depends on the availability of high-quality, consistent data. In many smallholder farms, particularly those in developing regions, this kind of data infrastructure is often lacking [135–139]. For instance, southeast Asian aquaponics systems highlighted in the case studies underscored the importance of real-time sensor data for effective nutrient management [140]. However, limited access to sensors and technology has resulted in inconsistent data collection, reducing the reliability of these forecasting models. Without accurate and comprehensive data, models struggle to generate precise and actionable forecasts.

To address the challenges of inconsistent and incomplete data, several techniques have been developed:

- Data Imputation: Data imputation techniques can be used to fill in missing values in agricultural datasets. Methods such as K-Nearest Neighbors (KNN), mean/mode substitution, and more advanced probabilistic models can help ensure that models do not suffer from incomplete data. These approaches are particularly useful in smallholder farms where data gaps are frequent. For example, imputation has been used in various crop yield prediction models to estimate missing weather data points, improving model performance and reliability [141].
- Ensemble Methods: Ensemble approaches, such as bagging and boosting, are effective in mitigating the impact of noisy or incomplete data by combining predictions from multiple models [142]. By training multiple models on different subsets of the data and averaging their predictions, ensemble methods can reduce the effect of outliers and missing values, enhancing robustness. This has been successfully applied in market yield predictions where inconsistent datasets from different farms are common.
- Transfer Learning: Transfer learning is an emerging approach in agricultural forecasting, particularly useful in data-scarce environments. By using pre-trained models developed with data-rich environments and fine-tuning them for application in data-scarce agricultural contexts, transfer learning can significantly improve the accuracy of forecasts. This is particularly advantageous in developing regions where the collection of extensive training data is infeasible. Studies have shown that transfer learning models trained with data from advanced farming systems can be adapted for smaller farms with much fewer data points, reducing the training burden while retaining model accuracy [143].

6.1.2. Data Gaps in Emerging Systems

Emerging systems like hydroponics and aquaponics often face additional challenges concerning data collection. The case study of hydroponic systems in Sweden showed a lack of standardized frameworks for data collection, which hindered the consistent application of predictive models [144]. In aquaponics, nutrient cycling dynamics are unique and complex compared to conventional farming, which further complicates data collection and limits the successful implementation of forecasting algorithms [145].

To mitigate these data gaps, data augmentation techniques can be employed. These methods involve generating synthetic data points by using existing data in creative ways, such as applying small transformations to generate new examples or using generative models like GANs (Generative Adversarial Networks). Data augmentation is particularly useful in environments where data collection is inconsistent or expensive [146].

6.1.3. Data Utilization

Integrating multiple data sources—such as sensor readings, historical yields, and climate forecasts—presents further challenges. In the Swedish hydroponic system, the effective integration of these data sources resulted in optimized irrigation and nutrient schedules [147]. However, the computational capabilities required for such integration are significant, and inconsistent data formats complicate efforts to create accurate, cohesive models.

To better integrate data from diverse sources, data normalization and standardization techniques are often required to bring different datasets into a consistent format, which can then be used by ML and DL models. Furthermore, data fusion techniques are being explored to combine data from disparate sources (e.g., satellite imagery, IoT sensors, and climate databases) into unified datasets, enabling the development of more comprehensive and cohesive forecasting models [148,149].

6.2. Scalability

Scaling forecasting models across various agricultural systems and geographic regions remains a formidable challenge. Extending these models to different contexts requires considerable flexibility and adjustment.

6.2.1. Geographic and Economic Constraints

Forecasting models are often region-specific, meaning that a model trained in one geographic location may not be applicable in another due to diverse environmental and socio-economic factors [150,151]. For example, the case study on vertical farms in the US showed distinct differences compared to similar systems in Europe, particularly regarding energy infrastructure and climate [152]. Additionally, small-scale farmers in developing regions face barriers related to access to technology and reliable data collection systems, which hampers their ability to leverage forecasting models effectively.

6.2.2. Technological Limitations

Many farms, especially those with limited resources, do not have access to advanced computational infrastructure, such as cloud services and real-time data collection tools, which are often required for sophisticated forecasting models [151]. The aquaponics systems in southeast Asia faced challenges in accessing the technological infrastructure needed to scale these models effectively. High-performance computing and skilled personnel are often limited in these areas, creating an additional barrier to the broad adoption of forecasting models.

6.2.3. Diverse Agricultural Systems

Agricultural systems vary widely, ranging from traditional soil-based farms to high-tech vertical farms, organic systems, and aquaponics. The case studies highlighted how models developed for one system, such as conventional farming, may not adapt easily to hydroponics or aquaponics, which have different data requirements—particularly around water quality and nutrient management. Developing universally applicable forecasting models requires considerable adjustments, making scalability a significant challenge.

6.3. Accuracy and Adaptability of Models

The intricate nature of forecasting models frequently results in compromises between precision and comprehensibility. These models must possess adaptability to various geographies and systems while still maintaining the ability to generate precise forecasts that are readily understandable and actionable.

6.3.1. Balancing Complexity and Interpretability

Advanced ML and DL models, such as Long Short-Term Memory (LSTM) and CNNs, often provide high accuracy—sometimes exceeding 90%. However, these complex models are typically difficult to interpret especially for smallholder farmers and agricultural stakeholders without technical expertise [153]. In the case of vertical farms in the US, even though forecasting models provided highly accurate predictions, farmers required simplified outputs to take meaningful action.

6.3.2. Accuracy Metrics for Forecasting Models

Assessing forecasting models requires more than simply considering accuracy percentages. Metrics like precision, recall, and F1 scores provide a more nuanced view of a model's performance, particularly in agricultural applications involving rare events, such as pest infestations or extreme weather conditions. For instance, models such as RFs and LSTMs have demonstrated precision and recall scores exceeding 90% in certain contexts, indicating strong reliability, but these metrics must be balanced to ensure effective outcomes in the broader agricultural environment [127].

6.3.3. Adaptability Across Regions

The adaptability of forecasting models is another key challenge. Models trained on datasets for specific crops or environments may struggle to adapt effectively to different contexts. The aquaponics case study in southeast Asia demonstrated that models need to accommodate diverse conditions, such as various crop types, climates, and integrated fish–plant systems. A forecasting model suitable for corn production in North America may not work effectively in a small-scale rice field in southeast Asia. To enhance adaptability, models need to be trained on more diverse datasets that account for these differences.

6.3.4. Real-Time Adaptation

Real-time data collection, crucial for dynamic adaptation of forecasting models, is often impractical in smallholder settings. For instance, the case study involving North American food processing facilities demonstrated that real-time adaptation ensured accuracy and relevance, but the continuous data input required is often beyond the reach of smaller farms. Model drift, wherein a model's accuracy degrades over time due to environmental or operational changes, also presents a major hurdle for long-term forecasting model deployment.

6.4. Explainability in AI Models

Another significant challenge is the lack of explainability in AI models. Advanced forecasting models, such as CNNs and LSTMs, often operate as "black boxes," making it difficult for farmers and stakeholders to understand how predictions are derived. This lack of transparency affects trust and may deter farmers from adopting these technologies. Recent advancements in Explainable AI (XAI)—using tools like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations)—offer potential solutions to make these models more accessible and transparent [154]. Including XAI techniques in agricultural forecasting models can help bridge the gap between model complexity and practical usability, ensuring that stakeholders can understand and trust the predictions generated [155].

6.5. Key Challenges and Insights from Case Studies

The case studies presented highlight the immense potential of forecasting models to improve resource management, boost yields, and enhance food processing efficiency. Examples like aquaponics in southeast Asia, vertical farming in urban US, and hydroponics in Sweden demonstrate how AI-driven predictions can revolutionize agricultural systems. However, these examples also bring to light key challenges that must be addressed.

6.5.1. Data Quality

The inconsistent and incomplete data collection seen in aquaponics systems affects model reliability. Improving data quality is essential for effective model predictions.

6.5.2. Enhancing Model Adaptability

Forecasting models have shown potential in specific environments, but scaling them across diverse agricultural systems and geographies remains a critical challenge. Efforts must be made to develop more adaptive and flexible models that can be effectively used across multiple agricultural settings.

6.5.3. Accuracy and Interpretability

High accuracy is valuable only if the predictions can be interpreted and used effectively by stakeholders. Balancing the sophistication of models with ease of use is crucial, particularly in contexts where users have limited technical proficiency.

6.5.4. Explainability

Incorporating XAI techniques into forecasting models can address the "black box" problem, allowing stakeholders to understand the rationale behind model predictions. This will enhance adoption and ensure that models can be used to their full potential [156].

6.5.5. Overcoming Barriers to Real-Time Data Integration

Continuous, real-time data are essential for maintaining model accuracy, but the infrastructure and costs associated with real-time adaptation present significant barriers.

To fully harness the potential of forecasting models, it is necessary to address these challenges through technological innovation, better infrastructure, and effective public-private partnerships. Only by doing so can we ensure that forecasting models contribute meaningfully to global food security, making agriculture more resilient, sustainable, and productive.

6.5.6. Environmental Impacts of Plasma and Ozone Treatments

Plasma and ozone treatments are increasingly employed in food processing to extend shelf life, reduce spoilage, and ensure food safety. While these technologies offer promising benefits in minimizing food waste and improving food quality, it is essential to consider their potential long-term environmental impacts.

- Ozone Treatment: Ozone is a powerful oxidizing agent used for disinfection and extending the shelf life of perishable foods [157]. However, the use of ozone comes with concerns regarding air quality and safety. When released into the atmosphere, ozone contributes to air pollution and can have harmful effects on respiratory health. Managing ozone emissions is thus critical to prevent unintended environmental and health consequences. Moreover, while ozone is effective in microbial inactivation, improper handling can lead to occupational safety risks for workers involved in food processing [158].
- Plasma Treatment: Plasma treatment, particularly high-voltage atmospheric cold plasma, is used for decontaminating food surfaces and extending shelf life [159]. Although it is effective at microbial inactivation without using chemicals, plasma treatments require significant energy consumption, which raises concerns about their carbon footprint. The production of plasma typically involves high voltage electricity, and unless renewable energy sources are used, this can result in high greenhouse gas emissions. Additionally, the equipment and infrastructure required for plasma treatment are costly and energy-intensive, potentially limiting their sustainability and scalability, particularly in resource-constrained environments.

As an alternative to plasma and ozone treatments, nanotechnology in food processing [160] offers innovative solutions with potentially lower environmental impact. For instance, nanomaterials used in active food packaging can enhance barrier properties against moisture, gases, and microbes, effectively reducing spoilage without the need for energy-intensive processes. Nanomaterials, such as metal-based nanoparticles, are also being explored for their antimicrobial properties, potentially reducing reliance on ozone and plasma treatments. By incorporating nanotechnology into food preservation systems, the industry can address both sustainability and food safety concerns while minimizing energy consumption and harmful emissions.Thus, it is essential to weigh the environmental impacts of plasma and ozone treatments against emerging alternatives like nanotechnology. Future research should focus on improving the efficiency of these technologies and developing sustainable guidelines for their use in food processing. By adopting holistic approaches, plasma, ozone, and nanotechnology can collectively contribute to environmentally friendly food processing systems that support both food security and environmental conservation.

6.6. Global Data Limitations

A major limitation in evaluating the potential of AI and forecasting models for food security lies in the availability of consistent, high-quality data on a global scale. Current research and existing datasets primarily focus on regional or localized agricultural practices, which are often driven by specific climate, market, or resource conditions [144]. This lack of globally integrated data restricts the training and deployment of AI models capable of effectively addressing food security challenges at an international level. As such, while significant progress has been made in regional implementations, more efforts are needed to integrate diverse regional datasets into a cohesive framework that can support AI-driven forecasting models on a global level.

6.7. Adaptability to Small-Scale and Low Infrastructure Settings

Forecasting models, while highly effective in controlled or high-tech environments, face challenges when adapted to small-scale or resource-limited agricultural settings. Smallholder farmers often lack the infrastructure required to collect and utilize the high-quality data needed by advanced forecasting models.

- Technological Barriers: Advanced forecasting models generally require cloud computing, consistent data collection, and sensor-based monitoring. However, many small-scale farmers do not have access to such infrastructure, limiting their ability to adopt these models effectively.
- Offline Data Collection: To address these limitations, models must be adapted for offline data collection, utilizing simpler technologies that do not require a constant internet connection. By enabling local storage and subsequent data analysis, farmers can make practical use of AI-based forecasting.
- Simplified Models: Instead of complex DL models like LSTMs, simpler models such as linear regression or decision trees could be utilized. These models can still provide valuable insights without demanding intensive computational resources.
- Leveraging Local Knowledge: A key aspect of adapting models to smallholder farms is incorporating local expertise into predictive models. Farmers' traditional knowledge about their crops and environment can be used to supplement data gaps, enhancing model relevance and accuracy.

7. Conclusions

This review highlights the transformative potential of forecasting models in addressing the challenges of global food security. The utilization of advanced technologies—such as artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), and big data analytics—enables these models to significantly improve agricultural productivity, food processing efficiency, and supply chain stability. Diverse case studies from the Netherlands, Sweden, southeast Asia, North America, and other regions demonstrate the practical applications of these models across both conventional and alternative agricultural systems, including aquaponics, hydroponics, and vertical farming. The literature reviewed in this paper shows that forecasting models can optimize resource management, improve yields, mitigate the adverse effects of climate change, and enhance market stability. By leveraging real-time data and predictive analytics, these models allow for informed decision making that boosts productivity while minimizing food wastage. For instance, in aquaponics and hydroponics systems, predictive models help manage nutrient cycles and environmental parameters to maximize efficiency and yield, while in vertical farming, forecasting models optimize energy consumption and harvest schedules. In food processing, AI-based models have been shown to extend shelf life, reduce spoilage, and enhance the overall supply chain efficiency.

Main Contributions: This review underscores the following key contributions of forecasting models:

- Agricultural Production: Forecasting models have demonstrated their ability to significantly improve crop yield predictions by analyzing historical data and real-time inputs. These applications have led to enhanced resource management and productivity gains, as evidenced by systems in Sweden and southeast Asia.
- Supply Chain and Food Processing: Models applied in food processing and distribution have improved efficiency, particularly for perishable products. The successful adoption of these models in North American food processing illustrates their potential to minimize waste and optimize logistics.

- Alternative Agriculture: In hydroponics and aquaponics systems, forecasting models have played a vital role in resource optimization, achieving significant reductions in water and fertilizer use while increasing yields.

Limitations: Despite the demonstrated potential, several limitations persist:

- Data Availability and Quality: High-quality, consistent data are a prerequisite for effective forecasting, yet they are often lacking, particularly in smallholder farms and emerging systems like hydroponics and aquaponics. Inconsistent data undermine model accuracy and limit the scalability of these tools across diverse agricultural practices.
- Scalability and Flexibility: The scalability of these models is restricted by their region-specific design, which limits their performance when applied to different geographic areas, climates, or agricultural systems. Case studies showed that forecasting models used effectively in urban vertical farms in the US required significant adjustments when used in other regions due to differences in energy infrastructure and market conditions.
- Explainability and Interpretability: Advanced forecasting models, especially those using DL algorithms like CNNs and LSTMs, often operate as "black boxes." The lack of transparency hinders trust and broad adoption among farmers and agricultural stakeholders. Recent efforts in Explainable AI (XAI) offer promising solutions, but these approaches need further integration and adaptation for agricultural applications.
- Real-Time Adaptation: Real-time forecasting demands continuous data collection, which may be impractical for many small-scale farms due to resource limitations. Additionally, model drift—where accuracy deteriorates due to changing environmental conditions—poses challenges for long-term model application.

Future Directions: Moving forward, several strategies are recommended to enhance the impact of forecasting models:

- Technological Innovation: Continued advancements in AI, ML, and DL are crucial to improving the precision and versatility of forecasting models. Enhanced models—such as Deep Neural Networks that better account for temporal and spatial data—could lead to more reliable predictions across varied agricultural contexts.
- Public–Private Partnerships: Collaboration between governments, academic institutions, and the private sector is essential to accelerate the development and deployment of forecasting technologies. Public investments in digital agriculture infrastructure could provide smallholder farmers with access to sophisticated predictive tools, while private enterprises can drive technological innovation and scalability.
- Explainable AI: Future research should focus on making AI models more transparent and understandable for non-expert stakeholders. Integrating XAI techniques such as SHAP and LIME will not only improve trust but also foster the broader adoption of forecasting tools.
- Accuracy Metrics and Model Evaluation: Employing advanced evaluation metrics, such as F1 scores, precision, and recall, would provide a clearer picture of model performance, particularly when dealing with rare events like pest outbreaks or extreme weather. These metrics could be instrumental in ensuring that models are not only accurate but also actionable in real-world scenarios.

In conclusion, forecasting models hold the potential to play an instrumental role in addressing global food security challenges by enhancing productivity, optimizing resource use, and reducing losses across the food supply chain. However, addressing the current challenges—particularly those related to data quality, model scalability, interpretability, and the infrastructure required for real-time forecasting—is crucial for realizing their full potential. By investing in technological innovation, fostering collaborations, and developing accessible, explainable tools, forecasting models can emerge as a vital component in building a sustainable, resilient, and productive global food system.

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