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Production and Global Apple Market Dynamics of U.S. Apples: Analysis and Forecasting with a Quadratic Trend Model

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ABSTRACT

Apple (*Malus domestica*) is one of the most economically significant horticultural crops in the United States, playing a pivotal role in both national agricultural production and international trade. However, few studies have been conducted to examine U.S. apple production and trade trends together with future production forecasting using recent data. This study addresses this research gap by analyzing U.S. apple production, exports, and imports from 1990 to 2024 and projecting production for 2025–2030. Annual secondary data were downloaded from FAOSTAT, the World Bank World Integrated Trade Solution (WITS), and the United States Department of Agriculture (USDA). Linear, quadratic, and exponential deterministic trend models were estimated by using ordinary least squares regression, with the exponential model fitted after log transformation. Model performance was evaluated through in-sample validation by using Mean Absolute Error (MAE), Mean Squared Deviation (MSD), and Mean Absolute Percentage Error (MAPE), and the model with the least forecasting errors was selected for forecasting. The results show that U.S. apple production remained comparatively stable between 1990 and 2024, fluctuating between around 4.0 and 5.5 million tonnes annually, whereas global production increased from 40.9 million tonnes to 97.9 million tonnes, which is largely driven by rapid production growth in China. Among the models assessed, the quadratic trend model achieved the highest forecasting accuracy (MAPE = 6.26%), indicating that U.S. apple production shows a nonlinear trend over time. The model forecasts production to increase gradually from approximately 5.08 million tonnes in 2025 to 5.43 million tonnes in 2030, although widening confidence intervals indicate Increasing forecast uncertainty over the forecast period. The originality of this study lies in providing an updated analysis of U.S. apple production and trade trends from 1990 to 2024 and applying the best deterministic trend model to forecast future production. The findings provide updated empirical evidence to support efficient resource allocation, production planning, market competitiveness, and evidence-based agricultural and trade policy under increasing economic, market, and climatic uncertainty.

INTRODUCTION

Apples (Malus domestica) are known for their high nutritional value, providing dietary fiber and bioactive compounds associated with positive health (Boyer & Liu, 2004). Apples are rich in fiber, antioxidants, and other bioactive compounds that improve human health. Regular consumption has been associated with a lower risk of chronic diseases such as heart disease, asthma, cancer, and diabetes (Hyson, 2011). Apple consumption may also support digestion, weight balance, brain function, and respiratory and metabolic functions (Hyson, 2011). According to Kantor and Blazejczyk (2023), apples were the leading fruit in total per person availability in the United States, followed by oranges, bananas, grapes, strawberries, pineapple, and watermelon.

Dolan (2009) states that in the U.S. throughout Apple cultivation rose with European settlement through the introduction of improved varieties and advances in orchard management. Over time, technological improvements in orchard systems, storage, and distribution have further improved efficiency and productivity of the U.S. apple industry (Zhang *et al.,* 2017). The US apple production is concentrated in major growing regions, particularly the Pacific Northwest and the Northeast, with Washington State as the dominant producer (64% of total production in 2023) due to its suitable arid climate, large mountain-fed irrigation systems, and pioneering advances in controlled-atmosphere storage and international marketing (Schotzko & Granatstein, 2004; USDA Economic Research Service, 2023). The United States remains a leading contributor to North American apple production, constituting approximately 90% of the region's output, with an estimated production of 4.9 million metric tonnes in the 2024/25 marketing year (Wikifarmer, 2024). The United States consistently holds second position in apple production in the world after China (FAO, 2026) and is 4th fourth-largest apple exporter after China, the European Union, and Italy, with

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fresh apple exports valued at approximately $931 million in 2023. US exports are primarily directed to Canada and Mexico, its leading destinations (TrendEconomy, 2023; OEC, 2023).

Although the US apple has a significant international share and Face Increasing domestic demand, annual production is almost stagnant, fluctuating between approximately 4.0 and 5.5 million tonnes per year from 1990 to 2024 (FAO, 2026). However, global apple production more than doubled over the study period, rising from 40.9 million tonnes in 1990 to 97.9 million tonnes in 2024 (FAO, 2026). Growth was overwhelmingly concentrated in China, whose production surged from 4.3 million tonnes in 1990 to over 51.3 million tonnes in 2024 (FAO, 2026). Furthermore, increasing climate-related risks in major production regions and tightening farm labor markets, which raise production costs and constrain harvesting capacity, further increase the challenges facing the US apple industry, contributing to variability in apple production trade patterns over time (Washington State University, 2025; USDA ERS, 2023). These challenges in the US apple industry highlight the need for continuous adaptation by producers and policymakers in response to climate-induced risks (Ariadi, 2022). Consequently, understanding long-term trends in apple production and trade is increasingly important for planning, investment, and policy development amid climate variability and market uncertainty. Furthermore, production forecasting supports improved decision-making by informing expectations about future supply and market conditions. Time-series and statistical methods are widely used to project production and trade patterns from historical data, enabling stakeholders to anticipate changes in supply and markets (Box *et al.,* 2015; Hyndman & Athanasopoulos, 2021).

Although numerous studies have used statistical and time-series models to forecast production for various crops, limited attention has been given to long-term forecasting of U.S. apple production using recent FAOSTAT datasets. Existing studies generally focus on US apple production or yield trends, regional production systems, but the use of advanced forecasting techniques to project future production is limited. Moreover, many earlier studies about the trend of US apple depend on older datasets and therefore do not capture the recent structural changes associated with recent technological advancements, labour shortages, climate-related production risks, and evolving global trade conditions. Consequently, there remains a requirement for an updated study that combines long-term production and trade analysis with a forecast with transparent forecasting methods to support agricultural planning and policy development in the U.S. apple sector. To address these research gaps, this study studies U.S. apple production, export, and import trends by using annual data from 1990 to 2024 obtained from FAOSTAT, the World Bank World Integrated Trade Solution (WITS), and the United States Department of Agriculture (USDA). This study compares linear, quadratic, and exponential deterministic trend models to identify the most appropriate for medium-term US apple production forecasting for the period 2025–2030. By integrating long-term production trends, international trade dynamics, and comparative evaluation of forecasting models using the most recent US apple production data available through 2024, this study extends the existing agricultural forecasting literature and provides updated empirical evidence for better production planning, understanding market competitiveness, and formulating trade policy. The findings are expected to help producers, exporters, policymakers, and other stakeholders in anticipating future production trends, efficient resource utilization, optimizing production and marketing strategies, enhancing market competitiveness, and formulating evidence-based trade policies under increasing economic, climatic, and market uncertainty.

The objective of this study

1. To analyse the US and global apple production, yield, and import-export dynamics
2. To develop and evaluate linear, quadratic, and exponential trend models to forecast US apple production for 2025-2030
3. To evaluate the usefulness of these forecasts for production, efficient market management, and trade policy formation

LITERATURE REVIEW

The U.S. apple industry has increasingly adopted technological and agronomic innovations to remain competitive under increasing environmental and market pressures, which enhance productivity and efficiency. These include precision irrigation, high-density planting systems, advanced orchard mechanization, and integrated nutrient and pest management strategies, all of which have helped to improve yields and labour efficiency across production areas (Robinson, 2007). Controlled atmosphere (CA) storage and related postharvest technologies have been shown to reduce post-harvest loss and improve apple quality by maintaining firmness, extending storage life, reducing physiological disorders, and enabling a more stable year-round supply in the U.S. apple industry (Cabote *et al.,* 2026).

Although there have been advances in apple production in the past few decades, risks to the U.S. throughout apple industry is also increasing due to climate-related risks from climate disruption, labour shortages, rising production costs, water scarcity, price pressure, and global competition. Apple production is highly influenced by climatic conditions and broader environmental changes as apple trees require adequate winter between 800 and 1,200 hours below 7°C-for dormancy release, bud break, and fruit set. Insufficient chilling can delay flowering and reduce fruit set, leading to lower yields (Pickson *et al.,* 2026; Petri & Leite, 2004). Furthermore, extreme weather events such as summer droughts, spring frosts, and heat stress lead to production losses and annual yield variability

(Vogel *et al.,* 2019; Taschetta-Millane, 2026). Marklein *et al.* (2020) show that increasing temperatures due to climate change will decrease chilling accumulation requirement in production regions, shift suitable producing areas toward higher latitudes and elevations. Moreover, climate change increases the frequency of damaging weather events, potentially disrupting long-term production patterns.

Market conditions also play a significant role in shaping production decisions, together with climatic influences. Demand for organic fruit has increased due to rising consumer preference for healthier and more sustainably produced foods, influencing production practices (Peng, 2019). Raising global competition, especially from China, together with trade policy uncertainty and exchange-rate fluctuations, has also intensified pressure in international apple markets, increasing challenges for US apple exporters working in globally competitive trade scenarios (GuruFocus, 2024; Taschetta-Millane, 2026). Understanding past trends will help us understand the Current situation of the US apple production, import, and export situation, and production forecasting will support future production decisions, policy formulation, and marketing decisions for efficient production. Accordingly, deterministic time-series trend models were employed in this study to forecast future production until 2030.

Modelling Agriculture Production Trend

To identify historical patterns and calculate future production levels, agricultural production forecasting frequently relies on deterministic time-series trend models (Kurumatani, 2020). Linear, quadratic, and exponential trend models represent different growth changes: linear models assume that change occurs at a constant rate over time, quadratic models account for upward and downward curvature in trends, and exponential models reflect proportional growth over time (Hyndman & Athanasopoulos, 2021; Box *et al.,* 2015). Because of their simplicity, computational efficiency, and easy interpretability, these approaches are widely used in agricultural economics. For example, maize production in Pakistan was analyzed by Tahir and Habib (2013), potato production and trade in the United States were examined by Ojha *et al.* (2025), and wheat production in Bangladesh was studied by Karim *et al.* (2010), and plantation crop production in Indonesia was analyzed by Nurfadila *et al.* (2022) using time-series trend models.

Despite the extensive use of time-series and trend-based models in agricultural forecasting, limited focus has been given to integrating production trends with international trade dynamics in the context of developed agricultural economies such as the United States. Furthermore, previous studies about the US apple rely on short-term forecasting horizons or older datasets, which may not properly capture recent structural variation in production systems, technological advancement, climate variability, and global market shifts. In addition, many studies focus on basic forecasting with annual crops without evaluating their performance in the context of long-term perennial crops such as apples, where production cycles and climatic sensitivity differ from annual crops. These research gaps highlight the requirement for a comprehensive and updated study that combines production and trade of the U.S. apple industry. In response to these gaps, this study focuses on long-term U.S. apple production and trade trends and applies deterministic trend models for production forecasting and their implications for decision-making.

MATERIALS AND METHODS

Data Sources and Study Period

This study uses secondary annual time-series data from 1990 to 2024 on U.S. apple production, yield, cultivated area, prices, and trade (exports and imports), along with selected global comparisons. Data were obtained from FAOSTAT, the United States Department of Agriculture National Agricultural Statistics Service (USDA NASS), the World Bank World Integrated Trade Solution (WITS), and other sources that provide standardized and internationally comparable agricultural statistics. The study period captures long-term dynamics in production, productivity, area cultivation, and trade within the U.S. apple industry. All data were downloaded in .xlsx format, arranged chronologically, and checked for basic consistency, with analysis and visualization done using Microsoft Excel and RStudio to ensure reproducibility and consistency of results.

The selected data provides no need a long-term time series that enables the analysis of structural changes in U.S. apple trade and production over time. The study design is intended to understand both long-term past trends, which are essential for evaluating deterministic trend models' behaviour, and medium-term forecasting.

Descriptive and Graphical Analysis

To summarize historical production patterns of apples in the US over the study period, descriptive statistical analysis was conducted. To examine fluctuations and long-term trends in U.S. apple production, US export trends, global production patterns, US cultivation area, US apple price movements, and yield changes from 1990 to 2024, time-series line graphs were generated in Microsoft Excel. In addition, to visualize the top apple-producing countries and the major apple-producing states in the United States, bar graphs were created. These graphical analyses helped identify relative production performance across countries and regions, as well as historical growth patterns. These visualizations also support the understanding of long-term structural dynamics in production, trade, and pricing patterns, which are essential for agricultural planning and policy analysis.

Trend Model Specification

Three deterministic trend models were estimated: linear, quadratic, and exponential, to forecast U.S. apple production. These models are commonly used in agricultural forecasting and represent different patterns of growth (Hyndman and Athanasopoulos, 2021). Production data for the period 1990–2024 were used, with time (t = 1, 2, …, 35) serving as the independent variable. The linear and quadratic models were estimated using ordinary least squares (OLS) regression, while the exponential model was estimated by applying OLS regression to the natural logarithm of production. The three functional forms no need:

Linear trend model:

$Y_t = a + bt$ (1)

Quadratic trend model:

$Y_t = a + bt + ct^2$ (2)

Exponential growth model:

$Y_t = ae\hat{}(bt)$ (3)

Where,

Y_t is U.S. apple production in year t;

t= Time trend variable, representing the observation period and indicating the direction and magnitude of change over time

a,b,c = Model parameters estimated from the data

a is the intercept parameter, which represents the estimated production level at the starting point of the trend; b is the linear trend coefficient representing the average annual change in production; and c is the quadratic coefficient that represents acceleration or deceleration in the production trend over time. The parameters a, b, and c were calculated from the historical production data.

This modelling approach is widely used in agricultural forecasting literature and offers a clear and interpretable framework for analyzing long-term US apple production trends and projecting production for the mid-term with the best-fit model.

Model Evaluation Metrics

Model performance was assessed by using in-sample forecasting, where fitted values from each model were compared with actual production data over the full study period (1990–2024). All models were assessed by using the same period of data to ensure comparability of forecasting accuracy. Three accuracy measures were used: Mean Absolute Error (MAE), Mean Squared Deviation (MSD), and Mean Absolute Percentage Error (MAPE) to evaluate and compare the forecasting performance of the models. These measures are widely used in time-series forecasting studies to assess forecast accuracy and model performance as they calculate the magnitude of the differences between observed and forecasted values (Astatkie, 2006). Each metric captures different aspects of prediction error, so the use of multiple evaluation metrics ensures a robust analysis of forecasting performance.

Mean Absolute Error (MAE)

Mean Absolute Error (MAE) estimates the average magnitude of errors between observed and predicted values without considering their signs. It is expressed in the same units as the original data and estimated as the mean of the absolute differences between actual and predicted values, making it easy to interpret. Smaller MAE values indicate more accurate predictions and better model performance (Willmott & Matsuura, 2005).

$MAE = (1/n)\ \Sigma|Actual_i - Forecast_i|$, (4)

Where:

MAE = Mean Absolute Error

n = Total number of years

Actuali = Actual value for the ith year

Forecasti = Forecasted value for the ith year

i = Observation index

|Actuali − Forecasti| = Absolute error for the ith observation

Mean Squared Deviation (MSD)

Mean Squared Deviation (MSD) estimates the average squared difference between observed and predicted values. Larger errors receive greater weight than smaller ones because the errors are squared before averaging, making MSD very sensitive to large deviations between observed and predicted values. Lower MSD values indicate closeness between observed and predicted values and, therefore, better model performance (Kobayashi & Salam, 2000).

$MSD = (1/n)\ \Sigma(Actuali - Forecasti)^2$,

Where:

MSD = Mean Squared Deviation

n = Total number of years

Actuali = Actual value for the ith year

Forecasti = Forecasted value for the ith year

i = year index

$(Actuali - Forecasti)^2$ = Squared error for the ith year

Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) expresses forecast errors as percentages of the observed values, making it helpful for comparing forecasting performance of different datasets and of different scales. It is widely used because of its interpretation in percentage terms and is calculated as the average of the absolute percentage differences between observed and predicted values. Like other metrics, lower MAPE values indicate higher forecasting accuracy and vice versa (Myttenaere *et al.,* 2016). Although MAPE is commonly used for interpretability in percentage terms, it may be sensitive to very small actual values; however, this limitation is not severe in this study, as production values remain relatively stable throughout the analysis period.

$MAPE = (100/n)\ \Sigma\ |(Actual_i - Forecast_i) / Actual_i|$

Where:

MAPE = Mean Absolute Percentage Error

n = Total number of years

Actuali = Actual value for the ith year

$Forecast_i$ = Forecasted value for the ith year

i = year index

$(|(Actual_i - Forecast_i) / Actual_i|$ = Absolute percentage error for the ith year

The model resulting in the lowest MAE, MSD, and MAPE values was selected as the optimal model for forecasting U.S. apple production.

RESULTS AND DISCUSSION

Global and U.S. Apple Production Trends (1990–2024)

Global annual apple production surged after 2010 due to expanding cultivation, improved management practices, and rising global demand, and more than doubled over the study period, rising from 40.9 million tonnes in 1990 to 97.9 million tonnes in 2024 (Agirbov *et al.,* 2024). This growth was highly concentrated in China, whose production surged from 4.3 million tonnes in 1990 to over 51.3 million tonnes in 2024, making it by far the dominant global producer holding more than half of the world's output share by the end of the period.

On the other hand, U.S. apple production shows a broadly stable trajectory, fluctuating between approximately 4.0 and 5.5 million tonnes throughout the study period without a clear long-term trend. These fluctuations in the US annual apple production reflect the influence of climatic variability including spring frost, winter chilling, and summer heat stress as well as periodic shifts in orchard renewal cycles, market conditions (Pickson *et al.,* 2026). The United States share of world production has declined substantially as Chinas output has grown, but it has maintained its position as the second-largest apple producer globally. This divergence indicates a structural shift in global apple production toward high-efficiency production systems in emerging economies, particularly China, while the United States appears to be operating in a mature production system, as indicated by production and productivity stabilization rather than expansion. This pattern aligns with literature indicating that developed agricultural economies tend to experience yield optimization rather than large-scale output expansion (Mabrouk *et al.,* 2026).

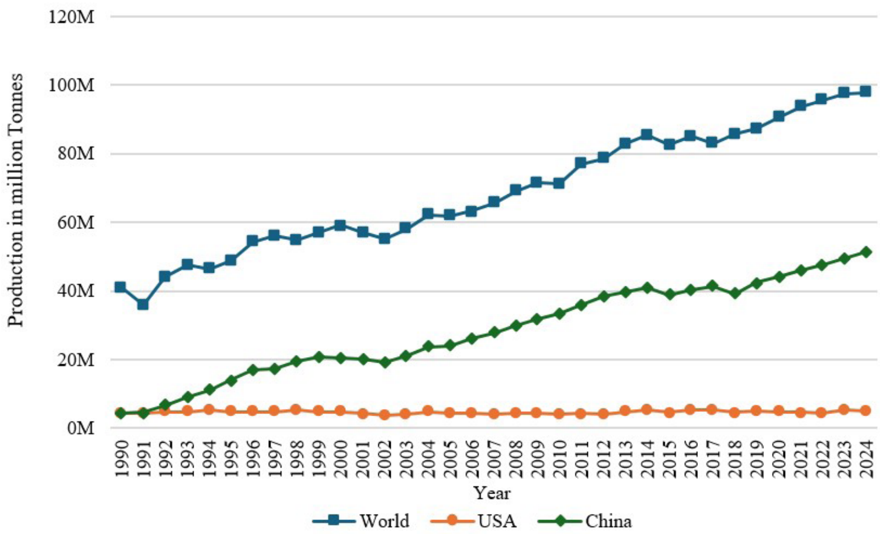

Figure 1: world, U.S., and Chinese apple production (million tonnes), 1990–2024
Source: FAOSTAT (FAO, 2026)

Apple Yield Trends: World, China, and the United States (1990–2024)

Figure 2 shows trends of global, Chinese, and U.S. apple

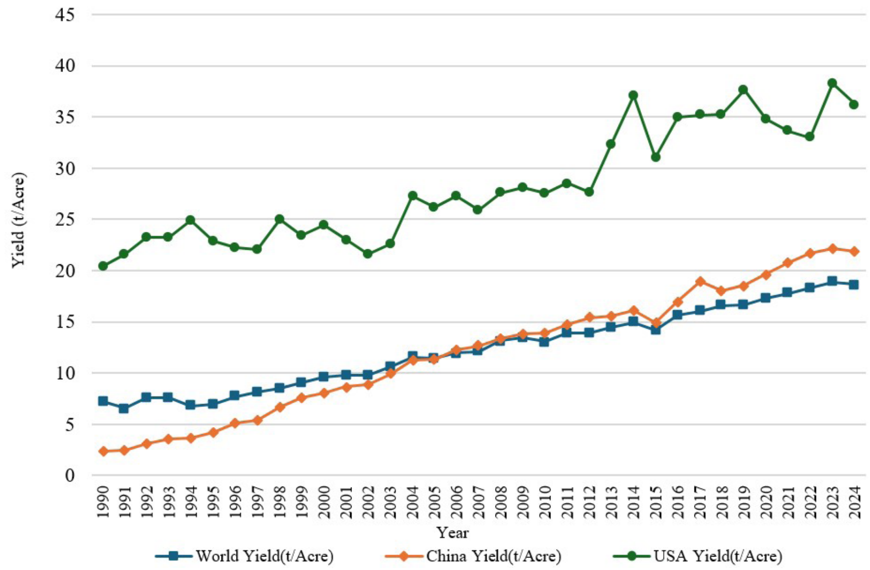

Figure 2: Apple yield (tons per acre) for the United States, China, and the world, 1990–2024
Source: FAOSTAT (FAO, 2026)

yields from 1990 to 2024. Global yield increased steadily over the period, with China showing particularly great and sustained improvement, especially after 2000, indicating the rapid adoption of modern production technologies and the intensification of orchard management (Jiao *et al.,* 2018). U.S. yield remained comparatively higher than the global average throughout the period but shows moderate fluctuations rather than a strong directional trend, which aligns with the production trend. It can be inferred from the relatively stable yield pattern in the United States that productivity gains from technological adoption may have reached a plateau, where incremental improvements in orchard management offset the limited effects of climatic variability. In contrast, China's sustained yield growth shows rapid technological catch-up and modernization of orchards, highlighting the role of technology diffusion in global agricultural productivity.

Leading Apple-Producing Countries (2023)

Apple production is highly concentrated among a small number of countries (Figure 3). China, representing more than half of the world's production, dominated global apple output with around 49.6 million tonnes of production in 2023. The United States was the second-largest producer with 5.15 million tonnes, which was followed by Turkey (4.60 million tonnes), India (2.88 million tonnes), and Russia (2.08 million tonnes) in 2023.

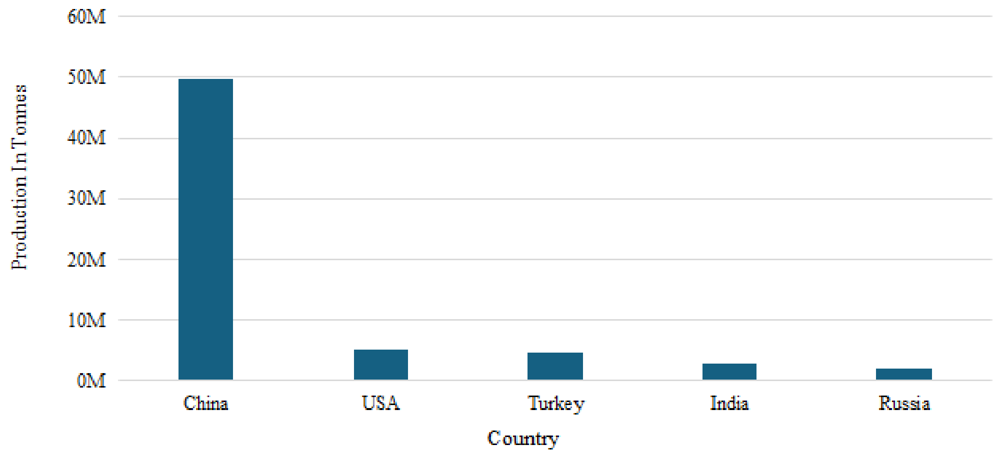

Figure 3: Apple production (million tonnes) of the top five producing countries in 2023
Source: FAOSTAT (FAO, 2026)

Fresh Apple Export Trends (2014–2024)

From 2014 to 2024, U.S. fresh apple exports range between 0.70 and 1.0 million tonnes per year (Figure 4). Exports decreased from a peak of around 980,000 tonnes in 2015 to a low of around 697,000 tonnes in 2022. A partial recovery occurs in 2023–2024, with export volumes rising to approximately 897,000 tonnes in 2024, representing renewed international demand for U.S. apples. The fluctuations in export volumes show exchange rate fluctuations, increasing sensitivity of the U.S. apple trade to global demand shifts, and competitive pressure from Southern Hemisphere exporters (Taschetta-Millane, 2026). This pattern suggests that export performance is becoming more volatile, highlighting the need for robust forecasting tools for trade planning. Despite these fluctuations, the United States was able to maintain the

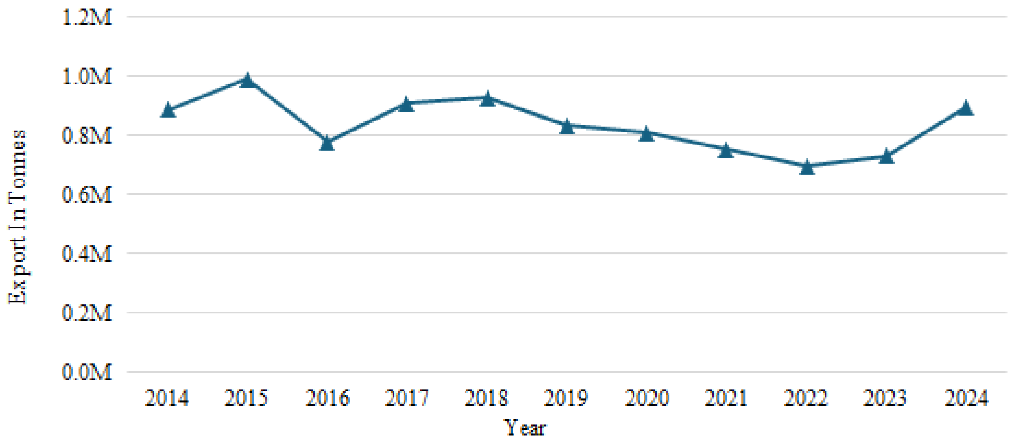

Figure 4: U.S. fresh apple export volumes (million tonnes) from 2014 to 2024
Source: FAOSTAT (FAO, 2026)

fourth position among global fresh apple exporters in 2024, after China, the European Union, and Italy (Table 2).

Table 1: Top five importing regions of U.S. fresh apples by quantity, 2024

Rank	Country	Imports ('000 tonnes)
1	Mexico	242.8
2	Canada	141.5
3	Other Asian countries (unspecified)	63.6
4	India	38.9
5	Dominican Republic	14.4

Source: World Bank WITS (World Bank, 2025)

Major Importers of U.S. Fresh Apples and Global Export Rankings (2024)

Mexico is the dominant market for U.S. fresh apples, absorbing approximately 242,800 tonnes in 2024, followed by Canada. India and other Asian markets are also increasingly important destinations. The Dominican Republic belongs to the top five destinations, highlighting the importance of nearby Caribbean markets.

The global fresh apple export market in 2024 was dominated by China, followed by the European Union and Italy, which collectively accounted for the largest export share (Table 2). The United States was ranked fourth, with 897,400 tonnes of exports, representing a competitive position. Chile's position as the fifth-largest exporter highlights the growing importance of Southern Hemisphere suppliers in meeting Northern Hemisphere market requirements during the off-season ("Southern Hemisphere Apple Exports," 2025). The concentration of export markets and suppliers indicates the oligopolistic structure of the global apple trade, as a small number of countries dominate supply. This concentration increases exposure to trade policy and geopolitical risks, making diversification of export markets an important consideration for the U.S. apple industry.

Table 2: Top five global exporters of fresh apples by quantity in 2024

Rank	Exporting Country	Export Quantity ('000 tonnes)
1	China	981.0
2	European Union	950.2
3	Italy	930.5
4	United States	897.4
5	Chile	553.9

Source: World Bank WITS (World Bank, 2025)

Geographical Concentration of U.S. Apple Production (2023)

U.S. apple production is highly geographically concentrated, with Washington State alone accounting for around 64% of national production due to its optimal combination of climate, water availability, soils, and well-developed commercial infrastructure required for apple production (Schotzko & Granatstein, 2004). New York (12%), Michigan (10%), Pennsylvania (5%), and California (3%) were the next largest producing states, while Virginia, Oregon, North Carolina, Ohio, and other states collectively accounted for the remaining 6% (USDA NASS, 2024). This high geographical concentration indicates that U.S. apple production is highly susceptible to region-specific shocks such as frost events, droughts, and water availability constraints in Washington State. From a policy perspective, this concentration highlights the importance of regional risk management strategies and investment in infrastructure to ensure production stability.

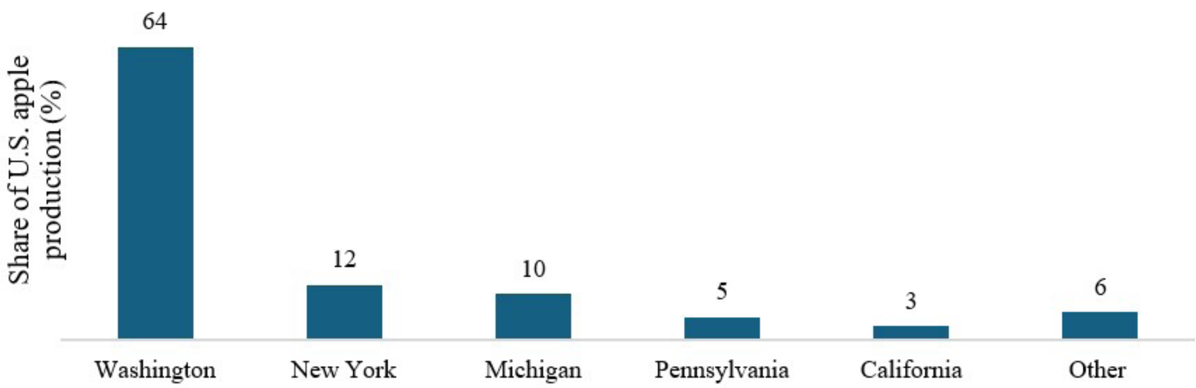

Figure 5: Share of U.S. apple production by state in 2023 (%)
Source: USDA NASS (2024)

Trends in total US Apple Cultivation Area and Fresh Apple Market Prices ($/lb)

The trend of Apple cultivation area in the United States indicates a decline from 2007 to 2024, with a sharper contraction around 2018, followed by relative stabilization (Figure 6). Despite the decline in total acreage, overall production has remained relatively stable, due to improvements in yield with improved varieties, high-density planting systems, and enhanced orchard management practices (Taschetta-Millane, 2026).

Fresh Apple Market Prices ($/lb) show a broadly upward trend from 2010 to 2024 (Figure 7). Fresh Apple Prices

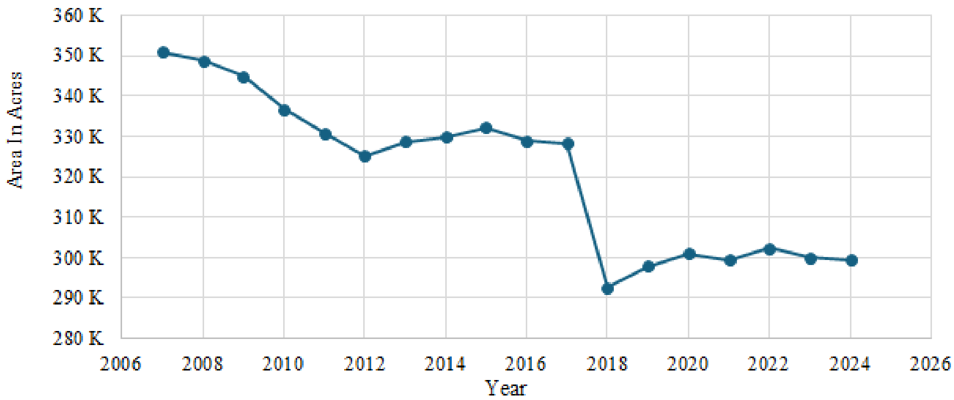

Figure 6: Trend in U.S. apple cultivation area (acres) from 2007 to 2024
Source: Authors' compilation based on the FAOSTAT database

remained comparatively stable between 2010 and 2019, followed by a sharp increase after 2020, reaching an all-time high in 2023 before a slight decline in 2024. The concurrent trends of declining acreage and increasing prices indicate that the market has compensated producers for reduced supply by a higher farmgate price, and supply-side constraints are increasingly influencing the market in the U.S. apple sector. This reflects a shift toward a more value-driven rather than volume-driven production system, where productivity gains rather than expansion of land area sustain output levels.

Market Fresh Apple Prices ($/lb) from 2010 to 2024

Overall, these results show that the U.S. apple industry is

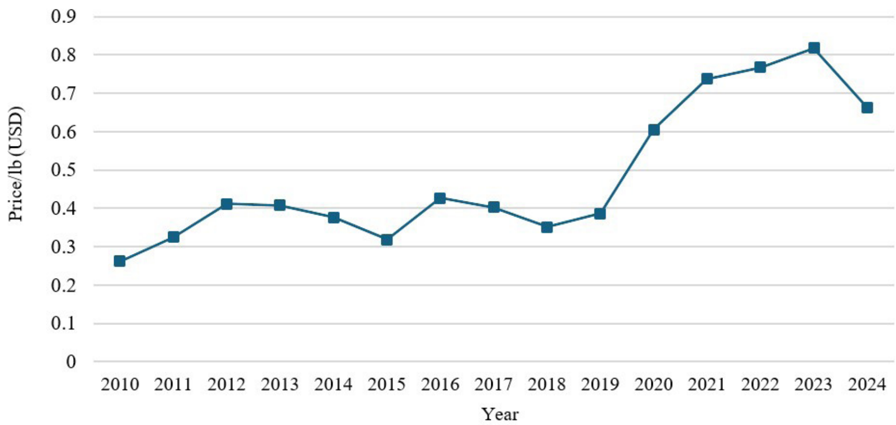

Figure 7: U.S. Fresh Apple Price Trends (USD/lb) 2010 to 2024
Source: Authors' compilation based on the FAOSTAT database

characterized by increasing concentration in production regions, structural stability in production, and growing sensitivity to climatic and market forces. In contrast, global production variations are increasingly shaped by the rapid advancement of technologies, cheap labor, and good market demand in emerging economies. These contrasting patterns highlight the requirement for forward-looking forecasting approaches that can capture past non-linear trends to generate forecasts, which is useful to inform trade competitiveness, production planning, and policy formulation in a changing global agricultural environment.

Forecasting Results and Model Evaluation

Descriptive Statistics of U.S. Apple Production from 1990 to 2024

The summary statistics for US apple production show a relatively stable production trend over the observed period (Table 3). Average production was approximately 4.64 million tonnes per year, with a standard deviation of

Table 3: Summary statistics of U.S. apple production (tonnes), 1990–2024

Statistic	Value
Mean production (tonnes)	4,643,860
Standard deviation	387,965
Minimum production	3,866,376
25th percentile (Q1)	4,382,416

Median (50th percentile)	4,665,199
75th percentile (Q3)	4,834,546
Maximum production	5,358,740
Range	1,492,364
Skewness	0.07
Kurtosis	2.31

Source: Authors' compilation based on the FAOSTAT database

about 387,965 tonnes, indicating low to moderate year-to-year dynamics. Production ranges from a minimum of 3.87 million tonnes to a maximum of 5.36 million tonnes per year, resulting in a total range of 1.49 million tonnes. The interquartile range spread from 4.38 million tonnes (Q1) to 4.83 million tonnes (Q3), showing that the middle 50% of production values were tightly clustered, which further indicates consistency in output levels.

The distribution is balanced with no strong distortion from extreme values, as shown by the median production (4.67 million tonnes), which is very close to the mean. The skewness value (0.07) confirms that the data distribution is almost symmetric, which means yearly production variations were evenly distributed above and below the mean. However, the kurtosis value (2.31) indicates that the data is slightly more peaked than a normal distribution and has a few unusual high or low production values, but these are not very extreme or frequent. Overall, US apple production during this period remained relatively stable with slight fluctuations and no strong evidence of structural instability or irregular volatility.

Forecasting Model Comparison

Given that U.S. apple production shows a relatively stable but non-linear historical pattern influenced by technological, climatic, and market factors. The quadratic trend model gives an appropriate framework for analysing historical trends and forecasting future production. Table 4 shows the forecasting accuracy metrics for three trend models estimated using US annual apple production data from 1990 to 2024. The quadratic trend model was the most accurate among the three models, achieving the lowest MAE (290,264.5 tonnes), MSD (1.24×10^{11}), and MAPE (6.26%). This indicates that the U.S. annual apple production trend does not follow a strictly linear or exponential path, but instead displays a nonlinear pattern over time, likely reflecting interactions between technological improvements, climatic variability, and long-term structural limitations in orchard expansion. This result aligns with earlier studies on crops, which reported that quadratic models better capture variation in agricultural production over time. For example, Abid *et al.* (2014) found that the quadratic trend model outperformed linear and exponential alternatives in forecasting maize production in Pakistan. Similarly, Limbu Sanwa *et al.* (2026) reported that the quadratic trend model is the most effective approach for forecasting U.S. tomato production. This study extends existing agricultural forecasting research by applying deterministic trend models to the most recent U.S. apple production data for forecasting, as well as analyzing long-term production and international trade trends.

Table 4: Comparison of forecasting model accuracy by using MAE, MSD, and MAPE metrics

Evaluation Metric	**Linear**	**Quadratic**	**Exponential**
MAE (tonnes)	317,921	290,265	317,268
MSD	1.43×10^{11}	1.24×10^{11}	1.43×10^{11}
MAPE (%)	6.9	6.3	6.9

Source: Authors' compilation based on the FAOSTAT database

U.S. Apple Production Forecasts from 2025 to 2030

Table 5 shows the forecasted annual U.S. apple production from 2025 to 2030, along with 95% confidence intervals. The quadratic trend model predicts a gradual upward trajectory in production, increasing from around 5.08 million tonnes in 2025 to 5.43 million tonnes in 2030, which represents an increase of around 347,000 tonnes (6.8%) over the six-year forecast period. From a policy and industry perspective, this gradual upward trend highlights that production growth is likely to remain modest, implying that improvements in productivity rather than area expansion will continue to drive supply. This has implications for storage infrastructure, investment planning, labor management, and export strategy. However, these forecasts are conditional on the continuation of historical trend behavior and do not clearly incorporate external shocks such as policy changes, extreme weather events, or global market disruptions. Therefore, results should be interpreted as baseline trend forecasts rather than precise predictive outcomes.

The forecast represents a steady increase in annual production, which aligns with past improvements in productivity despite a decline in cultivated area. The 95% confidence intervals widen over time, from about 805,000 tonnes in 2025 to 1,343,000 tonnes in 2030, indicating that uncertainty increases the further into the future (Hyndman & Athanasopoulos, 2021). Therefore, as actual production will also depend on weather, market, and policy factors that the model cannot capture, forecasts

Table 5: Forecasted U.S. apple production from 2025 to 2030 using the quadratic trend model

Year	Point Forecast (million tonnes)	Lower 95% CI (million tonnes)	Upper 95% CI (million tonnes)
2025	5.08	4.68	5.48
2026	5.14	4.69	5.59
2027	5.21	4.71	5.71
2028	5.27	4.72	5.83
2029	5.35	4.74	5.96
2030	5.42	4.75	6.09

Source: Authors' compilation based on the FAOSTAT database

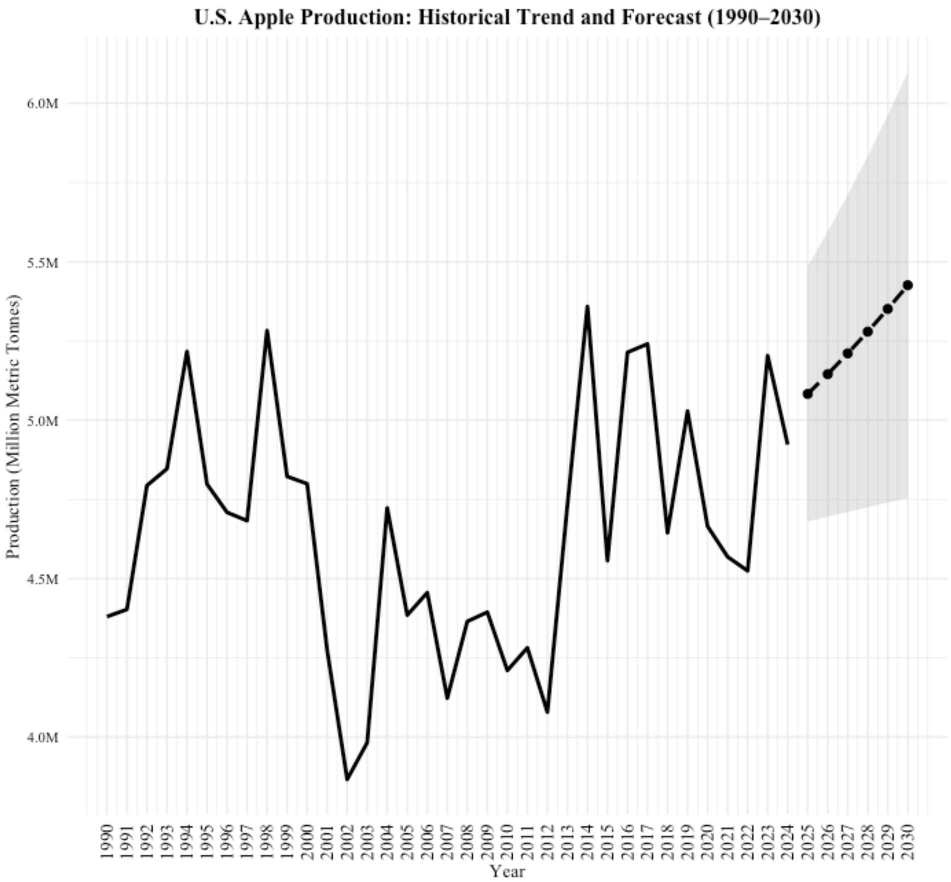

Figure 8: Historical (1990–2024) and quadratic trend model forecasted (2025–2030) U.S. apple production trend (million tonnes), with 95% confidence intervals

for 2029 and 2030 should be interpreted with caution (Atkinson *et al.,* 2013; IPCC, 2022; FAO, 2022).

CONCLUSION

This study gathered and analysed U.S. annual apple production and international trade trends from 1990 to 2024, including comparisons with global production and top global producers, exports, imports, major producing states, etc., and forecasted U.S. apple production until 2030 using a quadratic trend model. This study contributes to the agricultural forecasting and trade literature by analysing long-term production trends, international trade variations, and comparative deterministic projections using updated U.S. data through 2024. The results can be summarized into three main findings. First, U.S. annual apple production has been comparatively stagnant over the past 35 years, ranging from 4.0 to 5.5 million tonnes despite global growth. This represents a mature US apple industry where yield gains have covered declines in cultivated area, but global production expansion has reduced the U.S. share of global production. Second, the quadratic trend model performed best among the models evaluated, capturing the non-linear pattern in the data and producing the lowest errors, which aligns with previous similar studies in this field. It predicts a slight increase in US annual apple production from 5.08 million tonnes in 2025 to 5.43 million tonnes in 2030. However, confidence intervals broaden over time, so long-term forecasts should be interpreted carefully. Third, various external risks such as input costs, climate change, trade changes, and labour shortages can affect apple production and productivity. Furthermore, production volume is also highly concentrated in Washington State approximately 64% of U.S. production in 2025, making the sector susceptible to regional shocks. So, forecasts should be viewed as conditional rather than fully certain predictions. Overall, the findings provide practical guidance for producers, exporters, and policymakers by highlighting a structurally stable but non-expanding U.S. apple industry. The results indicate that future competitiveness on the global market will depend more on productivity improvements, technological adoption, labour efficiency, and trade strategy rather than expansion in the production area alone. These insights can help evidence-based decision-making in production planning, export strategy, and agricultural policy under increasing market and climatic uncertainty.

Limitations and Future Research

Although this study is useful in analysing scenarios and the US apple production trends, trade dynamics, and forecast, it has several limitations that should be considered when interpreting the results. First, trend-based forecasting models assume that historical production patterns will continue in the future and may not adequately capture unexpected events such as policy changes, extreme weather, market shocks, etc. (Kolambe & Arora, 2024). As a result, forecast accuracy generally decreases as the forecast horizon increases. Secondly, the analysis uses national-level data, which may not represent important variation among states, production systems, and apple varieties.

Future research can may improve forecasting accuracy using more advanced methods like ARIMA, SARIMA, state-space models, and machine-learning models, and by including factors like climate conditions, trade policies, and input costs to improve the accuracy (Abid *et al.,* 2014; Karim *et al.,* 2010; Tahir *et al.,* 2013). These models can better account for autocorrelation, nonlinear relationships, and short-term volatility. Machine learning approaches such as random forests, gradient boosting, and neural networks can also be employed to capture complex nonlinear relationships that traditional statistical models may miss (Kyriazos & Poga, 2024). Regional and state-level analysis of water availability, soil quality, greenhouse use patterns, and local adaptation strategies can also be considered in Future studies, particularly for major producing states such as Washington, New York, and Michigan (Davis *et al.,* 2025).

Furthermore, combining life-cycle assessment (LCA) with economic forecasting can quantify energy, carbon, and water footprints across various production systems could help quantify environmental impacts and support climate-smart planning. (Pawlak *et al.,* 2021). Additionally, analyzing consumer preferences and willingness to pay for apples grown organically would shed light on changing demand patterns that impact both domestic and international markets (Wang et al., 2010). Addressing these limitations in future research would improve the accuracy of agricultural production forecasting while providing stronger evidence to support trade policy, production planning, resource allocation, and long-term competitiveness in the U.S. apple industry.

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