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Price, Inventory, and Trade Dynamics in the U.S. Soybean Market with Structural Breaks and VAR Analysis

Dharma Raj Katuwal[1*], Bikesh Thapa[2], Anuj Dhakal[1], Rumita Limbu Sanwa[1], Alina Pokhrel[3]

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ABSTRACT

Soybeans play a vital role in global food, feed, and energy systems. Therefore, this study combines global and U.S. secondary data from FAOSTAT (2000-2023) with USDA balance sheets and trade statistics (2000/01-2023/24). Descriptive analysis employs indicators of self-sufficiency, import dependency, export intensity, and stock-to-use ratios. Market dynamics are examined by identifying multiple structural breaks using the Bai-Perron method, followed by Vector Autoregressive (VAR) estimation and Granger causality analysis linking U.S. soybean production, harvest price, export value, and ending stocks. Results show that global soybean harvested area expanded by 84%, while production increased by 130%. In contrast, U.S. cultivated area increased by only 13.8%, whereas production rose by 51%, confirming productivity-led growth. Brazil and the U.S. together account for more than two-thirds of global soybean production, and within the U.S., approximately 34-39% of total output is concentrated in the top three producing states. Econometric results identify four major structural shifts occurring around 2006, 2010, 2014, and 2020. Vector Autoregression (VAR) estimates indicate strong production persistence (lag 1 = 1.229, $p < .001$), a significant negative effect of ending stocks on production (-0.289, $p < .001$), and a short-run negative impact of production on prices (-0.901, $p < .10$), while export values exert a positive influence on prices (0.647, $p < .01$). Granger causality results reveal bidirectional relationships among prices, stocks, and production, suggesting that prices and inventories serve as key adjustment mechanisms. Hence, future research should focus on biofuel policy, inventory management, and energy–agriculture linkages to enhance market sustainability.

INTRODUCTION

Soybean is an economically significant crop worldwide. It was originated in China and have long been used as a staple crop in East Asian societies (Peng *et al.*, 2026). Historically, the cultivation of soybeans in the United States (U.S.) has been documented since 1765 (Hamza *et al.*, 2024). Across regions, soybean use and production evolved differently. In the Western Hemisphere, soybean production initially emphasized vegetable oil, whereas in many other regions, soybeans were prioritized as a cash crop (Carciochi *et al.*, 2019). Today, soybeans are a major source of protein for livestock and poultry feed (Sosulski *et al.*, 1980; Chiluwal, 2024) and contribute approximately 25% of the global edible oil supply (Mishra *et al.*, 2024). Soybean oil is widely used as cooking and salad oils and for frying, baking, and other food applications. Approximately 85% of total soybean production is processed into meal and vegetable oil, with most of this output used for animal feed, while only about 2% is processed into edible soy flour and protein products (Alsanie, 2021).

Soybean, often described as the "crop of the century" by The Financial Times, 2017 (Meyer *et al.*, 2017), has experienced rapid growth in both production and trade (Wang *et al.*, 2024; Karki, 2022). As a result, soybeans have surpassed wheat and coarse grains in global agricultural trade, accounting for approximately 10% of global agricultural trade (Lee *et al.*, 2016). The global soybean trade is highly concentrated among four countries: Brazil, the U.S., Argentina, and China. The U.S., Argentina, and Brazil together account for more than 80% of global supply, while China imports over 60% of globally traded soybeans (Gale *et al.*, 2019; Reis *et al.*, 2025). Consequently, the global soybean supply chain is geographically concentrated, with production centered in South America and consumption concentrated in Asia, which increases vulnerability to geopolitical and trade disruptions (Gereffi & Lee, 2012). China was a major producer and exporter of soybeans during the 1930s and 1940s. However, during the mid-20th century, trade and production dynamics shifted toward the Americas. Mechanization and improved varieties increased U.S. dominance in soybean production and exports, allowing the U.S. to surpass China in the 1950s (Langthaler, 2020). Alongside this shift, Brazil and Argentina expanded their soybean production, and Brazil surpassed the U.S. as the leading exporter in 2012. In 2024, Brazil exported 98.8 million tons of soybeans, accounting for approximately 50% of global exports, while the U.S. remained the second-largest exporter and Argentina ranked third (Peng *et al.*, 2026). More recently, geopolitical tensions between the U.S. and China during 2018–2019 led China to impose retaliatory tariffs of 25% on U.S. soybean imports, prompting importers to shift purchases from the U.S. to Brazil and other producers (American Soybean Association, 2025). Further trade frictions in 2024–2025 strengthened South America's position in the global soybean market (Adjemian *et al.*, 2021).

The tariff implications led to higher soybean stocks in

[1] Department of Agriculture, Food, and Resource Sciences, University of Maryland Eastern Shore, MD, USA
[2] Institute of Agriculture and Animal Science, Tribhuvan University, Kathmandu, Nepal
[3] Department of Entomology and Plant Pathology, University of Tennessee, TN, USA
[*] Corresponding author's e-mail: drkatuwal@umes.edu

most U.S. states, particularly in Northern Plains states such as North Dakota and South Dakota (Hitchner *et al*., 2019). Similarly, relatively high stocks in Illinois and Michigan weakened both cash and futures prices. Lower prices and higher stocks, in turn, reduced planting incentives. At the same time, favorable weather conditions in South America in 2019 increased global soybean production (Klein & Vidal Luna, 2021). Although China's initial agreement to purchase soybeans from the U.S. temporarily increased prices, demand declined sharply due to African swine fever in China (Mason-D'Croz *et al*., 2020; Cowley, 2020). As a result, soybean prices declined in both the U.S. and Brazil. At the beginning of 2019, farmers intended to increase soybean planting; however, by March, planted area had fallen to more than 5% below the previous year. Tariffs, large stocks, and declining prices played a major role in these planting decisions (Hitchner *et al*., 2019). Soybean production in the U.S. has followed a long-term upward trend, with Illinois consistently ranking as the top-producing state. The rich, deep soils of the U.S. heartland produce more corn and soybeans than any other region in the country (Garcia-Paredes *et al*., 2000; Egli, 2008; Nafziger, 2020). Nevertheless, production costs have increased substantially over time. In the 1970s, Iowa producers spent about $100 per acre, whereas today production costs exceed $500 per acre (Hart, 2017). The U.S. soybean market is highly competitive, characterized by free entry and exit and little product differentiation. Therefore, price remains a crucial factor influencing production decisions. When prices exceed costs, profits increase, and supply expands as new producers enter the market. Conversely, when prices are low, some producers exit. Prices and costs in the U.S. soybean market have fluctuated considerably over time. During the 1970s, soybean exports increased alongside rising prices and profitability, which encouraged supply expansion in the late 1970s and 1980s (Zulauf and Schnitkey, 2018; Peters *et al*., 2009). Subsequently, as supply expanded, costs rose, and prices declined in the late 1980s. In 2007, soybean prices again increased above $10 per bushel, peaked at approximately $14 in 2012, and declined after 2013 (United States Department of Agriculture [USDA], 2025). High prices during this period increased profitability and encouraged farmers to expand soybean planting to more than 80 million acres (Hart, 2017). Despite rising production, U.S. dependence on imports has increased, while exports have declined over time (USDA, 2023). Against this background, the objective of this study is to identify major structural shifts in U.S. soybean markets and to examine how prices, inventories, production, and trade adjust around these shifts.

MATERIALS AND METHODS

Descriptive Methods

The annual secondary data were extracted from the Food and Agriculture Organization of the United Nations (FAOSTAT) and the USDA. FAOSTAT was used to derive global soybean production metrics, including world soybean production and harvested area, for the years 2000-2023. Before analysis, the harvested area was converted to million hectares (Mha), and production values were converted to million metric tons (MMT). FAOSTAT data were also extracted on cultivated area and production trends in the U.S. for the years 2000-2023 to identify the top soybean-producing nations worldwide during that time.

For the years 2010-2024, state-level soybean production data for the top three soybean-producing states in the U.S. were obtained from the USDA and converted into MMT. To examine trends in total supply, total demand, and self-sufficiency, USDA data were used on the supply-use balance of soybeans in the U.S. for the marketing years 2000/01-2023/24. After recording the total supply and demand in MMT, the self-sufficiency ratio (SSR) was calculated as follows (Oktyajati *et al*., 2021; Hubbard & Hubbard, 2013; Paryanto *et al*., 2025):

$$SSRt(\%)=\text{Production }/\text{Domestic utilization}\times 100 \quad (1)$$

Where,

Production = Total U.S. soybean production.

Domestic utilization = Total domestic use of soybeans in the marketing year.

USDA data on soybean meal and soybean oil balances for 2000/01-2023/24 were used to compute import dependency, export intensity, and stock-to-use ratios, all expressed in percentage terms.

Import dependency was calculated as (Gjosheva *et al*., 2025; Sterling *et al*., 2025).

$$\text{Import dependency}(\%)=\text{ Import }/\text{Production + Import - Export}\times 100 \quad (2)$$

Export intensity was calculated as:

$$\text{Export Intensity}(\%)=\text{ Export }/\text{Production + Import - Export}\times 100 \quad (3)$$

Stock-to-use ratio was calculated as:

$$\text{Stock to use ratio }(\%)=\text{ Ending stock }/\text{U.S.total }\times 100 \quad (4)$$

Where imports, exports, domestic supply, ending stocks, and total use follow USDA commodity balance-sheet definitions and are measured in MMT before conversion into ratios.

USDA data on the production and usage of soybean oil in the U.S. by end-use category (food, feed, biofuel, and other uses) were taken from 2000/01-2023/24 and converted into MMT. Additionally, USDA trade statistics for the years 2000/01-2023/24 provided data on U.S. soybean trade, including import and export quantities, which were recorded in metric tons (t). The soybean trade balance was calculated using the methodology outlined by Arshad & Mukhtar (2019) and Tursunov (2025).

$$\text{Trade balance = Export (t) - Import (t)} \quad (5)$$

The computation shows that positive values indicate net export positions, while negative values indicate net import positions.

Econometric Analysis

In this study, three determinants of U.S. soybean production (logus) were analyzed: price at harvest (USD/

mt, logprice), ending stock (million metric tons, logend), U.S. export value (USD, logexp), and the lagged value of U.S. soybean production (logus). Stationarity was then examined using the Augmented Dickey–Fuller (ADF) test before estimating a Vector Autoregressive (VAR) model with structural break dummy variables. Pairwise Granger causality tests were subsequently applied to examine the dynamic relationships among the variables. Finally, diagnostic tests for serial correlation, heteroskedasticity, stability, and normality were conducted to evaluate model adequacy.

Stationarity Test (Unit Root Test)

Time series data analysis can result in spurious results if variables are non-stationary (Cheng *et al.*, 2021; Wong & Yue, 2024). A time series is considered stationary when its mean, covariance, and autocovariance remain constant over time; if these conditions change with time, the series becomes non-stationary (Gujarati, 2009). If a stationarity test indicates that a time series is stationary at its level (Y_t), it is classified as integrated of order 0 (I(0)); conversely, if it is stationary at the first difference (Y_t - Y_{t-1}), it is categorized as integrated of order 1 (I(1)) (Sathyanarayana & Mohanasundaram, 2025). This study uses the Augmented Dickey-Fuller (ADF) with a time trend to determine the maximum order of integration.

The Augmented Dickey-Fuller test with null hypothesis (d = 0) that a series is non-stationary is based on the following equation (Dangal & Gajurel, 2022):

$$\Delta Y_t=\alpha_1+\alpha_2 t+\delta Y_{t-1}+\sum_{i=1}^{n} d_i\Delta Y_{t-i}+\varepsilon_t \qquad (6)$$

Where, $\Delta Y_t = Y_t - Y_{t-1}$, α_1 is the constant term, t is the time trend, Δ is the first difference operator, n is the optimum number of lags, and εt is the pure white noise term.

Cointegration Test

Cointegration is the existence of a long-run association between dependent and independent variables (Nkoro & Uko, 2016). The cointegration test is conducted when the variables are non-stationary at the level but stationary in first differences (Birkel, 2014; Cross *et al.*, 2011). Although stationarity is assessed using differenced data, the cointegration test itself is conducted using level series to identify the long-run equilibrium (Acharya, 2019; Al-Masbhi & Du, 2021). The Johansen cointegration test was applied to determine the number of cointegrating vectors among the variables (Johansen, 1988).

The Johansen procedure provides two test statistics: the trace statistic and the maximum eigenvalue statistic (Hjalmarsson & Osterholm, 2010). The trace test examines the null hypothesis that the number of cointegrating vectors is less than or equal to r, while the maximum eigenvalue test examines whether the number of cointegrating vectors is equal to r (Ghimire *et al.*, 2015). The Johansen cointegration test is based on the Vector Autoregressive (VAR) framework (Roman *et al.*, 2020).

$$Y_t=C+\sum_{i=1}^{p} A_i X_{t-i}+e_t \qquad (7)$$

where Yt is a vector of endogenous variables, C is a vector of constants, Ai are coefficient matrices, p is the optimal lag length, and et is a vector of error terms.

Vector Autoregressive Method (VAR)

The Vector Autoregressive (VAR) model is a commonly used method for examining the dynamic behavior of economic time-series variables (Phaju, 2023). The VAR framework estimates a system of equations in which each variable is expressed as a function of its own lagged values and the lagged values of all other variables in the system (Lutkepohl, 2013; Usman & Bashir, 2022). In a VAR model, there is no prior distinction between endogenous and exogenous variables, which allows for simultaneity among the variables (Kristofersson & Anderson, 2006).

The general VAR(p) model is represented as follows (Nwanneako *et al.*, 2023; Li, 2024):

$$Y_t=A_1 y_{t-1}+A_2 y_{t-2}+A_p y_{t-p}+\mu_t+\varepsilon_t \qquad (8)$$

Where Ai for all i= 1,2,3… p are (k ´ k) parameter matrices. The error term mt = (m_{1t}, m_{2t} ….,m_{kt}) is zero mean white noise with k dimensions and a covariance matrix of: E (m_t, m'_t) = e_m

The VAR model matrix with notation: Y_{it}, i_{th} variable where i = 1,2,3…m; m being the time series variables in the system, and t is the length of the time series, is given by:

$$\begin{pmatrix} Y_{1t} \\ Y_{2t} \\ \vdots \\ Y_{mt} \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_m \end{pmatrix} + \begin{pmatrix} A_{11}^{(1)} & A_{12}^{(1)} & A_{1m}^{(1)} \\ A_{21}^{(1)} & A_{22}^{(1)} & A_{2m}^{(1)} \\ A_{m1}^{(1)} & A_{m2}^{(1)} & A_{mm}^{(1)} \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ \vdots \\ Y_{m,t-1} \end{pmatrix} + \dots + \begin{pmatrix} A_{11}^{(p)} & A_{12}^{(p)} & A_{1m}^{(p)} \\ A_{21}^{(p)} & A_{22}^{(p)} & A_{2m}^{(p)} \\ A_{m1}^{(p)} & A_{m2}^{(p)} & A_{mm}^{(p)} \end{pmatrix} \begin{pmatrix} Y_{1,t-p} \\ Y_{2,t-p} \\ \vdots \\ Y_{m,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{mt} \end{pmatrix} \qquad (9)$$

Where,

Yt = (y_{1t}, y_{2t},…,ymt) denotes (n´1) vector of time series variables

A_i denotes (n´N) coefficient matrices
e_t is an (n´1) unobservable zero-mean white noise.
In this study, the VAR model was specified with U.S. soybean production (logus) as the dependent variable, while harvest price (logprice), ending stock (logend), export value (logexp), and lagged production were explanatory variables.

Granger Causality Test

The Granger causality test was applied to examine the short-run causal relationships among the variables. A variable Y is said to Granger-cause another variable X if past information on Y improves the prediction of X beyond the information contained in past values of X alone (Clarke & Granato, 2005). The Granger causality framework was used to identify bidirectional, unidirectional, or independent relationships among U.S. soybean production, harvest price, exports, and ending stocks.

$$logus_t = \mu_{us} + \sum_{i=1}^{p} A_{1i}\ logus_{t-i} + \sum_{i=1}^{p} A_{2i} logprice_{t-i} + \sum_{i=1}^{p} A_{3i}\ logend_{t-i} + \sum_{i=1}^{p} A_{4i}\ logexp_{t-i} + \lambda t + \sum_{j=1}^{4} \theta_j\ seg_j + \varepsilon_{us,\,t} \qquad (10)$$

The Granger test between the U.S. soybean production and price at harvest can be written as:

$$logus = \sum_{i=1}^{n} b_i logprice_{t-i} + \sum_{i=1}^{n} c_i\ logend_{t-i} + \sum_{i=1}^{n} d_i\ logexp_{t-i} + \sum_{i=1}^{n} g_i\ logus_{t-i} + \mu_{2t} \qquad (11)$$

$$logprice = \sum_{i=1}^{n} a_i logus_{t-i} + \sum_{i=1}^{n} h_i\ logend_{t-i} + \sum_{i=1}^{n} r_i\ logexp_{t-i} + \sum_{i=1}^{n} m_i\ logprice_{t-i} + \mu_{3t} \qquad (12)$$

Where m_{2t} and m_{3t} are the disturbance terms, which are uncorrelated to each other. The causality model for other variables is the same. Bilateral causality occurs between logus and logprice if the coefficient for both variables, i.e., Sa_i ¹ 0 and Sb_i¹0. Independence between variables if both coefficient values are equal to zero, i.e Sa_i = 0 and Sbi= 0. Similarly, unidirectional causality is seen if Sa_i = 0 and Sb_i¹0 or Sa_i ¹ 0 and Sb_i =0.

Diagnostic Test

To assess the adequacy and stability of the established models, a series of diagnostic tests was carried out. The Breusch-Godfrey test was used to examine serial correlation. The Breusch-Pagan test was used to assess heteroskedasticity, and robust standard errors were used in cases where heteroskedasticity was found. The OLS-CUSUM test was used to evaluate model stability, while the Shapiro-Wilk test was used to evaluate residual normality.

RESULTS AND DISCUSSION

Global Soybean Production (2000-2023)

Figure 1 shows a distinct increasing trend in both harvested areas and total production from 2000 to 2023. The harvested area increased from 74.3 million hectares in 2000 to 136.9 million hectares in 2023, an approximate increase of 84% during the period. Production increased significantly, from 161.3 MMT to 371.2 MMT, an approximate rise of 130%. Similarly, production growth was especially significant for post-2010, specifically from 2010 to 2017. Production increased from 265.1 MMT to 359.5 MMT, an increase of 35.7%, whereas the area increased by only 22% during the same period. Despite changes in certain years (declines in 2012, 2018, and 2019), the overall trend shows that increases in yield, rather than land expansion, were the primary contributors to higher production. As of 2023, production remained increased despite a few changes in area, showing the significance of improved varieties (Rotundo *et al.*, 2024; Yofa *et al.*, 2021; Tekola *et al.*, 2018; Agarwal *et al.*, 2013), efficient management methods (Pagano & Miransari, 2016; Anand *et al.*, 2025), an increase in demand for meal and oil (USDA ERS, 2023), and intensified production systems for promoting steady growth.

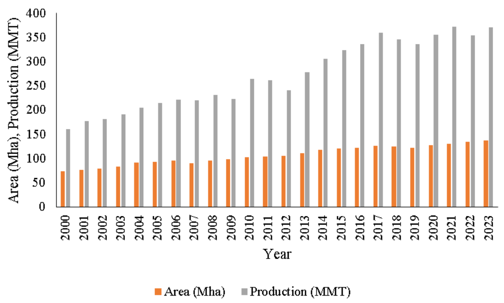

Figure 1: Global soybean production and harvested area, 2000-2023

Global Top Soybean Producer (2000-2023)

From 2000 to 2023, production trends varied significantly among key producing nations. The U.S. kept increasing production levels from 2000 to 2023, rising from 75.06 MMT to 116.96 MMT (see Figure 2). The maximum production was 121.53 MMT in 2021, despite a significant drop in 2019. Brazil demonstrated the strongest and most constant growth, increasing from 32.82 MMT in 2000 to 154.62 MMT in 2023. It exceeded all other nations after 2016 and has shown a continuous rise since 2013. Similarly, Argentina showed moderate development until 2015, reaching its peak of 61.45 MMT. After that, it experienced a continuous decrease to 25.00 MMT by 2023. Production in China showed stability at decreasing levels, fluctuating between 11.95 and 20.50 MMT, with a modest increase after 2018. India showed a consistent increase from 5.28 MMT in 2000 to 14.00 MMT in 2023. Paraguay appeared among the top five producing countries only in 2015 and 2021, with production of 8.86 and 10.60 MMT, respectively. These countries dominate global soybean production due to favorable agro-climatic conditions, large areas of suitable land, investment in improved varieties and agronomic practices, and strong integration with domestic and international oilseed markets (Qiao *et al.*, 2023; Staniak *et al.*, 2023).

Area and Production in the U.S. (2000-2023)

From 2000 to 2023, the cultivated area increased slightly

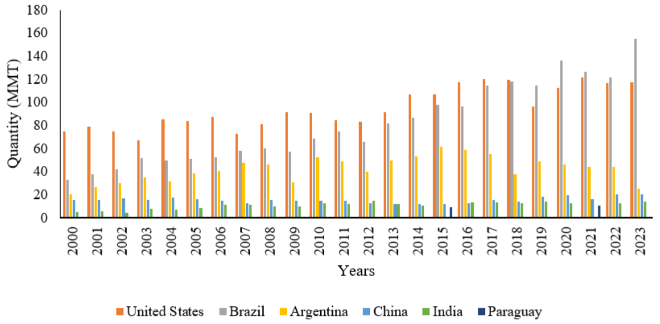

Figure 2: Global top soybean producing countries, 2000-2023

Cultivated Area and Production in the U.S. (2000-2023)

from 29.30 to 33.35 Mha (+13.8%), while production increased from 75.06 to 113.34 MMT (+51.0%) (see Figure 3). This indicates that the increase in production was primarily due to a yield increase rather than land expansion. The area showed relative stability from 2000 to 2013 (about 29-31 Mha), dropped to a low in 2007 (25.96 Mha), and then rose after 2014. After that, it achieved a peak of 36.24 Mha in 2017 before decreasing. In contrast, production grew consistently after 2003, exceeding 100 MMT from 2014 onward and reaching a peak of 121.50 MMT in 2021, despite a brief decline in 2019 (96.67 MMT). The increasing difference between area and production trends indicates a significant increase in average production per hectare throughout the period, with particularly significant improvements after 2013, indicating that the production increase, rather than changes in cultivated area. The factors that drive an increase in production are strong global demand, adoption of high-yielding improved varieties, and advances in agronomic and precision-farming practices (Voora *et al.*, 2020; Dilawari *et al.*, 2022; McFadden *et al.*, 2023; Schimmelpfennig, 2018).

Top 3 Soybean Producer U.S. States (2010-2023)

Production in Illinois, Iowa, and Minnesota shows a generally increasing pattern from 2010 to 2023, with year-to-year fluctuations but clear long-term growth (see Figure 4). Illinois rises from 12.69 MMT in 2010 to peaks above 18 MMT in 2018 and 2021, while Iowa increases from 13.51 MMT to over 17 MMT during the same period. Minnesota maintains a smaller yet steady production, mostly between 8 and 10 MMT after 2012. However, Indiana contributed only in 2014 and therefore does not significantly influence the long-term trend. When combined, the top three producing states account for approximately 34% to 39% of total U.S. production each year, with their highest shares recorded in 2010 (38.77%), 2022 (38.24%), and 2023 (37.74%). Although the contribution fluctuates slightly, the results show that these states consistently generate about one-third of national production, highlighting their continued importance in shaping U.S. production over time. The production is high in these states due to their fertile Mollisol soils, suitable climatic conditions with adequate rainfall, and corn–soybean rotation systems (Dahal, 2018)

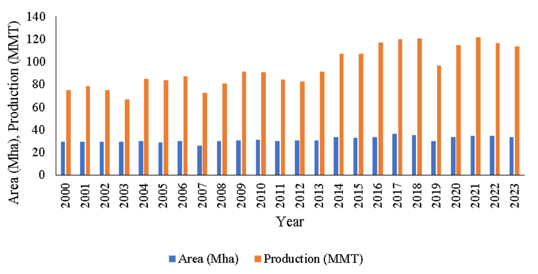

Figure 3: Soybean cultivated area and production trend in the U.S., 2000-2023

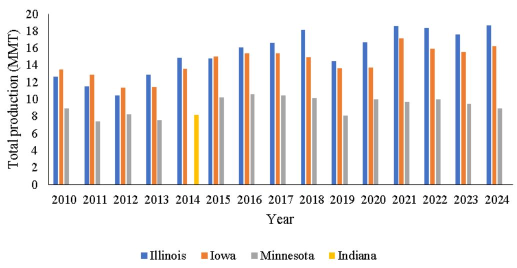

Figure 4: Top 3 soybean-producing U.S. states, 2010-2024

Supply, Demand, and Self-Sufficiency Trends in the U.S. (2000/01-2023/24)
From 2000/01 to 2023/24, total supply and demand showed a generally rising but inconsistent trend, while the SSR fluctuated around average (see Figure 5). This indicates a mostly balanced system with irregular surpluses and deficits. Total supply increased from 83.1 to 121.0 MMT, while demand increased from 76.4 to 111.6 MMT, showing a continuous rise in consumption along with increased production capacity. In the early 2000s, the SSR was close to 100%, indicating a state of self-sufficiency. However, fluctuation began mid-decade, with surpluses recorded from 2004/05 to 2006/07 (SSR >103%) and a significant drop in 2007/08 (87.6%), which indicates temporary increases in demand or decreases in supply. Beginning in 2014/15, supply growth increased, achieving its peak in 2018/19 at 132.8 MMT, which corresponded with the greatest SSR of 111.96%. After that, a significant decline occurred in 2019/20-2020/21, as demand growth exceeded supply, causing the SSR to drop below 95%. The post-2021 period shows recovered stabilization, with SSR returning to almost 100%, signifying an improved relationship between supply and demand. The results show a structurally stable system that is mostly self-sufficient in the long term but susceptible to sudden changes affecting production, demand structure, or market integration, illustrating the importance of policies that improve supply stability and control demand.

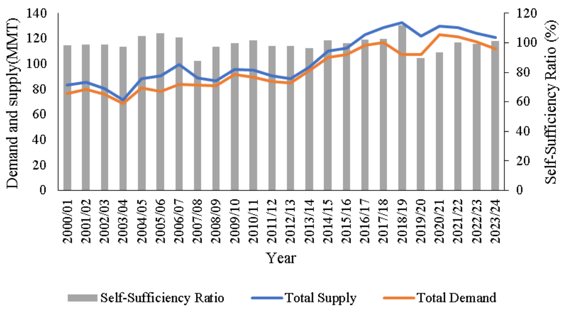

Figure 5: Supply, demand, and self-sufficiency trends of soybean in the U.S., 2000/2001-2023/2024

The supply and demand of soybeans in the U.S. are influenced by an interaction of productivity, environmental, and market-related factors. On the supply side, continuous improvements in yield, driven by genetic improvements, agronomic techniques, and the adoption of technology, have increased production, while decisions regarding planted area are affected by crop rotation with maize and relative price signals (Cerkasova, *et al.*, 2023; Rincker *et al.*, 2014). However, supply is susceptible to climate variability, such as temperature extremes, flooding, and rainfall fluctuations, which can result in yearly production changes (Quio *et al.*, 2023). On the demand side, soybeans serve as an essential component for animal feed, food items, and biofuel, linking domestic consumption to livestock and energy markets, while export demand—especially from China—significantly influences the absorption of U.S. production. Trade regulation, price volatility, and global market conditions collectively determine the equilibrium results for U.S. soybean supply and demand (Quio *et al.*, 2023; Chen & Yan, 2022).

Trends in U.S. Soybean Production and Utilization by Use Category (2000/01-2022/23)
From 2000/01 to 2022/23, U.S. soybean oil production increased almost 42% (from 8.36 to 11.90 MMT) (see Figure 6). During the same period, food, feed, and other applications decreased by around 13%, from 7.38 MMT to around 6.40 MMT, with their proportion of total production declining from almost 88% to about 54%. In contrast, the utilization of biofuels increased significantly, increasing from around 1% of production in 2000/01 to over 48% by 2022/23. This structural change indicates that the demand for soybean oil has been primarily driven by the biofuel industry, leading to higher market constraints and a closer correlation between soybean oil prices and energy markets, as well as biofuel policy trends. U.S. soybeans are being utilized in biofuel production due to their high oil content and established role as the principal domestic feedstock for biodiesel, supported by

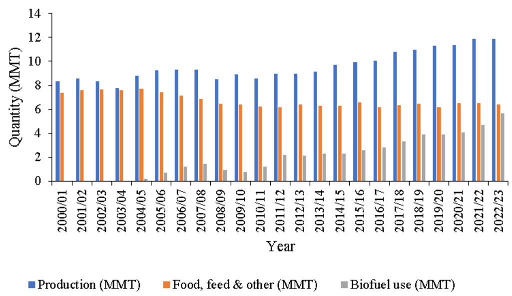

Figure 6: Annual trends in U.S. soybean production and utilization, 2000/01-2022/23

powerful legal initiatives like the Renewable Fuel Standard and an increasing need for renewable energy (Limb *et al.*, 2024; Brorsen, 2015). The increasing use of soybean-derived biodiesel is being driven by its need to reduce greenhouse gas emissions, its compatibility with current fuel infrastructure, and improvements in oil processing and conversion efficiency (Whistance *et al.*, 2023; Chandra *et al.*, 2025; Chen *et al.*, 2018). The environmental benefits of soybean oil compared to fossil fuels, in addition to ongoing investments in cleaner energy and carbon-reduction efforts, have increased domestic demand for soybean oil, thus driving the utilization of U.S. soybeans in the biofuel industry (DeCicco *et al.*, 2016; Pradhan *et al.*, 2012; Rajaeifar *et al.*, 2014).

Import Dependency, Export Intensity, and Stock-to-Use Dynamics

The import dependency increased gradually during the study period, increasing from 0.14% in 2000/01 to 1.52% in 2020/21, which shows the increased dependence on imports (see Figure 7). The growth was gradual in the first few years but rose after 2010/11, with import dependency rising from 0.45% to 0.87% by 2015/16 and nearly doubling by 2020/21. However, export intensity decreased overall, falling from 0.96% in 2000/01 to 0.66% in 2020/21. Despite a short-term rise in export intensity in 2010/11 (0.88%), it significantly dropped by 2015/16 (0.58%), which indicates a decreased priority for exports in relation to domestic supply.
The stock-to-use ratio had a decreasing trend, decreasing from 0.97% in 2000/01 to 0.66% in 2020/21, which signifies increasingly limited supply conditions over time. Following a period of relative stability, the ratio had a significant fall after 2010/11, which correlated

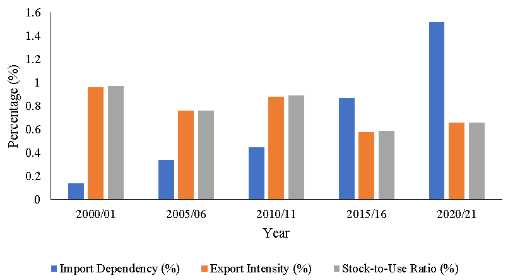

Figure 7: Import dependency, export intensity, and stock-to-use dynamics

with an increase in import dependency. By 2020/21, the combination of export intensity and stock-to-use ratios indicates diminished inventory buffers and increased pressure on domestic supply, hence supporting a shift towards increased import dependence and more vulnerability to market and supply-side problems.

U.S. Soybean Meal and Oil Supply Balance Dynamics (2000/01-2020/21) Soybean meal

The U.S. soybean meal market maintained a degree of self-sufficiency while being progressively sensitive to variations in demand. The import dependency increased gradually from 0.14% in 2000/01 to 1.52% in 2020/21, whereas export intensity showed fluctuations, decreasing from 0.96 in 2000/01 to 0.76 in 2005/06, increasing to 0.88 in 2010/11, then reducing to 0.58 in 2015/16, followed by a slight recovery to 0.66 in 2020/21. The stock-to-use ratio declined from approximately 0.97 in 2000/01 to 0.59 in 2015/16, with a little recovery to 0.66 in 2020/21, showing stricter market conditions and increased susceptibility to price volatility in recent years (see Figure 8a).

Soybean Oil

The figure shows distinct changes in structure in the U.S. soybean oil market. Import dependency remained low, increasing from 0.36% in 2000/01 to over 1% post-2015/16. This indicates continued domestic dominance with a modest rise in import reliance. Export intensity showed significant variation, reaching a peak of 14.4% in 2010/11 before decreasing to 6.9% in 2020/21. This shows fluctuations in global demand, biofuel policy changes, and global competition. The stock-to-use ratio decreased from approximately 15-16% in the early 2000s to 7.5% in 2015/16, with a minor rise to 8.5% by 2020/21, indicating limited market conditions and decreased inventory buffers (see Figure 8b).

Structural Change Analysis

Macroeconomic time series data can contain structural or institutional breaks (Kalsie & Arora, 2018). Standard ADF tests can assess a stationary series as non-stationary if structural breaks exist and are not adequately addressed

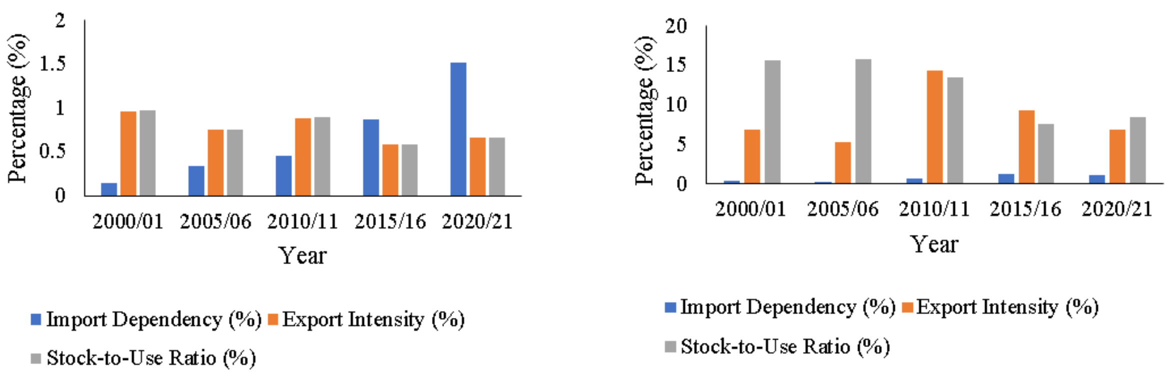

Figure 8: (a) U.S. soybean meal supply balance dynamics (b) U.S. soybean oil supply balance dynamics

(Hadri & Rao, 2008; Haldrup *et al.*, 2013). A structural change analysis method provided by Bai & Perron (1998) has been used in this study. This method of structural change analysis has been widely used in such as(Casini & Perron, 2018; Kristofersson & Anderson, 2006; Weideman *et al.*, 2017). The Bai-Perron multiple structural

Table 1: Results of Bai-Perron Multiple Structural Break Test

No. of breaks (m)	Breakpoint (Observation no.)	Break year(s)	RSS	BIC
0	-	-	268004.2	275.6
1	6	2007	113290.7	262.8
2	6, 19	2007, 2020	75854.4	260.2
3	6, 13, 19	2007, 2014, 2020	36036.3	250.0
4	5, 9, 13, 19	2006, 2010, 2014, 2020	20119.6	243.3
5	5, 9, 13, 16, 19	2006, 2010, 2014, 2017, 2020	19711.5	249.1
6	3, 6, 9, 13, 16, 19	2004, 2007, 2010, 2014, 2017, 2020	19967.3	255.5

break test applied to the level of the series identifies several statistically significant breaks. A lower Bayesian Information Criterion (BIC) indicates a better-fitting and more parsimonious model (Emiliano *et al.*, 2014; Sen & Bradshaw,
2017). Based on the BIC, the optimal model contains four breakpoints occurring around 2006, 2010, 2014, and 2020, indicating substantial regime shifts in the mean of

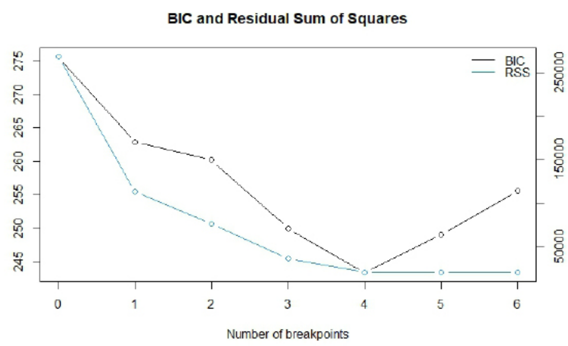

Figure 9: Graphical illustration of BIC and Residual sum of squares (RSS)

the series over time (see Table1 & Figure 9). Table

ADF Test

2 reports the Augmented Dickey-Fuller (ADF) unit root test results, indicating that lnus and lnprice are stationary at first difference, while lnend and lnexp achieve stationarity only after second differencing, suggesting apparent I(2) behavior in the series. However, as shown in Table 3, the variables show stationarity at levels after incorporating several structural breaks found using the Bai-Perron approach (seg1-seg4), supporting I(0) features. The expansion of biofuel mandates and energy-agriculture price integration in the mid-2000s (Kristoufek *et al.*, 2012), the shift into a Second Great Acceleration of global soybean trade marked by intensified globalization and food regime reorganization (Langthaler, 2022), the post-2008 Global Financial Crisis period marked by altered credit conditions and demand restructuring (Stiglitz, 2010), and the COVID-19-induced disruptions to agri-food supply chains and trade flows around 2020 (Weersink *et al.*, 2021; Mallory, 2021) were the possible shifters in the soybean market that correspond to these structural breaks. These results suggest that structural changes were the primary cause of the initial non-stationarity. Therefore, the variables meet the integration requirements for using the Johansen cointegration framework after considering structural breaks.

VAR Order Selection Criteria

Akaike's information criterion (AIC), Schwarz information criterion (SIC), and Hannan-Quinn criterion (HQC) have been used to determine the variance order

Table 2: ADF test result

Variables	At levels	At first difference	At second difference	Integration
	ADF			
Lnus	-3.124	-4.059**		I(1)
Lnend	-2.950	-3.404	-3.771**	I(2)
Lnprice	-2.061	-3.791**		I(1)
lnexp	-1.525	-2.883	-3.717**	I(2)

selection (Table 4). For the selection of criteria, different researchers have suggested different criteria for selection. For instance, Ivanov & Kilian (2005) states that the AIC produces accurate results for realistic sample sizes, HQC is suitable for data models, and for sample sizes smaller than 120, the Schwarz Information Criterion (SIC) is more accurate. Liew (2021) states that AIC is superior for sample size below 150, HQC for larger data, and SIC when parsimony order is required rather than true order. Asghar and Abid (2007) AIC was found suitable for sample sizes below 60, HQC for 120 and for equal to or greater than 240, SIC was found suitable. Lag 2 has been selected from all criteria

VAR Result

The estimated VAR equations are:

*logpricet=0.3269logpricet−1+0.1005logexpt−1+0.1383 logendt−1−0.9010logust−1−0.4938** logpricet−2+0.6465**logexpt−2+0.0527logendt−2−0.1499logust−2 − 0.0482*t − 1.1039 *** seg1 − 0.6526** seg2 − 0.4695* seg3 − 0.4483*** seg4 +ε1t (13)*

*logexpt=7logendt−1−0.3576logust−1−0.4116 logpricet−2+0.9641**logexpt−2+0.3030**logendt−2+0.0268logust−2− 0.0471t − 0.7708 seg1− 0.3411seg2 − 0.4030 seg3 − 0.2498 seg4 + ε2t (14)*

Table 3: ADF after detrending for structural breaks

Variable	ADF_stat	ADF_5pct	Adf_1	Integration
logprice	-3.894**	-3	-3.75	Stationary at levels
logexp	-3.655**	-3	-3.75	Stationary at levels
logend	-4.649**	-3	-3.75	Stationary at levels
logus	-5.860**	-3	-3.75	Stationary at levels

*Notes:**Significant at the 5%,*** significant at 1%*

logendt= −0.2353logpricet−1 − 0.5894 logexpt−1 − 0.4796logendt−1 + 4.5474 logust−1 − 0.7939 logpricet−2 − 0.6529 logexpt−2 − 0.2543logendt−2+1.0977 logust−2+0.1941*t + 3.4141** seg1 + 2.4338*seg2+2.0612*seg3+1.1715**seg4+ ε3t (15)*

*logust= −0.1188logpricet−1+0.1275logexpt−1−0.2895***logendt−1+1.2290***logust−1 + 0.2076 logpricet−2 − 0.2782* logexpt−2+0.1484** logendt−2+0.1469logust−2+ 0.0230t + 0.5624*

Table 4: Lag order selection criteria for the VAR model

Lag	AIC	SIC	HQC
1	-15.23	-14.24	-15.04
2	-16.26*	-14.47*	-15.91*

Notes: Lag length was selected using the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan–Quinn Criterion (HQC). The optimal lag length is indicated by an asterisk (*). All three criteria select a lag order of two.

seg1 + 0.3030seg2+0.2737***seg3+0.2417***seg4+ ε4t (16)*

The estimated VAR(2) model incorporating dummies of structural break shows complex interdependencies between U.S. soybean prices at harvest, export values, ending stocks, and domestic production (see Table 5). The price equation shows that there is a strong negative effect of lagged production on prices, with the first lag showing a coefficient of -0.9010. This clearly indicates that increased soybean production within the United

Table 5: Estimated VAR(2) results with structural break dummies

Sample size: 20								
Log Likelihood: 129.873								
Dependent	**Independent**	**Estimate**	**Std_Error**	**t_value**	**p_value**	**Sig.**	**R squared**	**Adjusted R square**
logprice	logprice.l1	0.326	0.220089	1.485327	0.181039		1	0.999
	logexp.l1	0.101	0.129552	0.775921	0.4632			
	logend.l1	0.138	0.093935	1.471991	0.184501			
	logus.l1	-0.901	0.474257	-1.89974	0.099244			
	logprice.l2	-0.494	0.1861	-2.65341	0.032779	**		
	logexp.l2	0.647	0.193071	3.348405	0.012278	**		
	logend.l2	0.053	0.048538	1.086262	0.313347			
	logus.l2	-0.150	0.291905	-0.51346	0.623431			
	trend	-0.048	0.017292	-2.78779	0.026994	*		
	seg1	-1.104	0.257417	-4.2883	0.003618	***		
	seg2	-0.653	0.231156	-2.82319	0.025655	**		
	seg3	-0.469	0.230116	-2.04007	0.080704	*		
	seg4	-0.448	0.132578	-3.38123	0.011739	***		

logexp	logprice.l1	0.228	0.485709	0.469558	0.652946		1	0.999
	logexp.l1	0.237	0.286652	0.807849	0.445758			
	logend.l1	-0.098	0.163086	-0.59884	0.568143			
	logus.l1	-0.358	1.10505	-0.32361	0.755687			
	logprice.l2	-0.411	0.566941	-0.72602	0.491385			
	logexp.l2	0.964	0.384925	2.504618	0.040716	**		
	logend.l2	0.303	0.109389	2.770123	0.027689	**		
	logus.l2	0.027	0.478556	0.055916	0.956971			
	trend	-0.047	0.041481	-1.13618	0.293278			
	seg1	-0.7708	0.619941	-1.2433	0.253782			
	seg2	-0.3411	0.555503	-0.61411	0.558562			
	seg3	-0.403	0.544991	-0.73938	0.483728			
	seg4	-0.2498	0.328354	-0.7607	0.471675			
logend	logprice.l1	-0.2353	0.866597	-0.27153	0.79382		0.993	0.975
	logexp.l1	-0.5894	0.519064	-1.1355	0.293544			
	logend.l1	-0.4796	0.282534	-1.69736	0.13344			
	logus.l1	4.5474	1.957836	2.322643	0.053187	*		
	logprice.l2	-0.7939	1.184342	-0.67035	0.524125			
	logexp.l2	-0.6529	0.835002	-0.78194	0.459878			
	logend.l2	-0.2543	0.219024	-1.16125	0.283603			
	logus.l2	1.0977	0.963019	1.139843	0.291848			
	trend	0.1941	0.069838	2.779213	0.027329	*		
	seg1	3.4141	1.086588	3.142058	0.016332	**		
	seg2	2.4338	0.973738	2.499445	0.041025	*		
	seg3	2.0612	0.954741	2.158892	0.067719	*		
	seg4	1.1715	0.611376	1.916239	0.096864	**		
logus	logprice.l1	-0.1188	0.162203	-0.73261	0.487599		1	0.999
	logexp.l1	0.1275	0.0868	1.469307	0.185205			
	logend.l1	-0.2895	0.054639	-5.29909	0.001124	***		
	logus.l1	1.229	0.202151	6.079574	0.000501	***		
	logprice.l2	0.2076	0.139735	1.485319	0.181041			
	logexp.l2	-0.2782	0.114829	-2.42274	0.045907	*		
	logend.l2	0.1484	0.025682	5.776439	0.00068	**		
	logus.l2	0.1469	0.169975	0.864132	0.416141			
	trend	0.023	0.006295	3.657443	0.008098			
	seg1	0.5624	0.104957	5.358523	0.001054	***		
	seg2	0.303	0.078475	3.86137	0.0062	***		
	seg3	0.2737	0.071985	3.802431	0.006694	***		
	seg4	0.2417	0.044014	5.491442	0.000915	***		

*Notes: The table reports coefficient estimates, standard errors, t-statistics, and p-values for the VAR(2) model including a linear time trend and structural break dummies (seg1–seg4). The dependent variables are the logarithms of U.S. soybean harvest price (logprice), export value (logexp), ending stocks (logend), and production (logus). Structural break dummies correspond to break years identified using the Bai–Perron multiple breakpoint test. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

States substantially reduces the harvest prices in the short run. Export values have a significant positive effect on prices at the second lag (0.6465, p<0.01). This shows that the demand effect from export values has a substantial influence within the time framework of one growing season. The presence of structural breaks can be seen in all equations, with particularly strong negative effect on prices (seg1: -1.1039, p<0.001; seg2: -0.6526, p<0.01) and positive effects on ending stocks (seg1: 3.4141, p<0.01), suggesting that external shocks-possibly related to trade policy changes, demand shifts in major importing countries, or supply chain disruptions-have asymmetrically affected different components of the U.S. soybean market. The export equation exhibits relatively stable autoregressive patterns with high persistence (0.9641 at lag 2), indicating that export values may be driven more by long-term contracts, previous trade value and stock of soybean relationships as well than by immediate price fluctuations. Ending stocks have the highest dynamics, with a strong positive first- order lag effect (4.5474, $p<0.05$), suggesting a positive relationship in which greater harvests result in an accumulation of stock, as would be expected when supply exceeds immediate demand. The production equation reflects a strong, persistent (1.2290 at lag 1, $p<0.001$) and significant negative relationship with ending stocks (-0.2895, $p<0.001$), implying that high stock levels may lower production in the subsequent year by discouraging planting decisions. The time trend variable reflects a significant positive influence on ending stocks (0.1941, $p<0.05$), showing a positive trend in storage capacity or inventory practices over time. Overall, the model reflects a valid dynamic of agricultural commodity markets, in which production levels influence prices positively, with trade serving a price support role, and inventory working as a buffer, with break points indicating a departure from normal conditions in U.S. soybean

Granger Causality Test

Granger causality provides insights into the direction of the relationship between the variables. Table 6 indicates a bidirectional relationship between US soybean production, price at harvest, and ending stock of soybeans. The export value of soybean however, exhibits a bidirectional relationship with price at harvest and ending stock of soybeans, but not with domestic soybean production. The result shows that the price signal plays an important role in coordinating market decisions in the supply chain. The prices also affect exports, showing the tight linkage between domestic price formation and international trade dynamics, where export demand influences prices while prices simultaneously affect export competitiveness. Similarly, the bidirectional relationship between exports and ending stocks indicates that stock-related decisions respond to export opportunities, while stock availability pressures export capacity. An important finding is that production does not Granger-cause exports, indicating that production levels alone do not predict future export values, which might be due to political and administrative dimensions of international trade. However, ending stocks Granger-cause production and production reciprocally affects stocks shows that the stock-production feedback loop, where high quantities in stocks signal, dampens the future planting decision. The combined evidence from the VAR coefficients and Granger causality tests has shown a market structure in which prices are the transmission mechanism of information, coordinating decisions in three dimensions-production, trade, and storage-while structural breaks highlighted the vulnerability of the system to external shocks that may fundamentally alter market relationships.

Table 6: Pairwise Granger causality test results for U.S. soybean market variables

Cause	Effect	Chi-square statistics	p-value
logprice	logexp	6.982708	0.00823***
	logend	4.554215	0.032838**
	logus	3.864493	0.049318**
logexp	logprice	6.982708	0.00823***
	logend	6.01041	0.014222**
	logus	0.634432	0.425734
logend	logprice	4.554215	0.032838**
	logexp	6.01041	0.014222**
	logus	5.047726	0.024658**
logus	logprice	3.864493	0.049318**
	logexp	0.634432	0.425734
	logend	5.047726	0.024658**

*Notes: The null hypothesis is that the "Cause" variable does not Granger-cause the corresponding "Effect" variable. Rejection of the null indicates predictive causality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Diagnostic Test

Serial Correlation Test

Table 7 reports the Breusch–Godfrey test results for each equation in the VAR system. In all cases, the p-values exceed 0.05, so we fail to reject the null hypothesis of no serial correlation. This indicates that the residuals do not show evidence of autocorrelation, supporting the adequacy of the selected lag structure and improving the reliability of statistical inference.

Table 8 presents the Breusch–Pagan heteroskedasticity test. The price equation shows evidence of heteroskedasticity ($p = 0.032$), and the ending-stocks equation is marginal (p = 0.0502). Therefore, robust (heteroskedasticity-consistent) standard errors were applied for the affected equations to ensure valid hypothesis testing and inference, while the export and production equations do not indicate heteroskedasticity at the 5% level.

Stability Test

The stability of the model was tested by using OLS-CUSUM. The CUSUM plots for all four equations-logprice, logexp, logend, and logus-remained well within the 5% significance boundaries (indicated by the red dashed lines) throughout the sample period. The cumulative sum of recursive residuals did not exhibit any systematic deviation from zero, and none of the CUSUM statistics crossed the critical bounds.

Normality Test

Table 9 shows the Shapiro–Wilk normality test results. Since all p-values are greater than 0.05, we fail to reject the null hypothesis that residuals are normally distributed. This suggests that the residual distribution is broadly consistent with normality assumptions, which supports the overall stability and interpretability of the VAR estimates and related impulse-response results.

Table 7: Breusch-Godfrey test for serial correlation

Variables	P value
Logprice	0.551
Logexp	0.293
Logend	0.374
Logus	0.243

Figure 10 shows the impulse response functions for all variable pairs in the VAR system. The diagonal elements reveal strong own-variable persistence, with most variables exhibiting oscillatory response over 8-10 periods. With narrow confidence, production shocks generate the most pronounced responses in ending stocks (peak response of 0.10 at period 2) and exports (0.05, significant through period 6). An increase in production leads to a statistically significant accumulation of ending stocks and a moderate increase in exports. With a wide confidence interval and positive oscillation near zero, production shocks show minimal impact on prices, indicating that supply adjustments are absorbed primarily through stock changes rather than immediate price corrections. Price shocks have a positive effect on export values with an immediate response of 0.05 that remains significant through period 4, suggesting that higher prices enhance export competitiveness or signal quality in international markets. The limited response of production to price signals indicates the inelasticity of planting decisions in the short to medium run, consistent with production cycles in agriculture.

Table 8: Breusch-pagan heterskadasticity test

Variables	P value
Logprice	0.0324
Logexp	0.5231
Logend	0.0502
Logus	0.7635

CONCLUSION

The soybean production has shown an increasing trend worldwide over the past two decades, with harvested area expanded by 84% and total production rising by 130%. A similar pattern is seen in the U.S., where soybean production increased from 75.06 MMT in 2000 to 116.96 MMT in 2023. During the same period, the land planted with soybeans expanded only slightly, from 29.30 to 33.35 Mha (+13.8%), contributing to a 51.0% increase in production. The top three soybean-producing states, Illinois, Iowa, and Minnesota, contribute approximately 34% to 39% of total U.S. production each year. From 2010 to 2023, production in these states showed a generally increasing pattern despite yearly fluctuations. They consistently generate about one-third of the nation's soybean production, showing their central role in the U.S. soybean supply. Similarly, total supply and demand increased over time, which has accompanied production growth, rising consumption, and structural changes in use.

Table 9: Normality test using Shapiro Wilk test

Variables	P value
Logprice	0.6933
Logexp	0.192
Logend	0.091
Logus	0.399

Moreover, the U.S. soybean oil production increased by nearly 42%, while the use of soybeans for biofuels shifted sharply, rising from around 1% of production in 2000/01 to over 48% by 2022/23, alongside a decline of about 13% in traditional food, feed, and other uses. The U.S. soybean market has also become slightly more reliant on imports, with import dependence increasing from 0.14% in 2000/01 to 1.52% in 2020/21, while the share of soybeans exported declined from 0.96% to 0.66%. A similar pattern is observed in the soybean meal market, where import dependency increased, and export intensity fluctuated over time. Results from the VAR coefficients and Granger causality tests indicate that prices play an important role as a transmission mechanism coordinating decisions across production, trade, and storage, while identified structural breaks show the system's vulnerability to external shocks. These findings suggest that future research should place greater emphasis on inventory management and biofuel-related demand shifts to enhance market stability under changing

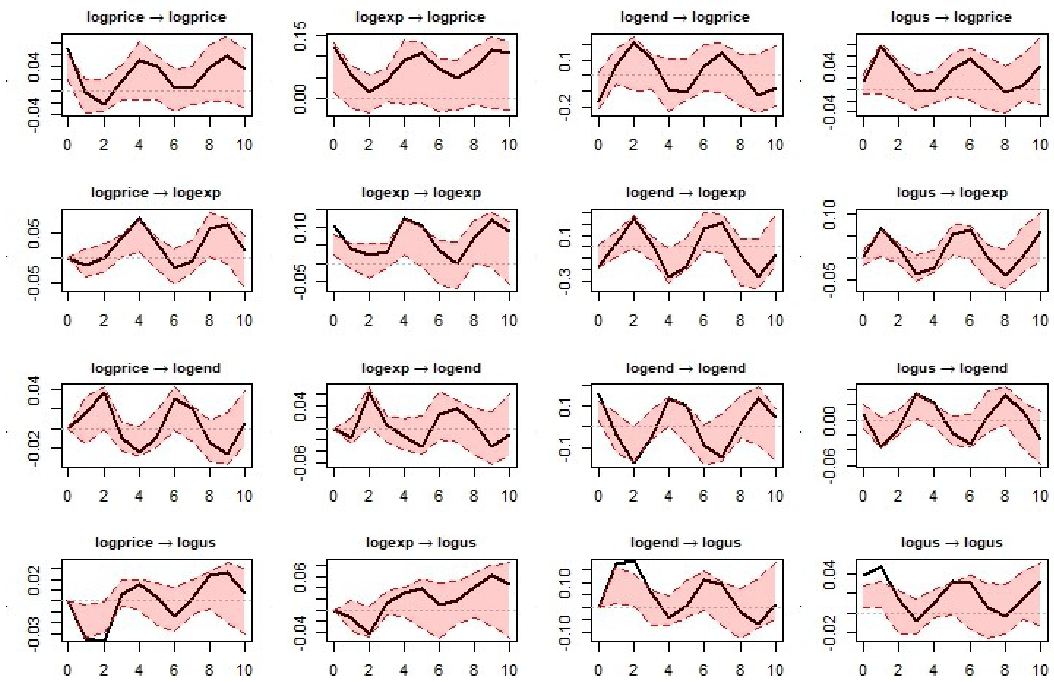

Figure 10: Impulse response function with 95% bootstrap confidence interval

global conditions.

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