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ARTICLE

Methodological proposal for market risk assessment in agriculture: a case study of the Hass avocado

Proposta metodológica para avaliação do risco de mercado na agricultura: estudo de caso do abacate Hass

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Abstract: This study addresses agricultural risks as an emerging category in risk assessment and focuses on measuring market risk and its impact on producers and financial entities. Since the lack of measurement can limit producers' decisions and hinder access to financing and planning measures to mitigate or transfer risks, a methodology is proposed and validated to evaluate market risk in the agricultural sector through a case study focused on the Hass avocado in Antioquia. The results lead to quantifying the market risk as high and proposing using three indicators associated with a historical context in avocado prices. Furthermore, risk qualification is similar when exploring risk measurement in a forecasting context due to a downward trend in forecast prices. In conclusion, it is determined that the proposed risk measurement methodology is adaptable to other agricultural systems and makes it possible to identify and understand market risks, tracing the route for making more informed decisions in production and financial leverage of the crop.

Keywords: Agricultural finances, risk management, agricultural risk, agricultural market risk, agricultural economy.

Resumo: Este estudo aborda os riscos agrícolas como uma categoria emergente na avaliação de riscos e se concentra na medição do risco de mercado e seu impacto sobre os produtores e as entidades financeiras. Como a falta de mensuração pode limitar as decisões dos produtores e dificultar o acesso ao financiamento e às medidas de planejamento para mitigar ou transferir riscos, é proposta e validada uma metodologia para avaliar o risco de mercado no setor agrícola por meio de um estudo de caso focado no abacate Hass em Antioquia. Os resultados permitem quantificar o risco de mercado como alto e propor o uso de três indicadores associados a um contexto histórico nos preços do abacate. Além disso, a qualificação do risco é semelhante ao explorar a medição do risco em um contexto de previsão devido a uma tendência de queda nos preços previstos. Em conclusão, determina-se que a metodologia proposta de mensuração de risco é adaptável a outros sistemas agrícolas e possibilita identificar e compreender os riscos de mercado, traçando o caminho para tomar decisões mais informadas na produção e alavancagem financeira da cultura.

Palavras-chave: finanças agrícolas, gestão de riscos, risco agrícola, risco de mercado agrícola, economia agrícola.

1 Introduction

Correctly measuring agricultural risks is crucial for producers and financial entities to make informed decisions regarding financial operations and the optimal capital structure of production systems (Birthal et al., 2021; Kahan, 2013b). Failure to do so prevents producers from determining the impact risks can have on their businesses and increases uncertainty in decision-making about mitigating or transferring them. Market risk plays a fundamental role in agricultural risks, as it reflects the effects of agroclimatic and health risks on supply and directly impacts financial risk (Grupo Banco Mundial, 2017).

Given the importance of the task, a thorough study into the most appropriate methodology for measuring market risk was conducted. This involved a comprehensive review of experiences in agricultural risk measurement, leading to the selection and design of algorithms using relevant methodologies. The result is a proposal for quantifying market risk in the agricultural sector that stands out from previous research approaches. Unlike those approaches, which are based on a single indicator for specific measurements, this research collects and structures a group of indicators considered relevant in measuring agricultural market risk, demonstrating the rigor and depth of the study.

Additionally, using inductive reasoning, the measurement of market risk will be addressed explicitly for the case of Hass avocado cultivation due to the notable dynamism exhibited by the avocado sector in Colombia, which ranks it among the top 10 crops with the most planted areas (Colombia, 2023), with 130,000 hectares planted and production of 1.09 million tons in 2023. Furthermore, it has gained international recognition due to its quality and versatility, with exports increasing from 5,543 tons in 2015 to 138,315 tons in 2024, with the Netherlands, the United States, and the United Kingdom as the main markets (Asociación Nacional de Comercio Exterior, 2025a).

Based on the arguments presented, the objectives of this research focus on identifying market risk measurement methodologies, which provide optimal results for producers' and financial entities' decision-making, developing algorithms for market risk assessment, and testing the feasibility of the proposal by measuring market risk in the Hass avocado production system in Antioquia.

As a main conclusion, this research contributes to understanding the risks faced by agricultural producers and suggests the potential transformative impact of the measurement proposal. The possibility of replicating this proposal in other agricultural production systems, given that the indicators used to measure market risk could improve the decision-making of financial entities regarding financing policies for these systems, is a significant step forward. Furthermore, based on measurement, agricultural producers could make decisions regarding activities to mitigate or transfer market risk, thereby reshaping the risk landscape in the agricultural sector.

2 The Hass avocado in Colombian agriculture

Colombia's agro-climatic conditions provide a competitive advantage in cultivating Hass avocado. The absence of distinct seasons permits harvesting for ten months of the year (except March and August) (Bernal Estrada & Díaz Diez, 2020, p. 301), positioning the country as a reliable and continuous supplier in international markets. This trait has been crucial in the commercial expansion of the product, enabling Colombia to increase its share of the world market and strengthen trade relations with large importers (Procolombia, 2025).

According to the Food and Agriculture Organization - FAO (Food and Agriculture Organization of the United Nations, 2024), during the year 2023 Colombia produced 1,085,765.75 tons of avocados, which positions it second among producers worldwide, after Mexico, which produced 2,973,344.42 tons. Bearing in mind that in 2010, when the first exports of Hass avocado were made in Colombia, the country ranked fourth with 205,443 tons; consequently, it is possible to infer that there has been sustained growth driven by favorable agroclimatic conditions (Rondón Salas et al., 2020) and growing international demand, especially for the Hass variety, which, as of 2012, had managed to be positioned in the Netherlands and, in more recent years, the United States, China, the United Kingdom, and Spain, achieving exports by 2024 that exceeded 309 million dollars, equivalent to about 138,315 tons (Asociación Nacional de Comercio Exterior, 2025a). The growing impact of Hass avocado cultivation in Colombia is also evident in its contribution to agricultural GDP. According to calculations in DANE's technical annexes (Colombia, 2025), this share increased from 0.1% in 2015 to 2% in 2024, reflecting an annual growth rate of 34.93% over the last decade.

The cultivation of the Hass avocado has become a strategy for agricultural diversification in regions traditionally dependent on coffee. States such as Antioquia, Caldas, and Risaralda have discovered an alternative that has enhanced employment generation for peasant families. This has resulted in processes that foster economic and social development in the producing regions (Asociación Nacional de Comercio Exterior, 2025b). Due to its profitability, increasing international demand, adaptability, role in diversifying national agriculture, and capacity to positively transform the agricultural and social landscape in the producing regions, the Hass avocado has established itself as a strategic crop for Colombia. It represents a significant opportunity for strengthening the Colombian agricultural-export sector.

3 Theoretical Foundation

The agricultural sector has faced a variety of risks associated with production (droughts, excessive rain or winds), the market (product price drops or input price increases), finance (inability to repay loans, low profitability, liquidity problems), and institutions (unexpected changes in government policies). Additionally, these risks have shown cascading effects, meaning that agricultural-climatic risk can affect production, increase sanitary risk, impact prices, and, therefore, market risk, which in turn produces effects on financial risk leading to changes in institutional policies (Pelka et al., 2015). Thus, current discussions in the field emphasize the importance of examining agro-risk management issues that evaluate these sources of risk (Kahan, 2013a; Komarek et al., 2020). Therefore, studying market risk measurement in the agricultural sector constitutes a potential contribution to agricultural finance.

Moreover, the need for more understanding of the risks faced by financiers and producers leads to credit rationing, which restricts financing opportunities for producers (Montoya & Montoya, 2022). This is why Dias et al. (2023) highlight the importance of credit access in the production of temporary crops in northeastern Brazil, emphasizing its relevance in regions prone to adverse climatic conditions. Similarly, Brum et al. (2023) underscore the importance of price analysis in the livestock market and suggest that dynamic linear models provide valuable information on price projections and future trends. Guimarães & Guanziroli (2023) explore the influence of investment funds on corn prices on the Chicago Board of Trade, indicating the additional risk that the presence of financial actors can generate in agricultural markets. Arias Vargas et al. (2022) highlight the relevance of modernizing the agricultural sector, supported by efficient management, to mitigate risk. Lastly, Carvalho & Felema (2022) propose an evaluation of economies of scale and scope in the production of pigs, chickens, and corn, highlighting the importance of understanding these concepts to reduce costs and improve competitiveness.

Overall, risk assessment in the agricultural sector must consider factors such as credit access, price dynamics, the influence of financial actors, and production system efficiency. The importance of evaluating risks in historical and forecast contexts (Ávila, 2009) is highlighted to support financial and production decisions in a well-founded manner. Within the framework of the idea above, the following sections present the calculation methodologies used according to the context of analysis and outline the properties, benefits, and application contexts of these methodologies.

3.1 Historical Context

3.1.1 Historical Volatility Calculation Methodology

Since the object of study is the behavior of agricultural product prices. The Chicago Mercantile Exchange (CME GROUP) is a global reference for measuring this object; the volatility calculation methodology proposed by CME GROUP, described by Piot-Lepetit & M'Barek (2011, p. 29) and used by Assouto et al. (2020) to calculate the volatility of corn cultivation and conclude that this volatility is a crucial aspect influencing producers' decisions to increase their production and planted areas, is used.

Additionally, according to the Food and Agriculture Organization (Food and Agriculture Organization of the United Nations, 2010), price volatility can significantly impact food security and the livelihoods of farmers and consumers, particularly in developing countries. Furthermore, the calculation of price volatility can be used to understand the effect of price changes on aggregate economic activity and the level of economic integration, as Gozgor (2019) did.

3.1.2 Value at Risk (VaR) Calculation Methodology on Price Fluctuation

Value at Risk (VaR) "is defined as the risk of loss on positions both on and off the balance sheet, arising from movements in market prices" (Arbeláez & Ceballos, 2005, p. 45). Although VaR is primarily used for risk measurement in financial markets, it is beneficial for assessing market price risk in the agricultural sector, as Chuan et al. (2010) did using fruit prices in China to identify different levels of risk in some fruits traded in this region.

Validation of this measurement methodology can also be found in Leucci et al. (2014), who used it to analyze food and energy commodity prices, identifying significant intertemporal relationships between corn, soybean oil, rapeseed, and petroleum prices. They determined that corn and soybean prices are mainly influenced by the energy market, especially in the United States, where competition for crops between food and biofuels affects the market.

Lastly, van Oordt et al. (2021) proposed, using extreme value theory and VaR, to demonstrate that agricultural commodity returns have fat tails due to productivity shocks. With nearly 90 years of data, they confirmed that eight agricultural products have fat-tailed return distributions, validating the risk methodology. They highlighted the frequency of extreme movements in these commodity prices, demonstrating their volatility in the market.

3.1.3 Beta Index Calculation Methodology

Although the Beta index "represents the sensitivity of stock returns to market changes" (Insana, 2022, p. 2), it has been used in risk measurement of other assets such as commodities, which also include agricultural products. A finding in using the index has important implications for portfolio hedging and risk management, as presented in Bonato's (2019) work, which examines changes in price and return dynamics in the agricultural market during the boom and bust period of 2007-2008. With intraday frequency data and the Beta GARCH model, an increase in correlations between agricultural commodities and between these and oil has been observed since 2006. Spillover effects became more noticeable before the price drop, anticipating an increase in correlations, and the optimal short hedge ratio in oil to protect a long position in an agricultural commodity also grew significantly after 2006.

3.2 Forecasting Moment

3.2.1 Box y Jenkins Models

Now, as a first forecasting methodology for agricultural market prices, the Box and Jenkins models can be considered, as used by Zou et al. (2007), who compared the predictive capability of ARIMA, artificial neural networks, and linear combination models to forecast wheat prices in the Chinese market. They concluded that the combined model significantly improves prediction accuracy compared to individual models, with the artificial neural network being the most effective and recommended model for forecasting future cereal prices in China.

Similarly, Marroquín Martínez & Chalita Tovar (2011) used the Box-Jenkins methodology to identify an autoregressive integrated moving average (ARIMA) econometric model that fits the time series behavior of nominal wholesale tomato prices in Mexico. Using this model, they made forecasts for 12 months, from December 2008 to November 2009.

At the same time, there is the work of Kitworawut & Rungreunganun (2020), who used the methodology for predicting corn prices in Thailand; Sabu & Kumar (2020), who used it to forecast areca nut prices in Kerala, India; Spriggs (2014), who employed the methodology to predict corn prices in Indiana; and KumarMahto et al. (2019), who used this methodology to predict sunflower seed prices in the Kadiri market, Anantapur district, and Andhra Pradesh, India.

Finally, there is the work of Şahinli (2020), who employed exponential smoothing methods and the Box-Jenkins methodology to forecast potato prices in Turkey, including Holt-Winters multiplicative (HWM) and additive (HWA). Using time series data from January 2005 to July 2019, they investigated and forecasted price trends for the end of 2019. They found that the ARIMA method provides acceptable accuracy in price predictions according to metrics such as MAPE, RMSE, and MAD.

3.2.2 Neural Networks

Li et al. (2010) serve as a reference in applying neural networks to predict agricultural product prices, focusing on using Artificial Neural Networks (ANN) to forecast short-term tomato prices. They compare a feedforward ANN model with the ARIMA time series model, using daily, weekly, and monthly wholesale price data from 1996 to 2010. Results show that the ANN model outperformed the ARIMA model in predicting prices up to a week in advance, with a positive correlation and a relative error of less than 5.0%.

On another note, Chuluunsaikhan et al. (2020) forecasted pork prices in South Korea from 2010 to 2019, employing classical statistics, machine learning, and deep learning models. They emphasized using Long Short-Term Memory Networks (LSTM), which yielded the best prediction model for pork prices in South Korea.

Similar studies include the work of Mulla & Quadri (2020), who used AI models to predict rice, arhar, bajra, and barley prices in India; Gu et al. (2022), who employed an LSTM model to predict cabbage and radish prices in the South Korean market; Q. Chen et al. (2019), using LSTM to predict cabbage prices in Fuzhou for the Chinese market; Purohit et al. (2021), who applied various LSTM methodologies to predict tomato, onion, and potato prices in India; Grewal & Daneshyari (2022), creators of a website in India showing agricultural producers future price behavior based on LSTM models; Jin et al. (2019), applying LSTM to predict Chinese cabbage and radish prices in the Korean agricultural market; P. Chen and Ye (2022) proposed a hybrid CNN + LSTM model for predicting agricultural prices. Finally, Z. M. Li et al. (2013) used a Convolutional Neural Network with a Genetic Algorithm (CNN-GA) to predict pork prices in the Chinese market.

4 Methodology

The research process carried out for market risk assessment is based on reviewing national and international experiences in the agricultural sector and gathering secondary sources of information such as articles and documents. The study employs a descriptive and quantitative analytical method (Méndez, 2020). Time series models are used to fill in missing data and correct outliers for data handling.

Thus, the research is structured into several levels:

a. Literature review on methodologies applied in the agricultural sector for modeling market and financial risk. Successful experiences are identified, and relevant aspects of their application are analyzed.
b. A breakdown of each identified methodology, including the application process and necessary assumptions. The complexity of information management is evaluated.
c. Evaluation and selection of the best methodologies, considering their adaptation to the Colombian context, as shown in Table 1, and available sources of information.
d. Design of algorithms reflecting the processes of the selected methodologies and their implementation in R and Python environments.
e. Methodological testing in the Hass Avocado production system.

To ensure a thorough and context-specific evaluation and selection of the methodologies in Table 1, a survey was conducted with 30 experts in agricultural economics, risk management, and financial modeling, focusing on the Colombian agricultural sector. These experts have between 5 and 15 years of professional experience in their respective fields, providing a solid basis for their assessments. The experts were asked to evaluate each methodology based on six specific criteria: Indicator Strength, Implementation Complexity, Degree of Recency, Degree of Use in Literature, Adaptability to the Colombian Context, and a final Selection Decision. Indicator Strength refers to the capacity of the methodology to produce accurate and relevant results for assessing market risk in agriculture.

- Implementation Complexity evaluates the level of technical difficulty and resources required to apply each methodology in practice.
- Degree of Recency measures how up-to-date the methodology is regarding recent academic and practical applications.
- Degree of Use in Literature indicates how frequently the methodology has been applied and cited in recent scientific studies, reflecting its acceptance and validation.
- Adaptability to the Colombian Context assesses how well the methodology fits the characteristics of the Colombian agricultural sector, including data availability, market dynamics, and institutional support.
- The final criterion, Selection Decision, summarizes whether the methodology was considered suitable for practical application in the study, based on the collective expert evaluation.

After analyzing the results from the expert evaluations, five methodologies were ultimately selected as the most suitable for assessing market risk in the Colombian agricultural sector. This selection was based on a comparative analysis of the evaluation criteria presented in Table 1, emphasizing the Adaptability to the Colombian Context. Priority was given to those methodologies that demonstrated strong indicator performance and widespread use in literature and proved practical and relevant under local market conditions. This approach ensured that the selected methodologies align with the specific needs, data availability, and operational capacities of Colombia's agricultural producers and institutions.

The consolidated results of these assessments are presented in Table 1, where the most suitable methodologies were highlighted according to the experts' consensus.

Table 1. Selected Methodologies for Market Risk Assessment

Methodology Type	Methodology	Indicator Strength	Implementation Complexity	Degree of Recency	Degree of Use in Literature	Adaptability to Colombian Context	Selected
Historical	Volatility Indicator	High	Low	High	High	High	Yes
Historical	Price Fluctuation VaR	High	Medium	High	High	High	Yes
Historical	Beta Index	Medium/High	Medium	Medium	Medium/High	High	Yes
Historical	Historical Mean	Low	Low	Low	Medium	Low	No
Historical	Historical Simulation	Low	Medium	Medium	Low	Low	No
Forecast	Box-Jenkins Methodology	Medium/High	Medium	Medium	High	High	Yes
Forecast	Neural Networks	High	High	High	High	High	Yes
Forecast	Moving Average	Medium	Low	Low	Medium	Medium	No
Forecast	Exponential Smoothing	Medium	Medium	Medium	Medium	Medium	No
Forecast	Monte Carlo Simulation	Medium	Medium	Medium/High	High	Medium	No
Forecast	GARCH-type Models	Medium	High	Medium/High	High	Low	No
Forecast	Support Vector Regression	Low	High	Medium	Medium	Low	No
Forecast	Holt-Winters	Medium	Medium	Medium	Medium	Low	No

Source: Own elaboration.

Finally, the information source used for methodology application is reported in the Agricultural Sector Price Information System (SIPSA) of the National Administrative Department of Statistics (DANE). Filters include the production system equal to Hass Avocado and the wholesale market. Finally, an AR model of order P methodology is applied for data imputation.

5. Results and Discussion

Figure 1 shows the time series of Hass Avocado prices, trending over time. We then apply the methodologies to this series for historical analysis and forecasting.

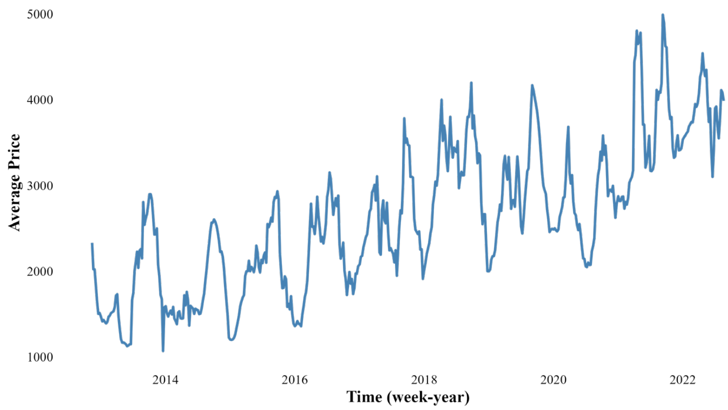


Figure 1. Imputed price series for Hass Avocado traded at the Wholesale Center of Antioquia 2012-2022.

Source: Own elaboration based on data from the Agricultural Sector Price Information System (SIPSA) - DANE.

5.1 Historical Context

5.1.1 Volatility Indicator

First, the historical volatility indicator is calculated for the series of returns of Hass Avocado prices. The result obtained was 0.26, indicating that the volatility of the returns of the Hass Avocado price series fluctuates around 26%. Considering this, the question arises: Is this volatility low, medium, or high? To answer this question, the same exercise is conducted for the price of Hass Avocado across all centers reported by SIPSA, and three volatility intervals are calculated based on the results obtained for all centers. These intervals are presented in Table 2.

Table 2. Intervals for measuring volatility of returns of Hass Avocado prices.

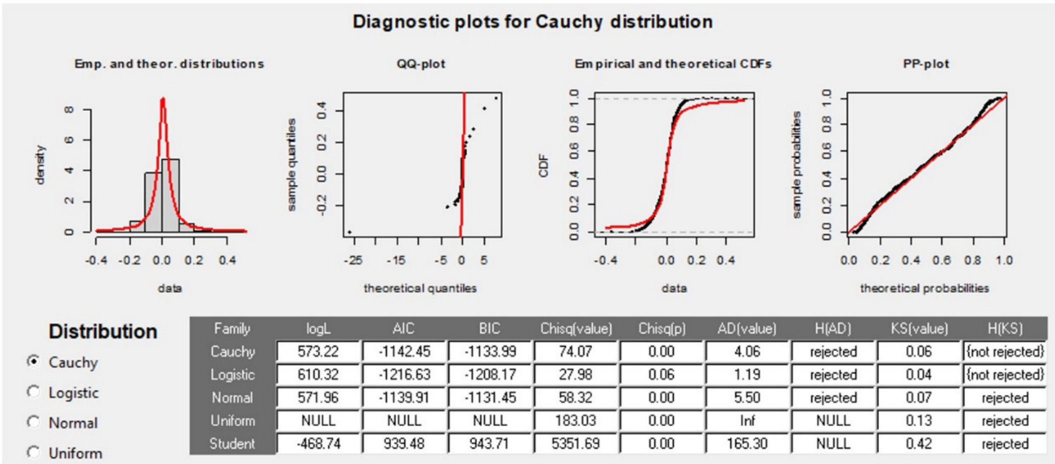
Level of volatility	Lower limit	Upper limit
Low volatility	0.0446205	0.1408297
Medium volatility	0.1408297	0.2370388
High Volatility	0.2370388	0.333248

Source: Own elaboration based on SIPSA-DANE data.

Therefore, it is concluded that the volatility of the returns of Hass Avocado prices traded at the Wholesale Center of Antioquia is high compared to the returns of prices at other wholesale centers across the country.

5.1.2 VaR (Value at Risk) of price fluctuations

To estimate Value at Risk (VaR), a histogram of price returns is first constructed, as illustrated in Figure 2. Subsequently, goodness-of-fit tests—including the Chi-squared, Kolmogorov-Smirnov, and Anderson-Darling tests—are applied to identify the probability distribution that best fits the data. The results indicate that the returns are best modeled by a Cauchy distribution, as also shown in Figure 2.



Family	logL	AIC	BIC	Chisq(value)	Chisq(p)	AD(value)	H(AD)	KS(value)	H(KS)
Cauchy	573.22	-1142.45	-1133.99	74.07	0.00	4.06	rejected	0.06	{not rejected}
Logistic	610.32	-1216.63	-1208.17	27.98	0.06	1.19	rejected	0.04	{not rejected}
Normal	571.96	-1139.91	-1131.45	58.32	0.00	5.50	rejected	0.07	rejected
Uniform	NULL	NULL	NULL	183.03	0.00	Inf	NULL	0.13	rejected
Student	-468.74	939.48	943.71	5351.69	0.00	165.30	NULL	0.42	rejected

Figure 2. Goodness-of-fit tests for returns of Hass Avocado prices traded at the Wholesale Center of Antioquia
Source: Own elaboration.

The estimators for this distribution were a location parameter of 0.0067 and a scale parameter of 0.0362. With these data, VaR can be calculated, providing the confidence interval within which the volatility of returns may fluctuate. This information is visualized in Table 3.

Table 3. VaR (Value at Risk) for price fluctuations of Hass Avocado traded at the Wholesale Center of Antioquia

97.5% confidence interval	97.5% confidence interval
-0.453705	-0.4671293

Source: Own elaboration.

Table 3 shows that Hass Avocado's price fluctuations are high, which aligns with the conclusion drawn from the historical volatility indicator.

5.1.3 Beta Index

Finally, the Beta coefficient is calculated for this price series, resulting in a value of 1.10. This indicates that the prices of Hass Avocado traded at the Wholesale Center of Antioquia are 10% more volatile than the average prices across all markets. As a general conclusion from this historical analysis, it can be stated that prices at the Wholesale Center of Antioquia are highly volatile compared to other wholesale centers in Colombia. For a financial institution, this information is crucial for assessing the cash flow sensitivity to support the financial debt of a Hass avocado producer. For the producer, it helps in considering the timing of selling their produce, as price volatility strongly impacts their income.

5.2 Forecast moment

Next, the selected methodologies for prediction context are developed: mean (Box-Jenkins and LSTM neural networks). The results obtained from these correspond to the possible future behavior of the price of Hass avocados, considering their mean and volatility.

5.2.1 Box y Jenkins Model

Based on the behavior depicted in Figure 3, the time series is represented to understand how the price of Hass avocados behaves each week from 2012 to September 2022 and to examine if the series shows any seasonality component that should be considered in the modeling. Thus, the result shown in Figure 3 indicates that, indeed, there is a seasonal pattern that needs to be accounted for in Box-Jenkins modeling. It also identifies that the series is not stationary in the mean. Therefore, the graph suggests that tests for stationary and seasonal unit roots should be applied.

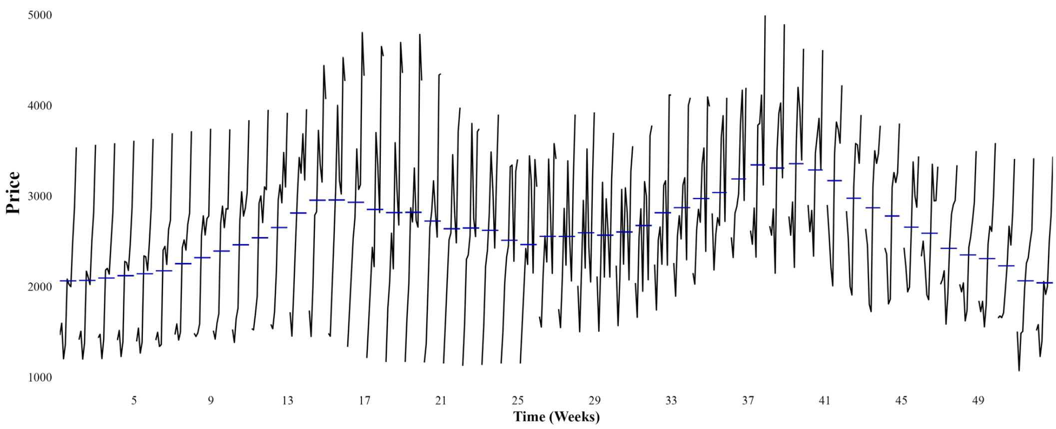


Figure 3. Monthplot for prices of Hass avocados traded at Antioquia's wholesale market.
Source: Own elaboration based on SIPSA-DANE data.

When performing the autocorrelation and partial autocorrelation function (ACF and PACF) plots of the series, reflected in Figure 4, it can be observed that the ACF decays slowly, suggesting a possible seasonal pattern. Therefore, it is determined that unit root tests should be conducted for both the stationary and seasonal components.

As a result, unit root tests are conducted for both components (stationary and seasonal), revealing the presence of at least one unit root in each. Following this, the optimal model order and coefficient estimation are determined. Various potential outliers in the series are considered during this process. Figure 5 illustrates the findings, indicating that the model order is SARIMA (0,1,1)(0,1,1) [52] with calculated coefficients. The time series analysis also identifies three types of outliers: one additive outlier in week 58, a temporary change in week 460, and a level shift in week 437. It should be noted that the model considers these outlier coefficients when used for prediction.

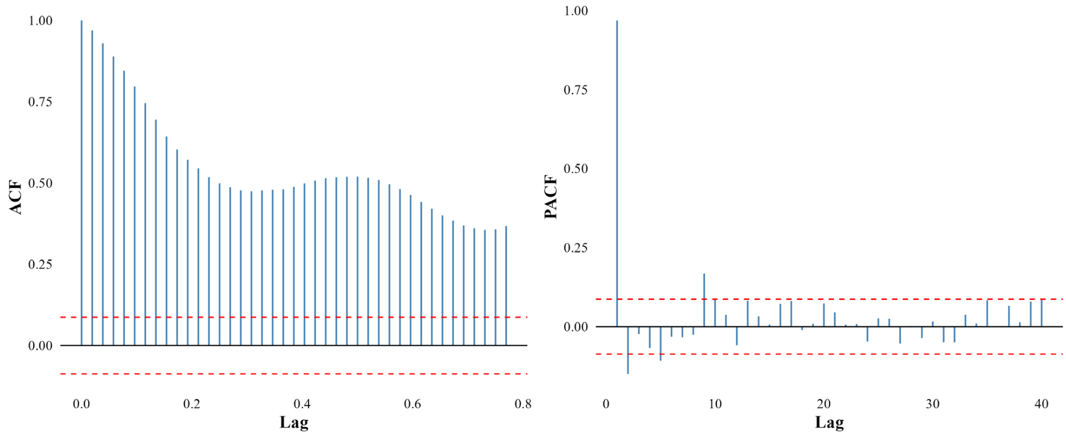


Figure 4. ACF and PACF for prices of Hass avocados traded at Antioquia's wholesale market.
Source: Own elaboration.

Avocado Hass Price Train
Regression with ARIMA(0,0,1)(0,1,1)[52] errors

	ma1	sma1	LS 437	AO 58	TC 460
Coefficients	0.0159	-0.9484	1250.0613	-542.5907	395.0810
Standard Error	0.0540	0.2336	184.1436	128.5592	129.7501

Figure 5. Summary model for prices of Hass avocados traded at Antioquia's wholesale market.
Source: Own elaboration.

After obtaining the model, errors are verified to ensure they are white noise and follow a normal distribution. For the former, the Ljung-Box test is applied, and this is graphically contrasted with the ACF depicted in Figure 6, revealing that the errors are white noise. Regarding the latter, goodness-of-fit tests are performed, demonstrating that the errors follow a normal distribution.

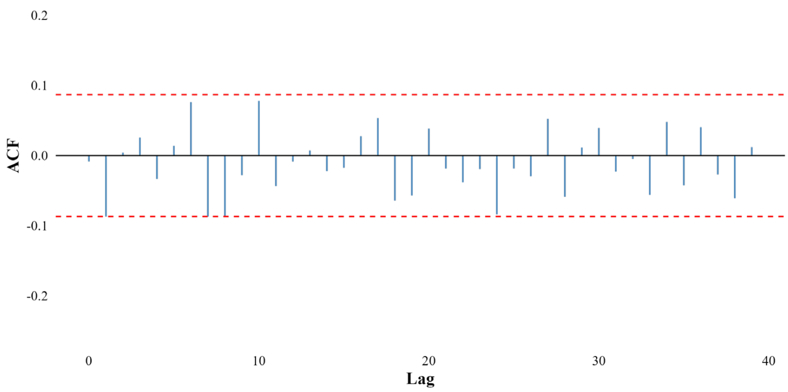


Figure 6. ACF of residuals from the ARIMA (0,1,1)(0,1,1)52 model.
Source: Own elaboration.

After verifying the assumptions of the Box-Jenkins models, the predictive capability of the ARIMA (0,1,1)(0,1,1) [52] model is assessed using the last 12 weeks as a test sample. The prediction results are depicted in Figure 7, showing that for the first four weeks, the prediction deviates outside the confidence intervals. However, the prediction improves in the subsequent weeks.

To determine the predictive capability of the model, we use Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are employed, with results detailed in Table 4. This table shows that the model used has good predictive ability, with a MAPE of 5% and MAE and RMSE of 203 and 237, respectively. These values are low compared to the Hass avocado price scale of 4,500 per kilogram. In other words, an average error of 203 against an average price of 4,500 indicates a low error.

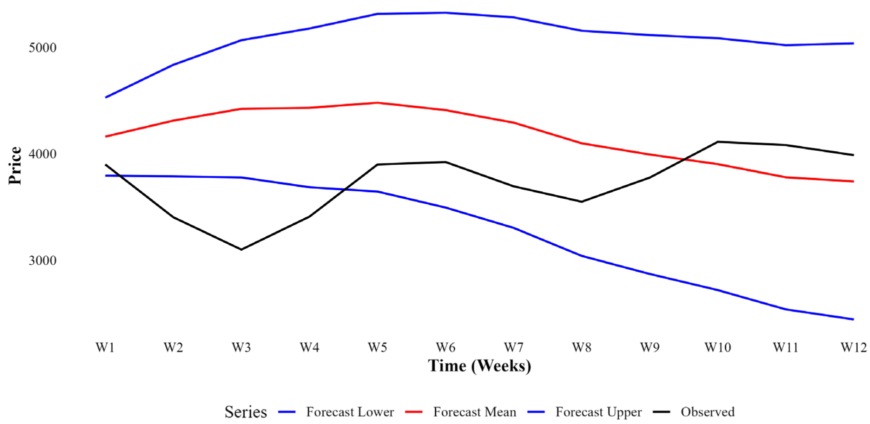


Figure 7. Comparison of the prediction of prices of Hass avocados traded at the Antioquia's wholesale market with respect to actual prices using the Box-Jenkins model.
Source: Own elaboration.

Table 4. Results of the Box-Jenkins prediction model.

Performance indicator	MAPE	RMSE	MAE
Result	5.619%	237.7815	203.0366

Source: Own elaboration.

Before plotting the behavior for the upcoming weeks between October and December (12 weeks), the LSTM neural network methodology will be applied. Subsequently, metrics such as MAPE, RMSE, and MAE will be compared with those obtained from the Box-Jenkins model. The model with the better metrics will be selected for the final prediction.

5.2.2 LSTM Neural Networks

The time series is initially transformed using Min-max scaling, and a 12-week time window methodology is applied to create an LSTM neural network. Subsequently, the network architecture is defined as shown in Figure 8, comprising three layers, MSE as the loss function and Adam as the optimizer, resulting in 2,661 trainable parameters. This compiled model trains and evaluates predictive capability using data from the last 12 weeks, which will be compared with the Box-Jenkins model.

Model: Sequential

	Output (shape)	Parameters (Number)
LSTM	(None, 20)	2640
Dropout	(None, 20)	0
Dense	(None, 1)	21

Trainable Parameters: 2661

Non-trainable Parameters: 0

Total Parameters: 2661

Figure 8. Architecture of the LSTM neural network model for the prices of Hass avocados traded at the Antioquia's wholesale market.
Source: Own elaboration.

After fitting the LSTM model with training data using 100 epochs and a batch size of 1, the results shown in Table 4 indicate an acceptable prediction fit compared to the actual data. It is important to note that these initial results are not final, as the neural network has not been tuned yet. The goal is to compare the untuned and tuned models to see how results improve when hyperparameters are adjusted.

The LSTM neural network architecture described in Figure 9 is obtained when tuning the hyperparameters. This figure has seven layers: the first layer has 25 neurons, the next four layers have 16 neurons each, the sixth layer has no neurons, and the final layer has one neuron. This structure results from using the Adam optimizer, linear activation functions, and He normal initialization for the initial weights. With this configuration, the total parameter count is 5,049.

Model: Sequential

	Output (shape)	Parameters (Number)
LSTM	(None, 25)	3800
Dense 1	(None, 16)	416
Dense 2	(None, 16)	272
Dense 3	(None, 16)	272
Dense 4	(None, 16)	272
Dropout	(None, 16)	0
Dense 5	(None, 1)	17

Trainable Parameters: 5049

Non-trainable Parameters: 0

Total Parameters: 5049

Figure 9. Final architecture of the LSTM neural network model for the prices of Hass avocados traded at the Antioquia's wholesale market with hyperparameter tuning.
Source: Own elaboration.

Table 5 compares the calibrated LSTM model to the initial model. The calibrated model shows better predictive power than the untuned model, demonstrating significant improvements in all three-evaluation metrics. Based on this comparison, the calibrated neural network is selected and compared with the results obtained from the Box-Jenkins model.

Table 5. Comparison of LSTM neural network models with and without hyperparameter tuning.

Performance indicator	MAPE	RMSE	MAE
Result of initial model (without hyperparameter tuning)	6.879%	307.5667	252.212
Tuned model result	6.129%	257.807	225.089

Source: Own elaboration.

On the other hand, Table 6 compares the models used for predicting the prices of Hass avocados traded at the Antioquia's wholesale market. The results show that the Box-Jenkins model performs better than the neural network model. Therefore, the Box-Jenkins model will be used for the final prediction of October, November, and December (12 weeks) to determine the behavior of Hass avocado prices. It is important to note that the Box-Jenkins model is selected for this case study. However, the LSTM neural network model may be more appropriate in other production systems due to its performance.

Table 6. Comparison of Box-Jenkins and LSTM models.

Performance indicator	MAPE	RMSE	MAE
Box-Jenkins Model	5.619%	237.7815	203.0366
LSTM Neural Networks	6.129%	257.807	225.089

Source: Own elaboration.

In this context, when making the final prediction, as shown in Figure 10, prices are trending downward. Therefore, if a Hass avocado producer sells their product between October and December 2022, they should consider that they will receive less income. On the other hand, if a financial institution decides to lend to a Hass avocado producer during these months, they should assess market risk considering this aspect to determine the feasibility of granting a loan.

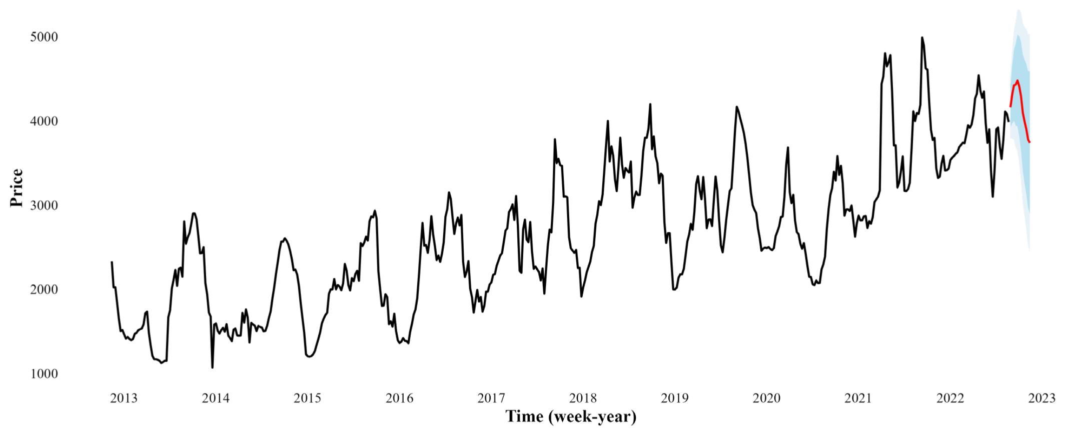


Figure 10. Prediction of prices of Hass avocados traded at the Antioquia's wholesale market for the periods October – December 2022.
Source: Own elaboration.

Our framework is built on three pillars that may limit its external validity. First, we calibrated each volatility band, VaR threshold, and β-benchmark using weekly producer prices from wholesale transactions in the SIPSA-DANE database. Therefore, the method depends on the availability of reliable farm-gate prices, which we sometimes had to impute instead of obtaining them directly. Second, we analyzed only one marketing channel—wholesaler to retailer—so we did not capture alternative routes such as direct farm-gate trading, export differentials, or processor premiums that influence price formation in other markets for crops. Third, we developed our forecasting module over a relatively short timeframe (2012-2022); therefore, long-term structural breaks, such as phytosanitary outbreaks, varietal changes, or policy shocks, could reduce its predictive power when we apply the tool to crops with significantly different market dynamics. In such cases, we need to recalibrate the model.

We must adjust several pipeline stages when we extend our methodology beyond Hass avocado. (i) Temporal granularity of price data: We must select an aggregation level (daily, weekly, monthly) that aligns with each crop's marketing rhythm, as this decision directly impacts VaR sensitivity and β-estimation windows. (ii) Risk-factor mapping: Since weather indices, quality grades, and export-market premiums weigh differently across commodities, we need to redesign the expert-weighting survey (Table 1) to reflect the unique exposure profile of the new crop. (iii) Benchmark construction: We may rely on ICE or CBOT futures prices for internationally traded crops, while niche products might require custom farm-gate baskets. To ensure that our volatility, VaR, and ranking outputs remain agronomically and commercially meaningful, it is necessary to audit data availability, test parameter stability under alternative sampling intervals, and conduct sensitivity analyses on benchmark selection each time the approach is replicated.

6 Conclusions

According to the submitted results, the developed methodologies effectively support decision-making for agricultural producers and financial entities. They provide indicators that allow for market risk evaluation, help producers understand and mitigate associated risks, and aid financial institutions in deciding on loan approvals with prior knowledge of this information.

In addition, the proposed methodology provides a versatile and scalable approach by offering effective indicators to assess market risk. This enables agricultural producers and financial institutions to make strategic decisions across agrarian sectors. Additionally, its adaptability allows stakeholders to customize the assessment process according to specific sector needs and changing market conditions, enhancing their capacity to manage and mitigate potential risks effectively.

Based on historical price analysis and prediction trends, a medium to high market risk was identified in the case study of Hass avocado producers selling their harvest at Antioquia's wholesale market. Therefore, it is recommended that producers seek strategies to mitigate this risk, while financial institutions are advised to consider grace periods for the last quarter of the year.

Advancement of market risk assessment in the national context is limited, as credit risk analyses primarily focus on client information and do not reflect on the operating environment. Hence, there is an urgent need to continue researching and developing methodologies for risk assessment in Colombia's agricultural sector.

These conclusions underscore the importance of robust and contextualized methodologies for assessing market risks in the agricultural sector. These methodologies are crucial for supporting informed decision-making and promoting financial stability among producers.

On the other hand, outside of Colombia, the methodology provides actionable insights for export-oriented fruit and vegetable chains in Mexico, Peru, Chile, and the Dominican Republic, where smallholders experience similar exposure to price fluctuations and credit limitations. Integrating our volatility and VaR indicators into existing guarantee funds or crop insurance schemes could enhance premium pricing and activate trigger conditions. Simultaneously, the predictive module can guide short-term marketing strategies such as coordinated harvest scheduling or staggered shipping programs to mitigate revenue losses during expected downturns.

At the policy level, Latin American development banks and agricultural ministries could employ the proposed framework to develop harmonized risk-assessment dashboards contributing to concessional loan scoring models and early warning systems for staple and high-value crops. Establishing regional data protocols that include wholesale, farm-gate, and export prices would facilitate cross-country benchmarking and foster a shared evidence base for negotiating trade standards and market risk financing. This collaborative approach can enhance the resilience of agri-food systems across the region by aligning producers' risk management decisions with the strategic objectives of public and private stakeholders.

As future work, the methodology developed in this study, applied specifically to Hass avocado cultivation traded at Antioquia's wholesale market, can be extended and adapted to any agricultural product. This adaptability would facilitate comprehensive market risk assessments across a broader range of agricultural commodities, considering their unique market dynamics, seasonality, and regional characteristics. Additionally, further research could explore incorporating advanced predictive analytics, machine learning techniques, and scenario analysis with more variables to strengthen risk mitigation strategies and enhance decision-making capabilities within diverse agricultural sectors.

Authors' contributions

FVB: Conception/design of the study and critical revision. RACM: Manuscript writing and critical revision. SASL: Conception/design of the study, data collection, data analysis and interpretation, manuscript writing, and critical revision. EAJE: Conception/design of the study, data analysis and interpretation, manuscript writing, and critical revision.

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Conflicts of interest:

nothing to declare.

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Not applicable.

Data availability:

Research data is only available upon request.

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