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Value at Risk and Markowitz Portfolio Optimization in Agricultural Sector Stocks

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Abstract
This study examines market risk in agricultural sector stocks listed on the Indonesia Stock Exchange (IDX) using the Value at Risk (VaR) approach based on historical simulation, both at the individual stock level and at the portfolio level. The data employed consist of daily closing price time series from January 2025 to December 2025, covering AALI, NSSS, TAPG, and SMAR. The estimation of portfolio VaR was preceded by the calculation of returns, expected returns, variances, standard deviations, and the variance–covariance matrix, which were subsequently utilized to construct the optimal portfolio under the Markowitz mean–variance framework. VaR was then measured at confidence levels of 90%, 95%, and 99%, assuming an initial investment value of IDR 1,000,000. The findings indicate that individual stock VaR increases as the confidence level rises, suggesting the presence of tail risk in the return distribution over the observation period. TAPG and NSSS consistently exhibit the highest VaR values, whereas AALI demonstrates relatively lower risk at the 90% and 95% confidence levels. The optimal portfolio comprises NSSS (59.49%), TAPG (28.27%), and SMAR (12.24%), yielding an expected portfolio return of 0.43% and a risk level (standard deviation) of 0.01899. The portfolio VaR is lower than that of the highest-risk individual stocks across the 90% and 95% confidence levels, underscoring the role of diversification and optimal weighting in mitigating downside risk.

Keywords: Agricultural Sector Stocks; Historical Simulation; Markowitz Portfolio; Value at Risk (VaR)

Introduction

Indonesia holds a significant position in global agricultural production due to its vast land resources and favorable soil conditions. The agricultural sector plays an important role in the national economy, particularly in employment and commodity trade (World Bank, 2020); (Pasaribu et al., 2021). However, agricultural commodity prices are highly volatile, and these fluctuations may affect farmers, producers, investors, and market participants through changes in income, business stability, and investment risk (Sari et al., 2023).

Fluctuations in agricultural commodity prices are influenced by supply and demand conditions, market timing, business cycles, geopolitical developments, changes in the market environment, and natural disasters. These sources of volatility create uncertainty not only for producers and consumers, but also for investors who hold agricultural-related assets. Therefore, market participants need appropriate risk management tools to anticipate potential losses and support more rational investment decisions (Billah et al., 2023).

Commodity price volatility may affect not only the real sector but also financial markets, as commodity price shocks can be transmitted to stock market dynamics (Ildırar & İşcan, 2015). In the agricultural sector, this condition exposes listed agricultural stocks to market risk arising from

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commodity price movements and broader financial market dynamics. Although agricultural commodities have been widely examined in relation to production, trade, and price instability, the risk characteristics of agricultural sector stocks in the capital market still require further empirical examination. Therefore, it is important to measure the potential losses of individual agricultural stocks and assess whether portfolio diversification can reduce aggregate downside risk.

The relevance of examining agricultural sector stocks in 2025 is supported by recent macroeconomic and sectoral conditions in Indonesia. Badan Pusat Statistik (2025) reported that the national economy continued to grow in the first quarter of 2025, while the Agriculture, Forestry, and Fisheries sector recorded notable growth from the production side. The year 2025 was selected because it represents the most recent period that reflects current market conditions, investor expectations, and sectoral dynamics in Indonesia's agricultural sector. This period is also relevant because agricultural sector stocks may respond to recent changes in commodity prices, sectoral performance, and broader financial market conditions. In addition, the use of daily stock price data during 2025 provides an adequate number of observations for short-term market risk measurement using historical Value at Risk and Markowitz portfolio optimization. Therefore, the observation period is consistent with the objective of this study, which is to assess recent downside risk and portfolio diversification opportunities, rather than to examine long-term market cycles.

Previous studies have examined risk in agricultural markets from different perspectives. Van Oordt et al. (2021) analyzed extreme price risk in agricultural commodities and found that agricultural markets may contain substantial tail risk. This finding indicates the importance of measuring potential losses beyond ordinary price fluctuations. However, the existing literature has focused more on agricultural commodity price risk than on the downside risk of agricultural sector stocks, particularly in emerging capital markets such as Indonesia.

In the Indonesian capital market context, empirical studies on Value at Risk (VaR) in agricultural sector stocks remain limited. Zebua et al. (2025) calculated VaR for agricultural sub-sector stocks using historical simulation and Monte Carlo methods, but their analysis was limited to SGRO and LSIP. Therefore, there is still limited empirical evidence on the application of historical simulation VaR across a broader selection of listed agricultural stocks. In addition, previous studies have not explicitly integrated historical simulation VaR with Markowitz portfolio optimization to compare the downside risk of individual stocks and an optimized portfolio. This study addresses this gap by analyzing AALI, NSSS, TAPG, and SMAR, estimating their individual VaR, constructing an optimal portfolio using the Markowitz model, and comparing whether diversification can reduce aggregate downside risk in Indonesian agricultural sector stocks.

Based on this background, this study focuses on assessing the market risk of agricultural sector stocks in Indonesia using a historical simulation-based Value at Risk (VaR) approach. The methodological contribution of this study is reflected in the integration of historical simulation VaR and Markowitz portfolio optimization within a single analytical framework. First, this study estimates the downside risk of each selected agricultural stock. Second, the optimal portfolio is formed by applying the Markowitz model. Third, it compares the VaR of individual stocks with the VaR of the optimized portfolio to evaluate whether diversification can reduce aggregate downside risk. Through this approach, the study provides empirical evidence on short-term market risk and portfolio-based risk management in the Indonesian agricultural equity market

Literature Review

Stock Market

The stock market plays an important role in agricultural sector development because it provides

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financing access for listed firms and serves as a mechanism for investors to assess firm prospects and risks. The stock market facilitates the mobilization of long-term funds and the allocation of capital from investors to firms requiring financing (Ngong et al., 2022). For agricultural companies, access to the capital market is particularly important because it can support business expansion, agricultural modernization, and sectoral development. However, once agricultural firms become publicly listed, their stock prices no longer reflect only operational performance, but also investor expectations, commodity price movements, and broader market conditions (Li et al., 2025). Therefore, agricultural stocks should be understood not merely as financing instruments, but also as financial assets exposed to sector-specific and market-wide risks.

Previous empirical studies show that agricultural commodity price movements can influence stock performance. Rokhim & Setiawan (2013) found that price shocks in commodities such as corn, sugar, and palm oil affect corporate gross profits and equity values in Indonesian food and beverage companies. Similarly, Oktrevina et al. (2022) showed that commodity prices and exchange rates are significant determinants of stock returns in the domestic agriculture and animal feed sectors. These findings indicate that commodity market volatility can be transmitted to stock prices through changes in production costs, revenue expectations, profitability, and investor behavior. However, these studies mainly focus on the determinants of stock performance and return movements, while the measurement of downside risk in agricultural sector stocks remains less explored. Therefore, further analysis is needed to estimate potential losses and assess whether portfolio diversification can reduce risk in agricultural sector stocks.

In Indonesia, the Indonesia Stock Exchange (IDX) serves as the official institution that facilitates securities trading, supports companies in going public, and ensures fair and efficient transactions (Halim, 2024). For listed companies, the capital market provides a relatively accessible and efficient source of financing compared with third-party loans, which may create interest expenses and financial pressure (Astuty, 2017). In emerging markets, stock markets may also show strong performance based on several market indicators (Tsouma, 2007). This context makes the Indonesian stock market relevant for examining agricultural sector stocks, particularly in relation to market risk, downside risk, and portfolio diversification.

Investment, Risk, and Return

Czubak and Pawłowski (2024) stated that investment is a strategic determinant that serves as a key factor in enhancing the performance and sustainability of the agricultural sector. Investment enables business actors to improve capacity, efficiency, and competitiveness while strengthening resilience to external shocks. They emphasized that through investment, agricultural business actors can adapt to changes in the business environment, including price fluctuations, policy changes, climate change impacts, and other external pressures. At the sectoral level, adequate and sustainable investment is also a crucial factor in supporting food security and reducing environmental footprints. In the context of agricultural companies integrated with capital markets, investment decisions also influence revenue prospects, cash flow stability, and corporate risk profiles, which are ultimately reflected in stock valuation and price movements.

Stock price can be used as a signal of how effectively a company is managed. A continuous increase in stock prices is often interpreted by investors and prospective investors as a signal that the company is able to manage its business effectively. This investor confidence provides significant benefits for issuers because higher confidence in a company’s performance can increase investor interest and demand for the company’s shares. Higher demand will increase stock prices, and if a high stock price can be maintained, investor confidence may also increase, which ultimately contributes to firm value enhancement (Astuty, 2017). Stocks also represent

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individual ownership in a business entity and can be purchased directly from corporations or traded among investors on stock exchanges (Ildırar & İşcan, 2015). However, stock price movements also contain uncertainty, especially in agricultural sector stocks that are exposed to commodity price changes, market conditions, and external shocks.

From a theoretical perspective, institutional investors face two different behavioral incentives, namely the incentive to control risk and the incentive to shift risk. When the incentive for risk management is stronger, a decline in risk-bearing capacity is usually followed by a lower tendency to take risks in investment decisions. Conversely, when the incentive for risk shifting is more dominant, deteriorating financial conditions may encourage institutional investors to increase their investment risk-taking behavior (Gorter & Bikker, 2013). This perspective indicates that investment behavior is closely related to how investors perceive and respond to risk. Therefore, investment decisions should not only consider expected return, but also the possibility of losses that may arise from market uncertainty.

Investment evaluation based solely on return is insufficient because risk must also be considered. Return and risk are two interrelated concepts, as investment decisions involve a trade-off between expected return and the associated level of risk. The relationship between risk and return is generally positive. As investment risk increases, investors generally require higher expected returns as compensation for bearing that risk. Risk is commonly associated with the degree of deviation between actual outcomes and expected outcomes. Therefore, risk can be understood as the possibility of differences between actual return and expected return (Azis et al., 2015). However, risk should not be understood only as overall return variability. In financial markets, asset returns often show non-normal characteristics, such as asymmetry, fat tails, and volatility clustering. Under these conditions, investors may face downside risk, which refers to the possibility of losses below an expected or acceptable return level, and tail risk, which refers to the possibility of extreme losses in the lower tail of the return distribution.

Brealey et al. (2011) stated that risk that can potentially be reduced through diversification is known as specific risk. This type of risk arises because various sources of uncertainty faced by a company are unique to that company or, in some cases, related to its closest competitors. However, another type of risk cannot be eliminated even when investors diversify their portfolios widely. This risk is known as market risk. Market risk originates from macroeconomic factors that affect all business activities, causing stock prices to move in the same general direction. Therefore, investors remain exposed to market uncertainty regardless of the number and variety of stocks held in their portfolios. In this context, the concepts of downside risk, tail risk, and Value at Risk are theoretically connected. VaR estimates the potential loss of an asset or portfolio over a specific period at a selected confidence level, while downside risk and tail risk explain why investors need to focus on potential losses rather than only average return, variance, or standard deviation. Wang & Zitikis (2021) explained that Expected Shortfall is relevant in risk measurement because it captures potential losses beyond the VaR threshold. This perspective shows that investment risk should also consider extreme losses that may occur under adverse market conditions. Therefore, the use of VaR in this study is relevant because it provides a quantitative measure of potential downside risk in agricultural sector stocks and their optimized portfolio.

In investment management, risk refers to the gap between expected return and actual return. Greater deviation between expected and actual returns indicates higher investment risk. Risk is generally measured using statistical dispersion measures, such as variance and standard deviation, where higher values indicate greater return fluctuation and higher investment risk. However, these measures do not specifically explain potential losses under adverse market conditions. Value at

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Risk and Expected Shortfall provide more targeted measures of downside risk. VaR estimates the loss threshold at a selected confidence level, while Expected Shortfall captures the average loss beyond that threshold. Therefore, Expected Shortfall complements VaR by explaining the severity of extreme losses in the tail of the distribution. Investor responses to risk may differ based on their risk preferences. Risk-seeking investors tend to choose higher-risk investments when several alternatives offer the same level of return. Risk-neutral investors expect return to increase proportionally with the level of risk borne. Meanwhile, risk-averse investors prefer lower-risk investments when faced with alternatives offering the same return. Therefore, understanding risk preferences is important because investors do not only evaluate expected return, but also consider the level of uncertainty attached to investment decisions (Halim, 2024).

Value at Risk

Stocks in the agricultural sector have risk characteristics that tend to be responsive to commodity price dynamics and various external factors, such as changes in trade policies, climate variability, and fluctuations in global demand. This sensitivity can trigger sharp changes in returns within a certain time horizon, causing investors to face higher return uncertainty than in more stable sectors. This condition requires a risk measurement approach that is not only descriptive but also capable of translating market volatility into operational risk information for asset allocation decisions. One relevant quantitative approach for this purpose is Value at Risk. VaR summarizes market risk into a single numerical measure by estimating the maximum potential loss that may occur over a specific horizon at a certain confidence level. In agricultural stocks, VaR is important because it can capture the financial consequences of extreme price movements that may arise from commodity shocks.

Value at Risk is widely used in financial risk management because it offers a simple and interpretable quantitative measure of risk. It is commonly applied in investment decision-making, supervisory assessment, and risk-based capital allocation. VaR generally estimates the maximum potential loss of an asset or portfolio within a certain time horizon at a selected confidence level. More specifically, VaR is formulated so that the probability of asset or portfolio losses exceeding the VaR value within a given time horizon is equal to a predetermined probability level (Hung et al., 2006). Gargallo et al. (2010) stated that VaR estimation has good coverage properties and tends to produce values closer to the data series compared with classical strategies. This indicates that VaR can provide a more accurate estimation of market risk.

Value at Risk estimation can be conducted using different approaches, including the parametric method, historical simulation, and Monte Carlo simulation. The parametric method estimates VaR by using key statistical measures, particularly the mean and standard deviation, and usually assumes a specific return distribution. This method is simple and efficient, but its accuracy may decline when return data show non-normal characteristics. Monte Carlo simulation is more flexible because it generates many possible return scenarios based on a selected model, but it requires stronger assumptions and more intensive computation. In contrast, historical simulation uses the empirical distribution of past returns without requiring a specific distributional assumption, making it suitable for capturing actual return movements in agricultural sector stocks that may be affected by commodity shocks and extreme market movements (Abad et al., 2014).

Research Method

This study uses secondary time-series data consisting of daily closing stock prices of agricultural-related companies listed on the Indonesia Stock Exchange (IDX) from January to December 2025, obtained from Yahoo Finance. The sample was selected using purposive sampling based on data completeness, trading availability, market relevance, and suitability for return, Value at Risk, and

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portfolio optimization analysis. Based on these criteria, four stocks were selected, namely AALI, NSSS, TAPG, and SMAR. Although the sample consists of only four companies and may not fully represent the entire agricultural sector, these stocks have relatively large market capitalization among agricultural-related issuers and meet the methodological requirements for historical simulation VaR and Markowitz portfolio optimization. The year 2025 was selected to capture the most recent short-term market risk conditions in Indonesian agricultural-related stocks. The use of a one-year daily observation period is consistent with the Basel market risk framework, which recognizes historical observation periods in VaR calculation and allows the use of historical simulation as one of the VaR modelling approaches (Basel Committee on Banking Supervision, 2011). Therefore, the findings should be interpreted as evidence from selected agricultural-related stocks rather than as a generalization of the entire agricultural sector.

The high volatility of financial markets has encouraged interest in designing and developing new risk management tools (Gargallo et al., 2010). Value at Risk, introduced by JP Morgan in 1994, VaR is used to estimate the maximum potential loss of an asset or portfolio over a specified holding period at a given confidence level. VaR is able to represent market risk in a single numerical value. Due to its conceptual simplicity and ease of interpretation, VaR has developed into a standard risk measure widely used in financial risk management practices (Zhou et al., 2016).

Value at Risk has become an established measure in financial risk management, particularly in the banking and financial industries, because it provides a quantitative estimate of potential losses in an asset or portfolio. VaR is also used in portfolio risk assessment and has become an important reference in risk-based capital management, including in regulatory practices related to capital buffer requirements. In general, VaR estimation involves determining the time horizon, setting the confidence level, constructing the return distribution, and calculating the potential loss at the selected percentile (Choudhry, 2006). In the historical simulation method, VaR is estimated from the empirical distribution of historical returns without assuming a specific theoretical distribution. Historical returns are ordered to identify the loss percentile corresponding to the selected confidence level, so the VaR value reflects the estimated maximum loss over the specified time horizon.

Historical simulation is a non-parametric method for estimating Value at Risk because it relies on historical return data without requiring a specific distributional assumption. This method applies current portfolio weights to historical asset return data to generate hypothetical portfolio returns (Ze-To, 2012). VaR is then calculated from the empirical distribution of historical returns by identifying the loss percentile that corresponds to the selected confidence level. Since the estimation is based on actual historical data, this approach allows VaR results to reflect price movements and volatility patterns that have occurred in the market (Sahroni & Zulfitra, 2024).

This approach provides a more realistic risk measurement because it is based on actual market behavior rather than a predetermined distributional model. The general formula used in the historical simulation method is as follows:

$$\text{Var}\ \alpha = -V0 \times R\,(1-\alpha)$$

$VaR\alpha$	= Value at Risk at confidence level α
$V0$	= Current portfolio value
$R(1-\alpha)$	= Lower-tail percentile of the historical return distribution at confidence level α

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α = Confidence level, such as 90%, 95%, or 99%

The confidence levels of 90%, 95%, and 99% were selected to provide a comparative assessment of potential losses under different degrees of risk tolerance. The 90% confidence level represents a lower risk threshold and is useful for observing moderate downside risk. The 95% confidence level represents a commonly used intermediate threshold in financial risk analysis (Choudhry, 2006; Jorion, 2007). Meanwhile, the 99% confidence level provides a more conservative estimate of extreme potential losses and is consistent with market risk measurement practices that emphasize tail risk, including the Basel market risk framework (Basel Committee on Banking Supervision, 2011). Using these three confidence levels allows this study to compare how VaR changes as the confidence level increases and to provide a more comprehensive view of downside risk in individual stocks and the optimized portfolio.

Portfolio VaR is calculated after determining the optimal stock composition using the Markowitz mean-variance model. This model identifies the stock weights that provide an efficient balance between expected return and risk. The VaR of the optimized portfolio is then estimated using the historical simulation method at selected confidence levels.

The stages in determining the optimal portfolio using the Markowitz model are as follows (Hartono, 2022); (Yunita, 2018).

1. Calculating the return of each stock

   $$R_{it} = \frac{P_t - P_{t-1}}{P_{t-1}}$$

   R_{it} = Return of stock i in period t

   P_{t-1} = Stock price in period t-1 or the previous period

   P_t = Stock price in period t or the current period

2. Calculating the expected return of each stock

   $$E\ (Ri) = \frac{\sum_{i=1}^{n} R_{it}}{n}$$

3. Calculating the variance of each stock

   $$\sigma i^2 = 1/n \sum (R_{it} - E\ (Ri))^2$$

4. Calculating the standard deviation of each stock

   $$\sigma i = \sqrt{\sigma i^2}$$

5. Calculating the covariance between two stocks in the portfolio

   $$\sigma_{12} = \sum_{i=1}^{n} \frac{[(R_{1i} - E(R_1)).(R_{2i} - E(R_2))]}{n}$$

6. Calculating the correlation coefficient between two stocks

   $$\rho_{12} = \frac{\sigma_{12}}{\sigma_1 \cdot \sigma_2}$$

   σ_{12} = Covariance between stock 1 and stock 2

   σ_1 = Standard deviation of stock 1

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σ_1 = Standard deviation of stock 2

7. Determining the optimal portfolio

The allocation of funds among selected stocks is an important stage in forming an optimal portfolio. In this study, portfolio weights are determined through an optimization process using Microsoft Excel Solver to obtain the best combination of return and risk. The optimal portfolio is selected based on the asset composition that provides efficient risk-return performance. After the optimal portfolio is formed, portfolio VaR is calculated using the historical simulation method. This analysis helps estimate the maximum potential loss of the portfolio at a given confidence level and evaluate the role of diversification in reducing overall investment risk.

Results and Discussion

Table 1 presents the four agricultural sector companies used as the sample in this study. These companies were selected as research objects for the analysis of Value at Risk (VaR).

Table 1. Sample of Agricultural Sector Stocks

No.	Stock Code	Company
1	AALI	PT Astra Agro Lestari Tbk
2	NSSS	PT Nusantara Sawit Sejahtera Tbk
3	TAPG	PT Triputra Agro Persada Tbk
4	SMAR	PT Sinar Mas Agro Resources and Technology Tbk

Before presenting the VaR estimation results, this study first illustrates the price movements of the selected agricultural stocks during the 2025 observation period.

Figure 1. Stock Price Movement of AALI, NSSS, TAPG and SMAR

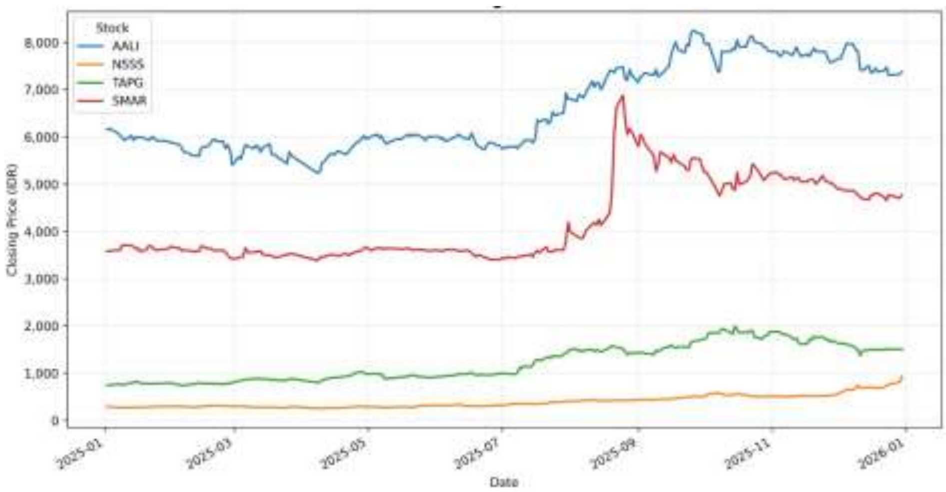

Figure 1 shows that the four agricultural stocks experienced different price movements during 2025. AALI had a relatively higher price level and showed an upward movement in the second half of the year. SMAR experienced a sharp increase around the middle of the observation period, followed by a correction afterward. TAPG showed a gradual upward trend, while NSSS moved at a lower price level with smaller absolute price changes. These different patterns indicate that each stock had different market responses and volatility characteristics, supporting the need for VaR analysis to measure potential downside risk.

Estimation Results of Individual Stock VaR

Based on the calculation of Value at Risk (VaR) using the historical simulation method, the

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estimated potential losses were obtained at three confidence levels, namely 90%, 95%, and 99%. This study assumes an investment value of IDR 1,000,000. The estimation results are presented in detail in Table 2 and show the estimated maximum potential loss during the observation period at each confidence level.

Table 2. Value at Risk Estimation Using the Historical Simulation Method

Confidence Level	AALI	NSSS	TAPG	SMAR
90%	-16.598	-21.677	-25.424	-20.552
95%	-20.306	-28.383	-35.761	-27.179
99%	-50.791	-68.393	-71.376	-49.407

Table 2 presents the Value at Risk (VaR) estimates for AALI, NSSS, TAPG, and SMAR stocks using the historical simulation method at confidence levels of 90%, 95%, and 99%, assuming an investment value of IDR 1,000,000. All VaR values are negative because they represent the maximum potential loss under adverse market conditions according to the selected confidence level. A consistent pattern is observed, where a higher confidence level is associated with a larger absolute VaR value. This indicates that when investors require a higher level of confidence in risk estimation, the loss threshold that must be anticipated also increases.

At the 90% confidence level, TAPG records a VaR value of -25,424. The negative value indicates potential loss. This means that, with a 90% confidence level, the maximum potential loss is estimated at IDR 25,424 from an investment value of IDR 1,000,000. This interpretation also applies to the VaR values of the other stocks.

At the same confidence level of 90%, NSSS records a VaR value of -21,677, followed by SMAR at -20,552 and AALI at -16,598. These results indicate that AALI has the lowest potential loss among the observed stocks. This pattern remains consistent at the 95% and 99% confidence levels. At the 95% confidence level, TAPG again shows the highest VaR value at -35,761, while AALI remains the lowest at -20,306. At the 99% confidence level, all stocks show a substantially higher potential loss, particularly TAPG at -71,376 and NSSS at -68,393. The sharp increase from the 95% to the 99% confidence level indicates the presence of strong tail risk in the historical data, namely rare extreme return events that have a large impact on potential losses.

The comparison among stocks shows that TAPG consistently has the highest VaR value across all confidence levels. Therefore, TAPG can be considered the riskiest stock in terms of downside risk based on the observation period. NSSS ranks second with relatively high VaR values, especially at the 99% confidence level, indicating strong exposure to extreme risk. SMAR is positioned at a moderate risk level, while AALI tends to be the most defensive stock because it has the lowest VaR value across all confidence levels. From a practical perspective, these findings suggest that conservative investors may allocate a larger portion of their investment to stocks with lower VaR values, while stocks with higher VaR values should be managed through position limits, diversification, or other risk mitigation strategies.

The higher VaR values of TAPG and NSSS indicate that both stocks had larger downside movements during the observation period. TAPG showed the highest potential loss across all confidence levels, while NSSS also recorded relatively high risk, especially at the 95% and 99% confidence levels. This suggests that both stocks were more exposed to extreme negative returns than AALI and SMAR. Therefore, the inclusion of these stocks in an optimized portfolio needs to be supported by proper weighting to reduce aggregate portfolio risk.

These findings also confirm the usefulness of the historical simulation method because the VaR estimates are derived from the empirical distribution of historical returns. As a result, this method is sensitive to extreme events that have actually occurred in the market. However, VaR interpretation still depends on the quality of historical data and the assumption that past risk patterns are sufficiently representative of future periods.

Estimation Results of Portfolio VaR

In analyzing portfolio Value at Risk (VaR), determining the optimal portfolio composition is an important stage because portfolio risk is influenced not only by the risk of each individual stock, but also by the relationship among stock returns. Therefore, portfolio optimization is needed to obtain an asset allocation that provides a more efficient balance between expected return and risk. In this study, the Markowitz mean-variance model is applied because it considers expected return, variance, covariance, and portfolio weights in forming the optimal portfolio. The benefit of diversification is assessed through the ability of the selected stock combination to reduce aggregate risk compared with holding individual stocks separately. This is relevant for agricultural sector stocks because the companies may face similar commodity-related risks, but they can still differ in return volatility and contribution to portfolio risk. Thus, the Markowitz model is used to identify the stock composition that can provide the most efficient risk-return structure before portfolio VaR is calculated.

Based on the calculation of four agricultural sector companies using daily stock price data for the period from January 2025 to December 2025, the expected return values are obtained as follows:

Table 3. Expected Return Values

No.	Stock Code	Expected Return
1	AALI	0,000922
2	NSSS	0,005352
3	TAPG	0,003347
4	SMAR	0,001581

Based on the information presented in Table 3, during the 2025 observation period, PT Nusantara Sawit Sejahtera Tbk. (NSSS) recorded the highest expected return, with an E(Ri) value of 0.005352. In contrast, PT Astra Agro Lestari Tbk. (AALI) had the lowest expected return, with an E(Ri) value of 0.000922.

Table 4. Standard Deviation and Variance Values

No.	Stock Code	Standard Deviation	Variace
1	AALI	0,017318	0,000300
2	NSSS	0,026420	0,000698
3	TAPG	0,027122	0,000736
4	SMAR	0,027671	0,000766

Standard deviation is a statistical measure used to represent the level of investment risk by measuring the deviation of returns from their expected mean value. A higher standard deviation reflects greater return volatility, indicating a higher level of risk. In addition to standard deviation, risk can also be measured using variance, which describes the degree of dispersion of returns from their mean value (Hartono, 2022). Referring to Table 4, PT Sinar Mas Agro Resources and Technology Tbk. recorded the highest standard deviation and variance, with values of 0.027671 and 0.000766, respectively. This indicates that SMAR had the highest level of return fluctuation among the observed agricultural sector stocks.

Table 5. Variance-Covariance Matrix

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Stock Code	AALI	NSSS	TAPG	SMAR
AALI	0,000299926	0,000104217	0,000177974	0,000111840
NSSS	0,000104217	0,000697995	0,000101356	0,000021668
TAPG	0,000177974	0,000101356	0,000735581	0,000089695
SMAR	0,000111840	0,000021668	0,000089695	0,000765709

As shown in Table 5, all estimated variance and covariance values are positive. Positive variance confirms the presence of return fluctuations in each stock during the observation period. Positive covariance indicates a tendency for stock returns to move together in the same direction. In other words, when one stock experiences an increase in return, the other stock in the pair tends to experience a similar movement, and vice versa.

The positive covariance values may be associated with the fact that the stocks analyzed belong to the same sector, namely the agricultural sector. Stocks within the same sector are generally exposed to similar industry-specific factors, such as commodity price movements, market demand, production conditions, and sectoral policies. Therefore, changes affecting one stock may also influence the movement of other stocks in the same sector.

The stock proportions forming the optimal portfolio based on the Markowitz model were obtained through calculations using Microsoft Excel with the Solver feature. The results are presented in Table 6.

Table 6. Optimal Portfolio Proportions of Agricultural Sector Stocks

No.	Stock Code	Perusahaan	Portfolio Weight
1	AALI	PT. Astra Agro Lestari Tbk	0%
2	NSSS	PT. Nusantara Sawit Sejahtera Tbk	59,49%
3	TAPG	PT. Triputra Agro Persada Tbk	28,27%
4	SMAR	PT. Sinar Mas Agro Resources and Technology Tbk	12,24%

Based on the Solver results presented in Table 6, three agricultural sector stocks were selected to form the optimal portfolio, namely NSSS with a proportion of 59.49%, TAPG with 28.27%, and SMAR with 12.24%. The portfolio generated an expected return of 0.43% with a risk level of 0.01899. The relatively higher risk of NSSS and TAPG can be explained by their larger daily return fluctuations during the observation period. Since historical simulation VaR and Markowitz optimization use realized daily returns, stocks with wider return dispersion and larger negative return observations tend to produce higher risk estimates.

However, in the Markowitz framework, portfolio selection is not determined only by individual risk, but also by expected return and covariance among stocks. Therefore, NSSS and TAPG remained in the optimal portfolio because their return contribution and interaction with other selected stocks improved the overall portfolio risk-return efficiency. The Solver optimization was carried out with the constraints that total portfolio weights must equal 100%, each stock weight must be non-negative, and short selling was not allowed. Under these constraints, AALI received a weight of 0% because its inclusion did not improve portfolio efficiency during the observation period.

Once the optimal portfolio was formed, its VaR was calculated using the historical simulation method. The portfolio VaR estimation results are reported in Table 7.

Table 7. Portfolio Value at Risk Estimation Using the Historical Simulation Method

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Confidence Level	Portofolio
90%	-16.344
95%	-21.598
99%	-40.851

Table 7 indicates that portfolio VaR increases in line with higher confidence levels. At the 90%, 95%, and 99% confidence levels, the portfolio VaR values are IDR 16,344, IDR 21,598, and IDR 40,851, respectively, assuming an investment value of IDR 1,000,000. This pattern indicates that the estimated potential loss becomes larger when the analysis moves toward a more conservative confidence level. The increase is not only a numerical change, but also reflects the distributional characteristics of portfolio returns. A higher VaR at the 99% confidence level reflects greater loss exposure in the lower tail of the return distribution, indicating that the portfolio remains exposed to extreme downside movements during unfavorable market conditions.

The difference between VaR values across confidence levels also provides insight into the severity of risk. The relatively moderate increase from the 90% to 95% confidence level suggests that losses under normal-to-moderate adverse conditions are still manageable. However, the larger increase at the 99% confidence level indicates the presence of tail risk, where rare market movements may generate losses that are substantially larger than those observed at lower confidence levels. This finding is important because investors may underestimate risk if they only rely on average return, standard deviation, or lower confidence levels. Therefore, the 99% VaR provides a more conservative view of potential losses that may occur during extreme market conditions.

Compared with individual stocks, portfolio VaR remains relatively lower than the VaR of high-risk individual stocks such as TAPG and NSSS, particularly at the 90% and 95% confidence levels. This result indicates that diversification through the Markowitz model helps reduce aggregate downside risk by combining stocks with different return patterns, risk levels, and covariance relationships. In other words, the risk reduction does not occur simply because several stocks are combined, but because the selected portfolio composition creates a more efficient risk-return structure. Although diversification cannot fully eliminate market risk, it can reduce exposure to stock-specific fluctuations and produce a more stable portfolio risk profile than holding high-risk individual stocks. Therefore, the portfolio VaR results support the role of diversification as a practical risk management strategy for agricultural sector stock investment.

Overall, these results confirm that portfolio formation provides benefits in downside risk management because the portfolio generates a more controlled estimate of maximum potential loss compared with an investment concentrated in a single highly volatile stock. This finding can also be interpreted in relation to Indonesia's economic conditions in 2025, when the national economy continued to grow and the Agriculture, Forestry, and Fishing sector showed positive performance (Badan Pusat Statistik, 2025). These conditions may have supported investor interest and return opportunities in agricultural-related stocks. However, favorable macroeconomic and sectoral conditions did not eliminate market risk, as agricultural sector stocks remained exposed to commodity price movements, investor expectations, and broader financial market fluctuations. This explains why individual stocks such as TAPG and NSSS still showed relatively higher risk despite the supportive economic background. Therefore, from a risk management perspective, portfolio VaR reflects the effectiveness of diversification in reducing exposure to stock-specific volatility while still capturing the risk associated with Indonesia's 2025 market conditions.

Conclusion

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This study concludes that Value at Risk (VaR) through the application of the historical simulation method for estimating maximum potential loss of agricultural sector stocks at different confidence levels. The results show that higher confidence levels produce larger absolute VaR values, indicating greater potential loss under more extreme market conditions. Among the stocks analyzed, TAPG and NSSS have higher downside risk, while AALI tends to show a more defensive risk profile at the 90% and 95% confidence levels. The Markowitz optimization results form an optimal portfolio consisting of NSSS at 59.49%, TAPG at 28.27%, and SMAR at 12.24%, with an expected return of 0.43% and portfolio risk of 0.01899.

The portfolio VaR results indicate that diversification and optimal weighting can reduce aggregate risk, particularly at the 90% and 95% confidence levels. For investors, these findings suggest that investment decisions in agricultural sector stocks should not rely only on expected return, but also on downside risk exposure and investor risk profiles. Conservative investors may prioritize stocks with lower downside risk or limit their allocation to high-VaR stocks. Moderate investors may consider a diversified portfolio with controlled exposure to higher-risk stocks such as TAPG and NSSS. Meanwhile, aggressive investors may include higher-VaR stocks to pursue higher return opportunities, but proper weighting, loss limits, and regular risk monitoring are still needed. For investment managers, the use of historical simulation VaR can support the setting of loss limits, portfolio rebalancing decisions, and risk-based asset allocation. Therefore, VaR and Markowitz optimization can serve as practical tools for managing investment risk in agricultural sector stocks, especially when market conditions are affected by commodity price movements and sectoral volatility.

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