Comparative Analysis of Quantile Autoregression and Prophet Models for IDX30 Index Forecasting

Ni Kadek Juliarini[1], Muhammad Rizal[2]

[1]STMIK Bandung Bali
[2]Kanwil Kemenag Kalimantan Utara

[1]Jl. Gatot Subroto Timur No.507, Denpasar, Bali
[2]Jl. Poros Bulungan Berau, Jelarai Selor, Kec. Tj. Selor, Kabupaten Bulungan, Kalimantan Timur
e-mail: juliarini.kdk@gmail.com[1], rhizalmuh99@gmail.com[2]

ABSTRAK

Peramalan indeks pasar saham tetap menjadi tantangan karena volatilitas, perubahan struktural, dan dinamika nonlinier dalam deret waktu keuangan. Meskipun Quantile Autoregression (QAR) dan Prophet telah banyak diterapkan dalam studi peramalan, bukti komparatif tentang kinerja mereka untuk indeks IDX30 di pasar saham Indonesia masih terbatas. Studi ini bertujuan untuk membandingkan akurasi peramalan model QAR dan Prophet dalam memprediksi indeks IDX30. Data harga penutupan bulanan dari Mei 2012 hingga Maret 2026 dibagi menjadi periode in-sample (Mei 2012–Maret 2020) dan periode pengujian out-of-sample (April 2020–Maret 2026). Pendekatan peramalan bergulir satu langkah ke depan digunakan untuk mengevaluasi kinerja model. Akurasi peramalan dinilai secara komprehensif menggunakan Symmetric Mean Absolute Percentage Error (sMAPE), Mean Absolute Error (MAE), dan Root Mean Squared Error (RMSE). Hasil menunjukkan bahwa model QAR secara signifikan mengungguli Prophet di semua metrik evaluasi. Model QAR mencapai sMAPE sebesar 3,47%, RMSE sebesar 21,62, dan MAE sebesar 16,01, yang secara substansial lebih rendah daripada sMAPE Prophet sebesar 8,22%, RMSE sebesar 53,27, dan MAE sebesar 38,71. Kinerja superior QAR menunjukkan kekuatannya dalam menangkap ketergantungan jangka pendek dan beradaptasi dengan volatilitas dan perubahan struktural. Secara praktis, QAR menawarkan implikasi penting bagi investor dan analis keuangan; tidak seperti Prophet, yang kaku terhadap tren jangka panjang, QAR menyesuaikan estimasi selama kondisi pasar ekstrem (kuantil atas/bawah), yang mengarah pada keputusan investasi dan manajemen risiko yang lebih tepat dan adaptif. Temuan ini menegaskan bahwa QAR menyediakan kerangka kerja peramalan yang lebih andal untuk indeks IDX30.
Kata kunci: IDX30; Saham; Peramalan; Autoregresi Kuantil (QAR); Prophet

ABSTRACT

Forecasting stock market indices remains challenging due to volatility, structural breaks, and nonlinear dynamics in financial time series. Although Quantile Autoregression (QAR) and Prophet have been widely applied in forecasting studies, comparative evidence on their performance for the IDX30 index in the Indonesian stock market remains limited. This study aims to compare the forecasting accuracy of QAR and Prophet models in predicting the IDX30 index. Monthly closing price data from May 2012 to March 2026 were divided into an in-sample period (May 2012–March 2020) and an out-of-sample testing period (April 2020–March 2026). A one-step-ahead rolling forecasting approach was employed to evaluate model performance. Forecast accuracy was comprehensively assessed using Symmetric Mean Absolute Percentage Error (sMAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The results demonstrate that the QAR model significantly outperforms Prophet across all evaluation metrics. The QAR model achieved an sMAPE of 3,47%, an RMSE of 21,62, and an MAE of 16,01, which are substantially lower than Prophet's sMAPE of 8,22%, RMSE of 53,27, and MAE of 38,71. The superior performance of QAR indicates its strength in capturing short-term dependencies and adapting to volatility and structural changes.

Practically, QAR offers critical implications for investors and financial analysts; unlike Prophet, which is rigid toward long-term trends, QAR adjusts estimates during extreme market conditions (upper/lower quantiles), leading to more precise and adaptive investment and risk management decisions. These findings confirm that QAR provides a more reliable forecasting framework for the IDX30 index.
Keywords: *IDX30; Stock; Forecasting; Quantile Autoregression (QAR); Prophet*

INTRODUCTION

Stock price movements in the capital market play a crucial role in finance because they influence investment decisions, portfolio management, and risk assessment. Accurate forecasting of stock prices is therefore important for investors, financial analysts, and policymakers seeking to understand future market conditions and reduce uncertainty in decision-making [1]. In Indonesia, one of the most important indicators of stock market performance is the IDX30 index, which consists of 30 highly liquid stocks with large market capitalizations listed on the Indonesia Stock Exchange (IDX). Due to its representation of leading companies in the Indonesian market, the IDX30 index serves as an important benchmark for evaluating market trends and investment opportunities.

Forecasting stock market indices is challenging because financial time series often exhibit complex characteristics, including volatility clustering, nonlinear behavior, structural changes, and asymmetric distributions. These characteristics frequently violate the assumptions underlying conventional forecasting approaches. For example, Ordinary Least Squares (OLS) focuses solely on conditional mean estimation and assumes homoscedastic errors, making it less suitable for modeling financial data characterized by extreme fluctuations and heterogeneous behavior. Quantile Regression (QR) offers an alternative framework by allowing the analysis of conditional distributions at different quantile levels without requiring the assumption of normality [2]. Consequently, QR can provide a more comprehensive understanding of market dynamics, particularly during periods of extreme gains or losses. For time series data exhibiting temporal dependence, Quantile Autoregression (QAR) extends the QR framework by incorporating autoregressive structures into conditional quantile modeling. This approach enables the model to capture both serial dependence and heterogeneous behavior across different quantiles simultaneously [3]. As financial markets often react differently under normal and extreme conditions, QAR provides a flexible framework for analyzing and forecasting financial time series characterized by volatility and asymmetric responses to market shocks.

Another forecasting approach that has gained considerable attention in recent years is Prophet. Prophet is a decomposable time-series forecasting model developed by Facebook (now Meta) that represents a time series as a combination of trend, seasonal, and holiday components. The model is designed to handle nonlinear trends, missing observations, and structural changes while maintaining relatively simple implementation and interpretation. Previous studies have demonstrated the effectiveness of Prophet in various forecasting applications, including financial and economic time series [1]. Recent developments in forecasting research have shown increasing interest in both quantile-based methods and decomposable forecasting approaches. Quantile-based models have been recognized for their ability to capture volatility, tail behavior, and heterogeneous dynamics commonly observed in financial markets [8],[9]. At the same time, Prophet has gained popularity due to its flexibility and forecasting performance across different domains [10],[11],[12].

Despite their growing application, empirical evidence comparing these two approaches in the context of emerging stock markets remains limited.

Nevertheless, existing literature still presents a significant research gap regarding both theoretical and empirical aspects. Most prior comparative studies have evaluated linear or mean-based models against decomposition models but have overlooked how these models perform when confronted with the extreme volatility and structural breaks that frequently affect emerging markets. While Prophet is highly flexible in capturing long-term trends and seasonal patterns, it inherently relies on a trend structure that tends to be rigid in the face of radical short-term shocks. Conversely, QAR offers great flexibility by modeling behavior conditional on specific quantiles (such as the median or extreme quantiles); however, its performance has rarely been tested in a direct head-to-head comparison with automated decomposition models like Prophet within highly dynamic market environments [13],[14],[15].

In Indonesia, previous forecasting studies have generally focused on applying individual forecasting models or comparing conventional statistical approaches [16],[17]. Comparative evidence between Quantile Autoregression (QAR) and Prophet for forecasting the IDX30 index remains scarce. This gap is particularly important because the IDX30 index exhibits several characteristics commonly associated with financial time series, including volatility clustering, nonlinear movements, and structural breaks, all of which present substantial challenges for forecasting models.

Therefore, this study aims to compare the forecasting performance of Quantile Autoregression (QAR) and Prophet in predicting the IDX30 index. The novelty of this study lies in providing empirical evidence on the relative effectiveness of a quantile-based autoregressive model and a decomposable time-series forecasting model under the dynamic conditions of the Indonesian stock market. The findings are expected to contribute to the financial forecasting literature while providing practical insights for investors, analysts, and market participants in selecting appropriate forecasting models for investment decision-making.

METHOD

Types of research

This type of research was conducted using a quantitative approach by comparing 2 models. The modeling was carried out using time series forecasting, namely the model Quantile Autoregression (QAR), and Prophet. Evaluation of the two time series forecasting models using sMAPE, MAE and RMSE values. Data analysis was performed using the R software application.

Data types and sources

This study uses secondary data obtained from yahoo finance.com. The data analyzed were monthly stock closing prices for the last 14 years, namely the period from May 2012 to March 2026 with a total of 167 observations as shown in Table 1.

Table 1. Data

No	Date	Closing stock price
1	May 1, 2012	325,38
2	June 1, 2012	340,96

3	July 1, 2012	361,07
:	:	:
166	February 1, 2026	439,82
167	March 1, 2026	388,56

Data analysis stages

The research process consists of three main stages: data processing, modeling, and evaluating. A brief explanation of the analysis stages can be seen in Figure 1:

1. Data Processing: This stage involves collecting and cleaning data of outliers to ensure the integrity of the information before analysis.
2. Modelling: The modelling process uses two approaches:
   a. Quantile Autoregression (QAR): This study employs a quantile level of τ = 50% (median). The use of the 50% quantile aims to capture the central tendency of IDX30 stock price movements, representing the most common market conditions. This approach was chosen because it is more robust against outliers and sharp market fluctuations compared to mean-based models, resulting in more stable and representative forecasts.
   b. Prophet: This model utilizes an additive approach that decomposes the time series into trend and seasonal components.
3. Evaluating: The forecasting performance of both models is evaluated using three primary metrics: Symmetric Mean Absolute Percentage Error (sMAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The model with the lowest error across these three metrics is subsequently selected to perform forecasting for future periods.

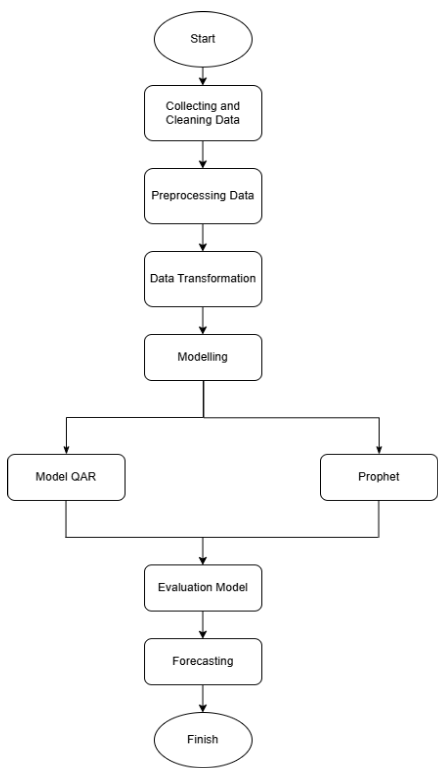

Figure 1. Flow chart

The research process begins with the data acquisition stage, which includes collecting, cleaning, and preprocessing data to ensure information integrity before analysis. Raw data is cleaned of outliers and missing values, then transformed to meet the technical assumptions required by each algorithm. According to [1], the data pre-processing stage is a crucial step in time series analysis to ensure that the statistical model can capture trend and seasonal patterns accurately. Once the data is ready, the modeling stage is carried out by dividing the workflow into two comparative paths. The first path uses a parametric statistical approach through Quantile Autoregressive (QAR). The QAR model aims to capture the dynamics of the time series at a certain quantile level τ by including the previous lag value, which is expressed mathematically as:

$$Q_{y_t}(\tau \mid \mathcal{F}_{t-1}) = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \varepsilon_t \tag{1}$$

The second path uses the Prophet model, which is based on an additive model. This model decomposes the time series into two main components: trend $g(t)$, seasonal $s(t)$, with the equation:

$$y(t) = g(t) + s(t) + \varepsilon_t \tag{2}$$

Where ε_t represents the error term which is assumed to be normally distributed.

After the modeling phase is completed, the procedure proceeds to the evaluation stage to measure the predictive performance of the models. This study utilizes three main evaluation metrics to provide a more in-depth and comprehensive analysis: *Symmetric Mean Absolute Percentage Error* (sMAPE), *Mean Absolute Error* (MAE), and *Root Mean Square Error* (RMSE). The use of sMAPE was chosen because it provides a more balanced assessment of accuracy compared to standard MAPE by dividing the absolute difference between the actual and predicted values by the average of both values. This is highly useful in time series research to ensure that the percentage error is not biased towards either very small or very large actual values [2],[12]. Furthermore, MAE is used to measure the average error in the same price units as the original data, while RMSE is used to assign a greater penalty to significant prediction errors, making it a crucial metric for detecting sharp fluctuations [3]. Mathematically, these metrics are formulated as follows:

$$\text{sMAPE} = \frac{1}{T}\sum_{t=1}^{T}\frac{|y_t - \widehat{y_t}|}{(|y_t| + |\widehat{y_t}|)/2} \times 100\% \tag{3}$$

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}|y_t - \widehat{y_t}| \tag{4}$$

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \widehat{y_t})^2} \tag{5}$$

Where y_t represents the actual data at time t, while $\widehat{y_t}$ is the predicted data from y_t at time t. The evaluation results, particularly the sMAPE value, are then classified using the criteria in Table 2. The lower the sMAPE, MAE, and RMSE values, the more accurate the forecasting model.

Table 2. Forecast Accuracy Rating Scale

sMAPE	Forecasting Accuracy Level
$\leq 10\%$	Very Accurate
$10\% < \text{sMAPE} \leq 20\%$	Accurate

$20\% < \text{sMAPE} \leq 50\%$	Quite Accurate
$> 50\%$	Not accurate

Table 2 shows the interpretation of the results obtained with sMAPE. This table classifies forecast accuracy based on the sMAPE value. The lower the sMAPE value, the more accurate the forecast, while a higher value indicates a less accurate forecast [4].

RESULT AND DISCUSSION

This section presents the empirical results of the study, beginning with an initial visualization of the IDX30 index to understand its underlying patterns and characteristics. The visualization serves as a foundation for identifying key features such as trend, volatility, and potential structural breaks, which are crucial in selecting and evaluating appropriate forecasting models. The initial data visualization is presented in Figure 2. Furthermore, the results of the forecasting models Quantile Autoregression (QAR) and Prophet are presented and compared using the Symmetric Mean Absolute Percentage Error (sMAPE) as the primary accuracy criterion. A comprehensive discussion is then provided to interpret the findings, highlight differences in model performance, and explain their implications in the context of financial time series forecasting.

Figure 2. Initial visualization of the IDX30 index time series (2012–2026)

Figure 2 presents the initial visualization of the IDX30 index over the period 2012–2026. The figure shows a clear upward trend from 2012 to approximately 2018, indicating a period of strong market performance. However, this upward movement is followed by noticeable fluctuations, reflecting the dynamic nature of financial markets. A significant decline is observed around early 2020, indicating the presence of a structural break in the series. This sharp drop is likely associated with external shocks affecting the financial market, leading to increased uncertainty. Following this period, the index enters a recovery phase; however, its movements become more volatile compared to the pre-2020 period. This behavior suggests the presence of volatility clustering, which is a common characteristic of financial time series data. In addition, no strong seasonal pattern can be clearly identified from visual inspection alone. Any potential seasonality should be verified through formal statistical procedures, such as seasonal decomposition or autocorrelation analysis. Therefore, seasonality is not considered a dominant characteristic of the IDX30 series in this study. Overall, the visualization highlights that the IDX30 time series is nonlinear, volatile, and subject to structural changes. Therefore, robust forecasting approaches that can accommodate these properties are required.

Building upon these findings, the dataset is subsequently divided into two parts to facilitate model estimation and evaluation. The in-sample (training) period spans from May 2012 to March 2020, while the remaining observations are treated as the out-of-sample (testing) period. This partitioning is intentionally designed to account for the structural break observed around early 2020, thereby enabling a more realistic assessment of model performance under changing market conditions. Using the in-sample data, parameter estimation is then carried out for each model. The Quantile Autoregression (QAR) model is estimated using only lagged values of the series, resulting in the following specification:

$$Q_{y_t}(0{,}5 \mid \mathcal{F}_{t-1}) = 31{,}79 + 1{,}07\, y_{t-1} - 0{,}13\, y_{t-2} \tag{4}$$

The results show that the coefficient of the first lag is greater than one, indicating a very strong dependence on the most recent observation. This further reinforces the notion that short-term dynamics play a crucial role in explaining the behavior of the IDX30 index. Meanwhile, the second lag retains a negative coefficient, suggesting the presence of a slight adjustment mechanism in the series. The QAR model provides a parsimonious representation of the IDX30 dynamics through its autoregressive quantile structure.

For comparison purposes, the Prophet model is also estimated using the same in-sample data. The model follows a decomposable time series structure defined as:

$$y(t) = g(t) + s(t) + \varepsilon_t \tag{5}$$

where $g(t)$ represents the trend component, $s(t)$ denotes the seasonal component, and ε_t is the error term. Based on the estimation results, the growth parameter is estimated at $k = 0{,}38$, indicating a positive underlying trend during the in-sample period. The offset parameter is $m = 0{,}56$, which reflects the initial level of the series. The model also incorporates multiple change points, as represented by the δ parameters. Most of these values are very close to zero, indicating that only minor adjustments are made to the trend over time. However, a few coefficients, such as $-0{,}204$, suggest the presence of more noticeable local changes, although these remain limited. This implies that the overall trend is modeled as relatively smooth, with only slight deviations. In addition, the seasonal component is captured through Fourier series, as reflected in the β coefficients, which exhibit both positive and negative values. This indicates the presence of cyclical patterns in the IDX30 index. The estimated observation noise is relatively low, with $\sigma_{obs} = 0{,}053$, suggesting that the model fits the in-sample data reasonably well.

Nevertheless, the reliance on smooth trend and seasonal components may limit the model's ability to capture abrupt structural changes, such as the sharp decline observed in early 2020. This characteristic is expected to influence the forecasting performance of the Prophet model in the out-of-sample period. Following parameter estimation, a one-step-ahead rolling forecasting approach is implemented to generate predictions for the out-of-sample period. This approach ensures that each forecast is based solely on information available up to the forecasting point, thereby closely mimicking real-world forecasting conditions. The comparison between the actual values and the forecasts produced by each model is presented in Figure 3.

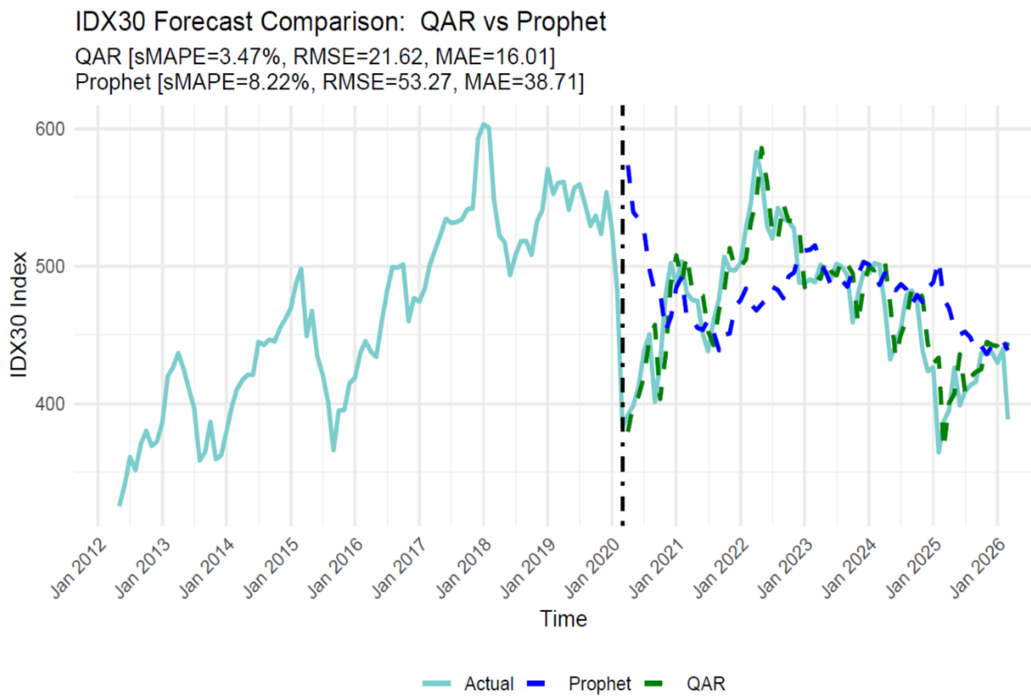

Figure 3. Comparison of actual and forecasted IDX30 using QAR and Prophet models.

This visual interpretation is consistent with the quantitative evaluation results. Among the two models, QAR achieves the lowest sMAPE (3,47%), while Prophet records a substantially higher error (8,22%). Similar findings are observed for MAE and RMSE. The QAR model produces an MAE of 16,01 and an RMSE of 21,62, whereas Prophet yields considerably higher values, with an MAE of 38,71 and an RMSE of 53,27. The consistently lower error values across all evaluation metrics indicate that QAR provides more accurate forecasts during the out-of-sample period. The lower MAE suggests that the average deviation between the forecasted and actual IDX30 values is substantially smaller for QAR. Likewise, the lower RMSE indicates that QAR is more effective in reducing large forecasting errors, which is particularly important in financial time series characterized by sudden fluctuations and extreme observations. Therefore, the superiority of QAR is not only supported by percentage-based accuracy measures such as sMAPE, but also by absolute and squared-error metrics.

Therefore, QAR can be identified as the best-performing model in this study. The lower forecasting error suggests that autoregressive-based modeling is more effective in capturing the dynamic behavior of the IDX30 index, particularly under conditions characterized by volatility and structural changes. The superior performance of the QAR model can be attributed to its ability to directly capture the autoregressive dependence structure of financial time series while accommodating heterogeneous behavior across different conditional quantiles. Financial market data such as the IDX30 index are characterized by volatility clustering, asymmetric responses to market shocks, and structural changes. Under these conditions, models focusing primarily on conditional means may fail to adequately represent extreme market movements. By modeling conditional quantile dynamics, QAR remains responsive during periods of heightened uncertainty and market stress, allowing it to better capture short-term fluctuations in the IDX30 index.

In contrast, Prophet relies on a decomposable time-series structure consisting of trend and seasonal components. Although this framework performs well for time series exhibiting relatively stable trends and recurring seasonal patterns, it may be less suitable for financial data where abrupt market shifts frequently occur [10], [11]. The sharp decline observed around early 2020, which represents a structural break associated with global market disruption, illustrates this limitation. Prophet tends to smooth sudden fluctuations through its trend decomposition mechanism, whereas QAR adapts more rapidly through its autoregressive structure. Consequently, QAR is better able to follow rapid market movements and produce forecasts that remain closer to the actual observations.

The relatively weaker performance of Prophet may be explained by the presence of a structural break around early 2020. Although Prophet incorporates automatic changepoint detection, its trend estimation mechanism is designed to favor smooth transitions over abrupt adjustments. As a result, the model may respond more slowly to sudden market disruptions, causing larger forecasting errors during periods of heightened uncertainty. In contrast, the autoregressive structure of QAR allows forecasts to adapt more directly to recent observations and changing market conditions. It is also important to note that Prophet performance may potentially be improved through alternative model specifications. Adjustments to the changepoint prior scale, the number of changepoints, or the inclusion of additional regressors may enhance the model's ability to capture abrupt market movements. However, this study employed the standard Prophet configuration to provide a baseline comparison with QAR. Future research may investigate whether optimized Prophet settings can improve forecasting performance under structural break conditions.

These findings are consistent with previous studies reporting that quantile-based models often outperform conventional forecasting approaches when financial series exhibit volatility, nonlinearity, and non-normal distributions [8], [9]. For example, Chavleishvili and Manganelli [8] demonstrated that quantile-based autoregressive frameworks are capable of capturing heterogeneous dynamics and tail risks more effectively than conventional mean-based models. The results highlight the importance of incorporating both distributional characteristics and temporal dependencies when forecasting stock market indices, particularly in emerging financial markets such as Indonesia.

Nevertheless, several limitations should be acknowledged. First, the analysis is based on monthly observations, resulting in a relatively limited sample size that may affect the generalizability of the findings. Second, only two forecasting models, namely QAR and Prophet, were evaluated. Other advanced forecasting approaches may produce different results under similar market conditions. Future studies are therefore encouraged to incorporate higher-frequency data, additional explanatory variables, and alternative forecasting techniques such as Long Short-Term Memory (LSTM), XGBoost, and hybrid statistical–machine learning models to provide a more comprehensive evaluation of forecasting performance.

Building on these findings, the analysis proceeds by extending the forecasting horizon beyond the out-of-sample period using the best performing model, namely Quantile Autoregression (QAR), which achieved the lowest sMAPE. In this stage, the QAR model is reestimated using the full available dataset to fully exploit all observed information before generating future forecasts. A multi step ahead forecasting approach is then implemented to produce predictions for the subsequent periods. The resulting forecasts represent the expected trajectory of the IDX30 index beyond the observed sample and provide insights into its potential future movements. The numerical results of these forecasts are summarized in Table 3, while their graphical representation together with the historical and out of sample data is presented in Figure 4. This visualization facilitates a clearer comparison between past dynamics and projected trends, highlighting the continuity and expected evolution of the index over time.

Table 3. Future Forecast of the IDX30 Index Using the QAR Model

Date	Forecast
Apr 2026	394,83
Mey 2026	402,55
Jun 2026	409,76
Jul 2026	416,44
Aug 2026	422,62
Sep 2026	428,34
Oct 2026	433,63
Nov 2026	438,53
Dec 2026	443,06
Jan 2027	447,36
Feb 2027	451,13
Mar 2027	454,73

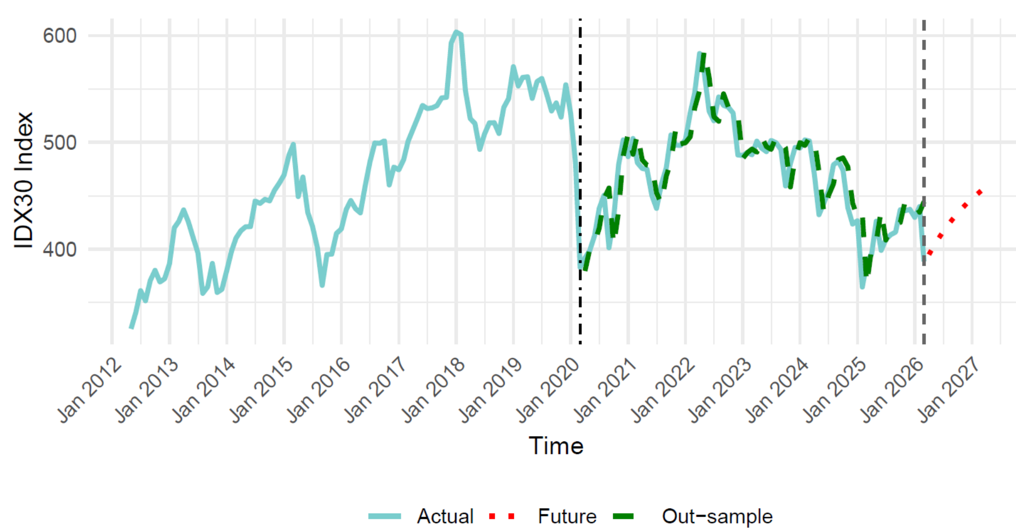

Figure 4. Out of Sample and Future Forecast of the IDX30 Index Using QAR Model

Building on this visualization, the numerical values in Table 3 indicate a clear and consistent upward movement of the IDX30 index throughout the forecast horizon. Starting from 394,83 in April 2026, the index is projected to increase gradually to 454,73 by March 2027. This steady progression suggests a recovery phase following previous fluctuations, with each month showing moderate and stable growth. The absence of sharp increases or declines implies that the model does not anticipate significant volatility in the near future, but rather a period of relatively stable market improvement. This upward trajectory is further reinforced by Figure 4, where the forecast line smoothly extends beyond the observed data. The continuity between historical, out-of-sample, and forecasted values indicates that the model successfully captures the underlying pattern of the series. In particular, the transition from the observed period to the forecast horizon appears seamless, suggesting that the projected values are consistent with past dynamics and not driven by abrupt or unrealistic assumptions.

Taken together, both the tabular and graphical results highlight the reliability of the Quantile Autoregression (QAR) model in producing coherent and plausible forecasts. The model's ability to generate stable and gradually increasing predictions reflects its strength in capturing short-term dependencies and adapting to recent trends. As a result, the forecasts provide a meaningful indication that the IDX30 index is expected to experience moderate but sustained growth over the coming periods, assuming no major external shocks disrupt the current trajectory.

CONCLUSION

This study compared the forecasting performance of Quantile Autoregression (QAR) and Prophet models in predicting the IDX30 index using monthly data from May 2012 to March 2026. Based on out-of-sample evaluation using sMAPE, MAE, and RMSE, the QAR model consistently outperformed Prophet. Specifically, QAR achieved an sMAPE of 3,47%, an MAE of 16,01, and an RMSE of 21,62, whereas Prophet recorded an sMAPE of 8,22%, an MAE of 38,71, and an RMSE of 53,27. These results suggest that QAR is more effective than Prophet in capturing the dynamics of the IDX30 index, particularly under conditions characterized by volatility and structural changes. From a practical perspective, the findings indicate that QAR may serve as a useful forecasting alternative for investors, portfolio managers, and financial analysts seeking to support investment planning and decision-making. Nevertheless, the results should be interpreted with caution because the study evaluated only two forecasting approaches and relied on monthly data from a single stock market index. Therefore, the findings do not necessarily imply that QAR is universally superior to all forecasting methods or across different market environments.

Several limitations should be acknowledged. First, the analysis was conducted using a relatively limited sample of monthly observations. Second, only QAR and Prophet were considered in the comparison, while other statistical, machine learning, and hybrid forecasting models were not examined. Third, potential seasonality and additional explanatory variables were not explicitly incorporated into the modeling framework. Future research is encouraged to include higher-frequency data, additional explanatory variables, and a broader range of forecasting approaches, such as LSTM, XGBoost, and hybrid statistical–machine learning models. Such extensions would provide a more comprehensive assessment of forecasting performance and improve the generalizability of the findings.

REFERENCE

[1] R. Anwar and L. Rassiyanti, "Analisis Komparasi Model Peramalan Prophet dan ARIMA dalam Memprediksi Harga Saham Penutupan PT ANTM," vol. 5, no. 1, pp. 57–74, 2025.

[2] R. Koenker and G. Bassett, “Regression Quantiles,” Econometrica, vol. 46, no. 1, pp. 33–50, 1978.
[3] R. Koenker and Z. Xiao, “Quantile Autoregression,” Journal of the American Statistical Association, vol. 101, no. 475, pp. 980–990, 2006.
[4] G. E. P. Box and G. M. Jenkins, Time Series Analysis: Forecasting and Control. San Francisco, CA: Holden-Day, 1976.
[5] S. Makridakis, “The M3-Competition: Results, Conclusions and Implications,” International Journal of Forecasting, vol. 16, no. 4, pp. 451–476, 2000.
[6] J. S. Armstrong, Long-Range Forecasting: From Crystal Ball to Computer. New York, NY: John Wiley & Sons, 1985.
[7] H. Hu, C. Zhao, J. Li, and Y. Huang, “Stock Prediction Model Based on Mixed Fractional Brownian Motion and Improved Fractional-Order Particle Swarm Optimization Algorithm,” Fractal and Fractional, vol. 6, no. 10, 2022.
[8] S. Chavleishvili and S. Manganelli, “Forecasting and Stress Testing with Quantile Vector Autoregression,” Journal of Applied Econometrics, vol. 39, no. 1, pp. 66–85, 2024.
[9] X. Zhang, H. Wang, and Y. Li, “Functional Quantile Autoregression,” Journal of Econometrics, vol. 244, no. 2, 2024.
[10] I. Ghosh and D. Pamucar, “Can Financial Stress Be Anticipated and Explained? Uncovering the Hidden Pattern Using EEMD-LSTM, EEMD-Prophet, and XAI Methodologies,” Complex & Intelligent Systems, vol. 9, pp. 4169–4193, 2023.
[11] A. Sunki, C. SatyaKumar, G. Surya Narayana, and V. Koppera, “Time Series Forecasting of Stock Market Using ARIMA, LSTM and FB Prophet,” MATEC Web of Conferences, vol. 392, 2024.
[12] K. Alim, B. Matsaany, and A. Rahmawati, “Diversification of Jakarta Islamic Index (JII) Stock Optimal Portfolio for the Period 2018–2023,” J Statistika, vol. 16, no. 2, pp. 585–593, 2023.
[13] F. Fitriyani, S. F. A., M. I. R., and T. A. T., “Peramalan Indeks Harga Saham PT Verena Multi Finance Tbk dengan Metode Pemodelan ARIMA dan ARCH-GARCH,” J Statistika, vol. 14, no. 1, pp. 11–23, 2021.
[14] J. Taylor, “Forecasting Value-at-Risk and Expected Shortfall Using Quantile Regression,” International Journal of Forecasting, vol. 40, no. 1, pp. 125–139, 2024.
[15] Y. Li, H. Wang, and X. Zhang, “Quantile-Based Forecasting of Financial Market Risk Under Structural Breaks,” Journal of Forecasting, vol. 43, no. 2, pp. 211–228, 2025.
[16] M. Ahmed and S. Khan, “Comparative Evaluation of Prophet and Machine Learning Models for Financial Time Series Forecasting,” Expert Systems with Applications, vol. 245, 2024.
[17] P. Verma and R. Sharma, “Stock Market Forecasting Using Prophet, LSTM, and Hybrid Approaches: A Comparative Study,” Applied Soft Computing, vol. 152, 2025.