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Modeling Inflation and Rupiah Exchange Rate Responses Using Bootstrap Aggregating Multivariate Adaptive Regression Spline in Indonesia

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ABSTRACT

This study aims to evaluate the performance of the Bootstrap Aggregating (Bagging) method applied to Multivariate Adaptive Regression Splines (MARS) in improving the predictive ability of biresponse models, compared to biresponse MARS models without bagging, using a case study of inflation and the rupiah exchange rate in Indonesia. Inflation and exchange rates are important macroeconomic indicators that are interrelated and play a crucial role in maintaining economic stability; therefore, a prediction model capable of accurately capturing simultaneous relationships and nonlinear patterns is required. The contribution of this study lies in the application of a biresponse nonparametric regression framework based on bagging to simultaneously model biresponse variables, which has rarely been explored in previous research that generally focuses on a single-response approach. The biresponse approach is used to accommodate the interrelationship between response variables, while the bagging procedure is implemented through a bootstrap technique with several replication scenarios to reduce prediction variance and improve model stability. The final prediction is obtained by averaging the results from all bootstrap models formed. The results of this study indicate that the application of Bagging MARS with 100 replications can significantly improve model performance, as shown by a decrease in the RMSE value from 132.40 to 92.08 and MAE from 70.71 to 52.12, as well as an increase in the R^2 value from 0.9997096 to 0.9998597. These findings indicate that the integration of the bootstrap technique in the Bagging MARS approach is effective in reducing model variability and producing more stable predictions. Practically, the Bagging MARS method has the potential to be used as an alternative in modeling interrelated macroeconomic indicators with nonlinear characteristics.

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A. INTRODUCTION

Macroeconomic stability is an important aspect in maintaining the sustainability of Indonesia's economic growth as one of the developing countries in Southeast Asia (Hashmi et al., 2021). In this context, inflation and exchange rate control are two key indicators that reflect a country's economic stability (Aizenman et al., 2016). Inflation describes changes in the price of goods and services that directly affect people's purchasing power and the balance between supply and demand (Rustam et al., 2019). Meanwhile, the exchange rate of the rupiah against the US dollar (USD/IDR) plays an important role in maintaining external balance through its influence on exports, imports, and international capital flows (Panggabean et al., 2025; Arisanti & Puspita, 2022). Inflation and exchange rates do not stand alone but are influenced by various macroeconomic variables such as interest rates, exports, imports, money supply (M2), world oil prices, and foreign exchange reserves (Sumantri & Fadli, 2022; Venkatesan & Ponnamma, 2017). Therefore, understanding the reciprocal relationship between macroeconomic variables is important because these interactions are dynamic and influence each other. The complexity of these relationships requires an analytical approach that can describe the interrelationships and patterns of interaction between variables more comprehensively.

Many studies have analyzed the macroeconomic factors that influence inflation and exchange rates. However, most of these studies model the two variables separately using a classical linear regression approach. In reality, inflation and exchange rates influence each other simultaneously, especially during periods of global economic instability such as 2022 to 2025, which is marked by the post-COVID-19 pandemic recovery phase. These conditions indicate that surging energy prices, supply chain disruptions, and monetary policy have led to an uncertain recovery period for the global economy (Knicker et al., 2025). This situation caused global inflation to surge from around 1.9% to 8.7% in 2020–2022, indicating significant pressure on price stability in various countries (Benn Steil, 2025). This sharp rise in inflation has the potential to cause economic and investment instability, reduce competitiveness, worsen the balance of payments, and disrupt financial market performance. In addition, inflation also hinders the process of optimizing the production of goods and services due to increased production costs (Yu et al., 2024).

Domestic inflationary pressures influenced by the depreciation of the rupiah exchange rate during the period 2022 to 2025 indicate a simultaneous interaction between the two variables, with the potential to form a nonlinear relationship due to asymmetric exchange rate transmission mechanisms (Indrawati et al., 2024; Mirza et al., 2023). Therefore, a modeling method is required that can capture nonlinear patterns and interactions among macroeconomic variables without imposing strict functional assumptions, such as Multivariate Adaptive Regression Splines (MARS) combined with the Bootstrap Aggregating (Bagging) technique. This approach represents a continuous nonparametric regression method with two response variables and is expected to be more adaptive to the variability of macroeconomic data. Multivariate Adaptive Regression Splines (MARS) was first introduced by Friedman in 1991 as a nonparametric modeling method capable of capturing nonlinear relationships among variables through a spline function approach and recursive partitioning regression (Friedman, 1991; Otok et al., 2020). Meanwhile, bootstrap aggregating or bagging, introduced by Breiman in 1996, is an ensemble technique used to reduce the variance of estimators in both classification and regression problems, thereby improving model stability, accuracy, and overall prediction performance (Şevgin, 2023; Uysal & Sonmez, 2023). The combination of the MARS algorithm with the bagging technique produces the Bootstrap Aggregating Multivariate Adaptive Regression Splines (Bagging MARS) method, which aims to improve model stability and prediction accuracy (Kulekçi et al., 2022).

Previous research conducted by Priambodo et al. (2024) on the application of the Bagging MARS method for modeling poverty indicators in East Java Province showed that the implementation of Bagging MARS was able to reduce the Generalized Cross Validation (GCV) value from 9.231184 to 3.84492 after the bagging process, indicating an improvement in model accuracy compared to a single MARS model. In addition, research by Çatal et al. (2023) on the practicality of the MARS and Bagging MARS algorithms in predicting pea plant height demonstrated that the Bagging MARS model produced a higher coefficient of determination (R^2) value of 0.811, compared to 0.752 for the MARS model, thereby significantly enhancing the stability and predictive accuracy of the model.

Although the MARS Bagging method has been proven to improve prediction accuracy in various fields, its application in the macroeconomic context is still very limited, especially for modeling inflation and exchange rates as response variables that interact simultaneously. Most previous studies still use a classical linear regression approach or only consider one response variable, thus failing to comprehensively capture the reciprocal relationships and nonlinear patterns between economic indicators. In addition, studies on the performance of MARS Bagging in dealing with the complexity and dynamics of Indonesia's macroeconomic data are still rare. This methodological gap indicates the need to develop a nonparametric ensemble-based biresponse modeling approach that is capable of representing simultaneous relationships between macroeconomic variables in a more flexible and accurate manner. Therefore, this study aims to develop and evaluate a nonparametric biresponse regression model based on Bagging MARS in modeling the simultaneous relationship between inflation and exchange rates in Indonesia and compare its performance with the MARS model without bagging so that it is expected to contribute methodologically to the development of biresponse modeling in nonlinear and interrelated macroeconomic data.

B. METHODS

This study uses secondary data on inflation and the rupiah exchange rate in Indonesia obtained from various official sources, namely Bank Indonesia (BI), the Ministry of Trade of the Republic of Indonesia (KEMENDAG), and the EIA (U.S. Energy Information Administration). This research is designed as a quantitative predictive modeling study employing a comparative ensemble approach to evaluate the performance of Bootstrap Aggregating Multivariate Adaptive Regression Splines (Bagging-MARS) in modeling the simultaneous responses of inflation and the rupiah exchange rate. The data used covers the period from January 2022 to August 2025, consisting of 44 monthly observations. The dataset was not divided into training and testing subsets because the bagging procedure relies on repeated resampling from the full dataset to construct multiple models, allowing all observations to be utilized to enhance model stability. The variables used in this study are presented in Table 1 below:

Table 1. Research Variables

Variables	Description
Y_1	Inflation rate (%)
Y_2	Rupiah exchange rate (USD/IDR)
X_1	BI rate (%)
X_2	Export (million US$)
X_3	Import (million US$)
X_4	Broad money supply (M2) (billion rupiah)
X_5	World oil price (USD per barrel)
X_6	Foreign exchange reserves (million USD)

The research steps applied in this study are as follows:

a. Preparing the dataset through data cleaning and normalization processes.
b. Conducting descriptive statistical analysis and scatterplot visualization to explore the relationships between response and predictor variables.
c. Testing the correlation between response variables using Pearson's correlation test.
d. Performing Multivariate Adaptive Regression Splines (MARS) modeling by combining several parameter values, namely Basis Function (BF), Maximum Interaction (MI), and Minimum Observation (MO), using the entire dataset to obtain the optimal parameter combination.
   1) Determining the number of basis functions (BF). Basis functions are used to identify knot locations and construct functions that model the relationship between independent variables and dependent variables (De Oliveira Celeri et al., 2024). The recommended number of basis functions is generally between two and four times the number of predictor variables (Friedman, 1991). Since this study involves six predictor variables, the number of basis functions considered is 12, 18, and 24.
   2) Determining the maximum interaction level (MI), where the commonly recommended MI values are 1, 2, and 3 (Eskandarinejad et al., 2025). Higher interaction levels may increase model complexity and reduce estimation efficiency (Liu et al., 2023).
   3) Determining the minimum observation (MO), which represents the minimum number of observations between knots, with candidate values of 0, 1, 2, and 3 (Efendi et al., 2021).

e. The optimal MARS model is selected based on the smallest Generalized Cross Validation (GCV) value for each response variable (Sabancı & Cengiz, 2022). The GCV value is calculated using the following formula (Sriningsih et al., 2023):

$$GCV(M) = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{f}_M(x_i))^2}{\left(1 - \frac{C(\bar{M})}{n}\right)^2} \tag{1}$$

f. Interpreting the best MARS model and grouping the basis functions according to the predictor variables that significantly influence the responses.
g. Applying bootstrap aggregating (bagging) to the MARS model using 25, 50, 100, and 150 bootstrap replications to evaluate model stability and predictive accuracy across different replication sizes.
h. Calculate RMSE, MAE, and R^2 for each bootstrap replication, and select the model with the lowest RMSE and MAE and the highest R^2 as the most accurate and stable model.
i. Determine the best Bagging MARS model.

C. RESULT AND DISCUSSION

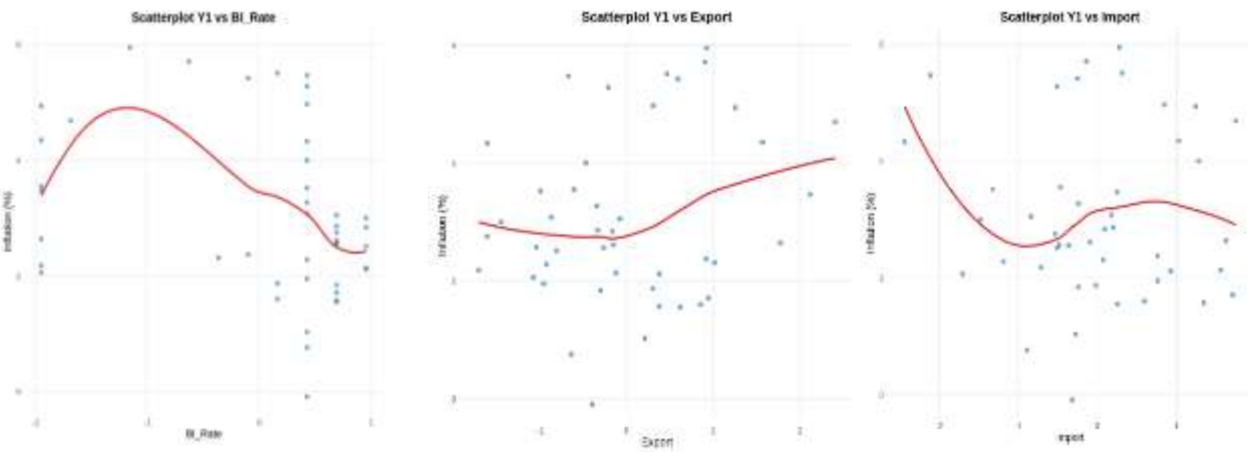
1. Descriptive Statistic

In this study, descriptive statistics are presented using summary tables and scatterplots. The summary tables describe the primary characteristics of each research variable, including the mean, median, minimum, and maximum values. The data employed in this study have been previously cleaned and prepared, making them directly suitable for modeling without the need for further preprocessing. Additionally, scatterplots are utilized to visually examine the patterns of relationships between the response variable and each predictor, thereby providing an initial evaluation of the appropriateness of applying a nonparametric modeling approach, as shown in Table 2.

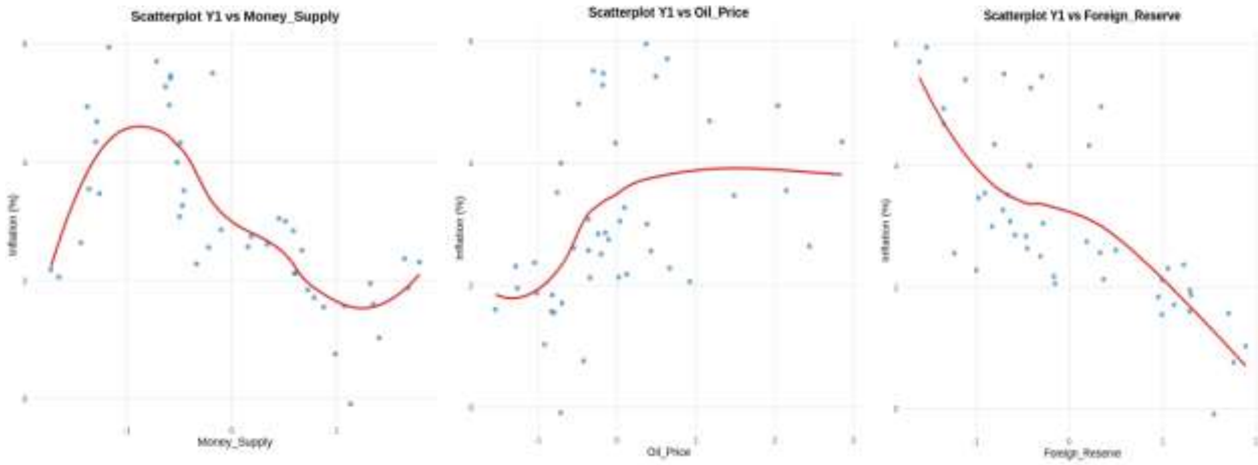
Table 2. Descriptive Statistic

Variable	Mean	Median	Minimum	Maximum
Y_1	3.049	2.695	-0.090	5.950
Y_2	15514	15582	14341	16827
X_1	5.347	5.750	3.500	6.250
X_2	22797	22453	19143	27929
X_3	19358	19272	15462	22151
X_4	8632260	8551470	7646789	9657084
X_5	84.90	82.38	64.45	122.71
X_6	142.6	140.3	130.2	157.1

Based on Table 2, the BI Rate variable (X_1) exhibits the lowest value compared to the other economic variables, with a minimum value of 3.049% and a maximum of 6.250%, reflecting changes in interest rate policy during the observation period. Meanwhile, the export value (X_2) shows considerable variation, with a maximum value of 27,929 million USD. The variable of money supply (X_4) has the highest scale and value compared to other variables, indicating an increase in liquidity in the economy. In addition, world oil prices (X_5) show quite sharp fluctuations, with a maximum value of 122.71 USD per barrel. The difference between the minimum and maximum values of these main variables indicates diverse economic dynamics during the study period, as shown in Figure 1 and Figure 2.

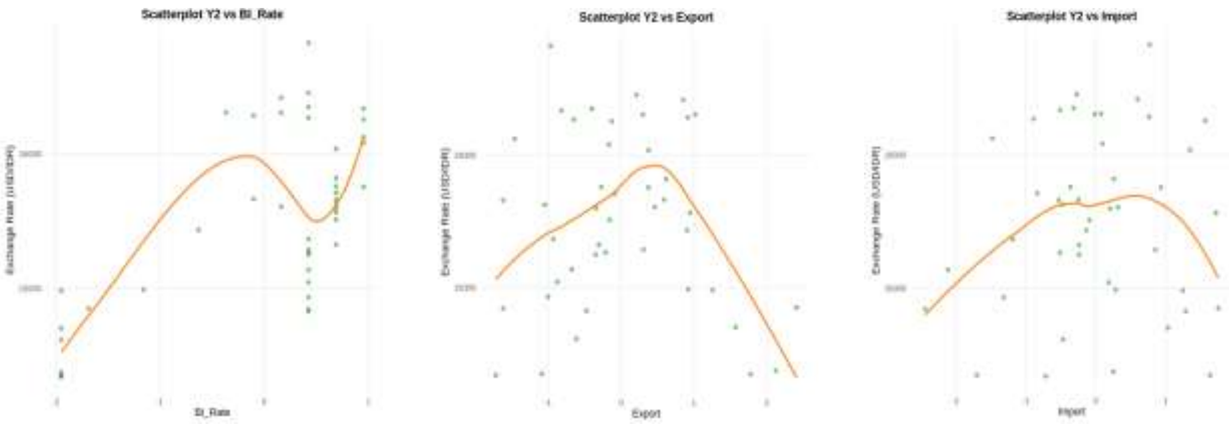


(a) Scatterplot Y1 vs BI_Rate (b) Scatterplot Y1 vs Export (c) Scatterplot Y1 vs Import

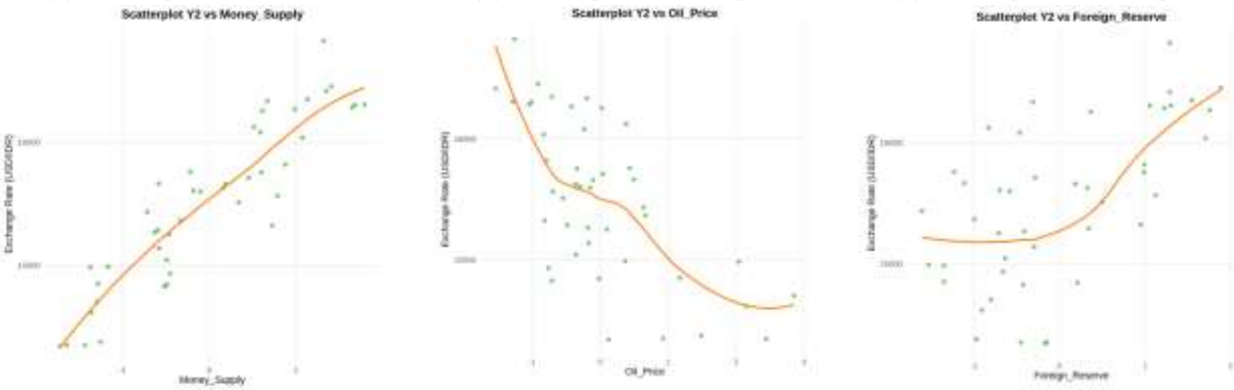


(d) Scatterplot Y1 vs Money Supply (e) Scatterplot Y1 vs World Oil Price (f) Scatterplot Y1 vs Import

Figure 1. Scatterplot of response 1 (Y1) versus predictor variables (X)



(a) Scatterplot Y2 vs BI_Rate (b) Scatterplot Y2 vs Export (c) Scatterplot Y2 vs Import



(d) Scatterplot Y2 vs Money Supply (e) Scatterplot Y2 vs World Oil Price (f) Scatterplot Y2 vs Import

Figure 2. Scatterplot of response 2 (Y2) versus predictor variables (X)

Based on Figure 1 and Figure 2, the distribution pattern of the data between the response variable and each predictor variable does not indicate a specific relationship, so a nonparametric regression approach is appropriate for analyzing this relationship. Next, Pearson's correlation test was conducted to examine the linear relationship between the two response variables. The test results produced a correlation of r = -0.4859 with a p-value of

0.0008, indicating a moderate and statistically significant negative relationship. Therefore, multiple response regression modeling is considered an appropriate approach to capture the complex relationship patterns between these variables.

2. Multivariate Adaptive Regression Spline Modeling

The Bagging MARS modeling process begins with the development of a single MARS model to identify the most optimal basis functions and variables that significantly influence the model. The initial stage of MARS modeling is carried out by searching for the best basis functions using a stepwise procedure (forward and backward) based on the minimum GCV value for each response variable. Next, MARS modeling is carried out by testing all combinations of basis function (BF) values, maximum interaction (MI), and minimum observation (MO) that have been determined previously. The best model is selected by considering the lowest GCV value presented in Table 3.

Table 3. Results of the Optimal Parameter Combination

Response	BF	MI	MO	GCV
Response 1 (Inflation rate)	12	1	1	0.686714
Response 2 (Rupiah exchange rate)	12	1	1	68891.802952

Based on the results of the bi-response MARS modeling, the optimal model was obtained from the parameter combination that yielded the smallest GCV value. For the inflation response, the best combination was BF = 12, MI = 1, and MO = 1, with a GCV value of 0.686714. Meanwhile, for the rupiah exchange rate response, the optimal combination was BF = 12, MI = 1, and MO = 1, with a GCV value of 68891.802952. In addition, the contribution of each predictor variable to the model was evaluated using variable importance analysis, and the results are presented in Table 4.

Table 4. Variable Importance

Response	Variable	GCV	RSS
Response 1 (Inflation rate)	X4	100.0	100.0
	X6	26.5	27.6
Response 2 (Rupiah exchange rate)	X4	100.0	100.0
	X6	21.9	31.1
	X1	11.4	20.5
	X5	11.3	17.1

Based on Table 4, for response 1 the broad money supply (X_4) variable contributed the most to inflation variation, followed by the foreign exchange reserves (X_6) variable. This aligns with macroeconomic theory, where money supply influences price levels and aggregate demand, while foreign exchange reserves help stabilize the currency and indirectly affect inflation (Sumantri & Fadli, 2022)(Venkatesan & Ponnamma, 2017).Meanwhile, variables BI rate (X_1), export (X_2), import (X_3), and world oil price (X_5) did not have a significant effect and were therefore not selected in the final model. For response 2, the broad money supply (X_4) variable is again the most influential variable on rupiah exchange rate variation. In addition, there are several other variables that also contribute significantly, namely foreign exchange reserves (X_6), BI rate (X_1), and world oil price (X_5). This is consistent with macroeconomic theory, where money supply affects currency valuation through liquidity and interest rate channels, foreign exchange reserves stabilize exchange rates, the BI rate influences monetary conditions, and World oil prices impact trade balances and capital flows (Sumantri & Fadli, 2022)(Venkatesan & Ponnamma, 2017). Meanwhile, variables export (X_2) and import (X_3) do not have a significant effect and are therefore not selected in the final model. Thus, the MARS model for two responses can be written as follows:

$$\begin{aligned}\hat{Y}_{\text{Inflation}} = {} & 6.741813 - 13.839393h\big(Broad\ money\ supply - (-0.286657)\big) - \\ & 4.490052h(-0.716125 - Broad\ money\ supply) - \\ & 1.265538h(Foreign\ exchange\ reserves - 0.208328) + \\ & 13.7449934h(Broad\ money\ supply - (-0.453733))\end{aligned}$$

$$\begin{aligned}\hat{Y}_{\text{Rupiah exchange}} = {} & 14053.1788 + 890.6402h(Broad\ money\ supply - (-0.18242)) \\ & + 537.6967h(1.05226 - Foreign\ exchange\ reserves) \\ & - 413.5130h(0.689181 - BI\ rate) + 992.6692h\big(World\ oil\ price - (-0.759667)\big) \\ & + 688.9254h(-0.759667 - World\ oil\ price) \\ & - 944.9791h\big(World\ oil\ price - (-0.300586)\big) \\ & + 404.4443h(Foreign\ exchange\ reserves - (-0.635608))\end{aligned}$$

3. Bootstrap Aggregating Multivariate Adaptive Regression Spline Modeling

Next, perform MARS modeling using bagging and a bootstrap replication count of 25, 50, 100, and 150 times to compare the stability and accuracy of the predictions produced for each replication count. After that, calculate the RMSE, MAE, and R^2 for each bootstrap replication, then select the model with the lowest RMSE and MAE and the highest R^2 as the most accurate and stable model, as shown in Table 5.

Table 5. Evaluasi Model Bagging MARS

B	RMSE	MAE	R^2
25	103.96119	59.25990	0.9998214
50	97.99693	57.22617	0.9998413
100	92.07822	52.11638	0.9998597
150	100.09739	55.92235	0.9998344

Table 5 presents the evaluation results of the Bagging MARS model with various numbers of bootstrap replications. The results indicate that the model performance improves as the number of replications increases from 25 to 100. This improvement is reflected in the decrease in RMSE from 103.96 to 92.08 and MAE from 59.26 to 52.12, as well as an increase in R^2 from 0.9998214 to 0.9998597, indicating more accurate predictions and a greater ability of the model to explain data variability. This phenomenon of improved performance demonstrates the stabilizing effect of the bagging method, whereby combining predictions from multiple resampled models reduces prediction variability and improves accuracy. However, at 150 replications, a slight increase in RMSE and MAE and a decrease in R^2 are observed, suggesting that increasing the number of replications beyond 100 does not yield significant performance gains and exhibits a diminishing returns effect. It should be noted that this analysis is based on a relatively small dataset (44 observations) with specific parameter settings (BF = 12, 18, 24; MI = 1, 2, 3; MO = 0, 1, 2, 3) and a limited observation period (January 2022–August 2025), so these findings may not be fully generalizable to other macroeconomic contexts or different time periods. Therefore, the model with 100 bootstrap replications can be considered the most accurate and stable Bagging MARS model for this dataset.

4. Comparison of MARS and Bagging MARS Performance

After calculating the RMSE, MAE, and R^2 values for each bootstrap replication to evaluate model performance, all results were then compared to identify the most accurate and stable model. The model with the lowest RMSE and MAE values and the highest R^2 value was selected as the best model, thereby determining whether the Bagging MARS method was able to improve performance compared to MARS without bagging, as shown in Table 6.

Table 6. Evaluation of MARS & Bagging MARS Models

Model	RMSE	MAE	R^2
MARS Biresponse	132.3996	70.71188	0.9997096
Bagging MARS Biresponse (B=100)	92.07822	52.11638	0.9998597

Based on Table 6, the comparison of results shows that Bagging MARS Biresponse with 100 bootstrap replications performs significantly better than MARS Biresponse without bagging. This can be seen from the significant decrease in RMSE and MAE values, which indicates that the model's prediction error rate has been greatly reduced after using bagging. In addition, the R^2 value increased from 0.9997096 to 0.9998597, which means that the model's ability to explain data variability also improved. Overall, these results indicate that the application of Bagging MARS successfully improves the accuracy and stability of the model compared to MARS Biresponse without bagging.

The results of this study are consistent with the findings of previous studies conducted by Priambodo et al. (2024); Çatal et al. (2023), which both show that the Bagging MARS method can improve model performance compared to MARS without bagging. In this study, the improvement in performance is demonstrated by a decrease in the RMSE value from 132.40 to 92.08 and the MAE from 70.71 to 52.12, as well as an increase in the coefficient of determination (R^2) value from 0.9997096 to 0.9998597, indicating that the Bagging MARS model is more accurate and better able to explain data variation. These results are in line with previous studies that reported a decrease in prediction error and an increase in R^2 after the application of bagging, so it can be concluded that this study supports and strengthens empirical evidence that the bootstrap aggregating approach in MARS is effective in improving model stability and accuracy, including in the case of modeling with biresponse variables.

D. CONCLUSION AND SUGGESTIONS

Based on the analysis results, the Bagging MARS method has been proven to improve model performance compared to Bi-response MARS without bagging. This is evidenced by a significant decrease in RMSE and MAE values, from 132.40 to 92.08 and from 70.71 to 52.12, respectively, and an increase in R^2 from 0.9997096 to 0.9998597, indicating that Bagging MARS is better able to explain data variations. This improvement demonstrates that the bootstrap replication process in bagging effectively reduces model variability, resulting in more stable and accurate predictions. However, the findings of this study should be interpreted within the context of certain limitations. The modeling process was conducted using a limited combination of basis functions (BF = 12, 18, 24), maximum interaction levels (MI = 1, 2, 3), and minimum observation values (MO = 0, 1, 2, 3), as well as a predefined set of bootstrap replications (25, 50, 100, and 150). In addition, the dataset consisted of 44 monthly observations from January 2022 to August 2025. Consequently, the results may be influenced by the specific macroeconomic conditions during this period and may not fully generalize to other datasets or timeframes. From a theoretical perspective, these findings contribute to the literature on bi-response modeling by demonstrating the effectiveness of Bagging MARS in capturing nonlinear interdependencies between simultaneously related macroeconomic variables, such as inflation and the rupiah exchange rate. From a practical standpoint, Bagging MARS can be utilized by researchers and policymakers as a robust predictive tool for modeling interrelated macroeconomic indicators, providing more reliable guidance for economic analysis and decision-making. For future research, it is recommended to explore a wider range of parameter combinations, longer observation periods, and comparisons with other ensemble methods such as Random Forest Regression, Gradient Boosting, and Boosted MARS. Further studies should also validate the model using external datasets under different economic conditions to ensure generalization capability.

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