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A comparative study of time series and machine learning methods in predicting Indonesia's greenhouse gas emissions

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Abstract: Greenhouse gas emissions are a contributing factor to global warming and climate change, which have widespread environmental, social, and economic impacts. As a developing country, Indonesia contributes significantly to greenhouse gas emissions, particularly from the energy, transportation, and land use sectors, while also being vulnerable to their impacts. In line with global commitments, Indonesia has set a target of reducing emissions by 31.89% by 2030 within its Nationally Determined Contribution (NDC) framework. However, the facts show that Indonesia's greenhouse gas emissions trend remained volatile between 2000 and 2019, with a tendency to increase more than decrease. This indicates that without strong and consistent policy intervention, the 31.89% emission reduction target by 2030 will likely be difficult to achieve. Therefore, predictive modeling of residential emissions is necessary to produce the most robust and accurate model. These predictions are expected to serve as a reference for the government in setting policy priorities and formulating strategic steps to address greenhouse gas emissions in a more targeted, measurable, and effective manner. Predictive modeling of greenhouse gas emissions was conducted using a quantitative research approach, with greenhouse gas emissions as the primary variable. Data used were from the Badan Pusat Statistik (BPS) covering the period 2000 to 2019. The modeling methods employed were time series modeling and machine learning. The two models were then compared to determine the best model to use as a basis for greenhouse gas emission control efforts.

Keyword: greenhouse gas emission, machine learning, prediction, time series

1. Introduction

Climate change is one of the most pressing global challenges of the 21st century, caused by increasing concentrations of greenhouse gases (GHGs) in the atmosphere. In Indonesia, increasing GHG emissions primarily originate from four main sectors: energy, transportation, industry, and forestry. According to a study by Pangestu and Ayuningsasi [1], energy consumption in the industrial sector has a positive and significant impact on national carbon emissions. This means that when energy consumption in the industrial sector increases, carbon emissions also tend to rise. This indicates that the intensity of fossil fuel use in industrial production processes is a significant factor in increasing carbon emissions. Furthermore, the industrial sector produces not only direct emissions from the combustion of fossil fuels but also indirect emissions from electricity and energy consumption to support factory operations and heating processes. Therefore, controlling energy consumption in the industrial sector through energy efficiency, the use of low-carbon technologies, and shifting to renewable energy sources is one of the main strategies in national emission mitigation [1].

The transportation sector plays a significant role in contributing to carbon dioxide (CO_2) emissions in Central Java Province. Research conducted by Hela and Ekawaty [2] found that increased economic activity in the transportation sector, as reflected in the Gross Regional Domestic Product (GRDP), positively impacted CO_2 emissions. This indicates that higher transportation activity, such as increased use of motorized vehicles and the intensity of movement of goods and people, leads to greater emissions. Furthermore, the industrial sector also significantly contributes to emissions, making these two sectors the main contributors to total carbon emissions in Central Java. Therefore, emission control efforts need to focus on energy efficiency and the use of environmentally friendly technologies in both sectors [2].

The forestry sector also plays a significant role in contributing to greenhouse gas emissions, particularly through forest fires and fertilizer use on converted land. Research by Silaban and Suharianto [3] found that emissions from the forestry sector in North Sumatra during the 2000–2023 period fluctuated, influenced by the intensity of forest fires and agricultural activities using nitrogen-based fertilizers. Forest fires not only release carbon dioxide (CO_2) from biomass burning but also cause the loss of forests' function as carbon sinks. Furthermore, the use of fertilizers on converted forest land also produces nitrous oxide (N_2O) emissions, which have a higher global warming potential than CO_2. Therefore, the forestry sector is a significant contributor to increased emissions, both directly through fires and indirectly through land degradation and fertilizer use. Mitigation efforts need to be directed at controlling forest fires, rehabilitating degraded land, and implementing sustainable agricultural practices to reduce emissions from this sector [3].

Based on the research results of Pramita, Kholisoh, and Lusia [4], the level of greenhouse gas (GHG) emissions in the energy sector in Indonesia shows a continuous increasing trend from year to year. A significant increase occurred in 2011 and 2019, reflecting the growth of energy activities that have a direct impact on increasing emissions. Descriptive analysis conducted showed that the standard deviation value of GHG emissions was 94,674.303, indicating a significant variation between the annual emission value and the average. In addition, the stationarity of the data is seen from the output results that increase or decrease regularly and constantly; if the data is not stationary, emission fluctuations become irregular with variance and mean that are not aligned with changes in the data. These findings show that GHG emissions in the energy sector in Indonesia tend to increase continuously with complex dynamics, influenced by variations in national energy consumption [4]. Based on these conditions, emission predictions are important.

The importance of emission forecasting lies in developing various policy scenarios, such as Net Zero Emissions targets by 2045, 2050, or 2060, which allow decision-makers to map different emission reduction pathways. By developing ambitious yet politically, technically, and institutionally realistic scenarios, emission forecasting serves as a strategic tool for evaluating the speed and intensity of interventions required at each timeframe, while ensuring that international commitments such as the Paris Agreement can be met and gradually increased [5].

Conventional approaches, such as trend extrapolation, have several fundamental weaknesses when applied to predicting greenhouse gas emissions in Indonesia. This method relies heavily on historical patterns assumed to be linear and stable, thus failing to capture nonlinear dynamics caused by changes in energy policy, fluctuations in industrial activity, or transformations in the national transportation system. Furthermore, this approach tends to ignore external variables that could potentially influence emission rates, such as the adoption of low-carbon technologies or decarbonization policies, because it focuses solely on the extension of past patterns. Another limitation of trend extrapolation is its inability to adapt to long-term structural changes in dynamic economic and environmental systems. In contrast, data-driven approaches such as machine learning can recognize complex multivariate relationships and learn from changing emission patterns without assuming linearity, resulting in more accurate and adaptive predictions to actual conditions [6].

The relevance of a comparative study between time series methods and machine learning approaches in the Indonesian context lies in the urgency of developing adaptive, accurate, and evidence-based forecasting models to support climate change mitigation policies. The complexity of greenhouse gas emission dynamics in Indonesia is influenced by various factors such as economic growth, energy policy, urbanization, and industrial and forestry activities. This condition demands analytical methods that can accommodate data fluctuations, non-stationarity, and dynamic intersectoral relationships. Conventional time series approaches have the advantage of simplicity and interpretability, but often lack flexibility when faced with nonlinear patterns or long-term structural changes. In contrast, machine learning-based approaches offer the ability to learn from a broader range of data, potentially producing more precise predictions in complex systems. A study by Subian, Mulkan, Ahmady, and Kartiasih [7] showed that the use of machine learning in the Indonesian economic context can improve prediction accuracy compared to conventional methods, confirming the relevance of similar comparative studies for application to the analysis and projection of national greenhouse gas emissions.

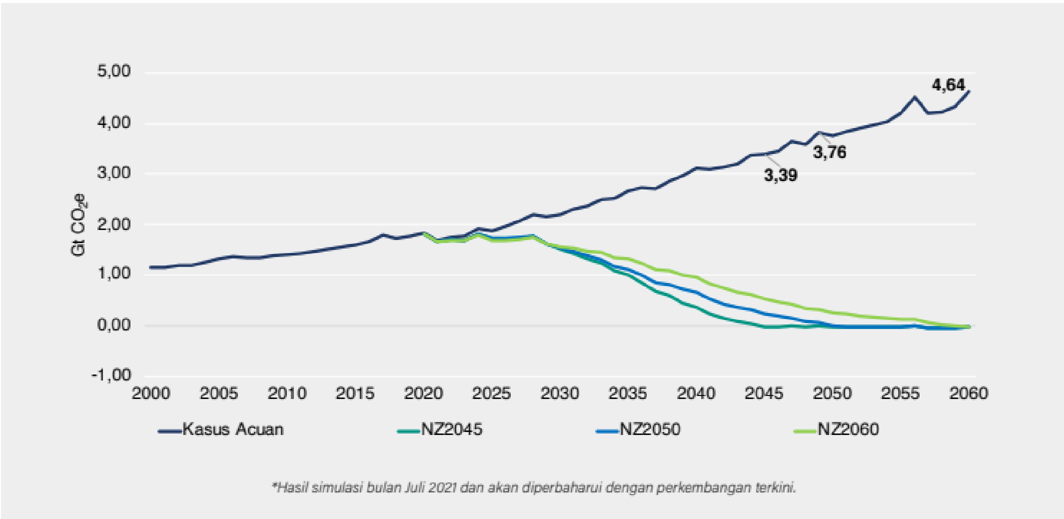
2. Research questions

1) How is the condition of greenhouse gas emissions in Indonesia from 2000 to 2019?
2) How is the quality of time series methods for predicting green gas emission in Indonesia?
3) How is the quality of machine learning methods for predicting green gas emission in Indonesia?
4) Which prediction method is best for predicting greenhouse gas emissions in Indonesia?

3. Literature Review

3.1. Overview of Greenhouse Gas Emissions in Indonesia

A comparative analysis of the "Reference Case" scenario (without new policies) with three net-zero scenarios shows that the implementation of ambitious climate policies could cause Indonesia's GHG emissions to peak around 2024 before starting to decline. Although the current baseline emission projection is 23.7% lower than the initial estimate in the climate commitment document (NDC), absolute emissions in all net-zero scenarios would still be significantly lower, ensuring that the national target can be significantly exceeded. Overall, these policies are projected to prevent emissions of 87 to 96 Gt CO_2e by 2060, a substantial contribution compared to the total remaining global carbon budget of 420 Gt CO_2e calculated by the IPCC to keep temperature rise below 1.5°C [8].



Sumber: Data historis untuk emisi berdasarkan Inventarisasi Gas Rumah Kaca Nasional hingga tahun 2020; hasil pemodelan untuk tahun 2021 dan seterusnya.

Figure 1. Bappenas Planning

3.2. Time Series Forecasting Methods

In several local studies in Indonesia, the results of the study showed that Holt-Winters is often the main choice when the data shows a clear seasonal pattern. According to Hidayatullah, Wulandari, and Ramadhani **[9]**, based on the analysis results, it can be concluded that the Holt-Winters method is significantly superior and more accurate than the ARIMA (Autoregressive Integrated Moving Average) method for forecasting sales at PT. Fresh Gifts of Nature for the period 2020–2024. This superiority is evidenced by the Mean Absolute Percentage Error (MAPE) value of the Holt-Winters method which is stable in the range of 8% to 10%, indicating a good level of forecasting accuracy. In contrast, the ARIMA method produces forecasts with a very high error rate (MAPE > 100%), making it unreliable for company sales data. Similarly, in a study on the number of international tourist arrivals to Ngurah Rai Airport, the Holt-Winters exponential multiplicative smoothing method produced lower errors than the ARIMA model, especially when logarithmic transformation and seasonal differencing were used.

Several local studies in the Indonesian Regressive Integrated Moving Average (IMR) domain also showed that Holt-Winters is often the primary choice when the data exhibits a clear seasonal pattern. However, according to Hidayatullah, Wulandari, and Ramadhani [9], several other studies have shown that the Prophet and ARIMA models have their own advantages under certain data conditions. Noviani, Danarwindu, and Prihatmoko [10] found that Prophet provided the most accurate forecasting results for warehouse receipt system transaction data due to its ability to handle fluctuating data and missing values. Meanwhile, research by Sulaiman and Juarna [11] on unemployment rates showed that ARIMA performs better on linear data without strong seasonal patterns, while Holt-Winters excels when the trend and seasonality are constant. Therefore, the choice of time series forecasting method for environmental data must consider trend stability, seasonality, and data quality.

3.3. Machine Learning for Emission Prediction

In several local studies in Indonesia, the results of the study entitled *Development of a Regional Feature Selection-Based Machine Learning System (RFSML v1.0) for Air Pollution Forecasting over China* by Fang et al. [12] compared three machine learning algorithms, namely Random Forest, Gradient Boosting, and Multi-Layer Perceptron, to predict $PM_{2.5}$ particle concentrations in various regions of eastern China. Researchers used the SAGE-based regional feature selection method to select the most relevant variables, such as meteorological factors, emissions, and pollutant data. The results showed that after feature selection, model accuracy increased significantly. The Gradient Boosting and Random Forest models showed the best performance with an increase in the coefficient of determination (R^2) value from 0.60 to around 0.70 in the 24-hour prediction. This study confirms that the integration of regional feature selection can improve the performance of air pollution prediction models in areas with complex environmental characteristics.

Another study by Zhu et al. [13] titled A New Prediction Method of Industrial Atmospheric Pollutant Emission Intensity Based on Pollutant Emission Standard Quantification compared the performance of Support Vector Regression and Random Forest Regression algorithms in predicting sulfur dioxide (SO_2) emission intensity from the coking industry in China. This study introduced a new approach by adding the emission standard quantification variable (QRPES) as an additional factor in the modeling. The results showed that the Root Mean Square Error (RMSE) value in the Support Vector Regression model decreased from 0.055 to 0.045 kilotons per year, while in the Random Forest model it decreased from 0.059 to 0.039 kilotons per year. In addition, the R^2 value increased from 0.890 to 0.926 for Support Vector Regression and from 0.881 to 0.945 for Random Forest. These findings demonstrate that the use of relevant external variables, such as emission regulations, can significantly improve the predictive ability of machine learning models.

3.4. Comparative Analysis in Previous Studies

A comparative study of statistical and machine learning approaches to emissions forecasting reveals significant methodological dynamics in contemporary environmental research. Traditional statistical approaches, such as exponential smoothing models, are considered capable of representing linear and seasonal patterns, but tend to be less adaptive to the nonlinear characteristics of environmental data and the influence of various external factors. In contrast, machine learning approaches such as Random Forest, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) have advantages in identifying complex relationships between variables and handling data nonstationarity more effectively [14].

Comparative studies conducted in China and India have shown that ML models can improve the accuracy of carbon emission forecasting compared to conventional statistical methods, especially in the context of fluctuating long-term data [15]. However, in Indonesia, research directly comparing the performance of the two approaches is still very limited. Most domestic studies still focus on classical time series methods without testing their comparative validity with ML algorithms, which are more adaptive to changing data patterns [16]. Thus, there is a research gap that needs to be bridged through empirical studies that critically assess the relative effectiveness of the two approaches in the context of national emission predictions up to 2030.

4. Method

This study employed an inferential quantitative research approach. Quantitative research uses numerical data to describe a phenomenon. The inferential approach is used to reveal population conditions based on sample data. The inferential approach used is an inferential approach for prediction.

4.1. Data Collection

The data used in this study is secondary data taken from documents belonging to the Badan Pusat Statistik (BPS). The data type used is time series, where data is collected over time. The time series in the data is a series of years starting from 2000 to 2019. The data collected is Greenhouse Gas (GHG) Emissions data from various sectors in Indonesia. The data collected has a ratio scale. Table 1 below illustrates the data structure used in the study.

Table 1. Data Structure Used In The Study

Year	Energy	IPPU	Agriculture	FOLU	Forest Fire	Waste	Total Emission
2000	317,609	42,883	99,314	500,019	161,571	64,832	1,186,228
2001	341,919	48,269	97,124	-144,329	50,885	67,602	461,470
:	:	:	:	:	:	:	:
2017	562,244	55,395	127,503	476,005	12,512	120,191	1,353,850

2018	595,665	59,262	110,055	602,188	121,322	127,077	1,615,569
2019	638,808	60,175	108,598	468,425	456,427	134,119	1,866,552

Source : [17] Badan Pusat Statistik, 2022.

Desciption:

Energy	:	GHG emissions from the energy sector mainly come from the combustion of fossil fuels.
Industrial Processes and Product Use (IPPU)	:	GHG emissions resulting from chemical process activities in industry
Agriculture	:	GHG emissions resulting from all agricultural and livestock activities
Forestry and Other Land Use (FOLU)	:	GHG emissions and carbon sequestration due to land use change, forest degradation, etc.
Forest Fire	:	GHG emissions released due to biomass burning in forest or land areas
Waste	:	GHG emissions resulting from waste management
Total Emission	:	Total GHG emissions

4.2. Data Analysis

The research data was processed using several stages to answer the research objectives, namely:

1) Data collection
2) Data cleaning
3) Data division into training and testing data
4) Data analysis using descriptive statistics (graphs and statistics) to describe emissions conditions in Indonesia from 2000 to 2019
5) Predictive modeling using time series methods
6) Predictive modeling using machine learning
7) Analysis of the best predictive model

5. Result

5.1. Overview of GHG Emissions in Indonesia from 2000 to 2019

The picture of GHG emissions in Indonesia can be seen from the GHG emission trend graph from 2000 to 2019. Figure 2 shows the distribution of GHG emission data in Indonesia from 2000 to 2019 which was processed from total emission data.

Figure 2. Distribution of GHG emission data in Indonesia from 2000 to 2019

Total GHG emissions are the sum of emissions from several sectors. Table 2 below presents statistics on GHG emissions in each sector.

Table 2. Statistics of Indonesia's GHG Emissions in Each Sector

Statistics/sector	Energy	IPPU	Agriculture	FOLU	Forest Fire	Waste
Mean	456,512	44,320	107,670	226,678	237,375	92,353
Median	429,444	41,992	106,755.5	188,558.5	197,051	88,498
Maximum	638,808	60,175	127,503	742,843	822,736	134,119
Minimum	317,609	35,910	97,124	-144,329	12,512	64,832
Standard deviation	94,674.30	78,98.26	8,087.53	251,678.00	201,760.31	19,884.65

5.2. GHG emission prediction using time series

The time series approach used in this study to predict GHG emissions used total emissions data from 2000 to 2019, divided into training and testing data. The time series approaches used were the Holt-Winters and ARIMA. The following are the results of modeling total GHG emissions using both approaches.

In this study, the Holt-Winters approach, supported by the Python programming language, was used to predict total GHG emissions. Based on the analysis, the most optimal Holt-Winters model was the one that integrated smoothing parameters for level, trend, and seasonality, with values of alpha=1.49×10^{-8}, beta=3.01×10^{-10}, and gamma=0.

In the training data, the Holt-Winters model showed an R^2 of 0.4677, meaning that approximately 46.77% of the data variability can be explained by this model. Its MAE was 225,566.21, MSE 99,164,300,643.55, and MAPE 22.78%. The AIC and BIC were 421.12 and 427.30, respectively. Meanwhile, in the testing data, the Holt-Winters model achieved an R^2 of 0.0776 (although low, it remains positive, indicating little predictive ability), MAE 193,046.93, MSE 43,534,143,436.94, and MAPE 13.24%. The AIC and BIC were 127.34 and 121.82, respectively.

The predicted results of total GHG emissions from 2020 to 2030 are shown in Figure 3 below.

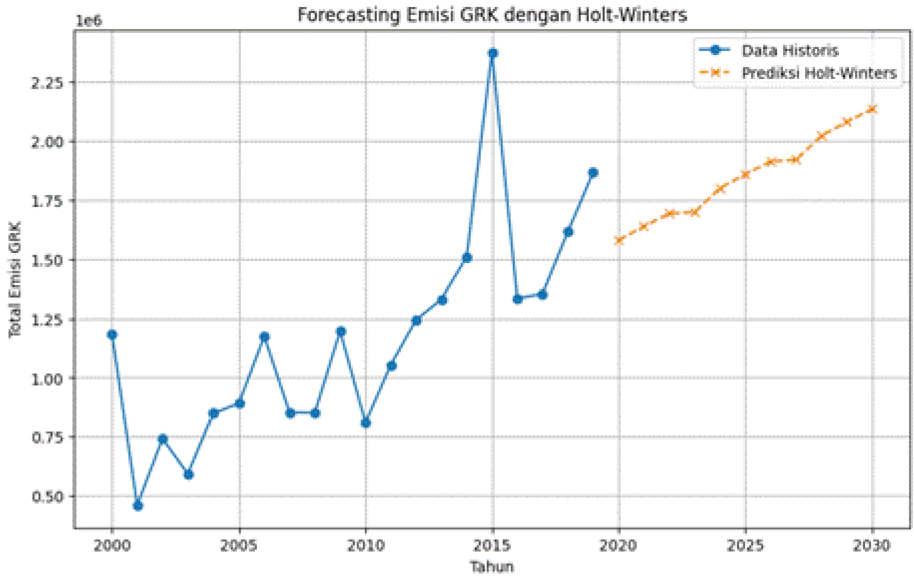


Figure 3. Prediction of Total GHG Emissions for 2020-2030 Using Holt-Winters

In ARIMA modeling, the most optimal model for predicting total GHG emissions is the ARIMA (0,1,1) model. The ARIMA model on the training data has an R^2 of 0.4530 (45.30% of variability explained), with an MAE of 260,018.06, an MSE of 108,184,604,947.88, and a MAPE of 25.16%. The AIC and BIC are higher, at 427.75 and 429.16, respectively. ARIMA on the testing data actually shows a negative R^2 (-5.2991), indicating worse performance than a simple baseline model (such as the average data). Its MAE is much higher (500,087.84), an MSE of 297,282,185,012.54, and a MAPE of 34.94%. The AIC and BIC are lower (121.02 and 119.80), but this is not enough to offset the failures in the main error metrics. Figure 4 below presents the predicted total GHG emissions from 2020 to 2030.

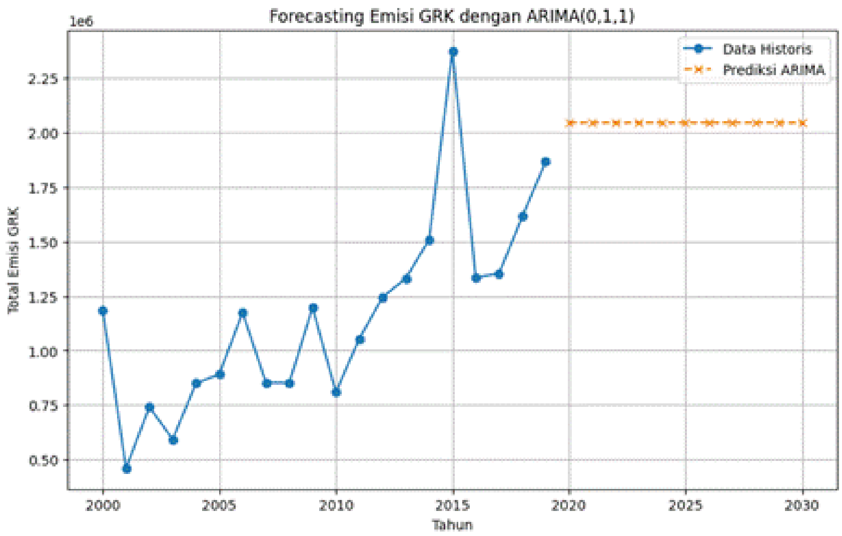


Figure 4. Prediction of Total GHG Emissions for 2020-2030 Using ARIMA

5.3. GHG emission prediction using machine learning

In this study, two machine learning approaches were used to predict greenhouse gas emissions: Classification and Regression Trees (CART) and Linear Regression. The models were trained using historical data from 2000 to 2015 and validated on observational data from 2016–2019, with projections up to 2030. The machine learning modeling evaluation in this study used R^2, Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) to assess model fit, prediction accuracy, and complexity penalties.

In the training data modeling using the CART approach, the R^2 value was obtained at 0.7109. MAE was 181,671.07, MSE was 53,862,006,829.33, MAPE was 19.22%, AIC and BIC were 522.76 and 554.44, respectively. While in the testing data modeling, the R^2 value was obtained at -2.8032. MAE was 363,726.00, MSE was 179,490,940,548.50, MAPE was 25.94%, AIC and BIC were 197.01 and 171.84, respectively. Figure 5 below shows the results of the prediction of total GHG emissions in 2020 to 2030 using CART.

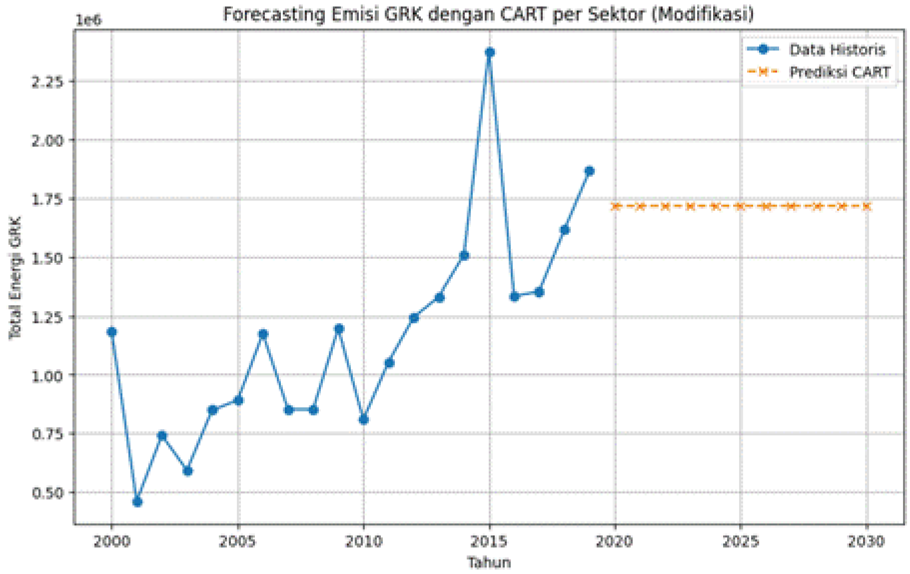


Figure 5. Prediction of Total GHG Emissions for 2020-2030 Using CART

Meanwhile, predictive modeling using linear regression displays a similar pattern in the training data with an R^2 value of 0.4966, MAE of 213,289.75, MSE of 93,795,568,625.64, MAPE of 20.45%, AIC and BIC of 453.64 and 455.18, respectively. In the testing data, the R^2 was obtained at -0.2108, MAE of 206,028.99, MSE of 57,140,725,931.81, MAPE of 14.66%, AIC and BIC of 114.43 and 113.20, respectively.

The results of the prediction of total GHG emissions in 2020 to 2030 using regression can be seen in Figure 6 below.

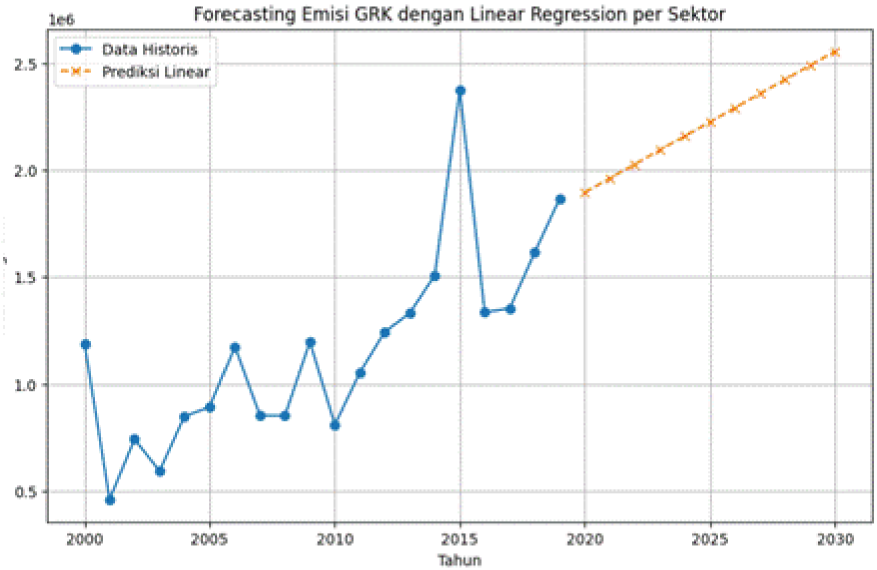


Figure 6. Prediction of Total GHG Emissions for 2020-2030 Using Linear Regression

5.4. *Discussion and Analysis*

The distribution pattern of GHG emissions in Figure 1, when viewed from total emissions data, shows a fluctuating pattern with an upward trend. The lowest total GHG emissions were found in 2001 and the highest in 2015. The largest reductions occurred in 2016 and 2021.

Based on the average and median values in Table 2, GHG emissions from energy contribute the largest GHG emissions compared to other sectors, followed by emissions from forest fires, FOLU, agriculture, waste, and the least comes from IPPU. When viewed from the minimum (min), maximum (max), and standard deviation values, GHG emissions produced in each sector vary quite a lot from year to year. The greatest emission diversity is found in the FOLU sector, which is 201,760.31, this diversity shows that changes in emissions produced from the FOLU sector from 2000 to 2019 are quite fluctuating.

In time series modeling, Holt-Winters outperforms the testing data model with significantly lower prediction errors, while ARIMA appears to experience overgeneralization or an inability to handle new data patterns, as evidenced by its negative R^2 and high MAPE. Based on metric evaluation, the Holt-Winters model is superior for predicting total GHG emissions. The Holt-Winters model performs significantly better on the testing data: a positive (albeit low) R^2, significantly lower MAE and MSE, and a MAPE of only 13.24% compared to 34.94% for ARIMA. This indicates that Holt-Winters is more capable of producing accurate and reliable predictions outside of the training data.

In predictive modeling using machine learning on training data, both models performed well. However, in testing data, both models produced negative R2 values, likely due to the relatively small amount of testing data. Overall, predictive modeling using linear regression was superior for modeling total GHG emissions, producing more stable predictions, while CART modeling produced constant or irregular predictions outside the historical range. Based on the results of predictive modeling using a time series and machine learning approach, the following summary results were obtained.

Table 3. Comparison of Predictive Modeling Results

Method	MAPE Testing	AIC Testing	BIC Testing	Prediction in 2030
Holt-Winters	13.24%	127.34	121.82	2,134,588
ARIMA (0,1,1)	34.94%	121.02	119.08	2,042,961
CART	25.94%	197.01	171.84	1,717,824
Linear Regression	14.66%	114.43	113.20	2,554,981

Based on Table 3, the best prediction method for predicting total GHG emissions in Indonesia is the linear regression model, with the lowest AIC and BIC values. Although all models still suffer from overfitting due to the small number of observations, the predicted total GHG emissions in 2030 using the best model are 2,554,981 thousand tons CO2e.

6. Consulition

Based on the research results, it is known that the distribution pattern of total GHG emissions in Indonesia from 2000 to 2019 fluctuated with an upward trend. Where the sector contributing the most emissions came from the energy sector. In predictive modeling using time series, the Holt-Winter model performed well in predictions, as indicated by lower prediction error values compared to ARIMA. Meanwhile, in machine learning models, predictive modeling with linear regression was better than CART because it produced more stable predictions. When comparing time series modeling and machine learning, the best model used to predict total GHG emissions in Indonesia is the regression model because it has the smallest AIC and BIC values.

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