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| RESEARCH ARTICLE

Forecasting CO_2 Emissions Per Capita in the Philippines Using Time Series Analysis

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| ABSTRACT

Forecasting carbon dioxide (CO_2) emissions per capita in the Philippines is crucial for evaluating individual contributions and informing targeted policies. It also helps anticipate potential environmental and social impacts while facilitating data-driven decision-making. This study analyzes the trends in CO_2 emissions per capita in the Philippines from 1979 to 2024. Various time-series models were constructed to select the best-fit model and to predict per capita emissions for 2027. The data were obtained from the website of Our World in Data. The results revealed a generally upward trend throughout the study period, despite short-term fluctuations and temporary decreases. Moreover, the first-order autoregressive (AR(1)) model emerged as the best fit, projecting an increase in per capita emissions to approximately 1.689 tonnes per person by 2027. These findings provide insight into potential future emission trajectories at the individual level and underscore the need for targeted interventions to effectively manage per capita emissions.

| KEYWORDS

Carbon dioxide, environmental issue, individual contribution, mathematical approach, per capita emissions, Philippines

| ARTICLE INFORMATION

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1. Introduction

Carbon dioxide can be regarded as both an adversary and a supporter of the planet, as it helps regulate Earth's temperature by retaining a portion of the radiant energy absorbed by the surface. While this natural process is vital for maintaining conditions suitable for life, the continuous increase in atmospheric CO_2 concentrations has raised concerns about long-term environmental change (Eldesouki et al., 2023). Nunes (2023) further noted that the leading factors behind the increase in atmospheric CO_2 concentrations are fossil fuel combustion, deforestation, agricultural practices, and cement production. Recent global assessments reported by Friedlingstein et al. (2025) indicate that continued fossil fuel combustion has elevated atmospheric carbon dioxide concentrations to 423 ppm in 2024 and has contributed to approximately 1.36 °C of human-induced warming, nearing the 1.5 °C threshold established under the Paris Agreement, which was adopted a decade ago.

Predictive modeling has become integral for understanding changes in emission patterns, guiding monitoring efforts, and supporting evidence-based planning. Numerous studies have applied regression and time series–based techniques to analyze and forecast carbon dioxide emissions. For instance, Iftikhar et al. (2024) used regression and time series methods to analyze CO_2 emissions in Pakistan, finding that the proposed hybrid combination forecasting technique produced accurate emission forecasts. Based on the optimal model, Pakistan's per capita CO_2 emissions are expected to reach 1.130215 metric tons in 2030. Similarly, Jena et al. (2021) developed a multilayer artificial neural network model to forecast CO_2 emissions, concluding that countries with currently high emissions are expected to increase emissions in the near future, while low-emitting countries may also experience substantial growth. Conversely, countries including the USA, Japan, the UK, France, Italy, Australia, and Canada are projected to reduce their emissions consistently. Collectively, these studies demonstrate the value of predictive modeling for analyzing emission trends and informing future projections.

Despite the predominant focus of previous studies on total national emissions, a gap persists in the understanding of per capita carbon emissions (Yang et al., 2023). Larsen (2025) argues that emissions comparisons should ideally also be conducted on a per capita basis, which is currently not always the case. Countries with relatively small populations may still be significant emitters if their per capita emissions are notably high, even when their total emissions are minimal. CO_2 emissions per capita refer to the average emissions per person in a specific country or region, calculated by dividing total emissions by the population (Ritchie et al., 2023). By accounting for population size, this measure provides a clearer understanding of individual contributions and supports more informed monitoring and planning decisions.

In the Philippine context, research has also predominantly focused on total carbon dioxide emissions. For instance, Ronario et al. (2022) investigated the factors influencing carbon dioxide emissions within the Philippine setting, Manalo et al. (2023) evaluated the role of energy production and consumption in CO_2 emissions in the Philippines and suggested strategies to reduce environmental impacts, and Valencia and Zhang (2022) analyzed the effects of agriculture, forestry, fishing, value added, livestock production index, and GDP on CO_2 emissions. However, studies that specifically examine and forecast CO_2 emissions per capita remain limited.

Hence, this study addresses this gap by examining the trend in carbon dioxide (CO_2) emissions per capita in the Philippines and constructing time-series models to identify the best-fit model for forecasting CO_2 emissions per capita for 2027. Using data from 1979 to 2024 obtained from Our World in Data, this study provides an exploratory assessment of historical patterns and projected trends. While the study does not establish causal relationships, the findings may serve as a basis for future studies and may contribute to evidence-based planning and strategies for managing per capita emissions.

2. Methodology

This study employed a quantitative approach, specifically, time-series analysis, to identify trends and patterns in carbon dioxide (CO_2) emissions per capita in the Philippines and forecast future values. Time series analysis is a commonly employed technique for analyzing historical data to generate future predictions (Alqatawna et al., 2023).

The study utilized available data on carbon dioxide (CO_2) emissions per capita (tonnes per person) in the Philippines from 1979 to 2024. The data were obtained from Our World in Data, a publicly available data portal produced by the Oxford Martin Programme and acknowledged as a leading source of accessible, evidence-based information that enables policymakers, researchers, journalists, and the public to comprehend better the scale of global challenges and the progress being made in addressing them (Oxford Martin School, 2025). The annual CO_2 emissions data are collected from the Global Carbon Project, while the population data are based on a long-term population series from Our World in Data, compiled from reputable sources including HYDE, Gapminder, and the United Nations World Population Prospects. Our World in Data processes and standardizes these datasets to yield consistent national-level estimates suitable for analysis.

The data extracted from Our World in Data were compiled, organized, and aligned by year, with 1979 coded as 1, 1980 as 2, and continuing sequentially to 2024 as 46. The data were analyzed using Microsoft Excel. First, a scatter plot was constructed to illustrate the trend of the carbon dioxide (CO_2) emissions per capita in the Philippines from 1979 to 2024. To identify the model that best fits the CO_2 emissions trend over time, various time-series models were explored, including linear, exponential, quadratic, cubic, quartic, moving average, and autoregressive models. Model performance was assessed using the coefficient of determination (R^2) and standard error, with the best-fit model defined as the one with the highest R^2 and the lowest standard error.

3. Results and Discussion

3.1 Trend of CO_2 emissions per capita in the Philippines

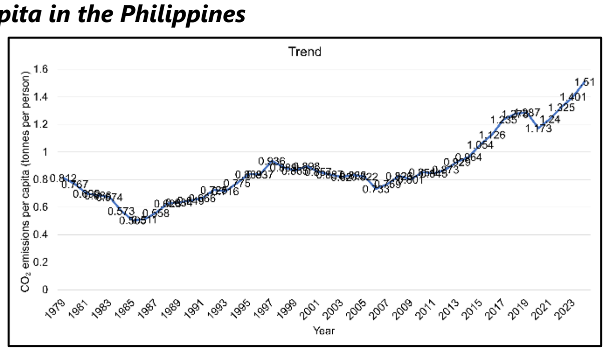

Figure 1. The trend of CO2 emissions per capita in the Philippines from 1979-2024

Figure 1 illustrates the trend in carbon dioxide (CO_2) emissions per capita in the Philippines from 1979 to 2024. In general, CO_2 emissions per capita showed a consistent upward trend over the study period, indicating a long-term increase despite short-term fluctuations and temporary declines. Although studies focusing specifically on per capita emissions remain limited, Wu et al. (2025) documented a comparable upward trend in global CO_2 emissions, providing broader contextual support for the observed trend. From 1979 to 1985, CO_2 emissions per capita declined steadily from approximately 0.812 to 0.505 tonnes per person. Beginning in 1986, emissions generally increased with noticeable fluctuations, reaching approximately 0.801 tonnes per person by 2009. From 2010 onward, CO_2 emissions per capita rose sharply and consistently, increasing from 0.854 tonnes per person to a peak of 1.510 tonnes per person in 2024.

In broader global studies, such rising trends in CO_2 emissions have often been associated with intensified economic activity, rapid urbanization, and growing dependence on fossil-fuel-based energy systems. Bahman et al. (2022) reported that rapid industrialization restricts the transition away from fossil-based energy systems, while Lamb et al. (2021) highlighted that the high demand for materials, floor area, energy services, and travel has contributed to emissions growth in industry, buildings, and transport sectors, particularly in Eastern Asia, Southern Asia, and South-East Asia. Although the primary focus of these studies is on total CO_2 emissions, they offer valuable contextual insights into the structural drivers typically associated with increased emissions.

3.2 Time Series Models

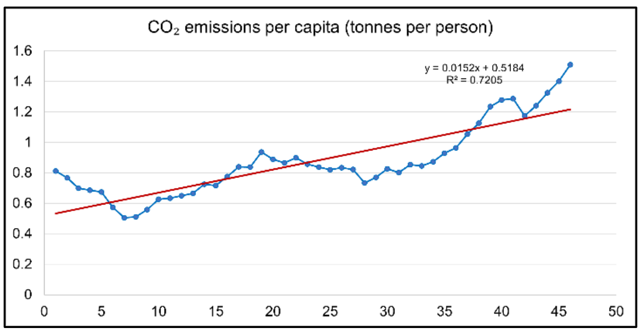

Figure 2. Linear Model

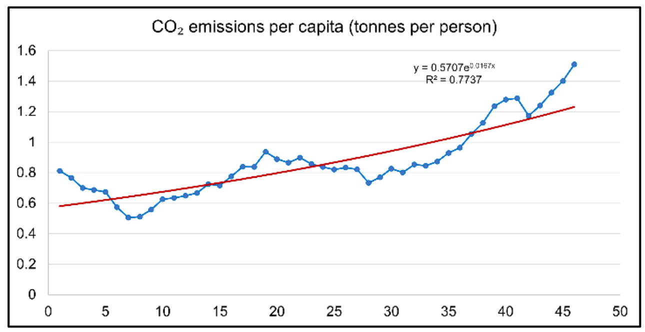

Figure 3. Exponential Model

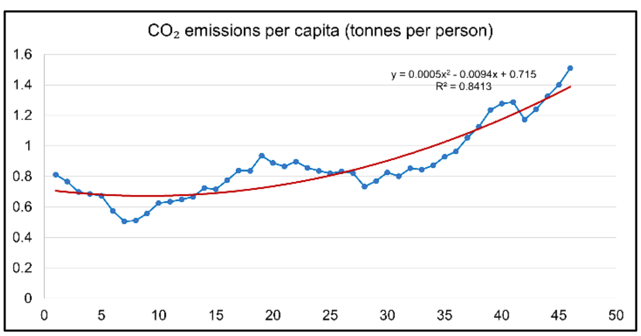

Figure 4. Quadratic Model

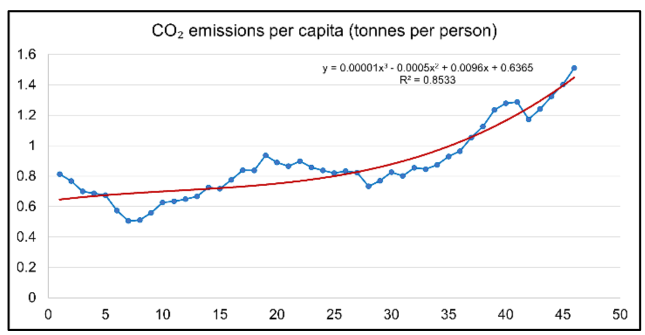

Figure 5. Cubic Model

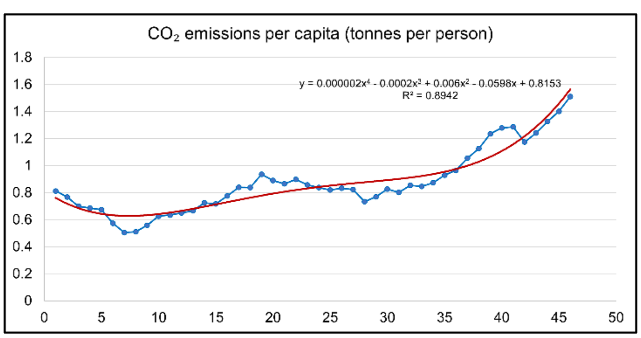

Figure 6. Quartic Model

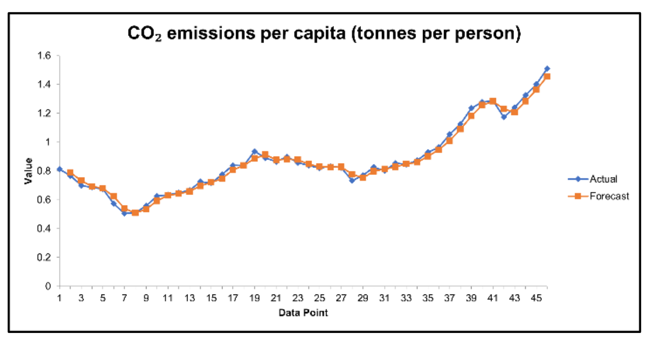

Figure 7. Moving Average Model

Figure 2 presents the linear model of CO_2 emissions per capita in the Philippines from 1979 to 2024, with the equation $y = 0.0152x + 0.5184$. The positive slope indicates a general upward trend in per capita emissions over time, suggesting a long-term increase at an average rate of roughly 0.0152 tonnes per individual annually. Nevertheless, the variability of the data points surrounding the regression line implies that this increase was not uniformly consistent throughout the observed period. The coefficient of determination ($R^2 = 0.7205$) suggests that the linear model explains 72.05% of the variance in CO_2 emissions per capita.

Figure 3 displays the exponential model of CO_2 emissions per capita in the Philippines from 1979 to 2024, with the equation $y = 0.5707e^{0.0167x}$. This model suggests that emissions per capita increase at approximately a constant rate over time, indicating accelerated growth as emissions rise. The coefficient of determination ($R^2 = 0.7737$) indicates that the exponential model explains 77.37% of the variance in CO_2 emissions per capita.

Figure 4 illustrates the quadratic model of CO_2 emissions per capita in the Philippines from 1979 to 2024, with the equation $y = 0.0005x^2 - 0.0094x + 0.715$. This model indicates that per capita emissions have followed a nonlinear path, exhibiting variations in the rate of increase over time. The model's curvature illustrates phases of gradual growth succeeded by more rapid increases in subsequent years. The coefficient of determination ($R^2 = 0.8413$) suggests that the quadratic model explains 84.13% of the variance in CO_2 emissions per capita.

Figure 5 shows the cubic model of CO_2 emissions per capita in the Philippines from 1979 to 2024, with the equation $y = 0.00001x^3 - 0.0005x^2 + 0.0096x + 0.6365$. The fitted curve in the model initially increases gradually, then slows, and finally rises more sharply in the later years. The shape of the curve reflects changes in curvature over time, indicating that the rate of increase in CO_2 emissions per capita is not constant across the observed period. The coefficient of determination ($R^2 = 0.8533$) indicates that the cubic model explains 85.33% of the variance in CO_2 emissions per capita.

Figure 6 displays the quartic model of CO_2 emissions per capita in the Philippines from 1979 to 2024, with the equation $y = 0.000002x^4 - 0.0002x^3 + 0.006x^2 -0.0598x + 0.8153$. The fitted curve indicates an initial decrease in CO_2 emissions per capita in the early years, followed by a gradual rise during the middle of the period and a more significant increase in the later years. The coefficient of determination ($R^2 = 0.8942$) indicates that the quartic model explains 89.42% of the variance in CO_2 emissions per capita.

Figure 7 displays the moving average model of CO_2 emissions per capita in the Philippines from 1979 to 2024 using an interval of 2, defined by $y = (Y_t + Y_{t+1})/2$, where Yt and Yt+1 represent the observed values in two consecutive years. The moving average model smooths short-term fluctuations in the data, allowing the underlying trend in CO_2 emissions per capita more apparent, while reducing year-to-year variability.

Table 1. Autoregressive result of CO_2 emissions per capita

	Coefficients	Standard Error	t Stat	P-value
Intercept	-0.0384	0.0329	-1.1680	0.2492
X Variable	1.0626	0.0370	28.7169	<.001

$F(1) = 824.66, p < 0.01, R^2 = 0.9504$

Table 1 presents the first-order autoregressive (AR(1)) model of CO_2 emissions per capita in the Philippines from 1979 to 2024, given by $y = -0.0384 + 1.0626y_{n-1}$. This indicates that current CO_2 emissions per capita are strongly dependent on its immediate past values. The lagged variable is statistically significant ($t = 28.72$, $p < 0.001$), the overall model is also significant ($F = 694.82$, $p < 0.01$), and the coefficient of determination ($R^2 = 0.9504$) indicates that the model explains 95.04% of the variance in CO_2 emissions per capita.

3.3 Best-Fit Model and Forecast of CO_2 Emissions per Capita in the Philippines

Table 2. Summary of Models with Corresponding Equations, R^2, and SE

Model	Equation	R^2	SE
Linear	$y = 0.0152x + 0.5184$	72.05%	0.1282
Exponential	$y = 0.5707e^{0.0167x}$	77.37%	0.1170
Quadratic	$y = 0.0005x^2 - 0.0094x + 0.715$	84.13%	0.0991
Cubic	$y = 0.00001x^3 - 0.0005x^2 + 0.0096x + 0.6365$	85.33%	0.2075

Quartic	$y = 0.000002x^4 - 0.0002x^3 + 0.006x^2 - 0.0598x + 0.8153$	89.42%	0.4826
Moving Average	$y = (Y_t+Y_{t+1})/2$	-	0.0470
Autoregressive	$y = -0.0384 + 1.0626y_{n-1}$	95.04%	0.0545

As shown in Table 2, the first-order autoregressive (AR(1)) model, which has an R^2 value of 0.9504 and a standard error of 0.0545, provides the optimal balance between explanatory power and predictive accuracy. This model accounts for 95.04% of the variance in CO_2 emissions per capita while maintaining a relatively low prediction error. Compared to the other models considered, the AR(1) achieves the best combination of a high R^2 and a low standard error, rendering it the most suitable choice for forecasting future trends. Despite the quartic model exhibiting a high R-squared value ($R^2 = 0.8942$), which signifies its ability to account for 89.42% of the variance in CO_2 emissions per capita and a considerable standard error of 0.4826, the AR(1) model still demonstrates superior performance. On the other hand, the moving average model with an interval of 2 yields the lowest standard error (SE = 0.0470), suggesting minimal average prediction error. However, since it does not produce an R-squared value, it cannot be solely considered the best-fit model.

The AR(1) is expressed by the equation $y = -0.0384 + 1.0626y_{n-1}$, where y_{n-1} is the carbon dioxide (CO_2) emissions per capita from the previous year. Using this model, the projected CO_2 emissions per capita in the Philippines for 2027 is approximately 1.689 tonnes per person, implying that each person is expected to contribute about 1.689 tonnes of CO_2. This forecast suggests a potential upward trend in emissions, highlighting the importance of monitoring and implementing measures to reduce carbon dioxide output.

4. Conclusions and Recommendations

The analysis of carbon dioxide (CO_2) emissions per capita in the Philippines from 1979 to 2024 indicates a generally increasing trend over the study period, accompanied by short-term fluctuations and temporary declines. This suggests a persistent increase in per capita emissions. However, the observed fluctuations and declines in some years suggest that the upward trend is not linear. In addition, various time series models were used to analyze the historical trend in CO_2 emissions per capita, with the first-order autoregressive (AR(1)) model providing the best fit, as indicated by R^2 and standard error comparisons. The AR(1) model forecasts that CO_2 emissions per capita in the Philippines will increase to approximately 1.565 tonnes per person in 2027, indicating that the upward trend in emissions is expected to continue, consistent with historical patterns. These findings offer valuable insights into future per capita emission trends and highlight the importance of targeted measures to mitigate rising emissions.

Based on the findings, individuals are encouraged to adopt energy-efficient practices, such as using energy-saving appliances, switching to LED lighting, minimizing unnecessary electricity use, and considering small-scale renewable energy options where feasible. Furthermore, educational initiatives and workshops may be organized to raise awareness of how daily decisions influence per capita CO_2 emissions. The emphasis could be placed on sustainable consumption practices, which encompass waste reduction, recycling, responsible purchasing, and the promotion of environmentally friendly products and services. In addition, future studies may strengthen the analysis and forecasting of CO_2 emissions per capita by using updated, more detailed datasets, including regional data where available. Although the AR(1) model performed best in this study, future research may apply advance time-series techniques, such as ARIMA, vector autoregression (VAR), or machine learning-based forecasting models, to improve predictive accuracy and accurately capture complex dynamic patterns in emissions. Expanding also the forecasts beyond 2027 would provide deeper insights to support long-term environmental planning and climate mitigation efforts.

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Conflict of Interest
The author declares no conflict of interest.

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