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# A Hybrid Regression–Fuzzy Framework for Climate Impact Assessment Using Primary energy consumption and $CO_2$ Emissions

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**Abstract**

This research aims to establish a relationship between primary energy consumption and $CO_2$ emissions and classify countries by their potential climate impact applying hybrid regression and Mamdani fuzzy logic. Data of 178 countries were analyzed using cross-sectional data of 2022, where primary energy consumption and $CO_2$ emissions were measured per capita. The system involved two inputs with three triangular and shoulder-shaped membership functions (Low, Moderate, High) and nine fuzzy rules. The results indicated that 96 (53.9%) countries belonged to High, 27 (15.2%) to Moderate, and 55 (30.9%) to Low potential climate impact categories. A bivariate linear regression model was estimated to analyze the relationship between primary energy consumption and $CO_2$ emissions by setting the former as an independent variable and the latter as a dependent variable. The results found a very weak positive association r = 0.0721 and p = 0.3385. The regression results demonstrated that 0.52% of the changes in $CO_2$ emissions per capita could be predicted by primary energy consumption per capita. The results suggest that potential climate impact is influenced by various factors, including energy sources, economic activities, industrialization, and energy efficiency. Therefore, the analysis employed a hybrid approach which combined statistical and fuzzy logic methodologies to address the climate change problem.

**Keywords:** primary energy consumption, $CO_2$ emissions, fuzzy Mamdani classification, climate impact, linear regression analysis

## 1. Introduction

In 2024, the global electricity demand increased by 4.3% driven by digitalization, industrial electrification, and the growing adoption of artificial intelligence. Nevertheless, the continued development of the industrial sector may also generate environmental consequences such as

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increasing primary energy consumption and associated emissions. Industrial activities expansion is closely associated with growing electricity demand, which consequently requires an adequate electricity supply to support economic and industrial activities (Ozturk et al., 2016) . Previous empirical studies have demonstrated a significant relationship between industrialization, primary energy consumption, and $CO_2$ emissions, with primary energy consumption contributing to higher carbon emissions (Shahbaz et al., 2014;Ali et al., 2026). Others recent studies also have employed panel econometric approaches to examine the relationship between primary energy consumption and carbon emissions (Puntoon et al., 2022; Jie & Rabnawaz, 2024; Yesbolova et al., 2024). Although these studies provide valuable estimates of statistical relationships, they do not directly address the categorization of countries into interpretable linguistic levels, such as Low, Moderate, and High, based on the combined levels of primary energy consumption and $CO_2$ emissions.

The increasing availability of environmental and electricity datasets has created a need for analytical methods that can quantify statistical associations and represent gradual differences in environmental conditions. Conventional regression models are useful for quantifying the statistical association between two variables; however, they do not directly provide a country-level categorization based on the combined levels of primary energy consumption and $CO_2$ emissions. In this study, the researchers integrating statistical analysis with fuzzy logic to assess the countries classification. Integrating statistical modeling with intelligent reasoning therefore offers a promising approach for environmental sustainability assessment (Zadeh, 1965; Anbari Moghadam et al., 2024; Hussain & Hussain, 2023). Fuzzy logic, particularly the Mamdani inference system, provides an interpretable alternative by transforming quantitative observations into linguistic categories such as Low, Moderate, and High (Lappas & Symeonidis, 2025; Jiskani et al., 2022; Karakas et al., 2023; Carrasco-Garrido et al., 2025) . Recent studies have demonstrated its application in environmental risk, sustainability, transportation, and policy assessment (Bartan et al., 2023) (Savran et al., 2024) (Şener Fidan, 2025). Previous studies have also employed fuzzy-based approaches to assess and compare countries according to multiple environmental, electricity, economic, and social indicators. For example, (Phillis et al., 2011) developed a fuzzy-based sustainability assessment model using 75 indicators to evaluate 128 countries, while Wang and Yang (2020) applied a fuzzy clustering approach to assess renewable-electricity sustainability across 27 European countries, incorporating electricity, economic, social, and environmental dimensions (Q. Wang & Yang, 2020) . These studies demonstrate the potential of fuzzy approaches to represent complex and gradual differences in sustainability conditions across countries. Like these studies, Tan et al. (2017) developed an adaptive neuro-fuzzy inference system to assess the sustainability performance of 128 countries (Tan et al., 2017) , while Muniz et al. (2024) applied a fuzzy system to construct an electricity sustainability index based on multiple electricity-related indicators in the Brazilian Amazon (Muniz et al., 2024).

Based on explanation above, this study proposes and applies a hybrid framework combining bivariate electricity–$CO_2$ regression with a data-driven Mamdani fuzzy inference system to provide transparent and reproducible country-level classification based on primary energy consumption and $CO_2$ emissions across 178 countries.

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## 2. Methods

### 2.1. Data and Analytical Framework

This study a quantitative method by combining bivariate regression and a Mamdani fuzzy inference system (FIS) to examine the relationship between primary energy consumption and $CO_2$ emissions and to classify countries based on their combined levels. Country-level data for 2022 were obtained from the International Electricity Agency (IEA), World Bank Open Data, and Our World in Data accessed on June 24, 2026. Primary energy consumption was measured in kilowatt-hours per person (kWh/person), while $CO_2$ emissions were measured in tonnes of $CO_2$ equivalent per capita (t $CO_2$e/capita). The analysis included 178 countries with complete observations for both variables.

### 2.2. Regression Analysis

The linear regression model used in this study is expressed as follows:

$$CO_2 = \beta_0 + \beta_1 EC + \varepsilon \quad (1)$$

In this equation, $CO_2$ denotes $CO_2$ emissions per capita (t $CO_2$/person), and EC represents primary energy consumption per capita (kWh/person). $\beta_0$ is the intercept, $\beta_1$ is the regression coefficient, and $\varepsilon$ is the error term. The model was used to examine the statistical association between primary energy consumption per capita and $CO_2$ emissions per capita across 178 countries. Model performance was assessed using the coefficient of determination ($R^2$) and the statistical significance of the regression coefficient.

### 2.3. Fuzzy Logic Analysis

To complement the regression analysis and represent gradual transitions between environmental conditions, a Mamdani fuzzy inference system (FIS) was employed to classify countries according to their primary energy consumption and $CO_2$ emission levels. Each input categorized into three linguistic categories such as Low, Moderate, and High. For the simple and interpretable representation of gradual transitions between linguistic categories, this study used triangular and shoulder-shaped membership functions (Pedrycz, 1994) Tekin, 2026). The rule base consisted of nine combinations of the two input variables as explained in the following section. This linguistic rule base approach adopted the Mamdani framework used in previous study (Chanapathi et al., 2019). The fuzzy rules were evaluated using the minimum operator for the logical AND condition and aggregated using the maximum operator such as used in the previous study (Barzegar et al., 2023) . A single normalized climate-impact score was then obtained by defuzzifying the aggregated fuzzy output.

## 3. Result and Discussion

### 3.1. Dataset

The final analytical dataset consists of 178 countries with observations for the two variables used in this study: primary energy consumption and per-capita $CO_2$ emissions in 2022. Primary energy consumption is measured in kilowatt-hours per person, while $CO_2$ emissions are measured in

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tonnes per person. The same 178-country sample was used for both the regression and fuzzy classification analyses to ensure consistency and comparability between the statistical and fuzzy-based results.

**Table 1.**

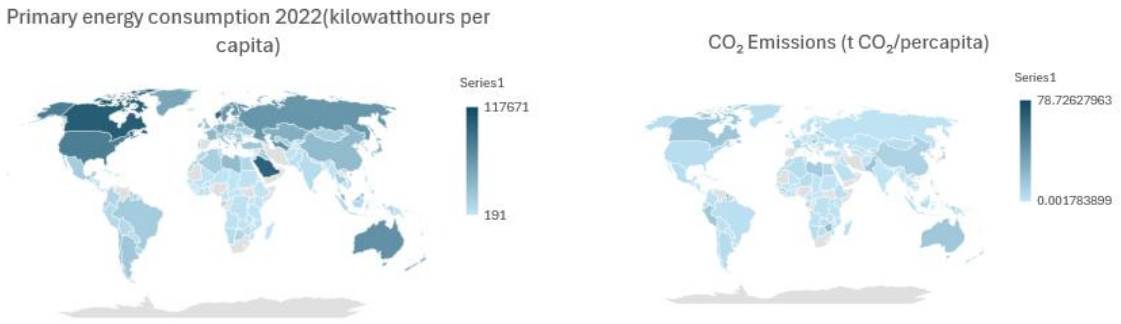
*Dataset of primary energy consumption and $CO_2$ Emissions*

| Country | Electricity (kWh/person) | $CO_2$ Emissions (t $CO_2$/person) |
|---|---|---|
| Brunei Darussalam | 117,671 | 20.9436 |
| Trinidad and Tobago | 115,685 | 0.7213 |
| Canada | 102,122 | 14.7839 |
| Kuwait | 102,111 | 5.0437 |
| Saudi Arabia | 97,903 | 1.9041 |
| … | … | … |
| Malaysia | 39,069 | 0.3867 |
| Indonesia | 9,860 | 4.4837 |
| India | 7,057 | 0.1633 |

Data were compiled from the International Electricity Agency (IEA), the World Bank Open Data platform, and Our World in Data, corresponding to 2022 and accessed between May and June 2026. After data cleaning, the final analytical dataset consisted of 178 countries with observations for primary energy consumption and per-capita $CO_2$ emissions. The same 178-country dataset was used for the regression analysis and the Mamdani fuzzy classification to ensure consistency and comparability between the two approaches.

**Figure 1.**

*Global Distribution of Primary energy consumption and $CO_2$ Emissions*




(a) Primary energy consumption (b) $CO_2$ Emissions

Figure 1 above visualizes the global distribution of primary energy consumption and $CO_2$ emissions levels.

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### 3.2. Regression Analysis

A bivariate linear regression analysis was performed to explore the relationship between the amount of electricity used per person in a country and the number of emissions per person in a country. 178 countries were analyzed using the data available. Primary energy consumption per person was used as an independent variable and was expressed in kilowatt-hours per person (kWh/person), while emissions per person were used as a dependent variable and were expressed in tons of $CO_2$ per person (t $CO_2$/person).

Pearson correlation coefficient was calculated to determine the direction and degree of linear association between two variables. The test revealed that the value of the coefficient is r = 0.0721 with a p-value of 0.3385. This suggests that the relationship between primary primary energy consumption and $CO_2$ emissions is very weak positive. However, the association was not statistically significant at 5%. In this study, the linear regression model was specified as:

$$y = \beta_0 + \beta_1 x \qquad (2)$$

where $y$ represents $CO_2$ emissions per capita (t $CO_2$/person), $x$ represents primary primary energy consumption per capita (kWh/person), $\beta_0$ is the intercept, and $\beta_1$ is the regression coefficient.

Based on the dataset, the estimated regression equation was:

$$\hat{y} = 3.9565 + 0.00002341x \qquad (3)$$

The coefficient of primary primary energy consumption was positive but statistically insignificant (p = 0.3385). This suggests that for countries with higher primary primary energy consumption per person, their emissions per person were also higher, on average, in the observed dataset. However, the very low correlation coefficient (r = 0.0721) and non-significant p-value indicate that the data do not provide enough statistical evidence of a systematic linear relationship between the two variables.

In practical terms, an increase of 1,000 kWh/person in primary energy consumption per capita is associated with an estimated increase of $0.00002341 \times 1{,}000 = 0.02341\ t\ CO_2$. Thus, an increase in 1,000 kWh/person in primary energy consumption per capita is associated with an approximate increase of 0.02341t $CO_2$/person in the observed data set. One must interpret this finding as an association and not a causal relationship, since the model only contains one explanatory variable and does not account for other variables that could affect the level of $CO_2$ per capita.

The coefficient of determination was ($R^2$ = 0.0052), while the adjusted coefficient of determination was (-0.0005). Thus, primary energy consumption per capita alone explains approximately 0.52% of the variation in $CO_2$ emissions per capita, among the 178 countries. The negative adjusted $R^2$ implies that the model provides almost no explanatory improvement, compared with a model that contains only the intercept.

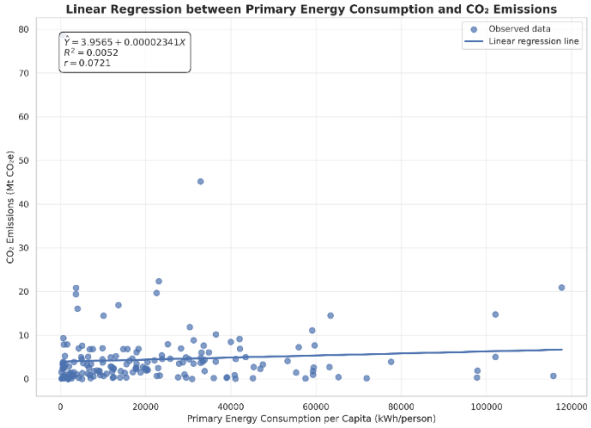
The low explanatory power suggests that primary energy consumption per capita alone is not enough to explain the variation of $CO_2$ emissions per capita, among the 178 countries. $CO_2$

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emissions per capita can also be affected by other factors including energy mix, reliance on fossil fuels, industrial structure, economic activity, energy efficiency, and technological conditions. Therefore, different levels in primary energy consumption per capita do not necessarily correspond to proportional changes in $CO_2$ emissions per capita, across countries. The following Figure 2 presents the scatter plot of primary energy consumption per capita against $CO_2$ emissions per capita, together with the fitted linear regression line.

**Figure 2.**

*Linear Relationship between Primary energy consumption per Capita and $CO_2$ Emissions per Capita*




As can be seen from Figure 2, most of the points are far from the fitted regression line with a slight positive slope. Thus, it can be concluded that there is a very weak positive correlation ($r = 0.0721$) and, consequently, a low coefficient of determination ($R^2 = 0.0052$) for the given variables, which implies the weak linear relationship between them over 178 countries.

### 3.3 Fuzzification

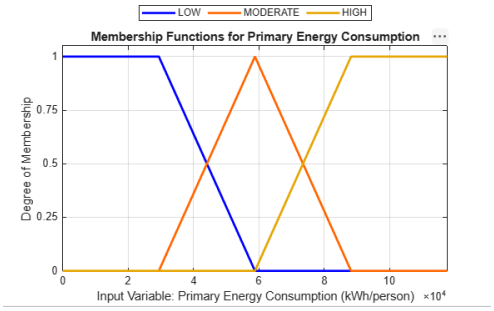
Fuzzification transforms crisp numerical values into linguistic categories by assigning each input value a degree of membership between 0 and 1. In this study, primary energy consumption and $CO_2$ emissions are represented using three linguistic categories: Low, Moderate, and High. Triangular and shoulder-shaped membership functions are used to represent gradual transitions between adjacent categories. This overlapping structure allows a country to partially belong to more than one linguistic category, which is appropriate for representing gradual differences in primary energy consumption and $CO_2$ emissions (Mahi et al., 2025). Following the distribution of data, the fuzzy membership functions are designed based on the range of input variables. This approach is consistent with previous studies that recommend using the empirical distribution of observed data to inform the parameterization of fuzzy membership functions rather than relying

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solely on subjective thresholds (T. Wang et al., 2026). The resulting membership functions for primary energy consumption are defined as follows.

**Figure 3.**

*Membership Function of Primary energy consumption*




The membership functions for primary energy consumption are defined as follows (Eqs. 4–6):

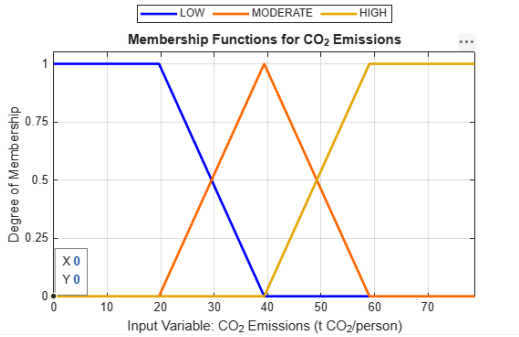
$$\mu_{EC,\text{low}}(x) = \begin{cases} 1, & 0 \le x \le 29417.75, \\ \frac{58835.50 - x}{29417.75}, & 29417.75 < x \le 58835.50, \\ 0, & x > 58835.50. \end{cases} \quad (4)$$

$$\mu_{EC,\text{moderate}}(x) = \begin{cases} 0, & x \le 29417.75, \\ \frac{x - 29417.75}{29417.75}, & 29417.75 < x \le 58835.50, \\ \frac{88253.25 - x}{29417.75}, & 58835.50 < x < 88253.25, \\ 0, & x \ge 88253.25. \end{cases} \quad (5)$$

$$\mu_{EC,\text{high}}(x) = \begin{cases} 0, & x \le 58835.50, \\ \frac{x - 58835.50}{29417.75}, & 58835.50 < x \le 88253.25, \\ 1, & 88253.25 < x \le 117671. \end{cases} \quad (6)$$

**Figure 4.**

*Membership Function of $CO_2$ Emissions*




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The membership functions for CO2 emissions are defined as follows (Eqs. 7–9):

$$\mu_{CO_2,\text{low}}(x) = \begin{cases} 1, & 0 \le x \le 19.6815, \\ \frac{39.363-x}{19.6815}, & 19.6815 < x \le 39.363, \\ 0, & x > 39.363. \end{cases} \quad (7)$$

$$\mu_{CO_2,\text{moderate}}(x) = \begin{cases} 0, & x \le 19.6815, \\ \frac{x-19.6815}{19.6815}, & 19.6815 < x \le 39.363, \\ \frac{59.0445-x}{19.6815}, & 39.363 < x < 59.0445, \\ 0, & x \ge 59.0445. \end{cases} \quad (8)$$

$$\mu_{CO_2,\text{high}}(x) = \begin{cases} 0, & x \le 39.363, \\ \frac{x-39.363}{19.6815}, & 39.363 < x \le 59.0445, \\ 1, & 59.0445 < x \le 78.726. \end{cases} \quad (9)$$

For each linguistic categories such as low, moderate and high, the primary energy consumption and $CO_2$ emissions a membership degree ranging from 0 to 1. These membership degrees are subsequently used as fuzzy values to determine the corresponding climate impact category.

### 3.4. Inference

The Mamdani inference process uses the degree of membership of primary energy consumption and $CO_2$ emissions to estimate the fuzzy climate impact. The rule base comprises two antecedents connected by an AND operator and one consequent, which represents the Climate Impact category. The rule's firing strength is estimated by using the minimum operator. The complete rules listed in the following table.

**Table 1.**

*Fuzzy Rules for Climate Impact Classification*

| Rule | Primary energy consumption | $CO_2$ Emission | Climate Impact |
|---|---|---|---|
| R1 | Low | Low | Low |
| R2 | Low | Moderate | Moderate |
| R3 | Low | High | High |
| R4 | Moderate | Low | Moderate |
| R5 | Moderate | Moderate | Moderate |

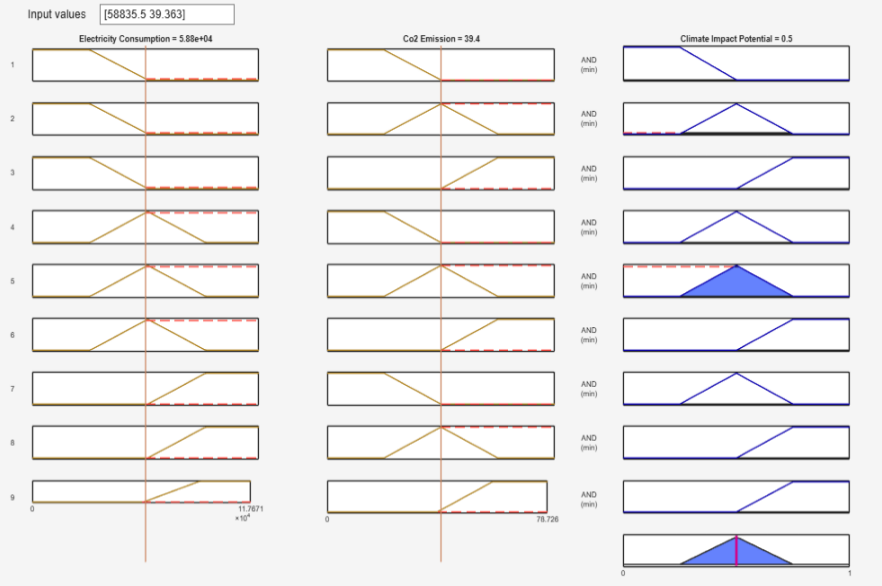
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| | | | |
|---|---|---|---|
| R6 | Moderate | High | High |
| R7 | High | Low | Moderate |
| R8 | High | Moderate | High |
| R9 | High | High | High |

The nine rules define all possible combinations of the three linguistic categories of electricity use and $CO_2$ emissions. The outputs of the firing rules are then aggregated to obtain the fuzzy Climate impact output, which is then de-fuzzified using the centroid method to get a crisp value. To demonstrate the use of the Mamdani inference rules, **Figure 5** below shows an example of the inference process using one combination of primary energy consumption and $CO_2$ emissions.

**Figure 5.**

*Example of Mamdani Fuzzy Inference for Climate Impact Assessment*




As can be seen from Figure 5, for the given primary energy consumption and $CO_2$ emission values several rules are triggered with different degrees of activation. These rules are then combined to form the aggregated fuzzy Climate Impact output. The overall behavior of the Mamdani inference system is further illustrated by the three-dimensional inference surface in Figure 6.

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**Figure 6.**

*Mamdani Fuzzy Inference Surface for Climate Impact*

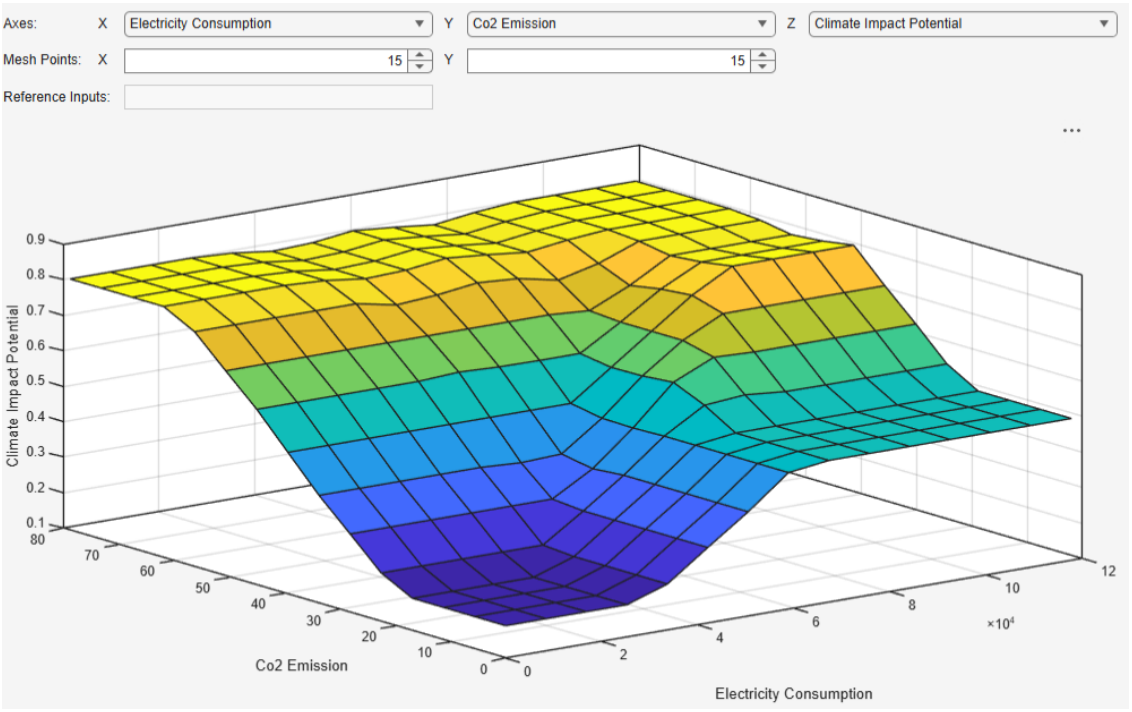



Figure 6 presents the behavior of the Mamdani fuzzy inference system for all possible input data concerning the primary energy consumption and the emissions of carbon dioxide. The output value of the Climate impact increases gradually from low to high input values, while the intermediate values are responsible for the transitional Climate impact values. That is why the Climate impact surface reflects the fuzzy rule base, which is the basis for the fuzzy inference system and forms a continuous output variable before its defuzzification.

### 3.5. Defuzzification

Defuzzification processes use the centroid approach to convert the outcome to a crisp value such as represented in the previous study (Saragih et al., 2026) . The output variable is Climate Impact which is categorized into three linguistic terms: Low, Moderate, and High, represented by center values numbers: 20; 50; 80, respectively. The following Figure 7 represents the membership function of Climate Impact.

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**Figure 7.**

*Membership Function of Climate Impact*

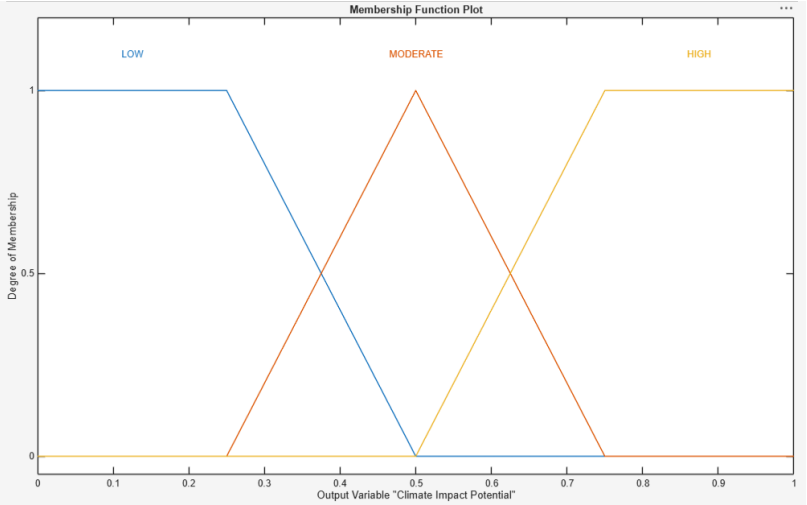



Figure 7 shows the membership functions of the Climate Impact output variable for the three linguistic categories. These membership functions are used to represent the fuzzy output before the defuzzification process. The defuzzification is performed using the centroid method:

$$z^* = \frac{\sum \alpha_i \, z_i}{\sum \alpha_i} \tag{4}$$

where $z_i$ represents the representative value of each output fuzzy set. The following Table 2 presents the defuzzification results for representative countries.

**Table 2.**

*Defuzzification Results of Climate Impact*

| Country | μlow | μmod | μhigh | z* | Category |
|---|---|---|---|---|---|
| Algeria | 0 | 0 | 0.8034 | 80.00 | High |
| Antigua and Barbuda | 0 | 0 | 0.7553 | 80.00 | High |
| Argentina | 0 | 0 | 0.7545 | 80.00 | High |
| Australia | 0 | 0 | 1.0 | 80.00 | High |
| Armenia | 0.38 | 0.65 | 0.34 | 49.23 | Moderate |
| … | … | … | … | … | … |
| Afghanistan | 1.0 | 0 | 0 | 20.00 | Low |
| Angola | 1.0 | 0 | 0 | 20.00 | Low |
| Bangladesh | 1.0 | 0 | 0 | 20.00 | Low |
| Benin | 1.0 | 0 | 0 | 20.00 | Low |

Based on the results above, the regression analysis shows a very weak positive correlation between primary energy consumption per capita and $CO_2$ emissions per capita across the 178 countries.

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Pearson's correlation coefficient was r = 0.0721 with a p-value of 0.3385, indicating that the relationship was not statistically significant. The regression model also produced $R^2 = 0.0052$ and an adjusted -0.0005, meaning that primary energy consumption per capita explained only about 0.52% of the variation in $CO_2$ emissions per capita. This low explanatory power may be related to differences in energy sources, economic structure, level of economic development, energy efficiency, and other factors that affect $CO_2$ emissions. Therefore, primary energy consumption per capita alone does not provide a strong explanation of differences in $CO_2$ emissions per capita across the 178 countries.

The Mamdani fuzzy classification complements the regression analysis by evaluating the combined levels of energy consumption and $CO_2$ emissions. Among the 178 countries, 96 (53.9%) were classified as High, 27 (15.2%) as Moderate, and 55 (30.9%) as Low. The predominance of the High category reflects the combined membership values of the two input variables under the applied fuzzy rules. However, the classification should be interpreted specifically as an energy–$CO_2$-based environmental impact classification, rather than as a comprehensive assessment of climate or environmental performance.

Overall, the regression and fuzzy approaches provide complementary information. Regression describes the statistical association between energy consumption and total $CO_2$ emissions, whereas the Mamdani system provides an interpretable classification based on their combined levels. Future research could incorporate additional environmental and socioeconomic indicators and validate the fuzzy rules using empirical data or expert knowledge to improve the robustness of the classification.

## 4. Conclusion

The proposed framework demonstrates that regression and fuzzy inference can provide complementary perspectives on cross-country energy and $CO_2$ patterns. However, the analysis is limited to two indicators and a single cross-sectional year. Future research could incorporate additional environmental and socioeconomic variables and further validate the fuzzy rules using empirical evidence or expert knowledge to improve the robustness and comprehensiveness of the classification framework.

## 5. Acknowledgments

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